Intervention and strategy analysis for web group-learning

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Abstract  Owing to the lack of face-to-face interactions, students using a web-based learning system are likely to study alone and with relatively little classmate support and pressure. Teachers in a web-based learning system may apply a group-learning model to overcome this problem. Teachers first need to organise, manage and monitor the group learning and they must take appropriate actions based on teaching strategies to improve the learning achievements of the students. To perform these tasks effectively, teachers must obtain relevant information by analysing the huge volume of web-access logs or by monitoring web interactions. This paper presents novel methodologies for developing instruments to assist teachers in performing intervention and strategy analysis. The proposed methodologies apply data mining tools provided by existing database management systems. Database techniques, including the multi-dimensional cube, are then applied to make student web logs meaningful and helpful to teachers in managing group learning. The associate rule mining tool is finally employed to assist teachers in analysing their pedagogical strategies. These tools relieve teachers of tedious data collection and analysis, allowing them to focus on managing the groups to promote students’ learning achievement.

Keywords:  Database; Data mining; Discourse analysis; Group; Internet; Intervention; Post-secondary; World-wide web

Introduction

Group-learning (Webb, 1989; Bricker et al., 1995; Monaghan & Clement, 1995) is an important approach widely employed to evaluate the success of an on-line course (Duin & Hansen, 1994). Johnson & Johnson (1991) indicate that students learn better when they learn together. The group-learning model is even more important for a web-based learning environment because the students cannot interact with teachers and classmates face-to-face. Moreover, a teacher in a web-based environment faces more difficulties in intervening with and observing students than a teacher in a traditional classroom. The teacher must attempt to manage and detect the learning situation by analysing web interaction logs. Thus, software instruments for managing group learning are important when implementing a web-based learning system (Kimball, 1995).
Several renowned group-learning models have been proposed in computer-based cooperative learning (Reinhard et al., 1994; Shotsberger et al., 1995). Those models have also been applied in network-based distance learning systems (Collis et al., 1997; Heeren, 1996). Without the possibility of obtaining relevant information through face-to-face interactions with students, teachers face difficulties in controlling and managing the learning progress of individuals and groups. The teachers do not know who to focus on, when to intervene and what to do to promote student learning achievement.

However, few effective methodologies are available for helping teachers in observing and managing group-learning activities on web-based learning systems. Particularly, in order to observe the learning of an individual student and the interactivity of a learning group, teachers must spend considerable time in analysing and searching for relevant or significant learning events from the vast and unorganised web log. Furthermore, the abnormal learning situations, such as students with low motivation in on-line discussion with teammates must be detected early (Ou et al., 1998; Waugh, 1996), so that the teacher can intervene promptly to help or encourage students.

To perform these tasks, teachers must expend considerable effort. Thus, the benefits of group learning may not be achieved without appropriate tools for assistance. When applying and managing group learning on a network-based system, teachers need to tackle the following two issues:

• Observation and intervention: To provide timely help for students, teachers may define specific situations of which they want to be notified so as to act accordingly. The situations involved are termed abnormal learning situations and include students rarely joining their group discussions or not participating in group tasks (Udvari-Solner, 1994). In such situations, teachers must intervene promptly to encourage or motivate the students, rather than discovering these situations at the end of the semester (Slavin, 1990).

• Discovery of the relationship between impact factors and learning situation: Collis et al. (1997) have identified some of the major instructional strategies for web-based group learning. The factors that impact intragroup and intergroup learning situations differ from course to course. Teachers must analyse the relationship between potential influences, such as teaching strategies and the learning context. However, lacking the information gained from interaction with students in classroom teaching, teachers face difficulties in adapting their instructional strategies to promote student learning. Thus, web-based teachers require tools to help them.

