ITEM REPLACEMENT TECHNIQUE FOR RECOMMENDATION SYSTEM

[1]K.Viswanath, [2]K.F Bharati

[1]M.Tech (CSE), [2]Assistant Professor
Department of CSE, JNTUACE, Anantapur, A.P.

***Abstract*: Many recommendation techniques have been developed over the past decade, and major efforts in both academia and industry have been made to improve recommendation accuracy. However, it has been increasingly noted that it is not sufficient to have accuracy as the sole criteria in measuring recommendation quality, and consider other important dimensions, such as diversity, confidence, and trust, to generate recommendations that are not only accurate but also useful to users. More diverse recommendations, presumably leading to more sales of long-tail items, could be beneficial for both individual users and some business models. The main aim of the project is to find the best top-*N* recommendation lists for all users according to two measures, they are accuracy and diversity. To get maximum diversity, Optimization based approaches are used while maintaining acceptable levels of accuracy in the proposed method.**

***Keywords*: Ranking, Recommended Systems, filtering, items, diversity**

1. Introduction

The expansion of e-trade, recommender frameworks have turned into a vital part of customized e-business benefits and are crucial for e-business suppliers to stay suitable. Community sifting is one of the proposal method, whose execution has been demonstrated in different e-trade applications. Collaborative Filtering(CF) mechanizes the "informal" process. It structures an indicator a mass that serves as a data hotspot for proposals.

Then again, traditional CF systems experience the ill effects of a couple of essential confinements, for example, the cool begin issue, information sparsity issue, and recommender dependability problem. [4],[5]Thus, they experience difficulty in managing high-association, learning concentrated spaces, for example, e-learning feature on interest. To query some of these issues, analysts have proposed procedures, for example, a crossover methodology joining CF with substance based filtering[4]. Because e-business Web locales for e-adapting regularly have different item classes, separating the numerous qualities of these classifications for substance based sifting is amazingly troublesome. Thus, it may be useful to conquer these impediments by enhancing the CF system itself. The structural engineering of recommender system is indicated in figure1. Traditional CF strategies build their suggestions in light of a solitary recommender bunch. Our CF strategy structures double recommender bunches a comparable clients' gathering and a specialist clients' gathering as sound data sources. At that point, it breaks down each bunch's impact on the target clients for the target item classes.

1.1 Challenges of Recommender Systems: Though, recommenders frameworks have been exceptionally effective in past, they likewise experience a few difficulties. Recommender frameworks, specifically, community sifting based recommender frameworks, confront three note worthy difficulties: chilly begin, information sparsity, and attack.

1.1.1 Cold Start: Cold begin is the potential issue for any information driven framework, including recommender frameworks that attempt to construct a model taking into account the current data. Frosty begin is the circumstance that the calculation's adequacy is low in light of the fact that things' (or clients') vector don't have enough appraised things to discover vectors like them[2]. In the substance based methodology, the frameworks must have the capacity to match things' qualities against significant peculiarities from clients' profiles. Accordingly, it needs to build a point by point model of clients' tastes and inclination. In this way, without having a sufficiently itemized model of clients' tastes and inclination, the framework would neglect to match it with the suitable things and thus to make an acclamation for clients. In the community separating approach, the recommender framework recognizes clients who offer comparable inclination with the dynamic client, and suggests things which the similarly invested clients favored (and the dynamic client has not yet seen). Because of the icy begin issue, this methodology would neglect to consider things which nobody in the framework has evaluated already. The frosty begin issue can be alleviated by applying half breed methodologies, for example, a blend of substance based and community oriented sifting methodologies.

1.1.2 Data Sparsity: The center of numerous recommender frameworks is to discover comparative clients or comparable things. Despite the fact that there are numerous calculations that can take care of this issue, pretty much every one of them fizzle when the measure of the vectors develops and passes a few limits [8]. At the point when the quantity of clients or things expands, the rating grid gets to a great degree inadequate. For instance, IMDB has records of more than 700K films. Regardless of the possibility that some individual can see and rank one thousand of them, the rating lattice remains to a great degree scanty. In these circumstances, discovering comparable clients gets to a great degree troublesome, and the majority of the current calculations neglect to discover comparative clients or things. One regular system to handle this issue is utilizing factorization routines to lessen the measure of the rating grid and make a framework with less number of more important and free gimmicks. Not with standing, taking care of amazingly meager rating lattices remains an open test for recommender frameworks [1].

