Implementation of Course Recommendation System based on Students' Course Selection Records

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Abstract

A course recommendation system is used to provide students some suggestions when choosing courses for online. Within courses, the most appropriate courses then are able to find out for making suggestions to students. It is worth to note that this system is not only can use in university or college, but also available for any level of education. This paper presents the recommendation system based on the Classification and Prediction Methodology. Naïve Bayesian Classification and the prediction methodology integrate to recommend the student course selection. The itemsets for generating course items are classified based on the Courses taken by the students. It exploits a Naïve Bayesian Classification and prediction methodology of course recommendations for students. The implementation of this system implies the Bayesian classifier and generates courses from the classified output. This system will be implemented by using ASP.NET, SQLServer 2005.

Keywords: Classification, Prediction Methodology, Naïve Bayessian Classification.

1. Introduction

E-learning is becoming increasingly popular in educational establishments, and learning on the Internet is gradually becoming a convenient way to obtain information. The rapid growth of e-learning has changed traditional learning behavior and presents a new situation to both teachers and students. Students need to spend a lot of time in seeking, and their learning experience is hard to record and reuse. Because of this reason, a mechanism named recommendation system (R.S.) is developed to improve the e-learning. In the view of education, the technology of R.S. is just right to solve the problem which there is too much information on the Internet, the open style environment. A R.S. in an e-learning context is a software agent that tries to "intelligently" recommend actions to a learner based on the actions of previous learners. In other words, a R.S. would preserve the records of learning actions from students. The system could give some advices to other students, and could assist them in choosing next learning objects based on the *Naïve Bayesian Classification and prediction methodology*. This paper is organized as follows: Session 1 introduces the paper, Session 2 will discuss the theoretical background, Session 3 will discuss the related work of the paper, the design and implementation are presented in Session 4, Session 5 describes the experimental results and Session 6 concludes the paper.

2. Theoretical Background

In this session, the background theory of Naïve Bayes classifier and its probabilistic model will be discussed.

2.1. Naive Bayes classifier

Bayesian classification is based on Bayes theorem. Bayesian classifier is known as the *naïve Bayesian classifier* to be comparable in performance with decision tree and neural network classifiers. Bayesian classifiers have also exhibited high accuracy and speed when applied to large databases. A naive Bayes classifier is a simple probabilistic classifier based on applying Bayes' theorem (from Bayesian statistics) with strong (naive) independence assumptions. A more descriptive term for the underlying probability model would be "independent feature model". In simple terms, a naive Bayes classifier assumes that the presence (or absence) of a particular feature of a class is unrelated to the presence (or absence) of any other feature. For example, a fruit may be considered to be an apple if it is red, round, and about 4" in diameter. Even though these features depend on the existence of the other features, a naive Bayes classifier considers all of these properties to independently contribute to the probability [8].

2.2. The Naive Bayes probabilistic model

The Naïve Bayes probabilistic model defines as follows:

Let H be some hypothesis, such as that the data sample X belongs to a specified class C. For classification problems, to determine P(H|X) it requires to calculate the probability that the hypothesis H holds given the observed data sample X.

P(H|X) is the posterior probability, or a posteriori probability, of H conditioned on X. For example, suppose the world of data samples consists of fruits, described by their color and shape. Suppose that X is red and round, and that H is the hypothesis that X is an apple. Then P(H|X) reflects the confidence that X is an apple given that is red and round [6].

$$P(C_i|X) = \frac{P(X|\ C_i)P(C_i)}{P(X)}$$

$P(C_i|X)$ = maximum posteriori hypothesis

$P(X)$ = constant.

3. Related Work

C. Zinn and O. Scheuer built student models, for instance, by exploiting the multi-faceted nature of human-human communication. In distance-learning environments, teacher and student have to cope with the lack of such direct interaction, and this must have detrimental effects for both teacher and student. The application of a Bayesian classification software package 'Autoclass' to define classes of catchments within the Murray Darling Basin, Australia using physiographic data derived from national-coverage spatial data sets is described in [5]. Two systems that perform naive Bayesian classification of structured individuals were discussed in [2]. The approach of 1BC is to project the individuals along first-order features. They described an individual in terms of elementary features consisting of zero or more structural predicates and one property; these features are treated as conditionally independent in the spirit of the naive Bayes assumption. The development of a predictive model to classify undergraduate students' class of graduation: first class, second class upper division, second class lower division, or third class with Bayesian Classification was applied in [3]. In A. Elhlees and K. K Chu and group used educational data mining to analyze learning behavior. In this case study, the students' records of Database course were collected. They applied data mining techniques to discover association, classification, clustering and outlier detection rules.