Owing to the difficulty in interpreting a web-based learning log, a feature space mapping mechanism for teachers was developed. This mechanism permits teachers to observe and understand student learning behaviour and data is then recorded in an unorganised web log in terms of features defined by themselves. Additionally, the relationships between students, strategies and learning outcomes are also represented in terms of the teacher-defined features. These relationships are represented in the form of association rules (Agrawal et al., 1996). Teachers can define the interesting features and abnormal learning situations which need to be observed. When a defined abnormal learning situation occurs, the tool will notify the teachers, allowing them to intervene immediately and offer assistance. In addition, teachers must
analyse the relationships between impacting factors, learning outcomes and learning features. However, applying the association rule mining tool will always produce numerous associated rules. Thus, the *meta-rule guided mining* technique (Han et al., 1996) is adopted to help teachers seek meaningful and interesting rules from the numerous associated rules derived from association mining tools.

The work described in this paper involves design methodologies to offer tools to assist teachers in observing, maintaining and motivating students in a web-based group-learning system by using data mining tools provided by database management systems. The experimental results demonstrate that these tools provide teachers with useful information derived from the profile and learning logs of students. Thus, they can reduce the load on teachers in managing web-based group-learning activities. The result of the questionnaire indicates that students were more motivated to learn and cooperated better with other group members. Group learning and using the assistance tools developed, significantly reduced the drop out rate in an experimental class on a Human-Computer Interface (HCI) course with 82 students at the National Open University in Taiwan. The support tools also provide information required for a teacher to manage group learning. Some of the data mining techniques employed in this study are now described.

**Applying data mining techniques to extract information for teachers**

The methodologies proposed adapted data mining tools provided by existing database management systems to overcome the issues identified above. *Data Mining* is one step involved in *Knowledge Discovery in Databases (KDD)* (Elder & Pregibon, 1996). Data mining attempts to search for specific, interesting and unknown patterns in a vast database (Zaïane et al., 1998) and was used in the web-based distance-learning environment to locate pertinent information and reduce the management burden of teachers. Two of the data mining techniques used in this work are introduced here: the *associated rules mining technique* (Agrawal et al., 1996) is employed for teachers in observing and intervening in the learning process, and the *meta-rule guided mining technique* (Kamber et al., 1997) is employed to identify potential influences on the learning situation or the effectiveness of the strategies.

**Associated rules**

Associated rules present the causal relationship between several events and factors. Meanwhile, the mining association rules define a set of rules of the following form:

\[
A_1 \land A_2 \land \ldots \land A_m \Rightarrow B_1 \land B_2 \land \ldots B_n
\]

where \(A_i\) (for \(i \in \{1, \ldots, m\}\)) and \(B_j\) (for \(i \in \{1, \ldots, n\}\)) and where \(A_i\) and \(B_j\) are the disjoint itemset in a database.

An *itemset* is a set of database records, which may be student profiles, learning actions or learning states. Meanwhile, an association rule comprises relative itemsets. An example of an association rule discovered in the system described as ‘if there is a student who is enthusiastic in provoking discussion within his group, the average grade of the group is usually high and is highly possible in completing the group assignments’. The formal expression of this association rule is as follows:

< group with a enthusiastic discussion invoker > \((A_i)\)

< the average grade is high > \((B_j)\) \& < the group complete group assignments > \((B_k)\)

Some terms relating to associated rule mining are: the support of an itemset is the fraction of the number of the itemset to the number of records in the containing database; the confidence of this association means the support of A of B divided by the support of A.

In the example above, the user may define the minimum support as 10% and the confidence as 85%. Such a definition implies that if the association rule holds, the following two conditions also hold:

- for 10% support: at least 10% of the groups in the database meet at least one of the three following conditions:
  - 'the group contains a member who actively provokes discussion' (A);
  - 'the group grade in leader groups' (B1);
  - 'finally succeed in the group tasks' (B2).
- for 85% confidence: at least 85% of the groups contain a discussion invoker (A), and have a high group average grade (B1) and complete group assignments (B2).

The support parameter is considered as an indicator of the reliability of the sample data. Meanwhile, the confidence parameter is considered as an indicator of the reliability of the discovered rules.

Meta-rule guided mining

A meta-rule guided data mining (Kamber et al., 1997) approach is proposed for finding multiple level association rules in large relational databases. Its template form is \( P_1 \land P_2 \land \ldots \land P_m \rightarrow Q_1 \land Q_2 \land \ldots \land Q_n \), where \( P_i \) (for \( i = 1 \) to \( m \)) and \( Q_j \) (for \( j = 1 \) to \( n \)) are either instantiated predicates or predicate variables.