1.1.3 Attacks: Attacks are intended to drive the recommender framework act in a manner that the assailant wishes. It could either prescribe some craved things or avoid prescribing of different things. An assault against a recommender framework comprises of a set of assault profiles, and every profile contains one-sided rating information connected with an imaginary client personality and a target thing. There are two noteworthy diverse sorts of assaults: Push assault or Nuke assault[4] . In a push assault, the recommender prescribes whatever the assailant wishes. The aggressor makes a profile whose rating is like that of the target client. Given the high similarity between the target client and the infused profile, the framework will more probable utilize the infused profile as a source to give proposal to the target client. The assailant in a nuke assault intends to keep the framework from prescribing a specific thing or to make the recommender framework unusable in all.

2. Literature Survey:

J. **Michael** et. al. [6] constructed a recommender calculation that works for compound items and administrations rather than simply singular things. For this they actualized CARD structure which fundamentally differentiates the utility space and assorted qualities space to evade the tradeoff in the middle of closeness and differences. The calculation he outlined is computationally productive and beats as far as differing qualities.

K. Shyong et. al. [8] said that client's advantage are constantly brimming with vulnerability which couldn't be tended to by top-N rundown of suggestions effortlessly. Rather than this creator proposed a cloud model which is influential at illuminating learning instabilities.

The study incorporates a careful portrayal of both substance based and community oriented systems for speaking to things and client profiles. At that point we examined about different endeavors via specialists in individual and in addition total differences. At last, it talks about patterns and future exploration which may lead towards the upcoming era of recommender frameworks.

Recommender frameworks have assumed a huge part in helping clients find applicable things from a colossal number of decisions, especially in e-business applications, for example, Amazon and Netflix. Recommender frameworks are likewise favorable to online substance suppliers. Case in point, as per Forrester Research (Schonfeld 2007), it is assessed that recommender frameworks represent 10% to 30% of an online retailer's deals. Netflix additionally reported that around 66% of their films leased were ones that clients might never have considered something else, yet were suggested by their recommender framework (Flynn 2006).With the developing interest for customized proposals, much work has been carried out in the course of the most recent decade on growing new proposal strategies, both in industry and the research world. The Netflix Prize competition1 (Greene 2006) is a decent case of the developing consideration for these suggestion procedures. In any case, regardless of critical advancement, current proposed strategies still have various significant difficulties to be tended to (Adomavicius and Tuzhilin 2005).

Adomavicius [9] proposed to classify previous methods as follows. Traditional recommender systems use the user's favorite weights. These weights are considered for every product characteristics are measured based on the whole ratings for the products of users. Knowledge based methods in which users openly condition their common favorites in an interactive elicitation mechanism. Systems in which the users can identify their estimate personal products. Jannach et al[9] estimated the developments on two dissimilar information sets, one again based on information from movies website and one from the antivirus. Mehrbakhsh [11] Proposed a way and dissimilar algorithmic methods to deal with such situations which are in fact quite ordinary in sensible sets.
Specifically, a large number of proposal calculations proposed in the recommender frameworks writing and in addition industry have concentrated on enhancing suggestion exactness, i.e., the precision with which the recommender framework predicts clients' appraisals for the things that they have not yet evaluated. While proposal exactness is without a doubt imperative, there is a developing comprehension that precision does not generally suggest helpfulness to clients, and depending on the precision of proposals alone may not be sufficient to discover the most significant things for every client (Herlocker et al. 2004, McNee et al. 2006, Shani and Gunawardana 2011). Consequently, not withstanding the precision of suggestions, this exposition examines the differing qualities of proposals that can mirror the capacity of recommender frameworks to go past the self-evident, top of the line things, and create more eccentric, customized, and long-tail suggestions. A commonplace recommender framework gives suggestions to a client by evaluating the evaluations of things yet to be devoured by the client, in view of the appraisals of things effectively expended. Suggestions to clients are made taking into account the anticipated evaluations of everything for every client (i.e., the things with the most exceptionally anticipated appraisals are the ones prescribed to the client). While the greater part of current recommender frameworks utilize a solitary numerical rating to speak to each client's inclination for a given thing, recommender frameworks in some e-business settings have as of late begun receiving multi-criteria appraisals that catch more exact data about client inclination concerning distinctive parts of a thing (e.g., catching client evaluations for the story and acting segments of every motion picture in a film recommender framework). Some substance based recommender frameworks (Balabanovic and Shoham 1997) utilization different substance properties for thing examinations and similitude figuring, the subjective client inclination for a thing are still caught by a basic general rating. Conversely, my paper concentrates on multi-criteria rating frameworks that permit clients to rate various diverse parts of a thing.

