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Recommendation Diversity using Optimization Techniques and Ranking Method

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Abstract— ***Recommender systems is becomes popular and used in many fields for gathering the information based on the user requirements. It is mainly used to help the user for accessing the process based on the relevant information. Many framework for recommendation systems based on the different algorithms are revolve around the concept of accuracy only but other important feature such as diversity of the recommendations are unnoticed. In this paper efficient optimization technique along with the novel ranking technique is proposed for providing more diverse recommendations by satisfying the requirements recommendation features. The proposed algorithm is compared with the existing item based ranking technique and simulated with many real world data sets.***

Keywords: Recommender systems, Collaborative filtering, Optimization technique, Novel ranking technique.

1. Introduction

Shoppers today face an unclear array of selection, whether they are shopping online, or at a store. To assist shoppers cope with all of these decisions, online merchants have deployed recommender systems that guide people toward products they are more likely to find interesting [1, 2].Recommender systems ([3],[4]) have been heralded as potentially powerful solutions to the ubiquitous information overload problems that plague the citizens of our online world. Users are finding it more and more difficult to access the right information at the right time by standard means, such as search engines, and this limits their ability to profit fully from the online rotation. Recommender systems try to solve this problem by offering a more intelligent and personalized way for users to seek out new information more quickly and easily. Many of these online recommender systems works by suggesting products that addition products people have purchased in the past. Others counsel products that complement those in their shopping cart at checkout time. If you have ever purchase a book at Amazon.com, or payment a movie from Netflix, you have probably used a recommender system. This diversity problem is a recognized shortcoming of content-based recommendation techniques ([10],[11]). A common solution is to consider alternative recommendation techniques that are less susceptible to the diversity problem. For example, PTV operates within the TV listings domain, recommending TV programs to users based on their learned viewing preferences [11]. PTV combines case-based recommendation with collaborative filtering in order to help guarantee a diverse set of recommendations. Similarly, CASPER [10], a job recommender system enhances a standard set of retrievals by using collaborative-filtering and client side personalization. Recommender systems have been accepted as a vital application on the Web by offering product advice or information that users might be interested in [12]. Most research up to this point has focused on improving the accuracy of recommender systems. In this paper we tend to argue that recommendation list diversification is also important in promoting user's satisfaction for the user's multiple interests, and propose a unique recommendation algorithm which aims to balance the recommendation accuracy and diversity by choosing diverse neighbors in trust based recommender systems. A series of experiments show that the rule will improve the recommendation diversity.

Recommender systems have emerged in the past several years as an effective way to help people cope with the problem of information overload [13]. Most research up to this point has focused on improving the accuracy of recommender systems. However, considering the vary of userpsilas interests lined, recommendation diversity is also important. In this paper we tend to propose a novel topic diversity metric which explores hierarchical domain knowledge, and valuate the recommendation diversity of the two most classic collaborative filtering (CF) algorithms with Movielens dataset.

Recommender system is one of the most effective technologies to alter info overload, which has been used in a lot of business systems. Traditionally, many recommender systems take a lot of specialize in prediction accuracy [14]. However, despite their pretty accuracy, they will not be helpful to users. A user's preference is filled with uncertainty, as well as randomness and fuzziness. Sadly, a hard and fast Top-N recommendation list certainly cannot describe these styles of uncertainty that has leaded a decline of user satisfaction. Cloud Model may be a powerful tool to explain uncertainty of data. In this paper, we tend to use Cloud Model to present user's preference and propose a improved user-based Top-N recommendation algorithm. Our experimental evaluation shows that our proposed algorithm can improve the diversity of recommendation list compared with the typical user-based collaborative filtering.

Personalized recommendation is effective to produce smart recommendations to totally different users to satisfy different wants [15]. However, it remains a challenge to create customized recommendation sensitive to the linguistics info of a user's specific context and to the dynamical of user interests over time. A user interest model supported user interest metaphysics is planned during this paper. The incrementally change algorithmic program of user interest model is represented supported Spreading Activation Theory. Victimization the metaphysics user interest model, the advice method is given well. Victimization Movie rating knowledge from Movielens, we tend to demonstrate that this recommendation algorithmic program offers improved customized recommendation performance, along side measures of MEA, diversity and cold-start performance. Finally, the steadiness of user interest model is analyzed.