To demonstrate how the meta-rule-guided techniques can be used, a database recording a previous HCI course, held in the autumn of 1998, is described. The following tables summarise several student profiles and learning logs on the web recorded in a relational database.

Original Data Schema and Aggregates:

| T1: Students (sid, name, birth_date, gender, education, cs_ability, group_id, att) |
| A1: Discussion(sid, ask_num, read_num, reply_num, since_date) |
| T2: Event(event_id, date, from_ip) |

T1 is the student profile table recording: \( sid \) (student ID); \( birth \_ date \), gender, education, cs_ability (computer skills), group_id, and att (learning characteristics). A1 is a view of aggregate query results that stored the total number of discussions. Meanwhile, T2 stores instructional and learning events of teachers and students.

A multidimensional query example of the study database is presented in follows:

\[ Q2: \text{Discover rules in the form of} \]
\[ \text{gender}(s:\text{Students.x}) \land Q(e:\text{Event.y}) \land R(d:\text{Discussion.z}) \]
\[ \text{From Students, Event_account.y, Discussion} \]
\[ \text{Where d.since_date > e.date in relevance to ALL} \]

The query (Q2) aims to discover the relationship between Student, Event, and Discussion. The variables \( x, y, z \) are attributes of three tables/views in the database, and the consequent is the amount of discussion since the event occurred. For example, when a teacher issues a question that should be answered within a time constraint in the discussion forum, it was discovered that male students appear to increase their level of reading and replying in the Discussion forum on the same day. The discovered rule is presented as follows:

\[ M1: \text{gender(s."male")} \land \text{event(e."timing_constrain_q")} \land \text{Discussion(d."inc_discuss")} \] (82%)

The next example (M2) illustrates a rule discovered in a group-learning experimental class: ‘if the group read amount significantly exceeds reply amount in the group discussion forum, there are 62% confidence in predicting that the group work is possibly failing’.

\[
\text{M2: } \text{Group Discussion(gd."read much more than reply") } \Rightarrow \text{Group Work(gw."Grade Failed") (62\%)}
\]

With the meta-rule guided mining method, teachers can attempt to discover the possible reasons for the learning attributes of students changing. One example is that M1 must explain the ‘inc_discuss’ feature, which refers to the increased amount of discussion after an event occurs. Another example is finding the reason for the ‘read much more than reply’ feature in M2. Having found the reasons for these two features, teachers could devise instructional strategies based on the discovered rules and act appropriately. The feature space concept will be introduced below and assists teachers to define learning features.

**Instruments to assist instructional management**

An analysis of instructional strategies, observation and intervention lead to a definition of instruments to support instructional management. The observation tool supports teachers in monitoring the learning situation and intervening promptly in the learning process. Simultaneously, the feature space concept allows teachers to define hierarchical learning features when observing the learning situation. Finally, the meta-rule guided mining method helps teachers to discover the relationship between impact factors and the learning situation. Thus, the devised rules offer guidelines for teachers to improve their teaching strategies for the next semester.

**Observation and intervention support**

One method of observing the learning behaviour of students on the Internet is to analyse the learning log. In a web-based learning system, the learning behaviours of all the students are recorded in the web log database. However, it is difficult for a teacher to discover the learning status of students from the web log. Usually, teachers face difficulties in locating the interesting events without the assistance of the website manager (Chang et al., 1998).

The feature space concept is proposed to transform an unorganised web log into information in terms familiar to teachers and is intended to present meaningful and clear information to assist teachers in detecting abnormal learning situations. The support tool is constructed based on the feature space and detects abnormal situations and reports to teachers, thus allowing them to intervene in student learning or change instructional strategies to promote learning performance as appropriate.

The feature space is constructed as a hierarchy of rules representing different levels of a learning situation. The features of a lower level are close to raw materials in the web log. Meanwhile, the features of a higher level represent more abstract information that is closer to the terms understood by teachers.

