AUTOMATIC DETECTION METHODS OF STUDENTS' LEARNING STYLES IN LEARNING MANAGEMENT SYSTEM

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AUTOMATIC DETECTION METHODS OF STUDENTS' LEARNING STYLES IN LEARNING MANAGEMENT SYSTEMS

ABSTRACT

Online learning has become a common phenomenon nowadays. Many distance-learning systems or platform distribute educational resources online. Meanwhile, in order to satisfy students' learning experience and to improve learning effectiveness, students' characteristics should be considered, from the point of view of knowledge level, goals, motivation, individual differences and many more. The focus of this thesis is on the learning style as the criterion. Students are characterized according to their own distinct learning styles. Identifying students' learning style is vital in an educational system in order to provide adaptivity. The first step towards providing adaptivity is knowing students' learning style. Past researches have proposed various approaches to detect the students' learning styles. However, the results obtained from the past researches have been disparate in terms of precision. Broadly speaking, the existing automatic detection approaches are only able to provide satisfactory results for specific learning style models and/or dimensions, or even only work for certain educational systems. The aim of this thesis is to study on an automatic detection of learning styles to address the existing issues, mainly focusing on improving the precision of detection. The first proposed approach for automatic detection is the construction of a mathematical model from the analysis of students' learning behaviour. This approach specifically explores the relationship between students' learning behaviour and their learning styles. However, the precision of the results obtained from this approach show only moderate precision, equivalent to the results obtained from the past researches. A possible reason for this is that the approach is designed for general applicable model with relatively loose conditions. To further improve the precision of the detection, this thesis next proposes tree augmented naïve Bayesian network for automatic detection of learning styles. Bayesian network has

emerged as widely a used method in this field but, then again, tree augmented naïve Bayesian network has the ability to improve the classification precision. The performance of tree augmented naïve Bayesian was evaluated in an online learning environment called Moodle. The experimental results are very encouraging. The proposed tree augmented naïve Bayesian network method is able to provide good results for all dimensions of Felder-Silverman learning style model, which can be seen as an appropriate method to detect learning styles with higher precision.

Keywords: learning styles, automatic detection, learning behaviour pattern, Bayesian network.

KAEDAH PENGESANAN AUTOMATIK GAYA PEMBELAJARAN PELAJAR DALAM SISTEM PENGURUSAN PEMBELAJARAN

ABSTRAK

Pembelajaran dalam talian telah menjadi fenomena biasa pada masa kini. Banyak sistem pembelajaran jarak jauh atau platform mengedarkan sumber pendidikan dalam talian. Sementara itu, untuk memenuhi pengalaman pembelajaran pelajar dan untuk meningkatkan keberkesanan pembelajaran, ciri-ciri pelajar harus dipertimbangkan, dari segi tahap pengetahuan, matlamat, motivasi, perbezaan individu dan banyak lagi. Fokus tesis ini adalah pada gaya pembelajaran sebagai kriteria. Pelajar dicirikan mengikut gaya pembelajaran mereka sendiri. Mengenal pasti gaya belajar pelajar adalah penting dalam sistem pendidikan untuk menyediakan penyesuaian. Langkah pertama ke arah penyesuaian ialah mengetahui gaya pembelajaran pelajar. Penyelidikan yang lalu telah mencadangkan pelbagai pendekatan untuk mengesan gaya pembelajaran pelajar. Walau bagaimanapun, keputusan yang diperoleh daripada penyelidikan yang lalu adalah berbeza dari segi ketepatan dan kejituan. Secara umum, pendekatan pengesanan automatik sedia ada hanya dapat memberikan hasil yang memuaskan untuk model gaya pembelajaran tertentu dan / atau dimensi, atau bahkan hanya berfungsi untuk sistem pengurusan pembelajaran tertentu. Tujuan tesis ini adalah untuk mengkaji pengesanan automatik gaya pembelajaran untuk menangani isu-isu yang wujud, terutamanya memberi tumpuan kepada meningkatkan kejituan pengesanan. Pendekatan pertama yang dicadangkan untuk pengesanan automatik ialah pembinaan model matematik dari analisis tingkah laku pembelajaran pelajar. Pendekatan ini secara khusus menerangkan hubungan antara tingkah laku pelajar dan gaya pembelajaran mereka. Walau bagaimanapun, kejituan keputusan yang diperoleh daripada pendekatan ini menunjukkan hanya kejituan sederhana, bersamaan dengan hasil yang diperoleh daripada penyelidikan yang lalu. Sebab yang mungkin untuk ini ialah pendekatan ini direka bentuk untuk model umum

yang berkaitan dengan keadaan yang agak longgar. Untuk meningkatkan kejituan pengesanan, tesis ini seterusnya mencadangkan pokok ditambah rangkaian Bayesian naif untuk pengesanan automatik gaya pembelajaran. Rangkaian Bayesian telah muncul sebagai kaedah yang digunakan secara meluas dalam bidang ini tetapi, sekali lagi, pokok ditambah rangkaian Bayesian naif mempunyai keupayaan untuk meningkatkan kejituan pengelasan. Prestasi pokok ditambah rangkaian Bayesian naif dinilai dalam persekitaran pembelajaran dalam talian yang dipanggil Moodle. Keputusan eksperimen sangat menggalakkan. Pendekatan pengesanan automatik dapat memberikan hasil yang baik untuk semua dimensi gaya pembelajaran model yang digunakan, yang dapat dilihat sebagai sesuai untuk mengesan gaya pembelajaran dengan ketepatan yang lebih tinggi.

Keywords: gaya pembelajaran, pengesanan automatik, tingkah laku pembelajaran, rangkaian Bayesian.

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TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF SYMBOLS AND ABBREVIATIONS

AEHS	:	Adaptive educational hypermedia system
ASSIST	:	Approaches to study skills inventory for students
BN	:	Bayesian network
CPT	:	Conditional probability table
CSA	:	Cognitive styles analysis
CSI	:	Cognitive styles index
DNA	:	Deoxyribonucleic acid
DT	:	Decision tree
FSLSM	:	Felder-Silverman learning style model
HMM	:	Hidden Markov model
ILS	:	Index of learning style
ITS	:	Intelligent tutoring system
IQ	:	Intelligence quotient
LMS	:	Learning management system
LS	:	Learning style
LSI	:	Learning style inventory
LSQ	:	Learning style Questionnaire
MBTI	:	Myers-Briggs type indicator
MLFF-NN	:	Multi-layer feedforward neural network
NN	:	Neural network
SA	:	Self-assessment
STDEV	:	Standard deviation

LIST OF APPENDICES

CHAPTER 1: INTRODUCTION

In this chapter, an overview of the thesis is presented. The chapter starts with a discussion on the background of the study and followed by statement of problem within which this study was conducted. The objectives and significance of the study is explained next. Then the structure of thesis is presented.

1.1 Background of the study

Today, an increasing number of academic institutions, such as universities, provide e-learning courses. Several of these e-learning courses are conducted as mixed-mode courses with a mix of online and traditional education methods, whereas others are conducted completely online. Accordingly, e-learning courses require an environment where they can be organized and managed. Usually, a learning management system (LMS) can fulfil this task by offering several features in providing support for teaching and managing online courses and tests. However, they do not usually consider students' individual differences because all students are treated equally.

Individual students are essential to both technology-enhanced learning and traditional learning. Each student has his or her own personal needs. Furthermore, students' characteristics differ from one another, such as ability, family background, personal goals, knowledge foundation, and learning style (Surjono, 2014; Yarandi et al., 2013). Several studies (Bajraktarevic et al., 2003; Graf & Kinshuk, 2007) regard learning style as a crucial factor in the learning process to determine learning effectiveness—courses regarded as easy by some students are considered difficult by others (Jonassen & Grabowski, 2012). Psychological and educational theories argue that students have various learning methods. For example, Felder and Silverman (1988) found that if a teaching style is not suitable for a student's learning style, students who have a strong preference for a particular learning style may have learning difficulties. From a theoretical perspective, when teaching considers students' learning styles, learning efficiency is greatly improved. However, when students' learning styles are not suitable, learning efficiency is reduced (Graf & Liu, 2010). Consequently, past researchers have found that learning styles should be considered to maintain students' motivation and promote effective learning (Harris & Reid, 2005; Shockley, 2005).

1.2 Statement of the problem

The goal of an adaptive educational system is to offer students courses that meet their individual needs, including learning styles. Many adaptive systems that focus on learning styles use collaborative methods that require students to fill out questionnaires to detect their learning styles. However, these questionnaires have several problems (fixed questions/results, significant time required, and lack of patience from respondents to answer questions). By using collaborative method, the actual learning behaviour pattern in the learning process may not serve as an effective source to detect learning styles. On the contrary, this implies that students' learning behaviour could be used data to infer their learning styles.

Previous studies use the actual learning behaviour pattern in the learning process to automatically detect learning styles. Several studies adopted a literature-based approach (Bernard et al., 2017; Cha et al., 2006; Crockett et al., 2011; Graf & Liu, 2008; Limongelli et al., 2009) with a deterministic interface system design based on pre-defined behavioural patterns to detect students' learning styles. Several researchers (Cabada et al., 2009; García et al., 2007; Zatarain-Cabada et al., 2009) have suggested data-driven approaches, including Bayesian networks, neural networks, and fuzzy models.

Several restrictions were identified in automatic detection approaches because literature-based approaches are uncertain, difficult, and complex when developing rules. Although these are rule-based methods for calculating learning styles based on the match number of behaviour patterns, it is possible that some patterns may not consider calculating the behavioural indicators of learning styles (Atman et al., 2009; Dung & Florea, 2012a). Simultaneously, the limitations of these data-driven approaches include high complexity and computational cost. Such as the neural network method (Latham et al., 2013; Hasibuan et al., 2019), it is very complex to define number of hidden layers and difficult to identify rules for both inputs and outputs. Thus, these approaches cannot easily be reused in other systems because the system and the entire learning process are highly integrated and coupled, so the approaches are tied to a specific system and cannot be generalized to other systems. Nonetheless, the precision of the detection results can be improved.

Although several data-driven approaches achieved very high detection precision results at more than 80%, they have several critical limitations. For example, the approach proposed by Cha et al. (2006) could identify a specific learning style dimension at 100% but can only identify students who have a strong learning style preference and not those with a balanced preference. Sheeba & Krishnan (2018)'s work could identify student's learning style at 89%, but only tested for limited learning style dimensions. The approach proposed by Latham et al. (2012) could identify students' learning style at 72%–86% but is limited to the Oscar intelligence tutoring system. Since automatic approaches have been proposed for LMSs, results have yielded between 66% and 77% of average precision in detecting learning styles (Bernard et al., 2017); an improvement could be made before using those approaches effectively. An automatic learning style detection approach with precision in detecting results, not tied to a specific learning system, and capable of identifying students with strong and balance preference is needed for practical use in educational platforms.

1.3 Objectives of the study

This thesis investigated the impact of different aspects of using learning styles to provide adaptivity in online learning environments, especially in learning style detection techniques and student modelling. The research goal of this study is to propose learning style detection methods to infer students' learning style automatically.

The objectives of this study are as follow:

1. To formulate a mathematical model based on correlational matrix to represent the relationship between learning behaviour patterns and learning styles for learning style detection in Learning Management System (LMS).
2. To develop a tree augmented naïve Bayesian classifier to enhance learning style detection in LMS.
3. To investigate the relationship of index of learning style semantic groups and learning behaviour patterns in learning management system for more accurate detection and provision of learning style.

1.4 Significance of the study

The research presented in this thesis addresses the limitation in designing and developing detection algorithms with the goals to improve the process of learning style detection and the detection precision results.

Existing automatic approaches in detecting learning styles for LMSs achieved an average precision between 66% and 77% (Bernard et al., 2017). As previously stated, the goals of this thesis are to improve the automatic detection precision results for practical use. Two new approaches have been proposed and evaluated. The first is the automatic detection of learning style using a correlation matrix of learning style dimension and learning behaviour. This approach is designed based on a simple correlational relationship and attempts to remove the reusable problem between student models and automated detection techniques and educational systems. The performance of this approach, at 58.77%–68.09% precision, is modest but promising. Hence, a further optimization algorithm is still required to improve performance.

The second approach is based on a tree augmented naïve Bayesian network. Tree augmented naïve Bayesian network combines the ability of Bayesian networks to represent dependencies with the simplicity of naïve Bayes. This approach worked with widely used LMS Moodle and achieved acceptable results at 71.99%–75.18% precision. The results are deemed better than those produced by existing approaches due to the small standard deviation and capability to identify not only students with strong learning style preference but also those with balanced preference unlike existing approaches. By improving the precision of automatic learning style detection, students could benefit directly because the learning styles are identified more accurately, which enables them to exploit their strengths related to learning styles and acknowledge their weaknesses. Furthermore, this information on learning styles could be used by teachers for advising their students more accurately, which would benefit the students.

It is crucial to consider which characteristics of the learning style model are supported by the educational system when building an accurate and holistic student model, that requires more detailed learning style preference characteristics information. In this work, one of the research objectives is to determine the preferences characteristic of every learning style dimension and their related behaviour patterns. Although the previous research (Graf et al., 2017) explored the semantic group preference characteristics and related learning behaviour, the exploration was based on the literature about learning style model theory. The correlation analysis method is able to associate between learning style semantic group preference characteristics and learning behaviour directly, which is unlike previous research. Thus, this correlation analysis method can be considered as an analysis tool. By using this tool, it allows to provide more detail and accurate description of students' preference characteristic. Based on the more detailed information, more accurate detection and provision of learning style could be provided.

1.5 Structure of the Thesis

The thesis is divided into 7 chapters. In the next chapter (chapter 2), a review of learning styles is provided, describing common learning style models, implications of learning styles in education, as well as criticism and challenges in the field of learning styles. And then introduces the general aspects of detection and adaption of educational systems, including reviews of different types of educational system and various detection techniques.

Chapter 3 presents an automatic detection of learning style approach based on correlation analysis of students' learning behaviour and learning styles.

Chapter 4 presents an automatic detection of learning style approach using tree augmented naïve Bayes to improve the precision of the correlation analysis approach.

Chapter 5 focuses on the analysis of experimental results for both approaches. The comparison was made between the two proposed approaches and past researches.

Chapter 6 summarizes the thesis by highlighting and discussing the findings.

Chapter 7 concludes the thesis and its limitation, and recommendation for future work.

CHAPTER 2: LEARNING STYLES AND ITS APPLICATION IN EDUCATIONAL SYSTEMS

This chapter introduces learning styles and reviews their models. It also analyses learning styles application in educational systems, highlights student modelling approaches and discusses automatic learning style detection methods.

2.1 Learning Styles

The learning style field is complex and is subjected to multiple influences, leading to different perspectives and concepts. The concept that individual learning and dealing with information has been influenced by these differences in learning settings in order to accommodate the teaching styles to account for these differences. Nevertheless, numerous contradictory theories have influenced the concept of learning style and the impact of teaching on the learning process, for instance: a clear definition of learning style is not available, lack of effective and reliable measurements to infer learning styles, the absence of DNA studies that reveal the genes that are related to learning styles (Coffield et al., 2004), lack of empirical research, convincing evidence and statistical importance to prove the value of learning styles (Akbulut & Cardak, 2012; Pashler et al., 2008) and the differences between psychologists in distinguishing between learning styles and cognitive styles (Brown et al., 2009; Coffield et al., 2004).

This results in the findings being split into four directions in the context. First, these terms could be employed interchangeably (Stash, 2007). Another direction suggests that the learning style is an umbrella that covers other traits of cognitive style (Coffield et al., 2004; Riding & Cheema, 1991; Wolf, 2007). Contradictorily, Allinson and Hayes (1996), and Brusilovsky and Millán (2007) argued that learning styles are a subset of cognitive styles that are narrower. According to Peterson et al. (2009), and Sadler-Smith (2001), learning and cognitive styles are two independent constructs. However, Kozhevnikov (2007) made a conclusion that the interrelationship between these traits remains an open question which is explainable by the overlap, that is obvious, between the interdependence between different learning's dimensions and cognitive style models, and their respective definition.

Learning style, learning strategies, and cognitive styles are often used in similar contexts and can even be interchanged. The definitions of learning styles, learning strategies, cognitive styles and their differences are described below.

"A clear definition for learning styles is unavailable since researchers have separately worked to tackle many issues in the field of style" (Lau & Yuen, 2010). Dunn and Dunn (1974) defined learning style as "the manner in which at least 18 different elements from four basic stimuli affect a person's ability to absorb and retain". Felder and Silverman (1988) defined it as "characteristic strengths and preferences in the ways 'learners' take in and process information". It is also defined as "a description of the attitudes and behaviours which determine an individual's preferred way of learning" by Honey and Mumford (1992). James and Gardner (1995) defined as "complex manner in which, and conditions under which, learners most efficiently and most effectively perceive, process, store, and recall what they are attempting to learn". Brusilovsky and Millán (2007) attempted to distinguish between learning and cognitive styles by defining the former as the preferred ways to learn for individuals. In another research, "an individually preferred and habitual approach to organizing and representing information" was the definition given for cognitive style (Brusilovsky & Millán, 2007; Chen & Macredie, 2002). Another definition by Allinson and Hayes (1996) stated it as "individual differences in information processing". Similarly, Clarke (1993) defined it as "essentially means the unique and preferred way in which individuals process information". In a nutshell, the definition of learning styles is defined as the preferred way to learn, process, and organize information.

2.1.1 Effects of learning style in learning environments

Many studies have reported the positive effects of incorporating learning styles in learning environments, especially educational learning systems. These effects could be seen in learning performances when teaching and learning style match, learning satisfaction (Popescu, 2010; Sangineto et al., 2008; Triantafillou et al., 2004; Vassileva, 2011), learner's navigational behaviour, learning patterns, learning time and learning efficiency and effectiveness.

The outcome of the learning process are positively affected by teaching style and the learning style if these two factors match well (Bajraktarevic et al., 2003; Biggs, 1987; Dorça et al., 2013; Felder & Brent, 2005; Felder & Silverman, 1988; García et al., 2005; Graf, 2009; Papanikolaou & Grigoriadou, 2004; Pask, 1976; Sangineto et al., 2008). Prior researches found impacts that are positive on learners' satisfaction (Popescu, 2010; Sangineto et al., 2008; Triantafillou et al., 2004; Vassileva, 2011), learners' navigational behaviour (Chen & Macredie, 2002; Stash & De Bra, 2004), learners' learning patterns (Chen & Liu, 2008), learning performance (Bajraktarevic et al., 2003; Lau & Yuen, 2009; Mampadi et al., 2011; Vassileva, 2011), learning efficiency and effectiveness (Dung & Florea, 2012b) and learning time (Graf & Kinshuk, 2007; Klašnja-Milićević et al., 2011).

In addition, learners' awareness of their own learning style can help them to choose and adopt the learning strategies that are most suitable for their learning style, thus saving learning costs. On the other hand, "forcing students to acquire a variety of learning materials that do not match their styles also can promote an individual's learning experience" (Zapalska & Brozik, 2006).

2.2 Learning Styles Models in Educational Systems

There are lots of learning style models in the literature, each of which proposes different instruments and classifications of learning types. Coffield et al. (2004) categorized 71 learning style models into 13 major models with respect to their theoretical significance in this field. Moreover, a great deal of researches had been made on different aspects of these learning style models over the past 30 years. For example, as described by Coffield et al. (2004), between 1985 and 1995, over 2000 publications about Myers-Briggs Type Indicator (Myers, 1962) were written, over one thousand articles were written on the Kolb learning style model (Kolb, 1984) and the learning style model of Dunn and Dunn (Dunn & Dunn, 1974).

Because the number of learning style models in the literature is huge, Coffield et al. (2004) divided the learning style models into five groups which are based on a few of the general idea supporting the model, whereby the views of the main theorists of the learning style had been reflected.

The first group deals with learning styles and preferences, primarily based on constitutional perspectives, including four modalities: visual, kinesthetic, auditory, and tactile (e.g. Dunn and Dunn, 1974). The second group relies on that fact the learning style reflects the deep-rooted features of the cognitive structure, which includes the patterns of abilities (e.g. Gardner, 1983). The third group uses learning style as a component of a relatively stable personality type (e.g. Myers, 1962). As for the fourth category, learning styles are seen as flexible learning and preferences of stable learning (e.g. Honey and Mumford,1992). The last group shifts from learning styles to learning strategies, orientations, approaches, and conceptions (e.g. Entwistle, 1998).

The next section reviews 7 commonly used learning style models from each learning style family. The selection of these models is contingent upon the review of Coffield et al. (2004), including the theoretical significance, wide usage, and their impact on other learning style models. In addition, the extent to which learning style models are used in technology-enhanced learning is viewed as a crucial criterion in this review.

2.2.1 Gardner's Multiple Intelligences Theory

In his theory of Multiple Intelligences, James & Gardner (1995) proposed that there is more to intelligence than the widely accepted traditional definition. Gardner's theory of multiple intelligences expands the traditional notion of intelligence (based on IQ testing) to describe eight different aspects of intelligence, as follows:

- Visual/Spatial, known as "picture smart‟, spatial intelligence describes the ability to visualize spaces internally in the mind, e.g. when navigating or playing chess.

- Linguistic/Verbal, which is also known as “word smart‟, linguistic intelligence describes the ability to use words to express ideas and understand other people.
- Logical/Mathematical, which is referred as “number smart‟, logical/mathematical intelligence describes the ability to reason and understand causal systems or manipulate numbers.
- Bodily/Kinesthetic, which is referred as “body smart‟, bodily/kinesthetic intelligence describes the ability to use one’s body skillfully.
- Musical/Rhythmic, known as “music smart‟, musical intelligence is the capacity to think in music, hearing, recognizing and repeating patterns.
- Interpersonal, which is referred as “people smart‟, interpersonal intelligence is the ability to understand other people.
- Intrapersonal, which is referred as “self smart‟, intrapersonal intelligence refers to an introspective and reflective understanding of oneself, one’s abilities, desires, reactions and weaknesses.
- Naturalistic – known as “nature smart‟, naturalistic intelligence describes the ability to nurture and relate information to the environment.

Although not specifically related to learning, Gardner proposes that teaching should broaden its traditional linguistic and logical focus to incorporate different activities that better serve students with strengths in different intelligences. Gardner has not defined a test to assess an individual’s Multiple Intelligences, as he believes it to be “more of an artistic judgement than of a scientific assessment" (Gardner, 2011). The EDUCE adaptive computerized educational system (Kelly & Tangney, 2006) successfully uses Gardner's Multiple Intelligences theory as a basis for dynamically modelling learners' characteristics and delivering adaptive learning material. However, the model has been criticized as it does not redefine intelligence, but rather describes different abilities and skills.

2.2.2 Myers-Briggs Personality Types

The Myers-Briggs Type Indicator (MBTI) (Myers, 1962) categorizes an individual's personality type and their approach to relationships. Although MBTI is not a learning style model, Coffield et al. (2004) reviewed it as part of the family of theories, proposing that learning styles is one observable aspect of personality. The scope of MBTI includes learning and it is widely used in consultancy and training as a career development and managerial tool (Furnham & Medhurst, 1995). The MBTI model has also been used in computerized learning. For example El Bachari et al. (2010) designed an adaptive e-learning system based on learner personality.

