Improving an aggregate recommendation diversity Using ranking-based tactics

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Abstract: The importance of Recommender systems is becoming more and more to single users and mluti users by providing personalized recommendations. Many of the algorithms proposed in recommender systems literature have been concentrating on improving the recommendation efficiency rate and other important issues of recommendation quality like diversity of recommendations, etc have been discussed. Trough this paper, we make you aware of various item ranking techniques that will generate recommendations which have considerably higher aggregate diversity over all users while maintaining comparative-levels of recommendation accuracy. Comprehensive empirical evaluation uniformly indicates the diversity in improving the proposed techniques by using several real-world rating datasets and rating prediction algorithms.

I. INTRODUCTION

For providing recommendations to each user, recommender systems generally perform two tasks:

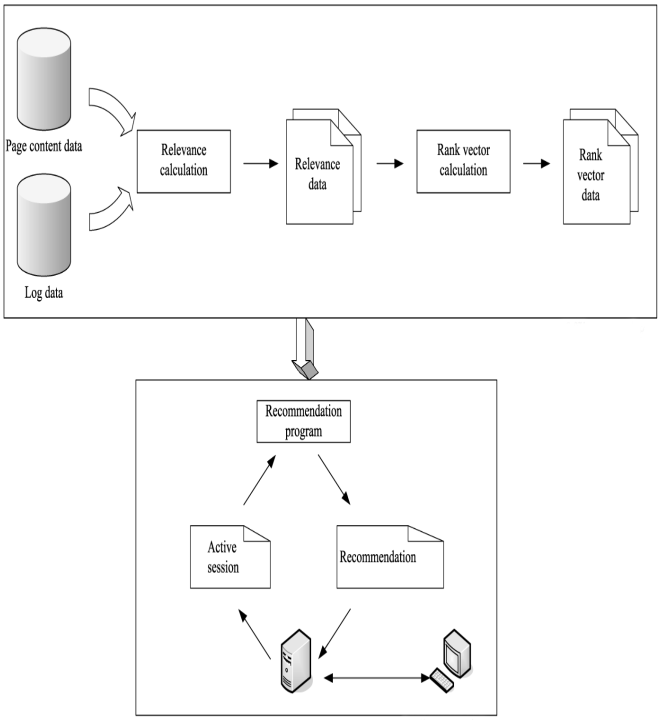
- Unrated item's rating is estimated by using some recommendation algorithm based on known user ratings information and also content information about the item (i.e. user demographics).
- The items that maximize the user's utility are found by the system depending on pre-predicted ratings and then it recommends them to user.

For improving the recommendation diversity as mentioned in the second task of finding best items for each user, various ranking approaches are proposed in this paper.

The awareness regarding the importance of aggregate diversity for recommender systems is growing. As discussed earlier, there has been a significant amount of work done on improving individual diversity (the issue of aggregate diversity) in recommender systems has been largely untouched. The current system using statistical accuracy metrics to provide relevant data. The complexity in finding the relevant content is increasing day by day. By using statistical accuracy metrics .So the main advantage of present system is that it is extremely efficient, as it is based on scalable sorting-based heuristics that take decisions based on the “local” data (i.e., information of each individual user) that doesn't need tracking of the “global” information (i.e., items recommended by many users).

Recommender systems or **recommendation systems** are a subclass of information filtering system that seek to predict the 'rating' or 'preference' that a user would give to an item (such as music, books, e commerce applications). Now a day's recommender system place a vital role to find out the user information germane data and recommender systems technologies have been introduced to help people deal with the vast amounts of information.

II. ARCHITECTURE



In general, Ranking is defined as a relation between a set of items among which the first is either ranked ">"(greater than), ranked "="(equal) or ranked "<"(less than) the second. Mathematicians define Ranking as a weak order of objects or preorder of objects. It is not compulsory a total order of objects because two different objects can have the same ranking. The rankings are totally ordered. For example, materials are totally

preordered by hardness, while degrees of hardness are totally ordered. By reducing detailed measures to a sequence of ordinal numbers, rankings make it possible to evaluate complex information according to certain criteria. Thus, for ex; an Internet search engine can rank the WebPages that it finds according to an estimation of their relevance, making it possible for the user quickly to select the pages they are likely to want to see.

