Granular Mining of Student's Learning Behavior in Learning Management System Using Rough Set Technique

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Abstract. Pattern multiplicity of user interaction in learning management system can be intelligently examined to diagnose students' learning style. Such patterns include the way the user navigate, the choice of the link provided in the system, the preferences of type of learning material, and the usage of the tool provided in the system. In this study, we propose mapping development of student characteristics into Integrated Felder Silverman (IFS) learning style dimensions. Four learning dimensions in Felder Silverman model are incorporated to map the student characteristics into sixteen learning styles. Subsequently, by employing rough set technique, twenty attributes have been selected for mapping principle. However, rough set generates a large number of rules that might have redundancy and irrelevant. Hence, in this study, we assess and mining the most significant IFS rules for user behavior by filtering these irrelevant rules. The assessments of the rules are executed by evaluating the rules support, the rules length and the accuracy. The irrelevant rules are further filtered by measuring different rules support, rules length and rules accuracy. It is scrutinized that the rules with the length in between [4,8], and the rules support in the range of [6,43] succumb the highest accuracy with 96.62%.

Keywords: Rough set, learning styles, discretization, rule generation, rule filtering, classification.

1 Introduction

Learning Management System (LMS) is an environment to support web-based learning content development. The main features of an LMS include content creation, content repository management, content delivery and interface, and learning process management such as course enrollment, assessment and performance tracking [1]. Educators are able to distribute information to students, produce content material, prepare assignments and tests, engage in discussions, manage

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distance learning and enable collaborative learning using forums, chats and news services. Several examples of popular LMS are Moodle [2], Blackboard [3] and WebCT [4]. Recently, Moodle, an acronym for Modular Object-oriented Dynamic Learning Environment has become one of the most commonly used LMS.

Moodle is an open source LMS that enable the creation of powerful, flexible and engaging online courses and experiences. Several e-learning researches have been conducted in order to enhance Moodle's performance [1, 5, 6]. Graf and Kinshuk [5] has extended Moodle's capability by implementing adaptation of the learning material based on the student's learning style. A standalone tool for automatic detection of learning styles in LMS has been implemented. Kerdprasop et al. [1] enhanced LMS functionality to individualize the learning content with induction ability. Romero et al. [6] had developed data mining tool to help instructors preprocess or apply mining techniques, such as statistics, visualization, classification, clustering and association rule mining from Moodle data. E-learning systems developed using Moodle accumulate an enormous amount of information which is very valuable for analyzing students' behavior and could create a gold mine of educational data [7]. Any LMS data can be mined in order to understand the dynamic behavior of students in the web. Such information can be used to improve the implementation of e-learning system by determine e-learning effectiveness and measure the success of various instructional effort [8].

Rough set theory, introduced by Zdzislaw Pawlak in the early 1980's is a mathematical tool to deal with vagueness and uncertainty [37]. The methodology is concerned with the classificatory analysis of vague, uncertain or incomplete information or knowledge expressed in terms of data acquired from experience. Unlike other soft computing methods, rough set analysis requires no external parameters and uses only the information presented in the given data. Rough set method does not need membership functions and prior parameter settings. It can extract knowledge from the data itself by means of indiscernibility relations and generally needs fewer calculations compare to fuzzy set theory. The attribute reduction algorithm removes redundant information or features and selects a feature subset that has the same discernibility as the original set of features. The selected features can describe the decision as well as the original whole features set, leading to better classification accuracy.

Meanwhile, the flexibility offered in any LMS allow the instructor to design and deliver various sources of learning material such as animation, power point, video, hypermedia and on-line tutorial easily. However, each individual student has their own learning preferences in order to comprehend the knowledge. They learn better when they are given a learning environment that is suitable with their learning style. By employing rough set, it is crucial to select the most vital attributes influencing the learning behavior of a student. The chosen attributes, observed from student behavior in Moodle are then engaged within a decision rule generation process, creating descriptive rules for the classification task. Decision rules extracted by rough set algorithms are concise and valuable, which can be benefit to identify student's learning style by enlightening some knowledge hidden in the data.

This chapter provides in-depth discussions on student's learning preferences and behavior while using e-learning system based on Felder Silverman learning dimension, such as processing, perception, understanding and input. The student's attributes are fed to rough set classifier to obtain the granularity of the significant features. To our understanding, none of the studies have been reported in implementing IFS features with significant rules for identifying learning styles. However, our focus will be more on extracting the significant rules for detecting the learning styles which is not previously done by other researchers in this area.

This chapter is organized as follows: Section 2 explains previous studies and issues related to student's behaviour while learning on-line, and followed by section 3 that describes the proposed integrated Felder Silverman learning style model. The development of e-learning system that incorporates learning resources for Felder Silverman learning dimension is described in section 4. Section 5 gives in-depth analysis on students' behavior while learning using hypermedia learning system. These include the analysis of the learners learning style distributions, preferences and their navigation behavior. The analysis is useful for providing parameters for classification of student's learning style based on student's learning characteristics while learning online.

In section 6, we present an intelligent data analysis approach based on rough set for generating classification rules from a set of data samples describing the student's behavior and activities during e-learning session extracted from Moodle log files. Section 7 discusses rules filtering approach to identify the most significant rules. Based on the generated rules, the diagnosis is executed to map student's learning style into IFS features. Section 8 gives conclusion of the chapter.

2 Related Work

The early research that concern with student's learning style used questionnaire to assess the student's learning characteristics [9, 10, 11, 12]. However, the exploitation of questionnaires is time consuming and unreliable approach for acquiring learning style characteristics and may not be accurate [13, 14, 15]. Most questionnaires are too long, hence, causing students to choose answers arbitrarily instead of thinking seriously about them. Even if the learning style has been determined, it still cannot notify the real characteristics of the students while learning on-line. In addition, once the profile is generated, it becomes static and doesn't change regardless of user interaction. In on-line learning environment, the student's learning characteristics are changed accordingly when different tasks are provided. Due to these problems, several studies have been conducted in detecting student's learning style that are based on the student's browsing behavior [16, 17, 18, 19]. This approach can be implemented successfully since the style of student's interaction with the system can be inferred accurately and can be used as attributes for adaptation purposes.

Various techniques have been used to represent student learning style such as statistics [17], Neural Network [19, 13], Decision Tree [20], Bayesian Networks [16], Naïve Bayes [15] and Genetic Algorithm [18]. Previously, we have successfully classified students' learning style using Backpropagation Neural Network (BPNN) [21]. However, BPNN lacks of explanatory power and difficult to identify rules concerning to the inputs and outputs [22].

Table 1 list several studies focusing on learning style detection for the past five years. Various techniques, approaches and purposes of detecting learning styles have been discussed extensively in the literature. It can be observed from the pattern of research conducted, the trend of research on detecting student's behavior recently have focus more on LMS. The trend shows that LMS has become a popular tool in developing e-learning materials due to the flexibility and robustness provided by the tool.

