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Recent Trends in Hybrid Recommendation Systems in e-commerce Domain

P. V. Nagavardhan[1] and B. Premamayudu[2]
[1]Research Scholar, Department of Information Technology, Vignan University, Guntur (Andhra Pradesh), India.
[2]Professor, Department of Information Technology, Vignan University, Guntur (Andhra Pradesh), India.

(Corresponding author: P. V. Nagavardhan)
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ABSTRACT: The rapid growth of internet led to exponential growth of data and information availability is just a click away. This changed the user purchase patterns using an e-commerce system which are tangentially different from normal brick and mortar model of selling. This paved path to the era of e-commerce where user interests and behaviors have to understood by the system and quickly recommend what the user may be interested on instead of user searching a product. This emphasizes the need of efficient recommendation systems which can quickly recommend a product or a service which is closely related to customer interest effectively and efficiently. The early age conventional recommendation systems are broadly based on collaborative filtering and content based filtering. Both these suffer with inherent drawbacks of cold start, scalability, non-availability of rating or feedback information on newly launched product and suffer with an assumption that personal information like user interest is available. This describes the need of more advanced hybrid recommendation systems which combines the best of both collaborative filtering and content based filtering and improve the relevance and accuracy of a recommendation system. Recommendation systems need high degree of parallel processing power and use of advanced technologies like cloud computing. This paper covers the latest trends and recent developments in the area of hybrid recommendation systems, compare their strengths and use of Cloud computing in parallel processing of hybrid recommendation systems.

Keywords: Collaborative Filtering, Content based Recommenders, Evaluation of recommender system performance, Hybrid Recommender System, Knowledge based Recommender System, Recommender Systems, Recommender Systems for e-commerce.

Abbreviations: RS, Recommender Systems; CBRS, Content Based Recommender Systems; CFRS, Collaborative Filtering Recommender Systems; KBRS, Knowledge Based Recommender Systems; GHGs, greenhouse gases; PCM, phase changing material; SC, solar chimney; HRS, Hybrid Recommendation Systems.

I. INTRODUCTION

Internet explosion started in early 20th century. The access to internet has increased from 5% of world population in 2000 to 75% of world population in 2020 [4]. The access to internet changed the customer buying pattern leading to the era of e-commerce. In the pre e-commerce age, it used to be a pull model where customers used to visit a physical shop and select the product of his interest. The growth of internet has changed the way goods are services sold to the customer. The birth of e-commerce has changed the way business is done. E-commerce made it possible that majority of products or services that a customer wants are available just a click away and are delivered at door step. It also changed the way user is selecting what he wants. This changed the earlier pull model to a push model, where the probable list of customer choices are shown to the customer and customer quickly selects the product that is suitable to his taste.

There are multiple e-commerce websites that offer services in the field of News, Jobs, Movies, real estate, travel destinations, product and services and recommend results that are suitable to customer needs. With the amount of data that is available on internet is growing and the time spent by customers on average on e-commerce sites are reducing. This emphasizes the need of advanced, more efficient, dynamic, scalable, adaptive recommendation systems that results in more accurate and close to customer needs in near real time.

Majority of the previous studies are focused on how to optimize the algorithm. With latest developments in cloud computing, lower compute costs shifts the focus from compute to better and more accurate results [11-15, 17, 18].

"A recommendation system is a software program which attempts to narrow down selections for users based on their expressed preferences, past behavior, or other data which can be mined about the user or other users with similar interests [8-10, 16].

II. CLASSIFICATION OF RECOMMENDER SYSTEMS

The three components of a simple recommendation system is attributes of user, attributes of items and an algorithm that matches these to suggest recommendations. Various recommendation systems evolved that extensively uses either one or more of the above components.

The user attributes or interests may be collected either implicitly or explicitly. An implicit collection of user interest is either by page views, button clicks or the type of products that custom buys frequently. An explicit collection of user data is based on product rating, feedback given for a given product or service.

The recommendation system can be broadly classified in to three types based on how and at what level the recommendation is provide. A **personalized recommendation system** matches the customer preferences to the attributes of the items available and find a close match to recommend. An **On-site recommendation system** recommends by drawing a similarity between the users and assumes similar products may also be liked by people in the same group. An off-site recommendation system can be complex and can take more time to come up with recommendations and suggest recommendations over an e-mail or a notification.

