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Spatial Item Recommendation using collaborative filtering

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Abstract: In the development of location-based social networks (LBSNs), spatial items have recommended and that has become an important way of helping users discover interesting locations to increase their engagement with location-based services. Although human movement exhibits sequential patterns in LBSNs, most current studies on spatial item recommendations do not consider the sequential influence of locations. we propose a sequential personalized spatial item recommendation framework (SPORE) which introduces a novel latent variable topic-region to model and fuse sequential influence with personal interest in the latent and exponential space. The advantages of modeling the sequential effect at the topic-region level include a significantly reduced prediction space, an effective alleviation of data sparsity and a direct expression of the semantic meaning of users' spatial activities. We evaluate the performance of SPORE on two real datasets and one large-scale synthetic dataset. The results demonstrate a significant improvement in SPORE's ability to recommend spatial items, in terms of both effectiveness and efficiency, compared with the state-of-the-art methods.

Keywords: *Location-based service, location-based social networks (LBSNs), temporal data, spatial item commendation, Locality Sensitive Hashing (ALSH) technique.*

1. Introduction

The rapid development of Web 2.0, location acquisition and wireless communication technologies have fostered a number of location-based social networks (LBSNs), such as Foursquare, Gowalla, Brightkite and Loopt, where users can check in at different venues and share life experience in the physical world via smart mobile devices [1]. A personalized location recommendation service, which encourages users to explore new locations [2], is an essential function of LBSNs. Because of that developing personalized recommender systems for LBSNs is used to provide users with spatial items e.g., a venue or an event associated with a geographic location, that has recently attracted increased research attention [3].Existing research on personalized spatial item recommendation mainly explores the geographic influence to improve the recommendation accuracy, based on the observation that the geographic proximity between spatial items affect users' check-in locations [3]. In terms of the temporal effect of user check-in activities in LBSNs, to our knowledge, only the temporal cyclic patterns of check-ins have been investigated [4]. The essential part of the LBSN is to encourages users to explore new locations [2] under personalized location recommendation service. Due to all this it attracted the huge attention of researcher to developed personalized recommender systems for LBSNs to provide users with spatial items. The main aim of LBSN is to suggest new POIs (Points of Interest) to a users according to his dedicated preferences and make easy his exploration of new areas of the city. Research on personalized spatial item recommendation is mainly depends on the geographic locations to improve the recommendation accuracy [3]. However, it has been observed that human mobility, in reality, exhibits sequential patterns, which serve as the basis for mobility prediction [5]. In previous analysis conducted

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on three publicly available real-world datasets, Foursquare, Gowalla and Brightkite in [6].

Low Sampling Rate

There are a number of studies that predicate locations on GPS trajectories [9]. At first glance, these approaches can be directly applied to LBSN data, since both the GPS and LBSN data contain location and time information. In the survey, access the datasets of Gowalla, twitter and LBSN. The LBSN data has low sampling compared to other in space and time

Huge prediction space

Sequential recommendation methods have been proposed in the literature [12], [13], [14], most of which are based on Markov chains. Consider there are a collection of V spatial items and the next item depends on the previous n items, the sequential recommendation methods then need to calculate $|V|^{n+1}$ free parameters in the n^{th} order Markov chain model.

Unifying personalization and sequential effect

The most of existing spatial item recommendation methods focusing on personalization[1],[2], build recommendations according to users personal choice, but ignore the sequential orders between spatial items. On the other hand existing sequential methods like Markov chain based methods, capture sequential patterns by assuming corresponding transition probabilities among items for all users, and take no notice of personalization. A system that only focuses on one of the two aspects may not produce ideal results. Therefore we focus on developing a new technique which uses or consider both the parameters to predict the spatial location.

To avoid all the problem in existing system we propose a Sequential PersOnalized spatial items REcommender system, called SPORE. SPORE mainly combines the sequential influence of visited spatial items and the personal interests of individual users in a principled way. We model personal interests and sequential influence based on the latent variable topic-region in SPORE. A topic-region z corresponds to a semantic topic (i.e., a soft cluster of words describing spatial items) and a geographical region (i.e., a soft cluster of locations of spatial items) at the same time. Given a target user u at time t, SPORE first chooses a topic-region z for u based on her personal interests and her visited items before t. The selected topic region z in turn generates a spatial item v following z's semantic and geographical distributions.

