A Survey of Point-of-Interest Recommendation in Location-Based Social Networks

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Abstract

With the rapid development of mobile devices, global position system (GPS) and Web 2.0 technologies, location-based social networks (LBSNs) have attracted millions of users to share rich information, such as experiences and tips. Point-of-Interest (POI) recommender system plays an important role in LBSNs since it can help users explore attractive locations as well as help social network service providers design location-aware advertisements for Point-of-Interest. In this paper, we present a brief survey over the task of Point-of-Interest recommendation in LBSNs and discuss some research directions for Point-of-Interest recommendation. We first describe the unique characteristics of Point-of-Interest recommendation, which distinguish Point-of-Interest recommendation approaches from traditional recommendation approaches. Then, according to what type of additional information are integrated with check-in data by POI recommendation algorithms, we classify POI recommendation algorithms into four categories: pure check-in data based POI recommendation approaches, geographical influence enhanced POI recommendation approaches, social influence enhanced POI recommendation approaches and temporal influence enhanced POI recommendation approaches. Finally, we discuss future research directions for Point-of-Interest recommendation.

Introduction

With the rapid development of mobile devices, global position system (GPS) and Web 2.0 technologies, location-based social networks (LBSNs) have become very popular and attracted lots of attention from industry and academia. Typical location-based social networks include Foursquare, Gowalla, Facebook Place, and GeoLife, etc.. In LBSNs, users can build connections with their friends, upload photos, and share their locations via check-in for points of interest (e.g., restaurants, tourists spots, and stores, etc.). Besides providing users with social interaction platforms, it is more desired for LBSNs to make use of the rich information (social relationships, check-in history and so on) to mine users' preferences on locations and recommend new places where users may be interested in. The task of recommending new interesting places is referred as point-of-interest (POI) recommendation. POI recommender systems have played an important role in LBSNs since they can not only meet users' personalized preferences for visiting new places, but also help LBSNs to increase revenues by providing users with intelligent location services, such as location-aware advertisements.

Although recommender systems have been widely studied and successfully adopted by many e-commerce web sites, such as Amazon, Netflix, Last.fm and Taobao etc., POI recommender systems have just emerged recently. Differing from traditional recommender systems, POI recommender systems have the following unique characteristics.

- **Geographical Influence**. As the Tobler's First Law of Geography reported that "Everything is related to everything else, but near things are more related than distant things" (Tobler 1970). For LBSNs, the Tobler's First Law of Geography implies that users prefer to visit nearby locations rather than distant ones and users may be interested in POIs surrounded a POI that users prefer. Geographical Influence is the most important characteristic that distinguish POI recommender systems from traditional recommender systems and heavily effect users' visiting behaviors.
- **Frequency Data and Sparsity**. In traditional recommender systems, user generally expressed their preferences by explicitly providing ratings for items (e.g., book, movie, music and so on), which are converted to user-item rating matrix. The ratings are often numerical values and fall into a numerical range, such as [1,5]. The higher rating corresponds the better satisfactory. Unlike to traditional recommender systems, a user's preferences are reflected by the frequency of check-in for locations, which are often transformed to user-location check-in frequency matrix. The frequency data have a large range compared with ratings. For example, user may check in thousands of times at some locations, while user may check in few times for other locations. In addition, the sparsity of user-location check in frequency matrix is dramatically higher than that of user-item rating matrix, which leads to bigger challenge for POI recommendation. For example, the sparsity of Netflix data set is around 99%, while the sparsity of Gowalla is about 2.08×10^{-4}.

- **Social Influence**. Based on the assumption that friends are tend to share more common interests and users often tend to their friends for suggestions, traditional recommender systems combine social relationships with ratings to improve the quality of recommendation. Several studies (Ma et al. 2008; Jamali and Ester 2010) have showed that social relationships are demonstrated to be beneficial for recommender systems. However, In POI recommender systems, previous studies (Ye, Yin, and Lee 2010) shown that around 96% of users share less that 10% common visited interests, indicated that a large number of friends share nothing in terms of POI. Hence, social influence contributes limited effects on users' check-in behaviors.

