Recommendation System based on Restricted Boltzmann Machine

Sarthak Malhotra

Dept. of Computer Science, Galgotias University Greater Noida, India

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Abstract - Recommendation systems are used to filter, prioritize and efficiently deliver relevant information from a cyber-ocean of information. Recommendation systems are one of the most significant applications of machine learning. This paper presents a novel framework of recommendation system which has the ability to recommend products to the individual users on the basis of the earlier purchase history and shopping experience. The main approach of this proposed model contains the use of Restricted Boltzmann machine (RBM), the proposed approach prove significant improvements over another baseline methods.

Key Words: **Collaborative filtering, Content-based filtering, Hybrid filtering technique, Recommendation systems**

I. INTRODUCTION

In most extensive language, Recommendation Engines are illustrated as a subclass of an information filtering system which seeks to predict the "rating" or "preference" a user shall give to an item. Thus, making the experience more personalized and lucid. These items can be products, books, movies, restaurants etc. These preferences are being predicted using two approaches, content- based approach which involves characteristics of an item and collaborative filtering approach which takes into account user's past behaviour to make choices. The recommendation system involves various techniques such as association mining, collaborative filtering and content filtering which are the three widely refined methods for powerful impact with the help of search engines[1].

Restricted Boltzmann machines are mostly used used in deep learning networks. Particularly, deep belief networks can be constructed by combining several RBMs and optionally finetuning the resulting deep networks with descent of gradient and back propogating the stack.

A restricted Boltzmann machine (RBM) is a category of artificial neural network. This category of generative network is basically useful for filtering, feature learning and classification, and it makes use of some types of dimensionality reduction to help intercept complicated inputs. With the help of RBM, we pass all the stock code of all the customers in the visible layer and then reconstruct the User Item matrix and thus, find the recommended product for a particular user on the basis of the purchase history[2].

This paper is structured as follows: Section II a description of the literature survey is done which describes the work done by various authors. Section III presents implementation of Restricted Boltzmann Machine technique followed by Results in Section IV. Finally, Section V concludes the paper.

II. LITERATURE SURVEY

A lot of methods and techniques have been proposed over the past few years to improve the accuracy of the recommendation systems and there is a need to optimize it to have good results. This section discusses the various approaches proposed by researchers to find better working techniques. While those which do not require training are called speaker independent system. The voice commands can be a fixed set of commands (as in this project) while more advanced ones come with natural speech recognition which can process complete sentences or phrases in multiple languages and accents of the speaker.

In a survey conducted more than half of the recommendation approaches made use of content-based filtering (55 %). Collaborative filtering was made use in application by only 18 % of the reviewed approaches, and the other graph-based recommendations by 16 %. Various other recommendation concepts mainly included stereotyping, item- centric and hybrid recommendations. The content-based filtering approach mainly made use of papers that the users had authored,

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tagged, browsed, or downloaded. One of the most frequently applied weighting scheme is TF-IDF. In addition to simple terms, n-grams, topics, and citations were utilized to model users information needs. Our review revealed some drawbacks of the current research. Firstly, it remains unclear which recommendation notion and addresses are the most promising. For instance, researchers reported various different results on the performance of content-based and collaborative filtering. Sometimes content-based filtering performed better than collaborative filtering and sometimes it performed unsatisfactory. I identified potential reasons for the obscurity of the results.

(1) Several evaluations had limitations. They were based on strongly abbreviated datasets, few participants in user studies, or did not use appropriate baselines.
(2) Some authors provided little information about their algorithms, which makes it difficult to re-implement the approaches. Consequently, researchers use different methods for the implementations of the same recommendations approaches, which might lead to variations in the results [3].
(3) I speculated that minor variations in datasets, algorithms or user populations inevitably leads to strong variations in the performance of the approaches. Hence, finding the most promising approaches is a challenge. Finally, few research papers had an impact on research paper recommender systems in practice. I also identified a lack of authority and long-term research interest in the field: 73 % of the authors published not more than one paper on research-paper recommender systems, and there was little cooperation among different co-author groups.