Table 1. Related studies on learning style detection

Author	**Learning Style Model**	**E-learning data**	**Identification Technique**
Kelly and Tangney (2004) [15]	Garderners Multiple Intelligence	On-line learning system	Naïve Bayes
Lo and Shu (2005) [19]	Kinestethic, Visual, Auditory	On-line learning system	Neural Network
Garcia P. et al (2007) [16]	Felder Silverman – 3 Dimension	On-line learning system	Bayesian Network
Villaverde J.E. et al. (2006) [13]	Recognition of learning style in e-learning – Felder Silverman	Simulated Data	Neural Network
Cha H. et al. (2006) [20]	Felder Silverman	On-line learning system	Decision Tree
West et al (2006) [23]	Investigate impact of learning style on e-learning	On-line class	Statistics
Ai and Laffey (2007) [8]	Pattern classification of student's performance	LMS	Web Mining
Garcia E. et al. (2007) [24]	Student activities and behavior	LMS	Association rule mining
Kerdprasop et al (2008) [1]	Classify student knowledge level	LMS	Rule induction rough set
Graf S. and Kinshuk (2008) [25]	Analysing Student's Behavior based on Felder Silverman	LMS	t-test, u-test
Romero et al (2008) [6]	Develop mining tool	LMS	Data mining

On the other hand, the common e-learning system, Moodle, was developed based on the social constructivism pedagogy support communication and collaboration among communities of learning through the activity modules which includes Forums, Wikis, Databases, Discussion Board, Chats, and Journals. Student can actively participate in discussion forum to discuss certain subject matter or to solve certain task assigned to them either individually or in a team. Moodle also supports import and export of SCORM/IMS Content Packaging standards. Hence, educators are able to create learning objects to deliver learning content and exercises to students and assess learning using assignments or quizzes. The options for importing learning objects from other sources enable educators to create very rich learning resources. Student activities, such as reading writing, submitting assignments, taking tests, performing various tasks and even communicating with peers were recorded and kept in log files [7]. User's personal information, their academic results and their history of interaction were kept in data base and very useful for educators to enhance learning environment.

Based on the flexibility offered in Moodle, this study has developed the learning resources for Data Structure Subject that consider Felder Silverman Learning Style model. The student activities while using the learning resources is analyzed in order to determine the relationship between the students's learning style and their learning preferences. In this chapter we identify significant parameters for classifying students learning style based on their characteristics while learning online. The information is needed to be stored in user profile for adaptation of learning materials based on learning style. In our study, we will classify the proposed IFS features of students learning styles by employing rough set technique granularity mining. This includes extracting the significant rules for detecting the learning styles.

3 The Proposed Integrated Felder Silverman Learning Style Model

A variety of learning style model has been used to characterize learning styles for students. Among them are Felder Silverman learning style [26], Kolb's theory of experiential learning [27], Howard Gardner Multiple Intelligence [28], Honey and Mumford [29] and Dunn and Dunn model [30]. In this work, we utilize Felder Silverman model to investigate the student's preferences of the learning material. The reason behind choosing this model is due to a considerable amount of literature on this subject.

The model has been successfully used in previous studies involving adaptation of learning material, collaborative learning and for traditional teaching [26, 31, 32]. Furthermore, the development of the hypermedia learning system that incorporate learning components such as the navigation tool, the presentation of the learning material in graphics form, simulation, video, sound and help facilities can easily tailored to the Felder Silverman learning style dimension.

Felder Silverman learning style model was developed by Felder and Silverman in 1998 [33]. This model categorized a student's dominant learning style along a scale of four dimensions: active-reflective (how information is processed), sensing-intuitive (how information is perceived), visual-verbal (how information is presented) and global–sequential (how information is understood). Table 2 describes the characteristics of students based on the learning dimensions.

Felder and Solomon developed Index of Learning Styles (ILS) questionnaire to identify the student's learning style. The objective of this questionnaire is to determine the dominant learning style of a student. This questionnaire can be accessed freely from web site [34] and is often used as instrument to identify learning style. The ILS questionnaire consists of 44 questions with two possible answers, A or B. These questions are separated into four groups, with eleven questions each. These groups correspond to four categories of Felder Silverman learning dimension (active-reflective, sensing-intuitive, visual-verbal, and sequential-global).

Table 2. Felder Silverman learning dimension and learner characteristics [33]

Learning Dimension	**Learner Characteristics**	
	Active	**Reflective**
Processing	Retain and understand information best by doing something active with it such as discussing it, applying it, or explaining it to others.	Prefer observation rather than active experimentation. Tend to think about information quietly first.
	Sensor	**Intuitive**
Perception	Like learning facts, often like solving problems by well-established methods and dislike complications and surprises. Patient with details and good at memorizing facts and doing hands-on work. More practical and careful than intuitors.	Prefer discovering possibilities and relationships. Like innovation and dislike repetition. Better at grasping new concepts and comfortable with abstractions and mathematical formulations. Tend to work faster and more innovative than sensors.
	Visual	**Verbal**
Input	Remember best what they see from visual representations such as graphs, chart, pictures and diagrams.	More comfortable with verbal information such as written texts or lectures.
	Sequential	**Global**
Understanding	Prefer to access well structured information sequentially, studying each subject step by step.	Prefer to learn in large chunks, absorb material randomly without seeing connections and then suddenly getting it. Able to solve complex problems quickly or put things together in novel ways once they have grasped the big picture.

Fig. 1 shows the learning style scales for each learning style dimension. The score are expressed with values between 11A to 11B for each dimension. If a student gets a score from 1 to 3 in any dimension, he/she has a mild preference and fairly balanced on the two dimensions. If the score is on scale 5 or 7, the student has moderate preference, and if the score is on scale 9 or 11 the student has a very strong preference for the dimension. The student with strong preferences for certain dimension must learn according to the environment that matches his learning style. He may have learning difficulty if he studies in the environments that are not suitable with his learning style.

ACT	11A 9A 7A 5A 3A 1A 1B 3B 5B 7B 9B 11B	**REF**
SNS	11A 9A 7A 5A 3A 1A 1B 3B 5B 7B 9B 11B	**INT**
VIS	11A 9A 7A 5A 3A 1A 1B 3B 5B 7B 9B 11B	**VRB**
SEQ	11A 9A 7A 5A 3A 1A 1B 3B 5B 7B 9B 11B	**GLO**

Fig. 1. Felder Silverman learning style scales [34]

Table 3. 16 learning styles based Integrated Felder Silverman learning dimension

Learning Styles	Label
Active/Sensor/Visual/Sequential	ASViSq
Reflective/Sensor/Visual/Sequential	RSViSq
Active/Intuitive/Visual/Sequential	AIViSq
Reflective/Intuitive/Visual/Sequential	RIViSq
Active/Sensor/Verbal/Sequential	ASVbSq
Reflective/Sensor/Verbal/Sequential	RSVbSq
Active/Intuitive/Verbal/Sequential	AIVbSq
Reflective/Intuitive/Verbal/Sequential	RIVbSq
Active/Sensor/Visual/Global	ASViG
Reflective/Sensor/Visual/Global	RSViG
Active/Intuitive/Visual/Global	AIViG
Reflective/Intuitive/Visual/Global	RIViG
Active/Sensor/Verbal/Global	ASVbG
Reflective/Sensor/ Verbal/Global	RSVbG
Active/Intuitive/Verbal/Global	AIVbG
Reflective/Intuitive/Verbal/Global	RIVbG

Without considering the scale, this study integrate the processing, perception, input and understanding learning styles to map the characteristics of the students into 16 learning style. Table 3 depicts the 16 learning styles that are proposed in Integrated Felder Silverman model. The rationale of the integration of these dimensions is to minimize the time consumption in diagnosing the learning styles.

