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Original Article

Elective course recommendation model for higher education program

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Abstract

Educational data mining (EDM) applies data mining techniques to resolve educational managing problems. This paper proposes a general process of EDM for elective course recommendations based on student grades. Furthermore, proper and inadequate reasons for applying conventional measurements in the course recommendation domain are studied and complemented with new proposed quality measurements. Several techniques were studied to establish a model for estimating the grades in elective courses. The experiments suggested that SVD classifier using course information gave the best results. The overall results indicate that the proposed model is able to provide personalized recommendations for individual students based on the student's abilities.

Keywords: collaborative filtering technique, educational data mining, course recommendation system, knowledge discovery

1. Introduction

The general objectives of EDM can be either improving the learning process and guiding a student's learning, or achieving a deeper understanding of the educational situation (Romeron & Ventura, 1992). One major problem is how the collected data provides useful information for advising students when they plan their own enrollment in courses, to select courses matching their own potentials (Ray & Sharma, 2011).

A recommender system aims to provide its users with relevant information. A model in a recommender system evaluates personal information of the user, and a model estimating scores for items not yet seen by the user is also developed. A successful recommender system can be based on collaborative filtering (CF) technique. The personalized guidance is based on prior opinions of other users, collected in a historical database. Similarities between the elements are evaluated, in order to find the most suitable collaborative elements.

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In the literature, the best performing algorithms for CF are based on the Singular Value Decomposition (SVD) (Cacheda, 2011; Kautkar, 2014). Thus, an SVD based algorithm was studied, and its parameters were assigned relevant descriptions in the elective course recommendations context. A general process of EDM for elective course recommendations based on student grades is proposed. Conventional measures of recommendation quality were studied. Their inadequacies in the context of elective course recommendations are explained, and a new proposed quality measurement is presented.

The remainder of this paper is organized as follows. Section 2 explains related prior work and Section 3 presents the proposed ideas. Section 4 exhibits the experimental results along with discussion. Section 5 concludes the paper with some final thoughts.

2. Related Work

Lee and Cho (2011) proposed an intelligent course recommendation system using content based CF. The system evaluated the relationship between each course via relevant fields of knowledge. The recommendation process started from assessing a student's weak subjects and analyzing individual abilities, to be able to advise the student about which fields of study would be suitable and which courses they should take. This approach was suitable for implementing in a small domain, where all fields of study were well specified.

Ray and Sharma (2011) presented a CF based approach for recommending elective courses. The main idea was to provide students with accurate estimates of their future grades. This information about student's performance was helpful on selecting elective courses. The estimated grades of elective courses were provided to users based on nearest neighbors in both user-based and item-based CFs. While a CF recommender system based on nearest neighbors technique was simple, the accuracy of results could be improved with other higher performance CF techniques.

3. Proposed Model

This research aims to introduce a general EDM process for elective course recommendations based on a student's grades. Furthermore, conventional measures of recommendation quality are studied. The usability and inadequacy of these measurements in the course recommendation domain are described. Further, the inadequacies are addressed by new proposed quality measurements for course recommender systems.

As depicted in Figure 1, data mining typically consists of three main steps: data preparation, data modeling, and results evaluation. Data preprocessing is the process of converting raw data collected from (education systems) into useful form. Subsequently, data modeling, i.e. typical data mining techniques such as classification, clustering, and association rules, are applied to those data in order to find a suitable model (representing educational situation issues). An interpretation is also necessary to explain the meaning of the model, and to extract information from it to humans. Finally, the success of data modeling is evaluated along with results evaluation.

