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A Survey on Approaches for More Accurate and Diverse Recommendations

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Abstract: ***Recommender systems are being extensively used in the present generation. Recommender systems are gradually increasingly harder to find the relevant contents of information in the vast abundant current age of information overload. Thus, recommender systems are needed to help individual users find the most relevant items or products or data sets from an abundant number of choices, collection. Through this gradually increase sales by exposing users to what they might like. E.g. In real time or real world applications consider a product say laptop, the laptop present in numerous patterns with different applications in number depending upon different user's requirements. Thus providing a user or the customer with relevant information about the product as per their requirements with the help of recommender systems would ease the work of an user. Hence we can conclude saying that the volume of information available in the current age is huge to individual users (for e.g., e-commerce sites applications such as Amazon, Netflix) and hence focusing in developing some recommendation techniques within both industry and academia. Most, research to date is focusing on improving the recommendation accuracy i.e. the accuracy with which the recommender system predicts users ratings for items that are yet to be rated. The diversity of recommendation also plays an important role to be considered, it is important to explore the relationship between the accuracy and diversity and also the recommendation quality. Empirical analysis consistently shows the diversity gains of different recommendation techniques which is being used in several real world rating applications or datasets and uses different rating prediction algorithms. Individual users and online content providers will also benefit from the proposed approaches, where in which each user can find more relevant and personalized items or products from accurate and diverse recommendations provided by these recommender systems. These approaches, ranking techniques and algorithms could potentially lead to increased loyalty and sales in e-commerce application sites, thus benefiting the providers as well.***

Keywords: Recommender systems, recommendation accuracy, diverse recommendation, empirical analysis, ranking techniques, collaborative filtering, performance evaluation metrics, aggregate diversity, RMSE, extensions of recommendation approaches.

I. **Introduction.**

Recommender systems represent an increasingly popular and important set of personalization technologies that help people to navigate through the vast amount of information. These systems try to estimate the ratings of unknown items or products for each user, often based on other users ratings and recommended the items with the highest predicted ratings. The recommendation problem is basically on ratings i.e. these recommender systems estimate ratings of the items or products that are yet to be used by the users, depending upon the ratings of items previously being used. Much research work is going on developing new algorithm focused on improving the accuracy of recommendations. However, relying on the accuracy alone may not be enough to find the most relevant items or products for a user. The diverse recommendations are also needed to have a highly personalized items as a result and utilize more opportunities for a user to get recommended such items[3]. Over last 10-15 years, recommender systems technologies have been introduced to help people deal with the abundant information[1][2][3][5][6][7][10] and they are widely used in research studies as well as in e-commerce applications i.e. few example Amazon, Netflix. The Netflix prize competition was an open competition held in 2006-09 for the best recommendation algorithms that could improve the accuracy of user's ratings predictions by 10% over Netflix's own recommendation engine.

Two approaches on improving recommender systems ratings in terms of both accuracy and diversity of recommendation has been a main objective of the paper. Initially we propose conventional approaches and then implementation of some new techniques for each new approach for combining these different proposed approaches. The following are the different approaches:

1. Developing new recommendation approaches that can incorporate multi-criteria rating information for more accurate recommendations.
2. Applying heuristic-based (memory based) ranking approaches for more diverse recommendations.
3. Developing more sophisticated optimization approaches for direct diversity maximization.
4. Combining the first two types of approaches i.e. the multi-criteria rating techniques and ranking approaches.

Thus, by the last approach we can overcome the trade-offs between accuracy and diversity [3]. Therefore, resulting in generation of a more accurate and more diverse recommendations as compared to the conventional single rating techniques.