Content based recommender system [CBRS] tries to match the attributes of items based on similarity calculated between the attributes of items in the past [1]. A typical CBRS works based on a classifier algorithm to classify and draw similarity. There are numerous CBRS available which works based on Bayer classification, Rule based classification or Regression based to name a few.

CBRS are helpful when product or service is newly launched and there is no rating or feedback available. Content based recommender systems are highly helpful in such cases as it compares only the attributes of the products which are similar.

Collaborative Filtering Recommender System [CFRS] uses user specific interests collected like ratings, feedback given or pages visited or viewed to make recommendations. CFRS can be broadly classified in to two types as **Memory based** or **Model Based** recommender systems. Memory based recommender systems are also called **Neighborhood based** recommender systems.

Neighborhood based recommender systems can be further classified in to User based collaborative filtering where the similarity between the users is used for recommendation or Item based collaborative filtering where the similarity between the items are used for recommendation. The neighborhood based recommenders are simple and easy to implement but lack full coverage of predictions.

Model based recommender systems generate predictive models applying Machine learning, data mining technologies. These systems use Bayesian methods, rule-based models, decision trees to name a few. Model based recommenders give good coverage of the ratings. However there is a prior learning or training of the system that is required which cannot directly work on out of the box data sets and hence applying this to new domain is time consuming.

The general challenges in CFRS is the sparse nature of the depending attributes like feedback or rating. As an example, a typical mobile phone user would like to buy latest mobile in the market, however as the mobile is newly launched in the market, it will have less ratings on the new phone, there by not coming as a top recommender by using CFRS even if it matches to use needs.

Content Based and Collaborative filtering recommendation systems suffer from challenges like Gray sheep, sparsity, first rater problem, cold start, synonymy, protection of privacy, shilling attacks etc.

Another common classification of recommender systems is **Knowledge based recommender systems** [KBRS]. A typical Knowledge Based recommender system [KBRS] does not use ratings for recommendations but the recommendations are deducted based on similarities between item attributes and requirements of users. A preformed knowledge base is used which consists of rules and similarity functions to use during the recommendation process. Another variation of KBRS is utility based recommender system which uses a pre computed utility function to generate the recommendations. The success of utility based recommendation system lies in appropriately defining the utility function upfront. KBRS are more useful where sufficient ratings are not available and the frequency of buying the item is not very often such as automobiles, real estate and travel destination and financial services.

Demographic recommendation system is relatively new recommendation system. It uses demographic information of the users which are collected from user either explicitly or implicitly. Rule based classifiers are generally used to compute the best recommendation for the user. Demographic recommender systems may not provide best results when used independently, however the results can be improved when combined with other recommendation techniques.

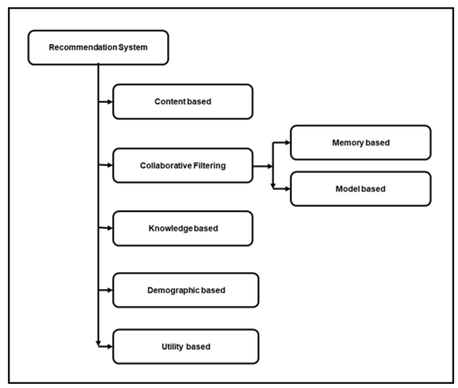

Fig. 1. Classification of recommendation systems.

Hybrid Recommendation System [HRS] combines the strengths of two or more recommendations systems to improve the robustness and relevance of recommendations and to overcome some of the gaps these recommendations systems suffer when used independently. The idea behind hybrid recommendation system is to enhance the accuracy and effectiveness of recommendation system by combining the individual benefits of multiple recommendation systems and overcome the disadvantages of one system by another. The rest of the paper discusses about latest trends and various hybrid recommendation systems that are proposed in the recent times.

III. PERFORMANCE EVALUATION OF RECOMMENDER SYSTEMS

The evaluation of performance of a recommender system is important to understand the effectiveness and usefulness of the algorithm. Broadly the performance evaluation of a recommender systems can be divided in to online evaluation and offline evaluation. In online evaluation, the user reactions are evaluated against the system recommendation. Offline evaluation methods are more common methods used in research and during training of the system.

The evaluation of a recommender system also changes based on the methods and algorithms used in the system. In a simple collaborative filtering or content based methods, we use similarities of items within each classification. Hence we can use similarity or dissimilarity as a measure. A/B testing is another effective measure to evaluate the effectiveness of one algorithm over another.

