Chapter I
State-of-the-Art Recommender Systems

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ABSTRACT

The aim of Recommender Systems is to help users to find items that they should appreciate from huge catalogues. In that field, collaborative filtering approaches can be distinguished from content-based ones. The former is based on a set of user ratings on items, while the latter uses item content descriptions and user thematic profiles. While collaborative filtering systems often result in better predictive performance, content-based filtering offers solutions to the limitations of collaborative filtering, as well as a natural way to interact with users. These complementary approaches thus motivate the design of hybrid systems. In this chapter, the main algorithmic methods used for recommender systems are presented in a state of the art. The evaluation of recommender systems is currently an important issue. The authors focus on two kinds of evaluations. The first one concerns the performance accuracy: several approaches are compared through experiments on two real movies rating datasets MovieLens and Netflix. The second concerns user satisfaction and for this a hybrid system is implemented and tested with real users.

INTRODUCTION

There has been a growth in interest in *Recommender Systems* in the last two decades (Adomavicius & Tuzhilin, 2005), since the appearance of the first papers on this subject in the mid-1990s (Resnick et al., 1994). The aim of such systems is to help *users* to find *items* that they should appreciate from huge catalogues.

Items can be of any type, such as films, music, books, web pages, online news, jokes, restaurants and even lifestyles. Recommender systems help users to find such items of interest based on some information about their historical preferences. (Nageswara Rao & Talwar, 2008) inventory a varied list of existing recommender systems and their application domain that have been developed in the academia and in the industry.

Three types of recommender systems are commonly implemented:

- collaborative filtering;
- content-based filtering;
- and hybrid filtering.

These systems have, however, their inherent strengths and weaknesses. The recommendation system designer must select which strategy is most appropriate given a particular problem. For example, if little item appreciation data is available then a collaborative filtering approach is unlikely to be well suited to the problem. Likewise, if item descriptions are not available then content-based filtering approaches will have trouble. The choice of approach can also have important effects upon user satisfaction. The designer must take all of these factors into account in the early conception of the system.

This chapter gives an overview of the state-of-the-art in recommender systems, considering both motivations behind them and their underlying strategies. The three previously mentioned recommendation approaches are then described in detail, providing a practical basis for going on to create such systems. The results from a number of experiments, carried out in the field of film recommendation, are then presented and discussed, making two novel contributions to the field. First, a number of baseline tests are carried out in which numerous recommendation strategy approaches are compared, allowing the reader to see their strengths and weaknesses in detail and on a level playing field. Second, a novel hybrid recommendation system is introduced that is tested with real users. The results of the testing demonstrate the importance of user satisfaction in recommendation system design.

RECOMMENDER SYSTEM APPROACHES

As previously introduced, recommender systems are usually classified into three categories: *collaborative, content-based* and *hybrid filtering*, based on how recommendations are made. We review in this section the main algorithmic approaches.

Collaborative Filtering

In collaborative filtering, the input to the system is a set of user ratings on items. Users can be compared based upon their shared appreciation of items, creating the notion of user neighbourhoods. Similarly, items can be compared based upon the shared appreciation of users, rendering the notion of item neighbourhoods. The item rating for a given user can then be predicted based upon the ratings given in her user neighbourhood and the item neighbourhood. We can distinguish three main approaches: *user-based*, *item-based* and *model-based* approaches. These approaches are formalized and compared in this section.

Let U be a set of N users, I a set of M items, and R a set of ratings r_{ui} of users $u \in U$ on item

$i \in I$. $S_u \subseteq I$ stands for the set of items that user *u* has rated.

The goal of collaborative filtering approaches is then to be able to predict the rating p_{ai} of a user *a* on an item *i*. User *a* is presumed to be *active*, meaning that she has already rated some items, so $S_a \neq \varnothing$. The item to be predicted is not yet known to the user, making $i \notin S_a$.

User-based Approaches

For user-based approaches (Resnick et al., 1994; Shardanand & Maes, 1995), the prediction of a user rating on an item is based on the ratings, on that item, of the nearest neighbours. So a similarity measure between users needs to be defined before a set of nearest neighbours is selected. Also, a method for combining the ratings of those neighbours on the target item needs to be chosen.

The way in which the similarity between users is computed is discussed below. For now, let *sim(a,u)* be the similarity between users *a* and *u*. The number of neighbours considered is often set by a system parameter, denoted by *K*. So the set of neighbours of a given user *a*, denoted by T_a, is made up of the *K* users that maximise their similarity to user *a*.

A possible way to predict the rating of user *a* on item *i* is then to use the weighted sum of the ratings of the nearest neighbours $u \in T_a$ that have already rated item *i*:

$$p_{ai} = \frac{\sum_{\{u \in T_a | i \in S_u\}} sim(a,u) \times r_{ui}}{\sum_{\{u \in T_a | i \in S_u\}} |sim(a,u)|} \qquad (1)$$

In order to take into account the difference in use of the rating scale by different users, predictions based on deviations from the mean ratings have been proposed. p_{ai} can be computed from the sum of the user's mean rating and the weighted sum of deviations from their mean rating of the neighbours that have rated item *i*:

$$p_{ai} = \overline{r_a} + \frac{\sum_{\{u \in T_a | i \in S_u\}} sim(a,u) \times (r_{ui} - \overline{r_u})}{\sum_{\{u \in T_a | i \in S_u\}} |sim(a,u)|} \qquad (2)$$

$\overline{r_u}$ represents the mean rating of user *u*:

$$\overline{r_u} = \frac{\sum_{\{i \in S_u\}} r_{ui}}{|S_u|} \qquad (3)$$

Indeed, supposing that items are rated between 1 and 5. One user may rate an item that he likes at 4 and an item that he dislikes at 1. Another user, however, may rate an item that he likes at 5 and an item that he dislikes at 2. By using deviations from the mean rating, the individual user's semantics, with respect to his appreciation of the items, is better accounted for.

The time complexity of user-based approaches is $O(N^2 \text{x} M \text{x} K)$ for the neighbourhood model construction and $O(K)$ for one rating prediction. The space complexity is $O(N \text{x} K)$.

Item-based Approaches

Recently, there has been a rising interest in the use of item-based approaches (Sarwar et al., 2001; Karypis, 2001; Linden et al., 2003; Deshpande & Karypis, 2004). Given a similarity measure between items, such approaches first define item neighbourhoods. The predicted rating for a user on an item is then derived by using the ratings of the user on the neighbours of the target item.