3. Proposed System

A recommendation system provides a solution when a lot of useful content becomes too much of a good thing. A recommendation engine can help users discover information of interest by analyzing historical behaviors. More and more online companies including Netflix, Google, Face book, and many others are integrating a recommendation system into their services to help users discover and select information that may be of particular interest to them. Adomavicius and Kon [4] propose to re-rank the list of candidate items for a user to improve the aggregate diversity. First, an ordered list of recommendations is calculated using any filtering technique. Second, for all items having a better expected rating than a given threshold, additional features are calculated, for instance the absolute and relative likeability of an item (how many users liked the item among all users or among all users who rated that item, respectively) and the item's rating variance.

According to these features, the candidate items are re-ranked and only the top-*N* items are recommended. This way, niche items are pushed to the recommendation lists and very popular items are rejected. While this re-ranking technique can improve the aggregate diversity, it comes at the expense of accuracy. The re-ranking approach, briefly discussed above can improve recommendation diversity by recommending those items that have lower predicted ratings among the items predicted to be relevant, by changing ranking threshold *T*R, but it does not provide direct control on how much diversity improvement can be obtained. To address this limitation, Item Replacement Technique, which attempts to directly increase the number of distinct items recommended across all users (i.e., improve the *diversity-in-top-N* measure). The basic idea behind this iterative approach is as follows. First, the standard ranking approach is applied to each user, to obtain the initial top-*N* recommendations, typically with the best accuracy. Then, iteratively, one of the already-recommended items is replaced by another candidate item that has not yet been recommended to anyone, thereby increasing the diversity by one unit, until the diversity increases to the desired level, or until there are no more new items available for replacement.

Since item replacement is made only when it results in an immediate improvement of diversity by on unit, we refer to this approach hereafter as an Item replacement approach. Each item replacement iteration is implemented as follows. The most frequently recommended item *i*old is replaced by one of the never-recommended items *i*new for the same user. Among all the users who got recommended item *i*old, a replacement occurs for user *u*max, who is predicted to rate item *i*old most highly, allowing for a possibly higher predicted rating value for the replacement item *i*new (and, therefore, for better accuracy). In other words, since any new candidate item for replacement *i*new is predicted to be lower than item *i*old for the chosen user, the higher the prediction of item *i*old, the higher the possibility of obtaining a high prediction of the new item *i*new.

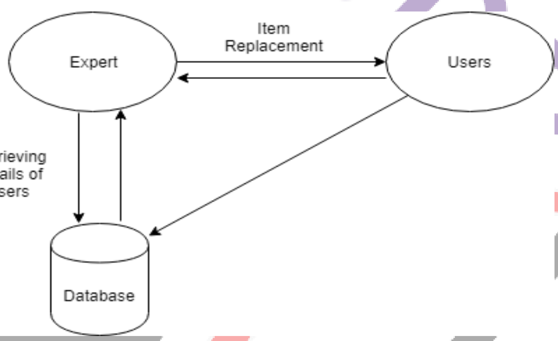

Fig1. Proposed System

As shown in Fig.1 the proposed system, there is a database consisting of the all products including different types like sports, movies etc. All the users are registered with the recommender system. All the details of the users are saved in the database. The details like user id, password, qualification, interests, and etc .While recommending the items to the users the proposed system will follow the Item Replacement Technique. As shown in the following algorithm.

