# Preference Learning in Recommender Systems

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**Abstract.** As proved by the continuous growth of the number of web sites which embody recommender systems as a way of personalizing the experience of users with their content, recommender systems represent one of the most popular applications of principles and techniques coming from Information Filtering (IF). As IF techniques usually perform a progressive removal of non-relevant content according to the information stored in a user profile, recommendation algorithms process information about user interests - acquired in an explicit (e.g., letting users express their opinion about items) or implicit (e.g., studying some behavioral features) way - and exploit these data to generate a list of recommended items. Although each type of filtering method has its own weaknesses and strengths, preference handling is one of the core issues in the design of every recommender system: since these systems aim to guide users in a personalized way to interesting or useful objects in a large space of possible options, it is important for them to accurately catch and model user preferences. The paper provides a general overview of the approaches to learning preference models in the context of recommender systems.

## 1 Introduction

How many times did you search something on the Web and you were not able to find successfully what were you looking for? The existence of a large quantity of information, in combination with the dynamic and heterogeneous nature of the Web, makes retrieval a hard task for the average user, who is usually overwhelmed by the abundant amount of information. In this context (we usually refer to this as *Information Overload* problem), the role of user modeling and personalized information access is becoming crucial: although it is too soon to deeply understand the long-term effects of this surplus of information in our habits and in daily life, it is clear that users need a personalized support in sifting through large amounts of available information according to their interests and preferences.

Information Filtering systems, like Recommender Systems, relying on this idea, adapt their behavior to individual users by learning their tastes during the interaction, in order to construct a profile that can be later exploited to select relevant items. Nowadays these systems represent the main solution to the information overload problem, because they are able to gather and exploit

heterogeneous information about users, emerging as one of the most useful tools to achieve a more intelligent information access. In the workflow of a typical recommendation process, *learning user preferences* is a primary step: catching and modeling user interests in an effective way can be a key issue for personalization goals. Gathering user characteristics, acquired through an explicit (e.g., directly asking to the user) or implicit process (e.g., observing the user behavior), can produce a user model to be exploited to enable adaptivity mechanisms during the interaction with an information system.

The problem of recommending items has been studied extensively, and two main paradigms have emerged. *Content-based* recommendation systems try to recommend items similar to those a given user has liked in the past, whereas systems designed according to the *collaborative* recommendation paradigm identify users whose preferences are similar to those of the given user and recommend items they have liked. Further, in literature we found also other noteworthy paradigms: *demographic recommenders*, whose aim is to categorize the user starting from personal attributes making recommendation based on demographic classes; *knowledge-based* systems, which exploit knowledge about how a particular item meets a particular user need ; *hybrid* systems, at last, combine different recommendation techniques trying to exploit their advantages and reducing at the same time their drawbacks. Each of above paradigms has particular methods to elicit user interests and preferences: most of them are related to Machine Learning area (probabilistic models, bayesian or neural networks, decision trees, association rules), but there are also some other techniques (so-called *heuristics*) which learn user profiles by exploiting preferences expressed by similar users (usually referred to as "neighbours") or processing textual contents describing the items liked.

The paper provides a general overview of the approaches to learning preference models in the context of recommender systems and it is organized as follows. Section 2 introduce general concepts and terminology about recommender systems. Preference learning issues in the area of recommender systems is presented in Section 3, where we also introduce the feedback gathering problem and some machine learning techniques used to acquire and infer user preferences. Conclusions are drawn in the last section.

## 2 Basics of Recommender Systems

Nowadays it is very important for people to be supported in their decisions, due to the exponential increase of available information. Everyday we get advices from other people: "Hey, check out this Web site", "I saw this book, you will like it", "That restaurant is very good!". When making a choice in the absence of decisive first-hand knowledge, choosing as other like-minded people have chosen in the past may be a good strategy. Recommender systems have the same role as human recommendations: they present information that they perceive to be useful and worth trying out. These systems are used in several application domains to support users in taking decisions, to help them in managing the ex-

ponential increase of information and, in general, to provide a more *intelligent form of information access*.

