Decision support system for course enrolment management using qualitative information

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Abstract: Most higher education institutions offer general guidelines and course information in regards to specific majors and future careers. However, one of the main problems faced by students is making optimal decisions in relation to their academic progress and status based on formal information available to them. In this context, this research proposes a decision support system that incorporates qualitative information, including use of the experiences of previous students in the recommendation process.

Keywords: data mining; decision support system; recommendation system; sequence data mining; qualitative information.

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1 Introduction

Decision support systems generally suggest recommended guidelines for an end user to choose. The systems increase the quality of service and meet the diverse needs of users based on the basic concepts of decision support systems that, generally speaking, similar profile users share certain preferences (Badrul et al., 2001; David et al., 2008; Hang et al., 2013; Leo et al., 2015). In the context of educational data mining, a decision support system for course enrolment management that shows recommendation-based solutions for better decision could be widely accepted. Currently, most higher education institutions offer academic itineraries and recommended guidelines for obtaining specific degrees and future careers but this sort of quantitative information is appropriate only for a student with high academic achievement. In other words, for students who have changed or transferred their majors, or who have had a low level of academic achievement, such information is not a proper guidance for choosing courses. To deal with this problem, this research presents a *decision support system* for course enrolment management that presents qualitative information based on the experience of previous students.

2 Decision support system

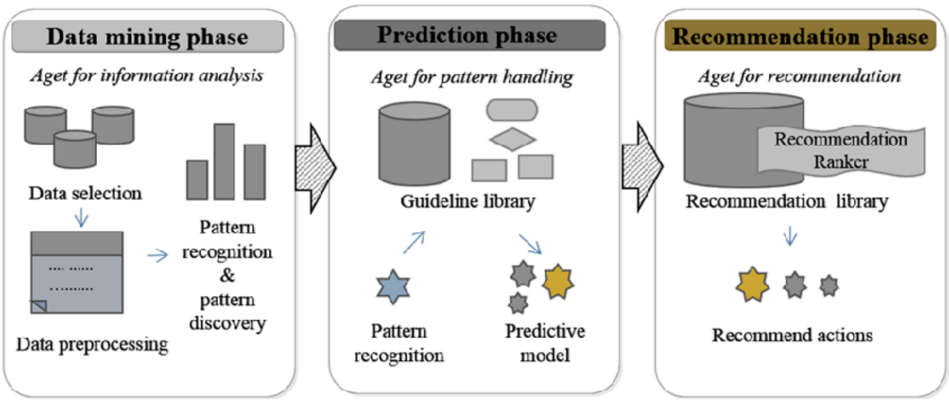
Data mining is an emerging technology for extracting unobvious patterns in datasets that can be sought, validated and used for prediction. The use of data mining has become a more common part of presenting the guidelines for wise decision-making in an environment of increasing complexity in a larger variety of information technology scenarios. In several examples where data mining techniques are used to learn a user model based on previous user ratings and recommend opinion of other individuals (Schafer, 2005). The decision support system applies data mining techniques to the problem of helping users find the courses they should enrol in by providing a list of top-N recommended courses or recommended actions for a given user. Course recommendation can be made using different methods. Recommendation can be based on previous student status and academic achievement results of past course enrolment history as a result of academic progress or major recommended courses offered by specific departments.

The overall process flow of decision support system is depicted in Figure 1. Based on the functionality of the component and objective, the process of decision support system can be categorised into three phases: *the data mining phase, the prediction phase and the recommendation phase.* The decision support system approach starts by extracting recommendable action patterns or un-recommendable decisions using various data mining techniques. In the prediction phase, after observing patterns in incoming event streams from an end user, the decision support system suggests predictive models. Finally, in the recommendation phase, an end user can see an appropriate list of top-N recommended courses or recommended actions to pre-empt the predicted incidents.

3 Methodology and procedure

The research uses a real dataset collected from Seoul Women's University. The data supplied is only from students in the Department of Multimedia, enrolled through the years 2008–2011. The data records are composed of student profiles, their cumulative G.P.A., achievement results and course enrolment history.

Figure 1 The process flow of decision support system (see online version for colours)



3.1 Data mining

In the data mining phase, the main objective of our research is to classify student groups that show similar academic achievement or interests and to discover recommended student models in accordance with each student's characteristics. Moreover, finding differential course enrolment sequential patterns will be used to provide positive and negative recommendations to a student through extensive evidence. To facilitate this, data mining techniques such as association and classification are applied to the datasets.

3.1.1 Sequence pattern mining

Sequence pattern mining is a more restrictive form of association rule mining in which the accessed items' order is taken into account. It tries to discover if the presence of a set of items is followed by another item in a time-ordered set of sessions or episodes (Agrawal et al., 1993; Cristobal et al., 2007). In this research, each student's course taken history can be a sequence. An important aspect of each student's course taken data are the extraction of frequent course enrolment patterns and the different timings of course taken decisions between groups of students. To deal with this, sequence data mining methods are used and several different patterns are discovered.