It is supposed that web-site managers maintaining the learning web-site understand the data structure of the web log and can define the lowest level learning features (Level-1) based on the structure of the web logs and database used by teachers. Web-site managers are necessary because most teachers do not understand the construction of web pages and database schema. The work of web-site managers allows teachers to define higher level features by combining the existing features.
defined by these web-site managers. Example features are shown in the tables.

**Table 1. Level-1: the lowest level of features defined by the web-site manager**

<table>
<thead>
<tr>
<th>Feature id</th>
<th>Feature name</th>
<th>Total degrees</th>
<th>Range</th>
<th>Abnormal</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.1</td>
<td>Login account</td>
<td>5</td>
<td>0 – MAX</td>
<td>--</td>
</tr>
<tr>
<td>1.2</td>
<td>Homework grades</td>
<td>5</td>
<td>0 – 100</td>
<td>--</td>
</tr>
<tr>
<td>1.3</td>
<td>Gender</td>
<td>2</td>
<td>1 – 2</td>
<td>--</td>
</tr>
<tr>
<td>1.4</td>
<td>Reply in discussion</td>
<td>5</td>
<td>0 – MAX</td>
<td>--</td>
</tr>
<tr>
<td>1.5</td>
<td>Read in discussion</td>
<td>5</td>
<td>0 – MAX</td>
<td>--</td>
</tr>
</tbody>
</table>

In Level-1 (Table 1), the web manager defined several low level feature spaces of a specific course. These feature spaces include:

- learning behaviour: number of login times (Feature 1.1), number of replies to messages (Feature 1.4) and number of messages read (Feature 1.5)
- personal profile: gender (Feature 1.3)
- portfolio: homework grades (Feature 1.2) and so on.

The total degree column indicates the number of periods by which the value this feature is divided.

Taking Feature 1.1 as an example: the number of login times is divided into five segments with the top 20% being assigned the degree of 5. Meanwhile, **number of login times** in the last 20% is assigned as degree 1. Generally, it is recommended that the value is always divided into 5 segments since this can give the teacher a uniform idea of the meaning. The **range** column presents the maximum and minimum value of each feature. However, not all of the features have a numerical value, for example the gender{male, female} feature. In these cases the web-site manager will transfer them into numeral code (such as, gender{1, 2}).

Following the definition of the entire Level-1 feature space, teachers can construct their own higher level feature space. The higher level feature space can be defined based on definitions of the lower level features. In this case, all the features of Level-2 (Table 2), can be constructed based on a single feature of Level-1. For example, the teacher constructed the feature named as ‘login frequently’ from feature 1.1, degree 5, and set the abnormal attribute as ‘N’ (not). Furthermore, the teacher also constructed the features named as ‘login seldom’ from Feature 1.1, degree 1, and set the abnormal attribute as ‘Y’ (yes). When a student exhibits the features selected as abnormal attributes (i.e. ‘Y’), the system will notify the teachers.

**Table 2. Level-2: defined by teachers combined from Level-1 only.**

<table>
<thead>
<tr>
<th>Feature id</th>
<th>Feature name</th>
<th>Combination</th>
<th>Operations</th>
<th>Abnormal</th>
</tr>
</thead>
<tbody>
<tr>
<td>2.1</td>
<td>Login frequently</td>
<td>1.1</td>
<td>5</td>
<td>N</td>
</tr>
<tr>
<td>2.2</td>
<td>Login seldom</td>
<td>1.1</td>
<td>1</td>
<td>Y</td>
</tr>
<tr>
<td>2.3</td>
<td>Homework success</td>
<td>1.2</td>
<td>5</td>
<td>N</td>
</tr>
<tr>
<td>2.4</td>
<td>Seldom reply in discussion</td>
<td>1.4</td>
<td>1</td>
<td>Y</td>
</tr>
<tr>
<td>2.5</td>
<td>Prefer reading in discussion</td>
<td>1.5</td>
<td>5</td>
<td>N</td>
</tr>
</tbody>
</table>

In Level-3, teachers defined the features termed ‘observer in discussion’ based on features 2.1, 2.4 and 2.5 (Table 3).
Observer in discussion describes students who login frequently, but seldom respond to questions from their classmates and read frequently in the discussion place. When a student falls into this category, the tool will notify the teachers because it is defined as an abnormal feature. Figure 1 gives an example hierarchy of a feature space: the operations of the feature space include AND, OR, and NOT. The definition and operations of the feature space permit teachers to define the learning events of interest individually. After defining the feature space, rules of interest could be extracted through association rule mining.

