ADOPTION OF BOOKS RECOMMENDATIONS TECHNIQUES WHILE USING FILTERING METHOS FOR UPHOLDING ACADEMICS IN THE EDUCATIONAL INSTITUTIONS.

Pooja Sharma[1], Swati Kiran[2], Nidhi[3], Shashank Kumar[4]

[1,2,3,4] Mangalmay Institute of Engineering & Technology, Greater Noida

ABSTRACT

Book Recommendation using Collaborative Filtering is a kind of filtering system that predicts a user's rating of an item. It recommends books to users by filtering through a large database of information using a ranked list of predicted ratings of items. Online Book recommendation system is a recommender system for those who love books. When selecting a book to read, individuals read and rely on the book ratings and reviews that previous users have written. In this project, Collaborative Filtering techniques are used. We are using Collaborative techniques such as Clustering in which data points are grouped into clusters. Algorithms such as K-means clustering and Gaussian mixture are used for clustering. The better algorithm was selected with the help of silhouette score and used for clustering. Matrix Factorization technique such as Truncated- SVD which takes a sparse matrix as input is used for reducing the features of a dataset. Content-Based Filtering System used a TFIDF vectorizer which took statements as input and return a matrix of vectors. RMSE (Root Mean Square Error) is used for finding the deviation of an absolute value from an obtained value and that value is used for finding the fundamental accuracy.

INTRODUCTION

Nowadays, online ratings and reviews are playing an important role in book sales. Readers were buying books depending on the reviews and ratings by others. Book Recommendation focuses on the reviews and ratings by others and filters books. In this paper, a collaborative recommender system is used to boost our recommendations. The technique used by recommender systems is Collaborative filtering. This technique filters information by collecting data from other users. Collaborative filtering systems apply the similarity index-based technique. The ratings of those items by the users who have rated both items determine the similarity of the items. The similarity of users is determined by the similarity of the ratings given by the users to an item. Content-based filtering uses the description of the items and gives recommendations that are similar to the description of the items. With these two filtering systems, books are recommended not only based on the user's behavior but also the content of the books.

Recommender systems are information filtering systems that deal with the problem of information overload [1] by filtering vital information fragment out of large amount of dynamically generated information according to user's preferences, interest, or observed behavior about item [2]. Recommender system has the ability to predict whether a particular user would prefer an item or not based on the user's profile. Recommender systems are beneficial to both service providers and users [3]. They reduce transaction costs of finding and selecting items in an online shopping environment [4]. Recommendation systems have also proved to improve decision making process and quality [5]. In e-commerce setting, recommender systems enhance revenues, for the fact that they are effective means of selling more products [3]. In scientific libraries, recommender systems support users by allowing them to move beyond catalog searches. Therefore, the need to use efficient and accurate recommendation techniques within a system that will provide relevant and dependable recommendations for users cannot be over-emphasized.

Avi Rana and K. Deeba, et.al. (2019) [1] proposed a paper "Online Book Recommendation System using Collaborative Filtering (With Jaccard Similarity)". In this paper, the author used CF with Jaccard similarity to get more accurate recommendations because general CF difficulties are scalability, sparsity, and cold start. So to overcome these difficulties, they used CF with Jaccard Similarity. JS is based on pair of books index which is a ratio of common users who have rated both books divided by the sum of users who have rated books individually. Books with a high JS index are highly recommended.

To ensure we keep this website safe, please can you confirm you are a human by ticking the box below. Recommendation system is software that suggests similar items to a purchaser based on his/her earlier purchases or preferences. RS examines huge data of objects and compiles a list of those objects which would fulfil the requirements of the buyer. Nowadays most ecommerce companies are using recommendation system to lure buyers to purchase more by offering items that the buyer is likely to prefer. Book recommendation system is being used by Amazon, Barnes and Noble, Flipkart, Good reads, etc. To recommend books the customer would be tempted to buy as they are matched with his/her choices. The challenges they face are to filter, set a priority and give recommendations which are accurate. RS systems use Collaborative Filtering to generate lists of items similar to the buyer's preferences. Collaborative Filtering is based on the assumption that if a user has rated two books to a user who has read one of these books, the other book can be recommended (Collaboration).CF has difficulties in giving accurate recommendations due to problems of scalability, sparsity and cold start. This paper proposes a recommendation that uses Collaborative Filtering with Jaccard Similarity (JS) to give more accurate recommendations. JS is based on an index calculated for a pair of books. It is a ratio of common users divided by the sum of users who have rated the two books individually. Larger the number of common users higher will be the JS Index and better recommendations.

