

# Automating “Word Of Mouth” To Recommend Classes To Students: An Application Of Social Information Filtering Algorithms

Queen Esther Booker, Minnesota State University, Mankato, USA

## ABSTRACT

*This paper describes the development of a system called OSRS (online student recommender system). We present quantitative and qualitative results obtained from the use of OSRS by current students.*

## INTRODUCTION

In the July 9, 2004 edition of the Chronicle of Higher Education, Zemsky and Massy explained to readers of the Chronicle why e-learning “went bust”, that is, why e-learning or online education failed to penetrate higher education [6]. In 2008, the Sloan Consortium reported that almost 4 million students or one-fifth of all higher education enrolled students took at least one online course in 2007, almost double the enrollment in online courses in 2004 [7] when e-learning had supposedly “went bust.”

The increase in enrollment is due to institutions of higher education expanding online programs to respond to the changing demand and need of online education. Yet, little has been done with one aspect of student support services – sharing information about which courses to take to fulfill requirements. Part of the lack of online student support for course advising or course recommendation is because many of the classes are filled with students who are enrolled in traditional face-to-face courses as well as online courses so the students can use the same advising structure and word of mouth processes as usual. But as institutions begin to move programs to online only, unlike students enrolled in traditional programs, online students are not limited in selection of courses to fill their general education requirements because they do not have to select classes to “fit around” other requirements needed for graduation within their majors or college. Thus online students experience more flexibility in course selection. However, these same students suffer from the lack of information generally received from upper classmen – recommendations on what to take based on personal preference or interests. Most students online or traditional receive recommendations from advisors who tend to recommend classes to students based on schedules or “what other students have found successful within the discipline.” This approach of word of mouth is not easily transferable to the online student. Not that the number of electives for general education is staggering. But if institutions position themselves accordingly, the number of enrollees in online programs could be. The volume of potential students may be considerably more than a group of individuals can handle. The system described in this paper is designed to provide that word of mouth approach that students miss when engaged in a pure online program.

Students have course evaluations available to them as well as blogs and postings of other students to help make decisions about which classes to take. The traditional students rely on friends and other people whose judgment they trust to make recommendations. However, technology can aid in helping students wade through the three types of information to find the classes students want and need.

An approach used to tackle the problem of helping the online student find the classes they want and need is a filtering technique called *social information filtering*, a general approach to personalized information filtering.

Social information filtering essentially automates the process of “word-of-mouth” recommendations: items are recommended to a user based upon values assigned by other people with similar tastes or interests. The system determines which users have similar taste via standard formulas for computing statistical correlations. [5]

Social information filtering systems make recommendations based on the quality of items, rather than more objective properties of the items themselves. Thus, these systems are likely to recommend items to the user, which are very different (content-wise) from what the user has indicated liking before. [2]

This paper details the implementation of a social information filtering based system called OSRS, which makes personalized general education course recommendations to students, with an ultimate goal of making it available to students online. Results based on the use of this system by over 300 of actual users are presented. Two promising algorithms are described, analyzed and compared. These results demonstrate the strength of social information filtering and its potential application as a support system for the growing online education market.

### **OSRS: PERSONALIZING THE ONLINE EXPERIENCE**

According to Shardanand, social information filtering automates a process of “word-of-mouth” recommendations. Social information filtering exploits similarities between the tastes of different users to recommend (or advise against) items. It relies on the fact that people’s tastes are not randomly distributed: there are general trends and patterns within the taste of a person and as well as between groups of people. A significant difference is that instead of having to ask a couple friends about a few items, a social information filtering system can consider thousands of other people, and consider thousands of different items, all happening autonomously and automatically. The basic idea is:

1. The system maintains a *user profile*, a record of the user’s interests (positive as well as negative) in specific items.
2. It compares this profile to the profiles of other users, and weighs each profile for its degree of similarity with the user’s profile. The metric used to determine similarity can vary.
3. Finally, it considers a set of the most similar profiles, and uses information contained in them to recommend (or advise against) items to the user. [5]

OSRS is a social information filtering system which makes personalized general education course recommendations. People describe their general interests to the system by rating general concepts covered in the general education requirements. These ratings constitute the person’s profile. This profile changes over time as the user rates his or her selected electives. OSRS uses these profiles to generate advice to individual users. OSRS compares user profiles to determine which users have similar taste (they like and dislike the same courses). Once similar users have been identified, the system can predict how much the user may like a particular course that has not yet been rated by computing a weighted average of all the ratings given to that course by the other users that have similar taste.