Discovering relationships between impact factors and learning situation support

The meta-rule guided mining algorithm can help teachers discover the possible causes and effects of learning situations. Teachers can attempt to find the possible factors that may result in an abnormal learning situation in the process of group learning, rather than at the end of a semester. They can then take proper actions to encourage student participation and promote learning according to the result of analysing the relationship of these factors. Moreover, a teacher can apply meta-rule guided mining to analyse relationships among learning behaviours and outcome in terms of teacher defined features. In the HCI course, teachers defined some of the feature space in Level-2: GROUP_READ_LESS means the total reading amount of a group is less than the average of all the groups; GROUP_REPLY_LESS means the total replies of a group is less than the average of all the groups; and the GROUP_READ_MUCH_MORE_THAN_REPLY means the group only writes a message after reading 10 or more. These kinds of patterns indicate that group members are reticent and contribute little themselves, instead members of the group prefer reading the discussion to writing. The last (MID_EXAM_GRADE FAILED) feature in Level-2 means the student fails to meet the exam criterion.

In Table 4, the system determined the possible factors relating to group discussion that caused the group to fail. The possible factors included: GROUP_READ_LESS, GROUP_REPLY_LESS and GROUP_READ_MUCH_MORE_THAN_REPLY, and...
or

MID_EXAM_FAILED.

Then teachers defined the new feature in Level-3 and set abnormal alert: GROUP_DISCUSSION_FAILED, which means that if one of the above features occurred, the group has great potential of failure in group discussion. Then, the system will email teachers and report the abnormal performance.

Table 4. The example of feature space of Level-2 and Level-3

<table>
<thead>
<tr>
<th>Level 2:</th>
</tr>
</thead>
<tbody>
<tr>
<td>Group_Read &lt; average(total_read)*30% ⇒ GROUP_READ_LESS</td>
</tr>
<tr>
<td>Group_Reply &lt; average(total_reply)*30% ⇒ GROUP_REPLY_LESS</td>
</tr>
<tr>
<td>Group_of_(Post/read) &lt; 0.1 ⇒ GROUP_READ_MUCH_MORE_THAN_REPLY</td>
</tr>
<tr>
<td>Grade &lt; 60 ⇒ MID_EXAM_GRADE_FAILED</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Level 3:</th>
</tr>
</thead>
<tbody>
<tr>
<td>(GROUP_READ_LESS AND GROUP_REPLY_LESS</td>
</tr>
<tr>
<td>AND GROUP_READ_MORE_THAN_REPLY)</td>
</tr>
<tr>
<td>OR</td>
</tr>
<tr>
<td>MID_EXAM_GRADE_FAIL ⇒ GROUP_DISCUSSION_FAILED (alert)</td>
</tr>
</tbody>
</table>

System implementation

A learning system that demonstrates the feasibility of the proposed methodologies and tools has been implemented. This system employed the Microsoft Internet Information Server™ (IIS) as the web-server, the Oracle™ DBMS 8.0 as the database in the Windows NT4.0 platform. All the applications on the server were written in Microsoft Active Server Page (ASP) programs.

The web-based learning system provides the teachers with support tools described in three main components. The first component is to construct a web group-learning system that records the learning behaviours and profiles of all the students in a database. In the second component, teachers must define all the learning situations in the higher level learning feature space based on the Level-1 features defined by the web manager. Finally, in the third component, teachers need to define an abnormal learning situation and discover the relationship and factors of the specific situation. The system will analyse the relationships between the learning logs and defined feature space, and attempt to discover the relevant association rules and abnormal learning situation, and then report to teachers by email. With the help of the information provided by the third component, teachers could apply proper instructional strategies and observe their effect. The following paragraphs describe these three primary components in more detail.