The original data sequence obtained for each student was from entrance year to graduate year, so we split it with a unique code for each semester of an SWU academic year. For example, the dataset shown in Figure 2 contains two sequences, one for each student A and B. A student A's sequence can be denoted as $S = <T1, T2, T3, T4>$, where each Transaction T_i is a collection of one or more events, i.e., $T1 = \{E1, E2\}$, $T2 = \{E4\}$, $T3 = \{E3\}$ and $T4 = \{E5, E6\}$.

Table 1 displays a partial example of different course taken decisions between groups of students, those who have jobs strictly related to their major or not with a minimum support threshold 0.7 and 0.6 (not showing whole patterns). Usually, the graduates who had a job that was strictly related to their major commonly took MT01005, MT01030 and MT01016 yet the graduates who had a job that was unrelated to their major commonly took MT01002 and MT01006. That means those three classes (MT01005, MT01030 and MT01016) could have an importance in order to have a major related job.

Figure 2 Example of sequence database

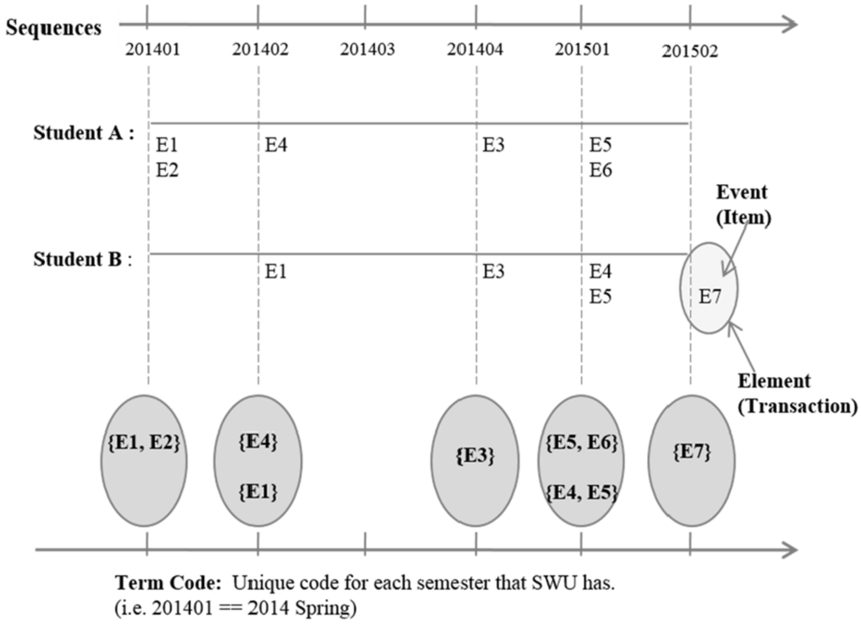


Table 1 Different top patterns of classes taken

	Top patterns	
Min-support threshold	*Employment related to major*	*Employment unrelated to major*
0.7	{MT01005}	{MT01002}
	{MT01030}	{MT01006}
	{MT01016}	
0.6	{MT01002}	{MT01002} → {MT01012}
	{MT01001}	{MT01001}
	{MT01029}	{MT01012}
	{MT01019}	
	{MT01016} → {MT01005}	
	{MT01016} → {MT01012}	