MBTI classifies a person's personality based on the following four dichotomies (The Myers and Briggs Foundation):

- Extroversion/Introversion describes the preferred focus of an individual on the outer world of people and things (extravert) or inner world of thoughts and ideas (introvert).
- Sensing/Intuition describes the way individuals perceive information – from their five senses (sensing) or from patterns and possibilities in the information (intuition).
- Thinking/Feeling categorizes the way individuals evaluate information – contingent upon logical judgements like true or false (thinking) or on subjective evaluations such as better or worse (feeling).
- Judging/Perceiving describes how individuals live their outer life – preferring a structured and decided (judging) or flexible and adaptive (perceiving) lifestyle.

The MBTI is evaluated using Form M (Myers et al., 1985), a 93-question forced-choice questionnaire resulting in one of sixteen MBTI types (based on the combinations of the dichotomies, e.g. ISTJ (Introversion, Sensing, Thinking, Judgment). The dichotomies are not independent, as each MBTI type represents a set of complex relationships between dichotomies known as type of dynamics and are described by positive and negative traits.

2.2.3 Riding's Cognitive Styles Analysis

The Cognitive Styles Analysis (CSA) as introduced by Riding and Cheema (1991), samples the processing activities between the primary sources, the cognitive inputs form and outputs to the external world.

The cognitive style analysis was developed for assessing the two dimensions (Wholist/ Analytical and Verbal/ Imagery) of cognitive style model (Riding & Cheema, 1991). There are 3 sub-tests involved. The first sub-test is to measure Verbal/ Imagery dimension by putting forth 48 statements (true or false for each statement) one at time in 12 minutes. The next two following sub-tests (3 minutes for each) are employed for measuring the Wholist/ Analytical dimension. In the second subtest, 20 items having pairs of complex geometric figures are presented so that the individual judges to be the same or different, and in the third subtest, 20 items are being presented. Each includes simple and also complex geometrical shapes so that it is up to the individual to determine if the complex shape contains the simple shape.

Although Sadler-Smith and Riding (1999) supported the construct validity of the CSA test and also the independence of the two dimensions of intelligence, Peterson et al. (2003) and Rezaei and Katz (2004) showed measurements of this test having low reliability.

2.2.4 Entwistle's Approaches and Study Skills Inventory for Students

Entwistle's research (Entwistle, 1981; Entwistle, 1998) focuses on students' strategies for learning, proposing that learning styles are not fixed by inherited characteristics, but are affected by the learning environment. The model describes students' approach to learning and intellectual development, and it applies to students within higher education. Entwistle's model differentiates between a learning style (a student's preferred way of approaching learning) and a learning strategy (a student's approach to a specific task based on the perceived requirements).

Three main approaches to learning are described by the model (Entwistle et al., 2001) as follow:

- Deep approach – this describes students who intend to understand ideas for themselves, taking an active interest and personal engagement in learning.
- Surface approach – these students intend to cope with the course requirements, memorizing facts and studying without reflecting on purpose or meaning.
- Strategic approach – this approach describes students who intend to achieve the highest possible grades by gearing the work to specific lecturers and being alert to assessment requirements.

The ASSIST inventory (Entwistle, 1997) aims to evaluate undergraduate students' learning approaches and their views on the effect of course organization and teaching. The inventory has 66 questions which uses a 5-choice Likert scale over three sections:

what is learning, approaches of learning and preferences for various kinds of course and teaching.

ASSIST is intended to be employed as a diagnostic tool for lecturers, students and course teams aiming to promote an environment that encourages the deep approach to learning. The strength of the model is its aim to describe strategies and approaches to learning and the attitude towards the development of intellectual skills in higher education. However, the model is complex and not easy for non-specialists to apply, and has not been adopted by any computer-enhanced learning systems.

2.2.5 Dunn & Dunn Learning Styles Model

Like several well-known learning styles models, the Dunn and Dunn model (Dunn & Dunn, 1974; Dunn & Griggs, 2003) has changed from its initial version in 1974 following additional research. Coffield et al. (2004) placed the model in the family of theorists who believe that learning styles are based on inherited traits, and although Dunn and Dunn acknowledged external factors like the environment, they believe that learning styles are fixed. The Dunn and Dunn model is popular in the USA, and is being used in a large number of primary schools, as it distinguishes between children and adults. The model was adopted for iWeaver (Wolf, 2002), an adaptive computerized learning environment that teaches Java programming. iWeaver matches learning material to learner preferences for two aspects of the model: perceptual (part of physiological) and psychological.

The model describes learning styles over five aspects called stimuli, and each stimuli has several factors, as follows:

Environmental factor includes preferences for sound, temperature, light, and seating/furniture design.

Emotional factor incorporates learner motivation, responsibility, and persistence level, and the need for structure.

Sociological factor describes preferences for learning individually, in pairs, with friends, as a team, with an authority or in varied approaches (and for children, motivation from teachers and parents).

Physiological factor describes perception inclinations (visual, kinesthetic, auditory, or tactile), time of day energy levels, the need for food, drink and mobility.

Psychological factor (which was added in later versions of the model) characterizes preferred information processing as global or analytic and impulsive or reflective.

The Dunn and Dunn learning style model uses a questionnaire that results in a high or low preference for every factor in the model. There are three different age levels of the Learning Styles Inventory for children (Dunn et al., 1981) with 104 questions being answered using a 3- or 5-choice Likert scale. The Building Excellence Inventory for adults (Rundle & Dunn, 2000) has 118 questions answered based on a 5-choice Likert scale.

The Dunn and Dunn model is easily understandable and incorporates motivation, social interaction and physiological and environmental factors. The model may also be applied widely to children and adults. However, the simplicity of the model's connections between brain function and psychological/physiological preferences has been questioned (Coffield et al., 2004) and the model describes instructional preferences rather than learning.

2.2.6 Kolb's Learning Styles Model

Kolb (1961) believes that learner's knowledge is created during the change of experience through the learning process. He identified learning cycles in four stages: concrete experiencing, abstract conceptualizing, reflective observing, and active experimenting.

Kolb's learning style model categorizes learners in two dimensions: the concrete-abstract dimension and the active-reflective dimension. The four poles of this diagram are considered to represent four different types of learning styles: diverging, assimilating, converging, and accommodating.

- Diverger learners are reflective observers and concrete experiencers. They look at things from various scenes. Diverger learners are sensitive and have the preference of watching over doing, prefer gaining information first and solve problems through imagination. They are best at viewing real situations from several different points of view. Learners with this style have a tendency to be more creative and like to work in teams.
- Converger learners are abstract conceptualizers and active experimenters. Learners with a converging learning style are good at finding practical application of theories and ideas. They prefer technical tasks. Learners prefer to work by themselves, thinking carefully and acting independently.
- Assimilator learners are abstract conceptualizers and reflective observers. Their biggest strength lies in the cognitive approach, preferring to think rather than to act. Learners of this style have a preference for lectures, readings, studying analytical models thoroughly, and taking time to think about things.
- Accommodator learners are concrete experiencers and active experimenters. They are opposite to assimilators as they prefer the 'hands-on' approach, and learn best from 'doing' rather than just 'thinking'. They tend not to like lectures and routine and do like becoming involved in new experiences.

Kolb's model is associated with the Learning Style Inventory (LSI) which was developed by Kolb (1961) for identifying learning styles. Learners are required to write twelve sentences about their learning preference. Every sentence has a choice of four points and the learners are required to rank the points based on what best describes their learning styles (Cassidy, 2004). The Kolb's learning cycle 'Experiential learning' can be applied to any kind of learning through experience approach.

2.2.7 Felder-Silverman Learning Style Model

In Felder-Silverman Learning Style Model (FSLSM) (Felder & Silverman, 1988), learners are grouped into 4 dimensions which are based on the primary dimensions of learning style domain and could be viewed independently of one other. The 4 dimensions are: processing (active/reflective), perception (sensing/intuitive), input (verbal/visual) and understanding (sequential/global) information. Although in the learning styles field, these dimensions are common, the manner they describe learners' learning styles could be considered as new (Coffield et al., 2004). Most learning style models derive statistically ubiquitous learner types from these dimensions. For examples, Myers-Briggs (1962), Gregorc (1982), Kolb (1984) as well as Honey and Mumford (1992), Felder and Silverman introduce the learning style (including odd values only) by using scales of -11 to +11 for each dimension. Thus, each learner's learning style is grouped by four integers between -11 and +11 for every dimension. The scales help to describe preferences of learning style in detail. Furthermore, the use of a scale allows for the expression of balanced preferences, indicating that the learner has no specific preference for either of the two extremes of the dimension.

The active/reflective dimension is similar to the corresponding dimensions in the Kolb model (Kolb, 1984). Active learners learn best by actively learning materials, applying materials and trying the things they learned out, practically. In addition, they are more inclined to communicate with others, prefer to learn through group work, they can discuss the materials they have learned. On the other hand, reflective learners would want to think and reflect on materials. With regards to communication, they would rather work on their own or with small groups of good friends.

The sensing/intuitive dimension is derived from the Myers-Briggs type indicator (Myers, 1962) and is similar to sensing/intuitive dimension in the Kolb's model (Kolb, 1984).

Sensing learners like to learn more facts and specific learning materials, by employing their specific examples of sensory experience as their primary source. They prefer solving problems with standard methods and often have more patience for details. In addition, sensing learners are more realistic and sensible; they are often more practical than intuitive learners. They also prefer to relate the materials they learn to reality. On the other hand, intuitive learners would rather use general principles than concrete examples as source of information. Apart from that, they prefer to learn abstract learning materials, like theory and its underlying meanings. They like to discover possibilities and relationships. They tend to be more innovative and creative than sensing learners. The important difference between this dimension and the active/reflective dimension is that the sensing/intuitive dimension is tied with preferred source of information, whereas the active/reflective encompasses the translation of perceived information into knowledge.

The third dimension, which is the visual/verbal dimension is linked with the preferred input mode. Visual learners are best at remembering what they see and this is inclusive of pictures, time-lines, diagrams, films, and demonstrations. Verbal learners remember what they hear, read or say.

The last dimension, sequential/global of understanding dimension is related to Pask (1976) learning style model, in which sequential preference indicates serial preference and global preference indicates holistic preference. The sequential learner follows linear reasoning process when solving problems. They tend to follow a logical step-by-step approach when looking for a solution. On the other hand, global learners use the process of holistic thinking and learn in huge leaps. They have the tendency to absorb learning materials nearly in a random manner without looking at the connections, but after having read many materials, they suddenly get a full picture. They can solve complex problems in a novel way and fuse things together. However, they might not have the ability to explain how they derived the solutions. Since understanding the whole picture is crucial to global learners, they have the tendency to look at the overviews and extensive knowledge, while sequential learners tend to get into the details.

To identify this learning style model, Felder and Soloman developed the Index of Learning Style (Felder & Soloman, 1997) with 44 questions. As highlighted before, every learner has a personal preference for every dimension. These preferences are represented by values between -11 and +11 for each dimension, with a step size of +/-2. This range is obtained from 11 questions from each dimension.

It can be observed from the instrument ILS as shown in Appendix A, each learning style has distinct characteristics. According to the instruction of FSLSM, the questions in the ILS are grouped based on the semantic similarity. These semantic groups are representing the characteristic preferences for each dimension. Table 2.1 shows the semantic groups and related questions that belong to these groups (Graf, 2007).

Table 2.1: Semantic groups related to the ILS questions

Style	Semantic groups	ILS questions (a)	Style	Semantic groups	ILS questions (b)
Active	Tying something out	1,17,25,29	Reflective	Thing about material	1,5,17,25,29
	Social oriented	5,9,13,21,33,37,41		Impersonal oriented	9.13,21,33,37,41
Sensing	Existing ways	2,30,34	Intuitive	New ways	2,14,22,26,30,34
	Concrete material	6,10,14,18,26,38		Abstract material	6,10,18,38
	Careful with details	22,42		Not careful with details	42
Visual	Pictures	3,7,11,15,19,23,27,31,35,39,43	Verbal	Spoken words	3,7,15,19,27,35
				Written words	3,7,11,23,31,39

				Difficulty with visual style	43
Sequential	Detail oriented	4,28,40	Global	Overall picture	4,8,12,16,28, 40
	Sequential progress	20,24,32,36,4 4		Non-sequential progress	24,32
	From parts to whole	8,12,16		Relations/con nections	20,36,44

2.2.8 Summary of learning styles models in educational systems

The most widely used learning styles, as discussed in Section 2.2, are summarized in Table 2.2.

Table 2.2: Summarizes the seven learning style models

Learning style models	Dimensions	Learning style inventory	Limitation
Gardner's Multiple Intelligences Theory	Linguistic/Verbal Visual/Spatial Logical/Mathematical Bodily/Kinesthetic Interpersonal Intrapersonal Naturalistic	Multiple intelligences developmental assessment scales (MIBS) includes 119 questions using 6-choice descriptive statements.	It does not redefine intelligence, but rather describes different abilities and skills.
Myers-Briggs Personality Types	Extroversion/Introversion Sensing/Intuition Thinking/Feeling Judging/Perceiving	A 93-questions forced-choice questionnaire resulting in one of sixteen MBTI types	The dichotomies are not independent, because each MBTI type represents a complex set of relationships between dichotomies.
Riding's Cognitive Styles Analysis	Wholist/Analytical Verbal/Imagery	2 sub-tests First sub-test: measure verbal/imagery Second test: measure the	Measurements of this test have low reliability

		wholist/analytical dimension	
Entwistle's Approach	Deep approach Surface approach Strategic approach	The ASSIST inventory has 66 questions, using a 5-choice Likert scale over three sections: what is learning, approaches of learning and preferences for various kinds of course and teaching.	Complex and not easy for non-specialists to apply.
Dunn & Dunn Learning Styles Model	Environmental Emotional Sociological Physiological	Children: 104 questions using a 3-choice or 5-choice Likert scale. Adults: 118 questions using a 5-choice Likert scale.	The simplicity of the model's connections between brain function and psychological/physiological preferences has been questioned (Coffield et al., 2004).
Kolb's Learning Styles Model	Diverger learners Converger learners Assimilator learners Accommodator learners	Learning Style Inventory (LSI) for identifying learning styles Learners are required to write twelve sentences about their learning preference; each has four points and the learners are required to rank the points based on what best describes their learning styles	This model was used in some early works in automatic learning style detection field. Current trends tend to use other models in order to fit learning platform better.
Felder-Silverman Learning Style Model	Processing: active/reflective Perception: sensing/intuitive	Index of Learning Style (Felder & Soloman, 1997) with 44 questions	The actual behaviour of students not always conform to the tendencies

	Input: verbal/visual Understanding: sequential/global		described in the model (Garf, 2009).

Felder-Silverman was the most preferred model of learning style used in the theories compared to other learning styles (Fasihuddin et al., 2017; Kumar et al., 2018; Ahmadaliev et al., 2018). This thesis adopts the Felder-Silverman learning style model due to the reasons below:

(1) FSLSM is the most extensively employed learning style model. Shockley (2005) analyzed the learning style model usage in an adaptive learning system in the past ten years and discovered that the FSLSM model usage tops the other model (50%), and the usage is much greater than the second Kolb's model (8.6%). The findings are consistent with Akbulut and Cardak (2012).

(2) FSLSM gives more detailed descriptions when compared to other learning style models and it has its reliability and accuracy proven (García et al., 2005).

(3) FSLSM yields a high operational Index of Learning Style instrument (Felder & Soloman, 1997), which has 44 questions (see Appendix A); eleven questions for every dimension, which require respondents to identify the preference and the degree of preference, each question has 2 answers to be chosen from.

2.3 Application of Learning Styles in Educational Systems

In the following review, the learning styles application in various educational systems is given. The review also focuses on the automatic learning styles detection employed in the systems. Feldman et al. (2015) found that the educational systems used to automatically detect learning styles in the following 3 categories:

1. Adaptive educational (hypermedia) system (AEHS): provide hypermedia learning content to meet students' different characteristics. This system has 3 criteria: "it must be a hypertext or hypermedia system, it must be having a user model, and it must have the ability to adapt the hypermedia using this model" (Brusilovsky, 1996).
2. Intelligent tutoring system (ITS): it uses techniques from artificial intelligence to give broader and better support for the students (Graf & Kinshuk, 2007). The primary aim is to assist students to solve problem.
3. Learning management system: emphasizes on the presentation of learning material and yields a set of features to support lecturers in constructing, administrating and managing of courses. It treats all students equally without considering students' learning style preferences.

Although this study is deployed in learning management system for data collection and result validation reasons, the purpose of learning style detection is for modelling students in order to provide adaptivity, whether it is AHES, ITS or adaptive LMS.

2.3.1 Adaptive Educational (Hypermedia) Systems

Adaptive educational (hypermedia) system, presently, is a common and upcoming concept in the computer science field, specifically in the sub-field of information systems (Brusilovsky & Peylo, 2003).

Today, the success rate of using adaptive educational (hypermedia) systems is reflected in the effective delivery of courseware through advanced personalization techniques. In addition, researchers from various other disciplines have the same opinion when it comes to personalization in e-learning environments: the tenet of modern teaching and learning paradigms is that every learning goals need a unique didactical approach.

The goal of Adaptive Educational Hypermedia System is to provide different didactical approaches including hypermedia content that meets the learners' specific needs. AEHS could be defined as hypermedia and hypertext systems which "reflect some of the user's features in the user model and apply it to adapt many of the system's visible aspects to the user". This means that, the system has to fulfill three criteria: "it must be a hypermedia or hypertext system, it must possess a user model, and it must have the ability to adapt the hypermedia by employing this model" (Brusilovsky, 1996). Taking into account the definition of AEHS, the adaptation process consists of two parts: firstly, it is necessary to construct and update the learners' model, which includes information on learners' adaptability, and secondly, it is necessary to employ this information in order to generate adaptive courses.

Brusilovsky (Brusilovsky, 1996, 1999; Brusilovsky & Peylo, 2003) distinguishes two major technologies in AHES: namely, adaptive presentation and adaptive navigation support.

The goal of adaptive presentation is to provide adaptive features based on content like text and multimedia presentation, and other information stored in the student model. The academic material pages are generated adaptively or collected from various sections based on every learner (Papanikolaou et al., 2002). The adaptivity of a system that has adaptive presentation is at the content level, with selections dynamically based on the learner model (Eklund & Brusilovsky, 1999).

For adaptive navigation support, the goal is to help students in locating the most relevant path in hyperspace. The features of adaptive navigation include the availability of maps, adaptive sorting, hiding, generation of links, and annotating, which is based on links. The page-link level adaptivity is static in content in a system with adaptive navigation, but changes the links' appearance (Eklund & Brusilovsky, 1999).

Bajraktarevic et al. (2003) conducted an experiment on sequential/global dimension based on Felder-Silverman model to show that students can benefit from learning material that are altered to match students' learning preferences. They apply two adaptation techniques, which are adaptive presentation and adaptive navigation in the process of designing hypermedia courseware to cater to preferred learning styles which have been detected.

2.3.2 Intelligent Tutoring System

The Intelligent Tutoring System emphasizes on using artificial intelligence techniques in providing learners with better and broader support. In a broad sense, an ITS builds a model of students' goals, knowledge and preferences and uses this to cater to every learner's learning style and to provide intelligent support. For instance, when an ITS platform found that a learner possesses a weakness in solving a specific problem, the program would ask him/her, in a repetitive manner, to solve similar problems until he/she achieves the passing score. Contradictorily, adaptive educational systems emphasize the differences between different learners or teams of learners (Brusilovsky & Peylo, 2003). Nevertheless, Graesser et al. (2005) defined ITS as adaptive educational systems which use intelligent technologies in providing individualized instruction.

According to Brusilovsky and Peylo (2003), there are three primary approaches to intelligent tutoring, and they are intelligent solution analysis, curriculum sequencing, and problem solving support.

Intelligent solution analysis adds intelligence to an ITS by providing students' feedback on erroneous or incomplete solutions, assisting them to learn from their mistakes. In SQL Tutor (Mitrovic, 2003), a technique called constraint-based modelling is used to model the syntax and semantics of SQL. The solutions from students are compared with the constraint model and intelligent feedback is given on errors so that students can learn from mistakes.

Curriculum sequencing systems introduce adaptation by providing students with learning material sequentially and style it best suited to their needs. Curriculum sequencing is the method used the most in an ITS and AEHS (Brusilovsky & Peylo, 2003). Personalization was traditionally contingent upon current knowledge, which aims in enhancing the learning experience by focusing on the tutoring on topics that are not prevalent or require improvement. In ELM-ART (Weber & Brusilovsky, 2001) student knowledge is modelled and presentation is adapted with the annotation of learning resource links to indicate recommended resources. Recently, personalization had been extended to include other individual characteristics which could impact learning, like the learner's emotions (Ammar et al., 2010; Graesser et al., 2005), personality (Leontidis & Halatsis, 2009) or learning style (Popescu, 2010). D'Mello et al. (2010) work mimicked the human tutors to promote engagement by catering to learner's emotions like boredom or frustration.

The methods of problem solving provide learners an intelligent assistance to assist them to arrive at a solution. This approach employs the constructivist style of teaching, like how it is employed by human tutors, to trigger learners in constructing their own knowledge and promoting an in-depth understanding of a topic. In ActiveMath (Melis et al., 2001) intelligent support is offered for mathematical theorem proving while in CIRCSIM-tutor (Woo et al., 2006), hints help students diagnose physiology problems.

For the three intelligent techniques used in an ITS, curriculum sequencing is the most commonly used. By combining all three intelligent approaches, an ITS could almost offer the support that is obtainable from a human tutor. Few ITS incorporate all three intelligent approaches (Graesser et al., 2005; Melis et al., 2001; Woo et al., 2006) as they are complex and time-consuming to develop. Nevertheless, all three technologies combined adds benefits as it provides a more effective learning experience and intelligent support that could assist in building confidence and also motivation (Graesser et al., 2008).

2.3.3 Learning Management System

Learning Management System is defined as "a technology based on website or software application used to plan, implement, and assess particular learning processes" by Alias and Zainuddin (2005). Baumgartner et al. (2002) defined LMS as "a learning management system is a server-side installed software, that helps in all kinds of learning material teaching through the internet and supports the organization for necessary processes". They also reported five crucial e-learning platform operation areas. Therefore, teachers could employ them in presenting content, providing communication tools for students like forums, chats and video conferences, create quizzes and assignments, evaluate student performance, and receive support in administration issues of courses, content, students, their progress and many more.

LMS can be viewed as an "empty" environment, creating and managing courses for teachers and filling up learning contents. However, the developers of the LMS decide how learning could be carried out in the LMS and build it based on the pedagogical strategy. The pedagogical strategy applied in LMS focuses on teaching students from a general perspective, regardless of the students' specific needs.

2.3.4 Summary of Application of Learning Styles in Educational Systems

The previous subsections described AEHS, ITS and LMS. As can be observed, AEHS and ITS emphasize on supporting learners by giving courses that meet their characteristics and needs, in which learning styles have been widely used to improve AEHS and ITS by proposing learning material that matches an individual's preferred styles (García et al., 2007; Popescu, 2010; Spallek, 2003; Stash & De Bra, 2004; Villaverde et al., 2006; Wang et al., 2005).

