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Recommendation System: A Systematic Overview on Methods, Issues and Solutions

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ABSTRACT

As the technology evolves, the Recommendation System (RS) is becoming a trending topic and widely applied in many fields such as e-commerce sites, health care, stock market, movie,song recommendation. This paper entirely focuses on various methodologies which is helpful to build a recommendation and also the challenges when developing a recommender system. In an e-business site when the user selects any product, then the recommendation will be provided by considering the relationships of user-user, user-item, item-item. In this paper, various methodologies adopted in the existing works are reviewed and summarized with its merits and detriments.Also, it will support the researchers and developers of the recommender system by providing a systematic review of the state-of-the-art recommender systems.

This paper gives a survey about the recommendation system, phases of recommendation, filtering techniques, challenges, and some of the research paper which could solve those challenges.

Keywords: Collaborative,Cold-Start Problem, Content-Based, Hybrid, Item-Item, Product recommender system, Recommender system,User-Item,etc.

1.INTRODUCTION

In today's technology, the web is playing a vital role in doing business transactions which in turn leads to the development of the recommender system. The Recommender System (RS) is coined to be a trending area in the research field. RS is introduced in the year of mid-1990s to choose a product(s) from the large set of available choices. When the number of choices is more, people may get confused with the product they are about to choose. For that, the best answer can be provided with the help of the recommender system. RS can be applied in any field like suggesting a movie, book, product, person. The major advantage behind implementing a recommender system is, it helps to reduce the searching time and surprise the users by showing relevant items where the user can look ahead for purchase which leads to an increase in the average purchase value of e-commerce site.

The Abundant amount of information is updating on the web day by day hence it is very tough for the people to look for and select the desired items. The recommendation can be offered bychecking the shopping cart of the customer, by analyzing the user-item interactions in terms of providing a questionnaire, and by predicting the ratings of the item from the user's perspective. So, the recommendation system can be expressed in terms of a web application which tries to predict user preferences. It identifies the data pattern by analyzing the dataset and learn the choices of the customer(s) and produces the results which could co-relate to the user's interest.

1.1 Phases of Recommendation System

Figure 1 illustrates the phases of the recommendation system which comprises three phases. As it is a cyclic procedure user's feedback will be collected by seeing the recommended items and it is again fed to phase 1 to improvise the accuracy in providing the recommendation.

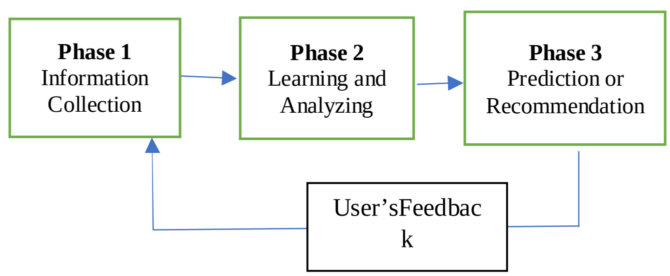

Figure 1: Phases of Recommendation system

1.2 Motivation of this Survey

The online shopping websites are growing rapidly and the popularity has reached its peak. As people are busy and bored with retail shopping, e-commerce sites are earning their profit in huge, compared to the retail shops. Though the business is increasing, on the other hand, it creates confusion for the user to purchase the desired product as the site is flooded with plenty of choices. Hence the recommendation system came into existence and it recommends the product to the user by considering the similar likings of the product and by analyzing the historical information of the users. Although all the e-commerce platform such as Amazon, Flipkart has implemented the recommender system, still it could be optimized with more conventional methods. Recently Machine Learning models, Deep-Learning algorithms have started its dominance in the field of optimizing the recommender systems. If the recommender system is optimized it should satisfy the customers which will, in turn, increase the sales of the e-business site. Hence herewith mentioned the working principle and various methods of implementing the recommender system which will be useful in recent trends while providing the suggestions to the user.

