USE OF WEB PAGE CREDIBILITY INFORMATION IN INCREASING THE ACCURACY OF WEB-BASED QUESTION ANSWERING SYSTEMS

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ABSTRACT

Question Answering (QA) systems offer an efficient way of providing precise answers to questions asked in natural language. In the case of Web-based QA system, the answers are extracted from information sources such as Web pages. These Web-based QA systems are effective in finding relevant Web pages but either they do not evaluate credibility of Web pages or they evaluate only two to three out of seven credibility categories. Unfortunately, a lot of information available over the Web is biased, false and fabricated. Extracting answers from such Web pages leads to incorrect answers, thus decreasing the accuracy of Web-based QA systems and other system relying on Web pages. Most of the previous and recent studies on Web-based QA systems focus primarily on improving Natural Language Processing and Information Retrieval techniques for scoring answers, without conducting credibility assessment of Web pages.

This research proposes a credibility assessment algorithm for evaluating Web pages and using their credibility score for ranking answers in Web-based QA systems. The proposed credibility assessment algorithm uses seven categories for scoring credibility, including correctness, authority, currency, professionalism, popularity, impartiality and quality, where each category consists of one or more credibility factors. This research attempts to improve accuracy in Web-based QA systems by developing a prototype Web-based QA system, named Optimal Methods QA (OMQA) system, which uses methods producing highest accuracy of answers, and improving the same by adding a credibility assessment module, called Credibility-based OMQA (CredOMQA) system. Both OMQA and CredOMQA systems have been evaluated with respect to accuracy of answers, using two quantitative evaluation metrics: 1) Percentage of queries correctly answered and 2) Mean Reciprocal Rank evaluation metrics. Extensive quantitative experiments and analyses have been conducted on 211 factoid questions taken from TREC QA track from

1999, 2000 and 2011 and a random sample of 21 questions from CLEF QA track for comparison and conclusions.

Results from methods and techniques evaluation show that some techniques improved accuracy of answers retrieved more than others performing the same function. In some cases, combination of different techniques produced higher accuracy of answers retrieved than using them individually.

The inclusion of Web pages credibility score significantly improved accuracy of the system. Among the seven credibility categories, four categories including correctness, professionalism, impartiality and quality had a major impact on accuracy of answer, whereas authority, currency and popularity played a minor role. The results conclusively establish that proposed CredOMQA performs better than other Web-based QA systems. Not only that, it also outperforms other credibility-based QA systems, which employ credibility assessment partially.

It is expected that these results will help researchers/experts in selecting Web-based QA methods and techniques producing higher accuracy of answers retrieved, and evaluate credibility of sources using credibility assessment module to improve accuracy of existing and future information systems. The proposed algorithm can also help in designing credibility-based information systems in the areas of education, health, stocks, networking and media, requiring accurate and credible information, and would help enforce new Web-publishing standards, thus enhancing overall Web experience.

ABSTRAK

Sistem soal jawab (QA) menawarkan cara yang cekap untuk memberikan jawapan yang tepat kepada soalan-soalan yang ditanya dalam bahasa asli. Dalam kes sistem QA berasaskan Web, jawapan diambil daripada sumber-sumber maklumat seperti laman Web. Sistem QA berasaskan Web ini berkesan dalam mencari laman Web yang berkaitan tetapi tidak menilai kredibiliti laman Web tersebut atau hanya menilai dua hingga tiga daripada tujuh kategori kredibiliti. Malangnya, kebanyakan maklumat yang disediakan melalui laman Web adalah berat sebelah, palsu dan fabrikasi. Pengekstrakan jawapan dari sistem QA berasaskan Web tersebut menunjukan jawapan yang kurang tepat, sejurusnya mengurangkan ketepatan sistem QA berasaskan Web dan sistem lain yang bergantung kepada laman Web. Kebanyakan kajian sistem QA berasaskan Web yang lepas dan yang terbaru pada asasnya tertumpu dalam memperbaiki teknik pemprosesan bahasa asli dan teknik capaian maklumat untuk pemarkahan jawapan, tanpa membuat penilaian kredibiliti laman Web.

Kajian ini mencadangkan satu algorithm penilaian kredibiliti untuk menilai laman Web dan menggunakan skor kredibiliti untuk kedudukan jawapan dalam sistem QA berasaskan Web. Model penilaian kredibiliti yang dicadangkan menggunakan tujuh kategori untuk menjaringkan kredibiliti, termasuk ketepatan, kuasa, mata wang, profesionalisme, popularitи, kesaksamaan dan kualiti, di mana setiap kategori terdiri daripada satu atau lebih faktor kredibiliti. Kajian ini cuba meningkatkan ketepatan dalam sistem QA berasaskan Web dengan membangunkan prototaip sistem QA berasaskan Web yang dinamakan Optimal Methods QA (OMQA), yang menggunakan kaedah menghasilkan ketepatan tertinggi jawapan, dan meningkatkannya dengan penambahan penilaian modul kredibiliti, yang dipanggil sistem Credibility-based OMQA (CredOMQA). Kedua-dua sistem OMQA dan CredOMQA telah dinilai dari segi ketepatan jawapan, menggunakan dua metrik penilaian kuantitatif: 1) Peratusan

pertanyaan yang dijawab dengan betul dan 2) metrik penilaian Mean Reciprocal Rank. Eksperimen kuantitatif dan analisis yang meluas telah dijalankan ke atas 211 soalan factoid dari trek TREC QA tahun 1999, 2000 dan 2011 dan sampel rawak 21 soalan daripada trek CLEF QA untuk perbandingan dan kesimpulan.

Hasil daripada kaedah dan teknik penilaian menunjukkan bahawa beberapa teknik meningkatkan ketepatan jawapan lebih daripada teknik lain yang melaksanakan fungsi yang sama. Dalam beberapa kes, gabungan teknik yang berbeza menghasilkan ketepatan jawapan yang lebih tinggi daripada menggunakan mereka secara individu.

Kemasukan kredibiliti skor laman Web meningkatkan ketepatan sistem dengan ketara. Antara tujuh kategori kredibiliti, lima kategori termasuk ketepatan, profesionalisme, kesaksamaan dan kualiti mempunyai kesan yang besar kepada ketepatan jawapan, manakala kuasa, popularitи dan mata wang memainkan peranan yang kecil. Keputusan muktamad membuktikan bahawa cadangan CredOMQA lebih berkesan daripada sistem QA berasaskan Web yang lain. Bukan sekadar itu, ia juga mengatasi sistem QA berdasarkan kredibiliti yang menggunakan sebahagian penilaian kredibiliti.

Ia dijangka bahawa keputusan ini akan membantu penyelidik/pakar-pakar dalam memilih kaedah QA berasaskan Web dan teknik menghasilkan ketepatan yang lebih tinggi dalam pengekstrakan jawapan, dan menilai kredibiliti sumber menggunakan algorithm penilaian kredibiliti untuk meningkatkan ketepatan yang sedia ada dan sistem maklumat kelak.

Model yang dicadangkan juga boleh membantu dalam merekabentuk sistem maklumat berasaskan kredibiliti termasuk bidang pendidikan, kesihatan, saham, rangkaian dan media, yang memerlukan maklumat yang tepat serta boleh dipercayai, dan membantu

menguatkuasakan piawaian Web-penerbitan baharu, sekali gus meningkatkan keseluruhan pengalaman Web.

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LIST OF SYMBOLS AND ABBREVIATIONS

API	:	Application Programming Interface
OMQA	:	Optimal Methods Question Answering
CredOMQA	:	Credibility-based Optimal Methods Question Answering
CSCL	:	Computer-Supported Collaborative Learning
IE	:	Information Extraction
IR	:	Information Retrieval
MRR	:	Mean Reciprocal Rank
NLP	:	Natural Language Processing
POS		Parts-Of-Speech
PerCorrect	:	Percentage of queries Correctly answered
QA	:	Question Answering
SEO	:	Search Engine Optimization
SNS	:	Social Networking Services
SWoRD	:	Scaffolded Writing and Rewriting in the Discipline
TF-IDF	:	Term Frequency Inverse Document Frequency
TREC	:	Text Retrieval Conference
WoT	:	Web of Trust

CHAPTER 1: INTRODUCTION

Question answering (QA) is a sophisticated form of information retrieval (IR) system characterized by information needs, where the information is partially expressed in natural language statements or questions (Hirschman & Gaizauskas, 2001). This makes it one of the most natural ways for humans to communicate with computers. Since QA systems involve natural language communication between computers and users, it has been the center of interest for natural language processing (NLP), IR and machine learning communities (McCallum, 2005). Requirements in QA are quite complex as compared with IR, because in IR complete documents are considered relevant to user's query, whereas in QA, only specific portions of information within the documents are returned as answers. A user in QA system is only interested in concise, comprehensible and correct answer, which may be in the form of an image, video, text, etc. (Gupta & Gupta, 2012; Kolomiyets & Moens, 2011).

Work on QA was initiated decades ago, with research ranging from natural language processing to data access or knowledge bases. These technologies are undergoing a process of resurgence, primarily due to popularity of Web which provides publicly available multimedia data (Kolomiyets & Moens, 2011). The growing power of querying in the context of multimedia data such as images, video, text or audio, with natural language expressions, and drawing conclusions from relevant content in text or any other media is gaining importance day by day.

Web has grown into one of the largest information repositories, making it the primary source of information for most users. It also has become a familiar way of acquiring and sharing information that also allows users to contribute and express themselves (Ward, 2006). CISCO (2016) Visual Networking Index Report suggests that, by 2017, there will be about 3.6 billion Internet users, i.e., more than 48% of the world's projected population

(7.6 billion). Continuous growth and popularity of Web is a result of its ease of access and low publication cost. Before the advent of the Web, the cost of information production was high and its distribution was limited, thus only people and institutions with authority or funds could benefit from them (Flanagin & Metzger, 2008). This is not the case in digital environment where content can be published on the Internet easily by any author without any restriction (Johnson & Kaye, 2000; Rieh & Danielson, 2007; Subramaniam et al., 2015). Now users can publish individual or collective knowledge that may involve experienced or inexperienced novices (Castillo, Mendoza, & Poblete, 2011; Morris, Counts, Roseway, Hoff, & Schwarz, 2012).

In order to find information on the Web, users increasingly rely on search engines to find desired information making it one of the most used services on the Internet today (Purcell, 2011). According to ComScore (2016) Search Engine Ranking Report of February 2016, users conducted 16.8 billion explicit core searches with Google sites, ranking first with 10.8 billion occupying 63.8% of explicit core searches. User requests information, expressed in the form of queries, were related to research, shopping and entertainment (Markham, 1998). Current search engines return a long list of potentially relevant documents without pinpointing the desired result. Thus in order to find answers, users select documents which seems more reliable based on their own assessment (Lankes, 2008; Westerwick, 2013).

The popularity of the Web has given rise to Web-based QA systems, which take advantage of data available over the Web and use it as information source for extraction of answers. Web-based search engines use search engines like Google, Yahoo, Bing, etc., to fetch relevant Web pages that potentially contain answer to the question asked (Gupta & Gupta, 2012). They are effective in providing concise answers to the questions asked, saving users the trouble of going through each search result.

1.1 Motivation

Though information available over the Web is substantial, yet it is often unreliable (Fogg et al., 2001b; Nakamura et al., 2007; Popat, Mukherjee, Strötgen, & Weikum, 2017; Tanaka et al., 2010a; Wu & Marian, 2011). Several studies claim that 20% of the Web pages on the internet are fake, spreading misinformation among Web users (Abbasi & Hsinchun, 2009; Abbasi, Zhang, Zimbra, Chen, & Nunamaker Jr, 2010; Aggarwal, Van Oostendorp, Reddy, & Indurkhya, 2014b; Chatterjee & Agarwal, 2016; Gyongi & Garcia-Molina, 2005; Popat et al., 2017). Fraud and deception is quite common in electronic market, affecting thousands of Web users every day (Abdallah, Maarof, & Zainal, 2016; Chua & Wareham, 2004; Gavish & Tucci, 2008). According to studies conducted by World Health Organization, thousands of deaths have been attributed to fake medical Web sites, while the number of people visiting such sites continues to rise each day (Abbasi, Fatemeh, Mariam, Zahedi, & Kaza, 2012; Easton, 2007); needless to say that trust and security is extremely important for such Websites, (Abbasi et al., 2012; Song & Zahedi, 2007).

Users take search engines for granted, which often provide them the information they need, but the truth of the matter is that they are only point information, without verifying the credibility or correctness of the source (Sullivan, 2002; Wu & Marian, 2011). Instead, search results are ranked on the basis of factors like advertising and search engine optimization (SEO) (Lohr, 2006; Tanaka, 2010). Though search engines identify the answers from Web sources, yet they lack credibility because they contain erroneous, misleading, biased and outdated information (Olteanu, Peshterliev, Liu, & Aberer, 2013a; Wu & Marian, 2011). This adversely affects the reliability of Web-based QA systems, which rely on search engines for answer extraction.

Unfortunately, most users consider results returned by search engines and content available on the Web as credible (Go, You, Jung, & Shim, 2016; Kakol, Nielek, & Wierzbicki, 2017; Lu, Yu, & Chen, 2017; Yamamoto & Shimada, 2016). According to one survey, two-thirds of the American population consider search engine result as "fair and un-biased" (Fallows, 2005). In the absence of search result credibility scores, it can be very difficult for a person to verify the correctness of information given without any prior knowledge (Giles, 2005; Miller, 2005). The same principle is true for computers, which require semantic data in order to understand the content given (Allemang & Hendler, 2011; Berners-Lee, Hendler, & Lassila, 2001; Weare & Lin, 2000).

Credibility of news on the internet is also a major concern as social media, blogs and Websites are being to spread false news and rumours (Aggarwal et al., 2014b; Allcott & Gentzkow, 2017; Popat et al., 2017). This has been observed during major events including the 2010 earthquake in Chile (Mendoza, Poblete, & Castillo, 2010), the Hurricane Sandy in 2012 (Gupta, Lamba, Kumaraguru, & Joshi, 2013b) and the Boston Marathon blast in 2013 (Gupta, Lamba, & Kumaraguru, 2013a). Fake news or rumours spread quickly on social media platforms like Facebook and Twitter, which can affect thousands of people (Sela, Milo-Cohen, Ben-Gal, & Kagan, 2017). Thus, evaluating credibility of information provided by Websites, social media platforms, and blogs is of utmost importance (Aggarwal et al., 2014b; Chatterjee & Agarwal, 2016; Gupta, Kumaraguru, Castillo, & Meier, 2014; Popat et al., 2017).

In order to verify correctness of information, the user has to rummage through a number of Websites for cross-checking its credibility (Li et al., 2016; Liu, Dong, Ooi, & Srivastava, 2011; Wu & Marian, 2011). In most cases, users are not satisfied with results from a single Web page, and prefer cross-checking more pages to corroborate evidence, thus spending more time to ascertain correctness of an answer (Wu & Marian, 2011,

2014). To illustrate this problem consider Figure 1.1 showing a list of search results for the query "first orbited the Earth", where each result shows a different answer. The correct answer, Yuri Gagarin, does not appear in the first result. Additionally, there are several pages which do not contain any answer at all.

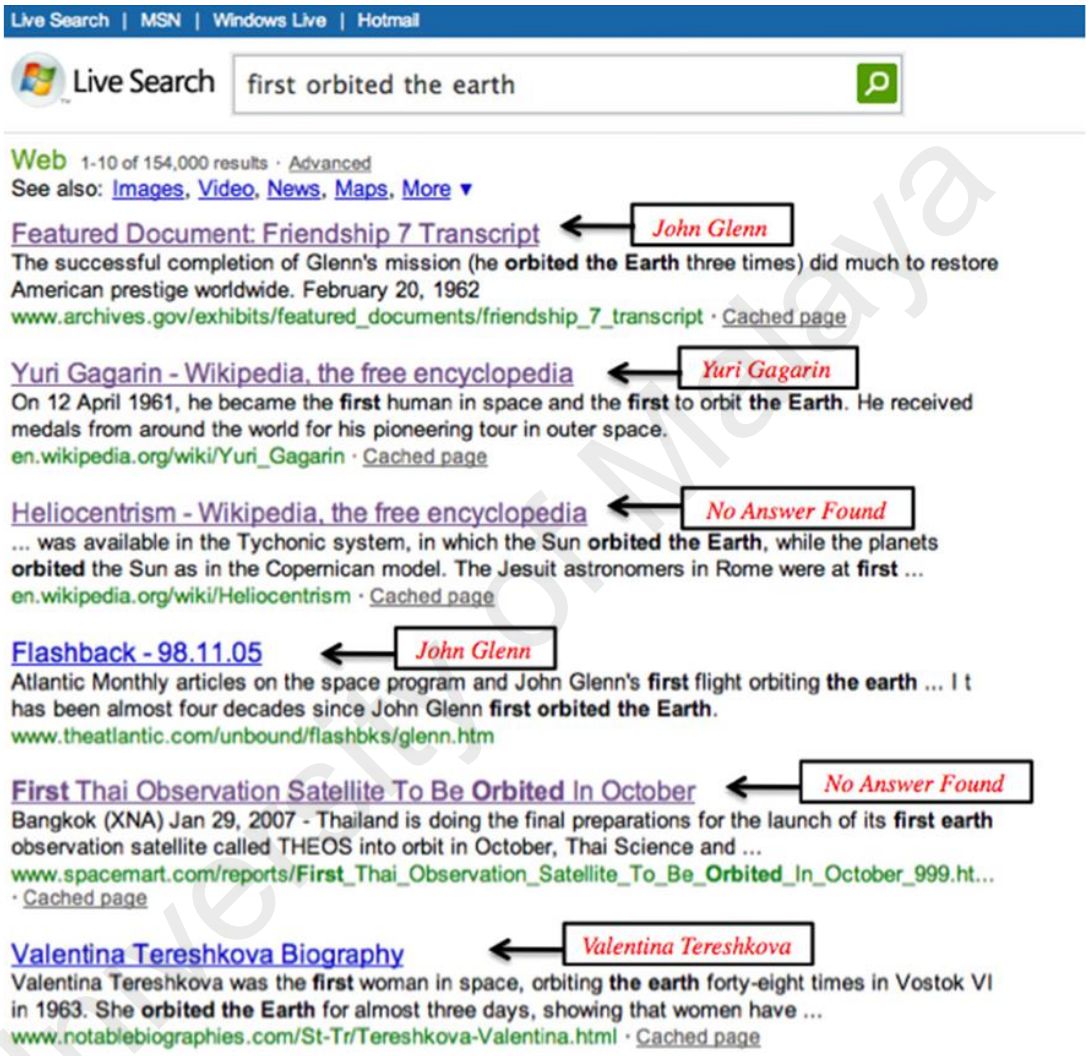


Figure 1.1: Results for the query ''first orbited the earth'' using MSN search (Wu & Marian, 2011)

A naive solution to solving this problem would be to aggregate answers found on multiple Websites, which may help in eliminating typos and help in promoting the frequent answer. However, this solution fails to consider the fact that answers extracted from different Web pages are not equal, as some Web pages are more credible than others (Wu & Marian, 2011). Scammers or spammers take advantage of such systems, which

rely on redundancy of answers for verification, by creating multiple copies of Web pages having incorrect answer, thus jeopardizing the outcome (Wu & Marian, 2011). Therefore, there is a need to rate Web pages based on their credibility and rank the answers accordingly.

Most Web users are neither capable of performing credibility assessment nor do they wish to undertake this exercise due to time constraint, motivation and convenience (Amin, Zhang, Cramer, Hardman, & Evers, 2009; Amsbary & Powell, 2003; Metzger, Flanagin, & Zwarun, 2003; Walraven, Brand-Gruwel, & Boshuizen, 2009). Without the support of credibility assessment naïve Web users, such as schoolchildren, can be misled easily with non-credible content, which is why educators consider it a topic of utmost importance and term it as one of the major "new media literacies" for students, and regards credibility assessment "the ability to evaluate the reliability and credibility of different information sources" being an essential part of the process (Jenkins, Purushotma, Weigel, Clinton, & Robison, 2009; Metzger et al., 2003). Table 1.1 lists different scenarios, indicating how lack of credibility assessment can cause inconvenience and some cases severe consequences to users.

Table 1.1: Possible consequences that affect users due to lack of credibility assessment

No.	User	Scenario	Consequences
1.	Ill person	The user is ill and decides to seek medical advice via the Web. The user does not check the credibility of the Website and follows the diagnosis mentioned.	Following the wrong diagnosis may worsen the condition or require serious medical attention.
2.	Media analyst	The user is searching for news material on an upcoming smart phone. This user will be required to differentiate between rumours and facts posted on different Websites.	The user may take content from a website which has posted rumours only and has not provided any sources.

Table 1.1 continued			
3.	Student	The user looking for an answer to the question "Who is the richest man in the world?"	The results return might be inaccurate and outdated depending upon how regularly the Websites are updated.

It is clear that users require guidance in credibility assessment, either in the form of training or tools for generating Web credibility score. Relying on information editors or professional gatekeepers for credibility assessment is ideal but not practical as new content on the Web is added at an alarming rate making it impossible to evaluate the available content (Flanagin & Metzger, 2007; Fletcher, Schifferes, & Thurman, 2017; Harris, 2008; Karlsson, Clerwall, & Nord, 2017; Metzger, 2007). Research shows students achieving better results by producing higher quality document when using credibility assessment tools for conducting assignments (Walraven et al., 2009; Walraven, Brand-Gruwel, & Boshuizen, 2013). Providing credibility assessment support not only brings confidence among users but also allows them to gain experience in evaluating credibility (Bråten, Strømsø, & Britt, 2009; List, Alexander, & Stephens, 2017; Metzger & Hall, 2005). This is why automated credibility assessment tools are becoming increasingly popular to help users in evaluating Web content (Tanaka et al., 2010b).

This has been the primary motivation of this research which suggests a credibility-based Web QA system that is capable of evaluating Web pages and scoring answers based on credibility. Web-based QA solutions such as Qualifier (Yang & Chua, 2003) and LAMP (Zhang & Lee, 2003), only focus on improving answer accuracy by enhancing existing methods and techniques. These systems are not ideal in addressing the issues as they provide only the popular answers, which may or may not be correct. Though some

Web-based systems, like Corrob and Watson, do include some credibility factors for evaluating Web sources, yet their systems do not include a dedicated credibility assessment module (Ferrucci et al., 2010; Wu & Marian, 2011). There are two major reasons behind the limitations of Web-based QA systems including 1) use of less optimal methods and techniques, and 2) not considering credibility of sources (Oh, Yoon, & Kim, 2013; Wu & Marian, 2011). These limitations affect Web-QA systems in a negative way by lowering accuracy of answers generated (Oh et al., 2013; Wu & Marian, 2011). The limitations in methods and techniques, and credibility assessment in Web-based QA systems is discussed briefly in Section 1.1.1 and 1.1.2.

1.1.1 Web-based QA systems methods and techniques

QA systems go through a series of steps in order to prepare the answer for the question queried. A typical QA system goes through four modules including question analysis, answer extraction, answer scoring and answer aggregation in order to prepare the answer to the question given, which are discussed in greater detail in literature review (Bouziane, Bouchiha, Doumi, & Malki, 2015; Gupta & Gupta, 2012). These kinds of systems consist of several methods in order to make this possible, each achieving a certain objective. With respect to QA systems, the term "method" refers to "an interesting or important part, quality and ability," whereas, "technique" refers to "a way of doing something" (Allam & Haggag, 2012; Bouziane et al., 2015; Kolomiyets & Moens, 2011). The "method" identifies one of the steps taken in order to accomplish a goal, while "technique" is the algorithm chosen for accomplishing it (Allam & Haggag, 2012; Bouziane et al., 2015; Kolomiyets & Moens, 2011). For example, string matching is a method of QA systems and its goal to merge two strings, which can be accomplished by using the cosine similarity or dice coefficient techniques (Wu & Marian, 2011). The "accuracy" shows capability of the system in returning correct answer to the question asked (Wu & Marian, 2011).

There has been substantial research on Web-based QA systems, and researchers have provided novel techniques for providing answers to the questions queried in different stages (Allam & Haggag, 2012; Bouziane et al., 2015; Gupta & Gupta, 2012; Kolomiyets & Moens, 2011; Srba & Bielikova, 2016; Wang et al., 2017). However, the material on method comparison with respect to answer accuracy is very limited. Research on comparison of methods and techniques will save researchers time in selecting the optimal option available without investing their time and effort in evaluating them.

When developing a QA system one tends to ask which set of methods should one choose from the rest. Generally it falls to the platform on which the QA system is being developed and therefore only the methods that are available are chosen. On the other hand, when having multiple options to choose from, it can become quite difficult to select one over the other (Bouziane et al., 2015; Wu & Marian, 2011). Therefore, it is necessary to evaluate the methods and techniques available and select the ones performing better than others in order to produce optimal answer accuracy.

1.1.2 Credibility assessment

Credibility is defined as "the quality or power of inspiring belief", representing a characteristic of a resource that highlights its expertise and trustworthiness (Fogg & Tseng, 1999a; Merriam-Webster Inc, 2003). When it comes to credible Web pages, it means that the Web page is trustworthy and the content provided it is of high quality and accurate. Schwarz and Morris (2011a) define a credible Web page as one "whose information one can accept as the truth without needing to look elsewhere. If one can accept information on a page as true at face value, then the page is credible; if one needs to go elsewhere to check the validity of the information on the page, then it is less credible". Credibility of a resource can be judged using credibility factors and credibility categories they belong to.

Credibility factors are the characteristics of a resource like content updated date, author details, content quality, etc. that are used to determine whether the resource is credible or not (Aggarwal et al., 2014b; Lu et al., 2017; Schwarz & Morris, 2011b). However, one cannot create a well-balanced credibility score by simply including a number of credibility factors. Instead, the factors should cover various aspects that define credibility, also called as credibility categories, as high credible site should achieve good scores in all credibility categories. A credibility category is an aspect of credibility such as trustworthiness, expertise, correctness, quality, etc., which contributes towards credibility following a certain theme determined by credibility factors relevant to it (Flanagin & Metzger, 2007; Fogg & Tseng, 1999a; Yamamoto & Tanaka, 2011a).

These credibility categories and their respective factors are essential in credibility assessment. In the case a user wants to find about the world's tallest man, he should only look into sources having the most updated content. Similarly, if the users wants to find answer to controversial topics such as whether Pluto is a planet, he should follow the verdict given by an authorized organization such as International Astronomical Union (Rincon, 2016).

By measuring credibility of a Web page, computer systems can determine whether the information provided is correct based on its credibility rating. A Web page earning a higher credibility score should be trusted more, and the answers found on it should accordingly be rated higher. This research endeavor to look into appropriate credibility categories for scoring Web pages, and credibility factors under each category to score them. This requires identification of credibility factors from literature and mapping onto credibility categories.

1.2 Research questions

The answers produced by Web-based QA systems are doubtful because they may have been extracted from Web pages containing fake answers. There are two key problems in the current Web-QA systems including 1) Web-based QA systems using methods and techniques producing lower accuracy of answers retrieved than others (as highlighted in section 1.1.1 and section 2.1), and 2) Web-based QA systems lacking a credibility assessment module to allow it evaluate credibility of Web pages (as highlighted in section 1.1.2, section 2.2 and section 2.3).

Based on the problems highlighted above, this research aims at improving answer accuracy in Web-based QA, taking into account credibility of the Web pages, from which answers are taken from.

Based on the motivation of this research, several research questions are required to be answered, in order to determine the methodology that may guide all stages of inquiry, analysis, and reporting. Therefore, this research aims to explore the following research questions:

RQ 1) How can credibility of Web pages be measured using credibility factors?

RQ 2) What combination(s) of methods and techniques, and credibility categories improve answer accuracy?

RQ 3) Does considering credibility in answer scoring help in increasing its answer accuracy?

1.3 Research objectives

Research objectives allows the research to list the steps needed to be taken in order to find answers to the research questions proposed. Several steps are taken to answer the research questions posed by this research. Two areas are focused to improve answer

accuracy in Web-based QA systems: selection of optimal methods and techniques, and development of credibility assessment module for ranking answers. A prototype Web-based QA system has been developed to evaluate answer accuracy of methods and techniques (that addresses problem highlighted in section 1.1.1), and to monitor the impact of Web sources credibility on answer accuracy (that addresses problem highlighted in section 1.1.2). The main objectives are given below

RO1. To design an algorithm for measuring credibility of Web pages (for RQ1)

RO2. To design and develop an enhanced Web-based QA system with credibility assessment (for RQ2)

RO3. To evaluate the impact of credibility assessment on accuracy of the answer by means of evaluation and comparison (for RQ3)

1.4 Contributions

The contribution of this research are as follows:

- *Optimal Methods for Question Answering (OMQA) system:* Many methods and techniques are available in Web-based QA systems making it difficult for researchers/experts to choose one over the other. This research provides comparative evaluation of these methods and techniques to highlight ones performing better than others. Moreover, it offers in-depth analysis, giving reasoning behind methods and techniques improved or decreased performing, along with ways to rectify the issue. This research also developed a Web-based QA system using the optimal combination of methods and techniques available, calling it OMQA system.
- *Credibility Assessment Algorithm:* This research defines credibility categories, including correctness, authority, currency, professionalism, popularity, impartiality and quality, onto which credibility factors can be mapped upon. Each

of these categories contributes towards credibility of the information source. Moreover, credibility factors from information systems and other areas literature are identified and mapped onto credibility categories for researchers' convenience, which may be used for conducting credibility assessment.

- *Credibility-based Optimal Methods for Question Answering (CredOMQA) system:* This research has developed a credibility assessment module that rates a Web page based on its credibility, and uses this score to rank answers. The module uses a number of credibility factors, relevant to Web pages, for scoring credibility categories to generate a well-balanced credibility score. The research also provides extensive evaluations results, conducted on Text Retrieval Conference (TREC) dataset, showing the impact of credibility score on answer accuracy and its effectiveness in achieving better results in comparison to other Web-based QA systems. This research added the credibility assessment module to OMQA, calling it CredOMQA system, enhancing accuracy of the system further.

1.5 Overview of research

Figure 1.2 shows the topics covered in this thesis and their relationships.

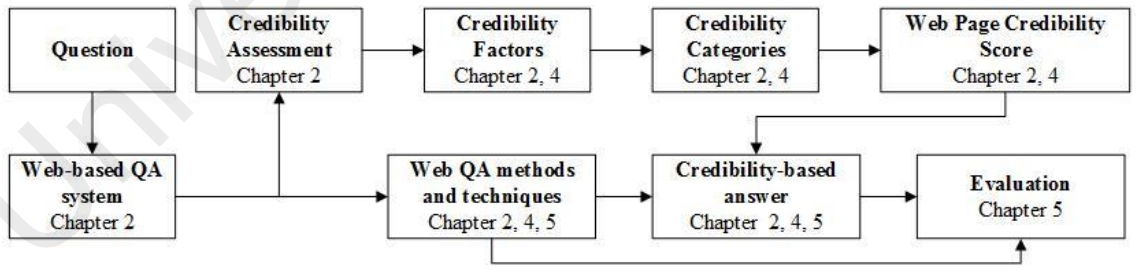


Figure 1.2 An Overview of the topics covered in this thesis

The figure lists the different topics covered by this research along with the chapters number and the flow in which they are covered. The research is focused towards improving answer accuracy in Web-based QA systems. For achieving this the question posed by the user needs to be addressed by a credibility-based Web QA system. For this,

the research covered literature on Web-based QA systems (section 2.1). In order to improve accuracy of answers the research covered methods and techniques used in Web-based QA systems (section 2.1) and defining a credibility assessment module (section 2.2 and section 2.3). Under Web-based QA systems methods and techniques, the research reviewed existing Web-based QA systems methods and techniques (section 2.1.4), defined evaluation criteria for evaluating them (section 3.3.3.3), generated results (section 4.1) and analyzed them (section 4.1.9). This allowed the research to develop a system called OMQA system, which uses optimal combination of methods and techniques in Web-based QA system that improve accuracy of answers. For introducing a credibility assessment module to OMQA system, the research covered literature on credibility (section 2.2), including its categories (section 2.2.3) and factors (section 2.2.4). Moreover, the research reviewed existing Web-based QA, credibility-based Web QA systems and credibility-based information systems, making use of credibility assessment (section 2.3). Based on the credibility categories and factors identified for evaluating credibility of a source, credibility categories scores (section 3.3.6) have been used to generate an overall credibility score of a Web page (section 3.3.7.8), which allows the system to judge the credibility of a source and generate a credibility-based answer score (section 3.3.8.4). This module is added to the OMQA system in order to form a CredOMQA system, and then evaluated based on the evaluation settings (section 3.3.3.4) and the evaluation metrics defined for evaluating accuracy of answers (section 3.3.3.5). At the end, results for CredOMQA system are generated (section 4.3) and analyzed them (section 4.3.10) to determine their impact on answer accuracy.

1.6 Structure of the thesis

This thesis is structured into the following chapters

- Chapter 2: Literature Review

  It provides literature on QA systems, and credibility assessment. The literature on QA systems includes introduction to QA systems, system types, characterization, Web-based QA system model, and Web-based QA systems methods and techniques. Literature on credibility assessment provides its definition, users perceptions on credibility, categories that define credibility, credibility factors used in information systems and credibility assessment in Web-based QA systems. Research gap is also provided to highlight areas where existing credibility-based Web QA systems can be improved.

- Chapter 3: Research Methodology

  It discusses research flow and methodology for research. The research flow outlines the process involved in achieving the research objectives and methodology covers the approach used for the research and defined criteria for conducting it. This chapter also discusses experimental design and the steps taken for evaluation. This includes data collection, data cleaning, experiment settings, process for generating top ranks answers, formulae and algorithms used for credibility assessment module, formulae for scoring answers, format for storing answers, and process for generating results for evaluation metrics.

- Chapter 4: Results and discussion

  The first part of the chapter shows findings from the tests conducted, which includes evaluation results of methods and techniques used in Web-based QA systems, and impact of credibility assessment on answer accuracy. This

research also compares system's result against other Web-based QA and credibility-based Web QA systems.

The second part of the chapter discusses the findings and analysis made from results shown in CHAPTER 4:. It includes drawing conclusions from answer accuracy results for Web-based QA systems methods and techniques, OMQA against other Web-based QA systems, impact of credibility assessment on OMQA system, and effectiveness of CredOMQA over other Web-based and credibility-based Web QA systems.

- CHAPTER 5: Conclusion

  It summarizes the findings made by this research. It also includes limitations faced during the research and possible future directions.

CHAPTER 2: LITERATURE REVIEW

This chapter reviews the background and current work in the area of Web-based QA systems and credibility assessment tools used in IR systems and Web-based QA systems. The chapter is divided into three main sub-sections including Web-based QA systems, credibility assessment, and credibility assessment in Web-based QA systems. The first sub-section covers Web-based QA systems, their brief overview, types and characterization, comparison of Web-based systems with state-of-the-art systems, Web-based QA model and methods and techniques found under such systems. The second sub-section encompasses credibility assessment, which covers credibility definition, user's perception, credibility categories and credibility evaluation techniques. The third sub-section discusses literature on Web-based QA systems and IR systems making use of credibility assessment and the factors used by them.

2.1 Web-based QA systems

In this sub-section, Web-based QA systems, their brief overview, types and characterization, comparison of Web-based systems with state-of-the-art systems, Web-based QA model and methods and techniques found under such systems are discussed.

2.1.1 QA systems types and characterization

Though all QA systems are capable of generating answers for questions asked in natural language, yet they are divided into different types based on characteristics used by the system. These characteristics include question and answer types it can address, complexity of methods and techniques used, type of information source used, domain addressed, and type of response generated.

QA systems are divided into two main groups with respect to type of methods and techniques used by them (Gupta & Gupta, 2012). The first group called "QA systems

based on NLP and IR", makes use of simple NLP and IR methods, while the second group called "QA systems reasoning with NLP" makes use of complex machine learning. NLP reasoners and semantic-based methods QA systems use a combination of NLP and IR methods to generate answer for the question asked (Gupta & Gupta, 2012). NLP components are used to allow the system to understand the question asked in natural language and generate appropriate response (Kolomiyets & Moens, 2011). IR components utilize resources, such as entity tagging, template element, template relation, correlated element and general element, to be able to fetch the correct and relevant information from the fetched documents (Kolomiyets & Moens, 2011). As QA is a complex process, the complexity of techniques used by the NLP and IR components can range from simple techniques (like NER and keyword matching) to complex techniques (like hypothesis generation, support evidence retrieval, machine learning solution, NLP reasoners and semantic-based methods).

There are many kinds of QA systems, such as Web-based QA systems, IR and information extraction-based (IE) QA systems, restricted domain answering system, and rule-based QA system, but they are generalized under the two main groups stated above. Table 2.1 shows characterization of these two QA system groups and examples of QA systems belonging to them.

Table 2.1: Characterization of QA systems (Gupta & Gupta, 2012)

Dimensions	QA system based on NLP and IR	QA systems Reasoning with NLP
Technique	Syntax processing, Named Entity tagging, and IR	Semantic Analysis or high reasoning
Data Resource	Free text documents	Knowledge Base
Domain	Domain Independent	Domain Oriented
Responses	Extracted Snippets	Synthesized Responses

Table 2.1 continued		
Questions type	Mainly factoid question types	All types of questions
Advantages	Timely efficient, effective for factoid questions, easier to setup	Able to answer complex questions with higher accuracy of answers
Disadvantages	Faces difficulty and has low accuracy score in answering complex questions	Methods requires high processing time. May require a powerful system to support methods
QA system examples	Qualifier (Yang & Chua, 2003), Corrob (Wu & Marian, 2011)	IBM Watson (Ferrucci et al., 2010), Virtual player for WWBM (Molino, Lops, Semeraro, de Gemmis, & Basile, 2015),

This thesis focuses primarily on NLP and IR-based QA systems, more specifically on Web-based QA systems, which belong to the same group, as the scope of research is towards Web. More details on other QA systems types can be found in Gupta's survey on QA systems (Gupta & Gupta, 2012).

Besides technique characteristic, QA systems can also be characterized by data resource, domain, response type and question type. Data resource indicates the type of resource used for information preparation, while domain shows the area covered by the system and response tells us about the mechanism used for answer generation. The question type characteristic indicates types of questions the QA system can answer, which can be of type factoid, list, definition, description, opinion, hypothetical, casual, relationship, procedural or confirmation as described briefly along with examples in Table 2.2 (Greenwood & Saggion, 2004; Kolomiyets & Moens, 2011; Wang, 2006).

Table 2.2: Question type descriptions and examples (Kolomiyets & Moens, 2011; Wang, 2006)

Question type	Description	Example
Factoid	Requires a single answer or fact	Who killed John F. Kennedy?
List	Requires two or more answers	List the provinces of Pakistan
Definition	Requires finding definition of a given term	What is a DNA?
Description	Requires definitional information of a given term	How do laser printers work?
Opinion	Requires opinion about an event or entity	Who will win the next Ashes series?
Hypothetical	Requires information about a hypothetical event	What if there was no Sun?
Casual	Requires explanation of an event or entity	Why does it rain?
Relationship	Requires explanation of relation between events or entities	How are Pluto and Saturn related?
Procedural	Requires the answer to be a list of instructions for accomplishing a given task	How to knot a tie?
Confirmation	Requires the answer to be given as either Yes or No	Was John F. Kennedy assassinated?

In addition to question types, QA systems define conceptual categories (i.e., person and location) to handle various answer types (Shim, Ko, & Seo, 2005). For example, "Who killed Martin Luther King" is a factoid question where the expected answer type is human. Among answer type taxonomy, the most famous with regard to factoid questions is the one defined by name (Li & Roth, 2002), which used six coarse-grained categories including abbreviation, description, entity, human, location and numeric.

The characterization of QA systems allowed this research to choose appropriate resources for building and evaluating a Web-based QA system. This includes looking into datasets containing factoid questions, literature on QA systems using NLP and IR based techniques, and using Web as information source.

2.1.2 Web-based QA systems vs state-of-the-art QA systems

Several state-of-the-art systems (Abney, Collins, & Singhal, 2000; Chen, Diekema, Taffet, McCracken, & Ozgencil, 2000; Harabagiu et al., 2000; Hovy, Gerber, Hermjakob, Junk, & Lin, 2000; Hovy, Hermjakob, & Lin, 2001; Molino et al., 2015; Pasca & Harabagiu, 2001; Prager, Chu-Carroll, Brown, & Czuba, 2006) have achieved high accuracy results; IBM's DeepQA project is a prime example (Ferrucci et al., 2010). IBM's Watson supercomputer, based on DeepQA project, beat two champions of the Jeopardy! TV quiz (Molino et al., 2015). It also goes through the same four modules including question analysis, answer extraction, answer scoring and answer aggregation for answer preparation and uses several NLP, IR and machine learning techniques. Though procedure is roughly the same, complexity of the techniques used are much higher, which is why they belong to QA systems reasoning with NLP group. For answering scoring alone, Watson employs more than 50 answer scoring techniques ranging from formal probabilities to counts to categorical features (Ferrucci et al., 2010). The virtual player for "Who wants to be a millionaire?" game is based on the same model, which outperformed human players based on average accuracy in answering the questions in the game correctly, playing it with their rules. Both of these systems are excellent for achieving highest accuracy, especially when dealing with complex question types.

Web-based QA systems, such as Corrob and Qualifier systems, in comparison use simple techniques such as Parts-Of-Speech(POS) tagger and NER, instead of including complete natural language or machine learning system (Dumais, Banko, Brill, Lin, & Ng, 2002; Kwok, Etzioni, & Weld, 2001; Liu, Wang, Chen, Zhang, & Xiang, 2014; Oh, Ryu,

& Kim, 2012; Oh et al., 2013; Radev, Fan, Qi, Wu, & Grewal, 2005; Wu & Marian, 2007a, 2011; Yang & Chua, 2002, 2003; Zhang & Lee, 2003). This is because Web-based QA systems are highly suitable for answering simple question types like factoid questions and can achieve decent answer accuracy using simple NLP and IR based techniques only.

It is because of the reasons stated above the research focused on reviewing Web-based QA systems, using simple NLP and IR based techniques. However, this research did survey some of the recent and state-of-the-art semantic-based QA systems (Fader, Zettlemoyer, & Etzioni, 2014; Ferrucci et al., 2010; Molino et al., 2015) which also make use of simple NLP and IR based techniques.

2.1.3 Web-based QA system model

As stated in Section 2.1.1, Web-based QA systems belong to the group of QA systems using NLP and IR-based techniques. One of the unique characteristic of Web-based QA systems is the use of Web pages as data resource, usually provided using search engines (Gupta & Gupta, 2012). These systems exploit redundancy of information available on the Web for getting quick answers to simple factoid questions (Gupta & Gupta, 2012).

This thesis considered a number of Web-based QA systems, each using unique combinations of methods and techniques. However, despite using different methods and techniques, they follow the same model as shown in Figure 2.1, which is defined based on comprehensive analysis of existing Web-based QA systems models and survey papers (Gupta & Gupta, 2012; Kolomiyets & Moens, 2011; Ng & Kan, 2010; Wang, 2006; Wu & Marian, 2011; Yang & Chua, 2003).

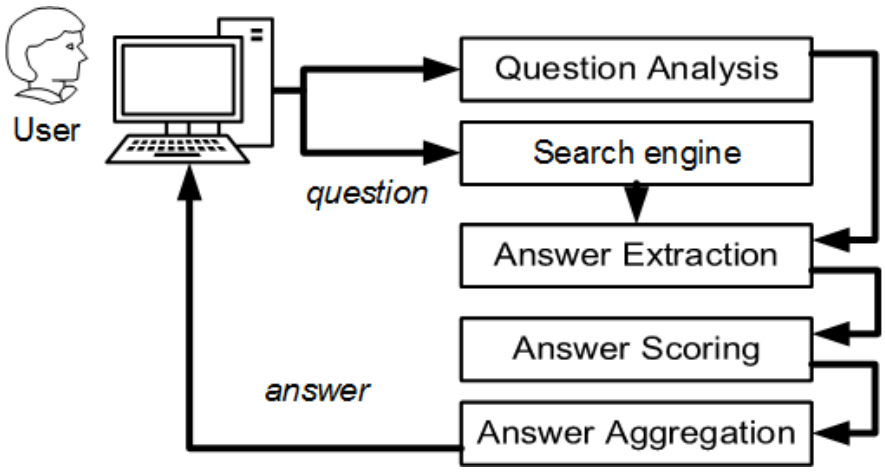


Figure 2.1: Web-based QA system model

Web-based QA systems go through a series of steps in order to prepare the answer for the question asked in natural language form, comprising four major modules: 1) Question analysis, 2) Answer extraction, 3) Answer Scoring and 4) Answer aggregation (Gupta & Gupta, 2012; Hirschman & Gaizauskas, 2001; Ng & Kan, 2010; Wu & Marian, 2011; Yang & Chua, 2003). The question asked by the user is forwarded by the system to question analysis module and search engine. The question analysis module is responsible for finding information from the question given and providing these details to the answer extraction module. Search engines are used for providing Web pages for the question asked, forwarding results to the answer extraction module. The Answer extraction module uses a combination of methods and techniques for extracting answer from the Web pages, using the information provided by question analysis module. The answers found are ranked by answer scoring module and similar answers are merged by answer aggregation, before returning ranked answer list to the user. These modules are discussed in detail in the next sub-section.

2.1.4 Methods and techniques in Web-based QA systems

This thesis covers fourteen Web-based systems and techniques used in state-of-the art systems, from 2001 to 2015, including Web-based QA systems like Corrob, Qualifier, Watson, virtual player for “Who wants to be a millionaire”, LAMP and GenreQA QA

systems (Ferrucci et al., 2010; Molino et al., 2015; Oh et al., 2012; Wu & Marian, 2011; Yang & Chua, 2003; Zhang & Lee, 2003). Methods and techniques found from Web-based QA systems and state-of-the-art systems, using simple NLP and IR methods and techniques are listed under Table 2.3 (question analysis), Table 2.4 (answer extraction), Table 2.5 (answer scoring) and Table 2.6 (answer aggregation).

Table 2.3: Methods and techniques identified for question analysis

Method	Techniques	Evaluated	Techniques for evaluation	References
Question parsing	Maximum entropy-inspired natural language parser, NER & POS tagging, keyword extraction, language to logic, stemming	X	Not evaluated	(Chen et al., 2000; Oh et al., 2012; Oh et al., 2013; Radev et al., 2005; Wu & Marian, 2007a, 2011)
Question classification	Question classifiers and taxonomy, handwritten rules, support vector machine, decision rule induction using Ripper, answer format, answer type, answer domain	X	Not evaluated	(Chen et al., 2000; Oh et al., 2012; Oh et al., 2013; Radev et al., 2005; Wu & Marian, 2007a, 2011)

Table 2.4: Methods and techniques identified for answer extraction

Method	Techniques	Evaluated	Techniques for evaluation	References
Selecting Top *K* results	Top *K* (where *K*=10, 25, 50, 100) Multiple information sources, Web pages or snippets, query formulation, top-k query processing, Top-N filter and threshold algorithm	✔	Top 20 or 10 or 5 Web pages or snippets	(Dumais et al., 2002; Kwok et al., 2001; Liu et al., 2014; Molino et al., 2015; Oh et al., 2012; Oh et al., 2013; Radev et al., 2005; Yang & Chua, 2002, 2003; Zhang & Lee, 2003)
HTML parser	Jericho HTML parser	x	Not evaluated	(Wu & Marian, 2007a, 2011)
Breaking into sentences	Maximum entropy-inspired natural language parser, Stanford natural language parser, sequencing based on text density	x	Not evaluated	
Information from external resources	Google keywords, WordNet keywords	✔	Google keywords, WordNet keywords or their combination	(Ferrucci et al., 2010; Pasca & Harabagiu, 2001; Radev et al., 2005; Yang & Chua, 2002, 2003)
Stop Word list	Remove stop words	x	Not evaluated	(Ferrucci et al., 2010; Molino et al., 2015)
Quote words processing	Match quote words in sentence matching	x	Not evaluated	(Yang & Chua, 2002, 2003)

Table 2.4 continued				
Sentence matching	Voting procedure, regex, scoring function based on vector space model and norm of the answer vector, probabilistic phrase re-ranking, match answer type, and use of relevance coefficient score	✔	Regex or keyword matching	(Dumais et al., 2002; Fader et al., 2014; Ferrucci et al., 2010; Kwok et al., 2001; Liu et al., 2014; Molino et al., 2015; Radev et al., 2005; Wu & Marian, 2007a, 2011; Yang & Chua, 2002, 2003; Zhang & Lee, 2003)
NER	Text chunker, fine-grained named entities, HMM-based NER, Stanford NER, NER system of LTP	✔	Alchemy, Stanford NER and their combination	(Wu & Marian, 2007a, 2011)
Removing unwanted answers	Remove unwanted answers from candidate answer pool	✔	Remove answers not matching answer type or question requirement	(Ferrucci et al., 2010; Molino et al., 2015)
Selecting top *N* sentences	Top 1 sentence for selecting candidate answer, select all answers matching rule on each Web page	✔	Top 1, 3 or 5 sentences	(Dumais et al., 2002; Kwok et al., 2001; Liu et al., 2014; Molino et al., 2015; Radev et al., 2005; Wu & Marian, 2007a, 2011; Yang & Chua, 2002, 2003)

Table 2.5: Methods and techniques identified for answer scoring

Method	Techniques	Evaluated	Techniques for evaluation	References
Frequency score	Instances of a word found within a one or multiple Web pages	✔	Count answer instances	(Dumais et al., 2002; Kwok et al., 2001; Liu et al., 2014; Radev et al., 2005; Wu & Marian, 2007a, 2011; Yang & Chua, 2002, 2003; Zhang & Lee, 2003)
Sentence match score	Keywords matched, n-gram, score function, probability score, relevance coefficient score, normalization score, density score, distributional score, z-score	✔	Score based on keywords and quote words found	(Dumais et al., 2002; Fader et al., 2014; Kwok et al., 2001; Liu et al., 2014; Radev et al., 2005; Yang & Chua, 2002, 2003; Zhang & Lee, 2003)
Prominence	Distance from keywords, L-R rule, probability score	✔	Position of answer in sentence	(Dumais et al., 2002; Ferrucci et al., 2010; Kwok et al., 2001; Molino et al., 2015; Radev et al., 2005; Wu & Marian, 2007a, 2011; Yang & Chua, 2002, 2003)

Table 2.6: Methods and techniques identified for answer aggregation

Method	Techniques	Evaluated	Techniques for evaluation	References
String matching algorithm	Cosine similarity, dice coefficient, answer tiling algorithm, suffix tree clustering	✔	Cosine similarity, dice coefficient or their combination	(Dumais et al., 2002; Kwok et al., 2001; Molino et al., 2015; Wu & Marian, 2007a, 2011; Zhang & Lee, 2003)

The tables show various methods available for each module, techniques available under each method, techniques selected for evaluation and references to the Web-based QA systems from which these techniques were taken. Figure 2.2 shows the methods used in OMQA system and are discussed briefly, under question analysis, answer extraction, answer scoring and answer aggregation sub-sections.

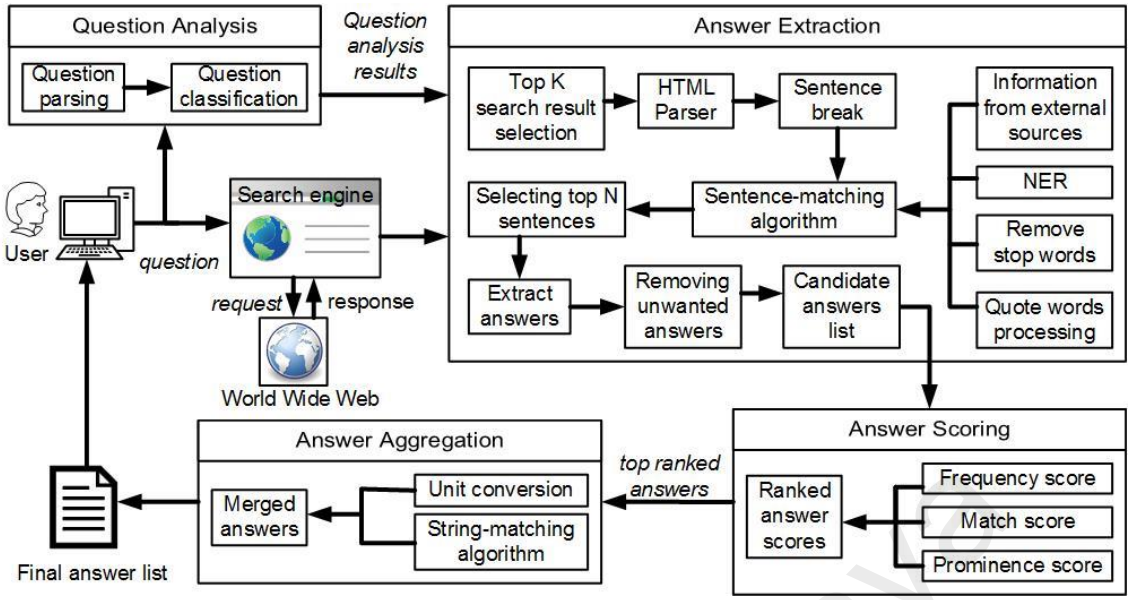


Figure 2.2: OMQA system's modules and their methods

2.1.4.1 Question analysis

The Web-based QA system begins with a question asked/provided to the system. Question analysis has two major objectives including question parsing and question classification.

(a) ***Question parsing***

The first objective is to parse the question to find additional information. The method may use techniques like keywords extraction, phrases that can be used to finding correct answers, and presence of quote words (Yang & Chua, 2003). These questions contain useful keywords that can be used by the answer extraction module. The keywords can also be parsed by NLP to categories, such as nouns and verbs, to help in the construction of improved matching rules for finding the best candidate answers. Techniques used by Web-based QA systems under question parsing include N-grams, POS tagging, answer format generation, decision rule induction, keyword extraction, etc. (Oh et al., 2012; Oh et al., 2013; Radev et al., 2005; Wu & Marian, 2011). N-grams is one of the simplest techniques for detecting sentence structure (Brill, Dumais, & Banko, 2002a). However, POS can provide detailed information, such as presence of nouns and verbs, phrase

chunking and more. Radev et al. (2005) applied a POS tagger to phrases and computed the probability of it, matching the question asked. Somasundaran, Wilson, Wiebe, and Stoyanov (2007) extracted list of keywords from the question and used it to perform sentence matching. Chen et al. (2000) suggested the use of POS to identify nouns and verbs and use WordNet to expand the keyword list further. These techniques allow question analysis module to extract keywords from the question and build rules to be used in answer extraction. Systems have reported to improve their accuracy (precision by 9.05%) by adding more techniques in question parsing (Ittycheriah, Franz, Zhu, Ratnaparkhi, & Mammone, 2000).

(b) ***Question classification***

The second objective is to classify the question asked to judge the expected answer type. The question may be about a person's name, place of birth, or an overall concept in some cases. This classification enables the question analysis module to provide relevant data to the answer extraction module and identify the expected answer type. There are several question classifiers suggested by researchers. One of the most popular techniques, taxonomies used for question classifier, is the one used by Li and Roth (2002), which has over 50 answer types. It includes types such as colors, religions and musical instruments. Qualifier QA system defined their own classifier, which uses two stages for classification (Yang & Chua, 2003). The first stage identifies general entities like human, location, time, number, object, description and other. The second level allows further classification of a general entity, like location. Further classification classes can include country, city, state, river, and mountain. Qualifier system is reported to have achieved over 90% accuracy on TREC-11 questions, using their own question classifier (Yang & Chua, 2003). The ISI taxonomy by Hovy, Hermjakob, and Ravichandran (2002) is another example of a large taxonomy that offers up to 140 different answer types and has been used in (Hovy et al., 2000; Hovy et al., 2001). Some systems also used SVM classifiers in question

classification (Wu, Zhang, Hu, & Kashioka, 2007). For convenience, this research selected person type questions only, which has a larger subset of question available under TREC QA track.

2.1.4.2 Answer extraction

Based on the question analysis results, the answer extraction module begins extraction of answers from the list of search results returned by the search engine. In order to find the correct answer from a pool of candidate answers, several methods are required to be introduced. Tasks are performed in sequential order by methods under answer extraction including 1) Top *K* search result selection, 2) HTML parser, 3) sentence break, 4) sentence-matching algorithm, 5) selecting top *N* sentences, 6) extract answers, and 7) removing unwanted answers. Methods like information from external sources, NER, remove stop words, and quote words processing are used by other methods like sentence-matching algorithm for meeting their objective.

(a) ***Top K search result selection***

Web-based QA systems forward the question as a query to a search engine, which in turn sends back the results found. Different techniques are available for fetching results. For example, the questions may be refined to enable the search engine to return better results (Dumais et al., 2002; Kwok et al., 2001). Moreover, the number of results returned by the search engine can be limited to results depth *K* (Yang & Chua, 2002, 2003). For a given query, the search engine returns 100 results (*K*=100) and ranks the candidate answers found from the Web pages. The Top 1 answer is the correct answer in this case. If the correct answer is ranked at Top 1 for results depth *K*=10 instead of *K*=100, then the accuracy of the answers can be maintained, thus avoiding unnecessary processing of search results. A research may choose between snippets from a document or the whole Web document. Searching answers through snippets is faster, but it may overlook other

candidate answers that can only be extracted by reading the whole Web document (Liu et al., 2014; Radev et al., 2005). However, snippets can be used in a system that wishes to consider more search results than parsing text from few documents only.

Most of the systems reviewed used Google Search to find relevant Web pages for the questions provided. Variations were found in the use of search engine because systems use several depths (i.e., Top 100, 50, and 25) of Web results. However, several systems such as Brill, Dumais, and Banko (2002b); Dumais et al. (2002); Kwok et al. (2001); Yang and Chua (2002); Yang, Chua, Wang, and Koh (2003); Zhang and Lee (2003) extract answers from Google snippets only and do not look for answers on Web pages. Corrob system defined their own Top K method that uses Zipf-like distribution that dynamically determines the number of pages it requires to predict the correctness of the answer safely (Wu & Marian, 2011). Some systems also consider credibility of Web pages for Top K selection, or filter out pages not meeting a certain threshold (Wu & Marian, 2011). This allows the system to use fewer pages for answer extraction while achieving similar or better accuracy of answers. Other systems have suggested the use of multiple sources for information retrieval, where, depending on the question asked, a particular source is chosen (Oh et al., 2012). This allows systems to retrieve only pages that are more likely to contain the correct answer. Answers ranked from different sources are re-ranked for forming the final ranked list. The system showed improved result that outperformed the lower boundary by about 18% but suffered a 5% loss upper boundary in MRR.

