

SELF-ORGANIZING MAP CLUSTERING METHOD FOR THE ANALYSIS OF
E-LEARNING ACTIVITIES

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I dedicated this work to my late father Mallam Wakil Jampai Bara.

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ABSTRACT

Students' interactions with e-learning vary according to their behaviours which in turn, yield different effects to their academic performance. Some students participate in all online activities while some students participate partially based on their learning behaviours. It is therefore important for the lecturers to know the behaviours of their students. But this cannot be done manually due to the unstructured raw data in students' log file. Understanding individual student's learning behaviour is tedious. To solve the problem, data mining approach is required to extract valuable information from the huge raw data. This research investigated the performance of Self-organizing Map (SOM) to analyze students' e-learning activities with the aim to identify clusters of students who use the e-learning environment in similar ways from the log files of their actions as input. A study on Meaningful Learning Characteristics and its significance on students' leaning behaviors were carried out using multiple regression analysis. Then SOM clustering technique was used to group the students into three clusters where each cluster contains students who interact with the E-learning in similar ways. Behaviors of students in each cluster were analyzed and their effects on their learning success were discovered. The analysis shows that students in Cluster1 have the highest number of interactions with the e-learning (Very Active), and having the highest final score mean of 91.12%. Students in Cluster2 have less number of interactions than that of Cluster1 and have final score mean of 75.65%. Finally, students Cluster3 have least number of interactions than the remaining clusters with final score means is 36.57%. The research shows that, students who participate more in Forum activities emerged the overall in learning success, while students with lowest records on interactions have lowest performance. The research can be used for early identification of low learners to improve their mode of interactions with e-learning.

ABSTRAK

Interaksi pelajar dalam e-pembelajaran berbeza mengikut tingkah laku mereka dan seterusnya, menghasilkan kesan yang berbeza kepada prestasi akademik mereka. Sesetengah pelajar mengambil bahagian dalam semua aktiviti yang disediakan dalam talian, manakala sesetengah pelajar hanya terlibat dalam sebahagian aktiviti sahaja berdasarkan tingkah laku pembelajaran mereka. Oleh itu, adalah penting bagi pensyarah untuk mengetahui tingkah laku pelajar mereka. Walaubagaimanapun, ianya tidak boleh dilakukan secara manual kerana data mentah dalam fail log pelajar adalah tidak berstruktur. Memahami tingkah laku pembelajaran setiap individu pelajar adalah membosankan. Untuk menyelesaikan masalah ini, pendekatan perlombongan data diperlukan untuk mendapatkan maklumat berharga daripada data mentah yang besar. Kajian ini menyiasat prestasi kaedah Self Organising Map (SOM) untuk menganalisis aktiviti e-pembelajaran pelajar dengan tujuan untuk mengenal pasti kelompok pelajar yang menggunakan persekitaran e-pembelajaran dengan cara yang sama. Satu kajian mengenai ciri-ciri pembelajaran yang bermakna dan kepentingannya ke atas kelakuan pelajar telah dijalankan dengan menggunakan analisis regresi berganda. Teknik SOM telah digunakan untuk mengumpulkan pelajar kepada tiga kelompok di mana setiap kelompok mengandungi pelajar yang berinteraksi dengan e-pembelajaran dalam cara yang sama. Kelakuan pelajar dalam setiap kelompok telah dianalisa dan kesannya terhadap kejayaan pembelajaran mereka ditemui. Analisa menunjukkan bahawa kelompok1 mengandungi pelajar yang mempunyai bilangan tertinggi interaksi dengan e-pembelajaran (Sangat Aktif), dan yang mempunyai min skor akhir tertinggi 91.12%. Kelompok2 pula mengandungi pelajar yang mempunyai bilangan interaksi yang kurang berbanding kelompok1 tetapi mempunyai min skor akhir 70.65%. Akhir sekali, kelompok3 mengandungi pelajar yang mempunyai sekurang-kurangnya beberapa interaksi daripada kelompok lain tetapi skor akhir mereka adalah 36.57%. Berdasarkan tindakan, kelompok1 disebut sebagai 'Sangat Aktif' manakala kelompok2 adalah 'Aktif' dan kelompok3 disebut sebagai 'kurang-Aktif'. Walaupun berdasarkan kejayaan tentu, kelompok1 adalah mengandungi Pelajar Tinggi, Kelompok2 mengandungi Pelajar Rendah manakala kelompok3 mengandungi pelajar sederhana. Hasil kajian ini dapat membantu pensyarah untuk mengetahui bahawa pelajar mempunyai tingkah laku pembelajaran yang berbeza dan setiap tingkah laku membawa hasil pembelajaran yang berbeza.