To unify personal interests and sequential effect in a principled way, traditional mixture models, such as LCALDA [16], combine multiple facets (e.g., personal interests and temporal effect) by introducing additional latent variables that act as "switches", to control which facet is currently active. To support real-time recommendation scenario, we further design an asymmetric Locality Sensitive Hashing (ALSH), extending the classical LSH technique, to significantly reduce the search space and produce top-k recommendations without examining all available spatial items.

2. Related Work

In this section, we discuss related work on location based social recommendations with spatial item. There are two main lines of research in spatial item recommendation. The first one focuses on GPS trajectory data. GPS trajectory data usually consists of a small number of users, but has dense location records. The other line of research is conducted on LBSN data, which has a low sampling rate in both space and time compared to GPS trajectories.

It has 4 existing approaches collaborative filtering, geographical influence, social influence, and sequential influence.

A. Collaborative filtering:

In existing recommendation techniques has used to point of interest system has collaborative filtering techniques on users" check-in data in GPS,LBSNs data and text data. The performance is limited for the GPS and LBSN system. This system limitation over to social influence, sequential influence, Social influence.

B. Geographical influence:

In Point of recommendation system has depends upon personal interest and geographical interest. In geographical interest user has visit any location then find out this related local preferences in system. The influence of geographical information of places on user check-in behaviours. These locations are used to user recommendation. The distance

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between two locations stayed by the same customer as a common delivery for all customers.

C. Sequential influence

Location based service stored a user activity as preferences as sequentially. In these sequential influences has different sequence format store. Like different location stored in sequential format. In some case has different user visit from same places in different way. So system confusing to stored sequence and recommendation time.

3. System Architecture

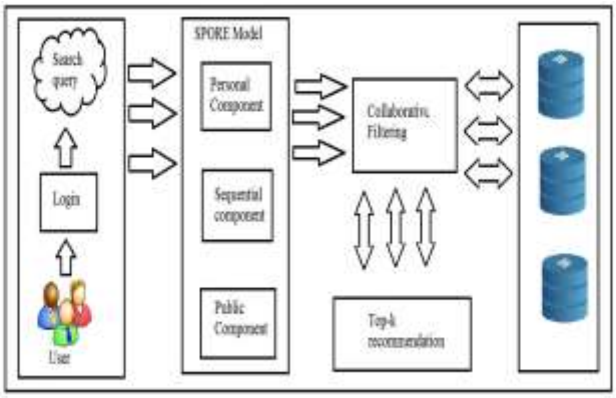

Fig. 1. System Architecture

User Module: User registers to site. Login and check current location to visited places. It has upload location and finds related location.

SPORE Module: It has three parts like personal, sequential and public component which extract to datasets.

Personal Component: Display the user personal interest location to find out collaborative filtering. User display common visited points.

Sequential Component: Display list of user regularly visited item. Which has display in sequential component.

Public Component: User visiting point classify in personal, sequential and public component. Public means government public stop available.

Experimental Setting

Datasets We conducted our experiments on two real datasets (Foursquare and Twitter) and one large synthetic dataset. The two real datasets are publicly available.

Foursquare. This dataset contains the check-in history of 4,163 users who live in California, USA, between Dec 2009 and Jul 2013. Each check-in activity contains the user-ID, item- ID, item-location, item-content and a check-in time.

Synthetic Dataset. To evaluate the online recommendation efficiency of ALSH when the number of spatial items is large, a large synthetic dataset was created following the distribution characteristics of the Foursquare dataset.

4. Preliminaries and Problem Formulation

Spatial item: Daily user activity for example public and private places.

Predecessor and Successor: It has show the both item recommendation with top k item. In top k has different types of values are available.

User Activity: In User activity has stored daily user activity means where to user visit or where to move on like club, party, office or any other personal or public places activity.

Problem 1: Spatial Item Recommendation: Given a user activity dataset D and a querying user u at time t (i.e., the query is q = (u, t)), our goal is to recommend a list of spatial items that u would be interested in.

Task 1: Extracting users' personal interests. This task models the users' personal interests. The user-item matrix is very sparse in LBSNs, which makes it difficult for traditional recommendation models

Task 2: Extracting sequential influence. This task models the influence of visited spatial items in a sequence. Faces the severe challenges of low-sampling rate and huge prediction space, which render the classical n^{th} order Markov Chain inefficient because its complexity increases exponentially w.r.t. n

Task 3: Fusing users' personal interests and sequential influence into a unified framework.

