A Location and Intention Oriented Recommendation Method for Accuracy Enhancement over Big Data

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Abstract. Big data recommendation systems provide recommendations based on user history and optimize this process using feedback information. Recent developments in location-based social networks reveal that spatial properties of users greatly affect their opinion. Traditional location-aware recommendation systems do not consider user intentions to produce personalized recommendations. This paper proposes LIOR, a Location and Intention Oriented Recommendation method that uses spatial properties of users and their intentions to produce personalized recommendations. LIOR hierarchically employs user location and rating information to generate location-aware predictions, it then integrates user intentions to produce highly accurate recommendations. Extensive experimental evaluation performed on a real-world location-aware Movielens dataset demonstrates that LIOR provides exceptional performance on producing recommendations, it is highly scalable, and efficiently reduces the sparsity problem.

Keywords: Intention-oriented recommendation · Location-based clustering · Spatial · Performance improvement

1 Introduction

Recommender systems assist users in finding items of interest from considerably large item space by utilizing community opinion (e.g., Amazon [1], Netflix [9]). Item-based collaborative filtering (CF) is a widely used recommendation technique which analyzes previous public opinions to ascertain underlying similarities between users and items and present top-k item recommendations to a

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target user [14]. Public opinions are usually represented by $(user, item, rating)$ triple which determines how much a user likes or dislikes an item.

In the current context, numerous systems generate location-aware ratings for users or items. For example, current social networks (e.g., Facebook) allow individuals to provide ratings of their visited places (eg., restaurants, cinemas, and parks) and are capable of storing location-aware ratings. Similar users tend to have same preferences, hence, there exists a correlation among similar user preferences and their intentions (e.g., watching a movie, visiting a place) [25]. The location-based ratings and user intentions provoke an interesting phenomena of location and intention-oriented recommendations where the recommender system utilizes spatial properties of users and their intentions while producing recommendations. Current recommendation systems ascertain that ratings are expressed using the $(user, item, rating)$ triple and are not capable of considering location and intention context to produce personalized recommendations [5].

This research proposes LIOR a location and intention-oriented recommendation method to provide highly accurate recommendations. LIOR generates recommendations using two latent information resources including *location* and *intention* represented by a five-tuple $(user, ulocation, uintention, item, rating)$.

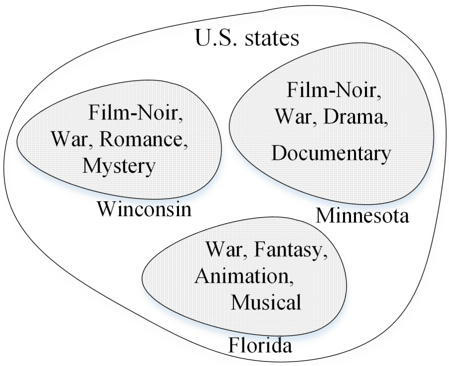

Fig. 1. U.S. states movie preferences in Movielens dataset [16].

The motivation for this research comes by the analysis of a real-world location-aware rating dataset, Movielens [8] and by ascertaining the significance of intentions in endorsing user opinion of doing some business activity (eg., watching a movie, buying a product). We observe two interesting characteristics: locality preferences and intention preferences that stimulate the need for location and intention-oriented recommendations. Locality preferences suggest that users from a specific location (e.g., neighbors) like items (e.g., food, movies, places) that are inherently distinct from people in other spatial regions [16,20,22]. Figure 1 suggest top-4 movie genres in three U.S. states, as all three lists are different, top movie preferences from the state of Florida are vastly disparate from the other states. The “Animation”, “Fantasy”, and “Musical” movie genres of Florida are not present in the preference list of other states. This fact implies that movie preferences are unique in different spatial regions. Intentions determine user's motivation of doing some activity (e.g., watching a movie, buying a product), hence, are a critical component for personalized recommendations. Intention preferences imply that user intentions are influenced by other users having similar taste. To predict user intention for an item, use the opinion of other similar users [25], in this regard, user-based similarity can ascertain current user intentions which can help to produce personalized recommendations in the future.

