Using Data Mining To Dynamically Build Up Just In Time Learner Models

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By

Wengang Liu

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Abstract

Using rich data collected from e-learning systems, it may be possible to build up just in time dynamic learner models to analyze learners' behaviours and to evaluate learners' performance in online education systems. The goal is to create metrics to measure learners' characteristics from usage data. To achieve this goal we need to use data mining methods, especially clustering algorithms, to find patterns from which metrics can be derived from usage data. In this thesis, we propose a six layer model (raw data layer, fact data layer, data mining layer, measurement layer, metric layer and pedagogical application layer) to create a just in time learner model which draws inferences from usage data. In this approach, we collect raw data from online systems, filter fact data from raw data, and then use clustering mining methods to create measurements and metrics.

In a pilot study, we used usage data collected from the iHelp system to create measurements and metrics to observe learners' behaviours in a real online system. The measurements and metrics relate to a learner's sociability, activity levels, learning styles, and knowledge levels. To validate the approach we designed two experiments to compare the metrics and measurements extracted from the iHelp system: expert evaluations and learner self evaluations. Even though the experiments did not produce statistically significant results, this approach shows promise to describe learners' behaviours through dynamically generated measurements and metric. Continued research on these kinds of methodologies is promising.

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List of Abbreviations

EDM	Educational Data Mining
LOF	List of Figures
LOT	List of Tables
ITS	Intelligent Tutoring System
AIED	Artificial Intelligent in Education
UM	User Modeling
AAAI	America Association on Artificial Intelligent
IEEE	Institute of Electrical and Electronics Engineers
ICALT	International Conference on Advanced Learning Technolgies
EM	Expectation Maximization
AH	Adaptive Hypermedia

Chapter 1

Introduction

The research in this thesis is an investigation on how to apply data mining rules, especially clustering algorithms, to e-learning usage data to dynamically create just in time learner models. We try to prove that the e-learning usage data can be used to derive general metrics that can be applied in an easy and economic way to improve the quality of e-learning processes.

1.1 Make Sense of Usage Data

E-learning systems are used for computer-based education and they have widespread use in many domains. As time goes on, more and more information about learners, learning objects, and interactive data can be collected and stored in e-learning systems. Among this information, usage data plays an important role to reflect the activities of learners and systems. In general, usage data is information which comes from learners and system activities during their interactions. Is there a way to re-use the usage data in an e-learning system? Is there a way to improve an e-learning system's ability by applying data mining technologies? After a half century of research into data mining and knowledge discovery, data mining theory has matured. Data mining algorithms have become more abundant and practical in real world applications as the computing capability increased. It is possible to make sense of usage data by applying data mining techniques in an e-learning system.

Let us consider an example. Assume there is a discussion forum subsystem in an e-learning system. Learners can post messages on the forum. The types of messages include posting a question and answering a question. The usage data collected from the forum for each learner includes:

- messages posted in the forum.
- question messages posted in the forum.
- answering messages posted in the forum.
- messages accessed by the learner.
- messages mostly navigated by the learner.

To find out the activity level of a learner in this discussion forum, clustering techniques can been used to divide learners into different groups such as a high active subgroup, a normal active subgroup and an inactive subgroup with respect to their usage data. This information will help both instructors and learners to realize their learning status in the group. To find out the most interesting topics, messages also can be grouped into an interesting set and an uninteresting set such that instructors can figure out the topics associated with message groups. In this way, the usage data collected from the discussion forum will make sense for both instructors and learners.

1.2 Issues of Using Usage Data

With rich usage data collected from e-learning systems, we try to make sense of this data by applying data mining techniques. There are some challenging issues that need to be navigated:

- Among patterns found from data mining techniques, can we prove these patterns are useful in an e-learning system? How could we determine that a pattern is useful or not?
- Can we predict learners' behaviours based on the usage data?

- As time goes on, the new data will be continuously collected; can we have a model to dynamically reflect changes? Is it possible to build up a just in time model?

- If a dynamic just in time model is available in real time, do we need pre-computations to prepare the usage data? What kind of computation ability do we need to handle the real time computations?

1.3 Thesis Objectives

In this thesis, we did some "proof of concept" research to study the above issues. We studied the relationships between usage data and learner characteristics and behaviours. This resulted a six layers model to create learner models. This is a dynamic model created by applying clustering techniques on the usage data collected from the real system. We implemented a test system to collect data and to create results. Two experiments have been used to evaluate and compare the results of the test system.

1.4 Thesis Contributions

The main contributions of this thesis include:

1. Some patterns found from the usage data, also called metrics and measurements to represent learners' characteristics, seem to be clearly useful in building learner models. Other patterns show promise to describe learners' behaviours, but remain unproven.

2. Usage data can be used to build learner models through our pilot studies, but we are in a long way from creating practical learner models.

3. Different clustering algorithms produce various results. Selection and determination of data mining algorithms and associated parameters will play an important role in creating learner models.

4. Pre-computation is necessary if anything like just in time modelling is to be achieved, and has been implemented in our test system.

1.5 Organization of Thesis

Chapter 2 reviews the literature and background knowledge about e-learning systems, learner models, data mining techniques, and educational data mining research. E-learning systems include learning content management systems, intelligent tutoring systems, adaptive hypermedia systems, and adaptive and intelligent web-based educational systems. Data mining techniques include classification algorithms, clustering algorithms, association rules, regression rules, and Bayesian network-based algorithms. Educational data mining research includes various data mining applications in e-learning systems, with special emphasis or research into data mining in learner modelling.

Chapter 3 describes a six layer learner model, which draws from usage data to create a dynamic learner model. We briefly introduce the raw data and the factor data that are filtered and sorted from the raw data. Then we present our purpose-based methodologies, the six layer learner model, and how the methodologies connect the data to the learner model. In this chapter, we argue that the six layer learner model, which dynamically reflects characteristics and preferences of learners, is an effective way to draw inferences from usage data. We also argue that pre-computation is necessary for real time computation.

Chapter 4 presents our empirical studies of our approach. There are two kinds of evaluations: expert evaluation and learner self evaluation. we compare the results of humans experts, learners with the results of our data mining techniques using measures such as accuracy, correlation coefficient. The average accuracy ratio is relative low; however, the correlation coefficient is high in most cases. While not definitive, the studies do suggest that continued research on these kinds of methodologies is promising.

Chapter 5 presents our conclusions and future research directions.

Chapter 2

Literature Review

In order to more easily discuss the current state of web based e-learning systems, educational data mining and my own research, it is useful to first look at the history that has brought educational research and data mining technologies together. This chapter will focus on web based educational theories such as adaptive intelligent e-learning and learner models, data mining algorithms, and educational data mining research. In this way, it is possible to highlight the most important contributions and provide a starting point in finding a deeper historical perspective.

2.1 Learner Modelling for E-learning Systems

2.1.1 E-Learning

E-learning is naturally associated with computer based learning, especially to be used in distance learning. However it can also be used in conjunction with traditional learning. Sometimes, it refers to virtual learning environments or managed learning environments combined with a management information system. The term e-learning is also called by some researchers e-training, online instruction, web-based learning, web-based training, web-based instruction, etc. (Romero and Ventura, 2007) Obviously, the main advantages of e-learning are flexibility and convenience. Learners can work at any place and at any time with an Internet connection for most e-learning environments. This enables the e-learning environments to expand temporal and spatial limitations.

Currently, there are three main types of web based e-learning systems (Romero and Ventura, 2007): particular web-based courses, learning content management systems, and adaptive and intelligent web-based educational systems. Web-based courses are normally specific courses published as web pages. The data sources of particular web-based courses are the content of the web pages, the organization of the content, the usage which describes information about learners' actions and communications, and learner profiles which records demographic information about learners. We will describe learning content management systems and adaptive intelligent web-based educational systems in the next sections.

2.1.2 Learning Content Management Systems

Developing a course to be taught on the Internet is difficult because it requires the system to do a combination of things: publishing content on web pages, supporting tools for self learning, and providing assessments of learning performance. Standard web-based courseware is incomplete as it focuses merely on providing content. Learning content management systems can implement this task better. Learning content management systems (LCMSs) are frameworks to support a variety of channels and workspaces to facilitate information sharing and communication for learners and instructors. LCMSs have the ability to let instructors distribute contents and information to learners, and to publish assignments and tests. LCMSs also have workspaces to let learners engage in discussions, i.e., to encourage collaborative learning with forums, chats, new services, etc. Allowing collaborative learning is very important for e-learning systems to capture some advantages of face-to-face communication.

Current commercial LCMS systems normally accumulate large log data files about learners' activities such as reading, writing, taking tests and communicating with other learners, and use a database to record all this information. Some good commercial LCMS systems include Blackboard(WebCT), Virtual-U and TopClass, etc. Open source LCMS include iHelp, aTutor and Moodle, etc.

iHelp

iHelp is an e-learning system developed by the Advanced Research in Intelligent Education Systems (ARIES) Lab in the Computer Science Department of the University of Saskatchewan. iHelp is made up of a number of web based applications designed to support both learners and instructors throughout the learning process[1]. The main components of iHelp are asynchronous iHelp Discussion forums, synchronous iHelp Chat rooms, the iHelp Learning Content Management Systems (also called iHelp Courses), iHelp Share and iHelp Lecture.

- iHelp Discussions: This threaded discussion forum provides workspaces for learners to converse with one another, with subject matter experts, and with their instructors and teaching assistants.

- iHelp Chat: This chat room provides workspaces for learners to have synchronous communication with one another and with their instructors and teaching assistants. The iHelp Chat system connects learners with their peers such that multiple chat channels will open at the same time. (Brooks et al., 2005)

- iHelp Courses: This LCMS system provides tools to support full on-line courses and is designed for distance learning. It provides learners with a portal to multimedia course content.

- iHelp Share: This is a collaborative learning tool to share information relevant to courses among learners.

- iHelp Lectures: This system provides multimedia lectures to learners so that learners can write messages and comments, make notes and tags on video clips, so that all learners can share this information.

Like other LCMS systems, iHelp collects and stores all information, such as personal information, pedagogical results, learners' interaction data, etc. into a

[1] http://ihelp.usask.ca

database. These data are the source data for our project, as we will discuss in the next chapter.

2.1.3 Adaptive and Intelligent Web-based Educational Systems

To meet the various needs of each individual learner, adaptive and intelligent systems provide an ideal way to extract requirements of learners and to recommend proper elements to a specific learner.

Intelligent Tutoring Systems

Intelligent tutoring systems (ITSs) apply techniques and methods from the field of artificial intelligence to provide and support better and broader tools for the learners of e-learning systems. In the ITS field, the well explored technologies are intelligent solution diagnosis, curriculum sequencing and instructional planning, and interactive problem solving support.

- intelligent solution diagnosis: provides analysis of learners' solutions, to support error feedback and to update learner models.
- curriculum sequencing and instructional planning: provides learners with a suitable individual sequence of learning objects and tasks, and finds optional sequences.
- interactive problem solving support: provides learners with intelligent help on solving problems by giving hints or other help.

Adaptive Hypermedia

Adaptive hypermedia (AH) is a technology that personalizes the content and presentation of applications to each individual user according to each user's preferences and characteristics (Frias-Martines et al., 2006). Unlike traditional learning and traditional e-learning, AH provides hyper links that enhance a learner's experience, by adapting to a learner's goals, abilities and knowledge of the subject. To provide personalized hyper links, AH needs to build and develop a relationship between the system and learners to better understand and satisfy the needs of learners. This process is called "personalization". Personalization normally draws on a user model, also called a "learner model" in the educational area.

The architecture of an adaptive hypermedia system usually has two parts: the service side and the client side. The service side accepts clients' requests and responds to clients according to designed rules, domain knowledge and knowledge about clients. Here, a learner model is necessary for the service side to respond to clients in a personalized way. Two basic adaptive tasks of adaptive hypermedia are classification, which classifies or maps data items into one of several predefined classes, and recommendation, which suggests interesting elements to a learner based on information about the learner. The basic technologies of adaptive hypermedia are adaptive navigation support and adaptive presentation.

Adaptive and Intelligent Web-based Educational Systems

Adaptive systems attempt to be more adaptive by building a model of the goals, preferences and knowledge of each individual learner, and using this model throughout the interaction with the learner in order to adapt to the needs of that learner (Brusilovsky and Peylo, 2003). Compared to particular web-based courses, which are based on static learning materials and do not consider the diversity of learners, the adaptive educational system is more intelligent and provides a better individualized learning environment. Adaptive systems can be more intelligent and useful by incorporating adaptive hypermedia technologies and intelligent tutoring system technologies together to assess and diagnose learners' performances.

Brusilovsky and Peylo (2003) sort modern adaptive and intelligent web-based educational systems technologies into five related groups from their origins as shown in Figure 2.1. The five adaptive and intelligent web-based educational systems technologies are: adaptive hypermedia, adaptive information filtering, intelligent class monitoring, intelligent collaborative learning, and intelligent tutoring.

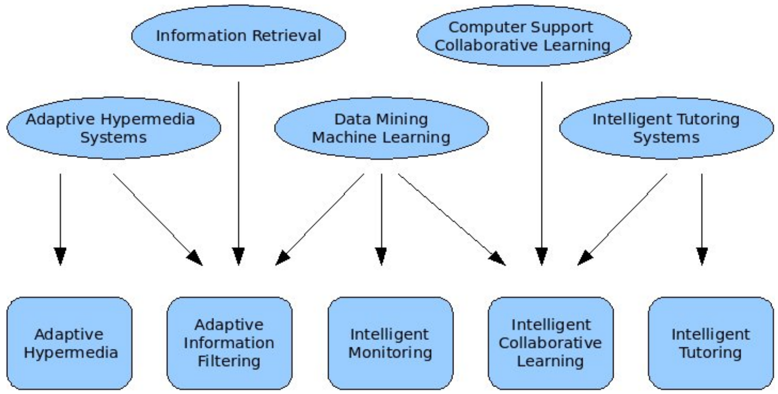


Figure 2.1: Five groups of modern adaptive and intelligent educational system technologies

(Brusilovsky and Peylo, 2003)

2.1.4 Learner Model

A learner model is defined as a set of information structures that represent learners' behaviours and preferences. The following learner behaviours are commonly considered: (Frias-Martines et al., 2006; Kobsa, 2001)

- the goals, plans, preferences, tasks of learners
- the classification of learners into subgroups
- the relevant common characteristics of specific learner subgroups
- the recording of learner behaviours
- the characteristics of learners based on their interaction histories
- the categorization of interaction histories into groups

Personalized learning provides a perfect learning environment such that learners can be uniquely identified, and progress can be individually monitored and assessed. The more information we can observe and collect, the better the learner model can be personalized to the learner's interests. A learner model can be built by a process such that the unobserved information or missing information about a learner can be inferred from observed or known information about that learner. There are two ways to build up a learner model: the user-guided approach and the automatic approach. While the user-guided approach explicitly produces elements such as age, gender, goals, plans, and tasks etc., the automatic approach produces elements derived from patterns of behaviour through a learning process. A typical learner model will include elements from both the user-guided approach and the automatic approach.

The user-guided approach gets information from surveys, questionnaires, registration and other documents or historical records. The collected elements usually consist of age, gender, major, grade, personal information, marks, hobbies, rules and self evaluations, etc. These elements may be initial values in some cases to be replaced by new values after they are learned from an automated approach. The automatic approach usually consists of steps such as data collection, preprocessing, pattern discovery, validation and interpretation.

2.2 Data Mining Algorithms

2.2.1 The Definition of Data Mining

Data mining and knowledge discovery in databases are two terms, but often these two terms are used interchangeably. Basically, data mining is the process of the extraction of patterns or models from observed data. The simple definition of knowledge discovery in databases is that knowledge discovery in databases is the process of identifying valid, potential, useful and ultimately understandable patterns in data (Fayyad et al., 1996). Originally, data mining was just one step in the overall knowledge discovery in database process. A common acceptable process (Goebel and Gruenwald, 1999) of knowledge discovery in databases consists of the following steps:

- understanding of the application domain and requirements
- selecting a target data set
- integrating and checking the data set
- data cleaning and preprocessing

- model development and hypothesis building
- choosing suitable data mining algorithms
- interpreting results
- verifying and testing results
- using the discovered knowledge

In the remainder of the thesis we will use the term “data mining” to refer both narrowly to the actual discoveries of patterns in the data and broadly to include the entire above process.

2.2.2 Data Mining Tasks

Goebel and Gruenwald (1999) survey data mining goals in the following categories. We should note that several methods may be applied together to achieve a desired result in real applications.

- *Prediction*: Given a data item and a predictive model, predict the value for a specific attribute of the data set.
- *Regression*: analysis of the dependency of some attribute values over other attribute values and automatic production of a model that can predict these attribute values for new records.
- *Classification*: Given a set of predefined categorical classes, determine to which of these classes a specific data item belongs.
- *Clustering*: Given a set of data items, partition or divide this set into a set of classes such that items with similar characteristics are grouped together.
- *Association*: Identify relationships between attributes and items such as the presence of one pattern implies the presence of another pattern.

- *Exploratory data analysis*: Exploratory data analysis is the interactive exploration of a data set without dependence on predefined assumptions and models, thus attempting to identify interesting patterns.

2.2.3 Categories of Data Mining Algorithms

The categories of data mining algorithms mainly include classification and prediction, clustering, and mining association rules. Here, we briefly list primary data mining algorithms, and outline details and descriptions combined with educational data mining applications in the following sections.

- Classification and Prediction
  - Classify nominal data: Decision Tree, Neural Networks, Bayes Classifier, Instance-based Reasoning, Support Vector Machines (Kernel Machines)
  - Predict continuous data: Linear Regression, Non-linear Regression, Neural Networks, Kernel Models
  - Probability: Bayesian Network, Hidden Markov Model (Dynamic Bayesian Net), Density Estimator, Fuzzy Methods
- Clustering
  - Partitional Methods: K-means and K-medians square-error methods, Mode-seeking methods, Graph based method, Mixture Distribution Models, Fuzzy c-means Methods
  - Hierarchical Methods: Bottom-up and Top-down methods
- Mining Association Rules
- Concept mining
- Database mining
  - Relational data mining

	Data Type				Data Mining Problem	
Data Mining Methodology	Labeled Data	Unlabeled Data	Separate Data Records	Time Series Data	Predication and Classification	Discovery of Data Patterns,Associations, and Structure
Decision trees	X		X		X	X
Association rules		X	X			X
Artificial neural networks	X	X	X	X	X	
Bayesian network	X	X	X	X	X	X
Hidden Markov Model	X	X		X	X	
Clustering		X	X			X
Support vector machines	X	X	X		X	

Table 2.1: Typical Use of Data Mining Methodologies for Various Data Types and Problems

  - Document warehouse
  - Data warehouse

- Graph mining
- Sequence mining
- Tree mining
- Web mining
- Software mining
- Text mining

Table 2.1 (Ye, 2003) lists some typical uses of data mining for various data types and different problems.

2.3 Educational Data Mining

In the past few years, lots of web-based educational systems have been deployed to provide more flexible web courses. These systems are not only based on static learning materials, but also some of them take into account the diversity of students using adaptive and intelligent techniques. To offer personalized learning environments, these systems build up learner models based on learners' goals, preferences and knowledge. Further, data mining and knowledge discovery techniques can play an important role in extracting the interesting and useful patterns about learners from logs of their behaviours.

Educational data mining (EDM) integrates data mining and knowledge discovery methods into educational environments. EDM is "concerned with developing methods for exploring the unique types of data that come from educational settings, and using those methods to better understand students, and the settings which they learn in".[2] Educational data mining is a process of converting raw data from educational systems to useful information that can be used to inform design decisions and answer research questions.

2.3.1 Data Mining Techniques in Educational Systems

In the educational field, data mining techniques can find useful patterns that can be used both by educators and learners. Not only may EDM assist educators to improve the instructional materials and to establish a decision process that will modify the learning environment or teaching approach, but it may also provide recommendations to learners to improve their learning and to create individual learning environments.

Romero and Ventura (2007) introduced an educational data mining cycle model showing that the application of educational data mining is an iterative cycle of hypothesis formation, testing and refinement. The knowledge mined from educational data mining should be used to facilitate and enhance the whole learning process. From this cycle model, we can see that the application of educational data mining can be oriented to different actors each with their own views (Zorrilla et al., 2005):

- Oriented toward learners: Purposes for EDM are to recommend to learners good learning experiences, effective learning sequences, useful resources, successful tasks carried out by other similar learners, and activities that would favour and improve their learning based on the tasks already done by other learners.

[2]http://www.educationaldatamining.org/index.html

- Oriented toward educators: Purposes for EDM are to get more feedback for instructors, classify learners into groups based on their behaviours and needs, find effective learning patterns, find more effective activities, discover the most frequently made mistakes, organize the contents efficiently for instructors to adopt instructional plans, evaluate the learning process, and evaluate the structure of course contents.

Many data mining algorithms can be applied in web-based educational systems with different data sources and purposes. The majority of applications use classification, clustering, association rules and text mining algorithms. Here we briefly describe these techniques with an emphasis on the applications of these techniques in various web-based educational systems.

2.3.2 Classification

Decision Tree

A decision tree is a special type of classifier, where each internal node denotes a test on a splitting attribute, each branch represents an outcome of the test, and leaf nodes represent classes or class distributions. (Han and Kamber, 2001) Let $X_1, ..., X_m, C$ be random variables where X_i has domain $dom(X_i)$; a classifier is a function

$$d : dom(X_1) \times ... \times dom(X_m) \mapsto dom(C) \tag{2.1}$$

There are two phases in constructing a classification tree from nominal attributes. In the growth phase, an overly large decision tree is constructed from the training data. To minimize the misclassification rate, impurity-based split selection methods will find the splitting criterion by minimizing an impurity function such as the information gain (entropy), the gini-index or the index of correlation χ^2. (Ye, 2003) For scalable data access, in which the training dataset is large, the main algorithms are: Sprint, which removes all relationships between main memory and size of the training dataset; Rainforest, a generic tree induction schema; and Boat, the only tree construction algorithm that constructs several levels of the tree in a single scan over the dataset (Ye, 2003).

In the pruning phase, pruning algorithms are used to prevent overfitting and to construct the final tree with minimized misclassification rate. The minimum description length (MDL) principle states that the best classification tree can be encoded with the least number of bits. The PUBLIC pruning algorithm combines the growth and pruning phase by computing a lower bound based on MDL principles. (Ye, 2003)

For numerical attributes, we can construct regression trees by applying decision tree algorithms. The decision tree applications include SPSS, SAS, and C4.5. [3]

Adopting decision tree and data cube technology to web log portfolios in assessing performances of students, Chen et al. (2000) discovered potential student groups based on similar characteristics to develop more effective pedagogical strategies. Murray and Vanlehn (2000) used dynamic decision theory to select rational and interesting actions within satisfied response time. Utilizing a machine-learned detector, Baker (2009) predicts students' off-task behaviours within an intelligent tutor, and finds best predicting models. Using simple and intuitive classifiers based on decision tree, Dekker et al.(2009) describes an educational data mining case study aimed at predicting students drop out cases.

2.3.3 Association Rules

Association rules discovery focuses on detecting and characterizing unexpected interrelationships between data elements (Ye, 2003). It typically returns all rules that satisfy user specified constraints with user defined good measures. An association rule is composed of two datasets, antecedent (A) and consequent (C). Two statistical terms, support and confidence, are used to describe these relationships. For an association $A \rightarrow C$,

$$support(A \rightarrow C) = support(A \cup C) \tag{2.2}$$

$$confidence(A \rightarrow C) = support(A \cup C)/support(A) \tag{2.3}$$

[3]http://www.kdnuggets.com

If support is high enough, the confidence is a reasonable estimate of the association rule.

The problem with finding association rules in this naïve way is the number of possible combinations of antecedents and consequents are very large; it is impossible to check all combinations for very large datasets. The Apriori algorithm uses user defined min-support such that $support(A \rightarrow C) \leq min - support$, to reduce the number of datasets that are considered. The frequent item set strategy further uses both min-support and min-confidence to reduce considered datasets.

There are two objective measures of "interestingness" used to identify the most interesting rules from thousands of association rules that satisfy user specified constraints on support and confidence. The most popular measure is lift, that is the ratio of the frequency of the consequent.

$$Lift(A \rightarrow C) = confidence(A \rightarrow C)/support(C) \tag{2.4}$$

The other measure is leverage, that captures both the volume and the strength of the effect.

$$Leverage(A \rightarrow C) = support(A \rightarrow C) - support(A) \times support(C) \tag{2.5}$$

Association rules can be used in numerical datasets by discretizing a numeric field into subranges.

Markellou et al. (2005) proposed an ontology-based framework to use the priori algorithm to discover association rules whose purpose was to provide personalized experiences to users. Their work has distinguished two stages in the whole process: one, offline, that includes data preparation, ontology creation and usage mining, and one, online, that concerns the production of recommendations. Lu (2004) used association fuzzy rules to discover associations between requirements of learners and a list of learning materials, which would then help learners find learning materials they would need to read. Association rules mining was used by (Monk, 2005) to reveal patterns from large volume datasets. Mostow et al.(2005) built a tool to find association rules from tutor-student interactions. By processing the vast quantity of data generated by students, Agapito et al. (2009) detects potential symptoms of low performance in e-Learning courses in two steps: generating the production rules of the C4.5 algorithm and filtering the most representative rules, which could indicate low performance of students. By using a pairwise test to search for the relationships between learning curves, Pavlik et al.(2009) show that test results can be expressed in a Q-matric domain model. Prata et al.(2009) present a model which can detect various students' speech acts within a computer supported collaborative learning environment. They found interpersonal conflict is associated with positive learning. Mercer and Yacef (2008) provided a case study to show how teachers can easily interpret association rules mined from educational data.