However, these systems often lack in terms of support for teachers and administrators' needs. There are some limitations when employing adaptive systems in actual teaching environment (Brusilovsky, 2004). For instance, the lack of integration in adaptive system as they only support a few features of technology-enhance education. Brusilovsky and Peylo (2003) reported that "AEHS could support all aspect of Web-enhanced education better than LMS, but every system could typically support only one function out of the many". In addition, contents created for one adaptive system cannot be reused for another adaptive system. Therefore, AEHS and ITS are not always used by educational institutions. In contrast, LMS provides great range of features which can assist lecturers and course developers to create, administrate and manage online courses, but it only provides few or no adaptivity (Graf & Kinshuk, 2007). According to Feldman et al. (2015), only 15% of the work of learning style detection surveyed adopted learning management system. In turn, 37% used adaptive educational hypermedia system. Therefore, learning style detection and adaptivity provision on LMS can meet the needs of practical use.

For both AHES and ITS or adaptive LMS, the student model plays a central role, as it contains information about individual student characteristics (e.g. learning style) as well as subject knowledge, whereby this information is employed as the basis to provide adaptivity.

Student modeling could be made statically or dynamically. Static student modeling is a method in which the student model is only initialized once (mainly when the student is registered into the course), e.g. a learning styles questionnaire (Papanikolaou et al., 2003). In contrast, dynamic student modeling methods often update information in the student model (continuously or periodically during tutoring, e.g. preferred learning resources (Popescu, 2010)). Although dynamic student modelling offers the advantage of a more current student model, the gathering of reliable information is difficult (as it is often uncertain and imprecise) and sometimes results in a weak student model (Brusilovsky & Millán, 2007).

There are two distinct approaches to student modelling: collaborative and automatic (Brusilovsky, 1996). In collaborative approach, learners are required to provide clear feedback that could be used to construct or update student models. For example, learners could give information to student modeling mechanism, whether the content is relevant to their learning goals or not. Another option is to allow the learners to adapt themselves, thus directly showing their expectations of the system. For example, the order of the links on the page could be changed according to the learners' preferences. On the learning style, the commonly used method is to let the students fill out the questionnaire to obtain information on their learning style. Whereas, the automatic student modeling method automatically constructs, and update student model based on the students' behaviour during their interaction with the system. The primary issue this problem has is in obtaining reliable information to build a robust student model although it enables students to emphasize on learning alone instead of giving explicit feedback on their preferences. Brusilovsky (1996) suggested that, this issue could be solved by using more reliable sources, like test results in student modeling.

Table 2.3 below show the comparison of educational systems. Overall, LMS has wide applicability scope than ITS and AEHS due to the simplicity and easy to use for lecturers and course developers, such as Moodle platform is the most widely used learning system so far. The application of automatic learning style detection methods for LMS would be much more valuable.

Table 2.3: Comparison of educational systems

	AEHS	ITS	LMS
Purpose	To provide hypermedia learning content to meet students' different characteristics.	Using artificial intelligence techniques in providing learners with better and broader support.	Open and empty environment for creating and managing courses for teachers and filling up learning contents
Adaptivity	Strong	Strong	Weak
Usability	Design for specific needs and requirements.	Design for specific needs and requirements.	Widely used; friendly support for lecturers in constructing, administrating and managing of courses.
Complexity	High	High	Low

The aim of this study is to extend LMS by incorporating adaptivity. An adaptive LMS requires a reliable student model. The key to a reliable student model is the detection of student's preference. In next section, the review of learning style detection method is introduced.

2.4 Learning Styles Detection Methods

Learning style is important as far as student modeling is concerned, it has led to developing many methods to get more reliable outcomes of students' preferences. In general, these methods could be categorized into two groups: collaborative and automatic. Figure 2.1 below shows the relationship between collaborative and automatic methods in general.

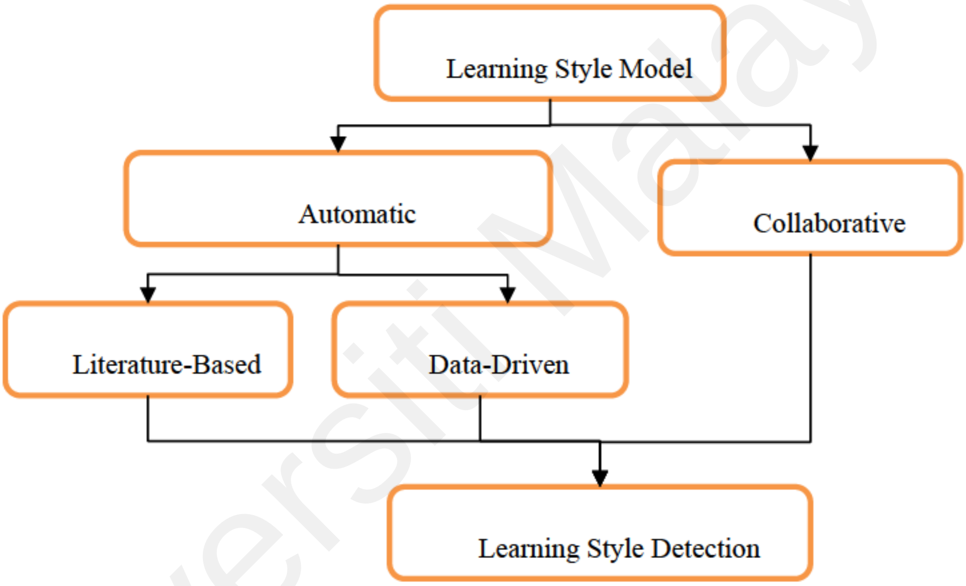

Figure 2.1: Relationship between the approaches and learning style models

2.4.1 Collaborative Approach

Collaborative approach is also called explicit approach, user-guided modelling (Belk et al., 2013) or explicit user feedback (Gauch et al., 2007). The data could directly be collected by using students' query methods. Nevertheless, the shortage of using these methods could not be overlooked, such as using questionnaire as the questions are fixed, and students may tend to answer questions arbitrarily. In addition, students may lack motivation and self-awareness about their learning preferences (Dung & Florea, 2012b; Feldman et al., 2015).

As reviewed in section 2.2, it is evident that various learning style models exist in psychological research, lots of psychometric instruments have been proposed. Based on this research's review, the most dominant learning style instruments or tests for collaborative approach are:

- Index of Learning Style (Brown et al.) of Felder and Soloman (1991)
- The Learning Style Questionnaire (LSQ) of Honey and Mumford (1992)
- The Learning Style Inventory (LSI) of Kolb (1961)
- Cognitive Style Index (CSI) of Allinson and Hayes (1996)
- Cognitive Style Analysis (CSA) of Riding and Cheema (1991)

The details of instruments or tests above are described in section 2.2. These instruments or tests are the basis of automatic approaches.

2.4.2 Automatic Approach

Many artificial intelligence methods have been proposed over the past years to automatically detect learning styles. This approach is a reflection of natural students' attitudes which could be representing their actual preferences more precisely in order to provide more accurate results. The key characteristics of this approach is automatic and dynamic student modeling. Automated student modeling means observing students' behaviours to infer their learning styles. The latter means updating the student model by using the collected information automatically.

According to Graf (2007), Pham & Florea (2013) and Hasibuan (2016), there are two main automatic learning style detection methods: literature-based and data-driven. The most obvious difference between literature-based approach and data-driven approach is the reliance on data availability. In the next sections, the literature-based and data-driven automatic learning style detection techniques are introduced.

2.4.2.1 Literature-Based Approach

The literature-based approach employs user models to obtain hints on learner's learning style preferences and later applies a simple rule-based approach to compute these preferences based on the number of matching hints. The relationship between behavioural patterns and learning style must first be identified. This approach is somewhat similar to the data-driven approach as this step is also required in the latter. Then, by applying a simple rule-based method, the user's behaviours and actions are tracked to serve as hints about their learning styles preferences. It was proposed by Graf and Viola (2009) to address the shortcomings of the data-driven methods. Nevertheless, the issue of making an estimation of how important different cues for calculating learning styles is must be considered (Dung & Florea, 2012b).

A detection method proposed by Abdullah (2015) using questionnaire-based and literature-based method on Moodle LMS, the detection results were precision value of 50%~80%. Another work (Imran, 2015) using literature-based method on Moodle LMS as well. The author used equations of students accessing learning materials, including reference, namely comment, reflection quizzes, discussion forum and so on. The results obtained at approximately at 60%~80%.

Graf and Viola (2009) pointed out that the main advantage of the literature-based approach is the ability to infer learning style without the need of training data. This indicates that the data-driven method relies only on the available datasets, while the literature-based method is directly dependent on the learning style model. Although this approach has the advantage of inferring learning style independently, the process of inferring learning style must be performed offline. Therefore, it cannot be adapted to meet students' needs immediately.

A few studies in the past researches (Carver et al., 1999; Dung & Florea, 2012b; Graf, 2009; Graf & Liu, 2008; Latham et al., 2012; Popescu, 2009; Sangineto et al., 2008) applied literature-based approach, while the rest used data-driven approach. The data-driven approach is considered to be the most commonly applied approach because the literature-based approach requires some information from psychologist and cognitive scientist in order to accurately make an estimation of the importance of the hints.

2.4.2.2 Data-Driven Approach

The data-driven approach is designed to build classifiers that imitates learning style instrument. The learning style in the data-driven method is automatically detected by the AI classification algorithm, which uses the user model as input and yields the learners' learning style preferences as the output. The advantage of this method is that it employs actual data to classify users. Therefore, it could be very much precise. Nevertheless, this approach relies heavily on the data that is currently available, so a representative data set is critical to create an accurate classifier. The next section reviews the automatic detection techniques of data-driven approach.

(a) ***Bayesian Networks***

In the automatic learning style detection field, Bayesian network approach is one of the most commonly used technique. Bayesian networks were used in Alkhuraiji et al. (2011), Carmona and Castillo (2008), García et al. (2007); Garcia et al. (2008), Ahmad and Shamsuddin (2010) and Kelly and Tangney (2006) and many more. The techniques used by past researches in Bayesian family including original Bayesian network, dynamic Bayesian network and naïve Bayes. Feldman et al. (2015) revealed the reasons behind the usage of Bayesian network in its natural representation of probabilistic information and also its capability to encode expert knowledge.

Probabilistic models are required in a non-deterministic relationship between class variable and the attribute set. This model is a directed acyclic graphical model whereby a set of variables indicates that nodes and arcs are representing "probability-dependent or causal relationships between variables" (Chrysafiadi & Virvou, 2013; Millán et al., 2010). The relationship between the behaviour mode and the learning styles represents the arrow of the network, and the learning style dimension represents the node of the network.

The Bayesian network approach has attracted the attention of researchers in the area of student modeling because of its strong mathematical foundation and also the natural capability in representing the probability of application of uncertainty (Millán et al., 2010). Piombo et al. (2003) and Alkhuraiji et al. (2011) proposed a framework for modeling FSLSM by employing Bayesian networks. The work of García et al. (2005) represents the basis for the particular application of this approach to adapt learning style. Bayesian networks are used to detect learners' LS implicitly by observing student's behaviour in the SAVER system (Jensen, 1996). It uses 11 behaviour patterns in the process of detecting three dimensions of FSLSM (active/reflective, sensing/intuitive and sequential/global). To assess the precision of their methods, two experiments were conducted in 2005 and 2007 (García et al., 2005, 2007). The results were compared with the results collected by filling the ILS directly of the sample.

The precision of the processing dimension in the García et al. (2007)'s experiment is low (58%) due to the lack of motivation in students using the communication tool in the system. In addition, the precision of this small sample cannot be generalized. Graf and Kinshuk (2007)'s study also used the same learning style model. The experiment was conducted with 75 students with 5 runs for each dimension. The average results of the four dimensions (perception, input, processing and understanding) were 62.50%, 65.00%, 68.75% and 66.25%, respectively. Although García et al. (2005, 2007) achieved promising results, Graf and Kinshuk (2007), on the other hand, concluded that the precision was modest. It is worth noting that these two experiments (Graf & Kinshuk, 2007) (García et al., 2005) were carried out under various environments and conditions. Nevertheless, Graf (2007)'s experiments may be more precise because they were carried out with a bigger sample and 5 runs for the results. Subsequent research by Abdullah et al. (2015) used Naïve-Bayes Tree classification technique to classify students' learning style as per FSLSM. In this work, the data collected through Blackboard LMS and learning styles were captured using ILS questionnaire, which has its own limitations to consider students' online usage behaviour. This method had an accuracy of 69.70%.

In order to fine tune the student model based on the learning style and provide an instant adaptivity, Carmona et al. (2007) used the dynamic Bayesian network by tracking the learning behaviours between students and learning objects. This could be solving the concept drift problems well (some leaners might change their behaviour to cater to the specific environmental needs) and provide immediate adaptation. However, the learning styles are not a changeable trait in a short time (Kozhevnikov, 2007; Witkin et al., 1977). Therefore, in order to update the user model, it may be a good solution to define some time intervals to assess changes in learner behaviour.

(b) ***2.4.2.2.2 Decision Trees***

The decision tree (Friedman et al., 1997) (DT) were used to classify students according to their learning style preference. Using some input variables (the learner's behaviour pattern), the value of a class could be predicted (learning style).

Cha et al. (2006) applied 58 kinds of behaviour patterns, by monitoring the behaviour of 70 students in an online learning environment, they automatically deduced students' learning style of four dimensions of the FSLSM. The Decision tree and the hidden Markov model (HMM) method were used. The error rate of processing, perception, input and understanding dimensions were achieved at 33.33%, 22.22%, 0% and 28.57% (DT), 33.33%, 22.22% 14.28% and 14.28% (HMM).

This indicates that the decision tree performs better in input dimension, while hidden Markov model achieves good results in understanding dimensions, because HMM is better in analyzing sequential data. Nevertheless, the data of balance preference of ILS has been excluded from the experiment, but only in the assessment process contains moderate and strong preferences. This leads to a prediction of students with moderate or strong tendencies. This may be a significant shortcoming of this model.

Özpolat and Akar (2009) used DT to detect learner's LS from the learning objects selection as opposed to the learner's behaviour during the interaction. Experiments of thirty graduates indicated that the precision of the results were 73.3%, 73.3%, 70% and 53.3% for the perception, understanding, processing and input dimensions, respectively.

By using DT and K-means methods and traditional statistics to explore the relationship between learning behaviour patterns and cognitive styles by analyzing data gathered by using Cognitive Style Analysis (Riding & Cheema, 1991), Chen and Liu (2008) found that the cognitive style has a significant influence on learner's learning patterns in online learning environment.

Kalhoro et al. (2016) introduced an automatic learning style detection method to infer students learning style from weblogs. Kolb's learning style theory was used to understand students' learning styles on the learning environment. Another recent work (Pantho, 2016) proposed an approach to classify VARK (Visual, Aural, Read/Write, Kinesthetic) learning styles by using Decision Tree C4.5 algorithm. The experiment was based on a large collection via a questionnaire which responded by 1205 students, then the collected data were classified using the Decision Tree C4.5 algorithm.

Cha et al. (2006) achieved the best results by using this technique. However, the major drawback of this approach is that it can only identify students learning style with a strong preference one way or another, and it cannot distinguish students with a balanced preference (Bernard et al., 2017).

(c) *2.4.2.2.3 Neural Networks*

Neural network (NN) is a computational model that is inspired by the brain's biological neural structure to solve classification problem. The precision of this model is considered to be one of the most accurate classifiers (Villaverde et al., 2006). Neurons represent the basic units in the network. There are three layers in each network: input layer, hidden layer and output layer.

Villaverde et al. (2006) used neural networks to model learners' behaviour using 10 behaviour patterns as network inputs. The output of the model represents the FSLSM dimensions. Nevertheless, the model has been assessed by simulation data that did not show the representation of the learners' natural attitudes. Kolekar et al. (2010) used neural networks in categorizing learners to the corresponding FSLSM by tracking their behaviour using an e-learning system. This model is selected for two reasons: it could automatically infer LS, without the intervention of learners and these models depend on historical data that could be used to differentiate user behaviour changes.

In the study of Lo et al. (2012), the behaviour of the students were tracked and analyzed using the multi-layer feedforward neural network (MLFF-NN), inferring the learner's cognitive style and adapting the learning content, and establishing the relationship between the identified cognitive style in the student model.

Latham et al. (2013) introduced their Oscar system with personalized learning resources, problem solutions, and feedback mode. In the Oscar system, the LS is triggered using tutoring conversational agents. The multi-layer perceptron artificial neural network is employed to derive the two dimensions of FSLSM (processing and understanding) because the applicability of such methods for non-linear modelling and handling of outliers and noise has been proven. Seventy-five undergraduates were assessed and compared with their ILS results, the precision was 89% and 84% of the two dimensions respectively.

Hmedna et al. (2016, 2017) proposed their automatic learning style detection method based on their behaviour on MOOC LMS. This study explored students' knowledge through neural network to increase their engagement and satisfaction. Another recent work (Hasibuan et al., 2019) used artificial neural network to predict student learning style based on their prior knowledge. However, these two works did not provide the detection results from the statistical perspective.

Using such method could accurately classify learners' learning styles. However, these approaches have high computational requirement, cost and complexity: "no theoretical rule defined to determine the optimal number of hidden neurons; complex to defined number of hidden layers; lack of descriptive power and difficult to identify rules for both inputs and outputs" (Sheeba & Krishnan, 2018). In Latham et al. (2012)'s work, these are very promising results over 80% precision, a significant drawback is that it is tied to the Oscar system and cannot be generalized to other systems. In addition, a separation exists between the provision of adaptivity and inferring learners' behaviour since the analysis process must be done off-line.

2.4.3 Summary of Learning Style Detection Approaches

Table 2.4 below summarizes the advantages and disadvantages of the collaborative and automatic learning style detection approaches.

As observed from the table, the automatic detection approach solves some problems in the collaborative approach associated with the questionnaire such as the lack of motivation for students, the answer choices and lack of awareness of their learning style.

However, the automatic detection method requires students to use the education system for a period of time for the purpose of automatic detection of learning style preferences, namely cold-start problem. It is because users do not have any previous profile in the system, the automatic detection method requires students to use the education system for a period of time in order to automatically detect learning style preferences. The discussion in detail is provided in the next two chapters. Furthermore, a common issue of automatic learning style detection method is high coupling between user models, automated detection techniques and educational systems. This renders it very difficult to use the proposed method again in other systems. Therefore, constructing a general method that can be integrated into more than one educational system will be very useful.

Table 2.4: Learning style detection approaches: pros and cons

	Collaborative approach	Automatic approach	
		Literature-based	Data-driven
Input for student model mechanism	Learners provide feedback to construct student model.	Learners' behaviour/action pattern when interacting with the learning system.	
Learning style detection method	Learners provide their LS preference via questionnaire.	Learners' behaviour served as hints about their LS.	AI classification algorithm.
Pros	Data can be extracted in a structured and standardized format	Dynamic process which means it can be used to build student model by scratch and updating it	This is a dynamic process which means it could be employed to build student models from scratch as well as update it.
	This provides data collected as authentic self-expressions	This reflects the natural attitudes of learners.	This reflects the natural attitudes of learners.
	Reduced noise and spurious data	More precisely represents their actual preferences.	More precisely represents their actual preferences.

		Depends solely on student behaviour and actions.	
Cons	Users might not be able to express their preferences explicitly.	"High complexity and computational cost"	"High complexity and computational cost"
	There is a high probability for arbitrary answers to be selected due to unclear questions or long questionnaire and this could be prone to bias.	Difficulty to measure and interpret users' behaviour.	Difficulty to measure and interpret users' behaviour.
	Data are static whilst learners' preference can change.	The classification process of learning and cognitive style patterns is offline.	The process of classifying learning and cognitive style patterns is offline.
	This approach can be perceived by users as disruptive, cumbersome and time-consuming process.		The precision of the results depends solely on the data available and identifying patterns of behaviour.

For automatic detecting approach, the techniques in the data-driven method as discussed in Section 2.4.2.2 are summarized in Table 2.5. It lists the studies that applied the technique to FSLSM model, the results in detecting the four FSLSM learning dimensions (processing, perception, understanding, input) as well as the advantages and limitations.

Table 2.5: Data-driven method: advantages and limitations

Techniques	Study	LS model	Number of variables	Results	Advantages	Limitations
Bayesian network	Ahmad and Shamsuddin (2010)	FSLSM	20	82%	Easy and simple to use.	Overfit easily.

	Alkhuraiji et al. (2011)	FSLSM	-	-	Easy to understand.	Too complex for small data sets
	Carmona and Castillo (2008)	FSLSM	6	-		
	García et al. (2007); Garcia et al. (2008)	FSLSM	14	Processing (Pr):66% Preception (Pe):80% Understanding (Un):72%		
Naïve Bayes	Kelly and Tangney (2006)	Gardner (MIDAS)	8	-	Fast to train and fast to classify. Handles real and discrete data. Handles streaming data well. Not sensitive to irrelevant features.	Assumes independence of features. Should train a large training set to use NB well. Low performance in large dataset.
Decision tree	Cha et al. (2006)	FSLSM		Pr:77% Pe:88% Input (In):100% Un:71%	Simple to use. Easy to understand. Require relatively little effort from users for data preparation. Easy to interpret and explain to executives.	Identifies subset of students only. Instability. Do not work well if you have boundaries. Do not work best if you have a lot of un-correlated variables. High variance. It is accuracy depends a lot on the data presented.
	Özpolat and Akar (2009)	FSLSM	4	Pr:70% Pe:73% In:53% Un:73%		
Neural network	Latham et al. (2012)	FSLSM	13	Pr: 100%/73%	Require less formal	

				Pe: 70%/80% In: 80%/71% Un: 82%/61%	statistical training. The ability to implicitly detect complex nonlinear relationship between dependent and independent variables. The ability to detect all possible interactions between predictor variables.	Greater computational burden. Proneness to over fitting. The empirical nature of model development.
	Lo et al. (2012)	Custom	7	Accuracy of 90%		
	Villaverde et al. (2006)	FSLSM		Accuracy of 69%		

It is difficult to decide on the most appropriate learners' behaviour to model. Selecting typical behaviours that discriminate between learning styles requires a detailed analysis of the chosen learning styles model. Even then, students do not always behave stereotypically as suggested by learning styles models (Coffield et al., 2004; García et al., 2007).

There are clear differences in the number of behaviour characteristics used by educational system to model learning styles – e.g. García et al. (2007) capture 11, Cha et al. (2006) capture 58 and Popescu (2010) captures over 100. This does not always lead to different levels of precision in modelling learning styles, as different modelling methods and learning styles models have different requirements.

To date, the method based on automatic detection of learning styles exhibits an average precision of 66%–77% (Bernard et al., 2017). These results are not meant to be used as a comparison between different methods because they are based on different data sets, but they provide insight into the automatic detection performance of the learning style and highlight its feasibility. According to previous studies, several approaches have demonstrated satisfactory results but only assessed certain learning style dimensions (Garcia et al., 2008; Villaverde et al., 2006). Moreover, some approaches achieved a precision of more than 80% but cannot be widely applied to educational systems or for learning styles dimensions. Latham et al. (2012)'s approach has a precision of 72%–86% but is only relevant to an ITS called Oscar, which is a natural language conversational agent. The study by García et al. (2007) achieved a precision of 77% for perception dimension, but the input dimension was not considered for detection. With Cha et al. (2006)' method, results achieved a precision of 67%–100% but only can detect students' learning styles under strong preference. Zaric et al. (2019) argued that this kind of works usually presents precision and reliability level of their models and its predictions, rather than the practical application. Consequently, a learning style detection method with high precision at higher reusability is more appropriate, especially when it is not tied to a specific educational system, accounts for all four dimensions of the FSLSM, and considers students with all levels of preference (strong, moderate, and balanced).