No framework exists that simultaneously integrates the two components into a unified model. Zhang et al. combine the sequential influence, geographical influence and social influence.

Algorithm 1: The Algorithm of ALSH

Input: all the spatial items V and a given query $\vec{q}$ (both $\vec{q}$and each item $\vec{v}$ are represented by a vector over K dimensions);

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Output: k spatial items with largest S in Equation ;

1 **Preprocessing**;

2 Scale each $\vec{v} \epsilon$ V to have $\| \vec{v} \|_2 \leq$ I < 1 ;

3 Append m scalars to each $v^{\rightarrow}$ as:

$H_1(v^{\rightarrow}) = [\vec{v}; \| \vec{v}\|^2_2 ; \| \vec{v}\|^4_2 ; . . . ; \| \vec{v}\|^{2m}_2]$;

4 Use hash function 21 to create hash tables for V ;

5 **Querying**;

6 Append m 0.5 to the query q: $h2(\vec{q}) = [\vec{q}0.5; 0.5; . . . ; 0.5]$;

7 Apply hash function 21 on the transformed query to probe buckets to find top-k items ;

8 Return the found top-k items;

Algorithm2: Collaborative Filtering

1. Start
2. for(i=0 to i< dataset)
3. checkPersonal(dataset[i])
4. checkSequential(dataset[i])
5. checkPublic(dataset[i])
6. stop
7. End

5. Mathematical Module

Framework has generated different types of spatial item like public, private and sequential item. It has depended upon user visiting point.

$$SM = \int_{i=0}^{n} Pc + \int_{i=0}^{n} Sc + \int_{i=0}^{n} Puc$$

Where,

SM=SPORE Model

Pc=Personal Component.

Sc=Sequential Component.

Puc=Public Component.

For eq(1) to implement spore model to different component.

$$cf = \frac{\sum(SM - SM')}{\sqrt{\sum(SM - SM')^2}} \qquad 2$$

Cf is finding out to item based collaborative filtering. It has found original value and similar values common attribute or item.

Where, Cf=collaborative filtering.

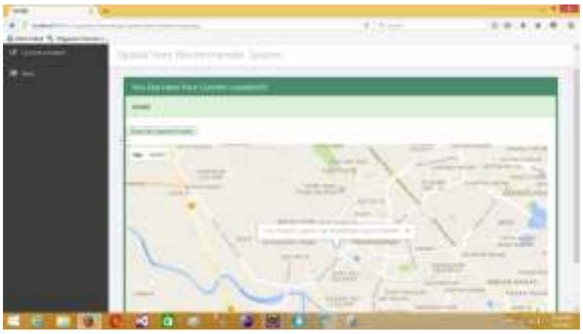
In eq (2) find ranking of data into model.

$$R = \int_0^n cf \qquad 3$$

Where R=Ranking.

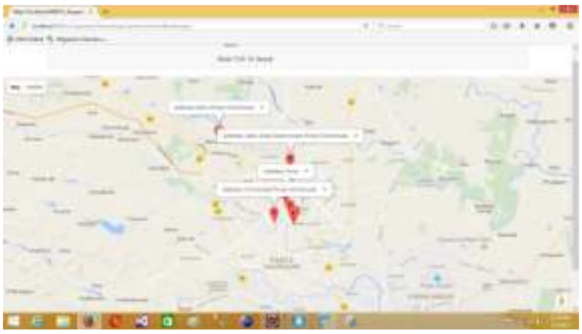
6. Result Analysis

Current Location:-The user is entered in the web application then search automatically detect location with interest.



Top 10 Location Display: You can share your location through virtually any Using collaborating filtering find out prediction then we get top 10 location.

Top geographical Location Display: A geographic location display is used present spatial or geographical data. Using knn algorithm in the application and display top 10 geographical locations



Execution Time: The execution time is a given task is defined used to the time spent by the system executing that task, added the time spent executing run-time on system services depend on the search location.

7. CONCLUSION

we proposed a novel sequential personalized spatial item recommendation framework (SPORE). To effectively overcome the challenges arising from low-sampling rate and huge prediction space, SPORE introduces a novel latent variable topic-region to model and fuse the sequential influence and personal interests in the latent space. A topic region corresponds to both a semantic topic and a geographical region.

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