Aggarwal [1] broadly classifies the evaluation of recommender systems using following general parameters

1. Accuracy of rating
2. Coverage of the mix
3. Confidence
4. Scalability
5. Robustness
6. Diversity

It is of utmost importance to keep the error rate low for any recommender system. There are multiple ways to calculate the error based on the mix of the sample set and nature of the problem being solved.

Let S be the set of entries, and E ⊂ S be the set of entries in the test set used for evaluation. Let r_{uj} be the value of the rating of entry (u , j) ∈ E, used in the test set. Let $\hat{r}_{uj}$ be the predicted rating of the entry (u, j) used by the training algorithm. The entry-specific error is given by $e_{uj} = \hat{r}_{uj} - r_{uj}$. The mean squared error, denoted by MSE can be calculated by using below formula.

$$MSE = \frac{\sum_{u,j} \in E\ e_{uj}^2}{|E|}$$

The square-root of this value is referred to as the root mean squared error (RMSE), and it is often used instead of the MSE

$$RMSE = \sqrt{\frac{\sum(u,j) \in E\ e_{uj}^2}{|E|}}$$

One characteristic of the RMSE is that it disproportionately penalize large errors because of the squared term within the summation. One measure, known as the mean-absolute-error (MAE), does not disproportionately penalize larger errors:

$$\mathrm{MAE} = \frac{\sum(u,j) \in E|e_{uj}|}{|E|}$$

Other related measures such as the normalized RMSE (NRMSE) and normalized MAE (NMAE) are defined in a similar way, except that each of them is divided by the range $r_{max} - r_{min}$ of the ratings:

$$NRMSE = \frac{RMSE}{r_{max} - r_{min}}$$

$$NMAE = \frac{MAE}{r_{max} - r_{min}}$$

IV. LATEST TRENDS IN HYBRID RECOMMENDER SYSTEMS

Guia *et al*., [7] presented Ontology based Recommendation system, a new hybrid approach that combines the simplicity of neighborhood based model of collaborative filtering with the efficiency of the ontology-based recommenders. "Ontology is a formal representation of the knowledge by a set of concepts within a domain and the relationships between those concepts".

Shilu *et al*., [6] presented a hybrid recommender system Clustered Content boosted Collaborative Filtering (CBCF) that combines the strengths of content based filtering and Collaborative filtering using KNN. The results are improved by using clustering. Naive Bayesian algorithm is used to classify data set based on ratings and then a classifier to learn a user profile. The learned profile is used to come up with rating. K-Mean algorithm is used to find the group that is closely related by updating the centroid repeatedly. Then a k-Nearest Neighbor [KNN] is used to find better similarity by applying weights. A pseudo user rating is generated by combining the results of both the recommender systems. The pseudo ratings are improved by replacing the actual user ratings iteratively to improve the quality of results.

Darvishy *et al.,* [5] proposed a hybrid recommendation system A Hybrid Approach for Personalized News Recommendation for suggesting news articles using content based filtering and collaborative filtering. A new unsupervised linear algorithm called ordered clustering is used along with similarity matrix to cluster the news item. The proposed framework aims at improving the accuracy of news recommendation by resolving the issues of scalability due to large news corpus, enriching the user's profile, representing the exact properties and characteristics of news items, and recommending diverse set of news items. This recommendation system starts with collecting user profile with explicit methods and store those details. Using collaborative filtering constructs long term user profile and then applies cluster on user profiles to group users in to specific classes. Constructs metadata for all the news items using content based filtering and then applies clustering to group the news articles in to groups that are of similar nature. Then applies HYPNER algorithm to combine the results. The combined results are prioritized based on rating and the recommendations are further optimized by limiting the results to only top X items by discarding the lower ranked items in the list. The novelty of hybrid HYPNER recommender system is that it suggests an ordered list of recommendations based on relevance.

Dineth Keshawa Jayathilaka *et al.,* [2] proposed a hybrid weight factorization recommendation system which performs CB and CF separately and combines the results and optimizes the results by assigning weights using weight factorization approach. The weights are adjusted continuously to fine tune the model for better results. It also uses latent factor model and bias latent factor model to enhance the results.

Hidayatullah *et al*., [3] proposed a hybrid recommender system using multi-objective ranked Bandits algorithm. Bandit's algorithm is generally used as a scheduling algorithm where each arm gives a recommendation with a probability. In this recommendation System, the user clicks are captured and the recommendations are improved after every user click, thus without any need of history. The RS will provide a list of preconfigured number of recommendations improving the chances of user selection.