4 Development of the Learning System

When designing the learning material, it is important to accommodate elements that reflect individual differences in learning [35]. Systems such as iWeaver [9], INSPIRE [10], CS383 [11] and SAVER [19] proposed several learning components to be tailored according to learning styles of the students. We adopted the components implemented in iWeaver, CS383 and INSPIRE in our system due to the success of the researches. The resource materials are categorized into communication tool using forum facility, learning resources, exercises and examples.

By utililizing Moodle features, the learning resources developed for this study were structured into components that are suitable for processing, perception, input and understanding dimension in Felder Silverman learning style model. Three chapters from Data Structure syllabus such as, Sorting, Searching and Linked List were integrated in the system. Among the resource materials provided in the learning systems are as follows:

- **Forum** – Provide mechanism for active discussions among students. Based on certain topics assigned, student's can post, reply and view discussions conducted in the forum. The activity is very useful for active learners, while reflective learners usually prefer to view the content of the forum.
- **Animation** – Provide simulations of various sorting, searching and link list operations. The process of how each technique is implemented can be viewed step by step according to the algorithm. The activity is useful specifically for visual learners.
- **Sample Codes** – Provide source codes for every algorithms discussed in class. Students can view and actively run various programs on sorting, searching and link list. They also were given tasks to do some modification to the source codes.
- **Hypertex**t – Provide learning content which has been composed into theory and concepts. The learning content has the topic objectives, sub modules, and navigation link. This learning resource is useful for sensor/intuitive students and sequential/global students. Sensor students can understand well fact materials, while intuitive learners can learn well the abstract materials.
- **Power Point Slideshow** – Provide learning materials that consist of example in the form of text, pictures and animations. Different colors of text are used to emphasized different facts in the example given.
- **On-line exercises** – Provide exercises in multiple choice questions which students can answer and get hint and feedback regarding their performance.

- **On-line Assessment**– Provide on-line quiz that consist of multiple choice questions and marks that can be displayed immediately after the student submit the quiz. Analysis of each item in the question is also provided in Moodle.

Fig. 2 is an example of the e-learning system developed for Data Structure subject. The system consists of the resource materials listed previously. The flexibility provided by Moodle allows the resource materials to be developed easily without requiring expertise in managing the e-learning system.

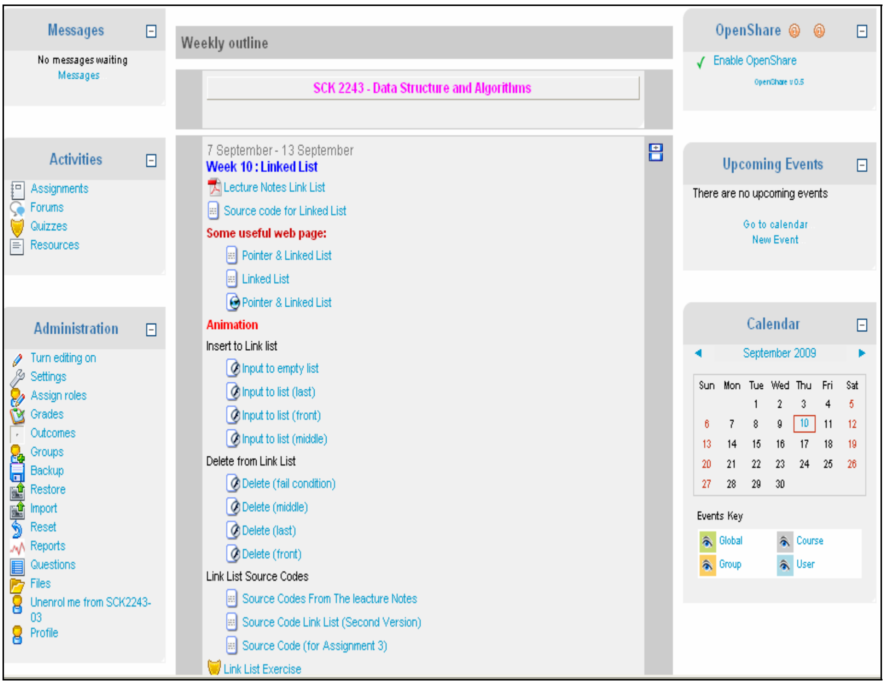


Fig. 2. Example of e-learning developed using Moodle

5 Experimental Setup

In order to determine which characteristics of the students can be used to identify their learning style, we have conducted experiments for 2 semesters. There were 110 students participated in this study. The experiments took place at Faculty of Computer Science and Information Systems, Universiti Teknologi Malaysia (UTM). Students' composition is categorized as follows: 70 students are from Computer Science stream and the other 40 students are from Computer Engineering stream. During study session, students' were required to participate in lab exercises, to work in group for problem solving, to explore self-study mechanism in using e-learning system, to take part in forum discussion and to acquire on-line quiz. The entire materials can be accessed through the e-learning system.

Fig. 3 shows the analysis process conducted in this study. Students were required to use the resource materials provided in the e-learning system. Every activity performed by the students, such as the student's involvement in forum, the frequency of accessing learning content, animation, exercises and on-line assessment were recorded and stored in log files. The data is pre-processed, analyzed and transformed into appropriate format in order to analyze and interpret the characteristics of the students based on Felder Silverman learning dimensions.