The possible choices of the similarity measure *sim(i,j)* defined between items *i* and *j* are discussed later. Then, as for user-based approaches, the item neighbourhood size *K* is a system parameter that needs to be defined. Given T_i, the neighbourhood of item *i*, two ways for predicting new user ratings can be considered:

1. using a weighted sum:

$$p_{ai} = \frac{\sum_{\{j \in S_a \cap T_i\}} sim(i,j) \times r_{aj}}{\sum_{\{j \in S_a \cap T_i\}} |sim(i,j)|} \quad (4)$$

2. using a weighted sum of deviations from the mean item ratings:

$$p_{ai} = \bar{r_i} + \frac{\sum_{\{j \in S_a \cap T_i\}} sim(i,j) \times (r_{aj} - \bar{r_j})}{\sum_{\{j \in S_a \cap T_i\}} |sim(i,j)|} \quad (5)$$

$\bar{r_i}$ is the mean rating on item *i*:

$$\bar{r_i} = \frac{\sum_{\{u \in U | i \in S_u\}} r_{ui}}{|\{u \in U | i \in S_u\}|} \quad (6)$$

The time complexity of item-based approaches is $O(M^2 \times N \times K)$ for the neighbourhood model construction and $O(K)$ for one rating prediction. The space complexity is $O(M \times K)$.

Model-based Approaches

A quadratic complexity is too high for huge datasets and many real applications need predictions that can be made very quickly. These considerations are the starting points of model-based approaches (Breese et al., 1998). The general idea is to derive a model of the data off-line in order to predict on-line ratings as fast as possible.

The first type of models that have been proposed consist of grouping users using clustering and then predicting a user rating on an item using only the ratings of the users that belong to the same cluster.

Bayesian models have also been proposed to model dependencies between items. The clustering of items has been studied extensively (e.g. Ungar & Foster, 1998; O'Conner & Herlocker, 1999). Also, models based on association rules have been studied by (Sarwar et al., 2000) and (Lin et al., 2002).

Probabilistic clustering algorithms have also been used in order to allow users to belong, at some level, to different groups (Pennock et al., 2000; Kleinberg & Sandler, 2004). And hierarchies of clusters have been proposed, so that if a given cluster of users does not have an opinion on a particular item, then the super-cluster can be considered (Kelleher & Bridge, 2003).

In such approaches, the number of clusters considered is of key importance. In many cases, different numbers of clusters are tested, and the one that leads to the lowest error rate in cross-validation is kept. Clusters are generally represented by their centroid, and then the predicted rating of a user for an item can be directly derived from the rating of its nearest centroid. If both user and item clustering are used, the predicted rating is the mean rating, on the item's group members, of the user's group members. This kind of algorithm needs to be run many times with random initial solutions in order to avoid local minima. A parameter *L* that represents the required number of runs must be introduced.

The time complexity of cluster-based approaches is then $O(N \times M \times K \times L)$ for the learning phase and $O(1)$ for one rating prediction. The space complexity, when both user and item clustering are considered, is $O((N+M) \times K)$.

Similarity Measures

The similarity defined between users or items is crucial in collaborative filtering. The first one proposed in (Resnick et al., 1994) is the *Pearson* correlation. It corresponds to the *Cosine* of deviations from the mean. Simple *Cosine* or *Manhattan* similarities are also traditional ones.

For these similarity measures, only the set of attributes in common between two vectors are considered. Thus two vectors may be completely similar even if they only share one appreciation on one attribute.

Such measures have drawbacks. For example, in the context of film recommendation, consider the case when one user is a fan of science fiction

while another only watches comedies. Furthermore, these users haven't rated any film in common so their similarity is null. Now they both say that they like *"Men In Black"*, a science fiction comedy. These users thus become completely similar according to the previously presented measures, given that their only common reference point was equally rated.

The *Jaccard* similarity, however, doesn't suffer from this limitation since it measures the overlap that two vectors share with their attributes. On the other hand, such a measure doesn't take into account the difference of ratings between the vectors. In this case, if two users watch the same films but have completely opposite opinions on them, then they are considered to be similar anyway according to Jaccard similarity.

When Jaccard is combined with the other similarity measures, a system can benefit from their complementarily. For example, the product of Jaccard with another similarity measure produces a new result. In this case, Jaccard serves as a weight. *wPearson* can thus represent a weighted Pearson measure, produced by the product of Pearson and Jaccard. Similarly, *wCosine* and *wManhattan* denote the combination of Jaccard with Cosine and Manhattan respectively. The values of Cosine-based similarity measures lie between −1 and 1 while the other similarity values lie between 0 and 1. Experimental results based on this weighted similarity measure are presented later. We will show that this similarity which is tailored to the type of data that is typically available (i.e. very sparse), tends to lead to better results.

Among the main drawbacks of collaborative filtering systems we can mention the *cold start* problem occurring when a new user has not provided any ratings yet or a new item has not yet received any rating from the users. The system lacks data to produce appropriate recommendations (for instance, the MovieLens recommender system requires at least 15 ratings before it is able to provide recommendations). For the new user problem (Nguyen et al., 2007) propose to exploit demographic data about the user such as their age, location and occupation to improve the first recommendations provided to a new user, without her having to rate any items. The new-item and new-user problems can also be addressed using hybrid recommendation approaches (these approaches will be described below).

Content-Based Filtering

Content-based recommendation systems recommend an item to a user based upon a description of the item and a *profile* of the user's interests. Content-based recommendation systems share in common a means for describing the items that may be recommended, a means for creating a profile of the user that describes the types of items the user likes, and a means of comparing items to the user profile to determine what to recommend. Item descriptors can be the genre of a film or the location of a restaurant, depending upon the type of item being recommended. Finally, items that have a high degree of proximity to a given user's preferences would be recommended.

A *User profile* may be built *implicitly* from the user's preferences for items, by searching for commonalities in liked and disliked item descriptions, based upon her past actions or *explicitly* through questionnaires about her preferences for the item descriptions.

A *User model* may be learned *implicitly* by an automatic learning method, using item descriptions as input to a supervised learning algorithm, and producing user appreciations of items as output.

User profiles are often represented as vectors of weights on item descriptions. Any other user model may be considered if an automatic learning method is used. If a rule induction algorithm was to be used in a film recommender, then user models could contain information such as "IF genre IS action AND actor IS Stallone THEN film IS liked". (Pazzani &Billsus, 2007) discuss the different ways to represent item contents and user profiles as well as the ways to learn user models.

Preferences indicate a relationship between a given user and data. In recommender system research, a preference must be both machine codable and carry useful information for making recommendations. For example, in the field of cinematography, the monadic preference *"I like Jackie Chan as an actor"* can be coded as a high score for films with this actor. In turn, films with this higher score will be more recommended than films that are not promoted in this way. In addition, dyadic preferences can be asserted such as *"I like comedies more than dramas"*, allowing a wide number of films to be compared.

While these preferences can be used to improve recommendations, they suffer from certain drawbacks, the most important of these being their limited *coverage*. The coverage of a preference is directly related to the coverage of the attribute(s) to which it is applied. An attribute has a high coverage when it appears in many items and a low coverage when it appears in few items. The coverage of the preference *"I like Jackie Chan as an actor"* is extremely low in most film databases. As such, recommenders that rely solely upon content-based preferences often require a large amount of user details before good recommendations can be made.

It is possible, however, to extend the coverage of a preference by employing the notion of similarity to attributes. A preference for one attribute can also be inferred for all other attributes that are very similar. For example, if *Jackie Chan* and *Bruce Lee* are considered to be very similar, then the preference *"I like Jackie Chan as an actor"* can be extended to include *"I like Bruce Lee as an actor"*. This extension, assuming that it does not contradict other given preferences, extends the coverage of the preference.