TABLE OF CONTENT

CHAPTER	TITLE	PAGE
	DECLARATION	ii
	DEDICATION	iii
	ACKNOWLEDGEMENT	iv
	ABSTRACT	v
	ABSTRAK	vi
	TABLE OF CONTENT	vii
	LIST OF TABLES	xi
	LIST OF FIGURES	xii
	LIST OF ABBREVIATIONS	xiv
1	INTRODUCTION	1
	1.1 Overview	1
	1.2 Problem Background	3
	1.3 Problem Statement	7
	1.4 Dissertation Aim	8
	1.5 Objectives	8
	1.6 Research Scopes	9
	1.7 Significant of the Research	9

2	LITERATURE REVIEW	11
	2.1 Introduction	11
	2.2 E-learning	12
	2.3 Learning Management System	12
	2.3.1 Moodle Learning Management System	13
	2.3.1.1 Activities Moodle Learning Management System	14
	2.4 Mining of E-learning Activities	16
	2.4.1 Meaningful Learning Characteristics	18
	2.5 Educational Data Mining	20
	2.6 Clustering	21
	2.6.1 Clustering Methods	22
	2.6.2 The K-Means Clustering Technique	23
	2.6.3 Fuzzy C-Means Clustering Technique	25
	2.6.4 Self-Organizing Map Clustering Technique	27
	2.6.5 Comparison between SOM and K-means	29
	2.7 Related Works on Student Learning Behavior Analysis	30
	2.8 Discussion	32
	2.9 Summary	32
3	RESEARCH METHODOLOGY	34
	3.1 Introduction	34
	3.2 Research process	34
	3.2.1 Step One: Problem Formulation	36
	3.2.2 Step Two: Data Description, Preparation and Preprocessing	37
	3.2.2.1 Dataset Description	37
	3.2.2.2 The Moodle LMS Activities	37
	3.2.2.3 Data Preparation & Preprocessing	40

	3.2.2.4 Data Selection	41
	3.2.2.5 Data Cleaning	41
	3.2.2.6 Data Transformation	43
	3.2.2.7 Data Normalization	43
3.2.3	Multiple Regression	45
	3.2.4 Step Three: SOM Clustering Implementation	45
	3.2.4.1 SOM Clustering Process	47
	3.2.5 Step Four: Result Validation	48
	3.2.5.1 Cluster Analysis	48
	3.2.5.2 Clustering Validation	49
3.3	Summary	49
4	RESULT ANALYSIS OF MEANINGFUL LEARNING CHARACTERISTICS	51
4.1	Introduction	51
4.2	Significance of Meaningful Learning Characteristics on Students' Learning Behaviors	52
4.3	Discussion	57
4.4	Summary	58
5	SOM CLUSTERING OF E-LEARNING ACTIVITIES	59
5.1	Introduction	59
5.2	SOM Clustering Experimental Result	59
	5.2.1 Data Preparation	60
	5.2.2 Creating the SOM Network	61
	5.2.3 Training the Network	62
	5.2.4 Result Evaluation	65
	5.2.5 Result Analysis	66
5.3	The Effects of Student's Learning Behavior in Relation to their Academic	

	Performance	67
5.4	Discussion	69
5.5	Summary	70
6	CONCLUSION	72
6.1	Introduction	72
6.2	Research Conclusion	72
6.3	Research Findings	73
6.4	Research Contribution	74
6.5	Research Limitations	75
6.6	Summary	75
	REFERENCES	77
	APPENDICES A-B	81

