E-MRS: Emotion-based Movie Recommender System

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Abstract

In the context of electronic commerce, recommender systems guide the user in a personalized way to interesting or useful objects in a large space of possible options. In order to provide reliable recommendation, the recommender systems need to exactly capture the customer needs and preferences into the user profile. However, for subjective and complexes products such as movies, music, news, user emotion plays surprising critical roles in the decision process. As the traditional model of user profile does not take into account the influence of user emotion, the recommender systems cannot understand and capture the constantly changing preferences of user. In this paper, we introduce an Emotion-based Movie Recommender System (E-MRS) as a solution to this problem. The objective of E-MRS is to provide adapted and personalized suggestions to users using a combination of collaborative filtering and content-based techniques. The recommendation is based on inferences about a user's emotions and preferences, as well as opinions of other similar users. This paper also discusses the system design and implementation, as well as its evaluation procedure. We believe that our system provides much better recommendation to users because it enables the users to understand the relation between their emotional states and the recommended movies.

Index Terms: *Emotion detection, collaborative filtering, content-based filtering, recommender system.*

1 Introduction

ELECTRONIC Commerce is the movement of everything involving business on the Internet and the World Wide Web. Electronic Commerce will lead to simpler, faster and more efficient business transactions because the customers can benefit from the increasing range and ease of access to information, products and services. However, in today's competitive business environment, providing value to the customer is very important for businesses to survive. The most effective way to provide value is to know the customers and serve them as individuals. Customers need to feel they have a unique personal relationship with the business [Peppers and Rogers 1997].

Recommender systems have become an answer to the need of personalization. The customer usually provides the recommender system with data such as the characteristics of the product he is looking for, his ratings, demographic data, etc. The recommender system applies one or several recommendation techniques on these data and then recommends products to the customers. In order to provide reliable recommendation, the recommender system needs to capture exactly the customer needs and preferences. However, for subjective and complexes products such as movies, music, perfume, the task of rating or describing the desired product characteristics is quite difficult for customers. Moreover, as user preferences for these subjective products change constantly according to their emotions, the traditional user profile is not sufficient to understand and capture these changes. To solve these problems, we propose to use an Emotion-based Recommender System (E-MRS) that can capture customer preferences according to their emotions. Emotion plays an important role in rational and intelligent behaviour, thus, we incorporate user emotions in to the recommendation process. This paper is organized as following: Section 2 review some of the related work, including the current recommendation techniques and some movie recommender system. Section 3 discusses the basic notion of emotion as well as the methods to detect emotion. Section 4 presents the architecture of E-MRS, an emotion-based movie recommender system. This section also describes the methodology and the UML modeling of our system. The validation procedure and the comparison of our system are given in Section 5. This is followed by a conclusion and future works.

2 Related Work

Recommender systems are any system that produces individualized recommendations as output or has the effect of guiding the user in a personalized way to interesting or useful objects in a large space of possible options [Burke 2000]. The e-commerce sites use these recommender systems to help the consumers in their decision-making processes by suggesting products and providing them with necessary information [Schafer et al. 2001]. The recommender systems have three main components:

- The product information;
- The information that user must communicate with the system at the beginning of the recommendation process; and
- An algorithm that combines product information and user information together to generate a recommendation.

According to [Burke 2002], there are five different recommendation techniques: collaborative filtering, content-based filtering, demographic filtering, utility-based and knowledge-based recommendation. However, as the sensitivity to on-line privacy is increasing: demographic filtering is not efficient because the users are reluctant to disclose their demographic information. Moreover, for complex and subjective domains like movie, music and news, the most suitable techniques are collaborative, content-based, knowledge-based or the combination of these techniques. *Collaborative filtering (CF)* systems recommend products to a customer based on the opinions of other like-minded customers who have already purchased and/or rated products from the same e-commerce site. These systems can identify cross-genre niche without domain knowledge. However, CF system simply looks at a target user's choices and has no understanding of their actual preferences. The system will not be able to make recommendations on items for which it has no information, or for users who are sufficiently dissimilar to all other users. Some examples of CF systems are Tapestry [Goldberg et al. 1992], GroupLens [Resnick et al. 1994]

According to [Burke 2002], the content-based filtering systems define each item by its associated features. They learn a profile of the user's interests based on the features present in the items that the user has rated. The systems make recommendations by analyzing the description of the items that have been rated by the user and the description of items to be recommended. The recommendations can be made even if the system has received a small number of ratings, as the recommendations are based on product features. However, content-based systems are limited by the features that are explicitly associated with the objects that they recommend [Burke 2002]. For example, content-based movie recommendation can only be based on written materials about a movie: actors' names, plot summaries, etc. Moreover, it is impossible to consider all features associated to subjective and complex products such as movie, music or news. An example of content-based filtering system is Reel.com's Movie Matches (www.reel.com).