2.3.4 Bayesian Network

Bayesian networks are a well developed technique in the machine learning area. Bayesian learning calculates the probabilities of hypotheses using training data, and makes predictions based on probabilities of hypotheses. Let d be the observed data; the probability of each hypothesis h is obtained by Bayes' rule: (Russell and Norvig, 2003)

$$P(h_i|d) = \alpha P(d|h_i)P(h_i) \tag{2.6}$$

We can then make a prediction about unknown X:

$$P(X|d) = \sum_i P(X|h_i)P(h_i|d) \tag{2.7}$$

Here, Bayesian learning is an optimal result. The main issue is that the hypothesis space is usually very large or infinite in real learning problems. An approximating hypothesis called maximum a posteriori (MAP) is adopted such that $P(X|d) \approx P(X|h_{MAP})$, and predictions are made based on this single probable hypothesis. The maximum-likelihood (ML) hypothesis, h_{ML}, is a simplification of MAP that chooses an h_i to maximize $P(d|H_i)$.

Naïve Bayes

In the Naïve Bayes model, the output variable, which is to be predicted, is the root node, and attribute variables are leaf nodes, with the assumption that attributes are conditionally independent of each other. Given complete data, which is a training dataset of attributes with respect to outputs, the entire joint probabilities distribution of a Naïve Bayes net can be easily learned by the maximum-likelihood parameter learning method, which maximizes the log likelihood. The task of prediction simply becomes choosing the most likely class by inference through the Bayes net. In this way, Naïve Bayes net is the most common Bayesian network model and has a wide range of applications.

Expectation Maximization

The expectation maximization (EM) algorithm can learn hidden variables using observed variables. EM has been widely used in clustering, Bayesian networks with hidden variables, and hidden Markov models. In general, EM computes expected values of hidden variables for each data element and then recomputes the parameters using the expected values. Let x be the observed values, element Z denote the hidden variables, and let H be parameters of the probability model. The EM algorithm is:

$$H^{i+1} = argmax_H \sum_Z P(Z = z|x, H^{(i)})L(x, Z = z|H) \tag{2.8}$$

In the EM algorithm, the E-step computes the summation, which is the expectation of the log likelihood of complete data with respect to the posterior distribution over the hidden variables. The M-step is the maximization of expected log likelihood with respect to the parameters. (Russell and Norvig, 2003)

Hidden Markov Model

A Hidden Markov Model (HMM) is a finite mixture model whose distribution is a Markov chain. Let E represent a sequence of observed data, X be a sequence of states, the transition model is $P(X_t|X_{t-1})$ for the first-order process, and the observation model is $P(E_t|X_t)$. For any finite t, we have a complete joint distribution over all variables:

$$P(X_0, X_1, ..., X_t, E_1, ..., E_t) = P(X_0) \prod_{i=1}^{t} P(X_i|X_{i-1}) P(E_i|X_i) \tag{2.9}$$

From this model, we can make predictions that are tasks to compute posterior distributions over future states; and find the most likely explanation which is the sequence of states that is most likely to have generated those observations.

HMM is a very general type of time series model since X can be any data structure. Since HMM has a wide range of applications, it is a good tool for time series mining and sequence patterns mining for use in data classification and data clustering methods. HMM is a specific case of a dynamic Bayesian network and can be represented by a dynamic Bayes net with a single discrete state variable. In both the EM algorithm and Markov Chain Monte Carlo (MCMC) data augmentation can be used to estimate HMM parameters.

Bayesian networks are the most popular algorithm used in mining learners information; and many researchers use Bayesian networks to build student models and to extract hidden information. (Conati et al., 2002) used a Bayesian network to manage a student model that provides long-term knowledge assessment, plan recognition, prediction of students' actions, and assessment of students' understanding and learning levels. Baker et al. (2004; 2006) developed a classifier to identify if a student is gaming the system in a way that leads to poor learning. They obtained significant success in detecting student misuse of cognitive tutors from students' response models. (Mayo and Mitrovic, 2001) provided a method to manage a long term student model using a Bayesian network, and to select the next rational tutorial action based on decision theory. (Jonsson et al., 2005) expanded this model and learned the model's parameters by using the HMM method and the EM algorithm. Arroyo et al. (2004) constructed a dynamic Bayesian network that infers unobservable learning variables to predict students' positive and negative learning attitudes from ITS log files. They used the maximum likelihood method to learn conditional probabilities that predict relations among variables. Winters (2005) found the fundamental topic of a course and the proficiencies of each student by using collaborative filtering techniques such as non-negative matrix factorization, sigmoidal factorization, and common-factor analysis. Using dynamic Bayesian network, Gong et al.(2009) create a Knowledge Tracing model to make inferences about students' knowledge and learning based on self-discipline. He found that high self-discipline students had significantly higher initial knowledge. Using Markov Decision Process technique, Stamper and Barnes(2009) promise a domain-independent use of data mining method to automatically generate adaptive hints in an intelligent tutor system. Based on the usage data and marks information, Romero et al.(2008) compared different data mining methods to classify students, and found the classifier model appropriate for educational use with both accuracy and comprehension. Bayesian graphical models are commonly used in building student models. Desmarais et al. (2008) designed a Naive Bayes Framework to explore the heuristic selection leading to better performance. Using data-driven modelling, Mavrikis (2008) compared Bayesian network, decision trees and logistic regression methods to reveal the possible educational consequences.

2.3.5 Clustering

Clustering is a process of grouping data into distinct clusters (groups, categories, or subsets) based on similarity among data. There is no universally accepted definition of clustering. (Everitt et al., 2001) Most researchers describe a cluster by considering the internal homogeneity and external separation (Hansen and Jaumard, 1997) for example features of objects are similar to each other in the same cluster, while features of objects are not similar when they are in different clusters. Three necessary steps in implementing clustering algorithms are: the representation of data, the definition of proximity among data, and applying clustering methods. The first step obtains features or attributes to appropriately represent raw data. The second step chooses a measurement to judge the similarity between two pieces of data such as Euclidean distance between two data points, or Mahalonobis distance. Both the similarity and dissimilarity should be examinable in a clear and meaningful way (Xu and Wunsch, 2005). When data becomes more complex such as in trees or sequences, determining similarity or dissimilarity becomes more difficult. Since clustering algorithms are highly data dependent, the choice of a measurement for similarity has a profound impact on clustering quality.

Here are two simple mathematical descriptions of two typical types of clustering. (Xu and Wunsch, 2005; Hansen and Jaumard, 1997)

Given a set of input $\mathbf{X} = x_1, ..., x_j, ..., x_N$, where $x_j = (x_{j1}, x_{j2}, ..., x_{jd})^T \in R^d$ and each measure x_{ji} is said to be a attribute.

- Partitional clustering seeks a K partition of $\mathbf{X}$, $C = C_1, ..., C_k (K \leq N)$, such that

  1. $C_i \neq \phi, i = 1, ..., k;$
  2. $\bigsqcup_{i=1}^{K} C_i = \mathbf{X};$
  3. $C_i \bigcap C_j = \phi, i, j = 1, ..., K$ and $i \neg j$.

- Hierarchical clustering attempts to construct a tree like nested structure of $\mathbf{X}$, $H = H_1, H_2, ..., H_Q (Q \leq N)$, such that $C_i \in H_m, C_j \subset H_l$, and $m\, limply C_i \in C_j or C_i \bigcap C_j = \phi$ for all $i, j \neq i, m, l = 1, ..., Q$.

For clustering algorithms, there are four basic steps in the clustering procedure. These steps are closely related to each other and affect the derived clusters. (Xu and Wunsch, 2005)

- Feature selection: Feature selection chooses distinguishing features from a set of candidate features or transforms to new and useful features from original ones. It should be used to reduce noise, to be easy to select and interpret.

- Clustering algorithm selection: The selection of clustering algorithm is essentially the selection of a proper proximity measure. The proximity measure directly impacts on the formation of the resulting clusters. The partition of clusters is an optimization problem once the proximity measure is determined. However, there is no clustering algorithm that can be universally used to solve all problems (Kleinberg, 2002). Therefore, it is very important to select an appropriate clustering strategy to solve the problem properly.

- Clustering validation: The different algorithms usually have different clusters. Therefore, it is necessary to use effective evaluation criteria to provide a certain degree of confidence for resulting clusters from selected clustering algorithms. Usually, there are three types of testing criteria: external indices, internal indices, and relative indices and they are defined from three clustering structures, known as partitional clustering, hierarchical clustering, and individual clustering. (Jain and Dubes, 1988)

- Results interpretation: The final purpose of clustering is to provide meaningful insights to solve a problem so that the partition needs to be interpreted carefully.

Clustering Algorithm Categories

Traditionally, accepted clustering algorithms are classified as hierarchical clustering or partitional clustering based on the properties of generated clusters. (Xu and Wunsch, 2005) In recent years, there are new categories of clustering algorithms based on techniques, theories and applications. The following is a mixture of these categorizations. (Xu and Wunsch, 2005)

- Hierarchical clustering
  - Agglomerative: single linkage, complete linkage, median linkage, centroid linkage...
  - Divisive: divisive analysis, monotheistic analysis...
- Squared error-based (Vector quantization): K-means, genetic K-means algorithm...
- Mixture density-based: expectation-maximization, Gaussian mixture density decomposition...

- Graph theory-based: highly connected subgraphs...
- Fuzzy: Fuzzy c-means, fuzzy c-shells...
- Neural network-based: learning vector quantization...
- Kernel-based: support vector clustering, kernel k-means...
- Sequence data: sequence similarity...
- Large-scale data: CURE...
- High dimensional data: PCA...

The techniques-based clustering algorithms such as graph based, neural network based and kernel based clustering algorithms can be used both in partition and hierarchical clusterings. We will briefly discuss the k-means clustering and expectation-maximization clustering in the following sections.

Distance and Similarity Measures

The first important issue of clustering algorithms is how to measure the distance or the similarity between two objects, or a pair of clusters in order to determine the closeness. In mathematics, a distance or similarity function on a data set is defined to satisfy the following conditions:

1. Symmetry: $D(x_i, x_j) = D(x_j, x_i)$;
2. Positivity: $D(x_i, x_j) \geq 0$ for all x_i and x_j;
3. Triangle inequality: $D(x_i, x_j) \leq D(x_i, x_k) + D(x_k, x_j)$ for all x_i, x_j and x_k;
4. Reflexivity: $D(x_i, x_j) = 0$ iff $x_i = x_j$;

There are some typical measures which can be used in determining the distance or the similarity.

The Euclidean distance is the most commonly used metric to measure the distance between a pair of elements or a pair of clusters such as in hierarchical linkage

Minkowski distance	$D_{ij} = (\sum_{l=1}^{d} \mid x_{il} - x_{jl} \mid^{1/n})^n$
Euclidean distance	$D_{ij} = (\sum_{l=1}^{d} \mid x_{il} - x_{jl} \mid^{1/2})^2$
City-block distance	$D_{ij} = \sum_{l=1}^{d} \mid x_{il} - x_{jl} \mid$
Sup distance	$D_{ij} = max_{1 \leq l \leq d} \mid x_{il} - x_{jl} \mid$
Pearson correlation	$D_{ij} = (1 - r_{ij})/2$

Table 2.2: Typical measures of distances

clustering, squared error-based k-means clustering and mixture densities EM clustering. (Han and Kamber, 2001) The Minkowski distance, City-block distance and Sup distance are normally used in fuzzy clustering algorithms.

Partitional method

A Partitional method divides a dataset into k clusters. K-means and k-medians are two popular square-error based hard partitional clustering methods that are iterative algorithms to minimize the least square error criteria. The mode-seeking method and grid-based methods are density based clustering methods that regard clusters as dense regions of data or grid of data structure in the data space separated by regions of relatively low density. Graph based methods transform clustering problems into a combinational optimization problem that can be solved by using graph algorithms and related heuristics such as cutting the longest edge of the minimum spanning tree to create clusters of nodes. Mixture distribution models assume data are generated based on probabilities that are dependent on certain distributions such as Gaussian distribution. A fuzzy c-means algorithm assigns a degree of certainty that specific data belong to certain clusters.

Hierarchical method

A hierarchical method creates a hierarchical decomposition of data and uses methods such as the following. The agglomerative (bottom-up) approach starts with each data element forming a separate group and then merges groups that are closest according to some distance measure (e.g. single link and complete link methods). The divisive approach starts with all data in the same cluster and then splits into smaller clusters in each iteration according to some measures.

Ayers et al. (Ayers et al., 2009) compare the performance of the three estimates of student skill knowledge under a variety of clustering methods including hierarchical agglomerative clustering, K-means clustering and model-based clustering using simulated data with varying levels of missing values. To support teacher's reflection and adaptation in intelligent tutoring systems, Ben-Naim et al. (2009) used a solution trace graph method to help teachers understand students' behaviours in an adaptive tutorial by post-analysis of the systems' data-log. In constructing an intelligent tutoring system, finding the level of learners' background knowledge is an unresolved problem. Antunes (2008) used sequential pattern mining methods to automatically acquire that knowledge. Baker and Carvalho (2008) compared hierarchical classifiers and non-hierarchical classifiers to identify exactly when a special behaviour occurs in the gaming detector systems.

K-means Clustering Algorithm

The k-means clustering algorithm is the best-known squared error-based algorithm which minimizes the squared error while partitioning elements into k clusters. The basic steps of k-means clustering algorithm are:

1. Initialize k clusters randomly or based on some prior knowledge. Calculate the cluster properties $M = [m_1, ..., m_k]$
2. Assign each element into the nearest cluster C_i based on the distance between elements and clusters
3. Recalculate the cluster properties based on the current partitioning
4. Repeat steps 2 and 3 until convergence is reached

The k-means clustering algorithm is very simple and works well in many practical problems. It is well studied and can be easily implemented in many applications. Obviously, the k-means clustering algorithm also has some disadvantages and lots of variants of k-means clustering algorithms have been developed in order to overcome its drawbacks. The main drawbacks include lack of a universal method to identify the initial partitions and the number of clusters, lack of a guarantee to converge to a global optimum, and sensitivity to outliers and noise.

Mixture Gaussian Model

The mixture Gaussian clustering model is a classic statistical method with an assumption that data is generated based on a mixture of k components that have multivariate Gaussian distributions.

Expectation Maximization is the most popular method of mixture densities-based clustering. From the probabilistic view, clustering presumes that the data objects are generated from a mixture distribution such that this distribution has k components and each component is a distribution in its own right. If the distributions are known, finding the clusters of a given data set is equivalent to estimating the parameters of underlying models. Let the random variable C denote the cluster components, with value 1,...,k; then, the mixture distribution (probability density) is defined as

$$p(x|\theta) = \sum_{i=1}^{k} p(x|C_i, \theta_i)P(C_i) \tag{2.10}$$

Here, θ is the parameter vector, $P(C_i)$ is the prior probability and $\sum_{i=1}^{k} P(C_i) = 1$, and $p(x|C_i, \theta_i)$ is the component density. The posterior probability for assigning a data point into a cluster can be calculated with Bayes's theorem while the parameter vector θ is decided. Multivariate Gaussian is the natural choice to construct the mixture density for continuous data.

The maximum likelihood estimation is an important statistical method to estimate parameters because it maximizes the probability of generating all the observations by giving the joint density function in logarithm form

$$\iota(\theta) = \sum_{j=1}^{N} lnp(x_i|\theta) \tag{2.11}$$

The best estimate can be achieved by solving the log-likelihood equations.

The expectation maximization algorithm is the most effective method to approximate the maximum likelihood since the analytical solution of the likelihood equation cannot be obtained in most circumstances. The standard expectation maximization algorithm calculates a series of parameter estimates $\theta^0, \theta^1, ..., \theta^T$, through the following steps:

1. initialize θ^0 and set t = 0
2. e-step: compute the expectation of the log-likelihood

$$Q(\theta, \theta^t) = E[logp(C|\theta)|X, \theta^t];$$

3. m-step: select a new parameter estimate that maximizes the Q-function, $\theta^{t+1} = argmax_\theta(\theta, \theta^t)$;
4. increase t = t+1; repeat steps 2 - 3 until the convergence condition is satisfied.

In ITS systems, following work that identifies which items produce the most learning, Pardos and Heffernan (2009) proposed a Bayesian method using similar permutation analysis techniques to determine if item learning is context sensitive and if so which orderings produce the most learning. Nugent et al. (2009) has implemented an approach to estimate each student's individual skill knowledge. The method has adapted several clustering algorithms including hierarchical agglomerative clustering, k-means clustering, and model-based clustering to introduce an automatic subspace method which first identifies skills on which students are well-separated prior to clustering smaller subspace. Using data mining techniques, Sacin et al. (2009) propose the use of a recommendation system to help students take academic decisions based on available information.

2.3.6 Regression

Regression problems involve the prediction of continuous outcomes. Linear regression is the simplest form of regression in which data is modelled using a straight line. The coefficients of linear regression can be solved by using the least squares method. Multiple regression is an extension of linear regression that involves more than one predictor variable. Nonlinear regression such as polynomial regression can be transformed to linear regression.

The common regression methods used in data mining are: linear regression, polynomial regression, robust regression, cascade correlation, radial basis functions (RBFs), regression trees, multilinear interpolation, group methods data handling (GMDH), and multivariate adaptive regression splines (MARS).

Regression methods were used by Feng (2005) to predict learners' knowledge levels from error sources. To determine the relative efficacy of different instructional strategies, Feng et al. (2009) used learning decomposition, an educational data mining technique, and logistic regression methods to determine how much learning is caused by different methods of teaching the same skill.

2.3.7 Support Vector Machines

Support Vector Machines (SVMs, also called kernel machines) use efficient training algorithms and can represent complex and/or nonlinear functions. The idea of SVMs is that data will always be linearly separable if they can be mapped into a space with sufficiently high dimensions. Various kernel functions can be used to map data into some corresponding feature spaces, which have support vectors to hold separating planes.

Support vector machines were used by Joachims (2001) in building learning models of text classification. A method called "power law of learning" was used by Koedinger and Mathan (2004) in determining whether students can flexibly use knowledge learned from a course. Makrehchi and Kamel (2005) combined together a vector space machine, weight regression, and similarity measures to build a social network in a small community.

Other data mining algorithms include instance-based learning (such as the nearest-neighbor model and the kernel model), neural networks, and distributed data mining methods.

Chen et al. (2004) proposed an approach to automatically construct an e-textbook via web content mining. They used a ranking strategy to evaluate the web pages and extract concept features from web contents. To extract from the discussion forum with viewable and useful information for instructors, Dringus et al. (2005) proposed a strategy using text mining to assess an asynchronous discussion forum. Their experiment shows that using text mining techniques in the query process could improve the instructor's ability to evaluate the progress of a threaded discussion. Hershkovitz and Nachmias (2009) investigate the consistency of students' behaviours regarding their pace of actions over sessions within an online course. The results suggest that pace is something not consistent. Web mining methods also were used by Merceron and Yacef (2003) to improve learning and teaching. By combining data mining and text mining methods together, Nagata et al. (2009) proposes a novel method for recommending books to pupils based on only local histories with an accuracy 60% performance. Rai et al. (2009) propose a technique that directly produces parameters to improve the understanding students' knowledge. Ritter et al. (2009) find a way to reducing the knowledge tracing space and parameters to improve great efficiency gains in interpreting specific learning and performance from students' models. Using heuristic classification model, Hubscher and Puntambekar (2008) described a method to integrate the knowledge discovered with data mining techniques, pedagogical knowledge and linguistic knowledge together.

As presented in previous sections, data mining techniques are promising for automatically creating learner models because they try to capture meaningful patterns that have been found in the interactive data. Learner models are implicitly and explicitly created in educational data mining applications, especially applications oriented toward learners in which the knowledge of learners must be captured in order to create a learning environment that can be individualized to each learner.

In the rest of the thesis we explore the general questions of how to create learner models automatically from observations of learner behaviours. In particular we propose an approach where EDM techniques allow us to observe stable metrics from learner behaviours that can be the basis for metrics and measurements that can be applied by an online system to understand learners as they interact with an educational system.

Chapter 3

Dynamically Mining Learners' Characteristics

"*The ecological approach shows promise not only to allow information about learners' actual interactions with learning objects to be naturally captured but also to allow it to be used in a multitude of ways to support learners and teachers in achieving their task.*" (McCalla, 2004)

3.1 Motivation

Unlike in traditional classrooms in which teachers observe learners' performances through direct observation and communication, and then adapt their personal strategies to improve learners' learning processes, most web-based e-learning systems try to add the ability to adjust learning contexts and contents to improve individuals' learning processes. Adaptive and intelligent systems are being built to investigate the personalization of learning contexts. To provide personalized contexts, an adaptive and intelligent e-learning system tries to meet the individual learner's needs by understanding what the learner's expectations are. There are two methods to gather the learners' characteristics, preferences and past experiences – the static method which uses surveys, questionnaires, existing documents and historical records to collection information, and the dynamic method which instead learns information about learners from data collected in real time. The core aspect of the dynamic method is the continual reuse of data, so that the knowledge learned from observations will continue to be applied to the system in order to strengthen and enrich its abilities to encourage better performances of learners.

Our work is done in the context of a real system, iHelp, where large amounts of usage data have been collected from the interactions among instructors and learners. The data collected from the iHelp system is organized into a database at a fine-grained level. This data is a combination of static information about learners and learning objects, as well as dynamic data coming from learner, instructor and system activities. Our basic research questions are: what kinds of learning patterns can we mine from the iHelp data set, and how we can use these patterns to facilitate pedagogical purposes. At the beginning, we tried to apply data mining techniques, such as classification and association rules mining, directly to the raw data sets. In this way, we created many results. The main issue of this method is that we cannot identify prominent learning patterns and irrelevant patterns from these results.

We needed to reason with this usage data at higher levels of granularity. Thus, in this chapter, we introduce a six layer model which mines dynamic learner models. The six layers include raw data layer, fact data layer, data mining layer, measurements layer, metric layer and application layer. The key components in this model are the metrics and measurement layers, which provide an efficient way to represent learners' characteristics and knowledge, and the data mining layer, which provides the tools to retrieve information.

The details of this chapter include how to collect data, why it is called purposes based method, why it is a six layer model, and how to implement in the real learning environment.

3.2 Data Collection

Our system focuses on the reuse of information collected by e-learning systems such as the iHelp system. Like other e-learning systems, iHelp records all information about interaction among learners, instructors, and the system into a database at a fine-grained level. Our interests are in the following three kinds of data:

- Data about learners: consists of personal information, knowledge structures, intentions, activity status, goals, previous experience and social activities.

- Data about learning objects: consists of knowledge contents, organized structures (which are a combination of text, graphics, web pages, reference links, and multimedia documents), pre-defined metadata, qualities, ratings and interest levels.

- Data about interactions: consists of observed attributes such as dwell time, following links, depth of navigation, sequence of navigation, recurring events like question and/or answer postings, chattiness and qualities of interactive events.

It is necessary to transform and filter raw data such that we can construct relations between learners and learning objects, and find information about interactions based on such relations.

3.2.1 Raw Data

We can directly use this data collection as the starting point for our analysis. The iHelp system consists of the components in Table 3.1; we briefly describe potential data collected from each component.

- iHelp LCMS: From this database scheme, we can find system information, management information, a learner's personal information although the learners remain anonymous by hiding their real identifications, course information, course id, learning object/module information, etc. The instructors and administrators collect and enter into the system to initialize the course management module.

- iHelp Discussion: From the iHelp asynchronous discussion forum, we can collect information such as login and logout events, messages read and written, contents of messages, messages threads, etc. This information records how learners are involved in the discussion activities.

- iHelp Chat: From the iHelp synchronous chat room, we can collect enter chat channel and leave chat channel events, messages read and written, contents of messages, etc. This information records how learners are involved in the chat room activities.

- iHelp Course: From this distance learning component of iHelp, we can collect login and logout events, contexts of web pages, relationships of web pages, navigation sequences, dwell time on web pages, quiz questions, marks of quizzes, etc. This information records how learners browse course web sites, and do on-line quizzes.

iHelp Share and iHelp Lecture will not be used in our analysis.

	login/logout	dwelltime	messages	events	sequence	marks	static
iHelp LCMS	Yes	Yes	No	Yes	Yes	No	Yes
iHelp Discussion	Yes	Yes	Yes	Yes	Yes	No	No
iHelp Chat	Yes	Yes	Yes	No	Yes	No	No
iHelp Course	Yes	Yes	No	Yes	Yes	Yes	No
iHelp Share	Yes	N/A	Yes	Yes	N/A	Yes	Yes
iHelp Lecture	N/A	Yes	N/A	N/A	No	No	No

Table 3.1: Potential data in each iHelp component

3.2.2 Fact Data

The raw data in the iHelp database mostly are events recorded in chronological order. For some kinds of events like dwell time and navigation times, we need to combine them in order to correctly describe learners' behaviours. In our analysis, we call this combined data "fact data" as it reflects real characteristics of learners. Not only does fact data represent characteristics of learners, but it also can represent features of learning objects. In Table 3.2, we see some examples of data types and the origin of each factor associated with learners.

Fact Data Name	Calculation	Original	Description
navigatetimes	Summation	iHelp lcms, Course	measures how many times a learner navigates web pages
contentnum	Summation of Distinct Events	iHelp Course	measures how many non-repeat web pages a learner has navigated so far
readingtimes	Summation Events	iHelp Discussion	measures how many times a learner reads posting messages of a specific topic
chatnum	Summation of Distinct Events	iHelp Chat	measures how many channels a learner involved

Table 3.2: Some fact data and their original sources

Here are database scripts to elicit fact data *navigatetimes*, *contentnum*, and *dwelltime* from raw data in the iHelp database.