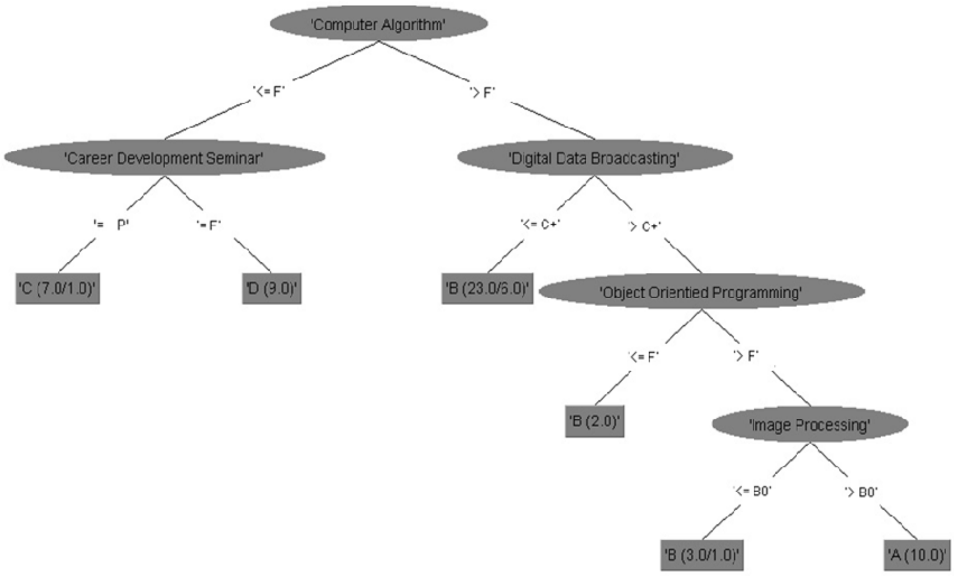
3.1.2 Classification analysis

Classification analysis takes a given collection of records (with general attributes and a class attribute) to find a classification model that can be used to predict the class label of unknown records (Han, 1998). In this research, the level of academic achievement (high, average and poor), status of employed graduates vs. unemployed graduates, and degree holding or non-degree holding was served as a class attribute to distinguish between objects of different classes. Using a decision tree classifier, a rule set of classification was generated which can be used as a great tool for making decisions.

$$\text{InfoGain }(\text{class}, \text{attribute}) = H(\text{class}) - H(\text{class} \mid \text{Attribute}). \tag{1}$$

In order to decrease the error rate, attribute selection was implemented. We used Information Gain (often referred to as InfoGain) attribute evaluator that evaluates the work of an attribute by measuring the Information Gain with respect to the class attributes. Table 2 shows a partial example of the ranking differences of the attributes based on the Information Gain attribute evaluator, with comparing the class attributes of subject with student attribute. Figure 3 displays one of the decision trees–student performance is assigned a class label and Table 3 shows detailed accuracy of each class.

Figure 3 A sample decision tree



Class level: Student performance (A: very high, B: high, C: average, D: poor).
Correctly classified instances: 79.6296%.

3.2 Prediction and recommendation

Based on the discovered patterns, we defined recommended student models with respects to student's current status. To classify the decision timing and to distinguish classification model with respect to the class label in a more refined fashion, we created several categories for decision-making. We presented a decision support system that incorporates qualitative information into the recommendation process and makes recommendations based on multiple decision points, profiles and sequential hierarchies. The user is presented with several recommendations. See the decision support system mode user interface in Figure 4.

Table 2 Rank of attribute based on the InfoGain

Ranked	*Attributes*	*Ranked*	*Attributes*
0.6612	MT01037	0.2809	MT01011
0.6545	MT01012	0.2769	MT01008
0.6374	MT01007	0.2358	MT01001
0.5792	MT01031	0.2273	MT01043
0.5758	MT01018	0.2088	MT01023
0.466	MT01029	0.2046	MT01039
0.4467	MT01006	0.1373	MT01032
0.433	MT01020	0.0292	MT01049
0.4255	MT01024	0	MT01013
0.4132	MT01016	0	MT01014
0.4	MT01045	0	MT01003
0.3731	MT01009	0	MT01004
0.3622	MT01030	0	MT01015
0.3317	MT01019	0	MT01017
0.3168	MT01005	0	MT01010
0.2995	MT01002	0	MT01052
0.2865	MT01036	0	MT01021

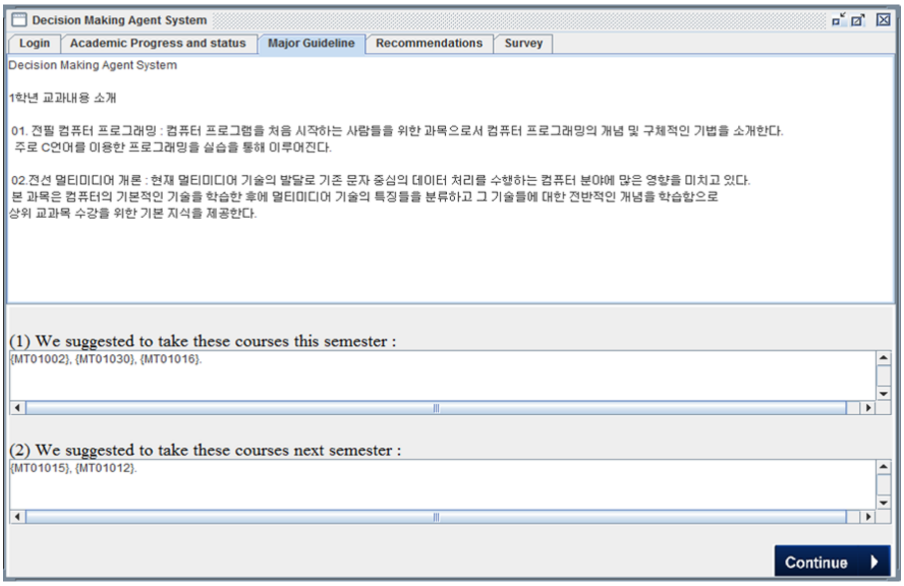
Table 3 Detailed accuracy by class

	TP rate	*FP rate*	*Precision*	*Recall*	*F-Measure*	*ROC area*	*Class*
	0.5	0.048	0.75	0.5	0.6	0.814	C (average)
	0.9	0	1	0.9	0.947	0.944	D (poor)
	0.857	0.212	0.72	0.857	0.783	0.764	B (high)
	0.909	0.047	0.833	0.909	0.87	0.927	A (very high)
Weighted avg.	0.796	0.103	0.802	0.796	0.79	0.842	

