Exploring Personalized University Ranking and Recommendation

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ABSTRACT

Finding the right university to study is still a challenge for many people due to the large number of universities worldwide. Although there exist a number of global university rankings, they provide non-personalized rankings as one-size-fits-all solution. This becomes an issue since different people may have different preferences and considerations in mind, when choosing the university to study.

This paper addresses this problem and presents a Recommender System to generate a personalized ranking list based on users particular preferences. The system is capable of eliciting users preferences, provided as ratings for universities, building predictive models on the preference data, and generating a personalized university ranking list that is tailored to the particular preferences and needs of the users.

We performed two sets of experiments. First, we conducted an offline experiment using a dataset of user preferences, collected by the early version of our system. This allowed us to cross-validate and compare different recommender algorithms and choose the most accurate recommender algorithm that can better suit the particular problem at hand. We integrated the chosen algorithm in the final implementation of our system. As the follow-up, we performed a user study in order to analyze whether or not the final version of our system is *usable* from the perception of users. The results showed that the system has scored well above the benchmark and users assessed it as “good” in term of usability.

KEYWORDS

Recommender systems, Collaborative filtering, Preference elicitation, University recommendation, Personalized university ranking

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1 INTRODUCTION

Recommender Systems (RSs) are developed to tackle the information overload and massive choice varieties by creating personalized suggestions that can better match users' preferences [22, 23]. Despite the wide range of applications of RSs, the main application is dominated by the domain of e-commerce such as digital products and entertainment (e.g., movie or music recommendation) [14, 25]. Previous research found that domain-specific RSs are important to advance the value of recommender algorithms [9, 19].

One of less-explored domains is the personal education, which still needs further attention, and may significantly benefit from the RSs integration [3, 6]. There is a large number of educational institutions, such as universities, which causes people to encounter the problem of finding a suitable university to study. Those potential users are not only the students who opt for university studies, but also the people who aim for a professional training or intend to do a life-long learning. For students, such a choice of selecting a university may even have a significant impact on their future life and career [16].

Although there have been limited studies attempting to build customized university rankings [13, 15, 20, 26], to the best of our knowledge, none of the current world-class university rankings offer a customized ranking list that is tailored to the particular preferences and needs of the users. In most cases, the search functionalities of these systems only allow users to filter the universities based on the geographical location or at most offer the possibility to shortlist the universities depending on the limited number of features or categories. An example of such a filtering system can be seen in [2] and many similar web applications. Moreover, popular world university rankings are typically built by computing an overall score for each university based on a set of pre-selected dimensions. Thus, such a score is typically generic and does not take into account particular needs and preferences of individual users. This may considerably limit the utility of the systems that offer these static rankings.

In this paper, we address the personal education advisory problem and propose a novel system that elicits the preferences of users and applies an effective model to predict the university preferences of a target user. The system then ranks the universities according to the predicted score for each university and generates a personalized ranking list for the user. In order to validate our model, we have performed different experiments to evaluate the system prototype.

In the offline experiment, we compared different recommender algorithms in order to conclude which one can provide a better accuracy in predicting the preferences provided by users to universities. Since Singular Value Decomposition (SVD) outperformed the other algorithms, we applied this algorithm for the recommendation generation in our system. Our second experiment is conducted from the user perspective, as we are interested to investigate the usability of the overall system. This is due to the fact that even the sophisticated algorithms may fail to achieve a high utility because different factors such as user interaction model and interface design can impact the system utility. Therefore, we performed a user study and adopted System Usability Survey (SUS) for the usability analysis. The results of user have revealed that the users consider that the system is of good usability.

2 EDUCATION ADVISORY SYSTEM

2.1 Recommendation Model

The techniques adopted for recommendation mainly focus on using a well-known recommendation model called Collaborative Filtering (CF) [14]. Techniques based on CF exploit ratings provided by a network of users in order to predict the missing ratings of the items. The items with the highest predicted ratings are recommended to users. [7] briefly describes the approaches based on CF.

Neighbourhood-based this kind of algorithm such as k-nearest neighbors (KNN) computes rating prediction exploiting two sets of preference data: the ratings of the user for other items and the ratings of other like-minded users. The item's rating prediction is computed based on how the item was rated by the users similar to the target user. The rating $\hat{r}_{u,i}$ for the user u and the item i is predicted in the following way.

$$\hat{r}_{u,i} = \bar{r_u} + \frac{\sum_{u' \in N_{i(u)}} sim(u,u')(r_{u',i} - \bar{r_{u'}})}{\sum_{u' \in N_{i(u)}} |sim(u,u')|} \tag{1}$$

where $\bar{r}_u$ denotes the average ratings of user u, $sim(u,u')$ is a similarity measure between two users u and u', and $N_{i(u)}$ is a set of users similar to user u (neighbours) who rated item i. We computed the similarity based on Cosine metric.