Several approaches are commonly followed to determine the similarity between attributes. Most traditionally, this falls within the remit of a domain expert who can construct, by hand, a rich ontology of the domain. While this approach remains popular within smaller domains, recommendation systems are often employed in large domains where instantiation by hand is impractical. Alternatively, measures of similarity can be used that exploit the wealth of information present on the internet. One such similarity metric, the *Normalised Google Distance* (Cilibrasi & Vitanyi, 2007), infers similarities between textual terms using their co-occurrence on websites, as found by *Google*. This metric tends to perform well under diverse conditions and, since it employs the internet, is not domain specific.

The Normalised Google Distance metric has proved useful in finding the similarity between attributes such as actors (Jack & Duclaye, 2008) in the domain of movies. Unfortunately, it is difficult to determine complete similarity matrices for large scale databases due to restrictions on the use of the Google API.

To evade such restrictions, similarity metrics that directly analyse the available recommendation system database are often preferred. For example, given two actors in a film database, a vector can be constructed for each one that describes their film history. The vector can contain information such as the genre of films in which they have played, the directors with whom they have worked and the actors with whom they have co-starred. A similarity measure such as wCosine can then be used to compare the two actor vectors.

As introduced above, another set of possible approaches for content-based filtering consists of using a classifier, like *Naive Bayes*, having as input the item descriptions and as output the tastes of a user for a subset of items. The classifier is trained over a set of items already considered by the user. It is then able to predict if a new item will be liked or not by the user, according to its content description (Adomavicius & Tuzhilin, 2005).

These content-based methods are thus able to tackle some limitations of collaborative ones. They are able to provide recommendations for new items even when no rating is available. They can also handle situations where users do not consider the same items but consider similar items.

However, to be efficient, content-based approaches need rich and complete descriptions of items and well-constructed user profiles. This is the main limitation of such systems. Since well-structured item descriptions are hard to come by in many domains, such approaches have mainly been applied in those where items are described by textual information that can be parsed automatically, such as documents, web sites and Usenet news messages (Pazzani & Billsus, 1997; Mooney & Roy, 1999).

Besides, content-based approaches can also suffer from *overspecialisation* (Zhang et al., 2002). That is, they often recommend items with similar content to that of the items already considered, which can lead to a lack of originality. On the other hand, privacy issues (Lam et al., 2006), such as users who do not want to share their preferences with others, are avoided.

A user's appreciation of an item is often based on more information than can be practically stored in an item's description. Even rich databases can omit information that may be crucial to a user when deciding if they like an item or not. In the case of films for instance, viewers generally select a film to watch based upon more elements than only its genre, director and actors.

Collaborative methods do not require such difficult to come by, well-structured item descriptions. Instead, they are based on users' preferences for items, which can carry a more general meaning than is contained in an item description. They have the advantage of providing a *meta* view on the interest and quality of the items. These complementary approaches thus motivate the design of hybrid systems.

Hybrid Filtering

In the case of hybrid filtering, both types of information, collaborative and content-based, are exploited. These technologies can be combined in various ways that make use of both user appreciations of items and their descriptor-based preferences. Other sources of data like social and demographic data about users can also be used.

The first direct way to design a hybrid recommender system is to independently run a collaborative and a content-based one, and then combine their predictions using a voting scheme.

In (Balabanovic & Shoham, 1997), the combination is performed by forcing items to be, at the same time, close to the user thematic profile, and highly rated by her neighbours. In (Pazzani, 1999), users are compared according to their content profiles, and the generated similarity measures are then used in a collaborative filtering system.

In (Polcicova et al., 2000; Melville et al., 2002), the rating matrix is enriched with predictions based on the content, and then collaborative filtering is run. In (Vozalis & Margaritis, 2004), the similarity between items is computed by using their content descriptions as well as their associated rating vectors. An item-based collaborative filtering algorithm is them launched. In this paper the authors also explore how several existing collaborative filtering algorithms can be enhanced by the use of demographic data about users. Two users could be considered similar not only if they rated the same items similarly, but also if they belong to the same demographic segment.

In (Han & Karypis, 2005), it is proposed to extend the prediction list of a collaborative filtering method to the items whose content are close to the recommended items. Based on the same idea, the content-based similarity between items is used in (Wang et al., 2006) in order to compare users not only according to their shared appreciations for some items, but by considering also their shared appreciations for items whose contents are similar.

A hybrid system can also be designed that follows a content-based filtering strategy and uses the data produced from collaborative filtering to enrich item similarity descriptions. At its core, it is a content-based filtering system that makes use of attribute similarities, similar to a

personalised information retrieval system where requests are null (Jack & Duclaye, 2007). Items are recommended that are similar to the user's likes but not to his dislikes. The similarities between genres, nationalities and language attributes are defined by hand, while the wCosine measure is used to calculate director and actor similarities. Each film also contains a unique identification attribute. This identifier is compared to the films that have been previously noted by the user. The notion of similarity, for attributes of this type, is that embodied in the collaborative filtering algorithms. The more that a strictly collaborative filtering algorithm recommends a film, the closer the film is to the user's profile. This type of hybrid system thus treats social data (found through collaborative filtering) as an attribute of an item, like any other. By weighing the importance of each characteristic, the system can vary from being purely content-based through to purely collaborative.

Collaborative filtering techniques are more often implemented than the other two and often result in better predictive performance. Collaborative filtering seems to be more suitable as the core method of the recommender system while content-based filtering offers solutions to the limits of collaborative filtering, as well as a natural way to interact with the users. Indeed, users should be allowed to exert control over the system, thus building a meaningful relationship, and leading to psychological benefits such as the increase of trust in recommendations. This naturally leads to the issue of evaluating the performance of a recommender system.

RECOMMENDER SYSTEM EVALUATION

The evaluation of a recommender system is an important issue. In most recommender system literature, algorithms are evaluated by performance in terms of accuracy. The estimated ratings are compared against the actual rating. In these approaches many measures can be used. The most widely used ones are:

1. *Mean Absolute Error* (MAE);
2. *Root Mean Squared Error* (RMSE);
3. *Precision* measures.

The first two measures evaluate the capability of a method to predict if a user will like or dislike an item, whereas the third measure evaluates its capacity to order a list of items based on user tastes. These measures thus carry different meanings (McNee et al., 2006). In the first two cases, the method needs to be able to predict dislike, but there is no need to order items. In the last case, however, the method only focuses on items that users will like and the order in which these items are ranked is important.

(Herlocker et al., 2004) have noticed that beyond the importance of the predictive performance of recommender systems, other crucial criteria that try to capture the quality and usefulness of recommendations may be taken into consideration in their evaluation. The *scalability* of the proposed system is for example an important characteristic that needs to be taken into account. The *coverage* of a method, that is the proportion of recommendations it can provide, can also be considered. Finally, the system's ability to provide a level of *confidence* in a recommendation (Basu et al., 1998) and to *explain* why a recommendation was made (Herlocker et al., 2000; Bilgic, 2004) can be used to define its potential interest to the user.

