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Recommended System

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Abstract: *In this study searched for the survey paper on recommendation system. Recommendation system sorts through massive amounts of data to identify interest of users and makes the information search easier. For that purpose many methods have been used. Collaborative Filtering (CF) is a method of making automatic predictions about the interests of customers by collecting information from number of other customers, for that purpose many collaborative base algorithms are used. Web Recommendation(WR) help the website visitors for easy navigation of web pages, quickly reaching their destination and to obtain relevant information. Content based filtering method(CBF) filtering is done based on customer's interested items. In content-based filtering technique, the web pages are recommended for a user very quickly from ancient database. In that database different content of items are added that the user has used in the ancient times and/or user's personal information and preferences.*

Keywords: Web Recommendation, Collaborative base filtering, pre-processing technique, Association rule are various parts of recommended system.

I. Introduction

The prototypical use case for a recommender system occurs regularly in e-commerce settings. A user, Jane, visits her favorite online bookstore. The homepage lists current bestsellers and also a list containing recommended items. A key feature of a recommender system therefore is that it provides a personalized view of the data, in this case, the bookstore's inventory. If we take away the personalization, we are left with the list of best-sellers – a list that is independent of the user. The aim of the recommender system is to lower the user's search effort by listing those items of highest utility. Recommender systems research encompasses scenarios like this and many other information access environments.

1.1 What is a Recommender System?

The definition of a recommender system has evolved over the past 14 years. A recommender system, or a recommendation system is a subclass of information filtering system that seeks to predict the "rating" or "preference" a user would give to an item.

This definition opens up the field of recommender systems to any application that computes a user-specific utility, encompassing many problems commonly thought of as database or information retrieval applications. Even this broad definition may be too narrow as some recommenders may operate on configurations as opposed to a fixed set S of all items and others make recommendations for groups .The definition may also be a bit misleading in that many recommender systems do not explicitly calculate utilities when they produce a ranked list of recommended items. The authors are careful to say that the goal is to choose the items with the best utility, not necessarily to compute the utility in some explicit way. From these considerations, two basic principles stand out that distinguish recommender systems research .A recommender system is personalized. The recommendations it produces are meant to optimize the experience of one user, not to represent group consensus for all. A recommender system is intended to help the user select among discrete options. Generally the items are already known in advance and not generated in a bespoke fashion. The personalization aspect of recommender systems distinguishes this line of research most strongly from what is commonly understood as research in search engines and other information retrieval applications. In a search engine or other information retrieval system, we expect the set of results relevant to a particular query to be the same regardless of who issued it. Many recommender systems achieve personalization by maintaining profiles of user's activity (long-term or short-term) or stated preferences .Others achieve a personalized result through conversational interaction.

1.2 What is Meant by Recommendation System?

Recommender systems are machine learning systems that help users discover new product and services. Every time you shop online, a recommendation system is guiding you towards the most likely product you might purchase. Recommender systems are like salesmen who know, based on your history and preferences, what you like.
Recommender systems are so commonplace now that many of us use them without even knowing it. Because we can't possibly look through all the products or content on a website, a recommendation system plays an important role in helping us have a better user experience, while also exposing us to more inventory we might not discover otherwise.

A. Some Examples of Recommender Systems in Action Include:

Product recommendations on Amazon, Netflix suggestions for movies and TV shows in your feed, recommended videos on YouTube, music on Spotify, the Facebook newsfeed and Google Ads.An important component of any of these systems is the recommender function, which takes information about the user and predicts the rating that user might assign to a product, for example. Predicting user ratings, even before the user has actually provided one, makes recommender systems a powerful tool.

