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Exploiting Sequential Influence for Personalized Location-Based Recommendation Systems

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Synonyms

Exploiting sequential check-in patterns for personalized location-aware recommendations; Mining sequential influence for personalized location recommendations

Definition

A personalized location-based recommendation system suggests a user to *visit* or *check in* some specific locations, e.g., restaurants, stores, and museums, that are in accordance with the preference of the user. The preferences of users to locations are usually derived from their check-in histories on locations. In reality, human movement exhibits sequential patterns that can be extracted from the check-in location sequences of users. For example, people usually go to cinemas or bars after restaurants since they would like to relax after dinner. The influence of sequential patterns on the check-in behaviors of users to locations has become increasingly important in location recommendations.

Historical Background

With the rapid advancement of mobile devices and location acquisition technologies, location-based social networks (LBSNs), such as Foursquare and Yelp, have attracted millions of users. In an LBSN (Fig. 1), users can make social friends with each other and share their experiences of visiting some specific locations, also known as *points of interest* (POIs), e.g., restaurants, stores, and museums, through performing check-in operations to these POIs in the LBSN via their handheld device. LBSNs generate plenty of check-in location sequences of users which reflect their preferences to locations. In location-based recommendation systems, it is crucial to recommend personalized POIs to users based on sequential influence learned from their historical check-in location sequences; this benefits for users to know new POIs and discover a city while for businesses to deliver advertisements to targeted customers.

In terms of the fact that human movement exhibits sequential patterns (Cho et al. 2011; González et al. 2008; Song et al. 2010), various mining techniques of sequential patterns were developed for location predictions (Monreale et al. 2009; Ying et al. 2014) that refer to predicting an *existing* location. It is not straightforward to

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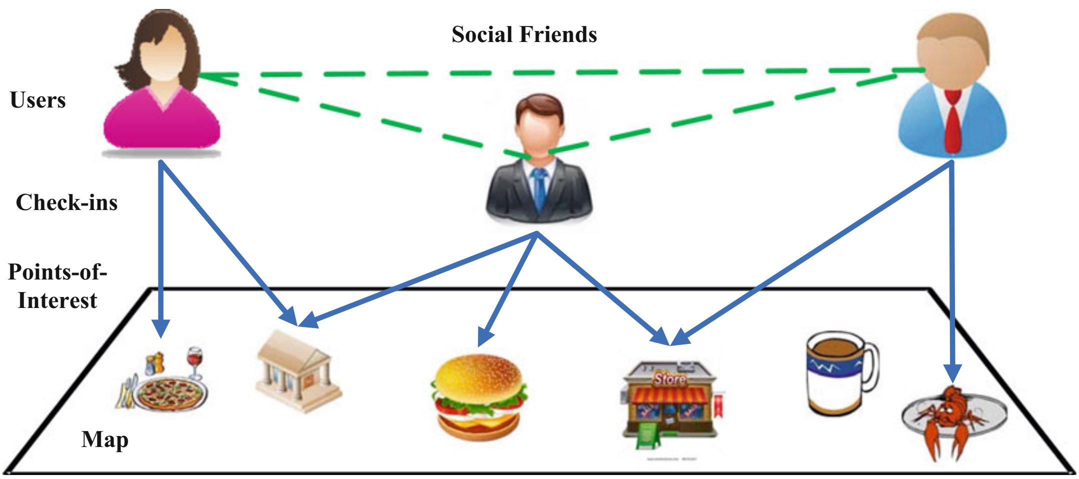

Exploiting Sequential Influence for Personalized Location-Based Recommendation Systems, Fig. 1 A location-based social network

apply these techniques in location recommendations that refer to recommending a *new* location. Recently, some techniques using sequential influence have been proposed for location recommendations, and they can be classified into three categories. (1) **First-order Markov chain.** The literatures (Chen et al. 2011; Cheng et al. 2011, 2013; Kurashima et al. 2010; Zheng et al. 2012) exploit the sequential influence based on the first-order Markov chain that only uses the latest visited location in the check-in history of a user to recommend a new location for the user. However, in reality, the new location depends on not only the latest visited location but also the earlier visited locations. (2) **Classical *n*th-order Markov chain.** In contrast, the work (Zhang et al. 2014c) considers all visited locations of a user to recommend her with a new location through the classical nth-order Markov chain. Unfortunately, it is prohibitively expensive to apply the classical nth-order Markov chain, because its computational cost increases exponentially with the order n. (3) **The *n*th-order additive Markov chain.** To this end, the study (Zhang et al. 2014b) contrives an efficient nth-order additive Markov chain that also takes into account all visited locations but only has the linearly computational cost with respect to the order n.