The actual studies about recommender system evaluation investigate the factors that affect user satisfaction. Evaluating a recommender system based on real users' opinions is important because, in many cases, recommending the set of items that maximise their predicted ratings does not necessarily lead to user satisfaction. For instance, users may estimate that such recommendations lack originality, or they may think that the proposed list of recommendations is not varied enough (Ziegler

et al., 2005). Users may also want to have some control over the system, rather than having little or no direct influence on the results.

The quality of recommendations is ultimately judged by the user of the recommendation system. Many recommendation systems suffer from the 'one-visit' problem where users login, use the system once and then never return. Even users who receive good recommendations can quit using a recommendation system because they become frustrated that they cannot express particular preferences or find that the system lacks flexibility and is not user friendly.

One of the most important aspects of user interaction is that of control. Users must feel like they are in control of their recommendations and that they can navigate themselves out of awkward situations. For example, when a system incorrectly learns a user's preferences, the user should be able to correct the error. While algorithms like collaborative filtering can predict a user's tastes well, they cannot take into account attribute-based preferences, for example, the possibility for the users to express that they do not like some genre of films and that they no longer want them to be recommended. Giving such control to the user not only improves the recommendations but also improves the users' interaction experience.

Explicit preference entry (EPE) interfaces are designed to allow users to explicitly indicate a preference to the system. There are many examples of EPE interfaces, from questionnaire-based entry forms (Miller et al., 2003) to dialogue systems (Krulwich, 1997). Blog recommenders, such as MineKey (www.minekey.com), and website recommenders, such as StumbleUpon (www.stumbleupon.com), often ask users to indicate their preferences with respect to general topic (e.g. sports, hobbies and arts). Similarly, MovieLens asks users to rate films that are presented in a list format. Unfortunately such interfaces are often boring to use. Many systems use interactive data visualisation techniques in order to provide a fun and engaging setting for the user. For example, both Music Plasma (www.musicplasma.com) and Amaznode (amaznode.fladdict.net) have shown how recommendations can be attractively visualised to the user. EPE interfaces can make use of data visualisation techniques in order to guide users into finding attributes that they know and hence help them to find familiar points at which express their preferences (Jack & Duclaye, 2008).

Another important issue regarding user interaction concerns the necessary diversification of the recommendations. One possible way proposed in (Ziegler et al., 2005) for recommendation diversification consists of selecting, among the list of items considered as the most appropriate to a user, a subset as diverse as possible. To do that, the item with the highest predicted interest is first selected. The system then chooses the item that optimises a criterion mixing its predicted interest and its difference with the first selected item. This process is iterated until the desired number of items is reached.

Explaining why a recommendation is given can also be useful for a user (Billsus & Pazzani, 1999). Explanations can be based on the neighbours used for the recommendation, in the case of collaborative filtering or based on the elements in the user profile that match those found in a film's attributes when a content-based filtering is used. In (Bilgic, 2004), this second type of information has been shown to be more expressive to the users. Explanation is useful for increasing user confidence in a recommendation. It also helps the user to understand how the system works, so that she is then able to provide more relevant information when constructing her profile and interacting with the system.

EXPERIMENTS

The experiments presented in this chapter use two real rating datasets that are publicly available in the movies domain: *MovieLens* (www.grouplens.

org) and *Netflix* (www.netflixprize.com). The first dataset contains 1,000,209 film ratings collected from 6,040 users on 3,706 films and the second contains 100,480,507 film ratings collected from 480,189 users on 17,770 films. These datasets are independent of one another. Ratings are integers ranging from 1 (meaning dislike) to 5 (meaning like).

Two complementary ways for evaluating recommender systems are proposed. The first one consists of evaluating the prediction performance of the system using the two movies datasets and cross-validation. The second focuses upon user satisfaction.

Performance Comparison

The MovieLens and Netflix datasets are divided into two parts in order to perform cross-validation, training the chosen model using 90% of the data and testing it on the last 10%. In reality, recommendation system designers would use all 100% of the data to train their systems but a portion is omitted here for testing purposes.

Given $T = \{(u,i,r)\}$ the set of (user, item, rating) triplets used for test, the Mean Absolute Error Rate (MAE) and Root Mean Squared Error (RMSE) are used to evaluate the performance of the algorithms:

$$MAE = \frac{1}{|T|} \sum_{(u,i,r) \in T} |p_{ui} - r| \quad (7)$$

$$RMSE = \sqrt{\frac{1}{|T|} \sum_{(u,i,r) \in T} (p_{ui} - r)^2} \quad (8)$$

The predicted ratings are rounded when the MAE is reported. First of all, this improves the results. Besides, rounding ratings is natural in practice, since real users generally prefer rating scales based on natural numbers than on real numbers.

We report the precision of the system that is the proportion of truly high ratings among those that were predicted to be high by the recommender system. Some precision measures specifically designed for the current context are used. $Precision_5$ concerns the proportion of maximum ratings in the test dataset, with a value for the maximum rating fixed to 5, which are retrieved as the best predicted ratings. Similarly, $precision_4$ stands for the proportion of test ratings higher than the maximum value minus one (i.e. 4) that are considered as the best ratings by the given recommender system.

Finally, the time spent learning the models and making predictions are also reported. The computer used for these experiments has 32GB RAM and 64 bits 3.40GHz 2-cores CPU.

Considering only the principal collaborative filtering approaches already leads to a lot of choices and parameters. When implementing a user- or item-based approach, one may choose:

1. a similarity measure: Pearson, Cosine, Manhattan, Jaccard, or the proposed combinations of Jaccard with the others;
2. a neighbourhood size K;
3. how to compute predictions: using a weighted sum of rating values (equations (1) and (4)), or using a weighted sum of deviations from the mean (2) and (5).

For model-based approaches, the following parameters need to be defined:

1. clustering users and/or items;
2. the number of clusters.

The clustering algorithm considered in this section is *Bisecting K-means* using *Euclidian* distance. *K-means* is the well-known full-space clustering algorithm based on the evolution of K centroids that represent the K clusters to be found, while Bisecting K-means is based on the

recursive use of (*K=2*)-means. At each step, the cluster that maximises its inertia is split.

A prediction scheme that is based on deviations from the mean has been shown to be more effective in (Candillier et al., 2007). So in the following, only the results using this scheme are reported.

One important aspect of collaborative filtering is the choice of the similarity measure used. Figures 1 to 3 show the Mean Absolute Error Rate obtained using the presented measures, varying the neighbourhood size *K* from 10 to the maximum number of possible neighbours, for both user- and item-based approaches, and on both MovieLens and Netflix datasets.