III. PROPOSED MODEL

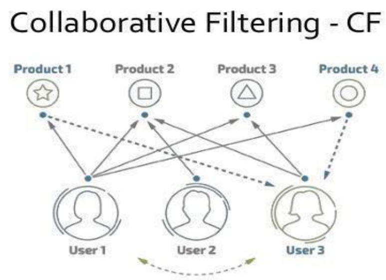
The proposed methodology consists of the following techniques of collaborative filtering and content based filtering and a study on Restricted Boltzmann Machines.

1**) Collaborative filtering (CF)** is a popular recommendation algorithm that bases its predictions and recommendations on the ratings or behavior of other users in the system. The elemental assumption behind this method is that other users' opinions can be selected and agglomerated in such a way as to provide a rational prediction of the active user's preference. There are two categories of CF:

User-based: It measures the similarity between target users and other users.
Item-based: It measures the similarity between the items that target users rates/interacts with and other items.

Assume there are m users and n items, we use a matrix size m*n to denote the past behavior of users. Each cell in the and matrix represents the associated opinion that a user holds. M{i, j} denotes how user i likes item j. Such matrix is called utility matrix.

Fig.1.
Collaborative Filtering



A. ***Item Based Filtering-*** The item-based CF recommends items based on their similarity with the items that the target user rated. Likewise, the similarity can be calculated with Pearson Correlation or Cosine Similarity. This method is quite stable in itself as compared to User based collaborative filtering because the average item has a lot more ratings than the average user[4].So an individual rating doesn't influences as much. To compute resemblance between two items, we look into the group of items the target user has rated and calculates how similar they are to the target item i and then selects k most similar items. Similarity between two items is computed by taking the ratings of the users who have rated both the items and thereafter using the cosine similarity function mentioned as under:

$$w_{ij} = \mathrm{sim}(i,j) = \frac{\sum_{u \in U_i \cap U_j} \hat{r}_{ui}\hat{r}_{uj}}{\sqrt{\sum \hat{r}_{uj}}\sqrt{\sum \hat{r}_{uj}}}$$

Fig. 2 Cosine Similarity Function

B. ***User Based Filtering-*** There are two options, Pearson Correlation or cosine similarity. Let us{i, k} denotes the similarity between user i and user k and v_{i, j} denotes the rating that user i gives to item j with v_{i, j} = ? if the user has not rated that item. One of this methods can be expressed as the followings:

$$u_{ik} = \frac{\sum_j (v_{ij} - v_i)(v_{kj} - v_k)}{\sqrt{\sum_j (v_{ij} - v_i)^2 \sum_j (v_{kj} - v_k)^2}}$$

Fig.3. Pearson Correlation

2. Content Based Filtering:-In the Content-based filtering, also referred to as cognitive filtering, recommendation of items is done by comparing the content of the items and a user profile. The content of each item is represented as a with set of descriptors or terms, typically the words that occur in a document. The user profile is represented with the same terms built up by analyzing the content of items which have instance.

Several issues have to be taken into consideration while implementing a content-based filtering system. First, terms can either be assigned automatically or manually. When terms are assigned automatically a method needs to be chosen which can extract these terms from items. Secondly, the terms have to be represented in such a manner that both the user profile and the items can be compared in an important way. Third, a learning algorithm has to be chosen that is able to learn the user profile based on seen items and can make recommendations based on this user profile.

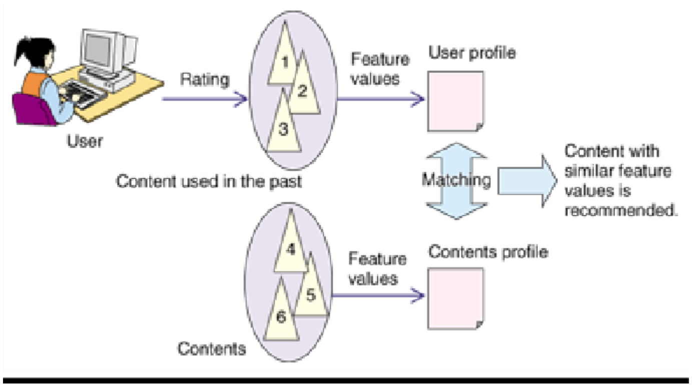


Fig.4.Content Based Filtering

3. Restricted Boltzmann Machine- A restricted Boltzmann machine (RBM) is a type of artificial neural network. This type of generative network is useful for filtering, feature learning and classification, and it employs some types of dimensionality reduction to help tackle complicated inputs. With the help of RBM, [5] we pass all the stock code of all the customers in the visible layer and then reconstruct the User- Item matrix and thus, find the recommended product for a particular user on the basis of the purchase history.