In this paper, we present a review of existing POI recommendation algorithms and discuss some research directions for POIs recommendation. According to the type of additional information integrated with check-in data by POI recommendation algorithms, we classify POI recommendation algorithms into four categories: pure check-in data based POI recommendation approaches, geographical influence enhanced POI recommendation approaches, social influence enhanced POI recommendation approaches and temporal influence enhanced POI recommendation approaches. Pure check-in data based POI recommendation approaches take check-in frequency as ratings and make an assumption that two users are similar if they have checked in a lot of common POIs. Then, conventional collaborative filtering approaches are adopted to make POI recommendations by averaging most similar users' preferences on candidate POIs. In geographical influence enhanced POI approaches, the distance between users and locations or the distance between POIs visited by users and POIs that are new places for users are considered in the process of POI recommendation. Geographical enhanced POI recommendation approaches generally assume that users tend to visit nearby POIs and the probability of visiting a new place decreases as the distance increases. Social influence enhanced POI recommendation approaches utilize social relationships among friends to enhance POI recommendation and assume that friends of LBSNs share much more common interests than non-friends. Temporal influence enhanced POI recommendation approaches assume that users' interests vary with time and users' visiting behaviors are often influenced by time since users visit different places at different time in a day.

The rest of this paper is organized as follows. We formalize the problem of POI recommendation in LBSNs in Section 2. Pure check-in data based POI recommendation approaches, geographical influence enhanced POI recommendation approaches, social influence enhanced POI recommendation approaches and temporal influence enhanced POI recommendation approaches are surveyed in Section 3. In Section 4, we discuss future research directions and conclude this survey.

Formalization of POI Recommendation

In a typical LBSNs, the POI recommender system consists a set of N users $U = \{u_1, u_2, ..., u_N\}$, and a set of M Locations $L = \{l_l, l_2, ..., l_M\}$, also called POIs. The set of POIs visited by user u is denoted by L_u. Each location is geocoded by <longitude, latitude>. Users' check-in information are converted to user-location check-in frequency matrix C. Each entry c_{ui} of C represents the frequency of check-in for location i by user u. The frequency of check-in reflects users' preferences on various locations. Typically, user only visited a small portion of locations existed in LBSNs, hence the matrix C is extremely sparse. In addition, each user keeps a list of trust friends and users' social relationships are transformed into social relationships matrix S, in which s_{uv} denotes the value of social trust u on v. In most cases, social relationships are binary, and $s_{uv} = 1$ means the existence of social relationship between user u and v, zero means no social relationship between them.

The goal of POI recommender systems is to learn users' implicit preferences according to users' history check-in history and provide users with new locations that user may be interested in.

The Taxonomy of POI Recommendation

In this section, we first review pure check-in data based POI recommendation approaches. Then, we divide POI recommendation approaches into geographical influence enhanced, social influence enhanced and temporal influenced enhanced according to which type of additional information are combined with check-in information to improve the quality of POI recommendation.

Pure Check-in Data Based POI Recommendation

Traditional recommender systems make recommendations by exploiting explicit ratings for items, which are not available in LBSNs. However, the frequencies of check-in recorded by LBSNs implicitly reflect users' preferences for POI. Hence,in order to produce POI recommendations, several studies (Berjani and Strufe 2011; Ye et al. 2011) adopted traditional recommendation algorithms to infer users' personalized tastes for POI by mining the check-in patterns of users.

With the available check-in information, existing recommendation approaches can be employed for POI recommendation in LBSNs by treating POIs as items, such as user-based collaborative filtering (Breese, Heckerman, and Kadie 1998) and item-based collaborative filtering (Sarwar et al. 2001; Linden, Smith, and York 2003). In (Ye et al. 2011), Ye et al. proposed user-based and item-based POI recommendation algorithms. User-based POI recommendation approach assumes that similar users have similar tastes for locations and makes POI recommendations based on the opinions of most similar neighbors. On the other hand, item-based POI recommendation approach assumes that users are interested in similar POIs. The core component of user-based POI recommendation algorithm is how to compute the similarity weight $sim(u, v)$ between user u and v. In (Ye et al. 2011), the authors adopted the cosine similarity measure to estimate