4. Design and Implementation

The overall system design can be seen in Figure 1. This system composed with two databases; Course Database which stores the Course information and Student Profile DB which stores the student information including course selection data.

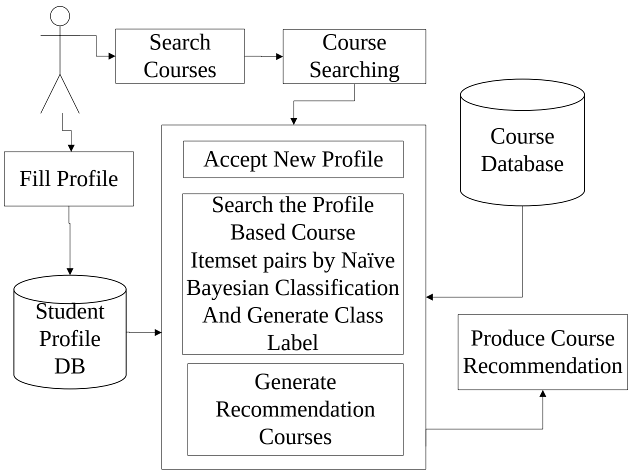


Figure 1 System Design

The processing of Search Courses, Filling Profile and Calculating the class labels are performed together with these databases. The course recommender is built by using data from NTU course information.

4.1 Algorithm for generating Course Recommendation

The algorithm for the course recommendation applied with classification can be categorized into, gets profile from the students, creates transactional identification for the related course item pairs, and calculates class label for recommendation and matches with course description. The algorithm steps can be seen as follows:

Step 1: Get student profile and course itemset pairs from database.

Step 2: Create Transaction Identification for generating class labels.

Step 3: From this point, the algorithm only sees identifier values.

Step 4: Calculate Bayes Classification and generate class labels for new student.

Step 5 Store class labels in Bayesian table.

Step 6: Match with the student profile identifier pairs in Bayesian table and get results from course taken records.

Step 7: Map identifier and attribute values from Course Database.

4.2. System Flowchart

The flowchart of the system can be seen in Figure 2. This system requires registering to view the course recommendation, so user must log in to the system. The course categories and contents can be chosen and can register for attending corresponding course categories. The recommender page will be shown after user chooses the course recommendation.

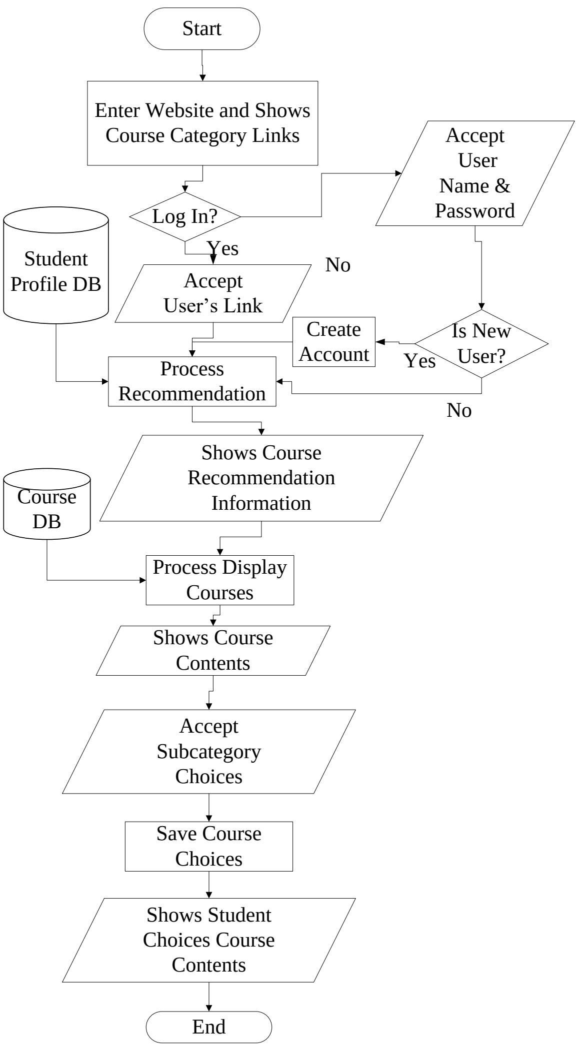


Figure 2 System Flowchart

4.3 Predicting Class Label using Naïve Bayesian Classification

To predict the class label for the student course taken data, it can be calculated as follows: For example, student "X (Age=20, Qualification=B.C.Sc (Hons), GPA=A) can take the course:
Course category name="Information Systems". Course type= "Coursework Only" Course group= "Core Courses", "Electives (Group A)", "Electives (Group B)". Bayesian table which consists of the student profile records of course taken can be built as shown in Table 1.