Component 1: Access log recording

Many factors may affect the learning performance of students. The system described here collected three primary dimensions of raw data: student profiles; learning log and curriculum pages. All of these data are stored in a database. The student profiles include the name, identity number, gender, age, education, and computer network skills. The learning log includes the access logs and actions taken by students on the web, thus implying the learning path. Meanwhile, the curriculum pages are representations of each location of the learning material web pages by a name of the curriculum context. For example, a page location:

http://vc.csie.ncu.edu.tw/ncu/credit/sub_homework.asp?hid=3&cid=157

is not easy for teachers to relate to the words ‘submit homework 3 of the HCI
Thus, the web manager will transfer these curriculum page locations into related phrases that are more readable to teachers. After the collection of all the three primary row data, teachers could define the learning features space via a web–based user interface in component 2.

Component 2: The definition and operations of feature space

After the server logs the profiles, learning paths and actions of the students, the feature-space mapping tool can assist teachers in extracting interesting and meaningful information from the vast of array of data. Teachers can select the interesting Level-1 data from the left window, and regulate the division value of each Level-1 data value into several degrees. For example, the extent of discussion in the group discussion place can be divided into three degrees, namely high (> 80% of average), average (> 50% of average and <= 80% of average), and low (<= 50% of average).

Once Level-1 data is defined, teachers can combine several Level-1 features into Level-2 features and so on. Figure 2 illustrates the feature-space mapping tool.

Component 3: Observation and strategies analysis tools

After defining features that teachers are interested in, the system provides a report about the learning situation of groups and students. A tool is also provided for observing student behaviour. The observation tool can detect abnormal learning performance and suggest possible explanations. Teachers then determine the instructional strategies to apply accordingly, and can promptly intervene in the learning process. In component three, two management tools were supported for observation and intervention:

- **Instructional observation and intervention tool:** When specific abnormal performance occurs and is detected by the system, the teachers will be informed. With the help of the feature space and the abnormal notification mechanism, teachers can reduce the effort in observing learning performance, and can intervene in the learning process of students at the right time.

- **Learning performance analysis tool:** This tool analyses all the learning records and provides information in terms of defined features. Teachers must determine the factors influencing learning performance. The relationship between learning
impact factors and learning outcome, allows teachers to reduce their efforts and increase their effectiveness in making instructional teaching decisions. When an abnormal learning situation occurs, the system will perform an ‘UPDATE’ operation to update the abnormal attribute in the database and make a database trigger at the same time. The Oracle database trigger system allows users to define relative procedures and is executed automatically. These predefined procedures will give a notification to teachers via email and a pop-up window in the web browser.

DBMiner (Han, 1996) is a commercial data mining system developed at Simon Fraser University, Canada. It helps the database administrator to mine out the meaningful information in a large amount of raw data. One of the functions in DBMiner is to discover the causal relationships between the raw data and the defined associated rules. However, the operation of associated rule mining in DBMiner is too difficult to use and the volume of mining results may be too huge to be handled by teachers. This research transferred the raw data of learning logs into the concepts of learning feature space and then mined these features with DBMiner.

Figure 3 illustrated that the learning feature space is both the input and output of DBMiner. In other words, teachers’ only need to handle information in terms of the meaningful features instead of the meaningless raw data in database. Therefore, the mining results are easily be recognised by teachers and assist teachers to make teaching decisions.

**Results and discussion**

This section presents some results of applying the proposed system to the HCI web-based distance learning course. The experimental result demonstrates the efforts of teachers in managing the learning environment are reduced, while the assistance tools successfully supported the observation of abnormal learning situations. Thus, teachers could intervene to assist students in group-learning. Finally, the learning performance analysis tools identified the relationships between impact factors and an abnormal learning situation in group learning, thus allowing teachers to improve their teaching strategies based on the derived rules.

The experimental HCI course involved 82 students (35 female and 47 male) with four or five students in each group and two teachers. The age spread was from 25 to 59 years with the average age being 35.3 years. Their educational backgrounds were spread from elementary school to bachelor degree. The students were grouped randomly.