LIST OF TABLES

TABLE NO.	TITLE	PAGE
2.1	Activities in Moodle LMS	14
2.2	Comparison Between SOM Clustering Method and K-means	30
2.3	Related Works on E-learning	31
3.1	E-learning Activities and their Score on MLCs	38
3.2	List of Selected E-learning Activities with their Weights	38
3.3	Selected Attributes and their Weights	39
3.4	Selected Attributes	42
4.1	Meaningful Learning Characteristics	52
4.2	Attributes Weights on Meaningful Learning Characteristics	53
5.1	SOM Cluster Membership	67
5.3	Showing Cluster and Final Score Means	68

LIST OF FIGURES

FIGURE NO.	TITLE	PAGE
1.1	Problem Formulation	6
2.1	Benefits of LMS (VISIONet Solution Info, 2014)	13
2.2	Moodle log report screen	14
2.3	Benefits of Mining of E-learning Activities	17
2.4	Educational Data Mining Process	20
2.5	The K-means Algorithm	24
2.6	C-means Algorithm	26
2.7	Self-Organizing-Map Architecture	28
3.1	Research Process Steps	35
3.3	Moodle Sample Raw Data	40
3.4	Data Preprocessing Step	41
3.5	Cleaned Data Sample	42
3.6	Data Transformed to CSV format	43
3.7	Sample of Normalized Data	44
3.8	Flowchart of SOM clustering Algorithm	46
3.9	Research Framework	47
4.1	Student Group Based on Meaningful Learning Characteristics	54
4.3	Multiple Regression Model Summary	55

4.2	Correlations Between Dependent and Independent Variables	55
4.4	MRA Ratio Test	55
4.5	MRA Test Interpretations	56
5.1	Flow Diagram of SOM Clustering Method	60
5.2	Sample of Normalized Data	61
5.3	SOM Network with 25 Neurons	62
5.4	Indicating Neurons Associated with Corresponding Instance	63
5.5	SOM Neighbor Distance Shows Distance Between the BMUs	64
5.6	SOM Network with 3 Neurons	64
5.7	SOM Inter-Cluster Distance	65
5.8	Clusters and Cluster Membership	65
5.9	SOM Cluster Membership Graph	66
5.10	Cluster Means	69

LIST OF ABBREVIATIONS

ACI	-	Active, Constructive, Intentional
FCM	-	Fuzzy C-Means
LMS	-	Learning Management System
Moodle-		Modular Object-Oriented Dynamic Learning Environment
MRA	-	Multiple Regression Analysis
SOM	-	Self-Organizing Map
UTM	-	Universiti Teknologi Malaysia

CHAPTER 1

INTRODUCTION

1.1 Overview

The advancement in information technology has enhanced the effectiveness of web-based education (e-learning) system. The e-learning system allows students from anywhere and at any time to carryout different learning activities such as reading, presentations, chatting and assignment. These activities usually take place via a platform called Learning Management System (LMS), a platform that utilizes various technologies mostly on the internet to provide access to the courses and facilitates communications between students and tutors and/or among the students. The LMS provides a large volume of heterogeneous data for use by the students and the tutors as well. The learning materials are enough to meet the requirements to achieve the learning objectives and accommodate student needs. The learning management system also contains information about students' personal information, learning styles & behaviors and usability preferences (Dráždilová et al., 2010), these information are stored in log files.

Even though the learning management system contains such huge amount of data, it however, does not provide a useful means of knowledge discovery about the data in the system's log files, thus making it challengeable to manually analyze the data (Alias et al., 2013).

. Another factor is the growth of data in the LMS, making the data unstructured, thus making it difficult to extract the desired information in the best or average case time (Félix et al., 2007). When considering the fact that learners are from different background such as educational, cultural and psychological, their learning styles and behaviors may also vary (Technology & Benha, 2010) & (Myszkorowski & Zakrzewska, 2013). The success of e-learning depends greatly on the learner's positive interest toward e-learning. To make the e-learning more effective, the e-learning environment must be adjusted to meet individual/student needs, but this is very difficult in terms of cost, time and storage management. A better way to solve the problems is to divide (classify) the students according to groups of certain similarities such as learning styles and behaviors. To achieve the process, a data mining approach is required.

