MoRe: A USER CONTROLLED CONTENT BASED MOVIE RECOMMENDER WITH EXPLANATION AND NEGATIVE FEEDBACK

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Abstract: Recommendation systems have become a popular approach for accessing relevant products and information. Existing approaches for movie recommendation systems are insufficient, because they do not provide transparency to the users through enabling them to view and edit their profiles. In addition, negative feedback, which is an important clue for the recommender, is not taken into account. In this paper we concentrate on the ideas of automatically generating user profiles from the user's item preferences, and enabling users to view and edit their profiles to get satisfaction. In addition, taking negative feedback for specific values is examined and discussed, which is observed to produce more accurate recommendations. The system also provides the explanations for the produced recommendations and allows users to modify their profile accordingly and see their modifications' effects on the results directly. Initial experimental results demonstrate that the system produces accurate recommendations and gets user trust and satisfaction with the transparency and explanation facility.

1 INTRODUCTION

Recommender systems help people to overcome information overload problem through providing personalized suggestions based on previous examples of a user's likes and dislikes. Several approaches have been developed in both the research and business fields (J. Alspector, A. Kolcz, N. & Karunanithi 1997, P. Resnick & H. R. Varian 1997). Two main effectively used approaches are the collaborative filtering (D. Billsus & M.J. Pazzani 1998) and the content-based approach (M. Balabanovic &Y. Shoham 1997, R. J. Mooney & L. Roy 2000). Several methods have also been investigated for integrating both methods in order to combine the advantages of each approach.

It is not possible to draw recommendations without taking sufficient user feedback. However, the information required for drawing recommendations should be as least as possible so that users will not be overloaded. We observe that recommendation systems that require the least input from the user while providing useful recommendations are rated the most satisfying. The recommendation process should be automated enough to draw a user profile directly from the user's preferred items, because this is the easiest information that the user can supply. Users can guide the system accordingly afterwards, however if the recommender will not allow them to view and update their profile, they would feel frustrated and give less trust to the recommender.

We believe that transparent user profiles and allowing users to edit them can provide more trust in recommenders. Open and editable user profiles allow users to change their profile to provide missing information and to correct errors in their profiles. In addition, negative feedback is also an important correction mechanism. If users are allowed to provide which data they would not want, this will be used to filter out many candidate suggestions.

There are very few examples of open and editable user profiles and almost no reported studies of open profiles for the movies domain that combines automated profile construction mechanism with transparency. MetaLens, a movie recommender system, where user feedback is taken for different dimensions is investigated in (Schafer, J.B., Konstan, J.A., & Reidl, J 2002). They take the values the user prefers for different dimensions, but

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not a negative feedback for different values of every dimension.

The incremental-critiquing approach proposed by McCarthy at (Kevin McCarthy, James Reilly, Lorraine McGinty, & Barry Smyth 2005) describes a system where the user has the option of directly updating the query of selection for the candidates. However, the system builds the implicit user model incrementally through taking user feedback, and it does not include an automated user profile construction mechanism through item similarities, which is a desirable feature for end-user satisfaction.

In this paper, we describe MoRe, a movie recommendation system, with particular emphasis on how to draw and update the user profile automatically and correct them through the user control. The remainder of the paper is organized as follows. Section 2 introduces our adaptive movie recommender. Section 3 presents the evaluation mechanism. Section 4 contains the concluding remarks and discusses topics for further research.

2 MoRe: A USER CONTROLLED MOVIE RECOMMENDER

2.1 Presentation of User Controlled Movie Recommendations

MoRe is a system for personalized movie access. Like many other content-based recommenders, the system constructs a user model representing user's interests from a set of evaluations. The evaluations are presented to the system in the form of ratings.

MoRe assembles its content from IMDb (www.imdb.com) and it periodically gathers new movie data and forms item profiles accordingly. The user preferences are kept in the form of ratings in the user profiles. A new user has to rate at least 10 movies initially. The ratings are presented as one to five stars. From those ratings, the system constructs a user model. After this step, there are 3 different views, namely, Ratings View, Profile View and Recommendations View.

From the Ratings View, users can see the movies that they have rated, and rate new movies. The personalization in the system is fully dynamic, so whenever the user rates new movies, user model is updated accordingly.

From the Profile View shown in Figure 1, users can observe and update their profile. In this view, first the dimensions and their scores are presented. Users can provide negative feedback for the dimensions and update dimension scores. Details of every dimension are displayed under the dimension scores.

