A Sentiment-Enhanced Personalized Location Recommendation System

Dingqi Yang†, Daqing Zhang†, Zhiyong Yu†, Zhu Wang‡
† Institut Mine-Telecom, Telecom SudParis, 9 Rue Charles Fourier, 91000 Evry, France
‡ Northwestern Polytechnical University, Xi'an 710072, Shaanxi, P. R. China
{dingqi.yang, daqing.zhang, zhiyong.yu}@it-sudparis.eu, transitwang@gmail.com

ABSTRACT

Although online recommendation systems such as recommendation of movies or music have been systematically studied in the past decade, location recommendation in Location Based Social Networks (LBSNs) is not well investigated yet. In LBSNs, users can check in and leave tips commenting on a venue. These two heterogeneous data sources both describe users' preference of venues. However, in current research work, only users' check-in behavior is considered in users' location preference model, users' tips on venues are seldom investigated yet. Moreover, while existing work mainly considers social influence in recommendation, we argue that considering venue similarity can further improve the recommendation performance. In this research, we ameliorate location recommendation by enhancing not only the user location preference model but also recommendation algorithm. First, we propose a hybrid user location preference model by combining the preference extracted from check-ins and text-based tips which are processed using sentiment analysis techniques. Second, we develop a location based social matrix factorization algorithm that takes both user social influence and venue similarity influence into account in location recommendation. Using two datasets extracted from the location based social networks Foursquare, experiment results demonstrate that the proposed hybrid preference model can better characterize user preference by maintaining the preference consistency, and the proposed algorithm outperforms the state-of-the-art methods.

Categories and Subject Descriptors

H.3.3 [**Information Search and Retrieval**]: Information Filtering; J.4 [**Computer Applications**]: Social and Behavioral Sciences

General Terms

Algorithms, Experimentation

Keywords

Recommendation System, Location Based Social Networks, Sentiment Analysis, Matrix Factorization

24th ACM Conference on Hypertext and Social Media
1–3 May 2013, Paris, France

1. INTRODUCTION

With the rapid growth of online information, more and more users need high-quality personalized services for the purpose of information retrieval. Recommendation systems are popular systems that leverage various techniques to suggest information items (e.g. movies, music, news, locations, etc.) that users are likely to be interested in. Typically, given a set of users' preference, such as preference profile or ratings of items, recommendation systems try to predict users' preference for unrated items. It has been widely studied in both academia and industry.

With the recent booming of location sharing services such as Foursquare[1], location recommendation is becoming an emerging research topic. In location sharing services, a user can check in at a venue and post a check-in message at the same time, expressing how she felt when visiting the place. Besides, they can also leave tips to comment on a venue[2]. Different from the classical recommendation systems with explicit rating records which reflect users' preference, location recommendation usually utilizes user's behavior, i.e. check-in, to model users' preference with regard to a venue [3, 7, 22, 30, 31]. Nevertheless, merely using check-in data has two shortcomings. First, check-in data of a user may not be sufficient to reflect her preference. Compared to web based rating services which capture users' preference on items, check-ins only represent users' habitual behaviors. Intuitively, users prefer those venues with high check-in frequencies. However, those less checked venues may not be necessarily less favored by users. Second, check-in frequency is directly considered as the degree of users' preference in location recommendation, the negative feedback in the comments made in each venue is not taken into account, which may introduce biases to the user preference measure. Besides user preference model, recommendation algorithm should also be improved to handle both inter-user and inter-venue relationships. The state-of-the-art location recommendation approaches only consider how user social network can influence recommendation results. But in fact, location recommendation needs to consider more factors such as geographical constraint, venue category and reviews, etc.

In this paper, aiming at solving the two aforementioned problems in location recommendation, we firstly propose a novel user preference model with extra information besides check-in and then extend matrix factorization model in classical social recommendation to capture both social and inter-venue influence.

[1]https://foursquare.com/
[2]Since "venue" is used to represent a location in Foursquare, we don't differentiate the two terms throughout this paper.