Matrix Factorization techniques such as SVD learns for both users and items factor vectors of the same size. Those vectors are inferred from the user's rating. Each element of the factor vector, assigned to an item, reflects how well the item represents a particular latent aspect. User factor vectors measure the preference of the user for each factor. The task of the factorization is to split the matrix of ratings R into two matrices S and M.

$$R \approx SM^T \tag{2}$$

Where S is $|U| \times F$ matrix, and M is $|I| \times F$ matrix. F represents the number of factors we wish to use. Then, predictions for the ratings are computed in the following way [11].

$$\hat{r}_{u,i} = \sum_{f=1..F} s_{uf} m_{if} \tag{3}$$

where s_{uf} denotes how much the user u likes the factor f and the value m_{if} denotes how strong the factor f is in the item i.

We have crawled the web and collected information for about 12003 universities, including the name, country and the official website. We used this information in the initial version of the system and collected a (small) rating dataset by sharing the link in our social network and requesting people to provide a number of ratings to the universities that are familiar to them. We collected 1515 ratings from 80 users provided to 551 universities. The ratings were provided in the range of [0,100].

Co-Clustering is a different algorithm that groups similar users and similar videos clusters [12, 21].The prediction of $\hat{r}_{ui}$ is computed by assigning the users and items to some clusters C_u, C_i and co-cluster C_{ui}:

$$\hat{r}_{ui} = \hat{C}_{ui} + (\mu_u - \hat{C}_u) + (\mu_i - \hat{C}_i)$$

where $\hat{C}_{ui}$ is the average rating of co-cluster C_{ui}, $\hat{C}_u$ is the average rating of u's cluster, and $\hat{C}_i$ is the average ratings of i's cluster, and clusters are assigned using a straightforward optimization method.

We used this dataset in order to compare a number of recommendation algorithms and to choose the best algorithm in terms of the prediction accuracy. We adopted different types of neighbourhood-based recommenders, i.e., KNN Basic, KNN With Means, and KNN With Baseline. The former is a simple version while KNN With Means is an extended version that simply takes it into account the mean ratings of each user. KNN with Baseline, on the other hand, takes into account the baseline rating. This is a factor that is estimated through a learning process. The number of neighbors for different versions of KNN algorithms is set to 40. We adopted two types of matrix factorization recommenders, i.e., SVD and SVD++ [17, 18]. The later is an extension of SVD as it is capable of taking into account implicit ratings [8]. The number of factors in SVD algorithm is set to 20.

2.2 System Implementation

We have designed and developed a system prototype that can interact with users and meanwhile learn personal preferences. The system is implemented using a LAMP stack: APACHE server to host the web project PHP files and custom PHP scripts for the specific server-side processing of user data, a MySQL database to hold the data, and custom JS/HTML/CSS for the front end implementation. We used the WordPress content management system and implemented a custom front-end theme, which was further changed to have a certain look and feel. We deployed our MySQL database, on a separate server, where we stored all the data: user data, universities data, ratings data, survey data, final recommendations. We used another server for hosting our recommendation engine and all of our recommendations computations, which we exposed and consumed using a set of RESTful API endpoints.