2.5 Conclusion

This chapter has given an overview of current development of learning styles, educational system and learning style detection techniques from a general point of view. The chapter especially reviewed the FSLSM and LMS in detail, which are most popular and widely used in the fields. The limitations of existing automatic detection methods regarding precision and extent of reusability have also been highlighted. Two new automatic learning style detection methods related to FSLSM and LMS are proposed in the following chapters.

CHAPTER 3: AUTOMATIC DETECTION OF LEARNING STYLE USING CORRELATION MATRIX OF LEARNING STYLE DIMENSION AND LEARNING BEHAVIOUR

In previous chapter, techniques for automatic detection students' learning style were introduced. These techniques address the problems associated with the use of questionnaires in traditional learning style assessment methods. However, results obtained through these techniques have issues in terms of precision and reusability which need to be addressed. For example, the existing automatic detection approaches are only able to provide satisfactory results for specific learning style models and/or dimensions. Some approaches only work for certain educational systems.

The aim of this study is to improve precision while guaranteeing the reusability of the automatic detection of learning style. A new method for detecting learning styles is proposed. This method adopts correlation analysis, an extensively used technique that identifies significant relationships among different attributes of data sets. These relationships reveal the relevance of attributes with respect to the target class to be predicted. Correlation analysis methods consider the relevance between data sets, thereby reducing the complexity of detection rules from educational system features, which enables building a more generic detection method untethered from any specific educational system. Consequently, this method is appropriate for addressing the reusability problem and enabling the use of more generic detection in educational systems.

In the following sections, an approach to automatically detect LS using correlation matrix of learning style dimension and learning behaviour in LMS is introduced. The first section describes the construction of the matrix. Then the detection and prediction of LS are introduced. Finally, it describes the pilot test conducted on this proposed approach and reports its result.

3.1 Construction of Correlation Matrix of Learning Style Dimension and Learning Behaviour

As reviewed in Chapter 2, there are almost 71 different learning style models (ÖZyurt et al., 2013), no matter how a learning style model is built, it is always perceived differently from different dimensions by students as they can even derive their own learning preferences from various learning style models. It is called 'custom model' which incorporates characteristics from one or several traditional learning style models to form a new learning style model (Feldman et al., 2015). Custom models could cover plenty of learning preferences and easy to extend for incorporating new learning style dimensions. The critical concern is the way to identify the exact nature of students' learning style in order to provide adaptive learning material. Therefore, to resolve this issue an approach is taken whereby it considers each learning style dimension as a semantic relation, building relationship with student *i* and *j*, and the weight a_{ij} (e.g., 0.8) representing similarity of student *i* and *j* on this dimension as depicted in Figure 3.1.

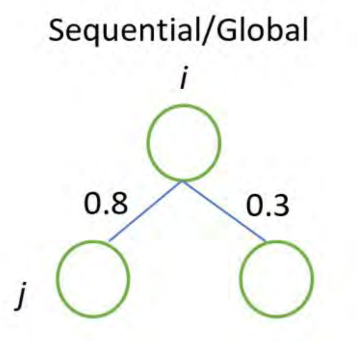

Figure 3.1: Sematic relation of *i* and *j*

Assuming *n* students' learning style are already known, Matrix M^t to map the weight of the semantic relation is constructed as follow: M^t is n*n matrix, a_{ij}^t is an element in M^t, then the value of a_{ij}^t:

$$a_{ij}^t = (e - e^{\sqrt{|p_i^t - p_j^t|}}) / (e - 1) \qquad (1)$$

$p_i^t \in [0,1]$ denotes the preference values of student *i* on dimension *t*. The above formula indicates the similarity of student *i* and *j* on the learning style dimension *t*. *e* is a mathematical constant that is approximately equal to 2.71. This equation named as "squashing function", because if there are more similarities, the corresponding semantic relation is more relevant, and vice versa. Therefore, if student *i* is a pure active learner and student *j* is a pure reflective preference, then $p_i^{active/reflective}$=0, $p_j^{active/reflective}$=1, and $a_{ij}^{active/reflective}$=0, indicating that there is no correlation. The similarity values between sample students can be stored in a $n*n$ matrix M^t, where M^t is obviously a symmetric matrix.

$$a_{ij}^t = \frac{e - e^{\sqrt{|p_i^t - p_j^t|}}}{e-1} = \frac{e - e^{\sqrt{|0-1|}}}{e-1} = 0$$

If student i and j are pure active learners, $p_i^{active/reflective} = p_j^{active/reflective} = 0$, then $a_{ij}^{active/reflective} = 1$.

$$a_{ij}^t = \frac{e - e^{\sqrt{|p_i^t - p_j^t|}}}{e-1} = \frac{e - e^{\sqrt{|0-0|}}}{e-1} = 1$$

If two students' combined preference values are >0.5, then the correlation similarity will be <0.5.

Table 3.1: Correlation matrix *M^t*

	i	*j*	*k*	*l*	...
i		a_{ij}^t	a_{ik}^t	a_{il}^t	...
j			a_{jk}^t	a_{jl}^t	...
k				a_{kl}^t	...
l					...
...					

The correlation matrix in Table 3.1 above is used to investigate the dependency between multiple variables at a given time. The table contains the specific correlation coefficients between each student on a specific learning style dimension, assuming that the more similar the learning style preference, the higher the correlation of their learning behaviours. Once the learning behaviour matrices of these students are built, a potential relationship or link between their learning styles and behaviour patterns could be discovered. Based on the known link, when new learners join in an e-learning environment, their learning style preference could be deduced from behaviour patterns, instead of having to complete learning style questionnaires.

3.2 Detection of Learning Styles

Assuming there are m unknown learning styles for new learners, replacing m students from n known learning style to build a new student group, its behaviour matrix is M, m_{ij} is the elements of M.

$$m_{ij} = \begin{cases} 1, \text{ student } i \text{ and } j \text{ have same behaviour sequence} \\ 0, \text{ other} \end{cases}$$

In behaviour sequence, set $A=\{a|a \in L \cup B\}$, set $L=\{o_1, o_2, \ldots\}$ is denoted for learning objects, and set $B=\{b_1,b_2,\ldots\}$ for behaviours. Examples of learning behaviours are 'participating in a discussion forum', 'doing an exercise' just to name a few.

Naturally, with learning objects that exist in large quantities and less samples for testing, the behaviour sequence, A, becomes varied and resulting in sparse matrix. In order to prevent sparse matrices, the proposed approach proactively provides feasible behaviour sequences, which guide students from different paths as shown in Figure 3.2, but will not contribute to learning styles and will have no effect on students' preference.

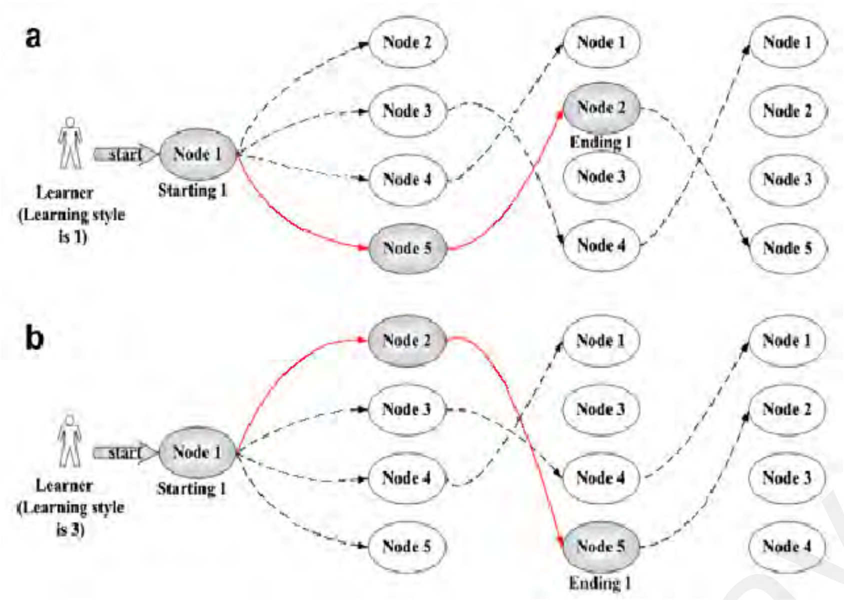

Figure 3.2: Learning path to avoid spare matrix

Considering behaviour matrix *M* as an image representation matrix; in order to detect *m* students' learning style, it need to be discovered the role of learning style preference in behaviour matrix. Then, based on the known learning style correlation matrix, near-to-similar combination of behaviour matrix can be determined. Subsequently, the behaviour matrix can be abstracted into a nonlinear programming problem. Setting Vector $X = (x_1, x2 \ldots x_t)$ for new learners' learning style, t is the dimension of learning style, and the objective function is:

$$\min f(x), \sum_{i=1}^{t} x_i^2 = 1 \qquad (2)$$

$$f(x) = var\left(M, \sum\nolimits_{i=1}^{t} x_i \cdot M^i\right) = (\sum_{i=1}^{n} \sum_{j=1}^{n} \left(m_{ij} - \sum_{h=1}^{t} x_h \cdot a_{ij}^t\right)^2)^{\frac{1}{2}}, \sum_{i=1}^{t} x_i^2 = 1 \qquad (3)$$

Equation (2) is an objective function of abstract non-linear programming, which is to minimize the differences of two matrices. $\sum_{i=1}^{t} x_i^2 = 1$ is the constraint condition to normalize the vector (to ensure $\forall x_i \in [0,1]$). Since M and M^i are symmetric matrices, therefore function *var()* can be set to solve two n(n-1)/2 dimension vectors' similarity, objective function is equivalent to the maximum similarity of these two vectors. Thus, equation (3) is to compute Euclidean distance of two vectors. Under optimal condition, $M = \sum_{i=1}^{T} x_i * M^i$, if there is an existing solution, then there is a unique solution of *X*.

3.3 Prediction of Learning Styles

The prediction assumes that once learners perform similar behaviour sequences, accordingly they have similar learning style preferences. Therefore, according to behavioural matrix *M* and optimal solution vector *X* (vector components of vector *X* represent the extent of each learning style dimension's influence on the behavioural matrix), if *n* students' learning style preference on each dimension is p_i^t (the prediction learning style value for student *i* on learning style dimension *t*), 0<*i*≤*n*, then the estimation/prediction values are:

$$\widehat{p_i^t} = \overline{p_j^t}_{m_{ij}=1} \tag{4}$$

Equation (4) represents the average learning style detected value of student *j* who has the same behaviour sequence with student *i* on learning style dimension *t*. The prediction values are recorded in the form of probability, x_t, indicating that learning style dimension *t* plays a decisive role in behaviour matrix (x_t close to 1) and eventually the learning style value on this dimension is predicted with the clustering. In addition, once the learning environment changes, it is still possible to obtain prediction values on different dimensions of learning style.

3.4 Pilot Evaluation of the Proposed Approach

The proposed approach to automatically detect student's learning style was evaluated with 33 1st year undergraduate students from Loránd university in Hungary who undertook a course on object-oriented programming. Moodle platform was used as a learning management system for the course. The tracking mechanism provided in the Moodle was used to record students' learning behaviours.

3.4.1 Method

This study used Felder-Silverman learning style model. The model has proven to be effective in many adaptive learning systems (García et al., 2007; Graf & Lin, 2007; Hong, 2004). Additionally, it is easy to do a benchmark comparison to confirm the performance of the proposed approach.

In order to evaluate the proposed approach, 33 undergraduate students participated, they were required to answer the ILS (Felder & Soloman, 1997) (see Appendix A) before taking the course. 33 students interacted with Moodle LMS for a course on object-oriented programming for seven weeks. Their learning behaviours were tracked and recorded. They were considered as ‘existing students’ in the database. The remaining 3 students (10% of total amount of students) were the newcomers into the Moodle LMS and their learning styles were administered using the ILS instrument at the end of the experiment. The aim is to compare the auto detection result with the ILS instrument for validation purposes.

3.4.2 Learning Objects

Each learning object was labelled with one subtype of any elements in the set of 16 types of combination from four learning style dimensions: Sensing/Intuitive, Visual/Verbal, Active/Reflective, and Sequence/Global. For example, learning object 1 is labeled as Active/Sensing/Visual/Sequential, while learning object 2 is only labeled as Visual. Grounded on the theoretical descriptions about learning styles' characteristics of Felder-Silverman and based on past researches (Graf & Liu, 2008; Hong, 2004; Popescu et al., 2008), the learning objects and their relevant behaviour in the pilot experiment were labeled as described in Table 3.2 and Table 3.3.

Table 3.2: Labels of learning objects in the experiment

LS dimension	Learning object
Active	Exercises, self-assessment, multiple-choice question exercises
Reflective	Examples, Outlines, Summaries, result pages

Sensing	Examples, explanation, facts, practical material
Intuitive	Definitions, algorithms
Visual	Images, graphics, charts, animations, videos
Verbal	Text, audio
Sequential	Step-by-step exercises, constrict link pages
Global	Outlines, summaries, all-link pages

Table 3.3: Relevant behaviour of learning objects

Learning object	Learning behaviour pattern
Exercises	Number of visits Time spent on exercise
Self-assessment/result pages	Time spent on the test Time of student checked his/her results Results on self-exercise Number of revisions before submission
Outline/summaries	Number of visits Time spent on outlines
Examples	Number of visits Time spent on examples
Content objects (explanation/ facts/practical material/ definitions/algorithms/ text/graphics)	Number of visits Time spent on content objects (explanation/facts/practical material/definitions/algorithms) Time spent on content objects including graphics Time spent on content objects including text
Navigation	Number of times skipped learning objects Number of time jumped back to previous learning object Number of visits of course overview page Time spent on the course overview page

3.4.3 Results

In this pilot experiment, the detection of student learning styles on two dimensions of Felder-Silverman model were assessed. The two dimensions are: input (visual/verbal) and understanding (sequential/global) dimensions. Once students' learning style are obtained (based on the sub-scales of Felder-Silverman's learning style model, see Figure 3.3), it should be mapped to the values of correlation matrix. Felder-Silverman's learning style model ranks students according to different levels as ±1, ±3, ±5, ±7, ±9, ±11. For example, a student categorized as '-9' in the understanding dimension has clear preference for sequential behaviour. On the other hand, a student categorized as '+11' in the understanding dimension shows a strong global behaviour. In order to match the value of correlation matrix, the ILS results were converted into normalized decimals between 0 and 1. The values 5-11 of active/sensing /visual/sequential were mapped onto the range of [0.7-1]; the values 5-11 of reflective/intuitive/verbal/global were mapped onto the range of [0-0.3]; the neutral values were mapped onto the range of [0.4-0.6]. The distribution of 30 students on sequential/global and visual/verbal dimensions are shown in Figure 3.4. The vertical bar represent the number of students and the value on horizontal bar indicate the learning style preference values which converting from [-11,+11] to [0,1], for example, two students with strong active learning style preference with the value 0.045 that actually represent the value -11 of FSLSM.

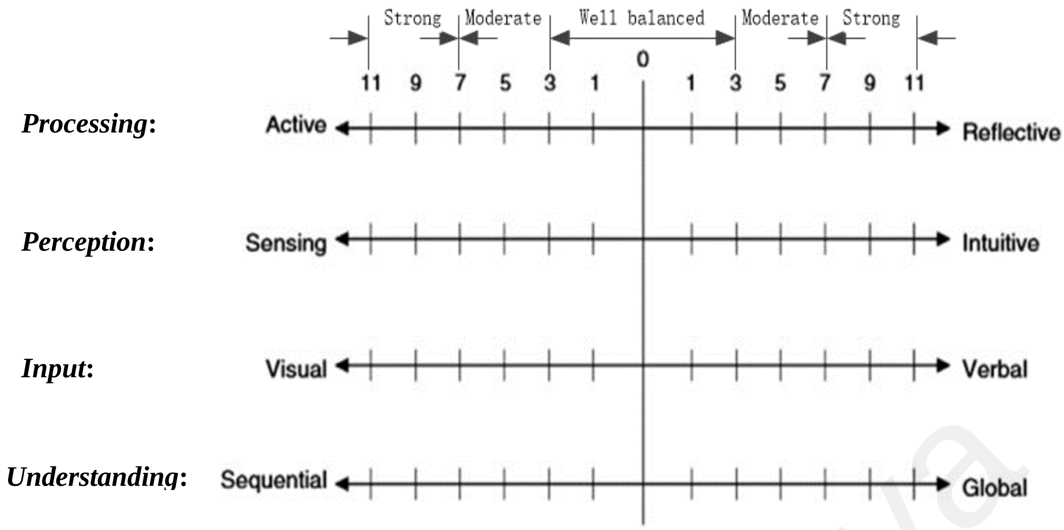

Figure 3.3: Scale of FSLSM

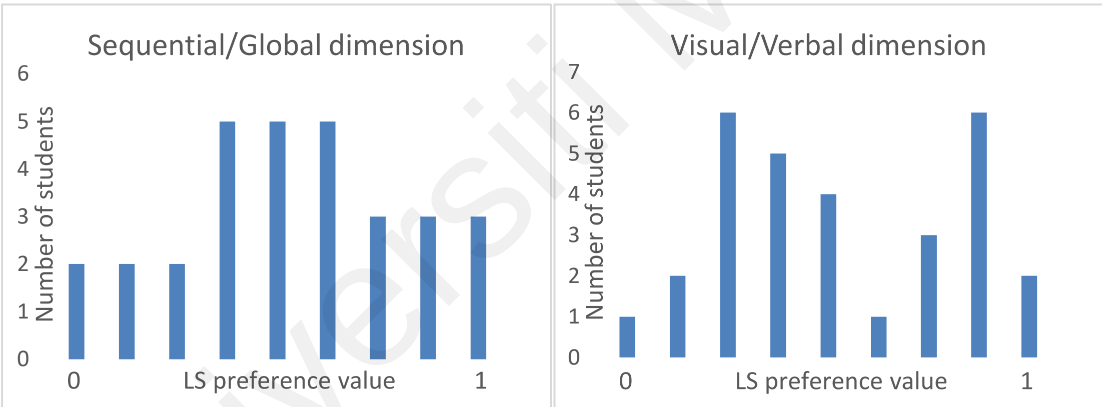

Figure 3.4: Distribution of 30 students' learning style

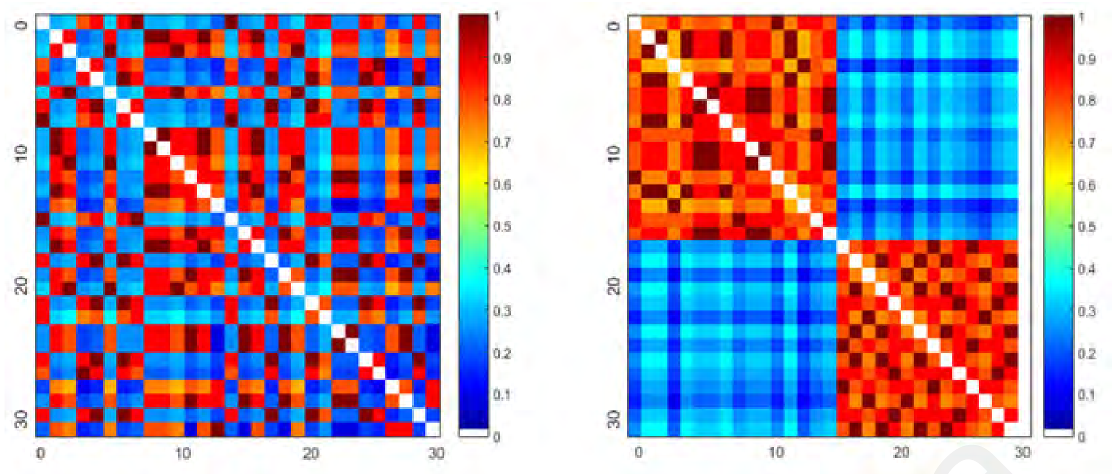

Figure 3.5: Correlation matrix of Visual/Verbal (left, M_1) and Sequential/Global (right, M_2) dimensions

Figure 3.5 and 3.6 show graphical representation of the matrices, which demonstrate the effectiveness of the detection process. The vertical and horizontal bars represent individuals, and the bars of color rule represent correlation coefficient. The corresponding correlation matrices of the students with respect to input and understanding dimensions are shown in Figure 3.5. As each element m_{ij} in the matrix approaches 1, the corresponding spot in position (i,j) is lighter (red), indicating stronger correlation. By contrast, if m_{ij} approaches 0, the corresponding spot is darker (blue). Figure 3.5 shows that the multidimensional space comprised two different types of mutual similarity relationships that corresponded to learning style dimensions of the students. The multidimensional space can be expanded by adding new types of mutual similarity relationships with respect to the new learning style dimensions, even if these learning style dimensions come from different learning style families. The sample learning style preference patterns were generated using Equation (1).

The scatterplot matrix shows the similarity by Tanimoto coefficient values of m_{ij}. Figure 3.6 (left) shows the comparison behaviour matrix, which included the newcomers (10% of the total number of students were replaced). It was discovered that only learning style correlation matrix M_2 (Figure 3.5, right) is more similar with the behaviour matrix M (Figure 3.6, left). With regard to the hypothesis of "the more similar the learning style preference, the higher the similarity of their learning behaviours", it can be deduced that the sequential/global dimension has a more important role in the learning process because their learning style preference matrix pattern and learning behaviour matrix pattern are consistent.

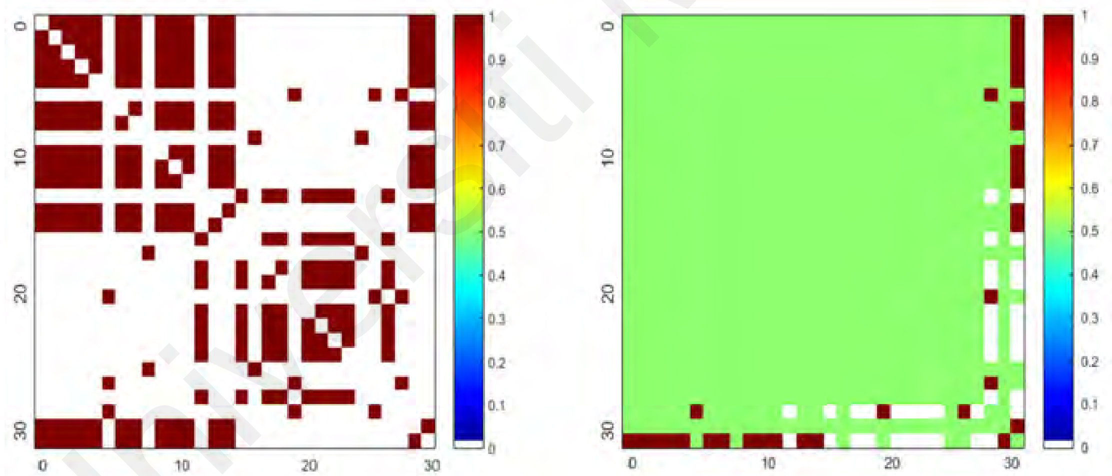

Figure 3.6: Behaviour matrix M (left), similarity comparison matrix M_X (right)

Therefore, the values of the newcomers' learning style could be calculated by the proposed approach, which is presented in Figure 3.6 (right). The figure shows a strong similarity between the behaviour matrix and correlation matrix made by the optimal solution x_i. The comparison matrix $M_x = M - \sum_{i=1}^{3} x_i * M^i$, x_i is the optimal solution. The learning style values of the newcomers x_i are (0.969 0.864 0.116).