The creation and management of personalized recommendations require mainly three distinct and important components: a user profile, an algorithm to update the profile given usage/input information, and an adaptive tool that exploits the profile in order to provide personalization. First, the system needs to be able to store relevant information about users that will be used to infer their preferences and needs. Such information are stored in an individual user profile. Second, if the system has to adapt with the user over time, some mechanism is needed to keep the profile up-to-date. This could happen through explicit data input or implicit recording of user behavior as she interacts with the system, or a combination of them. Third, the system needs some way to exploit the current profile data in making recommendations to the user. The types of information stored in the profile will depend on the goals of the system and the algorithms it employs in order to provide recommendations. Different approaches to recommendation will require different pieces of information about the user, thus the profile structure will differ from system to system.

In this section we will provide an overview of the main recommendation approaches and their benefits and weaknesses.

### 2.1 Collaborative Recommender Systems

In Collaborative Filtering (CF) systems recommendations are based on evaluations of users who share similar interests among them. The idea behind these systems is that a set of users which liked the same items in the past probably share the same preferences. Thus, picking a user from this set, we can suggest her all the unseen items which other users with similar tastes showed to like in the past. Opinions on items can be expressed as explicit user ratings on some scale ranging from bad to good, or as implicit ratings given by logging user actions. As an example of the latter, viewing or skipping items could be interpreted as positive and negative ratings respectively. CF systems analyze opinions of other users on items, thus they provide a liking degree not based on the nature of the item, but on human judgment.

The main advantage of collaborative methods is that items in different product categories can be recommended. Movies, images, art and text items are all represented by opinions of users and thus they can be recommended by the same system. In CF, a user profile simply consists of the data the user has specified. These data are compared to those of other users to find overlaps in interests among users. For example, the nearest neighbor approach, used in some collaborative recommender system [20], represents the preferences by the items rated (or purchased) by the user. The profile is represented by the user-item matrix [22] where for each cell $(u,i)$ we have the rate of the user $u$ on the item $i$. The recommender algorithm performs three tasks: it finds similar users, creates the nearest neighbors set for each user, infers the like degree for an unseen item based on the nearest neighbors behavior.

Terveen and Hill [38] claim three essentials are needed to support CF: many people must participate (increasing the likelihood that any one person will find other users with similar preferences), there must be an easy way to represent the user interests in the system, and the algorithms must be able to match people with similar interests. These three elements are not that easy to develop, and produce the main shortcoming of CF systems. Following the main limitations of collaborative systems [4, 18].

- New user problem - In order to make accurate recommendations, the system must first learn the preferences of the user from her ratings.
- New item problem (early rater) - Until new items are rated by a substantial number of users, the recommender system would not be able to recommend them.
- Sparsity problem - The number of ratings obtained is usually very small compared to the number of ratings to be predicted and the success of the collaborative recommender system depends on the availability of a critical mass of users. One way to overcome the problem of rating sparsity is to use user profile information when calculating user similarity. That is, two users could be considered similar not only if they similarly rated the same items, but also if they belong to the same demographic segment. For example, Pazzani uses gender, age, area code, education, and employment information of users in the restaurant recommendation application [25].
- Grey sheep problem (unusual user) - In a small or even medium community of users, there are individuals who would not benefit from pure CF systems because their opinions do not consistently agree or disagree with any group of people. These individuals will rarely, if ever, receive accurate predictions, even after the initial start up phase for the user and the system [11]. The majority of users falls into the class of the so-called "white sheep", those who have high correlation with many other users and who will therefore, in theory, be easy to find recommendations for. The opposite type of people are the "black sheep", those for whom there are no or few people who they correlate with. This makes it very difficult to make recommendations for them. On the positive side, for statistical reasons, as the number of users of a system increases the chance of finding other people with similar tastes increases and so better recommendations can be provided.
- Scalability problem - CF systems require data from a large number of users before being effective as well as requiring a large amount of data from each user. Therefore, the required computational resources become a critical issue to find users with similar tastes.
- Lack of transparency problem - Collaborative systems today are *black boxes*, computerized oracles which give advice but cannot be questioned. A user is given no indicators to consult in order to decide when to trust a recommendation and when to doubt one. These problems have prevented acceptance of collaborative systems in all but low-risk content domains since they are untrustworthy for high-risk content domains.