Recommendation systems are used in hundreds of different services - everywhere from online shopping to music to movies. Recommendation systems that implement a content-based (CB) approach recommend items to a user that is similar to the ones the user preferred in the past. Recommendation systems that implement Collaborative Filtering (CF) predict users' preferences by analyzing relationships between users and interdependencies among items; from these, they extrapolate new associations.

Hybrid approaches meld content-based and collaborative approaches, which have complementary strengths and weaknesses, producing stronger results. For this project, we used two datasets: Book crossing (BX) and Amazon Book Reviews (AB). The intention was to increase the number of ratings each book had The intersection of both datasets resulted in 36,493 books. That gave us a total of 321,310 users in the intersection. Our first task was to model the books in our datasets. We chose two different approaches to doing so, both of which produced one vector of real numbers per book. In order to do so, we manually went through a list of the most common stop words and phrases, setting aside those that functioned as modifiers for the word directly following them (i.e., "very" or "not") and those across which sentence sentiment tends to be negated. Those were the modifiers and sentence-level hinge words that we used in applying the traditional aspect sentiment analysis algorithm, [2] in conjunction with our collection of opinion words, to our text recommendation system that uses both user information and preferences. Assessment of predictive accuracy for the book recommendation system is a crucial aspect of evaluation.

Receiver operation characteristic (ROC) is widely used for evaluating the accuracy of the classifiers Forecasting is an essential part of every financial department, atmospheric science, and algorithms.ROC curve gives a visual technique to summarize the accuracy of the classifiers. It is widely used in statistical education and training. This research used clustering algorithms to increase the prediction capacity of the recommendation system.

The datasets were collected from the Goodreads-books repository of Kaggle.

About 900k ratings of 10k books were processed by using algorithms (k-means clustering and cosine function. Sensitivity, Specificity, Most organizations have their and were measured for the recommendation system when they sell products online. Almost all the websites are not developed of the buyer interest; the algorithms for the proposed model. The average sensitivity and average specificity were 49.76% and 56.74% respectively organizations' force add-on sells to buyers whereas the was 52.84%. These by recommending unnecessary and irrelevant products. A personalized recommendation system (PRS) helps individual users find exciting and useful products from a massive collection of items. A personalized recommendation system helps users find books, news, movies, music, online courses, and research articles. Most of the researcher results show that our proposed system can remove boring books from the recommendation list more efficiently. The ROC curve was plotted for sensitivity and specificity which shows that most of the datasets stay close to the diagonal ideal classifier. Prefers developed recommendation requires to the system. A vast recommendation system is a subclass of information filtering system that seeks to predict the "rating" or "preference" a user amount of real-time user data that is not realistic for most recommendation systems. Would give to an item. Collaborative approaches build a model from a we proposed a cosine distanced deal with the issue, we are beginning by asking users about categories (e.g. Suspense and thriller, romance etc.) and writers they are interested in. Based on these criterions, recommendations are being made. A parallel approach is followed where we find users with similar interests and a bigger and more accurate set of recommendation is returned based on the rating profile. To summarize the underlying approach, we are using hybrid model to provide personalized recommendations to individual user. This system is hybrid of content based as well as collaborative approach of recommender system. We are showing more accurate and Scalability of The Approach One vital and foremost issue of Recommender systems today is the scalability of algorithms with large real-world datasets. It is becoming challenging to deal with huge and dynamic data sets produced by item-users interactions such as preferences, ratings and reviews'. Sparse, Missing, Erroneous and Malicious Data: Generally, majority of the users do not rate most of the items and the ratings matrix becomes very sparse.The data sparsity problem arises that declines the chances of finding a set of users with similar ratings.This is the most eminent drawback of the CF technique.This concern can be alleviated by using some additional domain information.Our proposed system is more options that will increase the user experience and will raise the possibility of Hybrid to overcome designed issue and reduces buying books. Recommendation systems with strong algorithms are at the core of today's most successful online companies such as Amazon, Google, Netflix and Spotify. NETFLIX provides a subscription service model that offers personalized recommendations to help us find shows and movies of our interest.To do this, they have created a proprietary, complex recommendations system.Netflix uses the personalized method where movies are suggested to the users who are most likely to enjoy them based on a metric like major actors or genre.Machine learning is necessary for this method because it uses user data to make informed suggestions.This way Netflix methodology accounts for the diversity in its audiences and its very large catalogue. A new item can't be recommended initially when it is introduced to a content-based system with no ratings.The new-user problem is bit hard to handle because it is not possible to find similar users or to create a CB profile without previous preferences of a user dependency of rating-based system. It starts with general page where different books are shown to user based on their categories. User is been asked to fill certain information like their category preferences, liked authors, location and age for finding similar users. Based on this information, books are being recommended which in turn help to overcome problem.