In this paper, we tend to gift a hybrid recommendation approach for locating potential preferences of individual users. The planned approach provides a versatile answer that includes flat cluster into a cooperative filtering recommendation model to produce a high quality recommendation [16]. This facilitates to get user clusters that have various preferences from multi-view for rising effectiveness and variety of advice. The given algorithmic program works in 3 phases: knowledge preprocessing and flat cluster, selecting the acceptable clusters and recommending for the target user. The performance of planned approach is evaluated employing a public movie dataset and compared with 2 representative recommendation algorithms. The empirical results demonstrate that our planned approach is maybe reaching to trade-off on increasing the variety of recommendations whereas maintaining the accuracy of recommendations.

Search queries on massive databases, often return a large number of results, only a small subset of which is relevancy to the user. Once the user need to search the result for a particular query he or she find lot of difficulties when query results are massive in size. To overcome the searching and navigation difficulty the following contributions are made [18]. Design very good user interface to search the query using front end tools like VB.NET and it'll fetch the result from information like SQL SERVER 2005.For customized recommendation system Advanced Encryption Standard algorithm is employed to induce the user feedback in secured format. Query results are organized into a tree format taking tree management. Using many real-world ratings the great empirical evaluation shows diversity gains of proposed techniques. Ranking concept is employed to show the concepts in order based on more number of times that idea is accessed. Edge cut algorithmic program is employed to display the query result mostly related to the user expected ends up in tree format. Graph is generated supported spatial attributes. Ranking and categorization, which may even be combined, are planned to alleviate this data overload downside.

Recommender systems are becoming increasingly important to individual users and businesses for providing personalized recommendations [19]. However, while the majority of algorithms proposed in recommender systems literature have focused on improving recommendation accuracy (as exemplified by the recent Netflix Prize competition), another important aspect of recommendation quality, like the range of recommendations, have typically been unmarked. In this paper, we have a tendency to introduce and explore a number of item ranking techniques that can generate substantially more diverse recommendations across all users while maintaining comparable levels of recommendation accuracy. Comprehensive empirical analysis systematically shows the range gains of the proposed techniques using several real-world rating data sets and different rating prediction algorithms.

2. Methodology

2.1. Overview of IWO

Invasive Weed Optimization (IWO) is a meta-heuristic algorithm that mimics the colonizing behavior of weeds. The fundamental characteristic of a weed is that it grows its population entirely or predominantly in a geographically specified area which can be substantially large or small. There are four steps of the algorithm as described below:

Initialization a population: A certain number of weeds are randomly spread over the entire search space (Ddimensional). This primary population of each generation will be termed as$X = \{x_1, x_2, \dots, x_m\}$.

Reproduction: Each member of the population X is allowed to produce seeds within a specified region centered at its own position. The number of seeds produced by $x_i, i \in \{1,2,\dots,m\}$; depends on its relative fitness in the population with respect to the best and worst fitness. The number of seeds produced any weed varies linearly from *min seed* to *max seed* with *min seed* for the worst member and *max seed* for the best member in the population.

Spatial Dispersal: The generated seeds are being randomly distributed over the d-dimensional search space by normally distributed random numbers with zero mean and variance σ^2. However, the standard deviation σ is made to decrease over the generations in the following manner. If $\sigma max\ and\ \sigma min$ are the maximum and minimum standard deviation, then the standard deviation in particular generation (or iteration) is given by, where nmi represents the non-linear modulation index. This step ensures that the likelihood of dropping a seed in a distant area decreases nonlinearly so that the algorithm gradually moves from exploration to exploitation with increasing generations.

$$\sigma_{iter} = \sigma_{min} + \left(\frac{iter_{max} - iter}{iter_{max}}\right)^{nmi} (\sigma_{max} - \sigma_{min})$$

Competitive Exclusion: If a plant leaves no offspring then it might go extinct, otherwise they'd take over the globe. Thus, there's a need of some quite competition between plants to limit the maximum number of plants in a population. Initially, the plants in a colony will reproduce fast and all the produced weeds will be included in the colony, until the number of plants reaches a maximum value of pop_max. From then on, only the fittest plants, among the existing ones and the reproduced ones; are taken in the colony and the steps 1 to 4 are repeated until the maximum number of iterations (or function evaluations) have been reached. So, in every generation the population size must be less than or equal to pop_max. This method is known as competitive exclusion and is a selection procedure of IWO.