1. First script: Calculate dwell time for each navigation in current session

   CREATE OR REPLACE VIEW n_dwell_time (userid, contentid, exit_time, enter_time, dwelltime) *AS*

   SELECT userid, contentid, exit_time, enter_time, *IF*(exit_time='0000-00-00 00:00:00', 0, *TIME_TO_SEC*(*TIMEDIFF*(exit_time, enter_time))) *AS* dwelltime

   FROM __lcms.__user_navigation n

   WHERE courseid = (*SELECT* courseid *FROM* n_init)

   AND userid *IN* (*SELECT* userid *FROM* n_all_learners)

2. Second script: Filter out the navigating times, number of contentid, dwell time

   CREATE TABLE r_sum_contents

   SELECT d.userid, *COUNT*(d.contentid) *AS* navigatetimes, *COUNT*(*DISTINCT* d.contentid) *AS* contentnum, SUM(d.dwelltime) *AS* dwelltime

   FROM (*SELECT* * *FROM* n_dwell_time) *AS* d

GROUP BY d.userid

In this way we initially create a repository of fact data by transforming raw data. Throughout this conversion process, we collect useful raw data, and throw out unimportant details. Filtering is a classical technique that finds a few relevant items in a large pool of items, and is generally used in adaptive and intelligent systems.

3.3 Purpose-Based Methods

The key aspect of the ecological approach is the purpose-based use of the information associated with the content, to achieve a particular goal (McCalla, 2004). The pedagogical purpose determines what kind of characteristics of learners or learning objects have to be known to support this purpose, and what kind of information should be captured from e-learning systems to identify these specific characteristics of learners or learning objects.

This top-down method facilitates the identification of requirements and constraints for each particular pedagogical purpose at a high level before considering low level details, and clarifies which are candidates for data mining and machine learning techniques. This is in contrast to the bottom-up approach which requires us to find patterns from the raw data regardless of how or where these patterns are useful. It is extremely difficult to find useful and meaningful patterns directly from low level data.

3.3.1 Pedagogical Purposes

From e-learning systems such as iHelp, we know there are many pedagogical purposes which could be fulfilled to understand learners better, to provide personalized content or services. Both recommending content and finding peer helpers are such purposes. Recommending relevant content for a particular user requires us to compare this user to other users based on some important characteristics and experiences, and then to evaluate contents based on similar users' assessments (Tang and McCalla, 2005).

Finding peer helpers for answering a specific question requires us to evaluate users based on the domain of the problem to find potential expert candidates, and then to recommend the best helper by comparing users based on their characteristics and experiences. Pedagogical purposes have various forms. McCalla (2004) highlights some possible pedagogical purposes:

- recommending relevant learning objects to meet a learner's specific needs
- recommending learning patterns to improve a learner's skills
- finding information related to a particular learning object
- finding a peer helper to provide face-to-face help for a specific problem
- evaluating the effectiveness of learning objects
- finding similarities between learners
- determining semantic relationships between learning objects

The common points of these pedagogical purposes are that the purposes determine what characteristics and experiences of learners or learning objects are relevant and necessary to fulfil the purpose. So the purposes determine what information is relevant, where to look for such information, and how to combine the information together to support characteristics and experiences of learners and learning objects.

3.3.2 Methods Based on Purposes

In e-learning systems, learning content could be web pages, content of messages, research papers, courses of study, quizzes or tests, text books, and multimedia documents, etc. The term learning object may refer to any of these possibilities. The learner model refers to the characteristics, preferences and experiences of a learner. The term "metric" represents an aspect of learners' characteristics, preferences, and experiences the in the learner model. Metrics could be learners' activities, learners' social connections and learners' learning styles, etc.

We need a way to describe the relationships among information, characteristics of learners, and purposes. The purposes require and determine the relevant characteristics of learners. The information about learners, learning objects and interactions imply the possible characteristics of learners. Transformation from raw data into fact data does not change the meaning of the information. Characteristics, preferences and experiences of learners are naturally represented by metrics in the learner models. The purposes need to be implemented and achieved by applications. The purpose determines the relevant and necessary learner models, and how the learner model are be captured and retrieved from fact data. Data mining technique is a nature way to use existing information to support pedagogical goals.

To further illuminate the methods based on purposes, we highlight some interesting data fields (fact data), potential learning models (metrics), and some possible applications (purposes) in Figure 3.1. On the left-most rows are the attribute data fields; on the top columns are metrics; and on the right-most rows are purposes. In each cell, a letter "Y" implies that a learner model could use the particular attribute; a grey colour means such a learner model is essential for the correspondent purpose. For example, the activity level metric is derived from fact data such as login/logout, dwell time, events associating with learners and learning objects, information from discussion forums, information from chat room interactions, and quizzes events. The purpose of recommending a peer helper can use metrics such as activity level, social tendency, learning style, learning attitude, communication style, response tendency, and knowledge tendency.

3.4 Dynamic Learner Model

From the above discussion, it is clear that there are relations among information, learner model and applications. We can thus clearly foresee that information will be reused to build up learner models, and furthermore to support new applications, as in the ecological approach. This also is a dynamic process because we will count on the data to be updated in real time before the computing procedure happens. Based

Metrics / Events/Attributes	Activity level	Social Tendency	Learning Style	Learning Attitude	Interestings	Communication Style	Response Tendency	Learning Efficience	Knowledge Tendency	Metrics / Pedagogical Purposes
Login/Logout	Y			Y						Recommending peer helps
Dwell time	Y		Y	Y	Y			Y	Y	Recommending learning objects
Sequence of browsing events			Y		Y			Y	Y	Recommending learning patterns
Association of specific learning objects	Y		Y	Y	Y			Y	Y	Evaluation of learning objects
Association of specific learners	Y		Y	Y	Y			Y	Y	Finding similarity of learners
Reading discussion postings	Y	Y	Y	Y	Y		Y			Finding semantic relationships of learning objects
Writing discussion postings	Y	Y	Y	Y	Y	Y	Y		Y	Finding useless learning objects
Contexts of postings					Y	Y	Y	Y	Y	Finging information for learning objects
Reading chatroom messages	Y	Y	Y	Y	Y		Y			
Writing chatroom messages	Y	Y	Y	Y	Y	Y	Y		Y	
Contexts of messages					Y	Y	Y	Y	Y	
Doing quizzes	Y		Y	Y	Y					
Marks of quizzes				Y	Y			Y	Y	
Sequence of all events	Y	Y	Y		Y			Y		
Contexts of share parts					Y	Y	Y	Y	Y	

Figure 3.1: Relationships among purposes, metrics and attributes

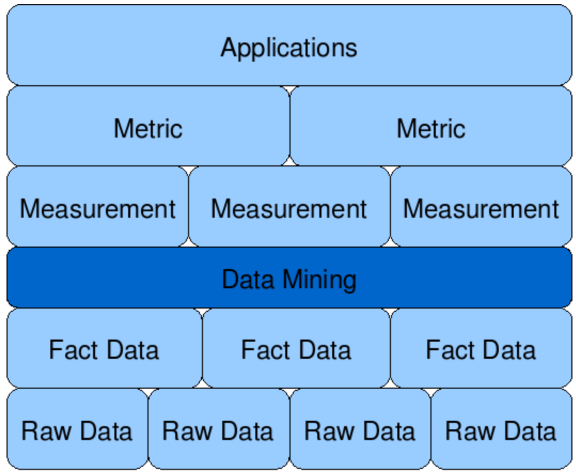


Figure 3.2: Six layers model

on this analysis, we can create the model which will produce the dynamic learner models.

3.4.1 Model

This model consists of six layers as Figure 3.2 shows. Each layer depends on the layer below. Based on previous analysis, the top application layer consists of the educational applications; the metric and measurement layers correspond to the learner models; and the bottom raw data and fact data layers correspond to information. The data mining layer represents the information retrieval procedure which dynamically creates and supports the measurements in this model. Here, each metric is composed by combining measurements of specific data relevance to it. As an example, the activity level metric, is built out of measurements such as activity level in reading discussion messages, activity level in browsing course materials, activity level in the chat room, etc.

Metrics represent aspects in the learner model, characteristics, preferences and experiences of learners. Metrics are at a level higher than measurements thus hiding the details of where the information comes from. The measurements supply more details to the metrics and can also be used individually to support the applications. The measurements are the results of patterns found in the raw information that are meaningful to the ultimate applications. The fact data are filtered and sorted from raw data as described in the data collection section.

3.4.2 Layers

There are four transitions in the model as information is interpreted from the lowest level raw data to serve the applications. Each transition is discussed below.

From Raw Data to Fact Data

Raw data is directly collected from an e-learning environment. The raw data includes static information such as learners' personal information and predefined preferences, dynamic information such as login/logout events, messages, sequence events, etc. We say the raw data are directly extracted from the e-learning system because they are already available there. So any computation for recording these data must have finished before we extract them.

Raw data is transformed to fact data about learners or learning objects. To obtain the fact data, we filter and sort the raw data under various predefined constraints and criteria. The common filtering conditions relate to the learners, the courses, the learning objects, etc. An example is setting the length of interval of sequence data to one or two hours; another is only counting messages from learners who are involved in the same course, etc.

One issue is what kind of fact data we can get from the raw data. It really depends on each particular e-learning system. We cannot create data without sources, but we may provide new information by combining some raw data together, such as creating frequency attributes. Usually learners must follow some routines in a closed learning environment while an open learning environment do not restrict learners' actions such as iHelp system. Data coming from closed e-learning environments are more likely to be interesting and of high density than data coming from open e-learning environments. The other issue is that fact data requiring filtering and sorting raw data may need large computations and may take a long time to finish. Because one feature of many e-learning systems is that the volume of data increases slowly on a daily basis, we have a chance to pre-compute fact data of this sort.

From Fact Data to Measurements

Fact data are transformed into measurements using data mining techniques. Unlike fact data, measurements have clearly determined and meaningful definitions relevant specifically to learning. In this way, we avoid judging and choosing the meaningful and useful hidden patterns from the data mining results; instead we have to decide which fact data should be used as the inputs. This is where purposes come in. The hope is that experts, such as instructors, can figure out which fact data are relevant to a measurement for the specific purposes of an application.

In general, both classification and clustering algorithms can be applied. If we have defined the classes of measurements and have the training data, we would choose classification and prediction data mining algorithms. Or if we do not have the classes of measurements, we can apply clustering algorithms to group the learners or the learning objects into different clusters. How to choose the number of clusters in clustering algorithms is always an issue; and the solution depends on the domain of knowledge about the problem; and here this issue is solved by combining expert opinions and the features of the particular measurement. For example, the activities of learners can be grouped into four levels as dormant, passive, active and hyperactive. Figure 3.3 shows data we used in a pilot study to be described later in the thesis. Figure 3.4 and 3.5 shows how we can apply cluster and classification algorithms to create different groups.

The measurements are the output of the fact data layer which either predicts the classes of instances or detects a number of clusters to group the instances. Learners can then be categorized appropriately as an instance of a class or as being in a particular cluster. The measurements expect the metrics to reflect more details such as for the activity metric: the activity level in browsing web pages, the activity level in reading messages, the activity level in doing quizzes, etc. The measurements also can focus on one aspect of the metrics such as restricting the learning style metric to active or reflective learners, or to global learners or sequence learners etc.

The measurements are selected and determined as to whether the purposes re-

userid	navigatetimes	contentnum	dwelltime	readingtimes	readpostingnum	navigatetimes
1	1372	610	88781	38	24	1372
2	997	368	70744	75	55	997
3	1467	597	127101	46	40	1467
4	1332	541	169548	347	224	1332
5	2887	604	310888	184	77	2887
6	1362	469	167575	167	88	1362
7	1969	506	195016	187	116	1969
8	5077	610	418163	894	232	5077
9	3304	538	292922	237	84	3304
10	1876	577	321062	228	154	1876
11	1165	481	106183	49	29	1165
12	0	0	0	0	0	0
13	570	274	26947	63	59	570
14	204	86	42183	361	152	204
15	826	322	98561	7	7	826
16	1367	559	225172	103	55	1367
17	2153	610	213898	413	230	2153
18	822	539	68115	24	15	822
19	1530	582	137899	88	40	1530
20	75	48	13540	2	2	75
21	2342	571	153957	480	231	2342
22	1	1	0	0	0	1
23	1957	610	234148	303	227	1957
24	1800	575	175551	330	229	1800
25	58	37	4197	0	0	58
26	1240	417	117046	413	225	1240
27	1376	579	69268	407	209	1376
28	3009	582	332563	357	165	3009
29	1374	555	289835	337	185	1374
30	0	0	0	55	47	0
31	1681	584	183692	455	232	1681
32	916	477	94596	5	5	916

Figure 3.3: Fact data in the pilot study

quire them and whether the fact data support their calculation. Not all of the measurements required by purposes can be computed from the fact data if we lack appropriate raw data, or if we lack the knowledge of how to capture them.

From Measurements To Metrics

Metrics reflect general characteristics of learners that may be important to an application. Each metric consists of several measurements. The metrics are abstractors without explicit values, used to categorize the measurements which have actual dynamic assigned values. By analyzing various pedagogical purposes, we list some potential metrics in Figure 3.1 that would be useful for a learning system. Some metrics rely on measurements based on interaction and usage data. Four we have explored are activity level, social tendency, learning style and knowledge tendency.

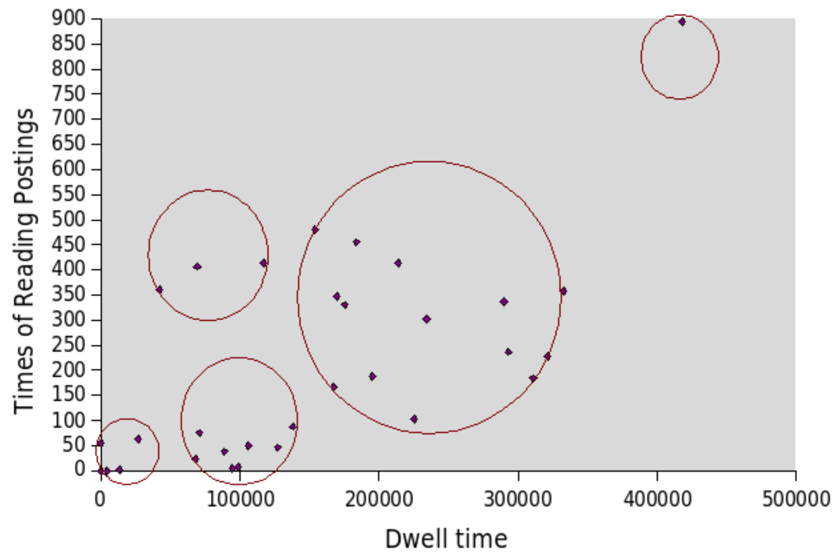


Figure 3.4: Clusters in the pilot study

The activity level metric measures learners' activities in iHelp system. The social tendency metric measures how learners connect with each other. The learning style metric defines what kinds of learning style a learner may have. The knowledge tendency metric measures learners' possible knowledge about learning objects. Other metrics may need richer information provided through other techniques such as text mining. We have not expanded these in this thesis.

From Metrics To Applications

The applications are the adaptive tools and components which use the metrics and measurements, to improve the ability and efficiency of the e-learning systems.

3.4.3 Dynamic Procedure

Modelling in this approach is a dynamic procedure because the computations will apply on the data accumulated to the current time rather than referring to static historical records. Whenever we need to compute the values of the measurements and metrics, we can use data mining techniques to retrieve them from the data, appropriately synchronized and updated. This dynamic procedure guarantees that the metrics and measurements really reflect the current status of the learner models.

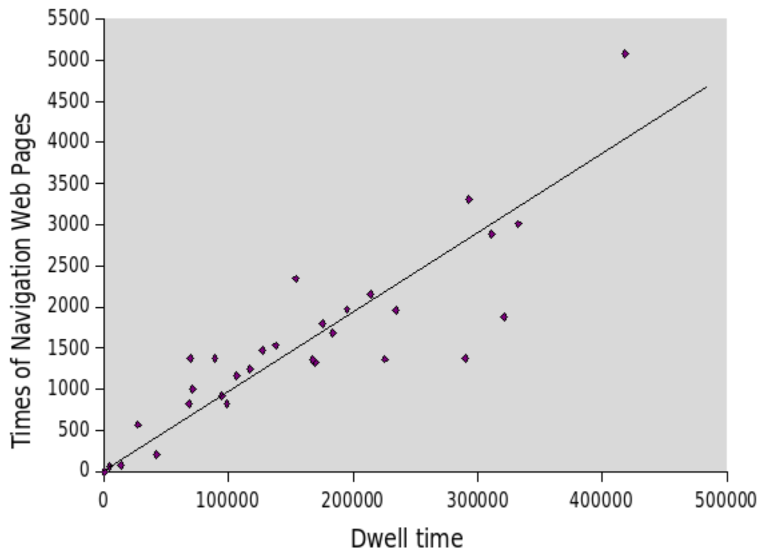


Figure 3.5: Classification in the pliot study

Since the system will collect more data as time passes, it is important to keep the learner models synchronized with the system to reflect the contributions of new data. It does not mean that historical records are not useful.

To dynamically compute the learner models, we must be concerned with efficiency issues in doing real time computations. There are two general questions about the computation time. Can we do the computation in reasonable time? And is there a possibility to do pre-computation? The solutions depend on how complex the data mining algorithms are, and the size, the length, the dimensions, and the scale of data. We argue that for applying data mining algorithms in educational data, pre-computation is often necessary to guarantee the key components can be computed in a reasonable time. Since the data preparing and filtering step is a time consuming task in data mining, this step is a good choice for pre-computation to speed up the whole procedure. This corresponds especially to the raw data to fact data and fact data to measurements transitions in our approach. Our experiments prove that the proper pre-computation is necessary and can be managed. Since "reasonable time" varies in the different situations, it is hard to find a universal solution.

3.5 Implementation of Dynamic Learner Modelling

To get first hand experience as to how this approach will work, we designed a pilot study that created and evaluated selected metrics and measurements to estimate dynamic learner models. To make things simple, we focused on the purpose of finding peer helpers in order to select and evaluate some metrics which relate with the usage data. Such metrics will give us insight as to the learners' characteristics, preferences and experiences. We will compare these automatically generated metrics with experts' opinions and learners' self evaluations in our experimental analysis.

3.5.1 Selection of Raw Data and Fact Data

We use raw data extracted from the iHelp system (See Table 3.1). The fact data are filtered and sorted from the raw data as shown in Table 3.3. Figure 3.6a shows how to set up the filtering conditions to extract the measurement data.

Fact Data Name	Computation	Description
navigatetimes	Sum	measure how many times a learner browse web pages
contentnum	Count Distinct	measure how many no repeat web pages a learner browses so far
dwelltime	Sum	measure how long a learner spends on browsing web pages
readingtimes	Sum	measure how many times a learner reads posting messages
readpostingnum	Count Distinct	measure how many posting messages a learner has read so far
totalmsg	Sum	measure how many messages a learner has written so far

Continued on next page

Table 3.3 – continued from previous page

Fact Data Name	Computation	Description
replymsg	Count	measure how many messages are written to reply other learners
newmsg	Count	measure how many messages are written as new (non-reply) messages
replyfrequency	Percentage	measure a ratio of reply messages over total messages
replyscale	Count Distinct	measure how many topics a learner replies to
sentnum	Sum	measure how many sentences a learner writes
chatnum	Count Distinct	measure how many channels a learner involves
event	Sum	measure how many times a learner is active in a channel
joined	Count	measure how many times a join event has happened so far
focused	Count	measure how many times a focus event has happened so far
scoretimes	Sum	measure how many times a learner completes quizzes
scorescale	Count Distinct	measure how many quizzes a learner has completed so far
scores	Sum	measure the sum of all quizzes' marks for a learner
total	Sum	measure how many hours a learner spends so far
high	Count	measure how many hours a learner has high concentration based on a pre-defined threshold
middle	Count	measure how many hours a learner has middle concentration based on a pre-defined thresholds

Continued on next page

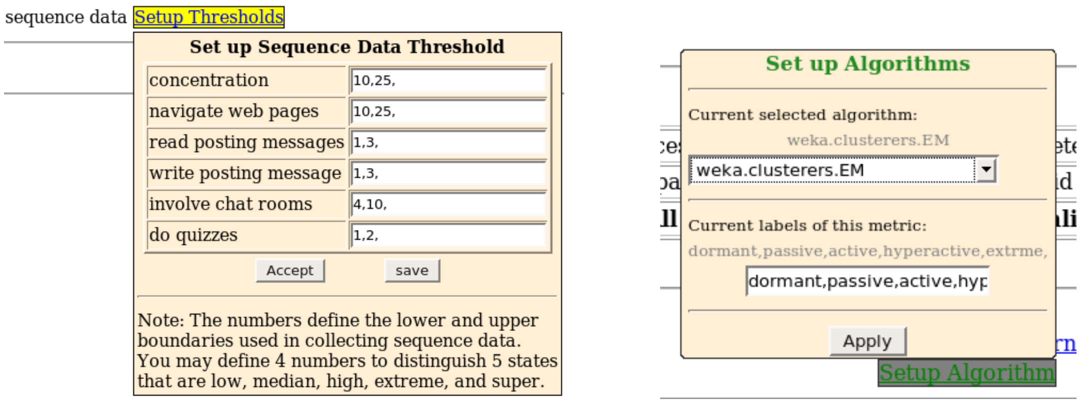
Table 3.3 – continued from previous page

Fact Data Name	Computation	Description
low	Count	measure how many hours a learner has low concentration based on a pre-defined thresholds
undefined	Count	measure how many hours a learner is on undefined status
global	Count	measure how many times a learner has changed events among web, read, write, chat, quiz
events	Sum	measure how many events happened for a learner so far
focus	Count	measure how many times a learner is working on the same context before changing events
unchange	Count	measure how many times a learner doesn't change context when events changed
userid	Distinct	alias name of learners

Table 3.3: The fact data

3.5.2 Selection of Data Mining Algorithms

As we do not have predefined classes for the measurements; we choose clustering algorithms to divide the learners into different groups, and then assign a label to each group. When preparing the data set we normalize the fact data into numeric data sets which are filtered from the raw data. It is natural to use Euclidean distance to measure distances between two numeric data sets. When we choose the clustering algorithms, we thus consider only those algorithms that can use numeric data and Euclidean distance. From the open source Weka (Witten and Frank, 2005) tools, we select four algorithms that fulfil these constraints, and make some modifications to match our situation.



(a) Setup parameters of sequence data **(b)** Setup clustering algorithms and labels

Figure 3.6: Setup parameters

The four clustering algorithms we used in this project are the expectation maximization clustering algorithm, simple k means clustering, x means clustering, and the farthest first clustering algorithm. Expectation maximization (EM) is a density-based algorithm that is favoured for incomplete data sets. Simple k-means, x-means and farthest first are three varieties of square error-based clustering algorithms that are simple and popular to use with Euclidean distance. To overcome overfitting and local maximization issues, we set the cross validation parameter to ten to reduce the chances that cluster centers fall into the local maximum. Considering that instructors normally categorize their students into limited groups, we predefine the number of cluster centers for each algorithm in order to compare with human evaluation results. Figure 3.6b shows how to set up the clustering algorithms and the clustering labels for each metric in the Weka toolkit.

Define the Labels of Clusters

The clustering tools form cluster centers. Since this process does not sort and order the cluster centers, we have to sort and assign a label to each cluster center based on their proprieties. The formula used to compute the propriety of centers is:

$$P_i = \sum_{i=j}^{n} W_j Sort(A_j^i) \tag{3.1}$$

Here, P_i is the propriety of the i^{th} center; $0 < i <$ the number of cluster centers; $0 < j <$ the number of attributes; W_j is the weight of the j^{th} attribute. High propriety implies a strong tendency or possibility, and low propriety implies low tendency or possibility with respect to the predefined labels of metrics. For instance, assume the mining tool finds two clustering centers based on six attributes, the first center has high propriety because it gets high values in four of six attributes so that we assign the "high" label to it.

When we consider the weights of attribute data, we should avoid the case that one attribute dominates the propriety if the weight of this attribute is large enough. We used instructors' input to decide the weights in our pilot studies.

3.5.3 Selection of Metrics and Measurements

We limit the metrics to those that can be ultimately computed from usage data (other kinds of mining, such as text mining, are beyond our scope). Depending on the available fact data, each metric consists of several measurements. Figure 3.7 shows how to add a new measurement, and how to change the attributes, the number of clusters, and the weights of attributes. In our pilot system, we used four metrics: the activity level, the social tendency, the learning style and the knowledge tendency. We have a total of fifteen measurements from which the important characteristics of these metrics are computed. We highlight these metrics and measurements in Table 3.4 because we will analyze the results for each measurement as well as the four overall metrics.

The activity level metric reflects how often a learner is involved in various learning processes such as browsing course materials, reading and writing messages, and doing practical quizzes. The social tendency metric records the frequency and degree that a learner communicates with other learners. The learning style metric reflects the learning habits of a learner such that we can categorize a learner in terms of being active or reflective, or a sequential or global learner. The knowledge tendency metric implies a learner's possibility of understanding the course materials, where a positive values translates to a high possibility of understanding.

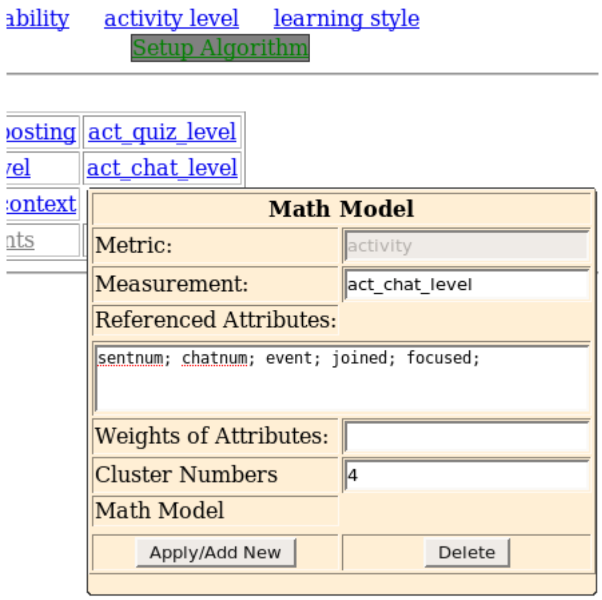


Figure 3.7: Setup referred attributes, the number of clusters and the weights of attributes

Here are more details on the measurements used to compute each of the four metrics:

- *Activity level metric:* decides a learner's activity level (see Figure 3.8). The measurements for this metric are:
  - Activity level based on browsing web pages
  - Activity level based on learner's dwell time in the iHelp system
  - Activity level based on joint posts in the iHelp discussion forum
  - Activity level based on reading messages
  - Activity level based on writing messages
  - Activity level based on iHelp chat room communication
  - Activity level based on the quizzes
- *Social tendency metric:* is the measure of social cognitive learning of a learner in the online environment (Laffey et al., 2006) (see Figure 3.9). This metric has the following measurements:

	metric	measurement
user model	activity	context activity
		dwell time activity
		discussion activity
		reading messages activity
		writing messages activity
		chat room activity
		quiz activity
	social tendency	navigation ability
		presence ability
		connectedness level
	learning style	active or reflective learning
		concentration level
		sequential or global learning
	knowledge tendency	context level
		quiz level

Table 3.4: Metrics and measurements in pilot study

- Social navigation: learning about and observing the actions of other learners
- Social presence: presence in asynchronous, text-based communications (Short et al., 1976)
- Social connectedness: the level of connectedness to each other

- *Learning style metric:* is a learner's learning style in the online environment (see Figure 3.10). This metric includes measurements:
  - Active or reflective learner: Active learners tend to learn something by acting with it – discussing it or explaining it to others. Reflective learners prefer to think about it quietly first.