First, we consider both check-ins and comments of venues in location recommendation. Unlike check-in messages which tend to express the real-time personal feeling, tips of a venue are more like customer reviews. For example, for an Italian restaurant, user may post a check-in message like "happy with my buddies here∼" and leave a tip like "Good place in center New York, I went there last Sunday night and had great spaghetti with reasonable price. But I had a very long waiting time, almost one hour just for appetizer!!!" Furthermore, according to the post[3], about two thirds of Foursquare users post tips on venues. Such information can then be used for personalized venue recommendation. In this paper, we use text-based sentiment analysis techniques to extract one's sentiment in tips and then convert it as a preference measure. We also propose a fusion framework to get a unified preference model from both check-ins and tips.

Second, venues in location recommendation can construct a similarity network according to their geo-distance, categories, reviews, etc. Similar to user social network, we believe that venue similarity can also influence recommendation performance. Therefore, we introduce a Location Based Social Matrix Factorization (LBSMF) model to capture the influence on recommendation from both user social network and venue similarity network perspectives.

The remainder of this paper is organized as follows. In section 2, we briefly survey the related work in three related domains. Section 3 describes the problem of both data model and approach. Section 4 and 5 detail the proposed preference model and algorithm, respectively. In section 6, we conduct a series of experiments using data collected from Foursquare for evaluation. Conclusion and future work is presented in section 7.

2. RELATED WORK

Our work is related to three main research threads: (1) sentiment analysis on social web; (2) recommendation systems in social network and (3) location recommendation.

2.1 Sentiment Analysis on Social Web

Sentiment analysis plays an important role in information retrieval. It sheds light on what people think, and how they feel about something or somebody under certain circumstance. This high level information can then be used in many applications such as customer review analysis, business and government intelligence, personalized recommendation, etc. With the booming of social web, sentiment analysis brings us deeper understanding about online social network [28]. Micro-blogs such as Twitter provide huge amount of data which can be used to discover collective sentiment knowledge [4, 5, 23, 27]. Many applications can then be built such as trend analysis of political election [11, 29], investigating consumer opinions of certain brands [15], detecting influenza epidemics [10] and searching the emotional web [17], etc. In location based social networks, Cheng et al. [8] conduct sentiment analysis of tips in Foursquare and investigate its impact on user mobility. In our work, with a different purpose, we conduct sentiment analysis of tips in Foursquare in order to extract users' preference about venues in LBSNs and argue that users' sentiment can be deployed in improving location recommendation performance.

[3]http://techcrunch.com/2011/08/04/klout-adds-foursquare-but-how-much-will-it-boost-my-score/

2.2 Social Recommendation Systems

A wide range of research work has been done in building recommendation systems using data mining technologies [1]. They mainly fall into three categories: memory-based approach, model-based approach and hybrid approach. Memory-based approaches explore historical rating records to predict unknown ratings without learning step, e.g., classical collaborative filtering methods. They focus on user-item rating matrix and attempt different strategies to estimate missing ratings. Model-based approaches use the learned model from historical data to predict unknown ratings. They leverage statistics and machine learning techniques to learn models from data in order to predict the missing ratings. Hybrid approaches combine the two aforementioned approaches with certain fusion criterion.

The recent growth of social network provides rich social information which can be deployed in recommendation. Unlike traditional recommendation systems assuming that users and items are independent from each other, recommendation systems in social network are able to take the social factor into account. The basic assumption is that users' preference is partially influenced by their social circles. For example, users often resort to their friends or someone they trust for recommendation.

According to social relationship type, social network can be divided into two categories: unidirectional and bidirectional. In unidirectional social network, users establish the relationship without the need of confirmation from others. One example is the follower and following relationship in Twitter[4]. Recommendation based on unidirectional social network can be called trust-based social recommendation [2, 12, 13, 19, 21, 24]. In bidirectional social network, the friend relationship can be established if and only if both sides accept it such as friendship on Facebook[5] and LinkedIn[6]. Recommendation based on bidirectional social network can be seen as friend-based social recommendation [14, 20]. While all these works focus on online social recommendation that considering user social network, we argue that considering venue similarity can also improve recommendation performance. Hence, we extend the classical matrix factorization approach by considering both user social influence and inter-venue influence in location recommendation.