LIOR provides top-k personalized recommendations in the same way as most of the other traditional recommender systems. However, LIOR is novel because of its characteristic of producing location and intention-oriented recommendations by employing locality preferences and user intentions. LIOR produces initial predictions by exploiting a user clustering strategy based on user preference locality. This technique partitions users on the basis of their location into different regions and use the item-based collaborative filtering technique on segregated users to produce locality-aware recommendations. LIOR then computes user intentions by employing the user-based similarity technique for each target user. We get the final recommendations by aggregating user intention attribute values with the predictions generated by $(user, ulocation, item, rating)$ tuple.

We experimentally evaluate LIOR using real-world location-aware Movielens big dataset by comparing with state-of-the-art location-aware recommendations techniques MLTRS [20], LARS [16], and ULA-LDA [22]. The results demonstrate that LIOR outperforms all these techniques on the basis of Mean Absolute Precision (MAP) and *accuracy* as well as efficiently reduces the sparsity problem. Hence, we propose a location and intention-oriented recommendation method that utilizes user location, intention, and rating information to enhance accuracy in big data service recommendation systems. This research provides the following contributions:

– We model the problem of location and intention-oriented recommendations and prove how intention and location-oriented hierarchical recommendations increase the service recommendation accuracy.
– This research proposes LIOR, a novel big data service recommendation method capable of producing effective recommendations by exploiting user locality preferences, user intentions, and rating information.
– Experimental evidence on a real-world Movielens dataset demonstrates that LIOR outperforms state-of-the-art location-based recommendation techniques as well as it is highly scalable for larger datasets.

Rest of this paper is organized as follows: Sect. 2 provides LIOR problem formulation while Sect. 3 discusses the detailed LIOR method. Section 4 elaborates the experimental evaluation whereas Sect. 5 explains the related work and comparison analysis. Section 6 provides a discussion on the results and finally, Sect. 7 concludes the paper and provides some future insights.

2 Problem Formulation for Location and Intention-Oriented Recommendation

In this section, we formalize the problem and provide preliminary knowledge about LIOR.

Definition 1: Intention Preferences. *The intention preferences denoted by $T_{(ij)}$ of a user u_i for an item/movie i_j is the desire of a user to watch a specific movie.*

In this research, we generate a user-item, intention matrix $T_{m \times n}$ where m is the set of movies and n is the set of users where each entry in T_{ij} contains intention values of the user u_i for the movie i_j in a range of $T_{ij} \in \{0, \ldots, 5\}$ based on a user intention of watching a movie. Higher values of T_{ij} range shows that a user is more inclined towards watching that specific movie. In this way, we extend traditional user-item, rating tuple to $(user, item, rating, uintention)$, where *uintention* is a numerical value, showing the current user's intention.

Definition 2: Locality Preferences. *Locality preferences suggest that users in a spatial geographical location share the same movie preferences as the other users in the same locality that are different from the people living in other regions.*

Locality adds location dimension $(user, ulocation,$ $item,$ $rating)$ in the user-item, rating matrix where user preferences are unique with respect to their locations. The location dimension accompanies a set of hierarchies in terms of the city, state, region, and country which affect user's preferences.

Definition 3: Multi-dimensional Ratings. *It is a set of a user given ratings for items at different levels of the multidimensional cube (e.g., user location) that are a discrete set of ordered numbers used to indicate the intensity of a user likes or dislikes an item in a range of 0–5.*

In this research, we propose that ratings are affected by both location and intention dimensions which extends the traditional user-item rating matrix into a multidimensional cube. We exploit traditional user-item rating matrix to calculate the item similarities and predictions at a specific location.