Knowledge-based recommendation systems suggest products based on inferences about a user's needs and preferences. These systems have no start-up problems and do not require user ratings. However, knowledge acquisition is very difficult, for example the system PickAFlick [Burke 2000].

Hybrid recommendation systems combine two or more recommendation techniques to gain better performance with fewer of the drawbacks of any individual one [Burke 2002]. For example, the system Recommendz [Garden and Dudek 2006] is combination of collaborative, content-based and knowledge-based filtering. The user profile not only contains the overall ratings of movies, but also includes desired features of each movie. The system presumes that a user's attitude toward a particular feature might vary with the quantity of the feature in question. For instance a user might have a high opinion of slapstick comedy in small amounts but not in large amounts. However, because the user preferences are continuously changing according to their emotions and circumstances, this model of user profiles cannot capture these changes in time.

The next section will discuss emotions and the methods to detect them.

3 Emotions

Emotion can be described as *"a state usually caused by an event of importance to the subject. It typically includes (a) a conscious mental state with a recognizable quality of feeling and directed towards some object, (b) a bodily perturbation of some kind, (c) recognizable expressions of the face, tone of voice, and gesture (d) a readiness for certain kinds of action"* [Oatley et al. 1996]. According to Picard et al. 2001], emotion can be defined as a sequence of changes of state, in a way interdependent and synchronized in response to the evaluation of the relevance of an external stimulus or intern. Moreover, emotions are important because they can influence interactions, behaviours and thinking [Goleman 1995]. For example, sometimes an emotion can change the content of a message and it means at times that it is not what was said that is most significant, but how it was said [Picard et al. 2001]. Therefore, in the human-human and human-computer interaction, it is necessary that the computer recognizes many differences among human emotional states.

Most people experience movies every day with affective response. For instance, joy when watching an excellent comedy, sadness when watching a late night romantic movie. For example, when Alice is in love, she would like to see romance movies with happy endings. But when she is sad, she may like an action movie to improve her feelings.

For these reasons, our present work aims to recommend movies based on emotions. To do so, we can recommend movie by the rules, in terms of the relationship between emotion and movie elements, observed by the psychological research. However, to the best of our knowledge, there are not any psychological rules linking emotion and movies. For example, when Alice is sad, what kind of movies she should watch in order to improve her feelings?

Another possible approach is to learn the rules by training. The user will be asked to answer a questionnaire (movie-emotion), indicating his film preferences according to his emotions, for example, which movies or what kind of movies you would like to see when you are sad, happy, etc. We choose to use this method to build up the basic rules for our system. The quality and quantity of these rules will be improved over time as there are more and more users joining the system. Our movie-emotion questionnaire is shown in Fig. 1.

Movie / Emotion	Love	Horror	Action	Humour	Fiction	Documentary
Joy						
Love						
Anger						
Sadness						

Figure 1. The movie-emotion questionnaire

Several psychology researchers tried to categorize emotions with the objective of classifying diverse emotional states. But this is a controversial point; they do not agree neither on a list of basic emotions nor on the criteria that identify them as in [Ortony and Tuner 1990].

Thus, we choose to base our work on the most well-known studies carried out by [Parrot 2001]. This research mentions six basic emotions: love, joy, surprise, anger, sadness, and fear. In our system, we consider only the four emotions: love, joy, anger, and sadness because the emotions of fear and surprised are momentary.

There are many ways to capture user emotion. For example, we can use mechanisms detecting emotions by voice and facial expressions [Cacioppo 2000]. These methods yield the most accurate results; however, they are very expensive and not practical for a recommender system.

We can evaluate the user emotion by asking the user to answer a questionnaire. This is a simple and inexpensive way to capture emotions but the accuracy is not warranted because the user may not tell the truth or have difficulties in expressing how he feels.

Some researchers agreed that colours have a strong impact on our emotions and feelings [Hemphill 1996; Mahnke 1996], and colour is a natural form to represent human emotions [Black 2002]. We choose this method of emotion detection because this method is not only simple but also easy to do and entertained for users. Although the accuracy is not as good as the sensors, there are many researches emphasizing on the relation between colours and emotions.

