



# Improvement of Lars\* by Adopting Travel Penalty Technique

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## Abstract:

*This paper performs operation on the ratings based upon location which is defined as Location Aware Recommender System (LARS\*). It achieves efficiency and performance by adopting the technique of user partitioning methods. It is spatially close to the users who are arising queries. It supports the three main classes such as spatial ratings for non spatial item, non spatial rating for spatial item and spatial rating for spatial item. The item location can be exploited using travel penalty and preference locality. The omitted access of spatial items can be eliminated by using this technique that favours the recommendation closer in travel distance to querying users.*

**Keywords:** Recommender System; Travel penalty; Collaborative Filtering

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## 1. INTRODUCTION

The identification of spatial items from a large search space can be done by using the recommender system by making use of community opinions. Several web services and Amazon uses the concept of Recommender system. The technique called collaborative filtering (CF) which analyzes the past community opinions to find similar users of k personalized items to a querying user. The community opinion allows the users to provide ratings for an item. For instance to access information about the restaurants in website. The users who are accessing the information can allow to implement their ratings. Thus the querying user can easily access the information. It is specifically built in order to provide better efficient result through triples. The triples are user, rating and item. The spatial rating for non spatial item are represented by four tuples such as user, rating, item and ulocation. User location is defined in terms of ulocation. The non spatial rating for spatial item is represented by four tuples such as user, rating, item and ilocation. Item location is defined in terms of ilocation. The spatial rating for spatial item can be represented as five tuples such as user, rating, item, ulocation and ilocation.

## 2. RELATED WORK

Movie Lens and Four square social network based on location are the real world dataset which makes use of the concept of database rating. The MovieLens must atleast contain the ratings of about 87K. The Four Square must contain atleast the rating of about 643K. In the MovieLens the ratings can be collected from U.S

people opinions. The Florida people provides the rating for multimedia is 4.1, for detective stories they provide the rating of about 3.9, for fighting series they provide 3.7. The rating depends upon the average of the opinions. Several countries provide different types of genres. The rating depends upon their location and opinions. In FourSquare the visit of the ratings will be observed. Rosseville provide the preference rating of about 10% and Brooklyn Park provide the rating of about 32%. Based upon the preference of visits the ratings should be collected and displayed to users. The travel distance is defined as the number of users travels over the data. Some users travel over 10 miles of data, while some other users travel 32 miles of data. The ratings are generated based upon the zip codes. For instance, in restaurants the ratings will depend upon the accessed user and item locations.

	Genres of movie	Average rating
Florida	Fighting series	4.1
	Dramatic series	3.6
	Entertainment	5.5
	Multimedia	4.5

## 3. OVERVIEW

The LARS\* is similar to Location Aware Recommender System (LARS). It adopts various location based ratings to generate various level of recommendations through a single framework. It provides the sequential access of queries up to the execution of 500 sequential queries. By using the technique of collaborative filtering it reduces the storage capacity comparing to that of LARS. However it avoids the theoretical splitting used by LARS. Based upon the travel penalty the items are retrieved. Thus it exhibits the better relationship between result accuracy and performance. The collaborative filtering technique can be performed through user queries.

#### 4. BACKGROUND

The travel distance is unknown to the users and the users can access from spatial region. Thus the preference locality and travel penalty techniques are adopted. The recommendations can be generated based upon the querying user  $u$ . The identification of user can be represented by  $U$ , item location is denoted by  $L$  and the limits of the numeric value can be represented by  $K$ . It allows continuous queries and the queries that can either be obtained through snapshots.

#### 5. LOCATION BASED RATINGS

##### A. Preference Locality

The items which are preferred and suggested by the users from a spatial region which is different than that of regular items. LARS uses the technique of preference locality for spatial ratings for non spatial data items. The user partitioning technique makes use of preference locality. However the user partitioning technique improves scalability. The ratings can be partitioned by building the pyramid structure. The structure can be built at various levels of hierarchy at different sizes depends on spatial region. The pyramid structure which maintains two primary factors such as locality and scalability.

##### B. Travel Penalty

Travel penalty is defined a travel locality. It provides information about the travel distance for the querying user. LARS uses the technique of travel locality for spatial ratings for spatial data items. It addresses the user and item location. The LARS\* is completely different than that of LARS. It provides a better way to maintain user partition structure and high locality gain. The user generates the rating through numerical values. The ratings are usually represented in matrix format. The matrix format uses the users and items as

dimensions. It maintains the user splitting structure in an efficient manner, since it reduces the omitted access of spatial items. It easily predicts the user recommendations of data.

#### 6. SYSTEM MODEL

##### A. Query Based Model

The users can be provided with a user id  $U$ , numeric limit  $k$  and location  $l$ . Based upon the location rating it provides recommendations. The recommendation generation phase generates the recommendations. However it supports several techniques such as snapshots and continuous queries. If there was a location changes then the recommendations can be updated by LARS\*. The similarity score can be calculated if there is atleast one matching string exhibits by the same user. The similarity score can be calculated using co-rated matrix. The model can be built by using the similarity scores. The size of the model can be denoted as  $n$ . The list  $L$  is generated by collecting the items which is having the same similarity score with greater score.