Algorithm 1

Step1: Initializing top-N recommendation list

Step2: Replacing already recommended item io_{ld} with the never recommended item in_{ew}

Step3: Repeat the process until maximum diversity is reached.

As shown above the process of the proposed system works. First top N recommendation list is generated by using the standard Ranking. And Items will be replaced by the never recommended items.

3.1Standard Ranking Technique

Recommending the items that are most highly predicted for each user.

Rank standard (i) = $R^*(u,i)^{-1}$ …eqn.(3.1)

Where R represents ratings, u user, I item

Typical recommender systems predict unknown ratings based on known ratings, using any traditional recommendation technique such as neighborhood-based or matrix factorization CF techniques. The predicted ratings are then used to support the user's decision-making. In particular, the most relevant N items are selected according to some ranking criterion, typically using predicted rating value as the ranking criterion: Rank standard (i) =R*(u, i)$^{-1}$. This standard ranking approach shares motivation with the widely used probability ranking principle in information retrieval literature that ranks the documents in order of decreasing probability of relevance. The power of -1 in the above expression indicates that the items with highest-predicted (as opposed to lowest-predicted) ratings R*(u, i) are the ones being recommended to user. Recommending the most highly predicted items selected by the standard ranking approach is designed to help improve recommendation accuracy.

As stated earlier, The main objective of the project is to find the best top-N recommendation lists for all users according to the following measures:

- Diversity
- Accuracy

A simple, absolute long-tail metric is used to measure aggregate diversity, using the total number of distinct items among the top-*N* items recommended across all users, referred to as the *diversity-in-top-N*. Diversity can be measured by the following equation.

$$\text{Diversity} = \bigcup_{u \in U} L_N(u) \quad \text{.........eqn. (3.2)}$$

Where Ln(u) represents list of all recommended items

Accuracy can be measured by the following equation.

$$\text{Accuracy} = \sum_{u \in U} |correct(L_N(u))| \Big/ \sum_{u \in U} |L_N(u)| \quad \text{..........eqn. (3.3)}$$

Where Ln(u) represents list of all recommended items. Accuracy is calculated as the percentage of truly relevant items, denoted by *correct* ($L_N(u)$) among the items recommended across all users. The Table1 represents about rating description.

Table 1: Rating description

Rating	**Description**
5	Excellent
4	Best
3	Good
2	Average
1	Bad

4.Results:

