

A study on Recommender Systems and its different approaches

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Abstract

“Recommender Systems” is an emerging technology that helps customers to find products of their interest. A recommender engine gives personalized suggestions of products by extracting knowledge from the previous users’ interactions to compute predictions [1]. The vast and ever increasing amount of items available on the websites has led to the development of many technologies providing a way to one of them, recommender systems. Many of the onlinetrading websites are already using recommender systems to help their customers find products of their interest[2]. In this paper, we present an explanation of how recommender system helps customers to find the product of their interest through the native Recommender System methods. The native recommender systems methods are classified into three main categories: content-based filtering, collaborative filtering, and hybrid recommendation approaches.

Introduction

Recommender systems are used by E-commerce sites to suggest products to their customers. A recommender system makes personalized product recommendations to users by extracting knowledge from the

previous user interactions with the system. Such services are particularly useful in the modern electronic marketplace which offers wide range of products. In fact a recommender system represents an added value both for consumers, who can easily find products they really like, and for sellers, who can focus their offers and advertising efforts. Several recommender systems have been developed that cope with different products, e.g. MovieLens for movies (see [Sarwar et al., 2001]), Jester for jokes [Goldberg et al., 2001], Ringo for music [Shardanand and Maes, 1995], GroupLens for usenet news [Miller et al., 2002] and many other (see e.g. [Schafer et al., 2001] for a review). A recommender system constructs a user profile on the basis of explicit or implicit feedback of the user with the system. The profile is used to find products to recommend to the user. In the simplest approach, the profile is constructed using only features that are related to the user under evaluation and to the products he/she has already considered. In those cases, the profile consists of a parametric model that is adapted according to the customer’s behavior.

Recommender systems have become an area of active research. They are especially important in the e-commerce industry because they help increase revenues and towards the betterment of customer experience. A lot of different techniques have been explored for different kind of recommender systems based on the desired objective and the data that is available to base the recommendations on. In this paper we focus on different techniques that are adopted to make predictions of products based on the objective and data available.

The products can be recommended based on the top overall sellers on a site, based on the demographics of the customer, or based on an analysis of the past buying behavior of the customer as a prediction for future buying behavior. Broadly, these techniques are part of personalization on a site, because they help the site adapt itself to each customer. Recommender systems automate personalization on the Web, enabling individual personalization for each customer.

Problem Statement

Too much data: information overload – customers have many options. Recommender Systems is one among many number of optimal ways to fetch profit to a company/sellers; Often, customers find difficult to choose an item among large amount of data available. Customers need suggestions of relevant products which help their navigation easy and most appealing. Sellers' lack of knowledge on suggesting

products or items to a new customer: It requires a most appealing suggestions of products to convert a new visitor into a buyer. Research says that it takes ratio of 1:5 times of investment to convert a new customer into a permanent customer, hence it takes a most appealing approach and accurate predictions on recommendation of products to a new customer.

Approaches of Recommender Systems

Approaches to Recommender Systems are categorized as

- Collaborative Filtering (CF): In Collaborative Filtering approach a user is recommended items based on the past ratings of all users collectively. Collaborative filtering is further divided into User based and Item based collaborative filtering.
- Content-based recommending: This method recommends items that are similar in content to items the user has liked in the past, or matched to attributes of the user.
- Hybrid approaches: These methods combine both collaborative and content based approaches.

Recommender Systems underlie upon a basic mechanism where Known user preferences are represented as a matrix of n users and m items, where each cell $r_{u,i}$ corresponds to the rating given to item i by the user u . This user ratings matrix is

typically sparse, as most users do not rate most items. The recommendation task is to predict what rating a user would give to a previously unrated item. Typically, ratings are predicted for all items that have not been observed by a user, and the highest rated items are presented as recommendations. The user under current consideration for recommendations is referred to as the active user. The same is presented in below figure

	Items					
	1	2	...	i	...	m
1	5	3		1	2	
2		2				4
:			5			
u	3	4		2	1	
:					4	
n			3	2		
a	3	5		?	1	

Collaborative Filtering

Collaborative Filtering (CF) systems work by collecting user feedback in the form of ratings for items in a given domain and exploiting similarities in rating behavior amongst several users in determining how to recommend an item.

User based collaborative filtering: A subset of users are chosen based on their similarity to the other active user, and a weighted combination of their ratings is used to produce predictions for this user. The algorithm below describes the User based approach:

In step 1, the weight $w_{a,u}$ is a measure of similarity between the user u and the active user a . The most commonly used measure of similarity is the Pearson correlation

coefficient between the ratings of the two users [30], defined below:

$$w_{a,u} = \frac{\sum_{i \in I} (r_{a,i} - \bar{r}_a)(r_{u,i} - \bar{r}_u)}{\sqrt{\sum_{i \in I} (r_{a,i} - \bar{r}_a)^2 \sum_{i \in I} (r_{u,i} - \bar{r}_u)^2}} \quad (1)$$

where 'i' is the set of items rated by both users, $r_{u,i}$ is the rating given to item i by user u , and \bar{r}_u is the mean rating given by user u . In step 3, predictions are generally computed as the weighted average of deviations from the neighbor's mean, as in:

$$p_{a,i} = \bar{r}_a + \frac{\sum_{u \in K} (r_{u,i} - \bar{r}_u) \times w_{a,u}}{\sum_{u \in K} w_{a,u}} \quad (2)$$

where $p_{a,i}$ is the prediction for the active user a for item i , $w_{a,u}$ is the similarity between users a and u , and K is the neighborhood or set of most similar users.