##### B. Collaborative Filtering

The collaborative filtering is based on item. This technique assumes there was an  $N$  number of users  $U = \{u_1, u_2, \dots, u_n\}$  and several number of items  $I = \{i_1, i_2, \dots, i_n\}$ . Based upon the querying user, the collaborative filtering provides  $k$  recommended items. The ratings can be represented as a matrix with users and items. To compute similarity, each item is represented as a vector in the user rating space of the rating matrix. The recommendations can be generated based upon the users who are arising queries. The list  $L$  which contains the similarity score items. This huge list can be limited through the user ratings. Thus the collaborative filtering filters the unnecessary items and providing the items related to the query. The similarities can be generated by using the vector matrix. The similarity matrix can be calculated by using the product of the individual vector to the Modulo of the individual vector.

##### • Non Spatial Rating For Non Spatial Item

It is a item based collaborative filtering technique and it makes use of the triple (user, rating and item) as the input. In some cases the location of the item and the location of the user cannot be specified. This can be solved by using the similarity score concept. Between all the items the similarity scores must be calculated. During the recommendation producing phase, the recommendations are produced and generated to the

users. But the location Aware Recommendation system uses the spatial location of item and user. The spatial rating uses the concept of pyramid which is partitioned by memory.

• *Spatial Ratings For Non Spatial Items*

It makes use of the idea of preference locality and the observations are unique. It partitions the user, rating and item based on uolocation attribute. It includes the factors such as locality, scalability and influence. The user locations are nearer to the querying user location are termed as locality. The scalability is defined as the efficiency management even the number of users get increased. The users should have the right to monitor size such as zip codes and block are termed as influence. The collaborative filtering generates personalized user recommendation depends on ratings of a specific spatial region. Even if the demands of several users gets increased it produce scalable results. In some cases based upon the zip code size the ratings can be provided. Hence it generates the result with greater accuracy.

➤ *Pyramid Structure Intuition*

The pyramid can be divided into H-levels. The pyramid covers the entire area through a grid of cells. To attain the highest recommendations the alpha cells are generated. The status of the user and the item can be denoted by beta cells. The lowest cost value should be holded by the gamma cells. If the recommendations gets increased then the beta cells acts as an intermediate between alpha cells and gamma cells. The H-levels are separated into four grid cells such as Recommendation model cell, empty cell and statistic cell. These cells are designed to achieve locality and performance. The pyramid level starts from lowest maintained grid and fills up to the root level. Each cell is a unique identifier. Alpha cells are high recommendation locality where the data partitioning and structure partitioning provide better performance results. The statistics of user, ratings and item can be provided by the statistics cell.

➤ *Query Evaluation*

The continuous query can be solved by finding the lowest maintained alpha cell. The recommended items can be obtained by item based collaborative filtering. The data and the space are partitioned. By using the hashing algorithm, the lowest level of the maintenance of the pyramid can be obtained. If the user ask the queries to the recommendations then the items can be retrieved from the sites and send it back to the user. The

location can be updated based upon the user access of items. The base cell of the pyramid acts as a collaborative filtering based upon the level of influence. Google maps, Facebook uses the concept of query evaluation.

➤ *Data structure Maintenance*

The scalability loss, scalability gain, locality loss and locality gain must be maintained. The spatial region which are huge can be maintained by the large pyramid cells. The full pyramid which maintains the entire statistics of items. The statistics of items can be maintained by constructing the statistics table. The statistics table holds the entire information about the levels of pyramid and its operations. The models can even rebuilt if any fault will occur. The children cell can also be rebuilt.

• *Spatial Ratings For Spatial Items*

It is similar to that of collaborative filtering technique but the only difference is  $P(u,i)$ .  $P(u,i)$  is the recommendation score of the partial pyramid cell that contains the query user. The user partitioning and travel penalty are used in spatial ratings for spatial items. Instead of collaborative filtering model used in wide system, the collaborative filtering of pyramid cell must be easy to obtain.

• *Non Spatial Ratings For Spatial Items*

It is based upon the tuples such as user, rating, item and ilocation. It produces recommendations based upon travel distance on travel penalty. Based upon the travel distance the users limit their choices. The influence level can also allow zoom level on web services. It ensures the early termination of data without travelling over long distances.

## 7. EXPERIMENTAL RESULTS

The data related to location and user can be collected from the people of U.S. In the Foursquare technique the ratings based on location can be collected from user, uolocation, rating, item and ilocation. The rating that can be collected from the user using mapping technique. By using uolocation, the location of the data items can be collected. The ratings that can be allotted based upon the users visit and the preference of the data. If there are multiple ratings then the rating value must be higher. The sparse produces inaccuracy of results. The synthetic dataset collect 5,00,000 ratings from 2000 different users with 1000 different items. However this operation can be performed by building the pyramid

structure of database. It can also makes use of the concept of snapshot queries and sequential queries. In MovieLens using this sparse matrix the accuracy level can be maintained and produce efficient results.

**8. COMPARISON OF LARS AND LARS\***

The advantages of LARS\* was found to be the improvement in scalability and efficiency and building the relationship between spatial data items to the user queries. The storage and the maintenance of the Location Aware Recommender System can be quietly improved through partitioning technique.

	Supportable features of LARS	Supportable features of LARS*
Alpha cell	Yes	Yes
Beta cell	No	Yes
Gamma cell	Yes	Yes
Locality	--	26%higher
Storage	--	38%higher
Maintenance	--	38%higher
Statistics	No	Yes

**9. CONCLUSION**

The drawbacks of traditional recommender can be eliminated by adopting partition methods and travel penalty technique. The sequential queries can be executed in efficient manner and the data structures adopted in this algorithm can be maintained properly without any interruption. The statistics table holds the entire information about the data items. Thus the experimental results prove that the function of Location Aware Recommender System provides greater efficiency and scalability in the location based ratings of spatial items.

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