2.3 Location Recommendation

Existing location recommendation can be divided into two categories: 1) generic location recommendation and 2) personalized location recommendation. First, generic location recommendation usually provide users the most popular venues according to public opinions such as in [6]. Due to the lack of individual preference, users receive identical recommendation from such systems. Second, personalized location recommendation aims at providing users with the most pertinent venues by considering individual's preference. Among various personalized location recommendation approaches such as collaborative filtering [16, 33], matrix factorization [3, 7, 30, 31, 32] and recommendation with random walk [22], matrix factorization is the most popular approach due to its online recommendation efficiency [13]. Since our approach falls into this category, we briefly survey the location

[4]https://twitter.com/

[5]http://www.facebook.com/

[6]http://www.linkedin.com/

recommendation using matrix factorization techniques.

Before the popularity of LBSNs, using experimental GPS dataset collected by 162 users, Zheng et al. [32] proposed a collective matrix factorization method to reveal interesting locations and activities for recommendation. With the advent of LBSNs, huge amount of digital traces about users' physical activities (e.g., check-ins, tips) become available. Different from using user-item rating records in classical matrix factorization approaches, location recommendation mainly takes user's check-ins as inputs. The most popularly used model is 0/1 scheme, i.e. the places users visited are labeled as 1 and non-visited as 0. Using this model, Ye et al. [30, 31] studied the geographical and social influence in point-of-interest recommendation based on collaborative filtering techniques. Another model is based on check-in frequency which quantifies users' preference on venues according to the number of their check-ins. With this scheme, Berjani et al. [3] developed a location recommendation system using matrix factorization methods. In [7], Chen et al. proposed a multi-center Gaussian model to capture the geographical influence and combined the matrix factorization with social regularization to perform the location recommendation. All of these location recommendation systems use the user check-in information to model user preference. However, recommendation merely based on user check-ins may introduce bias on measuring users' preference as mentioned in the introduction. To improve the accuracy of user preference modeling, we propose a hybrid preference model that combines user preference extracted from both user's check-ins and tips. Then by considering both social and inter-venue influence, we extend classical matrix factorization algorithm and provide recommendation leveraging the proposed hybrid preference model.

3. PROBLEM DEFINITION

The aim of this work is to recommend venues to users based on their check-ins and tips. The problem can be divided into two parts: 1)user preference modeling from heterogeneous data source and 2)location recommendation in form of missing preference prediction.

First, as two types of digital traces, i.e. check-ins and tips, are involved as inputs, the problem is how to build a unified user preference model, expressed as a user-venue matrix, taking into account users' preference in both check-ins and tips. While check-in data has the form of u-v pairs which means user u visited venue v, tip data has the form of u-v-t triplet which implies user u left a tip t on venue v. As tips are texts while check-ins are in numerical format, we needs obviously a mechanism to fuse these two heterogeneous data sources together.

Second, location recommendation aims at providing each user with a ranked list of venues according to one's preference. To perform venue ranking, we need to predict the missing preference from historical user-venue preference records. In addition to the user-venue preference matrix, there exist also inter-user social relationships and inter-venue relationships in terms of similarity, then the problem is how to extend the state-of-the-art matrix factorization technique to handle all three matrixes (user-venue preference matrix, user social relationship matrix and venue similarity matrix), in order to predict the missing preference value in the preference model effectively and efficiently.

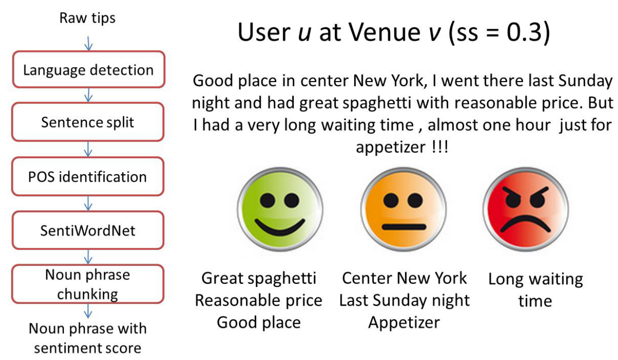


Figure 1: Sentiment analysis of tips

4. USER PREFERENCE MODEL

User preference about a place or an object can be reflected in her interaction with these entities. An efficient way to extract user preference is to learn from a user's interaction history. For Foursquare users, as they interact with the visited venues through check-ins and tips, in this paper, a Hybrid Preference Model (HPM) unifying user's preference in both check-ins and tips is proposed to build a user-venue preference matrix.