Scientific Fundamentals

Sequential Pattern Mining

A check-in location sequence of a user is a set of her visited locations ordered by her visited time in increasing order. A location sequence is often denoted by $s = \langle l_1 \to l_2 \to \cdots \to l_n \rangle$, also called n-gram sequence. $s' = \langle l_i \to l_{i+1} \to \cdots \to l_{i+j} \rangle$ $(1 \leq i \leq i + j \leq n)$ is called a subsequence of s.

In Markov chain models, sequential patterns are usually represented as a matrix of transition probabilities from one location or sequence to another location. The transition probabilities can be computed from the counts of subsequences in the collection of check-in location sequences of all users. Figure 2 demonstrates an example of aggregating counts of n-gram subsequences from check-in location sequence collection of all users. For instance, the subsequence $l_1 \to l_2$ occurs five times in the collection, and hence, its aggregate count is five. Note that the counts of n-gram $(n > 3)$ subsequences can be obtained using the same process.

In practice, to improve the search efficiency, the work (Zhang et al. 2014c) indexes the counts of all subsequences as a n-gram tree for the classical nth-order Markov chain, while the

Check-in location sequence collection	
s_1	$l_2 \to l_3 \to l_1$
s_2	$l_2 \to l_3$
s_3	$l_3 \to l_2$
s_4	$\mathbf{l_1} \to \mathbf{l_2} \to l_4$
s_5	$l_2 \to l_3 \to l_1$
s_6	$l_3 \to l_2 \to l_1$
s_7	$\mathbf{l_1} \to \mathbf{l_2} \to l_3$
s_8	$l_2 \to l_3 \to \mathbf{l_1} \to \mathbf{l_2} \to l_3$
s_9	$l_3 \to l_2$
s_{10}	$\mathbf{l_1} \to \mathbf{l_2} \to l_4$
s_{11}	$l_3 \to \mathbf{l_1} \to \mathbf{l_2} \to l_3$
s_{12}	l_1
s_{13}	$l_1 \to l_4 \to l_2$
s_{14}	$l_2 \to l_4 \to l_3$
s_{15}	$l_3 \to l_4 \to l_2$
s_{16}	l_4

$\Longrightarrow$

Subsequence count	
$l_1 : 10$	$l_1 \to l_2 \to l_3 : 3$
$l_2 : 15$	$l_1 \to l_2 \to l_4 : 2$
$l_3 : 13$	$l_1 \to l_3 \to l_2 : 0$
$l_4 : 6$	$l_1 \to l_3 \to l_4 : 0$
$\mathbf{l_1} \to \mathbf{l_2} : \mathbf{5}$	$l_1 \to l_4 \to l_2 : 1$
$l_1 \to l_3 : 0$	$l_1 \to l_4 \to l_3 : 0$
$l_1 \to l_4 : 1$	$l_2 \to l_1 \to l_3 : 0$
$l_2 \to l_1 : 1$	$l_2 \to l_1 \to l_4 : 0$
$l_2 \to l_3 : 7$	$l_2 \to l_3 \to l_1 : 3$
$l_2 \to l_4 : 3$	$l_2 \to l_3 \to l_4 : 0$
$l_3 \to l_1 : 4$	$l_2 \to l_4 \to l_1 : 0$
$l_3 \to l_2 : 3$	$l_2 \to l_4 \to l_3 : 1$
$l_3 \to l_4 : 1$	$l_3 \to l_1 \to l_2 : 2$
$l_4 \to l_1 : 0$	$\vdots$
$l_4 \to l_2 : 2$	
$l_4 \to l_3 : 1$	

Exploiting Sequential Influence for Personalized Location-Based Recommendation Systems, Fig. 2 An example of aggregating counts of n-gram subsequences (*right table*) from check-in location sequence collection of all users (*left table*)

study (Zhang et al. 2014b) organizes the counts of one-gram and two-gram subsequences as a location-location transition graph for the nth-order additive Markov chain.

Markov Chain Models

Based on the obtained sequential patterns, a personalized location-based recommender system can predict the probability of a user visiting a new location through using a variety of Markov chain models and then recommend the top-k locations with the highest visiting probabilities for the user.