Definition 4: Locality and Intention-Aware Tuple. *For a user u and item i, locality, and intention-aware tuple is an ordered set of values representing user, ulocation, uintention, item, and rating denoted by a 5-tuple $(user, ulocation, uintention, item, rating)$.*

The traditional user-item, rating tuple is represented by a 3-tuple $(user, item, rating)$, adding location and intention dimension converts it into a 5-tuple represented by $(user, ulocation, uintention, item, rating)$.

This section provides preliminary knowledge involved in the current study including intention and locality preferences, multidimensional ratings, and locality and intention-aware tuple. Next section elaborates the detailed recommendation generation procedure using LIOR.

3 Location and Intention-Oriented Recommendation Method

In this section, we describe how LIOR produces recommendations using location-based user ratings for items and user intentions denoted by the tuple $(user, ulocation, uintention, item, rating)$. We perform the recommendation process in three phases, in the first phase we, exploit locality preferences of the users to produce location-oriented predictions. For this purpose, LIOR employs user clustering strategy to partition $(user, ulocation, item, rating)$ tuple into different regions by utilizing user location attribute $(ulocation)$. Subsequently, we compute recommendations using item-based collaborative filtering on each partitioned cluster using Eqs. 1 and 2. In the second phase, user intentions are computed by employing the user-based collaborative filtering technique where similar users are first identified using Eq. 3, then intention values are computed by employing Eq. 4. In the third phase, we compute recommendations using location and intention preference-aware tuple $(user, ulocation, uintention, rating, item)$. LIOR leverages two main components, locality preferences and intention preferences of spatial users to enhance service recommendation accuracy as defined in the previous section. We explain LIOR components in the following subsections.

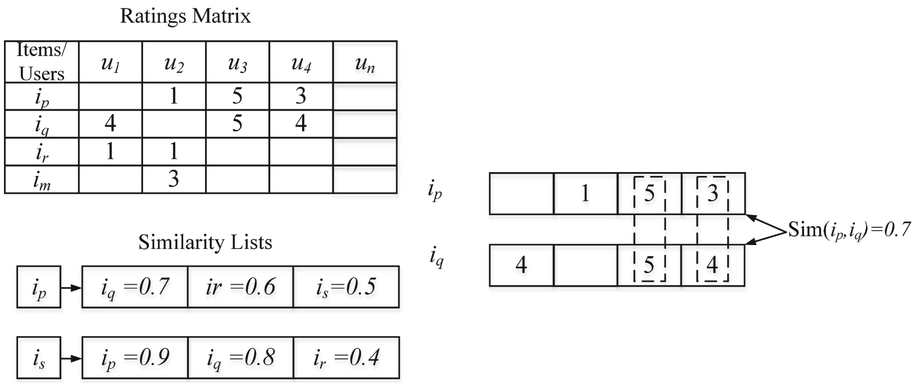

Fig. 2. Item-based similarity computation.

3.1 Item-Based Collaborative Filtering Computation

LIOR utilizes item-based collaborative filtering method to compute recommendations, we chose this technique because it is widely being used in multiple commercial systems [1]. The notion behind item-based collaborative filtering is that similar items will be rated in the same manner by the same users in the future.

Item-based collaborative filtering analyzes a set of n users and m items represented by $U = \{u_1, \ldots, u_n\}$ and $I = \{i_1, \ldots, i_m\}$ respectively. Users express ratings (usually numeric) about a set of items. The ratings are expressed as a matrix $(m \times n)$ where n and m represent dimensions of the matrix. The steps to compute item-based collaborative filtering involve similarity computation and prediction generation.

Similarity Computation. The recommendations are generated in two phases, the initial phase computes similarity $sim(i_p, i_q)$ for the item i_p and i_q which owns minimum one common rating given by the same user. Subsequently, a model is built that stores an ordered list $\mathcal{L}$ of items based on the similarity score of each item i as given in Eq. 1. The recommendations for a specific user u are generated by employing the formula of predicted ratings $(P_{u,i})$ using Eq. 2 for user u on every item i which is not previously rated by u. Prior to similarity computation, each similarity list $\mathcal{L}$ is reduced in a way that it only contains the items that are rated by the target user u.