**The result of group learning with the assisting tools**

The interaction among the students is one of the criterions used to evaluate group-learning performance. In the HCI course, the teachers also want to know about
intergroup discussion. The discussion channel of the system developed is a discussion board on the web, like Usenet. Teachers and students can post articles, reply to postings and read postings via the Internet. All the discussion behaviours were recorded in a database for analysis. Table 5 lists the amount of discussion in the group discussion boards for each group per semester.

At the end of the semester, the experimental results show that group #6 (Table 5) failed in group learning because the final grade of the group was below 60. Teachers tried to discover potential reasons for the failure of the group, and also set the abnormal learning performance notification in the feature space. Then, in the next semester, the teachers observed this situation and intervened to guide the students immediately instead of at the end of the semester.

**Table 5. The group performance in group discussion place**

<table>
<thead>
<tr>
<th>Group id</th>
<th>Read hit</th>
<th>Reply hit</th>
<th>Post/read</th>
<th>(post+read)/week</th>
<th>Mid exam</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>285</td>
<td>345</td>
<td>0.96</td>
<td>2.59</td>
<td>78</td>
</tr>
<tr>
<td>2</td>
<td>388</td>
<td>280</td>
<td>1.39</td>
<td>2.93</td>
<td>82</td>
</tr>
<tr>
<td>3</td>
<td>175</td>
<td>115</td>
<td>1.52</td>
<td>1.49</td>
<td>65</td>
</tr>
<tr>
<td>4</td>
<td>935</td>
<td>228</td>
<td>4.10</td>
<td>0.39</td>
<td>92</td>
</tr>
<tr>
<td>5</td>
<td>113</td>
<td>32</td>
<td>0.90</td>
<td>2.29</td>
<td>68</td>
</tr>
<tr>
<td>6</td>
<td>86</td>
<td>164</td>
<td>2.69</td>
<td>1.42</td>
<td>54</td>
</tr>
<tr>
<td>7</td>
<td>239</td>
<td>245</td>
<td>1.46</td>
<td>1.99</td>
<td>75</td>
</tr>
<tr>
<td>8</td>
<td>496</td>
<td>245</td>
<td>2.02</td>
<td>2.34</td>
<td>83</td>
</tr>
<tr>
<td>9</td>
<td>178</td>
<td>121</td>
<td>1.47</td>
<td>1.92</td>
<td>70</td>
</tr>
<tr>
<td>10</td>
<td>211</td>
<td>131</td>
<td>1.56</td>
<td>1.44</td>
<td>78</td>
</tr>
</tbody>
</table>

Average of Read/Group: 289.2 Average of Post/Group: 201.4 read/reply: 1.45
Average grade:75.5
30% of Average of POST/Group = 86.8 30% of Average grade = 60.4

**Observation and intervention on learning performance**

Teachers also attempted to observe the learning performance of student Johnson who is a member of group #6. Johnson’s profile is: male, 35-year-old, holding a bachelor degree in mathematics. Table 6 presents a snapshot of Johnson’s personal feature space at the beginning and at the end of the semester.

**Table 6. Personal features of student Johnson at the end of first three weeks**

<table>
<thead>
<tr>
<th>Feature id</th>
<th>Feature name</th>
<th>Explanation</th>
<th>After 3 weeks</th>
<th>At end of semester</th>
</tr>
</thead>
<tbody>
<tr>
<td>2.1</td>
<td>Login frequently</td>
<td>The login frequency is &gt; 80% of all</td>
<td>N</td>
<td>N</td>
</tr>
<tr>
<td>2.2</td>
<td>Login seldom</td>
<td>The login frequency is &lt; 30% of all</td>
<td>Y</td>
<td>N</td>
</tr>
<tr>
<td>2.7</td>
<td>Homework submission</td>
<td>Submit current homework after the deadline in time</td>
<td>N</td>
<td>Y</td>
</tr>
<tr>
<td>3.1</td>
<td>Prefer to help group members</td>
<td>Seldom help others</td>
<td>Frequently read the post more than reply to the post</td>
<td>Y</td>
</tr>
<tr>
<td>3.6</td>
<td>Prefer to help group members</td>
<td>Seldom help others</td>
<td>Frequently read the post more than reply to the post</td>
<td>Y</td>
</tr>
<tr>
<td>4.3</td>
<td>Success in test</td>
<td>The average grade of test &gt;= 60</td>
<td>N</td>
<td>Y</td>
</tr>
</tbody>
</table>

