Integrating the Anchoring Process with Preference Stability for Interactive Movie Recommendations

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Abstract. Many e-commerce sites employ collaborative filtering techniques to provide recommendations to customers based on the preferences of similar users. However, as the number of customers and products increases, the prediction accuracy of collaborative filtering algorithms declines because of sparse ratings. In addition, the traditional recommendation approaches just consider the item's attributes and the preference similarities between users; however, they are not concerned that users' preferences may be developed as their familiarity with or experiences during choice or preference elicitation grows. In this work, we propose an anchor-based hybrid filtering approach to capture the user's preferences of movie genres interactively and then achieve precise recommendations. To conduct this experiment, we recruited 30 users with different types of preference stabilities for movie genres. The experimental results show that the proposed anchor-based hybrid filtering approach can effectively filter out the users' undesired movie genres, especially for the user who has unstable movie genre preferences. The results suggest that the factor of the stability of users' preferences can be considered for developing effective recommendation strategies.

Keywords: Anchoring process, Genre-based fuzzy inference, Hybrid filtering, Interactive recommendation, Preference stability.

1 Introduction

Recommendation techniques are widely utilized in electronic commerce because of their potential commercial values. The collaborative filtering (CF) approach has been widely used in a large number of diverse applications [1] and enables websites to recommend products based on the preferences of peers whose interests are similar to those of the target user. GroupLens [8] and MovieLens [6] are two well-known collaborative recommendation systems that recommend news and movies respectively. Although CF offers a promising way to expand a user's profile of interests, it cannot overcome the problems of cold-start and sparse ratings (i.e., an individual can only vote for a small fraction of all items). The problem is usually resolved by employing hybrid methods, i.e., by combining content-based and CF techniques [1][4]. This hybrid filtering approach applies CF as the primary algorithm and triggers the

content-based filtering algorithm to make a recommendation. Common research problems in recommendation systems (RSs) are as follows.

- **The cold-start problem:** Cold-start refers to the time in which a new product is introduced into the market and thus has no previous ratings information available either for computing the correlations or training the models [5][8].
- **The rating sparsity problem:** Generally, most commercial RSs employ a large set of items and customers. Thus, the user-item rating matrix will be extremely sparse and also contain a few co-rated items by users [11]. When we use this sparse matrix to calculate similarity and make predictions, the results will be inaccurate.
- **Preference development problem:** In most existing RSs, users' preferences are predicted by analyzing the relationship between product ratings and users (Cheung, et al., 2003). Recent research studies have shown that a user's preference is correlated with his/her personality and prior knowledge [7][10]. However, a few researchers have considered how the stability of users' preferences will influence their decision making processes. Accordingly, considering the stability of the users' preferences to provide effective recommendations is worth investigating.

To tackle the aforementioned problems, we propose an anchor-based hybrid filtering (AHF for short) approach in order to take advantage of content-based and CF approaches in an effort to learn the user's movie genre preferences and then provide effective recommendations. Moreover, the user's preferences develop according to the growth in his/her familiarity with or experience of a specific product or service [9][12]. Thus, the user's preferences are likely to be stable over time, and the user is likely to be well aware of his/her preferences [9][12]. As mentioned previously, we can conclude that when the user's experience increases, the user's preferences become increasingly more stable. Accordingly, the anchoring process in the presented iMovie system is designed to determine how the stability of the user's preferences influences the recommendation results.

2 The Research Objectives and Movie Preference Types

2.1 The Research Objectives

The research objectives in this work are addressed as follows. Initially understanding the user's movie preferences is difficult due to the low numbers of ratings that have been collected in the system (application). Thus, we inferred the user's preference for movie genres via a series of interactive anchoring processes. Theoretically, we used the Analytic Hierarchy Process (AHP) [13], a well-known multi-criteria evaluation approach, to filter out undesirable movie genres and then identify the user's movie preferences for specific genres. Note that the contrast effect of the anchor theory has been applied in the AHP model to learn the user's movie preferences during the interactive process. Basically, any systematic shift in judgment away from an anchor is known as the contrast effect. Furthermore, we proposed an anchor-based hybrid filtering approach to tackle the problem of sparse ratings. Namely, after obtaining the

anchor point of the user, we will utilize the result to calculate the user's genre-based preference and then create the genre-based profile. Note that the genre-based fuzzy inference approach is executed in the back-end system to recommend movies to the user based on his/her genre-based profile [14].