Figure 2 demonstrates the steps to compute item-based similarity here, the similarity among item i_p and item i_q can be computed by first extracting users who have rated same items and then applying the similarity computation method on the co-rated items. Figure 2 shows the similarity value of 0.7 among i_p and i_q.

Prediction Generation. In the second phase, the predictions are generated by the sum of user u's rating for the item $(l \in \mathcal{L})$ divided by similarity of l for item i, denoted by $sim(i, l)$, where sum of the similarity of i, l is used to normalize the prediction. LIOR uses cosine similarity given in Eq. 1 because of its widespread adoption for similarity computation. The formula for rating prediction is given in Eq. 2. Equations 1 and 2 are derived from [15].

$$sim(i_p, i_q) = \frac{\overrightarrow{i_p} \cap \overrightarrow{i_q}}{||\overrightarrow{i_p}|| * ||\overrightarrow{i_p})||}. \tag{1}$$

$$P_{u,i} = \frac{\sum_{l \in \mathcal{L}} sim(i,l) * r_{u,l}}{\sum_{l \in \mathcal{L}} |sim(i,l)|} \tag{2}$$

Here, $P_{(u,i)}$ is the predicted rating which is the sum of a user u's rating on a similar item i and $r_{u,l}$ is the user u's rating for the item l. Moreover, the weighted sum is normalized by the sum of similarity scores to restrict the predictions within a predefined range. The predicted ratings are arranged according to the prediction score and top-k items are selected for the target user denoted by R_{itemCF}.

3.2 Intention Preferences Generation

LIOR utilizes the fact that similar users share the same item preferences to compute the intention values for the users [25]. To generate intention value for a target user u_i and a movie i_j, we first identify a set of nearest neighbors of u who have watched that specific movie i_j using the adjusted cosine similarity given in Eq. 3. The reason behind using adjusted cosine similarity is that the traditional cosine similarity measurement techniques treat missing values as 0 which produces a non-normalized similarity results. However, adjusted cosine similarity normalizes all the ratings prior to similarity computation. It provides a kind of Bayesian Regularization where the difference in rating scale of different users is normalized. For all the users in the dataset, centering value $\bar{r}$ is produced by computing every user's row mean and subtracting it from his/her rating values as given in Eq. 3. Subsequently, the intention values are generated by a weighted aggregate of the neighbors for the movie that the user have not watched previously using Eq. 4. This process has been performed for all the movies that a user have not watched to generate intention values. We derive Eqs. 3 and 4 from the [14,19] research and extend them for intention generation.

$$w_{(u,v)} = \frac{\sum_{i \in I} (r_{u,i} - \bar{r}_u)(r_{v,i} - \bar{r}_v)}{\sqrt{\sum_{i \in I} (r_{u,i} - \bar{r}_u)^2} \sqrt{\sum_{i \in I} (r_{v,i} - \bar{r}_v)^2}} \tag{3}$$

$$T_{(u,i)} = \bar{r}u + \frac{\sum_{u \in U} (r_{u,i} - \bar{r}_u) w_{(u,v)}}{\sum_{u \in U} w_{(u,v)}} \tag{4}$$

Here, $w_{(u,v)}$ is the adjusted cosine similarity between user u and user v, whereas $r_{u,i}$ and $r_{v,i}$ is the ratings of user u and user v for the movie i respectively. In the same way, $\bar{r}_u$ and $\bar{r}_v$ are the average ratings of user u and user v. $T_{(u,i)}$ is the intention prediction for a target user u for a movie i computed over a set of similar users U. Hence, a user-item intention matrix is generated ($T_{m \times n}$) for all the users n and movies m in the dataset.