For instance, the yellow colour is associated with positive emotions, for example joy, merry, good mood [Wexner 1954; Murray et al. 1957; Schaie 1961; Wexner 1982; Collar 1996; Ballast 2002]. The blue colour is associated with positive emotions, like pleasure and happiness [Schaie 1961; Kaya et al. 2004]. The green colour is associated with happiness, calmness, and feelings of relieving. [Kaya et al. 2004]. The black and grey colours are associated with negative emotions like sadness, depression, and loneliness [Murray et al. 1957; Odbert et al. 1942; Collar 1996; Schaie 1961]. The brown colour is associated with negative emotions, like sadness and depression [Collar 1996]. The red colour is associated with anger [Schachtel, 1943; Pecjak 1970; Frasson et al. 2005], and other studies show that red is associated with love, passion, excitation [Collar 1996; Pecjak 1970; Ballast 2002; Wexner 1982; Odbert et al. 1942; Murray et al. 1957]. The orange colour is associated with positive emotions, like cheerfulness [Collar 1996; Murray et al. 1957; Schaie 1961], but also with negative emotions, like fear and distress [Ballast 2002; Wexner 1982; Murray et al. 1957]. Others studies show that light colours are associated with positive emotions and dark colours with negative emotions [Boyatzis et al. 1994; Hemphill 1996].

Based on the above researches, this is the summary of the relation between colours and emotions used in our system. It is shown in Table 1.

The next section will present the architecture of our Emotion-based Movie Recommender System.

Emotions	Colours
Joy	Yellow, Light Orange, Blue, Green
Love	Light Red
Anger	Dark Red
Sadness	Brown, Grey, Black

Figure 2. Emotions and colours

4 Architecture

The architecture of E-MRS (Fig. 2.) is designed to recommend movies to users based on their emotions. To do so, the system captures user emotions by using a sequence of three colours. It will search for like-minded users who have similar emotion profiles and recommend movies with explanation. This system is a hybrid of two techniques: collaborative filtering and content-based filtering.

As illustrated by figure 2, the system is composed of six modules: User profiles, Film catalogue, Data management, Recommendation module, Emotion detector, and Interface.

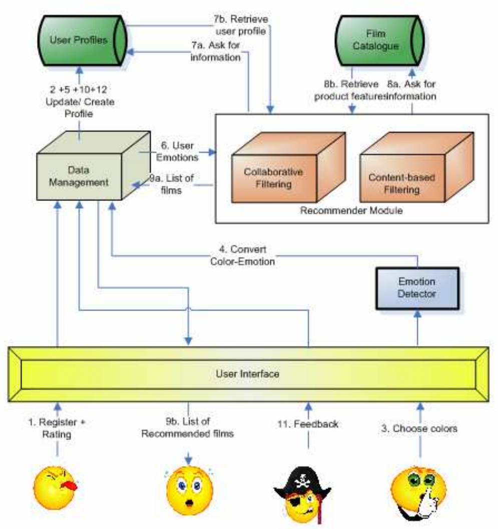

Fig. 2. Architecture of Emotion-based Movie Recommender System

Figure 3. Architecture of Emotion-based Movie Recommender System

- **User profiles** module contains information about personal data (e.g. login, password), emotion-movie relation, and user emotions (history of user emotional state). As mentioned earlier, in order to relate emotions to movies, the users have to answer a questionnaire about what movies or which categories of movies they liked to watch according to each emotion. Furthermore, the system captures user emotions by asking them to use 3 colours to decorate their avatar.

- **Film catalogue** consists of information about the movies being recommended and their features (e. g. name, genre, director, actors, and actress).

- **Data management** is used to create and update the Users profile. It also interacts with the Recommendation module in order to give the list of recommend films.

- **Recommendation module** searches for similar users and similar films, then recommend the most appropriate films to the target user according to his emotion. This module uses two recommendation techniques: collaborative filtering and content-based filtering

- **Emotion detector** detects current user emotion based on the colours chosen by the target user.

- **Interface module** focused on the user-friendly interaction between users and others modules.

The next section will describe the algorithms used in these modules.

4.1 Methodology-Algorithms

4.1.1 Emotion Detection Algorithm

The role of this algorithm is to determine, according to three colours chosen by the user, which is his emotional state. In order to do so, it will analyse the colour sequence by using the follow logic: if at least two of three chosen colours indicate the same emotion and this emotion becomes the current emotional state of the user. For example, if the user chose three colours: (yellow, blue, green) or (yellow, blue, black), then the user emotional state is joy. However, another possibility happens if the first chosen colour indicates of joy (positive emotion), the second one indicates love (positive emotion) and the last one indicates sadness or anger (negative emotion). In this situation, the emotions “joy-love” become the current emotional state of the user. On the contrary, if two chosen colours indicate negative emotion and one indicates positive emotion, sadness and anger become the current emotional state of the user. For example, if the user chose three colours: (yellow, light red, black), then the user emotional state will be positive emotions "joy-love". The Emotion Detection algorithm is shown in Table 2.