OSRS is currently a stand-alone system. Users sign up and interact with OSRS by coming to the researcher’s office. The system updates all newly information once the user has completed a session – whether it is to evaluate a course or to seek a recommendation.

The system was first populated during the fall of 2004 and has been continually updated through Fall 2008. When the user first accessed OSRS, he or she rated all the general education courses he or she had taken. This continued for three semesters. Beginning with spring 2006 registration, students were able to use the system to recommend classes as well as rate courses taken in fall 2005. If the user is not familiar with a course or does not have a strong opinion, the user is asked not to rate that item. New students are specifically not allowed to rate actual classes because they have no basis for evaluating the courses. The rating for the classes is listed in Table 1. OSRS scale for rating classes.

**Table 1: OSRS’s scale for rating classes**

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1	Best class I ever had.
2	Good course, worth the effort.
3	The course isn’t bad; it’s just OK.
4	I am neutral on the course
5	Barely interesting
6	I could hardly keep my eyes open or my mind from wandering
7	Worst class possible!

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The seven point scale was selected since studies have shown that the reliability of data collected in surveys does not increase substantially if the number of choices is increased beyond seven [5]. Because users rate courses in different ways, the ratings are not normalized. For example, some users only gave ratings to courses they liked while others gave rating whether they liked the course or not. An absolute scale was employed and descriptions for each rating point were provided to make it clear what each number means.

The user selects and rates courses based on his or her previous or current enrollments. Future systems can be tied to the registration system so that students can not rate courses they have not actually taken. Likewise, the system could be tied to an online evaluation system.

Once a person’s initial profile has been submitted, the user can ask OSRS for recommendations on general education requirements that still need to be fulfilled. Specifically, a person can ask OSRS to (1) suggest new classes that the user will enjoy, or (2) identify courses the user will likely dislike. OSRS processes the requests using a social information filtering algorithm, detailed in the next section. It then presents the person with the results. Every recommendation includes a measure of confidence which depends on factors such as the number of similar users used to make this recommendation, the consistency among those users’ values, etc. (cfr. [4] for details.) OSRS’s reply does not include any information about the identity of the other users whose profiles were used to make the recommendations.

In addition to making recommendations, OSRS provides students the opportunity to write a short review, which OSRS stores and shows users. However, specific references to instructors are omitted. When a user is told to try or to avoid a course, any reviews for that course written by similar users are provided as well. Thus, rather than one “thumbs-up, thumbs-down” review being given to the entire audience, each user receives personalized reviews from people that have similar taste.

**SOCIAL INFORMATION FILTERING ALGORITHMS**

Recommender systems apply data analysis techniques to the problem of helping users and 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. 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.

Social information filtering or collaborative filtering (CF) [3] is the most successful recommendation technique to date. The basic idea of CF-based algorithms is to provide item recommendations or predictions based on the opinions of other like-minded users. The opinions of users can be obtained explicitly from the users or by using some implicit measures. 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. In a typical CF scenario, there is a list of m users  $U = \{u_1, u_2, \dots, u_m\}$  a list of n items  $I = \{i_1, i_2, \dots, i_n\}$ . 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. There exists a distinguished user  $u_a$  called the active user for whom the task of a collaborative filtering algorithm is to find an item likeliness that can be of two forms: prediction or recommendation.

**Prediction** is a numerical value expressing the predicted likeliness of item for the active user. This predicted value is within the same scale as the opinion values provided by active user.

