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Recommendation System with Location, Item and Location and Item Mechanisms

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Abstract: Nowadays it is becoming very critical to find the relevant information in online information system, because it is very huge in various parameters like volume, structure etc., One of the solution to extract the useful information is the recommender system. These recommender system widely used in ecommerce website like Amazon, flipkart, ebay etc.,. The literature of recommender system tells that much work done previously, but user requirements changes day by day, so still there is a necessity of new approaches to extract the useful and meaningful information. For this purpose in this paper, we proposed a recommender system that recommends the user based on their searching location, item and location & item.

Keywords: Information; volume; recommender; location; item.

1. INTRODUCTION

Recommender systems predict the ratings of unknown items for each user using other users ratings, and recommend top N items with the highest predicted ratings[1-2]. There are many studies on developing algorithms to improve rating predictions the quality of recommender system is evaluated in many dimensions, and not only the accurate recommendations are sufficient to find most relevant items for users individually. The importance of diversity in recommendations has been investigated several studies. It increases sales by recommending items and it allows users to make decisions such as which item to buy The goal of recommender systems is to provide a user with highly distinct and diverse recommendations to give more options for users to get recommended such items. There is an inverse relationship between accuracy and diversity. Diversity should be increased by having minimal loss in accuracy [3-5]. Recommendation can not only be given to single product, it also allows recommending collection of products [6-7].

2. LITERATURE SURVEY

In this section we presents literature related to recommendation systems.

G. Adomavicius et. al., [8] is a paper on the overview of the field of recommender systems and describes the current generation of recommendation methods that are usually classified into the following three main categories: content-based, collaborative, and hybrid recommendation approaches. This paper also describes various limitations of current recommendation methods and discusses possible extensions that can improve recommendation capabilities and make recommender systems applicable to an even broader range of applications. These extensions include, among others, an improvement of understanding of users and items, incorporation of the contextual information into the recommendation process, support for multcriteria ratings, and a provision of more flexible and less intrusive types of recommendations.

J. J. Levandoski et. al., [9] is a paper on LARS, a location-aware recommender system that uses location-based ratings to produce recommendations. Traditional recommender systems do not consider spatial properties of users nor items, LARS, on the other hand, supports taxonomy of three novel classes of location-based ratings, namely, spatial ratings for non-spatial items, non-spatial ratings for spatial items, and spatial ratings for spatial items. LARS exploits user rating locations through user partitioning, a technique that influences recommendations with ratings spatially close to querying users in a manner that maximizes system scalability while not sacrificing recommendation quality. LARS exploits item locations using travel penalty, a technique that favors recommendation candidates closer in travel distance to querying users in a way that avoids exhaustive access to all spatial items. LARS can apply these techniques separately, or in concert, depending on the type of location-based rating available. Experimental evidence using large-scale real-world data from both the foursquare location-based social network and the Movie Lens movie recommendation system reveals that LARS is efficient, scalable, and capable of producing recommendations twice as accurate compared to existing recommendation approaches.

J. S. Breese et. al., [10] proposes Collaborative filtering or recommender systems which use a database about user preferences to predict additional topics or products a new user might like. In this paper authors describe several algorithms designed for this task, including techniques based on correlation coefficients, vector-based similarity calculations, and statistical Bayesian methods. Authors compare the predictive accuracy of the various methods in a set of representative problem domains. Authors use two basic classes of evaluation metrics. The first characterizes accuracy over a set of individual predictions in terms of average absolute deviation. The second estimates the utility of a ranked list of suggested items. This metric uses an estimate of the probability that a user will see a recommendation in an ordered list. Experiments were run for datasets associated with 3 application areas, 4 experimental protocols, and the 2 evaluation metrics for the various algorithms. Results indicate that for a wide range of conditions, Bayesian networks with decision trees at each node and correlation methods outperform Bayesian-clustering and vector-similarity methods. Between correlation and Bayesian networks, the preferred method depends on the nature of the dataset, nature of the application (ranked versus one-by-one presentation), and the availability of votes with which to make predictions. Other considerations include the size of database, speed of predictions, and learning time.

W. G. Aref et. al., [11] Window operations serve as the basis of a number of queries that can be posed in a spatial database. Examples of these window-based queries include the exist query (i.e., determining whether or not a spatial feature exists inside a window) and the report query, (i.e., reporting the identity of all the features that exist inside a window). Algorithms are described for answering window queries in & Ogr;(n log logT) time for a window of size n x n in a feature space (e.g., an image) of size $T \times T$ (e.g., pixel elements). The significance of this result is that even though the window contains n2 pixel elements, the worst-case time complexity of the algorithms is almost linearly proportional (and not quadratic) to the window diameter, and does not depend on other factors. The above complexity bounds are achieved via the introduction of the incomplete pyramid data structure (a variant of the pyramid data structure) as the underlying representation to store spatial features and to answer queries on them.