II. Recommender System Typology

Recommender systems research is characterized by a common problem area rather than a common technology or approach. An examination of the past four ACM Recommender System conferences shows that a wide variety of research approaches have been applied to the recommender systems problem, from statistical methods to ontological reasoning, and a wide variety of problems have been tackled, from choosing consumer products to finding friends and lovers. One lesson that has been learned over the past years of recommender systems research is that the application domain exerts a strong influence over the types of methods that can be successfully applied. Domain characteristics like the persistence of the user's utility function have a big impact: for example, a users' taste in music may change slowly but his interest in celebrity news stories may fluctuate much more. Thus, the reliability of preferences gathered in the past may vary. Similarly, some items, such as books, are available for recommendation and consumption over a long period of time – often years. On the other hand, in a technological domain, such as cell phones or cameras, old products become rapidly obsolete and cannot be usefully recommended. This is also true of areas where timeliness matters such as news and cultural events. See (Burke & Ramezani, 2011) for a more complete description of the factors that influence the choice of recommendation approach. It is not surprising therefore that there are multiple strands of research in recommender systems, as researchers tackle a variety of recommendation domains. To unify these disparate approaches, it is useful to consider the AI aspects of recommendation, in particular, the knowledge basis underlying a recommender system.

III. Knowledge Sources

Every AI system draws on one or more sources of knowledge in order to do its work. A supervised machine learning system, for example, would have a labeled collection of data as its primary knowledge source, but the algorithm and its parameters can be considered another implicit kind of knowledge that is brought to bear on the classification task. Recommendation algorithms can also be classified according to the knowledge sources that they use. There are three basic types of knowledge: x social knowledge about the user base in general, x individual knowledge about the particular user for whom recommendations are sought (and possibly knowledge about the specific requirements those recommendations need to meet), and finally x content knowledge about the items being recommended, ranging from

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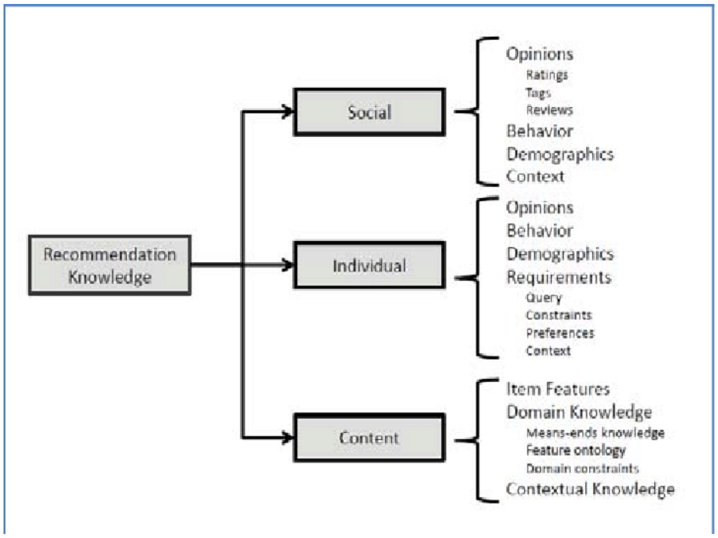
simple feature lists to more complex ontological knowledge and means-ends knowledge that enable the system to reason about how an item can meet a user's needs.

Different recommendation approaches draw from different parts of this spectrum of knowledge sources. The terms of the Netflix Prize competition made available only opinions in the form of ratings, but no requirements or demographic information about users (Bennet& Lanning, 2007). Good domain knowledge is notoriously difficult to assemble in this domain because of the complexity of representing and reasoning about narrative content, directorial style, etc.



The problem thus lent itself to a mathematical approximation technique working exclusively from ratings both social and individual. By contrast, the problem of recommending investment options reported in (Felfernig& Burke, 2008) can benefit from detailed knowledge about the customer's income and financial status, the other items in their portfolio, and their attitude toward risk. Other users' opinions and choices may be useful but are insufficient to make high-quality recommendations in this domain.

IV. Phases of Recommendation Process

4.1 Information Collection Phase

This collects relevant information of users to generate a user profile or model for the prediction tasks including user's attribute, behaviors or content of the resources the user accesses. A recommendation agent cannot function accurately until the user profile/model has been well constructed. The system needs to know as much as possible from the user in order to provide reasonable recommendation right from the onset. Recommender systems rely on different types of input such as the most convenient high quality explicit feedback, which includes explicit input by users regarding their interest in item or implicit feedback by inferring user preferences indirectly through observing user behavior. Hybrid feedback can also be obtained through the combination of both explicit and implicit feedback. In E-learning platform, a user profile is a collection of personal information associated with a specific user. This information includes cognitive skills, intellectual abilities, learning styles, interest, preferences and interaction with the system. The user profile is normally used to retrieve the needed information to build up a model of the user. Thus, a user profile describes a simple user model. The success of any recommendation system depends largely on its ability to represent user's current interests. Accurate models are indispensable for obtaining relevant and accurate recommendations from any prediction techniques.