The feature space reflects performance in the learning process. Table 6 presents two snapshots of Johnson’s personal feature space taken by the teacher to discover the changes between the two periods. Significantly, the difference of Johnson’s feature space is (2.1) (2.2) (3.1) and (4.3). In Table 6, the teacher defined the features of ‘login frequently’ (2.1), which means that the login frequency is 80% higher than the average of all the other students, and also the contrary feature ‘login seldom’ (2.2),
which means that the login frequency is below 30% of all the other students. The feature ‘prefer to help group members’ (3.1) indicates that students prefer reply to the questions posted by members of their own group rather than to those asked by others. The final difference in feature space is ‘Success or failure’ (4.3) meaning the average test grade of the student is below 60.

In Table 6, teachers set the abnormal notification as features (2.2) and (3.6). When these two observed abnormal features hold, the system will notify the teacher. In Table 6, Johnson has the features (2.1) (2.7) (3.1) and (4.3) early in the semester. These features occurred but did not represent abnormal learning performance. The system continued observing Johnson without notifying the teachers. In Table 6 (right) both the abnormal features (2.2) and (3.6) still occurred. Then the system notified the teacher that the observed abnormal learning performance occurred for a specific student. The teacher then decided to apply an instructional strategy to help this student’s learning.

Discovering the relationship between impact factors and learning situation

The meta-rule guided mining method helps teachers discover the possible reasons for why the observed features happened. The experimental HCI course derived some interesting rules displayed in Fig. 4 which illustrates that teachers selected the interesting features to be observed from the feature space, and then set the support and confidence level of rules to be mined. The system discovered the association rules in the form of features that present potential explanations of learning performance.

Table 7 illustrates that students with lower homework grades have 83% confidence that they do not login to the system often. \((\text{login}\_\text{less} \Rightarrow \text{P}\_\text{grad} = 1)\). Furthermore, students with lower homework grades have 85% confidence that their level of login and discussion is low \((\text{Login}\_\text{account} = 1 \text{ AND } \text{Discuss}\_\text{less} = 1 \Rightarrow \text{H}\_\text{grade} = 1)\). Significantly, rule \(A \Rightarrow B\) holds does not mean that \(B \Rightarrow A\) also holds.
The rule discovered in Table 7 shows that teachers should motivate students to login more frequently to avoid a fail grade. Naturally, this is not the only reason that causes students to fail and the system developed cannot guarantee to find every possible reason. However, it provides tools to discover some reasons for failure by analysing data of the web log, observed learning behaviour. It may provide information for teachers as to when and how to guide the students at the right time, and it reduces the teachers’ effort in managing group learning.

Conclusion

To assist a teacher in applying group leaning, this work has presented instructional instruments for intervening in the learning process and analysing teaching strategies. Without the proposed mechanisms, a teacher may spend considerable time in trying to analyse group-learning from a huge amount of unorganised web interactions and logs. Thus, the teacher may spend time that could otherwise be put in managing group learning and ensuring good learning achievement for the students. This work:

- implemented an instructional instrument for use by teachers in observing and managing the performance of group learning and thus reducing teacher effort;
- enabled teachers to observe and to intervene in group-learning objectively and determine the instructional strategies necessary to motivate students to learn with the help of meaningful feature space information.

After the instructional strategies were implemented, the meta-rule guided mining technique helped teachers to discover the possible causes for specific learning performance. When an abnormal learning feature occurred, the system notified the teachers and assisted their decision making in selecting a guiding approach.

The experimental results demonstrated that group interaction and learning performance were promoted by the method developed. Further, the failure ratio dropped and, simultaneously, the efforts of teachers were reduced markedly.

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