Data mining has various definitions by researchers, but its meaning and goal remained the same. It is the process of analyzing data from different perspectives and summarizing it into useful information, it can also be defined as the iterative and interactive process of discovering valid, novel, useful and understandable knowledge (patterns, models, rules, etc.) in massive databases. In e-learning, data mining (also called educational data mining) is an emerging discipline, concerned with development of methods for exploring the uniqueness of data that come from educational database, and use those methods to better understand learners and their learning settings (Efrati et al., 2014). These methods include classification, clustering, prediction and visualization. The process and phases of data mining in e-learning will be discussed in chapter three (research methodology) of this research. A data mining technique that groups students into certain similarities is called clustering.

Clustering is an unsupervised supervised partitioning of objects or patterns into groups of similar objects (clusters). More precisely, clustering technique groups data instances into subsets in such a manner that similar instances are grouped together, while different instances belong to different groups (Rokach & Maimon, 2010). To achieve the best result of clustering, different computational intelligence

methods such as Artificial Neural Networks, Fuzzy Logic, Decision Tree, K-means, Self-Organizing Map (SOM), etc. are used (Dráždilová et al., 2010).

Factors that affect students' interactions with e-learning include their learning behaviors. The learning behaviors of students are defined by meaningful learning characteristics. The meaningful learning characteristics show how students behave upon interaction with e-learning. However, students' learning behaviors cannot be identified directly from the log files. Data mining techniques can be used to extract the desired information from log files and use the information to identify students' learning behavior. Lack of knowledge about students' learning behavior may risk the students in their learning outcome. This is because the lecturer may not identify a certain student who has weakness in participating in some e-learning activities such as forum discussion or wiki (Tai et al., 2014), (Akcapynar et al., 2014) and (Alias et al., 2013).

1.2 Problem Background

The performance of students in e-learning environment depends on how meaningful the student learning behavior is. In other words, the success factor of e-learning is greatly dependent on meaningful learning characteristics that define student's way of interaction with the learning environment. Some students may have similarities in terms of learning behavior and vary with other students. Different learning behaviors yield different learning performance. Some learning behaviors can lead students to success while some can lead students to failure. Understanding individual learning behavior is tedious especially when they are many. Grouping such students according to their behaviors is a good solution that attracts the attention of many researchers such as (Zakrzewska, 2008) and (Zakrzewska, 2012). The idea of grouping students according to behaviors in interaction with the e-learning is to identify students that have weak learning behavior and improve the system to

motivate them, it also help the administrators to adjust the e-learning environment such that students in certain group would be treated easily.

Researchers used different methods for grouping students according how they interact with the e-learning. The problem of clustering students is associated with the choice of appropriate features/attributes that reflect their learning characteristics and the right algorithm (tool) to implement the analysis.

For example Fuzzy techniques was used by (Technology & Benha, 2010) to cluster students based on their behaviors into different categories, the author used five different attributes on the actions of students on the e-learning. The attributes include the learners' visit on the web based on On/Off campus, Day/Night hours, Class/Lab vs Non-class days, Number of hits and Number of Class-Notes download each attribute is weighted according to its impact on reflecting students' behavior. However, these attributes cannot justify student's learning behavior because it is based on time rather than actions.

In their work, (Alias et al., 2013) analyzed students' action and behavior while using Moodle e-learning system in order to identify the students behaviour. The authors used attributes such as Course_View, Assignment_View, Assignment_Submit, Assignment_I, Assignment_G and apply SOM clustering technique to group the students. They however did not state the significance of the meaningful learning characteristics on student learning behavior. Artificial Neural Network was also used by (Bernad et al., 2015) to identify students' learning styles and its relation to learning effectiveness. The approach was evaluated with data from 75 computer science undergraduate students including their behavior data in university courses and their results on the Index of Learning Style (ILS) questionnaire. (Octavia et al., 2015) used C-means clustering technique to analyze students' e-learning usage based on meaningful learning characteristics, active, authentic, cooperate, collaborative and intentional. The attributes used in the research are the 21 activities found in Moodle e-learning environment. The activities include assignment view, assignment submit, blogs, journal, chat, forum, etc.