In the Recommendations View shown in Figure 2, users can observe the produced movie recommendations. Explanations that describe the reasons for why those movies are recommended are also provided. Users can view the explanation, update their profile data accordingly, and can immediately see the new adapted recommendations.

2.2 Construction and Update of User Profiles

User profiles are constructed from the ratings and updated through the User Profile view. Content-based approach is used to form user profile. The content of each selected movie is represented as a weighted vector of dimension values. By processing the content data of the rated movies content matrix;

$$C = \{c_{m,i,k}; 1 < m < Nm, 1 < i < Dn, 1 < k < Fs\}$$

is formed. Here, Nm is the number of movies rated, Dn is the number of dimensions that are taken into account in the calculation process, and Fs is the number of values for each dimension. Users' interest profiles are also represented as content matrixes. The content matrix is modified whenever users modify their profile model or rate new items. When it comes to produce recommendations, the cosine similarity measure (B. Sarwar, G. Karypis, J. Konstan & J. Riedl 2000) is used to calculate the similarity between user profile and the item profiles.

2.3 Negative Feedback and Open User Profiles

The user model in MoRe is not only open but also editable. Each score for every value of dimensions and dimensions their selves can be modified. In addition, users can add new values and dimensions if the rated movies do not fully reflect the users' interests. Negative feedback facility is integrated into MoRe which increases accuracy and user satisfaction. For instance, if casting is a dimension in a user profile, then its data including specific scores for actors and actresses are shown in Casting tab. User can delete an actor here in order to provide negative feedback for him. In addition to this, he can add new actors and actresses together with their scores. Negative feedback is very valuable for the system accuracy and performance. For instance, think about a scenario where the user likes Mel

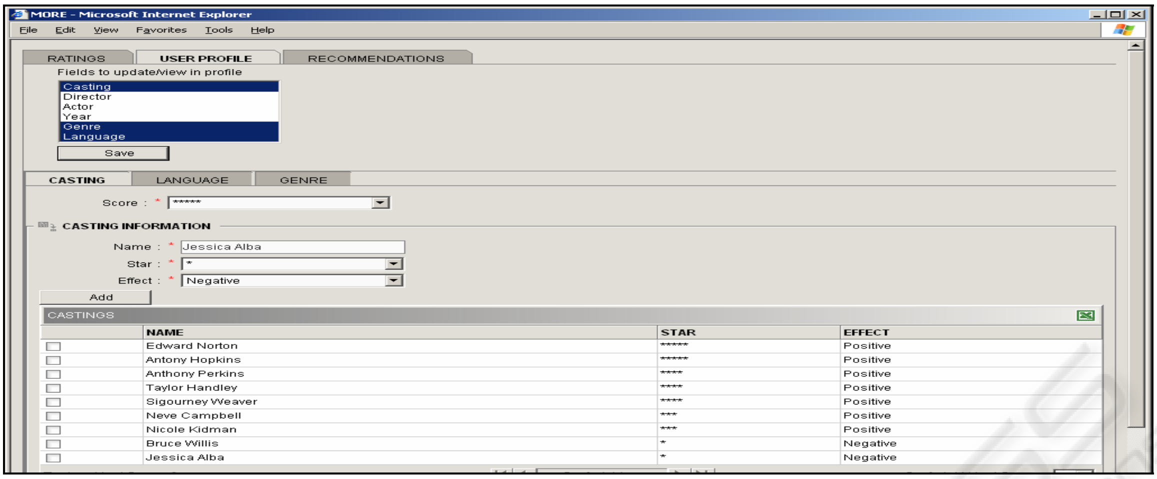

Figure 1: MoRe interface with the User Profile View.

