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ACHIEVING RECOMMENDATION DIVERSITY THROUGH RANKING-BASED TECHNIQUES

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ABSTRACT:

Recommender systems have become progressively vital to individual users and businesses for providing customized recommendations. However, whereas the bulk of algorithms projected in recommender systems literature have centred on rising recommendation accuracy (as exemplified by the recent Netflix Prize competition), alternative vital aspects of advice quality, like the range of recommendations, have usually been unknotted. During this paper, we tend to introduce and explore variety of item ranking techniques that may generate recommendations that have considerably higher mixture diversity across all users whereas maintaining comparable levels of advice accuracy. Comprehensive empirical analysis systematically shows the range gains of the projected techniques victimisation many real-world rating datasets and completely different rating prediction algorithms.

Keywords: aggregate, diversity, datasets.

1. INTRODUCTION:

System Analysis is 1st stage consistent with System Development Life Cycle model. This method Analysis may be a method that starts with the analyst. Analysis may be an elaborated study of the varied operations performed by a system and their relationships inside and out of doors the system. One side of study is shaping the boundaries of the system and deciding whether or not or not a candidate ought to contemplate alternative connected systems. Throughout analysis, information is collected from the obtainable files, call points, and transactions handled by the current system. Training, experience, and customary sense area unit needed for assortment of the data required to try and do the analysis

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EXISTING SYSTEM

Recommender systems are usually classified into three categories based on their approach to recommendation: content based, collaborative, and hybrid approaches.

- Content based recommender systems recommend items similar to the ones the user preferred in the past.
- Collaborative filtering (CF) recommender systems recommend items that users with similar preferences (i.e., “neighbors”) have liked in the past.
- Hybrid approaches can combine content-based and collaborative methods in several different ways.

Recommender systems can also be classified based on the nature of their algorithmic technique into heuristic (or memory-based) and model based approaches.

- Heuristic techniques typically calculate recommendations based directly on the previous user activities (e.g., transactional data or rating values). One of the commonly used heuristic techniques is a neighborhood-based approach that finds nearest neighbors that have tastes similar to those of the target user.
- Model-based techniques use previous user activities to first learn a predictive model, typically using some statistical or machine-learning methods, which is then used to make recommendations. Examples of such techniques include Bayesian clustering, aspect model, flexible mixture model, and matrix factorization.

PROPOSED SYSTEM

In this paper, we explore new recommendation approaches that can increase the diversity of recommendations with only a minimal (negligible) accuracy loss using different recommendation *ranking* techniques. In particular, traditional recommender systems typically rank the relevant items in a descending order of their predicted ratings for each user and then recommend top *N* items, resulting in high accuracy. In contrast, the proposed approaches consider additional factors, such as item popularity, when ranking the recommendation list to substantially increase recommendation diversity while maintaining comparable levels of accuracy. We propose the following ranking system Standard Ranking Approach, Item Popularity-Based Ranking, Reverse Predicted Rating Value, etc.

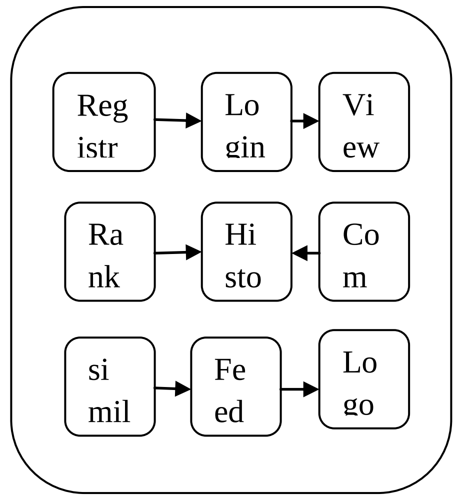

Fig 1: System Architecture

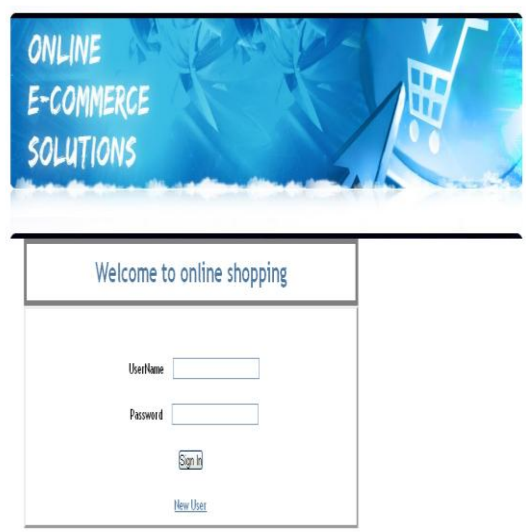

Fig 2: User Login Page

USER:

In this module user can view and purchase products, can also view his purchase history, view ones user profile, can give ranking to a particular product, view the recommendations of all the products, can also give feedback.