3.3 Location-Oriented Recommendations

LIOR employs preferences of spatial users for non-spatial items to produce location-oriented recommendations. Three attributes *locality*, *intentions*, and *ratings* are used to compute recommendations. The rating tuple $(user, ulocation, item, rating)$ is adaptively clustered into different regions on the basis of user *location* attribute. We use the item-based collaborative filtering technique for computing recommendations on the remaining three attributes $(user, item, rating)$ at each partitioned subset of users. Movielens dataset's zip code information has been used to trace the user's location. In Movielens dataset, zip code consists of 5 digits where different digit sets represent distinct locations in the USA. Hence, users can be divided into multiple spatial locations based on their zip code information.

Algorithm 1 shows the pseudo code for location and intention-oriented recommendations that takes the input of $(user, ulocation, uintention, item, rating)$ tuple and training set S_{train} and outputs top-k recommendations list. Algorithm 1 includes the user clustering strategy which hierarchically partitions users into three groups based on their location. This is achieved by sequentially comparing each user's zip code information with the target user u. The first cluster is extracted where the first digit of the zip code is the same as of the target user u. In the same way, the second cluster is obtained where the first three digits of the zip code are the same as of the target user u. The third cluster contains all the users in the training set. For each partitioned set, item-based collaborative filtering is applied to generate separate location-aware hierarchical recommendation lists: $R_{itemCF}L1$, $R_{itemCF}L2$, $R_{itemCF}L3$ respectively. To compute recommendations list for a target user u, all the recommendations lists are aggregated.

$$R_{locCF} = R_{locCF}L_1 + R_{locCF}L_2 + R_{locCF}L_3 \tag{5}$$

Algorithm 1. LIOR top-k items computation

Require: Tuple-($user, rating, ulocation, uintention, item$), training set ($S_{train}$) with zip code

Ensure: R_{LIOR} top-k recommendations

```
Generate sub-train 1 from S_train based on zip code[0]
Apply item-based CF method on sub-train 1
Get recommendation list R_locCF L_1
Generate sub-train 2 from S_train based on zip code[0-2]
Apply item-based CF method on sub-train 2
Get recommendation list R_locCF L_2
Apply item-based CF method on S_train
Get recommendation list R_locCF L_3
R_locCF = Σ_{R_locCF[i=1]}^{R_locCF[i=3]} R_locCF L_i
Get intention values from equation 4
Get recommendation R_locCF from equation 5
Aggregate R_locCF, T_u,i = R_LIOR = R_locCF + T_u,i
select top-k items
return  R_LIOR top-k recommendations
```

3.4 LIOR Recommendations

After computing location-aware predictions list R_{locCF} for a target user u and intention values $T_{u,i}$ for each user in the training set, the predicted ratings of top-k items of R_{locCF} for a target user are aggregated with the intention values of these items in the user-item, intention matrix, $T_{u,i}$ to get R_{LIOR} recommendation as given in the Eq. 6. Finally, top-k items from the aggregated R_{LIOR} list are presented to the target user u. LIOR effectively provides recommendations to the cold start users who have not previously rated any item. In this situation, the location-based user clustering is employed and spatial preferences at a particular location are recommended to the user.

$$R_{LIOR} = R_{locCF} + T_{u,i} \tag{6}$$

4 Experimental Evaluation

This section elaborates the experimental setup and evaluation of LIOR using the actual implementation in python. We perform experiments on a popular location-aware rating big dataset Movielens [8].

4.1 Dataset Description

The Movielens dataset consists of 1 million ratings for 6040 users who have rated 3900 movies. The dataset was taken from the famous movie rating recommender system Movielens at the University of Minnesota. In the Movielens dataset, each user's rating has been associated with the zip code which makes it as a real-world dataset comprising of location-aware rating records for non-spatial items.