Table 1: Advantages of Hybrid recommendation Systems.

S.No.	Hybrid Recommender System	Recommender Systems used	Advantages
1.	Ontology based RS	K nearest neighbor & Ontology	– Increases the number of products recommended. – Can be applied even if the similar product is not yet purchased. – System is scalable with good performance.
2.	Clustered Content boosted Collaborative filtering	Naive Bayesian classifier & Clustering	– Improved recommendation results. – Works even if there are no ratings available.
3.	HYPNER	Ordered clustering & K-mean	– Improved recommendation results – Ordered list of results – Scalability
4.	Hybrid Weight Factorization	Latent Factor Model & Bias Latent Factor Model	– Superior Performance – Better recommendations – Continuous improvement of results
5.	Multi-objective ranked Bandits algorithm	Multi objective ranked bandits	– Works without preexisting rating or user profile. – Suggests a list of items instead of a single item. – Can manage dynamic scenarios

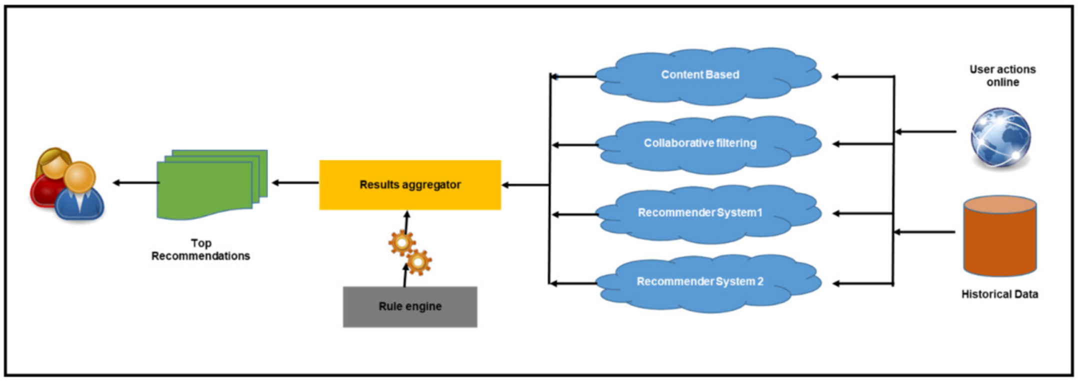

Fig. 2. Block diagram for a cloud based hybrid recommendation system.

V. CONSIDERATIONS FOR CLOUD BASED HYBRID RECOMMENDER SYSTEMS

The core strength of a hybrid recommendation system is to complement the drawbacks of single recommender system and build on the strengths of each system. This can only be achieved by combining more and more algorithms and improve the accuracy of the recommendation. But the execution of each recommendation system is time consuming and the need of the users is an online recommendation system which can come up with most accurate recommendations almost instantaneously. This poses a significant challenges to traditional hybrid systems in terms of response times. This can be addressed with the use of cloud technology.

A block diagram for a proposed cloud based hybrid recommender system is shown in Fig 2. The proposed system consists of four components (1) User data (2) Recommender system (3) Result aggregator 4. Rule engine

The user data can be captured online from user clicks and historical data from database/data mining system. Based on the desired accuracy, any number of recommender systems can be run parallel in a separate cloud environment each giving a recommendations individually. The results are then aggregated using result aggregator. The aggregated results are processed by rule engine based on preset rules and produces top recommendations for the user.

VI. CONCLUSION

In spite of numerous recommendation systems, the customer needs are constantly changing with a need to preserve privacy, customer usage scenarios moving from desktop to mobile, customers searching items by typing item to voice based commands on personal assistants like Alexa and Google Assistant, there is a need of more recommendation systems addressing these changing scenarios. There are more new segments entering into online like matrimony, jobs, e-learning etc. with different needs in each of these segments. There is a need for more customized recommendation systems for each of these domains. The technology landscape is quickly changing with more parallel processing available in the form of cloud computing. User behavior and usage pattern can be continuously mined using Data mining, a customized personal recommendation system can be created using artificial intelligence.

VII. FUTURE SCOPE

In the current survey, various hybrid recommendation systems are considered which have evolved in the recent past. Majority of these cover recommender systems for suggesting news articles or movies.

However e-commerce is evolving quickly and entering in to more new domains like Jobs, Matrimony, Property etc., where there is a need for more customized domain specific recommendation system which needs further study.

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Conflict of Interest. There is no conflict of interest in this work.

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