1.3 Working Principle of Recommender System

User-item Interactions – Retrieves information about users (analyzing the preference and profile of the user) and item (keyword, category)

Characteristic information - Retrieves information about product (rating of the particular product, no of purchases, likes given for the chosen product)

1.4 Various methods of implementing RS

Figure 2 depicts the illustration of various methods of implementing the Recommender System. The major implementation techniques of the recommender system are Collaborative, Content-Based.In addition to the Collaborative and Content-Based, the Hybrid technique is the one that combines any two filtering mechanisms. The classification extends to Demography, Community, and Knowledge-based technique which is discussed briefly.

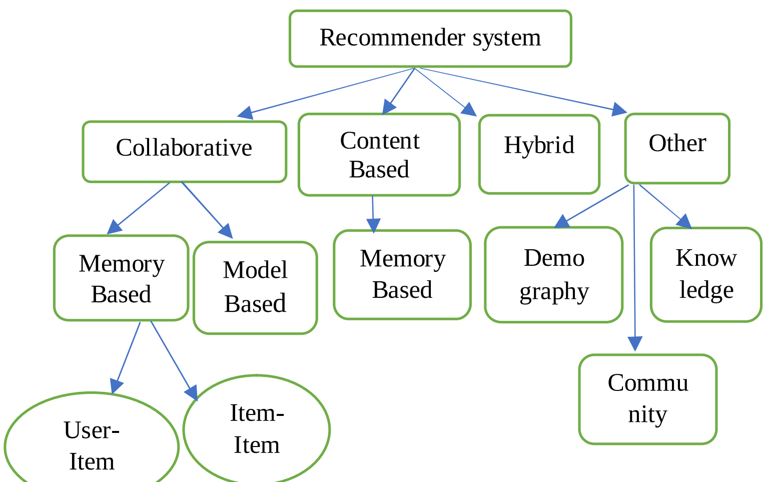

Figure 2: Methods of implementing the Recommender System.

1.4.1 Collaborative Filtering

The collaborative Filtering (CF) model works by analyzing the historical interactions of the users concerning the particular items which in turn produce new recommendations. It can be represented in terms of interaction matrix which composes of m×n where m represents the row of items and n represents the column of users. This collaborative model is further decomposed of memory-based and model-based.

Memory-based - Deals with the history of recorded value, basically follows K-Nearest Neighbor Search otherwise known as heuristic-based collaborative filtering which is further divided into Item –Item CF, User-Item CF.

Item –Item CF - It can be simply explained with the well-known phrase as in the online shopping site, 'Customers who bought this also bought'. For example, if a user, Bob likes item A also likes item B.

User – Item CF - It can be simply elaborated as Bob likes item 'A' and the users who are similar to Bob also like the same item 'A'.

Model-based – It provides recommendations by developing a model of user ratings. Algorithms under model-based CF are Bayesian Network and clustering which employs a probabilistic approach and uses the CF method to compute the value of user prediction by considering his/her ratings on other items.

1.4.2 Content-Based Filtering

In CBF, the prediction is offered by analyzing the user and item profile. It mainly focuses on maintaining the records of items in which any user is interested in recent times.Also, by observing the past activities of the user, the recommendations will be given.

1.4.3 Hybrid Filtering

As the name implies itisclear to know that the recommendation will be provided by combining one or two techniques. It is an efficient one as it combines different recommender systems. Figure 3 depicts the idea of hybrid filtering by combining CF and CBF.

In addition to the major techniques, the demographic filtering deals with collecting the age, gender, geographic location which is difficult to apply for real-world datasets. The CF and CBF require the history of user ratings whereas it is not required for demographic filtering. Based on the demographic data the recommender system observes the common attributes of age, gender, profession, marital status, location [22], and the recommendation will be provided to similar users. The community-based filtering recommends the data based on the community that collects and shares a common interest, whereas knowledge-based filtering is considered to be the intelligent one that provides the recommendation by analyzing the needs of the user.