(b) ***HTML parsing***

Next the answer extraction module works on converting the HTML Web pages or HTML snippets into plain text. This is done using an HTML parser, such as Jericho parser used in Corrob QA system (Wu & Marian, 2011), which removes tags from the HTML

document and converts it into plain text. However, snippets do not require this conversion as they are already in plain text form.

(c) ***Sentence break***

Irrespective of whether using snippets or whole Web pages, the plain text is required to be parsed into individual sentences. This is done to allow sentence matching algorithms to highlight sentences containing candidate answers. Researchers have used NLP components such as Stanford NLP for performing this task (Kwok et al., 2001; Liu et al., 2014; Wu & Marian, 2011).

Before a sentence-matching algorithm is used, some pre-processing is done based on the data provided by the question analysis module. This includes generating additional information from external sources, removal of stop words and quote words processing.

(d) ***Information from external resources***

External resources, such as Google and WordNet, can be used to find synonyms of words within a query, which was first proposed by Yang and Chua (2003) to be used in Web-based QA systems. They are helpful because the chances of extracting candidate answers have increased. For example, for the query "Who won the Nobel prize in literature in 1988?", using the keywords "won," "Nobel prize," "literature," and "1988" from the question may not be enough to find a sentence containing the correct answer. A sentence may have used the words "received," "awarded," or "gained" instead. Thus, techniques using external resources can assist by providing synonyms for words and by helping the sentence-matching method in retrieving the sentence that contains the correct answer. . This allows the sentence-matching algorithm to capture variety of sentences and thus increasing the chance of fetching the correct candidate answer.

Yang and Chua [6] proposed the use of information from external sources, such as Google keywords and WordNet, to expand the keywords for sentence matching. Thus, the algorithm captures a variety of sentences that increase the chance of fetching the correct candidate answer. Some methods in most systems include the removal of stop words that have little to no effect on matching and quote words processing that involves a group of keywords that need to be present in the matched sentence. Yang et al. (2003) reported an increase of 7.3% over just using the Web keywords.

(e) ***Removal of stop words***

Stop words removal method is used to remove unnecessary keywords from the question and sentences. These keywords are removed as they have little or no impact on sentence-matching for finding the correct answer. Some examples of stop words include a, the, would, is and it.

(f) ***Quote words processing***

Quote words processing checks whether the question contain quote words, which are group of keywords that need to be present in the matched sentence. For example, in the question "Name the actress who played the lead role in the movie 'The Silence of the Lambs'" the quote words are 'The Silence of the Lambs' that needs to be grouped together when conducting sentence-matching. Both stop words removal and quote words processing methods were found in almost every Web-based QA system and are considered as essential part of the QA system.

(g) ***Sentence-matching algorithm***

After conducting the necessary pre-processing the answer extraction is now ready to perform sentence-matching. The research looked into several Web-based systems, each providing a unique sentence-matching algorithm. However, these algorithms were generalized into two main approaches, including sentence matching using regular

expressions (regex) (Dumais et al., 2002; Wu & Marian, 2011; Yang & Chua, 2003) and sentence matching using a list of keywords (or scoring functions) (Ferrucci et al., 2010; Kwok et al., 2001; Liu et al., 2014; Molino et al., 2015; Oh et al., 2012; Oh et al., 2013; Radev et al., 2005; Zhang & Lee, 2003).

Regex sentence matching selects a sentence if the condition for the rule is held true (Dumais et al., 2002; Wu & Marian, 2007a, 2011; Yang & Chua, 2002, 2003). For example, for the question "Who is the President of USA?", the regular expression rule generated would be "X is the President of USA". This rule will be used for finding sentences that follow the same structure in hoping to find the answer that is placed at the position of "X". The benefit of using a regex is that the candidate answers selected have a high chance of being correct. Ravichandran and Hovy (2002); Soubbotin and Soubbotin (2001) used regex/surface pattern for extracting answers. These patterns were either hand written or generated automatically. This technique is excellent where order of words is important such as "birds that eat snakes". Though this technique gives excellent precision but it has a poor recall (Wang, 2006). This is because sentences can be written in many ways, and one regex may not cover all possible combinations. Moreover, relaxing the rule also tends to increase noise and thus decrease the overall accuracy of the answers. Having said that, Katz (1997) reported that using regex for certain questions that can benefit from the use of pattern matching can increase accuracy of the system drastically.

Keywords sentence matching is another technique in which the sentence having the highest number of keywords matched is selected (Kwok et al., 2001; Liu et al., 2014; Radev et al., 2005; Zhang & Lee, 2003). For example, for the question "Who is the President of USA?", the keyword matching technique will use the keywords "President" and "USA", and find sentences that use the same keywords found in the question. This

technique is more relaxed than the others and collects a large number of candidate answers.

(h) *Selecting Top N sentences*

Regardless of the technique used, different Web-based QA systems limited the number of Top *N* sentences matched (Wu & Marian, 2011). The literature suggests that some systems can record all the answers extracted from a Web page (Kwok et al., 2001), whereas some systems can limit the number of top sentences selected to *N* (Wu & Marian, 2011; Yang & Chua, 2003). Wu and Marian (2011) suggested to pick a single answer until the system was confident that it is the correct answer (using Zipf distribution). Yang and Chua (2003) recommended limiting the answers extract to N in order to avoid unwanted answers. This is because by considering too many answers in a page, the correct answer may get buried among a big collection of incorrect answers. However, by restricting N to a small number may not allow a correct answer to be determined conclusively (Wu & Marian, 2011). Thus, it is required that the value of N should neither be too high nor too low. For evaluation of selecting Top *N* sentences method, limits for *N*=1, 3, and 5 were set, where *N* is the number of sentences considered for extracting candidate answers.

The sentence-matching algorithm allowed answer extraction module to highlight sentences containing candidate answers, but a number of filters has to be applied to ensure that only the correct candidate answers are extracted. The literature highlights systems using two types of filters – NER and removal of unwanted answers.

(i) *NER*

NER is used to check whether a sentence contains the expected answer type, which allows to filter out unwanted sentences (Manning et al., 2014). For example, only person entities are selected using a NER if the answer to the question is expected to be a person.

Therefore, other entity types are ignored and the chances for error are reduced (Kolomiyets & Moens, 2011; Wu & Marian, 2011).

Among different NERs available, Stanford and Alchemy NER stand out. Stanford NER, developed by Manning et al. (2014), was used in Corrob QA system which has reported higher accuracy results over baseline system. Stanford NER also provides additional customization by all developers to choose from 3, 4, 7 classifier types. This proves useful when dealing with different document types involving documents, passages or sentences comprising many or a few possible categories. Similarly, Alchemy NER has been used in information systems for various information processing (Aggarwal et al., 2014b).

(j) ***Removing unwanted answers***

This method helps in removing unwanted answers from the candidate answer pool (Ferrucci et al., 2010; Molino et al., 2015). For example, for questions such as "Who killed Abraham Lincoln," any sentence extracted also cites the entity Abraham Lincoln along with other answers. Abraham Lincoln is removed from the candidate answer pool because the name cannot be the answer. However, an exception can be taken when the entity in the question is the correct answer and the answer is removed unintentionally. To avoid such a scenario, a check is placed to remove the unwanted answer when more than one answer is found in the sentence. For example, if the question asked is "Who killed X," and the answer is "Y killed X," then X is removed automatically. However, if X committed a suicide, the answer string would be "X killed himself." Only one answer can be found in the second string, and therefore X is not removed.

Literature shows that use of this method is normally followed in complex systems using hypothesis generation (Ferrucci et al., 2010). However, some conditional patterns can be defined to use this method for simpler Web-based QA systems as well. Brill et al.

(2002a) also suggested strategies for predicting wrong answers. Though many systems have suggested use of paragraph and sentence filtering, yet answer filtering is still rarely seen (Allam & Haggag, 2012).

The candidate answer list is scrutinized using NER and remove unwanted answer filters. The candidate answers list produced by answer extraction module is then forwarded to the answer scoring module.

2.1.4.3 Answer scoring

Web-based QA systems often encounter sentences containing one or more answers and require individual answers to be scored (Ferrucci et al., 2010; Oh et al., 2012; Wu & Marian, 2011). An answer scoring module allocates a score to rank each answer (Wu & Marian, 2011). The scores enable answers to be compared with one another to determine which one is more likely to be correct (Ferrucci et al., 2010; Molino et al., 2015). Answers can be scored in different ways, but the three main methods for scoring answers are based on the frequency of the answer, the value assigned to answer by a scoring function, and the prominence of the answer (Liu et al., 2014; Oh et al., 2012; Wu & Marian, 2011). The system decides whether to include one or more of the techniques for scoring answers and ranks them. Systems like Wu and Marian (2011) and Yang and Chua (2003) used multiple methods for scoring answers including frequency, scoring function and prominence of the answer.

(a) ***Frequency***

Frequency refers to the number of occurrences of a candidate answer (Wu & Marian, 2011; Yang & Chua, 2003). Every answer found in a sentence matched that is considered a single instance and multiple instances are recorded accordingly. If the same answer is found on a different Web page, both frequencies are added (Wu & Marian, 2011; Yang & Chua, 2003). The end result gives the frequency of an answer found on multiple Web

pages. For example, the answer Abraham Lincoln is found 2, 3, and 1 time/s from Web pages 1 to 3. Thus, its frequency score is 6 (Wu & Marian, 2011). Frequency technique is easiest to implement as it counts the number of occurrences of the answer from the candidate sentence (Yang & Chua, 2003). However, this technique can also be exploited if an incorrect answer is used numerous times on multiple Websites (Wu & Marian, 2011).

(b) ***Match score***

The match score method assigns a score to an answer depending on its relevance score or keyword match score (Oh et al., 2012). The score depends on the rule used for extracting the answer from the sentence such as number of keywords found in the candidate sentence, words from thesaurus, Google, WordNet or external keywords, mismatch words, quote words and more (Ittycheriah et al., 2000). This technique had a lot of freedom for improvement as more match scoring factors can be added to increase the likelihood of candidate answer being correct.

The literature identified a number of techniques making use of match-score technique. Oh et al. (2012) suggested to rank highest scored sentences on a Web page and considering them for answer extraction. McCallum (2005) formulated a scoring function that gives a probabilistic score for an answer. Similarly, Liu et al. (2014) used a relevance coefficient score for candidate answers while Dumais et al. (2002) used an N-gram scoring function. The literature also identified other systems making use of sentence matching score one way or the other for ranking candidate answers (Kwok et al., 2001; Yang & Chua, 2002, 2003; Zhang & Lee, 2003).

For example, the query “What was the name of the first Russian astronaut to do a spacewalk?” The search engine runs the query on the Web and returns the search results. One of the search results contains the sentence “Fifty years ago, Alexei Leonov clinched

a Soviet victory with the first ever spacewalk," for which the match score must be calculated. The keywords "first," "Russian," "astronaut," and "spacewalk" are identified from the query and are matched against the sentence. Some of these keywords have synonyms. Russian may be called a Soviet, or an astronaut can also be called a cosmonaut. The score calculated for the sentence is 3 given that three keywords are matched (i.e., first, Russian (or Soviet), and spacewalk) (Oh et al., 2012).

(c) ***Prominence score***

Prominence scoring method used by Wu and Marian (2011) scores answers depending on the positioning of a word within a sentence or its distance from the match rule. The answer that is in a better position within a sentence or is closer to the matched rule is assigned a higher score.

For example, consider the sentence "Ray shot and killed King in Memphis on April 4, 1968". In this sentence, the candidate answer Ray is placed at position 0 since it is the beginning of the sentence. If the question was "Who killed Martin Luther King?", then the candidate answer Ray is in a better position and thus has a better chance of being the correct answer. In comparison if the position of the candidate answer somewhere in the middle of the sentence then it is unlikely to be the correct answer (Doyle, 2014).

Regardless of the answer scoring method used, the answers are ranked with respect to the score assigned to them (Gupta & Gupta, 2012). This allows the answer scoring module to generate a ranked answer list, allowing the Web-based QA system to select the top ranked answers which are likely to be correct answers. However, these answers must undergo an answer aggregation phase before the final answer list can be compiled (Gupta & Gupta, 2012).

2.1.4.4 Answer aggregation

Before the final top answers list is generated, the answers are checked if similar answers can be merged in the numerical, string, or date format (Gupta & Gupta, 2012; Wu & Marian, 2011). The Answer aggregation module merges similar answers whether in numeric, string or date format (Wu & Marian, 2011). The module consists of methods like unit conversion and string matching. Unit conversion is useful, especially in date and numeric answer type, where it is important that all answers considered follow the same format (Wu & Marian, 2011). Since unit conversion is not within the scope of our research, it was not covered. String matching method is used to merge two identical strings . For example, the name John Doe may be written as Doe, John or J. Doe, both the answers should be merged.

The research found multiple systems making use of this method including (Dumais et al., 2002; Kwok et al., 2001; Wu & Marian, 2011; Zhang & Lee, 2003). The cosine similarity technique was used by Wu and Marian (2011) for string matching, but the research also found another technique called dice coefficient (Gomaa & Fahmy, 2013). Both cosine similarity and dice coefficient are used for string matching. Cosine similarity is a measure of similarity between two vectors of an inner product space that measures the cosine of the angle between them (Gomaa & Fahmy, 2013). Dice coefficient is defined as twice the number of common terms in the compared strings divided by the total number of terms in both strings (Gomaa & Fahmy, 2013). Apart from string matching method, the research also found answer tiling algorithm and suffix tree clustering methods for merging answers (Dumais et al., 2002; Kwok et al., 2001).

The answer aggregation module merges similar answers found in the ranked answer list returned by answer scoring module. After merging, the final ranked answer list is produced which is sent to the user.

2.1.5 Web-based QA systems summary

In this sub-section, the research covered background and literature on Web-based systems. This included details on types and characteristics of QA systems, comparison of Web-based systems with state-of-the-art systems and details on the working of Web-based systems. This allowed the research to define a model for Web-based QA system and highlight methods and techniques used in them.

Methods and techniques used in Web-based QA systems are required to be evaluated in order to select the ones performing better than others. Table 2.3 under Section 2.1.4, shows methods and techniques selected for evaluation. However, evaluating these will only improve answer accuracy using existing techniques.

This research aims at adding a credibility assessment module to the existing Web-based QA model shown in Figure 2.1, to evaluate its effect on answer accuracy. For this background and literature on credibility assessment needs to be looked into, covered in Section 2.2, to define a credibility assessment algorithm that can be used to evaluate Web pages based on their credibility for scoring answers.

2.2 Web credibility

This sub-section encompasses credibility assessment, which covers credibility definition, user's perception, credibility categories and credibility evaluation techniques

2.2.1 Defining credibility

Credibility is defined as "the quality or power of inspiring belief". Thus a credible Web page is one that is trustworthy and the content it provides is of high quality and accurate (Fogg, 2002a). Schwarz and Morris (2011a) defines a credible Web page as one "whose information one can accept as the truth without needing to look elsewhere. If one can accept information on a page as true at face value, then the page is credible; if one needs to go elsewhere to check the validity of the information on the page, then it is less credible". By measuring credibility of a Web page, the computer systems can determine whether the information provided is correct or not based on its credibility rating.

Credibility can be determined by a number of categories, consisting of credibility factors that contribute towards it. Fogg and Tseng (1999a) suggests that credibility is based on two key components: i) trustworthiness and ii) expertise. Trustworthiness of content is defined in terms of being well-intentioned, truthful and unbiased; while expertise is defined as being knowledgeable, experienced and competent. However, the five credibility categories defined by Meola (2004) including accuracy, objectivity, authority, currency, and coverage cover a lot of credibility factors. Here accuracy is the correctness of Web information, objectivity is content being un-biased, authority is reputation of author, currency is freshness of content and coverage is detail of the content. Many researchers accept accuracy, objectivity, authority, currency, and coverage as main categories to evaluate credibility of Web pages (Ostenson, 2014; Schwarz & Morris, 2011b; Yamamoto & Tanaka, 2011a). Flanagin and Metzger (2008) added to this by suggesting that credibility of content consists of objective as well as subjective parts.

Subjective components relate to user's perceptions or judgment, while objective components refer to properties of the source or content (Atique et al., 2016).

Additionally, credibility is also discipline-specific, where each discipline weighs credibility categories differently (Fogg & Tseng, 1999b; Schwarz & Morris, 2011b). For instance, psychology and communication put more emphasis on reputation and reliability of the source, while information science focuses on the correctness and quality of the content itself (Schwarz & Morris, 2011b).

Users' perception also need to be considered for the credibility assessment so as to address the difficulties faced by users when evaluating Web pages (Flanagin & Metzger, 2000, 2003, 2008; Metzger et al., 2003). By analysing users' perception, this research can provide necessary support that users lack in conducting proper credibility assessment. Therefore, the credibility assessment algorithm should cover sufficient categories to cater all kinds of credibility factors. Additionally, this research covers a wide variety of credibility factors that can be used in different domains (Aggarwal et al., 2014b; Lu et al., 2017; Sbaffi & Rowley, 2017). Users' perception on Web credibility assessment and related media should also be considered to allow the credibility algorithm to address the problem faced by the users. In the next upcoming sub-sections, this research looks into users' perceptions on Web credibility assessment and defines credibility categories and the type of factors covered by them.

2.2.2 Perceiving Web credibility and difficulties faced

Since the mid-1990s, checking for Web credibility has become an important topic due to ever-increasing volume of information on the Web (Kim & Johnson, 2009; Metzger & Flanagin, 2013). The area of Web credibility gained importance as people started considering the data available on the Web to be more reliable than other sources. Over the past decades, many studies have been conducted to understand people's perception of

Web credibility in different environments and the problems they faced during credibility assessment (Atique et al., 2016; Ayeh, Au, & Law, 2013; Castillo et al., 2011; Flanagin & Metzger, 2000, 2003, 2008; Metzger et al., 2003; Morris et al., 2012).

Studies show that the students and non-students (people who have completed studies) mostly rely on Web-based information (Flanagin & Metzger, 2000). These studies show students most frequently use Web for academic, entertainment and social purposes (Lackaff & Cheong, 2008; Rieh & Hilligoss, 2008). Shan (2016) survey checked whether students check trust online product reviews before purchasing them. On a scale of 1(don't review)-7(check review) from 113 students, with the average nearing 4.5(out of seven) showing that most students trust online reviews and use them before making purchase (Shan, 2016). Shen, Cheung, and Lee (2013) conducted a survey on 132 Hong Kong university students, where more than 60% of them agreed that they trust and use the information provided by Wikipedia without checking its credibility. Metzger et al. (2003) study on college students show that around 51% of the students used Internet daily, 30% used it several times a week, and 15% reported using it once in a week. Moreover, 80% college students used books and 72% used the Internet, more often for academic information than journals, newspapers and magazines (Metzger et al., 2003). The addition of new Web resources such as blogs and social media have added to the number of users turning to the Web for information, including news. From 1994 to 2008, reading the news online (at least 3 days per week) increased from 2% to 37% (Kohut, Doherty, Dimock, & Keeter, 2008) and this number has now grown further especially between the age of 18 to 24 (Greenslade, 2017; Nielsen & Schrøder, 2014). Social media technologies like Twitter are quite popular among users. It has led to institutionalization of crisis communication, in which new media plays a crucial role (Schultz, Utz, & Göritz, 2011). Blogs are also quite popular among users, as 77% of active Internet users read blogs regularly, totaling up to 346 million blog readers (Schultz et al., 2011).

These users consider Web information highly credible, sometimes even more than other resources such as television, magazines, and radio (Flanagin & Metzger, 2000; Kim, Sin, & Yoo-Lee, 2014; Metzger et al., 2003). Table 2.7 shows comparison between perceptions of students and non-students of different information sources. Studies show non-students consider Web information to be as credible as that from television, radio and magazines, but less credible than that from newspapers (Flanagin & Metzger, 2000; Metzger et al., 2003). On the other hand, students rate Web content less credible compared to other sources including newspaper, television and magazines (Kim et al., 2014; Metzger & Flanagin, 2013). These users are aware that newspapers follow an editorial process and thus the content produced is more credible (Flanagin & Metzger, 2000; Kim et al., 2014). However, they also consider Web content to be highly credible as general users do not expect content creators to be biased or contemptuous when sharing information (Flanagin & Metzger, 2000). Metzger et al. (2003) noted that despite students considered content on the Web to be less credible, they still relied heavily on it for doing homework and assignments.

Table 2.7: Comparison between students' and non-students' perceptions of credibility of information sources (Metzger et al., 2003)

Information Source	Students (n=436)	Non-Students (n=307)
Newspaper	4.74	4.28
Television	4.17	3.87
Magazine	4.14	3.91
Internet	4.09	4.06
Radio	4.07	3.84

Unfortunately, information on the Web can be fake and biased, and most of the Web users do not have enough experience to perform credibility assessment properly (Aggarwal et al., 2014b; Allcott & Gentzkow, 2017; Flanagin & Metzger, 2000; Gupta et al., 2013b; Iding, Crosby, Auernheimer, & Klemm, 2009; Rieh & Hilligoss, 2008). These

students are less motivated to pay greater attention to credibility issues unless it had social implications (Rieh & Hilligoss, 2008). They also show biasness towards certain Websites, such as education Websites were less critically evaluated than commercial Websites (Aggarwal et al., 2014b; Iding et al., 2009). These students often overlook highly credible documents produced by experts/professionals, librarians, research reports, even institutional repositories, due to lack of accessibility and familiarity with such documents (Lee, Paik, & Joo, 2012). These students also face difficulties evaluating messages on social media, such as Twitter, since they can only see account's user name, links in tweet and pictures to judge its credibility (Gupta et al., 2014). These users are poor judges of truthfulness based on content alone, and instead are influenced by heuristics such as user name when making credibility assessments (Morris et al., 2012). Same issues arise when dealing with blogs, since users mistrust blogs in general due to generic doubts about user-generated content and that they are mostly written by anonymous users (Rieh, Jeon, Yang, & Lampe, 2014; Yang, Counts, Morris, & Hoff, 2013). Due to their inability for doing credibility assessment, these students use document's content or their own opinion as criteria for judging its credibility, which often leads them to select less credible content (Lackaff & Cheong, 2008; Strømsø, Bråten, & Britt, 2011).

Web users face difficulties in evaluating credibility of Web page content, because they lack the skills to build evidence-based explanations that involve collecting facts from different sources (Aggarwal & Van Oostendorp, 2011; Aggarwal et al., 2014b; Korpan, Bisanz, Bisanz, & Henderson, 1997). This problem can be found at all levels including elementary, middle school, high school, university and postgraduate (Atique et al., 2016; Halverson, Siegel, & Freyermuth, 2010). At elementary level, most children appear to have weak evidence building skills and prefer selecting ambiguous data over authentic sources (Sandoval & Çam, 2011; Taylor, 2016; Wu & Hsieh, 2006). At middle school level, students find it difficult to make decisions about strength of evidence, which results

in treating all evidence provided as strong i.e. without any variation (Glassner, Weinstock, & Neuman, 2005; Johnson & Kaye, 2014; Pluta, Buckland, Chinn, Duncan, & Duschl, 2008). This is because these students struggle to construct, justify, and evaluate scientific arguments (Johnson & Kaye, 2014; Mathews, Holden, Jan, & Martin, 2008). At high school level, studies show that pupils face difficulties trying to explain or defend an issue as their reasoning is mostly based on superficial contextual information and not empirical evidence (Brem, Russell, & Weems, 2001; Dawson & Venville, 2009; Johnson & Kaye, 2014; Kolsto, 2001; Reiser, 2004; Sandoval & Millwood, 2005). Studies conducted for undergraduate students show them lacking deep understanding required to judge the quality of evidence, making them unable to select the best available evidence (Bendersky, Croft, & Diao, 2011; Lippman, Amurao, Pellegrino, & Kershaw, 2008; List et al., 2017). This is due to students' preference for ease of comprehension instead of relevant empirical and disconfirming evidence (Halverson et al., 2010; Treise, Walsh-Childers, Weigold, & Friedman, 2003). Even at postgraduate level, pre-service teacher consistently grounded their arguments in evidence, but they still exhibited a number of limitations such as collecting best resources and considering credibility factors for selecting them (Karlsson et al., 2017; Zembal-Saul, Munford, Crawford, Friedrichsen, & Land, 2002).

Though users lack skills to conduct credibility assessment and build evidence-based explanations, yet providing credibility factors, related to Web pages, can increase positive beliefs about credibility, which are important both for users and success of a Website (Freeman & Spyridakis, 2009a; Wogalter & Mayhorn, 2008). Credibility factors associated with Websites, such as domain suffixes (e.g., .com, .edu), quality seals, and organization/domain names, can affect user's credibility belief for Website's information (Rodrigues, Wright, & Wadhwa, 2013). Students and non-students, who spend more time on the Web showed significantly higher trust ratings for credibility factors relating to Web pages than users not spending much time on the Web (Wogalter & Mayhorn, 2008). Even

providing simple information, such as contact details, can dramatically improve Website's credibility belief among users (Freeman & Spyridakis, 2009a). Providing source characteristics, such as health information, published or authored by physicians, or major health institutions, also improve users' trust towards the Website (Sillence, Briggs, Harris, & Fishwick, 2007).

Reader characteristics and experience also affect credibility judgment as experience readers look into more factors for judging its credibility over novice users (Ahmad, Wang, Hercegfi, & Komlodi, 2011; Freeman & Spyridakis, 2009a). Robins and Holmes (2008); Robins, Holmes, and Stansbury (2010) show that there is a close relationship between people's visual design preferences and credibility assessment as people judge credibility of Web pages based on their preference of Web page's aesthetic characteristics. Moreover, experts consider more credibility factors to evaluate a content than a novice Web user (Fallow, 2005; Flanagin & Metzger, 2000; Metzger, 2007).

It is observed that both students and non-students lack the training or tools for judging and understanding evidence for verifying credibility. Moreover, their limit perception often leads them into selecting weak sources over highly credible sources. These users often have limited information to deal with, thus evaluating credibility of content becomes difficult. Keeping in view of users' lack of credibility judgement and weak skills for building evidence-based explanation, there is a need to define a credibility assessment algorithm. In the next sub-section, this research covers the categories that contribute towards credibility, and the credibility factors they cover.

2.2.3 Credibility categories

Credibility categories allow the system to evaluate credibility of a resource from multiple aspects. This research formed seven credibility categories based on literature provided by researchers, covered in Section 2.2.1 (Flanagin & Metzger, 2008; Fogg & Tseng, 1999a;

Meola, 2004), to be able to cover old credibility factors (such as, relevancy, update date, readability) and new ones (popularity on social media, likes and shares counts). These categories include correctness, authority, professionalism, popularity, currency, impartiality and quality, and are discussed in detail in their respective sub-sections.

2.2.3.1 Correctness

Correctness deals with the correctness of information provided (Meola, 2004). For example, a question asking "Who discovered Hawaii", the QA system expects to search for answers in Web pages closely related with the query given. If one of the Web pages given is "Hotels available in Hawaii", which is unlikely to contain the given answer should get a lower score. Hovland emphasized the importance of mentioning the source of the content in order to validate the correctness of the document (Hovland & Weiss, 1951). However, reliance on the source only is not enough, other factors like references or source of the content play an important role in determining content's correctness. The correctness increases further if references are cited to scientific data which also allows it to be verified from elsewhere (Fogg, 2002a; Fogg et al., 2001a). This helps in measuring correctness of the document against other known evidence-based guidelines and theories (Dochterman & Stamp, 2010). Similarly, correctness increases if the content is reviewed by peers and provides evidence for supporting an argument (Fritch & Cromwell, 2002; Meola, 2004). Another way to judge the correctness is to use social and heuristics approach which considers an answer credible if majority agrees with the answer or if endorsed by an expert on the topic (Metzger, Flanagin, & Medders, 2010). Another useful application is the use of digital watermarks for important document for verification (Hao & Su, 2012). Additionally, machine learning algorithms or semantic Web solutions can be used to conduct content analysis in analyzing content's correctness, provided that semantic data relating to the content is available (Archer, Smith, & Perego, 2008b; Olteanu, Peshterliev, Liu, & Aberer, 2013b).

Using correctness in QA systems

Correctness is ideal in scenarios where question's context or structure is important. For example, a user asks a question stating "Who killed Jack the Ripper?". In this question, it is important to understand that the user is asking about the person who killed Jack the Ripper and not the victims who were killed by him. Consider another example, where the user asks "Who was the first American to do spacewalk?". In this question, it is important fetch pages covering American astronauts only. It is quite possible that the search engine also returns pages cover astronauts from other nationalities as well, but a well-defined correctness module will only score Web sources that are relevant to the question more. Thus, correctness is ideal for questions where sequence of keywords and context of the Web sources is important (Molino et al., 2015; Wu & Marian, 2014).

2.2.3.2 Authority

Authority deals with the experience and popularity of the author, which includes author's qualifications and credentials in the Web community (Meola, 2004; Wathen & Burkell, 2002). Providing author's contact details, including his e-mail ID, also impacts authority (Freeman & Spyridakis, 2009b). In print media, author details are utmost importance as they provide author's biography as well his experience in the area to allow readers to judge the credibility of the content. This is especially true in the case of blogs, where contents written by known authors are considered more credible and contain less spelling errors than the ones written by an anonymous user (Chesney & Su, 2010). Using author's credentials, author's popularity on the Web can also be determined by looking into the number of article citations, author's prior contributions and awards received. This is quite important on medical Websites, where a patient feels more secure knowing that doctor prescribing medication is well reputed (Abbasi et al., 2012; Sbaffi & Rowley, 2017; Wald, Dube, & Anthony, 2007). Authority is also quite crucial for verifying information taken

from social media such as Twitter, where information has a higher credibility if it is posted by a verified user (Castillo et al., 2011; Chatterjee & Agarwal, 2016; Gupta et al., 2014). Moreover, it can be used to track author's popularity, by checking number of people following him or likes and shares of the published content (Morris et al., 2012).

Using authority in QA systems

Authority plays an important role in questions related to the content's author, content produced by an author or a quote by a person. For example, in the question "Who wrote Sherlock Holmes book?", authority category can play a pivotal in extracting the author name. In this question "Arthur Conan Doyle" is the correct answer and Web pages containing content written by the same author along with author details can assist the QA system in rating them higher. Similarly, for the question "Which book is George R. R. Martin currently working on?", the most credible answer would be the one that has been taken from a page where the author himself specifies the book he is currently working on. Similarly, the question "Who wrote the famous quote 'You too Brutus'?" requires the QA system to rate Web sources higher that mentions author who wrote the quote. In this case, Web page mentioning "William Shakespeare" as author of the quote will be rated higher. This can be applied to questions revolving around rumors regarding a specific person which can only be clarified by the person himself. Thus, authority category weighting can be increased in questions where question is regarding a specific person details like something he produced, said, or plan on doing (Lu et al., 2017; Shan, 2016).

2.2.3.3 Currency

It refers to the freshness and update frequency of the resource (Aggarwal et al., 2014b; Meola, 2004; Tanaka et al., 2010b; Yamamoto, Tezuka, Jatowt, & Tanaka, 2007). It is of utmost importance that Web pages considered for answer extraction are most recent for several reasons. First and foremost, it allows answers to be extracted from the same

timeline in case it is not explicitly mentioned in the question itself. For example, if the user asks "Who is the president of the United States of America?", then it is only logical to fetch data from the most recent sources (Aggarwal et al., 2014b; Tanaka, 2010; Yamamoto & Tanaka, 2011a; Yamamoto et al., 2007). Secondly, it also addresses answers to questions which may have changed over time. For example, Pluto was considered a planet by astronomers when it was discovered in 1930s, but current studies term it as a "dwarf planet" and not a regular planet (Aggarwal et al., 2014b; Tanaka, 2010; Yamamoto & Tanaka, 2011a; Yamamoto et al., 2007).

Currency can be tracked by extracting meta information and date stamps providing last update date of content (Aggarwal et al., 2014b; Stvilia, Twidale, Smith, & Gasser, 2005). Moreover, some application programming interfaces (API) also provides details on the frequency of updates applied to the content (Diffbot, 2016). Web pages having a higher currency score will allow the system to rate answers higher than others that have not been updated in years.

Many researchers have stressed on the importance of currency in measuring credibility. Presence of date stamp, showing that information is current, and monitoring how often the content is updated helps in measuring currency (Aggarwal et al., 2014b; Fritch & Cromwell, 2002; Schwarz & Morris, 2011b; Yamamoto & Tanaka, 2011a). This is useful as it makes sure that the most recent content is being used and that the answers within the page are not outdated. Apart from the last update date, the frequency with which the content is updated also contributes towards currency score of a Web page (Aggarwal et al., 2014b; Tanaka et al., 2010b; Yamamoto & Tanaka, 2011b). Yamamoto and Tanaka (2011a) checked the list of updated dates of the Web pages using the Wayback Machine of Internet Archive to evaluate currency of Web pages. Other

researchers used the date provided within meta data of HTML documents to determine their currency (Olteanu et al., 2013a; Pattanaphanchai, O'Hara, & Hall, 2012).

Using currency in QA systems

Currency category is useful in which questions mentioning date or requiring latest content. For example, if the user asks "Who was the richest man in the year 2000?" then the category can be used to rate Web pages archived for the following year. Though it is possible that some current page also contains details chronological details but finding an archived Web page belonging to the same year would be more beneficial. In another scenario, where the user may as "Who is currently the highest paid film actor?". In this scenario only the up to date content is require as pages contain answers for previous years would be considered false. Thus, currency category should be given more weighting in questions that mentions dates or require most current answers (Aggarwal et al., 2014b; Yamamoto & Tanaka, 2011a).

2.2.3.4 Professionalism

In most cases, users ignore good quality articles because of poorly managed Websites thus giving a biased and untrustworthy appearance (Bosch, Bogers, & Kunder, 2016; Lewandowski, 2012; Robins & Holmes, 2008). These include presence of advertisements, spelling errors, broken links and no multi-language support. Domain name or URL suffix plays a major role towards a Website's credibility (Fogg, 2002a; George, Giordano, & Tilley, 2016). Some users also place more trust in a Website if author's details are given, Website has a privacy policy and has a mission statement or objectives (Fogg et al., 2003a; George et al., 2016). Privacy certification mechanisms including data protection certification mechanisms, seals, and marks can help Website's achieve higher professionalism (Rodrigues et al., 2013). Some Websites also give credentials of members on the editorial board and the process taken for maintaining

quality of content, and often follow the "paid access to information" policy (Sanchez, Wiley, & Goldman, 2006a). Moreover, if the Web page is peer-reviewed or highly rated then it adds towards professionalism of the Website (Meola, 2004). In addition to meta data given by the Website itself, other details such as domain type of the page, Website's speed score, Website score given by reviewers, child safety rating and awards received contribute towards its professionalism score (Aggarwal, Oostendorp, Reddy, & Indurkhya, 2014a; Caverlee & Liu, 2007; Schwarz & Morris, 2011b). In addition to these, ratings given by qualified authors also contribute towards Website's professionalism (Pantola, Pancho-Festin, & Salvador, 2010b).

Using professionalism in QA systems

Professionalism category is useful where information should from organizations, education sector and government Websites needs to be rated higher. For example, for the question "Who is Pakistan's chief of army staff?" the information taken from the government of Pakistan would be considered more credible than information provided by other community Websites. Another example would be for the question "What is the visa for a tourist visa for Malaysia?". This information may also be provided a number of travel agents, which may provide increased prices for personal gain. Professionalism category score can be used to ensure prices taken from Malaysian embassy Web page gets a higher score. Professionalism category is helpful in this regard because the Web servers used for hosting such Websites are powerful, professional, and popular among experts, thus cover the factors used by this category. This is why professionalism category can benefit greatly in score Web pages taken from professional Websites (Aggarwal & Van Oostendorp, 2011; Aggarwal et al., 2014b).

2.2.3.5 Popularity

It deals with the Website's reputation among Web users, which may be determined by the number of times it is viewed and shared (Aggarwal & Van Oostendorp, 2011; Aggarwal et al., 2014b). Popularity may also be determined by looking into the number of users that have visited the Website or Web user's past experience with the Website itself. Social factors, such as the number of likes, shares, comments on the article, also contribute towards popularity (Aggarwal & Van Oostendorp, 2011; Aggarwal et al., 2014b; Gupta et al., 2014). A Website's content's credibility increases if it has been liked or shared by Web users on social media like Facebook, Twitter, Google+, Linkedin, etc (Metzger et al., 2010). Additionally, the popularity of Website's social media may also be used to determine its popularity, by checking its members count, global coverage, etc. Ranking in search engine also matters as it contributes to Website's popularity, as Search Engine Optimization(SEO) companies that generate these scores consider a number of popularity factors of a Web page to compute its score or rank (Aggarwal et al., 2014b; Schwarz & Morris, 2011a; Tanaka, 2010; Yamamoto & Tanaka, 2011b).

Using popularity in QA systems

Popularity category is quite important when dealing with questions involving popularity among Web users. For example, a user asks the question "Who is the most trending person on Twitter?". In this case, one needs to look into the Twitter's Web pages and highlight the person that has received the most popularity over a certain period of time. In another question "Who is the World's most famous football player?", the QA should rate Web page that are more popular among users. In the year 2017, one might argue that "Christano Ronaldo" and "Lionel Messi" are equally famous but by considering factors like followers on social media Websites, articles shared, and user traffic on respective pages, the popularity category can make a better judgement. In this

case Christano Ronaldo should be the correct answer since he has 53M followers on Twitter compared to 8.8M of Lionel Messi. Lastly, for the question "Who is Ronaldo?", the question maybe pointing towards all persons who have the name Ronaldo but the user is more likely to be more interested in Christano Ronaldo since he is more popular. In this case, the popularity category should rate the popular Webpages first. Thus, more weighting should be given to popularity category when questions involve public opinion or popularity among Web users (Aggarwal & Van Oostendorp, 2011; Aggarwal et al., 2014b; Gupta et al., 2014).

2.2.3.6 Impartiality

This check makes sure that the content presented is un-biased (Meola, 2004; Ostenson, 2014). This can be checked by checking the sentiment or tone of the article. An un-biased article will be well-balanced by being neutral on the matter, without being too positive or negative on the matter. Similarly, the tone of the content can give insight about its impartiality by making sure that the author's tone is not negative (Aggarwal et al., 2014a).

Researchers have used several factors for evaluating impartiality of content. Some systems generated summary of the content in order to check its biasness (Schwarz & Morris, 2011a). Shibuki et al. (2010a) proposed to generate mediatory summary of a query by using arguments found on different search results, in order to determine whether an argument posted on a Web page is positive or negative (Shibuki et al., 2010b). Sentiment scores also contribute to impartiality as it calculates whether the content is positive, negative or neutral (Aggarwal et al., 2014b). Similar to impartiality, Web content's tone can be used to judge its impartiality by checking if it contains ironic, humorous, exaggerated or overblown arguments (Aggarwal et al., 2014a). Content being peer-reviewed by a group of experts also adds up towards impartiality of the document (Meola, 2004).

Using impartiality in QA systems

Impartiality category score plays a significant role when evaluating any page's content. However, it excels when considering reviews or comparing different entities. For example, for the question "Who is the first king of England?", the article written should be neutral and written by higher authority(calculated using authority and professionalism). This is because this question is contraversal with many people have different views about it. Impartiality can assist here by making sure that the article is as neutral as possible and is more likely to contain the correct answer over others that too biased on the subject. Another question can be "How is the engine of Honda City 2017 model?". In this question, the user is interested in impartial reviews about the car. The Web is filled reviews that maybe biased in favor or not in favor of the car, and the impartiality category score can address this issue but scoring such Web pages lower. This category will allow comments like "The car offers 116 horsepower, which is decent in this car category" over subjective comments like "I didn't like the drive", "I think the car should had at least 150 horsepower instead of 116 horsepower". Lastly, for the question "Is Harvard university better than Oxford university?", then the QA system can look into reviews have received a high impartiality score to allow answers be extracted from it. Thus, impartiality score is important in almost all kind of questions but it excels more in questions involving reviews or comparison (Aggarwal & Van Oostendorp, 2011; Aggarwal et al., 2014b; Meola, 2004; Ostenson, 2014).

2.2.3.7 Quality

This category measures the standard written material. This can be determined by checking how well the article is written and whether the content has plagiarized or not (Molino et al., 2015; Oh et al., 2012; Wu & Marian, 2011). Any information indicating that the article

has been reviewed by a professional in the area will also enhance the quality of the article (Parsons, Duerr, & Minster, 2010).

There are several factors used for evaluating quality. Readability score is one of these factors, which usually shows the grade level of the audience that will be able to understand the content (Aggarwal & Van Oostendorp, 2011; Aggarwal et al., 2014b; Microsoft Word, 2016). Plagiarism ratio is another factor that can be used in assessing the quality of the content as original written materials are valued more over copied material (Wu & Marian, 2011). In the case where the content is taken from a journal or is peer-reviewed, ranking of the journal/proceeding can also be used for scoring quality (Lee, Sugimoto, Zhang, & Cronin, 2013; Parsons et al., 2010). The peer-review system also allows rating Websites containing quality material and for collaborative filtering of Web content as well (Herlocker, Jung, & Webster, 2012).

Using quality in QA systems

Quality category plays an important role in almost all question types as one expects the content to be well-written, original and in some cases of good article type. For example, for the question "What is theory of relativity?". In this question, the QA system is expect to find the article written by Einstein, which may be in the form of journal or book. In this case, the article type is check to ensure answers are fetch from the correct sources of high quality. Moreover, the content will also be well written and original allowing it to score higher than others stating the same facts. In another question "Name one of the major gods of Hinduism?" would also expect the article to be written by a professional author where the quality of the content is high having a high readability score. Similarly, for the question "What is the definition of inertia?", answer fetched from books and journals should be rated higher. Thus, quality is generally used in all question

types but is important in definition question types and with books, journals, and conference papers.

2.2.3.8 Credibility categories-summary

Credibility categories offer flexibility to not only computers but also users in assessing credibility of content with respect to different aspects. This is because each category may be valued differently by different domains and individuals. These categories also allow mapping existing or future credibility factors onto these defined categories in order to estimate resource's credibility correctly. Table 2.8 shows these categories and their description, highlighting credibility factors that they encompass.

Table 2.8: Categories and their description

Category	Description
Correctness	Correctness of the information provided by the author
Authority	Experience and popularity of the author. This includes author's qualifications and credentials in the Web community
Currency	Frequency of updates applied to the content
Professionalism	Policies and Website characteristic like speed and rating
Popularity	Website's reputation among Web users and reviewers
Impartiality.	Lack of bias in the content
Quality	Characteristics that reflect content's written quality like readability, originality and approved by editors or reviewers

From the categories defined, some of them are likely to contain more factors over others. For example, currency category can only be determined by a few factors including published date and update frequency, whereas popularity category can be determined by a large variety of credibility factors such as view count, share count, page rank, reviewer rating, users rating, and more. Likewise, some categories, like quality, are subjective as the score predicted may be viewed differently among users or systems. Nevertheless,

these categories contribute towards the final credibility score, and provide freedom to assign weightings to each category in case one is favored more over the other.

In the next sub-section, this research covers different information systems, highlighting credibility factors used and maps them to credibility factors. These factors may be selected depending upon the system or resource whose credibility is being evaluated.

2.2.4 Web credibility evaluation

Studies show that users lack training and skill sets to evaluate Web credibility accurately (Flanagin & Metzger, 2000, 2003, 2008; Metzger et al., 2003), as covered in Section 2.2.2, and thus require a credibility assessment module for evaluation (see Section 2.2.3). Over the years, researchers have suggested various evaluating techniques for aiding users in making these credibility judgments. This research has divided these techniques into two general techniques for evaluating credibility of Web content: 1) credibility evaluation by users, and 2) credibility evaluation by computers, as shown in Figure 2.3.

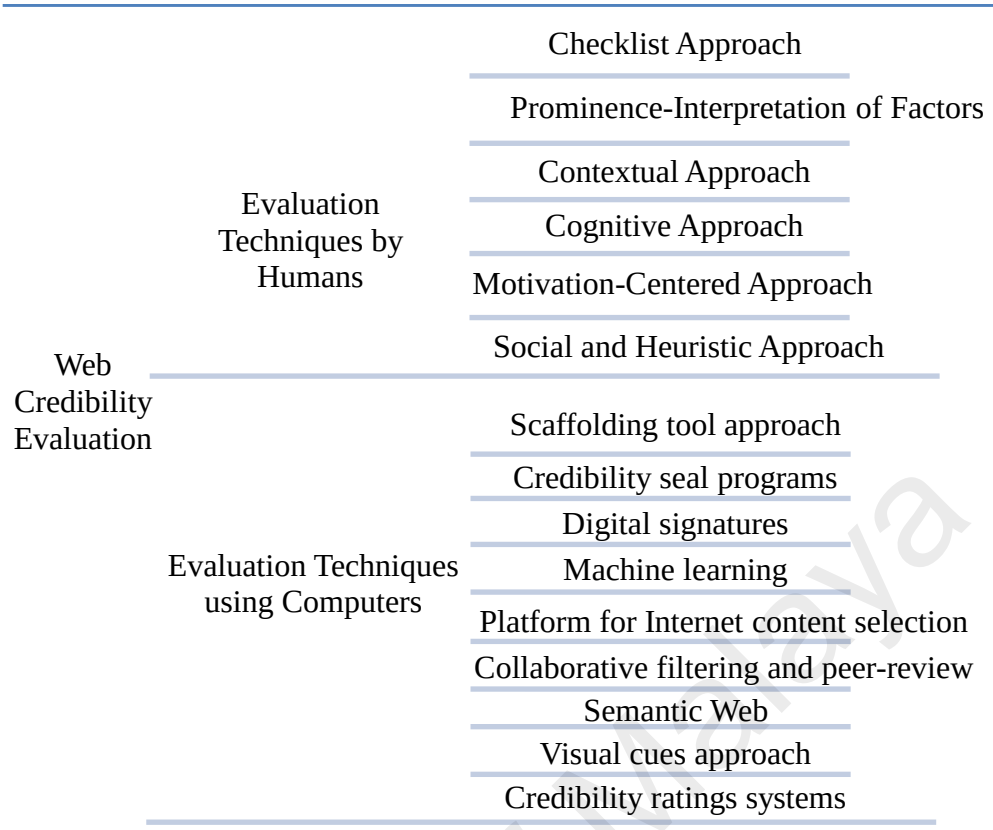


Figure 2.3: Web credibility evaluation techniques

2.2.4.1 Evaluation techniques by humans

This section covers different approaches adopted for evaluating credibility where the end judgment lies either with the user, educator or evaluation expert (Metzger, 2007). It highlights different approaches and skills required by Web users to evaluate Web credibility: checklist approach, cognitive approach, prominence-interpretation of factors approach, contextual approach, motivation-centred approach, and social and heuristic approach.

(a) ***Checklist approach***

Initial efforts at solving Web information credibility started out with the objective of promoting digital literacy. The American Library Association and National Institute for Literacy were two of the first groups to take this initiative (Kapoun, 1998; Rosen, 1998; Smith, 1997). Their objectives were aimed at assisting Internet users by providing them necessary training to evaluate online information. They found that the skills required for evaluating credibility were similar to the ones used during information evaluation in other

channels of communication. The research highlighted five criteria in the development of skills before a user was competent to evaluate credibility of Internet-based information: correctness, authority, objectivity, currency (newly added or updated), and coverage or scope (Alexander & Tate, 1999; Brandt, 1996; Fritch & Cromwell, 2001). Out of the five criteria, users only tend to check for any two. Some studies stressed about the importance of author information and references provided by the content as well its quality (Alexander & Tate, 1999; Brandt, 1996). Others stressed about its professional design, being official, Multilanguage support, and usability (Eysenbach & Köhler, 2002). Studies conducted by Flanagin and Metzger (2000, 2007); Metzger et al. (2003) show that most Internet users more often assessed a Website's credibility only on currency, comprehensiveness and objectivity, while verifying author's identity, qualifications, and contact information were evaluated the least. From these results, it can be concluded that the users prioritized criteria that were easy to evaluate rather than ones which were time consuming.

Sanchez, Wiley, and Goldman (2006b) showed that credibility assessment could be enhanced by providing training to the students. They identified four areas where the students required support: source of information; type of information being presented; how the information fits into an explanation of the phenomena; and evaluating the information with prior knowledge of the subject. Baildon and Damico (2009) also presented a similar model that went through a series of yes-no questions for evaluating credibility.

The checklist approach evaluates the content comprehensively and covers all of the categories falling under credibility. However, the approach demands a lot of time from the user to fully utilize it. The factors identified under checklist approach are listed in Table 2.9.

Table 2.9: Factors mapped into categories for checklist approach

Category	Factors Identified	References
Correctness	Ability to verify claims elsewhere (e.g., external links), citations to scientific data or references, source citations	(Alexander & Tate, 1999; Baildon & Damico, 2009; Brandt, 1996; Flanagin & Metzger, 2003; Fogg et al., 2003b; Fogg, 2002b; Sanchez et al., 2006b; Wathen & Burkell, 2002)
Authority	Author identification, author qualifications and credentials, presence of contact information	(Alexander & Tate, 1999; Brandt, 1996; Flanagin & Metzger, 2003; Fogg et al., 2003b; Fogg, 2002b, 2003; Freeman & Spyridakis, 2009a; Rieh, 2002)
Currency	Presence of date stamp showing information is current	(Alexander & Tate, 1999; Flanagin & Metzger, 2003; Fogg et al., 2003b; Fogg, 2002b, 2003; Wathen & Burkell, 2002)
Professionalism	Certifications or seals from trusted third parties, absence of advertising, absence of typographical errors and broken links, domain name and URL (suffix), download speed, multi-language support, notification or presence of editorial review process or board, Sponsorship by of external links to reputable organizations, presence of privacy and security policies, easy navigation, well-organized site,	(Baildon & Damico, 2009; Brandt, 1996; Flanagin & Metzger, 2003; Fogg et al., 2003b; Fogg, 2002b, 2003; Sanchez et al., 2006b; Wathen & Burkell, 2002)

Table 2.9 continued		
Professionalism	Interactive features (e.g., search capabilities, confirmation messages, quick customer-service responses), professional, attractive, and consistent page design, including graphics, logos, colour schemes	
Popularity	Past experience with source or organization (reputation), ranking in search engine output, likeability	(Flanagin & Metzger, 2003; Fogg et al., 2003b; Fogg, 2002b, 2003; Wathen & Burkell, 2002)
Impartiality	Message relevance, tailoring and Plausibility of arguments	(Alexander & Tate, 1999; Baildon & Damico, 2009; Flanagin & Metzger, 2003; Fogg et al., 2003b; Fogg, 2002b, 2003; Sanchez et al., 2006b)
Quality	Comprehensiveness of information provided, paid access to information, professional quality and clear writing	(Brandt, 1996; Flanagin & Metzger, 2003; Fogg et al., 2003b; Fogg, 2002b, 2003; Rieh, 2002; Wathen & Burkell, 2002)

It can be observed from the table that checklist approach covers a wide range of factors, mapping onto all credibility categories almost equally, except for professionalism category, which contains more factors than others. Some of the factors, such as download speed, ranking in search engine, may require the user to do some additional tasks in order to fetch relevant data as it is not available on the Web page itself. In conclusion, the approach covers all categories extensively but a lot of time must be committed in order to find the relevant details.

(b) ***Cognitive approach***

Fritch and Cromwell (2001, 2002) proposed a model for introducing a cognitive authority for assessing Web content information. By definition, cognition is the "mental process of knowing, including aspects such as awareness, perception, reasoning, and judgment" (Jonassen & Driscoll, 2003; Metzger & Flanagin, 2013). The model presented is iterative in nature, where information seekers evaluate the credibility and quality at levels of author, document, institution, and affiliations, and this is later integrated for global judgment. The model looks into factors such as verifying the author or institution information, and whether the content is reviewed by peers, and provides evidence for supporting an argument, layout and presentation of the content, regularly updated content and correctness of the document against other known evidence-based guidelines and theories. Though the factors overlap with the criteria set out for the checklist approach, the mechanism for evaluation differs. The cognitive approach gives importance to technological tools (such as Who-is, NSlookup or Dig for providing domain info, and Traceroute for providing network path details) for users for evaluating different criteria (Fritch & Cromwell, 2001, 2002).

Wathen and Burkell (2002) proposed an iterative model based on a review of literature in psychology and communication. The model divides credibility evaluation into three stages, each evaluating certain criteria. The first stage deals with the overall impression of the Website by looking at properties like appearance, colours, graphics and layout. The second stage verifies trustworthiness, correctness and currency of the document. The last stage takes into account factors relating to the user's cognitive state when evaluating the document. Therefore, the result may differ from user to user, depending on his or her experience of the topic at hand. Metzger and Flanagin (2013) highlighted the use of cognitive heuristics in credibility judgment. Their findings illustrate the types of cognitive

heuristic adopted by users to determine the credibility of the Web content and Web resources.

The cognitive approach introduces cognitive skills of the user for evaluating the content and thus the results produced differ between different users. This adds a new dimension for evaluating Web credibility but the results may be questionable if we take into account the person judgement. Table 2.10 lists factors identified under this approach.

Table 2.10: Factors mapped into categories for cognitive approach

Category	Factors Identified	References
Correctness	Correctness of the document against other known evidence-based guidelines and theories, trustworthiness, accuracy, user's cognitive state evaluating the document, provides evidence for supporting an argument	(Fritch & Cromwell, 2001, 2002; Metzger & Flanagin, 2013; Wathen & Burkell, 2002)
Authority	Verifying the author or institution information,	(Fritch & Cromwell, 2001, 2002; Metzger & Flanagin, 2013)
Currency	Regularly updated content Currency of the document.	(Fritch & Cromwell, 2001, 2002; Metzger & Flanagin, 2013; Wathen & Burkell, 2002)
Professionalism	Layout and presentation of the content, Website's visual appearance, colours, graphics and layout.	(Fritch & Cromwell, 2001, 2002; Wathen & Burkell, 2002)
Popularity	None	
Impartiality	None	
Quality	The content is reviewed by peers and depth of the article	(Fritch & Cromwell, 2001, 2002; Metzger & Flanagin, 2013)

The number of factors covered by cognitive approach is not as comprehensive as the checklist approach. This is because studies using cognitive approach did not test any factor belonging to categories such as popularity and impartiality. However, in comparison to the checklist approach, cognitive approach take into account user cognitive skills in evaluating factors.

(c) ***Prominence-interpretation of factors approach***

Though the checklist and cognitive approaches provide criteria for evaluating credibility, conventional Internet users nonetheless set their own criteria for measuring it. It is safe to say that Internet users perceive information differently as compared to researchers and set their own precedence and interpretation for evaluating credibility.

Eysenbach and Köhler (2002) conducted a study to verify this claim. The study involved 21 participants who were asked to identify the criteria they thought were important for evaluating credibility. The researchers reported that the criteria which the participants chose gave precedence to the official authority of the source, presence of scientific citations, professional design, ease of use, and multiple language or user's preferred language support. One interesting observation made by the researchers was that very few participants looked into the authenticity of the source while evaluating the Website.

Dochterman and Stamp (2010) explored how Web users make credibility judgments. They formed three focus groups, which were asked to examine Websites and comment on them. A total of 629 comments were collected about users' perceptions of Web credibility assessment. The focus groups narrowed down twelve credibility factors impacting their judgment, including authority, page layout, site motive, URL, crosscheck ability, user motive, content date, professionalism, site familiarity, process, and personal beliefs.

The Persuasive Technology Lab at Stanford university proposed some key components of Web credibility and presented a general theory called prominence-interpretation theory (Fogg, 2003). The theory was formed after conducting extensive quantitative research on Web credibility in various studies involving more than 6500 participants. It is based on two key components for evaluating information's credibility, i.e., prominence which means that the user notices something and Interpretation which means that the user makes a judgment about it. The factors identified under this approach are listed in Table 2.11.

Table 2.11: Factors mapped into categories for prominence-interpretation of factors approach

Category	Factors Identified	References
Correctness	Cross checking for verification, official authority of the source, presence of scientific citations, object characteristics including its type (journal vs forum), citation	(Eysenbach & Köhler, 2002; Fogg, 2003)
Authority	Author details, the characteristics of source dealt with details of the author	(Dochterman & Stamp, 2010; Fogg, 2003)
Currency	Content date	(Dochterman & Stamp, 2010; Fogg, 2003)
Professionalism	URL, site motive, multi-language or user's preferred language support, type of source (.com, .edu, etc.), information on the page, Website presentation, page layout, site familiarity, professional design, easy to use, presentation and structure of the document, Website's motives	(Dochterman & Stamp, 2010; Eysenbach & Köhler, 2002; Fogg, 2003)

Table 2.11 continued		
Popularity	Website reputation	(Dochterman & Stamp, 2010; Eysenbach & Köhler, 2002; Fogg, 2003)
Impartiality	User's experience, involvement of the user, individual differences, topic of the Website, task of the user, user's assumptions, skills and knowledge of the user, evaluation of context when it is being conducted, user motive and personal beliefs	(Fogg, 2003)
Quality	None	

The approach focuses mainly on the user's preferred factors and thus the results vary from user to user. Moreover, some of the categories may totally be ignored by users if they do not consider the category important. Two users with similar preferences may therefore have different results depending upon their experience with Web credibility assessment.

Prominence-interpretation approach, though focusing more on user preference for checking for credibility, yet it covers a large number of factors. The research found very few factors under authority, currency, popularity and none under quality. On the other hand, the remaining categories were covered extensively listing more than five factors in each category.

(d) ***Contextual approach***

Though the checklist and other comparable approaches do provide a complete guideline for credibility assessment, they are not practical to use and often require a lot of time to evaluate Websites (Meola, 2004). Some checklist approaches have over 100 questions per Web page visit, which affects the usability of the approach. Meola (2004) identified

the failings of the checklist approach and presented a contextual model to overcome these. Flanagin and Metzger (2000) highlighted the reluctance of users to spend too much time on evaluating the credibility of Web information, while Meola (2004) also challenged the need to perform validation on all Websites when there are professionals managing Websites properly. He distinguished Websites by dividing them into two categories, i.e., free Websites and fee-based Websites.