2.2. Improved IWO based on hybrid genetic (HGIWO)

In nature, evolution is mostly determined by natural selection, wherever individuals that are better are more likely to survive and propagate their genetic material. The encoding of genetic information is done in a way that admits asexual reproduction which results in offspring's that are genetically identical to the parent. The improved of IWO based on hybrid genetic algorithm refers combination of crossover and mutation thought of genetic algorithm, by the use of the cross factor arises out of solution set on behalf of new species. This process will lead to the population natural evolution as the same later than the previous generation population more adapt to the environment, thus the search to the global optimal solution.

In cross factor method, select half particles whose fitness value are higher directly go into the next generation, at the same time use the fitness good first half the particle's position and speed vector replace fitness the lower half of the particles, and keep the latter vector corresponding individual extreme unchanged. In cross mechanism, h Half after particles As to cross factor random combination pairing, the same crossover operation produce offspring as genetic algorithm, and generate offspring, and compare with father generation, half particle which fitness value is better go into the next generation. Thus, through the cross can increase the diversity of particles jumping out of the local optimum, at the same time, can increase convergence speed. In conclusion, this paper proposed an improved IWO algorithm, it is described as below

1. Generate random plants of *N*0 individuals from the set of feasible solutions
2. $i := 1$
3. Do

a. Compute maximum and minimum fitness in the colony.

b. For each individual $w \in W$

   I. Compute the number of seeds for w, corresponding to its fitness.

   II. Randomly select the seeds from the feasible solutions around the parent plant (w) in a neighborhood with normal distribution, the seed number is determined as Fig 1.

   III. Add the generated seeds to the solution set, W.

   IV. For that parent plant whose seeds number is limited to zero, select corresponding number of generated seeds to do hybrid operation.

$$seed(x) = P \times Parent(x) + (1.0 - p) \times Parent(x)$$

Where P is random value between 0 and 1. Add the generated seeds to the solution set, again.

c. If total number exceeds $pmax$.
   I. Sort the population N in descending order of their fitness.
   II. Truncate population of weeds with smaller fitness until $N = P_{max}$.

d. $i = i + 1$

4. Repeat 3 until the maximum number of iterations.

The main idea of these works is that not only incorporating demographic information of users in profile matching process of CF-based algorithms is important weighting should be assigned to these features including rating feature the motivation behind this idea is that "different users place different importance or priority on each feature of the user – profile. For example if a male user prefers to be given recommendations based on the opinions of the other men then his feature weight for gender would be higher than other features"[20].

Here we apply improved invasive weed optimization (IIWO) algorithm [21] for the same purpose with some little changes in selecting the potential similar users as described in the previous sub section and in the evaluation criteria.

After the optima weights have been found the two profiles are compared according to equation based on the Euclidean distance of the two profiles.

$$dist(u,v) = \sqrt{\sum_{i=1}^{z}\sum_{f=1}^{n} w_f * diff_{i,f}(u,v)^2}$$

Where

U is the test user and v is the user who may be a neighbor of user $u(u \neq v)$.

Z is the number of common items which both users have rated.

w_f is the test users weights for feature f.

$diff_{i,f}(u,v)^2$ is the difference in profile value for feature f between users u and v on the item i.

After calculating the distance each test user with all users like standard user based Pearson algorithm the most similar users are selected for generating recommendations for the test user. The most diverse users can be selected by choosing the k top nearest users or by choosing those who have a distance less than a specified threshold. In this work we selected users based on the second approach considering all users who have the distance less than half of the average distance of all the users to the test user as similar user to this user.