II. **Related Work**

1). Recommendations Process

Recommendation systems generally perform the following two tasks in order to provide recommendations to each user: 1) unknown ratings prediction and 2) recommendation generation. In many online applications, users provide feedback using numeric values for rating on the items/products/datasets that have been used or purchased or watched. In the prediction rating submitted for a subset of consumed items or products and may be even the information about the item or a product content or user demographics, a recommender system estimate ratings of items or a product that system finds items that the users have not yet been used, using some recommendation algorithms. In case of recommendation phase the system then finds items that maximize the users utility based on the predicted ratings and recommend those to the user. We can define the two phases of recommender system as below: let U be set of users and P be set of products or items available in the recommender systems. Then, the utility function that measures the usefulness or utility of a product or an item to a user can be specified as R: Users * Products--> Ratings, where Ratings represents some numeric value used by users to evaluate each product or item. Therefore, to estimate unknown ratings is the work of the recommender system in the prediction rating phase i.e.:–R*(u,p), based on the known ratings:- R(u,p). here R(u,i) represents actual rating that user u gave to product p and R*(u,p) represents the system predicted ratings for product p that user u has not rated before.
Given all the predictions for each user, now it is the recommendation phase, where the system selects the most relevant products i.e. products that optimize a user's utility, with respect to a certain ranking conditions. Formally, product $p_x$is ranked ahead of product p_yi.e. ($p_x<p_y$) if rank (p_x) <rank (p_y) where Rank: P→R. This function represents the ranking condition and standard ranking approach refers as follows: Rank $_{standard\ (p)}$ =$R^*(u,p)^{-1}$. here the recommended system rank the candidate products or items by their predicted rating values and recommend the most highly predicted N products to each user because users are generally only interested in most relevant recommendations. And the power of -1 indicates that the products with highest predicted are the ones being recommended to user is given by R*(u,i) ratings.

2). Recommendation Algorithm for Rating Predictions

The recommendation techniques for rating predictions based on their approaches are classified into 3 categories namely: content- based, collaborative and hybrid approach [1] [10]. Content based recommender systems are user preferred systems in their past. Collaborative filtering recommender systems are the systems with similar preferences to the users have liked in their past are recommended. Hybrid approach as the name says is the combination of both content based and collaborative methods in several ways [8].
Based on the nature of algorithmic techniques also the recommender systems can be classified in following ways: heuristic based and model based approaches. Heuristics based techniques are Re-ranking techniques i.e. the recommendations based directly on the past user activities (e.g. .transactional data, product rating values, movie ratings) [5] [8].here recommender systems use a database about user preferences to predict additional topics or products or items where a new user might like. One of most commonly used techniques is a neighbourhood based approach that finds nearest neighbours' that have tastes or choices similar to those of the base user i.e. the target user [2]. In case of model-based techniques use the activities of a previous user in order to initially learn a predictive model by using some statistical or machine learning methods, later these are used to make recommendations e.g. some techniques based on correlation coefficients, vector-based similarity calculations, statistical Bayesian methods[5,][6], matrix factorization, cluster models[5],[6]. The recommendation approaches proposed below can be used in conjunction with any recommendation algorithms and the results are evaluated using the empirical analysis. We use two most popular and extensively used CF techniques for rating predictions, it's a heuristic neighbourhood based technique and a model-based matrix factorization technique [5], [2].

III. **Accuracy of Recommendation**

Several statistical accuracy metrics, such as mean absolute error(MAE) and root mean squared error(RMSE) are presently being used to measure predictive accuracy i.e how well a system can predict an exact rating value for a specific item. The main objective is to generate top N-Recommendations in terms of both accuracy and diversity and here we have chosen to use decision-support metrics to evaluate how progressively a recommender systems would help a user's to select their relevant products or items from the set of all items or products or database. The decision-support metrics typically work with binary outcome therefore, the percentage of correctly predicted "relevant" products or items among all the sets are used to convert a numeric rating scale into a binary scale i.e.(relevant vs. irrelevant) this is achieved through the empirical analysis tests where we rate either by a 13-point(A+ to F) or a 5-point or 5-stars scale and the natural assumption is that users provide higher ratings for items or products that are most relevant to their(users) expecting levels. The rating is done between 11 and 13(A+,A,A- on a 13-point scale) or 4 and 5(on a 5-point scale) as relevant items and items with the lower ratings as irrelevant items) else we can use the threshold value between relevant and irrelevant items as 10.5 to 3.5(say for e.g.) said to be as a relevance threshold(T_H).[12],[1].