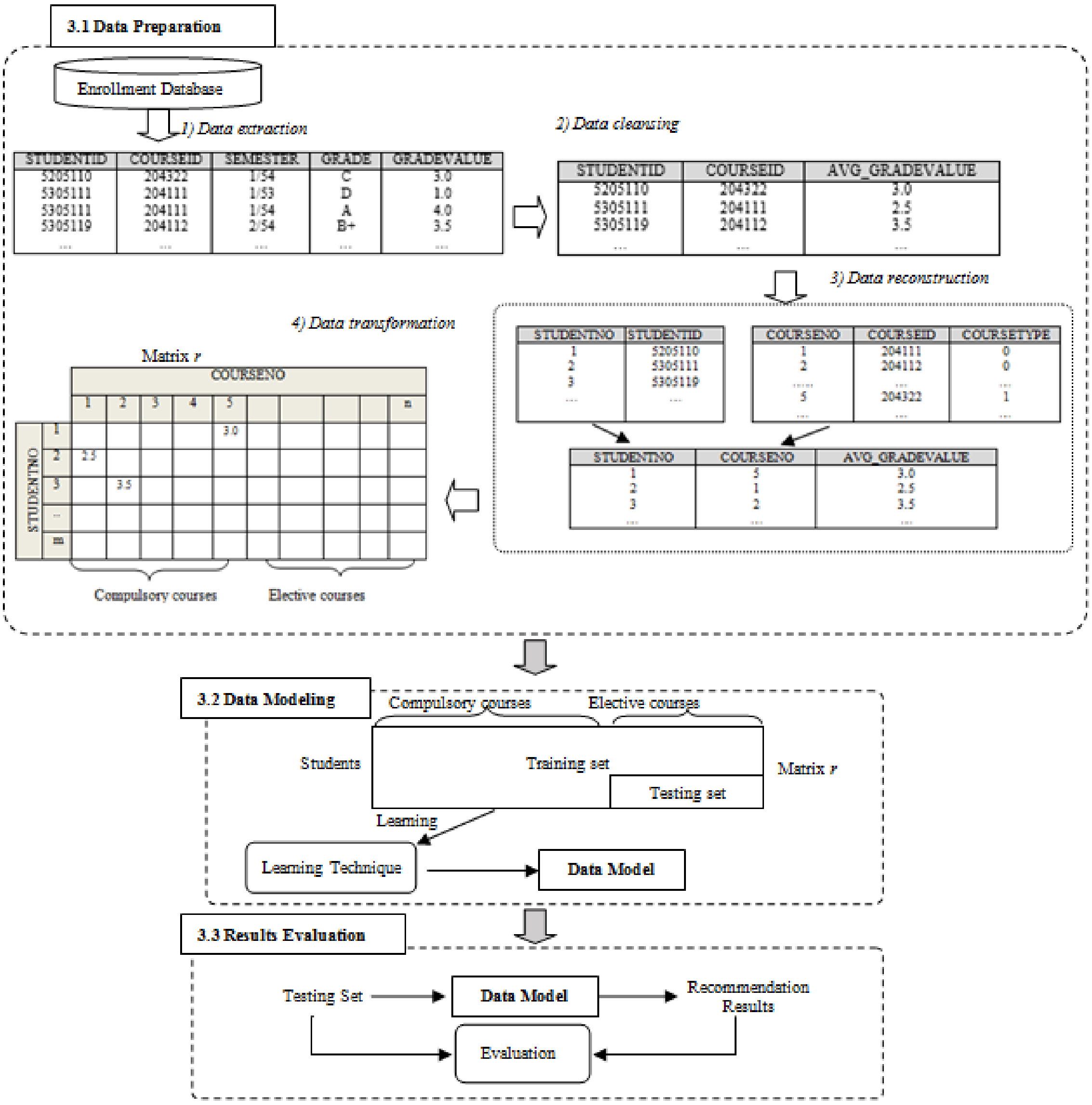

Figure 1. Elective course recommendations model.

3.1 Data preparation

The training data are historical data collected in the enrollment database. The attributes of each record for a student are grades, id, course ids, course types and the grades scored. The details of this are as follows.

1) Data extraction: historical data collected in the enrollment database are queried based on characteristics of the students. The studied records, which are assigned grades with grade point values (such as A, B+, B, or F), are retrieved. The values collected in GRADEVALUE are numerical values assigned to the grade point values.
2) Data cleansing: the data need to be cleansed. Some students can enroll in the same course for different semesters, and these records must be grouped into one record. The grade point values of re-enrollment courses are recalculated to averages.
3) Data reconstruction: the values in STUDENTID and COURSEID are transformed to sequential numbers from 1 to m and 1 to n, respectively. Here m is the number of students and n is the number of courses collected from the historical database.
   - In the case of STUDENTID, the values in this field are selected with DISTINCT option in SQL. Thus, duplicates of values are removed. Then, STUDENT ID is changed to STUDENTNO, where the values are assigned unique sequence numbers.
   - In the case of COURSEID, the value in COURSE TYPE can be either 'Compulsory Course' or 'Elective Course'. Next, the data in this field are selected with DISTINCT option and sorted to ascending order using SQL. The type of course is specified in COURSETYPE.
4) Data transformation: the historical records are transformed to a matrix (hereafter referred to as matrix r, *which is an* $m \times n$ *matrix*). The indexing of each element in matrix r, in terms of (row, column), reflects STUDENTNO and COURSENO, respectively.