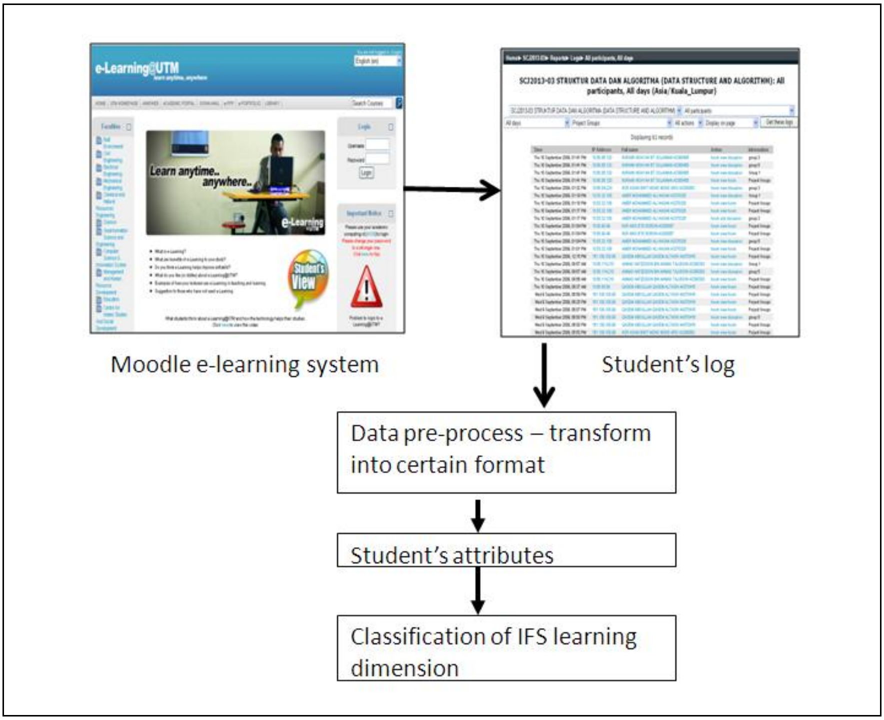


Fig. 3. The analysis process

5.1 Analysis of the Questionnaire

In order to determine the student's learning styles, the students were required to fill up the ILS questionnaire which can be accessed freely from website [34]. Fig. 4 shows the distribution of learning styles collected from 110 students taking Data Structure course in UTM. From the survey, we found out that there are only 13 learning styles exist among the group of students. Majority of the students, 28.2%, have Active/Sensor/Visual/Sequential learning styles followed by Reflective/Sensor/Visual/Sequential which is 19% among the sample group. The result is consistent with the studies done by Zywno [31] who concluded that the default learning styles among students is Active/Sensor/Visual/Sequential. However, in this study we found out that no students fall into 3 categories of learning style, which are Active/Intuitive/Verbal/Sequential, Reflective/Sensor/Verbal/Global and Reflective/Intuitive/Verbal/Global. The main reason for the absence is that there are only twelve students who have verbal learning styles. The small number of verbal students is not enough to cover the 16 learning styles.

The content of log files that contains every activity performed by the students, were transformed into appropriate format in order to analyze and interpret the characteristics of the students based on Felder Silverman learning dimensions. Fig. 5 shows an example of log data extracted by Moodle. The log contains the date and time of access, IP address, student name activity done during the interaction

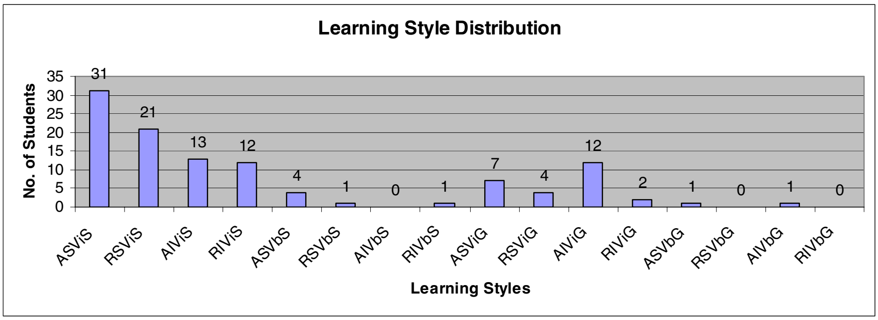
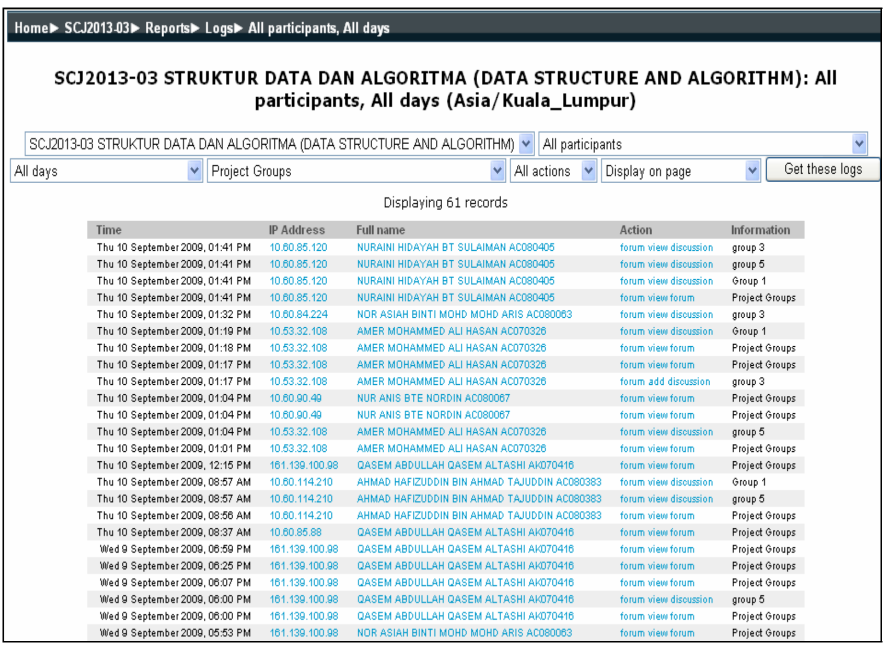


Fig. 4. Distribution of learning styles among UTM students


Home▶ SCJ2013-03▶ Reports▶ Logs▶ All participants, All days

SCJ2013-03 STRUKTUR DATA DAN ALGORITMA (DATA STRUCTURE AND ALGORITHM): All participants, All days (Asia/Kuala_Lumpur)

SCJ2013-03 STRUKTUR DATA DAN ALGORITMA (DATA STRUCTURE AND ALGORITHM) | All participants
All days | Project Groups | All actions | Display on page | Get these logs

