A STUDENT COURSE RECOMMENDER SYSTEM USING LINEAR CLASSIFIERS: AN EXPERIMENTAL SYSTEM

Queen E. Booker, College of Business, Minnesota State University Mankato, 150 Morris Hall, Mankato, MN 56001 507-389-2445, queen.booker@mnsu.edu
Fred L. Kitchens, Ball State University, Miller College of Business, WB 203, Muncie, IN 47306, 765-285-5305, fkitchens@bsu.edu
Carl Rebman, University of San Diego, Olin Hall 208, 5998 Alcalá Park, San Diego, CA 92110, 619-260-4135, carlr@sandiego.edu

ABSTRACT

Recommender systems are commonly used in e-commerce markets today, using historical data on user preferences and other available data on users and items to predict items a new user might like, using collaborative filtering methods using the history of user preferences to make the recommendations. In this paper, we compare the use of linear classifiers in a model-based recommender system to recommend elective courses to students. We compare our method with a traditional classification model. Our experimental results indicate that the use of the linear model performed similar to the collaborative filtering model in predicting courses students liked or disliked.

INTRODUCTION

Recommender systems are e-commerce based programs which attempt to predict items in which a user may be interested, given some information known about the user. Recommender systems work by collecting data from a number of users, comparing the collected data to similar data collected from others and calculating a list of recommended items for the user. Typical applications of the recommender system include of books, music CDs, or movies. The use of such a system could benefit the academic environment by providing students with a list of recommended classes, majors, and instructors at the beginning of his or her freshman year based on several factors such as courses taken in high school, student objectives in attending college, student study practices, student long term goals, and student personality. In this paper, we compare the use of a linear classifier model and a traditional collaborative filtering model to evaluate their effectiveness in selecting classes a user liked.

RECOMMENDER SYSTEM ALGORITHMS

Collaborative filtering (CF) algorithms apply data analysis techniques to the problem of helping users find the items they would like to purchase by producing a predicted likeliness score or a list of top N recommended items for a given user. Recommendation is defined as a list of items that the active user will like the most. Note that the recommended list must be on items not already purchased by the active user. Item recommendations can be made using different methods. Recommendations can be based on demographics of the users, overall top selling items, or past buying habit of users as a predictor of future items. The goal of a collaborative filtering algorithm is to suggest new items or to predict the utility of a certain item for a particular user based on the user's previous likings and the opinions of other like-minded users. Each user has a list of items within the list, about which the user has expressed his/her opinions. Opinions can be explicitly given by the user as a rating score, generally within a certain numerical scale. [1]

Recommender systems use many types of algorithms such as *mean squared differences* that measure the degree of dissimilarity between two user profiles, *nearest neighbor* which classifies items based on closest training examples in the feature space, *clustering* which classifies similar objects into different groups, or more precisely, the partitions a data set into subsets (clusters), so that the data in each subset (ideally) share some common trait - often proximity according to some defined distance measure, and the *Pearson algorithm* measures similarity between user profiles where the coefficient ranges from -1, indicating a negative correlation to +1 indicating a positive correlation between two users [1], and linear classifiers that use a linear function of its inputs on which to base its decision. [2, 3, 4]

EXPERIMENTAL DESIGN AND RESULTS

To test the models we collected data from 630 students on general education electives. The list consisted of 34 classes across 12 categories that students had to complete to meet the liberal arts requirement for the university. Students evaluated classes on a scale of 7 where 1 was “best class I ever had” to 7 “worst class I ever had.” In addition to rating the class, students also completed a learning styles inventory based on Honey and Mumford’s Learning Styles Questionnaire [5], questions from the Big Five personality inventory test (see http://www.outofservice.com/bigfive/info/ for more information) and five demographic questions: age, ethnicity, gender, year in college and whether full time or part-time. Ten data sets were created by randomly selecting 400 cases to develop the training model and 100 to test the model.

Quantitative Results

To evaluate each algorithm, a predicted value was established for each rating in the target set, using only the data in the source set. Three such target sets and data sets were randomly created and tested, to check for consistency in our results. In the source set, each person rated on average ten courses of the 34 possible. The median number of ratings was 3.7.

The mean absolute error and the standard deviation of errors of each predicted rating must be minimized was the criteria used to evaluate the algorithms as well as the percentage of target values for which the algorithm was able to compute accurate predictions. A summary of some of the results for different values of the number of accurate predictions is presented in Table 1.

	All		Extremes		
Method	MAE	SD	MAE	SD	*C**
Random Walk	1.3	1.8	1.4	2.4	48
Constrained Pearson r, *L*=.5	1.1	1.5	1.8	2.0	84
Constrained Pearson r, *L*=.6	1.1	1.3	1.5	1.7	81
Constrained Pearson r, *L*=.7	1.1	1.4	1.5	1.8	70
Logistic regression, threshold =.5	1.2	1.3	1.3	1.4	85
Logistic regression, threshold =.6	1.1	1.4	1.4	1.5	79
Logistic regression, threshold =.7	1.2	1.5	1.4	1.8	63

*where *C* is the number of correct predictions.

Table 1: Summary of Results for the Two Algorithms

As the table shows, no algorithm was successful at predicting with more than an 85% accuracy. But of the two algorithms, in terms of accuracy and the percentage of target values which can be predicted, the constrained Pearson *r* algorithm performed the best on the dataset if the error as well as the number of correct predictions is taken into consideration. At the .50 threshold, however, both the Constrained Pearson and the logistic regression performed relatively the same. However, the model development for the Constrained Pearson has the advantage of operating and re-optimizing in a dynamic manner more readily than the logistic regression model.

These results indicate that for the given data set, and the variables used, the linear classifier model was no better at predicting courses for students than the Constrained Pearson model.

CONCLUSION AND NEXT STEPS

This study was an experiment to determine if there is promise in using recommender algorithms to provide support for student course selection. The premise behind the research is that if students were able to select classes they would enjoy, such a program could reduce the number of students who leave higher education due to lack of satisfaction with the courses. The results show promise that such a system is feasible; however additional research must be completed to find a model or models that are more highly accurate in predicting appropriate courses. The next step would also be to match selected courses to a student's schedule. Certainly it is appropriate to test all the existing algorithms including neural networks as well as a host of variable models to determine if such a system is feasible for an accuracy level above 95%.

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