3.3 Experimental evaluation measures

To predict the performance of a model on new data, we need to access its error rate on a dataset that played no part in the formation of the classifier. During our evaluation, we have employed the usual machine learning metrics (Gerhard et al., 2014). They can be categorised into two main classes. Also we used stratified tenfold cross-validation (Lan et al., 2011). Thus, the learning procedure is executed a total of 10 times on different train datasets and finally, the 10 error estimates are averaged to yield overall error estimates. Decision support system research has used several algorithms for evaluating the quality of recommended patterns.

Figure 4 An example of the decision support system mode user interface (see online version for colours)



3.3.1 Predictive accuracy metrics

Mean absolute error (MAE) evaluates the average absolute deviation between a forecasted rating and the user's true rating. MAE (equation (2)) has been used as a measure for decision support systems in several cases (Breese et al., 1998; Herlocker et al., 1999; Shardanand and Maes, 1995).

$$\text{MAE} = \frac{\sum_{i=0}^{N} | p_i - r_i}{N}. \tag{2}$$

The lower, the MAE, the more accurately the decision supporting system engine predicts user ratings. Table 4 shows the results of prediction accuracy using four methods. From the results below, we can see that the NaiveBayes method produces the best results when we use it with performance data shown earlier in Figure 4.

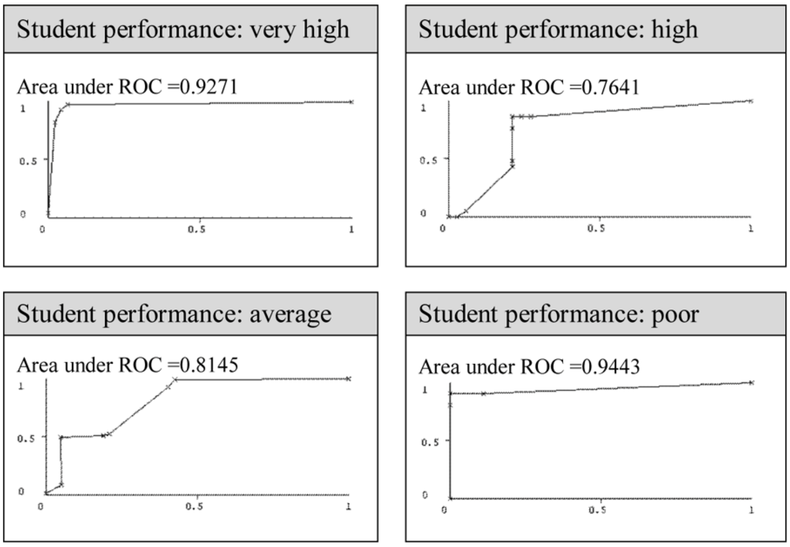
Table 4 MAE results for the prediction experiment

Dataset	*J48*	*IBk*	*RandomForest*	*NaiveBayes*
Performance data	0.143	0.1351	0.1312	0.1302

3.3.2 Classification accuracy metrics

A receiver-operating characteristic (ROC) curve is a graphical technique for displaying the trade-off between true positive rate and false positive rate (Tan et al., 2005). Figure 5 shows an example ROC curve–the jagged line–for the sample of test data shown earlier in Figure 4. The area under the ROC curve means the probability that a randomly chosen malicious sample will be correctly classified (Hanley and McNeil, 1982). Figure 5 illustrates the results of student performance dataset using J48 method–the weighted average of ROC curve area is 0.842. All models we used for decision support system research are with sufficiently high ROC curve area.

Figure 5 ROC curve for the data shown in Figure 4



4 Conclusion

Decision support systems could be used as an influential recommendation tool for extracting an additional value from user database. The most important point of this research is developing a decision support system that incorporates qualitative information into the recommendation process and makes recommendations based on multiple decision points, user profiles and sequential hierarchies. In order to find qualitative information, analysing course taken history datasets and discovering unobvious patterns using data mining techniques are proceeded to support students in a more appropriate way while they choose courses to enrol in. Also, by drawing several evaluation measures, we assessed the accuracy of classification models.

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