IV. **Diversity of Recommendation**

This is taken into count at either the individual or at the aggregate level. Individual diversity [1],[2] concentrates in preventing to provide too similar recommendations for the same user .e.g. based on an item attributes calculating the average similarity between all pairs of items recommended to a user to determine individual diversity with which a two questions arises they are: i) whether the items recommended to a user are of various kinds i.e. categorical diversity. ii) Whether the items recommended to a user are similar to each other i.e. item-to-item diversity. The loss of accuracy resulting from increased diversity is controlled by changing the granularity of the similarity metrics in the diversity conscious algorithms [1], [2], [10]. Aggregate diversity is contrast to individual diversity. Recommendations across all users are relatively less concentrated and impact of recommender systems on product or nan item type and their ability to sales techniques "long-tail [3] and "superstars" [4] effects in e-commerce applications e.g. a study made using data from an online shopping site, say flipkart.com it's an online shopping application site, demonstrated that recommendations increase sales of items or products in the long-tail, resulting in improved aggregate diversity. In contrast, the "superstar" literature indicates that the recommender systems promote so called "rich get richer" phenomenon [7], [9] where more popular or bestselling brands items or products are recommended compared to personalized ones. More diverse recommendations are progressing in more sales of Long-tail products or items, which could be beneficial for both individual users and some business models. e.g. diverse recommendations would help to build up consumers or users tastes for a niche(suitable) products[1],[2] might be on some particular sales of a books, movies, gadgets, so on.

V. **Trade-offs Between Accuracy and Diversity**

We could obtain relatively high accuracy because having trade-offs between accuracy and diversity we can recommend only popular items or products but this could also lead to a decline of other aspects of recommendation diversity e.g. blockbuster movies, that many users tent to like, and a gadget device with very high-end applications with a feasible price many user tend to purchase that product or an item. But maintaining accuracy while improving diversity leads to a difficult task because higher diversity could be achieved by trying to uncover and recommend highly personalized or idiosyncratic products or items for each user, this leads to a decline in the recommendation accuracy [3]. Consider an example where only popular items or long-tail type products are recommended to users for using from e-commerce application sites (amazon, Netflix, flip-kart, movie-lens [1] dataset ratings, here the item based CF techniques are used to predict unknown ratings. As candidate recommendations for each user, consider only the items that were predicted above the pre-defined relevance threshold, in order to ensure acceptable level of accuracy. Among these candidate items for each user we identify items that were rated by many users i.e. target number of known ratings , as popular items and items that were rated by the least number of users (smallest number of known ratings as long-tail items or products))[1],[2],[3]. As a result we obtain a top-1 recommendation tasks in a table below i.e. if the system recommends the most popular item, is likely to be the best-selling item i.e it is far more likely to many users to get the same recommendations. The accuracy measure by the precision-in top-1 metric is 82%, but only 49 popular items out of approx. 2,000 available distinct items were recommended across all users (2,828 users in total). The system can improve the diversity of recommendations from 49 to 695 items by recommending long-tail items to each user.

Quality Metric: / Top-1 recommendation of:	Accuracy	Diversity
Popular Item (item with the largest number of known ratings)	82%	49 distinct items
"Long-Tail" Item (item with the smallest number of known ratings)	68%	695 distinct items

TABLE-1 - Accuracy-Diversity Trade-offs: Empirical Example. (Note: Recommendations (top-1 item for each user) are generated for 2,828 users among the items that are predicted above the acceptable threshold 3.5 (out of 5), using a standard item-based collaborative filtering technique with 50 neighbours on Movie-Lens Data set.)

Thus, we can say that it is possible to obtain higher diversity by recommending less popular items. Anyhow the loss of accuracy is very negligible (substantial). Therefore, more exploration of new recommendations approaches is necessary to increase the diversity of recommendations with minimal accuracy loss or to increase both diversity and accuracy [1],[2],[5],[12].