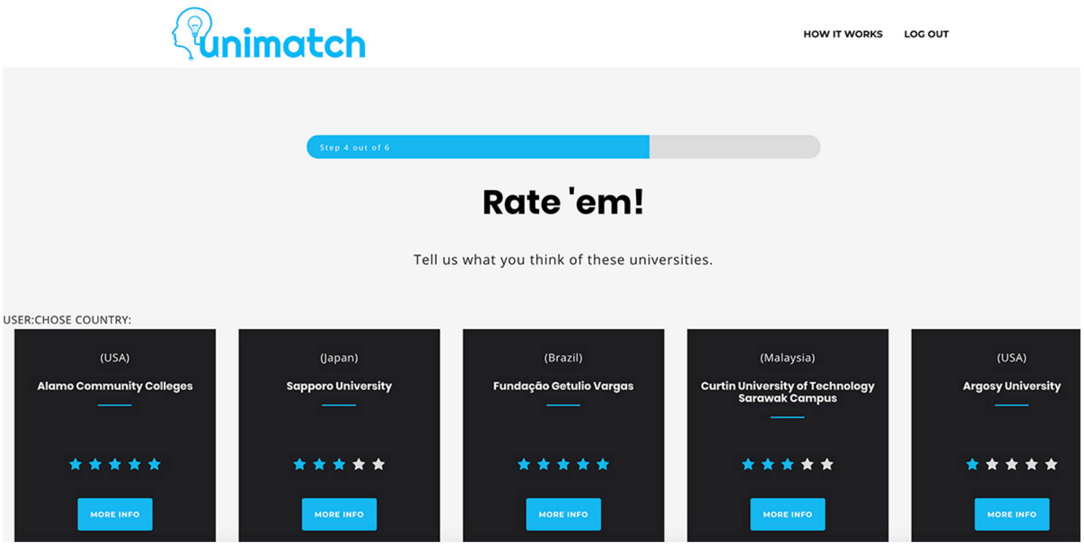

Figure 1: Preference elicitation in the system

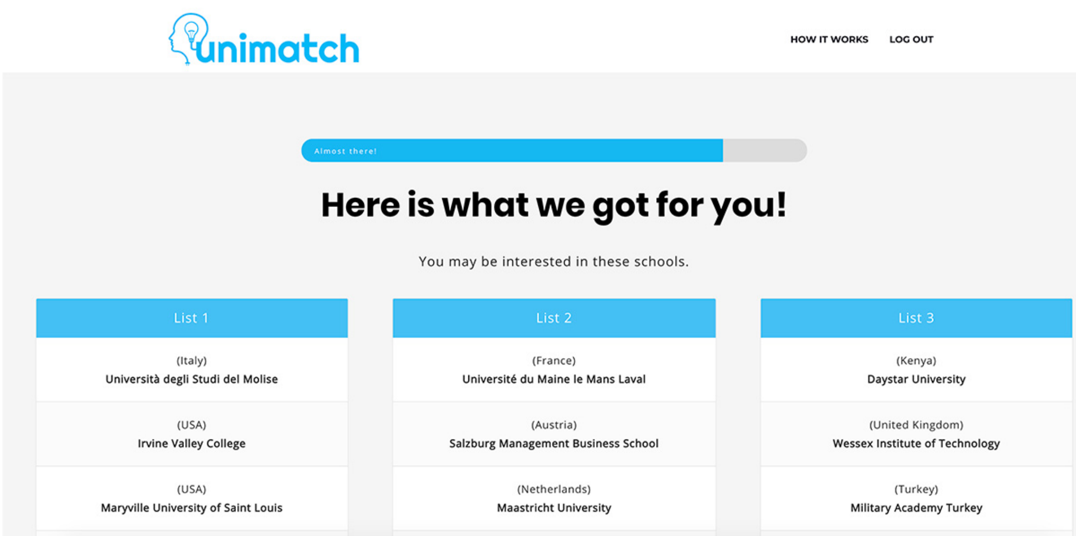

Figure 2: Comparing different recommendation lists, generated by different algorithms

3 EVALUATION

3.1 Offline Experiment

We randomly split the dataset into 5 disjoint subsets and perform 5-fold cross validation by considering each fold as a test set and the remaining folds a train set. We measured the quality of rating prediction in terms of Root Mean Square Error (RMSE), which computes the deviation of predicted ratings from their actual values in test set.

The results are presented in Table 1. As it can be seen, the best results have been achieved by SVD recommender algorithm. The overall RMSE value of SVD, computed by averaging the RMSE values of different folds, is 23.7. The next best recommender algorithm is SVD++ with the overall RMSE value of 24.1. As expected, the worse result is obtained by random baseline with the RMSE value of 36.5.

3.2 User Study

Apart from the offline experiment, we also conducted a user study, in which respondents were invited through different channels such as social media and email invitation. The respondents were requested to register and to input basic information about their demographics and complete a short questionnaire which includes questions that identify the personality characteristics of the user. We collect the personality characteristics of the users for future studies (e.g., in [1, 10]). Afterward, the users were requested to

Table 1: Results of offline experiment

Recommender	RMSE					
	fold1	fold2	fold3	fold4	fold5	mean
SVD	**22.0**	25.4	24.3	25.2	**21.5**	**23.7**
SVD++	24.2	**24.6**	**23.0**	**22.6**	26.0	24.1
SlopeOne	25.7	26.8	25.7	28.3	27.3	26.8
KNNBasic	24.9	28.4	26.8	29.2	28.9	27.7
KNNBaseline	23.5	25.7	25.9	25.7	23.7	24.9
KNNWithMeans	25.3	28.3	26.7	23.8	26.0	26.0
Co-Clustering	29.9	28.5	27.7	27.4	24.2	27.5
Random baseline	36.6	37.1	34.5	39.8	34.6	36.5

provide their preferences (see Figure 1) for the universities that are familiar to them. Finally, they were presented with recommendation (see Figure 2) and completed a survey to provide us their feedback on the quality of recommendation and usability of the system.