Figure 1 first shows the error rates of item-based approaches depending on the similarity measure used and the neighbourhood size. The optimum is reached with the weighted Pearson similarity and 100 neighbours. All similarity measures are improved when they are weighted with Jaccard, at least when few neighbours are considered. All these weighted similarity measures reach their optimum when 100 neighbours are selected. On the contrary, non-weighted similarity measures need much more neighbours to reach their optimum. 700 neighbours shall be selected when using simple Manhattan similarity, and 1500 when using simple Cosine or simple Pearson.

Figures 2 and 3 show that the same conclusions hold when using user-based approaches, as well as when the Netflix dataset is used instead of MovieLens. Weighted Pearson similarity always leads to the best results. Weighting the similarity measures with Jaccard always improves the results. 300 neighbours shall be considered for a user-based approach on MovieLens, and 70 for an item-based approach on Netflix. On the contrary, 2000 to 4000 neighbours need to be selected to reach the minimum error rate with non-weighted similarity measures.

The results have been presented for the MAE. They are highly similar to the other performance measures: RMSE and precisions. Beyond the improvement of predictive performance when the proposed weighting scheme is used, another

Figure 1. Comparing MAE on MovieLens when using item-based approaches with different similarity measures and neighbourhood sizes (K)

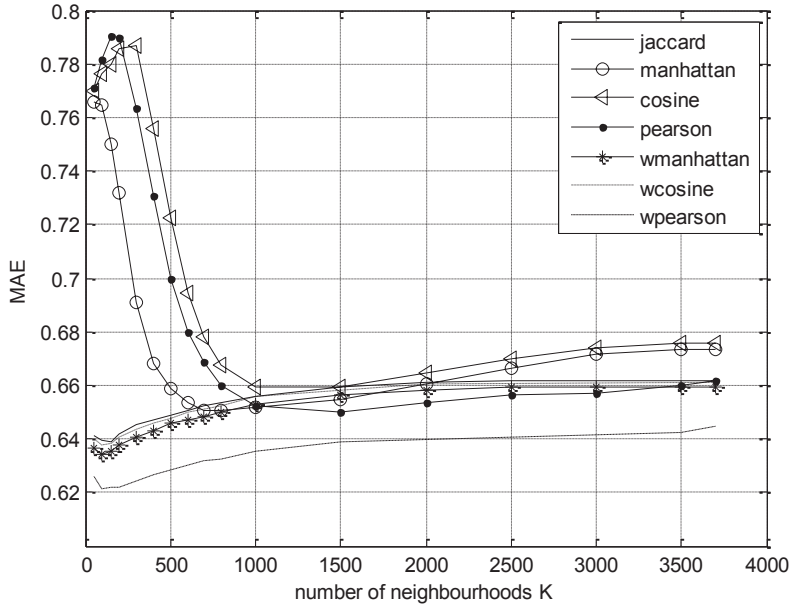


Figure 2. Comparing MAE on MovieLens when using user-based approaches with different similarity measures and neighbourhood sizes (K)

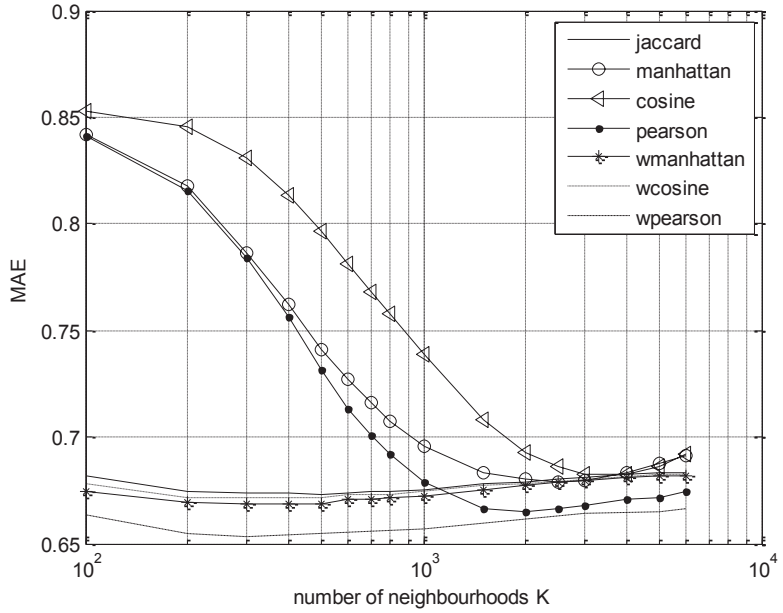
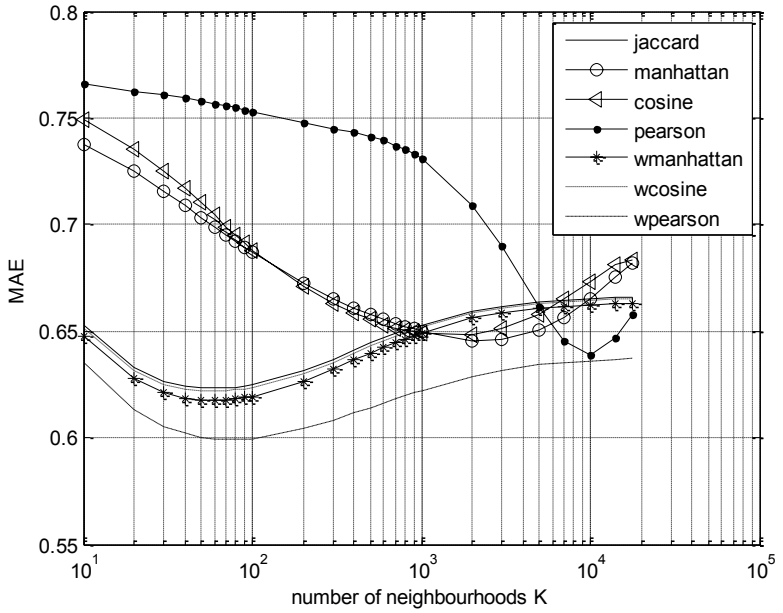


Figure 3. Comparing MAE on Netflix when using item-based approaches with different similarity measures and neighbourhood sizes (K)



important advantage is that fewer neighbours need to be selected, so that the algorithms also gain in scalability.

In fact, when a non-weighted similarity measure is used, the nearest neighbours do not share many attributes. They often have only one attribute in common. On the contrary, by using Jaccard similarity, the selected neighbours are those that share a maximum number of attributes. Jaccard searches to optimise the number of common attributes between vectors, but this may not be the best solution for nearest neighbour selection since the values of the vectors on the shared attributes may differ. So weighted similarity measures offer an interesting compromise between Jaccard and the other non-weighted measures.

Figures 4 and 5 then show the results obtained by using model-based approaches on both MovieLens and Netflix datasets. The three possible approaches are compared: user clustering, item clustering and double clustering. On MovieLens, user and item clustering behave the same and both outperform the double clustering. Optimal results are reached by using 4 item clusters. On Netflix however, using 70 user clusters leads to the best results.