3.2 Data modeling

Several models can be applied to transcribe the grades of a student s after attending course c. The baseline estimated grade of student s who attended courses c based on SVD-based technique, hereafter denoted as $\hat{r}_{s,c}$, is given by

$$\hat{r}_{s,c} = \bar{r} + b_s + d_c + \sum_{k=1}^{K}(p_{s,k} \times q_{c,k}) \qquad (1)$$

where $\bar{r}$ is the average of all elements that have been assigned values in the matrix r. $\bar{r}$ is implemented in both $\bar{r}_s$ (average grade of a student s) and $\bar{r}_c$ (average grade of course c). b_s, d_c, $p_{s,k}$, and $q_{c,k}$ denote model parameters, which are collected in $m \times 1$, $n \times 1$, $\mathrm{m} \times k$, and $n \times k$ matrices; respectively. m, n and k are number of students, number of courses and number of factors for approximately factoring matrix r. The optimal value of k for CF is 400 (Praserttitipong & Sophatsathit, 2012). b_s and d_c represent the observed deviations of student s from the average and the bias of observed deviations of course c from the average, respectively. $p_{s,k}$ and $q_{c,k}$ are the extent of interest/ability of student s on factor k and the extent to which the course possesses factor k.

The values of these parameters are initiated with small random numbers. Then, these values are iteratively improved during training or learning, to minimize a regularized square sum of errors between model predicted and true grades. This iteration was performed with stochastic gradient descent optimization. An algorithm for SVD-based model learning is as follows (Paterek, 2007).

- Assign to matrices b, d, p, and q small random numbers
- DO
  1) Compute the estimated grades of all studied records that have been collected in the historical database, by applying an Equation (1)

     $$\hat{r}_{s,c} = \bar{r} + b_s + d_c + \sum_{k=1}^{K}(p_{s,k} \times q_{c,k})$$

  2) Calculate the errors in estimated grades

     $$e_{s,c} = r_{s,c} - \hat{r}_{s,c}$$

  3) Update the model parameters

     - $b_s = b_s + \gamma(e_{s,c} - \lambda \cdot b_s)$
     - $d_c = d_c + \gamma(e_{s,c} - \lambda \cdot d_c)$
     - $p_{s,k} = p_{s,k} + \gamma(e_{s,c} \cdot q_{c,k} - \lambda \cdot p_{s,k})$
     - $q_{c,k} = q_{c,k} + \gamma(e_{s,c} \cdot p_{s,k} - \lambda \cdot q_{c,k})$

  4) Calculate the mean absolute error
- LOOP UNTIL mean absolute error ≤ 0.5

The constants γ and λ are the stochastic gradient descent method constants. The values of γ and λ were set to 0.005 and 0.02, respectively (Paterek, 2007). The iterative learning process repeats updating matrices b, d, p, and q, until the terminal conditions are reached. The appropriate measure in the terminal condition is the mean absolute error (MAE). The process is completed when the MAE is less than or equal to 0.50 (Praserttitipong & Sophatsathit, 2014), and this requirement does not lead to overfitting.

The model predicted grades were grouped to make the results less complicated. The student grades are classified into 3 classes as Good recommended class (the estimated grade is greater than or equal to 3.0), Fair recommended class (the estimated grade is greater than or equal to 2.0), and Bad recommended class (the estimated grade is below 2.0).

3.3 Results evaluation

Conventional measures of recommendation result quality are studied. The usability and inadequacy of these measures in the course recommendation domain are described.

3.3.1 Estimation accuracy evaluation

A typical quality measure for estimation results, MAE, measures the differences between estimates and actual grades, and is defined as follows

$$MAE = \frac{\sum_{s=1}^{m'}\sum_{c=1}^{n'}|r_{s,c}-\hat{r}_{s,c}|}{m'\times n'} \quad (2)$$

where r is an $m \times n$ matrix collecting the historical grades of students. The variables $r_{s,c}$ and $\hat{r}_{s,c}$ are actual grades and estimated grades of student s in course c. Further, m' is the number of students that have been graded in course c, and n' is the number of courses that have been studied by user s. Generally, lower MAE reflects higher accuracy of the grade estimates.