We compare LIOR with three state-of-the-art location-aware recommendations techniques:

- State of the art location-oriented recommender system MLTRS [20] which employs Latent Dirichlet Allocation method to recommend items. The recommendations are produced according to the ratings provided by the querying user at a specific location along with item tag information.
- Location-aware recommendations technique LARS [16] which uses adaptive pyramid structure-based user clustering strategy to partition users and produce recommendations.
- A probabilistic generative model ULA-LDA [22] which utilizes user location-aware ratings for modeling profile of users and generate recommendations.

4.2 Evaluation

To measure the quality improvement, we perform experiments from the perspective of the two most important evaluation metrics: Mean Absolute Precision $MAP@k$ and $accuracy@k$. The evaluation was performed by splitting all the rating records randomly into 80% training and 20% test rating items, hence, the training and test set have no overlap. For each target user u having location as $ulocation$ and intention as $uintention$ his/her rating records have been split into 80% to S_{train} in order to learn the model whereas 20% to S_{test} to evaluate the model. The purpose of this is to ascertain the accuracy with which test set items S_{test} have been recommended by LIOR method to each target user. Users usually like the items to be ranked in an ordered list therefore, a top-k list has been generated for each user and $accuracy@k$ is computed for every test case in the test set S_{test} by the following conditions:

- Ranking values of not rated items by a user u.
- An ordered list is generated according to the generated ranking values.
- A top-k list is computed for each user, if the item proposed to the current user also falls in the S_{test} then it is termed as a $hit@k$, otherwise it is denoted as a $miss$.

Evaluation metrics of $accuracy@k$ is selected to demonstrate the effectiveness of LIOR and has been proposed by [21,23] computed by using the Eq. 7.

$$Accuracy@k = \frac{\#hit@k}{|S_{test}|} \tag{7}$$

Where $\#hit$ corresponds to the total number of hits for every target user in the test set. In the same way, $|S_{test}|$ denotes the count of all test cases in the test set. We also utilize MAP to evaluate LIOR which is given in the Eq. 8.

$$MAP = \frac{AP}{|U|} \tag{8}$$

Here, AP denotes average precision which is calculated by using $Accuracy@k$ and is divided by the total number of users $|U|$. In our experiment, we compute AP using the accuracy values at k ranked items. The evaluation results have been presented in Fig. 3.

4.3 Evaluation Using *Accuracy@k*

The result of $Accuracy@k$ has been shown in Fig. 3a, on the items range of $\{2, 4, 6,\ 8, 10, 12{,}14, 16, 18, 20\}$. The comparison is performed with LARS, MLTRS, and ULA-LDA. It can be observed that LIOR perform exceptionally well in computing top-k recommendations and the values of *accuracy* were the highest among all the other techniques on all the values of k.

Analysis of the figure shows that the *accuracy* value of LIOR was 0.231 at $k = 8$ and 0.307 at $k = 20$ which is higher than all the compared techniques. It is also pertinent to note that intention values are playing a vital role in improving the recommendation accuracy which can be observed by analyzing the significantly improved results of LIOR as compared to LARS, MLTRS, and ULA-LDA.

4.4 Evaluation Using *MAP*

The result of MAP evaluation on top-k recommendations is shown in Fig. 3b. It can be observed that MAP values of LIOR outperformed all the compared techniques which demonstrate the consistency of LIOR on producing effective recommendations. MAP has also been computed on the set of top-k items where $k = \{2, 4, 6, 8, 10, 12, 14, 16, 18, 20\}$. The MAP values of LIOR, MLTRS, ULA-LDA, and LARS at $k = 10$ were 0.181, 0.161, 0.135, and 0.102 respectively. This improvement demonstrates that locality preferences and similar user-based intentions are playing a positive role in producing recommendations. It can be observed that MLTRS and ULA-LDA perform better than LARS because as compared to LARS, MLTRS and ULA-LDA also employs latent tag information along with the location to produce personalized recommendations.