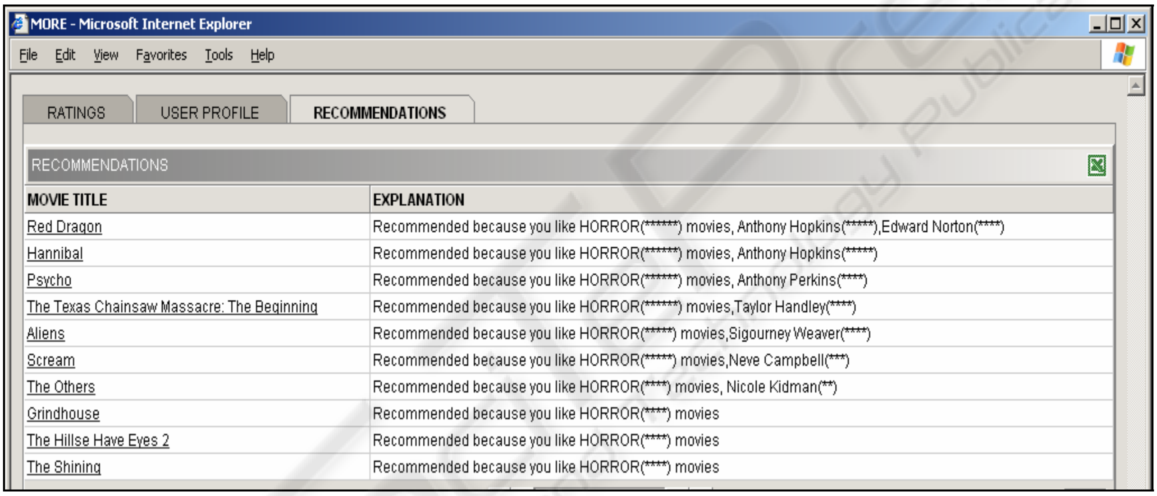

Figure 2: MoRe interface with the Recommendations View.

Gibson a lot, and rates all Mel Gibson movies with high scores. However, most of those rated movies are comedy films. In that case, the recommender will think that the user likes comedy movies and will base its recommendations on this figured out fact, which will lead to inaccurate results. In order to solve that problem, negative feedback feature is integrated in the system. For the scenario above, the user can provide negative feedback for comedy feature of genre dimension. In addition to this, he can specify that he does not want a dimension to be taken into account while producing recommendations. The personalization in MoRe is fully dynamic in the sense that each change in User Profile View or Ratings View (e.g. rating a new movie, updating the score of a dimension, etc.) causes the recommendation list to be updated on the fly. Thus users can examine the effects of the changes immediately after an update to the profile data, which we expected should lead to the improvement of the whole recommendation process.

2.4 Explanation Facility

Explanations of recommendations can be examined from Recommendations View. Explanations are provided in natural language so as to make this view more user-friendly. Dimensions and dimension values are displayed as explanation. For instance, in Figure 2, first recommended movie “Red Dragon” is suggested because of the Genre and Casting dimensions, where specific values of these dimensions are Horror, Antony Hopkins and Edward Norton. In this view, when the user clicks one of the explanations, details of the explanations are displayed in terms of dimension and value scores of these recommendations.

3 EVALUATION

For the evaluation of MoRe, we used MAE (Mean Absolute Error) (Thomas Hofman 2003) metric and conducted a user study. We used MovieLens dataset (www.grouplens.org) in order to conduct our tests. Discussion of this evaluation process is given in section 4. We automatically measured the accuracy of the pure content-based recommender with MAE, where no user interaction took place. Then we evaluated both this simple version and full version through a user study.

In order to find out the value of MoRe's open user profile and negative feedback features, an experimental study is performed. In conducting our user study, we examined the ideas presented in (Kirsten Swearingen & Prof. Rashmi Sinha 2000). At the evaluation phase, we concentrated on the usability and usefulness factors in user satisfaction. We attempted to confirm three hypotheses in the study:

H1: Recommendation systems that require the least input from the user while providing useful recommendations (according to the user) are rated the most satisfying.

H2: Users prefer transparency of their profiles through the recommendation process.

H3: Negative feedback increases the accuracy of the produced recommendations.

4 CONCLUSIONS

In this paper, a content-based approach to movie recommendation, with open user profiles and negative feedback facility is presented. Our main concern was to increase user satisfaction and trust to the recommender through providing transparency of their profiles, explanations of the produced suggestions and allowing them to update their profile information with negative feedback. We believe that transparency and editability of profiles can be applied to address the problems of trust and control in adaptive systems.

Currently, we established and examined which metrics we should use, and how we should conduct our user study. We make initial tests which have satisfactory results.

With the MAE metric, we observe that our full version with the user control performs better than the simple version, which is as expected, since the users correct errors in their profiles from the Profile View. Users find the explanation facility and open and editable user profiles very satisfying. We examined the time spent for examining profiles and explanations and the action taken after this process.

In order to get more valid data to make comparisons with the existing systems, we have to examine the system with more subjects, and get user feedback, after a usage of a long period.

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