3.3.2 Conventional classification evaluation

The quality measures for classification results include basic information retrieval metrics, i.e., accuracy, precision, recall, and F_1-measure. These metrics are calculated from the number of items that are either relevant or irrelevant and either contained in the recommendation set of a user or not. These numbers are elements of a contingency table also called the confusion matrix. The general form of confusion matrix for the course recommendation system is presented as Table 1.

The classification results are categorized into 2 groups: correctly classified results and incorrectly classified results. The correct classification results are named as *TB*, *TF*, and *TG*, which are defined as the number of correctly classified results labeled as class Bad, class Fair and class Good, respectively. The others classes have incorrect classifications. The evaluation measures for course classification results are as follows (Cacheda *et al.*, 2011).

1) Accuracy measures the correctness of the classification. The overall accuracy is

$$Accuracy = \frac{TB+TF+TG}{The\ total\ number\ of\ test\ items} \quad (3)$$

2) Precision measures the exactness of the classification. The precision is defined as

$$Precision = \frac{The\ number\ of\ correctly\ classified\ items\ in\ this\ class}{The\ number\ of\ items\ classified\ in\ this\ class} \quad (4)$$

Low precision score means there is a small number of correct classified items compared with incorrect items classified into that class. The perfect precision score is 1.0.

3) Recall measures the completeness of classification and is defined as

$$Recall = \frac{\text{The number of correctly classified items in this class}}{\text{The number of actual elements classification results}} \quad (5)$$

Low recall score indicates there is a small number of correctly classified items compared with the total number of items that actually belong to that class. The perfect recall score is 1.0.

4) F_1-measure is a combination of precision and recall. The quality in terms of both precision and recall is combined into a single score, calculated as the standard harmonic mean of precision and recall. F_1-measure for classification is defined as

$$F_1 = \frac{2}{\frac{1}{precsion}+\frac{1}{recall}} = \frac{2\times precsion\times recall}{precision+recall} \quad (6)$$

However, some relevant issues in course recommendations are not be probed by precision and recall. The inadequacies of precision are depicted in Figure 2, while the inadequacies of recall are shown in Figure 3.

- The low precision for class *Bad* indicates that there is a small number of correctly classified items in class *Bad*, compared with incorrect calls as *Bad*, as shown in Figure 2(a). Because of this error, the students are informed with an incomplete set of elective courses. This leads to a lost opportunity by not enrolling in some elective courses that could improve the student's grade point average (GPA). This means there are some extra elective courses classified in class Bad, even though they are fair or good courses. This situation is named lost opportunity recommendation case.
- The low precision for class *Good* means there are some courses falsely classified in class *Good*, that are actually *Fair* or *Bad*, as illustrated in Figure 2(b). These classification results are serious flaws.

Table 1. A general form of confusion matrix for the recommendation system.

		Recommended Classes			
		Bad	Fair	Good	Recall
Actual Classes	Bad	*TB*	*FBF*	*FBG*	$\frac{TB}{TB+FBF+FBG}$
	Fair	*FFB*	*TF*	*FFG*	$\frac{TF}{TF+FFB+FFG}$
	Good	*FGB*	*FGF*	*TG*	$\frac{TG}{TG+FGB+FGF}$
	Precision	$\frac{TB}{TB+FFB+FGB}$	$\frac{TF}{TF+FBF+FGF}$	$\frac{TG}{TG+FBG+FFG}$	

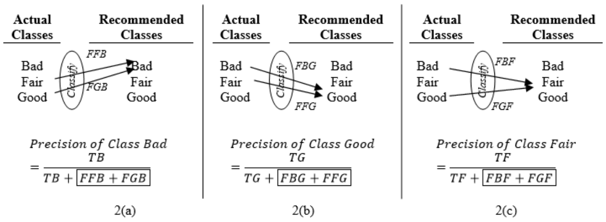

Figure 2. Impacts of errors in precision.

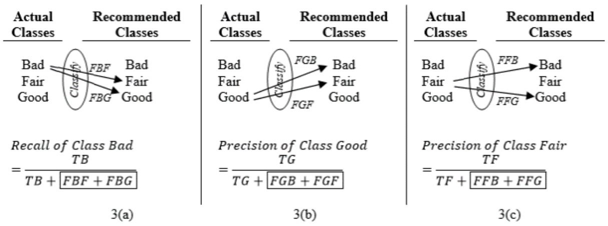

Figure 3. Impacts of errors in recall.