User will see random recommendations and predictions using different algorithms like SVD, KNN, RBM and Hybrid recommendations based on the books they've rated recently. Factors like authors and book name can be searched and the result will return books using algorithm. In this step we need to perform content-based filtering of books according to user preferences. In the final recommendation, based on type of user, recommendations will differ like if user is new some interest-based result will be shown to user, if user don't like to rate interest and similar books of past ordered books www.irjet.net p-ISSN: 2395-0072 will be shown to user else rating-based hybrid recommendations will be shown to user. We have conducted a set of experiments to examine the effectiveness of our proposed recommender system in terms Recommender system is defined as a decision making strategy for users under complex information environments[6]. Also, recommender system was defined from the perspective of E-commerce as a tool that helps users search through records of knowledge which is related to users' interest and preference [7]. Recommender system was defined as a means of assisting and augmenting the social process of using recommendations of others to make choices when there is no sufficient personal knowledge or experience of the alternatives [8]. Recommender systems handle the problem of information overload that users normally encounter by providing them with personalized, exclusive content and service recommendations. Recently, various approaches for building recommendation systems have been developed, which can utilize either collaborative filtering, content-based filtering or hybrid filtering [9], [10], [11]. Collaborative filtering technique is the most mature and the most commonly implemented. Collaborative filtering recommends items by identifying other users with similar taste; it uses their opinion to recommend items to the active user. Collaborative recommender systems have been implemented in different application areas. GroupLens is a news-based architecture which employed collaborative methods in assisting users to locate articles from massive news database [12]. Ringo is an online social information filtering system that uses collaborative filtering to build users profile based on their ratings on music albums [10]. Amazon uses topic diversification algorithms to improve its recommendation [13]. The system uses collaborative filtering method to overcome scalability issue by generating a table of similar items offline through the use of item-to-item matrix. The system then recommends other products which are similar online according to the users' purchase history. On the other hand, content-based techniques match content resources to user characteristics. Content- based filtering techniques normally base their predictions on user's information, and they ignore contributions from other users as with the case of collaborative techniques [14], [15]. Fab relies heavily on the ratings of different users in order to create a training set and it is an example of content-based recommender system. Some other systems that use content-based filtering to help users find information on the Internet include Letizia [16]. The system makes use of a user interface that assists users in browsing the Internet; it is able to track the browsing pattern of a user to predict the pages that they may be interested in. Pazzani et al. [17] designed an intelligent agent that attempts to predict which web pages will interest a user by using naive Bayesian classifier. The agent allows a user to provide training instances by rating different pages as either hot or cold. Jennings and Higuchi [18] describe a neural network that models the interests of a user in a Usenet news environment.