### 2.2 Content-based Recommender Systems

Unlike CF systems, where user opinions were a key element to learn user preferences and finding items to suggest, in content-based (CB) recommenders the ratings expressed by a single user have no role in recommendations provided to other users. The core of this approach is the processing of the contents describing the items to be recommended. The items can be very different depending on the number and type of attributes used to describe them. Each item can be described by the same small number of attributes with known set of values, but this is not appropriate for items, such as Web pages, news or documents, described by means of unstructured text. In this case there are no attributes with well-defined values and the use of document modeling techniques with roots in Information Retrieval [30, 3] and Information Filtering [5] research is desirable.

A method to represent unstructured data is the Vector Space Model (VSM). The VSM [34] is a spatial representation of text documents. In this model, each document is represented by a vector in a $n$-dimensional space, where each dimension corresponds to a term from the overall vocabulary of a given document collection. Formally, every document is represented as a vector of term weights, where each weight indicates the degree of association between the document and the term. The CB approach can be applied only in the domains where we can provide some textual metadata describing the items.

A CB recommender learns a profile of the user interests based on some features of the objects the user rated. Afterwards the system exploits the user profile to suggest relevant items by matching the profile representation against that of items to be recommended. The result of this matching is a binary or continuous relevance judgment, the latter case resulting in a ranked list of potentially interesting items. If data are represented by the VSM, the matching might be realized by computing the cosine similarity between the prototype vector and the item vectors. Many systems ask users for feedback on the recommended items so that the matching can be performed according the *relevance feedback*.

The CB paradigm has several advantages when compared to the CF one:

- User independence - CB recommenders exploit solely ratings provided by the active user to build her own profile.
- Transparency - Explanations of recommendations can be provided by listing content features or descriptions that caused an item to be recommended.
- New item - CB recommenders are capable of recommending items not yet rated by any user.

On the other hand, CB systems have several shortcomings:

- Limited content analysis - CB techniques are limited by the features that are associated either automatically or manually with the items. No CB system can provide good suggestions if the content does not contain enough information to distinguish items the user likes from items the user does not like. Some representations capture only certain aspects of the content, but there are many others that would influence a user's experience. For instance,

there often is not enough information in the word frequency to model the user interests in jokes or poems, while techniques for affective computing would be most appropriate. Again, for Web pages, feature extraction by using techniques for text representation completely ignores aesthetic qualities and multimedia information.
- OVER-SPECIALIZATION - CB recommenders have no inherent method for finding something unexpected. The system recommends only items scoring highly against the user profile, i.e. items similar to those already rated. This drawback is also called *serendipity* problem.
- NEW USER - Enough ratings have to be collected before a CB system can really understand user preferences and provide accurate recommendations. Therefore, when few ratings are available, such as for a new user, the system would not be able to provide reliable recommendations.

### 2.3 Other Approaches

- **Demographic Recommender Systems**
  These systems aim to categorize the user starting from personal attributes making recommendation based on demographic classes. *Grundy* [32], for example, recommends books by gathering personal information through an interactive dialogue matching users responses against a library of manually assembled user stereotypes. Pazzani [25] uses machine learning techniques to obtain a classifier based on demographic data. The representation of demographic information in a user model can vary greatly. *Grundy* system uses hand-crafted attributes with numeric confidence values, while Pazzani extracts features from users' home pages.
  The benefit of a demographic approach is that it may not require a history of user ratings of the type needed by collaborative and content-based techniques. However, up to our knowledge, there are not many recommender systems using demographic data because this form of information is difficult to collect: till some years ago, indeed, users were reluctant to share a big amount of personal information with a system. Nowadays with the exponential growth of social network and the continuous expansion of Web 2.0 platforms , the situation is changed towards a more open perspective, with users more trustful to sharing of information. Despite this, still today demographic approaches notice less success than others.
- **Knowledge-based Recommender Systems**
  These systems uses a knowledge-based (KB) approach to generate recommendations. All recommendation techniques make some kind of inference. KB approaches are distinguished in that they have functional knowledge: they have knowledge about how a particular item meets a particular user need, and can therefore reason about the relationship between a need and a possible recommendation [9]. The user profile can be any knowledge structure that supports this inference. In the simplest case, as in Google, it may simply be the query that the user has formulated. In others, it may be a more detailed representation of the user needs [39].