When the students are recommended wrong elective courses, it can cause many problems, such as the student flunking out due to poor GPA. This situation is named critical wrong recommendation case.

- The low precision for class *Good* means there are some courses falsely classified in class *Good*, that are actually *Fair* or *Bad*, as illustrated in Figure 2(b). These classification results are serious flaws. When the students are recommended wrong elective courses, it can cause many problems, such as the student flunking out due to poor GPA. This situation is named critical wrong recommendation case.
- The low precision for class *Fair* means there are some extra courses wrongly classified as *Fair*, as shown in Figure 2(c). This can be either a lost opportunity recommendation case or a critical wrong recommendation case.
- The low recall for class Bad implies that there are many critical wrong recommendation results, as illustrated in Figure 3(a).
- The low recall for class *Good* indicates that there are a small number of correctly classified items in class *Good*, as illustrated in Figure 3(b). This implies that there are many lost opportunity recommendation situations.
- The low recall for class *Fair* means there are some extra courses classified in class *Fair*, as shown in Figure 3(c). This can be either a lost opportunity recommendation case or a critical wrong recommendation case.

It can be seen that both precision and recall have meaning the differ by the class called. For example, both *FBG* and *FBF* indicate there are some bad elective courses classified or called as *Good* and *Fair*, respectively. However, the most serious situation in this case is caused by misclassifying bad courses as good. Thus, the incorrect calls must be weighed by their seriousness.

It can be concluded that new measures for the course recommendation system domain are called for. The confusion matrix for the course recommendation system is proposed as Table 2. The group of incorrectly classified results are designated into two subcategories; i.e., *Wrong* and *LostOp*, in order to distinguish by the implications of error type.

1) Lost metric: this is for evaluating the degree of lost opportunities in a recommendation problem. The elective courses classified in these classes are normally not recommended to students. Thus, the students are informed of an incomplete set of suitable elective courses. This leads to lost opportunity in enrollment to some elective courses that could have improved the GPA.

Table 2. A confusion matrix for the course recommendation system.

		Recommended Classes		
		Bad	Fair	Good
Actual Classes	Bad	*TB*	$Wrong_2$	$Wrong_3$
	Fair	$LostOp_2$	*TF*	$Wrong_1$
	Good	$LostOp_3$	$LostOp_1$	*TG*

The *LostOp* variable is defined as the number of incorrect calls, when the class is suitable for the actual abilities of the student. The numerical value after each category's name; i.e., 1, 2, or 3, indicates the significance of opportunity that the student loses. The variables $LostOp_3$, $LostOp_2$, and $LostOp_1$ are sorted according to the lost opportunity weighing. The measure of lost opportunity in recommendation problem is given as

$$Lost = \frac{(\alpha_1 \times LostOp_1) + (\alpha_2 \times LostOp_2) + (\alpha_3 \times LostOp_3)}{Thetotalnumberoftestitems} \quad (7)$$

where α_1, α_2, and α_3, are weights of impacts, here assigned the values 1, 2, and 3, respectively. A higher score of lost opportunity (*Lost*) indicates larger incompleteness in suggested elective courses.

2) Critical metric: This evaluates the critically wrong recommendations. These classification results are serious cases. Because the students are recommended wrong elective courses, these may lead to many other problems, such as flunking out.

The *Wrong* variable is defined as the number of incorrectly calling a class that in reality is more demanding than the actual abilities of the student. The largest errors are collected in $Wrong_3$; and the least crucial erroneous calls are counted by $Wrong_1$. The measure for critically wrong recommendations is

$$Critical = \frac{(\omega_1 \times Wrong_1) + (\omega_2 \times Wrong_2) + (\omega_3 \times Wrong_3)}{Thetotalnumberoftestitems} \quad (8)$$

where ω_1, ω_2, and ω_3 are weights of the impacts, here assigned as 2, 3, and 4, respectively. These weights were selected to be larger than α_1, α_2, and α_3. A higher score (*Critical*) indicates more unsuitable recommendations that could cause failed courses. These can lead to many other crucial problems.