Displaying 61 records

Time	IP Address	Full name	Action	Information
Thu 10 September 2009, 01:41 PM	10.60.85.120	NURAINI HIDAYAH BT SULAIMAN AC080405	forum view discussion	group 3
Thu 10 September 2009, 01:41 PM	10.60.85.120	NURAINI HIDAYAH BT SULAIMAN AC080405	forum view discussion	group 5
Thu 10 September 2009, 01:41 PM	10.60.85.120	NURAINI HIDAYAH BT SULAIMAN AC080405	forum view discussion	Group 1
Thu 10 September 2009, 01:41 PM	10.60.85.120	NURAINI HIDAYAH BT SULAIMAN AC080405	forum view forum	Project Groups
Thu 10 September 2009, 01:32 PM	10.60.84.224	NOR ASIAH BINTI MOHD MOHD ARIS AC080063	forum view discussion	group 3
Thu 10 September 2009, 01:19 PM	10.53.32.108	AMER MOHAMMED ALI HASAN AC070326	forum view discussion	Group 1
Thu 10 September 2009, 01:18 PM	10.53.32.108	AMER MOHAMMED ALI HASAN AC070326	forum view forum	Project Groups
Thu 10 September 2009, 01:17 PM	10.53.32.108	AMER MOHAMMED ALI HASAN AC070326	forum view forum	Project Groups
Thu 10 September 2009, 01:17 PM	10.53.32.108	AMER MOHAMMED ALI HASAN AC070326	forum add discussion	group 3
Thu 10 September 2009, 01:04 PM	10.60.90.49	NUR ANIS BTE NORDIN AC080067	forum view forum	Project Groups
Thu 10 September 2009, 01:04 PM	10.60.90.49	NUR ANIS BTE NORDIN AC080067	forum view forum	Project Groups
Thu 10 September 2009, 01:04 PM	10.53.32.108	AMER MOHAMMED ALI HASAN AC070326	forum view discussion	group 5
Thu 10 September 2009, 01:01 PM	10.53.32.108	AMER MOHAMMED ALI HASAN AC070326	forum view forum	Project Groups
Thu 10 September 2009, 12:15 PM	161.139.100.98	QASEM ABDULLAH QASEM ALTASHI AK070416	forum view forum	Project Groups
Thu 10 September 2009, 08:57 AM	10.60.114.210	AHMAD HAFIZUDDIN BIN AHMAD TAJUDDIN AC080383	forum view discussion	Group 1
Thu 10 September 2009, 08:57 AM	10.60.114.210	AHMAD HAFIZUDDIN BIN AHMAD TAJUDDIN AC080383	forum view discussion	group 5
Thu 10 September 2009, 08:56 AM	10.60.114.210	AHMAD HAFIZUDDIN BIN AHMAD TAJUDDIN AC080383	forum view forum	Project Groups
Thu 10 September 2009, 08:37 AM	10.60.85.88	QASEM ABDULLAH QASEM ALTASHI AK070416	forum view forum	Project Groups
Wed 9 September 2009, 06:59 PM	161.139.100.98	QASEM ABDULLAH QASEM ALTASHI AK070416	forum view forum	Project Groups
Wed 9 September 2009, 06:25 PM	161.139.100.98	QASEM ABDULLAH QASEM ALTASHI AK070416	forum view forum	Project Groups
Wed 9 September 2009, 06:07 PM	161.139.100.98	QASEM ABDULLAH QASEM ALTASHI AK070416	forum view forum	Project Groups
Wed 9 September 2009, 06:00 PM	161.139.100.98	QASEM ABDULLAH QASEM ALTASHI AK070416	forum view discussion	group 5
Wed 9 September 2009, 06:00 PM	161.139.100.98	QASEM ABDULLAH QASEM ALTASHI AK070416	forum view forum	Project Groups
Wed 9 September 2009, 05:53 PM	161.139.100.98	NOR ASIAH BINTI MOHD MOHD ARIS AC080063	forum view forum	Project Groups

Fig. 5. Sample log data in Moodle

and information of resources being accessed. Detailed discussions on the log analysis process can be referred in [36].

From the result of the analysis in [36], we conclude that the preferences of the students are consistent with the characteristics of the learning styles describe in Felder Silverman model. We further determine the parameters that represent the characteristics of the students based on Felder Silverman learning model. Table 4 lists the attributes for Felder Silverman learning dimension. The attributes can be used for mining the learning activities and preferences in e-learning environments. Such information is very useful for adaptation of learning materials and for analyzing the performance of the student's while learning on-line.

Table 4. Attributes description and values for IFS learning dimension

Attribute Name	Value	Dimension
Post and reply forum	Much/Few	
Number of exercise visited	Much/Few	
Number of simulation visited	Much/Few	Active/
Number of executing sample codes	Much/Few	Reflective
Number of viewing/reading forum content	Much/Few	
Hypertext coverage	Much/Few	
Number of backtrack in hypertext	Much/Few	
Viewing concrete material	Much/Few	
Viewing abstract material	Much/Few	Sensor/
Number of access to example	Much/Few	Intuitive
Number of exercise visited	Much/Few	
Exam delivery duration	Quick/slow	
Exam revision	Much/Few	
Number of Simulation visited	Much/Few	
Number of diagram/picture viewing	Much/Few	Visual/
Hypertext coverage	Much/Few	Verbal
PowerPoint Slide Access	Much/Few	
Hypertext – navigate linearly	Linear/global	
Hypertext coverage	Much/Few	Sequential
Number of visiting course overview	Much/Few	/global

6 Rough Set in Detecting Student Learning Style

Rough set offers some important techniques in managing an information system (IS), and consists of several steps leading towards the final goal of generating rules from information/decision systems. The main steps of the rough set approach are given below and the detail of each procedure can be found in [37].

- Mapping of information from the original database into the decision system format -Information System Table.
- Data Completion
- Data Discretization
- Reduct Computation
- Rules Derivation
- Rules Filtering
- Classification

Rough set approach is frequently used on attribute selection and feature selection [38, 39]. Redundant attributes will be removed to generate association rules that are more efficient. However, rough set usually generate an excessive amount of rules which might include redundant and duplicate rules. Therefore, it is important to mine the most significant rules to produce accurate classification since the main issue in rough set is to automatically extract an ideal, optimal and important rule. Variety of metrics has been used to measure rules generated by rough set, and these include rule confidence, accuracy, support, gain, chi-squared value, gini, entrophy gain and conviction. Many studies have been reported in mining the best rule; Li, 2006 [39] provide a rank of how important is each rule by rule importance measure, Ohrn, 1999 [40] used support/confidence value and [41, 42, 43] investigated the relationship of the rule support, length, and various number of rules at the classification phase. Bose, 2006 concluded that only the top 10% of the rule were really important and needed to be retained [41].

A general framework of rough set classification for detecting student learning style is presented in Fig. 6. The raw input data is designed based on the analysis of the student's learning style. The input data set is transformed into a decision system and pre-analysis is executed by eliminating data with incomplete value. The descretization process is employed for training and testing data set. The rules are

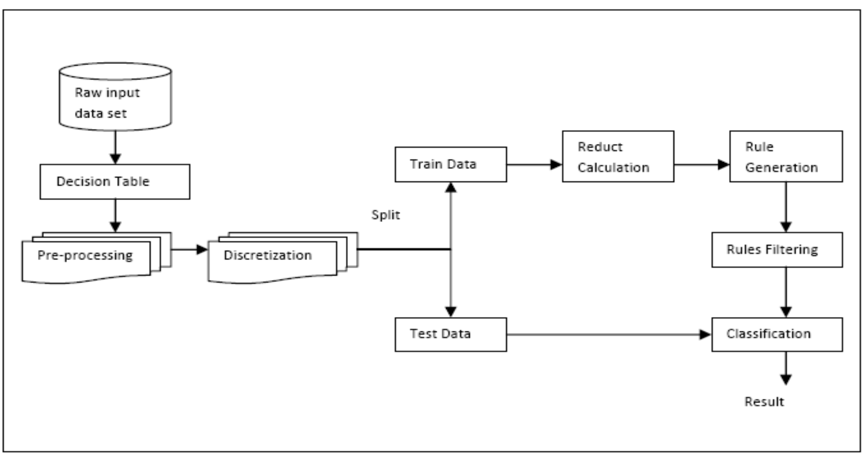


Fig. 6. Rough set frameworks for detecting students' learning style

generated from reducts by performing the attribute reduction algorithm. Consequently, these rules are filtered to get the most significant rule for the classification process. Detail discussions on classification and rule filtering process are given in the next subsection.

6.1 Data Design and Knowledge Representation

From the analysis of the learning components preferred by the students, we have simulated the data that represents the characteristics of the students based on the learning styles. Table 5 shows the decision table for IFS classifier. There are 20 identified attributes that will be mapped into 16 learning styles as listed in Table 3. Attributes A1 – A6 are used to identify Active/Reflective learners, attributes A7 – A13 are the characteristics of Sensor/Intuitive learners, attributes A14 – A17 are employed to identify Visual/Verbal learners and, attributes A18 – A20 are applied to identify Sequential/Global learners.