To investigate the issue of preference stability, we defined movie preference (MP) types based on the user's stability of movie genres, i.e., stable and unstable preferences for movie genres. The recommendation strategies are designed based on the user's MP type to see if the user's stability for movie genres will influence the recommendation results. We defined the genre-based movie preference types based on Simonson (2005)[12] and Kwon et al. (2009)[9] to extract the user's stability of preference to genres of movies. Researchers in the customer decision making area pointed out that the consumers often do not have well-defined pre-existing preferences that are merely revealed when they make choices among available products or services [3]. In this work, we measured the user's preference stability based on the user's variants of movie genres, which are introduced as follows.

Stable Preference: When the users have stable preferences, they are highly predictable if their preferences are revealed well [9]. Accordingly, we could infer the users' movie preference based on their previous records. Both the content-based filtering and anchor-based hybrid filtering (AHF) approaches would be effective.

Unstable Preference: It is difficult to customize the offers for the users who have unstable preferences [9]. Thus, the personalized content-based filtering approach would not be suitable for this type of user [2]. Therefore, a more elaborate approach to predict users' movie genre preferences is required. The proposed AHF approach may lead to a much better effect on recommendation results while people have unstable preferences for movie genres.

3 The Anchor-Based Hybrid Approach for Recommendations

3.1 Genre-Based User Movie Preference Modeling

Users have to rate at least fifty movies which they have seen initially. Based on the ratings, the recommendation system will infer the user's initial preference of movie genres. According to the result of the first rating, we use the genre-based fuzzy inference filtering approach (*G-Fuzzy* for short) which is similar to the content-based filtering approach to predict the ratings of a movie [14]. The method is described as follows.

User Preference Modeling: A movie may belong to more than one genre, for example, Toy Story III belongs to the animation, adventure, and comedy genres. Each user's movie preferences (*UP*) are expressed as a set of movie genres with associated scores, as shown in Eq. (1).

$$Genre_{user,j} = \frac{\sum_{k=1}^{n_j} r_k}{n_j} \quad (1)$$

where r_k denotes the ratings for movies belonging to genre j , and n_j is the number of movies that belong to the j th genre. Thus, $Genre_{j, user i}$ means the x th user's average movie preference for genre j . Accordingly, the UP of user x can be expressed as $UP_{user x} = (Genre_{x,1}, Genre_{x,2}, \dots, Genre_{x,n})$

3.2 The Anchoring Process

During the anchoring process, an AHP method is applied to calculate the weights of genres for adjusting the user's genre-based profile. In addition, the stability of the user's preference can be evaluated after iterations of interaction result.

Initially, we selected three movies, and then two of the three movies will be an anchor item and a target item respectively at each round, as shown in Fig. 1. Note that we adopted the contrast effect of the anchor theory. We sorted the scores of genres in ascending order in the user's genre-based profile first. We selected the movie of a genre type with the highest score, $genre^h$, and two movies of genre types with the lowest scores, $genre_{l1}$ and $genre_{l2}$, based on the user's original UP . Then, we asked the user to make a pair-wise comparison between the most favorite genre type of movie, i.e., the genre with the highest score, and the last two undesired genres of movies, i.e., the last two genres with the lowest scores. In this work, the size of the pair-wise comparison matrix is three which is based on the number of evaluation movies. Then, the relative weights of genres of movies can be calculated. Through a series of comparisons, we can filter out the genres which may not interest to the user and identify the genres which may interest the user. After the pair-wise comparisons at each round, the result may keep the same order of preferences for movie genres as the last round. If it does, we will not change the anchor movie in the next round. Otherwise, we will select as the anchor the genre with the highest weight in the previous round.