$sim(u, v)$, defined as follows.

$$sim(u,v) = \frac{\sum_{l_j \in L} c_{uj} c_{vj}}{\sqrt{\sum_{l_j \in L} c_{uj}^2} \sqrt{\sum_{l_j \in L} c_{vj}^2}} \tag{1}$$

Note that each entry c_{uj} of C is set as 1 if user u have visited location j, otherwise 0. User-location check-ins matrix represented in this way ignores the frequency of check-ins. Moreover, to overcome the data sparsity problem of POI recommendation, Ye et al. fused both user-based and item-based approach to make POI recommendation. Their experimental results show that user-based POI approach performs better than item-based approach since many POIs of LBSNs are visited by a few users, which leads to inaccurate item similarity compared with user similarity.

Besides the above memory-based collaborative filtering can be applicable to POI recommendation, model-based collaborative filtering approaches are also adopted for POI recommendation in LBSNs.

Since the great success of Netflix Prize competition, matrix factorization (Koren, Bell, and Volinsky 2009; Mnih and Salakhutdinov 2007; Lee and Seung 2001) based recommendation algorithms have gained a large popularity due to their effectiveness and efficiency in dealing with very large user-item rating matrix. It is intuitive that matrix factorization techniques can be employed for POI recommendation in LBSNs. Berjani et al. (Berjani and Strufe 2011) proposed regularized matrix factorization based POI recommendation algorithm in LBSNs by only utilizing user-location check-in data. They argue that lacking of explicit ratings is the main issue of POI recommendation in LBSNs. Hence, they used binary and binning preference definitions to derive pseudo ratings from check-in data and adopted regularized matrix factorization (RMF) (Koren, Bell, and Volinsky 2009) for POI recommendation. Specifically, each entry of matrix C is first transformed according to binary or binning preference definition. Then, the derived user-location rating matrix C' are decomposed into two low rank latent feature matrices $U \in \Re^{K \times N}$ and $V \in \Re^{K \times M}$, where $K \ll \min(N, M)$. Their proposed POI recommendation algorithm learns the latent feature matrices U and V by minimizing objective function 2.

$$\min_{U,V} \frac{1}{2} \sum_{(u,i) \in T} (c_{ui} - U_i^T V_j)^2 + \frac{\lambda}{2} ||U||_F^2 + \frac{\lambda}{2} ||V||_F^2 \tag{2}$$

where T indicates the set of the (u, i) pairs for known derived ratings and λ represents the regularization parameter.

Cheng et al. (Cheng et al. 2012) proposed probabilistic matrix factorization (PMF) (Mnih and Salakhutdinov 2007) based and probabilistic factor models (PFM) (Chen et al. 2009; Ma et al. 2011) based POI recommendation algorithms. PMF based recommendation approach assumes Gaussian distribution on observed check-in data and places Gaussian priors on the latent feature matrices U and V. The corresponding objective function of PMF based POI recommendation algorithm is defined as follows.

$$\min_{U,V} \sum_{i=1}^{N} \sum_{j=1}^{M} I_{ij} (g(c_{ij}) - g(U_i^T V_j))^2 + \lambda_1 ||U||_F^2 + \lambda_2 ||V||_F^2 \tag{3}$$

where $g(x) = \frac{1}{1+e^{-x}}$ is the logistic function. I_{ij} is the indicator function. If user i has checked in location j , I_{ij} takes the value 1, otherwise 0. On the other hand, PFM based POI recommendation approach models the frequency of check-in directly and places Beta distribution as priors on the latent feature matrices U and V. Their experimental results on Gowalla dataset show that PFM based POI recommendation algorithm achieves a little better results than PMF based POI recommendation algorithm.