4.2 Explicit Feedback

The system normally prompts the user through the system interface to provide ratings for items in order to construct and improve his model. The accuracy of recommendation depends on the quantity of ratings provided by the user. The

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only shortcoming of this method is, it requires effort from the users and also, users are not always ready to supply enough information. Despite the fact that explicit feedback requires more effort from user, it is still seen as providing more reliable data, since it does not involve extracting preferences from actions, and it also provides transparency into the recommendation process that results in a slightly higher perceived recommendation quality and more confidence in the recommendations.

4.3 Implicit Feedback

The system automatically infers the user's preferences by monitoring the different actions of users such as the history of purchases, navigation history, and time spent on some web pages, links followed by the user, content of e-mail and button clicks among others. Implicit feedback reduces the burden on users by inferring their user's preferences from their behavior with the system. The method though does not require effort from the user, but it is less accurate. Also, it has also been argued that implicit preference data might in actuality be more objective, as there is no bias arising from users responding in a socially desirable way and there are no self-image issues or any need for maintaining an image for others .

4.4 Hybrid Feedback

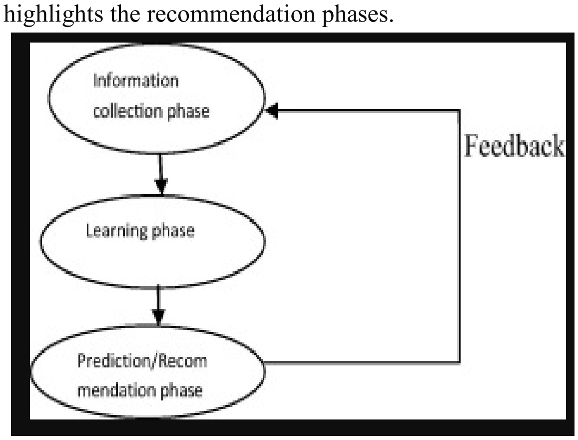
The strengths of both implicit and explicit feedback can be combined in a hybrid system in order to minimize their weaknesses and get a best performing system. This can be achieved by using an implicit data as a check on explicit rating or allowing user to give explicit feedback only when he chooses to express explicit interest.

4.5 Learning Phase

It applies a learning algorithm to filter and exploit the user's features from the feedback gathered in information collection phase.

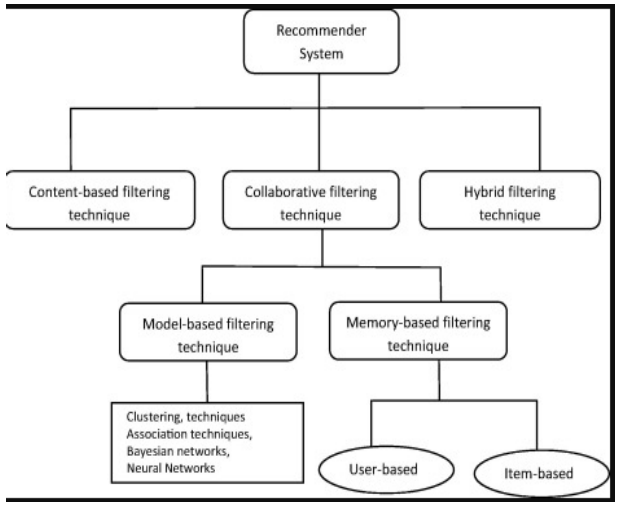
4.6 Prediction/Recommendation Phase

It recommends or predicts what kind of items the user may prefer. This can be made either directly based on the dataset collected in information collection phase which could be memory based or model based or through the system's observed activities of the user. highlights the recommendation phases.