Table 5. Decision table for IFS classifier

A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11	A12	A13	A14	A15	A16	A17	A18	A19	A20	Decision
1	1	1	1	1	1	1	1	0	1	1	0	0	0	1	0	1	0	1	1	ASViSq
1	1	1	1	1	0	1	1	0	1	1	0	1	0	0	0	1	0	0	0	ASViSq
1	1	1	1	0	0	1	1	0	1	1	1	0	1	1	1	1	0	1	0	ASViSq
1	1	1	1	0	1	1	1	0	1	1	1	1	1	1	1	0	0	1	1	ASViSq
0	1	1	1	0	1	1	1	0	1	1	0	0	0	1	0	1	0	1	1	RSViSq
0	1	1	0	1	1	1	1	0	1	1	0	1	0	0	0	1	0	0	0	RSViSq
0	1	1	0	0	1	1	1	0	1	1	1	0	1	1	1	1	0	1	0	RSViSq
1	1	1	1	1	1	1	0	1	1	1	0	0	0	1	0	1	0	1	1	AIViSq
1	1	1	1	1	0	1	0	1	1	1	0	1	0	0	0	1	0	0	0	AIViSq
1	1	1	1	0	0	1	0	1	1	1	1	0	1	1	1	1	0	1	0	AIViSq
1	1	1	1	0	1	1	0	1	1	1	1	1	1	1	1	0	0	1	1	AIViSq
0	0	0	1	0	1	1	0	1	1	0	1	0	0	0	1	1	0	0	1	RIVbG
0	0	0	0	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	1	RIVbG
0	0	0	0	1	0	1	0	1	0	1	0	0	0	1	1	1	1	0	1	RIVbG
0	0	0	0	0	1	1	0	1	0	1	0	1	0	1	1	0	1	1	0	RIVbG

7 Experimental Results

The analysis of the proposed study is validated by executing rough set rules measurement. Rules are generated from reducts. The rules may be of different types and on different formats, depending on the used algorithms. A decision rule can be denoted as $\alpha \rightarrow \beta$ which implies if α then β.

Rule measurement has three types [40]:

1. **Support measurement:**
Given a description contains a conditional part, α and the decision part β, denoting a decision rule $\alpha \rightarrow \beta$. The support of the pattern α is a number of objects in the information system A has the property described by α.

$$Support(\alpha) = \|\alpha\| \tag{1}$$

The support of β is the number of the object in the information system A that have the decision described by β.

$$Support(\beta) = \|\beta\| \tag{2}$$

The support for the decision rule $\alpha \rightarrow \beta$ is the probability of that an object covered by the description is belongs to the class.

$$Support(\alpha \rightarrow \beta) = \|\alpha \cdot \beta\| \tag{3}$$

2. **Accuracy measurement:**
Presented as the quantity accuracy of ($\alpha \rightarrow \beta$) that gives a measure of how reliable the rule is in the condition of (β). It is the probability that an arbitrary object covered by the description belongs to the class. It is identical to the value of rough membership function applied to an object x that match α. Thus accuracy measures the degree of membership of x in X using attribute B.

$$Accuracy(\alpha \rightarrow \beta) = \frac{Support(\alpha \cdot \beta)}{Support(\alpha)} \tag{4}$$

3. **Coverage measurement:**
Defined as a measurement of how well the pattern α describes the decision class defined through β. It is the probability that an arbitrary object, belonging to the class C is covered by the description D.

$$Coverage(\alpha \rightarrow \beta) = \frac{Support(\alpha \cdot \beta)}{Support(\beta)} \tag{5}$$

The rules are completed if any object belonging to the class is assigned with the coverage of 1. While deterministic rule are rules with the accuracy of 1, and the correct rules are rules with both coverage and accuracy equal to 1.

7.1 Rules Analysis of the Integrated Felder Silverman Learning Style

We designed 1184 simulated data based on the attributes for IFS dimensions shown in Table 5. 80% of the data is used for training and 20% for testing. In our study, ROSETTA tool [44] has been used for classification. To date, ROSETTA has been used successfully in data analysis in various applications since it provides various discretization, reduction and classification techniques.

In the analysis phase, extensive experiments have been conducted using various discretization techniques such as Boolean reasoning, Equal Frequency Binning, Entropy/MDL algorithm and Naive algorithm. (Please refer to [38] and [45] for further explanations on discretization technique. It is essential to choose an appropriate discretization method since performance of discretization methods differ significantly [46]. The experiments were conducted in order to choose the most significant discretization method for our data.

The discretized data are further processed to mine the significant rules using Genetic Algorithm and Johnson Algorithm. ROSETTA provides two options on discernibility; full discernibility and object related discernibility. With full discernibility,

Table 6. The testing result for various choices of discretization and reduction technique

Method of discretization	Method of reduction	No. of reducts	No. of rules	Testing accuracy
Boolean reasoning	Genetic algorithm (full reduct)	61	34710	84.81
	Johnson algorithm (full reduct)	1	546	83.96
	Genetic algorithm (object reduct)	76238	84854	90.72
	Johnson algorithm (object reduct)	426	505	91.56
Equal Frequency Binning	Genetic algorithm (full reduct)	61	34710	84.81
	Johnson algorithm (full reduct)	1	546	83.96
	Genetic algorithm (object reduct)	**76292**	**85253**	**92.41**
	Johnson algorithm (object reduct)	426	505	91.56
Entropy/MDL algorithm	Genetic algorithm (full reduct)	61	34710	84.81
	Johnson algorithm (full reduct)	1	546	83.9662
Naive algorithm	Genetic algorithm (full reduct)	46	26918	83.122
	Johnson algorithm (full reduct)	1	546	83.9662

a set of minimal attribute subsets that can distinguish all objects from each other is produced. With object related discernibility, reducts that can differentiate a certain object from others are generated. We used both options of discernibility and classified the data using standard voting classifier. A total of 12 different approaches have been conducted in classifying the data using rough set classifier.

Table 6 reveals the results of the experiments, and it shows that all approaches have more than 80% testing accuracy. The best testing accuracy is 92.41% which is achieved through Equal Frequency Binning and Genetic Algorithm for object reduction. Equal frequency binning usually generates high testing accuracy compare to other methods since it creates discretization intervals; an equal number of objects in each interval. Genetic algorithm reduction performed better than Johnson's algorithm since it provides a more exhaustive search [41].

Subsequently, the classifier performance with Equal Frequency Binning discretization and Genetic algorithm reduction is examined. The simulated data is randomly divided into 4 training and testing set with a partition of 80%, 70%, 60% and 50% accordingly. The classification results are depicted in Table 7. Higher consumption of data at training phase gives larger number of rules; hence yields better accuracy. The classifier with 80% training data and 20% testing data furnishes the highest accuracy and the largest number of generated rules.