A particular kind of KB systems implement the case-based reasoning (CBR). This recommender solves a new problem looking up a similar past solved one. In [21], four main steps of a CBR recommender are identified: *retrieve, reuse, adaptation*, and *retain*. The first step looks in the knowledge-base for a case similar to the new problem, then reuse the retrieved solution (making some adaptation, if necessary). Finally the new adapted case is stored in the case-library. In this system there is not a user preference elicitation because the main task of the recommendation algorithm is to retrieve the case most similar to the problem to solve.

The KB systems do not have a *ramp-up* problem ("early rater" problem and the "sparse ratings" problem) since its recommendations do not depend on a base of user ratings. Therefore KB approach is complementary to others [8].

– **Hybrid Recommender Systems**

They combine two or more recommender algorithms (the more frequent approach is to combine CF and CB) in order to emphasize their strengths and to level out their corresponding weaknesses. Robin Burke proposed a very analytical classification of hybrid systems [9], listing a number of hybridization methods to combine pairs of recommender algorithms.

- Weighted - The score (or votes) of a recommended item is computed from the results of all of the available recommendation techniques present in the system. The simplest combined hybrid would be a linear combination of recommendation scores.
- Switching - A switching hybrid uses some criterion to switch between recommendation techniques. Switching hybrids introduce additional complexity into the recommendation process since the switching criteria must be determined, and this introduces another level of parameterization.
- Mixed - Recommendations from several different recommenders are presented at the same time. This may be possible where it is practical to make large number of recommendations simultaneously.
- Feature Combination - Features from different recommendation sources are thrown together into a single recommendation algorithm. For example CF and CB techniques might be merged treating collaborative information as simply additional feature data associated with each example and using content-based techniques over this augmented data set.
- Cascade - The cascade hybrid involves a staged process because one recommender refines the recommendations given by another one.
- Feature Augmentation - Output from one technique is used as an input feature to another. This means that one technique is employed to produce a rating or classification of an item and that information is then incorporated into the processing of the next recommendation technique.
- Meta-level - The model learned by one recommender is used as input to another. This differs from feature augmentation: in an augmentation hybrid, we use a learned model to generate features for input to a second algorithm; in a meta-level hybrid, the entire model becomes the input.

## 3 Learning User Preferences in Recommender Systems

As stated by [7], a *preference* is an ordering relation between two or more items to characterize which, among a set of possible choices, is the one that best fits user tastes. *Preferences* are something able to guide our choices, discriminating items we like from those we don't like (or we like the least). In other terms, learning user preferences is a way to find the solution of a research (or optimization, in some case) problem whose space of possible solutions is represented by the set of the items the user can enjoy (namely, in recommender systems, the set of items that can be recommended). Although the semantics of the concept of preference is pretty clear, acquiring user preferences and working with them is a more difficult task. Indeed, the complexity of the problem of preference learning is strictly related to the number of dimensions used to represent the set of possible choices. So, in order to generate a user profile we need to *gather user feedbacks* in order to catch information about user prefences and *model* them using a specific representation. Next, this information can be processed (e.g. through Machine Learning-related approaches) in order to *learn user profiles* to be exploited in the recommendation process.

### 3.1 Feedback Gathering

The information filtering and information retrieval systems rely on relevance feedback (RF) to capture an appropriate snapshot of user information needs in order to allow the user to directly express her notion of relevance with respect to individual documents [5]. RF has been employed in several classes of personalization systems. Driven by the need for better representation of information needs, RF was initially introduced to support basic query expansion [33]. However, its success in inferring the user's notion of relevance on a per-document basis has lead to a subsequent adoption by information filtering and recommendation systems. RF approaches are based on a feedback gathering scheme, either explicit or implicit. In the former, object ratings of predefined scale are provided explicitly by users, while implicit feedback gathering techniques infer object relevance in a transparent fashion, by monitoring user interaction with the system.