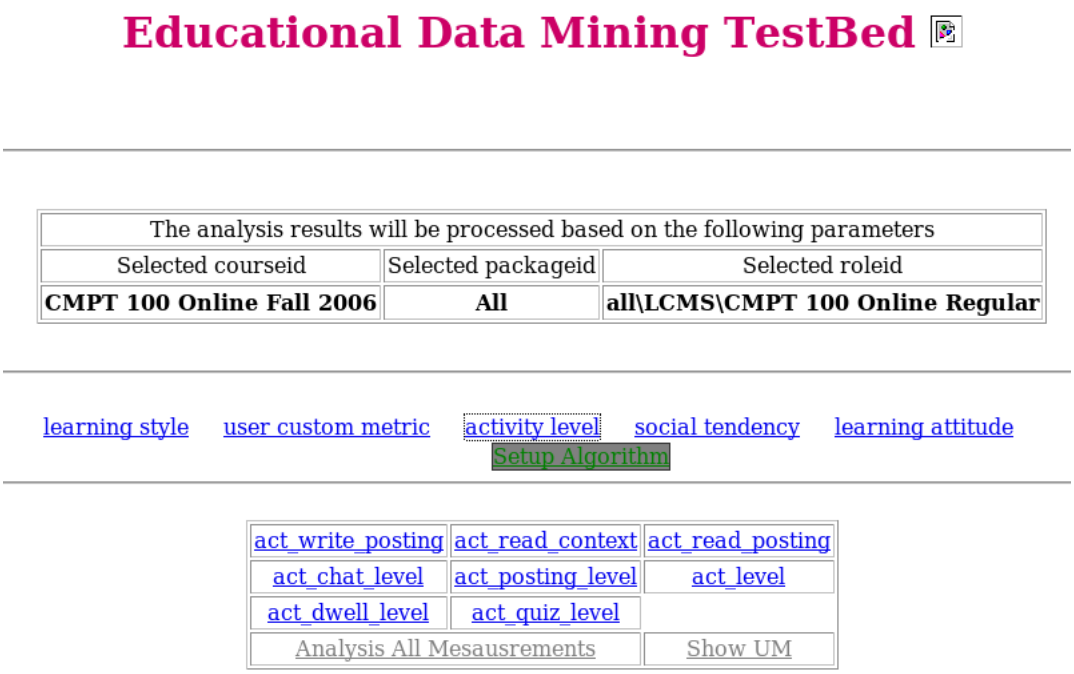


Figure 3.8: Activity level metric

- Sequential or global learner: Sequential learners tend to gain understanding in linear steps, with each step logically following the previous one. Global learners tend to learn in large jumps, absorbing materials randomly to look at the natural connections.
- Concentration: This measures the average time a learner spends on each piece of course material

• *Knowledge tendency metric:* defines a learner's attitude in the learning process (see Figure 3.11). Two measurements are:

- Knowledge tendency based on learning course materials
- Knowledge tendency based on doing practical quizzes

Figure 3.12 shows the process of computing one measurement which includes the cluster centers information, the distribution of the learner instances, and the labels assigned to each individual learner. A learner's dynamic learner model is presented in Figure 3.13 which includes all computing results of the measurements and metrics. Figure 3.14 shows the results of one metric for all learners.

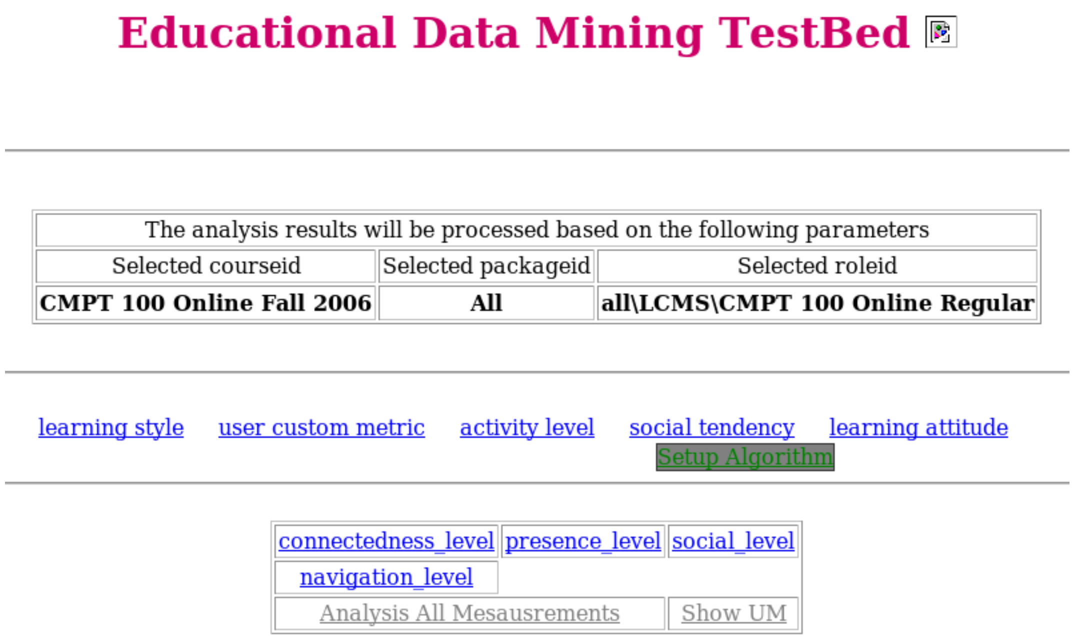


Figure 3.9: Social tendency metric

Based on the selected metrics and measurements, we ran several experiments to compare our data mining approach with human evaluations in order to prove the dynamic learner model is a useful way to represent the characteristics, preferences and experiences of learners. These experiments are described and discussed in the next chapter.

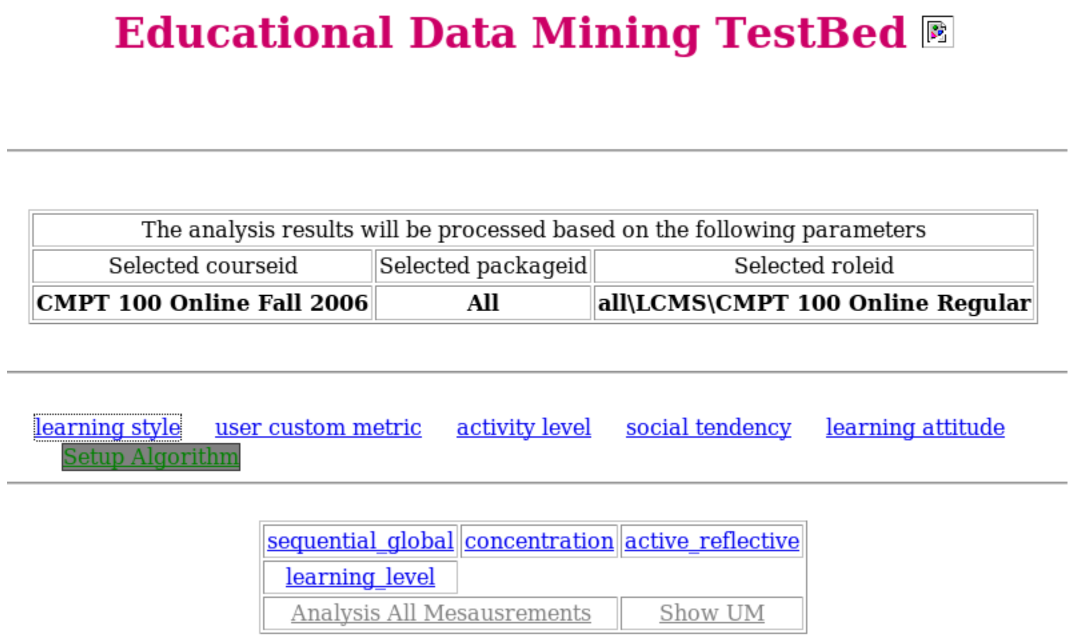


Figure 3.10: Learning style metric

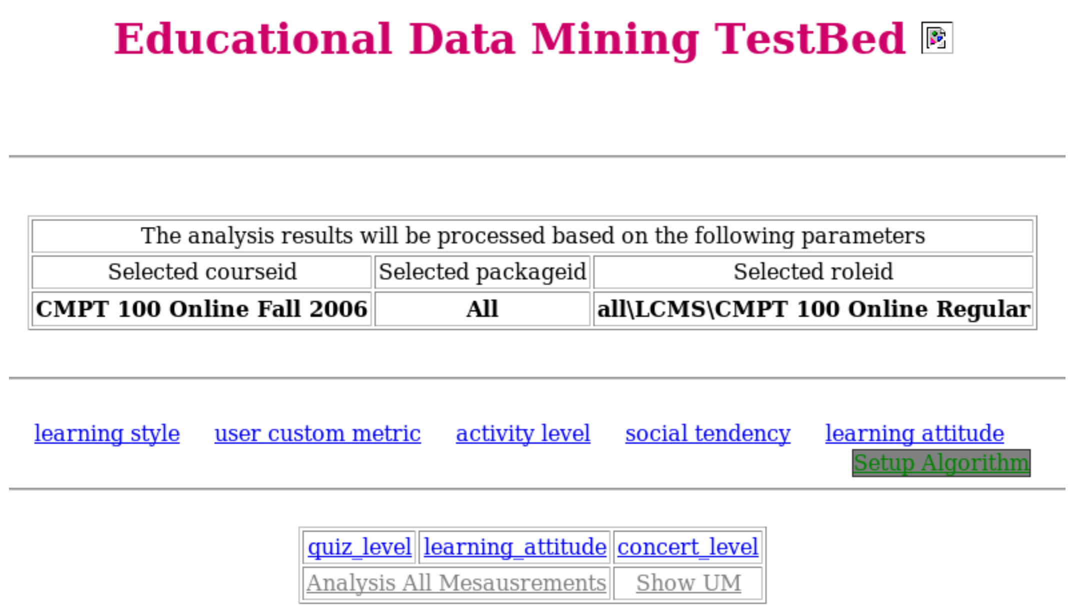
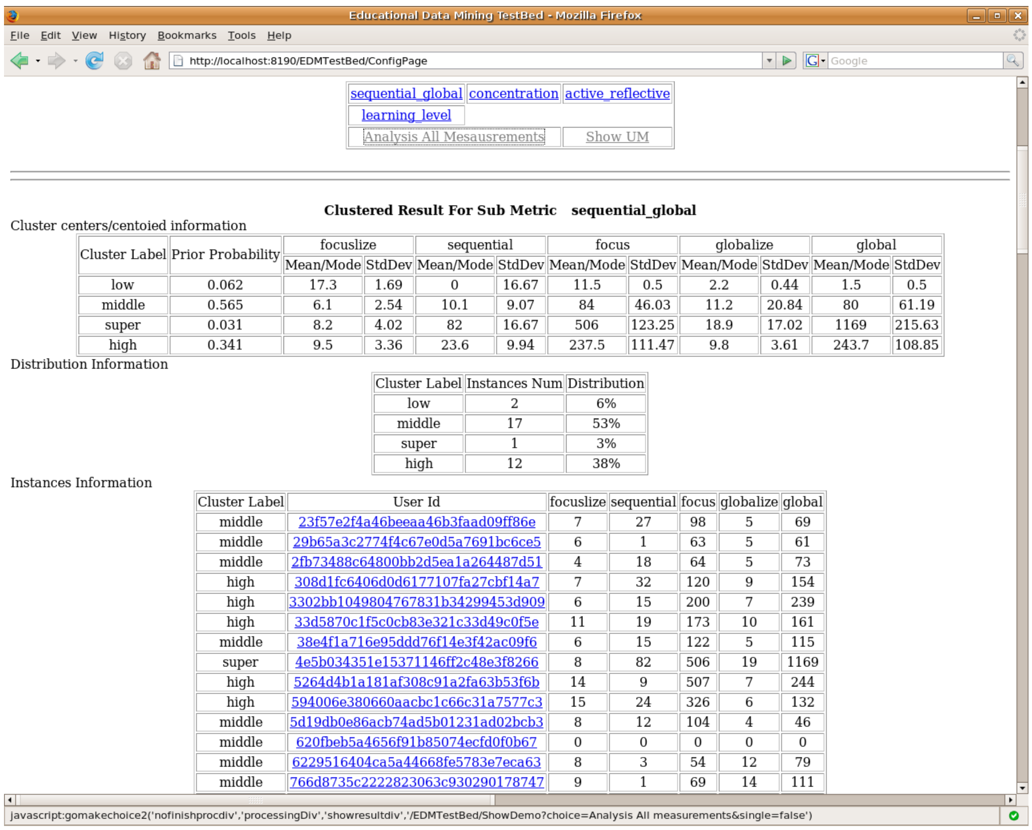


Figure 3.11: Knowledge tendency metric



Cluster Label	Prior Probability	focuslize		sequential		focus		globalize		global	
		Mean/Mode	StdDev	Mean/Mode	StdDev	Mean/Mode	StdDev	Mean/Mode	StdDev	Mean/Mode	StdDev
low	0.062	17.3	1.69	0	16.67	11.5	0.5	2.2	0.44	1.5	0.5
middle	0.565	6.1	2.54	10.1	9.07	84	46.03	11.2	20.84	80	61.19
super	0.031	8.2	4.02	82	16.67	506	123.25	18.9	17.02	1169	215.63
high	0.341	9.5	3.36	23.6	9.94	237.5	111.47	9.8	3.61	243.7	108.85

Cluster Label	Instances Num	Distribution
low	2	6%
middle	17	53%
super	1	3%
high	12	38%

Cluster Label	User Id	focuslize	sequential	focus	globalize	global
middle	23f57e2f4a46beeaa46b3faad09ff86e	7	27	98	5	69
middle	29b65a3c2774f4c67e0d5a7691bc6ce5	6	1	63	5	61
middle	2fb73488c64800bb2d5ea1a264487d51	4	18	64	5	73
high	308d1fc6406d0d6177107fa27cbf14a7	7	32	120	9	154
high	3302bb1049804767831b34299453d909	6	15	200	7	239
high	33d5870c1f5c0cb83e321c33d49c0f5e	11	19	173	10	161
middle	38e4f1a716e95ddd76f14e3f42ac09f6	6	15	122	5	115
super	4e5b034351e15371146ff2c48e3f8266	8	82	506	19	1169
high	5264d4b1a181af308c91a2fa63b53f6b	14	9	507	7	244
high	594006e380660aacbc1c66c31a7577c3	15	24	326	6	132
middle	5d19db0e86acb74ad5b01231ad02bcb3	8	12	104	4	46
middle	620fbeb5a4656f91b85074ecfd0f0b67	0	0	0	0	0
middle	6229516404ca5a44668fe5783e7eca63	8	3	54	12	79
middle	766d8735c2222823063c930290178747	9	1	69	14	111

Figure 3.12: Computing one measurement

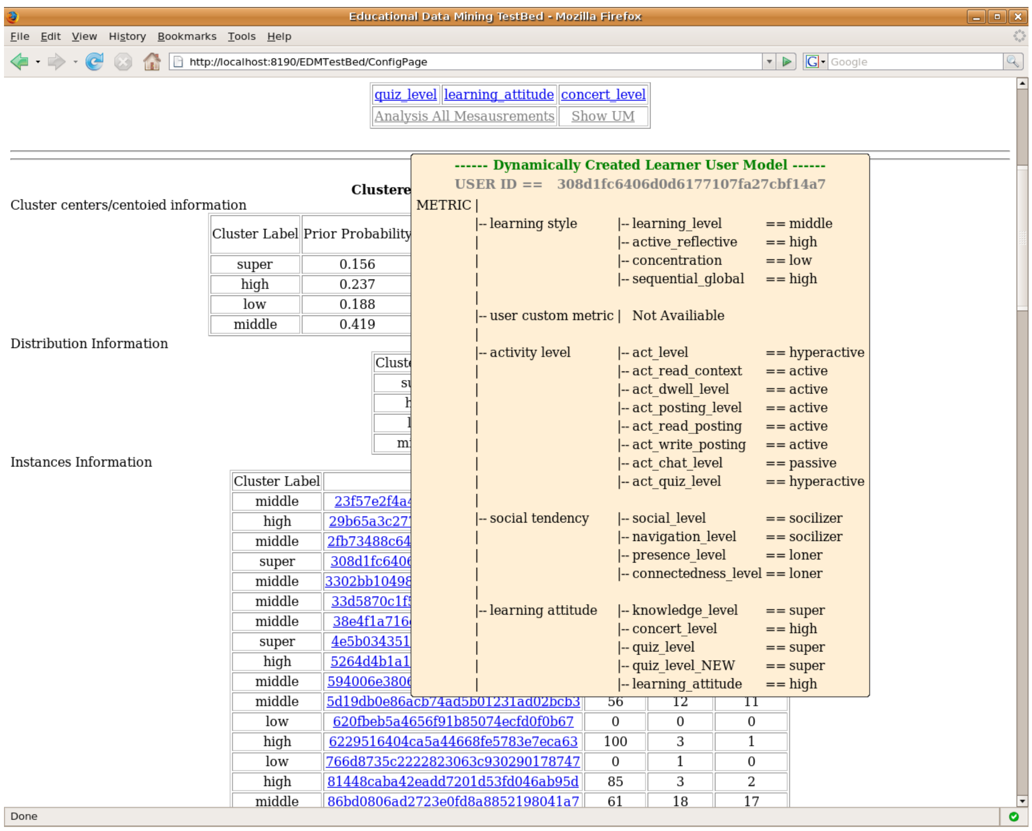
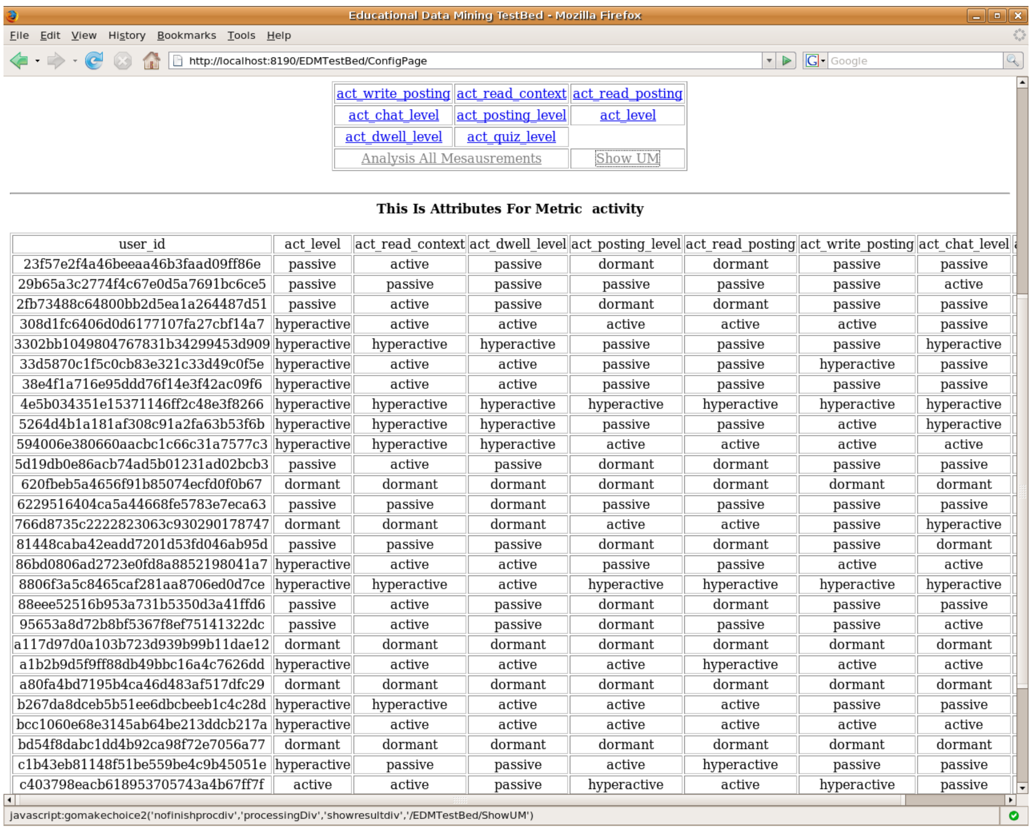


Figure 3.13: Dynamic learner model of a learner



user_id	act_level	act_read_context	act_dwell_level	act_posting_level	act_read_posting	act_write_posting	act_chat_level
23f57e2f4a46beeaa46b3faad09ff86e	passive	active	passive	dormant	dormant	passive	passive
29b65a3c2774f4c67e0d5a7691bc6ce5	passive	passive	passive	passive	passive	passive	active
2fb73488c64800bb2d5ea1a264487d51	passive	active	passive	dormant	dormant	passive	passive
308d1fc6406d0d6177107fa27cbf14a7	hyperactive	active	active	active	active	active	passive
3302bb1049804767831b34299453d909	hyperactive	hyperactive	hyperactive	passive	passive	passive	hyperactive
33d5870c1f5c0cb83e321c33d49c0f5e	hyperactive	active	active	passive	passive	hyperactive	passive
38e4f1a716e95ddd76f14e3f42ac09f6	hyperactive	active	active	passive	passive	passive	passive
4e5b034351e15371146ff2c48e3f8266	hyperactive	hyperactive	hyperactive	hyperactive	hyperactive	hyperactive	hyperactive
5264d4b1a181af308c91a2fa63b53f6b	hyperactive	hyperactive	hyperactive	passive	passive	active	hyperactive
594006e380660aacbc1c66c31a7577c3	hyperactive	hyperactive	hyperactive	active	active	active	active
5d19db0e86acb74ad5b01231ad02bcb3	passive	active	passive	dormant	dormant	passive	passive
620fbeb5a4656f91b85074ecfd0f0b67	dormant	dormant	dormant	dormant	dormant	dormant	dormant
6229516404ca5a44668fe5783e7eca63	passive	passive	dormant	passive	passive	passive	passive
766d8735c2222823063c930290178747	dormant	dormant	dormant	active	active	passive	hyperactive
81448caba42eadd7201d53fd046ab95d	passive	passive	passive	dormant	dormant	passive	dormant
86bd0806ad2723e0fd8a8852198041a7	hyperactive	active	active	passive	passive	active	active
8806f3a5c8465caf281aa8706ed0d7ce	hyperactive	hyperactive	active	hyperactive	hyperactive	hyperactive	hyperactive
88eee52516b953a731b5350d3a41ffd6	passive	active	passive	dormant	dormant	passive	passive
95653a8d72b8bf5367f8ef75141322dc	passive	active	passive	dormant	passive	passive	active
a117d97d0a103b723d939b99b11dae12	dormant	dormant	dormant	dormant	dormant	dormant	dormant
a1b2b9d5f9ff88db49bbc16a4c7626dd	hyperactive	active	active	active	hyperactive	active	active
a80fa4bd7195b4ca46d483af517dfc29	dormant	dormant	dormant	dormant	dormant	dormant	dormant
b267da8dceb5b51ee6dbcbeeb1c4c28d	hyperactive	hyperactive	active	active	active	passive	passive
bcc1060e68e3145ab64be213ddcb217a	hyperactive	active	active	active	active	active	active
bd54f8dabc1dd4b92ca98f72e7056a77	dormant	dormant	dormant	dormant	dormant	dormant	dormant
c1b43eb81148f51be559be4c9b45051e	hyperactive	passive	passive	active	hyperactive	passive	passive
c403798eacb618953705743a4b67ff7f	active	active	passive	hyperactive	active	hyperactive	passive

Figure 3.14: Computing one metric

Chapter 4

Analyzing the Metrics and Measurements

4.1 Introduction

We designed two experiments to evaluate the six layer model: one is an expert evaluation and the other is a learner self evaluation. Using data from the iHelp system, we compared our data mining results with human evaluation results. Then we analyzed the advantages and disadvantages of our approach.

The data used in the expert experiment was collected from the Cmpt 100 online course in term 1 of 2006 with 32 students using the iHelp system. The data used in the learner self evaluation was collected from the iHelp usage data in the Cmpt 100 online courses in term 1 of 2007 and in term 2 of 2008. There were 50 students in two classes, but only 14 students who did the self evaluations.

In the expert experiment, experts were required to evaluate each student's behaviours in terms of four metrics and 19 measurements [1] through their examinations of the iHelp usage data. The metrics are activity level metric, social tendency metric, learning style metric, and knowledge tendency metric with particular measurements associated with each metric. The average time an expert spent was about six to eight hours. In short this experiment asked the human experts to evaluate the students on the same metrics and measurements as the system did.

In the learner self evaluation experiment, we designed a questionnaire to collect information from students that provided an alternative way of generating the measurements of three metrics: social tendency metric, learning style metric, and

[1] 15 measurements and 4 totals

knowledge tendency metric.