Table 1 Bayesian Table

RID	Age	Qualification	GPA	TakeCourse
1	16...20	B.C.Sc(Hons:)	A	no
2	21...25	B.C.Sc(Hons:)	B^+	yes
3	25...30	B.E(Electronics)	A	no
4	21...25	M.C.Sc	A^-	no
5	31...35	B.C.Sc(Hons:)	A	yes
6	21...25	B.C.Sc(Hons:)	B^+	yes
7	21...25	M.C.Sc	A	yes
8	36...40	B.C.Sc(Hons:)	B^-	yes
9	21...25	M.C.Tech	A	yes
10	16...20	B.C.Sc	A^+	no
…	…	…	…	…

X=(Age="21…25 ", Qualification= "B.C.Sc(Hons:) ", GPA="A")

$P(C_1)$= P(TakeCourse ="yes")= 6/10 = 0.6

$P(C_2)$= P(TakeCourse ="no") = 4/10 = 0.4

$P(X,C_1)$ = P(Age = "21…25", TakeCourse = "yes") = 4/6 = 0.667

$P(X,C_2)$ = P(Age = "21…25", TakeCourse= "no") = 1/4 = 0.25

$P(X,C_1)$ = P(Qualification = "B.C.Sc(Hons:)", TakeCourse = "yes") = 4/6 = 0.667

$P(X,C_2)$ = P(Qualification = "B.C.Sc(Hons:)", TakeCourse = "no") = 1/6 = 0.25

$P(X,C_1)$ = P(GPA = "A", TakeCourse = "yes") = 3/6 = 0.5

$P(X,C_2)$ = P(GPA = "A", TakeCourse = "no") = 2/4 = 0.5

P(X| TakeCourse = "yes") = 0.667*0.667*0.5 = 0.223

P(X| TakeCourse = "no") = 0.25*0.25*0.5 = 0.031

$P(X|C_i)\ P(C_i) = P(X|C_1)$

$P(C_1$= P(X| TakeCourse = "yes") P(TakeCourse = "yes")

= 0.223*0.6

= 0.134

$P(X|C_i)\ P(C_i) = P(X|C_2)\ P(C_2)$

= P(X| TakeCourse = "no") P(TakeCourse = "no")

= 0.031*0.14

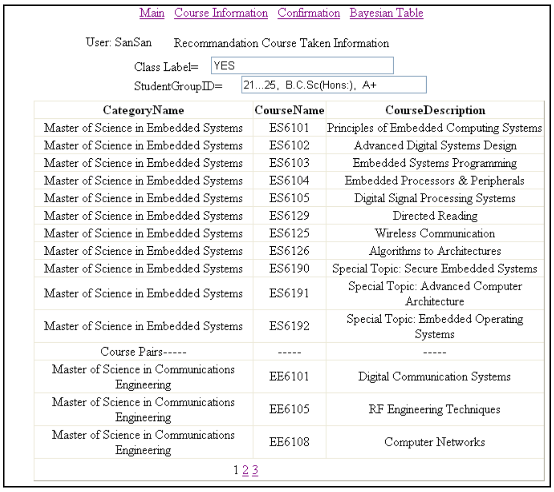
= 0.012

Therefore, the Naive Bayesian Classifier predicts TakeCourse ="yes" for sample X.

The related Course Information of the same student's profile from the Course Taken Table can be extracted and can be browsed the selected courses of the previous students.

5. Experimental Results

This system is tested over 200 students' course choices and their records are saved in Bayesian Table. Figure 3 shows the Recommender page for the new student. In this page, students can view the recommended courses which are computed by the Bayesian Classifier according to the students' profile information. The course categories, course names and course descriptions are recommended in this page.