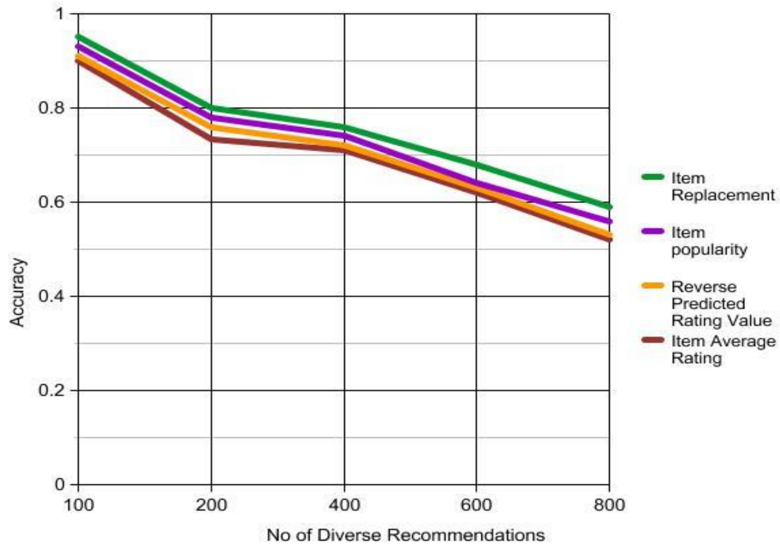

Fig 4.1 Accuracy and the diverse recommendations

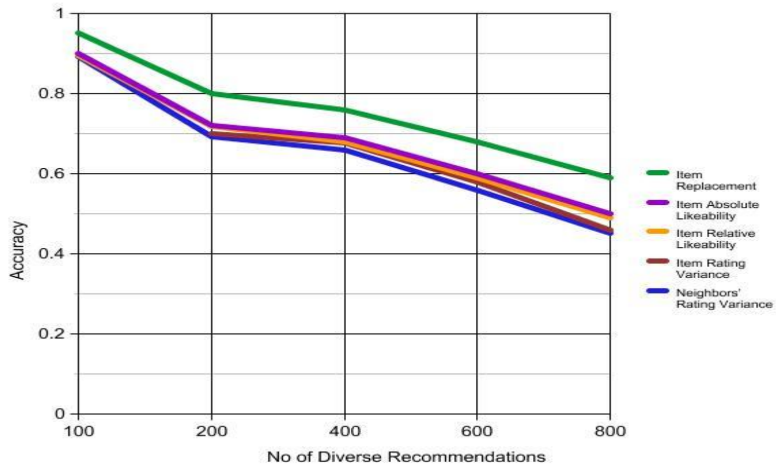

Fig 4.1.2 Accuracy and the diverse recommendations of proposed system

Experimental results show that the proposed technique gives high accuracy than existing technique, as shown in Fig4.1.2.

Conclusion

Suggestion differences have as of late pulled in extensive consideration as an imperative viewpoint in assessing the nature of proposals. Customary recommender frameworks normally prescribe the top-N most exceedingly anticipated things for every client, subsequently giving great prescient precision, however performing ineffectively as for suggestion assorted qualities. Thus, the proposed technique "Thing swap procedure for high total differing qualities in recommender framework" Improves the differences. The proposed procedure has a few points of interest over the suggestion re-positioning methodologies from former writing: acquiring further changes in differing qualities parallel to the level of precision. The proposed enhancement methodology has been composed particularly for the differing qualities in-top-N metric, which measures the quantity of different things among the top-N proposals. The confidence and trust can be improved.

References

[1] Nguyen Thanh Toan1, Phan Thanh cong1, Nguyen Thanh Tam2, Nguyen Quoc Viet Hung 3, and Bela Stantic3 (2018): Diversifying Group Recommendation

[2] Badrul Sarwar, George Karypis, Joseph Konstan, and John Riedl.(2000). Application of dimensionality reduction in recommender system-a case study. *Technical report, DTIC Document.*

[3] Andrew I Schein, Alexandrin Popescul, Lyle H Ungar, and David M Pennock, (2002). Methods and metrics for cold-start recommendations. *international ACM SIGIR conference on Research and development in information retrieval*. **pp.253–260**

[4] Ziegler, C.-N., McNee, S. M., Konstan, J. A., and Lausen.G, (2005). Improving recommendation lists through topic diversification. *In Proc. of the 14th international conference on World Wide Web* . **pp.22-32**

[5] Robert Bell Yehuda Koren and Chris Volinsky, (2009). Matrix factorization techniques for recommender systems. *In IEEE Compute*. **42 (8), pp.30-37**

[6] Michael J. Pazzani, (1999). A framework for collaborative, content-based and demographic filtering. *Artificial Intelligence Revi*. **13 (5-6), pp.393–408**

[7] Prem Melville, Raymond J. Mooney, and Ramadass Nagarajan., (2002). Content boosted collaborative filtering for improved recommendations. *In Proceedings of the Eighteenth National Conference on Artificial Intelligence (AAAI-02.***pp.187-192**

[8] Shyong K. Lam and John Riedl. Shilling , (2004). recommender systems for fun and profit. *13th international conference on World Wide Web*. **pp.393-402**

[9] Adomavicius, G., Manouselis, N., Kwon, Y., (2011). Multi-criteria recommender systems. Recommender Systems Handbook. *Springer US,* **pp. 769-803.**

[10] Jannach, D., Karakaya, Z., Gedikli, F., (2012). Accuracy improvements for multicriteria recommender systems. *In: Proceedings of the 13th ACM Conference on Electronic Commerce (EC 2012).* **pp. 674-689.**

[11]MehrbakhshNilashi, DietmarJannach, Othman bin Ibrahim, Norafida Ithnin,(2015):Clustering and regression-based multi-criteria collaborative filtering with incremental updates.*Inf. Sci.* **293: 235-250**