J. L. Herlocker et. al., [12] Recommender systems have been evaluated in many, often incomparable, ways. In this article, authors review the key decisions in evaluating collaborative filtering recommender systems: the user tasks being evaluated, the types of analysis and datasets being used, the ways in which prediction quality is measured, the evaluation of prediction attributes other than quality, and the user-based evaluation of the system as a whole. In addition to reviewing the evaluation strategies used by prior researchers, authors present empirical results from the analysis of various accuracy metrics on one con tent domain where all the tested metrics collapsed roughly into three equivalence classes. Metrics within each equivalency class were strongly correlated, while metrics from different equivalency classes were uncorrelated.

3. METHODOLOGY

The purpose of the system is to produce location-aware recommendations using each of the three types of location-based rating within a single frame work. It produces recommendations using spatial ratings for non-spatial items, i.e., the tuple (user, ulocation , rating ,item), by employing a user partitioning technique that exploits preference locality. It produces recommendations using non-spatial ratings for spatial items, i.e., the tuple (user, rating, item, ilocation), by using travel penalty. To produce recommendations using spatial ratings for spatial items, i.e., the tuple (user, ulocation, rating, item, ilocation) it employs both the user partitioning and travel penalty techniques to address the user and item locations associated with the ratings.

We have proposed a location-aware recommender system that uses location-based ratings to produce recommendations. It supports a taxonomy of three novel classes of location-based ratings, namely, spatial ratings for non-spatial items, non-spatial ratings for spatial items, and spatial ratings for spatial items. It exploits user rating locations through user partitioning, a technique that influences recommendations with ratings spatially close to querying users in a manner that maximizes system scalability while not sacrificing recommendation quality. It exploits item locations using travel penalty, a technique that favors recommendation candidates closer in travel distance to querying users in a way that avoids exhaustive access to all spatial items. IT* can apply these techniques separately, or together, depending on the type of location-based rating available. The structure is shown in Figure 1. In this, our system reads the user location, item, based on the location & item recommends the information that most relevant to users query.

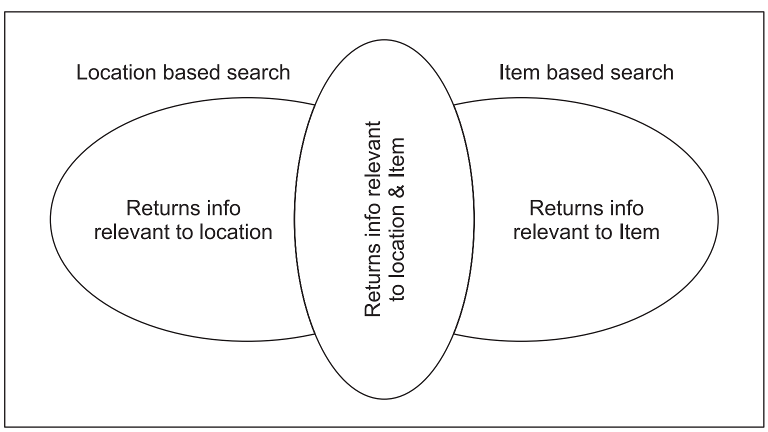

Figure 1: System structure

The most common recommender systems applications include:

- **Entertainment** - recommendations for movies, music, and IPTV.
- **Content** - personalized newspapers, recommendation for documents, recommendations of Web pages, e-learning applications, and e-mail filters.

- **E-commerce** - recommendations for consumers of products to buy such as books, cameras, PCs etc.
- **Services** - recommendations of travel services, recommendation of experts for consultation, recommendation of houses to rent, or matchmaking services.

3.1. Module Description

Our system has three modules namely *Spatial ratings for non-spatial items, Non-spatial ratings for spatial items, Spatial ratings for spatial items*

Spatial ratings for non-spatial items: The idea is to exploit preference locality, i.e., the observation that user opinions are spatially unique. We identify three requirements for producing recommendations using spatial ratings for non-spatial items:

Locality: Recommendations should be influenced by those ratings with user locations spatially close to the querying user location (i.e., in a spatial neighborhood);

Scalability: The recommendation procedure and data structure should scale up to large number of users;

Influence: System users should have the ability to control the size of the spatial neighborhood (e.g., city block, zip code, or county) that influences their recommendations.