From the two experiments' results, we learned that some measurements are useful in building just in time learner models; some only show promise to be headed in that directions; and some don't seem to be well supported at all. The expert experiment shows more positive results than the self evaluation experiment. Overall, we think that just in time computation of learner models shows promise to allow a system to track change in students' capabilities during the learning process.

4.2 Methods of Analysis

We use a confusion matrix to visualize and compare results, and analyze accuracy and inter-rater reliability.

4.2.1 Confusion Matrix

A confusion matrix is a visualization tool, a table, used in data mining and artificial intelligence systems. Columns of the matrix represent the instances of predicated results or tested results, while rows of the matrix represent the instances of actual results or true results. The diagonal elements represent matched compounds while the off-diagonal elements represent misclassified compounds.

Navigating contexts		**Data Mining Results**				
		dormant	passive	active	hyperactive	
Human Evaluation	dormant	4	0	1	0	5
	passive	2	4	1	0	7
	active	0	3	10	0	13
	hyperactive	0	0	2	5	7
		6	7	14	5	32

Figure 4.1: A confusion matrix

- Accuracy

  For binary problem cases, in which the outcomes are labelled either as positive or negative, we can easily calculate statistical characteristics such as accuracy, precision, recall, fall out and F-measures. For problems in which the outcomes are more than two states, we can only extend accuracy easily. In our study, we only calculate accuracy since we have multiple outcomes in all cases.

$$Accuracy(AC) = \frac{\sum_{k=1}^{n} n_{kk}}{\sum_{i=1}^{n}\sum_{j=1}^{n} n_{ij}} \tag{4.1}$$

where n_{ij} is an element of the confusion matrix.

4.2.2 Inter-rater reliability

To test the evaluation quality, we need to calculate the reliability. Strong reliability is important if we are to have a dependable measure in our user models. Generally, reliability has four types: inter-rater reliability, test-retest reliability, parallel-forms reliability, and internal consistency reliability. (Hogan et al., 2000) The inter-rater reliability is to be used to assess the difference between raters. The test-retest reliability is to be used to assess a measure from one time to another. The parallel-forms reliability is to be used to assess the consistency of two tests from the same content domain. The internal consistency reliability is to be used to assess the consistency of results across times within one test. We only used the inter-rater and internal consistency reliabilities in our study.

In comparing the data mining results and the expert evaluations results, we used kappa coefficient to measure the inter-rater reliability. Since our confusion matrices are multiple dimensional matrices rather than a binary matrix, it is hard to apply other popular methods such as intraclass correlation (ICC).

- Cohen's kappa (Inter-rater reliability measure)

  Cohen's kappa coefficient measures the agreement between two raters on classifying some items into predefined categories. The definition of kappa coefficient k is:

$$k = \frac{n\sum_{k=1}^{q} n_{kk} - \sum_{k=1}^{q}(\sum_{i=1}^{q} n_{ki}\sum_{j=1}^{q} n_{jk})}{n^2 - \sum_{k=1}^{q}(\sum_{i=1}^{q} n_{ki}\sum_{j=1}^{q} n_{jk})} \tag{4.2}$$

- Correlation coefficient (Internal Consistency Measure)

  Correlation coefficient is another statistical tool to measure pairwise correlation among two variables. It measures the tendency of the variables to increase or decrease together. It is better to demonstrate that the data mining results share a very similar curve tendency with the human expert's results, that they have a linear relationship.

$$r_{xy} = \frac{\sum(x_i - \bar{y})(y_i - \bar{y})}{(n-1)s_x s_y} \tag{4.3}$$

4.3 Experment I – Expert Evaluation

4.3.1 Experiment Information

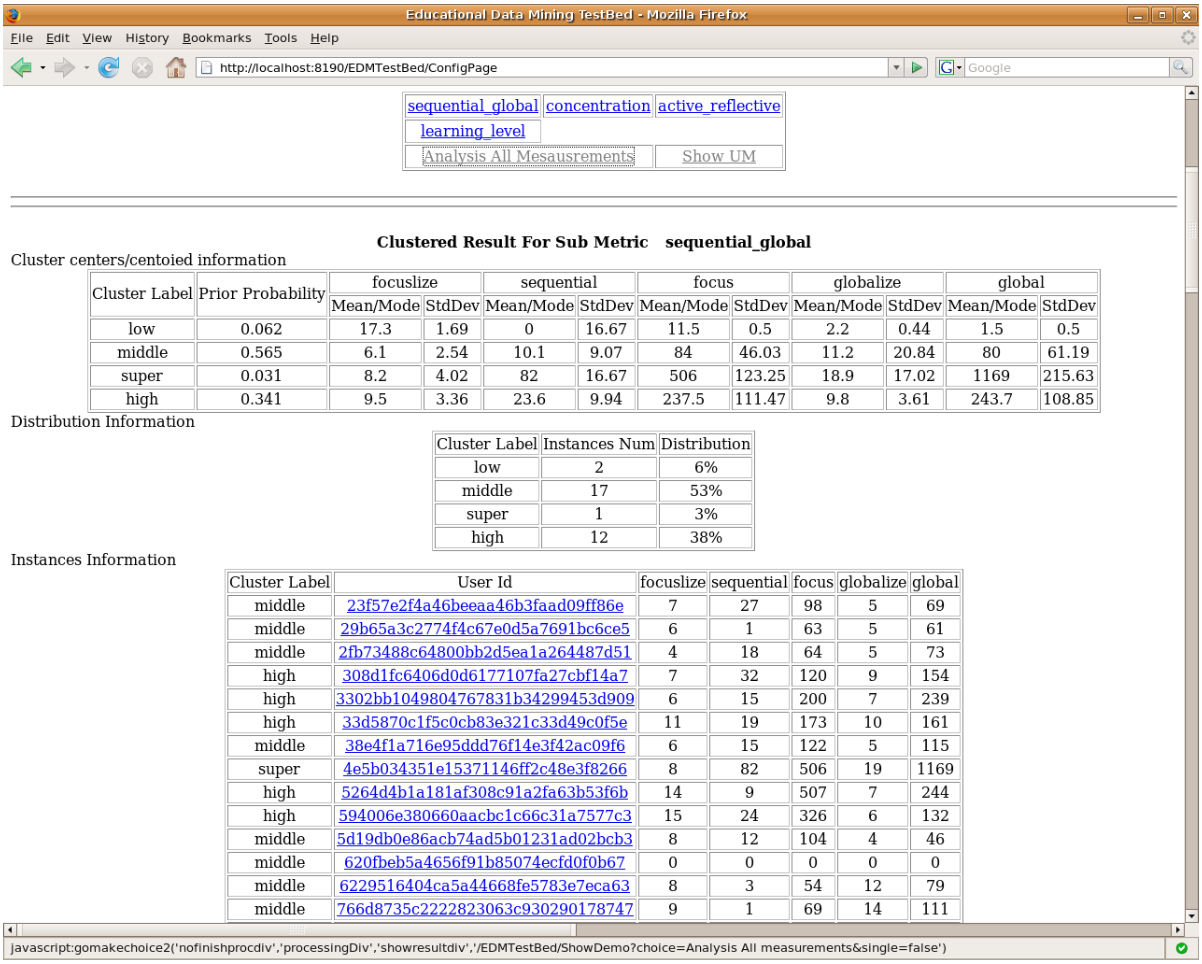
Summary of Raw Data

We chose to analyze iHelp data from one online class:

- Class Name: CMPT 100 online
- Term: 1
- Year: 2006 - 2007
- Size: 32 students

records	total	average per learner	maximal per learner
navigating web pages	46109	1441	5077
dwell time (in hours)	1318.93	41.22	116.16
discussion forum messages	177	5.5	33
reading messages	6655	208	894
chat room messages	1479	46	239
doing quizzes	366	12	39

Table 4.1: Summary of the raw data



Educational Data Mining TestBed - Mozilla Firefox

File Edit View History Bookmarks Tools Help

http://localhost:8190/EDMTestBed/ConfigPage

sequential_global concentration active_reflective
learning_level
Analysis All Mesausrements Show UM

Clustered Result For Sub Metric sequential_global

Cluster centers/centoied information

Cluster Label	Prior Probability	focuslize		sequential		focus		globalize		global	
		Mean/Mode	StdDev	Mean/Mode	StdDev	Mean/Mode	StdDev	Mean/Mode	StdDev	Mean/Mode	StdDev
low	0.062	17.3	1.69	0	16.67	11.5	0.5	2.2	0.44	1.5	0.5
middle	0.565	6.1	2.54	10.1	9.07	84	46.03	11.2	20.84	80	61.19
super	0.031	8.2	4.02	82	16.67	506	123.25	18.9	17.02	1169	215.63
high	0.341	9.5	3.36	23.6	9.94	237.5	111.47	9.8	3.61	243.7	108.85

Distribution Information

Cluster Label	Instances Num	Distribution
low	2	6%
middle	17	53%
super	1	3%
high	12	38%

Instances Information

Cluster Label	User Id	focuslize	sequential	focus	globalize	global
middle	23f57e2f4a46beeaa46b3faad09ff86e	7	27	98	5	69
middle	29b65a3c2774f4c67e0d5a7691bc6ce5	6	1	63	5	61
middle	2fb73488c64800bb2d5ea1a264487d51	4	18	64	5	73
high	308d1fc6406d0d6177107fa27cbf14a7	7	32	120	9	154
high	3302bb1049804767831b34299453d909	6	15	200	7	239
high	33d5870c1f5c0cb83e321c33d49c0f5e	11	19	173	10	161
middle	38e4f1a716e95ddd76f14e3f42ac09f6	6	15	122	5	115
super	4e5b034351e15371146ff2c48e3f8266	8	82	506	19	1169
high	5264d4b1a181af308c91a2fa63b53f6b	14	9	507	7	244
high	594006e380660aacbc1c66c31a7577c3	15	24	326	6	132
middle	5d19db0e86acb74ad5b01231ad02bcb3	8	12	104	4	46
middle	620fbeb5a4656f91b85074ecfd0f0b67	0	0	0	0	0
middle	6229516404ca5a44668fe5783e7eca63	8	3	54	12	79
middle	766d8735c2222823063c930290178747	9	1	69	14	111

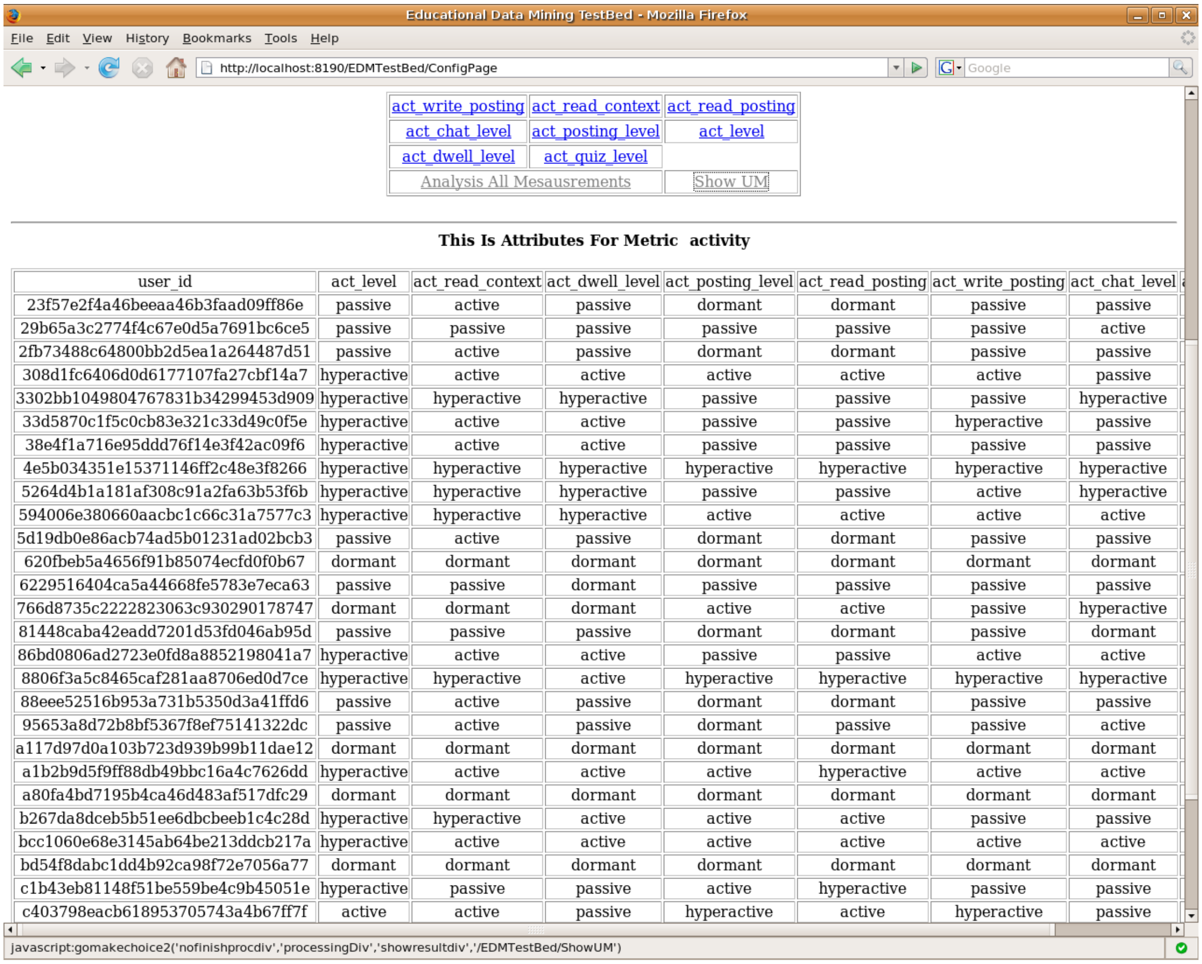
javascript:gomakechoice2('nofinishprocdiv','processingDiv','showresultdiv','/EDMTestBed/ShowDemo?choice=Analysis All measurements&single=false')

Figure 4.2: Result of one measurement

Data Mining Results

Just in time learner models (such as the one shown in Figure 4.4) based on metrics and measurements extracted from learner behaviour on iHelp are the models used in comparison to similar models built by the experts.

Figure 4.2 shows the computing results of one measurement with the information of cluster centers and distribution of population. Figure 4.3 shows the computing



user_id	act_level	act_read_context	act_dwell_level	act_posting_level	act_read_posting	act_write_posting	act_chat_level
23f57e2f4a46beeaa46b3faad09ff86e	passive	active	passive	dormant	dormant	passive	passive
29b65a3c2774f4c67e0d5a7691bc6ce5	passive	passive	passive	passive	passive	passive	active
2fb73488c64800bb2d5ea1a264487d51	passive	active	passive	dormant	dormant	passive	passive
308d1fc6406d0d6177107fa27cbf14a7	hyperactive	active	active	active	active	active	passive
3302bb1049804767831b34299453d909	hyperactive	hyperactive	hyperactive	passive	passive	passive	hyperactive
33d5870c1f5c0cb83e321c33d49c0f5e	hyperactive	active	active	passive	passive	hyperactive	passive
38e4f1a716e95ddd76f14e3f42ac09f6	hyperactive	active	active	passive	passive	passive	passive
4e5b034351e15371146ff2c48e3f8266	hyperactive	hyperactive	hyperactive	hyperactive	hyperactive	hyperactive	hyperactive
5264d4b1a181af308c91a2fa63b53f6b	hyperactive	hyperactive	hyperactive	passive	passive	active	hyperactive
594006e380660aacbc1c66c31a7577c3	hyperactive	hyperactive	hyperactive	active	active	active	active
5d19db0e86acb74ad5b01231ad02bcb3	passive	active	passive	dormant	dormant	passive	passive
620fbeb5a4656f91b85074ecfd0f0b67	dormant	dormant	dormant	dormant	dormant	dormant	dormant
6229516404ca5a44668fe5783e7eca63	passive	passive	dormant	passive	passive	passive	passive
766d8735c2222823063c930290178747	dormant	dormant	dormant	active	active	passive	hyperactive
81448caba42eadd7201d53fd046ab95d	passive	passive	passive	dormant	dormant	passive	dormant
86bd0806ad2723e0fd8a8852198041a7	hyperactive	active	active	passive	passive	active	active
8806f3a5c8465caf281aa8706ed0d7ce	hyperactive	hyperactive	active	hyperactive	hyperactive	hyperactive	hyperactive
88eee52516b953a731b5350d3a41ffd6	passive	active	passive	dormant	dormant	passive	passive
95653a8d72b8bf5367f8ef75141322dc	passive	active	passive	dormant	passive	passive	active
a117d97d0a103b723d939b99b11dae12	dormant	dormant	dormant	dormant	dormant	dormant	dormant
a1b2b9d5f9ff88db49bbc16a4c7626dd	hyperactive	active	active	active	hyperactive	active	active
a80fa4bd7195b4ca46d483af517dfc29	dormant	dormant	dormant	dormant	dormant	dormant	dormant
b267da8dceb5b51ee6dbcbeeb1c4c28d	hyperactive	hyperactive	active	active	active	passive	passive
bcc1060e68e3145ab64be213ddcb217a	hyperactive	active	active	active	active	active	active
bd54f8dabc1dd4b92ca98f72e7056a77	dormant	dormant	dormant	dormant	dormant	dormant	dormant
c1b43eb81148f51be559be4c9b45051e	hyperactive	passive	passive	active	hyperactive	passive	passive
c403798eacb618953705743a4b67ff7f	active	active	passive	hyperactive	active	hyperactive	passive

Figure 4.3: Results of one metric

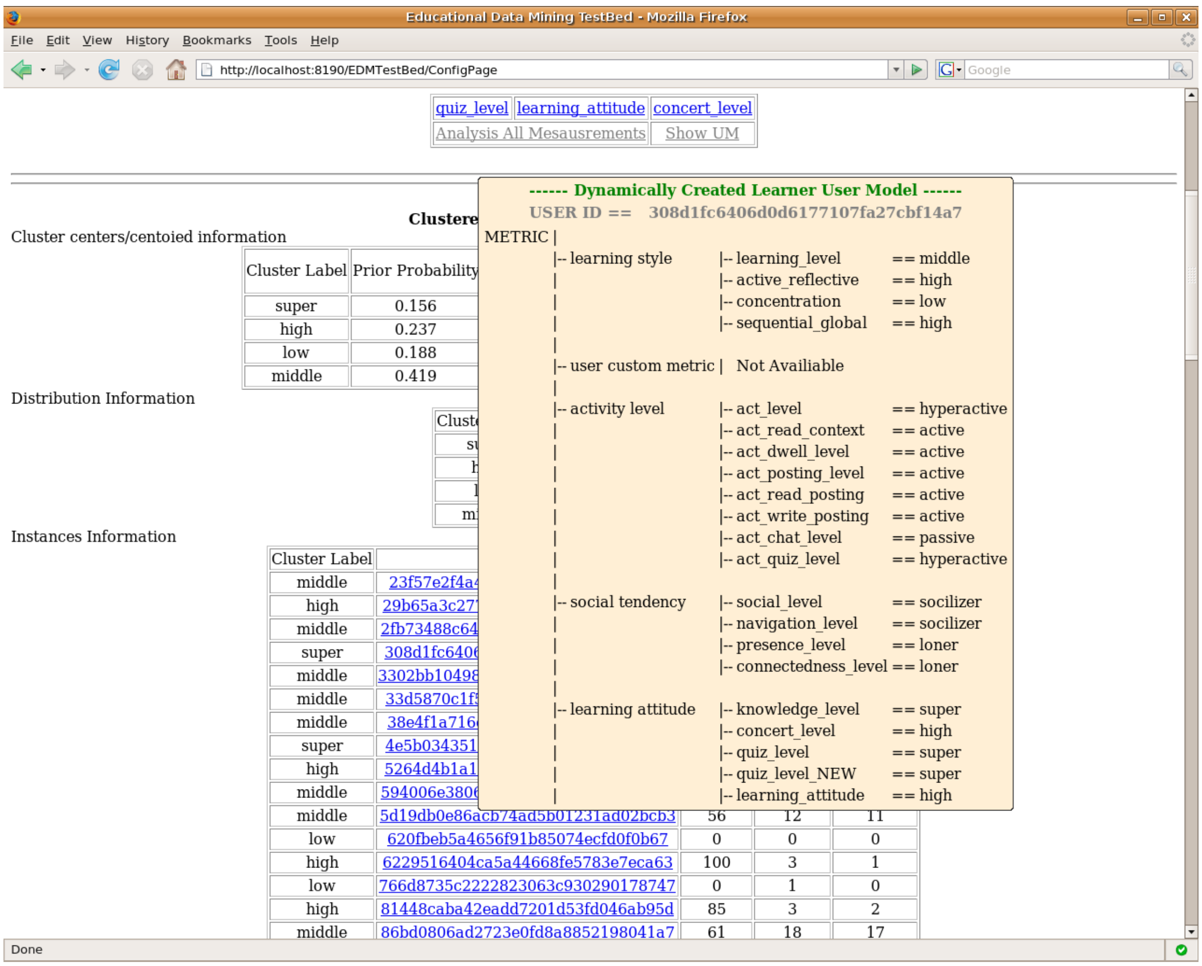


Figure 4.4: Result of one learner

results of one metric for all learners while cluster labels have been assigned to each measurement cluster groups. Figure 4.4 shows the results for one learner.

4.3.2 Expert Evaluation

In the expert evaluation, we ask experts to make their own judgements for each learner on each measurement of each metric. There are four metrics and fifteen measurements. The total records of each expert are: (4 + 15) * 32 = 608. Each expert spent approximately six to eight hours to take part in this evaluations during three days. A web server provides details about each learners and descriptions about information. Experts used a web browser to compare learners' information and to make judgement with confidence parameters. Figure 4.5 shows an example of an expert's evaluation of a learner. Results are directly stored into the database of the server. Experts could go backward to change, modify, and correct their evaluation results to get more precise comparison; and we keep tracking all changes in the database.

We predefine classification labels for each measurement and each metric. The classification labels are the same as the labels used in the dynamic clustering procedure. Experts assigned a label from this set for each record based on their own judgement. Experts also assigned each record a confidence level which we can use as a weighting factor in our later analysis of the evaluation results.

Four experts, who are instructors or have teaching experience, did the evaluation. Two of them finished all required evaluations, and other two only partially finished evaluations because it will take too long to evaluate all learners. Final analysis in this thesis is based only on results of the two experts who finished the total evaluations (to maximize consistency and reliability).

For each measurement, we wanted to compare the evaluations (for all 32 students) of the experts to the system. For this purpose we used a confusion metric, such as the one for "navigating contexts" in Figure 4.1. The left upper cell is the name of the measurement. The columns of the confusion matrix are system results; and the rows of the confusion matrix are human evaluation results. For example, the cell value

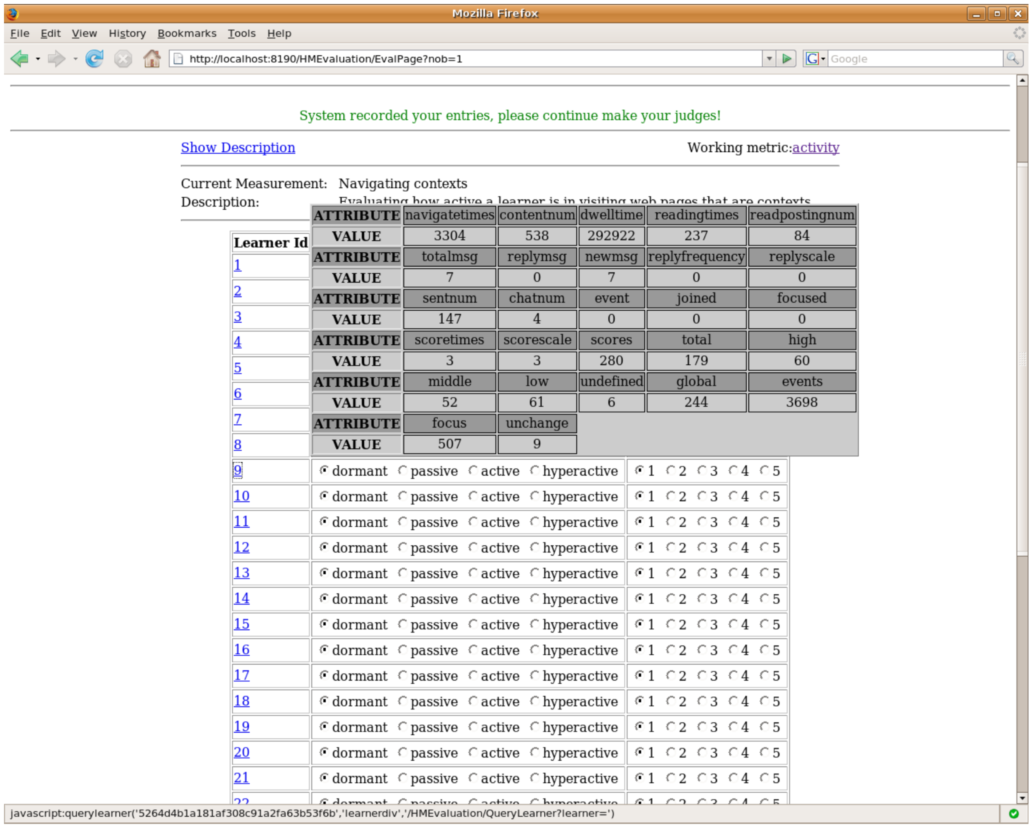


Figure 4.5: Human evaluation working page example

2 (in the row 2 and the column 1) means that the system assigned *passive* to two students and the expert assigned *dormant* to them. The entries in main diagonal of a confusion matrix are numbers of human results exactly matching system results. The entries outside of main diagonal are numbers of human results mismatching system results. The right-most column and the lowest row summarize each classification. In Figure 4.1, entries on the diagonal are the number of expert results that agree with system results; entries above the diagonal are the number of expert results that give high evaluations than the system results; entries below the diagonal are the number of expert results that give lower evaluation than the system results; entries on the bottom line and most right line summarize each classification. In Appendix A, we collect 76 confusion matrices for two experts by which each expert has 19 confusion matrices for each of the 15 measurements and 5 totals.