Tables 1 and 2 summarise the results of the best of each approach, including learning and prediction times, and precisions. Both user- and item-based approaches reach optimal results when the weighted Pearson similarity is used. On MovieLens, 300 neighbours are selected for the best user-based approach, and 100 for the best item-based one. On Netflix, considering 70 neighbours leads to the lowest error rate. User-based approaches, however, face scalability issues. It is too expensive to compute the entire user-user matrix. So instead, a clustering is first run, and then only the users that belong to the same cluster are considered as potential neighbours. Considering

Figure 4. Comparing MAE on MovieLens when using model-based approaches with different options and numbers of clusters (K)

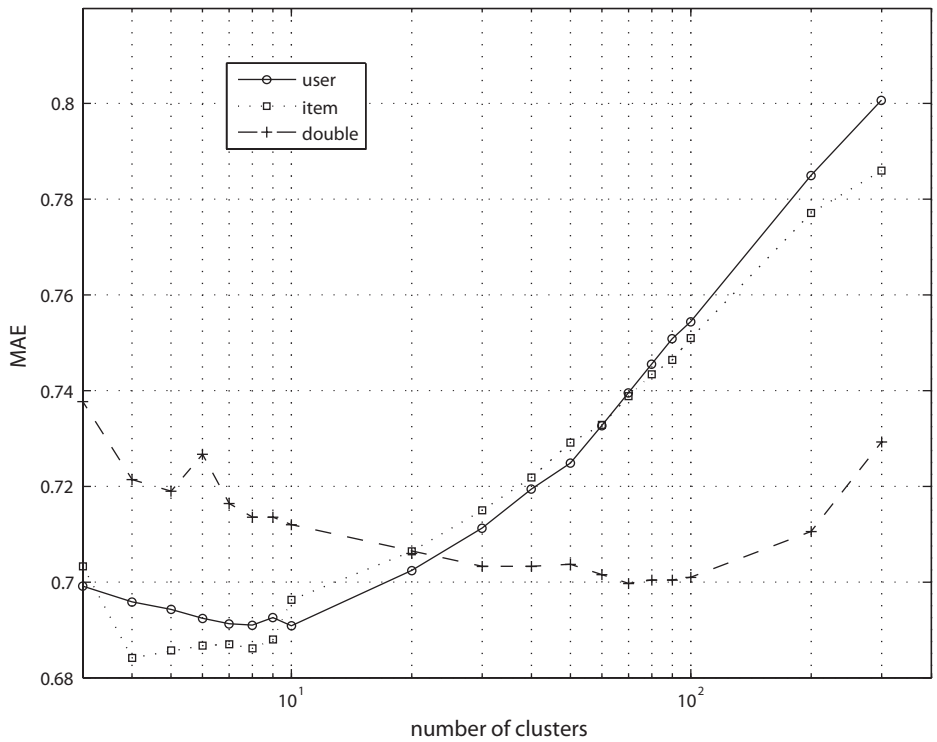
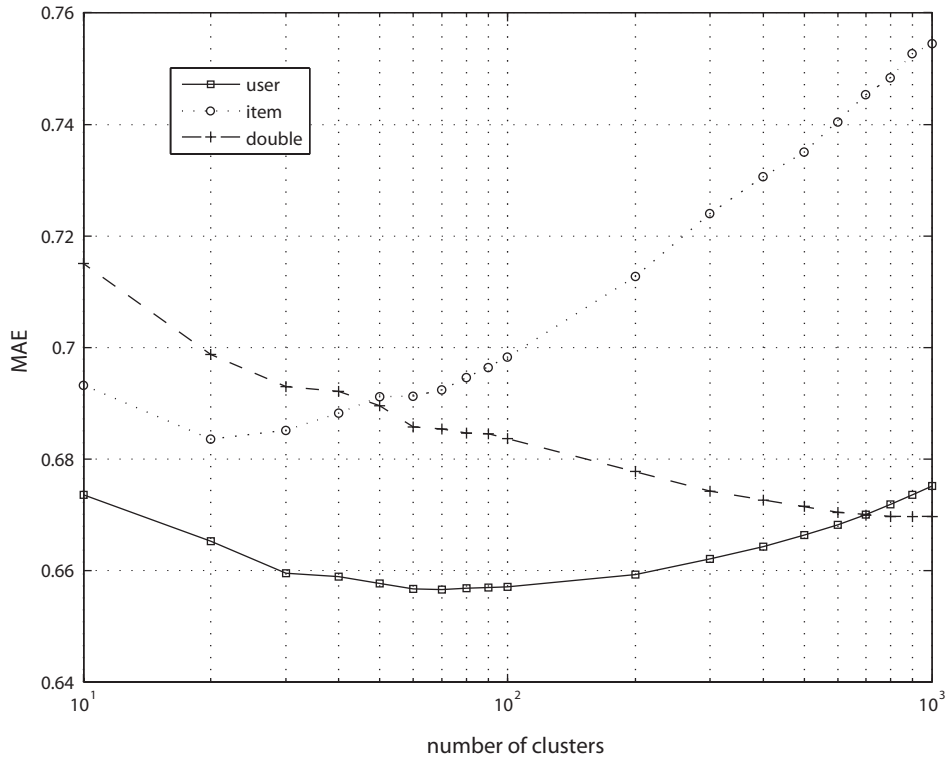


Figure 5. Comparing MAE on Netflix when using model-based approaches with different options and numbers of clusters (K)



many neighbours improves the results but a model based on 1,000 neighbours, selected starting from a clustering with 90 clusters, needs nine hours to learn, twenty eight minutes to predict, and 10GB RAM. The best overall results are reached using an item-based approach. It needs two and a half hours to learn the model on Netflix, and one minute to produce ten million rating predictions. A $precision_5$ of 0.6216 means that 62.16% of the best rated items are captured by the system and proposed to the users.

User Satisfaction

The recommendations from a semantically enriched content-based filtering algorithm, a collaborative filtering algorithm and a hybrid of these two algorithms have been compared

Table 1. Summary of the best results on MovieLens depending on the type of approach

	Parameter	*Learning time*	*prediction time*	*MAE*	*RMSE*	$precision_5$	$precision_4$
model-based	4 item clusters	**5 sec.**	**1 sec.**	0.6841	0.9172	0.5041	0.7550
user-based	300 neighbours	4 min.	3 sec.	0.6533	0.8902	0.5710	0.7810
item-based	100 neighbours	2 min.	1 sec.	**0.6213**	**0.8550**	**0.5864**	**0.7915**

Table 2. Summary of the best results on Netflix depending on the type of approach

	Parameter	*Learning time*	*prediction time*	*MAE*	*RMSE*	$precision_5$	$precision_4$
model-based	70 user clusters	**24 min.**	**3 sec.**	0.6566	0.8879	0.5777	0.7608
user-based	1,000 neighbours	9 h	28 min.	0.6440	0.8811	0.5902	0.7655
item-based	70 neighbours	2 h 30	1 min.	**0.5990**	**0.8436**	**0.6216**	**0.7827**

in a study with human participants. As well as considering the quality of the recommendations produced by the different algorithms, as judged by the participants, the participants' actions and comments are also analysed. In doing so, a number of conclusions can be drawn as to how user needs can be accounted for to produce more natural and satisfying interactions with recommendation systems.