**Explicit Ratings.** The use of explicit ratings is common in everyday life; ranging from grading students' work to assessing competing consumer goods (see Alton-Scheidl et al. [2] for a review). Although some forms of rating are made in free text form (e.g. book reviews), it is frequently the case that ratings are made on an agreed discrete scale (e.g. star ratings for restaurants, marks out of ten for films, etc). Ratings made on these scales allow these judgments to be processed statistically to provide averages, ranges, distributions, etc. A central feature of explicit ratings is that the evaluator has to examine an item and assign it a value on the rating scale. This imposes a cognitive cost on the evaluator to assess the performance of an object [24]. Indeed, the act of rating alters the user behavior

from her normal interaction pattern and, consequently, even less noticeable explicit feedback approaches are considered expensive. Since the results may not become immediately apparent, users tend to skip the rating task [15].

Also, explicit RF techniques disregard user knowledge on the current topic. Users are often unclear about their search interests. They browse for more information to clarify their need and re-formulate their query accordingly. The uncertainty in their search episodes increases the cognitive load during explicit RF, as users must decide on the relevance of an item with a lack of confidence.

Finally, the use of explicit ratings imposes privacy issues that have to be resolved [16]. Irrespective of the underlying reason, users are not always comfortable in providing direct indications of their interests. Due to the obtrusive nature of explicit ratings, not many users are willing to provide them. Hence, the performance of profile capturing and recommendation algorithms of such systems degrades, due to the dearth of ratings. In CF systems based on explicit feedback gathering policies, the sparsity of RF judgments can often render such systems unusable, since there are few previous assessments to learn from.

Explicit RF can relying also on critiquing examples. For instance, SmartClient [27] allows to plan travel arrangements. Users are required to critique examples of possible solutions. For instance, "the arrival time of this flight leg is too late." The interaction is cyclical: (1) the system provides example solutions, (2) the user examines any of them and may state a critique on any aspect of it, (3) the critique becomes an additional preference in the model, and (4) the system refines the solution set. Ricci and Nguyen [31] propose a similar critiquing interaction to provide recommendations of restaurants in a mobile context.

As discussed in Pu and Chen [26], the motivation for this methodology is that people usually cannot state preferences in advance but construct their preferences as they see the available options. However, because the critiques come from the user in response to the shown examples, the current solutions can hinder the user from refocusing the search in another direction (the anchoring effect). A complete preference model can be acquired only if the system is able to stimulate the user by showing diverse examples.

**Implicit Ratings.** Implicit RF gathering techniques are proposed as unobtrusive alternative or supplement to explicit ratings in order to state (indirect) assessment about usefulness of any individual item. Such techniques passively monitor user interactions with the system in order to estimate user interests [23]. Click-throughs, time spent viewing a document and mouse gestures are among the possible sources of implicit feedback [17]. The main benefits of implicit feedback, over explicit ratings, are that they remove the cognitive cost of providing relevance judgments explicitly and they can be gathered in large quantities and aggregated to infer item relevance. Since implicit judgments are derived transparently, they contain less indicative value than explicit ratings. Although the accuracy of implicit approaches has been questioned [24], recent studies have shown that they can be effectively adopted to state relevance feedback [40].

There are several types of feedback that can be implicitly captured. Nichols [24] presented a list of potential types of user behaviors that could be exploited as sources for implicit feedback. Kelly & Teevan [17] extended a classification of observable feedback behaviors according to two axes, *Behavior Category*[1] and *Minimum Scope*[2] to categorize actions that can be observed during user information seeking episodes. Their work has also focused on classifying existing scientific literature on implicit feedback according to Behavior Category and Minimum Scope. Unsurprising, a lot of analyzed works concerns examination with object scope, i.e. click-through or scrolling measures are largely investigated and exhibit a strong positive correlation with the explicit ratings. Such data can be easily captured in realtime at no considerable computational cost, while user behaviors that fall in the "Reference", "Annotate" and "Create" require a more precise control over individual services and applications and, thus, are hard to capture and benefits for estimating user interests are not fully clear.

### 3.2 Modeling User Preferences

Feedback gathering techniques allow to collect information about user tastes and interests. However, before this information can be exploited as input to learn preferences models, this data need to be modeled following a specific representation. Techniques for modeling information (we usually refer to this as *items*, in recommender systems) can be split depending on the kind of data which will be stored in the user profile. If we have to handle unstructured data (the ones usually exploited by CB recommenders) it is necessary to process them through some Information Retrieval-related techniques (such as stemming, lemmatization, indexing, and so on) which let us to shift from a textual source to a structured one. For structured data, like generic ratings or some well-defined attribute-value pairs (e.g. demographic data), instead, it is possible to represent them through a matrix, how usually happens in CF systems. In both cases all the information provided by the user, apart from their nature, can be also represented in a more complex way (semantic or neural networks, probabilistic models, etc.) so that we can use them as input for learning user profiles.