Despite the success of these two filtering techniques, several limitations have been identified. Some of the problems associated with content-based filtering techniques are limited content analysis, overspecialization and sparsity of data [12]. Also, collaborative approaches exhibit cold-start, sparsity and scalability problems. These problems usually reduce the quality of recommendations. In order to mitigate some of the problems identified, Hybrid filtering, which combines two or more filtering techniques in different ways in order to increase the accuracy and performance of recommender systems has been proposed [19], [20]. These techniques combine two or more filtering approaches in order to harness their strengths while leveling out their corresponding weaknesses [21]. They can be classified based on their operations into weighted hybrid, mixed hybrid, switching hybrid, feature-combination hybrid, cascade hybrid, feature-augmented hybrid and meta-level hybrid [22]. Collaborative filtering and content-based filtering approaches are widely used today by implementing content-based and collaborative techniques differently and the results of their prediction later combined or adding the characteristics of content-based to collaborative filtering and vice versa. Finally, a general unified model which incorporates both content-based and collaborative filtering properties could be developed [12]. The problem of sparsity of data and cold-start was addressed by combining the ratings, features and demographic information about items in a cascade hybrid recommendation technique in [23].

In Ziegler et al. [24], a hybrid collaborative filtering approach was proposed to exploit bulk taxonomic information designed for exacting product classification to address the data sparsity problem of CF recommendations, based on the generation of profiles via inference of super-topic score and topic diversification. A hybrid recommendation technique is also proposed in Ghazantar and Pragel- Benett [23], and this uses the content-based profile of individual user to find similar users which are used to make predictions. In Sarwar et al. [25], collaborative filtering was combined with an information filtering agent. Here, the authors proposed a framework for integrating the content-based filtering agents and collaborative filtering. A hybrid recommender algorithm is employed by many applications as a result of new user problem of content-based filtering techniques and average user problem of collaborative filtering [26]. A simple and straightforward method for combining content-based and collaborative filtering was proposed by Cunningham et al. [27]. A music recommendation system which combined tagging information, play counts and social relations was proposed in Konstas et al. [28]. In order to determine the number of neighbors that can be automatically connected on a social platform.

Lee and Brusilovsky [29] embedded social information into collaborative filtering algorithm. A Bayesian mixed-effects model that integrates user ratings, user and item features in a single unified framework was proposed by Condiff et al. [30].

PHASES OF RECOMMENDATION PROCESS

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 [31]. 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.

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 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 [32].

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 [32] and there are no self-image issues or any need for maintaining an image for others [33].

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.

Learning phase

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

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. Fig. 1 highlights the recommendation phases.

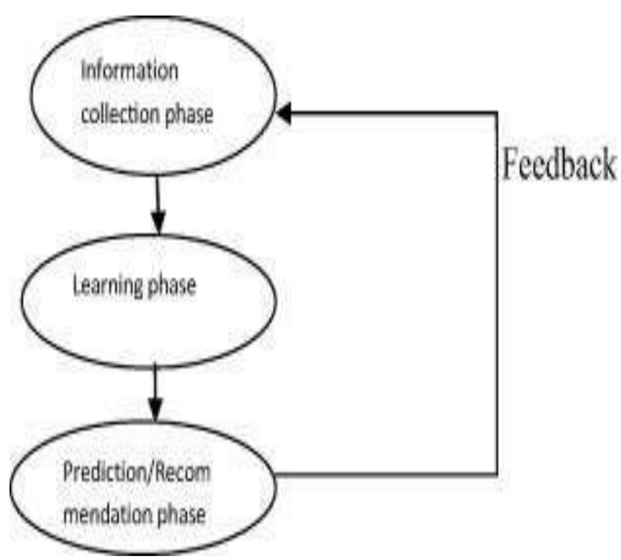

Figure 1. Recommendation phases.

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. Fig. 2 shows the anatomy of different recommendation filtering techniques.

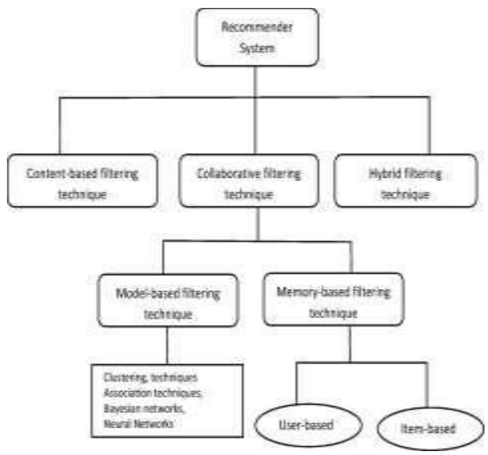

Fig 2. Recommendation techniques.