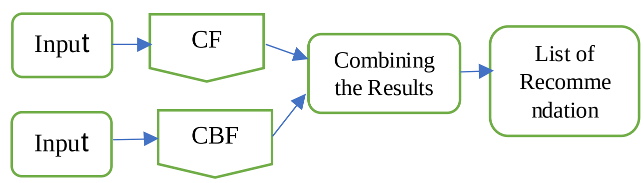

Figure 3: Illustration of Hybrid Filtering combining CF and CBF

1.5Challenges in Recommendation System

1.5.1 Scalability

The term 'scalability' refers to the support of a larger dataset. Many recommendation algorithms are available to produce accurate results with a small data set. While considering real-world sites like Amazon, Flipkart, and YouTube the dataset may be high and some available algorithms may fail to produce accurate results when it comes to the picture of larger data items.

1.5.2 Sparsity

Another challenge in the recommendation system is ‘sparsity’ which occurs when the product rate is missing. In some cases, most of the users will rate only certain items, so the remaining items may exist without any rating. It will become difficult when the user tries to construct the matrix based on the available rating. The solution can be obtained through CF incorporating the Naive Bayes approach [17].

1.5.3 Freshness

This problem arises when the user is already familiar with the product that the system is recommending. The system will consider the items based on its popularity hencethe possibility exists that the user might be aware of the items already.

1.5.4 Cold-Start Problem

When dealing with the recommendation system the important challenge is the cold-start problem which falls into two categories product and user cold –start. As the recommendation system works by analyzing the profiles of users and items, if the user or item is new to the system, then the system may feel difficult to retrieve the details of the user and the item which is referred to as the Cold-start problem. So, the solution can be provided by incorporating popularity-based item retrieval.

1.5.5 Privacy

It occurs with demographic filtering since the system will get all the primary information of the user to come with an accurate recommendation. But the user may not be interested in giving all such necessary details hence the user privacy will get compromised.

1.5.6 Shilling Attacks

The recommendation system could work based on the ratings given to the product. When a malicious user or a competitor enters the recommender system and given false ratings to the unwanted product the system may recommend the products to the user in which he/she may not be interested which results in poor performance and the quality of the recommendation engine will be degraded.

1.5.7 Shared Profile

One of the serious issues to be considered is ‘shared profile’. The recommendation engine will analyze the user profile and based on retrieved information the products will be recommended. But if there exists a scenario that the same profile is shared between the husband and wife having entirely different interests then the recommendation system will fail to prove its accuracy.

1.6 Applications of Recommender System

- E-Commerce sites (Flipkart, Amazon)
- Movie Recommendation (Amazon Prime, Netflix)
- News Article (Google News)
- Music and Video Related sites (Pandora, YouTube)
- Health Care
- Customer Relationship Management
- Tourism

1.7 Product Recommender System

It is a designed tool that intends to create and provide suggestions for the items to all the users by analyzing their profile. There are three basic types of connections the product recommender system creates. A relationship can be established between user-product, user-user, and product-product.

1. User-Product – It works based on predicting the user's individual product preferences.

2. User-User – The principle is based on similar people (profile matching) and preferences over a similar kind of product.

3. Product-Product – It is based on a similar group of products (e.g. bread and butter) that can be categorized into relevant groups.

The Product recommendation is a system that compares and consider the connections between the user and item, then it recommends the products or content accordingly.

1.8 Contribution of the paper

The main objective of this survey are as follows,

- Working Principle and description of various filtering techniques along with its classification
- An assessment of recent issues and challenges in the recommender system by correlating the related works and future trends of the recommender system.
- Literature study describes the methodologies adopted in recent times and the challenges identified for all the referred work.
- The performance evaluation of prior works along with the metrics.

1.9 Organization of the paper

This paper is organized as follows. Section II deals with the Related Works where the constraints, issues, and variety of techniques applied for recommending the products are explained elaborately and Section III narrates the summary of related works, followed by the conclusion.