Note that there are a few of studies purely exploit users' check-in information for POI recommendation. With rich additional information become available in LBSNs, most research works combine check-in data with additional information to produce POI recommendations since it is reported that additional information are helpful to improve the performance of traditional recommendation systems, such as social relationships enhanced recommendation approaches (Jamali and Ester 2010; Ma et al. 2008; Yang, Steck, and Liu 2012), content enhanced recommendation approaches (Agarwal and Chen 2010; Wang and Blei 2011; Bao and Zhang 2014), tagging enhanced recommendation approaches (Zhen, Li, and Yeung 2009; Wu et al. 2012) and item attribute enhanced recommendation approaches (Nguyen and Zhu 2013; Yu, Wang, and Gao 2014).

Geographical Influence Enhanced POI Recommendation

In LBSNs, there are physical interactions between users and POIs, which is a unique property distinguishing POI recommendation from traditional item recommendation. Moreover, the Tobler's First Law of Geography reported that "Everything is related to everything else, but near things are more related than distant things" (Tobler 1970). The Tobler's First Law of Geography is also represented as *geographical clustering phenomenon* in users' check-in activities. Two intuitions contribute this phenomenon: (1) users prefer to visit nearby POIs rather than distant ones; (2) users may be interested in POIs surrounded a POI that users prefer. Several studies (Ye et al. 2011; Yuan et al. 2013; Zhang, Chow, and Li 2014; Gao, Tang, and Liu 2012; Liu et al. 2013) argue that *geographical clustering phenomenon* in users' check-in activities, known as geographical influence, can be utilized to improve the POI recommender systems.

In (Ye et al. 2011), Ye et al. employed a power-law distribution (PD) to model users check-in behaviors, and proposed a collaborative POI recommendation algorithm based on geographical influence via naive Bayesian. The check-in probability y of two POIs visited by the same user is defined as follows.

$$y = a \times x^b \tag{4}$$

where x denotes the distance between two POIs. a and b are parameters of the power-law distribution, which are learned from observed check-in data. Then, they applied a linear curve fitting method to learn linear coefficients W, derived from a and b, by minimizing the loss function $E(W)$.

$$E(W) = \frac{1}{2}\sum_{n=1}^{N}\{y'(x_n^{'}, W) - t_n\} + \frac{\lambda}{2} \parallel W \parallel^2 \tag{5}$$

By employing naive Bayesian method, the likelihood probability for u_i to check in l_j as follows.

$$\begin{aligned} Pr[l_j|L_i] &= \frac{Pr[l_j \cup L_i]}{Pr[L_i]} \\ &= \frac{Pr[L_i] \times \prod_{l_y \in L_i} Pr[d(l_j, l_y)]}{Pr[L_i]} \\ &= \prod_{l_y \in L_i} Pr[d(l_j, l_y)] \end{aligned} \tag{6}$$

where $d(l_j, l_y)$ denotes the distance between POI l_j and l_y, and $Pr[d(l_j, l_y)] = a \times d(l_j, l_y)^b$.

On the other hand, Yuan et al. (Yuan et al. 2013) integrated geographical influence into POI recommendation by making a different assumption. In (Ye et al. 2011), the proposed POI recommendation algorithm assumes that the probability that a user checks in a new POI is estimated by the product of the probabilities of visiting all the pairwise POI, each pair consists of the new POI and each previously visited POI. While Yuan et al. (Yuan et al. 2013) assumed that the willingness that a user moves from a POI to another POI is a function of their distance. In detail, the willingness of user to visit a dis km far away POI and the probability that user will check in l_j , given user is currently at POI l_i, are defined by Equation 7 and 8, respectively.

$$wi(dis) = a \times dis^k \tag{7}$$

$$p(l_j|l_i) = \frac{wi(dis(l_i, l_j))}{\sum_{l_k \in L, l_k \neq l_i} wi(dis(l_i, l_k))} \tag{8}$$

where a and k are parameters of power-law distribution. Finally, Yuan et al. applied Bayes rule to compute the ranking score $P(l|L_u)$ for each new POI l given the historical POIs L_u of user u. Formally,

$$\begin{aligned} \widehat{c}_{u,l} &= P(l|L_u) \propto P(l)P(L_u|l) \\ &= P(l) \prod_{l' \in L_u} P(l'|l) \end{aligned} \tag{9}$$

where $P(l)$ is the prior probability that POI l is checked in by all users in dataset. Their experimental results show that their proposed POI recommendation performs much better than that of (Ye et al. 2011) in terms of precision and recall.