4.1.2 User profile vector

User profiles contain information about the movie ratings and the emotion related to each movie. This information is stored in the User Profiles Database.

At the registration time, the user will answer a questionnaire to express his opinion about which categories of films or which films correspond to each emotion. Each film selected by the user is considered as being rated implicitly 5 out of 5.

```
Choice1, Choice2, Choice3 = Colours chosen
by the user
State = User emotional state
Colours of JOY:          Colours of SADNESS:
Y  = Yellow              BR = Brown
LO = Light Orange        GY = Grey
B  = Blue                BK = Black
G  = Green
Colours of LOVE:         Colours of ANGER:
LR = Light Red           DR = Dark Red
Colours of positive      Colours of negative
emotions: Two choices    emotions: Two choices
in Joy and Love          in Anger and Sadness
IF Choice1 IN (Y,LO,B,G) AND Choice2 IN
   (Y,LO,B,G) AND Choice3 IN (Y,LO,B,G) THEN
  State = Joy
ELSE IF Choice1 = LR AND Choice2 = LR AND
    Choice3 = LR THEN
  State = Love
ELSE IF Choice1 = DR AND Choice2 = DR AND
    Choice3 = DR THEN
  State = Anger
ELSE IF Choice1 IN (BR,GY,BK) AND Choice2 IN
   (BR,GY,BK) AND Choice3 IN (BR,GY,BK) THEN
  State = Sadness
ELSE IF (Choice1 and Choice2 IN (Y,LO,B,G)
     AND Choice3 NOT IN (Y,LO,B,G)) OR
    (Choice2 and Choice3 IN (Y,LO,B,G)
     AND Choice1 NOT IN (Y,LO,B,G)) OR
    (Choice3 and Choice1 IN (Y,LO,B,G)
     AND Choice2 NOT IN (Y,LO,B,G)) THEN
  State = Joy
ELSE IF (Choice1 and Choice2 IN (BR, GY, BK)
     AND Choice3 NOT IN (BR,GY,BK)) OR
    (Choice2 and Choice3 IN (BR,GY,BK)
     AND Choice1 NOT IN (BR,GY,BK)) OR
    (Choice3 and Choice1 IN (BR,GY,BK)
     AND Choice2 NOT IN (BR,GY,BK)) THEN
  State = Sadness
ELSE IF (Choice1 and Choice2 = LR AND
     Choice3 <> LR) OR
    (Choice2 and Choice3 = LR AND
     Choice1 <> LR) OR
    (Choice3 and Choice1 = LR AND
     Choice2 <> LR) THEN
  State = Love
ELSE IF (Choice1 and Choice2 = DR AND
     Choice3 <> DR) OR
    (Choice2 and Choice3 = DR AND
     Choice1 <> DR) OR
    (Choice3 and Choice1 = DR AND
     Choice2 <> DR) THEN
  State = Anger
ELSE IF (Choice1 and Choice2 IN (Y,LO,B,G,
    LR) AND Choice3 NOT IN (Y,LO,B,G,LR)) OR
   (Choice2 and Choice3 IN (Y,LO,B,G,LR) AND
    Choice1 NOT IN (Y,LO,B,G,LR)) OR
   (Choice3 and Choice1 IN (Y,LO,B,G,LR) AND
    Choice2 NOT IN (Y,LO,B,G,LR)) THEN
  State = Joy and Love
ELSE IF (Choice1 and Choice2 IN (DR,BR,GY,
    BK) AND Choice3 NOT IN (DR,BR,GY,BK)) OR
   (Choice2 and Choice3 IN (DR,BR,GY,BK) AND
    Choice1 NOT IN (DR,BR,GY,BK)) OR
   (Choice3 and Choice1 IN (DR,BR,GY,BK) AND
    Choice2 NOT IN (DR,BR,GY,BK)) THEN
  State = Anger and Sadness
END IF.
```

Figure 4. The emotion-detection algorithm

The profile vector consists of four groups of user emotions: love, anger, joy, and sadness. Each emotion group E then contains information about the movie category or the name of each movie that the user would like to watch when he has the emotion E.