Fig. 1. The Pair-wise Comparisons (the First Round)

3.3 Adjust the User's Genre-Based Profile

The relative weights of genres of movies will be calculated based on the results of the anchoring process. The user's UP will be adjusted at each round. By adjusting the genre's score for each user, we filtered out the genres that are not of interest to users. After computing the movies' weights by AHP method, we normalized the user's genre-based profile. We used Equation (2) to normalize the user's genre-based profile.

$$GR_i = \frac{r_i}{\sum_{i=1}^n r_i}, \quad (2)$$

Where r_i is the rating of genre i , n is the total number of genres, and GR_i denotes the rating of genre i , which is normalized.

After normalizing the user's genre-based profile, the genres which are selected during the anchoring process were multiplied by the weights which are generated from AHP, as shown in Equation (3). In order to maintain the relative order of genres which are not selected, the unselected genre's score was multiplied with the highest weights.

$$pw_j = GR_j \times w_j, \quad (3)$$

GR_j is the normalized rating of genre j , w_j is the weight of the genre j derived from AHP evaluation results and pw_j denotes the proportional weight of the genre j .

4 Experimental Process

4.1 The Dataset

The front-end recommender system, iMovie, is built for collecting users' ratings on movies. We recruited the subjects who are interesting in watching movies in their leisure time. Thirty students at Fu-Jen Catholic University (Taipei) performed the rating and evaluation tasks. For the back-end database, we used one of the MovieLens's data sets, collected by the GroupLens research group at the University of Minnesota. MovieLens data sets have proven useful for the algorithm research of the recommender system, which contains 943 users, 1682 movies of 100,000 ratings and has been used in numerous collaborative filtering publications (<http://www.grouplens.org/node/12>). Notably, we adopted the genre-based fuzzy inference approach to build the model for recommending movies to users.

4.2 The Evaluation Metric

We used the *Genre preference ratio* to evaluate the effectiveness of the presented *Anchor-based Hybrid Filtering* approach in comparison with the *Genre-based Fuzzy Inference* approach. The metric aims to examine if the proposed approach can help subjects identify favorite or undesired genres of movies, and is introduced below.

Genre Preference Ratio (GPR): The genre preference ratio evaluates the percentage of recommended movies genres that fit the subject's favor or undesired movie genres. There are two types of GPR: favorite GPR (denoted as f_g) and undesirable GPR (denoted as d_g). Both types of GPR are calculated by Equation (4) to evaluate the effectiveness of filtering results based on the proposed anchoring process.

$$GPR = \frac{|\# \text{ of movies with favorite (undesired) genres}|}{|\text{Total number of recommended movies}|}, \quad (4)$$

Note that we will examine how many favorite or undesired genres of movies are preserved or filtered out in the subject's genre-based profile. Basically, the higher the number of favorite movie genres and the lower the number of undesired movie genres preserved in the profile, the better the approach is. Accordingly, we denoted the number (#) of favor and undesired genres of movies as $\#_f_g$ and $\#_d_g$, respectively.

5 Experimental Results

5.1 Evaluation of the Subjects' Preference Stability

We used the *Pearson Correlation Coefficient* to evaluate the stability of our subjects. When the correlation coefficient is above or equal to 0.8, there is a strong relationship with the subject's preference over time. On the contrary, there is the relatively weaker relationship with the subject's preference over time when it is below 0.8. Therefore, we separated the stability into the stable status (stability ≥ 0.8) and the unstable status (stability < 0.8). Table 1 shows that the average stability of all subjects is 0.7768. For stable preference subjects, the average stability is 0.8692 with 77% of subjects, whereas for unstable preference subjects, the average of stability is 0.5142 with 23% of subjects. It shows that a higher proportion of the subjects belongs to the group with a higher stability of movie-genre preferences.

Table 1. The Stability Values of Subjects

Subjects	Stability	Ratio of subjects
All subject	0.7768	100%
Stable subject	0.8692	77%
Unstable subject	0.5124	23%

5.2 Experiment 1: The Genre-Based Fuzzy Inference Approach

Fig. 2 and Fig. 3 show the results of genre preference filtering by the *Genre-based Fuzzy Inference (G-Fuzzy)* approach under various numbers of neighborhoods. The observations are given as follows.

The Results of Stable Subjects: Fig. 2 shows that the *G-Fuzzy* approach make it easier to select a higher number of subjects' preferred movie genres, but will select a higher number of subjects' undesirable movie genres when we increase the number of neighbors from 5 to 25. Overall, the number of neighbors at 15 or 20 achieves the best performance for stable subjects.