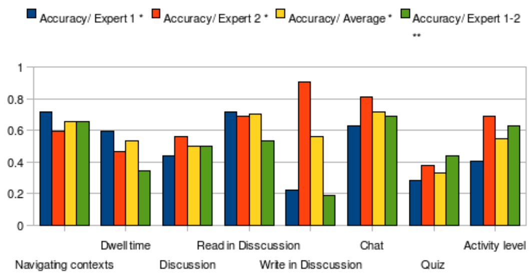
4.3.3 Results Analysis

Activity Level

The activity level metric is more straightforward than other metrics since it seems there are lots of data to support learners' activity events.

Measurements	Accuracy/ Expert 1 *	Accuracy/ Expert 2 *	Accuracy/ Average *	Accuracy/ Expert 1-2 **
Navigating contexts	0.72	0.59	0.66	0.66
Dwell time	0.59	0.47	0.53	0.34
Discussion	0.44	0.56	0.5	0.5
Read in Disscussion	0.72	0.69	0.7	0.53
Write in Disscussion	0.22	0.91	0.56	0.19
Chat	0.63	0.81	0.72	0.69
Quiz	0.28	0.38	0.33	0.44
Activity level	0.41	0.69	0.55	0.63

(a)

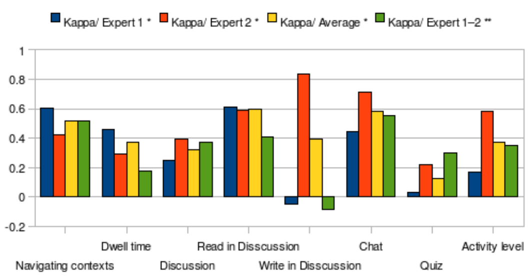


(b)

Figure 4.6: Accuracy results for activity level

Measurements	Kappa/ Expert 1 *	Kappa/ Expert 2 *	Kappa/ Average *	Kappa/ Expert 1–2 **
Navigating contexts	0.6	0.43	0.51	0.52
Dwell time	0.46	0.29	0.38	0.17
Discussion	0.25	0.39	0.32	0.37
Read in Disscussion	0.61	0.59	0.6	0.41
Write in Disscussion	-0.05	0.84	0.39	-0.08
Chat	0.45	0.71	0.58	0.55
Quiz	0.03	0.22	0.13	0.3
Activity level	0.17	0.58	0.38	0.35

(a)

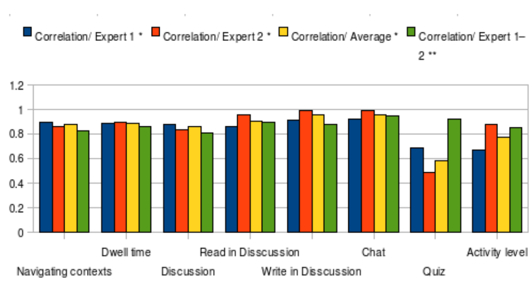


(b)

Figure 4.7: Kappa results for activity level

Measurements	Correlation/ Expert 1 *	Correlation/ Expert 2 *	Correlation/ Average *	Correlation/ Expert 1–2 **
Navigating contexts	0.89	0.86	0.88	0.82
Dwell time	0.88	0.89	0.89	0.86
Discussion	0.88	0.84	0.86	0.81
Read in Disscussion	0.86	0.96	0.91	0.89
Write in Disscussion	0.91	0.99	0.95	0.88
Chat	0.92	0.99	0.95	0.95
Quiz	0.68	0.49	0.58	0.92
Activity level	0.67	0.87	0.77	0.85

(a)



(b)

Figure 4.8: Correlation coefficient results for activity level

To understand the implications for the confusion matrix, we calculate the accuracy value which reflects the degree of agreement between the confusion matrices, Cohen's Kappa which measures inter-rater reliability, and the correlation coefficient which describes pairwise correlation.

Accuracy has a value between 0 and 1. The accuracy is 0 when evaluators have total disagreement, and is 1 when evaluators totally agree with each other. In general, a significant high accuracy value is more than 0.7. Kappa value is normally lower than the accuracy value because it considers the impacts on evaluators. Correlation coefficient will illustrate the inclination of pairwise values.

- Navigating contexts:[2] The average accuracy is 0.66. The average Kappa value is 0.51. The average correlation coefficient value is 0.88. This result is close to a statistically significant high value, and implies experts also make their decisions based on the normal distributions of selected fact data such as the number of times web pages have been surfed, the number of times login and logout events have happened, etc.. This measurement, as with most measurements, has a higher correlation coefficient value indicating that experts and system make judgements based on a similar baseline and have similar ways of judging.

- Dwell time: The average accuracy is 0.53 which is below the significant value. The Kappa value is 0.38, and the correlation coefficient is 0.89. An obvious reason is that fact data, such as the total dwell time and average dwell time of each access, have nonlinear distributions such that some learners have very small values and some learners have large values. It is a tough task for experts to make classifications.

- Reading messages in the discussion forum: This measurement has a significant accuracy value of 0.7. The Kappa value is 0.6, and the correlation coefficient is 0.91. The fact data selected for this measurement are total reading times and reading times per learner, etc., and are closer to standard normal distributions.

- Writing messages in the discussion forum: The average accuracy is 0.56. The Kappa value is 0.39, and the correlation coefficient value is 0.95 high. The sam-

[2]The formal definitions of all measurements used in this experiment can be found in equations 4.1, 4.2 and 4.3 early in this chapter.

ples of this measurement are relatively low compared to other measurements because lots of learners do not write messages in discussion forum. One expert gets a significant high value 0.91 and another gets a really low value 0.22. The reason is not clear in this case.

- Discussion forum overall: The average accuracy is 0.5. The Kappa value is 0.32, and the correlation coefficient is 0.86. This measurement is a combination of reading and writing, but it is not a simple additive measure. Experts need to consider both reading messages and writing messages, and have to balance their judgements between too few and too many posts in discussion forum.

- Chat room: The average accuracy is a significant high value of 0.72. The Kappa value is 0.58, and the correlation coefficient value is 0.95 which is high. This implies that the chat room is a relatively good place to observe learners' activities. Records of chat room interactions also have the potential for extracting more information rather than a simple counting of login events such as contents and tags. This observation can be used in future work.

- Quiz: The average accuracy is low at 0.33. The Kappa value is 0.13 low, and the correlation coefficient is 0.58. Since learners have freedom to repeat a quiz, this measurement not only use the marks in each quiz, but also factors that learners may game the quiz by repeatedly trying many times to get better marks. At the first design stage, we assigned more weights to quiz than other fact data. In the final experiment, we treated quiz marks the same as other fact data because we are not sure how heavy weight it should have.

- Activity level: The average accuracy is 0.55. The Kappa value is 0.38, and the correlation coefficient is 0.77. This measurement combines the above seven measurements together to get an overall view of activity level. As we expect to have a mean accuracy value from this measurement, the result is close to a simple mathematical mean of the above measurements.

The accuracy values, which measure the percentage of learners where experts and the data mining approach agree, are good on three measurements: navigating contexts, reading in the discussion forum, and activities in the chat room. We notice that the fact data are rich enough in these fields such that experts can easily judge learners based on this information. We also notice that these fact data are approximately in normal distributions which helps experts to make reasonable decisions. In most measurements, both experts get similar results. Both experts get low accuracy values in the quiz measurement because experts need to consider two things: the average score of each learner and how many times learners repeat doing the quiz questions. One interesting measurement is writing in discussion forums. One expert gets a 0.91 accuracy value while another gets only a 0.22 accuracy value. The possible reason is that the fact data inheriting this measurement is not enough compared to other measurements so that experts may find it hard to categorize learners into different groups.

To assess reliability, we also calculate the accuracy values in comparing two experts. These accuracy values are similar to the results of comparison of the data mining approach to the experts, except writing in the discussion forum measurement which is even lower. The results are shown on the right-most columns of Figure 4.6, 4.7, and 4.8.

When we review correlation coefficient values, we get significant positive results that six of seven measurements have coefficient values more that 0.85. It means that the judgements of experts are similar to the system's evaluations. It provides a possibility to build up a linear regression to predict experts' choices based on system results. Even in the *writing in the discussion* forum measurement which has a low accuracy value, the correlation coefficient values are relatively high which means experts' choices are close to the system results. But in *quiz* measurement, we get both low values of accuracy and correlation coefficient which means we cannot predict experts' choices from system results. The possible explanation is that the fact data we have chosen in the data mining approach may not match experts' choice of significant data on their judgement of how the data reflects real issues facing learners doing the quiz.

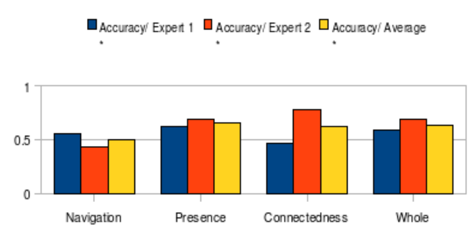
Social Tendency

The iHelp system records learners' behaviours on browsing web pages which contain course contents, and also tracks how learners interact and communicate through public forums and more privately chat rooms. Reading and writing messages in discussion forums and chat rooms provide us clues to realize the patterns in learners' social tendencies.

Social tendency is a complex concept since it involves human emotions combining with learners' activities in daily learning. This metric arises because there is abundant information to track messages in discussion forums and chat rooms. To compute the social tendency metric, we collect and filter raw data into various data categories. For example, we have three kinds of fact data about reply messages: the number of reply messages, the reply-frequency computed from tracking data, and the reply scale covered by reply messages. We count two kinds of events from the chat room: joined events tell us the size of a chat channel, and focused events tell us the density of a chat channel. When we have such fact data, it is natural to apply data mining clustering algorithms on fact data to group learners into three categories: loner, flamer, and socializer with respectively less, middle, and strong communication skills and tendency. Loners are those learners who have less communications with other learners. Socializers are those learners who like to share with other learners. Flamers are those learners whose behaviours are in between loners and socializers.

Measurements	Accuracy/ Expert 1 *	Accuracy/ Expert 2 *	Accuracy/ Average *
Navigation	0.56	0.44	0.5
Presence	0.63	0.69	0.66
Connectedness	0.47	0.78	0.63
Whole	0.59	0.69	0.64

(a)



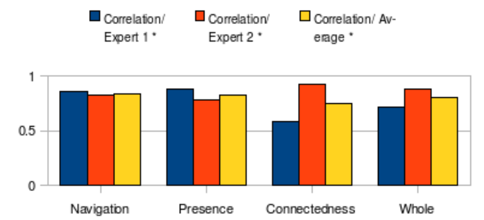
(b)

Figure 4.9: Accuracy results for social tendency

- Navigation ability: The average accuracy value is 0.5. The correlation coefficient value is 0.84. This measurement is computed by combining the number

Measurements	Correlation/ Expert 1 *	Correlation/ Expert 2 *	Correlation/ Average *
Navigation	0.86	0.82	0.84
Presence	0.87	0.78	0.83
Connectedness	0.58	0.92	0.75
Whole	0.71	0.88	0.8

(a)



(b)

Figure 4.10: Correlation coefficient results for social tendency

of reading messages in both of discussion forums and chat rooms.

- Presence ability: The average accuracy value is 0.66. The correlation coefficient value is 0.83. This measurement is computed by combining writing messages in both discussion forums and chat rooms.

- Connectedness level: The average accuracy value is 0.63. The correlation coefficient value is 0.75. This measurement is computed by using fact data that indicate lively connections between learners: messages that replies to other messages, group size [3] and density of chat channel.

- Social tendency: This is the aggregate result to describe learners' social tendency by combining navigation ability, presence ability, and connectedness with equal weights. The average accuracy value is 0.64. The correlation coefficient value is 0.8.

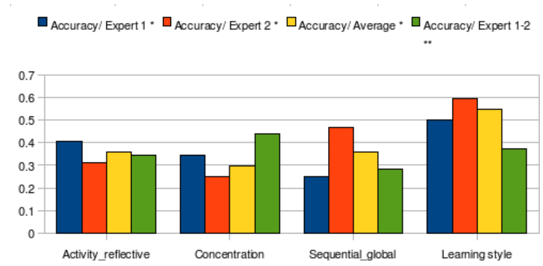
The results of presence ability and connectedness level are close to a significant improvement with average values of 0.66 and 0.64. Both experts get close judgements except in the connectedness level. One expert gets lower accuracy and correlation coefficient values respectively 0.47 and 0.58, while another expert gets higher accuracy and correlation coefficient values, respectively 0.78 and 0.92. Although they used same fact data, they have different results. This indicates a direction that there is much space to improve clustering quality by carefully selecting and filtering the tracking data in future work.

[3] The formal definitions of fact data can be found in chapter 3.

Learning Style

Measurements	Accuracy/ Expert 1 *	Accuracy/ Expert 2 *	Accuracy/ Average *	Accuracy/ Expert 1-2 **
Activity_reflective	0.41	0.31	0.36	0.34
Concentration	0.34	0.25	0.3	0.44
Sequential_global	0.25	0.47	0.36	0.28
Learning style	0.5	0.59	0.55	0.38

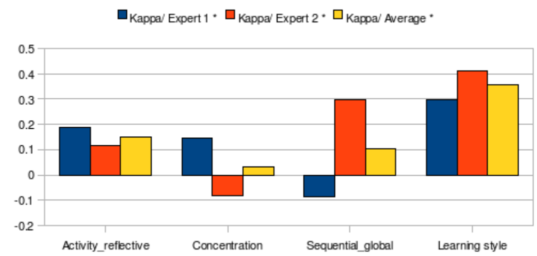
(a)



(b)

Figure 4.11: Accuracy results for learning style

Measurements	Kappa/ Expert 1 *	Kappa/ Expert 2 *	Kappa/ Average *
Activity_reflective	0.19	0.12	0.15
Concentration	0.15	-0.08	0.03
Sequential_global	-0.08	0.3	0.11
Learning style	0.3	0.41	0.35

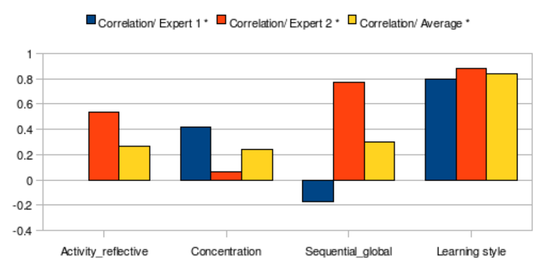


(b)

(a)

Figure 4.12: Kappa results for learning style

Measurements	Correlation/ Expert 1 *	Correlation/ Expert 2 *	Correlation/ Average *
Activity_reflective	0	0.53	0.27
Concentration	0.41	0.06	0.24
Sequential_global	-0.17	0.77	0.3
Learning style	0.79	0.88	0.84



(b)

(a)

Figure 4.13: Correlation coefficient results for learning style

A major goal of this research has been to find useful patterns about learning style by mining the tracking data from the iHelp system. There are two steps to achieve this purpose. The first one is to decide what kinds of learning styles we will focus on, and the second step is to filter the proper fact data to feed into the data mining procedure. We chose three kinds of learning styles: active vs reflective, concentration level, sequential vs global learning. We think various statistical summary data will help to distinguish and group learners according to these styles. Data related to activity level will be used to analyze a learner as having an active or reflective learning style. To group learners into different concentration levels, we create high, middle, low and undefined fact data which focus on the number of hours each learner spends interacting with learning objects. For sequential vs global learning style, we used *global*, *event happened*, *focus count*, etc., fact data to calculate a learner as having a sequential or a global learning style. Details and formal definitions of these fact data are described in Chapter 3.

Here are the results comparing the experts to the system on learning style measurements:

- Active/Reflective learning: The average accuracy value is 0.36, the Kappa value is 0.15, and the correlation coefficient value is 0.27.

- Concentration level: The average accuracy value is 0.3, the Kappa value is 0.03, and the correlation coefficient value is 0.24.

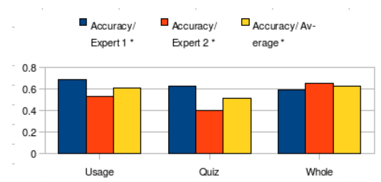
- Sequential/Global learning: The average accuracy value is 0.36, the Kappa value is 0.11, and the correlation coefficient value is 0.3.

- Learning style: The average accuracy value is 0.55, the Kappa value is 0.35, and the correlation coefficient value is 0.84.

Results are worse than expected: the accuracy values of the three learning styles are all less than 0.4, and the correlation coefficient values record the lowest results in this expert experiment. It appears the fact data cannot be directly linked to the learning style metric. When we create various fact data, we set up some threshold values to reduce the massive data size and to filter the raw data. The selection of these threshold values will have a heavy effect on the quality of filtering fact data. The lesson we learned from this experiment is that we should try to optimize threshold values in future work.

Knowledge Tendency

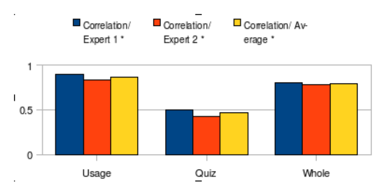
Measurements	Accuracy/ Expert 1 *	Accuracy/ Expert 2 *	Accuracy/ Average *
Usage	0.69	0.53	0.61
Quiz	0.63	0.41	0.52
Whole	0.59	0.66	0.63



(a) (b)

Figure 4.14: Accuracy results for knowledge tendency

Measurements	Correlation/ Expert 1 *	Correlation/ Expert 2 *	Correlation/ Average *
Usage	0.89	0.83	0.86
Quiz	0.5	0.43	0.47
Whole	0.81	0.78	0.8



(a) (b)

Figure 4.15: Correlation coefficient results for knowledge tendency

Predicting learners' knowledge level is one important research goal, but we do not have proper information to really measure learners' knowledge level. Instead, we try to indicate the possible tendency that learners may have while they are interacting with learning objects and tracking systems. Many researchers have explored quiz and exam marks for such purposes. Since learners can randomly choose to do a quiz and repeat it many times, we suspect some learners may game the quiz such that marks on that quiz are not as useful as they should be. In future work, we need to design and use tools such that we can eliminate such gaming.

Following are the results comparing the knowledge tendency measurements for experts:

- Usage level: The average accuracy value is 0.61, the correlation coefficient value is 0.86. This measurement is computed by combining learners' activities in browsing course contexts, reading and writing messages, and how efficiently learners spend time interacting with learning objects.

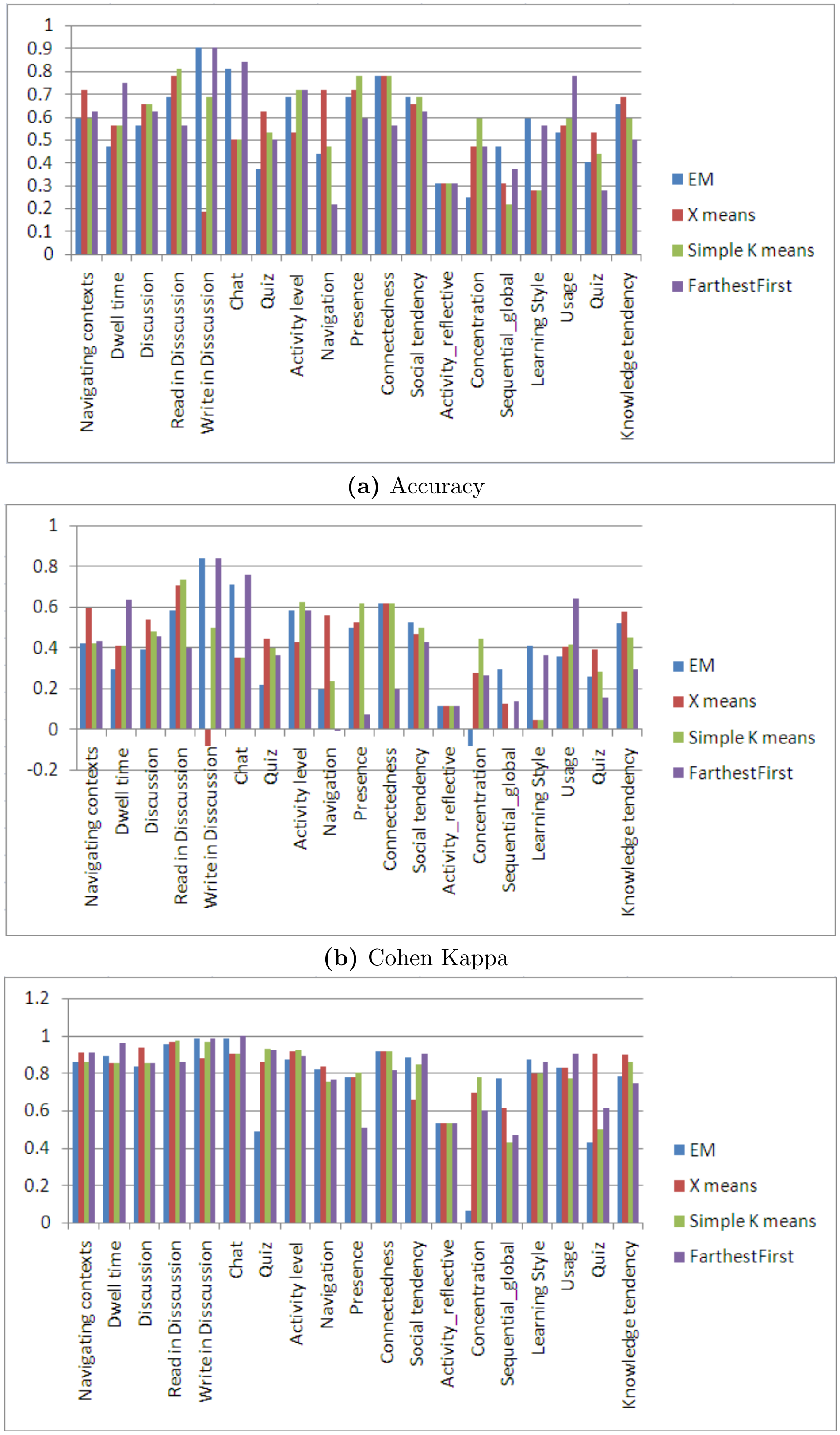
- Quiz level: The average accuracy value is 0.52, the correlation coefficient value is 0.47. This measurement is computed based on learners' marks doing online quizzes.

- Knowledge tendency: The average accuracy value is 0.63, the correlation coefficient value is 0.8.

Effect of Various Clustering Algorithms

Based on the same sample data, different data mining algorithms will produce different results. As we showed in the previous chapter, we implemented four clustering algorithms: EM, X means, simple K means, and farthest first. Figure 4.16 illustrates the comparison among these algorithms based on one expert's evaluations. No single algorithm obviously dominates the others. The EM algorithm is a good choice for the writing in discussion forum measurement, and the connectedness measurement, but is a bad choice for the activity-reflective measurement. The X means algorithm does well in the three measurements of discussion forum, connectedness, and knowledge tendency, but does worst in the write in discussion forum measurement. The simple k means algorithm does a good job in some measurements, but does a bad job in the sequential-global measurement. The farthest first algorithm gets a bad result in the navigation measurement, and gets good results in the usage and write in discussion forum measurements. In the correlation coefficient chart, the EM gets the worst results in the two measurements of quiz and activity-reflective, and other algorithms get similar results in most of the measurements.

The lesson we learn from comparing results of the four algorithms is that we may get better results if we can choose different clustering algorithms for each specific measurement. This requires more research to deeply understand and carefully select a specific algorithm based on each specific requirement of a particular measurement. We used equal weights in this experiment for the various input data. The alternative is to assign a weight factor for each element of raw data for clustering algorithm. Different weight factors may dramatically change the results. In future work we will introduce an experiment with varying weights.



(a) Accuracy

(b) Cohen Kappa

(c) Correlation Coefficient

Figure 4.16: Results of different algorithms

4.3.4 Conclusion of Expert Evaluation

We designed the expert experiment to verify that the data mining method can make judgements that are consistent with those made by people.

Accuracy is calculated for confusion matrices. Cohen's Kappa is computed for inter-rater reliability, and correlation coefficient is used for pairwise correlation. As we have shown above, we describe these three statistical values for each single measurement. Some measurements have better accuracy than others. Kappa values are low in all metrics, and correlation coefficient values are relatively high in all metrics. On the whole, the activity metric has better results than the others, while the learning style metric is ranked the worst in this experiment. The features of the activity level metric can be directly computed by combining some factor data which are summarized from the fact data of iHelp system, and these help both experts and data mining algorithms to label learners in similar ways. On the other hand, the complexities of learning style and social tendency metrics lead to high inconsistency between experts' results and the data mining algorithm's results.

It only takes a few seconds to compute all learners' results using the system, but it takes several hours to do the same thing using experts. It is easy to recalculate results while adding new data or adjusting parameters at any time using data mining methods, but it is impossible to rapidly repeat the process with experts. To gain statistically significant results, we need more experts in this kind of experiment, but it is hard to find more experts who are willing to spend several hours to do the detailed and careful analysis required. In our first human evaluation, only two experts finally finished such a boring task. This is tough work for experts to do, and we will not pursue further evaluation using experts. Instead, we look to alternative methods for judging learners based on their own self-evaluations from questionnaires designed to extract the measurements data for each metrics.

4.4 Experiment II – Learner Self Evaluation

The purpose of learner self evaluation is to find an alternative method to verify the metrics and measurements created by the data mining methods.

4.4.1 Experiment Information

In the 2007-2008 school year, we carried out two separate learner self evaluations, both in the CMPT 100 online class. The learners in those online classes browsed course materials, read and wrote messages in discussion forums, chatted in chat rooms, asked questions and took quizzes through the iHelp online class web site. All of the learners' activities were recorded in a database. These formed the raw data for computing the measurements and metrics, as discussed in Chapter 3.