**Recommendation** is 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.

There are several popular social filtering algorithms:

- The *mean squared error*. The *mean squared error* measures the degree of dissimilarity between two user profiles,  $U_x$  and  $U_y$  by the mean squared difference between the two profiles and making recommendations by considering all users with a dissimilarity to the user which is less than a certain threshold  $L$  and computing a weighted average of the ratings provided by these most similar users, where the weights are inverse proportional to the dissimilarity.
- *Clustering*. Clustering is the classification of similar objects into different groups, or more precisely, the partitioning of 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.
- *The nearest neighbor algorithm*. *Nearest neighbor* classifies items based on closest training examples in the feature space. The training examples are mapped into multidimensional feature space. The space is partitioned into regions by class labels of the training samples.
- *The Constrained Pearson r Algorithm*. The *Constrained Pearson r* algorithm first computes the correlation coefficient between the user and all other users. Then all users whose coefficient is greater than a certain threshold  $L$  are identified. Finally a weighted average of the ratings of those similar users is computed, where the weight is proportional to the coefficient. [1]

The researchers used the mean squared difference and the constrained Pearson r algorithms because both had shown most promise in earlier evaluations of similar noisy data.

## POPULATING THE DATABASE

OSRS became available to the students during fall 2004. The service was originally populated by students enrolled in college of business classes taught by the researchers. Additional students began participating in the system through word of mouth or enrollment in subsequent courses with the researcher. The number of people completing the ratings grew to over 1000 during the second semester of operation. Students who had never taken a course at the university were unable to establish profiles using existing courses so a proxy system was established using information from courses they took in high school. Thanks to this overwhelming user interest in rating their classes in an alternative format, the researchers were able to accumulate an enormous amount of data on which to test various social information filtering algorithms.

## QUANTITATIVE RESULTS

The study used the mean squared difference and the constrained Pearson r algorithms. For the tests, the profiles of 100 people were considered. Following Shardanand, to test the different algorithms, 20% of the ratings in each person's profile were then randomly removed. These ratings comprised the *target set* of profiles. The remaining 80 % formed the *source set*. 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 thirteen courses of the 112 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 two 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 are presented in Table 2.

Table 2: Summary of Results for the Two Algorithms

Method	All		Extremes		C*
	MAE	SD	MAE	SD	
Mean Squared Difference, $L=2.0$	1.3	1.8	1.4	2.4	80
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

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

As the table shows, no algorithm was successful at predicting with an accuracy of more than 84%. 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. As expected, there is a tradeoff between the average error of the predictions and the percentage of target values that can be predicted. This tradeoff is controlled by the parameter  $L$ , the minimum degree of similarity between users that is required for one user to influence the recommendations made to another. The results are consistent with those provided by Shardanand [4].

## QUALITATIVE RESULTS

Although the two algorithms results were less than spectacular, consideration was given to post-OSRS use evaluation. Researchers asked students in the subsequent semester to evaluate the use of OSRS as a tool for aiding in course selection. As of this writing over 500 students have used OSRS to identify or recommend courses to fulfill their general education requirement. The users completed a questionnaire that was available through Zoomerang to evaluate the system. The results described in this section are all based on user feedback and observed use patterns.

As with most social information filtering systems, OSRS is becoming more competent as the database obtains more data from students. As the number of user scores used to generate a prediction increases, the deviation in error decreases significantly. The more people use the system, the greater the chances are of finding close matches for any particular user. The system will need to reach amass a certain number of data points and users before it becomes truly useful, though. The feedback received to date indicated mixed results with about three-fourths of the students feeling at least neutral on the recommended classes in which they enrolled with more than 50% rating the courses as a 3 or lower. However, the majority of students using the system have found the service useful in at least providing in a centralized automated format all of the electives in for each general education requirement.

Thus, OSRS has potential for growth. Beyond the recommendations, there are other ways in which OSRS can be appealing based on the online student's needs. In addition to grouping students based on similar interests and courses, online students can find online clubs, learning communities, etc that are oftentimes missing from the social aspects of the online learning experience.

## CONCLUSIONS AND FUTURE WORK

Experimental results obtained with the OSRS system have demonstrated that using social information filtering methods to aid students in general education requirements selections can be useful to the student. OSRS has been tested and used in a real-world application and received a positive response. The next steps are to examine more algorithms, increase accessibility of OSRS to an online environment where more students from the University can have access to the system, and increase the type of uses to support the ever growing online student community.

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