Instead of making power law distribution (PD) assumption (Ye et al. 2011; Yuan et al. 2013), Cheng et al. (Cheng et al. 2012) assumes that users tend to check in around several centers and captures the geographical influence via modeling the probability of a user's check-in on a location as a Multi-center Gaussian Model (MGM). Given the multi-center set C_u, the probability of check-in POI l by user u is defined by:

$$P(l|C_u) = \sum_{c_u=1}^{|C_u|} P(l \in c_u) \frac{f_{c_u}^{\alpha}}{\sum_{i \in C_u} f_i^{\alpha}} \frac{N(l|\mu_{c_u}, \Sigma_{c_u})}{\sum_{i \in C_u} N(l|\mu_i, \Sigma_i)} \tag{10}$$

where $P(l \in c_u) \propto 1/d(l, c_u)$ is the probability of the POI l belonging to the center c_u. $\frac{f_{c_u}^{\alpha}}{\sum_{i \in C_u} f_i^{\alpha}}$ denotes the normalized effect of check-in frequency on the center c_u and parameter α maintains the frequency aversion property. $N(l|\mu_{c_u}, \Sigma_{c_u})$ is the probability density function of Gaussian distribution with mean μ_{c_u} and covariance matrix Σ_{c_u}. Moreover, the MGM adopts a greedy clustering algorithm on the check-in data to find the centers. Their experimental results show that MGM outperforms PMF based and PFM based POI recommendation algorithms.

Moreover, Zhang et al. (Zhang, Chow, and Li 2014) argued that the geographical influence on individual users' check-in behaviors should be personalized when LBSNs recommend new POIs to users, and should not be modeled as a common distribution, e.g., PD (Ye et al. 2011; Yuan et al. 2013) and MGM (Cheng et al. 2012). To the end, Zhang et al. used kernel density estimation (KDE) (Silverman 1986) to model the geographical influence as a personalized distance distribution for each user. Specifically, the probability density function of distance y is defined by Equation 11.

$$f(y) = \frac{1}{|X_u|\sigma} \sum_{x \in X_u} K(\frac{y - x}{\sigma}) \tag{11}$$

where X_u is the sample of distances between each pair of POIs in the union set of user $u's$ home residence h_u and L_u. $K(.)$ is the normal kernel:

$$K(x) = \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}} \tag{12}$$

The probability of user u visiting new POI l given the union set $h_u \cup L_u$ is defined as:

$$\begin{aligned} p(l|L_u) &= 1 - \prod_{i=1}^{n+1}(1 - p(l_i \to l)) \\ &= 1 - \prod_{i=1}^{n+1}(1 - \frac{1}{|X_u|\sqrt{2\pi}} \sum_{x \in X_u} e^{-\frac{x^2}{2}} \end{aligned} \tag{13}$$

where $p(l_i \to l)$ is probability of user u visiting POI l triggered by the geographical influence of POI l_i.

$$p(l_i \to l) = \frac{1}{|X_u|} \sum_{x \in X_u} K(\frac{y_i - x}{\sigma}) \tag{14}$$

Their experimental results show that their proposed POI recommendation approach provides significantly superior performance compared to PD based POI recommendation approaches (Ye et al. 2011; Yuan et al. 2013) and MGM based POI recommendation approaches (Cheng et al. 2012).

In addition, Liu et al. (Liu et al. 2013) proposed a geographical probabilistic factor analysis framework for

POI recommendation by combining geographical influence with Bayesian non-negative matrix factorization (BNMF). Specifically, they used a Gaussian distribution to represent a POI over a sampled region, reflecting the first law of geography. Moreover, Bayesian non-negative matrix factorization model is used to capture user preferences from check-in data. Their experimental results show that the proposed POI recommendation method outperforms nonnegative matrix factorization (NMF), RMF, PMF and BNMF model. At the same time, they found that NMF and BNMF based approaches perform better than PMF and RMF based methods.