Table 7. Comparison of classification with various partition of training and testing data

% Training Data	% Testing Data	RHS Support	LHS Length	Number of Rules	Testing Accuracy
80	**20**	**1-43**	**4-15**	**85253**	**92.41**
70	30	1-39	4-16	80827	82.54
60	40	1-36	4-14	74832	78.90
50	50	1-32	4-14	66700	73.3

Consequently, for better accuracy, the partition of 80% training data and 20% testing data is chosen, and the rules generated by this classifier are further examined for filtering and mining the most significant rules. Example of the generated rules is shown in Table 8. Each generated rule is associated with the right hand side (RHS) support and left hand side (LHS) support, accuracy, coverage, and length. The definition of the rule statistics are as below [41]:

1. LHS SUPPORT – the number of records in the training data that fully exhibit the property described by the IF-THEN conditions.
2. RHS SUPPORT – the number of records in the training data that fully exhibit the property described by the THEN conditions.
3. RHS ACCURACY – the number of RHS support divided by the number of LHS support.
4. LHS COVERAGE – the fraction of the records that satisfied the IF condition of the rule. It is obtained by dividing the support of the rule by the total number of records in the training sample.

5. RHS COVERAGE - the fraction of the records that satisfied the THEN conditions. It is obtained by dividing the support of the rule by the total number of records in the training sample that satisfied the THEN CONDITION.
6. LENGTH – the number of conditional elements in the IF part.

From the experiment conducted, rough set method generates a large number of reduct and rules, with 76292 reducts and 85253 rules. Reducts are used to generate decision rules. A reduct is able to generate several rules and it can be seen from the experiment that the classifier produce 85253 rules from 76292reducts generated. Table 8 extracts several rules with higher rule support and lowest rule support. The decision rule, at the left side, is a combination of values of attributes such that the set of all objects matching this combination have the decision value at the rule's rough side. The rule derived from reducts can be used to classify the data. The set of rules is referred as classifier and can be used to classify new and unseen data.

Table 8. Sample of the rules generated by rough set

Rules	LHS support	RHS support	RHS accuracy	LHS coverage	RHS coverage	LHS length	RHS length
PRForum(1) AND Abstract(0) AND Simulation1(0) AND HtextCov1(1) AND Linear/global(1) => Label(ASVbG	43	43	1	0.045407	0.614286	5	1
PRForum(1) AND Abstract(1) AND Simulation1(1) AND Linear/global(1) => Label (AIViG)	35	35	1	0.036959	0.5	4	1
PRForum(1) AND Abstract(0) AND Simulation1(1) AND Linear/global(0) AND Courseview(0) => Label(ASViSq)	32	32	1	0.033791	0.484848	5	1
PRForum(1) AND Abstract(0) AND Simulation1(1) AND Linear/global(0) AND HTextCov2(1) => Label(ASViSq)	29	29	1	0.030623	0.439394	5	1
PRForum(0) AND HtextCov(1) AND Concrete(1) AND HtextCov1(0) AND Linear/global(0) AND Courseview(0) => Label (RSViSq)	14	14	1	0.014784	0.28	6	1
PRForum(0) AND Simulation(0) AND codeExec(0) AND HtextCov(0) AND ExmRvsion(0) AND HtextCov1(1) AND pptAccess(1) AND Linear/global(1) AND HTextCov2(0) => Label(RIVbG)	1	1	1	0.00105597	0.0204082	9	1
PRForum(0) AND Simulation(1) AND codeExec(1) AND forumView(0) AND HtextCov(1) AND Abstract(1) AND Exmple(1) AND Exmdlvry(0) AND ExmRvsion(1) AND HtextCov1(1) AND HTextCov2(0) AND Courseview(1) => Label(RIVbG)	1	1	1	0.00105597	0.0204082	12	1

When rules are generated, the numbers of objects that generate the same rule is typically recorded and represent LHS rule support. The highest LHS rule support from this experiment is 43 and the lowest LHS support is 1. Meanwhile the minimum LHS length of the conditional elements in the generated rules is 4 and the maximum length of the rules is 15. The accuracy of the rules is 1 since there is no inconsistency in the decision system (inconsistency rule is the rule that has several decisions in the THEN part). The value of rule support, rule coverage and accuracy are computed based on equation (3), equation(4) and equation (5).

However, not all rules are important and it is vital to choose the rules that are significant in the classification process. Due to the large number of rules, it is difficult to analyze these rules manually. The following section will discuss the rule filtering approach in order to obtain the granularity of the significant features.

7.2 Rule Filtering

Rule filtering involves the process of eliminating insignificant rules from the generated rule sets. The criteria of the filtering process are as follows:

1. Filtering based on the left hand side (LHS) length.
2. Filtering based on the left hand side (LHS) support.
3. Overall testing accuracy

The rule filtering entails the stepwise elimination of insignificant rules based on the criteria mentioned above.

7.2.1 Filtering the Rule Length

Table 9 illustrates the experimental results on the impact of filtering the rules based on various rule length. Fig. 7 exhibits the classification accuracy of reducing the rules based on the selected length. Rule filtering is done by continuously

Table 9. Classification accuracy with various LHS rule length

LHS length	No. of rules	Testing accuracy
4-15	85253	92.41
4-14	85237	92.41
4-13	85078	92.41
4-12	84219	92.41
4-11	81015	92.41
4-10	71744	92.41
4-9	55180	92.41
4-8	**35764**	**92.41**
4-7	18398	91.56
4-6	5673	85.23
4-5	498	51.05

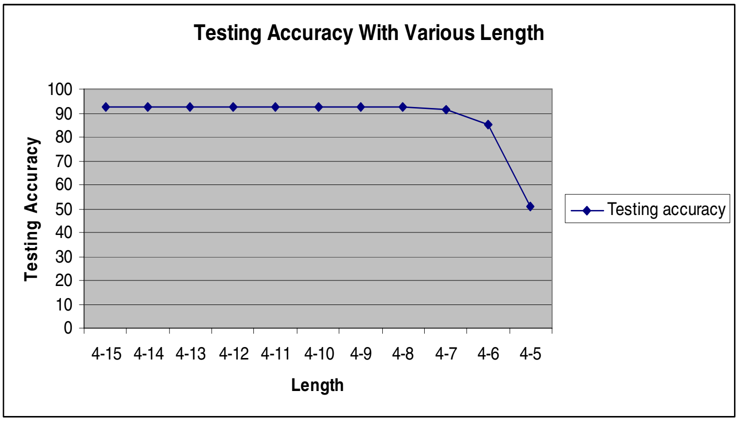


Fig. 7. Classification accuracy with various rule LHS length

eliminating the rule with the highest length and so forth. The result shows that the classification accuracy is similar despite rules reduction from the maximum LHS length of 15 to LHS length of 8. However, by filtering the rule from LHS of length 7 to 5, the accuracy rate decreases tremendously. This implies that the rules with shorter length are more important than the longest length. Subsequently, further filtering process is executed by opting for the rules with LHS of length 4 to LHS length 8.