To collect learner self evaluations, we designed a self evaluation questionnaire, and posted it to the class web site. Learners were encouraged to finish the evaluation questionnaires without any pressure. Here are the response statistics for each class, one in term 1 and one in term 2.

Term 1: The class size was 24. Four learners responded to the self questionnaire.

Term 2: The class size was 26. Ten learners responded to the self questionnaire.

4.4.2 Learner Self Evaluation

The self evaluation questionnaire had 16 questions. The goal of this experiment was to find out the differences between how learners think of themselves and how the measurements evaluated them. Since there was no necessity to evaluate learners' activity levels in the self questionnaire, we designed the questionnaire such that questions were related only to measurements of social tendency, learning style, and knowledge tendency. There were four questions related to the social tendency metric, five questions related to the learning style metric, and seven questions related to the knowledge tendency metric. The questionnaire is listed in Appendix B. To use the questionnaire, we assigned a score to each answer, then matched each measurement to a combination of scores of answers. The details are in the following table.

Metric	Measurement	Questions	Scores
Learning Style	Active or reflective	14, 16	is active with answer 14.a and 16.bcd. is reflective with answer 14.b and 16.aed.
	Concentration	13	is high with answer a, is low with answer b
	Sequential or global	15,17	is sequential with answer 15.a and 17.a, is global with answer 15.b and 17.c
Social Tendency	Navigation	9,11	is low with answer a, is high with answer d
	Presence	10,12	is low with answer a, is high with answer d
	Connectedness	9,10,11,12	$low <= 5, medium <= 9, high > 9$
Knowledge Tendency	Usage	2,3,4,5	$low <= 8, medium <= 10, high <= 14, super > 14$
	Quiz	6	is low with answer a, is super with answer d
	Whole	7	is low with answer a, is super with answer d

Table 4.2: Matching self evaluations to measurements

Using this simple and straightforward method, we determined each individual's answers to categories of measurements. Here, we assumed some threshold values to map onto the system's qualitative values for each measurements, and we discussed these threshold values with the instructor to make sure these values constituted realistic judgements. This assumption will affect the results. We did not try to fit different threshold values to the experimental results because we think human justification is more important in evaluating learners' behaviours in an online education environment, and we did not want to overfit the data.

Although we had two self evaluation experiments with four learners in term 1 and ten learners in term 2, the sample size is still small. So we combined the data from the two terms together such that we have 14 learners to process in our statistical analysis, even though there might be subtle differences among the classes.

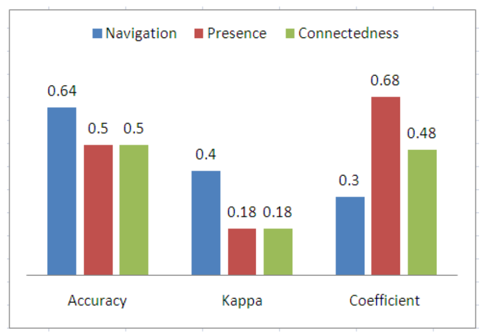
4.4.3 Analysis of Results

We used the same statistical comparisons as in the expert study: accuracy, Cohens' Kappa and correlation coefficient.

Social Tendency

	Accuracy	Kappa	Coefficient
Navigation	0.64	0.4	0.3
Presence	0.5	0.18	0.68
Connectedness	0.5	0.18	0.48

(a)



(b)

Figure 4.17: Results of social tendency metric

- Navigation: There are two questions about this measurement: how many messages learners like to read from the discussion forum and also in the chat room. The accuracy value is 0.64, the Kappa value is 0.4, and the correlation coefficient value is 0.3. The accuracy value revealed that the learners have a good realization about their own navigation behaviours.

- Presence: Two questions about this measurement are how learners answer questions in the discussion forums, and how they talk with other learners in chat rooms. The accuracy value is 0.5, the Kappa value is 0.18, and the correlation coefficient value is 0.68.

- Connectedness: This measurement is calculated by combining four questions together. The accuracy value is 0.5, the Kappa value is 0.18, and the correlation coefficient value is 0.48.

Learning Style

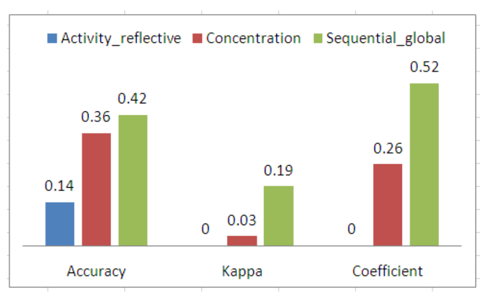
- Active/reflective: There are two questions about this measurement. One question is about learners' actions when learning a new subject for the first time. The other question is about learners' behaviour when having difficulty with a concept. We determined a learner to have an active vs reflective learning style using the answers to these two questions. The accuracy value is low at 0.14. We clearly failed in this measurement to match the system and learner evaluations.

- Concentration: The question related to this measurement is learners' behaviour when reading course materials in a limited time. The accuracy value is 0.36, the Kappa value is 0.03, and the correlation coefficient value is 0.26. These values also are not very high.

- Sequential/global: Two questions about this measurement are how learners prepare for an exam and how learners prepare for a quiz. The accuracy value is 0.42, the Kappa value is 0.19, and the correlation coefficient value is 0.52. The result shows that we may have ability to calculate this measurement in the learner model.

	Accuracy	Kappa	Coefficient
Activity_reflective	0.14	0	0
Concentration	0.36	0.03	0.26
Sequential_global	0.42	0.19	0.52

(a)



(b)

Figure 4.18: Results of learning style metric

Knowledge Tendency

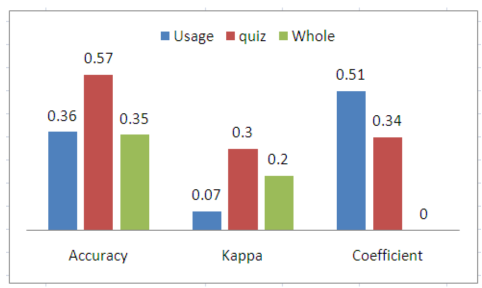
- Usage: There are four questions about this measurement: the degree to which learners like to spend time pursuing course materials, to be involved in discussion forums and chat rooms, to communicate with other learners. The accuracy value is 0.36, the Kappa value is 0.07, and the correlation coefficient value is 0.51. The result is worse than we expected.

- Quiz: The question related to this measurement is how hard learners prepare for a quiz. The accuracy value is 0.57, the Kappa value is 0.3, and the correlation coefficient value is 0.34.

- Tendency: The question related to this measurement is how learners evaluate themselves in understanding the course materials. The accuracy value is 0.35, the Kappa value is 0.2, but the correlation coefficient is low at zero.

	Accuracy	Kappa	Coefficient
Usage	0.36	0.07	0.51
quiz	0.57	0.3	0.34
Whole	0.35	0.2	0

(a)



(b)

Figure 4.19: Results of knowledge tendency metric

4.5 Conclusions of Learner Self Evaluation Experiment

In the combination of the two self evaluations there were 14 learners involved in the experiment. This was not enough to get statistically significant results. To improve the analysis, we should encourage more learners to be involved, and we should expand the experiment to further sections in future work.

In the self evaluations, we calculated measurements of social tendency, learning style and knowledge tendency which are more general characteristics of learners. We matched these measurements to answers of learners in questionnaires. One issue is how to avoid learners possibly misunderstanding the questions when we designed the questionnaires. Unfortunately in the current experiments, we lacked effective tools to determine this and to reduce the impact when learners did not understand the questions. If we can combine the questionnaire with static information such as personal information about learners, we may reduce the human errors to get more precise results in future work.

Chapter 5

Research Contributions and Future Directions

The goal of this research has been to show that just in time learner models can be created from analyzing learners' online tracking data. This approach consists of filtering raw data, selecting pedagogical applications and applying data mining methods. This has led to measurements and metrics that can be calculated for each individual learner to represent that learner's characteristics and behaviours.

5.1 General Comments on the Two Experiments

From the two experiments' results, some measurements seem to be useful in building just in time learner models; some measurements only show promise to be leading in the right directions; some measurements have not found much support. The expert experiment, in which experts observed and evaluated learners as the third party, shows much more positive results compared to the self evaluation experiment, in which learners evaluated themselves. Table 5.1 and Table 5.2 show a summary of the accuracy values and correlation coefficient values for the expert experiment and the self evaluation experiment.

5.1.1 Expert Experiment

From the expert experiment, Table 5.1, there are at least six measurements providing positive results to build just in time learner models with accuracy value greater than 0.6 and coefficient correlation values greater than 0.8. These measurements in-

Correlation Coefficient	Accuracy		
	< 0.4	04 - 0.6	> 0.6
< 0.4	2	1	0
0.4 - 0.6	1	1	1
0.6 - 0.8	0	1	1
> 0.8	1	4	6

Table 5.1: Summary of expert experiment

Correlation Coefficient	Accuracy		
	< 0.4	04 - 0.6	> 0.6
< 0.4	3	1	1
0.4 - 0.6	1	2	0
0.6 - 0.8	0	1	0
> 0.8	0	0	0

Table 5.2: Summary of self evaluation experiment

clude three measurements from the *activity level* metric: *navigating context*, *read in discussion forum*, *chat activity*; two measurements from the *social tendency* metric: *presence* and *social tendency*; and one measurement from the *knowledge tendency* metric: *usage*. As we look through these six measurements, we observe two common facts: (i) six measurements are deeply related to learners' browsing web site behaviours in online courses, and (ii) we have collected abundant information into the database to support the measurements. In other words, the more information we have, the more positive results we can get. In online education environments, these six measurements can help instructors to observe and evaluate learners' learning behaviours as in traditional class rooms.

Some measurements show promise to describe learners' behaviours. There are seven measurements belonging to this category. These measurements either have relatively high accuracy values, or have relatively high correlation coefficient values. Two of them are *connectedness* measurement and *knowledge tendency* measurement with accuracy values greater than 0.6. Four of them are *dwell time* measurement, *discussion* measurement, *write in discussion* measurement, and *navigation* measurement with correlation coefficient values greater than 0.8. In total, we have 13 out of 19 measurements with positive and possibly positive results in the expert measurements. These measurements are mainly in the *activity level* metric and the *social tendency* metric. The results support that the instructors at least will have a helpful tool to dynamically observe and evaluate learners' performance in online education environment.

Six measurements had negative results in the expert experiment, with lower accuracy values or lower correlation coefficient values. Those measurements in the *learning style* metric especially have lower values in both accuracy and coefficient values. The results are negative, and we could not find a way to improve them because we have the limitation and constraints of using only data captured in the online environment. We probably have to dispose of the idea of building a learner style metric using only just in time data.

5.1.2 Self Evaluation Experiment

The self evaluation experiment only includes measurements from the social tendency, learning style, and knowledge tendency metrics. Although there are no statistically significant positive results from the self evaluation experiment, we do find some similar results in respect to the expert experiment. As in the expert experiment, the social tendency metric gets more positive results than the learning style and knowledge tendency metrics. Three measurements of the *social tendency* metric have accuracy values greater than 0.5 (see Table 5.2; and the *presence* measurement has correlation coefficient value greater than 0.6. Similar to the expert experiment, the measurements of the *learning style* metric have the worst negative results.

Analyzing the results from the two experiments, the measurements of the activity level metric have high positive results; the measurements of the social tendency metric have positive and possibly positive results; the measurements of the knowledge tendency metric have mixed positive and negative results; and the measurements of the learning style metric have negative results.

5.1.3 Issue of Metric vs Measurement

In our approach, we have constructed four levels to build just in time learner models. From top to bottom, they are the metric level, the measurement level, the fact data level and the raw data level. The raw data are stored in the database of the tracking system. The fact data are filtered and computed in a pre-computation process. The measurements are the data mining results and output. The metrics are a combination of some measurements to describe one general characteristic of learners. In other words, we first compute individual measurements, and then combine a group of measurements to build up a metric. Each measurement has a specific meaning and is a fine grained result. On the other hand, each metric represents an abstract concept including a group of measurements. The results of each individual measurement is more useful and reliable measures, and our validations and examinations are based on each individual measurement rather than the metrics. For example, the three measurements of the social tendency metric can be used separately in different applications. The navigation measurement describes how a learner watches others; the presence measurement describes how a learner shows themselves to others; and the connectedness measurement describes how a learner interacts with others.

5.1.4 Just In Time Model

A goal of this research has been to compute learner models just in time as we need them instead of keeping static learner models. We do not use the historical learner models in our computations, instead recomputing the metrics and measurements based on the current available fact data and raw data. In this way, any changes in learners will be automatically recognized in the form of new measurements. Through two experiments, we have shown that just in time computations are possible and in some cases they lead to useful measurements.

5.1.5 Top Down

Top down computation of measurements promises to allow the calculation of results quite rapidly when compared to computations using a pure bottom up data mining approach. In our approach, the first step is to decide the purpose of the applications such that we can figure out the necessary metrics and measurements to support the applications. The second step is to find the raw data and retrieve the fact data to support the measurements. The last step is to mine the fact data to find patterns that can be used in creating formula that can later be used to directly calculate the measurements based on the available fact data.

5.2 Lessons Learned

To validate the approach, we designed two experiments: expert experiment and self evaluation experiment. While results from the two experiments have similar outcomes, the results from the expert experiment are somewhat better. However, each expert needs to spend six to eight hours to finish the evaluations. Only two experts actually finished the evaluations because it took too long to do it. Learners finished a self evaluation in just ten minutes. Self evaluations are simple and easy to organize, but more work needs to go into the questionnaire design to get more useful questions. More questions are needed to match each measurement. More concrete questions are needed to identify learners' intentions and goals. Several surveys collected from different time points in a course would be helpful to track learners' changing behaviours in e-learning environments.

Pre-computation is necessary and reasonable. It is a time consuming task to organize the raw data because of its huge volume in the database. In our experiments, it took about 10 minutes to collect and filter the raw data from the database. This led to more tractable fact data; which was easier to use for the data mining algorithms, and more meaningful to the educational context. Because the data volume of online courses would not suddenly increase in a relative short period such as 24 hours, it is reasonable to pre-process raw data once per day so that the data size will be under control for instructors.

The choice of data mining algorithms has an important impact on the results. We used four clustering algorithms in our approach. A clustering algorithm worked well for some measurements but not all. We did not find a single algorithm which can dominate over others. When we used clustering algorithms, we assigned an equal weight to each fact data element, because we did not sort and order the data in the two experiments. For good learner modelling, perhaps the promise is to let human teachers choose the right weights for fact data elements that fit the particular educational context in which the metrics and measurements are to be used. In our implementation, we designed an interface such that instructors can assign different weights to dramatically change the mining results. This is useful if some fact data are more important than others to create a specific measurement. In the future, it is worth to continue moving in this direction.

5.3 Future Work and Directions

The main drawback to the two experiments is that the number of evaluators is too low to get statistically significant results. It is easier to have more learners involved in the self evaluation than to get more experts in the expert evaluation. However, we need to improve and design a better self evaluation questionnaire to attract more learners to participate while at the same time get better questions. More involvement of instructors in the design of the questionnaire may be helpful.

We have selected four metrics and 15 measurements in the two experiments. The results of two experiments show that there is some promise that the activity metric and the social tendency metric can be useful to compute some attributes of just in time learner models. This is only the first step of our research. A next step is to do much more extensive data mining and testing to get truly statistical significant measurements. Then we need to show how we can use these measurements to build just in time learner models in actual pedagogical applications. One such application may be the *recommendation of peer helpers*, an original task of the iHelp system and one task for this thesis research.

Overall, we think that just in time computation of learner models is a promising way of dealing with change during the learning process. Because of the relatively high correlation coefficient results in the two experiments, we can at various time points, apply classification algorithms to predict learner behaviours. A promising direction may be to keep old predictions and combine this information with the latest updated predictions to improve the accuracy of the just in time learner model. Such a hybrid approach may be informed by cognitive and pedagogical theories of how learners change, as well as possibly contributing insight into such theories.

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Appendix A

Confusion Matrices

To compare the data mining approach to human evaluations, we created a confusion matrix for each measurement. In each matrix, the rows represent human results, and the columns represent data mining results. There are nineteen matrices for each expert, and nine matrices for the learner self evaluation experiment.

A.1 Confusion Matrices of First Expert

Navigating contexts		**Data Mining Results**				
		dormant	passive	active	hyperactive	
Human Evaluation	dormant	4	0	1	0	5
	passive	2	4	1	0	7
	active	0	3	10	0	13
	hyperactive	0	0	2	5	7
		6	7	14	5	32

Figure A.1: Activity metric - navigating context measurement

Dwell time		**Data Mining Results**				
		dormant	passive	active	hyperactive	
Human Evaluation	dormant	4	0	0	0	4
	passive	0	2	0	0	2
	active	0	11	8	1	20
	hyperactive	0	0	1	5	6
		4	13	9	6	32

Figure A.2: Activity metric - dwell time measurement

Discussion		**Data Mining Results**				
		dormant	passive	active	hyperactive	
Human Evaluation	dormant	5	0	0	0	5
	passive	9	1	1	0	11
	active	0	8	5	0	13
	hyperactive	0	0	0	3	3
		14	9	6	3	32

Figure A.3: Activity metric - discussion measurement

Read in Disscussion		Data Mining Results				
		dormant	passive	active	hyperactive	
Human Evaluation	dormant	4	0	0	0	4
	passive	7	8	0	0	15
	active	0	0	10	0	10
	hyperactive	0	0	2	1	3
		11	8	12	1	32

Figure A.4: Activity metric - read in discussion measurement

Write in Disscussion		Data Mining Results				
		dormant	passive	active	hyperactive	
Human Evaluation	dormant	5	0	0	0	5
	passive	13	1	0	0	14
	active	0	9	0	0	9
	hyperactive	0	0	3	1	4
		18	10	3	1	32

Figure A.5: Activity metric - write in discussion measurement

Chat		Data Mining Results				
		dormant	passive	active	hyperactive	
Human Evaluation	dormant	12	0	0	0	12
	passive	4	7	0	0	11
	active	0	3	1	3	7
	hyperactive	0	0	2	0	2
		16	10	3	3	32

Figure A.6: Activity metric - chat room measurement

Quiz		Data Mining Results				
		dormant	passive	active	hyperactive	
Human Evaluation	dormant	6	0	0	0	6
	passive	0	1	7	0	8
	active	0	12	0	4	16
	hyperactive	0	0	0	2	2
		6	13	7	6	32

Figure A.7: Activity metric - quiz measurement

Whole		Data Mining Results				
		dormant	passive	active	hyperactive	
Human Evaluation	dormant	2	0	0	0	2
	passive	3	1	0	0	4
	active	1	12	9	3	25
	hyperactive	0	0	0	1	1
		6	13	9	4	32

Figure A.8: Activity metric - activity measurement

Navigation		Data Mining Results			
		loner	flamer	socilizer	
Human Evaluation	loner	9	0	0	9
	flamer	6	6	5	17
	socilizer	0	3	3	6
		15	9	8	32

Figure A.9: Social tendency metric - navigation measurement

Presence		Data Mining Results			
		loner	flamer	socilizer	
Human Evaluation	loner	6	0	0	6
	flamer	7	11	3	21
	socilizer	0	2	3	5
		13	13	6	32

Figure A.10: Social tendency metric - presence measurement

Connectedness		Data Mining Results			
		loner	flamer	socilizer	
Human Evaluation	loner	6	0	0	6
	flamer	12	3	0	15
	socilizer	5	0	6	11
		23	3	6	32

Figure A.11: Social tendency metric - connectedness measurement

Whole		Data Mining Results			
		loner	flamer	socilizer	
Human Evaluation	loner	7	0	0	7
	flamer	7	6	0	13
	socilizer	0	6	6	12
		14	12	6	32

Figure A.12: Social tendency metric - tendency measurement

Activity_reflective		Data Mining Results				
		low	middle	high	super	
Human Evaluation	low	4	2	3	2	11
	middle	0	6	2	1	9
	high	0	5	3	1	9
	super	2	0	1	0	3
		6	13	9	4	32

Figure A.13: Learning style metric - activity vs reflective measurement

Concentration		Data Mining Results				
		low	middle	high	super	
Human Evaluation	low	1	4	0	0	5
	middle	1	7	0	0	8
	high	5	6	2	0	13
	super	4	0	1	1	6
		11	17	3	1	32

Figure A.14: Learning style metric - concentration measurement

Sequential_global		Data Mining Results				
		low	middle	high	super	
Human Evaluation	low	0	3	4	1	8
	middle	0	5	4	0	9
	high	1	8	3	0	12
	super	1	1	1	0	3
		2	17	12	1	32

Figure A.15: Learning style metric - sequential vs global measurement

Whole		Data Mining Results				
		low	middle	high	super	
Human Evaluation	low	7	0	0	0	7
	middle	3	7	1	0	11
	high	0	8	1	0	9
	super	0	0	4	1	5
		10	15	6	1	32

Figure A.16: Learning style metric - style measurement

Usage		Data Mining Results				
		low	middle	high	super	
Human Evaluation	low	6	5	0	0	11
	middle	0	5	1	0	6
	high	0	1	8	3	12
	super	0	0	0	3	3
		6	11	9	6	32

Figure A.17: Knowledge tendency metric - usage measurement

Quiz		Data Mining Results				
		low	middle	high	super	
Human Evaluation	low	6	0	7	0	13
	middle	0	10	0	0	10
	high	0	3	0	1	4
	super	0	1	0	4	5
		6	14	7	5	32

Figure A.18: Knowledge tendency metric - quiz measurement

Whole		Data Mining Results				
		low	middle	high	super	
Human Evaluation	low	8	0	0	0	8
	middle	3	6	0	0	9
	high	1	7	3	0	11
	super	0	0	2	2	4
		12	13	5	2	32

Figure A.19: Knowledge tendency metric - tendency measurement

A.2 Confusion Matrices of Second Expert

Navigating contexts		Data Mining Results				
		dormant	passive	active	hyperactive	
Human Evaluation	dormant	6	0	0	0	6
	passive	0	2	1	1	4
	active	0	5	8	1	14
	hyperactive	0	0	5	3	8
		6	7	14	5	32

Figure A.20: Activity metric - navigating context measurement

Dwell time		Data Mining Results				
		dormant	passive	active	hyperactive	
Human Evaluation	dormant	4	8	1	0	13
	passive	0	5	5	0	10
	active	0	0	3	3	6
	hyperactive	0	0	0	3	3
		4	13	9	6	32

Figure A.21: Activity metric - dwell time measurement

Discussion		Data Mining Results				
		dormant	passive	active	hyperactive	
Human Evaluation	dormant	13	1	0	0	14
	passive	1	2	0	0	3
	active	0	6	0	0	6
	hyperactive	0	0	6	3	9
		14	9	6	3	32

Figure A.22: Activity metric - discussion measurement

Read in Disscussion		Data Mining Results				
		dormant	passive	active	hyperactive	
Human Evaluation	dormant	11	1	0	0	12
	passive	0	6	0	0	6
	active	0	1	4	0	5
	hyperactive	0	0	8	1	9
		11	8	12	1	32

Figure A.23: Activity metric - read in discussion measurement

Write in Disscussion		Data Mining Results				
		dormant	passive	active	hyperactive	
Human Evaluation	dormant	17	1	0	0	18
	passive	1	9	0	0	10
	active	0	0	2	0	2
	hyperactive	0	0	1	1	2
		18	10	3	1	32

Figure A.24: Activity metric - write in discussion measurement

Chat		Data Mining Results				
		dormant	passive	active	hyperactive	
Human Evaluation	dormant	16	1	0	0	17
	passive	0	5	0	0	5
	active	0	4	2	0	6
	hyperactive	0	0	1	3	4
		16	10	3	3	32

Figure A.25: Activity metric - chat room measurement

Quiz		Data Mining Results				
		dormant	passive	active	hyperactive	
Human Evaluation	dormant	6	0	6	0	12
	passive	0	0	1	0	1
	active	0	6	0	0	6
	hyperactive	0	7	0	6	13
		6	13	7	6	32

Figure A.26: Activity metric - quiz measurement

Whole		Data Mining Results				
		dormant	passive	active	hyperactive	
Human Evaluation	dormant	6	0	0	0	6
	passive	0	4	0	0	4
	active	0	8	8	0	16
	hyperactive	0	1	1	4	6
		6	13	9	4	32

Figure A.27: Activity metric - activity measurement

Navigation		Data Mining Results			
		loner	flamer	socilizer	
Human Evaluation	loner	6	0	0	6
	flamer	8	0	0	8
	socilizer	1	9	8	18
		15	9	8	32

Figure A.28: Social tendency metric - navigation measurement

Presence		Data Mining Results			
		loner	flamer	socilizer	
Human Evaluation	loner	13	4	2	19
	flamer	0	7	2	9
	socilizer	0	2	2	4
		13	13	6	32

Figure A.29: Social tendency metric - presence measurement

Presence		Data Mining Results			
		loner	flamer	socilizer	
Human Evaluation	loner	13	4	2	19
	flamer	0	7	2	9
	socilizer	0	2	2	4
		13	13	6	32

Figure A.30: Social tendency metric - connectedness measurement

Whole		Data Mining Results			
		loner	flamer	socilizer	
Human Evaluation	loner	14	1	1	16
	flamer	0	4	1	5
	socilizer	0	7	4	11
		14	12	6	32

Figure A.31: Social tendency metric - tendency measurement

Activity_reflective		Data Mining Results				
		low	middle	high	super	
Human Evaluation	low	6	9	3	2	20
	middle	0	1	4	0	5
	high	0	2	1	0	3
	super	0	1	1	2	4
		6	13	9	4	32

Figure A.32: Learning style metric - activity vs reflective measurement

Concentration		Data Mining Results				
		low	middle	high	super	
Human Evaluation	low	0	12	0	0	12
	middle	4	5	0	0	9
	high	7	0	2	0	9
	super	0	0	1	1	2
		11	17	3	1	32