Strategies

It is not always possible to assign rankings uniquely. For example, in a race or competition two (or more) entrants might tie for a place in the ranking. When computing an ordinal measurement, two (or more) of the quantities being ranked might measure equal. In these cases, one of the strategies shown below for assigning the rankings may be adopted. A common shorthand way to distinguish these ranking strategies is by the ranking numbers that would be produced for four items, with the first item ranked ahead of the second and third (which compare equal) which are both ranked ahead of the fourth.

III. SYSTEM DESIGN:

There are different schedules, such as

1. Establishing the opinion:

In this module, we get the opinions from various people about business, e-commerce and products through online. The opinions may be of two types. Direct opinion and Provisional opinion. Direct opinion is to post a comment about the components and attributes of products directly. Provisional opinion is to post a comment based on metaphorical of two or more products. The examination may be positive or negative.

2. Approbation Technique:

However, the quality of endorsements can be evaluated along a number of dimensions, and expect on the accuracy of recommendations alone may not be enough to find the most consistant items for each user, these studies argue that one of the goals of recommender systems is to provide a user with highly personalized items, and more diverse approbations result in more opportunities for users to get recommended

such items. With this motivation, some studies proposed new recommendation methods that can increase the diversity of recommendation sets for a given individual user. They can give the feedback of such items.

3. Rating Prophecy:

It starts with the rating of unrated items that are estimated depending on the available information (i.e., typically using known user ratings and information about item content) using some recommendation algorithm. Analytical techniques typically calculate recommendations based directly on the previous user activities. For each user, ranks all the predicted items according to the predicted rating value ranking the candidate (highly predicted) items based on their predicted rating value, from lowest to highest (as a result choosing less popular items).

4. Ranking Admittance:

Ranking items according to the rating variance of neighbors of a particular user for a particular item . There exist a number of different ranking approaches that can improve recommendation diversity by recommending items other than the ones with topmost predicted rating values to a user. A comprehensive set of experiments was performed using every rating prediction technique in conjunction with every recommendation ranking function on every dataset for different number of top-N recommendations.

IV. SYSTEM IMPLEMENTATION

Implementation is one of the stages of the project. In implementation stage the theoretical design is turned into a working system. Hence it could be considered that the most critical stage in achieving a successful and new system in giving user the confidence that the new system will work effectively.

The implementation stage involves a proper and careful planning, investigation related to the existing system and it's constraints (i.e., considerations) on implementation, designing of methods for achieving the changeover and evaluation of changeover methods. Implementation is the process of converting a new system design into operation. It is the phase that focuses on user training, site preparation and file conversion for installing a candidate system. The important factor that should be considered here is that the conversion should not disrupt the functioning of the organization.

ADVANTAGES

Unauthorized access to this information can be restricted by using symmetric cryptography algorithm. Asymmetric cryptography algorithm can be used for Authenticating. A patient's information can be accessed by patient him/her self and respective Doctor only.

V. RELATED WORK

Novelty and Diversity in Endorser Systems

Novelty and diversity are different though related notions. The novelty of a piece of information generally refers to how different it is with respect to "what has been previously seen", by a specific user, or by a community as a whole. Diversity generally applies to a set of items, and is related to how different the items are with respect to each other. This is related to novelty in that when a set is diverse, each item is "novel" with respect to the rest of the set. Moreover, a system that promotes novel results tends to generate global diversity over time in the user experience; and also enhances the global "diversity of sales" from the system perspective. Another fundamental take on diversity is defined in ad-hoc IR in terms of query interpretations or aspects. The adaptation of this perspective to a recommendation task certainly deserves investigation. For reason of available space, we leave it aside in the present paper, and we only discuss here –besides novelty itself– notions of diversity that result from a novelty model, as we shall see. Moreover, we focus on novelty and diversity as perceived by the end-user, i.e. we do not cover here the system or the business perspective. Finally, we assume an application scenario where the items that the user has already chosen in the past are not recommended again leaving out scenarios such as recommendation for grocery shopping (where the same products are bought periodically), or personalized music playlist generation (where it is generally ok to recommend known music tracks). We distinguish two main notions upon which recommendation novelty and diversity can be defined: item popularity and similarity. Recommendation novelty and diversity can be modeled upon the novelty and dissimilarity of recommended items, which in turn we formalize in terms of user-item interaction models, and distance functions. Novelty and diversity can be measured generically, that is, irrespective of