2. RELATED WORKS

In the e-commerce site, if any new item is launched, it may suffer from the cold-start problem since there is a lack of user interactions with the particular item. Table 1 depicts the recommendation aspects of user and item and the reason for the cold-start problem. Due to the increased blurring between the boundaries of e-business sites and social networking sites almost all the sites support ‘social login’, where the users can have an account on social networking sites such as Facebook, Twitter, and Instagram. Each user may post the details of the recently purchased product in their social networking blog and the data can be taken from their blog. Hence the solution for the cold start problem is proposed by Zhao, Wayne et.al [22] by linking the users across the social networking sites with e-business sites. The demographic attributes such as age, gender, education, profession, marital status, and user interest are extracted from the social network profile. The implementation of Microblogging provides a solution to the cold start problem without considering the historical purchase of users. The extracted user features are integrated into feature-based matrix factorization which is taken as a step towards the cold-start product recommendation.

To know the embeddings with the product, a few existing methodologies applied the Word2Vec method to extract the context information. In Word2Vec, each product ID is categorized into token and the purchase history of users is converted into a sequence of timestamps. Instead of applying the Word2vec, the paragraph vector (Para2vec) method is applied in the mentioned work of Zhao and Wayne [22] as suggested by Le, Quoc[12], and it can be applied to the variable length of texts. To train the product embedding, the Continuous Bag-Of-Words model (CBOW) and the Skip-gram model are used. The major difference between the CBOW and the skip-gram model is the direction of prediction. The CBOW model considers the surrounding context i.e. the purchase pattern of users, to do the prediction, whereas the skip-gram model prediction is based on the current product.

Another way of solution is also proposed for the cold-start problem by implementing the conversational recommender system which is introduced by Z.K.A.Baizal et.al [24].The conversational recommender system (CRS) is developedas a recommender system that aims at the continuous interaction between the user and the system. And the interaction is developed by repeatedly providing the sample products or questions to the user

Table 1: Recommendation Aspects of Users Vs Items

Recommendation Aspect	**Existing Users**	**New Users**
Existing Items	The recommendation can be provided by applying the existing filtering techniques such as collaborative, content-based, and Hybrid.	The recommendation is based on popularity-based item retrieval.
New Items	The recommendation is based on analyzing the user profile and historical interactions with the item.	Results in **Cold-Start**

In the initial stage of interaction, the recommendation system provides some choices of requirements to the user, where the user has to select the options, in the division of required, not required, and optional.In general, the users will not like a random interaction, hence the refinement of the query model as proposed by Z.K.A.Baizal et.al [25] will assure the efficient interaction with the user.The above-mentioned framework encompasses the ontology structure and the interaction scheme is based on the functional requirements of the product. The basic idea behind the work is query refinement in CRS which covers under the ontology structure.

Meng-Yen Hsieh et.al provided another method of solution for the cold start problem by exploring the web scraping [15] technique. Keyword Aware Recommender System will eliminate the cold start phase by introducing the technique of WEB crawling. To provide a solution through the web- crawling technique, the phase of work is divided into three parts: Mobile Client, Server, and Extra Data Part. In the first phase of Mobile Client, the user's smartphones are taken, since the mobile client can capture and translate the user's behavior information into semi-structured or structured formats.

Two connections are established with the server, where the first phase is established to deliver information and the role of another one is to query data items from the server. To complete the translation process, APPs installed in the smartphone are considered to be a user preference. When analyzing the server part, the task is to perform the rating prediction for cold-start users. It can be built by the four-stage process involves, Acquiring Data, Extracting Keywords, Checking the similarity of Keyword and the final stage is Estimating the Rating. The final module, 'Extra Data Part' gets extra-textual information from the user related to the behavior and then the items will be recommended. The motto of gathering textual data is to expand keyword spaces where the technique of WEB crawling is applied.

Though the recommender system is familiar in recommending the products in e-business sites it's not restricted to e-commerce alone whereas it could be applied to the e-learning system. A learning system accompanied by electronic resources is considered to be the E-leaning system. The use of computers and the internet plays a major role in E-learning. The recommendation based on E-learning is proposed by D.Wu et.al [2]. To enhance the e-learning system and to gain recommendation, a fuzzy tree-structured learning activity model and a learner profile model is considered for gathering the activities and profile of learners. A fuzzy tree matching-based hybrid learning activity recommendation approach is introduced that will take advantage of both the knowledge-based, collaborative filtering-based recommendation approaches, and considers both the semantic and CF similarities between learners. In addition to the existing filtering techniques,some advanced recommender techniques like social network-based recommender systems, fuzzy recommender systems, context-aware-based recommender systems, group,and mobile recommender systems can be followed to provide suggestions.