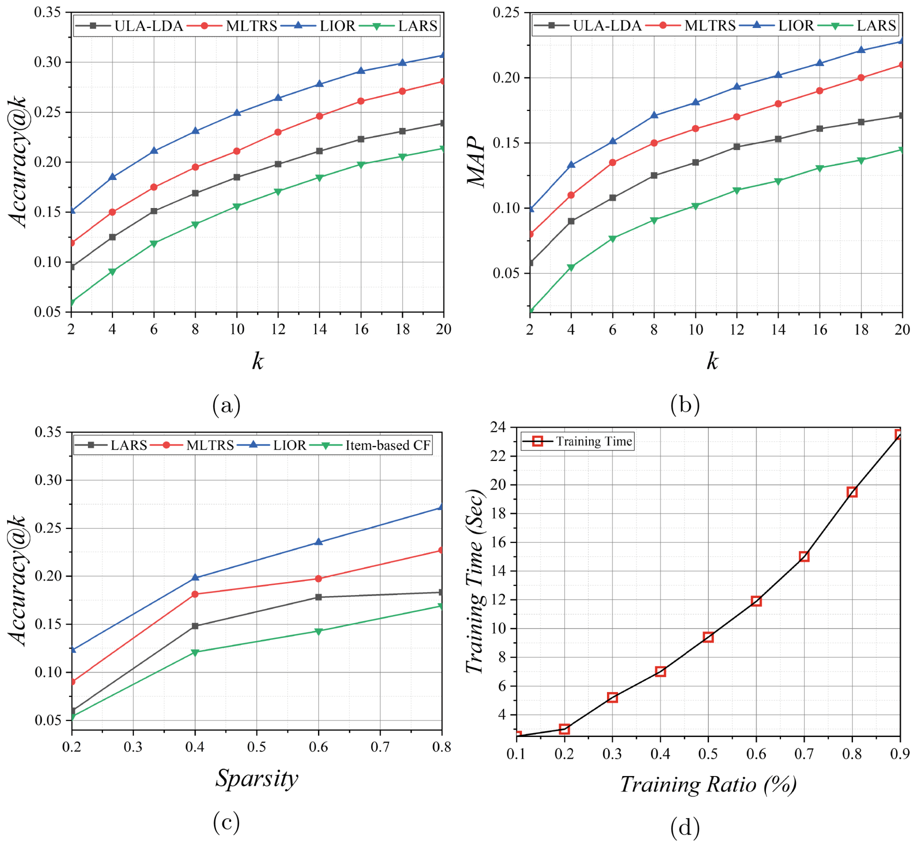

Fig. 3. Evaluation of LIOR method using different measures.

4.5 Dealing with Sparsity

We evaluate LIOR by varying different data sparsity levels (e.g., 0.2, 0.4, 0.6, 0.8) on Movielens dataset at $k = 10$. Figure 3c shows the accuracy of all the techniques on different data sparsity levels. The accuracy values increase with the increase of sparsity in all the approaches. LIOR still provides better results on all the sparsity levels. The accuracy values decrease with the decrease in data sparsity however, the accuracy values in LIOR decrease smoothly as compared to other techniques which shows the positive impact of hierarchical clustering strategy on reducing sparsity problem. The improved accuracy of LIOR is also evident that user intentions have a positive impact on increasing recommendations accuracy and decreasing the sparsity problem.

4.6 Scalability on Larger Datasets

We perform the experiments to evaluate the scalability of LIOR using different percentages of data. Training time is observed on each percentage of the data as a metric for scalability evaluation. As can be observed from Fig. 3d which demonstrate that the time required for training the model increases in a linear way with the increase in the amount of training data. This experiment demonstrates the feasibility of LIOR to be applied to larger datasets.

The above results proclaim that LIOR outperformed novel location-oriented recommendation techniques including LARS, MLTRS, and ULA-LDA. The results signify that user location and intention information positively affect the accuracy of recommendations and alleviates the sparsity problem.