The film database was generated from two sources. Film details (used for content-based filtering) came from an in-house Orange database while user ratings (used for collaborative filtering) came from Netflix. A database of 3,626 films was produced by taking the intersection of films from both data sources. Each film was described by five characteristics: actors; directors; genres; languages; and nationalities.

A recommendation system interface was constructed with three primary screens: a login screen, a profile manager and a recommendation screen. The login screen allowed the participant to enter their username and be identified by the system. On first identification, a user profile is created. The participant could manage their profile using the profile manager, which allowed for both monadic and dyadic preferences to be expressed. Monadic preferences could be expressed for any of the five characteristics and films themselves (e.g. *"I like Charlie Chaplin as an actor"* and *"I dislike Scary Movie"*) on a 3-point scale (like, neutral, dislike). Dyadic preferences could be expressed for the relative importance of each of the five characteristics and films themselves (e.g. *"the genre is more important than the director"* and *"the actor is less important than the film"*).

The first recommendation algorithm was a content-based algorithm that interpreted monadic and dyadic preferences with respect to the five film characteristics. Item attributes were also semantically enriched with the notion of similarity. The similarities among directors and actors were derived using the wCosine measure and the complete in-house database. Genre, language and nationality similarities were constructed by hand, since there were a manageable number, by ontology experts. The second algorithm was an item-based collaborative filtering algorithm that used the wPearson similarity. Finally, a hybrid algorithm that acted as a content-based algorithm, where collaborative filtering data appeared as a single film attribute, was put in place.

Thirty participants were recruited. All were experienced computer users who had received a university level education. Six participants had already used a recommendation of some sort while the rest had not. Participants were given an instruction sheet that explained the how the interface could be operated. The study took around thirty minutes to complete per participant.

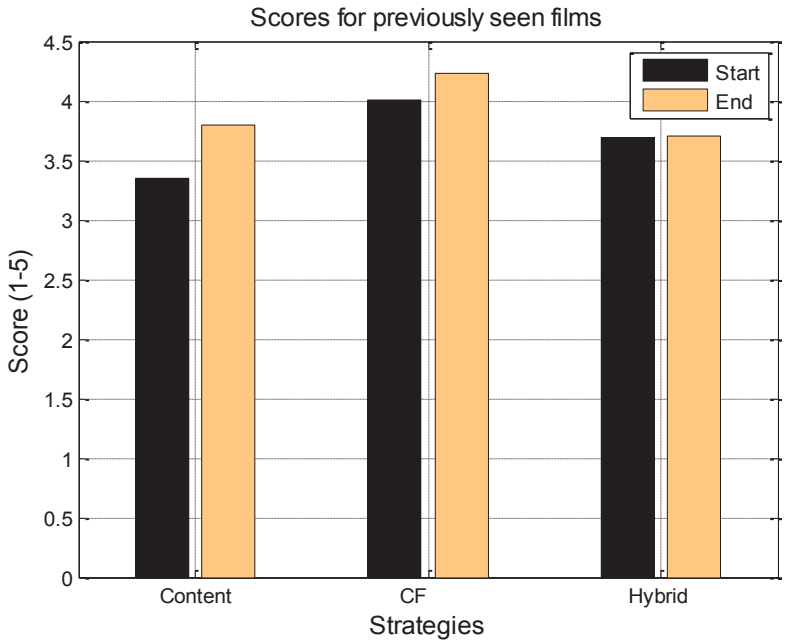
Participants were asked to enter some of their film preferences and then to request some recommendations. It was stressed that they should only enter as many or as few preferences as they would normally do so in the comfort of their own home. There was no pressure to enter any particular type of preference (film or film attribute).

The system showed a single list of recommendations produced by the three algorithms within. Each algorithm produced five recommendations. Recommendations for films that were the direct subject of preferences were not produced (i.e. if a user noted that they liked Titanic then it would not be recommended to them). The fifteen total recommendations were randomly ordered in a list with duplicate recommendations being removed. Such duplicates could be produced by different the different algorithms recommending the same film. The participant was then asked to score each of the recommendations. If they had already seen the film then they were asked to give a score as to how much they liked it, on a scale from 1-5 (1 being the least and 5 being the most). If they had not already seen the film, then they were asked how much they would like to see it, on the same scale from 1-5. As the semantics of the scale may differ depending upon the question, it is important to analyse the results separately.

After scoring all films, the participant was asked to return to the profile manager to enter more preferences and to ask for recommendations once more. The scores given for recommendations were not used to influence neither the user's profile nor future recommendations and were for study use alone. On requesting a second list of recommendations, the participant was asked to score them. Once all films were scored, the participant then had the choice to quit the system or to repeat the preference entry followed by recommendation scoring process. On choosing to quit the system, the participant was given a short questionnaire to complete.

The participants scored at least two recommendation lists. The difference between the average scores given to seen films in their first list of recommendations is compared with the average scores given to seen films in their last list of recommendations (Figure 6). On receiving the first recommendations, the collaborative filtering algorithm produces significantly better results (mean = 4.00; standard deviation SD = 0.91) than the content-based filtering algorithm (mean = 3.35; SD = 1.13). Given the final recommenda-

Figure 6. Average scores given by the participants to the recommended films that they had already seen before



tion, the collaborative filtering algorithm (mean = 4.23; SD = 0.66) produces significantly better results than both the content-based filtering (mean = 3.79; SD = 0.89) and hybrid (mean = 3.70; SD = 0.88) algorithms. The content-based filtering algorithm is the only algorithm that significantly improves between the first and last recommendations given. The content-based and collaborative filtering algorithms tend to improve when more preferences are available while the hybrid filtering algorithm remains stable.

Similarly, the same average scores can be found for unseen films. In this case, no significant differences were found between the scores produced by the three algorithms although there was a trend for each algorithm to produce better results when more preferences were available. Participants have reported a strong desire to watch the unseen films that were recommended (mean score of 4 out of 5 for the statements *"I found new films that I want to watch"*, 5 being equivalent to strongly agree).

Participants were asked to enter as many preferences into their profile as they felt comfortable with. They were not encouraged to enter any particular type of preference. In comparing the profiles created by users in the first round of the study, with those at the end of the study, the average constitution tends to change in quantity alone (Figure 7). The number of preferences that are given for films is comparable to the number of preferences that are given for film attributes (the five characteristics). Out of the film attributes, participants tended to give their preferences for genres.

In the questionnaire, participants were also asked to indicate which type of characteristics they were comfortable in giving preferences for or against (Table 3). The majority of participants were comfortable giving preferences for films and many indicated that they were comfortable giving preferences for actors, genres and directors. Only a few participants were comfortable giving preferences for nationalities or languages. In addition, a number of participants indicated that they would like to express preferences for the release dates of films, a characteristic that was not present in their profile.