3) Balanced accuracy metric: This evaluates the overall accuracy of course recommender system based on the standard harmonic mean of *accuracy* and *ErrorClassified*, where *ErrorClassified* is defined as the balance of *Critical* and

Lost. Because *accuracy* and *ErrorClassified* do not exactly satisfy *Accuracy=1-ErrorClassified*, these values need to be normalized. The *ErrorClassified* is based on the standard harmonic mean (Cacheda *et al.*, 2011) as

$$ErrorClassified = \frac{average(\alpha_1,\ \alpha_2,\ \alpha_3) + average(\omega_1,\ \omega_2,\ \omega_3)}{\frac{average(\alpha_1,\alpha_2,\alpha_3)}{Lost} + \frac{average(\omega_1,\omega_2,\omega_3)}{Critical}} = \frac{2+3}{\frac{2}{Lost}+\frac{3}{Critical}} = \frac{5 \times (Lost \times Critical)}{(2 \times Critical)+(3 \times Lost)} \quad (9)$$

Thus, the *balanced accuracy* based on the concept of the standard harmonic mean (Cacheda *et al.*, 2011) is proposed as

$$BalancedAccuracy = \frac{2}{\frac{1}{accuracy} + \frac{1}{(1-BalancedError)}} = \frac{2 \times Accuracy \times (1-BalancedError)}{Accuracy+(1-BalancedError)} \quad (10)$$

A higher $BalancedAccuracy$ indicates better accuracy achieved with a tolerable error in classification based elective course recommendations.

4. Experimental Results and Evaluation

The data in this experiment were collected from enrollment records of 438 students who studied in the Department of Computer Science, Faculty of Science, Chiang Mai University, during academic years 2006-2010. The grades they had scored in 74 courses were collected in a historical enrollment database, with 21 compulsory courses and 53 elective courses. This database had 11,158 study records. All academic years were given equal priority.

These records were divided into training and testing sets for split testing. Since the records represented data in two different categories (i.e., compulsory courses and elective courses), stratified sampling was used to select the training sets. The records in the testing set were randomly sampled from the records for elective courses, while the rest were used as training set. Thus, the records in the training set were historical enrollment information for both compulsory courses and elective courses. The testing elements were randomly selected and others were training set. Because of comparatively small amount of data, the size of each testing set was approximately 10% of the records. Five training and testing set pairs were used in several testing approaches.

4.1 Testing approaches

The grade estimates of a student for an elective course *c* ($\hat{r}_{s,c}$) were evaluated according to several approaches. There were 12 experiments conducted. The details of the testing approaches were as follows.

1) The average grade of each student: the grade estimates gave an average grade earned by the student

$$\hat{r}_{s,c} = \overline{r_s} \quad (11)$$

2) The average grade in a course:

$$\hat{r}_{s,c} = \overline{r_c} \quad (12)$$

3) Combination of the two previous measures

$$\hat{r}_{s,c} = average(\overline{r_s}, \overline{r_c}) \quad (13)$$

4) User-based CF: This approach applied a user-based CF with Pearson correlation (Cacheda *et al.*, 2011) as follows.
   - First, the similarities between a current student *s* and other students were calculated. A similarity value between student *s* and student *t* based on Pearson correlation technique could be evaluated as

$$sim_{s,t} = \frac{\sum_{c=1}^{n}(r_{s,c}-\bar{r}_s)(r_{t,c}-\bar{r}_t)}{\sqrt{\sum_{c=1}^{n}(r_{s,c}-\bar{r}_s)^2}\sqrt{\sum_{c=1}^{n}(r_{t,c}-\bar{r}_t)^2}} \quad (14)$$

   - Then, a subset of *k*-students who were the most similar to student *s* are selected. In this experiment, *k* was set to 7. The grade estimate was calculated as

$$\hat{r}_{s,c} = \bar{r}_s + \frac{\sum_{t=1}^{k}(r_{t,c}-\bar{r}_t)}{k} \quad (15)$$

5) Item-based CF: This approach applied an item-based CF with Pearson-correlation (Cacheda *et al.*, 2011) as follows.
   - First, the similarities between a course *c* and other courses *d* were calculated as follows:

$$sim_{c,d} = \frac{\sum_{s=1}^{m}(r_{s,c}-\bar{r}_c)(r_{s,d}-\bar{r}_d)}{\sqrt{\sum_{s=1}^{m}(r_{s,c}-\bar{r}_u)^2}\sqrt{\sum_{s=1}^{m}(r_{s,d}-\bar{r}_d)^2}} \quad (16)$$

   - Then, a subset of *k*-courses which were the most similar to a course *c* are selected. In this experiment, *k* was set to 7. The grade estimates were evaluated as

$$\hat{r}_{s,c} = \frac{\sum_{d=1}^{k} r_{s,d}}{k} \quad (17)$$

6) Combination of (4) & (5):

$$\hat{r}_{s,c} = average(\hat{r}_{s,c} from\ Equation\ 15, \hat{r}_{s,c} from\ Equation\ 17) \quad (18)$$