In contrast with the checklist approach, the model proposed by Meola in 2004 emphasized on shifting of the information externally. Meola stated that information is located within its wider social context, facilitating reasoned judgments of information quality', thus introducing external information for verifying the information. The model proposed three techniques for achieving this: using peer reviewed and editorially reviewed resources, comparing information with credible resources, and corroborating information from multiple sources. Meola stressed that the contextual approach is more practical and easier to use. Moreover, it takes less time to guide users towards adopting credible resources and train them, rather than going through a checklist for every website. Table 2.12 lists the factors found under the contextual approach.

Table 2.12: Factors mapped into categories for contextual approach

Category	Factors Identified	References
Correctness	Comparing information with credible resources, Corroborating information from multiple sources	(Meola, 2004)
Authority	None	
Currency	None	
Professionalism	None	
Popularity	None	
Impartiality	Using peer-reviewed and editorial reviewed resources	(Meola, 2004)

Table 2.12 continued		
Quality	Using peer-reviewed and editorial reviewed resources	(Meola, 2004)

The contextual approach tries to cover the disadvantages found in the existing approaches by taking the context of the content into consideration. This saves users' time on credibility assessment for content that has already been reviewed by experts. Though it does not address all the categories falling under credibility assessment.

Unlike other approaches, where a number of factors are considered, contextual approach only compares the information given in the selected credibility sources. This is also the reason why this approach only covers limited categories including correctness, impartiality and quality. Only these three categories are covered as peer-reviewed content is considered under the credibility categories mentioned above.

(e) ***Motivation-centred approach***

While evaluating Web information credibility using humans, Metzger (2007) looked into the benefits and shortfalls of different approaches and suggested a dual processing model that considers both users' motivation and their ability to evaluate. Besides motivation, users' experience and knowledge is also catered for in this approach. This is useful for users who are seeking specific or targeted information. The user can also be given the option to adopt the detailed list of factors used in the checklist or contextual approach, if required. Depending upon the severity or importance of credibility assessment, the necessary approach can be adopted. The model is divided into three phases: exposure phase, evaluation phase, and judgment phase. The exposure phase asks the user about his or her motivation and ability to evaluate. Depending upon the option chosen, the process can be taken to the next stage. The evaluation phase offers options to the user for evaluation. These options include no evaluation if the content does not require credibility

assessment, heuristic or peripheral evaluation which considers only simple characteristics like design or layout, and systematic or central evaluation for users who want rigorous and accurate credibility assessment. Finally, the judgment can be made in the final phase (Metzger, 2007).

The motivation-centred approach, tries to address the problems in other solutions by following a dual processing model approach. Based on the user's motivation and experience, the model is adjusted to provide the optimal evaluation mechanism for that user. This allows the user to get the desired Web credibility assessment without overwhelming an inexperienced user with a lot of factors to check. The categories and the factors taken into consideration by this approach are listed in Table 2.13:

Table 2.13: Factors mapped into categories for motivation-centred approach

Category	Factors Identified	References
Correctness	Systematic or central evaluation	(Metzger, 2007)
Authority	Systematic or central evaluation	(Metzger, 2007)
Currency	None	
Professionalism	Heuristic or peripheral Evaluation	(Metzger, 2007)
Popularity	Heuristic or peripheral Evaluation	(Metzger, 2007)
Impartiality	Check user's exposure on the basis of his or her motivation and ability to evaluate	(Metzger, 2007)
Quality	None	

The approach uses both heuristic and systematic evaluation for conducting credibility assessment. The heuristic approach covers professionalism and popularity categories as they are evaluated by the user based on his personal experience. If the assessment is still not satisfactory then it can be done more rigorously by looking into categories that require additional information to be fetched like correctness, authority and impartiality. In comparison to other approaches, motivation-centered approach provides a systematic flow where additional credibility assessment is only done if required.

(f) ***Social and heuristic approach***

Most researchers assume that, for credibility assessment, users work in isolation and put in a lot of time and effort for effective evaluation (Metzger et al., 2010). However, not all Web users have the time and the skills necessary for conducting an effective evaluation, and have to rely on solutions that involve others for making credibility assessments including use of group-based tools.

Metzger et al. (2010) conducted a study to examine 109 participants and their evaluation of Web credibility using the social and heuristic approach. By using social computing, Website users reached a conclusive decision by getting involved in discussions. Among social factors, the participants focused on social information (good and bad reviews), social confirmation of personal opinion, endorsement by enthusiasts on the topic and resource sharing via interpersonal exchange. Among the cognitive heuristics factors that the participants used were reputation, endorsement, consistency, expectancy violation, and persuasive intent.

Savolainen (2011) analysed 4,739 messages posted to 160 Finnish discussion boards. Factors for the evaluation of quality and the judgment of information credibility were suggested for effective credibility assessment. For evaluation of quality of the information content of the message, the most frequently used criteria pertained to the usefulness, correctness, and specificity of information. Credibility assessment included the reputation, expertise, and honesty of the author of the message.

The approach tries to address the Web credibility assessment problem by taking advantage of the social element of the Web and users' heuristics skills for finding the solution. This is done by suggesting strategies for finding the answer in discussion boards. This allows the user to locate answers suggested by expert users on a given topic. In most cases, the approach points towards solved solutions that are related to a user's question.

This allows the user to use social and heuristics skills for each reaching a credibility answer without taking too much time. Table 2.14: lists the factors and the credibility categories used for evaluating.

Table 2.14: Factors mapped into categories for social and heuristic approach

Category	Factors Identified	References
Correctness	Correctness, and specificity of information.	(Metzger et al., 2010; Savolainen, 2011)
Authority	Expertise of the author, reputation of the author	(Savolainen, 2011)
Currency	None	
Professionalism	None	
Popularity	Social factors include social information (good and bad reviews), social confirmation of personal opinion, endorsement by enthusiast on the topic and resource sharing via interpersonal exchange. cognitive heuristics factors include reputation, endorsement, consistency, expectancy violation, and persuasive intent.	(Metzger et al., 2010; Savolainen, 2011)
Impartiality	Endorsement by enthusiast on the topic, honesty of the author of the message	(Savolainen, 2011)
Quality	For evaluation of message's quality usefulness, endorsement by enthusiasts	(Metzger et al., 2010)

This approach covers categories like popularity extensively, but some categories are not covered at all including professionalism and currency. This is because the focus is mainly limited to the answers provided by users on discussion/community boards. By doing this, only factors relating to the content itself and user providing the solution is looked into.

2.2.4.2 Evaluation techniques using computers

One of the shortfalls of using humans as evaluators for credibility assessment is that the results vary depending upon users' perception and interpretation of the information. Moreover, the methods are either too time consuming, require user training or, in some cases, require motivation to perform the task. Therefore, researchers have proposed methods using computers for evaluation or assistance in Web information credibility evaluation.

Metzger (2007) suggested alternative approaches to human evaluation. She emphasized the problems faced when conducting evaluation with humans and the benefits that can be achieved using computers. She suggested various approaches including credibility seal programmes (for assisting users in located trusted Websites), credibility rating systems, directories, databases, or search engines showing credible content only, a platform for Internet content selection labels that establish the credibility of Internet information, digital signatures, collaborative filtering, and peer review (Metzger, 2007). Most of these approaches or their variants are being used today for evaluating Web information credibility along with new approaches. The approaches discussed are: scaffolding tool approach, visual cues approach, credibility seal programmes, credibility ratings systems, digital signatures, platform for Internet content selection, collaborative filtering and peer-review, machine learning, and semantic Web.

(a) ***Scaffolding tool approach***

Scaffolding tools provide helpful features to make the credibility assessment process easier. Some of these systems are in the form of Web-based learning platforms while others assist in fetching credible information off the Web.

STOCHASMOS, a Web-based learning platform, acts as a scaffolding tool for helping students in scientific reasoning (Kyza & Constantinou, 2007; Kyza & Edelson, 2005).

This is done by helping students to construct evidence-based explanations. The platform provides features including omnipresent tools, inquiry environment tools and STOCHASMOS reflective workspace tools.

Nicolaidou, Kyza, Terzian, Hadjichambis, and Kafouris (2011) shared a credibility assessment framework for supporting high school students. This framework helps students to develop skills for assessing credibility of information over the Web. The results gathered from the group discussion showed that the students became aware of the credibility criteria, allowing them to identify sources of low, medium and high credibility. The exercise was done using the STOCHASMOS learning environment. When using the framework for solving socio-scientific problems, the students went through passive prompts to identify and rate credibility from 1 (low) to 5 (high) (Nicolaidou et al., 2011). The framework required students to insert evidence (including its source) to support an argument. Moreover, the evidence had to be rated on criteria related to credibility containing funding, author's background, type of publication and whether the study included comparison between groups of studies.

This approach guides users to make better credibility judgements by providing an interface using computers. Instead of doing the work manually, the approach helps users do the task more easily by providing a mechanism to find evidence related to content's credibility. However, it does not provide any credibility assessment on its own. Table 2.15 lists the factors identified under this approach.

Table 2.15: Factors mapped into categories for scaffolding tool approach

Category	Factors Identified	References
Correctness	Evidence-based scientific reasoning	(Kyza & Constantinou, 2007; Kyza & Edelson, 2005; Nicolaidou et al., 2011)
Authority	Author's background	(Kyza & Constantinou, 2007; Kyza & Edelson, 2005; Nicolaidou et al., 2011)
Currency	None	
Professionalism	Domain type, domain or source's funding, includes evidence of low, moderate and high credibility in the learning environment	(Kyza & Constantinou, 2007; Kyza & Edelson, 2005; Nicolaidou et al., 2011)
Popularity	None	
Impartiality	None	
Quality	Supports collaboration and peer review, publication type, whether the study included comparison between groups of studies	(Nicolaidou et al., 2011)

Scaffolding tool approach covers a good variety of credibility categories. This is done by providing relevant information to user, for conducting credibility assessment properly. From the systems reviewed, most of the important categories were covered except for impartiality, popularity and currency. This is because the tool didn't provide any popularity statistics of the Web site which are normally done by search engines or other SEO organizations Web sites. Similarly, categories like impartiality have to be evaluated by the users themselves as no information, such as conflicting arguments, sentiment score or tone of the content is provided to the user.

(b) ***Visual cues approach***

Most search engines and Web pages do not show all the relevant information that is necessary for making an accurate credibility assessment. Using visual cues to show the score of different characteristics affecting credibility can greatly help Web users in selecting credible Web resources (Schwarz & Morris, 2011b; Yamamoto & Tanaka, 2011a).

Yamamoto and Tanaka (2011a) highlighted the problems of Web search engines. Instead of results list, showing only titles, snippets, and URLs for search results, visualization about the Website's correctness, objectivity, authority, currency and coverage may also be presented to enhance the credibility judgment process. Credibility factors such as referential importance using Google's PageRank, reputation of source, objectivity of content using LexRank algorithm, authority of page creator, topic coverage and update frequency. Moreover, results are re-ranked by predicting the user's credibility judgment model through users' credibility feedback for Web results.

Schwarz and Morris (2011b) also presented a similar approach in which they identified different factors that are not available for end users. Moreover, some of the important features, such as popularity among specialized user groups, are currently difficult for end users to assess but do provide useful information regarding credibility. The factors were gathered from search results and the Web page itself. For search results, expert popularity, summary, URL, awards, title, result rank, page rank, and overall popularity were selected and for the Web page itself factual correctness, expert popularity, citations, familiarity with site, title, domain type, look and feel, author information, awards, page rank, overall popularity, popularity over time, number of ads and where people are visiting from were selected. The proposed solution presents visualizations designed to augment search

results and thus lead to Web pages that most closely match the most promising of these features.

Another research, a semi-automated system was proposed that facilitates the reader in assessing the credibility of information over the Web (Shibuki et al., 2010a). The method provides a mediatory summary of the content available on Web documents. A mediatory summary is one where both positive and negative responses are included in the summary in such a way that the user is guided towards the correct conclusion. This is done based on the relevance of a given query, fairness, and density of words. Moreover, the final summary is generated by comparing documents retrieved in both the submitted query and the inverse query.

In contrast to scaffolding tool approach, visual cues approach provides relevant information to users for making better credibility judgements; users do not have to find that information themselves. The relevant information is provided either in terms of scores or information relating to each category. The approach is quite comprehensive and covers all the categories of credibility. Table 2.16 lists the factors identified under this approach.

Table 2.16: Factors mapped into categories for visual cues approach

Category	Factors Identified	References
Correctness	Referential importance of Web page, citations, relevance of a given query, factual correctness,	(Schwarz & Morris, 2011b; Shibuki et al., 2010a; Yamamoto & Tanaka, 2011a)
Authority	Social reputation of Web page, expert popularity, author information, author awards	(Schwarz & Morris, 2011b; Yamamoto & Tanaka, 2011a)

Table 2.16 continued		
Currency	Freshness of Web page, update frequency of Web page	(Yamamoto & Tanaka, 2011a)
Professionalism	Domain type, Website awards, title, no spelling errors, number of ads	(Schwarz & Morris, 2011b)
Popularity	Social reputation of Web page, result rank, page rank, overall popularity, popularity over time, where people are visiting from familiarity with site	(Schwarz & Morris, 2011b; Yamamoto & Tanaka, 2011a)
Impartiality	Content typicality of Web page and its summary, positive and negative responses of the given query, fairness, tone of content	(Shibuki et al., 2010a; Yamamoto & Tanaka, 2011a)
Quality	Content typicality of Web page, coverage of technical topics on Web page, density of words	(Yamamoto & Tanaka, 2011a)

As compared to the scaffolding approach, visual cues provide credibility assessment score based on the factors used by the system for evaluating each category. Not only does the approach cover all categories but also uses a number of factors for evaluating each one of them. The only negative about the visual cues approach is that the scores are based on the system itself and does not allow freedom to the user in prioritizing one category over another. However, by providing visual cues for each category, it can be used to judge which sources are better with respect to a specific category.

(c) ***Credibility seal programmes***

Credibility seal programmes suggest trusted Websites to Internet users by marking a Website with an approval logo. Verification entities such as TRUSTe, BBB, and Guardian e-Commerce verify Websites by looking into sites' privacy policies (Jensen & Potts, 2004). This helps in highlighting credible Websites from fake ones, as among most visited Websites 77% of them share their privacy policies (Adkinson, Eisenach, & Lenard, 2002; Tsai, Egelman, Cranor, & Acquisti, 2011; Wu, Huang, Yen, & Popova, 2012).

TRUSTe is dedicated to building a consumer's trust towards the Internet. By signalling the user, the programme assures the user that the Website is credible. TRUSTe does an initial evaluation of the Website and its policies to verify its consistency with TRUSTe licensee's requirements. After initial evaluation, a privacy program is placed that continues to monitor the Website and its policies periodically. All initial and periodic reviews are conducted at TRUSTe's facility by accessing the Website and its policies. If TRUSTe finds a Website not following its stated privacy practices then action is taken, including complaint resolution, consequences for privacy breach, and privacy education to consumers and business (Benassi, 1999). To prevent unauthorized use of the trademark, TRUSTe provides a "click to verify" seal which links the user to TRUSTe secure server to confirm Website's participation. Rodrigues et al. (2013) reviewed prior seal programme approaches and suggested an approach that enables these programmes to unlock their full potential by the use of more comprehensive privacy certification mechanisms, including data protection certification mechanisms, seals, and marks. The factors covered by this approach are listed in Table 2.17.

Table 2.17: Factors mapped into categories for credibility seal programmes

Category	Factors Identified	References
Correctness	None	
Authority	None	
Currency	None	
Professionalism	Privacy policies, meeting the requirement of the license, this includes complaint resolution, consequences for privacy breach, privacy education to consumers and business, privacy certification mechanisms including data protection certification mechanisms, seals, and marks	(Adkinson et al., 2002; Benassi, 1999; Jensen & Potts, 2004; Rodrigues et al., 2013; Tsai et al., 2011; Wu et al., 2012)
Popularity	None	

Table 2.17 continued		
Impartiality	None	
Quality	None	

Credibility seal programmes act as filter to allow credible information only. One of the shortfalls of credibility seal programmes approach is that information provided to user is often limited due coverage of fewer credibility categories. This is because only the Websites marked as credible by seal programmes are considered for answer extraction and a Website containing the necessary info may be ignored. Moreover, the approach addresses only a few credibility categories.

As compared to other approaches, credibility seal programmes only cover professionalism score as the factors covered by them fall under this category only. Though, it certainly helps in selecting Websites that have been marked as credible by authentic organizations, the quality of the content or Website's popularity still remains a question mark. Unless an expert plans to focus primarily on professionalism other approaches must be considered for giving a better overall credible assessment of the Web page.

(d) ***Credibility rating systems***

The rise in online social networking Websites and collaborative editing tools has allowed users to share content and approve information because of features such as rating tools, comment boxes, collaborative linking and community-editable content. These tools allow users to give feedback, suggest changes, criticize and, in some cases, edit information. Social navigation tools, recommendation systems, reputation systems, and rating systems are all different types of social feedback systems for Websites serving the same purpose (Aggarwal et al., 2014b; Dieberger, Dourish, Höök, Resnick, & Wexelblat, 2000; Gupta

et al., 2014; List et al., 2017; Metzger, 2005; Rainie & Hitlin, 2004; Resnick & Varian, 1997; Shardanand & Maes, 1995).

Giudice (2010) conducted a study to determine the impact of audience feedback on Web page credibility. For the study, three practice and eight experimental Web pages containing audience feedback in the form of thumbs-up and thumbs-down were chosen. These pages had four types of rating: good (90% positive, 10% negative), bad (10% positive, 90% negative), neutral (50% positive, 50% negative) or no rating. Moreover, a range of audience feedback, consisting of high (20,000 audience members) and low levels (2,000 audience members), was also used for checking the behaviour of the participants (Giudice, 2010). A total of 183 participants underwent the study. The results showed that the participants considered a Web page more credible if it had a good rating from its audience. The study also showed that the size of the audience had no major impact on the participants' decision (Giudice, 2010). Gupta et al. (2014) system is based on the same principle in which the system rates credibility of tweets. This system uses factors such as tweet source, time since tweet, content of tweet, presence of swear words, number of followers of author, number of re-tweets, number of mentions, and reviewers score for the tweet. List et al. (2017) also developed a system where users can check content's information, trustworthiness rating and citation to content.

A rater rating system proposed by Pantola, Pancho-Festin, and Salvador (2010a) measures the credibility of the content and the author, based on the rating the author has received. For computing the overall credibility of an article, an algorithm goes through several steps including determining a set of raters, getting the set of ratings, computing consolidated ratings, computing credibility rating, computing contributor reputation, and computing rater reputation.

Adler and Alfaro (2007) proposed a content-driven reputation system that calculates the amount of content added to or edited by authors which is preserved by subsequent authors. This allows younger authors and editors to gain a good reputation if the content is considered material of high quality by the original author, and penalized if it is the other way round. Tests conducted on Italian and French Wikipedia, having over 691,551 pages, showed that changes performed by low reputation authors resulted in poor quality material (less credible), i.e., a larger than average probability of having poor quality.

Papaioannou, Ranvier, Olteanu, and Aberer (2012) proposed a decentralized social recommender system for credibility assessment. The system takes into account social, content and search-ranking components before passing a final judgment. Wang, Zou, Wei, and Cui (2013) also proposed a trust model of content using a rating supervision model. The model analyses the behaviour and trustworthiness of the network entities using Website's content data, changes in data with respect to time and its application. An artificial neural network is applied on these dimensions to form a trust model for checking data credibility. The RATEWeb framework also provides a mechanism for providing trust in service-oriented environments (Malik & Bouguettaya, 2009). It is based on a collaborative model in which Web services (a software application that supports direct interaction with other software applications using XML messages) share their experience of service providers with other Web services using feedback ratings. These ratings are used to evaluate a service provider's reputation.

Although the approach looks promising, because ratings help Web users in judging the credibility of content, some programmes do use unfair means to get high ratings to mislead users (Liu, Yu, Miao, & Kot, 2013a; Liu, Nielek, Wierzbicki, & Aberer, 2013b). A two-stage defence algorithm has been proposed by Liu et al. (2013b), which defends

against attackers that imitate the behaviour of trustworthy experts and gain a high reputation, thus resulting in attacks on credible Web content.

In contrast to credibility seal programmes, credibility rating systems use the ratings provided by experts and users. The process is easy enough to involve all kinds of users for rating a Website's content. Though useful, it does require the raters to be active so that they may be able to rate all new content when it is added. Moreover, if everyone is able to rate content, inexperienced raters may overshadow the ratings submitted by expert raters. The factors used under this approach are listed in Table 2.18.

Table 2.18: Factors mapped into categories for credibility rating systems

Category	Factors Identified	Reference
Correctness	Audience feedback in the form of thumbs-up, thumbs-down, ignores rating submitted by unqualified authors, content's context, content source	(Adler & Alfaro, 2007; Aggarwal et al., 2014b; Dieberger et al., 2000; Giudice, 2010; Gupta et al., 2014; List et al., 2017)
Authority	Determining set of raters, getting the set of ratings, computing consolidated ratings, computing credibility rating, computing contributor reputation and computing rater reputation, followers count	(Adler & Alfaro, 2007; Aggarwal et al., 2014b; Gupta et al., 2014; List et al., 2017; Pantola et al., 2010b)
Currency	Updates to the document, creation time	(Aggarwal et al., 2014b; Gupta et al., 2014; Wang et al., 2013)
Professionalism	User ratings for the page, different content features of Web page, domain type, link integrity, affiliations, interactivity and usability of website, aesthetics, domain experts review, no swear words	(Adler & Alfaro, 2007; Aggarwal et al., 2014b; Gupta et al., 2014; List et al., 2017; Malik & Bouguettaya, 2009; Wang et al., 2013)

Table 2.18 continued		
Popularity	Ranking in the search result, Website ranking, traffic details, number of re-tweets, number of mentions, rating among reviewers	(Aggarwal et al., 2014b; Dieberger et al., 2000; Giudice, 2010; Gupta et al., 2014; Papaioannou et al., 2012)
Impartiality	Sentiment value, tone of content	(Aggarwal et al., 2014b; Gupta et al., 2014)
Quality	Similarities with other online content, primary or secondary source, readability	(Adler & Alfaro, 2007; Aggarwal et al., 2014b)

This approach covers a wider range of credibility category, as compared to credibility seal programmes. This is because the approach offers users' and experts' ratings for a number of things, including the content itself, the author and features of the Website as well (Aggarwal & Van Oostendorp, 2011; Aggarwal et al., 2014b). This allows the approach to rate several categories based on the ratings given by the reviewers. Furthermore, these reviewers also look into additional factors like content's last update date and plagiarism ratio, thus scoring it for quality and currency category. Overall, credibility rating systems cover all categories for evaluation them, though not extensively.

(e) ***Digital signatures***

The digital signatures approved is an electronic way of showing the authenticity of a document. It gives the reader a reason to trust the document because it has been created by an authentic entity (Asokan, Shoup, & Waidner, 1998b; Dunjko, Wallden, & Andersson, 2014; Ford & Baum, 2000; Wallden, Dunjko, Kent, & Andersson, 2015).

Digital signatures can also be used as a characteristic for identifying credible and authentic documents. Kundur and Hatzinakos (1999) presented an approach for applying digital watermarking to multimedia documents to authenticate them for court cases,

insurance claims and similar types of situations, and to make them tamper-proof. The technique embeds watermarks so that tampering of the document may be detected when reading in localized spatial and frequency regions. Yang, Campisi, and Kundur (2004) proposed a double watermarking technique for applying digital signatures to cultural heritage images. The same can be applied to electronic text documents as well to verify the author of the content. The Joint Unit for Numbering Algorithm (JUNA) project applies a visible watermark on text, images, multimedia documents instead of using complex methods for embedding them within the electronic file (Hailin & Shenghui, 2012). In combination with cloud computing concepts, the model proves to be more practical, lower in cost, and a safer copyright protection scheme than others. In another technique, researchers propose an anti-copy attack model for digital images by embedding and watermarking the images (Chunxing & Xiaomei, 2011). The current version of digital signatures is quantum digital signatures which is based on use of quantum states for managing public and private keys (Dunjko et al., 2014; Wallden et al., 2015). Table 2.19 lists the factors found under digital signatures approach.

Table 2.19: Factors mapped into categories for digital signatures

Category	Factors Identified	References
Correctness	Digital watermarks	(Asokan, Shoup, & Waidner, 1998a; Chunxing & Xiaomei, 2011; Dunjko et al., 2014; Hailin & Shenghui, 2012; Kundur & Hatzinakos, 1999; Wallden et al., 2015; Yang et al., 2004)
Authority	Digital watermarks	(Asokan et al., 1998a; Chunxing & Xiaomei, 2011; Dunjko et al., 2014; Hailin & Shenghui, 2012; Kundur & Hatzinakos, 1999; Wallden et al., 2015; Yang et al., 2004)
Currency	None	

Table 2.19 continued		
Professionalism	Digital watermarks	(Asokan et al., 1998a; Chunxing & Xiaomei, 2011; Dunjko et al., 2014; Hailin & Shenghui, 2012; Kundur & Hatzinakos, 1999; Wallden et al., 2015; Yang et al., 2004)
Popularity	None	
Impartiality	None	
Quality	None	

Digital signatures provide an easy mechanism to verify the credibility of a document. This proves quite useful for measuring correctness and authority of the document. However, its scope is limited and thus not all categories of credibility are covered.

Similar to credibility seal programmes approach, digital signatures only provides credibility assessment for correctness, authority and professionalism categories. This is because these signatures are used for verifying whether the document is taken from the original source, thus verifying both the author and the source (Dunjko et al., 2014; Hao & Su, 2012; Wallden et al., 2015). Similarly, it also adds in to the Website's reputation by providing a mechanism for users to verify the document's credibility (Lu et al., 2017). However, simply replying on the digital signatures is not enough, as the content itself needs to be verified as well. Thus, use of other approaches is required in order to give a clearer picture on the credibility of a resource.

(f) ***Platform for Internet content selection***

The purpose of this platform is to select and show credible content only (World Wide Web Consortium, 2003). The idea was originally put forward by Resnick and Miller (1996), whereby they emphasized the importance and need for a platform that filters credible information. This is also useful for selecting content appropriate for certain age groups such as children and teenagers. The system does this by using labels (metadata)

associated with Internet content that may contain information relating to privacy, code signing, and so on.

The platform for Internet content selection project has now been superseded by a protocol for Web description resources which is based on Web 3.0 (Archer, Smith, & Perego, 2008a). This was done because of the limitations in the existing architecture of the Internet where computers were not able to understand the semantics and relationship between different contents and Web pages. However, researchers have been investigating solutions related to this. proposed a platform that allows credibility assessment of cross-language content(Geng, Wang, Wang, Hu, & Shen, 2012).

This approach is similar in concept to seal programmes but with the flexibility to look into metadata covering different credibility categories. This provides a fast and easier mechanism for credibility assessment but requires structured data on Websites. Moreover, it is not able to determine categories such as impartiality and quality of the content without the support of semantics and relationships between contents (Höffner et al., 2016). Table 2.20 lists the factors identified under this approach.

Table 2.20: Factors mapped into categories for platform for Internet content selection

Category	Factors Identified	References
Correctness	Labels (metadata) associated with Internet content that may contain information relating to its source	(Geng et al., 2012; Resnick & Miller, 1996)
Authority	Labels (metadata) associated with Internet content that may contain information relating to author details	(Geng et al., 2012; Resnick & Miller, 1996)
Currency	None	

Table 2.20 continued		
Professionalism	Labels (metadata) associated with Internet content that may contain information relating to privacy, code signing, etc.	(Geng et al., 2012; Resnick & Miller, 1996)
Popularity	None	
Impartiality	None	
Quality	None	

This approach aims at providing most of the important information through meta data found in HTML content. However, it is only able to cover categories like correctness, authority and professionalism. This means that the approach itself cannot be used to provide the overall credibility score of a resource and thus evaluations from other approaches cover other categories, which need to be considered as well

(g) ***Collaborative filtering and peer review***

Peer review and collaborative filtering approaches are among the most trusted approaches because experts rate the content (Wang & Yang, 2012; Yazdanfar & Thomo, 2013). Loll and Pinkwart (2009) suggested a technique using the benefits of this approach. They suggested that the model should be used for eLearning application to promote credible content to learners.

PeerGrader was one of the first systems for helping students in peer evaluation (Gehringer, 2000, 2001). The system allowed students to submit their work to be reviewed blindly by other students. This enabled students to gain experience in grading and improving the quality of their work. Although the solution was useful, it depended upon the reviewer's active and quick response to articles and assignments. Another Web-based collaborative filtering system, Scaffolded Writing and Rewriting in the Discipline (SWoRD) system, addressed this problem by allowing multiple students or teachers to

review an assignment (Cho & Schunn, 2007; Cho, Schunn, & Wilson, 2006). Todd and Hudson (2011) conducted an experiment on twenty-five undergraduate students taking a public relations course in which he introduced peer-graded evaluation and monitored improvements in students' writing skills. Students showed a positive feedback with scores ranging from 4.8 to 5.6 on a seven-point scale. Wang and Yang (2012) applied Drupal recommender system, which provides user suggested topics, on a platform being used by a group of students. The students using the system showed improvement in terms posts frequency and class performance over their counterparts.

Peer review also plays a major role in judging the quality and credibility of articles submitted to conferences and journals. The process involves multiple reviewers assessing an article for plagiarism, quality and credibility (Parsons et al., 2010). Peer review also enhances the credibility of the data published, and the author of a peer-reviewed paper receives greater recognition than the author of a report. Mulder, Pearce, and Baik (2014) experimented peer-review with university students which improved the accuracy and quality of the assignments produced as they were reviewed by their peers.

Peer review can also be used for reviewing Websites or content and rating them. This is also known as collaborative filtering. Just like the credibility rating systems, Websites are evaluated by people but in this case they are experts in the area and their recommendations are considered highly authentic (Su & Khoshgoftaar, 2009). The collaborative filtering technique may also adopt memory-based ratings (set by a panel) which gives a predict rating using existing data or hybrid recommenders (Su & Khoshgoftaar, 2009). Yazdanfar and Thomo (2013) applied collaborating filtering to recommended credible URLs to twitter users by considering credibility factors such as rating of URL, correctness of content on URL and reviewed period of URL.

The categories and factors covered by different techniques used under collaborative filtering and peer review approach are listed in Table 2.21.

Table 2.21: Factors mapped into categories for collaborative filtering and peer review

Category	Factors Identified	References
Correctness	Content reviewed by an editorial board	(Cho & Schunn, 2007; Gehringer, 2000, 2001; Mulder et al., 2014; Parsons et al., 2010; Su & Khoshgoftaar, 2009; Todd & Hudson, 2011; Wang & Yang, 2012; Yazdanfar & Thomo, 2013)
Authority	Author's prior contributions	(Cho & Schunn, 2007; Gehringer, 2000, 2001; Mulder et al., 2014; Parsons et al., 2010; Su & Khoshgoftaar, 2009; Todd & Hudson, 2011; Wang & Yang, 2012; Yazdanfar & Thomo, 2013)
Currency	Content's published date	(Cho & Schunn, 2007; Gehringer, 2000, 2001; Mulder et al., 2014; Parsons et al., 2010; Todd & Hudson, 2011; Wang & Yang, 2012; Yazdanfar & Thomo, 2013)
Professionalism	Editorial board members listed	(Parsons et al., 2010; Su & Khoshgoftaar, 2009; Yazdanfar & Thomo, 2013)
Popularity	Ranking of journal or proceeding	(Parsons et al., 2010; Su & Khoshgoftaar, 2009; Yazdanfar & Thomo, 2013)

Table 2.21 continued		
Impartiality	Editorial Boards	(Parsons et al., 2010; Su & Khoshgoftaar, 2009; Yazdanfar & Thomo, 2013)
Quality	Reviewer's experience, content reviewed by an editorial board, ranking of journal or proceeding, selection of journals and conference papers meeting the requirements	(Cho & Schunn, 2007; Gehringer, 2000, 2001; Mulder et al., 2014; Parsons et al., 2010; Su & Khoshgoftaar, 2009; Todd & Hudson, 2011; Wang & Yang, 2012; Yazdanfar & Thomo, 2013)

In conclusion, collaborating filtering and peer review approach is dependent on the activity of experts reviewing the content (Najafabadi & Mahrin, 2016). For it to be successful it is necessary for newly added content to be reviewed in a timely fashion (Najafabadi & Mahrin, 2016). Other than that, the peer-reviewed content is considered more credible than others. Moreover, the approach is comprehensive enough covering nearly all the credibility categories.

(h) ***Machine learning approach***

This approach focuses on learning the contents of the Web document or resource in order to come up with a reasonable assessment (Olteanu et al., 2013a). However, it is vital to identify the features, which the algorithm should look into to ensure accurate measurement.

Olteanu et al. (2013a) proposed an algorithm that looks into the content and social features for addressing traditional Websites as well as social networking Websites like Facebook and Twitter. The algorithm maps the result on a 5-point Likert scale using supervised algorithms. A test conducted on datasets showed 70% or more precision and recall as well as improving the absolute error (MAE) by 53% in regression.

Machine learning works best with a structured data Website but is not dependent on it (Olteanu et al., 2013a). If designed properly, a good machine learning algorithm will be able to cover all the credibility categories. However, this requires training and may lead to unexpected results at times. Moreover, the solution is not cost-effective and companies providing such solutions may ask users to pay a small fee in order to use its credibility assessment features. The factors covered by machine learning approach are listed in Table 2.22.

Table 2.22: Factors mapped into categories for machine learning

Category	Factors Identified	References
Correctness	Metadata features, Link structure	(Olteanu et al., 2013a)
Authority	Author details under metadata	(Olteanu et al., 2013a)
Currency	Metadata features	(Olteanu et al., 2013a)
Professionalism	Content features including text-based features, appearance and Web page structure	(Olteanu et al., 2013a)
Popularity	Social features including online popularity of the Web page,	(Olteanu et al., 2013a)
Impartiality	Reviews by experts	(Olteanu et al., 2013a)
Quality	Reviews by experts	(Olteanu et al., 2013a)

As compared to other approaches, machine learning approach covers all credibility categories and provides credibility assessment using minimal human assistance. Though the solution is expensive, it is able to fetch data from structured and unstructured content (Ferrucci et al., 2010; Gupta & Gupta, 2012). This is ideal when dealing with users that have little to no credibility assessment training.

(i) ***Semantic Web***

Semantic Web simply means giving meaning to the Web (Allemang & Hendler, 2011; Berners-Lee et al., 2001; Höffner et al., 2016; Lopez, Uren, Sabou, & Motta, 2011). It

focuses on the inclusion of semantic content to enable computers to understand the content available on the Web compared to unstructured and semi-structured documents in a Web of data (Kanellopoulos & Kotsiantis, 2007). It uses resource description framework (RDF) documents for storing metadata and uses Web ontology language for defining ontologies. With machines able to understand the content available on the Web, judging the credibility of content will become much easier.

One of the main platforms using the semantic Web is the protocol for Web description resources, which is the W3C recommended method for describing Web resources and documents. Using a protocol for Web description resources, one can access the metadata related to Web documents using resource description framework documents, Web ontology language, and a hypertext transfer protocol. This allows Web users to select and make decisions on Web resources of interest. Moreover, the credibility of the content can also be verified using semantic reasoners (Archer et al., 2008a). The HETWIN model uses semantic technologies for evaluating the credibility and trustworthiness of Web data (Pattanaphanchai et al., 2012). The factors identified under semantic Web approach are listed in Table 2.23.

Table 2.23: Factors mapped into categories for semantic Web

Category	Factors Identified	References
Correctness	Metadata related to Web documents using RDF, OWL and HTTP protocols, content analysis, OWL expression, Rules, metadata about correctness and relevance of documents to evaluating credibility	(Archer et al., 2008a; Kanellopoulos & Kotsiantis, 2007; Pattanaphanchai et al., 2012)
Authority	The meta data relating author	(Archer et al., 2008a; Kanellopoulos & Kotsiantis, 2007; Pattanaphanchai et al., 2012)

Table 2.23 continued		
Currency	Metadata relating updates to document	(Archer et al., 2008a; Kanellopoulos & Kotsiantis, 2007; Pattanaphanchai et al., 2012)
Professionalism	Metadata relating to privacy policies	(Archer et al., 2008a; Kanellopoulos & Kotsiantis, 2007; Pattanaphanchai et al., 2012)
Popularity	None	
Impartiality	Content analysis	(Archer et al., 2008a; Kanellopoulos & Kotsiantis, 2007; Pattanaphanchai et al., 2012)
Quality	Content analysis	(Archer et al., 2008a; Kanellopoulos & Kotsiantis, 2007; Pattanaphanchai et al., 2012)

The Semantic Web is the future of the Web and can be regarded as Web 3.0. The inclusion of semantics allows Web reasoners to do content analysis with ease and cover credibility categories not covered by other approaches. However, since not all content over the Web is structured (i.e. being able to be processed by semantic Web reasoners), some important content may be overlooked. Though ideal, it does require Websites to maintain structured data.

Semantic Web is an extended version of the platform for Internet content selection approach. Not only is it able to use the data provided in the meta data, but is also able to do reasoning to provide answers to the questions asked. Furthermore, the approach also does content analysis in order to cover credibility categories such as impartiality and quality.

2.2.4.3 Issues in the existing Web credibility evaluation approaches

Although researchers have come up with solutions to measure Web credibility, as can be seen in Section 2.2.4.1 and 2.2.4.2, but these techniques have several key issues. These techniques cover credibility categories partially and limited credibility factors for some resources (like social media and blogs) and domains (like medical and stocks). Because these techniques do not cover all credibility categories, the credibility score produced is biased towards certain aspect of the resource only. Moreover, these techniques also do not contain enough credibility factors for some resources widely used nowadays like social media and blogs, which depend on credibility factors like share count, view count, resource followers and more (Castillo et al., 2011; Gupta et al., 2014; Schultz et al., 2011). Furthermore, the combination of credibility factors used for a technique for evaluating the credibility of one particular Web resource may not be useful for evaluating another (Schwarz & Morris, 2011b). For example, when evaluating medical Websites, they require and emphasize on different set of credibility factors, such as correctness and authority, but educational Websites may focus more on quality of the content. A well-balanced credibility assessment system needs to consider all of these issues when evaluating a resource.

When developing a well-balanced credibility assessment system, lessons can be learned from existing evaluation techniques. Models for assessment using humans are perhaps the easiest to implement, as the evaluator only needs to be aware of the criteria for evaluating a document or Website. However, studies have shown that it is impractical and time-consuming to check each and every criterion when evaluating the credibility of a Web page (Meola, 2004). Moreover, the assessment is affected by the evaluator's experience and motivation (Metzger, 2007). To address these issues, users should be trained or let experienced users do the evaluation for them. The alternative solution is computer evaluation, which does seem more practical in assisting users regarding

credibility of a page. However, any one solution can only be applied to a limited number of Web pages and resources. For instance, semantic Web solutions provide the best possible solution for judging the credibility of an electronic document but this is only possible if the Web document is written using Web ontology language and metadata is stored in ontologies (Archer et al., 2008a; Berners-Lee et al., 2001). Similarly, credibility ratings, peer review, and digital signatures might only be available for a small number of documents. This poses a major problem for some of the newer Web systems available such as social networking services (SNS), blogs, forums, Wikis and computer-supported collaborative learning (CSCL) environments, as they are not rated immediately (Flanagin & Metzger, 2007; Harris, 2008; Metzger, 2007). These issues should also be considered when developing a well-balanced credibility assessment system

Therefore, this research will use the credibility assessment algorithm, comprising the defined categories and select credibility factors that affect Web pages. In the next sub-section, this research covers credibility assessment module in Web-based QA systems and the credibility factors used by other credibility-based QA system

2.3 Credibility assessment in Web-based QA systems

Web-based QA systems are very efficient in providing quick answers to simple questions using NLP and IR-based techniques, but their accuracy is affected due to the amount of fake Web pages and content on the Web (Gyongi & Garcia-Molina, 2005; Wu & Marian, 2011). Work on question answering systems dates back to mid-1960s, while Web-based QA systems started to gain popularity at the start of year 2000 (Black, 1964; Kwok et al., 2001). Over the years advancements have been made in Web-based QA systems in terms of improving extracting techniques and intelligent answer deduction, but there has been little emphasis on scoring the sources. Therefore, this research suggests developing a credibility assessment module for Web-based QA system, to allow scoring answers based

on credibility of source. This research looks into literature to find credibility factors used by Web-based QA systems and information systems that can be introduced in the credibility assessment module.

When reviewing Web-based QA systems, most of the systems focused primarily on either answer extraction or answer scoring. This is because these systems focus more on relevancy of the answer extracted, rather than looking into credibility of the source. These systems suggest methods like use of external resources, voting procedure, and probabilistic phrase re-ranking algorithm, that focus on improving techniques for answer extraction and scoring, but do not consider credibility assessment of sources (Ferrucci et al., 2010; Kwok et al., 2001; Liu et al., 2014; Molino et al., 2015; Oh et al., 2012; Radev et al., 2005; Wu & Marian, 2011; Yang & Chua, 2003).

However, some Web-based QA systems did introduce Web credibility assessment partially. Wu and Marian (2007b, 2011) Web-based QA system used two credibility factors (covering correctness and quality credibility categories) including search result rank and originality of the Web page by calculating a plagiarism score. Oh et al. (2013) suggested using three credibility factors including document quality, authority and reputation of answer sources for scoring answers based on their credibility. Honto?search by Yamamoto et al. (2007) evaluates information's trustworthiness based on popularity and currency credibility categories. This Web-based QA system evaluates popularity of the content by providing popularity estimation of the phrase and its counter examples available on the Web, and evaluates currency by monitoring changes in content with respect to time. Though these systems do consider some credibility factors, yet they can be enhanced much further by covering all credibility categories and by including more credibility factors. In the evaluations conducted by these systems, Corrob states to be achieving .772 in MRR only by covering correctness and quality categories, while

GenreQA states to be achieving .743 in MRR using currency, professionalism and quality categories (Oh et al., 2012; Wu & Marian, 2011). By covering all credibility categories Web pages more credible than others will get a higher score, allowing answers extracted from them to be ranked higher in the answer list and thus improving respective QA system's accuracy of answers (Aggarwal & Van Oostendorp, 2011).

Since, there are limited Web-based QA systems considering credibility assessment, this research started looking into Information Systems (IS). IS provide detail information to users regarding Web pages or content provided by performing information processing (Aggarwal et al., 2014b). There are many computer-based evaluation techniques through which credibility can be measured, and have been covered earlier in Section 2.2.4.2. These evaluation techniques are covered here by divided under two categories: credibility estimation and computer-aided credibility support systems.

Systems such as TrustRank (Gyöngyi, Garcia-Molina, & Pedersen, 2004) and CredibleRank (Caverlee & Liu, 2007) fall under the category of credibility estimation, where they used various factors to assign scores to Web pages before ranking the search results. These systems used link structure, organization, amount of spam and advertisements found on the Web page for scoring credibility of Web pages. The language modeling approach by Banerjee and Han (2009) is another example, which tried to verify answer validity by evaluating the reliability of the sources. This was done by checking the relevance between the document containing the candidate answer and the question's context model.

Among computer-aided credibility support system, the WISDOM system (Akamine et al., 2009) is quite popular. The WISDOM system evaluates credibility based on: information content that extracts major phrases and contradictory phrases, information senders that classifies Web pages on the basis of axes such as individuals vs. organizations

and profit vs. nonprofit organizations, and information appearances showing the distribution of positive and negative opinions related to the topic. It clusters the information collected according to senders and opinions made. Schwarz and Morris (2011a) system, also provides visual cues to assist users in credibility assessment of individual Web page and search results. Factors considered by the system were divided under three feature categories: on-page, off-page, and aggregate features. Tanaka et al. (2010b) also provided credibility results for Web pages by assessing them on the basis of content analysis, social support analysis and author analysis from Web content, images and videos. Later, Yamamoto and Tanaka (2011b) expanded this system by maps scores recorded from various factors into main credibility aspects: correctness, authority, currency, coverage, objectivity. Additionally, search results are re-ranked according to the predicted user's credibility judgement. The automated Web Credibility Assessment Support Tool (WebCAST), which is an upgrade of its predecessor (Aggarwal & Van Oostendorp, 2011), evaluates Web pages credibility based on all seven credibility categories and using multiple credibility factors criteria like type of website, popularity, sentiment, date of last update, reputation and review based on users' ratings reflecting personal experience (Aggarwal et al., 2014b). WebCast uses real-time databases like Alchemy API, Alexa API, Google API, Web of Trust (WoT) API for retrieving data relating to credibility factors (Aggarwal et al., 2014b).

Literature on Web-based QA systems and IR systems using credibility assessment, allowed us to identify factors that can help in assessing Web credibility. The credibility factors identified from Web-based QA systems and IR systems reviewed, are listed in Table 2.24 and Table 2.25. Table 2.24 covers the credibility factors identified under correctness, authority, currency and professionalism credibility category, while Table 2.25 covers popularity, impartiality and quality credibility categories.

Table 2.24: Credibility factors indentified for correctness, authority, currency and professionalism credibility categories from Web-based QA systems and information retreival systems

Paper	Correctness	Authority	Currency	Professionalism
Aggarwal and Van Oostendorp (2011); Aggarwal et al. (2014b)	Website purpose	Author details and expertise	Last update date	Domain type, link integrity, affiliations, interactivity and usability of website, aesthetics, domain experts review
Akamine et al. (2009)	Major phrases	N/A	N/A	Information sender class
Banerjee and Han (2009)	Relevance between source and question's content model	N/A	N/A	N/A
Caverlee and Liu (2007)	N/A	N/A	N/A	Website's outlinks, linkages with blacklist pages
Gyöngyi et al. (2004)	N/A	N/A	N/A	Organization, spam, link structure
Oh et al. (2012); Oh et al. (2013)		Author information		Reputation of Website
Schwarz and Morris (2011a)	N/A	N/A	N/A	Advertisements on page, domain type, awards, expert rating
Tanaka et al. (2010b); Yamamoto and Tanaka (2011b)	Topic coverage, topic depth, analysis of majority, dominance, and reputation of target content	Blogger and Newspaper ranking system	Update frequency and content's freshness	N/A

Table 2.24 continued				
Wu and Marian (2007b, 2011)	Search result rank, relevance	N/A	N/A	N/A
Yamamoto et al. (2007)	Major phrases	N/A	Update frequency	N/A

Table 2.25: Credibility factors indentified for popularity, impartiality and quality credibility categories from Web-based QA systems and information retreival systems

Paper	Popularity	Impartiality	Quality
Aggarwal and Van Oostendorp (2011); Aggarwal et al. (2014b)	Website ranking and traffic details	Sentiment value, tone of content	Primary or secondary source, readability
Akamine et al. (2009)	N/A	Positive/Negative statements	N/A
Banerjee and Han (2009)	N/A	N/A	N/A
Caverlee and Liu (2007)	N/A	N/A	N/A
Gyöngyi et al. (2004)	N/A	N/A	N/A
Oh et al. (2012); Oh et al. (2013)			Quality of document
Schwarz and Morris (2011a)	Share count, traffic stats, geographic reach, dwell time, re-visitation pattern, , page rank	N/A	Spelling errors

Table 2.25 continued			
Tanaka et al. (2010b); Yamamoto and Tanaka (2011b)	hyperlinks to the content, geographical social support, proximity of geographical support, social bookmarks	Sentiment value	N/A
Wu and Marian (2007b, 2011)	N/A	N/A	Similarity detection using SpotSigs
Yamamoto et al. (2007)	N/A	N/A	N/A

Literature review analysis show that most Web-based QA systems do not consider credibility assessment, and systems that do so only consider few credibility categories as compared to seven. Literature on IS helped this research in identifying the credibility factors that can be used in credibility assessment module for Web-based QA systems. These factors can be used to score for each credibility category to produce a well-balanced credibility score. In section 2.4, the research highlights the research gap in Web-based QA systems and credibility-based Web QA systems, and the direction this research can take in order to fill those gaps

2.4 Research gap

As stated earlier in section 2.3, existing Web-based QA systems and credibility-based QA systems either do not evaluate credibility of Web pages for scoring answers, or they do so partially, i.e., only covers some credibility categories. Moreover, the number of factors covered in each credibility category is often limited. For example, Wu and Marian's (2011) Corrob system only uses Zip-f distribution (or search engine rank) for calculating correctness of Web page, and SpotSigs technique for calculating its quality, as highlighted previously in Table 2.24 and Table 2.25.

Since, credibility-based Web QA systems used limited credibility factors and only covered some credibility categories, the search was expanded to IS. Web QA systems allowed the research to identify more credibility factors under each credibility category. In comparison to credibility-based QA systems, some information systems cover four to seven categories.

These findings are summarized in the form of a research gap table that highlights the categories least addressed by these systems, as shown in Table 2.26. The table shows the paper sharing details regarding the credibility-based QA system (represented as QA in the table) and information systems (represented as IS in the table) and the type it belongs to. The table also shows credibility categories covered by these systems, which are abbreviated as correctness (Corr), authority (Auth), currency (Curr), professionalism (Prof), popularity (Pop), impartiality (Im), and quality(Qual). A system covering a particular category is highlighted as a tick mark.

Table 2.26: Resarch gap for credibility categories comprising credibility-based Web QA systems and information systems

Paper	Type	Corr	Auth	Curr	Prof	Pop	Im	Qual
Oh et al. (2012); Oh et al. (2013)	QA		✓		✓			✓
Wu and Marian (2007b, 2011)	QA	✓						✓
Yamamoto et al. (2007)	QA	✓		✓				
Aggarwal and Van Oostendorp (2011); Aggarwal et al. (2014b)	IS	✓	✓	✓	✓	✓	✓	✓
Akamine et al. (2009)	IS	✓			✓		✓	
Banerjee and Han (2009)	IS	✓						
Caverlee and Liu (2007)	IS				✓			

Table 2.26 continued								
Gyöngyi et al. (2004)	IS				✓			
Schwarz and Morris (2011a)	IS				✓	✓		✓
Tanaka et al. (2010b); Yamamoto and Tanaka (2011b)	IS	✓	✓	✓		✓	✓	

As shown in Table 2.26, each credibility-based QA system only covers two to three categories, where popularity and impartiality are not covered by any one of them. Also authority, currency, and professionalism categories have one occurrence only under QA systems. In comparison, some information systems a wider range of credibility categories, but only one of them covers all seven categories. The research gap tables shows that the credibility-based QA systems to be developed by this research needs to consider all seven credibility categories and use a number of credibility factors under them if available, as required under research objectives 1 and 2. Moreover, more emphasis needs to be given towards credibility categories, such as authority, currency, popularity, impartiality and quality, which have not been covered extensively by many credibility-based QA systems and information systems in comparison to categories such as correctness and professionalism.

The research gap table allowed the research to highlight key weaknesses in existing credibility-based QA systems. By not covering all seven credibility categories, the reliability of the credibility scores can always be questioned (Aggarwal & Van Oostendorp, 2011; Aggarwal et al., 2014b; Wu & Marian, 2011). Moreover, the research also needs to cover more factors under these categories instead of selecting limited factors only. Finally, the impact credibility categories that are not used much often will allow

research to determine their impact on accuracy of answers, and whether they should be considered in evaluating credibility in future systems.

CHAPTER 3: RESEARCH METHOLODY

This chapter is divided into three sections. The first section explains the research flow for achieving the research objectives and defines the chosen research methodology in order to answer the research questions posed in Section 1.2. The second covers reasons for selecting a particular methodology and explains the selection criteria for conducting research. The third section covers the experimental design, explaining the steps taken for conducting evaluations.

3.1 Research flow

Defining a research design allows the research to highlight the steps that are taken in order to meet the research objectives of this thesis. The research goes through these steps one after another, forwarding the output of the previous step to the next step. Figure 3.1 shows the research design and steps involved including 1) Web credibility assessment, 2) develop a Web-based QA system (OMQA system), 3) develop a credibility-based Web QA system (CredOMQA system) and 4) evaluation, which are discussed in greater detail in the sub-sections below.

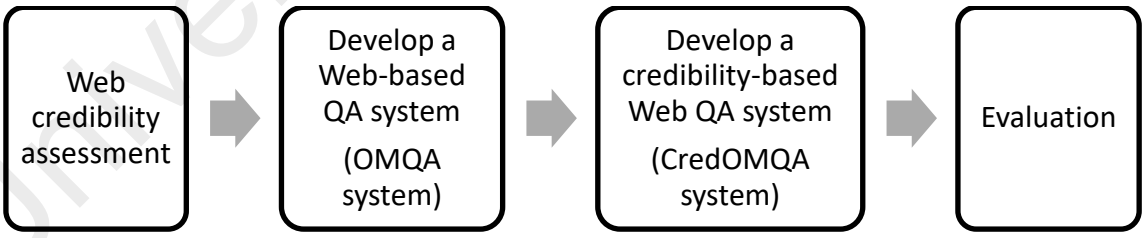


Figure 3.1: Research flow

3.1.1 Web credibility assessment

The first step of the research flow is to provide an algorithm for evaluating credibility of Web page. This is defined in order to address the first objective of the research, which is *"To design an algorithm for measuring credibility of Web pages"*. In this step, the research starts by reviewing existing systems making use of Web credibility assessment.

By reviewing these systems, the research is able to identify credibility categories that affect Web credibility assessment. The research defined seven categories for measuring credibility, as covered in section 2.2.3. Moreover, reviewing these systems allowed the research to identify credibility factors, for each credibility category, that can be used for measuring credibility of a Web page. These factors are identified in section 2.2.4. By defining credibility categories and using credibility factors identified, Web credibility of a Web page can be measured. In this way the research is able to define a credibility assessment algorithm allowing it to measure credibility scores of Web pages.

3.1.2 Develop a Web-based QA system

The second step of the research design is to design and develop a Web-based QA system called OMQA system. This is done in order to address the second research objective, which is *"To design and develop an enhanced Web-based QA system with credibility assessment"*. The OMQA systems needs to be developed first, before it can be combined with a credibility assessment module to form a credibility-based QA system called CredOMQA system. In order to develop a Web-based QA system or OMQA system, the research defined a Web-based QA system model, as covered in section 2.1.3, using which OMQA can be designed and developed. The research developed different modules of a Web-based QA system, as per specifications of the Web-based QA model, including question analysis, answer extraction, answer scoring and answer aggregation. The research found existing system using different techniques for each method, which are listed in section 2.1.4. The research added these methods and techniques into OMQA system for evaluation purposes. Using this system the research will be able to evaluate methods and techniques available for them, as well as, generate results for baseline systems such as Qualifier and Corrob*. Upon successfully designing and developing the OMQA system, the task of adding credibility assessment module to the OMQA system can be started.

3.1.3 Develop a credibility-based Web QA system

The OMQA system developed allows the research to evaluate existing methods and techniques found in existing systems. However, the research still requires to add a credibility assessment module to this system in order to it to evaluate the effect of Web credibility on accuracy of answers. Adding a credibility assessment module for scoring answers also accomplishes the second research objective of this thesis.

In order to evaluate credibility score of a Web page the research used the credibility assessment algorithm defined in the first step, and credibility factors identified for evaluating credibility of Web-source covered in section 2.2.4 and section 2.3. This allows the research to add a credibility assessment module to the existing OMQA system, thus calling it CredOMQA system.

The addition of this module allows the research to generate results using credibility-based answer scores on CredOMQA system. In addition, results for other Web-based QA baseline systems, which make use of Web credibility score for scoring answers, are generated.

3.1.4 Evaluation

Step four involves evaluation of results to be generated by systems developed earlier steps two and three including OMQA system and CredOMQA system respectively. This step also covers the third research objective of the thesis, which is *"To evaluate the impact of credibility assessment on accuracy of the answer by means of evaluation and comparison"*. The first evaluation conducted in this step is the analysis of accuracy of answers produced by Web-based QA systems methods and techniques. This also includes generation of results for baseline system using a subset of methods and techniques available in the OMQA system. The second evaluation conducted analyzing the change in accuracy of answers after adding a credibility assessment module into the OMQA

system to form CredOMQA system. The results generated by CredOMQA system were compared other baseline credibility-based Web QA system systems, which targeted specific credibility categories only. The results from both of these evaluations were analyzed in order to conclude findings of the research and the implication of credibility assessment on Web and other systems relying on it.

The evaluation step also requires to have an understanding on the type of methodology adopted by the research. This is because methodology defines the type of data to be used to conduct these evaluations and the type of results that are expected to be generated and evaluation metrics that may applied on them. This is discussed in section 3.2 and 3.2.1.

3.2 Methodology

There are two basic approaches to research: 1) quantitative and 2) qualitative (Creswell, 2013). Quantitative approach involves generation of data in quantitative form, which may undergo rigorous quantitative analysis. Inferential, experiment and simulation approaches are all sub-classification of quantitative approach. Qualitative approach is concerned with subjective assessment of attitudes, opinions and behavior. The data generated in qualitative analysis are either in non-quantitative form or do not require rigorous quantitative analysis, whereas qualitative approaches involve focus group interviews, projective techniques and depth interviews for collection of data.

3.2.1 Reasons for choosing quantitative analysis

This research chose quantitative approach for answering the posed research questions and accomplishing objectives stated for this research, keeping in view the nature of research questions and objectives defined. The reasons for choosing quantitative approach over qualitative approach are stated hereunder:

1. *Web-based QA systems*: Web-based QA systems involve use of quantitative data, such as questions and their answers in order to evaluate answer accuracy. Literature on Web-based QA systems also uses extensive quantitative analysis for evaluating answer accuracy, which is why this research also chose it (Oh et al., 2012; Wu & Marian, 2011).
2. *Credibility assessment in Web-based QA systems*: Under credibility assessment, both quantitative and qualitative approaches are found in the literature (Molino et al., 2015; Ostenson, 2014). Qualitative approaches are used for judging perceptions and behavior of users towards credibility, while quantitative approaches are employed for evaluating impact of credibility assessment on various systems with respect to the evaluation metric chosen. Since this research intends to analyze the effect of credibility assessment in Web-based QA systems, thus quantitative approach was chosen.
3. *Evaluating answer accuracy*: Both Web-based QA systems and credibility assessment modules are required to be evaluated by this research, with respect to answer accuracy. Evaluating answer accuracy involves generating answers for various methods and techniques, and credibility-based answers. The answers generated are then evaluated with respect to answer accuracy using various evaluation metrics. Both answer generation, result generation and results analysis involve rigorous quantitative analyses, which is why quantitative analysis has been adopted for this research.