Recently, Lian et al. (Lian et al. 2014) proposed a weighted matrix factorization based POI recommendation approach, named GeoMF. Particularly, GeoMF augments users' and POIs' latent feature vectors with activity area vectors of users and influence area vectors of POIs, respectively. Moreover, GeoMF imposes sparse and non-negative constraints on both user latent feature vectors and POI latent feature vectors. Based on this augmented model, GeoMF can not only captures the geographical clustering phenomenon from the perspective of two-dimensional kernel density estimation (KDE), but also can explain the reason of why integrating geographical influence into matrix factorization is beneficial to POI recommender systems. The objective function of GeoMF is defined as follows.

$$\min_{U,V,X\geq 0} \parallel W \odot (R - UV^T - XY^T) \parallel_F^2 + \alpha(||U||_F^2 + \beta||V||_F^2) + \lambda \parallel X \parallel_1 \quad (15)$$

where W is a weighted matrix whose entry w_{ui} represents the confidence of user u for POI i. X and Y denote users' activity area matrix and POIs' influence area matrix, respectively. Note that POIs' influence area matrix Y are computed by using two-dimensional kernel density estimation. Their experimental results show that matrix factorization based POI recommendation approach based on 0/1 rating matrix performs better than the same factorization model based on frequency matrix. Moreover, weighted matrix factorization is superior to other kinds of matrix factorization models, i.e., matrix factorization (Berjani and Strufe 2011; Gao et al. 2013) and Bayesian non-negative matrix factorization (Liu et al. 2013; Cheng et al. 2012).

Social Influence Enhanced POI Recommendation

Social influence enhanced recommendation approaches have been extensively explored in traditional recommender systems, include memory-based methods (Jamali and Ester 2009; Massa and Avesani 2007; Golbeck 2006) and model-based methods (Jamali and Ester 2010; Ma et al. 2008). Inspired by the assumption that friends of LBSNs share more common interests than non-friends, several POI recommendation approaches improve the quality of recommendation by taking social influence into consideration (Ye, Yin, and Lee 2010; Cheng et al. 2012).

In (Ye, Yin, and Lee 2010), Ye et al. proposed friend-based collaborative filtering (FCF) approach for POI recommendation based on common visited check-ins of friends. When making POI recommendations, FCF only considers the preferences of friends, instead of every user of LBSNs. In FCF, the predicted rating of user u_i on l_j is computed according to Equation 16.

$$\widehat{r}_{i,j} = \frac{\sum_{u_k \in F_i} r_{k,j} w_{i,k}}{\sum_{u_k \in F_i} r_{k,j}} \quad (16)$$

where F_i is the set of friends with top-n similarity, $w_{i,k}$ is directional social influence weight u_i on u_k. Note that FCF focuses on the efficiency instead of effectiveness of POI recommender systems. Hence, FCF brings minor improvement over user-based POI recommendation in terms of precision. In their later work (Ye et al. 2011), Ye et al. derived the social influence weight between two friends based on both of their social connections and similarity of their check-in activities. Formally,

$$w_{i,k} = \eta \frac{|F_k \cap F_i|}{|F_k \cup F_i|} + (1-\eta)\frac{|L_k \cap L_i|}{|L_k \cup L_i|} \quad (17)$$

where η is a tuning parameter and F_k denotes the friend set of user u_k.

Cheng et al. (Cheng et al. 2012) proposed probabilistic matrix factorization with social regularization (PMFSR), which integrates social influence into PMF. PMFSR learns the latent preferences of users or the latent characteristics of POI by minimizing the following objective function.

$$\min_{U,V} \sum_{i=1}^{N}\sum_{j=1}^{M} I_{ij}(g(c_{ij}) - g(U_i^T V_j))^2 + \lambda_1||U||_F^2 + \lambda_2||V||_F^2 + \beta \sum_{i=1}^{N}\sum_{f\in F_i} sim(i,f) \parallel U_i - U_f \parallel_F^2 \quad (18)$$

where $sim(i, f)$ is the similarity between user u_i and his friend u_f.