SOM clustering method was applied by (Akcaynar et al., 2014) to analyze data obtained from 74 undergraduate students who took Computer Hardware course, the researchers use ten (10) attributes of each student for the clustering. The attributes include login count, assignment count, total time spent on discussion forum and so on. The result was made by using MATLAB software. Three different clusters were found and are termed as higher learners (cluster1), medium learners (cluster2) and low learners (cluster3). The researchers only grouped the students but did not discuss on the effects of students' behavior of each cluster to their learning success.

Based on the literature, some limitations were identified such as identifying the significance of meaningful learning characteristics on student's learning behavior and identifying the effects of students' learning behavior in each cluster on their learning success. These problems are formulated in Figure 1.1.

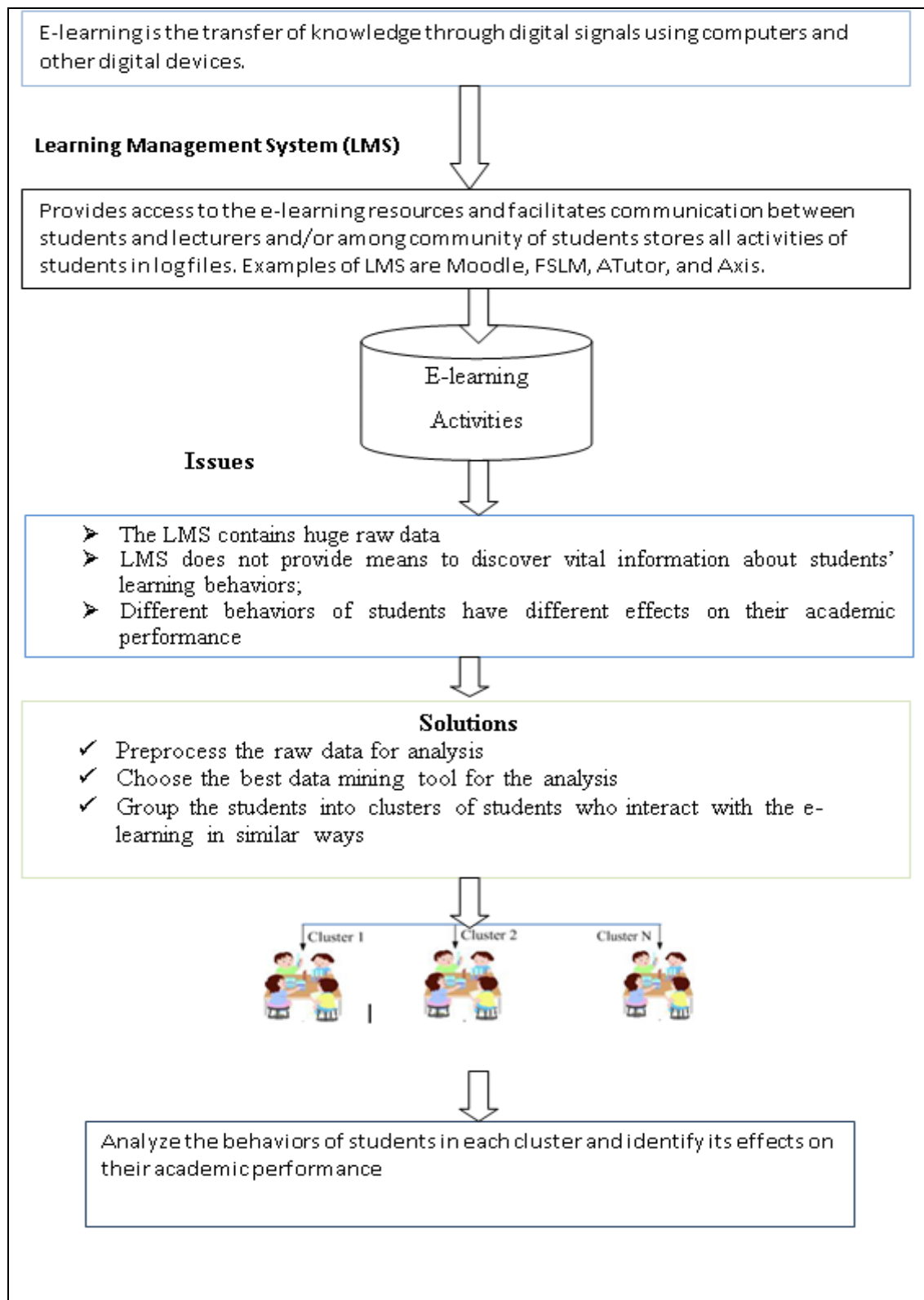


Figure 1.1 Problem Formulation

1.3 Problem Statement

Unlike traditional face-to-face learning system in which the learning activities take place via direct physical contact, the e-learning system supplements and eases the activities of learning through electronic devices such as the computer. The learning materials are uploaded online and the students can access them at anytime from anywhere. Most activities such as course viewing and course downloading, assignment submission, discussion forum and assessments are done online via a platform called learning management system. However, students' interactions with the LMS vary according to their learning behaviors. Some students are highly active; some are medium active while some are low active. Students also vary prioritizing the e-learning activities. Some students pay more attention on attendance and compulsory assignment while some will give priority to most of the activities such as participating in discussion forums, participation in class exercise and searching for additional learning material other than the ones produced by the lecturers.

In order to improve the e-learning such that the aforementioned variation among the students will be minimized, the following issues are put into consideration.

1. What are the significances of meaningful learning characteristics on students' learning behaviors upon interaction with e-learning environment?
2. Does Self-Organizing Map (SOM) capable of grouping the students into clusters of students with similar ways of interaction with the e-learning environment?
3. What are the effects of students' behaviors from each cluster on their learning performance?

This research is concerned with students' involvement in e-learning. It studies and analyzes the effects of students' behaviors to their learning performance upon carrying out the e-learning activities. The research used data obtained from log files of Computer Science undergraduate students taking a Data Structure course at