Initially, the RS works by analyzing the particular user and tries to find another like-minded user who is having a similarity in ratings, gender, age, location, and the recommendation will be provided based on user similarities. The second technique item-based filtering recommends the items by considering a single item and find similar users who are all interested in a particular item, which is based on item similarities. With the extension of the above method, a neural network can be employed in the name of Neural Attentive Item Similarity (NAIS), which is applied as a technique for item-based collaborative filtering as proposed by Xiangnan He et.al[18]. NAIS is an attention network that can distinguish the historical items in the user profile, which marks a large space in predicting the item. And this work is considered to be the first neural network model in item-based filtering.

In the existing methodologies, the system worksbased on the Factored Item Similarity Model (FISM) [11] where the items are represented in terms of vector and present the similarity between two items. It provides accurate recommendations and it is suited for the online recommendation engines. To refresh the recommendation for new interaction, the embedding vector has to be updated. The NAIS model is constructed upon FISM, maintaining the same features with FISM. This category is a bit expensive one such that it has to learn the importance of interacted items. But it is possible with advanced neural representation learning.

To deal with the recommender systems, personalization of content plays an important role where the basic principle behind is predicting the personalized ratingof users for the items newly arrived. The rating can be predicted by learning semantic meaning from textual content and by analyzing the historical information of users to improve rating prediction. The work is based onasymmetrically modeling the users and items and the proposed framework is named SEMA by J. Zhang and C. Chow which follows the expansion of Semantic mEanings and teMporaldynAmics [10]. It mainly targets three characteristics namely deep learning-based, hierarchical, and symmetrical. The architecture of the SEMA has four components namely semantic learning, temporal dynamic learning followed by rating prediction, and parameter training.

The experiences about the user product will be known by the RS by analyzing the reviews and comments given by the user for any product. In general, the recommendation will be done by extracting the meaning from the text by using word2vec and by using the bag-of-words method. Instead of applying the above methods, the proposed work employed a neural network in the form of RNN, which is highly engaged in the domain of natural language processing (NLP). In the RNN, to learn the meanings from the text, each word is mapped into the embedding vector. To model the long sequences, Long Short-Term Memory (LSTM) is employed.

All the above-mentioned work supports the recommendation by considering the individual users, but the recommendation can be enhanced to the group of people known as, Group Recommender System (GRS) [7]. In practice, users are carrying out their daily routines such as watching TV, dining out for dinner with some group of people. Hence, the recommender system must consider suggestions for a group of people which is called Group Recommender System (GRS). But the group members will not share a common preference hence to provide recommendations for all the members in a group, it will be a challenging one. Figure 4 portrays the process of GRS.

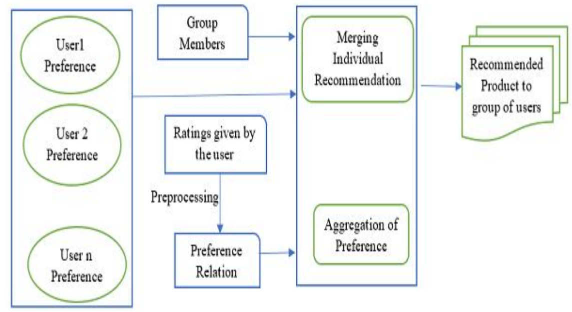

Figure 4: Process of Group Recommendation System

Existing methodologies establish the GRS based on the feedback, ratings given for the items, but the preference assessment is not taken into account.When the recommendation is designed for a group of users, the individual user's profiles are collected and analyzed, to model the group profile. The work suggested by Z. Guo, W. Zeng, et.al [21] established a preference relation instead of considering the absolute one. To predict unknown preferences in candidate items, a multi-variate extreme learning machine model is introduced, and to generate recommendations to the group of users, Borda voting rule is employed based on predicted results. In general, the users will always communicate their preference based on providing a rating to any item and the higher rating denote that the user highly prefers the item. Preference relation between any item (i,j) will be denoted in terms of xi,xj. If the value of i>j then it can be concluded that the user k, prefers the item i, compared to j and vice versa.