Although social influence shows an important impact on the performance of traditional recommender system, the experimental results of above mentioned social influence enhanced POI recommendation approaches show that social influence weights litter than geographical influence and check-in activities. We argue that the users' check-in activities need physical interactions between users and locations, which limit the contributions of social influence. While watching movies, listening music and buying products existed in traditional recommender systems are not limited by physical interactions since users can conduct these activities through web sites.

Temporal Influence Enhanced POI Recommendation

There exists studies that consider temporal influence in traditional recommender systems, such as matrix factorization based approach (Koren 2010), random walk based approach (Xiang et al. 2010). However, in traditional recommendation systems, temporal influence is used to as a factor that decays the weights of ratings. On the contrary, POI recommendation systems generally use temporal influence to make POI recommendation for a specific temporal state.

Yuan et al. (Yuan et al. 2013) assume that users tent to visit different locations at different time and proposed time-aware POI recommendation algorithm. Specifically, they proposed POI recommendation algorithm extends the user-based POI recommendation algorithm by leveraging the time factor when computing the similarity between two users as well as considering the historical check-ins at time t, rather than at all time to make POI recommendation. The recommendation score that user u check in a new POI l at time t is defined as.

$$\widehat{c}_{u,t,l}^{(t)} = \frac{\sum_v w_{u,v}^{(t)} c_{v,t,l}}{\sum_v w_{u,v}^{(t)}} \tag{19}$$

where $c_{v,t,l}$ is binary, and $c_{v,t,l} = 1$ if user u has checked in POI l at time t, otherwise 0. $w_{u,v}^{(t)}$ denotes the temporal behavior similarity between u and v, defined as follows.

$$w_{u,v}^{(t)} = \frac{\sum_{t \in T} \sum_{l \in L} c_{u,t,l} c_{v,t,l}}{\sqrt{\sum_{t \in T} \sum_{l \in L} c_{u,t,l}^2} \sqrt{\sum_{t \in T} \sum_{l \in L} c_{v,t,l}^2}} \tag{20}$$

In their experiments on Foursquare and Gowalla, they found that the POI recommendation approach enhanced by time information always outperforms user-based POI recommendation approach, which ignores the time information.

Gao et al. (Gao et al. 2013) proposed matrix factorization based POI recommendation algorithm with temporal influence based on two temporal properties: (1) non-uniforms: a user exhibits distinct check-in preferences at different hours of a day; (2) consecutiveness: a user tends to have more similar check-in preferences in consecutive hours. To model the non-uniforms property, they defined $U_t \in \Re^{N \times K}$ and $V \in \Re^{M \times K}$ to describe the time-dependent user check-in preferences under temporal state t and represent the characteristics of POI, respectively. By solving the optimization problem of Equation 21, they obtained time-dependent user latent feature matrices U_t and time-independent POI latent feature matrix V.

$$\min_{U_t \geq 0, V \geq 0} \sum_{t=1}^{T} \| Y_t \odot (C_t - U_t V^T) \|_F^2 + \alpha \sum_{t=1}^{T} ||U_t||_F^2 + \beta ||V||_F^2 \tag{21}$$

where $C_t \in \Re^{N \times M}$ is the user-location check in matrix at temporal state t and Y_t is the corresponding indicator matrix. Moreover, they modeled the temporal consecutiveness property by introducing a temporal regularization term into Equation 21. Formally,

$$\sum_{t=1}^{T} \sum_{i=1}^{N} \psi_i(t, t-1) \| U_t(i,:) - U_{t-1}(i,:) \|_F^2 \tag{22}$$

where $\psi_i(t, t-1)$ is the temporal coefficient that measures the similarity of u_i's check-in preferences between temporal state t and $t-1$, computed by cosine similarity measure. Finally, they proposed POI recommendation approach learns latent user feature matrices U_t and latent POI feature matrix V by solving the following objective function.

$$\begin{aligned} \min_{U_t \geq 0, V \geq 0} & \sum_{t=1}^{T} \| Y_t \odot (C_t - U_t V^T) \|_F^2 + \alpha \sum_{t=1}^{T} ||U_t||_F^2 \\ & + \beta ||V||_F^2 + \lambda \sum_{t=1}^{T} Tr((U_t - U_{t-1})^T \Sigma_t (U_t - U_{t-1})) \end{aligned} \tag{23}$$

Their experimental results show that their proposed POI recommendation algorithm performs better than user-based and NMF (Lee and Seung 2001) based POI recommendation algorithms.