the user they are delivered to, or they can actually take into account the target user. In a generic approach, the diversity in a list of items can be measured, for instance, in terms of the objective variety of items in the list (e.g. as pair wise dissimilarity), and novelty can be defined in terms of how many users are familiar with the items. In a user-relative approach, novelty can take into account what the specific target user has already seen, and diversity can consider the variety of interests within his individual user profile. Metrics may just analyze the composition of recommended lists, or they may also take into account that the top positions have a higher impact on the effective diversity and novelty value of the list. A metric may strictly focus on novelty, leaving relevance for a complementary metric to capture it, or actually require items to be relevant for their novelty to be counted in. Which among all such variants is more appropriate depends on the evaluation goals and requirements, the specifics of the recommendation task and/or the application domain.

In real world settings, recommender systems generally perform the following two tasks in order to provide recommendations to each user. First, the ratings of unrated items are estimated based on the available information (typically using known user ratings and possibly also information about item content or user demographics) using some recommendation algorithm. And second, the system finds items that maximize the user's utility based on the predicted ratings, and recommends them to the user. Ranking approaches proposed in this paper are designed to improve the recommendation diversity in the second task of finding the best items for each user.

Data mining (the analysis step of the "Knowledge Discovery in Databases" process, or KDD), an interdisciplinary subfield of computer science, is the computational process of discovering patterns in large data sets involving methods at the intersection of artificial intelligence, machine learning, statistics, and database systems. The overall goal of the data mining process is to extract information from a data set and transform it into an understandable structure for further use. Aside from the raw analysis step, it involves database and data management aspects, data pre-processing, model and inference considerations, interestingness metrics, complexity considerations, post-processing of discovered structures, visualization, and online updating.

The term is a buzzword, and is frequently misused to mean any form of large-scale data or information processing (collection, extraction, warehousing, analysis, and statistics) but is also generalized to any kind of computer decision support system, including artificial intelligence, machine learning, and business intelligence. In the proper use of the word, the key term is discovery[citation needed], commonly defined as "detecting something new". Even the popular book "Data mining: Practical machine learning tools and

techniques with Java" (which covers mostly machine learning material) was originally to be named just "Practical machine learning", and the term "data mining" was only added for marketing reasons. Often the more general terms "(large scale) data analysis", or "analytics" – or when referring to actual methods, artificial intelligence and machine learning – are more appropriate.

The actual data mining task is the automatic or semi-automatic analysis of large quantities of data to extract previously unknown interesting patterns such as groups of data records (cluster analysis), unusual records (anomaly detection) and dependencies (association rule mining). This usually involves using database techniques such as spatial indices. These patterns can then be seen as a kind of summary of the input data, and may be used in further analysis or, for example, in machine learning and predictive analytics. For example, the data mining step might identify multiple groups in the data, which can then be used to obtain more accurate prediction results by a decision support system. Neither the data collection, data preparation, nor result interpretation and reporting are part of the data mining step, but do belong to the overall KDD process as additional steps.

The related terms data dredging, data fishing, and data snooping refer to the use of data mining methods to sample parts of a larger population data set that are (or may be) too small for reliable statistical inferences to be made about the validity of any patterns discovered. These methods can, however, be used in creating new hypotheses to test against the larger data populations.

V. CONCLUSION

The use of mobile healthcare systems we will be able to increase the prosperities to patients by providing better quality of patient care with reduced authenticative and medical costs. The question of security has raised interesting research issues related to wireless and normal healthcare networks. Here, we introduce the tactics of trust evaluation with a demoralized trust management authority and we are also proposing a novel trust evaluation model that will efficiently calculate the trust-worthiness of mobile healthcare devices and dynamically manages the medical nodes. Furthermore, we provide a secure multicast mechanism based on the trust evaluation model (that we mentioned earlier), which offers you a flexible protection to dynamic and agile environments and also it improves the security of a pervasive and mobile healthcare system.

The analysis of our experimental results clearly said that, compared to traditional schemes, such as the linear trust computation model or the group-based management system, our trust model can honestly improve the security and accuracy of the network while also reducing the complexity of the traditional trust schemes and thus improving efficiency. Therefore, our trust-based multicast scheme provides an excellent answer for guaranteeing secure and reliable communications in wireless and normal healthcare networks.

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