Non-spatial ratings for spatial items: The idea is to exploit travel locality, i.e., the observation that users limit their choice of spatial venues based on travel distance. Traditional (non-spatial) recommendation techniques may produce recommendations with burdensome travel distances (e.g., hundreds of miles away). It produces recommendations within reasonable travel distances by using travel penalty, a technique that penalizes the recommendation rank of items the further in travel distance they are from a querying user. Travel penalty may incur expensive computational overhead by calculating travel distance to each item. Thus, we employs an efficient query processing technique capable of early termination to produce the recommendations with-out calculating the travel distance to all items.

Spatial ratings for spatial items: A salient feature of this system is that both the user partitioning and travel penalty techniques can be used together with very little change to produce recommendations using spatial user ratings for spatial items. The data structures and maintenance techniques remain exactly the same as of *Spatial ratings for non-spatial items, Non-spatial ratings for spatial items*; only the query processing frame-work requires a slight modification. The only difference is that the item-based collaborative filtering prediction score P(u,i) used in the recommendation score calculation is generated using the (localized) collaborative filtering model from the partial pyramid cell that contains the querying user, instead of the system-wide collaborative filtering model as was used.

3.2. Result Description

Recommendations generated based on user location that are shown in Table 1, from the Table 1, it is observed that, the user searches for movie theaters, our system read the user location, based on the location, our system recommends the movie theaters in a ranking order with rating.

Recommendations generated based on item location that are shown in Table 2, from the table it is observed that, our system read the item, based on the item, our system recommends items in a ranking order with rating.

Recommendations generated based on location and Items that are shown in Table 3, from the table 3 it is observed that, the user searches for movie theaters, our system read the user location and item, based on the bothe location and item, our system recommends list in a ranking order using rating. Figure 2 shown the information in graphically.

Table 1
Recommendations based on user location

Location	*Type*	*Name*	*Rate*
Rajahmundry	Theater	Anand Regency	3
Rajahmundry	Theater	River Bay	3
Rajahmundry	Theater	Shelton	3
Rajahmundry	Theater	Leela Pavilion	2.5

Table 2
Recommendations based on Item location

Location	*Type*	*Name*	*Rate*
Bhimavaram	Theater	Multiplex	3.5
Bhimavaram	Theater	Vijayalaxshmi	3.5

Table 3
Recommendations based on user & item location

Location	*Type*	*Name*	*Rate*
Bhimavaram	Theater	Multiplex	3.5
Bhimavaram	Theater	Vijayalaxshmi	3.5
Rajahmundry	Theater	Anand Regency	3
Rajahmundry	Theater	River Bay	3
Rajahmundry	Theater	Shelton	3
Rajahmundry	Theater	Leela Pavilion	2.5

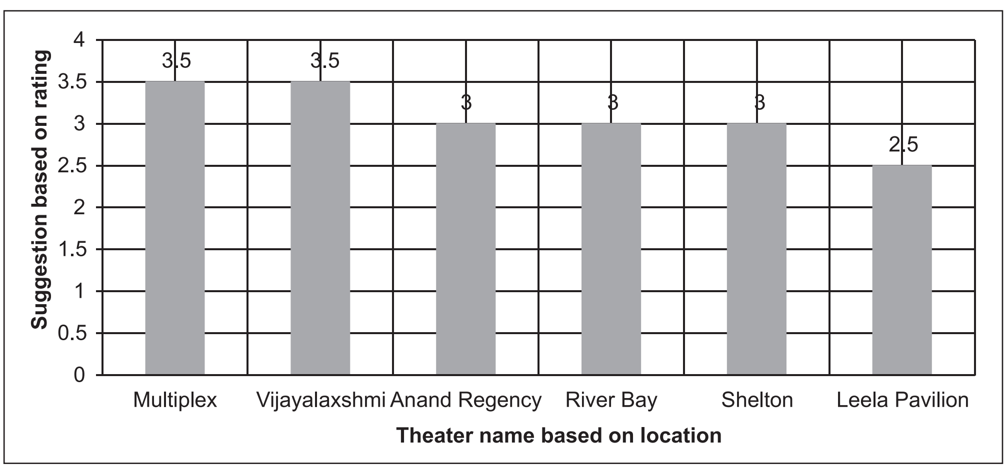

Figure 2: User suggestions

4. CONCLUSIONS

In this paper, we proposed a recommender system with three processes called location, item, both location and item based searches. Experimental analysis using real and synthetic data sets show that this system is efficient, scalable, and provides better quality recommendations than techniques used in traditional recommender systems.

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