3.2.2 Research selection criteria

Since this research is based on quantitative approach, several selection criteria are required to be specified in order to conduct quantitative analysis systematically. For this, selection criteria are being defined for review of Web-based QA and credibility-based

systems, data collection and evaluation metrics. The criteria set for selecting papers for review are listed in Table 3.1.

Table 3.1: Web-based QA system and credibility-based systems selection criteria

Characteristic	Criteria
QA system type	Web-based
Data resource	Web pages (Free text documents)
Domain	Domain independent (Web)
Year	Year 1999 onwards
Question Type	Factoid
Response	Single answers (from Web pages and snippets)
Evaluation	Answer accuracy
Web-based QA systems methods and techniques type	NLP and IR-based QA systems
Credibility factors	Relevant to Web credibility assessment

The table lists several characteristics of Web-based QA and credibility-based systems, and criteria specified for selecting them. The focus is on Web and its credibility. Therefore, QA systems type, data resource, domain and credibility factors have been restricted to Web relevant systems only. The research encompasses the systems introduced from 1999 onwards as work on Web-based QA systems and Web credibility assessment started to flourish since then. For question type, the research specifies factoid questions only, since it is the question type addressed by Web-based QA systems. More detailed discussion on selection of dataset, for evaluation purposes, is discussed in Section 3.3.1. Similarly, the response generated by prototype systems (OMQA and CredOMQA) is set to single answers, since factoid questions have one correct answer only. For evaluation, the research is designed to evaluate Web-based QA and credibility-based Web QA systems with respect to answer accuracy. More detailed discussion on evaluation metrics under answer accuracy is covered in Section 3.3.3.5. For evaluation methods and

techniques under Web-based QA systems, the research focuses on NLP and IR-based QA systems, since Web-based QA systems belong to the same category. Lastly, selection of credibility factors is limited to Web only, as the focus of research is towards evaluating search results credibility, used in Web-based QA systems.

Different stages under experimental design have been set out to meet the specified requirements. It helps generate quantitative data, on which extensive quantitative analysis has been conducted.

3.3 Experimental Design

This section discusses different stages of evaluation design for Web-based QA systems, including evaluation for methods and techniques, and credibility assessment module. Figure 3.2 shows different stages for conducting experiment and collection of evaluation results.

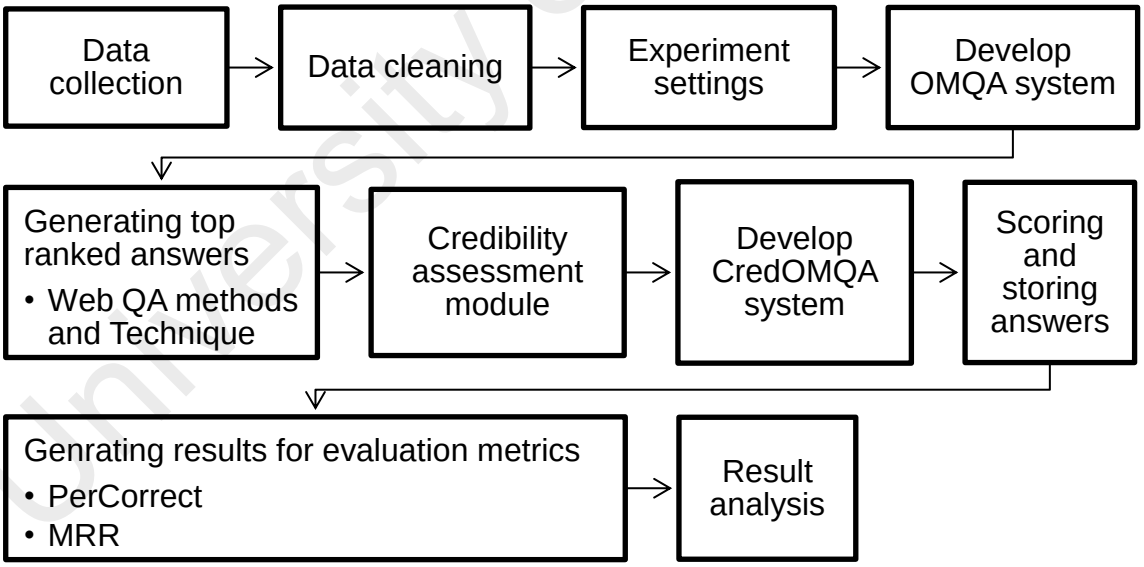


Figure 3.2: Experimental Design

The figure shows experimental design for this research, comprising ten stages. These stages are discussed in the following sub-section including 1) data collection, 2) data cleaning, 3) experiment settings, 4) develop OMQA system, 5) generating top ranked

answers, 6) credibility assessment module, 7) develop CredOMQA system, 8) scoring and storing answers, 9) generating results and 10) result analysis.

3.3.1 Data collection

Data collection is a dataset, which comprises questions used for evaluating system against evaluation metrics (Kolomiyets & Moens, 2011). These data collections are usually taken from organizations that provide them for researchers and experts to conduct experiments, to facilitate them in comparing results with other systems using the same data collection. Since the scope of this research is towards evaluation of Web-based QA systems, thus this research uses a dataset consisting of factoid questions and their answers. For this purpose, QA tracks from Text Retrieval Conference (TREC) and Conference and Labs of the Evaluation Forum (CLEF) have been used (Chen et al., 2000; Magnini et al., 2004; Voorhees, 1999).

Both TREC and CLEF organizations promote research in IR, including work on QA systems. TREC is a co-sponsored organisation by the National Institute of Standards and Technology and U.S. Department of Defence, and is responsible for promoting research in IR (Voorhees, 1999). The CLEF Initiative (Conference and Labs of the Evaluation Forum, formerly known as Cross-Language Evaluation Forum) is a self-organized body that focuses research on multilingual and multimodal information with various levels of structure (Magnini et al., 2004). Both of these organization provide tracks, i.e., datasets for a number of IR areas, and QA (chosen for this research) track is one of them. These QA tracks contain test questions, top documents ranked list, judgement set, pattern set and correct answers to the test questions. Datasets from both of these organizations are well received by the IR community and are the widely used datasets for QA system evaluations (Allam & Haggag, 2012; Bouziane et al., 2015; Kolomiyets & Moens, 2011; Mollá-Aliod & Vicedo, 2010; Webber & Webb, 2010).

The dataset chosen for evaluation purposes comprises factoid questions taken from TREC and CLEF QA tracks. The reason for selecting factoid questions is that Web-based QA system make use of simple methods and techniques and are more ideal for answering factoid questions. Secondly, the question type for evaluation purposes is restricted to Person type only which also falls under factoid question type.

As for the dataset, the larger dataset has been chosen from TREC QA track (*QN*=211), while a random sample (*QN*=21) is taken from CLEF dataset to compare findings in both of these datasets, where *QN* indicates the number of questions. Other QA systems have used datasets of same size or smaller for evaluation (Oh et al., 2012; Wu & Marian, 2011; Yang & Chua, 2003).

3.3.2 Data cleaning

These datasets contain a lot of information, some of which is considered superfluous for the purpose of this research. Accordingly, information such as top documents ranked list, judgement set, pattern set for questions has been excluded from these datasets. This is because the proposed prototype Web-based QA system generated its own data; thus such information was not needed. Figure 3.3 shows a screen shot showing TREC dataset stored in a text file after data cleaning.

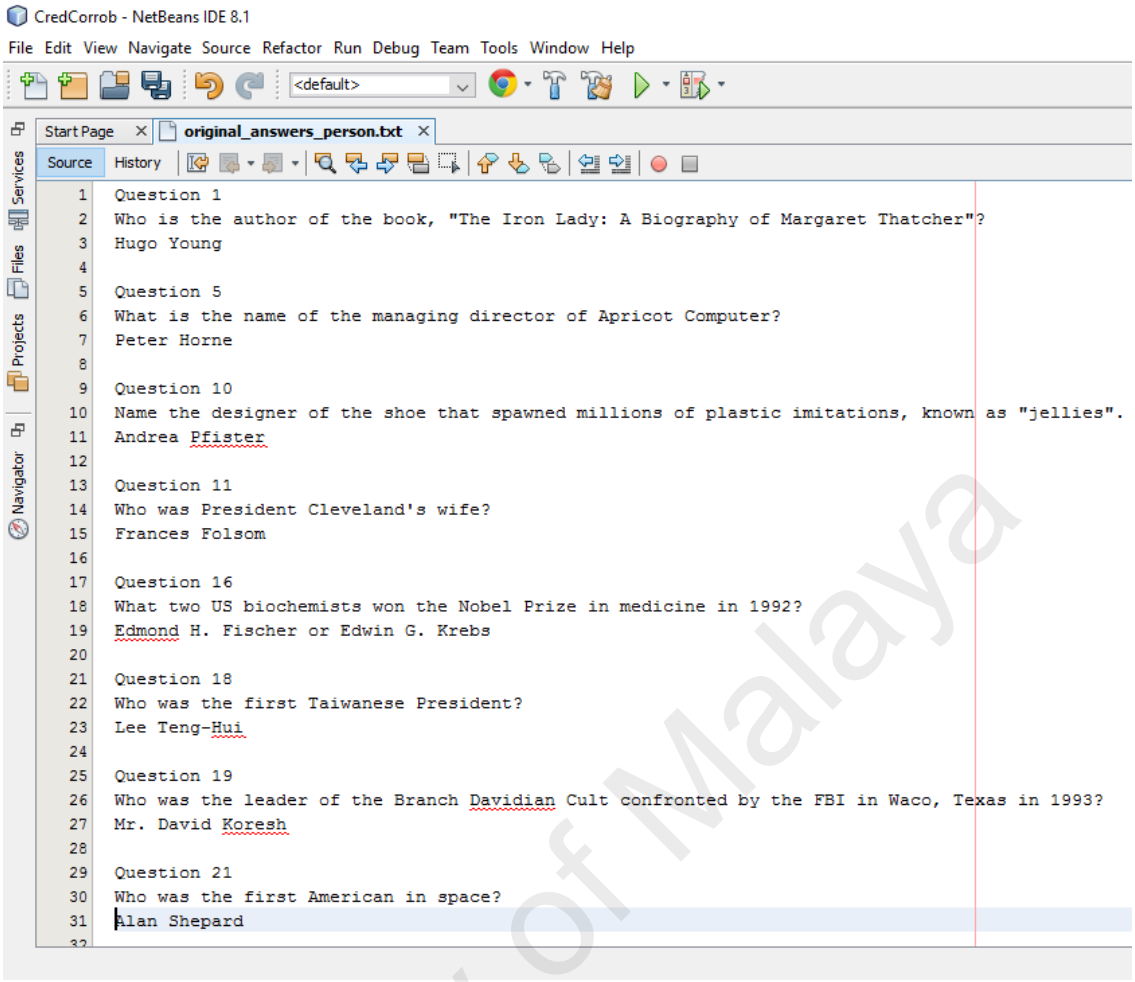


Figure 3.3: TREC dataset after data cleaning

The figure shows dataset stored in a file comprising three rows of data for each question. This includes question number, question text and correct answer to the question. An empty line is left to indicate the start of the next question. In this way, data collection is read by the system to evaluate the Web-based QA system.

Both of these datasets contain useful questions, but since they date back to 1999-2003, some of the answers are outdated. The questions and answers were cross-checked by an expert, a researcher in the field of IR, from a university in Malaysia, to verify their validity and update them if incorrect. For example, the answer to the question “Who is the tallest person” has to be updated from Gabriel Estavo MonJane to Sultan Kosen.

3.3.3 Experiment settings

3.3.3.1 Experiment system setup

The Web-based QA system, on which the experiments were conducted, were tested on a Windows machine running Windows 10 operating system. This system comprised 4GB RAM and core i5 @1.8Ghz Intel processor.

3.3.3.2 Technologies used for evaluation

The credibility-based Web QA system was developed using PHP 5.6.1 Web server language, JavaScript and HTML. In addition to use of programming languages, a number of libraries and APIs were used to develop a prototype credibility-based Web QA system, called CredOMQA system. These technologies are listed below:

- *Stanford NER and POS Parser*: For tagging word entity type and parsing sentence with respect to POS
- *WordNet*: For providing synonyms for keywords
- *Alchemy, Alexa, Diffbot, Google, Mozscape, Web of Trust (WOT) APIs*: For fetching credibility data for Web pages
- *SeoStats Library*: For providing readability, social media and other stats
- *TFIDF*: For providing relevancy score
- *SpotSigs*: For evaluating originality of Web page

Techniques for evaluating the results generated by credibility-based Web QA systems were also developed, using PHP and Rgraph for plotting data. The evaluation functions developed were based on the evaluation metrics defined for this research.

3.3.3.3 Evaluation settings for Web-based QA systems' methods and techniques

In order to evaluate Web-based QA systems' methods and their techniques, it is important to use appropriate methods and parameter values that have the least effect on the method

being evaluated. Therefore, this research defined default values from each method that were most appropriate for evaluating other methods, as highlighted in Table 3.2.

Table 3.2: Evaluation settings for Web-based QA systems methods and techniques

Method/technique name	Parameter values	Default values
TopK search result doctype	Web pages/Snippets	Web pages
TopK search result depth	*K* = 5/10/20	*K* = 20
Information from external resources	Google/WordNet/Combination/ No	Combination, except for TopK search result
NER	Alchemy/Stanford/Combined NER	Stanford NER
Stopwords removal	Yes/No	Yes
Quote words processing	Yes/No	Yes, except for TopK search result and information from external resources
Sentence-matching algorithm	Keywords/Regex sentence-matching	Keywords sentence-matching
Remove unwanted answers	Yes/No	Yes, except for TopK search result, and information from external resources
Top N Sentences	*N* = 1/3/5	*N* =3, except *N* =5 for scoring and aggregation
Answer scoring	Frequency/MatchScore/Prominence	Frequency
Answer aggregation	Dice coefficient(.85)/cosine similarity(0.80)/Combination	Combination

Reasons for choosing a particular default parameter for a particular method used in experiment were specified in each case, starting with information source. This study

selected Web pages as the default parameter value since other methods benefit the most from it, such as TopN sentences benefit more from Web pages as compared to snippets. For example, the result of adding information from external resources is more apparent on Web pages than snippets. Similarly, result depth *K* was set to 20, to allow other methods more content to work with. For information from external resources, keywords from both WordNet and Google were considered as default values. For NER, Stanford NER was chosen as it is a popular choice among QA systems. Stopwords removal and quote words processing was conducted in all method evaluations as it is widely accepted as a mandatory step in answer extraction. However, for TopK search results evaluation (and information from external resources), methods including removal of unwanted answers, quote words processing and information from external resources were removed for two reasons: 1) Web pages benefited more compared to snippets from the inclusion of these methods, 2) this study intended to show how accuracy is increased/decreased with the inclusion of these methods in later tests. For sentence matching, this study used keywords sentence-matching as it helped achieve high answer accuracy results and thus provided more room to show a steep increase or decrease in accuracy. For Selecting TopN sentences, the study selected *N*=3 in order to keep a balance between less and many answers to work with. However, *N* was set to 5 for answer scoring and aggregation as the study aimed to work with more answers to see how much accuracy is impacted. Among answer scoring, frequency method was selected only as it is the most common scoring method in QA systems. Finally, under answer aggregation, combination of both dice coefficient and cosine similarity were used to benefit from the advantages of both techniques. In the tests, the value for cosine similarity was set to 0.8, and that for dice coefficient was set to 0.85.

Figure 3.4 shows a screen shot of source code used for experiment settings for evaluating Top *K* results selection using snippets. The function matchTopKSnippet is

defined, containing experimenting settings for evaluating snippets information source. This research also offers comments to facilitate the reader in understanding these settings, within the code, as shown from line 360 to 372. The screen shows no functions for methods like remove unwanted answers and fetching adding keywords form WordNet. On line 384, a function call is being made to search for keywords, where the parameter for resource is set to snippets, indicating that correct settings are being used.

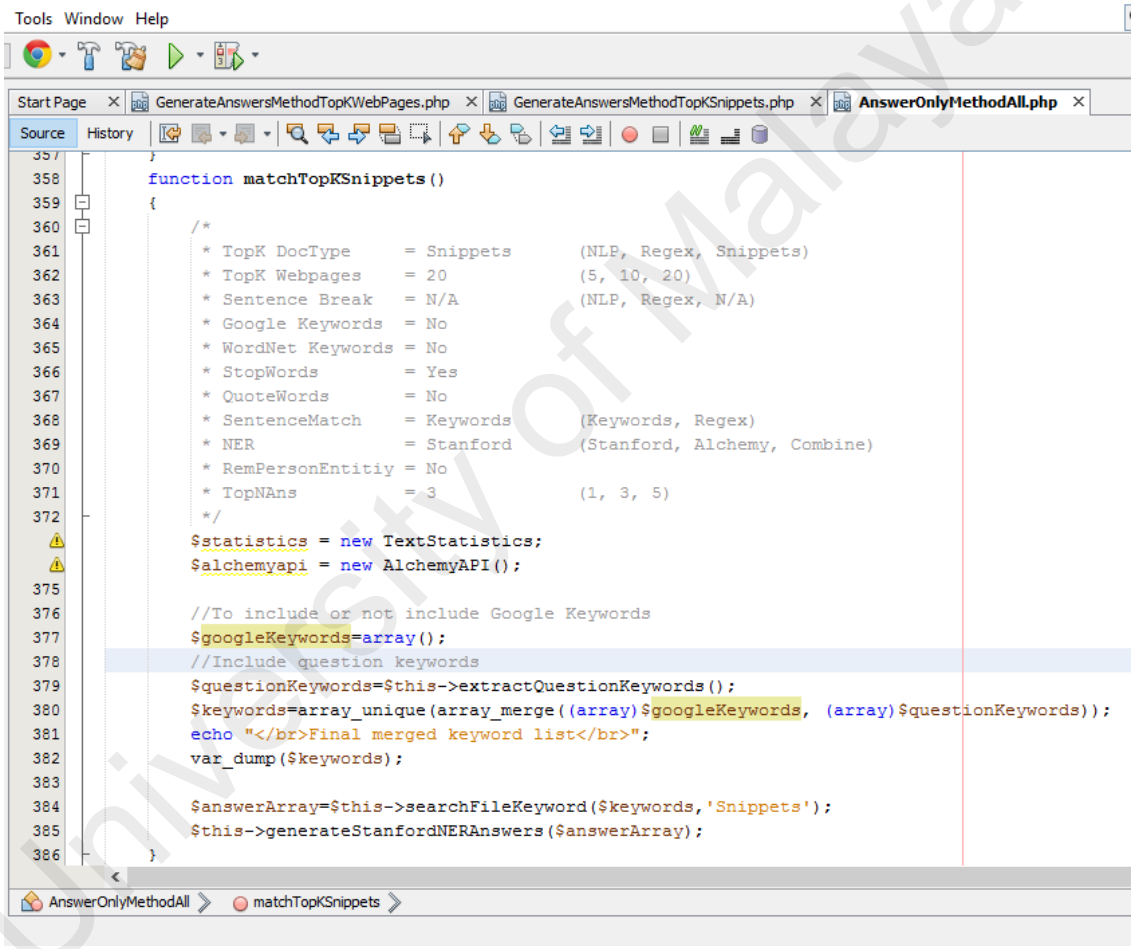


Figure 3.4: Experiment settings for evaluating Top *K* results selection using snippets

3.3.3.4 Evaluation settings for Web-based QA and credibility-based Web QA systems

Credibility assessment module provides credibility scores for answers taken from Web pages, thus it needs to be applied on a Web-based QA system producing answers. The

evaluation results for Web-based QA systems' methods and techniques highlighted techniques achieving better accuracy than others, as shown in Section 4.1. Thus, for the purpose of this research, credibility assessment was applied on the combination of methods and techniques producing the highest accuracy. Similarly, other Web-based QA systems, which covered some credibility categories (such as Corrob and GenreQA), the credibility scores produced were applied on the method and techniques used by them. Scores for Corrob and GenreQA are shown, using and not using credibility assessment, where * notation is used to show that it is using credibility assessment. This research also included such Web-based QA systems, like LAMP and Qualifier, which did not apply credibility assessment, to show the difference when not using credibility assessment. Table 3.3 shows the evaluation settings for Web-based QA and credibility-based Web systems including LAMP, Qualifier, Corrob, GenreQA, and OMQA and CredOMQA systems suggested by this research (Oh et al., 2012; Wu & Marian, 2011; Yang & Chua, 2003; Zhang & Lee, 2003).

Table 3.3: Evaluation settings for OMQA, CredOMQA, and baseline systems Web-based and credibility-based QA systems

System name	Methods and techniques	Credibility categories
OMQA	Information source = Web pages and Top *K* = 20 Information from external resource = WordNet and Google keywords Quote words processing = Yes Stop words removal = Yes NER = Stanford NER Removal of unwanted answers = Yes Sentence-matching algorithm = keyword matching Top *N* sentences = 3 Answer scoring = Frequency Answer aggregation = Cosine similarity and Dice coefficient	

Table 3.3 continued		
Cred OMQA	Information source = Web pages and Top *K* = 20 Information from external resource = WordNet and Google keywords Quote words processing = Yes Stop words removal = Yes NER = Stanford NER Removal of unwanted answers = Yes Sentence-matching algorithm = keyword matching Top *N* sentences = 5 Answer scoring = Frequency Answer aggregation = Cosine similarity and Dice coefficient	Correctness Authority Currency Profession-alism Popularity Impartiality Quality
LAMP	Information source = Snippets and Top *K* = 20 Information from external resource = No Quote words processing = No Stop words removal = Yes NER = Stanford NER Removal of unwanted answers = No Sentence-matching algorithm = keyword matching Top *N* sentences = 3 Answer scoring = Frequency Answer aggregation = Cosine similarity and Dice coefficient	None
Qualifier	Information source = Snippets and Top *K* = 20 Information from external resource = Yes Quote words processing = Yes Stop words removal = Yes NER = Stanford NER Removal of unwanted answers = No Sentence-matching algorithm = keyword matching Top *N* sentences = 3 Answer scoring = Frequency Answer aggregation = Cosine similarity and Dice coefficient	None

Table 3.3 continued		
Corrob	Information source = Web pages and Top *K* = 20 Information from external resource = WordNet and Google keywords Quote words processing = Yes Stop words removal = Yes NER = Stanford NER Removal of unwanted answers = Yes Sentence-matching algorithm = keyword matching and regex Top *N* sentences = 1 Answer scoring = Frequency Answer aggregation = Cosine similarity	Correctness Quality (α=0.75)
GenreQA	Information source = Web pages and Top *K* = 20 Information from external resource = WordNet and Google keywords Quote words processing = Yes Stop words removal = Yes NER = Stanford NER Removal of unwanted answers = Yes Sentence-matching algorithm = keyword matching Top *N* sentences = 3 Answer scoring = Match score Answer aggregation = Cosine similarity	Currency Professionalism Quality (α=0.75)

Table 3.3 shows OMQA system, CredOMQA system and baseline Web-based QA system's name, methods and techniques used by the system, and credibility categories covered. Starting with LAMP, which focuses on using snippets as the information resource, and uses fewer methods such as not using quote words processing, information from external resources and removing unwanted answers (Zhang & Lee, 2003). LAMP also does not perform credibility assessment on Web pages. Qualifier system, provides a little enhancement over LAMP system by introducing external resources for improving

sentence-matching and quote processing. This study evaluated the Qualifier system on both snippets and Web pages, because the addition of these methods have different effects on these resources (Yang & Chua, 2003). Qualifier system also does not perform any credibility assessment. Corrob system makes good additions of answer removal filter, and uses combination of techniques, such as both regex and keywords for sentence-matching, but limited sentences matched *N* to 1 (Wu & Marian, 2011). Corrob system does use credibility assessment and evaluates Web pages based on correctness and quality categories, where α is set to 0.75. GenreQA uses more sentences matched (*N*=5) and match score for ranking answers, compared to Corrob system (Oh et al., 2012). For credibility assessment, GenreQA focus on currency, quality, and professionalism credibility categories, where α is set to 0.75.

OMQA, suggested by this research, uses combination of methods and techniques producing highest accuracy of answers in the results, as shown in Table 3.3. The CredOMQA systems, which adds credibility assessment module to OMQA system, is evaluated for credibility categories with different values of α (between 0 and 1). The combination of methods and techniques used by the OMQA system is listed in Table 3.3. Using the evaluation defined for baseline QA systems, OMQA and CredOMQA systems, evaluation was carried out with respect to the evaluation metrics defined.

3.3.3.5 Evaluation metrics

Evaluation metrics allow researchers to evaluate their findings based on the scores received. They also provide a measure to compare the system's standing vis-à-vis other systems using the same dataset used by other systems. Since one of the questions this research aims to address is to see whether the inclusion of credibility scores of Web pages improves accuracy of answers, therefore, evaluation metrics concerning accuracy of answers in Web-based QA systems were selected. Thus, Mean Reciprocal Rank (MRR)

and Percentage of queries Correctly answered (PerCorrect) evaluation metrics were selected, as both of them highlight different aspects of accuracy of answers in QA systems (Bouziane et al., 2015; Kolomiyets & Moens, 2011; Wu & Marian, 2011). Both of these metrics have also been used in other Web-based QA systems as well, allowing this research to compare its accuracy with other systems (Wu & Marian, 2011; Yang & Chua, 2003). In addition to these evaluation metrics, two-sample t-test using one tail is performed on MRR for significance testing in order to highlight the difference between OMQA system and other baseline systems, and CredOMQA system (Garson, 2012). Significance testing highlights whether the difference between two systems mean that are being compared is significant or not.

In order to explain the evaluation metrics and significance testing and their calculations, an example dataset is defined. The data from this example is used to show how values for MRR, PerCorrect and one-tail t-test are calculated. In our example, two QA systems are considered namely system A and system B, which generate top ranked answers for five questions. The example dataset is shown in Table 3.4.

Table 3.4: Example dataset

System Name	Correct answers found for each question				
	Question 1	Question 2	Question 3	Question 4	Question 5
System A	Rank 1	Rank 2	Rank 2	Rank 2	Rank 2
System B	Rank 1	Rank 2	Rank 2	Rank 5	Rank 5

The table above shows ranked answers found for two systems A and system B. Looking at system A, it can be seen that for question 1 the correct answer is found at rank 1, and in the remaining questions the correct answer is found at rank 2. Similarly, for system B, it was able to find the correct answer at rank 1 for question 1 and 2, at rank 2 for question 3, and at rank 4 for question 4 and 5.

(a) ***PerCorrect***

PerCorrect represents the percentage of questions correctly answered at different ranks, such as top-1, top-2, top-3, top-4, and top-5, in the corroborated answer list (Wu & Marian, 2011). It helps in highlighting whether the system excels at finding answers early, or low down the order. Equation 3.1 shows the formula for calculating PerCorrect for a particular top rank *n* (Wu & Marian, 2011).

$$PerCorrect(n) = \frac{100}{QN}\sum_{i=1}^{QN} rank(Q_i, n) \qquad \textbf{Equation 3.1}$$

In Equation 3.1, *PerCorrect (n)* calculates the percentage of correct answers found between rank 1 and *n*, where *n* can be between 1 and 5. *QN* is the number of questions considered and *rank* (Q_i, n) checks if the correct answer, for the question Q_i, is found at rank *n* or higher.

Let us use the example dataset shown in Table 3.4 for calculating PerCorrect of system A and system B. Let us calculate PerCorrect at top-1 for system A. The number of correct answers found for system A is 1 out of 5 questions. Thus, *rank* (Q_i, n) will return 1, where n=1, and *QN* will be 5. Therefore, PerCorrect at top-1 for system A will be 100*1/5 giving us 20%. In short, 20% or 1 (out of 5) of the questions are found at rank 1 in a sample size of QN=5. Similarly, PerCorrect at top-2 for system A will return 5 for *rank* (Q_i, n), where *n* will be 2 since answers at rank 2 or above need to be considered. Thus, PerCorrect at top-2 for system A will be 100*5/5, where both *QN* and *rank* (Q_i, n) have the value 5, and will give 100%. In short, 100% or 5 (out of 5) of the correct answers are found at PerCorrect top-2 for system A. Since, PerCorrect top-2 is already 100% for system A, top-3, top-4 and top-5 will be 100% as well. In this way, PerCorrect for system B will be calculated as well and will yield the following results as shown in .Table 3.5. It shows the

percentage of correct answers found at each rank and the frequency of correct answers out of total questions *QN*=5.

Table 3.5: PerCorrect results for example dataset for *QN*=5

System Name	PerCorrect percentage at different ranks				
	Top-1	Top-2	Top-3	Top-4	Top-5
System A	20%(1)	100%(5)	100%(5)	100%(5)	100%(5)
System B	20%(1)	60%(3)	60%(3)	60%(3)	100%(5)

(b) ***MRR***

TREC suggests MRR as the default evaluation metrics for evaluating their sample (Kolomiyets & Moens, 2011). The metric shows the capability of the system in reaching the correct answer early. A higher MRR score shows that the system is able to find the correct answers at higher ranks. Similarly, a system receiving a low MRR score is able to find correct answers at lower ranks, such as top-4 and top-5. MRR is calculated by taking reciprocal of the rank where the correct answer was found. If the correct answer is not found, then it is assigned an MRR score of zero. Consider a scenario where the correct answer was found at rank 1, the MRR score is 1/1. Similarly, if the answer is found at rank 2, then its MRR score is ½. The equation for calculating MRR is shown in Equation 3.2(Kolomiyets & Moens, 2011).

$$MRR = \frac{1}{QN}\sum_{i=1}^{QN}\frac{1}{rank(Q_i)} \qquad \textbf{Equation 3.2}$$

In Equation 3.2, *QN* represents number of questions considered and $rank(Q_i)$ is the rank of the topmost correct answer of question *i*.

Let us calculate MRR for each question and the average MRR of system A and B using the sample dataset. Look at question 1 for system A, it is able to find the correct answer

at rank 1. For calculating system A's MRR for question 1 would 1/ rank(Q_1), where rank(Q_1) is 1 and will yield 1/1 that is 1. Similarly, for question 2 it would be ½ or 0.5 since rank(Q_2) is 2. The same process is done for the remaining question. System A's MRR for each question would be 1, 0.5, 0.5, 0.5, 0.5 respectively. Using these results system A's MRR can be calculated, which is the average of the MRRs of all questions, which is (1+ 0.5 + 0.5 + 0.5 + 0.5)/QN where QN is 5 and will give 0.6. Similarly, MRR for system B can be calculate using the same mechanism and will yield the following results, as shown in .

Table 3.6: MRR results for example dataset for *QN*=5

System Name		MRR for each question				
	System MRR	Q1 MRR	Q2 MRR	Q3 MRR	Q4 MRR	Q5 MRR
System A	0.6	1	0.5	0.5	0.5	0.5
System B	0.48	1	0.5	0.5	0.2	0.2

(c) *Two-sample t-test using one tail*

T-test is a type of hypothesis test that is used to compare means of one or two sample populations to determine whether they are equal or not (Garson, 2012). It is called a t-test as the sample population is represented using a single number called a t-value. There are many variations of t-tests including one-sample t-test, two-sample t-test which can be paired or un-paired and using one tail or two tail t-test for showing result(Garson, 2012). In our tests, two-sample t-test is chosen as the research would like to compared the difference between two systems (Bruin, 2016). Moreover, one tail is chosen as the aim is to only test whether the average mean of the first system is less than the second system. Two-tail is performed when it is not known whether the first system will be better or worse (Bruin, 2016). In short, one-tail is unidirectional and two-tail is bi-directional. In our tests, one-tail is used in order to highlight whether baseline system is performing less

than OMQA system or CredOMQA system, depending upon which is being used for comparison. The formula for performing a two-sample t-test is given below in Equation 3.3 (Bruin, 2016).

$$T = \frac{\overline{x_1} + \overline{x_2}}{\sqrt{\frac{{s_1}^2}{QN_1} + \frac{{s_2}^2}{QN_2}}} \qquad \textbf{Equation 3.3}$$

In the equation $\overline{x_1}$ and $\overline{x_2}$ shows the average mean of the two systems being compared with and QN_1 and QN_2 is the number of questions for each system when calculating mean. The variances are represented as s_1 and s_2 for system 1 and system 2. This allows the system to calculate the T value for the t-test.

The second step is to calculate the critical values for the significance test of the two systems being compared (Bruin, 2016). The critical value υ is calculated using variances s_1 and s_2 of the two sample population and their population size QN_1 and QN_2 as shown in Equation 3.4 (Bruin, 2016).

$$\upsilon = \frac{\left({{s_1}^2}/{QN_1} + {{s_2}^2}/{QN_2}\right)}{{\left({s_1}/{QN_1}\right)^2}/{(QN_1 - 1)} + {\left({s_2}/{QN_2}\right)^2}/{(QN_2 - 1)}} \qquad \textbf{Equation 3.4}$$

The t-test critical value υ and t-test value T are compared with respect to the confidence level set for the t-test (Garson, 2012). This is done to confirm if the hypothesis set by the system is true or not. By default null hypothesis H_0 is considered which stats that both systems are equal (Bruin, 2016). Confidence level γ of the results, which is usually set at 0.01 (99% confidence), 0.05 (95% confidence) and 0.1 (90%) confidence (Bruin, 2016). In our tests, confidence level γ has been tested for 90% and 95% that is 0.1 and 0.05 respectively as it has been used by several studies (Cumming & Finch, 2005; Tellex, Katz, Lin, Fernandes, & Marton, 2003; Zhou, He, Zhao, & Hu, 2015; Zhou, Zhao, He, & Wu, 2014). P-value is calculated which is difference between t-test value T and t-test critical

value v. If the difference between the two is lower than the confidence level set for the test, then the systems are significantly different, with system A less than system B thus rejecting the null hypothesis H_0. Otherwise, the null hypothesis is not rejected and both systems are not considered significantly different. Equation 3.5 shows the formula used for calculating P-value for significance testing comparison (Bruin, 2016)

$$P - value\ (T < v) = v - T, \text{ where } \gamma=0.1 \qquad \textbf{Equation 3.5}$$

Consider the example dataset for performing significance test between system A and system B. First average mean of both systems A and B are calculated, which are .6 and .48. Then variance of both sample sets are also calculated which are 0.05 and .107 for system A and B respectively. Higher value of variance shows that there is more inconsistency in the sample population. Using these values, . This is then computed with the confidence level set for the test and critical values for the sample . At the end the final P-values are calculated which are shown in the table below.

Table 3.7: T-test results for systems used in example dataset for *QN*=5

System Name	Sig test P-value
System A	0.0889
System B	

The P-value of system A is given since system A is being compared with System B. P-value for system B is not calculated as significance testing is not performing on the same dataset. As it can be seen that P-value for system A is less than 0.10. Thus P-value is within the 90% confidence level, so it is safe to say that system A is significantly better than system B.

3.3.4 Develop OMQA system

Based on the literature covered on methods and techniques in section 2.1.4 OMQA system is developed. The modules and methods used in OMQA systems have been highlighted in Figure 2.2. As highlighted in literature, a number of methods and techniques are available in Web-based QA systems. In order to evaluate the different methods and techniques OMQA system is developed. OMQA systems has a number of techniques available for each method, which are selected for evaluation and are highlighted in section 2.1.4. These are covered briefly below.

Starting with question analysis, the OMQA system uses various techniques like keywords extraction, quote-words extraction and stopwords removal. Though methods under question analysis are not evaluated, yet the OMQA system did perform question parsing and question classification before sending data to the answer extraction module.

In the answer extraction module, OMQA system goes through a twelve methods. Each of these methods has one more techniques to choose from. The method and their techniques available under the answer extraction module are highlighted in Table 2.4 along with the techniques selected for evaluation. Our reasons for selecting a subset of techniques for evaluation is due to their popularity by most QA systems and ease of use. For example, under Top *K* results selection OMQA system can perform this operation using Web pages or snippets and set *K* to 5, 10 or 20. This allows the system to evaluate different techniques under Top *K* results selection and generate results for different baseline systems. Similarly, there are two techniques available under sentence-matching including keyword matching and regex matching, and both of them can be used by the OMQA system.

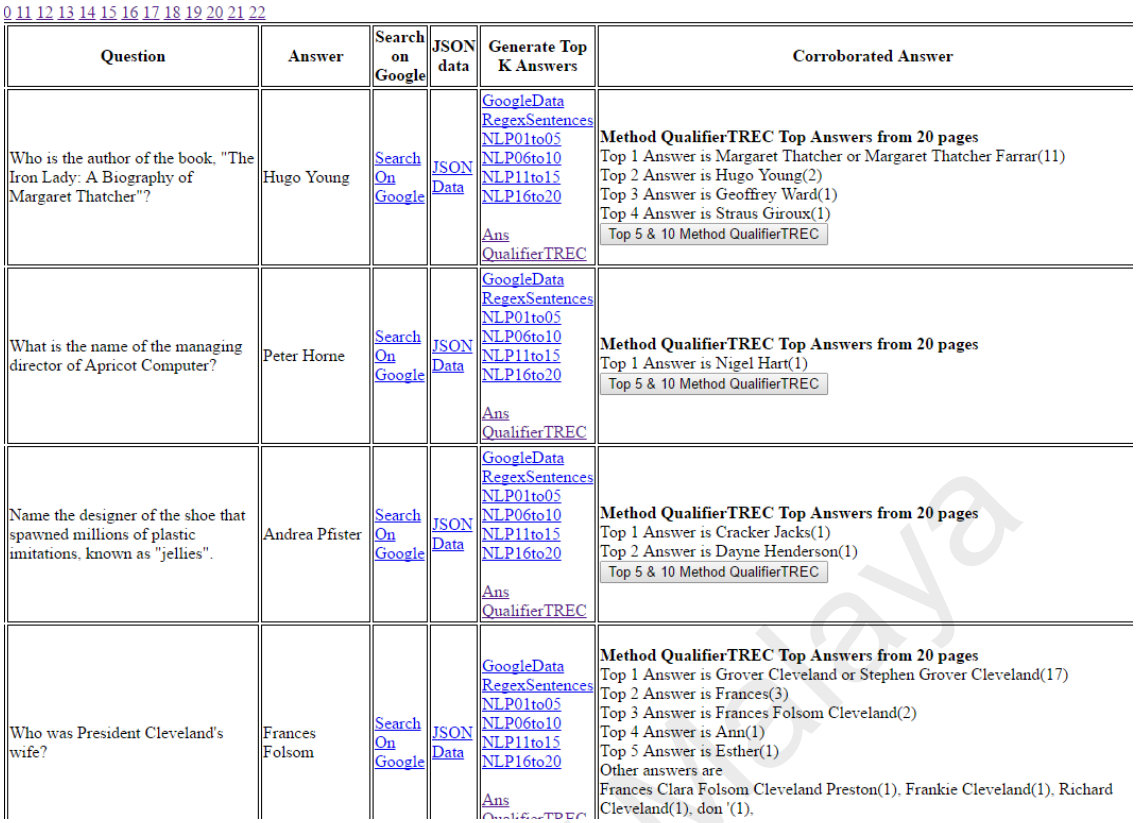
In the answer scoring module, OMQA system has three methods to choose from including frequency, match-score and prominence score. All of these methods are

included in the OMQA system and are highlighted in Table 2.5. Similarly, in the answer aggregation module the OMQA system has a two techniques available under string matching including cosine similarity and dice coefficient. Since, both of these techniques can be used by QA systems so both of them are included in the OMQA system so that they may be evaluated.

Using all the methods and techniques available, the OMQA is capable of generating comparison results for different techniques available under each method. This is done using the experiment settings specified for methods and techniques in section 3.3.3.3. Additionally, the system is capable of producing results for baseline systems based on the methods and techniques used by these systems, which have been highlighted in section 3.3.3.4. Once results for different methods and techniques are generated, the OMQA system selects the ones performing better than others to produce its own results. This allows the OMQA system to use optimal methods and techniques available in literature to produce highest accuracy of answers.

3.3.5 Generating top ranked answers

Using the cleaned data collection and experiment settings for Web-based QA systems methods and techniques, and other Web-based QA systems, the OMQA system is now capable of generating top ranked answers. Figure 3.5 shows the interface designed for the prototype, providing valuable information and functions to generate top ranked answers.



0 11 12 13 14 15 16 17 18 19 20 21 22

Question	Answer	Search on Google	JSON data	Generate Top K Answers	Corroborated Answer
Who is the author of the book, "The Iron Lady: A Biography of Margaret Thatcher"?	Hugo Young	Search On Google	JSON Data	GoogleData RegexSentences NLP01to05 NLP06to10 NLP11to15 NLP16to20 Ans QualifierTREC	**Method QualifierTREC Top Answers from 20 pages** Top 1 Answer is Margaret Thatcher or Margaret Thatcher Farrar(11) Top 2 Answer is Hugo Young(2) Top 3 Answer is Geoffrey Ward(1) Top 4 Answer is Straus Giroux(1) Top 5 & 10 Method QualifierTREC
What is the name of the managing director of Apricot Computer?	Peter Horne	Search On Google	JSON Data	GoogleData RegexSentences NLP01to05 NLP06to10 NLP11to15 NLP16to20 Ans QualifierTREC	**Method QualifierTREC Top Answers from 20 pages** Top 1 Answer is Nigel Hart(1) Top 5 & 10 Method QualifierTREC
Name the designer of the shoe that spawned millions of plastic imitations, known as "jellies".	Andrea Pfister	Search On Google	JSON Data	GoogleData RegexSentences NLP01to05 NLP06to10 NLP11to15 NLP16to20 Ans QualifierTREC	**Method QualifierTREC Top Answers from 20 pages** Top 1 Answer is Cracker Jacks(1) Top 2 Answer is Dayne Henderson(1) Top 5 & 10 Method QualifierTREC
Who was President Cleveland's wife?	Frances Folsom	Search On Google	JSON Data	GoogleData RegexSentences NLP01to05 NLP06to10 NLP11to15 NLP16to20 Ans	**Method QualifierTREC Top Answers from 20 pages** Top 1 Answer is Grover Cleveland or Stephen Grover Cleveland(17) Top 2 Answer is Frances(3) Top 3 Answer is Frances Folsom Cleveland(2) Top 4 Answer is Ann(1) Top 5 Answer is Esther(1) Other answers are Frances Clara Folsom Cleveland Preston(1), Frankie Cleveland(1), Richard Cleveland(1), don '(1),

Figure 3.5: Generating top rank answers for Web-based QA systems methods and techniques, and baseline Web-based QA systems

The interface shows valuable information relevant to each question. It comprises nine columns including the question count, question serial number, question text, correct answer, function to search engine results for query, collect JSON data, functions to generate top ranked answers, top answers found, and functions for generating PerCorrect/MRR graphs. The first four columns show the information fetched from dataset file (after performing cleaning), covered in Section 3.3.2. The question text can be used to view Google search results using “Search on Google” function. The “JSON date” function is provided to view details fetch using the Google analytics API, providing details for research results in JSON format.

Top answers for methods and techniques, and other Web-based QA systems, are generated through three functions: 1) Google data, 2) sentence break, and 3) answer generation functions. The first function, Google data, extracts data returned by Google

analytics API consisting of details such as search results' URL, snippets for URLs, and Google keywords, which are stored on hard disk. The second function, breaks Web pages into sentences using two functions—regex and NLP break functions. Regex break function performs sentence break using regex expressions while NLP break performs it using NLP techniques. These sentences are also stored on hard disk. Third set of functions is answer generation functions, which are defined for every method and technique, and baseline Web-based QA system, to be evaluated. The methods and techniques evaluated are listed in Table 2.3, Table 2.4, Table 2.5 and Table 2.6, based on the experiment settings defined in Table 3.2. These functions go through all the modules of a Web-based QA system to generate rank answers. These answers are also stored in text files on the computer so that they could be used for evaluation. More details on stored answers are covered in Section 3.3.8.

These results can be viewed in two ways: 1) top ranked answer list or 2) PerCorrect and MRR graphs. The top rank answer list is generated using answer scoring and answer aggregation modules, depending upon the technique specified for the function. The graphs use the same data but show them in the form of PerCorrect and MRR graphs.

3.3.6 Credibility assessment module

Similar to generation of top answers, credibility scores for Web pages are generated as well. These Web credibility scores are generated using a number of credibility factors used for scoring credibility categories. Before they can be generated, the system fetches data related to credibility factors, such as readability score, impartiality score, originality score, etc. Figure 3.6 shows functions defined for fetching credibility factors data and credibility score generation functions.

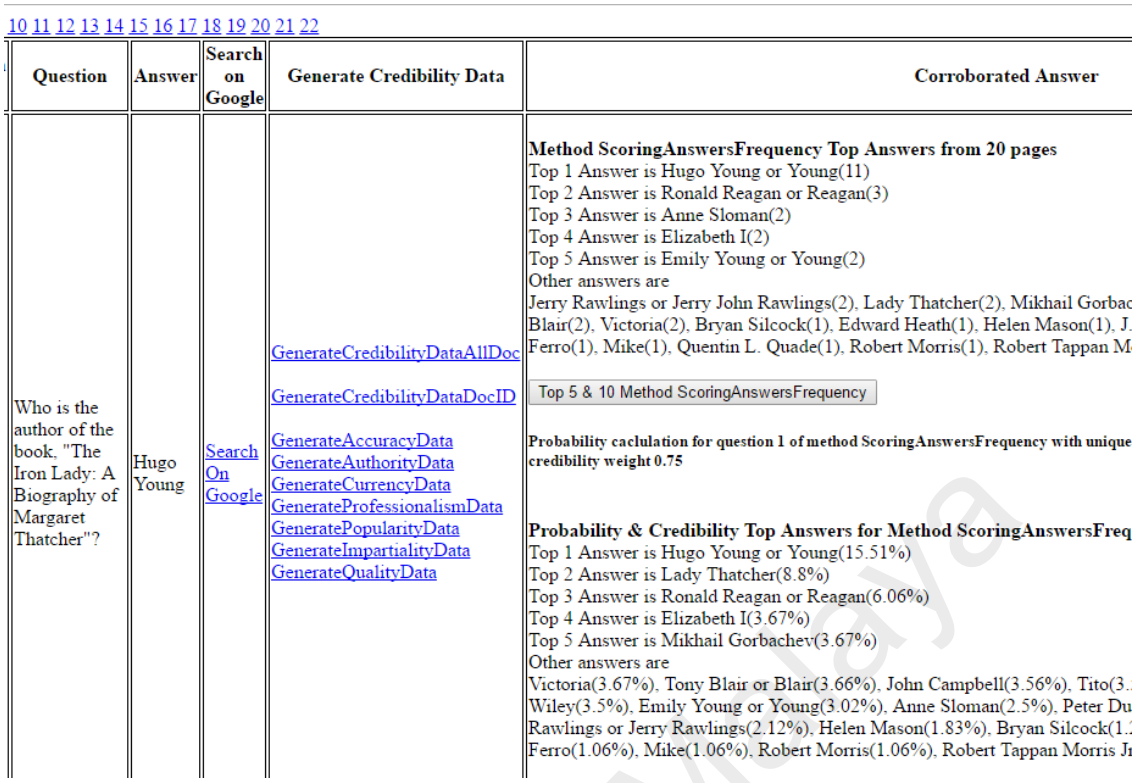


Figure 3.6: Credibility assessment module and functions

Similar to the interface discussed in Section 3.3.4, the credibility-assessment module is able to generate credibility factors data for each question. The first four columns of the interface show information for a question, including question count, question number, question text and correct answer for the question. The fifth column, i.e., search on Google, shows the results of the query on Google search engine. The sixth column provides a list of functions used for generating credibility factors data. This data is for scoring credibility categories and generating ranked answer list based on credibility scores of Web pages. The last column, i.e., the seventh column of the interface, shows ranked answer list generated using credibility scores and without them, to help compare the differences.

3.3.7 Develop CredOMQA system

Credibility-based answers are generated by using a credibility assessment module alongside OMQA system, which is referred to as CredOMQA system as shown in Figure

3.7. This figure is an extension of the Web-based QA model, shown in Figure 2.1, by adding a credibility assessment module.

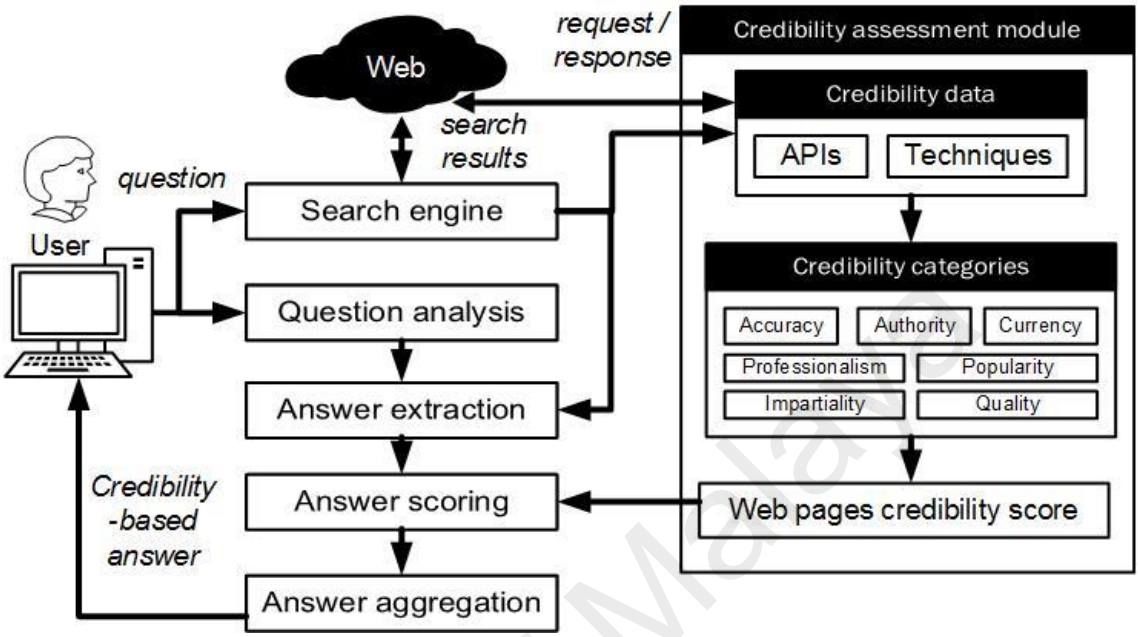


Figure 3.7: Generating credibility-based answers, using a credibility assessment module

As shown in Figure 3.7, the CredOMQA system uses credibility assessment module for producing credibility-based answers. The CredOMQA system forwards the search results, returned by search engine, to credibility assessment module for processing. Credibility data is generated for search engine results, to allow these Web pages to be scored. The credibility data is acquired from various resources, such as APIs, including Alchemy, Diffbot, and WOT and techniques like Term Frequency Inverse Document Frequency (TF-IDF) and SpotSigs. Once Web pages credibility data is acquired, respective functions for generating credibility category scores are executed. These credibility categories use a number of credibility factors. Using credibility categories scores the aggregate credibility score is computed which is the average of all seven credibility categories scores. Figure 3.8 shows a sample result for a Web page, showing computations being made for evaluating currency and professionalism categories scores.

Currency

Diffbot date: Fri, 11 Jul 2003 00:00:00 GMT

Currency score is assigned using the following breakdown

if year <1 then score is 100

if year >=1 and <5 then score is assigned between 0 and 99.99 depending upon how close the date is

If year >=5 then score assigned is 0

Currency score is 0%

Professionalism

Alexa rank via AWS

```
C:\wamp\www\EvaluateCredibility\AlexaUrlInfo.php:125:
object(SimpleXMLElement)[10]
  public 0 => string '7' (length=1)

C:\wamp\www\EvaluateCredibility\AlexaUrlInfo.php:127:
object(SimpleXMLElement)[11]
  public 0 => string '51' (length=2)
```

Online Since:
Global Rank: 7
Median Load Time V: 1694
Median Load Time P: 51
Google Speed score =68

```
C:\wamp\www\EvaluateCredibility\evaluateCredibility.php:955:
object(stdClass)[14]
  public 'numberResources' => int 118
  public 'numberHosts' => int 25
  public 'totalRequestBytes' => string '26593' (length=5)
  public 'numberStaticResources' => int 62
  public 'htmlResponseBytes' => string '233039' (length=6)
  public 'cssResponseBytes' => string '390509' (length=6)
  public 'imageResponseBytes' => string '3112864' (length=7)
  public 'javascriptResponseBytes' => string '770130' (length=6)
  public 'otherResponseBytes' => string '18742' (length=5)
  public 'numberJsResources' => int 13
```

Figure 3.8: Scoring credibility categories using credibility data

As shown in Figure 3.8, currency category and professionalism category scores are being computed using the values acquired for various credibility factors related to them. Currency category is using published date for content in order to rate its credibility. Similarly, professionalism category is using factors like Alexa global rank, mean load time, Google page rank, and others to calculate it. Similar to currency and professionalism computation, other credibility categories are also evaluated. Formulae and algorithms used for evaluating these credibility categories are discussed in correctness, authority, currency, professionalism, popularity, impartiality and quality sub-sections below.

3.3.7.1 Correctness

This research used two credibility factors for evaluating correctness category: 1) TF-IDF score and 2) Google search result rank. Both of these factors allow credibility assessment module to determine the relevancy of a Web page to the question given (Ramos, 2003; Wu & Marian, 2011).

The first credibility factor used for measuring correctness category was TF-IDF score. TF-IDF score for a Web page was calculated using *TF-IDF* score of each word shown in Equation 3.6, where *WordFrequency* shows the occurrences of the word in page *p*, *ND* represents the total number of documents considered and *DocumentWithWords* indicates number of pages that contain the word *w (Ramos, 2003)*. While Equation 3.6 is used to calculate the TF-IDF score of a single keyword, Equation 3.7 is used to sum *TF-IDF* scores of all keywords for a given page, to give *TF-IDF* score for page *p*. Finally, these scores are normalized between 0 and 1, as shown in Equation 3.8, with β set to 0.4. In Equation 3.8, *max* is used to return the highest *TF-IDF* score among all pages considered (Ramos, 2003).

$$TFIDF(w,p) = WordFrequency(p) * \log_2(ND/DocumentsWithWord(w,ND)) \quad \textbf{Equation 3.6}$$

$$TFIDFscore(p) = \sum_{i=1}^{n} TFIDF(w_{i,}, p) \quad \textbf{Equation 3.7}$$

$$NormalizedTFIDFscore(p) = \left(\beta + \frac{(1-\beta)TFIDFscore(p)}{\max(\$TFIDFscore(p))}\right) \quad \textbf{Equation 3.8}$$

The second credibility factor for scoring correctness category is Google search rank (Wu & Marian, 2011). Web pages were scored based on their ranking in the Google search results returned. The rank of a Google search result is normalized, i.e., the sum of all *NormalizedRankScore* is equal to 1 (Wu & Marian, 2011). Equation 3.9 shows the formula used for normalization of the search rank of a page, where *NormalizedRankScore*

is the score given to a page based on its Google search rank denoted by *GoogleSearchRank*. The exponent is set to 2 so that the scores degrade quickly, thus giving more emphasis to pages with higher *GoogleSearchRank (Wu & Marian, 2011).*

Once *NormalizedTFIDFscore* and *NormalizedRankScore* of a Web page are calculated, aggregate correctness category score can be measured. Average of both scores is taken in order to calculate correctness category score as indicated in Equation 3.10.

$$NormalizedRankScore(p) = (1/(GoogleSearchRank(p))^2 \quad \textbf{Equation 3.9}$$

$$Accuracy = \frac{NormalizedTFIDFscore(p) + NormalizedRankScore(p)}{2} \quad \textbf{Equation 3.10}$$

3.3.7.2 Authority

This research evaluates authority of a Web page by considering two credibility factors—author name and author contact information. Presence of author name assures that content is not written by an anonymous user. Presence of author's contact information, which can include phone number, e-mail and social networking ID, is useful for finding further details or get in contact with the author. Both of these credibility factors provide useful details regarding the author, thus increasing credibility of the content. The research also intended to consider author experience, but could not find any API that could do it as well. Furthermore, it is important to retrieve author experience data for the exact same person whose name is mentioned as author. Since many authors can have similar full names and API is unavailable for achieving this task, only two factors were considered: 1) author name and 2) author profile.

Author name credibility factor was retrieved using Diffbot (2016) API, which uses a combination of extraction and machine learning techniques to find author name within

the content. Presence of author name is the primary requirement for evaluating authority score. The presence of an author name gives the page 60% authority score (Diffbot, 2016). Author name is given precedence over the author profile because the information on the link can only be verified against the name given (Diffbot, 2016). In order to make sure that the author name provided is not fabricated, it was tested against an NER to validate it as a person entity type. Formula for scoring author name score is shown in Equation 3.11, where *AuthorName* finds author name on a page *p* (Diffbot, 2016).

$$AuthorNameScore(p) = \text{IsNotNull}\big(AuthorName(p)\big) = \\ = \text{true}\ ?\ 60\%\ :\ 0 \qquad \textbf{Equation 3.11}$$

The second credibility factor, author contact information, is also retrieved using Diffbot (2016) API. The presence of author profile information on page was given 40% of authority score. The URL format was verified using regex. Formulae for scoring author URL score is given in Equation 3.12 where *AuthorURL* return profile link for author on page *p* (Diffbot, 2016).

$$AuthorURLScore(p) = \text{IsNotNull}\big(AuthorURL(p)\big) = \\ = \text{true}\ ?\ 40\%\ :\ 0 \qquad \textbf{Equation 3.12}$$

Equation 3.11 shows an if-else (if denoted by '?') structure that assigns 60% score (out of 1) if an author name is present, else (denoted by ':'), it is assigned a zero score (Diffbot, 2016). Similarly, if the condition for URL not being NULL is true, then it is assigned a score of 40%, else it is assigned 0, as shown in Equation 3.12 (Diffbot, 2016). For example, for a Web page the API is able to find "Sarah Connor" as the author name and "Contact me on twitter: @SarahConnor" for author URL then it will received an authority score of 60% for author name and 40% for author URL. Thus, its authority score would be 100%.