The general profile vector is:

$$N = \{\underbrace{\{\text{Films: Ratings}\}}_{\text{Love}}, \underbrace{\{\text{Films: Ratings}\}}_{\text{Anger}}, \underbrace{\{\text{Films: Ratings}\}}_{\text{Joy}}, \underbrace{\{\text{Films: Ratings}\}}_{\text{Sadness}}\}$$

For example, the user u chooses film A, B for the emotion "love", film C for "Anger" and film D for "Joy", the profile vector of u is: $u = \{\{A : 5, B : 5\}, \{C : 5\}, \{D : 5\}, \{\}\}$

When receiving film recommendation proposed by the system, the user can give feedback by rating how much this film is appropriate to his current emotion.

For example, the system recommend film F for emotion "love", the user does not agree that he would like to watch this film while he's in love, so he rates this film as 1 over 5.

The profile vector of u becomes:
$u = \{\{A : 5, B : 5, F : 1\}, \{C : 5\}, \{D : 5\}, \{\}\}$

4.1.3 Recommendation algorithm

The recommendation algorithm is in fact a cascade hybrid of two techniques: a collaborative filtering and a content-based recommendation.

Collaborative filtering:
We now give a detailed description of how our collaborative filtering approach can be applied in the recommendation process.

For a given database U of user profiles, and a target user u, a movie m, an emotion e, the executive steps of the CF algorithm can be outlined as following:

- **Step 1:** Extract the profile vector of the target user u from the database.
  We take into account the information of user preferences available from the User Profiles database U.
  For example, for the target user u, his profile vector is $u = \{\{A : 5, B : 5, F : 1\}, \{C : 5\}, \{D : 5\}, \{\}\}$
- **Step 2:** Search for other users who have rated at least one movie in common with the target user u.

In order to reduce the computing user-film matrix, the system will consider only the users who have rated at least one movie-emotion in common with the target user u.

For example:
Let U_n is a sub collection of U, containing only users

who have at least one movie-emotion in common with u.

$U_n =< u_1, u_2, u_3 >$
There are 3 users in U_n with:
$u_1 = \{\{A : 5, F : 2\}, \{C : 5\}, \{E : 5\}, \{I : 5\}\}$
$u_2 = \{\{B : 5\}, \{\}, \{G : 5\}, \{H : 4\}\}$

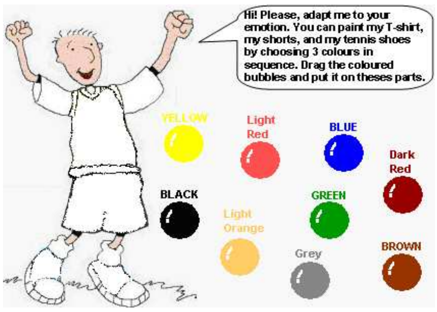

Figure 5. Screenshot of the user interface

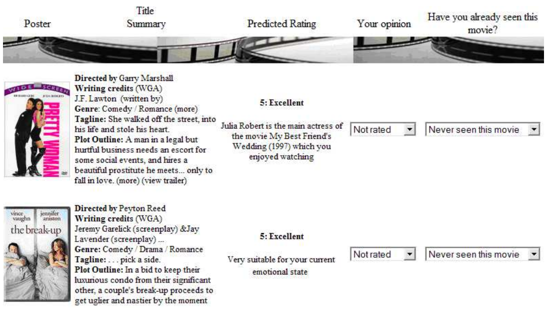

Figure 6. Screenshot of the film list

However, according to [Hill et al. 1995], users do not provide consistent ratings when asked to rate the same movie at different times. As a result, it is impossible to create an algorithm more accurate than the variance in a user's ratings for the same item [Herlocker et al. 2000]. Even when accuracy differences between recommender systems are measurable, they are usually too small to be noticed by the users.

Another problem is that some recommender systems produce highly accurate but totally useless recommendations to users. For example, Lord of the Rings is a very famous movie and nearly all of the movie lovers have already seen it. So, it is useless to recommend it again to the users.

Therefore, in order to make the evaluation results to be more reliable, we propose to use the precision and mean absolute error with consideration to novelty factor.

- *Mean absolute error (MAE)* measures the average absolute deviation between a predicted rating and the user's true rating. Thus, it can measure how close the recommender system's predicted ratings are to the true user ratings.