Figure A.33: Learning style metric - concentration measurement

Sequential_global		Data Mining Results				
		low	middle	high	super	
Human Evaluation	low	2	8	0	0	10
	middle	0	7	2	0	9
	high	0	1	5	0	6
	super	0	1	5	1	7
		2	17	12	1	32

Figure A.34: Learning style metric - sequential vs global measurement

Whole		Data Mining Results				
		low	middle	high	super	
Human Evaluation	low	9	6	0	0	15
	middle	1	6	2	0	9
	high	0	2	3	0	5
	super	0	1	1	1	3
		10	15	6	1	32

Figure A.35: Learning style metric - style measurement

Usage		Data Mining Results				
		low	middle	high	super	
Human Evaluation	low	6	5	0	0	11
	middle	0	6	7	2	15
	high	0	0	2	1	3
	super	0	0	0	3	3
		6	11	9	6	32

Figure A.36: Knowledge tendency metric - usage measurement

Quiz		Data Mining Results				
		low	middle	high	super	
Human Evaluation	low	6	0	7	0	13
	middle	0	2	0	0	2
	high	0	6	0	0	6
	super	0	6	0	5	11
		6	14	7	5	32

Figure A.37: Knowledge tendency metric - quiz measurement

Whole		Data Mining Results				
		low	middle	high	super	
Human Evaluation	low	9	0	0	0	9
	middle	3	7	0	0	10
	high	0	5	3	0	8
	super	0	1	2	2	5
		12	13	5	2	32

Figure A.38: Knowledge tendency metric - tendency measurement

A.3 Confusion Matrices of Self Evaluation

Navigation		Data Mining Results			
		loner	flamer	socilizer	
Human Evaluation	loner	5	0	1	6
	flamer	1	1	0	2
	socilizer	3	0	3	6
		9	1	4	14

Figure A.39: Social tendency metric - navigation measurement

Presence		Data Mining Results			
		loner	flamer	socilizer	
Human Evaluation	loner	5	0	1	6
	flamer	1	0	2	3
	socilizer	2	1	2	5
		8	1	5	14

Figure A.40: Social tendency metric - presence measurement

Connectedness		Data Mining Results			
		loner	flamer	socilizer	
Human Evaluation	loner	6	0	0	6
	flamer	3	1	2	6
	socilizer	2	0	0	2
		11	1	2	14

Figure A.41: Social tendency metric - connectedness measurement

Activity_reflective		Data Mining Results				
		low	middle	high	super	
Human Evaluation	low	2	3	6	3	14
	middle	0	0	0	0	0
	high	0	0	0	0	0
	super	0	0	0	0	0
		2	3	6	3	14

Figure A.42: Learning style metric - activity vs reflective measurement

Concentration		Data Mining Results				
		low	middle	high	super	
Human Evaluation	low	0	0	0	0	0
	middle	1	4	3	2	10
	high	1	1	1	1	4
	super	0	0	0	0	0
		2	5	4	3	14

Figure A.43: Learning style metric - concentration measurement

Sequential_global		Data Mining Results				
		low	middle	high	super	
Human Evaluation	low	0	1	0	0	1
	middle	1	3	0	0	4
	high	0	0	0	0	0
	super	1	3	2	3	9
		2	7	2	3	14

Figure A.44: Learning style metric - sequential vs global measurement

Usage		Data Mining Results				
		low	middle	high	super	
Human Evaluation	low	0	1	0	0	1
	middle	2	3	1	0	6
	high	1	2	2	2	7
	super	0	0	0	0	0
		3	6	3	2	14

Figure A.45: Knowledge tendency metric - usage measurement

Quiz		Data Mining Results				
		low	middle	high	super	
Human Evaluation	low	0	0	0	1	1
	middle	1	3	0	0	4
	high	0	0	0	1	1
	super	1	1	1	5	8
		2	4	1	7	14

Figure A.46: Knowledge tendency metric - quiz measurement

Whole		Data Mining Results				
		low	middle	high	super	
Human Evaluation	low	0	0	0	0	0
	middle	0	1	0	0	1
	high	3	2	3	0	8
	super	2	2	0	1	5
		5	5	3	1	14

Figure A.47: Knowledge tendency metric - tendency measurement

Appendix B

Self Evaluation Questionnaire

Here, we list the questionnaires that we used in the online course self evaluations. The first part is the consent form, and the second part are questions.

B.1 Consent Form

DEPARTMENT OF COMPUTER SCIENCE

UNIVERSITY OF SASKATCHEWAN
CONSENT FORM

Research Project: Applying Data Mining in E-learning System

Investigators: Dr. Gordon McCalla, Professor, Department of Computer Science, mccalla@cs.usask.ca
Wengang Liu, Department of Computer Science, wel475@mail.usask.ca

____
Name

I hereby agree to participate this survey and give the permission to use the data from this survey only for this research. **I understand None of my identifying information will be shared with anyone outside of the Investigators, in any case. I understand None of information of this survey will be used or linked to my academic or educational records, in any case.**

______________________________ ________________________
Participater Signature Date

Figure B.1: Consent Form

B.2 Questionnaire

1. Please enter NSID.

2. The more time I spent in iHelp Courses, the more I understood.

    (a) strongly disagree

(b) somewhat disagree
(c) neither agree or disagree
(d) somewhat agree
(e) strongly agree

3. I learned from other people's discussion forum postings.
   (a) strongly disagree
   (b) somewhat disagree
   (c) neither agree or disagree
   (d) somewhat agree
   (e) strongly agree
4. I believe I added value to the online discussion forum.
   (a) strongly disagree
   (b) somewhat disagree
   (c) neither agree or disagree
   (d) somewhat agree
   (e) strongly agree
5. I learned from communicating with others in the chat room.
   (a) strongly disagree
   (b) somewhat disagree
   (c) neither agree or disagree
   (d) somewhat agree
   (e) strongly agree
6. I tried to do my best on the practice quizzes.
   (a) strongly disagree
   (b) somewhat disagree
   (c) neither agree or disagree
   (d) somewhat agree
   (e) strongly agree
7. I believe I understood courses materials.
   (a) strongly disagree
   (b) somewhat disagree

(c) neither agree or disagree
(d) somewhat agree
(e) strongly agree

8. My midterm mark was
   (a) ________________
   (b) don't want answer
9. I liked to read discussion forum postings
   (a) not at all
   (b) some of them
   (c) most of them
   (d) most of them and multiple times
10. I answered others' questions in a discussion forum
    (a) no
    (b) yes, if I believed I knew the right answer
    (c) yes, if my answer could make the question more clear
    (d) yes, because I liked to share my opinions
11. I liked to see what people are saying in the chat room
    (a) not at all
    (b) sometimes
    (c) often
12. I liked talking to people in the chat room
    (a) not at all
    (b) sometimes
    (c) often
13. If I had one hour to read course material web pages for a course, I prefer to
    (a) focus on one or two pages to understand them fully
    (b) quickly browse many pages to get the main ideas
14. When learning a new subject for the first time, I prefer to
    (a) work alone
    (b) work with others

(c) both of the above or it depends on the situation

15. When I studied course materials for an exam, I prefer to

    (a) review course materials in order from beginning to end
    (b) review course materials based on what I think is important

16. If I had trouble with a concept I prefered to (please rank in order from most to least prefered)

    (a) ___ re-read the appropriate modules in iHelp Courses
    (b) ___ use iHelp Discussion to get answers from others
    (c) ___ enter iHelp Chat room to talk with others
    (d) ___ contacted the instructor
    (e) ___ look for other sources such as textbook, notes, websites

17. I prefered to do the practice quizzes in the following way:

    (a) first reading the relative pages in order, then doing the quiz
    (b) first doing the quiz, then reading the relative pages
    (c) reading which ever pages I felt like and then doing the quiz

Appendix C

Scripts of Filtering Fact Data

In the data mining approach, we computed the measurements of each metric based on filtered fact data. Here, we list the scripts used to filter the raw data to the fact data.

```
package messages;
/**
 *
 * @author wel475
 *
 */
public class EDMDBMessages {

    private static String pre = "__";

    private static String lcms =  pre + "lcms";
    private static String ihelp = pre + "ihelp";
    private static String discussion = pre + "discussion";
    private static String chat = pre + "chat";

    public static String[] surveyViews = {
        "DROP TABLE IF EXISTS __wel475.n_init;",

        "CREATE TABLE __wel475.n_init ( "
            + "courseid INT, "
            + "packageid INT, "
            + "roleid INT "
            + "); ",

        "INSERT INTO __wel475.n_init (courseid, packageid, roleid) "
            + "VALUES (10, 0, 0), (5,0,0);",


        "CREATE OR REPLACE VIEW __wel475.n_all_learners AS "
            + "SELECT nsid AS userid FROM __wel475._self_evaluation_survey "
            + "UNION "
            + "SELECT nsid AS userid FROM __wel475._self_evaluation_survey_old",

            |
        "CREATE OR REPLACE VIEW __wel475.n_packages_discussId_chatId AS "
            + "SELECT DISTINCT '0' AS packageid, '0' AS discuss_categoryid, channelid AS chat_forumid "
            + "FROM __march2908__courses.__link_content_chat "
            + "WHERE courseid in (SELECT courseid FROM __wel475.n_init)",


        "CREATE OR REPLACE VIEW __wel475.n_contentid_packages AS "
            + "SELECT DISTINCT contentid, courseid "
            + "FROM __march2908__courses.__content "
            + "WHERE courseid in (SELECT courseid FROM __wel475.n_init) ",

        "CREATE OR REPLACE VIEW __wel475.n_dwell_time (userid, contentid, exit_time, enter_time, dwelltime) AS "
            + "SELECT userid, contentid, enter_time AS exit_time, enter_time, '300' AS dwelltime "
            + "FROM __march2908__courses.__user_navigation "
            + "WHERE courseid in (SELECT courseid FROM __wel475.n_init) "
            + "AND userid IN (SELECT userid FROM __wel475.n_all_learners)",
```

Figure C.1: Scripts of filtering fact data part 1

```
"CREATE OR REPLACE VIEW __wel475.n_postings AS "
    + "SELECT * "
    + "FROM  __march2908__discussion.__posting p "
    + "WHERE userid IN (SELECT userid FROM __wel475.n_all_learners)",

"CREATE OR REPLACE VIEW __wel475.n_posting_read AS "
    + "SELECT * "
    + "FROM  __march2908__discussion.__posting_read p "
    + "WHERE userid IN (SELECT userid FROM __wel475.n_all_learners) ",


"CREATE OR REPLACE VIEW __wel475.n_channelid AS "
    + "SELECT DISTINCT name, channelid AS id "
    + "FROM __march2908__courses.__link_content_chat c, __march2908__chat.__channel ch "
    + "WHERE courseid in (SELECT courseid FROM __wel475.n_init) "
    + "AND c.channelid = ch.id ",

"CREATE OR REPLACE VIEW __wel475.n_channel_sentences AS "
    + "SELECT *  "
    + "FROM __march2908__chat.__message " |
    + "WHERE channel_id IN "
        + "(SELECT id FROM __wel475.n_channelid) "
    + "AND username IN "
        + "(SELECT userid FROM __wel475.n_all_learners) ",

"CREATE OR REPLACE VIEW __wel475.n_channel_event AS "
    + "SELECT * "
    + "FROM __march2908__chat.__user_channel_event u "
    + "WHERE channel_id IN "
    +   "(SELECT id FROM __wel475.n_channelid) "
    +   "AND username IN "
    +   "(SELECT userid FROM __wel475.n_all_learners) ",

"CREATE OR REPLACE VIEW __wel475.n_scores AS "
    + "SELECT * FROM __march2908__courses.__user_scored u "
    + "WHERE courseid IN "
    +   "(SELECT courseid FROM __wel475.n_init) "
    + "AND userid IN "
    +   "(SELECT userid FROM __wel475.n_all_learners) "

};
```

Figure C.2: Scripts of filtering fact data part 2

```
/**
 * Those are creating views sql scripts.
 * We don't change them during execution.
 */
public static String[] independentViews = {
    //# Since Create view in a procedure can't include a parameter or variable,
    // so we need create an init table to allow update in the future.
    "DROP TABLE IF EXISTS __wel475.n_init;",

    "CREATE TABLE __wel475.n_init ( "
        + "courseid INT, "
        + "packageid INT, "
        + "roleid INT "
        + "); ",

    "INSERT INTO __wel475.n_init (courseid, packageid, roleid) "
        + "VALUES (27, 433, 3123);",


    //find all students registered in the specific course  since they have a specific role id
    "CREATE OR REPLACE VIEW __wel475.n_all_learners AS "
        + "SELECT userid FROM " + ihelp + ".__summary_user_role s "
        + "WHERE admins = 'N' AND roleid = "
        + "(SELECT roleid FROM __wel475.n_init) "
        + "UNION "
        + "SELECT userid FROM " + ihelp + ".__link_user_role s "
        + "WHERE roleid = "
        + "(SELECT roleid FROM __wel475.n_init)",

    // find all packages, discuss_categoryid, and chat_forumid
    "CREATE OR REPLACE VIEW __wel475.n_packages_discussId_chatId AS "
        + "SELECT DISTINCT packageid, discuss_categoryid, chat_forumid "
        + "FROM " + lcms + ".__course_content c "
        + "WHERE courseid = (SELECT courseid FROM __wel475.n_init)",

    // find all content id
    "CREATE OR REPLACE VIEW __wel475.n_contentid_packages AS "
        + "SELECT DISTINCT contentid, packageid "
        + "FROM " + lcms + ".__course_content c "
        + "WHERE courseid = (SELECT courseid FROM __wel475.n_init)",

    // calculate dwell time for each navigation in whole session
    "CREATE OR REPLACE VIEW __wel475.n_dwell_time (userid, contentid, exit_time, enter_time, dwelltime) AS "
        + "SELECT userid, contentid, exit_time, enter_time, IF(exit_time='0000-00-00 00:00:00',0,"
        + "TIME_TO_SEC(TIMEDIFF(exit_time, enter_time))) AS dwelltime "
        + "FROM " + lcms + ".__user_navigation n "
        + "WHERE courseid = (SELECT courseid FROM __wel475.n_init) "
        + "AND userid IN (SELECT userid FROM __wel475.n_all_learners) ",
```

Figure C.3: Scripts of filtering fact data part 3

```
//find out all posting id for a course id
"CREATE OR REPLACE VIEW __wel475.n_categoryid_postid AS "
    + "SELECT postingid, categoryid "
    + "FROM " + discussion + ".__link_posting_category l "
    + "WHERE categoryid IN "
    + " (SELECT discuss_categoryid FROM __wel475.n_packages_discussid_chatid) ",

//# filter postings that written by learners
"CREATE OR REPLACE VIEW __wel475.n_postings AS "
    + "SELECT * "
    + "FROM " + discussion + ".__posting p "
    + "WHERE postingid IN "
    + " (SELECT postingid FROM __wel475.n_categoryid_postid) \t"
    + "AND userid IN  \t"
    + " (SELECT userid FROM __wel475.n_all_learners) ",

// filter out the information that learners read postings
"CREATE OR REPLACE VIEW __wel475.n_posting_read AS "
    + "SELECT * "
    + "FROM " + discussion + ".__posting_read p "
    + "WHERE postingid IN  "
    + " (SELECT postingid FROM __wel475.n_categoryid_postid) "
    + "AND userid IN "
    + " (SELECT userid FROM __wel475.n_all_learners) ",

//# find out channel id for a course
"CREATE OR REPLACE VIEW __wel475.n_channelid AS "
    + "SELECT * "
    + "FROM " + chat + ".__channel c "
    + "WHERE name IN  "
    + " (SELECT chat_forumid FROM __wel475.n_packages_discussid_chatid) ",

//# filter out all sentences for a course
"CREATE OR REPLACE VIEW __wel475.n_channel_sentences AS "
    + "SELECT *  "
    + "FROM " + chat + ".__message "
    + "WHERE channel_id IN "
    + " (SELECT id FROM __wel475.n_channelid) "
    + "AND username IN "
    + " (SELECT userid FROM __wel475.n_all_learners) ",

//# all channel events

"CREATE OR REPLACE VIEW __wel475.n_channel_event AS "
    + "SELECT * "
    + "FROM " + chat + ".__user_channel_event u "
    + "WHERE channel_id IN "
    +   "(SELECT id FROM __wel475.n_channelid) "
    +   "AND username IN "
    +   "(SELECT userid FROM __wel475.n_all_learners) ",
```

Figure C.4: Scripts of filtering fact data part 4

```java
/**
 * Those are creating views with packages options of sql scripts.
 */
private static String[] independentPackagesViews = {
    // filter out dwell time for one specific package id
    "CREATE OR REPLACE VIEW __wel475.n_dwell_time_package AS "
        + "SELECT * "
        + "FROM __wel475.n_dwell_time d "
        + "WHERE contentid IN "
        + "(SELECT contentid FROM __wel475.n_contentid_packages c WHERE packageid = "
        + " (SELECT packageid FROM __wel475.n_init)) ",

    // find out all posting id for a package
    "CREATE OR REPLACE VIEW __wel475.n_categoryid_postid_package AS "
        + "SELECT * "
        + "FROM __wel475.n_categoryid_postid "
        + "WHERE categoryid = "
        + " (SELECT discuss_categoryid FROM __wel475.n_packages_discussid_chatid WHERE packageid = "
        + "     (SELECT packageid FROM __wel475.n_init)) ",

    //filter out postings that belongs to one package
    "CREATE OR REPLACE VIEW __wel475.n_postings_package AS "
        + "SELECT * "
        + "FROM __wel475.n_postings p "
        + "WHERE postingid IN "
        + "(SELECT postingid FROM __wel475.n_categoryid_postid_package) ",

    //filter out the information that learners read postings for one package
    "CREATE OR REPLACE VIEW __wel475.n_posting_read_package AS "
        + "SELECT * "
        + "FROM __wel475.n_posting_read "
        + "WHERE postingid IN "
        + " (SELECT postingid FROM __wel475.n_postings_package) ",

    //# find out channel id for one package
    "CREATE OR REPLACE VIEW __wel475.n_channelid_package AS "
        + "SELECT * "
        + "FROM __wel475.n_channelid "
        + "WHERE name = "
        + " (SELECT chat_forumid FROM __wel475.n_packages_discussid_chatid "
        + " WHERE packageid = (SELECT packageid FROM __wel475.n_packageid)) ",

    //# filter out all sentences for a package
    "CREATE OR REPLACE VIEW __wel475.n_channel_sentences_package AS "
        + "SELECT * "
        + "FROM __wel475.n_channel_sentences "
        + "WHERE channel_id =  "
        + " (SELECT id FROM __wel475.n_channelid_package) ",

};
```

Figure C.5: Scripts of filtering fact data part 5

```java
/**
 * This method returns all views that we need update them during execution time.
 * @param dependentFactor current working target
 * @return updated statements
 */
public static String[] getDependentViews(String dependentFactor){

    String[] dependentViews = {
    //# Join togeter user and content
    "CREATE OR REPLACE VIEW __wel475.n_join_user_content (userid, navigatetimes, contentnum, dwelltime) AS "
        + "SELECT n.userid, IF(c.navigatetimes, c.navigatetimes, 0), IF(c.contentnum, c.contentnum, 0),"
        + "IF(c.dwelltime, c.dwelltime, 0) "
        + "FROM __wel475.n_all_learners n "
        + "LEFT JOIN __wel475.r_sum_contents" + dependentFactor + " c "
        + "ON n.userid = c.userid ",

    //Join together user and writing posting messages
    "CREATE OR REPLACE VIEW __wel475.n_join_user_postings_write AS "
        + "SELECT n.userid AS userid, IF(c.totalmsg,c.totalmsg,0) AS totalmsg, IF(c.replymsg,c.replymsg,0) "
        + "AS replymsg, IF(c.newmsg,c.newmsg,0) AS newmsg "
        + "FROM __wel475.n_all_learners n "
        + "LEFT JOIN __wel475.r_sum_postings" + dependentFactor + "  c "
        + " ON n.userid = c.userid ",

    // Join together user and reply frequece
    "CREATE OR REPLACE VIEW __wel475.n_join_user_reply AS "
        + "SELECT n.userid AS userid, IF(c.reply_frequency, c.reply_frequency, 0) AS replyfrequency, "
        + "IF(c.reply_scale, c.reply_scale, 0) AS replyscale "
        + "FROM __wel475.n_all_learners n "
        + "LEFT JOIN __wel475.r_sum_reply" + dependentFactor + "  c "
        + "ON n.userid = c.userid ",

    //# Join together user and reading posting messages
    "CREATE OR REPLACE VIEW __wel475.n_join_user_postings_read "
        + " (userid, readingtimes, readpostingnum)  AS "
        + "SELECT n.userid, IF(c.readingtimes, c.readingtimes, 0), IF(c.postingnum, c.postingnum, 0) "
        + "FROM __wel475.n_all_learners n "
        + "LEFT JOIN __wel475.r_sum_postings_read" + dependentFactor + " c "
        + "ON n.userid = c.userid",

    //# join together user and chat channels
    "CREATE OR REPLACE VIEW __wel475.n_join_user_channel "
        + " (userid, sentnum, chatnum) AS "
        + "SELECT n.userid, IF(c.sentnum, c.sentnum, 0), IF(c.chatnum, c.chatnum, 0) "
        + "FROM __wel475.n_all_learners n "
        + "LEFT JOIN __wel475.r_sum_channel" + dependentFactor + " c "
        + "ON n.userid = c.userid ",
```

Figure C.6: Scripts of filtering fact data part 6

```
//# Join together user and quizs
"CREATE OR REPLACE VIEW __wel475.n_join_user_scores "
    + "(userid, scoretimes, scorescale, scores) AS "
    + "SELECT n.userid, IFNULL(c.score_times, 0), IFNULL(c.score_scale, 0), IFNULL(scores, 0) "
    + "FROM __wel475.n_all_learners n "
    + "LEFT JOIN __wel475.r_sum_scores" + dependentFactor + " c "
    + "ON n.userid = c.userid ",

// concentration
"CREATE OR REPLACE VIEW __wel475.n_sum_concentration "
    + "(userid, total, high, middle, low, undefined) "
    + "AS "
    + "SELECT userid, COUNT(concentration), SUM(IF(concentration = 'Hight', 1, 0)), "
    + "SUM(IF(concentration = 'Middle', 1, 0)), SUM(IF(concentration = 'Low', 1, 0)), "
    + "SUM(IF(concentration = 'undefined', 1, 0)) "
    + "FROM __wel475._seq_code" + dependentFactor + "  "
    + "GROUP BY userid ",

// join concentration
"CREATE OR REPLACE VIEW __wel475.n_join_user_concentration "
    + "(userid, total, high, middle, low, undefined) "
    + "AS "
    + "SELECT n.userid, IFNULL(c.total, 0), IFNULL(c.high, 0), IFNULL(c.middle, 0), "
    + "IFNULL(c.low, 0), IFNULL(c.undefined, 0) "
    + "FROM __wel475.n_all_learners n "
    + "LEFT JOIN __wel475.n_sum_concentration c "
    + "ON n.userid = c.userid ",

// sequential
"CREATE OR REPLACE VIEW __wel475.n_sum_sequential "
    + "(userid, global, events, focus, unchange) "
    + "AS "
    + "SELECT c.userid, COUNT(c.event), SUM(c.count), SUM(c.count) - SUM(c.scale), "
    + "SUM(IF(c.unchange = 'true', 1, 0)) "
    + "FROM __wel475._seq_event" + dependentFactor + " c "
    + "GROUP BY c.userid ",


// join sequential
"CREATE OR REPLACE VIEW __wel475.n_join_user_sequential "
    + "(userid, global, events, focus, unchange) "
    + "AS "
    + "SELECT n.userid, IFNULL(c.global, 0), IFNULL(c.events, 0), "
    + "IFNULL(c.focus, 0), IFNULL(c.unchange, 0) "
    + "FROM __wel475.n_all_learners n "
    + "LEFT JOIN __wel475.n_sum_sequential c "
    + "ON n.userid = c.userid "

};
```

Figure C.7: Scripts of filtering fact data part 7

Appendix D

Fact data to Measurements and Metrics

We used Weka clustering algorithms to compute the measurements and metrics from the fact data. Here are the fact data elements that clustering algorithms used to mine the measurements.

Fact Data		Measurements
navigatetimes, contentnum, dwelltime	====>	navigating contexts
dwelltime	====>	dwell time
totalmsg, replymsg, newmsg, readingtimes, readpostingnum	====>	discussion
readingtimes, rea,dpostingnum	====>	read in discussion
totalmsg, replymsg, newmsg	====>	write in discussion
sentnum, chatnum, event, joined, focused	====>	chat
scoretimes, scorescale, avgscore	====>	quiz
navigatetimes, contentnum, dwelltime, totalmsg, replymsg, newmsg, readingtimes, readpostingnum, sentnum, chatnum, scoretimes, scorescale, avgscore	====>	whole

Figure D.1: Activity metric

Fact Data		Measurements
readingtimes, readpostingnum, chatevent, chatjoin	====>	navigation
totalmsg, replymsg, newmsg, sentnum, chatnum	====>	presence
replyfrequency, replyscale, sentnum, focused	====>	connectedness
readingtimes, readpostingnum, event, joined, totalmsg, replymsg, newmsg, sentnum, chatnum, focused	====>	whole

Figure D.2: Social tendency metric

Fact Data		Measurements
navigatetimes, contentnum, dwelltime, totalmsg, replymsg, newmsg, readingtimes, readpostingnum, sentnum, chatnum, scoretimes, scorescale, avgscore	====>	active_reflective
total, high, middle, low, undefined	====>	concentration
global, globalize, focus, focuslize, unchange	====>	sequential_global
navigatetimes, contentnum, dwelltime, totalmsg, replymsg, sentnum, total, high, middle, global, focus, unchange	====>	whole

Figure D.3: Learning style metric

Fact Data		Measurements
dwelltime, total, high, low, unchange	====>	context
scoretimes, avgscore, unchange	====>	quiz
dwelltime, total, high, scoretimes, socres, unchange	====>	whole

Figure D.4: Knowledge tendency metric