The aggregate authority score is shown in Equation 3.13, which is the sum of *AuthorNameScore(p)* and *AuthorURLScore(p)*. Author score is 100 if both author name and author profile URL is found on page *p (Diffbot, 2016).*

$$Authority(p) = AuthorNameScore(p) + AuthorURLScore(p)$$

Equation 3.13

3.3.7.3 Currency

This research used Web page content's date of publication or the date of update, whichever is more recent, as credibility factor for measuring currency category . The date extracted helped in rating Web pages depending upon how recent and updated the content was.

This research used Web page content's date of publication or the date of update, extracted from Diffbot API (Diffbot, 2016). Currency score is given, depending on the bracket range in which the date lies. The defined range is similar to the one used by Aggarwal et al. (2014b), as shown in Table 3.8.

Table 3.8: Currency category factors and conditions for scoring (Aggarwal et al., 2014b)

Factor	Condition	Score Range
Last update date	< 1 year (less than a year)	100%
	> 1 year and < 5 years	0.1%-99.99%
	> 5 years	0%
	Date not mentioned	0%

As shown in the table, Web pages published or updated within a year are considered most current, and thus are given the highest score. Web pages not published within a year are scored depending upon whether they are published within the last five years or not. Web pages older than five years are considered outdated, thus are given zero currency score. However, Web pages published between one to five years are scaled been 0.1%

(close to 5 years) to 99.99% (close to 1 year) (Aggarwal et al., 2014b). For example, A Web page that is last updated 2 years ago will received a currency score of 80% since it lies between 1 to 5 years bracket and the further it is from 1 year mark the lower score it will get.

Since there is only one factor under currency, thus score for the date of publishing or the date of last update is used as the aggregate currency score, as shown in Equation 3.14.

$$Currency(p) = LastUpdateDate(p) \quad \textbf{Equation 3.14}$$

In Equation 3.14, *LastUpdateDate(p)* shows credibility factor score evaluated from the content, when published or last updated, where *p* represents the Web page whose currency is being evaluated.

3.3.7.4 Professionalism

This research covered eight credibility factors for evaluating professionalism category score. Other studies have limited this to one to four factors only (Aggarwal et al., 2014b; Oh et al., 2012). These include 1) domain type, 2) Alexa median load time percentage, 3) Google speed score, 4) Mozscape domain authority, 5) Mozscape page authority, 6) WoT trustworthiness users' rating, 7) WoT child safety users' ratings, and 8) WoT experts score (Aggarwal et al., 2014b; Alexa API, 2017; Mozscape API, 2017; SEOstats, 2017; Web of Trust API, 2017). Table 3.9 lists these credibility factors, and conditions used for scoring them.

Table 3.9: Professionalism category factors and conditions for scoring (Aggarwal et al., 2014b; Alexa API, 2017; Mozscape API, 2017; SEOstats, 2017; Web of Trust API, 2017).

Factor	Condition	Score range
Domain type	others	0%
	com	3.571%
	info, net	18.57%
	edu, ac, org	78.57%
	Gov	100%
Alexa median load time	>50	80%-100%
	<=50	0-79.9%
Google speed score	0-100	0%-100%
Mozscape domain authority	0-100	0%-100%
Mozscape page authority	0-100	0%-100%
Trustworthiness and child safety based on users' ratings	0-19 (very poor)	0%
	20-39 (poor)	24.66%
	40-59 (unsatisfactory)	73.06%
	60-79 (good)	73.97%
	80-100 (excellent)	100%
WOT experts' score	Negative (malware or viruses, poor customer experience, phishing, scam, potentially illegal)	Deducted
	Questionable (misleading claims or unethical, privacy risks, suspicious, hate, discrimination, spam, potentially unwanted programs, ads / pop-ups)	Deducted
	Neutral (Online tracking , Alternative or controversial medicine, Opinions, religion, politics, other)	Added
	Positive (good site)	Added

The first credibility factor used is domain type, where a Web page is given a score depending on the domain type it belongs to. Domain type in a URL always ends with an extension of two or three characters. These characters can signify country or type of organization the domain is associated with. For example, Web pages ending with '.gov' are government pages, while ones ending with .com are commercial pages. Thus, Web pages that belong to government, county or organization domain types merit higher score over commercial domain type. Therefore, this research defined weightings for scoring Web pages based on their domain type. It used the same weightings for domain types, as defined by Aggarwal et al. (2014b) in their credibility assessment system.

The second credibility factor used for evaluating professionalism category is median load time (Alexa API, 2017). This factor allows the research to judge whether the Web page is keeping a balance in maintaining good speed load time and not overloading the page with unnecessary features. This was scored by fetching Web page median load time using Alexa API (Alexa API, 2017). Alexa median load time percentage shows the percentile of pages slower than the current page. As in example, a Web page having a 98^{th} percentile is very fast and its load time is faster than 98% of the pages on the Web. Thus, this research assigns 80%-100% weighting to the Web pages whose median load time is faster than 50% of Web pages. Similarly, the Web pages that are equal or slower than this are assigned score between 0%-79.99% (Alexa API, 2017).

This research used page speed score as the third credibility factor for measuring professionalism (Google, 2017). The research chose Google page speed score, whose score is fetched from Google analytics API, which measures performance of a page for mobile and desktop devices, where the URL is fetched twice, once for each agent (Google, 2017). The score assigned is between 0 and 100, where a score of 85 and above shows the page is working well. The score is measured with respect to time taken to

above-the-fold load and time taken to full page load. The score given by Google page speed is used, as it is, without defining any weightings for score ranges (Google, 2017).

The fourth credibility factor used is domain authority score, which is the score assigned to a domain by an SEO organization, using a number of factors (Mozscape API, 2017; SEOstats, 2017). This research has used domain authority score as shared by Mozscape via Mozscape API, which predicts how well a domain is likely to rank on the search engine and uses factors such as Web index, link counts, trust rank, and others. The score given by Mozscape for domain authority has been used (Mozscape API, 2017).

The fifth credibility factor used is page authority score, which is similar to domain authority but scores the page on the domain instead (Mozscape API, 2017). The research uses Mozscape API for fetching Mozscape page authority score for a Web page. The score is generated using multiple factors such as Web index, link counts, trust rank and others. Both Mozscape domain and page authority are scored on a 100-point logarithmic scale, where the score is easier to gain from 20-30 as compared to climbing from 70-80 (Mozscape API, 2017). This means that there is a much bigger difference between Web pages of score 90 and 80, than 50 and 40. Both of these measures are important as page authority represents strength of a single page, whereas domain authority represents the strength of all pages within the domain and subdomains. For weighting, the research used the same scores as provided by Mozscape for page authority (Mozscape API, 2017).

The sixth, seventh and eighth credibility factors for measuring professionalism are users' trustworthiness rating, users' child safety rating and Web page's expert rating (Aggarwal et al., 2014b; Web of Trust API, 2017). These three ratings have been taken from WoT API, where users and experts assign ratings to pages on a scale of 1-100 and give description as well (Web of Trust API, 2017). These ratings are essential as they highlight important characteristics of Web pages such as child safety, awards received,

traces of scam or spam, and others. WoT uses crowd sourcing approach which gathers ratings and reviews from millions of users about their feedback on Web pages they visit (Aggarwal et al., 2014b).

The sixth and seventh credibility factors, i.e., user ratings for Web page's trustworthiness and child safety, provided ratings for Web page in terms of its trustworthiness and content being suitable for children. Both of these ratings have an estimate score and a confidence score. Therefore, average of both of these ratings was used to score user ratings for trustworthiness and child safety. For example, Web page's trustworthiness scores are 40 in estimated score and 60 in confidence score, then its user rating is (40+60)/2 which is 50. These ratings were also categorized as very poor (0-19), poor (20-39), unsatisfactory (40-59), good (60-79) and excellent (80-100), depending upon the rating given by the user (Aggarwal et al., 2014b). These categories were scored as 0% for very poor, 24.66% for poor, 73.06% for unsatisfactory, 73.97% for good and 100% for excellent rating, as defined and suggested by (Aggarwal et al., 2014a).

The eighth credibility factor, expert ratings, provided ratings in terms of verbal categories, including negative, questionable, neutral or positive. Since a Web page can have multiple categories scores, thus they are combined to produce an aggregate reviewer score. Characteristics such as malware, poor customer experience, phishing, scam, potentially illegal fall under negative category and thus their scores were deducted as a result. Similarly, if a Web page also contained questionable characteristics or if it was highlighted as a blacklisted website then its score was deducted as well. Characteristics under neutral and positive were simply added to the final reviewer score, while others like negative and questionable were deducted from aggregate expert score. For example, Web page has two positive and one negative characteristics including excellent customer service(score 60) and privacy policy (score 70) as positive and presence of malware as

negative (20). The expert rating calculated will add and subtract scores depending upon the characteristic category. In the example, the expert rating score will be 60+70 or 130 for adding the positive characters, while the score of negative characteristic will be deducte making the final score 130-20 or 110. Any score higher than 100 is ceiled at 100 which is the maximum, while the negative scores are changed to zero.

The eight credibility factors, mentioned in Table 3.9, are used to compute professionalism category score. The score is evaluated as average of all eight credibility factors, as shown in Equation 3.15.

$$
\begin{aligned}
&Professionalism(p) \\
&\quad = (DomainTypeScore(p) \\
&\quad + MedianLoadTimeScore(p) \\
&\quad + SpeedScore(p) + DomainAuthority(p) \\
&\quad + PageAuthority(p) \\
&\quad + TrustworthinessScore(p) \\
&\quad + ChildSafetyScore(p) + ExpertScore(p))/\,8
\end{aligned}
$$

Equation 3.15

In Equation 3.15, the eight variables used represent the credibility factors used by this research for evaluating professionalism, whereas p represents a Web page whose professionalism is being evaluated.

3.3.7.5 Popularity

This research evaluated popularity of Web pages using five credibility factors including social media share count, Web page rank given by three SEOs including Google, Alexa and Mozscape, and traffic rank of Web page given by Alexa (Aggarwal et al., 2014b; Alexa API, 2017; Google, 2017; Mozscape API, 2017). Social media share factor and Mozscape MozRank are factors that have not been used in other studies. These credibility

factors and conditions for scoring them are covered in Table 3.10: Popularity category factors and conditions for scoring.

Table 3.10: Popularity category factors and conditions for scoring (Aggarwal et al., 2014b; Alexa API, 2017; Google, 2017; Mozscape API, 2017)

Factor	Condition	Score range
Social media shares	>=10,000	100%
	>=5,000 and <10,000	80%-99.99%
	>0 and <5,000	0.1%-79.99%
	= 0	0%
Google rank	0-10 (higher is better)	0%-100%
Alexa global and traffic rank	1-100	100%
	101-1,000	54.66%-99.9%
	1001-10,000	46.58%-54.65%
	10,001-50,000	0.1%-46.57%
	>50,000	0%
Mozscape MozRank	0-10	0%-100%

This research used social media share count as the first credibility factor for measuring popularity (SEOstats, 2017). Social media is one of the growing trends on the Web and people use the service to share all kinds of information, thus tracking statistics relating to it can allow judge popularity of a Web page (Chatterjee & Agarwal, 2016). This research used SEOstats[1], which is an open source PHP library to get SEO-relevant Website metrics, including article share count on social media Web pages such as Facebook, Twitter, GooglePlus, VKontakte, Pinterest, Linkedin, Xing, Delicious, Digg and Stumpleupon (SEOstats, 2017). Depending upon the social media share count of a Web page, they were scored depending upon the bracket range for share count. The research defined a score of 100% for Web pages having equal or more than 10,000 share count,

[1] https://github.com/eyecatchup/SEOstats

score of 80%-99.99% for share count between 5,000 to 10,000, and score of 0% to 79.99% for share count between 0 and 5,000, allowing Web having a higher share count to score higher (SEOstats, 2017).

The second credibility factor used is Google page rank (Google, 2017). Google page rank, retrieved via Google analytics API, is the score assigned by Google to a Web page between 0 and 10 on an exponential scale. Web pages such as usa.gov and twitter.com are page rank 10 domains which have the highest volume inbound links of any Web pages on the Web (Google, 2017). Similarly, pages with page rank 5 have decent inbound links, with 3 and 4 having a fair amount while new Web sites are given a 0 score. The score assigned by Google page rank was scaled to 0% to 100% for evaluating popularity category.

The third and fourth credibility factors for evaluating popularity category include global rank and traffic rank given by Alexa, retrieved using Alexa API (Alexa API, 2017). Alexa global ranks shows three month average traffic rank where traffic rank shows current rank earned by a Web page. This is determined by a combination of unique visitors and page views for a given page. The credibility factors are scored depending upon the bracket range in which global and traffic rank of a Web page lies. This research used the suggested ranges given by Alexa for defining them. As shown in Table 3.10, Web pages ranking between 1 and 100 are assigned 100% score, and Web pages ranking in other brackets are scored accordingly (Alexa API, 2017).

The fifth credibility factor used is the popularity rank assigned to Web pages by Mozscape (Mozscape API, 2017). Retrieved via Mozscape API, the score represents link's popularity on the Web. Mozscape ranks Web pages between 0-10, where 0 is assigned to newly published Web pages and 10 for Web pages having high link

popularity. This research scales this score from 0% to 100%, in order to use it for evaluating popularity category score (Mozscape API, 2017).

The five credibility factors, mentioned in Table 3.10, were evaluated using conditions for scoring. Aggregate popularity category score is calculated by taking average of the five credibility factor scores, as shown in Equation 3.16.

$$Popularity(p) = SocialMediaShareScore(p) + GoogleRank(p) + AlexaGlobalRank(p) + AlexaTrafficRank(p) + MozRank(p))/5$$

Equation 3.16

Equation 3.16 shows *SocialMediaShareScore, GoogleRank, AlexaGlobalRank, AlexaTrafficRank,* and *MozRank,* which are credibility factors used to evaluate popualarity of a page *p.* The average of these five credibility factors is being taken to compute the aggregate popularity score.

3.3.7.6 Impartiality

This research used sentiment score of the Web page to judge impartiality of a Web page (Aggarwal et al., 2014b; Diffbot, 2016). Table 3.11 lists conditions for scoring sentiment credibility factor.

Table 3.11: Impartiality category factors and conditions for scoring (Aggarwal et al., 2014b; Diffbot, 2016)

Factor	Condition	Score range
Sentiment	>0.3 and <=1 (Positive)	41.89%
	>=-0.3 and <=0.3 (Neutral)	100%
	<-0.3 (Negative)	0%

Impartiality of the content was estimated using sentiment score fetched using Diffbot API (Diffbot, 2016). Diffbot uses a combination of artificial intelligence, computer

vision, machine learning and NLP techniques for conducting sentiment analysis of the article. It looks for words that carry a negative and positive connotation from the words present in the article, such as 'not' for negative and 'good' for positive, and estimates the overall sentiment score of the content. The API returns a sentiment score where the value ranges from -1 (very negative) to +1 (very positive) (Diffbot, 2016). For scoring, precedence was given to articles being positive over articles have a negative sentiment value. Since the values are in numerical form, a range was defined for each category where content was rated as neutral if sentiment score was between -0.3 and 0.3, positive if between >0.3 and 1, and negative if between <0.3 and -1. The range for being neutral was not set to zero as it is difficult to achieve a near perfect zero score (Tanaka et al., 2010b). For example, two reviews are received one have a sentiment score of 0.2 and the other having a score of -0.5. It is clear that the first review is neutral so it will be scored as 1 and the other is negative so it will be scored as 0. Thus the first review is given a higher score so answers extracted from that are given more weighting

The sentiment value was also used for calculating the accumulative impartiality of the article, as shown in Equation 3.17.

$$Impartiality(p) = Sentiment(p)$$ **Equation 3.17**

In the equation, *Sentiment* score indicates whether a score is negative, neutral or positive and is scored accordingly. The *Sentiment* score calculated for a Web page is indicated as p.

3.3.7.7 Quality

This research used two credibility factors evaluating content's quality--its readability and plagiarism (or originality) score (Microsoft Word, 2016; Wu & Marian, 2011). The

factors used for scoring readability and plagiarism, based on conditions defined for scoring, are shown in Table 3.12.

Table 3.12: Quality category factors and conditions for scoring (Microsoft Word, 2016; Wu & Marian, 2011)

Factor	Condition	Score range
Flesch Kincaid Reading Ease	>=60 and <=70	100%
	>70 and <=100	99.99%-0%
	>=0 and <60	0%-99.99%
Flesch Kincaid Grade Level	>=7.0 and <=8.0	100%
	>8.0 and <=12.0	99.99%-0%
	>=0 and <7.0	0%-99.99%
Dale Chall Readability Score	>=6.0 and <=6.9	100%
	>6.9 and <=10.0	99.99%-0%
	>0% and <6.0	0%-99.99%
Originality using SpotSigs	>0.18	0%
	<=0.18	100%

This research used three techniques for evaluating readability score including 1) Flesch–Kincaid reading-ease tests, 2) Flesch–Kincaid grade level tests and 3) Dale–Chall readability formula (Microsoft Word, 2016). Readability score indicates the ease with which a content can be read. An ideal readability score is one, which is neither too high nor too low, so as to accommodate more Web users. A content having a lower readability will look unprofessional to adults while a content having a high score will be unreadable for college students. Thus, this research assigned 100% score for content having readability score between 70 and 80 for Flesch Kincaid reading ease (Microsoft Word, 2016). This range was chosen as it compensates most Web users and is also the suggested score by Microsoft Word for documents to aim at (Microsoft Word, 2016). Similarly, for Flesch Kincaid grade level, Grade 7 to 8 was considered for 100% score and a range of 6.0 to 6.9 for Dale Chall readability score, which are equivalent to that of Flesch Kincaid

reading ease 60 to 70 readability score range (Microsoft Word, 2016). The average of these three readability scores was used as the aggregate readability score of Web page, as shown in Equation 3.18.

$$Readability(p) = \frac{(FleschKincaidReadingEase + FleschKincaidGradeLevel\ DaleChallReadabilityScore)}{3}$$ **Equation 3.18**

The second credibility factor used for evaluating quality of content is plagiarism ratio or originality of the content. This factor helped in checking whether the content is primary or secondary source of information. The research used SpotSigs technique for comparing originality of two documents. It was used to counter check originality of search result with other search results. The threshold value was set to .18, which is the threshold used by Australian OA journal for accepting journal submissions (Australian OA Journal, 2017). If the condition is satisfied, the search result, higher up in search results, was considered original whereas the latter was considered plagiarized. For example, if doc 5 and doc 8 are found to be similar then doc 5 is considered original and doc 8 is considered plagiarized.

The aggregate quality of a Web page is calculated by taking average of readability score (shown in Equation 3.18), and originality score, as shown in Equation 3.19.

$$Quality(p) = {(Readability(p) + Originality(p))}/{2}$$ **Equation 3.19**

The equation shows *Readability* credibility factor, evaluating content readability and *Originality* evaluating plagiarism ratio of a page *p*.

3.3.7.8 Web page credibility score

This research evaluated Web page credibility score, based on the scores of seven credibility categories. Equal weightings were assigned to all categories, thus average score of the seven categories was considered as credibility score of a Web page. Equation 3.20 shows the formula used for evaluating Web credibility score of a Web page

$$CredibilityScore(p) = (Accuracy(p) + Authority(p) + Currency(p) + Professionalism(p) + Popularity(p) + Impartiality(p) + Quality(p))/7$$

Equation 3.20

In the equation, *CredibilityScore* of a page *p* is evaluated using scores of the seven credibility categories. These include *Correctness*, *Authority*, *Currency*, *Professionalism*, *Popularity*, *Impartiality*, and *Quality*, whose scores are evaluated for a page *p*. These scores are taken as average in order to compute its *Credibility*.

3.3.8 Scoring and storing answers

Both Web-based QA systems and credibility-based Web QA system produce answers, which are scored using various techniques and then stored according to the format specified for a particular scoring technique. The saved answer files are also used for generating other files, like top answers, and evaluations purposes. The scoring techniques and their answer storage format are discussed under scoring techniques used in this research. The scoring techniques available are frequency, match-score, prominence and credibility-based answer scoring and are discussed in the sub-sections below:

3.3.8.1 Frequency score

This research scored answers, based on their frequency, by counting number of instances of the answer on all search result pages. The formula used for frequency score is shown in Equation 3.21 (Wu & Marian, 2011):

$$Frequency(a) = \sum_{i=1}^{K} count(a, p_i) \qquad \textbf{Equation 3.21}$$

In the equation, *Frequency* of an answer *a* is calculated by counting the number of instances of answer *a* on page $p_{i,}$ where *i* is between 1 and *K*. Frequency of answers found from page 1 up to *K* are added up, where *K* is the number of search results returned by the search engine.

Frequency storing techniques require answers to be stored in a certain format to be able to generate frequency-based ranked answer list again. For storing answers, each instance of an answer is stored on an independent line, where each line number represents search results from which the answer was found. Figure 3.9 shows the answers store for the question "What was the name of the first Russian astronaut to do a spacewalk?" and for the method "Top sentences selected for *N*=3" using frequency scoring technique.

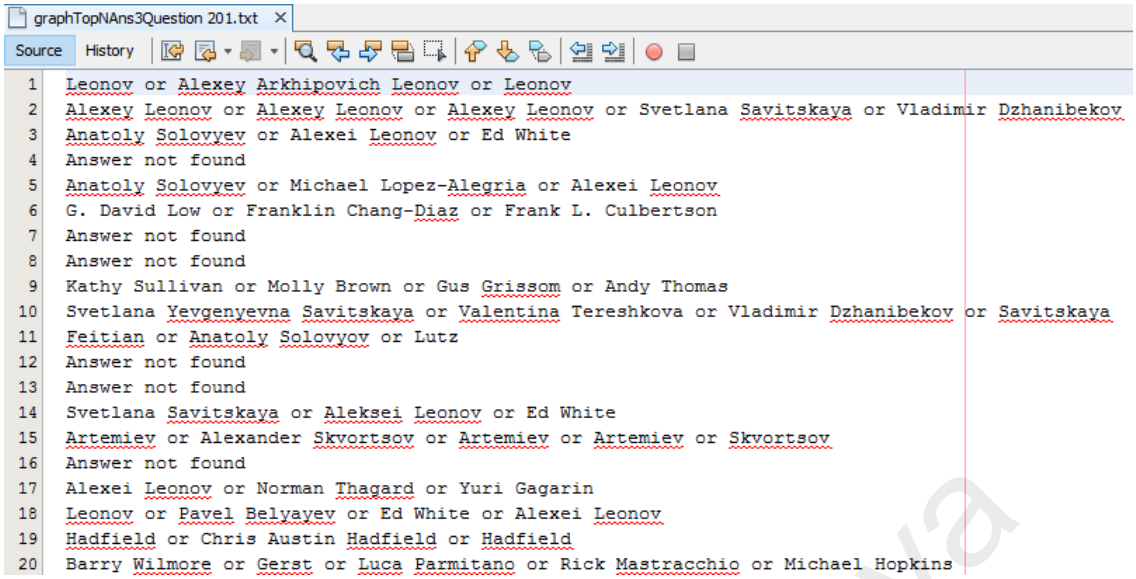


Figure 3.9: Stored answers format for a question using frequency scoring technique

The figure shows answers being stored in a text file for frequency scoring format. The answers are stored in twenty lines, where each line number shows the answers found on that particular Web page. For example, for Web page 7, no answers were found. Moreover, it is possible that multiple answers are found at one Web page, where one answer can also be found multiple times.

3.3.8.2 Match Score

The research scores answers, based on match score, using two conditions: 1) number of keywords found, and 2) presence of quote words in the sentence containing the answer. Equation 3.22 shows the formula used by this research for evaluating match score of an answer (Oh et al., 2012):

$$matchScore(a) = count(keywords, sentence) + count(quoteWords, sentence). \quad \textbf{Equation 3.22}$$

As shown in the equation, *matchScore* for an answer *a* is calculated by using *count*, which counts number of keywords (*keywords)* and quote words (*quoteWords)* found in a

given *sentence*. The greater the number of quote words and keywords found in a sentence, the higher will be answer's match score.

In order to store answers generated using match-score technique, the text file must store both answer and score it received from the match score algorithm. This is done by storing the answer followed by the score it received, enclosed within square brackets. Figure 3.10 shows the format used for storing answers using match score technique:

Figure 3.10: Stored answers format for a question using match score technique

The figure shows a text file containing both answers and its match score, enclosed within square brackets. Each line indicates answers (and its match score) found for search result *K*, where *K* is between 1 and 20. For example, in line 1, four instances of Leonov are found. Though they are the same answers but two of these instances have a match score of 5, while the other two have a match score of 4. This highlights that some instances of Leonov were found from a sentence having a higher match score than others.

3.3.8.3 Prominence score

This research calculates prominence score of an answer by considering its position within the sentence, from which the answer was taken (Bouziane et al., 2015). Equation 3.23, Equation 3.24, and Equation 3.25 show the formulae used for computing prominence, derived from literature and word prominence algorithms (Doyle, 2014; Offerijns, 2012; Wu & Marian, 2011):

$$keys = arrayKeys(words, word) \quad \textbf{Equation 3.23}$$

$$positionSum = arraySum(keys) + count(keys) \quad \textbf{Equation 3.24}$$

$$prominence = \left(count(words) - \left(\frac{positionSum - 1}{count(keys)}\right)\right) * \left(\frac{100}{count(words)}\right) \quad \textbf{Equation 3.25}$$

In Equation 3.23, *keys* is an array that uses *arrayKeys()* function to store positions of the *word* in a sentence represented as *words*. For example, for the sentence "Ray shot and killed King in Memphis on April 4, 1968", position of the *word* "Ray" is 0 since index starts from 0. Equation 3.24 shows calculation of *positionSum*, which is the sum of each position of *word* that is being analyzed. This is done by summing up all positions of *word*, using *arraySum(keys)* and number of its occurrences in the sentence using *count(keys)*. For example, if *word* occurs on position 2 and 5, then *arraySum(keys)* is 7 and *count(keys)* is 2, thus *positionSum* is 9. The results from Equation 3.23 and Equation 3.24 are used in Equation 3.25 to calculate *prominence* of the answer. Table 3.13 shows some examples of prominence of a word being calculated:

Table 3.13: Prominence calculation examples

Scenario	Computation
The prominence of a *word* in the first position in a 10-word (*words*) sentence that has unique words only is	(10 - ((1 - 1) / 1)) * (100 / 10)) = 100%
If that same *word* is the last word in the sentence, prominence will be	(10 - ((10 - 1) / 1)) * (100 / 10)) = 10%.
If that *same* word occurs twice on position 1 and 10, prominence will be	(10 - ((11 - 1) / 2)) * (100 / 10)) = 50%

Similar to match score technique, prominence scoring technique requires both answer and its prominence score to be stored. This is done by recording the instance of the answer, followed by its prominence score, enclosed within square brackets. Figure 3.11 shows the answer format used for prominence scoring technique:

```
1  Leonov[17.857142857143] or Alexey Arkhipovich Leonov[33.333333333333] or Leo
2  Alexey Leonov[34.210526315789] or Alexey Leonov[20] or Alexey Leonov[20] or
3  Anatoly Solovyev[3.3333333333333] or Alexei Leonov[6.6666666666667] or Ed Wh
4  Answer not found[11.111111111111]
5  Anatoly Solovyev[6.25] or Michael Lopez-Alegria[0] or Alexei Leonov[7.692307
6  G. David Low[71.428571428571] or Franklin Chang-Diaz[66.666666666667] or Fra
7  Answer not found
8  Answer not found
9  Kathy Sullivan[5.5555555555556] or Molly Brown[14.285714285714] or Gus Griss
10 Svetlana Yevgenyevna Savitskaya[2.6315789473684] or Valentina Tereshkova[0]
11 Feitian[10.526315789474] or Anatoly Solovyov[0] or Lutz[40] or Ed White[2.94
12 Answer not found
13 Answer not found
14 Svetlana Savitskaya[4.5454545454545] or Aleksei Leonov[0] or Ed White[0] or
15 Artemiev[100] or Alexander Skvortsov[4.1666666666667] or Artemiev[40] or Art
16 Answer not found
17 Alexei Leonov[17.647058823529] or Norman Thagard[22.222222222222] or Yuri Ga
18 Leonov[58.333333333333] or Pavel Belyayev[22.222222222222] or Ed White[6.25]
19 Hadfield[80] or Chris Austin Hadfield[0] or Hadfield[100] or Hadfield[86.206
20 Barry Wilmore[23.333333333333] or Gerst[23.333333333333] or Luca Parmitano[0
```

Figure 3.11: Stored answers format for a question using prominence scoring technique

As shown in the figure, the text file comprises both answers and their prominence score. Each line in the file represents a search result whose answers (and their prominence scores) are shown. For example, in line number 1, Leonov answer is recorded four times,

but each of its instance has a different prominence score. This shows that each instance of Leonov is taken from a different sentence, where each instance of Leonov has a different score.

3.3.8.4 Credibility-based answer score

This research scored answers based on their credibility using two values including 1) Web page credibility score, from which the answer is taken and 2) answer percentage (evaluated using frequency of answer) (Wu & Marian, 2011). Existing credibility-based QA systems like Corrob* also used combination for traditional and Web page credibility score for producing credibility based answers(Wu & Marian, 2011). Moreover, the weighting between answer percentage and Web page credibility is controlled using a smoothing factor to control ratio between them.

Frequency of an answer *a* can be determined by evaluating its frequency score, shown in Equation 3.21. However, this score is normalized between 0 and 1, in order to bring it to the same range as that of credibility score. Equation 3.26 shows the formulae used for calculating answer percentage for an answer on *a* page *p*, while Equation 3.27 shows the formula used for calculating answer percentage on all pages *K*:

$$AnswerPercentageOnPage(a,p) = \frac{Frequency(a,p)}{\sum_{i=1}^{n} Frequency(a_i,p)} \qquad \textbf{Equation 3.26}$$

$$AnswerPercentage(a) = \sum_{j=1}^{K} AnswerPercentageOnPage(a,p_j) \qquad \textbf{Equation 3.27}$$

In Equation 3.26, percentage of an answer on page, denoted by *AnswerPercentageOnPage(a,p)*, is evaluated by dividing *Frequency* of answer *a* to the sum of *Frequency* of all answers found on page *p*, where *n* is the total number of answers found on that page. In Equation 3.27, aggregate *AnswerPercentage* of an answer *a* is equated by adding answer percentage of the answer on all pages, where *p* is between 1 and *K* (maximum number of Web pages considered for answer extraction).

For calculating credibility-based answer score, the answer percentage (shown in Equation 3.27) is used along with the credibility score of page *p* (shown in Equation 3.20). The formula used for calculating credibility-based answer score is shown in Equation 3.28:

$$CredibilityAnswerScore(a) = \sum_{i=1}^{n} \big(\alpha * AnswerPercentageOnPage(a, p_i) + (1-\alpha) CredibilityScore(p_i)\big) \quad \textbf{Equation 3.28}$$

Weightings for both *AnswerPercentageOnPage* and *CredibilityScore* are controlled using a smoothing variable α, where its value is between 0 and 1. This allows the researcher to identify the ideal weight for α where answer accuracy is the highest. Increase in the value of α increases the weighting for *AnswerPercentageOnPage* while at the same time decreases the weighting for *CredibilityScore* instead.

Credibility-based answers are stored using the same format as specified for frequency score technique. This is because answer percentage can be derived from frequency scoring technique, thus the answer file format can be used for both scoring techniques. However, the additional step taken in credibility-based answer scoring technique is that credibility scores of Web pages are stored in an independent file. Figure 3.12 shows the format for storing credibility scores of Web pages:

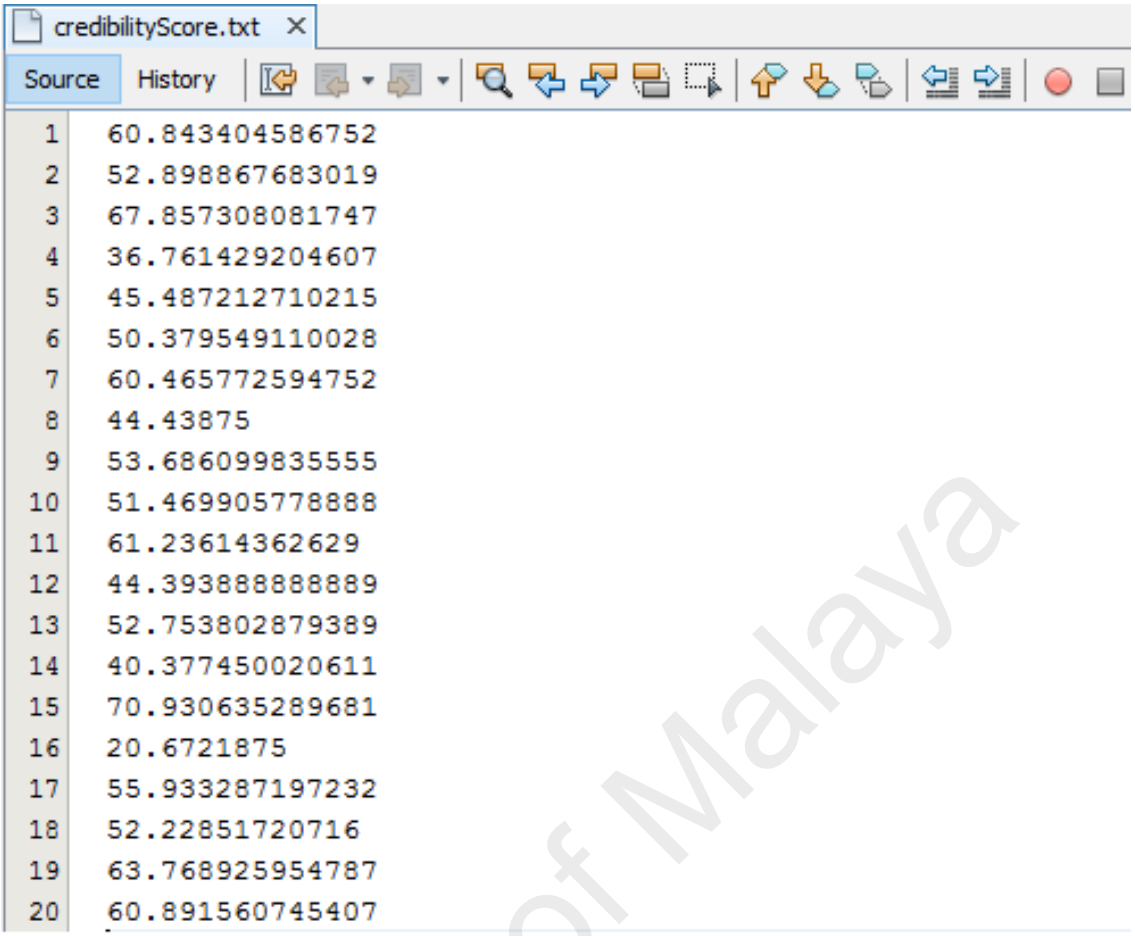


Figure 3.12: Format for storing Web pages credibility scores

As shown in the figure, scores of Web pages are stored into 20 independent lines. This is because each line represents a Web page, and the score on that line represents credibility score of that page. The credibility score range is between 0 and 100, where a higher score indicates higher credibility for the page.

3.3.9 Generating results for evaluation metrics

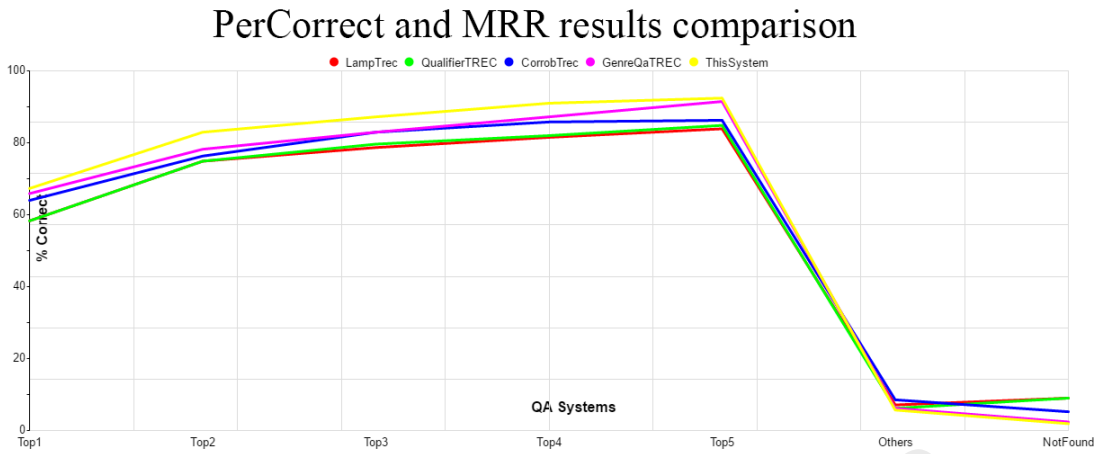
The answer files can be used to generate a number of results including top answers, PerCorrect and MRR. Figure 3.13 shows the top answers file generated using stored answers for a question, shown earlier in Figure 3.9.

```
1  Aleksei A. Leonov
2  Alexei Leonov or Alexey Leonov or Leonov
3  10
4  Aleksei Leonov or Leonov
5  4
6  Svetlana Savitskaya or Svetlana Yevgenyevna Savitskaya or Savitskaya
7  4
8  Artemiev
9  3
10 Ed White
11 3
12 Alexander Skvortsov or Skvortsov
13 2
14 Anatoly Solovyev
15 2
16 Hadfield
17 2
18 Vladimir Dzhanibekov
19 2
20 Alexey Arkhipovich Leonov
21 1
22 Anatoly Solovyov
23 1
24 Andy Thomas
25 1
```

Figure 3.13: Top answers file generated from answers file

As shown in the figure, the file contains answers along with their score, depending upon the scoring function used. The first row shows the correct answer for the question. An answer (and its variations) are written in one line and its score on the next available line. Score value may vary among different scoring technique for which top answer file is being generated. In this way, an answer and score pair occupy two lines. This process continues until all answers from the answer file are written onto the top answer file for the question.

The stored answers can be used for different evaluation purposes, but this research chose PerCorrect and MRR evaluation metrics since they focus on evaluating answer accuracy of the system. For generating results, the research defined two functions, one for plotting PerCorrect, and the second for MRR. Figure 3.14 shows an example of a graph, plotted using the data stored in answer files:



Method	MRR	Top1	Top2	Top3	Top4	Top5	Others	Not Found
LampTREC	0.690363349131112	58.2938388625599%	74.8815165876785%	78.6729857819919%	81.5165876777255%	83.8862559241719%	7.10900473933655%	9.00473933649299%
QualifierTREC	0.6932859399684	58.2938388625599%	74.8815165876785%	79.6208530805699%	81.9905213270149%	84.8341232227499%	6.16113744075839%	9.00473933649299%
CorrobTREC	0.731595576619277	63.9810426540289%	76.3033175355455%	82.9383886255929%	85.7819905213279%	86.2559241706169%	8.53080568720389%	5.21327014218019%
GenreQaTREC	0.755371248025289	65.8767772511859%	78.1990521327019%	82.9383886255929%	87.2037914691949%	91.4691943127969%	6.16113744075839%	2.36966824644559%
This system	0.777725118483419	67.2985781990529%	82.9383886255929%	87.2037914691949%	90.9952606635079%	92.4170616113749%	5.68720379146929%	1.89573459715649%

Figure 3.14: Generating results using stored answer files

The graph in Figure 3.14 shows useful information such as MRR and PerCorrect percetanges at different ranks. In this figure, different QA systems are being compared including LAMP, Qualifier, Corrob, GenreQA and results from OMQA system. The columns show results for PerCorrect and MRR evaluation metrics. The PerCorrect evaluation metric columns includes Top1, Top2, Top3, Top4, Top5, others (correct answers found besides Top5), and not found (answers for which no correct answers were found), while MRR column shows score for MRR evaluation metric.

3.3.10 Results analysis

Based on the results generated, as shown in Figure 3.14, results analysis can be analyzed. The results generated are for four modules (including question analysis, answer extraction, answering scoring and answer aggregation) under Web-based QA systems methods and techniques , and credibility assessment module in Web-based QA systems. Their results and analysis are discussed in greater detail in CHAPTER 4:.

CHAPTER 4: RESULTS AND DISCUSSION

The chapter is divided into three sections. These are listed below:

1. Results for Web-based QA systems methods and techniques
2. Results for OMQA systems vs baseline systems
3. Results for CredOMQA vs baseline systems

In the first evaluation section, methods and techniques found in the existing Web-based QA systems were evaluated. This helped in highlighting methods that improved accuracy of answers. Additionally, multiple techniques available for each method were evaluated as well, whether to choose one over the other or combine available techniques for achieving higher accuracy. Results from this stage allowed the research to suggest combinations of methods and techniques that produce optimal accuracy of answers in Web-based QA systems, and use them in OMQA system. In the end, a result analysis summary of methods and techniques found under the answer extraction, answer scoring and answer aggregation is provided.

In the second evaluation section, OMQA system which is using optimal methods and techniques is compared against baseline systems not using credibility assessment. This allows the research to highlight the success of OMQA by using methods producing optimals. In the end analysis summary for the OMQA vs baseline results is provided.

In the third evaluation section, credibility of Web pages was evaluated using credibility assessment module, producing credibility-based answer scores. This credibility assessment module is added to the existing OMQA system to form CredOMQA system. After selecting the optimal value for α in credibility-based answer scores, CredOMQA is evaluated, for individual credibility categories and all categories colectovely, against

other Web-based and credibility-based Web QA systems. In the end, a summary of the results is provided

4.1 Results for Web-based QA systems methods and techniques

This sub-section shows PerCorrect and MRR results generated for the methods and techniques in Web-based QA systems and their analysis. Each method (and techniques under it) was evaluated, using the evaluation settings listed in Table 3.2. The evaluation results for these Web-based QA methods and techniques are shown in the subsequent sub-sections.

4.1.1 Analysis of Top *K* search results selection method

Figure 4.1 shows the PerCorrect and Table 4.1 shows the PerCorrect and MRR results for the content from Web pages or snippets, with results depth *K* set to 5, 10, and 20.

Table 4.1: PerCorrect and MRR comparison of content resource with *K*=5, 10, or 20; *N*=3 for techniques of Web pages and snippets from *QN*=211

Technique	Parameter values	MRR Score	PerCorrect percentage at different ranks				
			Top-1	Top-2	Top-3	Top-4	Top-5
Web pages	*K*=5, *N*=3	0.655	53.08% (112)	72.04% (152)	77.25% (163)	81.04% (171)	82.46% (174)
Snippets	*K*=5, *N*=3	0.618	52.61% (111)	65.40% (138)	71.56% (151)	72.51% (153)	74.88% (158)
Web pages	*K*=10, *N*=3	**0.717**	**58.77% (124)**	**78.20% (165)**	**84.36% (178)**	**87.68% (185)**	**89.57% (189)**
Snippets	*K*=10, *N*=3	0.661	55.45% (117)	69.19% (146)	77.25% (163)	80.57% (170)	81.99% (173)
Web pages	*K*=20, *N*=3	0.702	57.35% (121)	76.78% (162)	81.52% (172)	84.83% (179)	88.63% (187)
Snippet	*K*=20, *N*=3	0.690	58.29% (123)	74.88% (158)	78.67% (166)	81.52% (172)	83.89% (177)

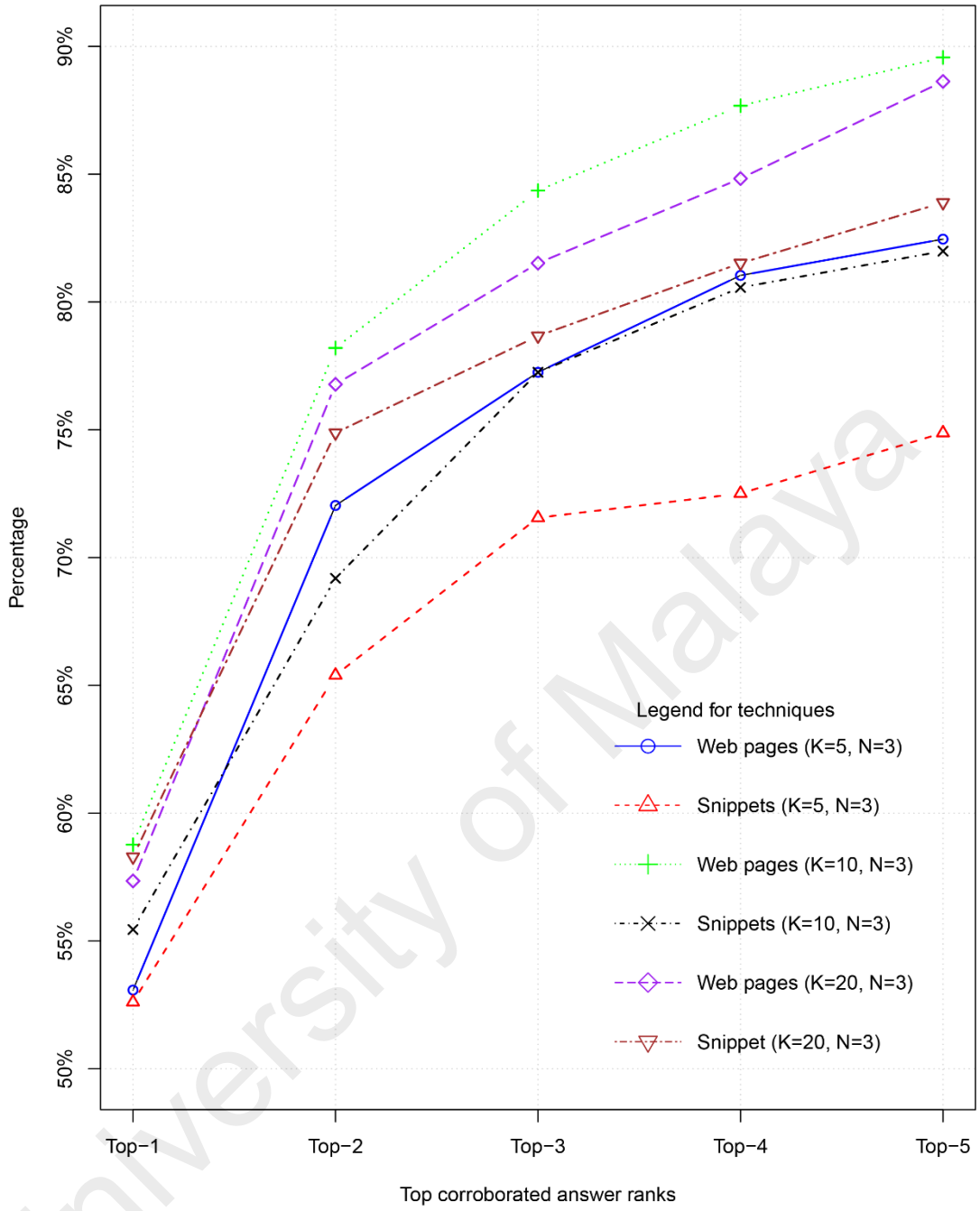


Figure 4.1: PerCorrect comparison of content resource with *K*=5, 10, or 20; *N*=3 for techniques of Web pages and snippets

The results listed in Figure 4.1 and Table 4.1 show PerCorrect results for Web pages and text provided by search engine snippets, at different depths, showing accuracy of answers achieved. The results show that answers taken from Web pages achieved higher accuracy of answers compared to snippets in almost all occurrences of *K*. PerCorrect results show that Web pages have the highest PerCorrect percentage at top-5 with *K*=10

with 89.57%. The lowest percentage 52.61% was scored by snippets at result depth *K*=5 at top-1 corroborated answer. The pattern was the same for top-2 to top-5 corroborated answer ranks.

In the case of MRR results, Web pages received the highest MRR with *K*=10, and the lowest MRR was obtained by snippets for *K*=5. At all MRR ranks, Web pages were able to find the correct answer quicker in comparison to snippets. The difference between the two techniques was larger when results depth *K* was 5 and 10, but started to decrease when it was set to 20 instead. Additionally, Web pages achieved higher MRR value when result depth *K* was 10. The MRR results also correlate with the PerCorrect findings, which shows that Web pages for *K*=10 yield the most accuracy and is also able to fetch the correct answer quicker.

From the PerCorrect results for snippets, it was observed that accuracy of answers improved upon increasing the value of results depth *K*. An increase of 5% to 10% was observed when result depth *K* was increased from 5 to 20. It is highly possible that accuracy of answers for snippets may be improved further by increasing the value of results depth *K* beyond 20. However, higher accuracy can be achieved from limited Web pages when extracting content from Web pages instead of snippets. This is because more candidate answers are extracted from Web pages compared to snippets thus allowing the answer with a higher match score to be selected as the candidate answer over others. This is not usually the case with snippets where the passage given contains one answer only, thus having limited freedom in choosing candidate answers (Yang & Chua, 2003).

The trend observed for Web pages was different than that for snippets as PerCorrect percentage increased when the value of results depth *K* was increased from 5 to 10, but started to decrease, though slightly, when *K* was increased to 20. It can be concluded that

as results depth *K* is increased beyond 10, the frequency of incorrect answers increased more compared to correct answers.

When comparing both snippets and Web pages, Web pages achieved higher percentages in PerCorrect as compared to snippets technique. Not only did they score higher in terms of accuracy of answers, but also required fewer pages to accomplish the task. The difference between these techniques starts to close in as the value of the results depth *K* is increased. Though these techniques were not evaluated with respect to time taken to process a query, snippets do provide faster performance as Web pages have a higher word count compared to them. Web pages achieved a higher accuracy of answers than snippets in almost all scenarios.

Figure 4.2 shows results from Web pages and snippets (with *K* set to 20), for the question "What was the name of the computer in '2001: A Space Odyssey'?" answer to which is "HAL".

Method TopKWebPages Top Answers from 20 pages
Top 1 Answer is HAL or Hal(11)
Top 2 Answer is Dave Bowman or Bowman(9)
Top 3 Answer is David Bowman or Bowman(8)
Top 4 Answer is Kubrick(6)
Top 5 Answer is Arthur Clarke or Arthur C. Clarke or Clarke(4)
Other answers are
Hunter(3), Kaminsky(3), Kimball(3), Poole(3), Chandra(2), Dave(2), David Stork(2), Floyd(2), Martin Balsam or Balsam(2), Stanley(2), Alex DeLarge(1), Chesley Bonestell(1), Ciment(1), Daphne(1), Douglas Rain(1), Frank(1), Gary Lockwood(1), Herakles(1), Herbert A. Simon(1), Homer(1), Horatio Hidalgo(1), Jack Nicholson(1), Jack Torrance(1), Jesus(1), Jonah(1), Nina Persson(1), Noah(1), Ostwald(1), Robert Sawyer(1), Willard(1), Willy Ley(1),

Method TopKSnippets Top Answers from 20 pages
Top 1 Answer is Stanley Kubrick or Kubrick(6)
Top 2 Answer is Clarke(5)
Top 3 Answer is Arthur C. Clarke(4)
Top 4 Answer is Dave(3)
Top 5 Answer is HAL or Hal(2)
Other answers are
Douglas Rain(1), Frank(1), Gary Lockwood(1), Keir Dullea(1), Socrates(1),

Figure 4.2: Web pages and snippets ranked answers results comparison

The figure shows rank answer list for Web pages and snippets. Web pages technique was able to fetch more candidate answers using Web pages, while the total number of answers fetched using snippets was quite less. As a result, Web pages technique ranked the correct answer “HAL” at rank 1 having frequency score 11, while snippets only managed to find two occurrences of it, thus ranking it at rank 5. This shows that answer extraction techniques can greatly benefit from Web pages over snippets, since it contains more content, thus the chances of fetching more correct answers is higher.

As judged by the results shown in Figure 4.2, the top sentence matched *N* benefit greatly, in terms of answer accuracy, when extracting answers from Web pages. As snippets only contain a few sentences, changing the value of the top sentence matched *N* affects Web pages more than snippets, as discussed under analysis of selecting top N sentences method. Therefore, snippets provide fast processing and adequate accuracy when dealing with top-1 corroborated answer only. However, Web pages provide higher PerCorrect percentage and accuracy of answers than snippets at all top corroborated ranks.

In conclusion, Web pages prove to be ideal in finding the correct answer the quickest as it has higher MRR values compared to snippets for all values of *K*. However, the difference between snippets and Web pages becomes closer as the value of *K* is increased to 20. PerCorrect findings show that snippets benefit more when the value of *K* is increased, and accuracy of answers begins to decrease for Web pages instead. Nevertheless, Web pages are still favored over snippets as they provide higher PerCorrect percentage as well as higher MRR values. Thus, Web pages are the preferred choice for IR and information seeking experts in fetching correct and relevant results.

4.1.2 Analysis of information from external resources method

Figure 4.3 shows PerCorrect and Table 4.2 shows PerCorrect and MRR results for method that utilizes information from external resources using Google and WordNet keywords.

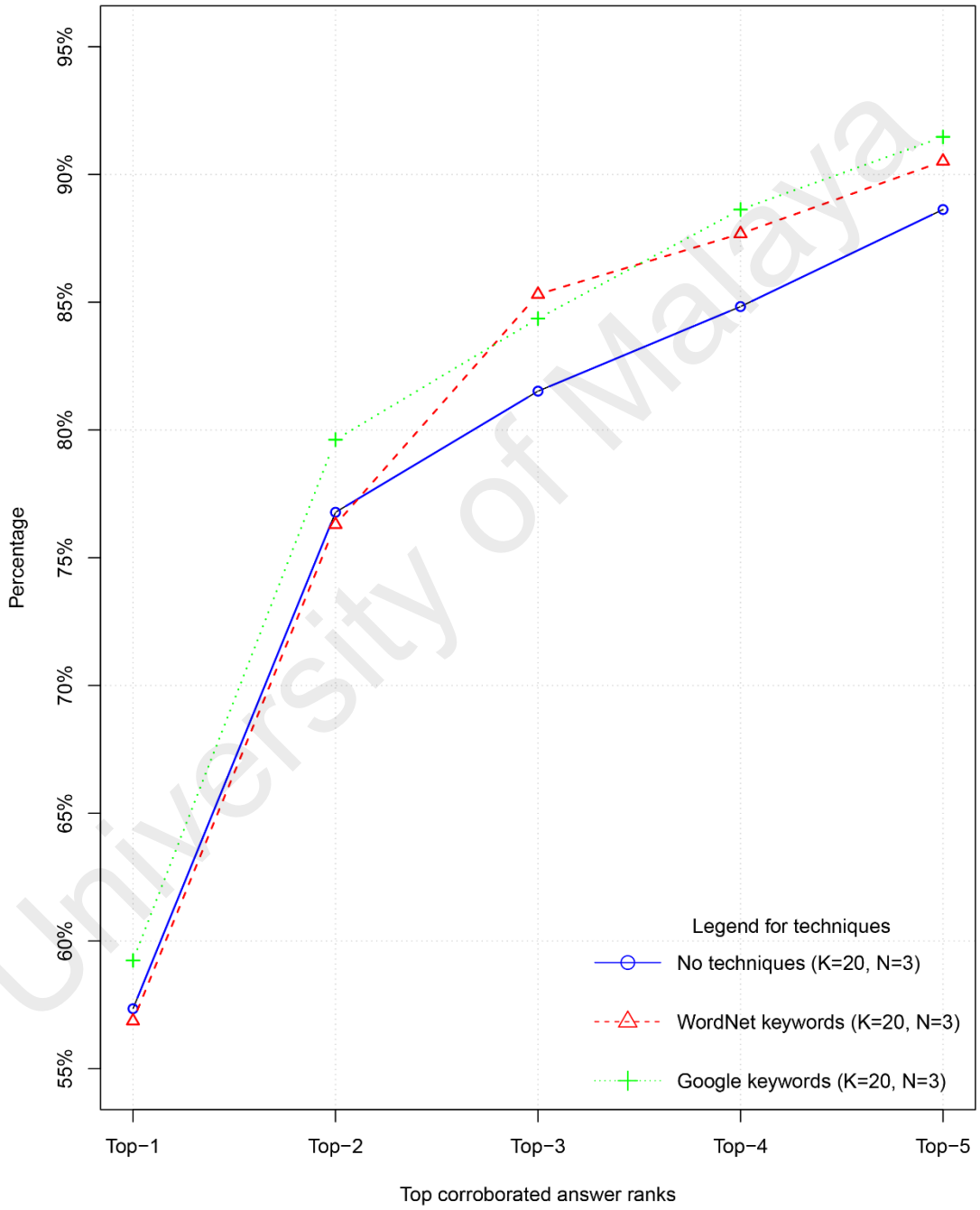


Figure 4.3: PerCorrect comparison of information from the external resource methods with *K*=20, *N*=3 for no techniques, WordNet keywords, and Google keywords for *QN*=211

Table 4.2: PerCorrect and MRR comparison of information from the external resource methods with *K*=20, *N*=3 for no techniques, WordNet keywords, and Google keywords for *QN*=211

Technique	Parameter values	MRR Score	PerCorrect percentages at different ranks				
			Top1	Top2	Top3	Top4	Top5
No techniques	*K*=20, *N*=3	0.702	57.35% (121)	76.78% (162)	81.52% (172)	84.83% (179)	88.63% (187)
WordNet keywords	*K*=20, *N*=3	0.708	56.87% (120)	76.30% (161)	**85.31% (180)**	87.68% (185)	90.52% (191)
Google keywords	*K*=20, *N*=3	**0.726**	**59.24% (125)**	**79.62% (168)**	84.36% (178)	**88.63% (187)**	**91.47% (193)**

The figure and table shows the techniques name, evaluation setting for that technique, and PerCorrect results for them. Starting with PerCorrect results, Google keywords had the highest PerCorrect percentage at top-5 corroborated answer with results depth *K*=20 at 91.47%, followed by WordNet keywords at 90.52%. Google keywords also had the highest PerCorrect percentage at higher ranks including top-1 and top-2 ranks. When external resources were not used, answer accuracy decreased with the lowest percentage recorded at top-1 corroborated answer with 57.35%. When moving from top-1 to top-2 corroborated answer rank, a significant increase close to 20% was observed for all techniques. However, when moving from the top-2 to top-3, WordNet keywords increased by 9% as compared with other techniques, with a 5% increase. In the remaining ranks, all techniques answer accuracy increased gradually, between 3% and 5% at each corroborated answer rank.