When mapping the detection values to the ILS scale, the positive learning style preference values on the area 0.7-1 onto the ILS scale were 5-11. The results indicate that two of the newcomers out of total 3 of newcomers are categorized as 'global 9 (+9)' and 'global7 (+7)' while the other was categorized as 'sequential 11 (-11)' in the understanding dimension. The results were compared with the newcomers' learning style values (administered via the ILS instrument) to verify the validity of the results. Table 3.4 shows positive results for all newcomer students hence provide evidence that the proposed approach is viable to identify student's learning style.

Table 3.4: Comparison between questionnaire and detection

	Student 1	Student 2	Student 3
FSLSM preference	Global 9	Global 7	Sequential 11
Detected result	0.969	0.864	0.116

Since the pilot experiment shows positive results, one of the aims of developing correlation analysis method that is generic and reusable for practical use is achieved. It is reusable because the method considers the relevance between learning style correlational matrix and learning behaviour matrix data sets for LS detection, and the components of the matrix such as learning behaviour, related patterns and learning objects are inherent in any LMS. However, due to the dataset is deemed small in the pilot experiment, based-on the obtained data, another four runs (five runs in total) with random 3 students (as newcomers) were tested for the preliminary precision of the results (according to García et al.(2007)'s equation, refer to Section 5.2.3.1 for details). Table 3.5 illustrates the reliability of the detection result precision based on the five runs. However, through the pilot test, the precision of the results obtained at around 60% was not satisfied when comparing with past works. Further details of the evaluation and results of this approach will be presented in Chapter 5.

Table 3.5: Reliability of the detection results

Learning style dimension	Mean	STDEV	Confidence interval	Confidence levels
Processing	0.57	4.21%	(56-61%)	85%
Perception	0.63	8.78%	(60-71%)	78%
Input	0.61	8.99%	(57-69%)	77%
Understanding	0.63	8.21%	(58-67%)	79%

3.5 Summary

The proposed approach attempts to detect students learning style automatically. It is designed based on simple correlational relationship and attempted to remove the reusable problem between user models and automated detection techniques and educational systems. The detection method is based only on indications gathered from the students' behaviour during an online course, more specifically, by constructing behaviour matrix and learning style correlation matrix that reflect the relationship of current learning style dimensions. The performance of this approach was tested through pilot experiment, which included 33 students and assessed on two dimensions of FSLSM. While the approach reveals a generic method for a LMS and is viable to identify students' learning style, its' moderate precision, however, needs to be improved. The next chapter presents another approach for better detection result in LMS.

CHAPTER 4: IMPROVING THE DETECTION OF LEARNING STYLE BY USING TREE AUGMENTED NAÏVE BAYESIAN.

In last chapter, in order to solve the reusable problem, a mathematical model based on correlational matrix for learning style detection method was proposed. By using mathematical algorithm-based framework, the detection method is able to deploy in various educational systems. However, the small data set used in the pilot study produced detection results with moderate precision. To balance the reusable issue and detection precision, another approach based on tree naïve Bayes network to obtain better result of learning style detection is introduced.

In this chapter, a proposed automatic detection approach presumes the students' learning style based on preset learning style for solving cold-start problem in the early stage of detection. Then, the tree augmented naïve classifier is used to establish the learning style classification model, which can dynamically acquire and revise the learner's learning style. An experiment was conducted to test the proposed approach. The result shows that this model yields more accurate results in comparison with the Bayesian network approaches. The first section describes the Bayesian network techniques applied in learning style detection field. Then it describes the construction of the Bayesian network. Finally, the detection algorithm based on the tree augmented naïve Bayesian network is introduced.

4.1 Overview of tree augmented Bayesian network

4.1.1 Bayesian network revisited

Bayesian network is an uncertain relationship representation and reasoning model based on probability analysis and graph theory. Bayesian network is a Directed Acyclic Graph where nodes represent random variables and arcs represent probabilistic correlation between variables (Jensen, 1996).

The absence of edges in a Bayesian network denotes statements of independence. A Bayesian network encodes the following statement of independence about each random variable: a variable is independent of its non-descendants in the network given the state of its parents (Pearl, 2014). A Bayesian network also represents a particular probability distribution, the joint distribution over all the variables represented by nodes in the graph. This distribution is specified by a set of conditional probability tables (CPT). Each node has an associated CPT that specifies this quantitative probability information. Such table specifies the probability of each possible state of the node given each possible combination of states of its parents. For nodes without parents, probabilities are not conditioned on other nodes. These are called the prior probabilities of these variables.

Naïve Bayesian is a simple structure that has the classification node as the parent node of all other nodes. No other connection is allowed in a naïve Bayesian network as shown in Figure 4.1.

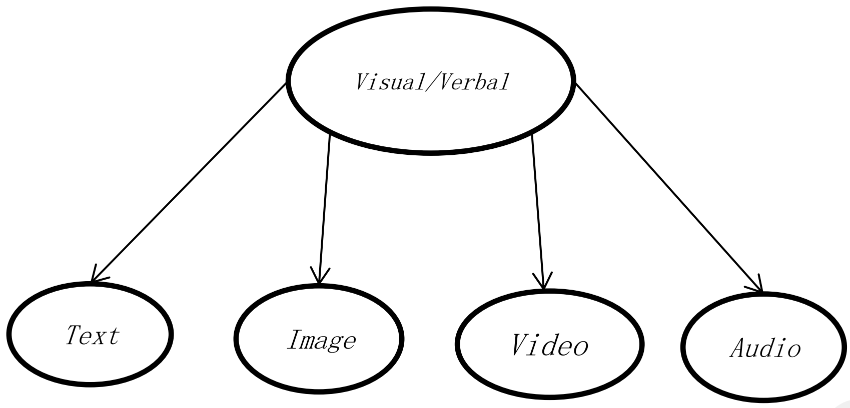

Figure 4.1: A simple naïve Bayesian

Past studies (Beech et al., 2017) found that Bayesian networks are very suitable to be employed as the detection technique for adaptive education domain. However, the general Bayesian network is too complex for small datasets, and easy to overfit (Kozma, 1991). Naïve Bayesian avoids this problem due to the hypothesis class' simplicity prevents it from overfitting. The naïve Bayesian classifier is an effective classifier due to two advantages that it has over other classifiers. Firstly, it is easy to be constructed, as the structure is given a priority besides no structure learning procedure is required. Secondly, the classification process is very efficient. Both advantages are derived by assuming that all features are independent of each other. The simple structure only contains two layers, the classification node as the parent node of all other nodes. No other connection is allowed in the naïve Bayesian network as shown in Figure 4.1. There is only one connection link between node *visual/verbal* and all leaf *node text, image, video, audio*. The naïve Bayes assumes that all leaf nodes are conditionally independent, which means two or more events are dependent when a third event occurs.

But, the conditional independence assumption in the naïve Bayes is rarely true in reality. In adaptive educational domain, the naïve Bayesian assumption is (nearly) always violated due to the variables are often interconnected.

4.1.2 Tree Augmented Naïve Bayesian Network

Due to the requirement of each node must be independent, which renders the naïve Bayesian network structure unreasonable, resulting in the poor accuracy of naive Bayesian classifier. Friedman et al. (1997) studied tree augmented naïve Bayesian, which extend naïve Bayesian by allowing tree-like structures to be used to represent the dependencies among attributes. Figure 4.2 shows node *visual/verbal* and all leaf nodes *text, image, video, audio* with their respective arcs from node *visual/verbal*, from a tree (Khor et al., 2009). As can be seen from the figure, there are extra edges between the network attributes, which allow to capture the correlations among them (Carvalho et al., 2007). By adding the extra edges, tree augmented naive Bayesian network overcomes the limitation of naïve Bayesian network, which can help to capture the correlations between learning objects in order to provide more precise result.

Thus, tree augmented naïve Bayesian makes a good compromise between general Bayesian network and naïve Bayesian. Also, the structure of tree augmented naïve Bayesian is simple enough to avoid overfit and strong dependencies can be taken into account.

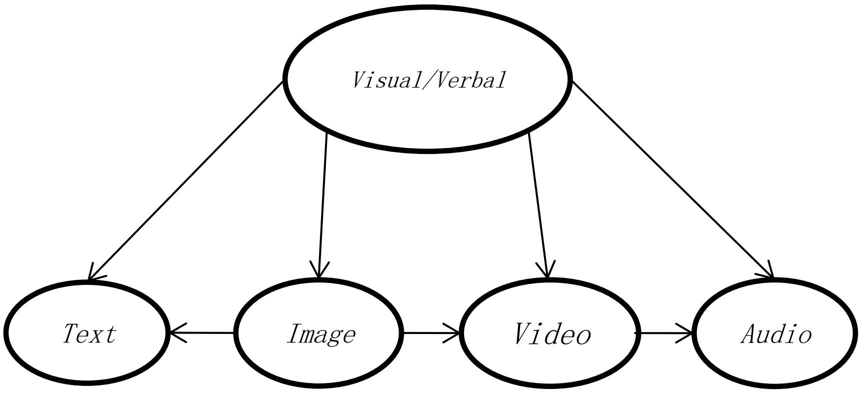

Figure 4.2: A simple tree augmented naïve Bayesian structure

Unlike naive Bayesian networks, tree augmented naïve requires a learning procedure that constructs the model structure. At present, the typical tree augmented naïve learning procedure to construct the tree augmented naïve classifier by using conditional mutual information.

The algorithm for learning tree augmented naïve models is a variant of the Chow and Liu (1968) algorithm for learning tree-structured Bayes nets. Let *C* represent the class variable, and $\{X_i\}_{i=1}^{n}$ be the features (non-class variables). The tree augmented naïve learning procedure is as follows:

1. Compute the conditional mutual information:

$$\mathrm{I}(X_i; X_j|\mathrm{C}) = \sum_{x_i, x_j, c} P(x_i, x_j, c) \log \frac{P(x_i, x_j|c)}{P(x_i|cP(x_j|c))}$$

According to probability theory and information theory, the mutual information of two random variables is a quantity that measures the mutual dependence of the two random variables. Using conditional mutual information to test the conditional independence of $I(X, Y, Z)$, where $P(.)$ is the empirical distribution, computed from the training data. Intuitively, this quantity represents the gain in information by adding X_i as a parent of X_j given that C is already a parent of X_j.

2. Build a complete undirected graph on the features $\{X_1, ..., X_n\}$, where the weight of the edge between X_I and X_j is $I(X_i; X_j \mid C)$.
3. Find a maximum weighted spanning tree of the completed undirected graph.
4. Pick an arbitrary node of the maximum weighted spanning tree as the root and set the direction of all edges to be outward from the root to build a directed graph.
5. Add a class node and an arc between the class node as well as attribute node to construct tree augmented naïve model.

In the current Bayesian network classifiers, tree augmented naïve is considered as a widely accepted Bayesian classifier with wide applicability and good comprehensiveness for performance, efficiency and space-time complexity.

4.2 Learning Style Detection Model Based on Tree Augmented Bayesian Network

4.2.1 Preset LS

As aforementioned problem, the cold-start problem caused by users do not have any previous profile in the system, the automatic detection method requires students to use the education system for a period of time in order to automatically detect learning style preferences hence to provide adaptive learning materials.

The cold start problem in educational system caused by the learner does not have any previous configuration data in the system. Subsequently, the system could not provide adaptation to learner needs until enough data is collected and analyzed. There are two solutions proposed by past researches: i) requires the learner to self-report learning style preferences to initialize the student model and then update them by observing their behaviour (Chen & Liu, 2008; Graf & Viola, 2009) ii) initializing student model by default (Carmona et al., 2007). However, the studies found that there was a relationship between cross-cultural differences, other backgrounds, demographic characteristics and learning styles, which concluded that "culture do have distinctive learning style patterns and learning styles are a function of both nature and nurture" (Guild, 1994). Yamazaki (2005) and Joy and Kolb (2009) studied the relationship between a particular culture and a certain learning style using Kolb's LSI. The results show that each particular culture has adopted a certain learning style.

In order to solve cold- start problem and also to avoid the inconvenience of filling up lengthy learning style questionnaires, this study suggests that the learning style of students to be pre-set at the beginning of learning. The conclusion drawn from the analysis of adult learning style in Shockley (2005) study found that learners are mostly reflective in the processing dimension, intuitive in the perception dimension, prefer visual for their input method, and more in sequential as a way to progress understanding. In addition, researchers have also studied learners' learning style characteristics in different disciplines (biology, commerce, chemistry, finance, accounting, etc.). The results generally prove that the students' learning styles are characterized by disciplines and specialties. Learning style is also affected by cultural, background, different countries (Graf & Liu, 2010). Therefore, in order to identify students' learning style, a pilot experiment was conducted to verify the effectiveness for this method (the detail of this pilot experiment is not included in this thesis, because it used partial data from main experiment in Chapter 5, the experiment procedure and setting are same as the main experiment). The experiment gathered 46 second year undergraduates from Loránd university in Hungary. The experiment began on March 13, 2017, lasted for 7 weeks and data collected in May 2017. They were given the opportunity to use the same online learning management system Moodle for the same taught module object-oriented programming. Before starting the course, they were required to fill up the ILS questionnaires online. Figure 4.3 shows that students' learning style in four dimensions are more inclined to active, intuitive, visual and sequential learning styles. Only the processing dimension is different from Shockley (2005)'s result, but the other dimensions are the same. Besides, it was discovered that the bioinformatics students require more practical work, while most of the other courses require students to collaborate in a group. Therefore, it can be concluded that bioinformatics students prefer the active learning style in processing dimension. In sum, the pre-set learning style preferences for these students are active, intuitive, visual and sequential.

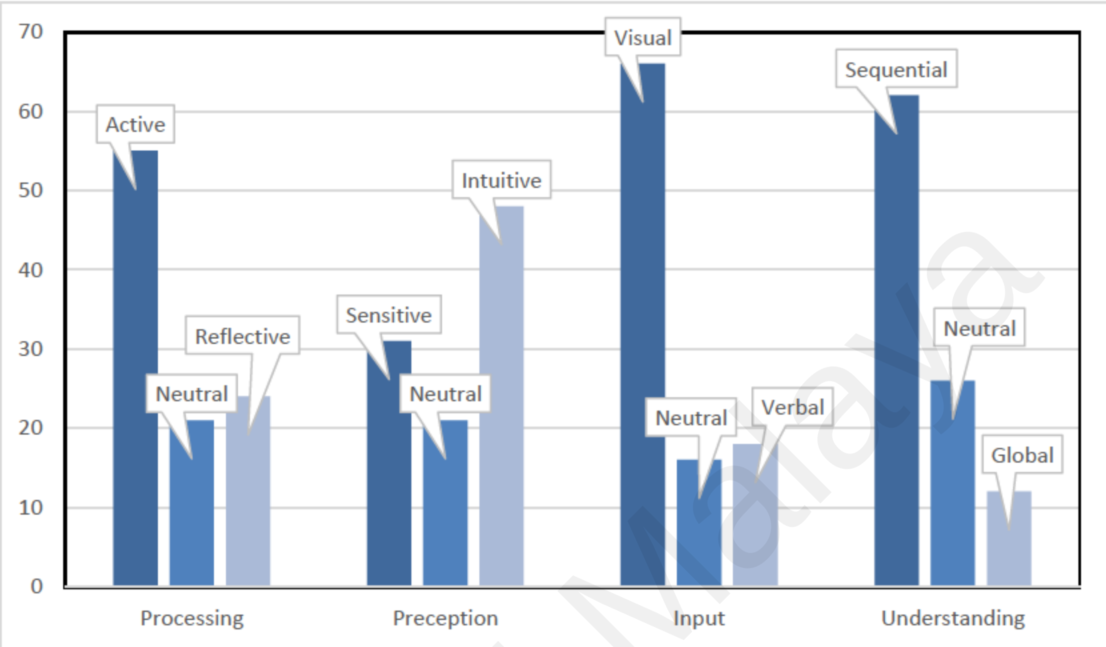

Figure 4.3: Distribution of students' learning styles

4.3 Construction of LS Detection Model based on Tree Augmented Naïve Bayesian Network

Students enter the system with preset learning styles. Their learning styles will be updated individually based on their learning behaviour as they interact with the system. This learning style detection model is constructed based on tree augmented naïve Bayesian network to mine data from students' learning behaviour. The learning behaviours of learners mainly include visiting the forum, sending and receiving e-mail, watching videos, carrying out exercises, collaborating, communicating via forum and many more. Based on the previous researches and literatures (Carmona et al., 2007; García et al., 2007; Romero & Ventura, 2010), a FSLSM-based learning style Bayesian network model was built as shown in Figure 4.4.

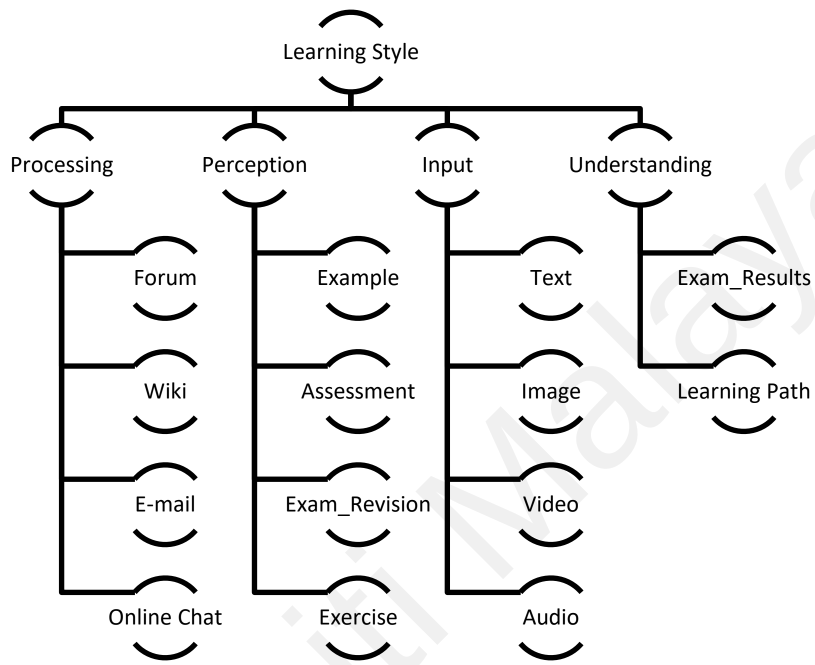

Figure 4.4: Bayesian network modeling a student's learning style

At processing dimension, active learners work well in groups whereas reflective learners work better by themselves or at most with one person. Learners can be assessed from their WIKI, forums, online chat and e-mail usage to identify if they are active or reflective.

Sensors prefer facts, data and experimentation whereas intuitors prefer principles and theories. Sensors are patient with detail but do not like complications whereas intuitors are bored by detail and welcome complications. If a learner likes a specific learning material, learns through examples and case studies, and carefully examine the questions -- these characteristics indicate that the learner tends to be a sensor. Otherwise, he/she prefers intuitive learning.

The input dimension mainly determines the learning style based on the type of learning materials. Visual learners like to learn using pictures, diagrams, video, and animation materials. If learners like to learn using text and audio materials, this indicates that they are verbal learners.

Sequential learners learn in a step by step manner, follow linear processes according to the learning contents. On the other hand, global learners make intuitive leaps and may struggle to explain how they came up with solutions. Additionally, if a learner does not read or learn the relevant learning contents, but he/she is able to complete the test and obtain high marks, it could be inferred that he/she is a global learner.

In the following paragraph, the processing (*Pro*) dimension node is used to illustrate model construction and algorithm implementation. There are two classification of Processing (*Pro*) nodes: active (*Pro1*) and reflective (*Pro2*). WIKI, Forum, Online Chat, and E-mail are child nodes. The degree of usage according to learner's participation are as follows:

(1) WIKI (*W*): very frequently (*W1*), occasionally (*W2*), never (*W3*).

(2) Forum (*F*): post (*F1*), reply (*F2*), read (*F3*), never (*F4*).

(3) Online-chat (*C*): very frequently (*C1*), occasionally (*C2*), never (*C3*).

(4) E-mail (*E*): very frequently *(E1*), occasionally (*E2*), never (*E3*).

Table 4.1 shows the training dataset from the learning system. Rows represent all students as training data, and columns represent all relevant features of processing dimension, the values indicate the students' behaviour and preference respectively.

Table 4.1: Training data set of processing dimension

User	Processing dimension	Forum	Wiki	Online chat	e-mail
1	*Pro1*	*F1*	*W1*	*C1*	*E1*
2	*Pro1*	*F1*	*W1*	*C2*	*E1*
3	*Pro1*	*F1*	*W1*	*C1*	*E2*
4	*Pro2*	*F2*	*W1*	*C3*	*E1*
5	*Pro1*	*F2*	*W1*	*C1*	*E1*
6	*Pro1*	*F2*	*W1*	*C2*	*E3*
7	*Pro2*	*F3*	*W1*	*C3*	*E3*
8	*Pro1*	*F3*	*W1*	*C1*	*E1*
9	*Pro2*	*F4*	*W1*	*C3*	*E2*
10	*Pro1*	*F4*	*W2*	*C3*	*E1*
…	...	...	...	...	...

Table 4.2: CPT of node *Pro*

Pro	Value
Pro1	16/36
Pro2	20/36

Table 4.3: CPT of node *W*

W	*Pro*	
	Pro1	*Pro2*
1	4/7	1/8
2	2/7	3/8
3	1/7	4/8

Table 4.4: CPT of node *F*

F	*Pro*	
	Pro1	*Pro2*
F1	5/7	0
F2	1/7	2/8
F3	1/7	2/8
F4	0	4/8

The CPT table of node *Pro* can be calculated according to the conditional probability *P(A/B)=P(AB)/P(B)* (refer to Table 4.2). In fact, the CPT table of node *Pro* is the prior probability as well. The prior probabilities of node *W* and *F* are shown in Table 4.3 and Table 4.4.

4.4 Detection Algorithm based on Tree Augmented Naïve Bayesian Network

The steps of learning style detection by tree augmented naïve Bayesian network are:

(1) The establishment of the Processing node tree augmented naïve Bayesian network structure. This step consists of several sub-steps:

Step 1. The conditional mutual information between the *W, F, C, E* and *Pro* attribute variables is calculated according to the procedure of tree augmented naïve calculation as described above in section 4.3. The results are:

$I_p(W; F/Pro) = 0.236\ 978$ $\quad$ $I_p(W; C/Pro) = 0.224\ 639$

$I_p(W; E/Pro) = 0.175\ 241$ $\quad$ $I_p(F; C/Pro) = 0.136\ 257$

$I_p(F; E/Pro) = 0.106\ 573$ $\quad$ $I_p(W; E/Pro) = 0.068\ 372$

Step 2. Construct the weighed undirected graph by weighing the conditional mutual information between pairs of attribute variables, as shown in Figure 4.5.