V. Recommendation Filtering Techniques

The use of efficient and accurate recommendation techniques is very important for a system that will provide good and useful recommendation to its individual users. This explains the importance of understanding the features and potentials of different recommendation techniques. The anatomy of different recommendation filtering techniques.



5.1 Content-Based Filtering

Content-based technique is a domain-dependent algorithm and it emphasizes more on the analysis of the attributes of items in order to generate predictions. When documents such as web pages, publications and news are to be recommended, content-based filtering technique is the most successful. In content-based filtering technique, recommendation is made based on the user profiles using features extracted from the content of the items the user has evaluated in the. Items that are mostly related to the positively rated items are recommended to the user. CBF uses different types of models to find similarity between documents in order to generate meaningful recommendations. It could use Vector Space Model such as Term Frequency Inverse Document Frequency (TF/IDF) or Probabilistic models such as Naïve Bayes Classifier , Decision Trees or Neural Networks to model the relationship between different documents within a corpus. These techniques make recommendations by learning the underlying model with either statistical analysis or machine learning techniques. Content-based filtering technique does not need the profile of other users since they do not influence recommendation. Also, if the user profile changes, CBF technique still has the potential to adjust its recommendations within a very short period of time. The major disadvantage of this technique is the need to have an in-depth knowledge and description of the features of the items in the profile.

VI. Pros and Cons of Content-Based Filtering Techniques

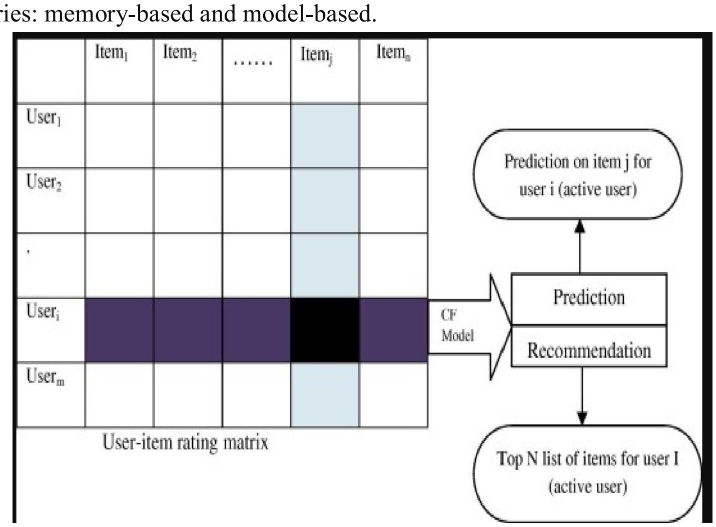
CB filtering techniques overcome the challenges of CF. They have the ability to recommend new items even if there are no ratings provided by users. So even if the database does not contain user preferences, recommendation accuracy is not affected. Also, if the user preferences change, it has the capacity to adjust its recommendations in a short span of time. They can manage situations where different users do not share the same items, but only identical items according to their intrinsic features. Users can get recommendations without sharing their profile, and this ensures privacy . CBF technique can also provide explanations on how recommendations are generated to users. However, the techniques suffer from various problems as discussed in the literature . Content based filtering techniques are dependent on items' metadata. That is, they require rich description of items and very well organized user profile before recommendation can be made to users. This is called limited content analysis. So, the effectiveness of CBF depends on the availability of descriptive data. Content overspecialization is another serious problem of CBF technique. Users are restricted to getting recommendations similar to items already defined in their profiles.

Examples of Content-Based Filtering Systems:

- News Dude is a personal news system that utilizes synthesized speech to read news stories to users.
- TF-IDF model is used to describe news stories in order to determine the short-term recommendations which is then compared with the Cosine Similarity Measure and finally supplied to a learning algorithm (NN).
- CiteSeer is an automatic citation indexing that uses various heuristics and machine learning algorithms to process documents.
- LIBRA is a content-based book recommendation system that uses information about book gathered from the Web.