The Results of Unstable Subjects: These results are similarly to the results of subjects with a highly stability of genre preference of movies. Fig. 3 shows that the *G-Fuzzy* approach make it easier to select a higher number of subjects' preferred movie genres, but will select a higher number of subjects' the subjects' undesirable movie genres when we increase the number of neighbors form 5 to 30. Overall, the number of neighbors at 15 achieves the best performance for unstable subjects. Furthermore, this result shows that the approach is more effective for filtering out undesirable movie genres for subjects with unstable movie preferences than those with stable ones. That is, it will not select the four most undesirable genres of movies as that of stable users, as shown in Fig. 2.

Discussions: Fig. 2 and Fig. 3 show that the *G-Fuzzy* approach has good performance for stable or unstable user groups when numbers of neighborhoods are 15 or 20.

Fig. 2. The GPRs of the Genre-based Fuzzy Inference Approach of Stable Users

Fig. 3. The GPRs of the Genre-based Fuzzy Inference Approach of Unstable Users

5.3 Experiment 2: The Anchor-Based Hybrid Filtering Approach

Fig. 4 and Fig. 5 show the results of genre preference filtering by the *Anchor-based Hybrid Filtering (AHF) approach* under various numbers of neighborhoods. The observations are given as follows.

The Results of Stable Subjects: Fig. 4 shows that the *AHF* approach make it easier to select a higher number of subjects' favorite movie genres. It also makes it easier to select a lower number of subjects' undesirable movie genres when we increase the number of neighbors from 5 to 30. Overall, the number of neighbors at 15 achieves the best performance for stable subjects.

The Results of Unstable Subjects: Fig. 5 shows that the *AHF* approach makes it easier to select a higher number of subjects' favorite movie genres. It also makes it

easier to select a lower number of subjects' undesirable movie genres when we increase the number of neighbors from 5 to 30. The results for unstable users are somewhat different from stable users as shown in Fig. 5 and Fig. 4. That is, the numbers of neighbors at 20, 25, or 25 achieve the best performance for the unstable subjects.

Discussions: Fig. 4 and Fig. 5 show that the *AHF* approach also has good performance for stable or unstable user groups. Interestingly, it is especially good for users with unstable preferences.

Fig. 4. The GPRs of the Anchor-based Hybrid Approach of Stable Users

Fig. 5. The GPRs of the Anchor-based Hybrid Approach of Unstable Users

5.4 Comparing Results of Groups with Different Stability

According to the evaluation results, we discovered that the number of neighbors at 15 can achieve the best performance for the two approaches on average. We set the number of neighbors at 15 to analyze the performance of the experiments. The discussions are summarized as follows.

Observation 1: The GPR of the *AHF* approach is better than the *G-Fuzzy* approach for selecting subjects' most favorite genres of movies for both stable and unstable user groups, as shown in Fig. 6. It indicates that the proposed *AHF* approach is good for helping subjects select movies which will be of interest to them.

Observation 2: The *AHF approach* achieves the best performance for the subjects who have unstable preferences for movie genres, as shown in Fig. 6. Some of the cases show that it has good performance at selecting two or three genres which are relevant to the subjects' preferences. Similarly, some of cases also show that the anchoring processes can effectively filter the subjects' undesired movie genres, especially for subjects who have unstable preferences. The *AHF approach* can also achieve good performance for subjects with unstable movie genres preferences. The *G-Fuzzy* approach achieves the worst performance for subjects with unstable movie genres preferences.

Fig. 6. The GPRs of Two Approaches for Stable and Unstable User Groups

6 Conclusions and Future Works

A series of experiments were conducted in this research to preliminarily evaluate our research questions. The experimental results show that the proposed *Anchor-based Hybrid Filtering* approach can effectively capture the user's preferences and filter out their undesired movie genres. In addition, the approach can produce effective recommendations, especially for the user who has unstable movie genre preferences. We will continue evaluating whether applying the proposed anchor-based approach in the front-end *iMovie* system can precisely recommend movies. We will have an in-depth analysis for applying different recommendation strategies by considering the users' preference stabilities.

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