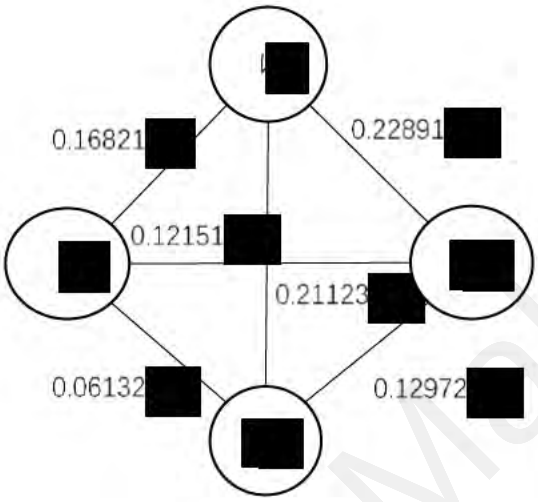

Figure 4.5: Weighted undirected graph

Step 3. Sort the weight $e_{i,j}$ in descending order, $e_{i,}$ representing weight between the corresponding nodes: $e_{w,f}$, $e_{f,c}$, $e_{w,e}$, $e_{w,c}$, $e_{f,e}$, $e_{c,e}$.

Step 4. Build the maximum weighed spanning tree: $e_{w,f}$, $e_{f,c}$, $e_{w,e}$.

Step 5. Establish a directed tree using node C as the root node, and increase the class variable node, the arcs between class variable node and attribute node. The tree augmented naïve Bayesian network structure is established with the class variable as the parent node of all the attribute nodes, as shown in Figure 4.6.

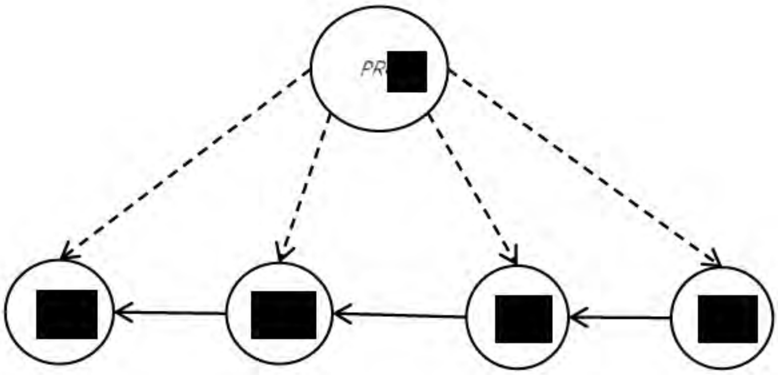

Figure 4.6: Tree augmented naïve Bayesian network structure

(2) the establishment of tree augmented naïve Bayesian network parameters

According to the learning process parameter above, CPT table of node *C, F, W* and *E* can be calculated separately, as shown in Table 4.5 to Table 4.8, respectively.

Table 4.5: CPT of node *C*

C	*Pro=Pro1*	*Pro=Pro2*
C1	8/16	4/20
C2	5/16	4/20
C3	3/16	12/20

Table 4.6: CPT of node *F*

F	*C*					
	C1	*C2*	*C3*	*C4*	*C5*	*C6*
	Pro1	*Pro1*	*Pro1*	*Pro2*	*Pro2*	*Pro2*
F1	3/9	3/5	1/3	0	1/2	2/11
F2	2/9	2/5	1/3	0	0	1/11
F3	2/9	0	1/3	2/4	1/2	3/11
F4	1/9	0	0	2/4	0	5/11

Table 4.7: CPT of node *W*

W	*F*							
	F1	*F2*	*F3*	*F4*	*F1*	*F2*	*F3*	*F4*
	Pro							
	Pro1	*Pro1*	*Pro1*	*Pro1*	*Pro2*	*Pro2*	*Pro2*	*Pro2*
W1	3/7	3/6	1/2	1	0	0	1/6	1/8
W2	2/7	2/6	1/2	0	2/3	1/2	2/6	3/8
W3	2/7	1/6	0	0	1/3	1/2	3/6	4/8

Table 4.8: CPT of node *E*

E	*W*					
	W1	*W2*	*W3*	*W1*	*W1*	*W1*
	Pro					
	Pro1	*Pro1*	*Pro1*	*Pro2*	*Pro2*	*Pro2*
E1	5/7	3/7	1	0	1/8	0
E2	1/7	3/7	0	1/3	2/8	4/9
E3	1/7	1/7	0	2/3	5/8	5/9

(3) tree augmented naïve Bayesian network reasoning

Assume a given student's learning behaviour set is frequent access to WIKI, reading posts, occasional chatting online, occasional e-mailing ($X = \{W1, F3, C2, E2\}$). Respectively, $P(X|Y_i)P(Y_i), i=1, 2$. The prior probability $P(Pro_i)$ for each class can be calculated from the training data, is *P(Pro*="active")=16/36, *P(Pro*="reflective")=20/36. The prior probability can be derived as follows:

$$P(X|Pro1) = \prod_{i=1}^{4} p(X_i|Pa(X_i)$$
$$= p\left(x_0 = \frac{\text{W1}}{F3}, pro1\right) * p\left(x_1 = \frac{\text{F3}}{C1}, pro1\right) * p\left(x_2 = \frac{\text{C1}}{pro1}\right)$$
$$* p\left(x_2 = \frac{\text{E2}}{W1}, pro1\right) = \frac{1}{2} * \frac{2}{9} * \frac{8}{16} * \frac{1}{7} = 0.0765$$

Similarly,

$$P(X|Pro2) = \prod_{i=1}^{4} p(X_i|Pa(X_i)$$
$$= p\left(x_0 = \frac{\text{W1}}{F3}, pro2\right) * p\left(x_1 = \frac{\text{F3}}{C1}, pro2\right) * p\left(x_2 = \frac{\text{C1}}{pro2}\right)$$
$$* p\left(x_2 = \frac{\text{E2}}{W1}, pro2\right) = \frac{1}{6} * \frac{3}{11} * \frac{4}{30} * \frac{1}{3} = 0.00303$$

Therefore, the preliminary result of the tree augmented naïve Bayesian network for *X* is: *Pro*= "active". Then:

P(Pro=Pro1)=P(X/Pro1)/(P(X/Pro1)+P(X/Pro2))=0.963=96.3%

P(Pro=Pro2)=P(X/Pro2)/(P(X/Pro1)+P(X/Pro2))= 0.037=3.7%

The scales of index for each dimension's learning style of FSLSM are: 1,3,5,7,9,11. Where 1 and 3 represent learning styles that are fairly well-balanced on the two dimensions of the scale, 5 and 7 indicate a moderate preference for one dimension of the scale, and 9 and 11 indicate a very strong preference for one dimension of the scale. Therefore, 50% to 100% are divided into three levels, corresponding to the FSLSM preference levels. A probability between 50%~66.7% indicates fairly well-balanced, 66.8% ~ 83.4% indicates moderate preference, 83.5% ~ 100% shows a strong preference. According to the above calculation, the results show a strong tendency for the ‘active' on the processing dimension.

4.5 Summary

In this chapter, the tree naïve Bayes network method is introduced to improve the precision of learning style detection results. This method is designed to solve some issues of using Bayesian network in learning style detection field. The evaluation and data analysis of the two different approaches for detecting learning styles are discussed in the following chapter.

CHAPTER 5: EXPERIMENT AND RESULTS

In Chapters 3 and 4, two automatic learning style detection approaches are proposed based on different considerations. Whereas the correlation analysis approach emphasizes the compatibility of the detection method across different educational platforms, the tree augmented naïve Bayesian network approach focuses on improving the precision of the detected results in the LMS.

This chapter describes the main experiment for both proposed approaches using the same data set. The first step is the data exploration for determining the students' relevant preferences and behaviour, then the data regarding the preferences and students' behaviour for inferring the learning style is collected. Although the results are not meant to be used as a comparison between different methods, especially for previous studies because they are based on different data, to increase comparability with previous studies, some experiment settings are based on previous representative studies' settings. This chapter also presents an experimental method that includes participants and design, materials, and data collection. Finally, this chapter discusses the method of evaluation and analysis of results for both approaches separately.

5.1 Procedure for data exploration

As depicted in Figure 5.1, the procedure for student data exploration can be divided into two parts. In the first step, it is necessary to determine the learning behaviour of students through the LMS. This is typically conducted based on the literature, specifically on the FSLSM and related studies in this field, that examines the features of LMS, thresholds for data classification, and learning behaviour patterns for each learning style dimension. The second step is preparing and using student learning behaviour data to infer learning style preferences. This procedure is applicable to both proposed approaches.

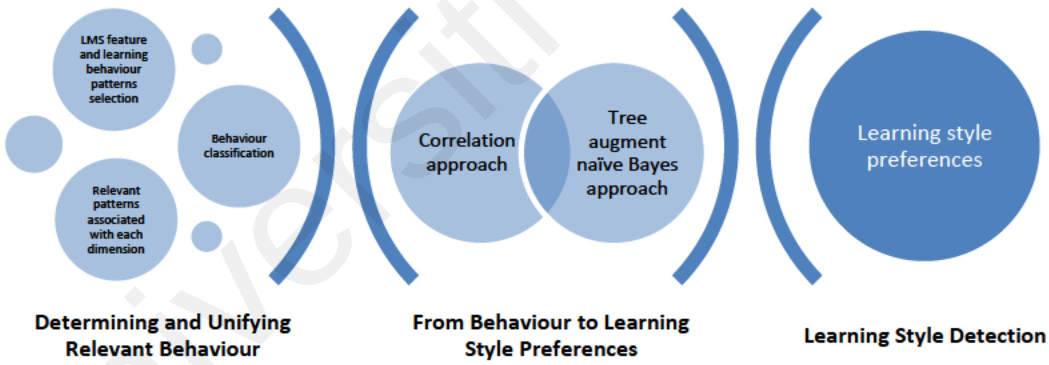

Figure 5.1: Automatic learning style detection concept

5.1.1 Determining and unifying relevant behaviour

The purpose of the automated student modelling approach is to identify learning styles based on the student's learning behaviour in the LMS. Obtaining deeper insight into behaviours is vital to ensure the feasibility of this approach for broader LMSs and its usefulness in the detection of learning styles. The choice of LMS features and learning behaviour patterns is based on two requirements. First, the patterns need to be relevant to FSLSM— those patterns and features were identified from the literature in this field, particularly about FSLSM. Second, the information about the learning behaviour pattern should be able to be tracked by most LMSs and should be made available to both lecturers and course developers—only the patterns and features commonly used in most LMSs and by teachers and course developers are chosen.

The following sub-sections introduce the features and patterns and discuss how to classify the occurrence of behaviour with patterns. This classification can be distinguished between different behaviours, such as the number of visits or time spent on a particular type of learning object. The related patterns for every learning style on each dimension are then described.

5.1.1.1 Selected features and patterns

This section describes the selection of the same LMS features (selected in the previous pilot study described in Chapter 3). The LMS features include content objects, examples, outlines, exercises, self-assessments (SAs), and discussion forums. Furthermore, patterns of student navigation behaviour were considered.

The pattern is regarded as a combination of the type of learning materials (e.g., content, outline, and examples) and the frequency and duration that the students spend on those learning objects. For the SA, the total number of questions answered and time spent on learning materials are considered patterns. Furthermore, questions that involve facts or concepts, details or outlines, images or text, and proposing a new solution or interpreting a given solution, are all considered. Another pattern for handling SAs is the amount of time spent on results. For the exercises, the number of visits and the time spent are also considered patterns. Furthermore, performance on the development of a new solution or a given solution, and the time of the students reflected in the exercise results, are combined with the behaviour in the SA test. For the forum, the patterns include the number of visits and time and posting frequency. Concerning navigation behaviour, the pattern includes the frequency of skipping learning objects through the navigation menu, the frequency of visiting on the course overview page, and the associated time spent.

As described previously, the patterns introduced are considered based on their commonality in most LMSs and their relevance to the learning style dimension on the FSLSM. The following sub-section presents recommendations for classifying behaviour occurrences and discusses the relevant patterns and corresponding behaviour.

5.1.1.2 Classification of the learning behaviour

The classification of learning behaviour is given based on the patterns described in the previous section. The classification is necessary to apply both proposed approaches to broader LMSs and ensure they are sufficiently generic for different learning style traits.

Three items scales are used: high, medium, and low. Classification is based on a general threshold, not the average behaviour in the corresponding courses. The advantage of using a general threshold is that the outcomes in the form of a recognized learning style do not depend on other students' behaviours. In contrast, using average behaviour to derive the threshold results in a predefined distribution of learning styles for every pattern may be unsuitable for small- to medium-sized teams. A general threshold is used to ensure the approaches are suitable for small and medium-sized groups. However, as argued by Alberer et al. (2003) and Roblyer and Wiencke (2003), depending on the course structure, theme, and student experience, the general threshold may vary between courses. In the subsequent paragraphs, the threshold recommendations based on García et al. (2007)'s research and used by many previous studies are discussed. Table 5.1 summarizes the recommended thresholds.

Rovai and Barnum (2007) found that more than 50 forums visited and more than 10 postings per week indicate above-average behaviour, whereas fewer than 7 forums visited and fewer than 1 posting per week indicate below-average behaviour. No advice was given on the amount of time a student spent on the forum. However, depending on the number of visits given, 30 minutes per week can be assumed to be higher than average and 5 minutes per week lower than the average.

Table 5.1: Suggested thresholds for behaviour patterns (García et al., 2007)

Type of Material	Patterns	Description	Thresholds	
Outline	Outline-visit	% of outline visiting	75%	150%
	Outline-duration	% of outline duration	50%	75%
Content	Content-visit	% of content objects visiting	75%	100%
	Content-duration	% of content objects duration	50%	75%
Example	Example-visit	% of example visiting	25%	75%
	Example-duration	% of example duration	50%	75%
Exercise	Exercise-visit	% of exercise visiting	25%	75%
	Exercise-duration	% of exercise duration	50%	75%
Self-assessment	self-assessment-visit	% of performed self-assessment questions	25%	75%
	self-assessment-duration	% of time spent on self-assessment tests	50%	75%
	self-assessment-overview	% of questions that correctly answered about overview	50%	75%
	self-assessment-detail	% of questions that correctly answered about detail	50%	75%
	self-assessment-facts	% of questions that correctly answered about facts	50%	75%
	self-assessment-concepts	% of questions that correctly answered about concepts	50%	75%
	self-assessment-images	% of questions that correctly answered about images	50%	75%
	self-assessment-text	% of questions that correctly answered about text	50%	75%
	self-assessment-revisions	% of time spent on revising the answer	20%	50%
	self-assessment-develop	% of questions that correctly answered about new developing	50%	75%
	self-assessment-results	Time spent on the result page	30s	60s
Forum	Forum-visit	Visiting time every week	7	50
	Forum-duration	Visiting duration every week	5m	30m

	Forum-post	Number of postings every week	1	10
Navigation	Navigation-overview-visit	% of overview page visiting	10%	20%
	Navigation-overview-duration	% of duration on overview page	50%	75%
	Navigation-skip	% of times to skip a learning object via the navigation menu	1%	2%

According to García et al. (2007), thresholds for accessing examples, exercises, and SA could be fixed at 25% and 75% of the total available number of each, respectively. For accessing content objects, assuming students read to understand the topic, 75% and 100% of the total available number are used as the thresholds. In contrast, 50% and 75% can be set as the thresholds for the time spent on content objects, exercises, examples, and SA of the expected learning time for students who are highly interested in the corresponding type of learning objects. For the time taken for the results of an exercise or SA, the thresholds are assumed to be 30 to 60 seconds. The threshold for the performance of a particular type of problem can be assumed to be correctly answering 50% and 75% of the questions. According to García et al. (2007)'s recommendation, the threshold for revising the answers of exercises and SA questions is considered to be 20% and 50% of total questions answered. The threshold for the frequency of a double-wrong in answering SA questions was assumed to be 25% and 50% of those who asked the same question twice.

According to Graf and Viola (2009), the recommended thresholds for accessing outlines are 75% and 150% of the total available outline amount. The threshold for the course overview page is set as 10% and 20% of the total learning object quantity, and

50% and 75% are set as the time spent on the overview page and outlines for the predefined time. Concerning skipping learning objects, the relationship between the total number of students skipping learning objects and the total number of learning objects is examined, the thresholds settings are that students use the navigation menu to skip learning objects at 1% and 2%.

A significant issue is that a longer time spent does not actually reflect that learning occurs. An alternative threshold is proposed for managing the time spent by students on a particular type of learning object. This threshold represents the maximum amount of time a learner is expected to spend on a learning object of the respective type. These maximum amounts of time are critical values designed to avoid this high time span rather than discover when students are doing something else and continuing to run online courses. If the recorded values exceed these thresholds for the corresponding type of learning object, the average value is used instead.

5.1.1.3 Relevant patterns associated with each dimension

The description of the patterns associated with each learning style dimension and relevant information about the frequency of occurrence are discussed in this sub-section.

According to FSLSM, for the processing dimension, active students can be predicted based on less time spent to outline, fewer visits to course content, less time spent on examples, a high number of visits to exercises, a low number of visits to and less time spent with SAs, and less time spent on the forum and posting in the forum. The opposite behaviour pattern indicates a reflective preference.

For the perception dimension, sensing students can be predicted based on a low number of visits to and less time spent with course content, a high number of visits to and more time spent with examples, a high number visits to exercises, a high number of visits to SAs, more time spent on SAs and preferring to remain at the details, facts, revisions, and results of SAs, and caring less about the concepts and development of SAs. The opposite behaviour pattern indicates an intuitive preference.

For the input dimension, the behaviour pattern of visual students can be predicted based on a less time spent visiting course content, more time spent on images than text, less time spent visiting the forum and avoiding posting in the forum. The opposite behaviour pattern indicates a verbal preference.

For the understanding dimension, sequential preference can be predicted based on a low number of visits and less time spent with outlines, more time spent on SAs and preferring to remain at the details but caring less about the development, fewer visits to the overview page, and less time spent with and an aversion to skipping learning content. The opposite behaviour pattern indicates a global preference.

Consequently, each dimension contains a relatively large number of patterns. Many patterns provide more detailed information and are especially important for LMS development that incorporates learning styles in general rather than in a specific system, because it may not be possible to obtain information about specific patterns.

5.1.2 From behaviour to learning style preferences

The preceding section describes patterns available to identify learning styles, the classification manner of the data from these patterns with the aim to distinguish between high, medium, and low occurrences of the respective behaviours, and which patterns imply specific dimensions of learning styles. Accordingly, we are ready to manage the raw data on student behaviour in the LMS database.

The next step from learning behaviour to learning style is to compute the ordered data of each pattern, which are prepared as input data for detecting learning styles for both proposed approaches. This process is described in the following section.

5.1.2.1 Construction of input data for each approach

Raw data must be generated from the LMS database. The data was processed using two matrixes for building the input data. One matrix contains ordered data for building patterns, in which the rows represent all students, and columns represent all relevant patterns. The values 0 to 3 are assigned to classify students' behaviour for each pattern. The values 1, 2, and 3 represent low, medium, and high frequency of occurrence of students' learning behaviours. For the second learning style matrix building for each learning style dimension, the rows represent all students, and the columns represent all relevant patterns of learning style dimension, including the ordered data from the pattern matrix for the relevant learning style dimension patterns.

5.2 Method

This sub-section presents an experimental method that includes participants and design, materials, and data collection.

5.2.1 Participants and design

A total of 96 undergraduate students from Loránd University in Hungary participated in the study. Student behaviour is captured in an online object-oriented programming course based on the Moodle LMS. Students are requested to complete the Index of Learning Styles questionnaire to assess their learning styles. The learning content of online courses is then introduced. The duration of the course was 14 weeks. It has lecture and practice sections where students must complete and submit seven assignments. The entire process is managed by Moodle. The purpose of employing an LMS is to ensure that students are being provided with additional learning materials and opportunities to facilitate learning.

The data must satisfy three requirements used as input data for this experiment. First, record the time taken to complete ILS questionnaires. For those who completed the ILS questionnaire within 5 minutes, the data was removed because the learning style collection was unreliable. Second, the data obtained from students who completed at least four assignments were included. The requirement is not to include those who dropped out because the data for these students did not reflect representative behaviour. Third, only the data of the students who took final exams were included. This is a crucial requirement to ensure that final exam preparation is included in each student's data.

5.2.2 Materials

The online course includes nine topics. Seven chapters discuss the main concepts of object-oriented programming, and each topic is introduced in a chapter. Furthermore, introductory chapters and chapters on the practical application of object-oriented programming are provided. In total, the course includes 512 content objects. It provides an outline and SA in all chapters. These seven SAs also include 140 questions. There are seven examples and seven exercise sets in each of the seven main chapters. The exercise includes 140 questions. SAs and exercises present questions to students and provide the correct answers to those questions. However, the pedagogical aims differ between SAs and exercises. SAs include theoretical questions, and students can verify whether they understand the theoretical aspects of the knowledge. The exercises include questions that are practical, in which students must either identify new methods of solving a given problem or elaborate on the predefined solutions, so they can verify whether they can apply the theoretical knowledge.

Furthermore, the course includes a forum. Seven marked assignments are listed in these seven chapters to verify the student's knowledge, with each assignment being divided into one or two chapters. These tasks must be conducted in a team of two. Several days after the submission, every student must propose a solution to answer the question. Towards the course completion, every student must pass a written test. Although some tasks are conducted in a team of two, the course was designed to allow all students to study everything and inspect all topics.

5.2.3 Evaluation Methods

This section introduces how to evaluate the two proposed student learning style automatic detection approaches, comparing the effectiveness of the tree augmented naïve Bayesian network approach and correlation analysis in detecting learning styles. The examination is based on the data collected from the online course and is used as input data for both methods to infer the learning style. Ten percent of the students (ten students) were test data and the rest were training data.

The data was collected by the author in June 2017, with 96 second-year undergraduate students (59 males and 37 females) studying for the same taught module. (This data set includes the 46 students for 7 weeks study from the pilot experiment described in Chapter 4, section 4.2.1). The students were given the opportunity to use the same Moodle online learning system as their predecessors and were introduced to it in a similar manner. The behaviour of students was tracked in an online course in the LMS, and the students were asked to fill out the ILS questionnaire to provide their learning styles. Learning styles were explained in detail. Figure 5.2 shows the distribution of students' FSLSM preference in four dimensions. The overall distribution is consistent with the pilot experiment's distribution in Chapter 4.