Faculty of Computing, University Teknologi Malaysia. The research is aimed to investigate the performance of SOM clustering technique to obtain clusters of students who have similar was of interacting with the e-learning environment, and analyze the effects of their behaviors on their learning performance. Students who have high grades are termed as highly active while those with fewer grades are termed as low active. The proposed model will improve the existing model by identifying the low active students and convert them to become highly active.

1.4 Dissertation Aim

The main aim of this research is to investigate the performance of Self Organizing Maps (SOM) algorithm in grouping e-learning students into clusters of students who have similar ways of carrying out their activities in e-learning environment, and to identify the effects of students' learning behavior in relation to their academic performance from each Cluster in order to identify High-Active and Low-Active students; and to improve the Low-Active students to become High-Active.

1.5 Objectives

This dissertation is intended to achieve the following objectives:

1. To study and analyze the significance of meaningful learning characteristics on student's learning behavior upon their interaction with e-learning.
2. To investigate the performance of Self-Organizing Map (SOM) clustering technique in grouping students into clusters of students with similar ways of interaction with the e-learning.

3. To correlate the effects of students' learning behavior in relation to their academic performance in order to improve the comprehensibility of e-learning environment.

1.6 Research Scopes

The scopes of this dissertation are described as below:

- 1) The research focuses on students' behavior upon interaction with the e-learning environment as the input data;
- 2) Multiple regression analysis was done in SPSS
- 3) The dataset is obtained from log files of 22 Computer Science undergraduate students taking a Data Structure course from Faculty of Computing, Universiti Teknologi Malaysia;
- 4) The Self-organizing Map (SOM) phases are done using MATLAB.

1.7 Significant of the Research

This research is aimed to describe students' involvement in e-learning. It demonstrates how data mining methods are implemented to analyze the activities of students as they interact with the e-learning environment. The output of the research is the clusters of students who use the e-learning environment in the same manner. The research result is useful to lecturers by providing feedback about the learning behavior of students and how the behavior affects the student's academic performance. It can also be used to trace student who is at risk of failing a particular course, this can be done if the lecturer discovers that a new student's learning behavior resembles that of students who previously failed the course. The research can also help lecturers to identify and improve the structure of a particular course or topic within a course that the students find it difficult to comprehend. Therefore, the

overall achievement of this research is to improve the comprehensibility of e-learning environment by understanding the behaviors of the students.

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