Content-based filtering

Content-based filtering is a type of recommendation system that makes recommendations to users based on their past interactions with content, as well as the characteristics of the content itself.

The system analyzes the content metadata, such as genre, author, director, actors, or keywords, and identifies patterns and similarities among items that have been interacted with by the user. This analysis helps the system to understand the user's preferences and to suggest similar content that they are likely to be interested in.

Content-based filtering is typically used for recommending products or services that are similar in characteristics to those the user has previously engaged with. For example, if a user has previously purchased action movies, the system might recommend similar movies that are also classified as action.

One of the advantages of content- based filtering is that it does not require information about other users or their preferences to generate recommendations, which makes it more privacy-friendly than other recommendation systems such as collaborative filtering. However, it may struggle to recommend items that are outside the user's previously defined interests or preferences.

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 past [34], [35]. 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 [36], Decision Trees [37] or Neural Networks [38] 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.

4.1.1. 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 [39]. 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 [12]. 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 [40] 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 [41] 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). Cite Seer is an automatic citation indexing that uses various heuristics and machine learning algorithms to process documents. Today, CiteSeer is among the largest and widely used research paper repository on the web. LIBRA [42] is a content-based book recommendation system that uses information about book gathered from the Web. It implements a Naïve Bayes classifier on the information extracted from the web to learn a user profile to produce a ranked list of titles based on training examples supplied by an individual user. The system is able to provide explanation on any recommendations made to users by listing the features that contribute to the highest ratings and hence allowing the users to have total confidence on the recommendations provided to users by the system.

Collaborative filtering

Collaborative-based filtering recommender systems try to search for look-alike customers an offer products based on what his or her look alike has chosen.

Let us understand with an example. X and Y are two similar users and X user has watched A, B, and Cmovies. If the Y user has watched B, C, and D movies then we will recommend A movie to the Y user and D movie to the X user.

YouTube has shifted its recommendation system from a content-based to a Collaborative based filtering technique. If you have experienced sometimes there are also videos that are not at all related to your history but then also it recommends it because the other person similar to you has watched it.

In Collaborative Filtering, we tend to find similar users and recommend what similar users like. In this type of recommendation system, we don't use the features of the item to recommend it, rather we classify the users into clusters of similar types and recommend each user according to the preference of its cluster.

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 [43]. 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 as shown in Fig. 3. The technique of collaborative filtering can be divided into two categories: memory-based and model-based [35], [44].

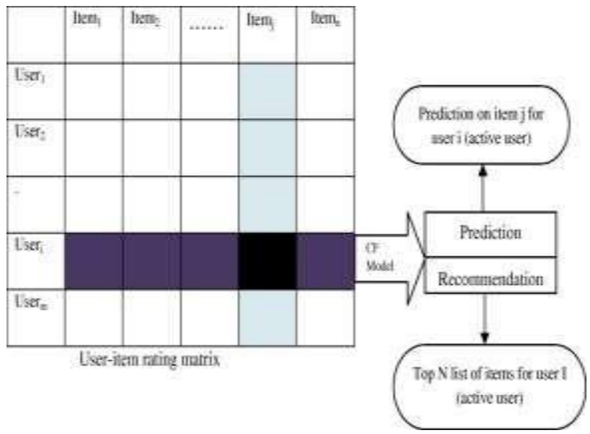

Figure 3. Collaborative filtering process.

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 [45], [46]. 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 item/user. The two most popular similarity measures are correlation- based and cosine-based. Pearson correlation coefficient is used to measure the extent to which two variables linearly relate with each other and is defined as [47], [48] Cosine similarity is different from Pearson- based measure in that it is a vector-space model which is based on linear algebra rather that statistical approach. It measures the similarity between two n-dimensional vectors based on the angle between them. Cosine-based measure is widely used in the fields of information retrieval and texts mining to compare two text documents, in this case, documents are represented as vectors of terms. The similarity between two items u and v can be defined as [12], [43], [48]

Similarity measure is also referred to as similarity metric, and they are methods used to calculate the scores that express how similar users or items are to each other. These scores can then be used as the foundation of user- or item-based recommendation generation. Depending on the context of use, similarity metrics can also be referred to as correlation metrics or distance metrics [12].