Conclusion and Future Research Directions

With the prevalence of location-based social networks, personalized POI recommendation techniques have attracted lots of attention from industry and academia since they not only help users explore new places but also increase the revenues of LBSNs providers. In this paper, we present a brief survey over the task of POI recommendation in LBSNs. We first characterize the unique properties existing in POI recommendation, which distinguish POI recommender systems from traditional recommender systems. Furthermore, we classify POI recommendation algorithms into four categories: pure check-in data based POI recommendation approaches, geographical influence enhanced POI recommendation approaches, social influence enhanced POI recommendation approaches and temporal influence enhanced POI recommendation approaches based on the type of additional information integrated with check-in data by POI recommendation algorithms.

From the existing studies, we summarize the following observations: (1) although all kinds of additional information are useful for improving the recommendation quality of POI recommender systems, check-in data, geographical influence and temporal influence show more significant impacts on the POI recommendation than social influence. Particularly, geographical influence plays the most important role in POI recommendation. (2) for modeling users' check-in behaviors, personalized distance distribution for each user is better than universal distributions, e.g., PD and MGM. (3) model-based POI recommendation approaches are more efficient and effective than memory-based POI recommendation approaches, which is consistent with their performance in traditional recommender systems. In addition, user-based POI recommendation approaches are more suitable for POI recommendation in LBSNs than item-based approaches. (4) among matrix factorization based POI recommendation approaches, NMF and BNMF models perform better than RMF and PMF models. Moreover, weighted MF based factorization model outperforms NMF and BNMF models.

Despite some research works have studied the problem of POI recommendation in LBSNs, POI recommendation just emerges recently and several interesting research directions are worthy of exploring. First, in LBSNs, the frequencies of check-in for POIs vary dramatically and users' check-in frequency intuitively reflects the degree of users' preferences for POIs. However, the reviewed works reported that making POI recommendation based on 0/1 rating matrix is better than on check-in frequency matrix. Hence, it is desirable for POI recommender systems to adopt suitable approaches to model check-in frequency data. Rank-based collaborative filtering approaches (Yi et al. 2013; Shi, Larson, and Hanjalic 2010) may be applicable to POI recommendation since rank-based collaborative filtering approaches infer users' preferences from pairwise comparisons rather than numerical ratings. Second, it is reported that social influence enhanced POI recommendation approaches have not achieve important improvements compared with the state-of-art POI recommendation methods. Beside the decision process of POI selection is influenced by the geographical property of POIs, a possible reason is that social influence enhanced POI recommendation approaches take all social relations as homogeneous social connections and ignore different types of social relations. Social relations in LBSNs are heterogeneous and consist of different types of social relations (such as friendships and memberships etc), and users tend to different social circles for suggestions according to different objectives. Hence, it would be useful for POI recommender systems to consider different types of social relations. Third, since users often involve several social networks, information derived from other social networks would be beneficial for POI recommendation in LBSNs. In this case, POI recommendation based on transfer learning (Pan and Yang 2010) is a potential research direction. Fourth, LBSNs provide rich additional information for enhancing the performance of POI recommender systems, i.e. check-ins, geographical information, social relationships and temporal information. A unified recommendation framework is desirable for POI recommender systems to boost the performance of POI recommender systems by joint all kinds of additional information. Finally, As the rapidly growing amount of users and POIs available in LBSNs, POI recommender systems suffer seriously from scalability problem. Hence, parallelized computing methods, e.g, MapReduce (Dean and Ghemawat 2008) and Spark (Zaharia et al. 2012), are worthy of exploiting to speed up the computation process of POI recommendation.

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