In MRR results, Google keywords obtained highest MRR, followed by WordNet keywords. The results show that Google keywords is able to retrieve the correct answer quicker than other techniques. Though the difference in MRR between no external

resource used and WordNet was less than 0.01, the technique did improve accuracy of answers, even if marginally. When comparing MRR results between Google keywords and no external resources techniques, the difference goes up to 0.025, showing that adding keywords help in increasing accuracy of answers.

Google keywords had the highest answer accuracy in all corroborated answer ranks, except at top-3. Though the difference between using and not using external keywords was not significant, nevertheless accuracy did improve at all corroborated answer ranks. These externals resources have more impact on queries where the keywords provided by the question itself are not sufficient in finding the best matches on Web pages. Normally the system uses the keywords in the question. Adding a set of keywords in the form of synonyms increases its chances of finding the correct answer. Techniques such as WordNet and Google keywords increase the keyword pool and help sentence matching method for finding additional candidate answers. Results show that Google keywords perform better than WordNet keywords, which might be due to use of Google search engine for answer extraction.

External resources method is best used when answer extraction is done on Web pages in comparison to snippets. This is because Web pages contain more information and have a higher chance of catching sentences containing keywords from external resources. Therefore, external resources help increase the accuracy of answers, even if it is by a small margin. The combination of multiple external information resources can also produce better results. This point is highlighted in the example shown in Figure 4.4, for the question “What was the name of the first Russian astronaut to do a spacewalk?” and correct answer was “Aleksei A. Leonov”.

Method InfoExtNone Top Answers from 20 pages
Top 1 Answer is Alexey Leonov or Leonov(5)
Top 1 Answer is Ed White(5)
Top 3 Answer is Christopher Hadfield or Hadfield(4)
Top 3 Answer is Svetlana Savitskaya or Svetlana Yevgenyevna Savitskaya or Savitskaya(4)
Top 5 Answer is Michael Lopez-Alegria(3)

Method InfoExtWordNet Top Answers from 20 pages
Top 1 Answer is Alexei Leonov or Alexey Leonov or Leonov(9)
Top 2 Answer is Ed White(7)
Top 3 Answer is Svetlana Savitskaya or Svetlana Yevgenyevna Savitskaya or Savitskaya(4)
Top 4 Answer is Aleksei Leonov or Leonov(3)
Top 4 Answer is Oleg Artemiev or Artemiev(3)

Method InfoExtGoogle Top Answers from 20 pages
Top 1 Answer is Alexey Leonov or Alexei Leonov or Leonov(8)
Top 2 Answer is Ed White(6)
Top 3 Answer is Aleksei Leonov or Leonov(4)
Top 4 Answer is Artemiev(3)
Top 4 Answer is Chris Hadfield or Hadfield(3)

Figure 4.4: No technique, WordNet keywords and Google keywords ranked answer results comparison

The figure above shows rank answer results for three techniques. Though all the techniques are able to rank the correct answer at rank 1, but the frequency of correct answers is different among them. When no external resource is used, the system ranked both Ed White and Alexei Leonov as top 1 answer. However, when using external resources like WordNet and Google keywords, the frequency of Alexei Leonov answer increased, making it the only answer at top 1 rank.

The reason why external resources are able to improve frequency of answers is because external resources method has a major impact on the sentence-matching algorithm, which performs sentence matching for extracting candidate answers. Expanding the keyword pool can improve the chances of finding a sentence that may contain the correct answer. Therefore, the use of information from external resources is recommended for improving the accuracy of answers as it complements a well-defined sentence-matching algorithm.

In conclusion, Google keywords provide the best results in both PerCorrect and MRR. WordNet keywords comes in second place, but achieved better results when not using any techniques. The research implies that using combination of both keywords

techniques, in order to expand the keywords list, would increase the chances of extracting correct candidate answers.

4.1.3 Analysis of NER method

Figure 4.5 shows PerCorrect results and Table 4.3 shows PerCorrect and MRR results vis-a-vis the NER method, using Stanford, Alchemy, and the combination of the two NER techniques.

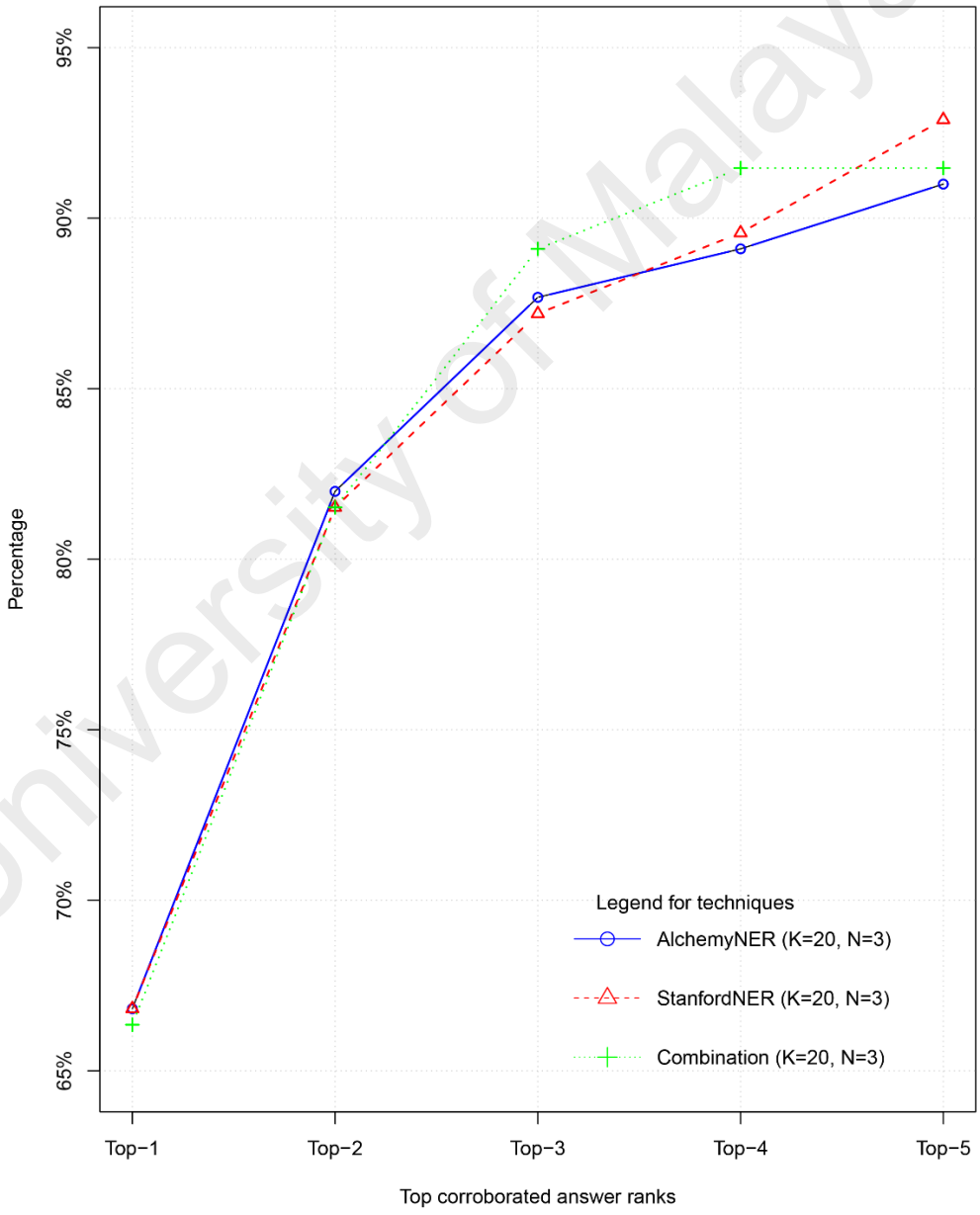


Figure 4.5: PerCorrect comparison of NER method with *K*=20, *N*=3 for the StanfordNER and AlchemyNER techniques and their combination for *QN*=211

Table 4.3: PerCorrect and MRR comparison of NER method with *K*=20, *N*=3 for the StanfordNER and AlchemyNER techniques and their combination for *QN*=211

Technique	Parameter values	MRR Score	PerCorrect percentages at different ranks				
			Top-1	Top-2	Top-3	Top-4	Top-5
Alchemy NER	*K*=20, *N*=3	0.770	**66.82% (141)**	**81.99% (173)**	**87.68% (185)**	89.10% (188)	91.00% (192)
Stanford NER	*K*=20, *N*=3	**0.773**	**66.82% (141)**	81.52% (172)	87.20% (184)	**89.57% (189)**	**92.89% (196)**
Combination	*K*=20, *N*=3	0.771	66.35% (140)	81.52% (172)	89.10% (188)	91.47% (193)	91.47% (193)

The PerCorrect results in Figure 4.5 and Table 4.3 show that at higher corroborated ranks (top-1 and top 2), the highest PerCorrect percentage was scored by Alchemy NER with 66.82% and 81.99% respectively. However, the rankings changed down the order as combination of two NERs achieved higher accuracy at top-3 and top-4 (89.10% and 91.47% respectively), while Stanford NER had a higher PerCorrect percentage at top-5 rank (92.89%). Overall, the lowest PerCorrect percentage was recorded at top-1 by combination of two NERs with results depth *K*=20 at 66.35%. However, in the remaining corroborated answer ranks, the combination of both NERs was either the highest or the second highest, and Alchemy NER was at the lowest.

Table 4.3 also shows MRR results for an NER method, showing Stanford NER and combination of the two NERs performing better than Alchemy NER itself. Stanford NER achieved the highest accuracy with 0.773, followed by the combined NER. Alchemy NER received the lowest at 0.770. This research shows that compared with the other two techniques, Stanford NER produces more accurate results, and the correct answer can be found the earliest using it. However, the difference between the three techniques is negligible and thus, any of the three techniques may be chosen for NER.

Alchemy NER technique was able to achieve highest PerCorrect percentages at higher corroborated ranks (top-1 and top-2), but its accuracy deteriorated in the remaining ranks. However, the difference between Alchemy NER and the other techniques was less than 1% between top-1 to top-3 ranks. Looking at the positives and negatives of the techniques, it was observed that Alchemy NER had difficulty identifying mythical names, such as Zeus, in some sentences but ran smoothly when dealing with normal names, like Tom, Jack, etc. On the plus side, Alchemy NER was effective in identifying the full names of people, and not breaking them into separate entities.

Stanford NER technique shows better results at lower corroborated answer ranks, i.e., top-5, by scoring the highest PerCorrect percentage of 92.89% compared to other techniques. However, its accuracy was lower at higher ranks such as top-2 and top-3. During evaluation, Stanford NER faced problems in detecting entity types, at times. There were scenarios where Stanford NER was unable to detect the desired entity type in a sentence, and thus would skip a valid candidate answer. However, this pattern varied from sentence to sentence as the same person's name, which could not be detected in one sentence, was identified in the other. Another issue found with Stanford NER was that the technique could not tag a person's full name as one cohesive unit but rather broke it down into individual names instead. For example, the name Abraham Lincoln was identified as two separate person type entities. For addressing this issue, additional coding had to be done for detecting full names in sentences when using Stanford NER.

The third technique is the combination of Stanford and Alchemy NER, which records entities detected by both of them. This allows the technique to be able to find more entities.If one NER was unable to detect an entity type, the other NER technique would be able to detect it instead. Though the technique did not achieve the highest accuracy at top-1 or top-2 ranks, it did score higher accuracy at top-3 and top-4 instead, while secured

2nd highest accuracy at top-5 rank. Hence, the combination of NER was able to achieve higher accuracy than NER techniques used individually at top-3 and top-4. The combination ensured that entity types were not overlooked and all possible candidate answers in a sentence were considered. This might also be the reason why the technique was able to reach its max PerCorrect percentage at top-4, and not increasing in accuracy at top-5. One of the shortfalls of combining multiple NERs is that incorrect entities detection may lower answer accuracy of the system. Nevertheless, such occurrences are infrequent, and accuracy should not be affected much.

Figure 4.6 shows ranked answer results for the question "Who is the Greek god of the Sea", where the correct answer is "Poseidon or Nereus".

Method AlchemyNER Top Answers from 20 pages
Top 1 Answer is Amphitrite(4)
Top 2 Answer is Helene or Helen(3)
Top 3 Answer is Nereides(2)
Top 4 Answer is Poseidon(2)
Top 5 Answer is Tethys(2)

Method StanfordNER Top Answers from 20 pages
Top 1 Answer is Poseidon(13)
Top 2 Answer is Nereus(6)
Top 3 Answer is Helene or Helen(3)
Top 4 Answer is KETO or Keto(2)
Top 5 Answer is Polyxena(2)

Method CombineNER Top Answers from 20 pages
Top 1 Answer is Poseidon(13)
Top 2 Answer is Nereus or Nereus or(6)
Top 3 Answer is Amphitrite(4)
Top 4 Answer is Helene or Helen(3)
Top 5 Answer is KETO or Keto(2)

Figure 4.6: Alchemy NER, Stanford NER, and Combination NER ranked answer results comparison

In the figure, ranked answers for all three NER techniques are shown. As it can be seen Alchemy NER had the least frequency for answers, where the highest frequency is only four for the answer Amphitrite and only two occurrences of Poseidon were found. As mentioned earlier, this is because Alchemy NER is not good at recognizing mythological names. On the other hand, Stanford NER faced no issues detecting them and had a higher

frequency of Poseidon—scored thirteen compared to two of Alchemy NER. Similarly, combination of both NER also faced no such issues since the entities not being detected by Alchemy NER were recovered using Stanford NER instead.

NER method has a major impact on sentence-matching algorithm and removes unwanted answer methods. It helps the sentence-matching algorithm identify entity types present within the sentence. If the intended entity type is not present within the sentence, then it can be skipped altogether. Similarly, if the NER is unable to detect a valid entity type present in the sentence, answer accuracy of the system is likely to be affected. Same as sentence-matching algorithms, removing unwanted answers method is also affected by the NER chosen for the system. If the NER is unable to detect a valid entity from the question itself, the unwanted answer(s) would decrease accuracy of answers (Kolomiyets & Moens, 2011).

In conclusion, Stanford NER achieved better MRR results than the other two but only by a small margin. Under PerCorrect, every technique achieved better results at different top corroborated answer ranks. However, Stanford NER and combination of the two NERs performed better than Alchemy NER. The research found occurrences where both Alchemy and Stanford NER were unable to detect valid entity types, thus use of combination of both NERs is recommend to avoid errors. Even though Alchemy NER had the weakest results, it can still be used in the combination of NERs technique.

4.1.4 Analysis of the removal of unwanted answers method

Figure 4.7 shows the PerCorrect and Table 4.4 shows the PerCorrect and MRR results for techniques for removal and non-removal of unwanted answers. The table lists the technique names, evaluation settings for these techniques, MRR values and PerCorrect percentages achieved at different ranks including Top-1, Top-2, Top-3, Top-4, and Top-5.

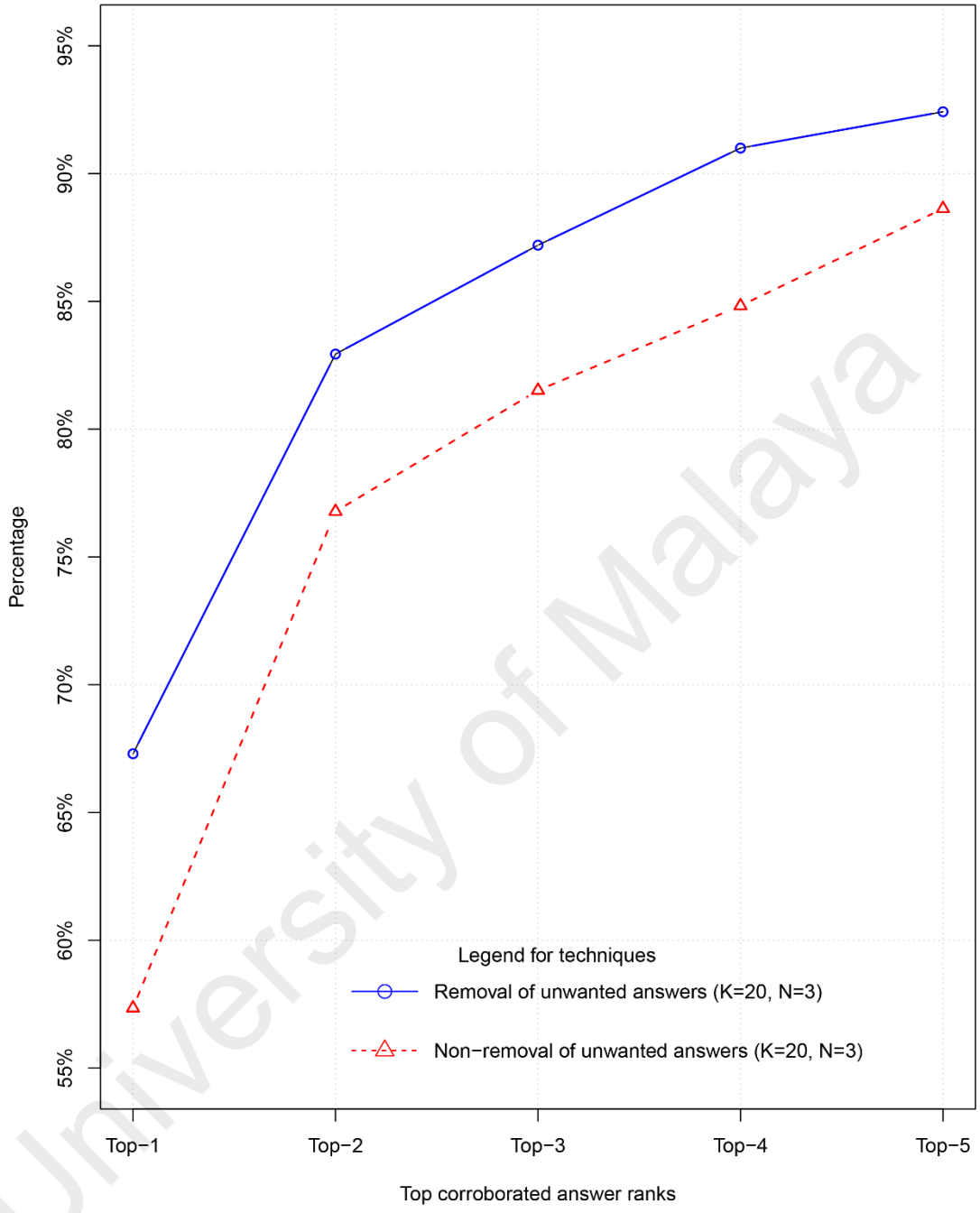


Figure 4.7: PerCorrect comparison of removal and non-removal of unwanted answers *K*=20, *N*=3 for *QN*=211

Table 4.4: PerCorrect and MRR comparison of removal and non-removal of unwanted answers *K*=20, *N*=3 for *QN*=211

Technique	Parameter values	MRR Score	PerCorrect percentages at different ranks				
			Top-1	Top-2	Top-3	Top-4	Top-5
Removal of unwanted answers	*K*=20, *N*=3	**0.778**	**67.30% (142)**	**82.94% (175)**	**87.20% (184)**	**91.00% (192)**	**92.42% (195)**
Non-removal of unwanted answers	*K*=20, *N*=3	0.702	57.35% (121)	76.78% (162)	81.52% (172)	84.83% (179)	88.63% (187)

In PerCorrect results, the highest accuracy was achieved by removing unwanted answers with a PerCorrect percentage of 92.42% at top-5 corroborated answer rank, 67.30% at top-1. The lowest accuracy was obtained by the technique containing unwanted answers with a score of 57.35% at top-1 corroborated answer rank. Thus, removing unwanted answers technique is able to achieve higher PerCorrect percentages than non-removal of unwanted answers technique at all top corroborated answer ranks.

Table 4.4 also shows the MRR comparison between the removal and non-removal of unwanted answers and the difference is significant. The removal of unwanted answers had an MRR value of 0.778, which is 0.076 higher than the other technique. It indicates that it is the best technique to obtain the correct answer quickly. The non-removal of unwanted answers achieved an MRR value of more than .70. However, the difference between the two techniques cannot be neglected.

Removal of unwanted answer technique achieved higher PerCorrect percentage at all top corroborated answer ranks and had considerable margin against the other technique. The increase was steeper in the higher ranks as compared to lower ranks. This is because most of the correct answers are placed higher in the corroborated list generated by

removal of unwanted answer technique, and the remaining correct answers were placed between top-3 and top-5 ranks. The difference between the top-4 and top-5 corroborated answer ranks was roughly 1.5%, which shows that most of the correct answers were found till top-4 rank. This technique is quite useful in ruling out a particular answer that cannot be the correct answer in a particular question. This allows to create a wider margin between the top 2 ranked answers, thus clarifying the answers that are more likely to be correct for the question.

The lowest accuracy in all top corroborated answer ranks was obtained because of the non-removal of unwanted answers. The difference between the two techniques has always been significant except at top-5 rank. This is understandable because most of the correct answers were not able to be placed at higher ranks, thus the percentage starts to increase once correct answers are being found at lower corroborated ranks instead. However, the technique scored 89% accuracy at the top-5 rank, which indicates that around 11% of the answers are either pushed further down or are not found by the system at all. Thus the accuracy of the Web-based QA system is deeply affected as correct answers are pushed to lower corroborated answer ranks instead. When unwanted answers are not removed from the candidate answers pool, the technique may push the correct answers down the lower ranks.

This study observed a huge increase in accuracy in both techniques when moving from top-1 to top-2 corroborated answer rank, but the pattern changed as it went to lower ranks. In the case of removal of unwanted answers technique, accuracy increased gradually when it went to the top-4 rank but increased afterwards by 1.42% when going to the top-5 answer rank. This was not the case when removal of unwanted answers was not used. Increase in answer accuracy was more gradual as it increased close to 4%–5% in each rank. Removal of unwanted answers increased accuracy of answers by 20%–43% at

different ranks. Even if the research considers correct answers that may have been removed unintentionally, the difference between the two techniques remains significant.

Figure 4.8 shows ranked answer results for non-removal and removal of unwanted answers technique, for the question “Who killed Martin Luther King?” of answer “James Earl Ray”.

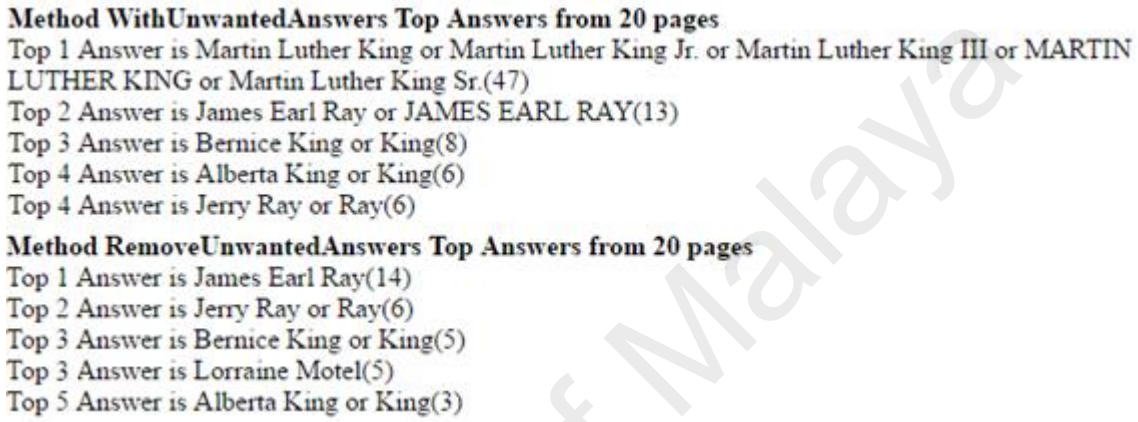


Figure 4.8: Non-removal and removal of unwanted answers technique ranked answer results comparison

The figure shows ranked results for both of the techniques. Starting with non-removal of unwanted answers technique, it ranks James Earl Ray at rank 2 and has a very high frequency of 47 for Martin Luther King at rank 1. Certainly, Martin Luther King is not the correct answer, but for the Web-based QA system it is just a name which can be considered as a candidate answer. The reason for this high frequency is that most of the sentences selected by sentence-matched algorithm, for extracting answer, have a high probability of containing the name Martin Luther King as well. Thus, besides extracting other person entities in the sentence, the name Martin Luther King is extracted as well. When using removal of unwanted answers technique, the name Martin Luther King is excluded from the ranked answer list since it cannot be the correct answer. This allows James Earl Ray to move higher up in the rank, allowing removal of unwanted techniques to achieve higher answer accuracy.

This method is dependent on the NER method as it gives the method the ability to identify entities within the question which may be selected as unwanted candidate answers. If the technique used by the NER method is unable to detect an entity within the question itself, it will be unable to remove the unwanted answer. The removal of unwanted answers may affect the answer scoring module. For example, if the scores assigned to answers found on a Web page are in terms of probability, removing one of the answers from the equation increases the likelihood of others being the correct answer. Thus, removing answers indirectly affects the answer scoring module and how the answers are ranked. Therefore, removing unwanted answers helps eliminate noise and increase accuracy of answers by widening the gap between correct and incorrect answers.

In conclusion, removal of unwanted answers improves answer accuracy by a huge margin in both PerCorrect and MRR results. Though it should only be used with strict conditions to avoid scenarios where a correct answer may be removed instead.

4.1.5 Analysis of the sentence-matching algorithm method

Figure 4.9 shows the PerCorrect and Table 4.5 shows the PerCorrect and MRR results for the sentence-matching method using keywords and regular expression techniques. They lists technique name, evaluation settings for that technique, and the results achieved for MRR and PerCorrect ranks.

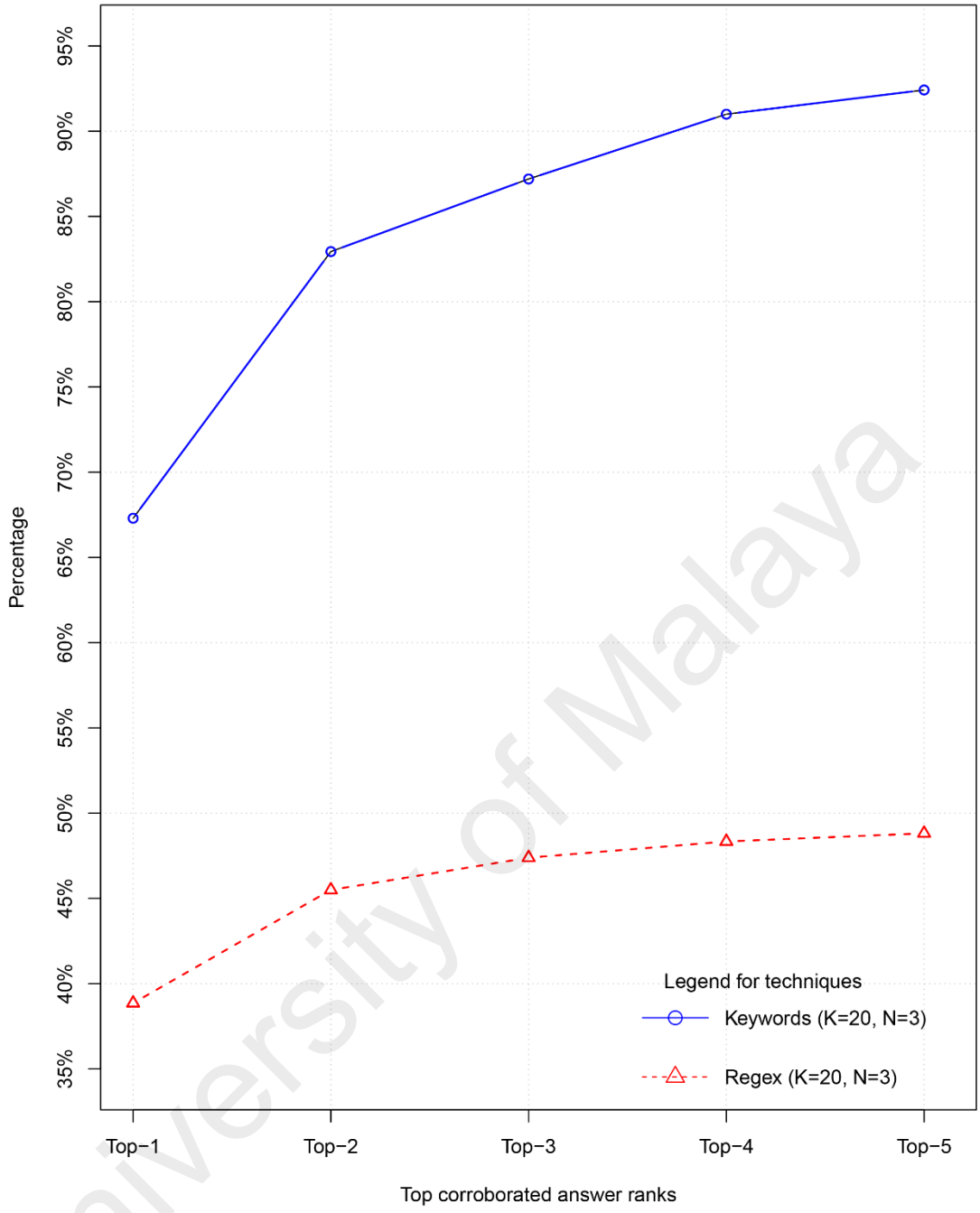


Figure 4.9: PerCorrect comparison of sentence matching algorithm methods with *K*=20, *N*=3 for techniques keywords and regex for *QN*=211

Table 4.5: PerCorrect and MRR comparison of sentence matching algorithm methods with *K*=20, *N*=3 for techniques keywords and regex for *QN*=211

Technique	Parameter values	MRR Score	PerCorrect percentages at different ranks				
			Top-1	Top-2	Top-3	Top-4	Top-5
Keywords	*K*=20, *N*=3	**0.778**	**67.30% (142)**	**82.94% (175)**	**87.20% (184)**	**91.00% (192)**	**92.42% (195)**
Regex	*K*=20, *N*=3	0.431	38.86% (82)	45.50% (96)	47.39% (100)	48.34% (102)	48.82% (103)

In PerCorrect results, keyword matching had the highest accuracy in the all top corroborated answer rank, having 92.42% at top-5 rank and 67.30% at top-1 with result depth *K*=20. Regular expression only managed a PerCorrect percentage of 38.86% at top-1 rank and 48.82% at top-5 rank, improving only 10% in accuracy from top-1 to top-5. The trends of both techniques were different. Keyword matching technique increased drastically from top 1 answers to top 2 answers by approximately 16%. On the other hand, regular expression technique only managed to increase close to 7%. For top 2 to top 5 answers, increase in accuracy for keywords improved gradually in each step unlike regular expressions that increased only by 3%.

Table 4.5 also shows the MRR results for the sentence matching method and its techniques. The difference between the two techniques is 0.347; keyword matching secured the highest MRR value of 0.778, which is the largest difference encountered between any two techniques during the evaluation. The keyword technique MRR score is between 1 and 0.50, showing, on the average, it should be able to fetch the correct answer at top-1 or top-2, whereas regular expression technique accuracy lies between top-2 and top-3 corroborated answer ranks.

Sentence matching, using keywords technique, achieved higher accuracy than other techniques at all top answer ranks. The keywords technique was able to achieve a higher

accuracy score because the matching rule used by the technique is more relaxed in selecting candidate answers. As the technique is based on selecting answers found in sentences containing the highest keywords found count, it was able to extract more answers (Kolomiyets & Moens, 2011). It is considered more relaxed because the keywords can occur anywhere in the sentence, whereas the keywords have to match the pattern and their position within it, in regular expression technique. In keyword sentence matching, missing keywords from the sentence are not important; thus, the technique can always fetch answers. However, this aspect can also be counterproductive as a Web page not containing the correct answer at all will force the sentence matching technique to fill the candidate answer pool with incorrect answers. Thus, a limit is placed in selecting answers to avoid such a scenario.

Regular expression technique did not perform well in the PerCorrect evaluation for all top corroborated ranks. Except for a small increase in correct answer percentage from top-1 to top-3, the accuracy almost became static until the top-5 rank. Its score is low because match rules defined for extracting answers are strict (Kolomiyets & Moens, 2011; Wu & Marian, 2011). The extracted sentences from sources have to match the pattern defined exactly, for regular expression to be selected. Candidate answers may be selected from this selection. A simple sentence can be written in a number of ways, thus limiting the number of patterns considered for extraction (Kolomiyets & Moens, 2011). Therefore, the correct answer may be overlooked in some cases because the sentence containing the answer may not have matched the pattern defined for regular expression. This technique appears strict on paper. It is necessary to ensure that only the correct answer is extracted, which is a unique characteristic of regular expression technique. The technique may be strict in extracting candidate answers, but the answers fetched are more likely to be correct answer compared with the candidate answers of the keywords technique (Kolomiyets & Moens, 2011). Thus, using this technique in combination with the keywords technique

can provide better results, as compared with using the keywords technique only. Another way to improve this technique is by introducing as many patterns as possible, by replacing synonyms for keywords and defining five to six sentence patterns for regular expression sentence matching.

Keyword matching is the clear winner in this experiment. The difference is significant given that keywords sentence matching reached 28%–44% answer accuracy, which is higher than that of regular expression sentence matching. The accuracy of regular expression can be increased by including more variations for regular expressions at the cost of making the technique more complex. One benefit of using regular expressions over keyword matching is the low percentage of incorrect answers found.

Figure 4.10 and Figure 4.11 provide two examples of ranked answer results for keyword and regex sentence-matching algorithms for comparison. Figure 4.10 provides answers for the question "Who is the fastest swimmer in the world?" for which the correct answer is "Michael Phelps". Figure 4.11 also provides ranked answer results, but for the question "Who was the first U.S. president ever to resign?" for which the correct answer is "Nixon".

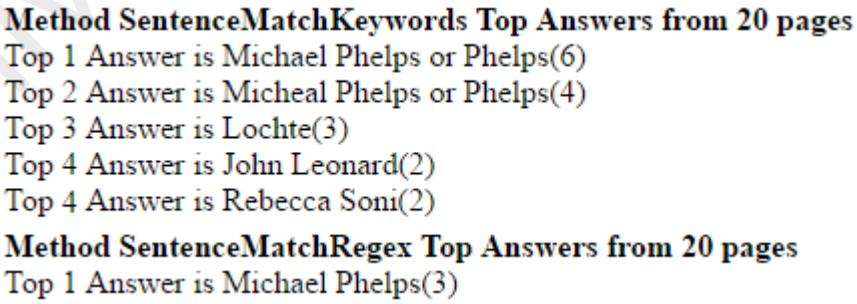


Figure 4.10: Keyword and regex sentence-matching algorithms ranked answers results comparison

In the figure above, both techniques are able to fetch the correct answer at top 1 rank. However, there are two notable differences between the results of these two techniques:

1) difference in frequency scores for the same answer, and 2) number of candidate answers found. Though keyword sentence-matching algorithm is able to find more occurrences of the answer Michael Phelps, it also fetched candidate answers that are incorrect answers to the question. On the other hand, regex sentence-matching algorithm is able to fetch the correct answer "Michael Phelps" only, despite being unable to find many occurrences of it. However, not being able to find all occurrences of the correct answer, due to limited regex patterns, can prove troublesome in other questions, which is highlighted in the example shown in Figure 4.11.

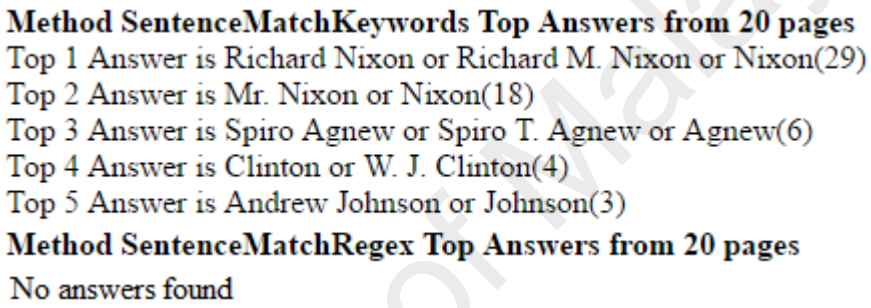


Figure 4.11: Keyword and regex sentence-matching algorithms ranked answers results comparison

Figure 4.11 shows ranked answer results for both techniques. In this example, not only is the keywords sentence-matching algorithm able to find the correct answer, but is able to find many occurrences of it also, allowing the answer to receive a high score. On the other hand, regex sentence-matching technique is not able to find any answers at all. This is because regex sentence-matching algorithm is not able to find any sentences matching the regex patterns used by this technique.

This method greatly benefits from the use of information from external resources. By expanding the list of keywords to be matched against, sentence matching techniques have a better chance of finding sentences that are likely to contain the correct answer. The information source type also plays an important role here. If Web pages are considered, the method has more room for finding candidate answers. On the other hand, restricting

the method to snippets only reduces the number of candidate answers. Web pages provide more space for sentence matching method to find the correct answer, whereas in snippets it completely relies on extracting answers from limited content shown by snippets. Moreover, knowing the number of answers being considered for fetching answers is important. An adequate balance is necessary for setting the value for *N*. Keeping it too low may result in skipping the correct candidate answers, but setting the value too high will attract incorrect answers into the candidate answers pool. Lastly, the NER method can affect the accuracy of sentence matching method as well. An entity that is not detected by the NER method is ignored by the sentence-matching algorithm, and thus the answer accuracy of the method is decreased.

Keyword sentence matching produces higher answer accuracy than regular expression sentence matching. However, it fetches many answers, including incorrect ones, and thus creates noise. This problem is ideally addressed by using a combination of both keyword and regular expression sentence matching techniques, that is, applying regular expression sentence matching and then keyword sentence matching in case no matches are found.

In conclusion, keywords sentence matching algorithm achieved much better results than regular expressions in both PerCorrect and MRR results. However, regular expression can still be used in combination with keywords technique, as an answer captured by regular expression technique has a very high percentage chance of being correct.

4.1.6 Analysis of selecting top N sentences method

Figure 4.12 shows PerCorrect and Table 4.6 shows PerCorrect and MRR results for this method, using different values for top sentences matched *N* (1, 3 or 5), that is, the number of sentences selected for fetching answers.

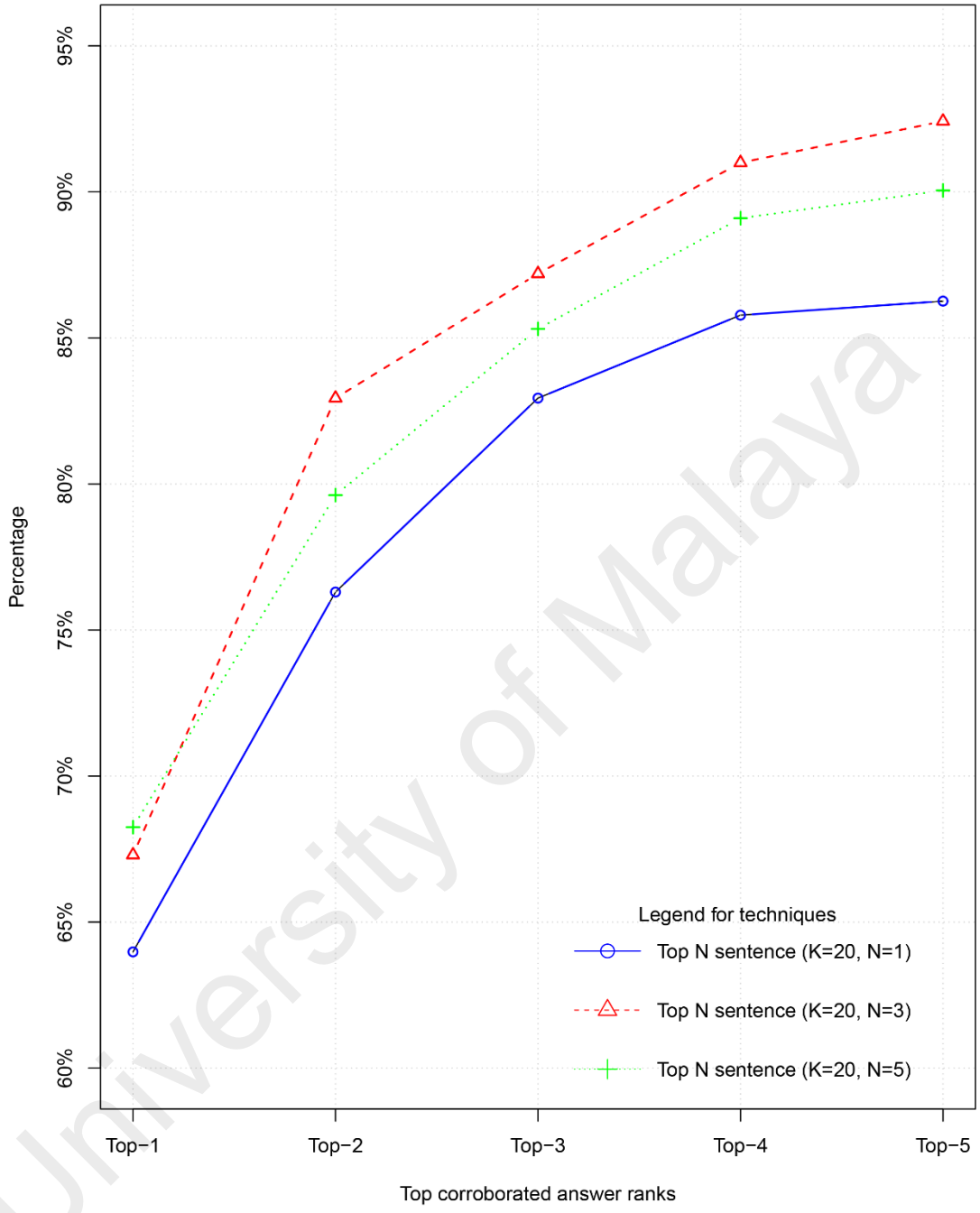


Figure 4.12: PerCorrect comparison of Top N sentences for *N*=1, *N*=3, or *N*=5 with *K*=20 for *QN*=211

Table 4.6: PerCorrect and MRR comparison of Top N sentences for *N*=1, *N*=3, or *N*=5 with *K*=20 for *QN*=211

Technique	Parameter values	MRR Score	PerCorrect percentages at different ranks				
			Top-1	Top-2	Top-3	Top-4	Top-5
Top N sentence	*K*=20, *N*=1	0.732	63.98% (135)	76.30% (161)	82.94% (175)	85.78% (181)	86.26% (182)
Top N sentence	*K*=20, *N*=3	**0.778**	67.30% (142)	**82.94% (175)**	**87.20% (184)**	**91.00% (192)**	**92.42% (195)**
Top N sentence	*K*=20, *N*=5	0.770	**68.25% (144)**	79.62% (168)	85.31% (180)	89.10% (188)	90.05% (190)

The PerCorrect results in Figure 4.12 and Table 4.6 shows that, at top-1 rank, the highest PerCorrect percentage was scored for *N*=5 with 68.25% correct answers found, while at top-5 it was achieved for *N*=3 at 92.42%, with results depth *K*=20. The lowest accuracy for top-5 corroborated answer rank was attained by top sentences matched *N*=1 at 86.26%, and scored 63.98% for top-1 rank. At a glance, *N*=3 achieved better PerCorrect percentages than both *N*=1 and *N*=5 techniques.

Table 4.6 also shows MRR results for top *N* sentences method for *N*=1, *N*=3, and *N*=5. The highest MRR value of 0.778 was achieved for *N*=3, followed by *N*=3 at 0.770 and *N*=1 at 0.732. All techniques achieved decent MRR scores, but the highest score for *N*=3 shows that correct answer can be fetched the fastest using this technique when *N*=3 score remained close to *N*=5. Though *N*=5 fetches correct answer sooner than *N*=3, it is still takes a lot of processing time. If an expert keeps a balance between performance and adequate accuracy, he/she can choose *N*=3 over *N*=5.

The PerCorrect for *N*=1 results increased gradually until it reached the top 4 rank and increased slightly afterwards. The technique had the lowest accuracy compared with *N*=3 and *N*=5. This is because by limiting *N* to 1, the number of sentences selected for

extracting candidate answers is lowered. The findings indicate that this affects accuracy in a negative way thus sentences likely to contain the correct answers get omitted in this way. Moreover, accuracy that becomes almost static at the end indicates less room for improvement given that only a few answers are beyond the top-5 rank.

When changing *N* to 3, the technique performed considerably better than for *N*=1. It continuously and gradually increased until top-5 rank. The technique was able to score the highest accuracy at all top answer ranks except at top-1 rank. The gradual increase indicates that a moderate number of candidate answers are extracted by setting *N*=3; the candidate answers may include the correct answer. The balance between performance and accuracy can be maintained by keeping *N*=3. The technique was not able to secure the highest accuracy but was still able to achieve decent accuracy using half of the sentences used for *N*=5.

When considering five sentences for the top *N* sentence selection, the technique had the highest accuracy at top-1 rank. It also rose steadily until it reached rank 4, after which only a small increase occurred. The technique was not able to secure highest accuracy at all ranks, and the number of candidate answers considered was almost double than that of *N*=3, thus making the technique attract more incorrect answers. Hence, the processing may be ignored with regards to accuracy as the technique is good in terms of accuracy for higher ranks such as top-1 corroborated answer rank.

The results showed that top sentences for *N*=3 technique was ahead in terms of accuracy between the top-2 and top-5 corroborated answer ranks. In comparison, only *N*=5 managed to secure higher accuracy at N=3 at top-1 rank, but had lower accuracy in the remaining ranks. Sentences matched *N*=1 had lower accuracy than both *N*=3 and *N*=5. In terms of processing time, *N*=5 requires more time to process queries since number of

sentences used for extracting sentences is being increased. Therefore, the value for *N* can be set lower if maintaining a balance between accuracy and performance is desired.

Figure 4.13 shows an example of rank answer results comparison between Top N sentences techniques, for the question "What is the name of the managing director of Apricot Computer?" with correct answer "Peter Horne".

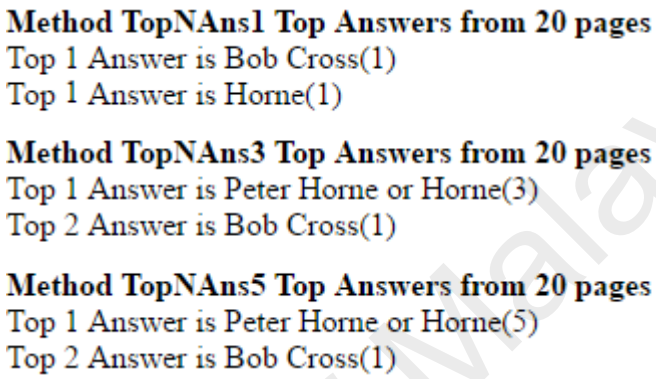


Figure 4.13: Top N Sentence for *N*=1, 3, 5 ranked answer results comparison

The figure shows results for Top *N* = 1, 3 and 5 sentence selection techniques. For *N*=1, though the technique was able to find the correct answer at rank, yet it had to share its rank with another candidate answer making it unclear which one of them is the correct answer. Additionally, the total candidate answers returned by *N*=1 sentence match technique were less as compared to the other two techniques. For *N*=3, the frequency score of the answer Peter Horne increased, making it clear that it is the correct answer. Similarly, *N*=5 increased its score further. This shows that *N*=3 is able to provide the correct answer more prominently over *N*=1, while at the same time requires less sentences to reach that conclusion.

The experiment was performed on Web pages because snippets only contained a few sentences and did not completely show the effect of increase and decrease of value of the top sentences matched *N*. In sentence matching method, the rule used to identify a sentence that contains a candidate answer determines the sentences to be selected.

Therefore, setting the value *N*=3 or *N*=5 can yield more accurate results. The accuracy of answers increases if the limit for sentences to be matched is increased.

In conclusion, the method achieved the best results in both PerCorrect and MRR for *N*=3. However, *N*=5 is still viable as its results are quite close to *N*=3, and can achieve better results at top-1 corroborated answer rank.

4.1.7 Answer scoring test results

Figure 4.14 shows PerCorrect and Table 4.7 shows PerCorrect and MRR results for the answer scoring test for different methods, including frequency of answers, match-score of answers, prominence of answers, and the combination of match score and prominence:

Table 4.7: PerCorrect and MRR comparison of scoring methods with *K*=20, *N*=5 for techniques frequency, scoring answers, prominence, and prominence and match-score for *QN*=211

Technique	Parameter values	MRR Score	PerCorrect percentages at different ranks				
			Top-1	Top-2	Top-3	Top-4	Top-5
Frequency	*K*=20, *N*=5	**0.770**	**68.25% (144)**	**79.62% (168)**	**85.31% (180)**	**89.10% (188)**	90.05% (190)
Match-score	*K*=20, *N*=5	0.755	65.88% (139)	78.20% (165)	82.94% (175)	87.20% (184)	**91.47% (193)**
Prominence	*K*=20, *N*=5	0.702	59.72% (126)	75.36% (159)	80.09% (169)	82.94% (175)	84.83% (179)
Prominence* Match-Score	*K*=20, *N*=5	0.681	57.82% (122)	71.09% (150)	77.73% (164)	81.99% (173)	83.89% (177)

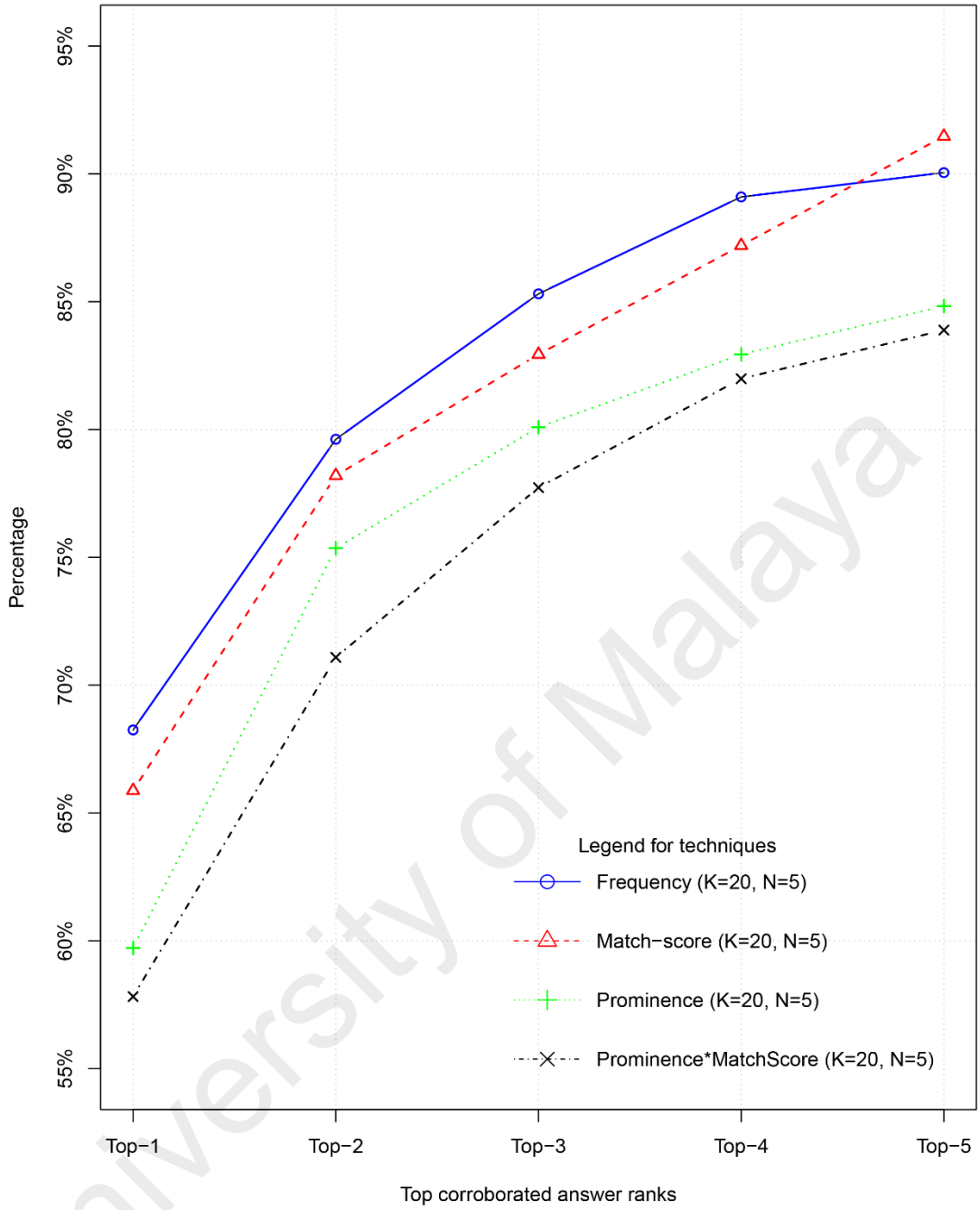


Figure 4.14: PerCorrect comparison of scoring methods with *K*=20, *N*=5 for techniques frequency, scoring answers, prominence, and prominence and match-score for *QN*=211

The PerCorrect results in Figure 4.14 and Table 4.7 show that frequency and match-score scoring techniques achieve higher percentages than other techniques. While frequency technique achieved the highest percentages between top-1 and top-4 corroborated ranks, yet the highest accuracy at top-5 was achieved by match score with a value of 91.47%, while frequency score achieved 90.05% instead. The lowest was scored

by the combination of match score and prominence technique in all corroborated ranks, with the lowest recorded at 57.82% for the top-1 corroborated answer rank.

Table 4.7 also shows MRR comparison of the scoring methods. The highest MRR at 0.770 was scored by frequency technique, followed by match score technique at 0.755. Again, frequency techniques gains upper hand in MRR as well, making it ideal for fetching correct answers quicker compared to other techniques. The combination of prominence and match score scored the lowest at 0.681. The MRR results tend to agree with the PerCorrect findings, thus indicating that the correct answer is fetched early by the frequency or match score technique.

Frequency scoring technique is easy to implement and is quite effective in achieving decent accuracy. One of the possibilities of the technique that makes it obtain higher accuracy than the other techniques is that the top answers generated have a few cases only in which the frequencies of the two answers are quite close or almost equal. If such a scenario occurs, match score and prominence technique can assist in distinguishing the better one between the two answers.

Match score also performed considerably well compared with prominence and the combination of prominence and match score technique. It did not achieve higher accuracy than the frequency technique, but it maintained a close score in most ranks as it increased gradually. The technique was able to surpass the accuracy of frequency technique at the top-5 rank, thus showing the potential of the technique. Match score answers are effective when scoring answers based on a sentence from which the answer is found and when distinguishing the scores of two answers that may be equal in terms of frequency. The formula used for generating a match score for the answers is simple (i.e., it only uses the number of keywords found in the sentence). Accuracy can be increased even higher by

considering more factors for generating match score, including frequency of the answer, because it already has decent accuracy.

Prominence scoring technique and its combination with the match score technique had the lowest accuracy in all top answer ranks. The concept behind prominence is good, but the chances of having more than one candidate answers in a sentence are less. Considering prominence alone tends to lower the score of correct answers that may have been placed poorly in the sentence but have the sole answer in the sentence. Therefore, the prominence score should only be considered when dealing with two or more answers in a sentence and as a factor for distinguishing the better answers from the available pool. The low score of the combination of prominence and match score technique could be due to low score of the prominence technique.

Figure 4.15 shows sample results for the four scoring techniques for question “Who leads the star ship Enterprise in Star Trek?” of answer “Captain Kirk or Jim Kirk”.

Method ScoringAnswersFrequency Top Answers from 20 pages
Top 1 Answer is Jim Kirk or Kirk(15)
Top 1 Answer is Jonathan Archer or Archer(15)
Top 3 Answer is Henry Archer or Archer(12)
Top 4 Answer is Khan(6)
Top 5 Answer is Alexander(5)
Method ScoringAnswersMatchScoreAnswers Top Answers from 20 pages
Top 1 Answer is Jim Kirk or Kirk(57)
Top 2 Answer is Jonathan Archer or Archer(49)
Top 3 Answer is Henry Archer or Archer(39)
Top 4 Answer is Khan(36)
Top 5 Answer is Picard(20)
Method ScoringAnswersProminence Top Answers from 20 pages
Top 1 Answer is Albert Einstein(1100)
Top 2 Answer is Jim Kirk or Kirk(797.63903060949)
Top 3 Answer is Jonathan Archer or Archer(778.16228230417)
Top 4 Answer is Henry Archer or Archer(749.7761183832)
Top 5 Answer is Khan(354.04419652435)
Method ScoringAnswersProminenceMatchScore Top Answers from 20 pages
Top 1 Answer is Jim Kirk or Kirk(29.587894143809)
Top 2 Answer is Jonathan Archer or Archer(22.65297073126)
Top 3 Answer is Khan(22.323535721948)
Top 4 Answer is Henry Archer or Archer(21.603855387068)
Top 5 Answer is Albert Einstein(11)

Figure 4.15: Frequency, match-score, prominence and prominence*match-score scoring techniques ranked answer results comparison

In the figure, top 5 answers from each scoring technique including frequency, match-score, prominence, and prominence*match-score are listed. Starting with frequency scoring technique, though it is able to rank the correct answer at rank 1, yet the rank is shared with another candidate answer making it unclear which one of them is correct. On the other hand, the scores assigned by match-score technique show a clear difference between the top two answers, making it apparent that the correct answer is Jim Kirk. This shows that match-score of answers can be looked into if frequency of two answers is the same. Moving forward to prominence technique, the correct answer Jim Kirk moved down to rank 2, and another candidate answer Albert Einstein, which is not even included in top 5 answers for frequency and match-score techniques, is placed at top 1 rank. Though, prominence*match-score technique also managed to place Jim Kirk at top 1

rank, yet it is apparent that this is due to inclusion of scores assigned by match-score technique and not prominence scores of answers.

Therefore, frequency and match score technique showed promising results, and a combination of the techniques could increase their accuracy further. Prominence scoring technique did not score well in terms of accuracy, but it remains a useful factor to consider when dealing with answers that have more than two answers in a sentence.

In conclusion, frequency answer scoring provides the best PerCorrect and MRR results. Though match score achieved lower results than frequency technique, it has more room for improvement and with fine adjustment to the technique, it has the potential to achieve equal if not better results.