2.3 Ranked explore and commit

The first algorithm we present is a simple greedy strategy that assumes that user interests and documents do not change over time. As we will see, after T time steps this algorithm achieves a payoff of at least $(1 - 1/e - \epsilon)OPT - O\left(k^3 n/\epsilon^2 \ln(k/\delta)\right)$ with probability at least $1 - \delta$. OPT denotes the maximal payoff that could be obtained if the click probabilities p_{ti} were known ahead of time for all users and documents, and $(1 - 1/e)OPT$ is the best obtainable polynomial time approximation [22].

As described in Algorithm 1, Ranked Explore and Commit (REC) iteratively selects documents for each rank. At each rank position i, every document d_j is presented a fixed number x times, and the number of clicks it receives during these presentations is recorded. After nx presentations, the algorithm permanently assigns the document that received the most clicks to the current rank, and moves on to the next rank.

Algorithm 1 Ranked Explore and Commit

1. Input : Documents $(d_1, \dots, d_n)$ parameters ϵ, δ, k.
2. $x \leftarrow \lceil 2k^2/\epsilon^2 log(2k/\delta) \rceil$
3. $(b_1, \dots, b_k) \leftarrow k\ arbitrary\ documents$
4. $for\ i = 1 \dots .k\ do$
5. $\forall j.p_j \leftarrow 0$
6. $for\ counter = 1 \dots x\ do$
7. $for\ j = 1 \dots .n\ do$
8. $b_i \leftarrow d_j$
9. Display $\{b_1, \dots, b_k\}$ to user; record clicks
10. If user clicked on b_i then $p_j \leftarrow p_j + 1$
11. End for
12. End for
13. $j^* \leftarrow argmax_j p_j$
14. $b_i \leftarrow d_{j^*}$
15. End for

2.4 Data

The proposed recommendation ranking approaches were tested with several movie rating data sets, including MovieLens (data file available at grouplens.org), Netflix (data file available at netflixprize.com), and Yahoo! Movies (individual ratings collected from movie pages at movies. Yahoo.com). We tend to preprocessed every data set to include users and movies with significant rating history, that makes it possible to have sufficient number of highly predicted items for recommendations to each user (in the test data). The basic statistic information of the resulting data sets is summarized in Table 1. For every data set, we randomly chose 60 percent of the ratings as training data and used them to predict the remaining 40 percent (i.e., test data).

3. Experiment results and evaluation

In this section, we have a tendency to present hardiness analysis of the proposed techniques with respect to several parameters: number of neighbors used in heuristic-based CF, number of features used in matrix factorization CF, number of top-N recommendations provided to each user, the value of predicted rating threshold, and the level of data sparsity.

We tested the heuristic-based technique with a different number of neighbors (15, 20, 30, and 50 neighbors) and the model-based technique with a different number of features ($K = 8, 16, 32, \text{and } 64$).The different parameter values may result in slightly different performance (as is well known in recommender systems literature), the elemental behavior of the proposed techniques remains robust. In another words, using the recommendation ranking techniques with any of the parameter values, it's possible to get substantial diversity improvements with only a small accuracy loss.

We also vary the number of top-N recommendations provided by the system. Note that, where it's intuitively clear that top-1, top-5, and top-10 recommendations can provide different accuracy and diversity levels (i.e., it's lot of easier to accurately recommend one relevant item than relevant ten items, and it's lot of easier to have more aggregate diversity when you can provide more recommendations), once more we have to observe that, with any number of top-N recommendations, the proposed techniques exhibit strong and consistent behavior, i.e., they permit to obtain substantial diversity gains at a small accuracy loss.

In addition, our finding that the proposed ranking approaches help to improve recommendation diversity is also robust with respect to the "highly predicted" rating threshold value. In particular, with a different threshold, the baseline recommendation accuracy and diversity of the standard ranking approach can be very different, and the no. of actual recommendations that are produced by the system (i.e., in case there is a limited number of items that are predicted higher than the minimum threshold) might modification. However, once more we have to observe the same consistent ability of the proposed ranking approaches to achieve substantial diversity gains with only a small accuracy loss. Also note that there is an implicit natural assumption of recommender systems selectivity that is associated with some ranking approaches, i.e., the assumption that recommender systems will use some reasonably high value of threshold value which substantially narrows the set of possible recommendations to only the relevant items for each user. If recommender systems aren't selective (i.e., if a huge number of items are considered relevant to each user), then proposed ranking approach (such as based on reverse predicted rating value) would retain better ability to provide more aggregate diversity in recommendations than non personalized re-ranking approaches (such as based on item popularity).