The process of multivariate extreme learning is explained below to work with unknown preferences. It consists of four stages, as in a neural network it has an input layer, a primary and secondary hidden layer, and an output layer. Feature vectors obtained from items are fed to the input layer and it will be transformed into N-dimensional feature space in the primary hidden layer. The secondary hidden layer combines the set of hidden nodes and merges them into one. Finally, the preference relation will be obtained in the output layer. Later by employing the Borda voting rule [21], it combines the preference feedback of individual users into group profiles to produce recommendation results.

The motto ofthe recommender system is improved customer satisfaction. If the customer purchases any product and finds the product is satisfied, then the user may write a review of the particular product. Hence Dau et.al [1] proposed a novel method of providing recommendations by analyzing the reviews and comments given by the customer. The adopted work focuses on a sentiment-aware deep recommender system along with the neural network which will analyze the user sentiments incorporated with every product which will further improve the performance of the recommender system.The Long Short Text Memory (LSTM)works iteratively and it will better learn the sematic information of words. To extract the sentiment associated with the reviews semi-supervised topic modelling is incorporated. This modelling will classify sentiments based on positive and negative reviews.

In addition to all the above service-based recommendations can be provided by considering the service-based systems (SBS) which is proposed by Xie, Fang et al [19]. In the adopted work [19], a new service-based recommendation is proposed where the Heterogeneous Information Network (HIN) is framed which comprises SBS, Services, and composition relations. To learn the word vectors from the SBS and Services, a word embedding technique is applied. Further, the combinational weights of different similarities are enhanced using the Bayesian algorithm. Finally, the service-based recommendation will be provided to the users by applying the Collaborative Filtering technique.

All the traditional recommendation algorithms perform well in providing good quality recommendations. But in reality, the interest of users varies over time. Hence the algorithms should provide accurate results over time. To overcome this limitation, Z. Cui et.al[20] proposed a method called time correlation coefficient with improved K-means along with cuckoo search (CSK-means), called TCCF. The implementation of the clustering algorithm clusters similar users further the enhancement of TCCF is done based on the user's preference pattern which will analyze the user behavior and results in a good quality recommendation.

The previous methods described above, concentrates on text-based search and recommendation, whereas the suggestion can also be obtained through content-based image retrieval technique (CBIR). As online shopping platforms are growing tremendously in this era and the purchase of the products on e-commerce sites is getting increased day by day. To increase the revenue and to comfort the users F.Ullah and B.Zhang[3] proposed a novel idea of an image-based search approach. Usually, the search will be carried out based on the keywords and the meaningful keywords will be extracted by applying the frequency match algorithm.In contrast this work [3] entirely relies on the idea of image-based search approach.

To classify the products, Random Forest (RF) classifier is used, and to extract the features JPEG coefficients are used. A Random Forest is a known supervised learning classifier composed of a bunch of decision trees bundled together and it could be popularly applied to data science. It does not require feature scaling, categorical feature encoding, and requires a little amount of parameter tuning. The accuracy of random forest classifiers depends on the number of trees in the forest, if higher the number of trees then the accuracy is the improved one.

The images are taken from the Amazon image dataset. Random Forest classifier under the ML model is applied to determine the category of the product. Feature extraction on images is done based on the JPEG coefficients which are converted into a feature vector. Random forest classifier learns the feature distribution for various categories of objects. To enhance the results further, the RF model is enhanced further with DL algorithms which yield up to 85% accuracy of results. To find similar images, the similarity matching will take place by extracting and comparing the feature vectors of query and category images. To accomplish this task, Euclidean distance calculation is employed between the vectors of category images and query images. Obtained values are sorted in ascending order where the top 20 are selected as the possible items for recommendation.