Similarity based on Pearson correlation measures the extent to which there is a linear dependence between two variables. Alternatively, one can treat the ratings of two users as a vector in an m -dimensional space, and compute similarity based on the cosine of the angle between them, given by:

$$w_{a,u} = \cos(\vec{r}_a, \vec{r}_u) = \frac{\vec{r}_a \cdot \vec{r}_u}{\|\vec{r}_a\|_2 \times \|\vec{r}_u\|_2} = \frac{\sum_{i=1}^m r_{a,i} r_{u,i}}{\sqrt{\sum_{i=1}^m r_{a,i}^2} \sqrt{\sum_{i=1}^m r_{u,i}^2}} \quad (3)$$

When computing cosine similarity, one cannot have negative ratings, and unrated items are treated as having a rating of zero. Research says that Pearson correlation generally performs better.

Item-based Collaborative Filtering: User based collaborative filtering do not scale well for large number of users, because of the computational complexity of the search for similar users. As an alternative, we have item-to-item Collaborative Filtering where rather than matching similar users, they match a user's rated items to similar items. This often results in improved recommendations. In this approach similarities between pairs of items i and j are computed offline using Pearson correlation, given by:

$$w_{i,j} = \frac{\sum_{u \in U} (r_{u,i} - \bar{r}_i)(r_{u,j} - \bar{r}_j)}{\sqrt{\sum_{u \in U} (r_{u,i} - \bar{r}_i)^2} \sqrt{\sum_{u \in U} (r_{u,j} - \bar{r}_j)^2}} \quad (4)$$

where U is the set of all users who have rated both items i and j , $r_{u,i}$ is the rating of user u on item i , and \bar{r}_i is the average rating of the i^{th} item across users. Now, the rating for item i for user a can be predicted using a simple weighted average, as in:

$$p_{a,i} = \frac{\sum_{j \in K} r_{a,j} w_{i,j}}{\sum_{j \in K} |w_{i,j}|} \quad (5)$$

where K is the neighborhood set of the k items rated by a that are most similar to i .

Content-based Recommending

Content-based recommender systems work with profiles of users that are created at the beginning based on their implicit and explicit feedback. In the recommendation process, the engine compares the items that were already positively rated by the user with the items he did not rate and looks for

similarities. Those items that are mostly similar to the positively rated ones, will be recommended to the user. A content based recommender system would find out items from the list that the user has already viewed and positively rated. Then, it would compare those items with the rest of the items from the list and look for similarities. Similar items would be recommended to the user.

There are different algorithms of measuring similarities among items in data base and those in users profile. One of such approaches is cosine similarity. Representing items as vectors on a coordinate space it measures angles between vectors and gives out their cosine value. Vectors \vec{w}_c and \vec{w}_s of two items with attributes are compared in cosine similarity function as follows:

$$u(c, s) = \cos(\vec{w}_c, \vec{w}_s) = \frac{\vec{w}_c \cdot \vec{w}_s}{\|\vec{w}_c\| \times \|\vec{w}_s\|} = \frac{\sum_{i=1}^K \vec{w}_{ic} \vec{w}_{is}}{\sqrt{\sum_{i=1}^K w_{ic}^2} \sqrt{\sum_{i=1}^K w_{is}^2}}$$

Hybrid approach

Hybrid approach is a combination of collaborative filtering and content-based filtering could be more effective in some cases. Hybrid approaches can be implemented in several ways: by making content-based and collaborative-based predictions separately and then combining them; by adding content-based capabilities to a collaborative-based approach (and vice

versa); or by unifying the approaches into one model. Several studies empirically compare the performance of the hybrid with the pure collaborative and content-based methods and demonstrate that the hybrid methods can provide more accurate recommendations than pure approaches. These methods can also be used to overcome some of the common problems in recommender systems such as cold start and the sparsity problem.

Netflix is a good example of the use of hybrid recommender systems. They make recommendations by comparing the watching and searching habits of similar users (i.e. collaborative filtering) as well as by offering movies that share characteristics with films that a user has rated highly (content-based filtering).

A variety of techniques have been proposed as the basis for recommender systems: collaborative, content-based, knowledge-based, and demographic techniques. Each of these techniques has known shortcomings, such as the well-known cold-start problem for collaborative and content-based systems (what to do with new users with few ratings) and the knowledge engineering bottleneck in knowledge-based approaches. A hybrid recommender system is one that combines multiple techniques together to achieve some synergy between them.

Following are some of the hybridization techniques:

- Switching: The system chooses among recommendation components and applies the selected one.
- Mixed: Recommendations from different recommenders are presented together.
- Feature Combination: Features derived from different knowledge sources are combined together and given to a single recommendation algorithm.

Conclusion

Recommendation systems have definitely opened new options of searching and filtering information. Internet stores have accelerated profits, music lovers have discovered new artists unknown to them before, and tourists might take a look at new interesting places. Having all these options available, the customers save their time. Recommendation systems are not limited to only computers and mobile devices, but some of its types can also be used in shopping centres and any other trading areas hence increasing the sales and profit of seller and finding most suitable product for the customer.

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