Participants also commented in the questionnaires that they would have preferred a preference

Figure 7. Evolution of the profile information given by the participants

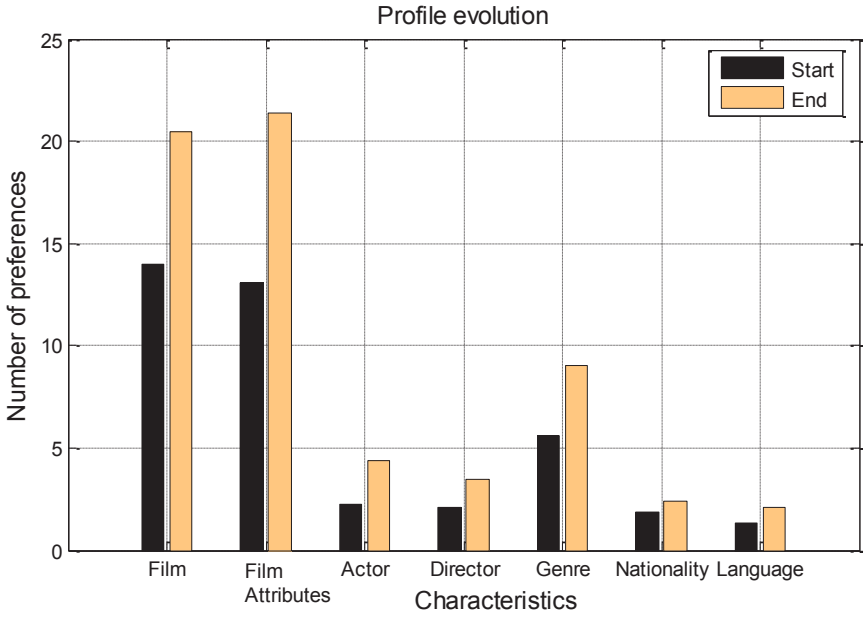


Table 3. Film characteristics declared as important by the participants

Characteristic	% of Participants
Films	75
Actors	58
Genres	54
Directors	42
Language	17
Nationality	12

rating scale that was richer, such as a 5-point scale that begins at "hate", rising through "dislike", "neutral" and "like" and finishing at "love". As well as enriching the scale, they also expressed an interest in declaring complex preferences that were interdependent or contextual. For example, they would have liked to have expressed a preference for *"Charlie Chaplin"* but only in some of his films and not in all of them.

To summarise, these experiments with real users confirm that collaborative filtering systems have better predictive performance than content-based and hybrid systems. On the other hand, content data have been shown to be important to provide an efficient interaction with users.

Collaborative filtering holds a very powerful kind of information that is not found in item data. It allows tastes to be aligned with one another even when items have no attributes in common. This is the main reason for its good performance.

The content strategy offers items because of the proximity of item attributes. The results for this strategy faired well, which is probably due to the semantic similarity encoded between item attributes.

The hybrid strategy appears to have been pulled between the two. The user was allowed to control how much each of the characteristics were taken into account. Perhaps, however, the user should not be able to control this as many complained that they did not know which settings to select. Also, it appears that the mixed information was not best handled by the current system. Further research into hybrid systems is necessary in order to understand the best way in which they can be integrated.

Participants were also asked how they thought that the system operated after receiving all of their recommendations. It is interesting to note that no participants were conscious of the working of the collaborative filtering algorithm. All participants who offered an explanation of the system's logic focused upon the correspondence between individual characteristics of films, such as actors and directors and the preferences that they had indicated. This shows that users are conscious of attribute-based decisions. The use of content data in interacting with the users seems to be a good technique for gaining the user's trust. It also encouraged them to try and influence the system by making profile modifications.

The participants entered as much information about film attributes as they did about films. Although the suitable algorithms were not yet in place in this study in order to exploit the both of them effectively, it is important to note that users want to express both types of information. An interesting effect was also witnessed. The more that users added their film attribute preferences, the more they began to see the system's logic. Seeing the logic of a system is extremely important when asserting control. In fact, users wanted to be guided by the system in order to give it the most useful information. In controlling the system, users appeared to feel more responsible for its actions. In doing so, they were more willing to correct its mistakes. Systems that do not allow users to correct mistake often leave users feeling as if they have hit a dead-end and don't know where to go next.

FUTURE TRENDS

In this chapter, many issues concerning recommender systems have been presented. At the core

of these systems is the concept of item appreciation predictions. Current research for improving such is largely focussed on the combination of different approaches. In that field, many *ensemble methods* can be considered (Paterek, 2007), (Takacs et al., 2007). Specific combinations of different recommender systems are also proposed (Bell et al., 2007). Algorithms that are able to learn the similarity metric instead of using predefined ones are also in development (Bell et al., 2007). Taking the temporal evolution of ratings in account, where more recent ones are counted more than older ones, is also proving useful.

The accuracy performances of the current best recommender algorithms are now very similar and can't really be distinguished (for example the best results of the NetFlix Prize http://www.netflixprize.com/leaderboard differentiate only on the third decimal place). In practice, users can't see these differences so it is therefore useful to consider factors other than accuracy, that try to capture quality and usefulness (e.g. coverage, algorithmic complexity, scalability, novelty, confidence and trust, and user satisfaction) (Herlocker et al., 2004).

Experiments with real users suggest that systems should guide them in constructing their profiles. This issue is encouraging new research that is related to the field of *Active Learning* (Cohn et al., 1996). Indeed, which items should be rated to optimise the accuracy of collaborative filtering systems, and which item attributes are more critical for optimal content-based recommendations, are issues that are worth exploring. This naturally raises the parallel issue of how to design an efficient user interface for such an interaction.

CONCLUSION

In the field of recommender systems, collaborative filtering methods often result in better predictive performance than content-based ones, at least when enough rating data are available. Recommending items based on a set of users' preferences for items carries more meaning than item content information alone. This is especially true with films, since viewers generally choose a film to watch based upon more factors than its genre, director and actors.

On the other hand, content-based filtering offers solutions to the limits of collaborative filtering and provides for a more natural way to interact with users. This issue of designing user-friendly interfaces should not be underestimated. Users must feel like they are in control of their recommendations and that they can navigate themselves out of awkward situations. Otherwise, even if the recommender system is accurate in its predictions, it can suffer from the 'one-visit' problem, if users become frustrated that they cannot express particular preferences or find that the system lacks flexibility. Creating a fun and enduring interaction experience is as essential as making good recommendations.

Focusing on collaborative filtering approaches, item-based ones have been shown to outperform user-based ones. Besides their very good results, item-based approaches also have faster learning and prediction times, at least for datasets that contain more users than items and they are able to produce relevant predictions as soon as a user has rated their first item. Moreover, such models are also appropriate for navigating in item catalogues even when no information about the current user is available, since they can also present a user with the nearest neighbours of an item that she is currently interested in. Finally, the learned neighbourhood matrix can be exported to systems that can exploit items similarities without compromising user privacy.

An important issue in recommender system now is to explore criteria that try to capture quality and usefulness of recommendations from the user's satisfaction perspective like coverage, algorithmic complexity, scalability, novelty, confidence and trust, user interaction.

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