First-Order Markov Chain. Given a check-in location sequence of a user $s = \langle l_1 \to l_2 \to \cdots \to l_n \rangle$, most works (Chen et al. 2011; Cheng et al. 2011, 2013; Kurashima et al. 2010; Zheng et al. 2012) derive the probability of the user visiting a new location l_{n+1} by employing the first-order Markov chain that assumes the probability of visiting the new location l_{n+1} only relies on the latest visited location l_n, i.e.,

$$\Pr(l_{n+1}|s) = \Pr(l_{n+1}|l_n) = \frac{N(\langle l_n \to l_{n+1} \rangle)}{N(\langle l_n \rangle)}, \tag{1}$$

where $N(\langle l_n \rangle)$ and $N(\langle l_n \to l_{n+1} \rangle)$ are the counts of location l_n and subsequence $\langle l_n \to l_{n+1} \rangle$ in the collection of check-in location sequences of all users, respectively.

Consider Fig. 2 again and assume $s = \langle l_1 \to l_2 \rangle$. Then we have:

$$\Pr(l_3|s) = \Pr(l_3|l_2) = \frac{N(\langle l_2 \to l_3 \rangle)}{N(\langle l_2 \rangle)} = \frac{7}{15},$$

$$\Pr(l_4|s) = \Pr(l_4|l_2) = \frac{N(\langle l_2 \to l_4 \rangle)}{N(\langle l_2 \rangle)} = \frac{3}{15}.$$

Classical nth-Order Markov Chain. Given a check-in location sequence of a user $s = \langle l_1 \to l_2 \to \cdots \to l_n \rangle$, the work (Zhang et al. 2014c) estimates the visiting probability $\Pr(l_{n+1}|s)$ of the user to the new location l_{n+1} based on the classical nth-order Markov chain, given by:

$$\Pr(l_{n+1}|s) = \frac{N(\langle l_1 \to l_2 \to \cdots \to l_n \to l_{n+1} \rangle)}{N(\langle l_1 \to l_2 \to \cdots \to l_n \rangle)}, \tag{2}$$

where $N(\langle \cdot \rangle)$ is the count of subsequence $\langle \cdot \rangle$ in the collection of check-in location sequences of all users. The classical nth-order Markov chain considers all the visited location $l_1, l_2, \ldots, l_n$ of the user to predict her visiting probability to the new location l_{n+1}. However, it needs to enumerate all n-gram subsequences in the check-in collection, the number of which is exponentially increasing with regard to the order n.

Given the counts of n-gram subsequences in Fig. 2 and assuming $s = \langle l_1 \to l_2 \rangle$, we have:

$$\Pr(l_3|s) = \frac{N(\langle l_1 \to l_2 \to l_3 \rangle)}{N(\langle l_1 \to l_2 \rangle)} = \frac{3}{5},$$
$$\Pr(l_4|s) = \frac{N(\langle l_1 \to l_2 \to l_4 \rangle)}{N(\langle l_1 \to l_2 \rangle)} = \frac{2}{5}.$$

The nth-order Additive Markov Chain. The recent study (Zhang et al. 2014b) proposes an efficient nth-order additive Markov chain to predict the visiting probability. The developed additive Markov chain only exploits the one-gram and two-gram subsequences and significantly reduces the computational cost. Formally, given a check-in location sequence of a user $s = \langle l_1 \to l_2 \to \cdots \to l_n \rangle$ and a new location for the user l_{n+1}, the visiting probability $\Pr(l_{n+1}|s)$ is computed by:

$$\Pr(l_{n+1}|s) = \sum_{i=1}^{n} W(l_i) \cdot \frac{N(\langle l_i \to l_{n+1} \rangle)}{N(\langle l_i \rangle)}, \quad (3)$$

where $N(\langle l_i \rangle)$ and $N(\langle l_i \to l_{n+1} \rangle)$ are the counts of the one-gram and two-gram subsequences, respectively, and $W(l_i)$ is the weight of the location l_i in the sequence s on the next location l_{n+1}. Since the locations with recent check-in time usually have stronger influence on a new possibly visiting location than the locations with old check-in time (Cho et al. 2011; González et al. 2008; Song et al. 2010), the weight should lean toward recently visited locations, e.g., in the study (Zhang et al. 2014b) given by:

$$W(l_i) = \frac{2^{-\alpha(n-i)}(1-2^{-\alpha})}{1-2^{-\alpha n}}, \quad (4)$$

where $W(l_i)$ represents the sequence decay weight with the decay rate parameter $\alpha > 0$ and the larger α is, the higher is the decay rate.