Overall 67 respondents participated into our experiment while only 46 completed all the necessary steps. Among the respondents there were 50 males, 14 females and 3 people refused to disclose their gender. Majority of our respondents were between the age of 25 and 34 (37%), holding a Bachelor's degree (73%) and they were from Italy, Russia or Germany. We adopted the System Usability Survey (SUS) [4] that is a ten-item questionnaire based on a five-point Likert scale ranging from "strongly disagree" (1) to "strongly agree" (5). We note that the average SUS score computed in a benchmark of 500 studies is 68 [24]. The survey questions are listed here:

- **Q**1: *I think that I would like to use this recommender system for finding the right university.*
- **Q**2: *I found the recommender system unnecessarily complex.*
- **Q**3: *I thought the recommender system was easy to use.*
- **Q**4: *I think that I would need the support of a technical person to be able to use this recommender system.*
- **Q**5: *I found the various functions in this recommender system were well integrated.*
- **Q**6: *I thought there was too much inconsistency in this recommender system.*
- **Q**7: *I would imagine that most people would learn to use this recommender system very quickly.*
- **Q**8: *I found the recommender system very cumbersome to use.*
- **Q**9: *I felt very confident using the recommender system to find my preferred university.*
- **Q**10: *I needed to learn a lot of things before I can get going with the recommender system.*

Some of these questions are positively formulated where others negatively formulated. Table 2 represents how users replied to the questions. In the table, positive questions are marked as *"pos"* and negative ones marked as *"neg"*.

The user study results obtained from SUS showed that our respondent's have assessed usability of our system higher than the benchmark (i.e., 68). While the actual values given by users ranged from 42.5 (lowest) to 100 (highest), the average was 72.9 with a median score of 75. The final SUS evaluation score assigns the system a grade of B usability level and an adjective rating of "Good".

As it can be seen in Table 2, for positive questions, majority of users replied as "Agree" while for negative questions, majority of users replied "Strongly Disagree" or "Disagree". This means that majority of users positively evaluated the system usability even when replying to the individual questions. To further investigate the results, we have looked at the comments of the users with the lowest scores (below 51) and the highest (above 80). The users that scored below 51 (4 people out of 46 and only 1 of them left a comment), expressed concern about the lack of clarity based on which criteria they were supposed to rate the universities.

Table 2: Result of user study. Positively formulated questions are marked as *"pos"* and negatively formulated questions are marked as *"neg"*.

User Replies	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10
	pos	*neg*	*pos*	*neg*	*pos*	*neg*	*pos*	*neg*	*pos*	*neg*
S. Disagree	7	26	4	**54**	4	17	2	30	0	**43**
Disagree	17	**39**	2	30	4	**52**	4	**52**	4	37
Neutral	22	28	9	9	30	20	7	15	28	9
Agree	**41**	7	**48**	7	**50**	11	**50**	2	**48**	9
S. Agree	13	0	37	0	11	0	37	0	20	2

One notable feedback was the lack of the information about the universities, for example, existing average ratings for the university and a link to a homepage of the university. To address that, we specifically abstained from providing any existing rating information in order to avoid the unnecessary bias. The system also provided a "More Info" link to each school's official website under the Likert scale. The link was opening in a new tab in order not to disrupt the rating process. From the users who assigned higher score than 80 (12 people out of 46 and 4 of them left comments), we found that one person considers the difficulty of rating university due to the lack of knowledge of those universities.

4 CONCLUSION

In this paper, we have targeted a new application domain, personal education selection, to exploit RSs. Users in this domain expect to have a personalized university ranking and advisory. We have therefore proposed a novel system that can elicit user preferences, in term of ratings for universities, and built a personalized university ranking list based on user preferences. From the offline evaluation, we have showed that SVD is an effective algorithm in our system. Furthermore, we have implemented a system prototype to assist the users to select the suitable university. We have also evaluated the system in order to understand the usability of the system from the user perspective. The evaluation results showed that our proposed system is of higher usability compared to the benchmark score.

As future work, we plan to conduct more experiments with larger datasets. We will also conduct user studies to consolidate algorithms that can learn from other sources of information e.g., social media profile of users. We will also redesign the user interface and improve the interaction model by taking advantages of novel design elements [5].

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