5 Related Work and Comparison Analysis

There is a recent trend to incorporate user and items latent information along with the ratings to generate personalized recommendations. Social networks provide access to the personalized information of users which can be utilized to increase recommendation accuracy [13,17]. Wang et al. [10] use trust-based similarity, whereas zhang et al. [24] use auxiliary information from social networks to increase recommendation accuracy. Recently, location-based recommendations have gained immense popularity, these techniques mainly employ location information associated with the user and/or item to produce personalized recommendations [4,11,12]. Lian et al. propose an implicit feedback-based location recommendation technique to deal with the cold start users [6]. Chen et al. present explicit semantic analysis and deep neural networks-based personalized news recommendations system [3]. Stepan et al. utilize spatial, temporal, and social information for location recommendations. However, the drawback of these techniques is that they do not consider location-based ratings for computing recommendations [18].

Sarwat et al. [16] propose LARS which partitions users into multiple clusters and compute recommendations by only considering ratings of the same cluster users. However, they did not consider user intentions for computing personalized recommendations. Yin et al. [22] propose a location-oriented probabilistic mixture prediction model which utilizes user interest and the influence of locality preference to compute recommendations. Wang et al. [20] propose Memetic algorithm which considers *rating*, *location*, and *tag* information to produce recommendations. However, most of the times item tags are incomplete and ambiguous which lead to misinterpretation of the user's interests. As compared to these techniques, LIOR employs locality preferences along with intentions to produce high-quality recommendations.

Intention-oriented recommendations help in producing recommendations based on user underlying motivations of doing a business activity. User intentions are highly affected by the preferences of similar users [25]. Zhao et al. [26] link users on Weibo social network with ecommerce website JingDong to provide recommendations to cold start users however, they did not consider the problem of user location preferences on producing recommendations. Meng et al. [7] propose aspect2vec a user query intention extraction approach in which query aspects are represented as vectors and nodes by employing users latent information from their social networks. Still, authors did not observe spatial preferences of users which strongly affect user search intentions. Bhattacharya et al. [2] proposed a recommendation system that monitors user browsing patterns on the web to extract user intention and produce recommendations. They used an indirect method to infer user intentions however, location impact on these intentions have not been considered by the authors.

6 Discussion

The results and comparison analysis demonstrate the need for intention and location-aware recommendations and prove that ratings, location, and intentions are vital information sources to improve recommendations accuracy. Although, we achieve higher accuracy on top-k items recommendations, however, there is still a need to incorporate contextual information to produce personalized recommendations. Similarly, user-based similarity provides an estimate of the user intentions of buying a product or doing an activity, though realistic information can be extracted from the user's social media data to generate more accurate recommendations.

7 Conclusion and Future Work

In this research, we presented LIOR, a location and intention-oriented recommendation method to increase recommendations accuracy. We propose that ratings, location-based similarity, and user intentions strongly influence user preferences. For a target user, LIOR sequentially clusters all the users into multiple regions based on their location similarity with the target user. It then computes item-based collaborative filtering on each cluster to generate predictions. Afterward, the user's intentions are extracted by employing the user-based collaborative filtering technique. Finally, location-aware predictions and intentions are aggregated to compute LIOR recommendations. We performed comprehensive experiments on real-world location-aware Movielens big dataset. Our results reveal that LIOR outperformed state-of-the-art location-based recommendation techniques including LARS, ULA-LDA, and MLTRS in terms of MAP, *accuracy*, and reducing the sparsity problem. The experiments also proclaim that LIOR is highly scalable for larger datasets.

For the future work, we will extend LIOR by extracting user's intention-oriented data on multiple user-interaction platforms like location, IoT, user demographics, and integrating temporal impacts to develop a diverse intention-oriented service recommendation system. We intend to provide personalized recommendations by incorporating user's social network information and analyzing the impact of spatial-temporal-aware ratings using contextual information from social media.

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