7) Weighted user-based CF: This approach also applied a user-based CF with Pearson correlation as in Equation (14). The similarity values were taken into account. The grade estimates were

$$\hat{r}_{s,c} = \bar{r}_s + \frac{\sum_{t=1}^{k} sim_{s,t} \times (r_{t,c}-\bar{r}_t)}{\sum_{t=1}^{k}|sim_{s,t}|} \quad (19)$$

8) Weighted item-based CF: This approach also applied an item-based CF with Pearson correlation as in Equation (16):

$$\hat{r}_{s,c} = \frac{\sum_{d=1}^{k} sim_{c,d} \times r_{s,d}}{\sum_{d=1}^{k}|sim_{c,d}|} \quad (20)$$

9) Combination of (7) & (8):

$$\hat{r}_{s,c} = average(\hat{r}_{s,c} from\ Equation\ 18,\ \hat{r}_{s,c} from\ Equation\ 20) \quad (21)$$

10) SVD based on student info:

$$\hat{r}_{s,c} = \bar{r}_s + b_s + d_c + \sum_{k=1}^{K}(p_{s,k} \times q_{c,k}) \quad (22)$$

11) SVD based on course info:

$$\hat{r}_{s,c} = \bar{r}_c + b_s + d_c + \sum_{k=1}^{K}(p_{s,k} \times q_{c,k}) \quad (23)$$

12) Combination of (10) & (11):

$$\hat{r}_{s,c} = average(\hat{r}_{s,c} from\ Equation\ 22,\ \hat{r}_{s,c} from\ Equation\ 23) \quad (24)$$

4.2 Experimental results and discussion

4.2.1 Estimation accuracy

The estimation accuracies evaluated by MAE as described in an Equation (1) are shown in Figure 4 for several CF techniques.

The SVD based on student and course information gave the lowest 0.5543 MAE, indicating that this approach gave the best estimation accuracy.

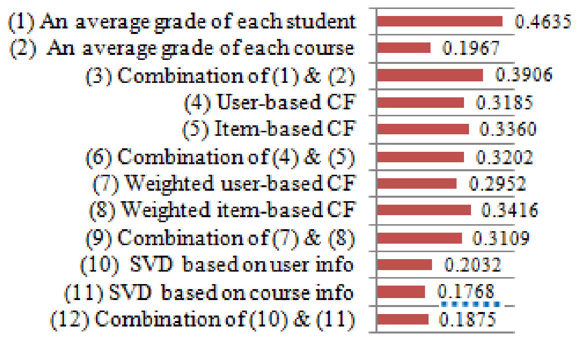

Figure 4. Comparison by MAE of alternative CF recommender techniques.

4.2.2 Classification evaluation

The estimated grades derived from CF techniques were further assessed after grouping them into the 3 classes Good, Fair, and Bad by these rules.

*/*Classification rules-based for actual grades */*
IF $r_{s,c} \geq 3.00$ then actual class = Good
ELSEIF $r_{s,c} \geq 2.00$ then actual class = Fair
ELSE THEN actual class = Bad
*/*Classification algorithm for recommended classes */*
IF $\hat{r}_{s,c} \geq 3.00$ then recommended class = Good
ELSEIF $\hat{r}_{s,c} \geq 2.00$ then recommended class = Fair
ELSE THEN recommended class = Bad

The evaluations by conventional measures are shown in Figure 5. The results in terms of *Lost*, *Critical*, and *Balanced accuracy* proposed are shown in Figure 6.

In Figure 5, the classification *accuracy* of SVD-based techniques was the highest, with average accuracy above 60%. The *Accuracy* of SVD based on course information was the highest at 0.6314 or approximately 63%. To illustrate an advantage of our proposed SVD-based algorithm, the results were compared to those of Anuradha and Velmurugan (2015). In that work, several classifications based on content-based filtering were applied to student information. The contents of the information were about attendance, class test, seminar, lab work and assignment marks; etc. The overall accuracy was also about 60%, even though their approach was much more complicated that an SVD-based algorithm. Additionally, the *Precision and F_1-Measure* show that SVD based on course information was the best alternative. The *Recall* of user-based CF was the highest, a bit higher than that of SVD based on course information.