In the next section we will survey several Machine Learning techniques for learning user profiles in different recommender systems.

### 3.3 Techniques for Learning User Profiles

According to [1], recommendations techniques can be grouped into two general classes: model-based and memory/heuristic based. The same classification can be made for techniques for learning user profiles: offline learning techniques (used in model-based recommender systems) and online learning techniques (used in

[1] The Behavior Category (Examine, Retain, Reference, Annotate and Create), refers to the underlying purpose of the observed behavior.

[2] Minimum Scope (Segment, Object and Class), refers to the smallest possible scope of the item being acted upon.

memory-based recommender systems). Most systems learn user profiles using an online learning approach, building and updating the model in order to make recommendations in real-time. Offline learning methods, instead, fit better in domains where, as stated in [22], user preferences change slowly with respect to the time needed to build the model.

The application of Machine Learning techniques is a typical way to fulfil the task of learning user profiles in model-based recommender systems. A common approach is to learn the user profile by building a *classifier*, e.g. a model able to assign a category to a specific input [22]. The classifier is learned by an inductive process from a *training set*, i.e. a collection of items labeled with the categories they belong to. In this approach the problem of learning user profiles is considered as a binary categorization task: each item has to be classified as interesting or not with respect to the user preferences. Therefore, the set of categories is $C = \{c_+, c_-\}$, where $c_+$ is the positive class (user-likes) and $c_-$ the negative one (user-dislikes). Classifiers may be implemented using many different machine learning strategies including probabilistic approaches, neural networks, decision trees, association rules and Bayesian networks. In this section we will provide a general overview of these techniques.

**Naïve Bayes.** It is the most used probabilistic algorithm and belongs to the general class of Bayesian classifiers. These approaches generate a probabilistic model based on previously observed data. It is usually used in CB systems where the items to recommend are represented by textual documents. Thus, the model estimates the *a posteriori* probability, $P(c|d)$, of document $d$ belonging to class $c$. This estimation is based on the a priori probability, $P(c)$, the probability of observing a document in class $c$, $P(d|c)$, the probability of observing the document $d$ given $c$ and, $P(d)$, the probability of observing the instance $d$. Using these probabilities, the Bayes theorem is applied to calculate $P(c|d)$:

$$P(c|d) = \frac{P(c)P(d|c)}{P(d)} \tag{1}$$

To classify the document $d$, the class with the highest probability is chosen:

$$c = argmax_{c_j} \frac{P(c_j)P(d|c_j)}{P(d)}$$

$P(d)$ is generally removed as it is equal for all $c_j$. As we do not know the value for $P(d|c)$ and $P(c)$, we estimate them by observing the training data. However, estimating $P(d|c)$ in this way is problematic, as it is very unlikely to see the same document more than once: the observed data is generally not enough to be able to generate good probabilities. The naïve Bayes classifier overcomes this problem by simplifying the model by making the independence assumption: all the words or tokens in the observed document $d$ are conditionally independent of each other given the class. Individual probabilities for the words in a document are estimated one by one rather than the complete document as a whole. The conditional independence assumption is clearly violated in real-world

data, however, despite these violations, empirically the naïve Bayes classifier does a good job of classifying text documents [19, 6].

Although naïve Bayes performances are not as good as some other statistical learning methods such as nearest-neighbor classifiers or support vector machines, it has been shown that it can perform surprisingly well in the classification tasks where the computed probability is not important [14]. Another advantage of the naïve Bayes approach is that it is very efficient and easy to implement compared to other learning methods.