4.1.8 Answer aggregation results

Figure 4.16 shows PerCorrect and Table 4.8 shows PerCorrect and MRR results for string-matching techniques of answer aggregation method. The techniques evaluated for this experiment were dice coefficient, cosine similarity, and their combination.

Table 4.8: PerCorrect and MRR comparison of the answer aggregation methods with *K*=20 and *N*=5 for dice coefficient, cosine similarity, and combination techniques for *QN*=211

Technique	Parameter values	MRR Score	PerCorrect percentages at different ranks				
			Top-1	Top-2	Top-3	Top-4	Top-5
Dice Coefficient	*K*=20, *N*=5	**0.776**	**68.72% (145)**	**81.04% (171)**	85.31% (180)	**89.57% (189)**	**90.52% (191)**
Cosine similarity	*K*=20, *N*=5	0.757	65.88% (139)	78.20% (165)	**86.26% (182)**	89.10% (188)	**90.52% (191)**
Combination	*K*=20, *N*=5	0.770	68.25% (144)	79.62% (168)	85.31% (180)	89.10% (188)	90.05% (190)

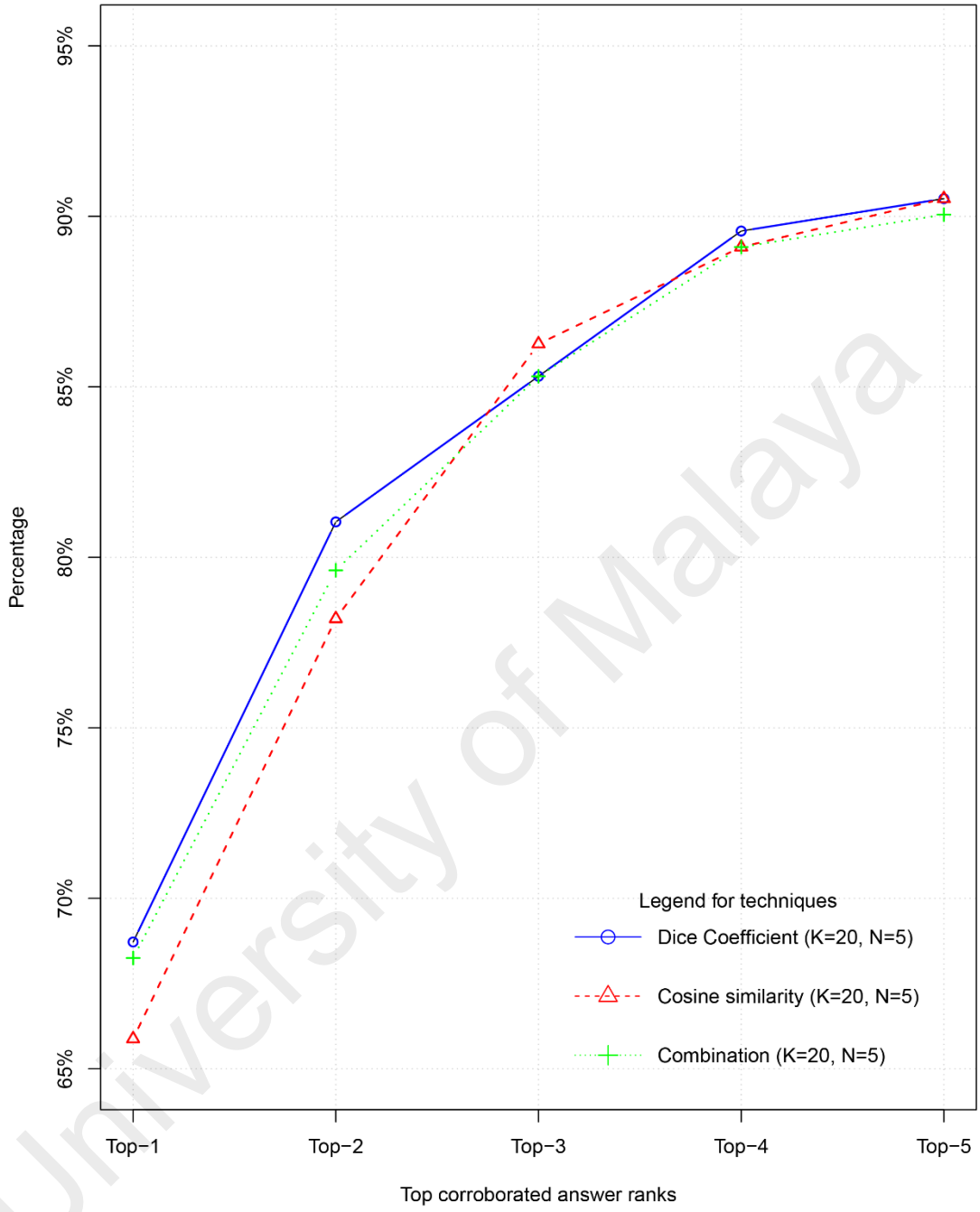


Figure 4.16: PerCorrect comparison of the answer aggregation methods with *K*=20 and *N*=5 for dice coefficient, cosine similarity, and combination techniques for *QN*=211

Figure 4.16 and Table 4.8 shows PerCorrects results for three answer aggregation techniques. The results show that at higher corroborated ranks, including top-1 and top-2, dice coefficient achieved higher PerCorrect percentage whereas in the remaining ranks

the percentages were pretty even with the other answer aggregation techniques. Dice coefficient and cosine similarity achieved the highest accuracy score of 90.52% for the top-5 corroborated answer rank, while combination of the two techniques scored 90.05 at the same rank. At top-1 Dice coefficient had the highest PerCorrect percentage of 68.72% while cosine coefficient scored the lowest with 65.88%.

Table 4.8 also shows MRR results for answer aggregation techniques. Dice coefficient achieved the highest MRR with 0.776, and cosine similarity scored the lowest at 0.757. The MRR results show a unique aspect of the results compared with the PerCorrect results. Combination of the two string similarity techniques was unable to achieve the highest accuracy at any of the PerCorrect results, but it remains a viable technique. Hence, it is a viable technique for achieving correct answers quickly.

Dice coefficient achieved high accuracy in almost all top answer ranks except top 3. The difference between dice coefficient technique and cosine similarity was significant at higher ranks. The combination of both the techniques was the only technique that came close to dice coefficient. The pattern for the results shows a steady increase until the top-4 corroborated answer rank, and the increase from top-4 to top-5 rank was merely 1%. Dice coefficient provides higher accuracy results than the other techniques by a decent margin at higher ranks and by a minor margin at lower ranks. It obtained higher accuracy than cosine similarity because most of the candidate answers found were single words. Dice coefficient technique provides more accurate results when dealing with single-word names than cosine similarity.

The trend followed by cosine similarity results was nearly identical to that of dice coefficient, except that the cosine similarity results scored lower at higher ranks but redeemed itself by scoring the highest at the top-3 and top-5 ranks. The technique did not perform as good as the dice coefficient because it performs better for names that contain

more than one word (Wu & Marian, 2011). This attribute is unique and useful, but the frequency of such candidate answers was lower than that of singular names.

The trend followed by the combination of two string-matching techniques was similar to the trend found in the individual techniques. The combination of two techniques performed moderately. The technique was expected to score higher than the individual techniques. The combination showed high accuracy at high ranks for cosine similarity; this was not the case at the lower ranks because the accuracy was either identical to one of the techniques or lower.

Dice coefficient scored high accuracy results for top-1 and top-2 corroborated answer ranks, followed closely by the combination of dice coefficient and cosine similarity. However, the combination of both techniques was on a par with the dice coefficient at the later stages. Cosine similarity scored relatively low in the first two top answers and then jumped to be on a par with its competitors. The difference was noticeable for the top-1 and top-2 corroborated answer rank, but the accuracy results became almost equal for the remaining top answers. Therefore, both dice coefficient and the combination of the two techniques provide higher accuracy results than cosine similarity.

When evaluating these two techniques in initial testing, it was observed that cosine similarity more accurately handled candidate answers, which consist of two or more words, whereas dice coefficient showed improved results when dealing with candidate answers, which contain one word only. Two scenarios were evaluated in the initial testing for string matching. In the first scenario, the string “Alexey Arkhipovich Leonov” was compared with “Alexey Leonov,” as both strings represent the same person. For this comparison, the dice coefficient returned a value of 0.66, whereas cosine similarity returned .81. Thus, dice coefficient indicated that it is not a match, but cosine similarity indicated that it is. In the second scenario, the string “Alexey Leonov” was compared

with “Alexei Leonov,” with both strings representing the same person but with a slight variation in the name. In this comparison, the dice coefficient returned a score of 0.9 compared with the cosine similarity score of 0.5. The dice coefficient merged both answers, whereas cosine similarity left the answers as they were.

To highlight the differences in the working of these two techniques, this research provides rank answer results for two questions evaluated. Figure 4.17 and Figure 4.18 show ranked answer results for cosine similarity and dice coefficient in two independent questions. Figure 4.17 shows the results for the question “What was the name of the first Russian astronaut to do a spacewalk?” with answer “Aleksei A. Leonov”. Figure 4.18 shows the ranked results for the question “Who was the first American in space?” with answer “Alan Shepard”.

Method AnswerAggregationCosine Top Answers from 20 pages
Top 1 Answer is Alexei Leonov or Leonov(9)
Top 1 Answer is Alexey Leonov or Alexey Arkhipovich Leonov or Leonov(9)
Top 3 Answer is Ed White(8)
Top 4 Answer is Aleksei Leonov or Leonov(6)
Top 5 Answer is Svetlana Savitskaya or Svetlana Yevgenyevna Savitskaya or Savitskaya(5)

Method AnswerAggregationDice Top Answers from 20 pages
Top 1 Answer is Alexey Arkhipovich Leonov or Alexei Leonov or Alexey Leonov or Leonov or Aleksei Leonov(14)
Top 2 Answer is Ed White(8)
Top 3 Answer is Chris Austin Hadfield or Hadfield(5)
Top 3 Answer is Svetlana Savitskaya or Svetlana Yevgenyevna Savitskaya or Savitskaya(5)
Top 5 Answer is Oleg Artemiev or Artemiev(4)

Figure 4.17: Cosine similarity and dice coefficient ranked answer results comparison

In the first question, both of the aggregation techniques are able to rank the correct answer at top 1 rank, but with clear differences. Cosine similarity lists three different variations of the name Alexei Leonov, which reflect the same person with slight differences in spellings. Cosine similarity technique does not aggregate these strings resulting in a low frequency score for the correct answer. On the other hand, it manages to combine string “Alexey Arkhipovich Leonov” with “Alexey Leonov” just fine. Dice

coefficient manages to combine all of these strings together since it is allows slight variations in answer names.

Method AnswerAggregationCosine Top Answers from 20 pages
Top 1 Answer is Alan Bartlett Shepard Jr. or Alan Shepard or Alan B. Shepard or Alan Bartlett(27)
Top 2 Answer is John Glenn or Glenn(15)
Top 3 Answer is Yuri Gagarin or Gagarin(12)
Top 4 Answer is Gus Grissom or Grissom(7)
Top 5 Answer is Virgil Grissom or Grissom or Virgil(6)

Method AnswerAggregationDice Top Answers from 20 pages
Top 1 Answer is Alan Shepard or Alan B. Shepard (19)
Top 2 Answer is John Glenn or Glenn(15)
Top 3 Answer is Yuri Gagarin or Gagarin(12)
Top 4 Answer is Gus Grissom or Grissom(7)
Top 5 Answer is Tom(3)

Figure 4.18: Cosine similarity and dice coefficient ranked answer results comparison

In the second example, ranked answer results are shown for both of the answer aggregation techniques. In this example, cosine similarity lists Alan Shepard as the correct answer at rank 1 and is able to aggregate four variations of the same answer successfully. On the other hand, dice coefficient is only able to aggregate two of the variations successfully, achieving a lower frequency score in comparison to the same answer aggregated by cosine similarity.

Both of these examples show the benefits of using both of the aggregation techniques. The combination of both of these techniques can be used intelligently to benefit from the advantages and overcome shortfalls of each technique.

In conclusion, dice coefficient achieved better results in both PerCorrect and MRR results. However, the combination of the two answer aggregation techniques is useful for scenarios where dice coefficient may not be able to merge two or more correct answers.

4.1.9 Web-based QA methods and techniques analysis

Evaluation results for Web-based QA systems methods and techniques, shown in Section 4.1, highlight research techniques, or combination of them, performing better than others with respect to PerCorrect and MRR evaluation metrics. Table 4.9 shows summary of these findings, which consist of three columns, including module name, method name and summary of the evaluation results for that method. This research evaluated methods and techniques under Web-based QA systems module including 1) question analysis, 2) answer extraction, 3) answer scoring, and 4) answer aggregation which are discussed below:

Table 4.9: Evaluation results summary for Web-based QA systems methods and techniques

Module	Method	Summary
Answer extraction	TopK search results selection	Web pages had higher accuracy overall, whereas snippets performed better while dealing with Top1 answer only. Web pages also achieved better results for K=10, while snippets performed better for K=20.
	Information from external resources	Inclusion of Google and WordNet keywords improved answer accuracy over not using any external resources
	NER	Difference between the NERs results was almost negligible, though combined NER seems better as it avoids situations where an entity may not be detected
	Removal of unwanted answers	Removing unwanted answers played a vital role in improving accuracy of answers, both at higher and low corroborated answer ranks
	Sentence-matching algorithm	Keywords sentence-matching provided a much higher accuracy compared to regex. Regex require writing of additional rules to be effective.
	Selecting TopN sentences	Sentences matched N=3 produced highest answer accuracy, though N=5 can also be considered where the focus is towards top 1 answer only.

Table 4.9 continued		
Answer scoring	Frequency, match score, and prominence	Frequency scoring method provided higher answer accuracy at most corroborated answer ranks, though match score technique is recommended, as the method can be improved by including more factors
Answer aggregation	String matching	Though dice coefficient provided higher accuracy at top corroborated answer ranks, combination of techniques is more reliable and is nearly equivalent.

4.1.9.1 Answer extraction methods and techniques analysis

This research evaluated a number of methods under answer extraction module including top *K* search results selection, information from external resources, NER, removal and non-removal of unwanted answers, sentence-matching algorithm, and selecting top *N* sentences methods. Findings from top *K* result selection show that answers taken from Web pages allow other methods and techniques achieve higher answer accuracy than using snippets. The system fetches more answers and improves accuracy of answers from a Web page. Moreover, limiting the search results to the top *K*=10 is enough to achieve the highest accuracy, as increasing the result depth further does not improve accuracy, and the system is required to process more Web pages for finding answers. Selecting an HTML parser, which can filter out unwanted information, in order to extract only relevant information, is essential when dealing with Web pages. The text handed over by the parser needs to be broken down into individual sentences. Regular expressions show higher accuracy, but selecting Stanford NLP for breaking sentences remains the better option because it is not prone to errors as compared to regular expression technique. Extracting information from external resources helped in terms of improving accuracy and making sure answers that are similar in context are considered. The removal of unwanted answers proved to be an essential part of the system because accuracy increased at different depths. The results also showed that keyword sentence matching performs better in almost all scenarios than regular expressions. However, the

combination of regular expressions and keyword matching can be used to ensure that only the correct answer is extracted and answers that increase noise only are ignored. Finally, the results suggest that the highest accuracy was achieved when limiting the number of sentences to *N*=3 for answer selection, but adequate answer accuracy can still be achieved for top sentences matched *N*=5.

4.1.9.2 Answer scoring methods and techniques analysis

Four methods were evaluated under the answer scoring module. Scoring answers using frequency showed the highest accuracy achieved for answers, and it was closely followed by scoring answers using the answer's match score. Improvement is needed when considering match scores because it is dependent on the technique used for selecting the top N sentences matched. Scoring answers using prominence of an answer within a sentence and the combination of prominence and match score had the least accuracy.

4.1.9.3 Answer aggregation methods and techniques analysis

Under answer aggregation module, this research evaluated string-matching algorithms. The results show that dice coefficient had the highest accuracy. However, this study recommends using the combination of dice coefficient and cosine similarity because both techniques perform well under different circumstances.

4.2 Results for OMQA system vs baseline systems

This sub-section shows PerCorrect and MRR results generated for OMQA system vs baseline systems and analysis from the results.

4.2.1 PerCorrect and MRR results

The research is able to identify methods and techniques performing better than others. The evaluations are performed on the OMQA system which comprises of all of these techniques. The same OMQA system can be used to select the methods and techniques performing better in terms of accuracy of answers in order to produce optimal results. Figure 4.19 shows the summary of results from section 4.1 and their selection in the OMQA system.

Method	Techniques evaluated	Better accuracy
TopK search result doctype	Web pages/ Snippets	Web pages
TopK search result depth	*K* = 5/10/20	Top *K* = 20
Information from external resources	Google/ WordNet/ Combination/ No	Combination
NER	Alchemy/ Stanford/ Combined NER	Stanford NER
Sentence-matching algorithm	Keywords/ Regex sentence-matching	Keywords
Remove unwanted answers	Yes/No	Yes
Top N Sentences	*N* = 1/3/5	*N* = 3
Answer scoring	Frequency/ MatchScore/ Prominence	Frequency
Answer aggregation	Dice coefficient(.85)/ cosine similarity(0.80)/ Combination	Combination

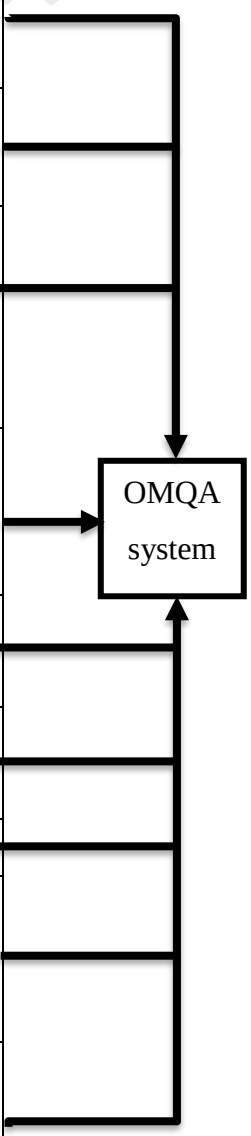


Figure 4.19: Results showing optimal methods and techniques and their selection in OMQA system

The OMQA system, using recommended methods and techniques, is compared against baseline systems reviewed from literature. The research generated results for these Web-based QA systems using the methods and techniques they have used, according to their specifications. For evaluation, four Web-based QA systems' results were generated including LAMP (Dumais et al., 2002; Kwok et al., 2001; Zhang & Lee, 2003), Qualifier (Liu et al., 2014; Yang & Chua, 2002, 2003), Corrob (Wu & Marian, 2007a, 2011) and GenreQA (Oh et al., 2012; Oh et al., 2013), and other systems based on the same architecture. While other Web-based QA systems were also reviewed, their techniques were either not available or not evaluated in the current study. The evaluation settings for these systems are listed in Table 3.3 and covered in detail in Section 3.3.3.4.

The OMQA system was tested against these baseline systems on TREC and CLEF datasets. Figure 4.20 and Table 4.10 shows comparison results of baseline systems against OMQA on TREC dataset. The figure shows PerCorrect and table shows MRR, PerCorrect and P-value (significance test) results along with Web-based QA systems' names that achieved them.

Table 4.10: OMQA system vs baselines on TREC dataset for *QN*=211

Web-based QA system	MRR		PerCorrect percentages at different ranks				
	Score	Sig test P-value	Top-1	Top-2	Top-3	Top-4	Top-5
LAMP	0.690	8.08E-12 (**)	58.29% (123)	74.88% (158)	78.67% (166)	81.52% (172)	83.89% (177)
Qualifier (Snippets)	0.693	1.94E-11 (**)	58.29% (123)	74.88% (158)	79.62% (168)	81.99% (173)	84.83% (179)
Qualifier (Web pages)	0.702	2.49E-09 (**)	57.35% (121)	76.78% (162)	81.52% (172)	84.83% (179)	88.63% (187)
Corrob	0.732	1.33E-06 (**)	63.98% (135)	76.30% (161)	82.94% (175)	85.78% (181)	86.26% (182)

Table 4.10 continued							
GenreQA	0.755	0.01223 (**)	65.88% (139)	78.20% (165)	82.94% (175)	87.20% (184)	91.47% (193)
OMQA	**0.778**		**67.30% (142)**	**82.94% (175)**	**87.20% (184)**	**91.00% (192)**	**92.42% (195)**

Note: Sig test P-value, the different levels of asterisk represent the following: (*) indicates significant difference (90% confidence since P-value < 0.10), (**) indicates significant difference (95% confidence since P-value < 0.05), and no asterisk means that difference between systems is not significant

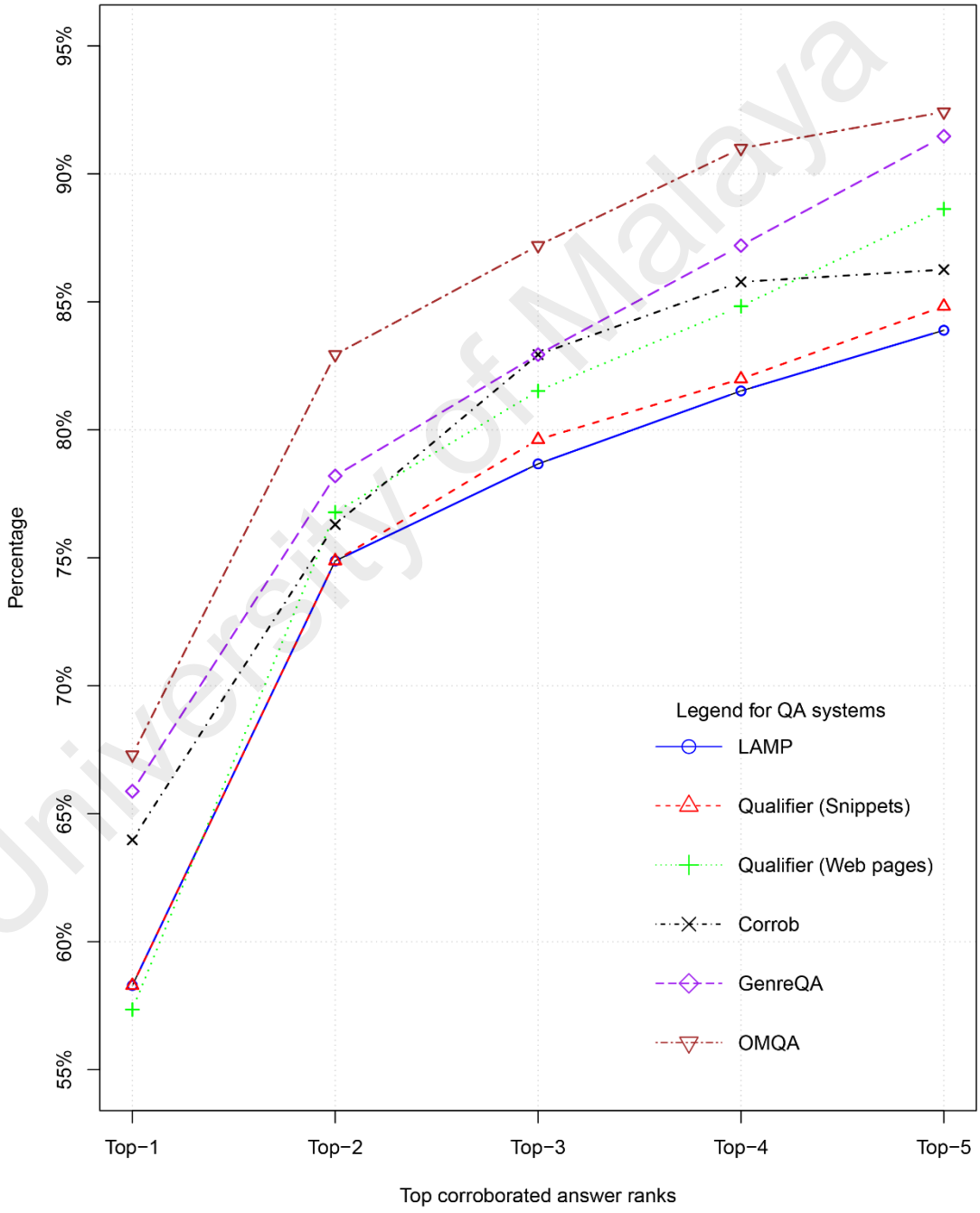


Figure 4.20: OMQA system vs baselines on TREC dataset for *QN*=211

Evaluation results on TREC dataset demonstrate that methods and techniques suggested by this study allow OMQA performing better than existing baseline systems in answer accuracy. This can be validated from the significance test results where all baseline systems have a P-value less than γ=0.1 and γ=0.05, showing 90% and 95% confidence respectively, showing that all of them are significantly lower than OMQA system. Starting with LAMP, which uses snippets as information source, it scored low percentages in both MRR and PerCorrect results, which was also highlighted when evaluating Web pages and snippets. Qualifier system using snippets achieved slightly better accuracy which is outcome of the use of information from external resources, but performed much better when using Web pages instead. Though a slight decrease in accuracy at top-1 rank, it achieved a higher accuracy in the remaining corroborated answer ranks and improved MRR score as well. Corrob system, despite performing well at earlier ranks, falls short once it reaches top-5 rank. The limitation to *N* resulted in fewer candidate answers being extracted, thus lower answer accuracy at lower corroborated ranks. GenreQA performing better than others was able to achieve results closer to the proposed QA system. The OMQA system was able to surpass other QA systems in both MRR scores and PerCorrect percentages at different corroborated answer ranks. The results show the system achieving higher percentages at top-1 and increases steadily at other ranks as well. The system was able to reach 91% at top-4 rank, whereas the best percentage by any other QA system was 91.47% at top-5. This improved even further and the highest percentage the system scored was 92.47% at top-5 rank. The reason behind its success is that it addressed the issues found in other QA systems and is able to achieve better accuracy by using the optimal parameter values and techniques under each method (Bouziane et al., 2015).

Figure 4.21 and Table 4.11 shows the results from CLEF dataset conducted on a random sample of 21 person type questions. The figure and table lists the systems' names,

and percentages attained at different top corroborated ranks, including top-1, top-2, top-3, top-4, and top-5 and P-value for significance test. The table also shows MRR results for these systems.

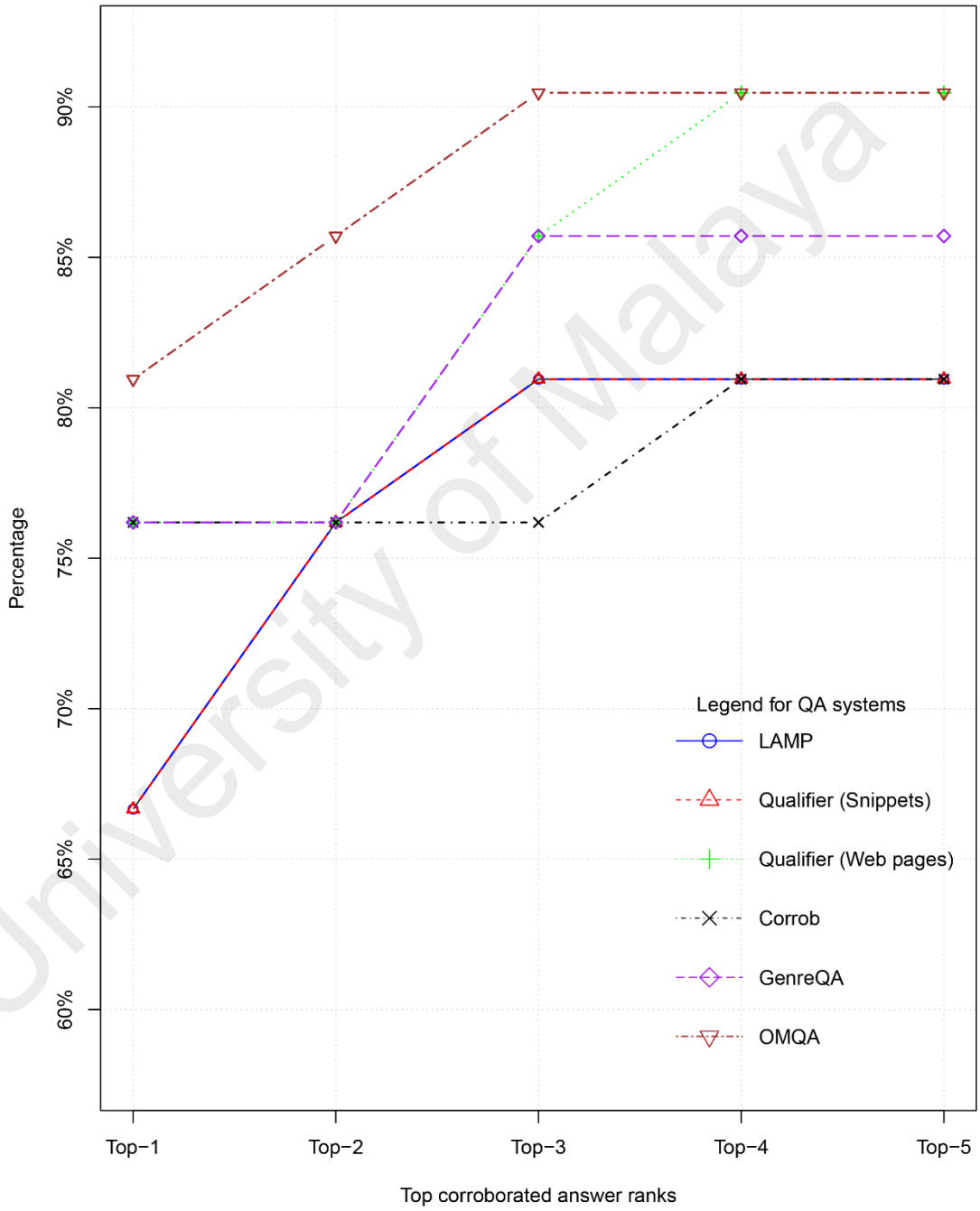


Figure 4.21: OMQA system vs baselines on CLEF dataset for *QN*=21

Table 4.11: OMQA system vs baselines on CLEF dataset for *QN*=21

Web-based QA system	MRR		PerCorrect percentages at different ranks				
	Score	Sig test P-value	Top-1	Top-2	Top-3	Top-4	Top-5
LAMP	0.730	0.0132 (**)	66.66% (15)	76.19% (17)	80.95% (18)	80.95% (18)	80.95% (18)
Qualifier (Snippets)	0.730	0.0132 (**)	66.66% (15)	76.19% (17)	80.95% (18)	80.95% (18)	80.95% (18)
Qualifier (Web pages)	0.805	0.0868 (*)	76.19% (17)	76.19% (17)	85.71% (19)	**90.47% (20)**	**90.47% (20)**
Corrob	0.773	0.0593 (*)	76.19% (17)	76.19% (17)	76.19% (17)	80.95% (18)	80.95% (18)
GenreQA	0.793	0.0648 (*)	76.19% (17)	76.19% (17)	85.71% (19)	85.71% (19)	85.71% (19)
OMQA	**0.849**		**80.95% (18)**	**85.71% (19)**	**90.47% (20)**	**90.47% (20)**	**90.47% (20)**

Note: Sig test P-value, the different levels of asterisk represent the following: (*) indicates significant difference (90% confidence since P-value < 0.10), (**) indicates significant difference (95% confidence since P-value < 0.05), and no asterisk means that difference between systems is not significant

Figure 4.21 and Table 4.11 shows the comparison results of the QA systems on this dataset. Significance testing done using t-test shows 90% confidence that all baseline systems are significantly lower than OMQA system. Even at 95% confidence (γ=0.05) two baseline systems including LAMP and Qualifier (Snippets) are significantly lower except for Qualifier(Web pages), Corrob and GenreQA baseline systems. As expected, the results show that LAMP and Qualifier systems using snippets score lower than other systems due to their reliance on snippets information source. Though Qualifier system uses additional methods than LAMP system, it could not surpass it because these methods are less effective on snippets. This is proved when the resource is changed to Web pages, allowing Qualifier to achieve higher MRR scores and PerCorrect percentages. Corrob system also scored high at top-1 rank but only increased slightly for the remaining ranks

as sentences matched *N* is set to 1. This is also the reason Corrob scored lower than Qualifier, despite being able to remove unwanted answers. This observation is confirmed in GenreQA results, where sentences match *N*=5, allowing it to score higher than Corrob system.

The system suggested by this study was able to achieve higher MRR scores and PerCorrect percentages than other QA systems. Taking the positives from both Qualifier using Web pages, Corrob and GenreQA systems, making slight adjustments to methods and techniques, the selection allowed it to gain a comfortable lead compared with the other QA systems. The only questions OMQA system and other baselines was not able to answer was due to inability of the NERs in detecting entities such as horse's name "Little Sorrel" and mythological name "Neptune". Despite this, the OMQA system was able to achieve a respectable answer accuracy in comparison to other baseline systems. Thus, the results from CLEF dataset also support and acknowledge the effectiveness of the methods and techniques in achieving higher answer accuracy.

4.2.2 OMQA system vs baseline systems result analysis

The results from Web-based QA systems methods and techniques highlighted the ones performing better than others, which are used in the OMQA system. This OMQA system was evaluated against other baseline system. The results show that the suggested system was able to perform better than other systems in both MRR and perCorrect results. The reasons for this success is simply due to use of optimal combination of methods and techniques, which was not the case in baseline Web-based QA systems. For example, the research suggests use of Web pages over snippets. LAMP system uses snippets as information source and thus scored results are much lower than systems using Web pages instead. The same pattern was found in other systems, thus showing the selection of

correct combination of methods and techniques is vital to increase answer accuracy in existing Web-based QA systems.

4.3 Results for CredOMQA system vs other baselines

This sub-section shows PerCorrect and MRR results for CredOMQA system which is a combination of OMQA system and credibility assessment module. The tests includes evaluation of individual credibility categories and all categories for computing credibility-based answer score. First the CredOMQA system is evaluated for selecting the ideal value of of α used in Equation 3.28. Since the value has to be between 0 and 1, this study chose 4 intervals for evaluation, including 0, 0.25, 0.50, and 0.75, where 1 was excluded since it will return the same results as that of OMQA system by giving it 100% weighting and giving 0% weighting to Web credibility. Once an ideal value of α is selected then the CredOMQA system is evaluated for individual categories. This is done for highlighting credibility categories that had the biggest or lowest impact on accuracy of answers. At the end the CredOMQA system is evaluated using all categories for generating credibility-based answer score and compared its results against baseline systems.

Four Web-based and credibility-based Web QA systems were chosen as baseline for comparing results for the prototype credibility-based Web QA system, proposed by this research. These baselines system are: LAMP (Dumais et al., 2002; Kwok et al., 2001; Zhang & Lee, 2003), Qualifier (Liu et al., 2014a; Yang & Chua, 2002, 2003a), Corrob (Wu & Marian, 2007b, 2011) and GenreQA (Oh et al., 2012; Oh et al., 2013). Among these baseline systems, LAMP and Qualifier do not use credibility scores, while Corrob and GenreQA systems make use of Web credibility scores for scoring answers. The settings used for these baseline systems are listed in Table 3.3. This research also shows

results for OMQA and CredOMQA system in order to highlight how much answer accuracy is increased by introducing credibility assessment to OMQA system.

4.3.1 Selecting ideal value of α for CredOMQA system

Before CredOMQA system can be evaluated against other baseline systems, it is necessary to select the ideal value of α for generating credibility-based answer score. The α is a smoothing factor, which is used to to control the weighting between *AnswerPercentageOnPage* and *CredibilityScore* in Equation 3.28. MRR results were generated for CredOMQA system against individual categories and using all categories combined for different values of α incuding α=0, α=0.25= α=0.50 and α=0.75 and are shown in Table 4.12.

Table 4.12: MRR results for CredOMQA system using credibility categories for different values of α for *QN*=211

Web-based QA system	MRR scores for different α values			
	α=0	α=0.25	α=0.50	α=0.75
CredOMQA(Correctness)	0.778	0.790	0.794	**0.796**
CredOMQA(Authority)	0.601	0.760	0.779	**0.786**
CredOMQA(Currency)	0.592	0.753	0.778	**0.789**
CredOMQA(Professionalism)	0.771	0.781	0.786	**0.795**
CredOMQA(Popularity)	0.765	0.777	0.787	**0.789**
CredOMQA(Impartiality)	0.772	0.788	0.790	**0.797**
CredOMQA(Quality)	0.793	**0.802**	0.783	0.798
CredOMQA(All categories)	0.785	0.794	0.791	**0.797**

The MRR results show that in most cases CredOMQA system using individual credibility categories and using all categories attained highest MRR scores for α=0.75. The only exception is CredOMQA(Quality) which scored better for α=0.25. Despite this, CredOMQA(Quality) MRR score at α=0.75 is still higher than other CredOMQA

combinations for α=0.75. Thus, the α=0.75 is selected as the ideal value for CredOMQA system in the upcoming evaluations.

There are two reasons for credibility-based answer scores performing better at α=0.75 than other values. The first reason is that relying only on credibility of source does not gives the best results (Wu & Marian, 2011). Systems like Corrob* reported better results when the threshold for considering a Web page as credibility was made lenient instead of being strict. CredOMQA using correctness. The second reason is that by not considering *AnswerPercentageOnPage,* factors like frequency of answer being fount and its match-score is neglected. Thus, with α=0.75 more weighting is given to *AnswerPercentageOnPage* but *CredibilityScore* of answer score is still considered giving ideal MRR scores in almost all results.

4.3.2 CredOMQA using correctness

Figure 4.22 shows PerCorrect and Table 4.13 shows PerCorrect and MRR results for correctness category answer score. The figure and table lists systems' name which includes baseline systems, OMQA system and CredOMQA system scores using correctness category score. In the table (*) notation is used with baseline systems for indicating the system using credibility-based answer scores, such as Corrob*, GenreQA* and correctness category scores, while LAMP, Qualifier, Corrob, GenreQA and OMQA do not.

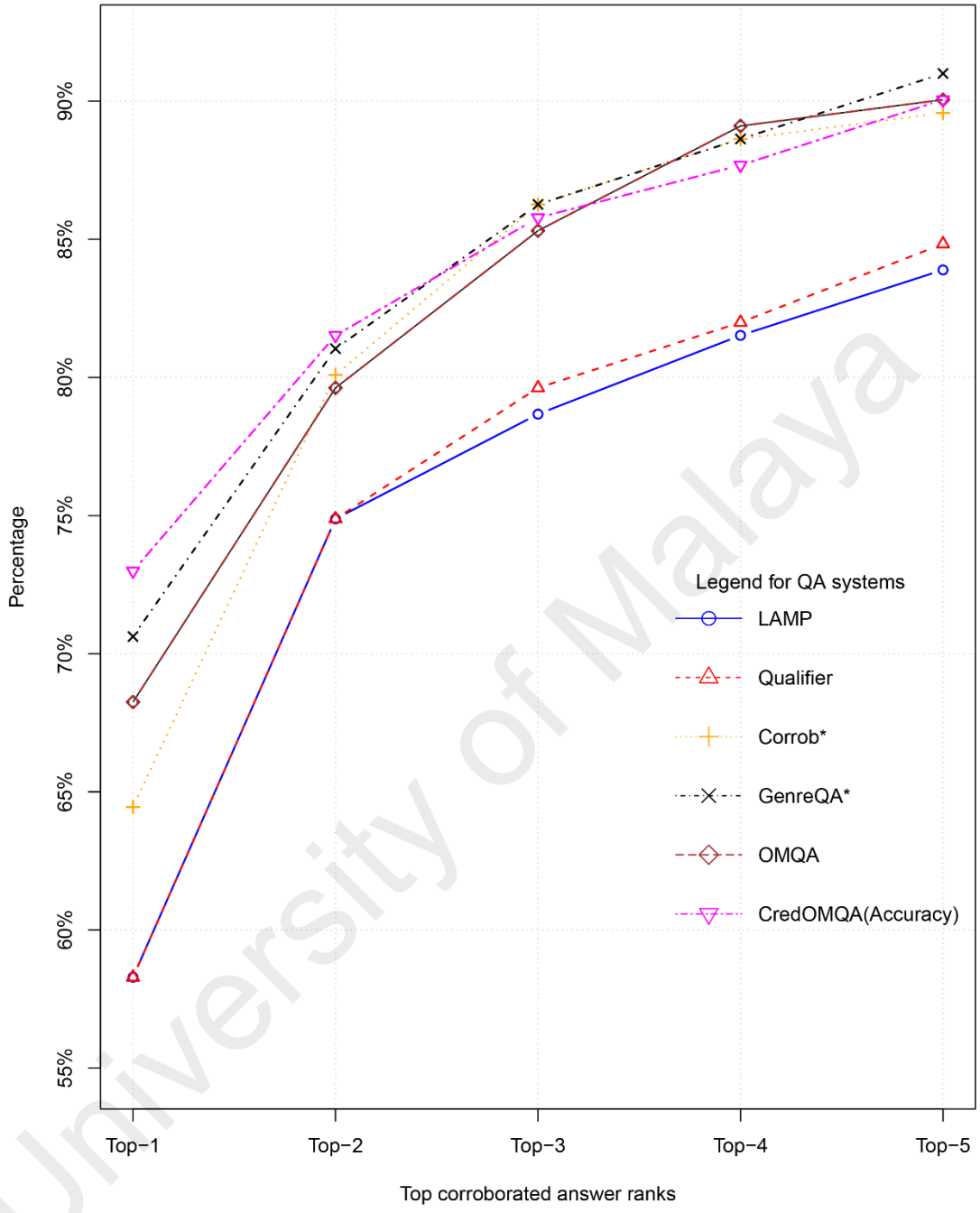


Figure 4.22: PerCorrect results for CredOMQA using correctness for *QN*=211

Table 4.13: PerCorrect and MRR results for CredOMQA using correctness for *QN*=211

Web-based QA system	MRR		PerCorrect percentages at different ranks				
	Score	Sig test P-value	Top-1	Top-2	Top-3	Top-4	Top-5
LAMP	0.690	3.162E-15 (**)	58.29% (124)	74.88% (159)	78.67% (167)	81.52% (173)	83.89% (178)
Qualifier	0.693	8.110E-15 (**)	58.29% (124)	74.88% (159)	79.62% (169)	81.99% (174)	84.83% (180)
Corrob	0.732	7.433E-10 (**)	63.98% (136)	76.30% (162)	82.94% (176)	85.78% (182)	86.26% (183)
Corrob*	0.751	3.199E-06 (**)	64.45% (137)	80.09% (170)	**86.26% (183)**	88.63% (188)	89.57% (190)
GenreQA	0.755	7.868E-06 (**)	65.88% (140)	78.20% (166)	82.94% (176)	87.20% (185)	**91.47% (194)**
GenreQA*	0.786	0.0371 (**)	70.62% (150)	81.04% (172)	**86.26% (183)**	88.63% (188)	91.00% (193)
OMQA	0.770	0.0001 (**)	68.25% (145)	79.62% (169)	85.31% (181)	**89.10% (189)**	90.05% (191)
CredOMQA (Correctness)	**0.796**		**72.99% (155)**	**81.52% (173)**	85.78% (182)	87.68% (186)	90.05% (191)

Note: Sig test P-value, the different levels of asterisk represent the following: (*) indicates significant difference (90% confidence since P-value < 0.10), (**) indicates significant difference (95% confidence since P-value < 0.05), and no asterisk means that difference between systems is not significant

The results in Figure 4.22 and Table 4.13 show that best results were achieved by CredOMQA system using correct category as it attained highest scores in MRR and PerCorrect percentages at top-1 and top-2. In the remaining PerCorrect ranks, the highest percentages were scored by baseline systems including GenreQA, GenreQA*, Corrob* and our system OMQA system. LAMP baseline system had the worst results as it scored lowest in both MRR and all PerCorrect ranks.

Results show that by considering correctness category, the accuracy of the CredOMQA system improved over OMQA system significantly. This can also be verified by the significance test performed showing 95% confidence is significance difference between the two systems. In comparison to other baseline systems, the difference between CredOMQA(Correctness) system and other baseline systems is also significant with 95% confidence in signifance testing.

It can be concluded that CredOMQA system using correct category performed better than baseline systems and the OMQA system, including baseline systems conducting credibility assessment. Additionally, the reason we believe this category performed better was due to the introduction of TFIDF method in addition to the search results rank (Wu & Marian, 2011). This ensured that documents achieving a higher TFIDF score considered the keywords used for answer extraction by the Web-based QA system instead of relying on the rank given by the search engine only (Wu & Marian, 2011). Thus, an introduction of a scoring method to check the relevancy of the document, with respect to keywords used, helped in improving accuracy of answers.

4.3.3 CredOMQA using authority

Figure 4.23 shows PerCorrect and Table 4.14 shows the PerCorrect, MRR and testing results for CredOMQA(Authority) system against baseline systems. The significant test is done using t-test, which shows whether a baseline system is significantly different than CredOMQA(Authority) system or not using different confidence levels including 90% and 95%.

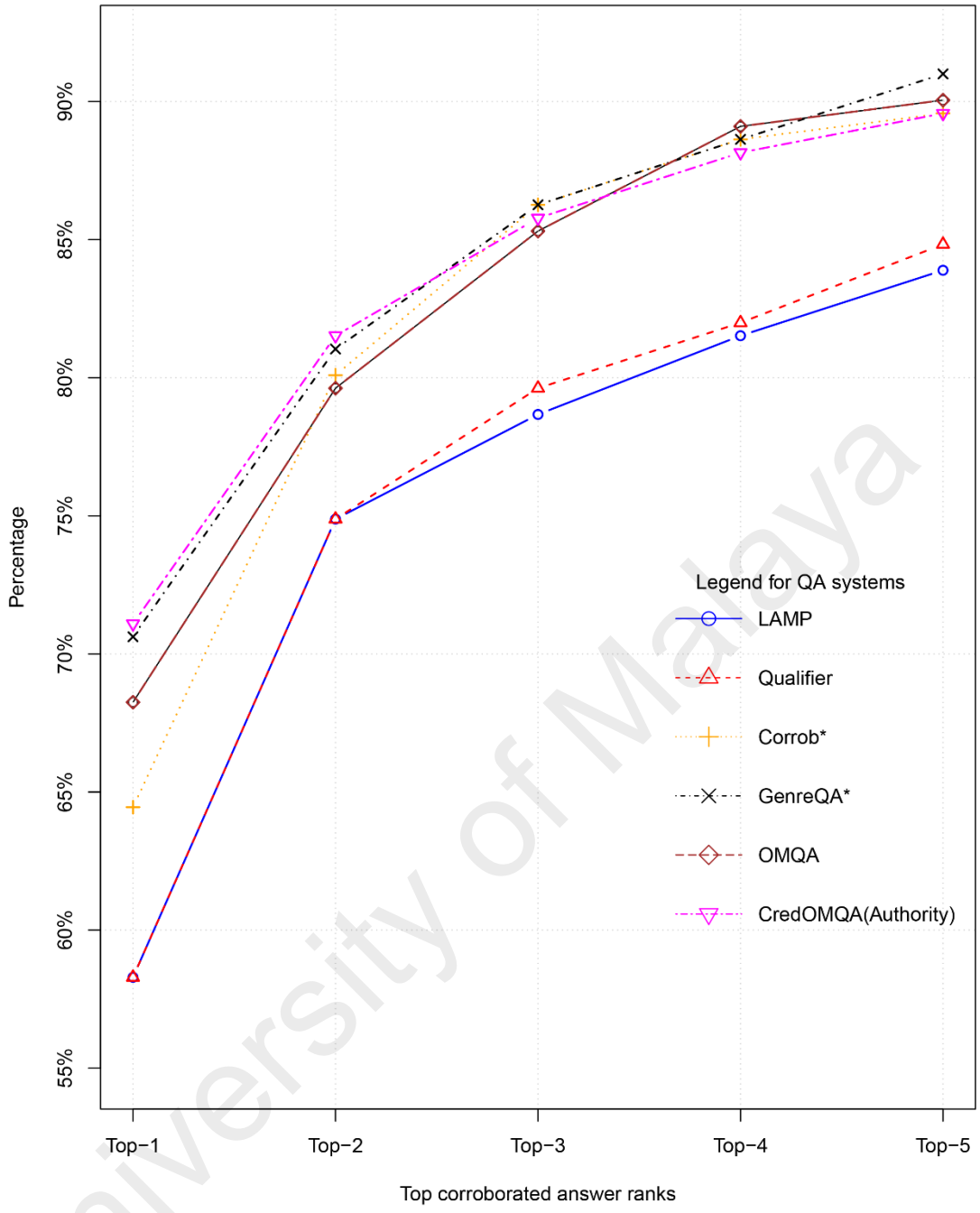


Figure 4.23: PerCorrect results for CredOMQA using authority for *QN*=211

Table 4.14: PerCorrect and MRR results for CredOMQA using authority for *QN*=211

Web-based QA system	MRR		PerCorrect percentages at different ranks				
	Score	Sig test P-value	Top-1	Top-2	Top-3	Top-4	Top-5
LAMP	0.690	5.905E-14 (**)	58.29% (124)	74.88% (159)	78.67% (167)	81.52% (173)	83.89% (178)
Qualifier	0.693	1.479E-13 (**)	58.29% (124)	74.88% (159)	79.62% (169)	81.99% (174)	84.83% (180)
Corrob	0.732	1.007E-08 (**)	63.98% (136)	76.30% (162)	82.94% (176)	85.78% (182)	86.26% (183)
Corrob*	0.751	3.943E-05 (**)	64.45% (137)	80.09% (170)	**86.26% (183)**	88.63% (188)	89.57% (190)
GenreQA	0.755	0.000116 (**)	65.88% (140)	78.20% (166)	82.94% (176)	87.20% (185)	**91.47% (194)**
GenreQA*	**0.786**	0.46269823	70.62% (150)	81.04% (172)	**86.26% (183)**	88.63% (188)	91.00% (193)
OMQA	0.770	0.00200528 (**)	68.25% (145)	79.62% (169)	85.31% (181)	**89.10% (189)**	90.05% (191)
CredOMQA (Authority)	**0.786**		**71.09% (151)**	**81.52% (173)**	85.78% (182)	88.15% (187)	89.57% (190)

Note: Sig test P-value, the different levels of asterisk represent the following: (*) indicates significant difference (90% confidence since P-value < 0.10), (**) indicates significant difference (95% confidence since P-value < 0.05), and no asterisk means that difference between systems is not significant

The PerCorrect results in Figure 4.23 and Table 4.14 shows that CredOMQA(Authority) system achieved the best results by scoring highest MRR score and highest PerCorrect percentages at rank top-1 and top-2. On the other hand, GenreQA* also achieved great results by also scoring highest MRR score in the results and achieving highest PerCorrect percentage at top-4 rank. When comparing both CredOMQA(Authority) and GenreQA* together, though both of them share the same MRR score, yet CredOMQA(Authority) will be preferred as QA systems having higher

accuracy at top-1 and top-2 PerCorrect ranks are considered better (Wu & Marian, 2011). Apart from deciding whether CredOMQA(Authority) did better than GenreQA*, it is clear that both of these systems did improve accuracy of answers over non-credible version of QA systems including OMQA and GenreQA system respectively.

Despite CredOMQA(Authority) achieving highest results in comparison to other baseline systems, its MRR score is much lower than CredOMQA system using other baselines. For example, CredOMQA(Correctness) also achieved better results than other baseline systems but had a much higher MRR score than CredOMQA(Authority) in the results, that is 0.796 in comparison to 0.786 to that of CredOMQA(Authority).

When looking at significance testing results, it shows that CredOMQA(Authority) system is significantly better than majority of the baseline systems. The only exception here is the GenreQA*. For all other baseline systems, with 95% confidence it can be stated that CredOMQA system is significantly better than all baseline systems except GenreQA*.

In conclusion, though CredOMQA(Authority) achieved higher results than most baseline systems, yet its difference between other credibility-based like GenreQA* system was not significant. The category did not perform as good as other credibility categories due to several reasons. One of the factors for scoring low on the results is that most of the sources (from where answers were extracted) did not mention the author name or the URLs (Diffbot, 2016). Figure 4.24 shows authority scores, for question “Who was the first Prime Minister of Canada?”, which shows that only 3 out of 20 search results mentioned both author name and contact details.

1	0
2	0
3	0
4	0
5	0
6	0
7	0
8	0
9	100
10	100
11	0
12	100
13	0
14	0
15	0
16	0
17	0
18	0
19	0
20	0

Figure 4.24: Authority score given to 20 Web pages for the question "Who was the first Prime Minister of Canada?"

Apart from mentioning author names and contact details, there were several other issues. The Web pages that achieved high authority score did not contain relevant data to the question. For example, most of the articles on Wikipedia do not contain any author details but may very well contain relevant data to the question (Pantola et al., 2010b). On the other hand, blogs do provide author details and URLs but the information presented is often not as good as that provided by other sources (Diffbot, 2016). This should raise some awareness among content writers in providing author details for not only improving credibility of the resource but also improving the ranking of answers (Ostenson, 2014).

4.3.4 CredOMQA using currency

Figure 4.25 shows PerCorrect and Table 4.15 shows PerCorrect and MRR results for CredOMQA system using currency category answer score. The figure and table lists the results for baseline systems, OMQA system and CredOMQA(Currency) system.

Table 4.15: PerCorrect and MRR results for CredOMQA using currency for QN=211

Web-based QA system name	MRR		PerCorrect percentages at different ranks				
	Score	Sig test P-value	Top-1	Top-2	Top-3	Top-4	Top-5
LAMP	0.690	3.48E-14 (**)	58.29% (124)	74.88% (159)	78.67% (167)	81.52% (173)	83.89% (178)
Qualifier	0.693	8.76E-14 (**)	58.29% (124)	74.88% (159)	79.62% (169)	81.99% (174)	84.83% (180)
Corrob	0.732	9.13E-09 (**)	63.98% (136)	76.30% (162)	82.94% (176)	85.78% (182)	86.26% (183)
Corrob*	0.751	2.94E-05 (**)	64.45% (137)	80.09% (170)	**86.26% (183)**	88.63% (188)	89.57% (190)
GenreQA	0.755	8.48E-05 (**)	65.88% (140)	78.20% (166)	82.94% (176)	87.20% (185)	**91.47% (194)**
GenreQA*	0.786	0.2938	70.62% (150)	**81.04% (172)**	**86.26% (183)**	88.63% (188)	91.00% (193)
OMQA	0.770	0.00144 (**)	68.25% (145)	79.62% (169)	85.31% (181)	**89.10% (189)**	90.05% (191)
CredOMQA (Currency)	**0.789**		**72.04% (153)**	80.57% (171)	85.31% (181)	88.15% (187)	89.57% (190)

Note: Sig test P-value, the different levels of asterisk represent the following: (*) indicates significant difference (90% confidence since P-value < 0.10), (**) indicates significant difference (95% confidence since P-value < 0.05), and no asterisk means that difference between systems is not significant

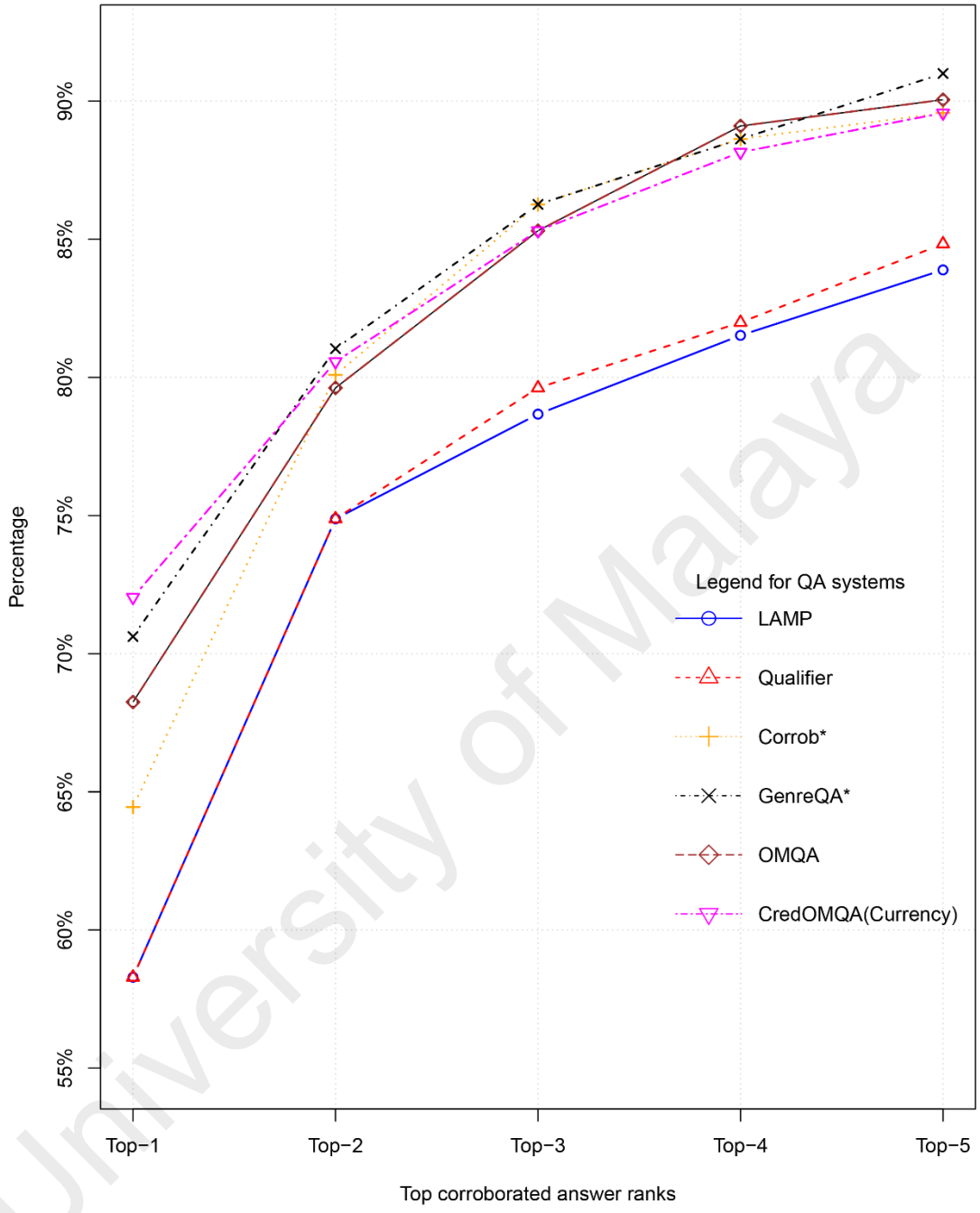


Figure 4.25: PerCorrect results for CredOMQA using currency for *QN*=211

Table 4.15 and Figure 4.25 show CredOMQA(Currency) system best results as compared to other baseline systems as it scores the highest MRR and achieves highest PerCorrect percentage at top-1 rank. In the remaining PerCorrect ranks, highest percentages is shared among different baseline systems. A close second would be

GenreQA* whose MRR is close to CredOMQA(Currency) and also scored highest PerCorrect percentage at in the middle PerCorrect ranks like top-2 and top-3.