However, if there are any perturbation in the image, there is a possibility of decreased recommendation accuracy. But Jinhui Tang [8] proposed a solution for this issue by implementing the Adversarial Multimedia Recommendation (AMR), based on the Adversarial Learning. The basic idea behind the approach is the construction of an adversary in the target image and to train the model to work well under the affect of the adversary.

3. SUMMARY OF RELATED WORKS

The above-explained related works are summarized in a tablewhere table 2 specifies the experimental data, Recommendation Service provided, and table 3 includes the adopted techniques, purpose of the existing work, possible enhancements. Section 3.1 narrates the challenges identified from the existing work.

Table 2: Summarization of the analyzed papers

S.no	Author	Recommendation Service	Interactions Based on	Experimental Data
1.	Dau, Aminu (2019)	Sentiment Aware Deep Recommendation	User -Item	Amazon Review Datasets
2.	D.Wu, J.Lu (2015)	Knowledge-based recommendation	Learner Profile Model	Movie Lens
3.	F.Ullah and B.Zhang (2020)	Image-Based Product Recommendation	Item	Amazon Image Dataset
4.	Gulzar, Leema (2018)	Personalized Course Recommendation	User	Professor and Student Information Dataset
5.	JianWang, Yi Zhang (2013)	On_time Product Recommendation	User-Item-TimeStamp	E-commerce data from Shop.com
6.	Lin, Jovian (2013)	Cold Start App Recommendation	Web Crawling based on Mobile APP and Twitter Data	Apple's iTunes App Store and Twitter
7.	McAuley, Julian (2015)	Accessory Recommendation	User-Item	Amazon Webstore
8.	Xiangnan He, Zhankui He (2018)	Movie Recommendation	Item	Amazon and Yelp
9.	Zhao, Wayne (2015)	Cross-site cold-start product recommendation	User -Item	Weibo and JingDong
10.	Z.K.A. Baizalet. al (2016)	Product Recommendation	User	HD online game

Table 3: Techniques Applied in the analyzed papers

Ref. ID	Techniques Applied	Purpose	Possible Enhancements	Evaluation Metric
[1]	LSTM Encoder and Semi-Supervised topic modeling	It helps to know about the user and his/her sentiment towards any product to improve the efficiency of the recommender system.	The scope of enhancement can be done by considering implicit and explicit feedback.	Mean Square Error (MSE)
[3]	Random Forest Classifier (RF) and JPEG Co-efficient.	Introduced a novel approach for image-based search in an online shopping site and provides a solution for computer vision problems.	It can be further enhanced by merging nonimage transformation with images.	Precision Recall and F1-Score
[7]	Group Recommender system based on Pre-GROD and GROD.	Designed to Provide recommendations for the group of people by considering the social aspects of the individual user.	Other opinion models can also be explored concerning the evolution of user opinions.	Mean Absolute Error (MAE), Root Mean Squared Error (RMSE)
[15]	Web Scraping and Keyword Extraction	It deals with the big challenge of the 'cold-start problem' in the recommender system.	Advancement in Recommendation service can be extended by incorporating various user domains such as mobile and IoT devices.	MAE and RMSE
[18]	Neural Attentive Item Similarity Model in replacement to FISM.	Identifies the most important item from the user's history to recommend products.	Exploration can be done by considering the personalized ranking on item-based collaborative filtering to improve the performance of the Recommender System.	Hit Ratio (HR) and Normalized Discounted Cumulative Gain (NDCG)

3.1 Identified Challenges

The major challenge of the recommender system is the Cold-start problem. As proposed by Meng-Yen Hsieh [15] Web crawling can be used to eliminate the cold start issue. But the challenge to be noted is, it may take extra time to become familiar with the core application and the scraping language needs to be adjusted. If the website developer intends to introduce some changes, then the web scraping process may not work. Zhao, Wayne [22] explains, the cold start problem can be eliminated by linking user-profiles taken from the social network site and e-commerce site there by the recommendation can be provided. But if the user does not have any profiles on the social network then the system may find it difficult to recommend the product. J. Zhang and C. Chow [10] describes the method to learn the semantic meaning from textual content and to analyze the historical information where the Semantic Meanings and Temporal Dynamics is carried out which will identify the preference of users on items by analyzing the historical information, but the user interest is not the static one. The user history will get varied based on user moods and needs.