Model-based techniques

Memory-based techniques refer to a class of recommendation algorithms that rely on the user's past interactions with items to generate recommendations. These techniques are generally simple and straightforward to implement, and they don't require complex calculations or models.

One of the most common memory-based techniques is the user-based collaborative filtering algorithm. This algorithm generates recommendations based on the ratings of similar users. For example, if user A has rated several items highly, the algorithm will identify other users who have rated those items highly as well. The algorithm will then recommend items that these similar users have rated highly but that user A has not yet interacted with.

Another memory-based technique is item- based collaborative filtering. This algorithm generates recommendations based on the similarity between items. For example, if user A has interacted with several items, the algorithm will identify other items that are similar to those items based on their characteristics. The algorithm will then recommend these similar items to user A. Memory-based techniques have some advantages over other recommendation techniques. They are simple and easy to implement, and they can be effective in situations where there is limited data or where the data is highly sparse. However, these techniques also have some limitations, such as the inability to handle large datasets or the inability to capture long-term user preferences.

RESULT

In this project, we have recommended the books for a user using the model trained using K-Means Clustering which is a Collaborative Filtering Technique. We have also compared different models built using different methods and identified the best model and justifies why it has chosen that model. This paper proposes a book recommendation algorithm based on collaborative filtering and interest. Collaborative filtering uses cosine similarity for analysis, and the interest degree uses the basic attributes of the book as a measurement index. The goal of the next step is to optimize the collaborative filtering algorithm and at the same time to optimize the measurement indicators, so as to have better convergence results. The System has adequate scope for modification in future if it is necessary.

Development and launching of Mobile app and refining existing services and adding more service, System security, data security and reliability are the main features which can be done in future. The API for the shopping and payment gateway can be added so that we can also buy a book at the moment. In the existing system there are only some selected categories, so as an extension to the site we can add more categories as compared to existing site.

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.

REFERENCES

1. J.A. Konstan, J. Riedl Recommender systems: from algorithms to user experience User Model User-Adapt Interact, 22 (2012), pp. 101-123

2. C. Pan, W. Li Research paper recommendation with topic analysis In Computer Design and Applications IEEE, 4 (2010) pp. V4-264
3. Pu P, Chen L, Hu R. A user-centric evaluation framework for recommender systems. In: Proceedings of the fifth ACM conference on Recommender Systems (RecSys'11), ACM, New York, NY, USA; 2011. p. 57–164.
4. Hu R, Pu P. Potential acceptance issues of personality-ASED recommender systems. In: Proceedings of ACM conference on recommender systems (RecSys'09), New York City, NY, USA; October 2009. p. 22–5.
5. B. Pathak, R. Garfinkel, R. Gopal, R. Venkatesan, F. Yin Empirical analysis of the impact of recommender systems on sales J Manage Inform Syst, 27 (2) (2010), pp. 159-188.
6. Rashid AM, Albert I, Cosley D, Lam SK, McNee SM, Konstan JA et al. Getting to know you: learning new user preferences in recommender systems. In: Proceedings of the international conference on intelligent user interfaces; 2002. p. 127–34.
7. Schafer JB, Konstan J, Riedl J. Recommender system in e-commerce. In: Proceedings of the 1st ACM conference on electronic commerce; 1999. p. 158–66.
8. P. Resnick, H.R. Varian Recommender system's Commun ACM, 40 (3) (1997), pp. 56-58, 10.1145/245108.24512.
9. A.M. Acilar, A. Arslan A collaborative filtering method based on Artificial Immune Network Exp Syst Appl, 36 (4) (2009), pp. 8324-8332.
10. L.S. Chen, F.H. Hsu, M.C. Chen, Y. Hsu Developing recommender systems with the consideration of product profitability for sellers, Int J Inform Sci, 178 (4) (2008), pp. 1032-1048