Main Course Information Confirmation Bayesian Table

User: SanSan Recommandation Course Taken Information

Class Label= YES

StudentGroupID= 21...25, B.C.Sc(Hons:), A+

CategoryName	CourseName	CourseDescription
Master of Science in Embedded Systems	ES6101	Principles of Embedded Computing Systems
Master of Science in Embedded Systems	ES6102	Advanced Digital Systems Design
Master of Science in Embedded Systems	ES6103	Embedded Systems Programming
Master of Science in Embedded Systems	ES6104	Embedded Processors & Peripherals
Master of Science in Embedded Systems	ES6105	Digital Signal Processing Systems
Master of Science in Embedded Systems	ES6129	Directed Reading
Master of Science in Embedded Systems	ES6125	Wireless Communication
Master of Science in Embedded Systems	ES6126	Algorithms to Architectures
Master of Science in Embedded Systems	ES6190	Special Topic: Secure Embedded Systems
Master of Science in Embedded Systems	ES6191	Special Topic: Advanced Computer Architecture
Master of Science in Embedded Systems	ES6192	Special Topic: Embedded Operating Systems
Course Pairs-----	-----	-----
Master of Science in Communications Engineering	EE6101	Digital Communication Systems
Master of Science in Communications Engineering	EE6105	RF Engineering Techniques
Master of Science in Communications Engineering	EE6108	Computer Networks

1 2 3

Figure 3 Recommender Page Information

The following figures show the summarized charts of the tested system records. Column presents the total number of course taken student and Row presents Age ranges, Qualification and GPA. The total number of the course taken students by age, qualification and GPA are summarized from the course selection table of students' database. These records are collected by the students' course taken according to the students' registrations.

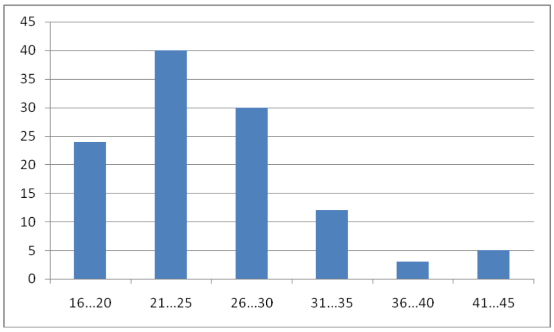


Figure 4 Total Number of Course Taken Students by Age

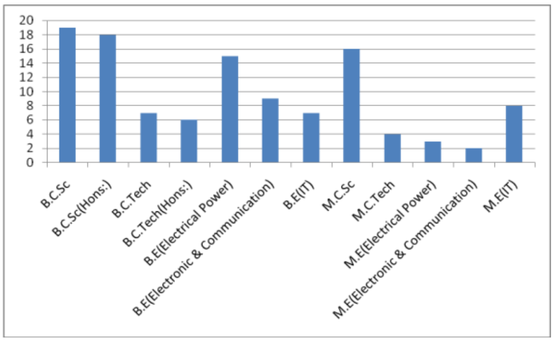


Figure 5 Total Number of Course Taken Student by Qualification

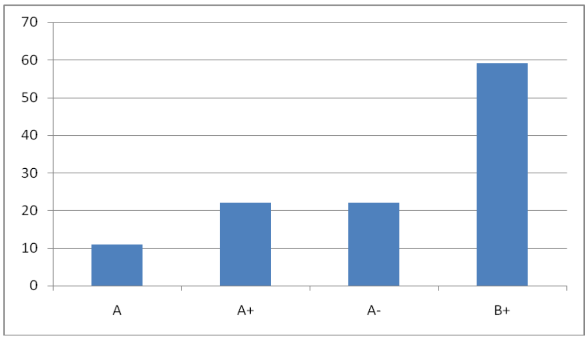


Figure 6 Total Number of Course Taken Students by GPA

5. System Accuracy

The total number of course taken students' class label is defined as "Yes", and the accurate number of the students who took course are defined as "t-Yes". Alternatively, the total number of course not taken students is defined as "No" and the accurate number of students who not taken are defined as "t-No" in the equations below.

$$\text{Sensitivity}= \frac{\text{t-Yes}}{\text{Yes}}, \quad \text{Specificity}= \frac{\text{t-No}}{\text{No}}$$

$$\text{Accuracy}= \text{Sensitivity}\ \frac{\text{Yes}}{\text{Yes+No}} + \text{Specificity}\ \frac{\text{No}}{\text{Yes+No}}$$

The resulted accuracy records that are calculated from the formula below can be seen in Table 2. The resulted probability value of this system indicates the accuracy value that operates the accurate classification of the students' records.

Table 2 System Accuracy Measurement Table

No.	t-Yes	t-No	Accuracy
1	12	20	0.16
2	56	41	0.49
3	60	70	0.65
4	104	73	0.89
5	120	80	1

6. Conclusion

This paper presented the Course Recommender system based on Bayesian classification. By using course recommendation process, the preference courses from students can be generated.

The implementation of this system enables the appropriate courses for making suggestions for students. The course pairs generated by this system will provide the students frequently chosen courses for future time. This system can exploit any of course recommendations for any university. For the educational point of view, this system benefits the teachers for analyzing the students' choices for courses.

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