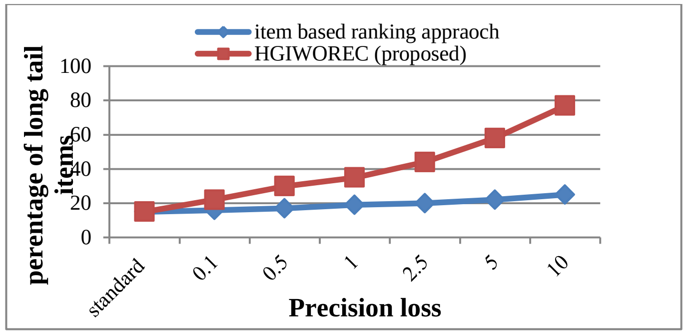

Fig.1. Proportion of long-tail items among recommended items. Note: Percentage of Long-Tail Items = Percentage of recommended items that are not among top-20 percent most popular items. Since recommendation diversity is measured by using the total number of distinct items that are being recommended across all users, one might probably argue that, whereas the variety are often simply improved by recommending a few new items to some users, it should not be clear whether the proposed ranking approaches would be able to shift the overall distribution of recommended items toward additional individual, "long-tail" recommendations. Therefore, in this section, we have to explore how the proposed ranking approaches change the actual distribution of recommended items in terms of their popularity. Following the popular "80-20 rule" or the economic expert principle, we define the top-20 percent of the most frequently rated items in the training data set as "bestsellers" and the remaining 80 percent of items as "long-tail" items. We have to calculate the percentage of long-tail items among the items recommended across all users by the proposed ranking approaches as well as by the standard ranking approach. The results are shown in the above graph.

Finally, the data sets we used for our experiments were obtained using a specific sampling (preprocessing) strategy by selecting items and users with largest number of ratings, which resulted in relatively dense rating data sets. Thus, for robustness analysis, we have to generated sparser data sets from the initial MovieLens data set by applying different sampling strategies that have been used in prior literature [23].

5. Comparative study

Figure 2: Performance Comparison

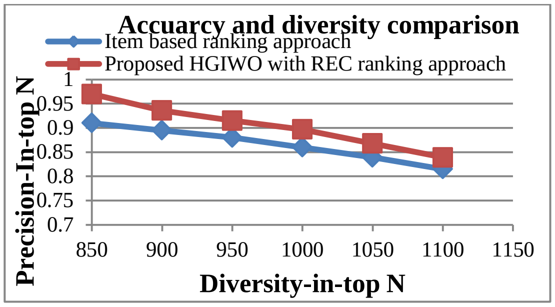

Table 1: Performance Comparison

Diversity in Top-N	Item based ranking approach	Proposed HGIWO with REC ranking approach
850	0.91	0.97
900	0.895	0.936
950	0.88	0.915
1000	0.86	0.897
1050	0.839	0.868
1100	0.815	0.839

As Table 1 and Fig. 2 demonstrate, item popularity- based ranking approach and Ranked Explore and Commit are compared with each other. The ranks explore and commit outperforms by ranking the high recommendation. The graph depicts that the accuracy and diversity of both ranking are compared and the proposed ranking approach increased the recommendation accuracy by 5.2 percent and diversity by 8.2 percent.

5. Conclusion

The user requirements are most important factor in the development of the business. Many methods are used to satisfying the user requirements. Recommender system is one of the important methods in satisfying the user requirements and many algorithms are proposed for improving the recommendation quality. The item based ranking technique is also one of the existing methods. Although the item based ranking method improves the quality, the obtained results in the recommender system are not efficient one. In this paper proposed algorithm is the combination of optimization algorithm and novel ranking technique. The proposed algorithm in this paper is focused on the certain features of the recommender systems such as accuracy and diversity of the recommendations. The real world datasets is used for the simulation of the proposed recommender system and it is compared with the existing system.

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