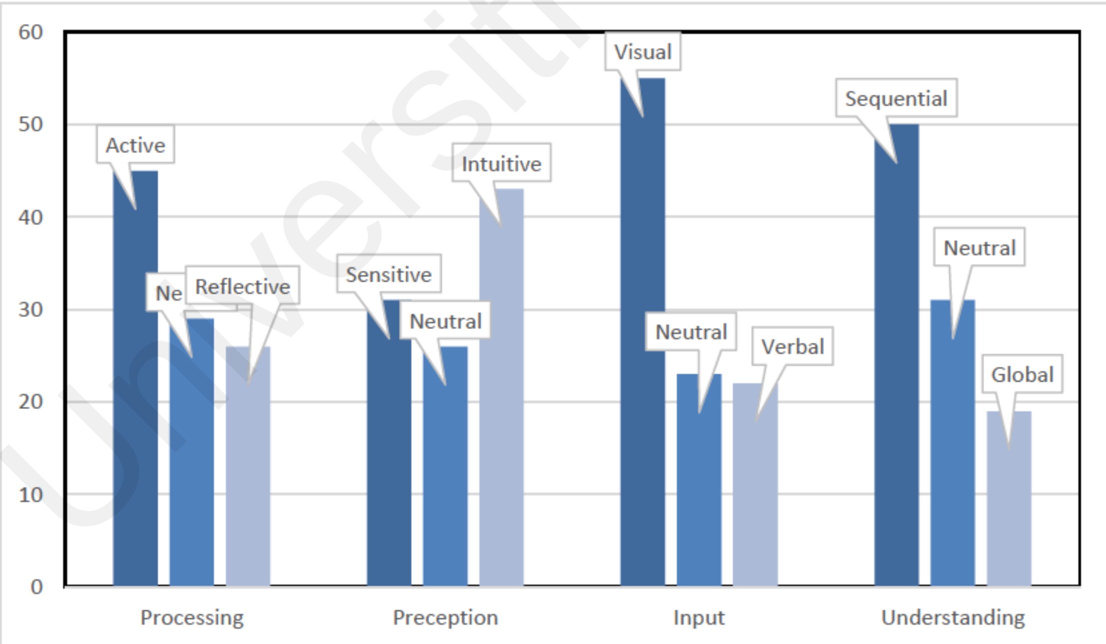

Figure 5.2: Distribution of students' learning styles

The LMS must be able to track the required behaviour and store this information in the database. Many different types of learning objects exist and can be composed into individual courses that fit the students' preferred methods of learning to assess their learning styles. For instance, the number of postings and the time each student spent on an example must be stored.

The experiment was conducted over a period of 14 weeks, during which web log data were collected. Each log entry illustrates the page in the system accessed by the user. The entries were sorted into sessions to enable the analysis of user interactions (see Appendix B for a sample of the log data). Log entries belonged to a single session if the IP address was the same for a specific time frame: separate entries occurring within an hour of each other. Although this procedure may have generated some slippage in the identification of single-user browsing sessions, it seems reasonable and was applied consistently throughout.

5.2.3.1 Correlation Analysis Approach

The model to compute learning style is based on and trained using the sample data in a data-driven method. As described in Chapters 3 and 4, the data are separated into training and test data sets.

The ILS value is then mapped again to the three-item scale with the same threshold previously described. The range is set from 0 to 1 to scale the results of the correlation analysis method, using threshold values of 0.25 and 0.75. These thresholds illustrate the first and last quarters (0–0.25 and 0.75–1) to indicate one or the other extreme preference on a learning style dimension. The second and third quarters indicate a balanced learning style. Four-quarter splitting is superior to the result range, divided into three parts. Moreover, because of its characteristics, the correlation analysis method is more useful for identifying the preference of the extreme situation only if a strong indication exists.

With reference to the scaled ILS values (LS_{ILS}) and the scaled results of the correlation analysis approach ($LS_{predicted}$), the following equation (García et al., 2007) was used to assess the precision of the approach.

$$Precision = \frac{\sum_{i=1}^{n} \mathrm{sim}\left(LS_{predicted}, LS_{ILS}\right)}{n} \cdot 100$$

5.2.3.2 Tree naïve Bayes approach

The central concept of the data-driven method is to use data when training the model. As described in Chapter 4, the data were processed using the tree augmented naïve Bayesian network learning procedure. The data contain information about students' behaviour and learning styles administered using the ILS instrument. The training data are then used to train the tree augmented naïve Bayesian network, and the test data are used to test to confirm the proposed approach in identifying a student's learning style based on his or her learning behaviour.

Assessing the precision of the tree augmented naïve Bayesian network results includes not only correctly identifying the specific learning styles but also comparing with the learning styles as administered using the ILS instrument. The measurement used, as proposed by García et al. (2007), is described in Section 5.2.3.1.

Similar to the description from the previous section, where $LS_{predicted}$ represents the value detected by the tree augmented naïve Bayesian network, $\mathrm{LS}_{\mathrm{ILS}}$ refers to the value from the ILS questionnaire, mapping to the three-item scale, and n represents the number of students. The function Sim compares its two-parameter values of $LS_{predicted}$ and LS_{ILS}, 0 if the values calculated with the proposed method and ILS are opposite: 1 if the values are equivalent and 0.5 if one value is neutral and the other one is an extreme value.

Three runs were performed to produce reliable outcomes. Each run is inclusive of learning procedure, drawing inference, testing the network, and computing precision measurements. For every run, different training and test data sets were used. The average value of the three runs is used as the result of the corresponding tree augmented naïve Bayesian network method.

5.3 Results

Table 5.2 presents the average result comparison obtained by using the tree augmented naïve Bayesian network approach and correlation analysis approach. Tree augmented naïve Bayesian network produced results superior to those of the correlation analysis approach for each dimension. The results obtained using tree augmented naïve Bayesian network ranged from 71.99%–75.18%, which are acceptable and indicate high accuracy. Moreover, the results of correlation analysis present moderate precision, ranging from 58.77%–68.09%. Both approaches achieved the lowest results concerning the processing dimension.

Table 5.2: Results achieved by using two approaches

Proposed Methods	Processing	Perception	Input	Understanding
Tree augment naïve Bayes	71.99%	74.69%	74.27%	75.18%
Correlation analysis	58.77%	65.01%	68.09%	66.20%

Table 5.3 presents the results achieved using the proposed methods for each run and the average result for every learning style dimension. Table 5.4 illustrates the reliability of the detection results at 95% confidence intervals. The average result presents high precision and its reliability test proof based on the confidence level statistics. A further discussion of the outcomes is provided in the next chapter.

Table 5.3: Results achieved by using proposed methods

		Processing	Perception	Input	Understanding
Correlation analysis	Run1	62.32%	68.05%	71.61%	73.23%
	Run2	56.61%	59.53%	65.19%	62.15%
	Run3	57.38%	67.46%	67.47%	63.22%
Tree augmented naïve Bayes	Run1	69.76%	83.76%	81.43%	78.43%
	Run2	70.89%	73.55%	69.85%	73.32%
	Run3	75.33%	66.76%	71.53%	73.79%

Table 5.4: Reliability of the results by using proposed methods

		Processing	Perception	Input	Understanding
Correlation analysis	Mean	0.58	0.65	0.68	0.66
	Standard Deviation	3.10%	8.52%	9.41%	6.11%
	Confidence interval	(57-63%)	(60-69%)	(66-72%)	(63-74%)
	Confidence levels	86%	79%	76%	81%
Tree augmented naïve Bayes	Mean	0.72	0.75	0.74	0.75
	Standard Deviation	2.94%	8.56%	6.26%	2.82%
	Confidence interval	(70-76%)	(67-84%)	(70-82%)	(74-79%)
	Confidence levels	88%	79%	82%	89%

5.4 To evaluate the correlation analysis method for investigating the relationship between learning style semantic group preference and learning behaviour

Based on the evaluation results, the correlation analysis method has the ability to detect learning style by building the relationship between students' learning style matrix and their learning behaviour matrix. Due to correlation analysis technique is good at identifying significant relationships among different attributes of data sets, this technique may also be able to investigate the learning style preference in more detail. If is feasible, then this method can be used as an analysis tool that uses for analysing students' detailed learning style preference characteristic directly from their learning behaviour.

To explore more detail information about students' learning style, it is essential to assess the relationship between learning style semantic group and learning behaviour by correlation analysis method.

Similar to the process introduced in Chapter 3, two matrices are built: learning style semantic group matrix and behaviour matrix. The method of building the behaviour matrix is unchanged, and the values of the semantic group matrix are based on answers to ILS questions. For example, the semantic group "try something out" is reflected in ILS questions 1, 17, 25, and 29, so if a student answers these questions with option A, count his or her value with 4 (1+1+1+1); in contrast, the value equals 0 (0+0+0+0) when answering with option B and vice versa. The process of building the semantic group correlation matrix is identical to that introduced in Chapter 3, Section 3.1.

Based on these two matrices, the analysis was conducted to examine the degree of relevance of the identified semantic groups to learning behaviours. The analysis was conducted based on the data collected in the main experiment described in Chapter 5 and administered with the ILS questionnaire. Table 5.5 expresses the frequency of each learning style semantic group.

Table 5.5: Frequency of each LS semantic group

Dimension	Semantic groups	Question No.	No. students	% of total
Active /Reflective	"Try something out"	1, 17, 25, 29	56	58%
	"Social oriented"	5,9,13,21,33,37,41	45	47%
	"Think about material"	1,5,17,25,29	31	32%
	"Impersonal oriented"	9.13,21,33,37,41	19	20%
Sensing /Intuitive	"Existing ways"	2,30,34	29	30%
	"Concrete materials"	6,10,14,18,26,38	27	28%
	"Careful with details"	22,42	20	21%
	"New ways"	2,14,22,26,30,34	39	41%
	"Abstract material"	6,10,18,38	31	32%
	"Not careful with details"	42	34	35%
Visual /Verbal	"Pictures"	3,7,11,15,19,23,27,31,35,39, 43	55	57%
	"Spoken words"	3,7,15,19,27,35	19	20%
	"Written words"	3,7,11,23,31,39	27	28%
	"Difficulty with visual style"	43	20	21%
Sequential /Global	"Detail oriented"	4,28,40	49	51%
	"Sequential progress"	20,24,32,36,44	58	60%
	"From parts to the whole"	8,12,16	44	46%
	"Overall picture"	4,8,12,16,28,40	31	32%
	"Non-sequential progress"	24,32	25	26%
	"Relation/connections"	20,36,44	28	29%

A rank correlation analysis was used for learning behaviour and learning style preferences using Kendall's tau. The results of the correlation analysis are presented in Table 5.6, with the significant results highlighted in bold font, using a significance level of 0.05. The values presented include a limited set of learning behaviours to illustrate the analysis in the table below.

Table 5.6:Correlation analysis of LS semantic groups and learning behaviour

Dimension		Semantic groups	Kendall	Learning behaviour					
				Visit exercise	Visit forum	Visit outline	Visit example	Visit SA	Visit content
Processing	Active	"Try something out"	tau	**0.235**	0.025	**-0.257**	**-0.197**	**0.286**	**-0.190**
			p	**0.015**	0.821	**0.014**	**0.033**	**0.013**	**0.038**
		"Social oriented"	tau	0.171	**-0.279**	0.039	0.173	0.110	-0.031
			p	0.056	**0.014**	0.631	0.262	0.169	0.771
	Reflective	"Think about material"	tau	**-0.336**	0.154	**0.212**	0.171	**-0.283**	**0.286**
			p	**0.010**	0.138	**0.019**	0.138	**0.013**	**0.013**
		"Impersonal oriented"	tau	0.121	**0.316**	0.193	0.078	0.132	0.311
			p	0.251	**0.011**	0.201	0.711	0.106	0.129
Perception	Sensing	"Existing ways"	tau	**0.225**	-0.031	0.237	**0.397**	**0.257**	0.128
			p	**0.016**	0.771	0.288	**0.009**	**0.014**	0.311
		"Concrete materials"	tau	0.042	0.131	0.088	**0.300**	0.110	**-0.286**
			p	0.811	0.210	0.727	**0.011**	0.172	**0.013**
		"Careful with details"	tau	-0.081	0.132	0.066	0.032	**0.197**	0.081
			p	0.333	0.106	0.418	0.551	**0.033**	0.466
	Intuitive	"New ways"	tau	0.110	-0.022	0.031	**-0.210**	**-0.332**	0.166
			p	0.169	0.811	0.810	**0.019**	**0.010**	0.058
		"Abstract material"	tau	0.037	-0.155	0.032	**-0.279**	-0.175	**0.235**
			p	0.812	0.061	0.790	**0.014**	0.251	**0.015**
		"Not careful with details"	tau	0.110	**0.333**	0.128	0.066	0.037	0.021
			p	0.172	**0.010**	0.311	0.401	0.801	0.810
Input	Visual	"Pictures"	tau	-0.036	0.019	0.129	0.117	0.040	**-0.336**
			p	0.461	0.790	0.179	0.182	0.449	**0.010**
	Verbal	"Spoken words"	tau	0.080	0.113	-0.076	0.105	0.125	-0.036
			p	0.231	0.201	0.397	0.189	0.221	0.461
		"Written words"	tau	0.061	**0.286**	0.021	-0.121	0.042	**0.316**
			p	0.379	**0.013**	0.810	0.211	0.811	**0.011**
		"Difficulty with visual style"	tau	0.111	0.081	0.037	0.077	0.013	0.166
			p	0.219	0.466	0.812	0.501	0.933	0.058
Understanding	Sequential	"Detail oriented"	tau	0.166	0.039	**-0.257**	0.040	0.037	0.061
			p	0.058	0.878	**0.014**	0.449	0.812	0.379
		"Sequential progress"	tau	0.123	0.175	**-0.190**	0.121	0.042	-0.036
			p	0.216	0.221	**0.038**	0.197	0.811	0.461
		"From parts to the whole"	tau	0.013	0.028	**-0.286**	0.011	0.110	-0.175
			p	0.933	0.789	**0.013**	0.897	0.169	0.251
	Global	"Overall picture"	tau	-0.175	0.037	**0.197**	0.037	-0.031	0.013
			p	0.251	0.388	**0.033**	0.801	0.771	0.933
		"Non-sequential progress"	tau	0.120	0.111	**0.257**	0.118	0.129	0.129
			p	0.187	0.176	**0.014**	0.204	0.179	0.179
		"Relation/connections"	tau	0.125	0.074	**0.255**	0.009	0.031	0.166
			p	0.221	0.388	**0.014**	0.931	0.810	0.058

Based on the results, a significant value presents the high impact of a semantic group on the respective learning behaviour. For example, for the processing dimension, the significant values (tau=0.235, p=0.015) reveal that the preference for 'try something out' has a greater influence than that of social orientation preference for learning behaviour, by visiting exercises. In other words, visiting exercises is an indicator that a student belongs to this group 'try somethings out' instead of the 'social preference' at active dimension. Meanwhile, for the reflective learning style, the significant values (tau=-0.197, p=0.033) show that there is negative correlation between the behaviour, visiting example, and the semantic group 'try somethings out'. This indicates visiting example is not an indicator for that semantic group. Students with 'try something out' preference are expected to have lower visit at examples behaviour. This agrees with FSLSM, because examples show how problems can be solved rather than letting students do it actively by themselves.

In contrast, no significant values were found regarding the semantic groups 'spoken words' and 'difficulty with visual style', indicating that there is no significant correlation can be found between these two semantic groups and all learning behaviour. That means these semantic groups preferences do not influence all these learning behaviours. The reason is that there is no relevant learning content including in the experiment: graphic-based and audio/video-based.

Thus, it can be observed that there are three categories of results:

1. The p-value is significant, and tau is positive, which means that learning behaviour has positive correlation with that semantic group and is an indicator.

2. The p-value is significant, and tau is negative: which means that learning behaviour has negative correlation with that semantic group and is not an indicator.
3. The p-value is not significant for the learning behaviour.

Then the tau values are shaded (in Table 5.6 and see Appendix C): i) if this result agrees with FSLSM theory, then the cell should be shaded green; ii) if this result does not agree or not explicitly stated in FSLSM theory, then the cell should be shaded yellow.

There are some yellow cells can be found, one possible reason is the learning object materials or LMS features used in the experiment may also affect the semantic group preference. For example, the content objects in the experiment made up of abstract material, then the negative tau value of 'concrete material' semantic group shows a low interest in the content. On the other hand, 'abstract material' students prefer to learn from content material, thus the positive tau indicated this. For the semantic group 'picture', the negative tau can be found at visiting content, because the 'picture' students did not prefer to learn from the content objects which are mainly in written words in the experiment. By contrast, a positive tau value is observed from semantic group 'written words' at visiting content. The students who have a preference for a 'sequential progress' prefer to navigate in a sequential way, thus, they tend to use next button rather than navigation menu, the negative tau value at navigation menu and visit outline indicated this. On the other hand, the positive tau value for ‘non-sequential progress’ can be found at navigation menu and outline.

Then, to validate the results, the original data of all students’ ILS questions that are related to the semantic group preference were used to categorize their learning behaviour. This is the method based in the literature according to the FSLSM used in past studies. The validation process is based on the comparisons between the results of these two methods; specifically, the total number of the semantic groups (results of the correlation analysis method) that agrees with FSLSM theory (results from the literature) were counted. The results from the literature are based on analysing the students’ ILS questions, and the semantic groups preferences can be calculated from their answers. Then according to each student’s semantic group preferences from the literature and his/her relevant learning behaviours, we checked whether they are consistent with the results shown in Table 5.6 for each semantic group. The measurements are based on the match percentages. For example, 56 out of the total 96 students had a preference for the semantic group of ‘try something out’. Among them, 34 students with a preference for the ‘try something out’ group and an inclination toward the relevant learning behaviour are consistent with the correlational indicators shown in Table 5.6 for this semantic group. Thus, a 61% match was found for the semantic group ‘try something out’. The validation results are shown in Table 5.7. Overall, 64% of the semantic groups matched when studied using the correlation analysis method and FSLSM theory. Therefore, the correlation analysis method is viable to be used as an analysis tool.

Table 5.7: Validation result of analyzing semantic groups

Dimension	Semantic groups	Total no. students with the semantic group preference	No. of student matches	% match
Active /Reflective	"Try something out"	56	34	61%
	"Social oriented"	45	26	57%
	"Think about material"	31	19	62%
	"Impersonal oriented"	19	11	56%
Sensing /Intuitive	"Existing ways"	29	19	67%
	"Concrete materials"	27	17	62%
	"Careful with details"	20	13	66%
	"New ways"	39	24	61%
	"Abstract material"	31	22	70%
	"Not careful with details"	34	21	61%
Visual /Verbal	"Pictures"	55	38	69%
	"Spoken words"	19		-
	"Written words"	27	18	66%
	"Difficulty with visual style"	20		-
Sequential /Global	"Detail oriented"	49	29	59%
	"Sequential progress"	58	40	69%
	"From parts to the whole"	44	28	64%
	"Overall picture"	31	21	69%
	"Non-sequential progress"	25	17	67%
	"Relation/connections"	28	17	61%
Mean				64%

In conclusion, the correlation analysis method is able to associate between learning style semantic group preference characteristics and learning behaviour except "spoken words" and "difficulty with visual style", which are consistent with the relationship between original learning style classification and learning behaviour. The result indicate correlation analysis method can build a relationship between learning style semantic group and learning behaviour. This means the correlation analysis method can be used as an analysis tool for analysing LS preference characteristic and related learning behaviour. Detailed discussion is provided in section 6.3.

5.5 Conclusion

In this chapter, an evaluation of the precision performance of the correlation analysis and tree augmented naïve Bayesian network at detecting learning styles was conducted. The experiment results of the two methods demonstrated that the tree augmented naïve Bayesian network approach was superior to the correlation analysis approach. A more detailed discussion and comparison to other approaches in the literature are provided in the next chapter.

CHAPTER 6: DISCUSSION

The results reveal that both approaches have the potential to detect learning styles. Based on the results, the tree augmented naïve Bayesian network approach outweighed the correlation analysis approach across all FSLSM dimensions with precisions of 72.0%–75.2%. Hence, the results are acceptable. The results demonstrated that the approach of tree augmented naïve Bayesian network is effective in detecting learning styles within LMS. This chapter discusses two main contributions of the thesis concerning the proposed approaches' precision performance at detecting learning styles and the relationship between students' preference characteristics and FSLSM dimensions. This chapter also highlights several implications of the findings.

6.1 The precision performance at detecting learning styles

As presented in Table 6.1, correlation analysis methods obtained moderate results, whereas tree augmented naïve Bayesian network methods achieved superior results.

First, if studying the results of the two proposed methods longitudinally, a lower precision is obtained for the processing dimension for both methods, which can be explained by the few behavioural patterns used and limited usage of chat and email. The investigation into this issue and arguments proposed by students who claim to have a preference for active/reflective fall into two main categories: some students expressed that the course did not require much work for collaboration, whereas others prefer face-to-face interactions. Furthermore, the setting concerning the processing dimension should include more teamwork or motivate the usage of collaborative tools to obtain improved detection results.

For other dimensions, the precision of each method is relatively higher than the processing dimension because of the relatively large number of patterns and learning objects, such as exercises and examples, such that relevant and abundant student data can be obtained. The special case is the understanding dimension; the learning objects for assessing this dimension are relatively small, resulting in fewer behaviour patterns, but those patterns are easy to identify—the times during which students visit outline and skip learning objects—because the learning behaviour patterns related to this dimension have considerable directivity.

Table 6.1: Comparison of results

	Learning style dimensions				Average	STDEV
	Processing	Perception	Input	Understanding		
Correlation analysis	58.8%	65.0%	68.1%	66.2%	64.5%	4.02%
Tree augment naïve Bayes	72.0%	74.7%	74.3%	75.2%	74.0%	1.42%
Literature-based (Graf & Viola, 2009)	79.3%	77.3%	76.7%	73.3%	76.7%	2.49%
Bayesian network (Graf & Viola, 2009)	62.5%	65.0%	68.8%	66.3%	65.7%	2.27%
Bayesian network (García et al., 2007)	58.0%	77.0%	-	63.0%	66.0%	9.85%
Naïve Bayesian network (Özpolat & Akar, 2009)	70.0%	73.3%	53.3%	73.3%	67.5%	9.58%

Second, for comparing with previous studies, only limited reference values were available for comparison with the results achieved in this study, due to the differences in the experimental environments and data sets used. For a relatively fair comparison, the following criteria are considered: (1) using a similarity precision metric; most related works use a similarity precision metric, so the benchmarks are selected to compare to respective related research accordingly, (2) adopting FSLSM, (3) focusing primarily on the Bayesian network family because the Bayesian network is the most widely used method in previous studies—the tree augmented naïve Bayesian network method proposed in Chapter 4 uses the algorithm from the Bayesian network family, and (4) application to the LMS; those learning style detection methods associated with specific intelligence tutoring systems or adaptive educational systems are not considered.

Based on the aforementioned criteria, the performance results of the proposed approaches were compared to the previous related studies that used a similarity metric (García et al., 2005) to calculate the precision and tested using an LMS. The proposed approaches were compared to (1) a literature-based approach (Graf & Viola, 2009), (2) two Bayesian network approaches (García et al., 2007; Graf & Viola, 2009), and (3) a naïve Bayesian network approach (Özpolat & Akar, 2009). Other recent related studies were not compared because they have either not conducted any evaluation (Carmona & Castillo, 2008), used simulated data (Dorça et al., 2013), or only tested for limited learning style dimensions (Sheeba & Krishnan, 2018). In contrast, the study by Cha et al. (2006) could be used for the classification of a subset of students (the data of students having a preference of a balanced learning style has been removed). Furthermore, the approach of learning style identification proposed by Latham et al. (2012) was not included in the comparison because the natural language conversational agent in Oscar renders a detection approach very specific to that ITS.