**Rocchio's method.** Some linear classifiers consist of an explicit profile (or prototypical document) of the category [37]. The Rocchio's method is used for inducing linear, profile-style classifiers. It relies on an adaptation to text categorization of the well-known Rocchio's formula for relevance feedback in the VSM [33]. This algorithm represents documents as vectors so that documents with similar content have similar vectors. Each component of such a vector corresponds to a term in the document . The weight of each component is computed using the TF-IDF [35] term weighting scheme. Learning is achieved by combining document vectors (of positive and negative examples) into a prototype vector for each class in the set of classes $C$. To classify a new document $d$, the similarity between the prototype vectors and the corresponding document vector representing $d$ are calculated for each class (for example by using the cosine similarity measure), then $d$ is assigned to the class with which its document vector has the highest similarity value. More formally, Rocchio's method computes a classifier $\overrightarrow{c_i} = \langle \omega_{1i}, \ldots, \omega_{|T|i} \rangle$ for category $c_i$ ($T$ is the *vocabulary*, that is the set of distinct terms in the training set) by means of the formula:

$$\omega_{ki} = \beta \cdot \sum_{\{d_j \in POS_i\}} \frac{\omega_{kj}}{|POS_i|} - \gamma \cdot \sum_{\{d_j \in NEG_i\}} \frac{\omega_{kj}}{|NEG_i|} \tag{2}$$

where $\omega_{kj}$ is the TF-IDF weight of the term $t_k$ in document $d_j$, $POS_i$ and $NEG_i$ are the set of positive and negative examples in the training set for the specific class $c_j$, $\beta$ and $\gamma$ are control parameters that allow setting the relative importance of *all* positive and negative examples. To assign a class $\widetilde{c}$ to a document $d_j$, the similarity between each prototype vector $\overrightarrow{c_i}$ and the document vector $\overrightarrow{d_j}$ is computed and $\widetilde{c}$ will be the $c_i$ with the highest value of similarity.

**Decision trees learners.** Decision trees are trees in which internal nodes are labeled by terms, branches departing from them are labeled by tests on the weight that the term has in the test document, and leafs are labeled by categories. Decision trees are built by recursively partitioning training data, that is text documents, into subgroups, until those subgroups contain only instances of a single class. The test for partitioning data is run on the weights that the terms labeling the internal nodes have in the document. The choice of the term on which to operate the partition is generally made according to an information gain or entropy criterion [41]. The most widely-used decision tree learner applied to profiling is ID3 [28].

**Decision rule classifiers.** Are similar to decision trees, because they operates in a similar way to the recursive data partitioning approach described above. An advantage of rule learners is that they tend to generate more compact classifiers than decision trees learners. Rule learning methods usually attempt to select from all the possible covering rules (i.e. rules that correctly classify all the training examples) the "best" one according to some minimality criterion. Some examples of inductive learning techniques are Ripper [12], Slipper [13], CN2 [10] and C4.5rules [29].

**Neural networks.** Neural networks model complex relationships between input and output cells. The user interests are represented by the output cells and each of them are achievable by a specific pattern in the network. When an error occurs, there is a backward propagation until the responsible cell is achieved, so the cell parameters are adjusted.

**Bayesian network.** It represents a probability distribution by a direct acyclic graph. There are random variables (nodes) and relations among them (arcs). The nodes represent attributes and the arcs represent probability correlations. In [36] a method integrating Case Based Reasoning and Bayesian Network for the user profiling task is shown. Bayesian Network is employed to model quantitative and qualitative relationships between items that users have liked. Bayesian Network is generally used in those situations where user interests change slowly.

**Nearest neighbor algorithms.** These algorithms, also called lazy learners, simply store training data in memory, and classify a new unseen item by comparing it to all stored items by using a similarity function. The "nearest neighbor" or the "$k$-nearest neighbors" items are determined, and the class label for the unclassified item is derived from the class labels of the nearest neighbors. A similarity function is needed, for example the cosine similarity measure is adopted when items are represented using the VSM. Nearest neighbor algorithms are quite effective, albeit the most important drawback is their inefficiency at classification time, since they do not have a true training phase and thus defer all the computation to classification time.

## 4 Conclusions

In this paper we surveyed the methods for learning user profiles in recommender systems. Firstly, we introduced the basics of recommender systems by describing the main approaches presented in literature, namely the content-based and the collaborative one. We also introduced other important approaches, such as the demographic and the knowledge-based one, and some hybrid systems combining different types of recommendation strategies. In the second part of the chapter we focused our attention on the process of learning user preferences, by describing 1) the techniques to get implicit or explicit user feedback and 2) the most successful

and widely used machine learning methods to learn user profiles in recommender systems.

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