VII. Collaborative Filtering

Collaborative filtering is a domain-independent prediction technique for content that cannot easily and adequately be described by metadata such as movies and music. Collaborative filtering technique works by building a database (user-item matrix) of preferences for items by users. It then matches users with relevant interest and preferences by calculating similarities between their profiles to make recommendations . Such users build a group called neighborhood. An user gets recommendations to those items that he has not rated before but that were already positively rated by users in his neighborhood. Recommendations that are produced by CF can be of either prediction or recommendation. Prediction is a numerical value, Rij, expressing the predicted score of item j for the user i, while Recommendation is a list of top N items that the user will like the most. The technique of collaborative filtering can be divided into two categories: memory-based and model-based.



7.1 Memory Based Techniques

The items that were already rated by the user before play a relevant role in searching for a neighbor that shares appreciation with him . Once a neighbor of a user is found, different algorithms can be used to combine the preferences of neighbors to generate recommendations. Due to the effectiveness of these techniques, they have achieved widespread success in real life applications. Memory-based CF can be achieved in two ways through user-based and item-based techniques. User based collaborative filtering technique calculates similarity between users by comparing their ratings on the same item, and it then computes the predicted rating for an item by the active user as a weighted average of the ratings of the item by users similar to the active user where weights are the similarities of these users with the target item. Item-based filtering techniques compute predictions using the similarity between items and not the similarity between users. It builds a model of item similarities by retrieving all items rated by an active user from the user-item matrix, it determines how similar the retrieved items are to the target item, then it selects the *k* most similar items and their corresponding similarities are also determined. Prediction is made by taking a weighted average of the active users rating on the similar items *k*. Several types of similarity measures are used to compute similarity between user.

7.2 Model-Based Techniques

This technique employs the previous ratings to learn a model in order to improve the performance of Collaborative filtering Technique. The model building process can be done using machine learning or data mining techniques. These techniques can quickly recommend a set of items for the fact that they use pre-computed model and they have proved to produce recommendation results that are similar to neighborhood-based recommender techniques. Examples of these techniques include Dimensionality Reduction technique such as Singular Value Decomposition (SVD), Matrix Completion Technique, Latent Semantic methods, and Regression and Clustering. Model-based techniques analyze the user-item matrix to identify relations between items; they use these relations to compare the list of top-N recommendations. Model based techniques resolve the sparsity problems associated with recommendation systems.

7.3 Pros and Cons of collaborative filtering techniques:

Collaborative Filtering has some major advantages over CBF in that it can perform in domains where there is not much content associated with items and where content is difficult for a computer system to analyze (such as opinions and ideal). Also, CF technique has the ability to provide serendipitous recommendations, which means that it can recommend items that are relevant to the user even without the content being in the user's profile . Despite the success of CF techniques, their widespread use has revealed some potential problems such as follows.

Examples of Collaborative Systems

- Ringo is a user-based CF system which makes recommendations of music albums and artists.
- GroupLens is a CF system that is based on client/server architecture; the system recommends Usenet news which is a high volume discussion list service on the Internet.
- Amazon.com is an example of e-commerce recommendation engine that uses scalable item-to-item collaborative filtering techniques to recommend online products for different users.

VIII. Hybrid Filtering

Hybrid filtering technique combines different recommendation techniques in order to gain better system optimization to avoid some limitations and problems of pure recommendation systems . The idea behind hybrid techniques is that a combination of algorithms will provide more accurate and effective recommendations than a single algorithm as the disadvantages of one algorithm can be overcome by another algorithm. Using multiple recommendation techniques can suppress the weaknesses of an individual technique in a combined model. The combination of approaches can be done in any of the following ways: separate implementation of algorithms and combining the result, utilizing some content-based filtering in collaborative approach, utilizing some collaborative filtering in content-based approach, creating a unified recommendation system that brings together both approaches.

IX. Conclusion

Recommender systems open new opportunities of retrieving personalized information on the Internet. It also helps to alleviate the problem of information overload which is a very common phenomenon with information retrieval systems and enables users to have access to products and services which are not readily available to users on the system. This paper discussed the two traditional recommendation techniques and highlighted their strengths and challenges with diverse kind of hybridization strategies used to improve their performances. Various learning algorithms used in generating recommendation models and evaluation metrics used in measuring the quality and performance of recommendation algorithms were discussed. This knowledge will empower researchers and serve as a road map to improve the state of the art recommendation techniques.

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