Research by García et al. (2007) has been used in many previous studies for comparing precision performance. Graf and Viola (2009), Bernard et al. (2017), and Dung and Florea (2012b) also benchmark García et al. (2007) to evaluate the performance of their approaches. Based on the proposed approach, the use of tree augmented naïve Bayesian network could provide even greater precision. For the perception dimension, the result achieved by García et al. (2007) is 77.0% (based on only one run), which is higher than correlation analysis method (65.0%) and slightly higher than tree augmented naïve Bayes method (74.7%), with the average result achieved of 66.76%–83.76% (Chapter 5, Table 5.3). The result for the processing dimension of tree augmented naïve Bayes method ranged from 69.76% to 75.33% (Chapter 5, Table 5.3), and the average is 72.0%, which is far superior to Garcia et al. (2007) at 58.0% and correlation analysis method at 58.8%.

For the understanding dimension, García et al. (2007) argued that inexperienced students engaging in an online learning environment might negatively affect the learning style detection process. Therefore, the detection result may lean towards certain learning style preferences. In this study, Moodle LMS is widely used as a teaching and learning aid. The programming course was incorporated within the LMS and delivered to 96 second-year students who fully participated in the study. Hence, they are experienced with online learning. This ensures that the results were obtained in a natural and balanced environment. The average results achieved for this understanding dimension are 66.2% (correlation analysis) and 75.2% (tree augmented naïve Bayes).

For the input dimension, there was no result assessed by García et al. (2007). However, when comparing with the naïve Bayesian network approach proposed by Özpolat and Akar (2009), the precision result for the input dimension of two proposed methods improved significantly. The performance of the rest of the dimensions of tree augmented naïve Bayes method is slightly higher than in Özpolat and Akar's approach.

According to the literature-based approach proposed by Graf and Viola (2009), the accuracy rate in this study for most of the dimensions (with the exception of the understanding dimension) was slightly below that of Graf and Viola (2009). In their research, the same data sets were used to evaluate the literature-based and Bayesian network approaches. The precision of results obtained by the Bayesian network approach is lower than that of their literature-based approach. The results of the Bayesian network approach by Graf (2009) were 62.50%, 65.00%, 68.75%, and 66.25% for processing, perception, input, and understanding dimensions, respectively. They concluded that the reason for the lower precision of the Bayesian approach is the relatively small quantity of training data. The primary strength of the literature-based approach is the ability to predict learning styles without requiring training data. In contrast, the data-driven approach relies solely on available data sets. The literature-based approach can produce high-precision results when this rule-based method is well-matched with the courseware. However, it is very complex to set these rules based on available learning objects. Once they are well-matched, it is difficult to reuse to another LMS because the learning objects are different. In addition, the estimation of the importance of different hints that were used to compute the learning styles is difficult for computer science researchers because of the knowledge requirement in the fields of psychology and cognitive science to precisely estimate the importance of hints (Feldman et al., 2015). The literature-based approach is, perhaps, a double-edged sword with high precision but also high complexity, high computational cost, and low compatibility.

Based on the comparison and analysis of the results, the tree augmented naïve Bayesian network approach in this study achieved the best standard deviation (STDEV). The tree augmented naïve Bayesian network approach has the ability to detect the learning styles for all four dimensions of FSLSM with high precision. The tree augmented naïve Bayesian network approach is a significant improvement in the Bayesian network family for reliability and stability. For the perception dimension, Garcia's approach has slightly higher precision than the tree augmented naïve Bayesian network approach, but in other dimensions, it can predict LS preference correctly with only 58% and 63% precision. The results are comparable between the two proposed approaches in this thesis because the same data set are used in the main experiment. With tree augmented naïve Bayesian network leading for all dimensions, the approach is suitable for high precision and stability for the detection of all dimensions.

According to Bernard et al. (2017), the current average precision is between 66% and 77%, in which the authors did not include some higher precision research due to the inability to generalize (the results were only obtained in certain conditions or environments). However, it is comparable with two proposed methods in this thesis because the two proposed methods were evaluated through real experiments (not based on simulation data), and both methods are able to work on an LMS (not limited in specific or custom educational systems). Based on the results achieved by the tree augmented naïve Bayesian network method, the average precision for the four dimensions is between 72% to 75%, which suggests that the approach overall achieved and partially exceeded the current average precision. Furthermore, the STDEV results imply that there is no obvious short board dimension and no significant difference in detection results across all dimensions.

6.2 Discussion and implication for two proposed methods.

Both methods in this thesis are novel in the field of automatic learning style detection. The first method borrows the correlation matrix frequently used in recommendation systems but is new for detecting learning style. The second method uses tree augmented naïve Bayesian network. Although the Bayesian network family is the most commonly used method for detecting learning style, no previous study adopts this particular tree augmented naïve Bayesian network method. This method inherits the advantages of the Bayesian network and addresses several shortcomings of the previous methods.

The two proposed methods remove the traditional learning style detection problem. Although the methods require students to complete the learning style questionnaires in certain stages, their goals are the initialization of the correlation analysis approach and verification for both proposed approaches. The proposed methods have the ability to consider FSLSM and all levels of preferences (balanced, medium, and strong). Although several past studies (Cha et al., 2006; Deborah et al., 2015; Garcia et al., 2008) achieved a high precision with detection results, these methods only function for limited dimensions or levels of preferences. The correlation analysis method addressed high complexity and computational cost issue. Because the method considers the relevance between learning style correlational matrix and learning behaviour matrix data sets for LS detection, and the components of the matrix such as learning behaviour, related patterns and learning objects are inherent in any LMS. Tree augmented naïve Bayes method partially addressed high complexity problem, because Bayesian network in its natural representation of probabilistic information, the relationship between the behaviour mode and the learning styles represents the arrow of the network, and the learning style dimension represents the node of the network, that results in this method can be easily deployed to any LMS without complex setting.

For the correlation analysis approach, the concepts and methodology used in the development of the mathematical model can also be applied to other learning style approaches and other LMSs after some modifications. However, the performance of the precision results for the correlation analysis approach is modest for all learning style dimensions compared to the tree augmented naïve Bayesian network approach, and slightly lower than in previous studies because the training data set is relatively small for the proposed approach for a typical class size, and this approach does not fit small data sets well. In the experiment, when considering possible variables, for example, the perception dimension has four different features, so 81 (3^4) possible states exist given each feature could have three different states. The ideal value for the predicted amount is 10% of the total number (Khan et al., 2019), and using dozens of students as input data might lead to unsatisfactory results. Based on findings from the experiments, the correlation analysis approach is not suggested for use in small data set environments. Furthermore, the correlation analysis approach requires further optimization algorithms for improvement. Heuristic search algorithms could be incorporated for optimization, such as the simulated annealing algorithm. Granville et al. (1994) found that "the simulated annealing method converges to the global optimal with probability 1, when the time of iteration is sufficiently large.” The convergence time is met because the solution space of this issue is comparatively small. This suggests an avenue for future research.

The correlation analysis approach cannot obtain satisfactory results in current conditions for a typical class size. To compromise between reusability and detection precision, tree augmented naïve Bayesian network is designed for learning style detection. A Bayesian network is an attractive method in the educational domain because it frequently involves uncertainty; moreover, a transparent, easily understandable model is necessary (Hämäläinen et al., 2011). The nodes of a Bayesian network are easily matched to the learning object features in an LMS and can be applied to another LMS after some modifications based on the LMS’s features. Nevertheless, for small data sets, the traditional Bayesian networks are too complex as the models easily overfit.

In contrast, the naive Bayes model can solve this problem. The network structure of naïve Bayes comprises only two layers: the class variable in the root node and all other variables in the leaf nodes. Furthermore, all leaf nodes, given the class value, are assumed to be conditionally independent. In real-world scenarios, the so-called assumption of naive Bayes is usually not realistic. However, this model has worked exceptionally well in practice because, according to Domingos and Pazzani (1997), the naive Bayes assumption is not a necessity but only optimally sufficient condition for naive Bayes. Naive Bayes classifiers have performed exceptionally well in empirical tests when compared to other classifiers that are more advanced, such as decision trees and traditional Bayesian networks, specifically with small data sets of not more than 1000 rows (Domingos & Pazzani, 1997).

Due to the variables being interconnected most of the time, the naive Bayes assumption is frequently violated in the educational domain. Nevertheless, surprisingly, the naive Bayes classifier could tolerate high dependencies between independent variables (Hämäläinen et al., 2011). In experiments by Hämäläinen and Vinni (2006), only when the conditional probability between two leaf node values was $P(F = 0|E = 0) = 0.96$ did model accuracy suffer. The average mutual information between the variables was high, $AMI(E, F) = 0.178$, of the same magnitude due to the dependencies between class variable and leaf variables ($AMI \in [0.130, 0.300]$). The impact on classification accuracy was nearly equivalent to that of the linear regression model.

Tree augmented naïve Bayesian network models (Friedman et al., 1997) improve naive Bayes models by allowing dependencies. Otherwise, the tree augmented naïve Bayesian network model structure is similar to the naive Bayes model. However, in addition to the class variable, each leaf node could depend on another leaf node. This usually results in a satisfactory compromise between a naive Bayes model and a traditional Bayesian network: the model structure is simple enough to elude overfitting, and strong dependencies could be considered. In the Bayesian network family classifiers empirical tests by Friedman et al. (1997), the tree augmented naïve Bayesian network model outperformed the standard naive Bayes.

Based on the results of the main experiment in Chapter 5, tree augmented naïve Bayesian network has higher learning style precision detection than the Bayesian network because the conditional independence assumption is loosened by the tree augmented naïve Bayesian network algorithm, which agrees with reality (the interconnection between variables). When compared with naïve Bayesian, the extra edges between the network attributes in tree augmented naïve Bayesian network are allowed to capture correlations among them (Carvalho et al., 2007). Furthermore, every attribute could have an augmenting edge that encodes statistical dependencies between attributes. Therefore, the joint probability of tree augmented naïve Bayesian network depends on the probabilities conditioned on class and the parent node attribute (Dhakar & Tiwari, 2014). Such interconnection does exist given that the ILS consists of four dimensions of learning styles and each dimension; for example, the active or reflective dimension is viewed as a continuum with one learning style preference on the left and the other preference on the right. As another example, during a student's online learning process, numerous internal connections exist between learning objects that are within the same learning style dimension (e.g., "online chat" usually exists together with a "forum" section); when the correlation of this interconnection between attributes is higher, the result of tree augmented naïve Bayesian network is superior. The only downside of the tree augmented naïve Bayesian network algorithm is that it requires slightly more processing time compared to that of the Bayesian network (average 1.66s for Bayesian network, 1.52s for correlation analysis and 1.89s for tree augmented naïve Bayesian network) because tree augmented naïve Bayesian network must build the tree by using the Bayesian network tree as its foundation.

Practically, even a small loss in detection precision can result in serious consequences to students when learning styles are used in giving adaptive feedback during the learning process, which could lead to a mismatch in learning materials. The results of the tree augmented naïve Bayesian network method are superior to those of the previous study across all learning style dimensions. For example, as presented in Table 6.1, tree augmented naïve Bayesian network has an average precision of 74.0%, which produced an increase in precision to 6.5%. Although the proposed approach produced only a small increase in precision, it also resulted in more accurate detection of a student's learning style, thereby supporting students to learn by adapting the learning materials according to their preference. The increase in precision can be attributed to the average precision of all participants participating in the present experiment and is more likely to improve significantly towards the precision rate of learning style detection for each individual student. Furthermore, the low STDEV value of the results indicates that this method could help to maintain the learning environment and future adaptivity provision in consistent and stable conditions.

6.3 The relationship between student semantic group preference characteristics and the learning behaviours

Correlation analysis method can be used as an analysis tool that uses for analysing students' detailed learning style preference characteristic directly from their learning behaviour, which is verified by the experiment in section 5.4. This tool can help to investigate more detailed LS preference characteristics information from students' learning behaviour.

Existing online educational systems, including LMS, primarily incorporate learning styles with general designs in mind, but, in practice, not all aspects of learning styles are appropriate for specific courses.

In adaptive systems courses, it is usually the case that most adaptive systems are limited to particular functions of online education and only support special functions, such as presenting the content of or methods in which the quizzes are used. Although the LMS includes numerous features that may support various aspects of learning style models, several aspects of the learning style model may be lost, often because the instructor does not include the corresponding features. Thus, when establishing a holistic and accurate student model, it is crucial to consider what learning style model aspects could be identified and what cannot be done due to the unavailability of information (such as insufficient LMS features for support), in order to do so, more detailed learning style preference characteristic is required.

Studying learning style semantic groups is vital because it assesses each learning style dimension more gradual distinction, resulting in more detailed learning style preference characteristic information. For example, in FSLSM, which always include two extremes within a single dimension (e.g., students can only be categorized into active, reflective, or natural preference in a single dimension). As presented in Table 2.1 in Chapter 2, the semantic groups are determined from different sets of ILS answers. For instance, the semantic groups "detail oriented" (refer to answer A of questions 4, 28, and 40) and "overall picture" (refer to answer B of questions 4, 8, 12, 16, 28, and 40) are not inferred from same set of questions. Thus, they do not represent completely opposite preference characteristics, which means student may have these two semantic groups to varying degrees at the same time. For example, a student may have a strong "detail oriented" preference but also can understand the "overall picture." This allow to assess students' preference characteristic in more detail and accurate.

More detail and accurate description of students' preference characteristics is important for relating the learning style model with LMS features, which leads to a more precise detection of students' learning styles and therefore enhance the potentials of adaptivity provision in the LMS.

The correlation analysis method, introduced in Chapter 3, was used to infer students' learning style from their learning behaviour. Moreover, this method can be used to investigate the relationship of FSLSM semantic group preference with learning behaviour in more detail. Several previous studies examined the FSLSM semantic group, which investigate the semantic group through original learning style theory. Such as in Graf et al. (2017)'s work, the investigation of learning styles is based on the literature about FSLSM, which are semantic similarity of ILS questions, and then summarize and categorize related learning behaviours according to these theorical information, the process shows in Figure 6.1. By contrast, the proposed correlation analysis method can directly associate the relationship between learning style semantic group preference and learning behaviours, which is based on the actual behaviour. This process establishes more accurate information for automated student's learning style detection and adaptivity provision.

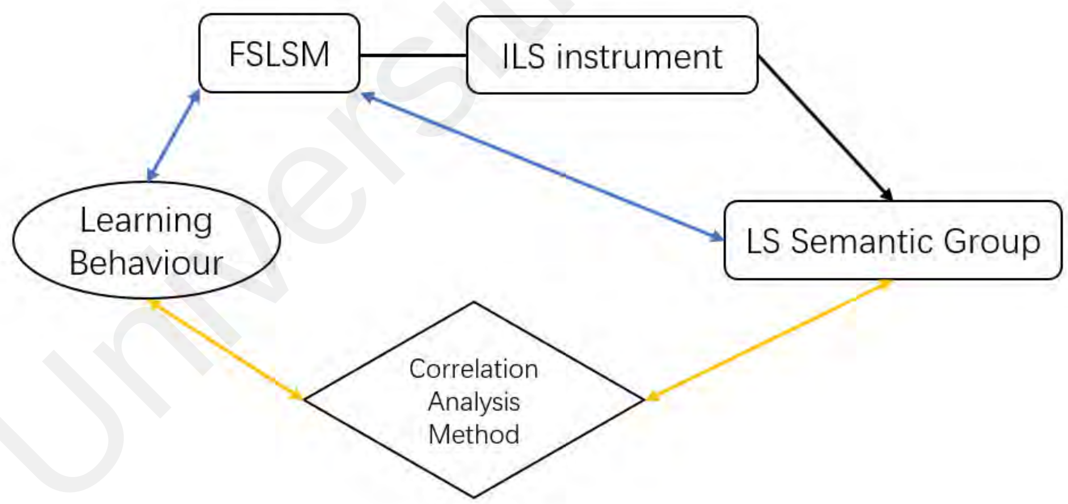

Figure 6.1: The association between semantic group and learning behaviour

The implication of the analysis is to provide more direct associations between student preference characteristics and learning behaviours, which leads to more accurate detection of learning styles. Furthermore, the proposed correlation analysis method could be applied to analyse students' data (i.e. LMS log file) for course developers in order to provide learning style preference support in greater detail. The analysis results define whether using learning objects in educational systems favours students with particular learning styles to enable providing relevant support. For example, when active students tend to exhibit "social orientation," this leads to a low frequency of visit forum but a high number of posts; reflective students tend to be "impersonal oriented," which results in a high frequency of visit forum but few posts, so both learning style preferences may meet together in the forum. By using the correlation analysis method, two learning style semantic group preference can be precisely distinguished, then course developers are suggested to adjust the setting of LMS features or learning contents based on this analysis accordingly. Thus, this correlation analysis method can be considered as an analysis tool which uses for analysing students' learning style preference characteristic directly from their learning behaviour.

6.4 Conclusion

The purpose of this study is to improve learning style detection precision. Accordingly, two different approaches—correlation analysis and tree augmented naïve Bayesian network—are proposed for solving the problem for practical application. The more detailed investigation between learning style preference characteristics and learning behaviour could be considered a theoretical contribution.

Using the practical and theoretical contributions for identifying students' learning styles could help improve detection precision with fewer mismatches for students. Moreover, adaptive learning systems could enable accurate personalization, which would improve learning satisfaction (Popescu, 2010), enhance performance (Ford & Chen, 2001), and reduce learning time (Graf et al., 2009).

Furthermore, students could benefit directly from more precise learning styles identification by maximizing their strengths with respect to learning styles and analysing their weaknesses. Moreover, instructors could use this learning style information in providing more precise advice to benefit their students.

CHAPTER 7: CONCLUSIONS AND FUTURE WORK

This chapter summarizes the work conducted within this thesis and discusses the significant research contributions and highlights potential future work in this area.

7.1 Thesis contributions

In summary, this thesis has made three contributions with respect to the research objectives outlined below:

1. To formulate a mathematical model based on correlational matrix to represent the relationship between learning behaviour patterns and learning styles for learning style detection in LMS.
2. To develop a tree augmented naïve Bayesian classifier to enhance learning style detection in Learning Management System.
3. To investigate the relationship of index of learning style semantic groups and learning behaviour patterns in learning management system for more accurate detection and provision of learning style.

7.1.1 Development of automatic detection of learning styles as a mathematical model addresses the reusability issues of automatic detection of learning styles approach.

The proposed detection approach is designed to be generic, flexible, and applicable to different online learning platforms. Moreover, it is simple and direct. It is based on the data gathered from students' learning behaviour and by constructing a behaviour and learning style correlation matrix to establish students' learning style preferences. Therefore, it could solve the problem of automatic detection of learning styles approaches being tied to the LMS. However, because the approach requires a large data set for training, and typical class sizes in university could not meet the requirement, the precision of the detection result is modest but promising.

7.1.2 Development of automatic detection of learning styles in learning management system with tree augmented naïve Bayes addresses both issues of applicability and precision of detection.

To further improve the precision of the detection result of the correlation analysis approach and maintain relatively high applicability, tree augmented naïve Bayesian network was proposed (Chapter 4). This approach adopts a Bayesian network, which is the most widely used detection technique in this domain. The simple structure of tree augmented naïve Bayesian network avoids overfitting while also accounting for dependencies among the random variables.

The advantages of the proposed tree augmented naïve Bayesian network approach are twofold.

First, while the proposed tree augmented naïve Bayesian network approach can detect student learning styles automatically, it is still static given that data collection on student learning behaviour and calculation on learning style preferences is performed at a specific point of time. The tree augmented naïve Bayesian network approach, however, may lay the groundwork for future work into dynamic student modelling where information about student learning behaviour is captured in real time to respond almost instantly in providing personalized learning materials to students.

Second, the proposed approaches have the potential for more reliable detection of learning styles compared to administering learning style instruments on a one-off basis prior to learning to take place.

7.1.3 Precision performance of the correlation analysis approach and tree augmented naïve Bayes approach at detecting learning styles improve for all FSLSM dimensions.

The two automatic learning style detection approaches were designed, developed, and evaluated. Based on the results of the evaluation, the tree augmented naïve Bayesian network approach yielded superior results to correlation analysis in detecting learning style preferences for each of the four dimensions of the FSLSM. Compared with previous studies, the results of the tree augmented naïve Bayesian network approach are promising for detecting learning styles in LMS with higher precision. The results of STDEV value were lowest, indicating that the approach can produce high precision results for all dimensions of FSLSM. Furthermore, when focusing on Bayesian network detection approaches, which are the most widely used data-driven techniques in the learning style detection domain, the tree augmented naïve Bayesian network approach improves the performance of the Bayesian network family.

7.1.4 Investigation of the relationship between student learning behaviour and the FSLSM semantic groups preferences for more accurate detection and provision of learning style.

The correlation analysis approach can also address the relationship between the FSLSM semantic group and learning behaviour. The characteristic preferences of the FSLSM semantic group were investigated. In contrast to previous studies that analysed using ILS questions, the investigation in this study associates semantic group preference and learning behaviour directly, more closely examining the relationship between the preferences characteristics and their related learning behaviour in detail and differentiating them. More detailed information about how students really prefer to behave could help in considering students' preference characteristics more accurately, resulting in more precise learning style detection and student modelling. In contrast, this information could guide learning object selection to favour students with certain learning styles, thus providing lecturers and course developers with the opportunity to specify the learning objects based on the required types of learning objects and generate and present adaptive courses that fit the students preferred learning styles.

7.2 Future work

This study forms a basis for future research into the development of dynamic student modelling for adaptive LMS. First, a significant criticism in the area of automatic detection of learning styles is that they are characterized by a huge number of small-scale applications of specific models to small samples of students in particular contexts (Coffield et al., 2004). For example, the number of participants used in the previous studies is rather small: 27 (Bousbia et al., 2010), 75 (Crockett et al., 2011), 44 (Dung & Florea, 2012b), 27 (García et al., 2007), and 75 (Graf & Viola, 2009). Most of the existing approaches were evaluated with participants from computer science backgrounds, and few studies were conducted with elementary and high school students. Future studies should include a larger number of participants in diverse contexts.

Another avenue for future research is to assess the precision performance of the correlation analysis and tree augmented naïve Bayesian network on a different learning management platform with different courses to confirm the proposed approaches. Moreover, the optimization algorithm for correlation analysis suggests an extension of this study to improve detection precision. Heuristic search algorithms are a suitable choice to be considered for optimization.

In this thesis, an investigation was conducted about students' behaviour and their learning styles. However, more work is needed to explore students' learning style behaviours in online learning environments to discover which factors are affecting their achievement and how to adjust and adapt the methods by which instruction is delivered. A greater understanding of students' learning styles may eventually lead to the widespread acceptance and use of adaptive educational systems.

As highlighted in the previous section, this research provides a base for future research in the dynamic student modelling field. This study could be considered the basis for developing a dynamic student modelling method in which data about student behaviour is immediately processed, and the student models are updated instantly. Moreover, the data can be analysed in more detail, such as to eliminate exceptional behaviour or monitor changes in learning patterns during the detection process.

To facilitate the widespread use of two learning style detection approaches, both approaches are planned to encapsulate the main components into open-source web services, which can be invoked by any LMS. The organization of the learning resources will also be wrapped in a standard manner that complies with open standards, such as learning object metadata.

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