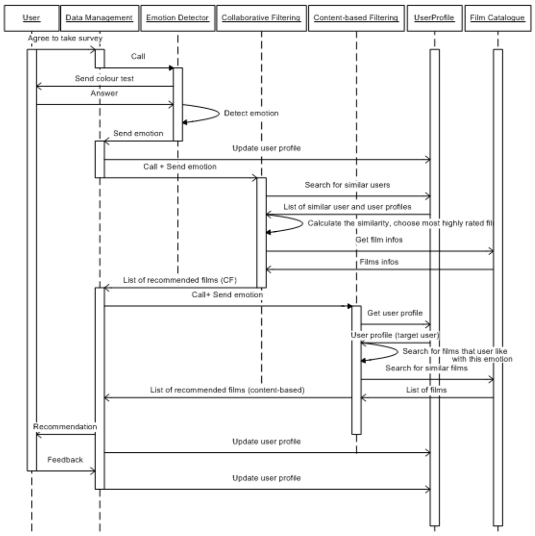

Figure 7. UML Sequence diagram

- *Precision* is defined as the ratio between the number of well-recommended items and the total number of rated recommendations. Well recommended movies are movies which the users have never seen before and are rated at least 4 out of 5.

The main goal of our tests is to measure how close our system's recommended products are to the true user's needs and preferences. Another goal is to determine precision of the Emotion detector.

After providing a list of movie recommendation to the users, the system will ask them to evaluate each movie and to specify whether they have already seen that movie (see Fig. 4.).
The users are also invited to answer a survey at the end of the recommendation process:

- Questions about the overall evaluation of the user about the system,
- Questions about the user interface and recommendation explanations, and
- Questions about the quality and the precision of the Emotion detector.

All responses from this survey will be stored and calculated in order to determine the user satisfaction after using the system.

Comparison with other systems Table 3 shows the comparison between our system E-MRS and four other recommender systems: PickAFlick, Recommendz [Garden and Dudek 2006], MovieLens, and Amazon (www.amazon.com).

System / Criteria	E-MRS	PickAFlick [Burke 2000]	Recommendz	MovieLens	Amazon
Domain	Movie	Movie	Movie	Movie	Various products
Interaction with users	- Questionnaire (at time of registration) - Sequence of colors	- Choosing movies (like)	- Rating movies	- Ratings movies	- Ratings
Techniques used	- Collaborative (user) - Content-based	- Knowledge-based	- Collaborative - Content-based	- Collaborative (users)	- Collaborative (items)
Profile	- Emotions - Relation Emotion-Movie - Ratings	- Chosen movies	- Two lists of movies (like and dislike) - Ratings - Desired features	- Ratings	- Buying history - Wish list - Ratings
User's feedback	- Ratings	- No	- Ratings	- Ratings	- No
Explanations	- Yes	- No	- No	- No	- Yes
Recommendation basis	- User emotion - Item similarity - Neighbourhood users' ratings	- Multiple retrieval strategies - Item similarity		- Neighbourhood users' ratings	- Item similarity

Figure 8. Comparison with other systems

PickAFlick [Burke 2000] is a knowledge-based recommender system using multiple retrieval strategies, different ways of assessing the similarity of items. However, the user profile does not reflect the real preferences of the target user.

Recommendz requires the users to state clearly the reason why they like or dislike a movie in term of “movie feature”, for example: adventure, action, bittersweetThe disadvantage of this approach is that the movies domain is subjective and complex, so that it is impossible to incorporate all the possible features.

MovieLens is a pure collaborative filtering recommender system. As the user profile contains only the user ratings, it cannot capture the real reason why the user like or dislike a movie.

Amazon is well known as a pioneer in e-commerce and product recommendation. The recommendation technique is simple, and considers only the similarity between items chosen by users and other items in the database.

5 Conclusion

E-MRS has the novelty of incorporating user emotions into the user profile to provide users with well-recommended products based on their emotional state. Because movie is a complex and subjective domain, it is necessary to incorporate user emotion into the user profile.

Users can give their feedback about how a recommended movie meets their preferences. This feedback (in the form of user's rating) improves the recommendation quality over time. Last but not least, the system explains to the users the movie recommendations in plain English, describing the choices and the underlying reasoning.

The ability to recognize emotion is an aspect of human intelligence that has been argued to be even more important than mathematical and verbal intelligences. Because emotion can influence interactions, behaviours and thinking of the user, we believe that E-MRS with the Emotion detector can greatly improve the efficiency of the movie recommendation. However, the precision of this module should be validated. Moreover, the relation between colours and emotions depends on culture, religion of user. We shall consider these aspects in a future work, as well as the system implementation and validation.

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