Given the counts of n-gram subsequences in Fig. 2 and assuming $s = \langle l_1 \to l_2 \rangle$ (i.e., $n = 2$) and $\alpha = 1$, we have:

$$W(l_1) = \frac{2^{-1}(1-2^{-1})}{1-2^{-2}} = \frac{1}{3},$$
$$W(l_2) = \frac{1-2^{-1}}{1-2^{-2}} = \frac{2}{3},$$
$$\Pr(l_3|s) = \frac{1}{3}\frac{N(\langle l_1 \to l_3 \rangle)}{N(\langle l_1 \rangle)} + \frac{2}{3}\frac{N(\langle l_2 \to l_3 \rangle)}{N(\langle l_2 \rangle)}$$
$$= \frac{1}{3} \times \frac{0}{10} + \frac{2}{3} \times \frac{7}{15} = \frac{14}{45},$$
$$\Pr(l_4|s) = \frac{1}{3}\frac{N(\langle l_1 \to l_4 \rangle)}{N(\langle l_1 \rangle)} + \frac{2}{3}\frac{N(\langle l_2 \to l_4 \rangle)}{N(\langle l_2 \rangle)}$$
$$= \frac{1}{3} \times \frac{1}{10} + \frac{2}{3} \times \frac{3}{15} = \frac{1}{6}.$$

Key Applications

Industries

Mobile location-based services (LBS) have been increasingly important for various industries. According to a new research report in BergInsight (2013), the revenue of mobile LBS is forecasted to grow from EUR$325 million in 2012 to EUR$825 million in 2017. The mobile LBS market in the North America is also forecasted to grow from US$835 million in 2012 to US$1,295 million in 2017. The personalized location-based recommendation systems can make LBS (e.g., Foursquare and Yelp) more prevalent through providing high quality of location recommendations to their users.

Tourism

Tourism is one of the biggest industries worldwide. According to the World Tourism Organization (UNWTO), receipts from international tourism in destinations around the world grew by 4 % in 2012 reaching US$1,075 billion. This growth is equal to the 4 % increase in international tourist arrivals which reached 1,035 million in 2012 (UNWTO

2013). UNWTO predicts the average growth rate of international tourist arrivals is 3.3 % a year until 2030 (UNWTO 2011). By integrating the personalized location-based recommendation systems into tourist information systems, we can provide personalized location recommendations for users and help them avoid information overload so as to save their trip planning time. Thus, the personalized location-based recommendation systems will add direct or indirect values into the tourism industry.

Businesses

The global real-time mobile location-based advertising and marketing market will grow from $1.66 billion in 2013 at a compound annual growth rate of 54 % to $14.8 billion in 2018 (BergInsight 2014). For example, Foursquare is a popular location-based social network. Ninety-three percent of storefronts with local channels are on Foursquare, because people are using their phones to connect with businesses more than ever and 95 % of mobile users rely on their devices for local search. Moreover, 90 % of mobile phone searches result in either a purchase or a visit (Foursquare 2013). We can apply the personalized location-based recommendation systems to deliver more personalized location-aware advertisements to their potential customers. Thus, the personalized location-based recommendation systems can improve marketing strategies and revenues for businesses.

General Public

With the help of personalized location recommendations, people are much easier and more convenient to learn about nearby events, products, and/or places of interest that are relevant to their preferences. Consequently, the personalized location-based recommendation systems are beneficial for people to explore new places in their home city and especially when they are travelling in a new city. Therefore, they can definitely improve the quality of people's daily life.

Future Directions

In practice, the additive Markov chain is effective and efficient to predict the visiting probability of a user to any new locations for location recommendations. Designing more sophisticated weighing methods in Eq. (4) for the additive Markov chain will be one future direction. One way is to integrate the social friendships between users into the weights, since friends are likely to share more common interests on locations, e.g., friends often go to some places like movie theaters or restaurants together or a user may travel on places highly recommended by her friends (Zhang and Chow 2013; Zhang et al. 2014a; Zhang and Chow 2015). Another way is to fuse the geographical distance between locations into the weights, because the geographical proximity of locations significantly affects users' check-in behaviors, e.g., users tend to visit locations close to their homes or offices and also may be interested in exploring the nearby places of their visited locations (Zhang and Chow 2013; Zhang et al. 2014a; Zhang and Chow 2015). Further, we need to investigate how to recommend a trip of POIs and how to take temporal influence into account to capture the change of users' preferences on POIs.

Cross-References

▶ Geospatial Semantic Web: Personalization
▶ Location-Based Services: Practices and Products
▶ Spatio-temporal Queries on Road Networks, Coding Based Methods
▶ Trajectories, Discovering Similar

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