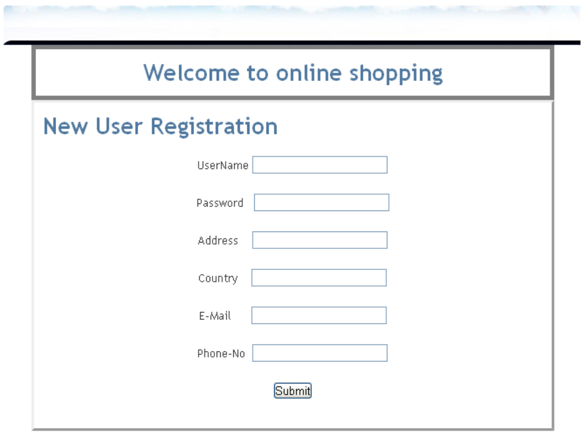

Fig 3: New User Registration Page

ADMIN:

In this module admin will calculate the similarities of two users for a particular product and the similarities between two items can also check the similarities, update the recommendations data.

NEIGHBORHOOD-BASED CF TECHNIQUE:

A neighbourhood-based CF technique can be user-based or item-based, depending on whether the similarity is calculated between users or items.

MATRIX FACTORIZATION CF TECHNIQUE:

It is mainly used to improve accuracy. Many MFCF Tech have been developed to solve the problems of data scarcity, over fitting and converges speed.As users ratings are composed of sum of preferences it induced by singular value decomposition.

ITEM-POPULARITY-BASED RANKING:

Item-popularity-based ranking approach ranks items directly based on their popularity, from lowest to highest, where popularity is represented by the number of known ratings that each item.

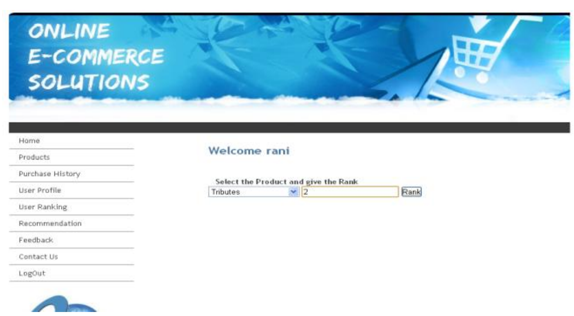

Fig 4: Ranking Page

CONCLUSION:

Recommender systems have made significant progress in recent years and many techniques have been proposed to improve the recommendation quality.

However, in most cases, new techniques are designed to improve the accuracy of recommendations, whereas the recommendation diversity has often been overlooked. In particular, we showed that, while ranking recommendations according to the predicted rating values (which is a de facto ranking standard in recommender systems) provides good predictive accuracy, it tends to perform poorly with respect to recommendation diversity. Therefore, in this paper, we proposed a number of recommendation ranking techniques that can provide significant improvements in recommendation diversity with only a small amount of accuracy loss. In addition, these ranking techniques offer flexibility to system designers, since they are parameterizable and can be used in conjunction with different rating prediction algorithms (i.e., they do not require the designer to use only some specific algorithm). They are also based on scalable sorting based heuristics and, thus, are extremely efficient. We provide a comprehensive empirical evaluation of the proposed techniques and obtain consistent and robust diversity improvements across multiple real-world datasets and using different rating prediction techniques.

FUTURE WORK:

In particular, additional important item ranking criteria should be explored for potential diversity improvements. This may include consumer-oriented or manufacturer oriented ranking mechanisms, depending on the given application domain, as well as external factors, such as social networks. Also, as mentioned earlier, optimization-based approaches could be used to achieve further improvements in recommendation diversity, although these improvements may come with a (possibly significant) increase in computational complexity. Moreover, because of the inherent trade off between the accuracy and diversity metrics, an interesting research direction would be to develop a new measure that captures both of these aspects in a single metric. In addition, user studies exploring users’ perceptions and acceptance of the diversity metrics as well as the users’ satisfaction with diversity sensitive recommender systems would be an important step in this line of research. Finally,exploration of recommendation diversity when recommending item bundles or sequences (instead of individual items) also constitute interesting topics for future research. In summary, we hope that this paper will stimulate further research on improving recommendation diversity and other aspects of recommendation quality.

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