Just like CredOMQA(Authority), CredOMQA(Currency) achieved lower MRR score as compared to other credibility categories. This means that CredOMQA(Currency) despite achieving better results than other baseline systems, its accuracy can still be improved much further.

The significance results show CredOMQA(Currency) is significantly better than most of the baseline systems. This also includes significant improvement over OMQA system, based on which CredOMQA(Currency) is developed. For all baseline systems, except GenreQA*, CredOMQA(Currency) achieved significantly better results with 95% confidence in the significance testing. This also includes Corrob* system which also conducts credibility assessment. Though, CredOMQA(Currency) results were not significantly different than GenreQA*, yet CredOMQA(Currency) is still preffered over it for achieving higher MRR scores and having better PerCorrect percentages at top-1 and top-2 ranks.

In conclusion, CredOMQA(Currency) showed significant improvement over OMQA system and achieved significantly better results than most of the baseline systems. One of the reasons for this category to have a low accuracy turnover is that most Websites do not update their Web pages regularly (Diffbot, 2016). If that was not all, they fail to mention the last time the page was updated, leaving the user clueless about source's credibility with respect to currency (Diffbot, 2016). Like authority, currency is among those categories that are often neglected by content writers and Web users when conducting credibility assessment of the resource. Figure 4.26 shows the currency scores for the question "Who is the author of the book, "The Iron Lady: A Biography of Margaret Thatcher"?".

```
1  0
2  0
3  0
4  0
5  2.08
6  0
7  0
8  0
9  0
10 0
11 0
12 0
13 0
14 0
15 54.17
16 0
17 0
18 100
19 0
20 0
```

Figure 4.26: Currency score given to 20 search results for the question "Who is the author of the book, "The Iron Lady: A Biography of Margaret Thatcher"?"

As shown in the figure above, only 3 out of 20 Web pages are from the last 5 years. In the figure, score on each line indicates the currency score given to a Web page, thus 17 out of 20 Web pages are outdated for this question. Though currency is important in questions where the timeline needs to be strict, the range maybe relaxed for other question when this is not the case (Oh et al., 2012). Currently, the threshold was set to 5 years beyond which the Web pages were marked as non-credible. Judging by the results, this condition can be relaxed a bit. Another way to improve the percentage is to include more factors that affect currency category score (Aggarwal et al., 2014b).

4.3.5 CredOMQA using professionalism

Figure 4.27 shows the PerCorrect results and Table 4.16 shows PerCorrect and MRR results for CredOMQA system using professionalism category against other baseline systems.

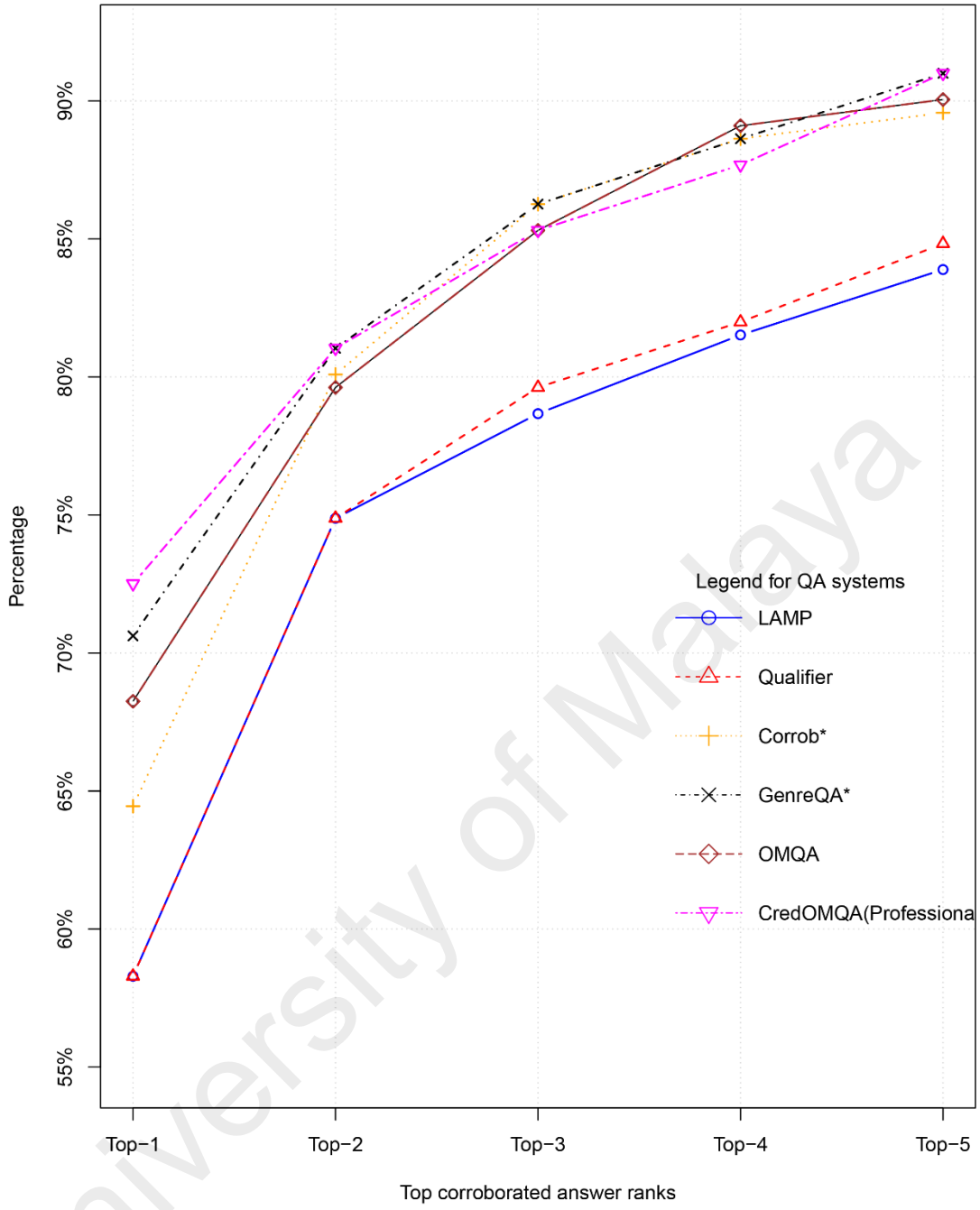


Figure 4.27: PerCorrect results for CredOMQA using professionalism for *QN*=211

Table 4.16: PerCorrect and MRR results CredOMQA using professionalism for *QN*=211

Web-based QA system name	MRR		PerCorrect percentages at different ranks				
	Score	Sig test P-value	Top-1	Top-2	Top-3	Top-4	Top-5
LAMP	0.690	3.382E-15 (**)	58.29% (124)	74.88% (159)	78.67% (167)	81.52% (173)	83.89% (178)
Qualifier	0.693	8.676E-15 (**)	58.29% (124)	74.88% (159)	79.62% (169)	81.99% (174)	84.83% (180)
Corrob	0.732	9.844E-10 (**)	63.98% (136)	76.30% (162)	82.94% (176)	85.78% (182)	86.26% (183)
Corrob*	0.751	4.565E-06 (**)	64.45% (137)	80.09% (170)	**86.26% (183)**	88.63% (188)	89.57% (190)
GenreQA	0.755	7.072E-06 (**)	65.88% (140)	78.20% (166)	82.94% (176)	87.20% (185)	**91.47% (194)**
GenreQA*	0.786	0.042292 (**)	70.62% (150)	**81.04% (172)**	**86.26% (183)**	88.63% (188)	91.00% (193)
OMQA	0.770	0.000184 (**)	68.25% (145)	79.62% (169)	85.31% (181)	**89.10% (189)**	90.05% (191)
CredOMQA (Profession-alism)	**0.795**		**72.51% (154)**	**81.04% (172)**	85.31% (181)	87.68% (186)	91.00% (193)

Note: Sig test P-value, the different levels of asterisk represent the following: (*) indicates significant difference (90% confidence since P-value < 0.10), (**) indicates significant difference (95% confidence since P-value < 0.05), and no asterisk means that difference between systems is not significant

Results from Figure 4.27 and Table 4.16 show that CredOMQA(Professionalism) achieved the best results compared to all other baselines by scoring highest MRR score and achieving highest PerCorrect percetages at ranks top-1 and top-2. Scoring higher in PerCorrect top-1 and top-2 is considered better as compared to scoring better in other ranks (Wu & Marian, 2011). CredOMQA(Professionalism) also scoed much better than

GenreQA* and Corrob* systems , which also use credibility assessment for scoring answers.

CredOMQA(Professionalism) also scored much higher than CredOMQA system using categories such as authority and currency. In short, CredOMQA(Professionalism) not only did CredOMQA(Professionalism) scored better than baseline systems but its accuracy of answers is also quite high with a clear margin of difference. This is evident in the signifance testing as well.

The signifance testing results show us CredOMQA(Professionalism) showing significant improvement over OMQA system. Additionally, there is significant difference between CredOMQA(Professionalism) and other baseline systems as well. The results show that P-value of all baseline systems (including Corrob* and GenreQA*) was significantly lower than γ=0.05, showing CredOMQA(Professionalism) being significantly better than others with confidence level of 95%.

In conclusion, professionalism category is among the categories that had a major impact on improving accuracy of answers. The inclusion of reviewer's score and reputation given to Web pages helped a lot in segregating credible resources from non-credible ones, thus promoting the correct answers even higher (Aggarwal et al., 2014b). Furthermore, this category contained many factors compared to others, covered in greater detail in Section 3.3.7.4, thus producing a score with less variation. This is because even if the values for some of the factors were not found or extracted, the overall impact on the professionalism score was less as there were other factors to consider as well (Aggarwal et al., 2014b).

4.3.6 CredOMQA using popularity

Figure 4.28 shows PerCorrect results and Table 4.17 shows PerCorrect and MRR results for CredOMQA using popularity category. The table also shows significance testing

results showing difference between CredOMQA(Professionalism) system against baseline systems.

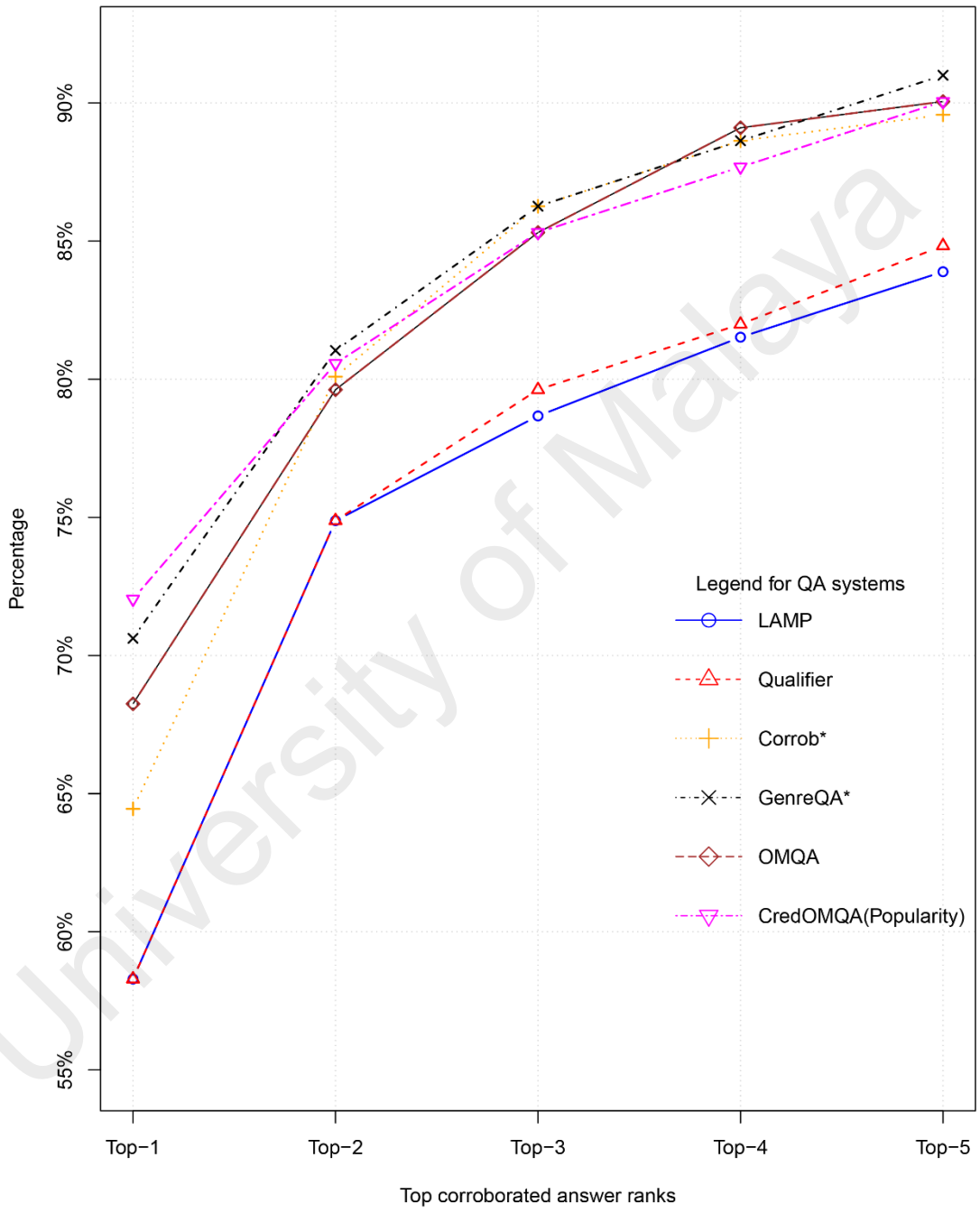


Figure 4.28: PerCorrect results for CredOMQA using popularity for *QN*=211

Table 4.17: PerCorrect and MRR results CredOMQA using popularity for *QN*=211

Web-based QA system name	MRR		PerCorrect percentages at different ranks				
	Score	Sig test P-value	Top-1	Top-2	Top-3	Top-4	Top-5
LAMP	0.690	5.98E-14 (**)	58.29% (124)	74.88% (159)	78.67% (167)	81.52% (173)	83.89% (178)
Qualifier	0.693	1.49E-13 (**)	58.29% (124)	74.88% (159)	79.62% (169)	81.99% (174)	84.83% (180)
Corrob	0.732	1.88E-08 (**)	63.98% (136)	76.30% (162)	82.94% (176)	85.78% (182)	86.26% (183)
Corrob*	0.751	6.07E-05 (**)	64.45% (137)	80.09% (170)	**86.26% (183)**	88.63% (188)	89.57% (190)
GenreQA	0.755	0.00017 (**)	65.88% (140)	78.20% (166)	82.94% (176)	87.20% (185)	**91.47% (194)**
GenreQA*	0.786	0.43116	70.62% (150)	81.04% (172)	**86.26% (183)**	88.63% (188)	91.00% (193)
OMQA	0.770	0.00292 (**)	68.25% (145)	79.62% (169)	85.31% (181)	**89.10% (189)**	90.05% (191)
CredOMQA (Popularity)	**0.789**		**72.04% (153)**	80.57% (171)	85.31% (181)	87.68% (186)	90.05% (191)

Note: Sig test P-value, the different levels of asterisk represent the following: (*) indicates significant difference (90% confidence since P-value < 0.10), (**) indicates significant difference (95% confidence since P-value < 0.05), and no asterisk means that difference between systems is not significant

The results in Figure 4.28 and Table 4.17 show that CredOMQA(Professionalism) achieved better results than other all baseline systems by scoring the highest MRR score and achieving highest PerCorrect percentage at top-1 rank. GenreQA* is slightly behind CredOMQA(Professionalism) and is to achieve MRR at 0.786.

CredOMQA(Professionalism) also scored lower in PerCorrect and MRR scores in comparison to CredOMQA system using other categories like correctness and

professionalism. This results in close gap between CredOMQA(Professionalism) and credibility-based Web QA systems like GenreQA*.

In significance testing, CredOMQA(Professionalism) system has a significant difference against most baseline systems, except for GenreQA*. Though the difference between GenreQA* is not signifant, it does not mean GenreQA performed better. As for other baseline systems, with confidence level of 95%, CredOMQA(Professionalism) shows significant improvement over others.

In conclusion, CredOMQA(Professionalism) shows results higher than baseline systems, but did not show significant improvement against credibility-based QA systems like GenreQA*. This is due to lower scores in comparison to other credibility categories. Despite not achieving optimal results, yet the category scored higher than most baseline systems. This is credited towards the inclusion of multiple factors acquired from various SEO organizations which provide Web pages ranks, traffic details and social media share count. In general, a Web page needs to achieve respectable scores in all of these factors for achieving a higher credibility score, that may help in improving the score of answers found on the page as well. Many Web pages try to exploit popularity by addressing limited factors only, which are addressed by a particular search engine. This research suggests using a number factors, covered by several SEO organizations, to make it difficult for Web pages to exploit popularity scores. Furthermore, share count of an article is also difficult to address by the content creator alone.

4.3.7 CredOMQA using impartiality

Figure 4.29 shows PerCorrect results and Table 4.18 shows PerCorrect and MRR results for CredOMQA system using impartiality category answer score against other baseline systems.

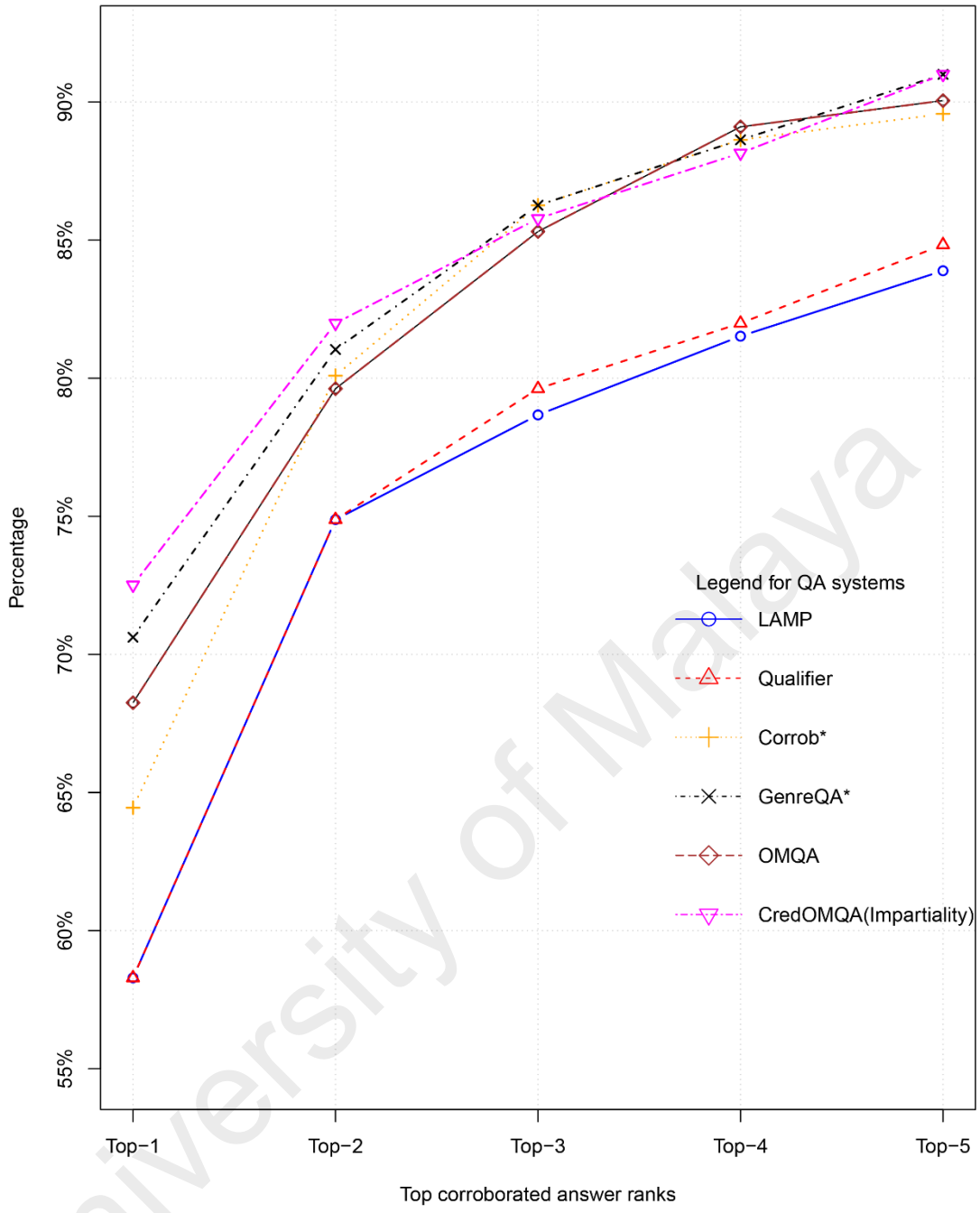


Figure 4.29: PerCorrect results CredOMQA using impartiality for *QN*=211

Table 4.18: PerCorrect and MRR results for CredOMQA using impartiality for *QN*=211

Web-based QA system name	MRR		PerCorrect percentages at different ranks				
	Score	Sig test P-value	Top-1	Top-2	Top-3	Top-4	Top-5
LAMP	0.690	2.83E-15 (**)	58.29% (124)	74.88% (159)	78.67% (167)	81.52% (173)	83.89% (178)
Qualifier	0.693	6.79E-15 (**)	58.29% (124)	74.88% (159)	79.62% (169)	81.99% (174)	84.83% (180)
Corrob	0.732	5.53E-10 (**)	63.98% (136)	76.30% (162)	82.94% (176)	85.78% (182)	86.26% (183)
Corrob*	0.751	2.78E-06 (**)	64.45% (137)	80.09% (170)	**86.26% (183)**	88.63% (188)	89.57% (190)
GenreQA	0.755	5.43E-06 (**)	65.88% (140)	78.20% (166)	82.94% (176)	87.20% (185)	**91.47% (194)**
GenreQA*	0.786	0.03129 (**)	70.62% (150)	81.04% (172)	**86.26% (183)**	88.63% (188)	91.00% (193)
OMQA	0.770	0.00011 (**)	68.25% (145)	79.62% (169)	85.31% (181)	**89.10% (189)**	90.05% (191)
CredOMQA (Impartiality)	**0.797**		**72.51% (154)**	**81.99% (174)**	85.78% (182)	88.15% (187)	91.00% (193)

Note: Sig test P-value, the different levels of asterisk represent the following: (*) indicates significant difference (90% confidence since P-value < 0.10), (**) indicates significant difference (95% confidence since P-value < 0.05), and no asterisk means that difference between systems is not significant

Results in Figure 4.29 and Table 4.18 show that CredOMQA(Impartiality) system achieved the best results in comparison to baseline systems. This is because it achieved the highest MRR score and also score highest PerCorrect percentages at top-1 and top-2 rank. In comparison GenreQA* and Corrob* had MRR scores much lower than CredOMQA(Impartiality), which also conducted credibility assessment for scoring answers

CredOMQA(Impartiality) not only achieved higher scores than baseline systems but also had among the highest MRR and PerCorrect scores attained by CredOMQA system against other credibility categories. Thus, impartiality should be highly prioritized for achieving high accuracy of answers.

In significance testing, the results also show baseline systems are significantly different and lower than CredOMQA(Impartiality) system. All the baseline systems, including credibility-based Web QA systems like Corrob* and GenreQA* were significantly lower in terms of accuracy compared to CredOMQA(Impartiality) system with a confidence level of 95%.

In conclusion, impartiality category shows that it is among the categories that improved percentage of correct answers the most. Though there was only one factor considered under impartiality, i.e., sentiment of the content, yet the scores had a major impact on accuracy of answers (Diffbot, 2016; Schwarz & Morris, 2011b). One of the reasons for this category's success is that the factor is difficult to exploit (Diffbot, 2016). This is because an ill-intentioned content writer will try to write material that will support his cause by increasing the frequency of an incorrect answer deliberately or being biased in general (Wu & Marian, 2011). By doing this, he/she is likely to show some bias in the content, thus allowing sentiment score to give it a lower rating (Diffbot, 2016). This category in particular will encourage content writers to be un-biased and keep the tone of the article positive when sharing content on the Web and thus achieve decent ranking in credibility based systems (Fletcher et al., 2017).

4.3.8 CredOMQA using quality

Figure 4.30 shows PerCorrect results and Table 4.19 shows PerCorrect and MRR results for CredOMQA system using quality category answer score against baseline systems.

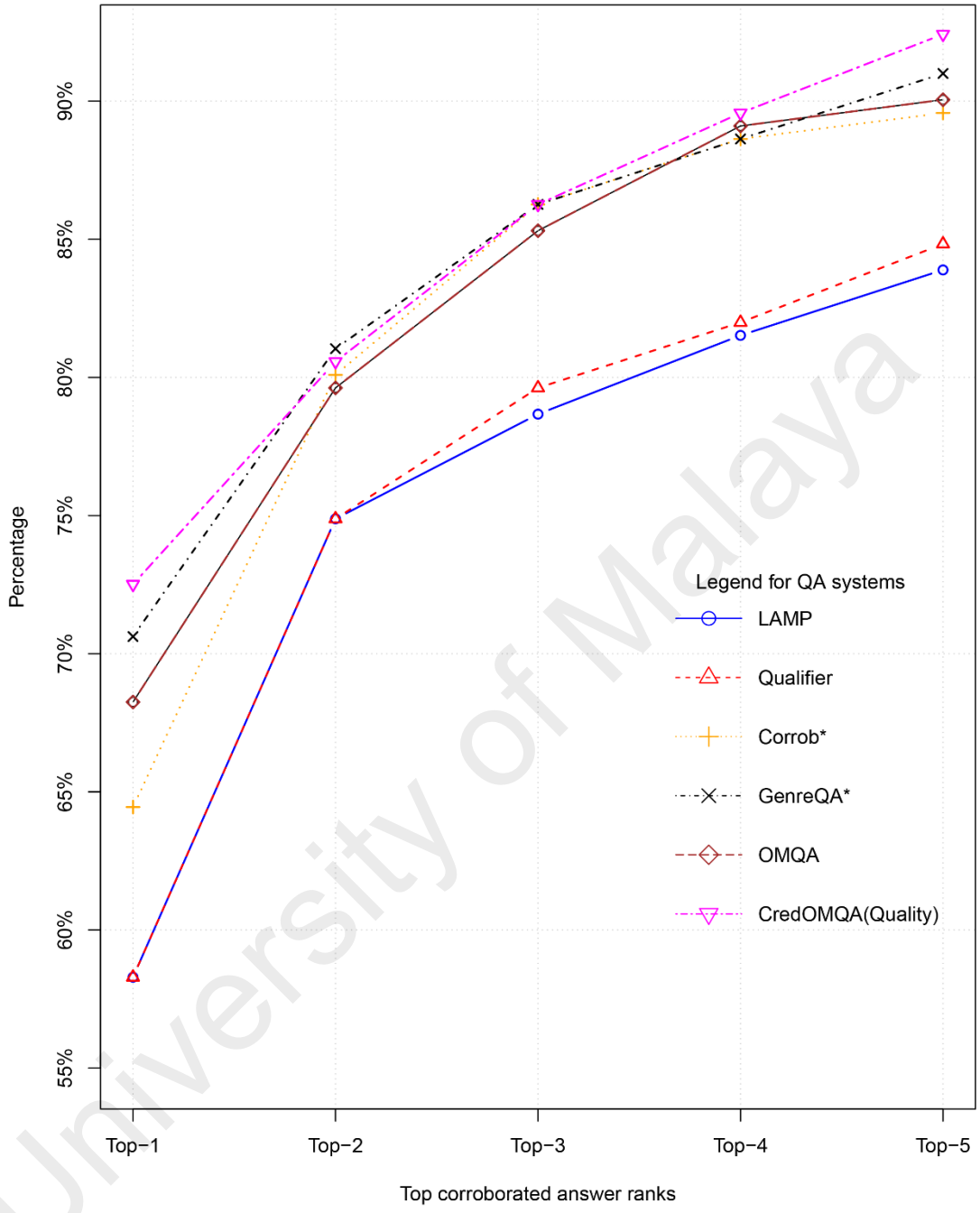


Figure 4.30: PerCorrect results for CredOMQA using quality for *QN*=211

Table 4.19: PerCorrect and MRR results for CredOMQA using quality for *QN*=211

Web-based QA system name	MRR		PerCorrect percentages at different ranks				
	Score	Sig test P-value	Top-1	Top-2	Top-3	Top-4	Top-5
LAMP	0.690	6.855E-16 (**)	58.29% (124)	74.88% (159)	78.67% (167)	81.52% (173)	83.89% (178)
Qualifier	0.693	1.777E-15 (**)	58.29% (124)	74.88% (159)	79.62% (169)	81.99% (174)	84.83% (180)
Corrob	0.732	1.913E-10 (**)	63.98% (136)	76.30% (162)	82.94% (176)	85.78% (182)	86.26% (183)
Corrob*	0.751	8.158E-07 (**)	64.45% (137)	80.09% (170)	86.26% (183)	88.63% (188)	89.57% (190)
GenreQA	0.755	1.192E-06 (**)	65.88% (140)	78.20% (166)	82.94% (176)	87.20% (185)	91.47% (194)
GenreQA*	0.786	0.00908 (**)	70.62% (150)	**81.04% (172)**	**86.26% (183)**	88.63% (188)	91.00% (193)
OMQA	0.770	3.285E-05 (**)	68.25% (145)	79.62% (169)	85.31% (181)	89.10% (189)	90.05% (191)
CredOMQA (Quality)	**0.798**		**72.51% (154)**	80.57% (171)	**86.26% (183)**	**89.57% (190)**	**92.42% (196)**

Note: Sig test P-value, the different levels of asterisk represent the following: (*) indicates significant difference (90% confidence since P-value < 0.10), (**) indicates significant difference (95% confidence since P-value < 0.05), and no asterisk means that difference between systems is not significant

Figure 4.30 and Table 4.19 results show CredOMQA(Quality) system achieving the best results among all other baseline systems. This is because CredOMQA(Quality) system achieved not only the highest MRR score, but had highest PerCorrect percentages at all ranks except top-2 rank. Credibility-based QA systems like Corrob* and GenreQA* fell much shorter in terms of answer accuracy by only being achieve to achieve MRR scores of 0.751 and 0.786 respectively, where as CredOMQA(Quality) system is almost 0.8.

In comparison to other credibility categories, CredOMQA(Quality) system achieved the highest MRR score. This shows that CredOMQA(Quality) system not only achieved better results than baseline systems but also achieved optimal results for significantly improving accuracy of answers. This is also provided in significant testing results as well.

The significant tests share the same picture, clearly showing CredOMQA(Quality) system having significant difference than baseline system in terms of improvement. At confidence level 95%, CredOMQA(Quality) system is significantly different than all baseline systems including GenreQA*. Moreover, CredOMQA(Quality) system is the only category which still shows significant difference against all baseline systems even if the confidence level is extended to 99%.

In conclusion, CredOMQA(Quality) system had the most impact in improving accuracy of OMQA system. This shows that readability and originality scores of the content have a major impact on improving accuracy of answers (Oh et al., 2012; Wu & Marian, 2011). These factors not only help assess the credibility of sources but they also improve the ranking of correct answer, thus improving answer accuracy of the system as well (Wu & Marian, 2011). Readability makes sure that content writers target most of the audience on the Web and not a particular group of people (Microsoft Word, 2016). By keeping the ideal readability level towards college students, it can be ensured that the content is easily readable by most users on the Web including adults and young students (List et al., 2017). The second factor, named originality, makes sure that only unique content is shown to the end users. In case a copy of the original content is found, then answers found from the given sources is given a low answer score, thus promoting sharing of original content (Wu & Marian, 2011).

4.3.9 CredOMQA using all credibility categories

Figure 4.31 shows PerCorrect results and Table 4.20 shows PerCorrect and MRR results for CredOMQA system using all credibility categories. The table also consists of significant test results conducted to compare baseline systems with CredOMQA(AllCategories) system.

Table 4.20: PerCorrect and MRR results CredOMQA using all credibility categories for QN=211

Web-based QA system names	MRR		PerCorrect percentages at different ranks				
	Score	Sig test P-value	Top-1	Top-2	Top-3	Top-4	Top-5
LAMP	0.690	9.059E-16 (**)	58.29% (124)	74.88% (159)	78.67% (167)	81.52% (173)	83.89% (178)
Qualifier	0.693	2.342E-15 (**)	58.29% (124)	74.88% (159)	79.62% (169)	81.99% (174)	84.83% (180)
Corrob	0.732	2.618E-10 (**)	63.98% (136)	76.30% (162)	82.94% (176)	85.78% (182)	86.26% (183)
Corrob*	0.751	1.531E-06 (**)	64.45% (137)	80.09% (170)	86.26% (183)	88.63% (188)	89.57% (190)
GenreQA	0.755	2.244E-06 (**)	65.88% (140)	78.20% (166)	82.94% (176)	87.20% (185)	91.47% (194)
GenreQA*	0.786	0.014606 (**)	70.62% (150)	81.04% (172)	**86.26% (183)**	88.63% (188)	91.00% (193)
OMQA	0.770	6.018E-05 (**)	68.25% (145)	79.62% (169)	85.31% (181)	**89.10% (189)**	90.05% (191)
CredOMQA (AllCategories)	**0.797**		**72.51% (154)**	**81.52% (173)**	85.31% (181)	87.68% (186)	**91.94% (195)**

Note: Sig test P-value, the different levels of asterisk represent the following: (*) indicates significant difference (90% confidence since P-value < 0.10), (**) indicates significant difference (95% confidence since P-value < 0.05), and no asterisk means that difference between systems is not significant

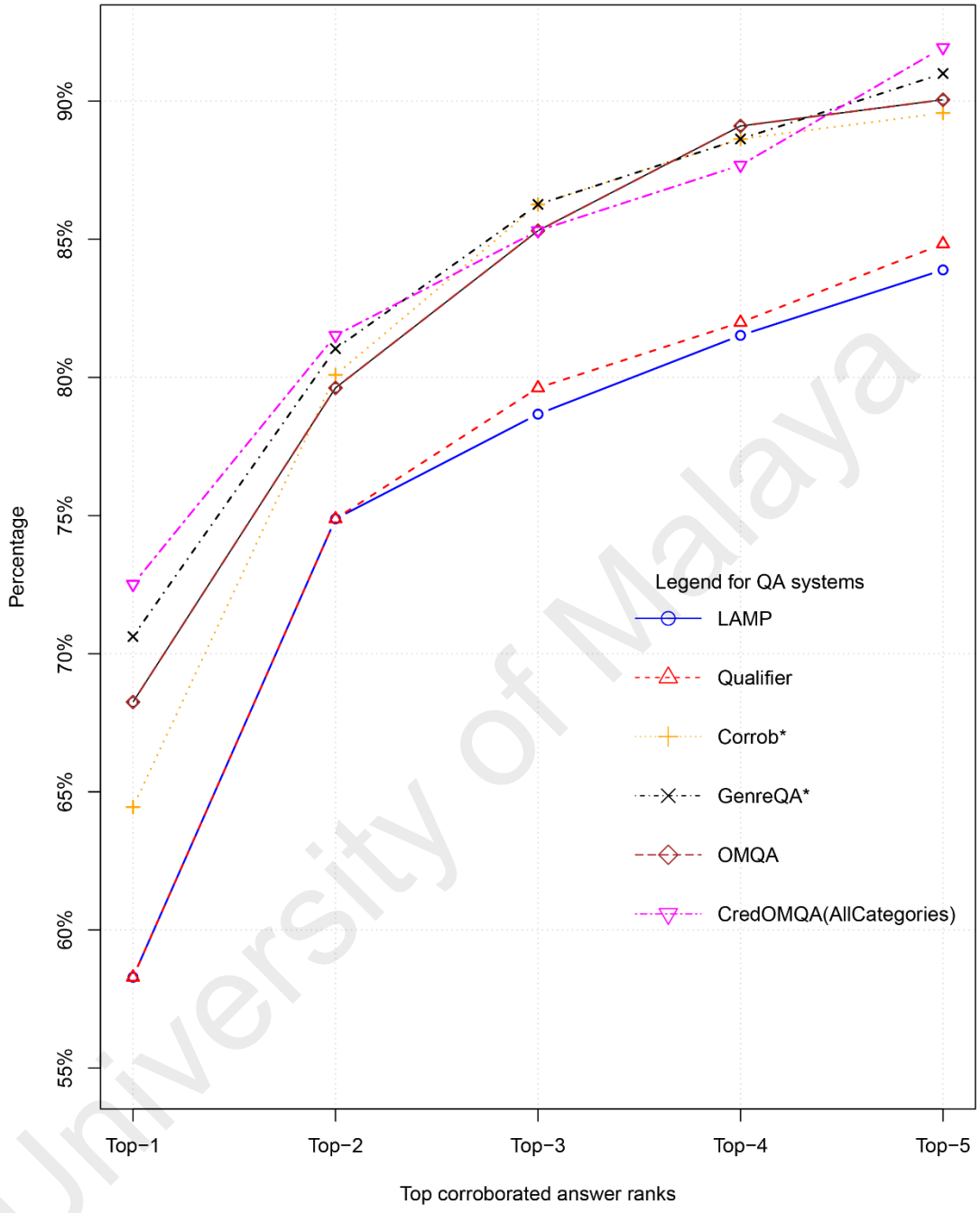


Figure 4.31: PerCorrect results for CredOMQA using all credibility categories for *QN*=211

Figure 4.31 and Table 4.20 share the same result, indicating CredOMQA(AllCategories) system achieving the best results in comparison to all baseline systems. This is because CredOMQA(AllCategories) achieved the highest MRR

score and is also able to achieve highest PerCorrect percentages at top-1, top-2 and top-5 ranks.

CredOMQA(AllCategories) also achieves one of the highest MRR and PerCorrect percentages in comparison to CredOMQA system using individual categories. Though, its accuracy is not as high as CredOMQA(Quality), it is still able to keep a score closer to it.

The drastic difference between CredOMQA(AllCategories) and other baseline is confirmed by looking at the significance test results. The results show that there is significant difference between CredOMQA(AllCategories) and other baseline systems including credibility-based Web QA systems like Corrob* and GenreQA*. Moreover, CredOMQA(AllCategories) is able to achieve this with confidence level at 95%.

In conclusion, credibility answer score showed improved results both in PerCorrect and MRR. Though when considering all categories, it is possible that CredOMQA(AllCategories) accuracy is affected by categories such as authority and currency, that in particular did not perform well . By assigning more weigting to credibility categories like correctness, professionalism, impartiality and quality, the accuracy of CredOMQA(AllCategories) can be extended even further (Wu & Marian, 2011). Despite this, credibility answer score still was able to maintain a healthy percentage by scoring not only higher than baseline systems but also keeping a decent margin.

4.3.10 CredOMQA system result analysis

In this sub-section, the summary of analysis for CredOMQA system results are discussed.

4.3.10.1 Analyzing impact of α on accuracy of answers

Looking at the impact of α on credibility and its categories, it was seen that the ideal values were achieved when α was set to 0.75. For other values of α, either CredOMQA system did not perform well and the results varied as well.. For α=0.75, the PerCorrect results at top-1 and top-2 improved for almost all categories and in MRR results. This shows that in order to reach the correct answer quicker it is better to giving more weighting to frequency while also giving 0.25% of the weighting to credibility (Wu & Marian, 2011). Moreover, α=0.75 should be preferred as it gives better resulst at higher PerCorrect ranks (Wu & Marian, 2011).

4.3.10.2 Credibility categories analysis

The research evaluated the impact of credibility categories, including correctness, authority, currency, professionalism, popularity, impartiality and quality, on answer scoring with respect to answer accuracy. From the evaluation, it was observed that among the seven credibility categories, four of them (correctness, professionalism, impartiality and quality) had a major impact on improving answer accuracy. Especially, quality category which significantly improved accuracy of answers than other baselines even if confidence level is extended to 99%. Though, categories like authority, currency and popularity did not show significant difference in comparison to GenreQA* baseline system, its accuracy is still higher than it. Moreover, for all other baseline systems, these three categories also showed significant difference.

Among the different credibility categories, impartiality and quality stood out the most as they improved the OMQA system's PerCorrect percentages, i.e. CredOMQA system, up to 5%-6% at various corroborated ranks. By giving more weighting to these two categories, the ranking of correct answers is likely to improve further. This is also verified by looking at the improvement in answer accuracy results for Corrob* and GenreQA*

systems, over Corrob and GenreQA respectively, which considered quality category score for scoring answers. For example, Corrob* system improved its PerCorrect percentage from 76.30% to 80.09% at top-2 rank, while GenreQA* improved from 65.88% to 70.62%, which is much contributed to the inclusion of quality category score used by both of these systems. The accuracy of CredOMQA (AllCateogies) can be improved even further by reducing weighting of the least impactful categories like authority and currency.

4.3.10.3 Analyzing the impact of credibility-based answer score

In conclusion, credibility answer scores improved answer accuracy not only for CredOMQA system over OMQA system, but also for Web-based QA systems (Corrob* and GenreQA*). This certainly shows that considering credibility of sources is useful in increasing accuracy of the system. Though the credibility assessment algorithm is used for Web-based QA systems here, it can easily be implemented for other systems used in networking, education, and health domains which rely on data on the Web for processing information (Lu et al., 2017; Sbaffi & Rowley, 2017).

CHAPTER 5: CONCLUSION

This chapter highlights major contributions made by this research, limitations faced and possible future directions.

5.1 Answers to the research questions

Based on the motivation of the research (covered in section 1.1), three research questions were raised (covered in section 1.2). In this section, the research discusses the steps and the objectives met in order to answer these research questions. The research questions and their answers are discussed below

RQ1. How can credibility of Web pages be measured using credibility factors?

This research designed an algorithm for measuring credibility of Web pages in order to achieve RO1 which states *"To design an algorithm for measuring credibility of Web pages"*. This algorithm is defined in this thesis in section 3.3.6 and 3.3.8.4. It uses a number of credibility factors belonging to credibility categories. The research identified the factors such as readability score, sentiment score, originality score, content update date, author name, and others scoring different credibility categories and measuring overall credibility of Web pages

RQ2. What combination(s) of methods and techniques, and credibility categories improve answer accuracy?

The research designed and developed a Web-based QA system called OMQA system, in order to answer RQ1 and achieve RO2 which states *"To design and develop an enhanced Web-based QA system with credibility assessment"*. This OMQA system considers methods and techniques used by Web-based QA system and the OMQA

system is extended further by including a credibility assessment module named CredOMQA system (containing credibility categories) for evaluation, as covered in section 4.1 and 4.3. The research evaluated various methods and techniques and credibility categories based on answer accuracy evaluation metrics, highlighting that not all techniques provided equal answer accuracy. Instead, some techniques performed better than others, while in some cases a combination of techniques provided better accuracy than the techniques themselves. For example, for sentence-matching algorithm, keyword matching provide higher answer accuracy than regex technique. Similarly, combined NER and string-matching techniques achieved higher accuracy than some individual techniques. Moreover, a number of methods depended on other methods, using the optimal technique under a particular method which improved results for other methods as well.

Likewise, some credibility categories like impartiality and quality had more pronounced impact on answer accuracy. Though, four out seven categories (including correctness, professionalism, impartiality and quality) improved answer accuracy significantly, yet three out of these (including authority, currency and popularity) achieved better but not significant results than systems like GenreQA*. Categories such has quality and impartiality categories had a major impact on answer accuracy, having up to 6% higher PerCorrect percentage than other baseline methods.

RQ3. Does considering credibility in answer scoring help in increasing its answer accuracy?

The results gathered from the CredOMQA (AllCategories) system were analyzed, as mentioned in RO3 which states *"To evaluate the impact of credibility assessment on accuracy of the answer by means of evaluation and comparison"*, to address this question. Evaluation results, covered in section 4.3.9, show that

CredOMQA(AllCategories) system was able to achieve higher answer accuracy than other baseline QA systems. It highlights that credible Web pages, having higher credible score, are more likely to contain correct answers thus producing higher answer accuracy. Thus, inclusion of credible assessment in Web-based systems improves accuracy of the system.

5.2 Major contributions

- The research defines a credibility assessment algorithm for evaluating credibility of resources, including categories that contribute towards it, and the types of factors it encompasses. (see CHAPTER 2:, section 2.2.3)
- It identifies credibility factors found in various information systems, maps them onto credibility categories and uses them for evaluation of Web pages. (see CHAPTER 2:, , section 2.2.4 and section 2.3)
- The research developed an algorithm designed for measuring credibility of Web pages, which includes defining of formulae for scoring individual credibility categories contributing towards overall credibility of a Web source. (see CHAPTER 3:, section 3.3.7)
- The research has developed a prototype Web-based system incorporating a credibility assessment module called CredOMQA system, employing multiple methods and techniques identified from literature. (see CHAPTER 3:, section 3.3.4 and section 3.3.7)
- This research provides evaluation results for methods and techniques available in Web-based QA systems, which show that certain techniques, and in some cases combination of techniques, provide higher answer accuracy than individual techniques. These results also show relationship of methods with one another, and how the way improving one method can benefit the other. (see CHAPTER 4:, section 4.1 and section 4.2)

- Lastly, it provides evaluation results showing the impact of credibility assessment on answer accuracy in Web-based QA systems. The CredOMQA system, using the proposed credibility assessment algorithm, achieved higher answer accuracy in comparison with the baseline Web-based and credibility-based Web QA systems tested against. (see CHAPTER 4:, section 4.3)

5.3 Implications of research

This research has implication in the following areas

- **Web-based QA systems:** The introduction of credibility assessment in Web-based QA systems would allow users to have greater confidence in the answer given by the system, making them more credible and accurate. Moreover, evaluation results will allow research in selecting optimal methods and techniques achieving higher answer accuracy.
- **Web surfing and searching:** The research will impact the area of Web surfing, searching, and other services using Web pages as credibility assessment module allows the system to generate a credibility score for Web pages, allowing users to judge its credibility based on the score received in various credibility categories. It helps users select the most credible source, instead of cross-checking a number of sources to verify the information given.
- **Web publishing standards:** Use of credibility assessment in Web services will enforce new Web publishing standards, making content writers provide necessary credibility details, such as, content publishing date, author details, plagiarism ratio of content, readability score, etc.
- **IR, information seeking and heuristics:** The research shall have wider implications because credibility assessment allows researchers/experts in using new ways to improve answer accuracy. Instead of enhancing and improving

retrieval and heuristics methods, sources can be scored with respect to credibility factors related to them. Thus experts would start considering credibility of sources to filter out non-credible sources, thus saving precious time and resources spend on computation.

- **Diverse domains:** The research will impact diverse areas as credibility assessment would prove beneficial to domains such as education, medical, media, stocks and networking. Students who are not capable of conducting proper credibility assessment may use automatic assessment tools to select best sources. Enforcing credibility standards will highlight official medical Web sites on the search engines, lowering percentage of fake Websites. Media, where news required to be accurate and credible, especially on social media, where users are easily mislead by disinformation and propaganda. Finally, stocks and networking domains heavily rely on digital market which unfortunately is heavily affected by fraud and deception. The introduction of credibility assessment in both of these domains would increase accuracy of data by considering credible sources for IR.
- **Credibility assessment in online news:** Credibility of online news has become even more important in today's age due to the rise in fake news on social media platforms like Twitter and Facebook. Providing automatic credibility assessment can not only stop false news from spreading but can also force users to go through a check list of things before news is posted online.

5.4 Limitations

Limitations faced by this research are highlighted below:

Processing time: One of the major limitations in this research was the processing time required to process different methods. Parse Web pages in individual sentences is among the methods that required a lot of processing time. As the research extracted

answers from Web pages, these pages needed to be broken down into individual sentences, using NLP, in order to apply sentence-matching algorithm onto them. Considering each query can have up to 100 Web pages, processing all Web pages required a lot of time (Wu & Marian, 2011). Thus, the max number of Web pages considered for each query was limited to 20, which still required a decent processing to time for covering all 211 TREC questions.

Limited literature: Some of the methods available from literature discussed their working but provided little detail on how to re-produce them (Kolomiyets & Moens, 2011). Regex for sentence-matching is one such example. Literature only provided some examples on creating regex for a question, without proffering an algorithm for creating one on another platform (Wang, 2006; Wu & Marian, 2011). Moreover, only limited examples were covered while the system from literature used only a handful of regex for a question. Despite these limitations, this research tried to generate enough regex expressions to provide satisfactory sentence-matching for the system (Bouziane et al., 2015). Apart from regex sentence-matching, the research faced difficulty in re-producing question classifiers, probabilistic phrase re-ranking and n-gram score function.

Limited API transactions: Another limitation faced was limited transactions per day for APIs used by the system (Aggarwal et al., 2014b). This required delayed evaluation process as a certain number of days are required to be passed before the transaction counter is reset.

Limited credibility APIs: Though the research was able to find a handful of APIs for credibility factors listed in literature, yet there were hardly any APIs available for certain credibility factors (Aggarwal et al., 2014b). Some of the credibility factors that could not be included due to unavailability of APIs, include author qualification or

experience based on name provided, detecting presence of privacy and security policies, detecting presence of editorial board and their qualifications, etc (Lu et al., 2017).

Connectivity issues: Evaluation required running a batch of methods and techniques in order to generate the desired top answers list or credibility score. At times, due to internet connectivity issues or disconnection from requested server, data for method or technique could not be processed successfully. This caused certain queries to be processed again, or requiring a specific method or technique to be rerun after identifying it from the list of processes done.

Addressing factoid question type only: The current system is only able to handle factoid questions only. Thus, there are a number of other question types like list, definition and procedural questions types that the CredOMQA system cannot handle at the moment (Gupta & Gupta, 2012). Moreover, among factoid questions, the current system is only handle person type answers only, which needs to be extended to time, location and entity types (Gupta & Gupta, 2012).

Lack of semantic-based techniques: It was stated that Web-based QA systems do not rely on complex techniques for answering questions. However, in some of the questions sematic-based approaches can play a major role (Ferrucci et al., 2010). For example, in the question "Name birds that eat snakes", the QA system needs to understand the question semantic that the expected answer needs to be birds only (Molino et al., 2015). Unfortunately, most Web-based QA system types use keyword for finding answers, where it may only focus on finding sentences mentioning the keywords bird, snake and eat without focus on the requirement of the question. Thus, the addition of semantic-based techniques can allow the system to properly understand the question and provide the correct answer (Höffner et al., 2016).

Limited to text-based answering: The current system is able to answer text-based questions only. There other data types out there where question answering can be applied including images, videos, and audios. Moreover, the QA system also needs to extend its capabilities in performing queries on databases and ontologies(Gupta & Gupta, 2012).

Multiple datasets: Some of the systems reviewed in literature used multiple datasets for answering questions (Oh et al., 2012). This provides excellent accuracy of answers as the system can consider a specific dataset for answer questions belonging to a certain domain (Oh et al., 2012). For example, when dealing with medical questions the QA system can select medical databases only for answer extraction.

Providing results in real-time: The current system is developed on a PC. The credibility-based answers generated require question answer processing and Web pages credibility-assessment to be done. The current system takes around 4-10 mins to answer a single question. By deploying the CredOMQA system on a powerful server the questions can be answered in real-time.

5.5 Lessons learnt

In this sub-section, the research highlights the lessons learnt from the problems faced during the course of the study and steps that can be taken to avoid them.

Usage of server: All results were processed on a PC due to which a lot of time needed to be spent in generating results. Not only that, most of the batch requests need to be done one at a time since the PC would either take too long to process a particular request or timeout. This was also one of the limitations of our research as well. This could had been avoided if the QA system was deployed on a powerful server allow the system to generate results quickly and also be able to process multiple requests in parallel. Moreover, a server

with 24/7 internet, data backup and power backup would had ensured that all transactions are processed successfully and their backup is also being maintained by the server.

Choice of platform: Our main reason for choosing Php was due to our experience on the given platform. However, the research faced a lot of issues when trying to find off the shelf solutions for the given platform, which were easily available on other platforms like Python and Java. If more time was spent in choosing a platform which offers the most off the shelf solutions then it would had allowed the research to only include those solution instead of developing themselves.

Storing results in Databases: Currently all results are saved in text file format. Though it seemed easier at first but storing results for all methods, techniques, credibility categories, baseline systems and others is a huge problem. Not only it makes the data unmanageable but makes it difficult for us to find relevant data. If the results were stored in relational databases instead it would had allows us to form relationships between different tables and allow generate results easily using structured query language offered by a database management system. Moreover, databases is more suitable when multiple processes are being performed at the same time since it caters for concurrent access.

Full licensed plan for APIs: Due to financial issues of the project only free licensed APIs were chosen that offered limited transactions only. This caused the project of often wait until more transactions were available to be performed. By buying a fill licensed plan for API, the transaction limits could had been avoided allowing the QA system to perform as much transactions as possible. This would had saved a lot of time and also had allowed the QA system to generate answer much quickly.

Reviewing Web-based QA systems: A lot of time was spent on reviewing different Web-based and credibility-based Web QA systems. Reviewing these systems involved

identifying methods and techniques, and credibility factors used by these systems. This process could had been improved by first reviewing survey papers on Web-based QA systems and credibility-based Web QA systems (Allam & Haggag, 2012; Kolomiyets & Moens, 2011; Mollá-Aliod & Vicedo, 2010; Webber & Webb, 2010). This is because most of these survey papers have provided details on most of the methods and techniques used by Web-based QA system and credibility factors used by them. Moreover, they have identified the state-of-the-art Web-based QA systems available that can be used for comparison purposes. By reviewing survey papers first, and then individual Web-based QA systems would had saved more time and made the process smoother.

OMQA system architecture: The OMQA system architecture went through different revisions. This is because new modules and its methods were added to it as they were identified by reviewing different systems. Later on, the research came across survey papers which have defined model of a general Web-based QA system (Gupta & Gupta, 2012). Thus, different revisions of OMQA system could had been avoided if the model of general Web-based QA system was followed from the start (Gupta & Gupta, 2012).

Relative scoring: Initially only absolute values of answer scores and credibility factor scores were used. This caused problems when computing an aggregate score using multiple scores with different ranges. This problem could had been avoided sooner if the scores were scored between 0 to 1 instead of their absolute values.

Significant testing: Initially, when computing results only PerCorrect and MRR evaluation metrics were used. Though these metrics are great for portraying accuracy of Web-based QA systems, yet they need to be looked into greater detail when comparing systems having nearly equal MRR scores. It was realized later that significant testing is a better way of showing significance difference between two systems, instead of providing evidence by looking at percentages different PerCorrect levels.

5.6 Future work

This research identifies the following directions for future work.

Evaluating complex question types: The current research conducted evaluation on Web-based QA systems using factoid questions. It would be interesting to see how answer accuracy is impacted by credibility factors on complex question types including list, definition, procedural and others. More importantly, to see whether question classification such as what, why, where, when and how classifications, and expected answer types are affected differently or not?

Evaluating semantic-based QA systems: In future, the research would also like to work on complex systems using machine learning and semantic-based approaches. The availability of complex methods will allow the research to address some of the complex question types and also address limitations that were not possible to address using NLP and IR-based techniques

Semantic-based techniques in credibility assessment: Just like using semantic-based techniques can assist in improve accuracy of methods and techniques used in question analysis and answer extraction, it can also be applied to credibility assessment. Semantic-based techniques can be applied to categories like correctness, authority and currency. For example, semantic-reasoning can be applied for questions like “Name birds that eat snakes” where simple sentence-matching keywords might return answers contain “Snakes that eat birds” instead without understanding the structure and context of the question. Semantic-based techniques can also be used to build evidence to support an argument which was not possible using NLP and IR-based techniques.

Assigning weights from case to case basis: Individual weights were not assigned to the categories in the study (i.e. correctness for example was not considered to be more important than professionalism), hence future studies could further investigate if results can be improved when specific importance is given to each of the categories (i.e. by assigning weights).

Multiple datasets: Highlighted in limitations as well, in future research would like to expand the system to multiple datasets. This would allow the QA system to select the most appropriate dataset for the question asked and also be able to rate answers fetched from a specific dataset higher based over others for a given question. Moreover, the system needs to be expand to make use of databases and ontologies.

Addressing disagreeing views: Disagreeing views is a very interesting topic where a conclusion facts needs to be drawn from multiple Webpages of equal weightages that are stating conflicting facts. As an example, the birth date of Napoleon Bonaparte, an important topic among historians where it is debated whether Napoleon was born French or Italian, and whether his date of birth is August 15, 1769 or as January 7, 1768 . The research would like to look into algorithms along with credibility information of Web sources used to compile factors from multiple sources and suggest conclusive facts relating to the question asked.

Other data types: The research would also like to explore credibility assessment on other data types including images and videos. The current research focused primarily on text data, as dealing with other data types would have required different methods and techniques for evaluation and even additional and different credibility factors for credibility evaluation.

Other domains: In the future, this research could be expanded also like to evaluate credibility assessment on other types of systems like social media platforms, blogs, databases that may be providing stocks, networking and education information. This would require further research in exploring new credibility factors for evaluating credibility categories.

5.7 Conclusion

The research successfully and categorically answered all the research questions. It also designed and implemented an algorithm for measuring credibility of Web pages and developed a prototype credibility-based Web QA system. This prototype system is the first of its kind to have a dedicated credibility assessment module and to cover all seven categories concerning credibility of Web sources. This system greatly improved accuracy of answers in comparison to QA system not using Web credibility assessment. The research is confident that Web credibility assessment will have wider implications for improvement of credibility of Web sources.

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