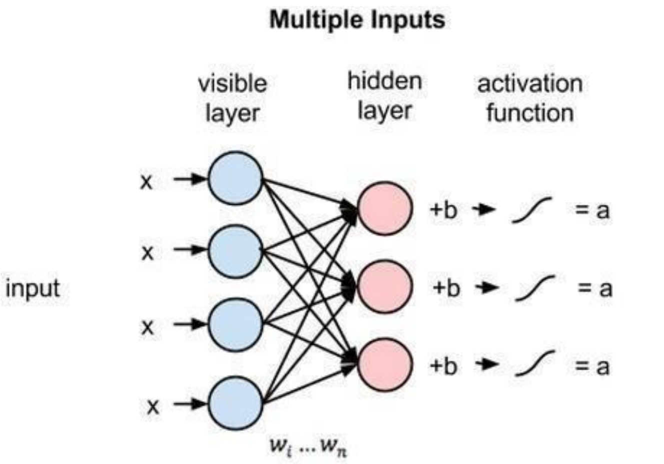


Fig.5. Restricted Boltzmann Machine

Data sparsity is a crucial problem in recommender systems. Data sparsity plays an important role in recommendation systems. Data sparsity problem is discussed in collaborative filtering approach. In the work, it is concluded that the data sparsity negatively affects in the recommendations which is provided by collaborative filtering. For instance, in newspaper domain, some recent news is just rated by few people. In such condition, even if the news is highly important or crucial for people and have high rating only by few people, the chances of being recommended to other users is very slim[4].

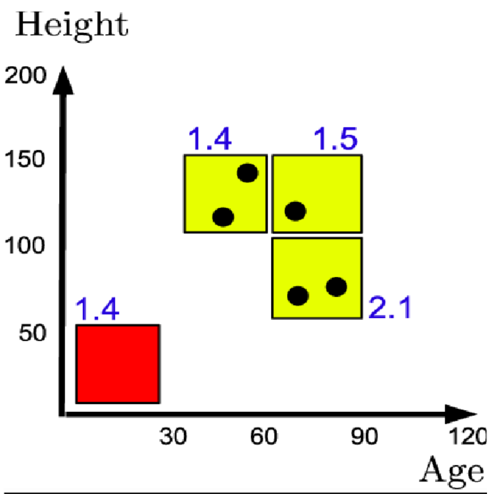


Fig 6. Data Sparcity

The recommendation engine was built by implementation of RBM, which includes the following formulae-

-(∂log p (v) / ∂Wij) =Ev[p(hi | v).vj] – vj (i) . sigm(Wi .v (i) +ci)----- eqn (1)

-(∂log p (v) / ∂ci) = Ev[p(hi | v) –sigm (Wi . v (i))----- eqn (2)

-(∂log p (v) / ∂bj) = Ev[p(vj | h)] –vj (i)------------- eqn (3)

IV.EXPERIMENT RESULT:-

Our experiment was conducted on Movie data set for evaluating the performance of Recommendation system. The proposed system shows results of the movies similar to the type of movie searched. The system will show the movies present in the dataset based on rating and similarity. Suppose a cartoon movie is searched, the system will recommend other cartoon movies in the dataset. Suppose a movie has a rating "U", the system will show other movies with the same rating. At the same time, you can login into the system and logout of the system which shows the systems' efficiency in terms of implementation and time.

V. CONCLUSION

Recommendation systems are rapidly becoming a decisive tool in Ecommerce on the web for a personalized shopping experience. New technologies are in demand that can dramatically improve the scalability of recommendation systems. In this paper, I have presented and experimentally evaluated a recommendation systems with the help of restricted Boltzmann machine (RBM). My results show that RBM-led technique hold the potential to scale to large data sets and at the same time produce high-quality recommendations of items for a particular movie.

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