The performance of the recommendation can be enhanced by considering the interaction of the user and the system. Z.K.A. Baizal [25] explains the interaction between the user and the system is done based on refining the query. The user has to select options like mandatory, optional, not required. If the preference is too general then the refinement has to be done by posing more questions. Hence the process will be repeated until the exact ontology structure is created based on the choice of the user, which will be a bit time-consuming process. As mentioned by D.Wu et.al [2] If the recommendation is considered under the fuzzy methodfor more accuracy, more rules need to be incorporated in fuzzy, which will further increase the time exponentially. And the exact solution depends on the direction of the decision.

If the recommendation is based on a group of people then it is denoted as a Group Recommender System (GRS) In the previous work as mentioned by Jorge Castro et.al [7] the recommendation for the group of the audience is provided by considering the social aspects of individual behavior but the system is not implemented based on real online users, hence the results might get vary as there is a probability of attitude change for the users based on their shopping moods. To recommend the product based on the sentiments associated with the item, the Sentiment Aware Deep Recommender system is introduced [1]. This methodology consists of LSTM comprised of four layers that always interact with one another to produce output. Hence the LSTM will always require high memory bandwidth as it has the presence of a linear layer in each cell. So, if the performance is explained in terms of hardware, LSTM becomes quite inefficient.

4. DISCUSSION

Implementation of the recommender system will always create an exciting user experience even though the focus is on increasing the revenue and sales of e-business sites. RS has become the most versatile part of E-commerce engines. Initially, this survey describes the phases and applications of the recommender system and it is further extended to challenges of the recommender systems. Section I describes the filtering techniques like collaborative filtering and content-based filtering approaches. In simple words, the former recommends the product based on the similarity measure between the users and by analyzing the historical information of the users where the latter recommends the product based on the content of the user (user profile preferences) and the items (description of the items such as size, color).

Section II describes various methodologies adopted in recent years to enhance the performance of the recommender system. In addition to that, techniques to eliminate the cold start problem,one of the major challenges in the recommender system is explained. As time evolves the NN has played a better role in the name of Neural Attentive Item Similarity for recommending a product. Further, the recommendation is enhanced to the group of people by applying the technique of opinion-based group dynamics and preference relation where the target is about recommending a product to the group of users though there exists diversity among users as the RS is not restricted to the choice of individual users. The textual description, Keyword-Based recommendation may lead to recommending a non-related product at times, hence the RS has migrated towards the image-oriented search approach. As the image processing methodologies are getting updated, product retrieval based on image features covers under Artificial Intelligence has opened a new finding in the Recommender System.

Section III summarizes the analyzed work by providing information about the type of recommendation service, experimental data, techniques applied, and possible enhancements. In addition to the above, few challenges are identified, which will be useful for the developers of the recommender system to identify the bottleneck and selection of recommendation algorithms.

5. CONCLUSION

This survey provides an overview of the recommender system with the methodologies adopted along with its advantages and disadvantages. The recommender system is especially effective when people deal with the issue of information overload. Depending on the nature of the input data, recommendation and prediction can be done in various ways such as analyzing the profile of the user, determining the maximum likelihood, estimating the profile matching, etc. All these work processes described in this survey will be useful for the researches to create a faster and efficient recommender engine. While dealing with the recommendation, data is an important asset. If the available data is metadata, the content-based mechanisms can be implemented to provide suggestions to the user. On the other hand, if there is a large number of user interactions, the recommendation can be provided by implementing collaborative filtering techniques. At last, if the recommendation system is described from the user's point of view, it creates interesting experiences and satisfaction in purchasing the product by looking at various choices. From a business point of view, it generates more revenue. Finally, it is hoped that this survey will provide a comprehensive overview to understand the various domains and scenarios of the recommender system.

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