VI. **Recommendation Ranking Approaches**

1). Incorporating multi-criteria rating information to improve recommendation accuracy this is carried out by using a similarity based approach to extending standard collaborative filtering techniques [2] and aggregation function based approach [1].

2). Heuristics based ranking approach to improve aggregate recommendation diversity is carried out using some Re-ranking techniques such as standard ranking approach [1],[2], item-popularity based ranking [1], controlling the accuracy-diversity tradeoff i.e. parameterized ranking approaches [2].

3). Optimization-based approaches to maximize aggregate recommendation diversity are achieved using following few techniques namely: greedy approach for diversity improvement [1],[10], max-flow based approach for diversity maximization [1], integer programming approach for diversity maximization approach [1].

4). Exploring combined approaches to overcome the accuracy-diversity tradeoff could be achieved using multi-criteria rating information technique for accurate recommendations[1],[2], ranking based approach for diverse recommendations [1],[2].

VII. CONCLUSION

One of the important goals of recommender systems is to recommend to truly like individual users what they would i.e. using different recommendation techniques in order to bring accurate recommendations. Many recommendation algorithms are designed to improve this recommendation accuracy. However, the goal of improving recommendation diversity, which can benefit both individual users, business applications, online content providers and retailers, has been largely ignored in recommender system literature. Thus, we need to explore more towards developing new techniques that can improve both accuracy and diversity by augmenting traditional recommendation techniques. All of the proposed approaches in this paper are general and flexible in that they can build upon a wide variety of existing recommendation techniques.

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REFERENCES

[1] G. Adomavicius and A. Tuzhilin, “Toward the Next Generation of Recommender Systems: A Survey of the State-of-the-Art and Possible Extensions,” *IEEE Trans. Knowledge and Data Eng., vol. 17, no. 6, pp. 734-749, June 2005.*
[2] R. Bell, Y. Koren, and C. Volinsky, “The BellKor Solution to the Netflix Prize,” www.netflixprize.com/assets/ProgressPrize KorBell.pdf, 2007.
[3] C. Anderson, The Long Tail. Hyperion, 2006
[4] S. Breese, D. Heckerman, and C. Kadie, “Empirical Analysis of Predictive Algorithms for Collaborative Filtering,” *Proc. 14th Conf.Uncertainty in Artificial Intelligence, 1998.*
[5] R.M. Bell, Y. Koren, and C. Volinsky, “The Bellkor 2008 Solution to the Netflix Prize,” http://www.research.att.com/~volinsky/ netflix/ProgressPrize2008BellKorSolution.pdf, 2008.
[6] J. Bennett and S. Lanning, “The Netflix Prize,” Proc. KDD-Cup and Workshop at the 13th ACM SIGKDD Int’l Conf. Knowledge and Data Mining, 2007.
[7] D. Billsus and M. Pazzani, “Learning Collaborative Information Filters,” Proc. Int’l Conf. Machine Learning, 1998.
[8] S. Zhang, W. Wang, J. Ford, F. Makedon, and J. Pearlman, “Using Singular Value Decomposition Approximation for Collaborative Filtering,” *Proc. Seventh IEEE Int’l Conf. E-Commerce Technology (CEC ’05), pp. 257-264, 2005.*
[9] W. Knight, “Info-Mania’ Dents IQ More than Marijuana.”.NewScientist.comNews, *http://www.newscientist.com/article.ns?id=dn7298, 2005.*
[10] Y. Koren, “Collaborative Filtering with Temporal Dynamics,” Proc. 15th ACM SIGKDD Int’l Conf. Knowledge Discovery and Data Mining, pp. 447-456, 2009.
[11] B.M. Sarwar, G. Karypis, J. Konstan, and J. Riedl, “Analysis of Recommender Algorithms for E-Commerce,” Proc. ACM Conf. Electronic Commerce, pp. 158-167, 2000