7.2.2 Filtering Based on the Rule Support

Table 10 demonstrates the results of filtering the rules based on various LHS support. In this experiment, we filter the rules by eliminating the rules with the minimum support starting with LHS support 1 until LHS support 15. The results reveal that the classification accuracy gradually increases by eliminating the rule with minimum LHS support of 2 to minimum LHS support of 5. The rules within the range of 6-43 give the highest accuracy, 96.20%. Meanwhile, the accuracy rate decreases by eliminating the LHS support from 10 onwards. The result implies that the rules with lower LHS support are non-essential and doesn't have effect on the accuracy, unlike rules with higher support of 6 – 43, which are really vital for higher accuracy.

We further choose the rules with the length between 4-8 and the support in the range of 1-43 to 10-43 for additional classification. Table 11 shows that rules with LHS support of 5- 43 give the highest accuracy, followed by the rule with LHS support of 6-43 and 7-43. To decide on the best range of the rule support for the classifier, we compute the average accuracy for three classifiers which is 96.6%. The classifier with the rule support of 6-43 has the accuracy of 96.62 and 4290 rules in this range. The rules generated in this classifier are only 5% from the initial set of rules generated by rough set.

Table 10. Classification accuracy with various LHS support

Genetic algorithm with object reduct	**LHS support**	**No. of rules**	**Testing accuracy**
All rules	1-43	85253	92.41
	2-43	65109	92.41
	3-43	24008	94.1
	4-43	16106	94.94
Rules with minimum support < 10	5-43	7441	95.78
	6-43	5063	96.20
	7-43	3086	95.78
	8-43	2163	92.83
	9-4	1439	87.76
	10-43	1041	83.96
	11-43	732	78.48
Rules with minimum support >= 10	12-43	546	74.68
	13-43	432	70.88
	14-43	335	62.45
	15-43	284	59.49

Table 11. Classification accuracy for rules with various support and LHS length between 4-8

Rule support	Testing accuracy	No of rules
1-43	92.41	35764
2-43	93.25	28991
3-43	94.94	14868
4-43	94.1	10843
5-43	**97.47**	**6051**
6-43	**96.62**	**4290**
7-43	**95.78**	**2792**
8-43	91.98	2004
9-43	87.34	1370
10-43	84.81	1003

Fig. 8 shows the performance comparison of two classifiers using the same rule support but different rule length. The rule length being considered in this study is (4-15) which is the rule length of the original rules generated, and (4-8) is the range of the rule length that gives the highest accuracy (Table 9). The comparison result illustrates that even though the rule length has been reduced; as a whole, the accuracy rate is not much affected compared to the classification rates with the initial rule length. However, for some range of rule support, such as 5- 43 and 6-43, the rules with reduced length are able to give higher accuracy.

Fig. 9 shows the comparison of number of generated rules which has the same rule support but different rule length. The rule length being considered in this study is (4-15) which is the rule length of the original generated rules and (4-8) is the range of the rule length that gives the highest accuracy as depicted in Table 9. The result shows that by reducing various rule support, the number of rules in both range of length (4-15 and 4-8) is decreasing. However, the rules with the length of (4-8) has fewer number of rules compared with the rules with the length of (4-15). The results illustrated that most of the initial rules generated by rough sets were redundant and unimportant. By filtering the rules based on the rule support and rule length, we are able to extract the most significant rule for better accuracy.

Table 12 provides the comparison of implementing Neural Network (NN) and rough set. Rough set with filtered rules are much better in term of classification accuracy and number of rules. It is observed that rough set is able to find the most significant rules by filtering the rule length and rule support. Meanwhile, the

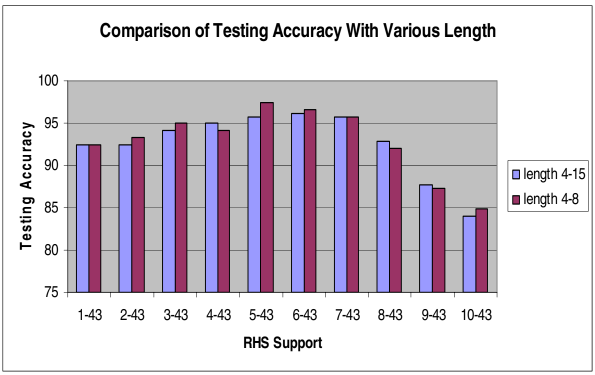


Fig. 8. Comparison of testing accuracy with various rule length

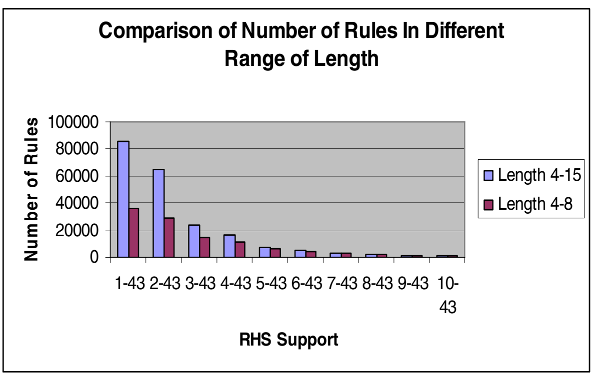


Fig. 9. Comparison of number of rules in different range of rule length

experiments with NN showed that the network is able to classify the learning dimension of a student by examining the students' interaction in the hypermedia learning system. The results showed that NN performed well in identifying the learning styles; however Rough Sets with reduced rules give the highest accuracy. The results revealed that the filtered rules give successful classification rate.

Table 12. Comparison of the classification accuracy result

Algorithm	Classification Accuracy
Rough Set with initial generated rules - 85253 rules	92.41
Rough Set with filtered rules -4290 rules	96.62
Neural Network	94.75

8 Conclusion and Future Work

In this study, we proposed an integrated Felder Silverman learning style model by analyzing student's preferences while using e-learning system developed using Moodle. The flexibility of Moodle allows developing an e-learning system that incorporates various learning resources based on Felder Silverman learning style model. We have identified significant characteristics related to Felder Silverman learning dimension: active/reflective, sensor/intuitive, visual/verbal and sequential/global. We found out that the preferences of the students are consistent with the characteristics of the learning styles describe in Felder Silverman model. These outcomes can be benefited by educators who wish to incorporate various learning material in their e-learning presentations by associating the content with the student's learning style.

From the conducted experiments, we conclude that rough set is able to correctly classify learner characteristics into 16 integrated Felder Silverman learning dimensions. Initially, rough set generate excessive rules associated with each class. However, we mine the granularity of these rules by identifying the most significant rules for better accuracy. This is achieved by filtering the rules. These rules are reduced based on the rule support and the rule length. From our experiments, we found that the rules with higher support and minimum length are much significant compared to the rules with less support and minimum length. The results depict that the classification is better with highest rule support and minimum rule length, and only 5% from the initial set of rules generated by rough set is significant.

For future, we are going to extend the research by incorporating a recommendder system in Moodle. Such system will recommend the learning materials and learning tasks based on the IFS learning style. The classifier will be integrated into Moodle in order to diagnose the learning behavior of a student and map the behavior into IFS. Data extracted from Moodle log must be preprocessed and fed to the classifier to identify the student's learning style. The information is crucial in order to develop a recommender system in LMS.

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