Moreover, *Lost*, *Critical*, and *Balanced accuracy* were assessed for more extensive evaluation of the course recommendations. As depicted in Figure 6, the *lost opportunity recommendation* returned by SVD on course information was the lowest. The *Lost* value was 0.1768. This indicates less lost opportunity by this approach than with the others tested. The *critical wrong recommendation* returned by SVD based on course information was also the lowest at 0.2830. This signifies that there was less critically wrong recommendations with this approach than with the other approaches. Furthermore, the *Balanced accuracy* computed as standard harmonic mean of *Accuracy* and *ErrorClassified* is shown in Figure 6, and SVD based on course information had the highest value, i.e. the best score.

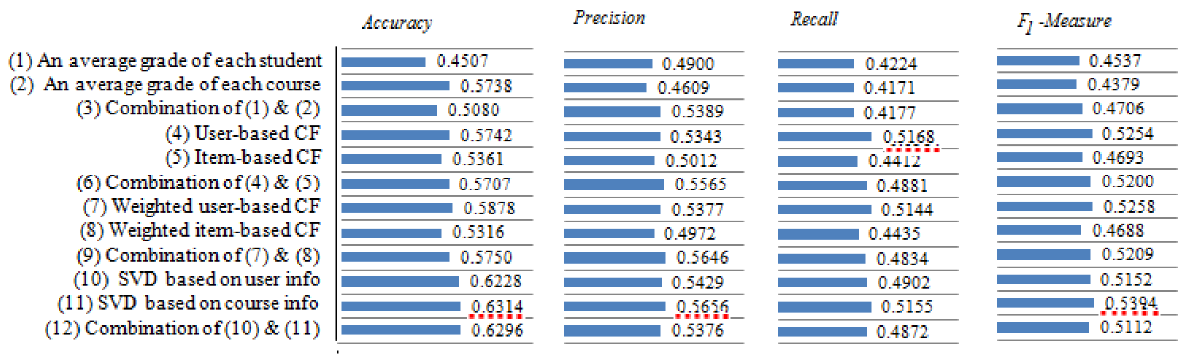

Figure 5. Comparing conventional measures of classification results from different CF recommender techniques.

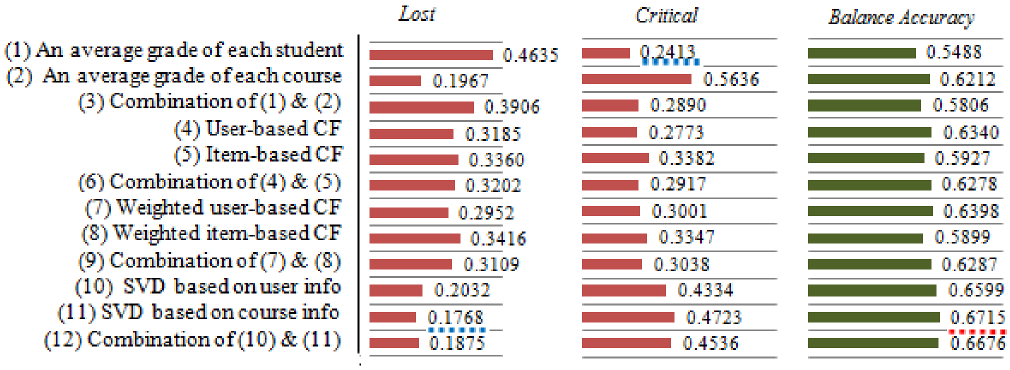

Figure 6. Comparing proposed measures of classification results from different CF recommender techniques.

It can be concluded that SVD based on course information was the most proper approach for implementing an elective course recommendation system. It had acceptable scores in all aspects considered. This is because the data matrix, especially the part representing elective courses, tends to be sparse, and SVD is a better match with this situation than the others techniques.

5. Conclusions

This paper proposed a general process for EDM in elective course recommendations based on student grades. These grades are collected in a historical database via routine work. Furthermore, new quality measures for the course recommender system were proposed in order to complement the inadequate precision and recall measures. The experimental results show that SVD-based technique using course information gave the best recommendation results by several measures, among the approaches tested. However, SVD has limitations regarding the density of the data matrix. The accuracy of this technique may suffer with dense data matrix that can present a large number of data patterns. Thus, some effort to address such issues is called for. Further investigation on combining both course and student centered approaches is a challenge that remains to be explored.

Acknowledgements

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