4.1 Tips Data Processing

Tips are short texts that often describe users' comments about venues, which can be converted to a sentiment score based on the content. As shown in Figure 1, we present an example of the tips left at an Italian restaurant. The left part of Figure 1 illustrates the tip processing flow. We use dictionary based unsupervised sentiment analysis method and only process the tips in English in our study. More sophisticated sentiment analysis techniques can also be used to improve the performance, but they are not the main focus of this research. Firstly, the language detection component filters out non-English tips at the beginning. Then tips are split into sentences and the part-of-speech (denoted as POS in Figure 1) is identified, e.g., "good" is an adjective, "place" is a noun, "went" is a verb, etc. We first obtain a sentiment score for each word by looking it up in SentiWordNet [26] with the corresponding part-of-speech tag. Noun-Phrase Chunking technique is then performed to extract phrases e.g., "good place", implying whether a user likes or dislikes a venue. A positive, zero and negative value of this measure indicates the positive, neutral and negative sentiment, respectively. The overall sentiment score (denoted as *ss* in Figure 1) is the sum of all the sentiment scores of each word in a tip and is normalized into [-1, 1], where -1 and 1 represent the most negative and positive sentiment, respectively.

The implementation is based on NTLK toolkit [18] and SentiWordNet3.0 [26]. The processed result of the example tip is shown in the right panel of Figure 1. From the positive phrase set, we can see user u prefers the food (i.e. "great spaghetti"), price (i.e. "reasonable price") and place (i.e. "good place") of this restaurant v. The negative phrase set shows that user u doesn't like the "long waiting time" in this restaurant v. The neutral phrase set usually contains the vocabularies without any sentiment. In this paper, we leverage the overall sentiment score of a tip to evaluate users' preference.

4.2 Preference Extraction and Fusion

Based on the number of check-ins and sentiment scores obtained from tips, a user-venue preference matrix can be built. Without loss of generality, we use a five-point preference scale in the preference matrix, where 1 represents for "Poor", 2 for "Fair", 3 for "Good", 4 for "Very Good" and 5 for "Excellent". Due to the power law distribution of user-venue check-in numbers [9], the number of check-ins is mapped as follows: one check-in corresponds to 2, two check-ins to 3, three check-ins to 4, and four or more check-ins to 5, resulting in a *check-in preference matrix*.

As the sentiment score extracted from tips contains more precise information about a user's preference on a venue, it should be considered together with the number of check-ins to characterize a user's preference about a venue. The mapping scheme should also consider its statistical distribution. As shown in the left part of Figure 2, the distribution of sentiment scores is highly centralized around 0, i.e. neutral sentiment. This implies that most of the tips have the sentiment around neutral. Furthermore, a slight bias towards positive sentiment is also observed, which implies people tend to leave more positive tips at the venues where they checked in. Considering such a distribution of sentiment scores, we propose a mapping scheme for sentiment scores (presented in the right part of Figure 2), resulting in a *sentiment preference matrix*.

Having two preference matrices, the fusion criteria aim at resolving the conflict of the same entry in two matrices. The fusion framework is based on two assumptions as follows:

1. *One time check-in venues cannot reveal sufficient information about user's feeling about the venues.* In this case, sentiment preference is assumed to be more accurate and used as the final preference. For example, if a user left a very positive tip (i.e., 5 points) on a venue that she checked only once (i.e., 1 point), the final preference will be 5.
2. *A repeated customer (i.e. users who check in a venue at least twice) usually prefers the venues she visited. The preference from tips may have some impact on the overall preference.* In this case, sentiment preference is used to amend check-in preference within 1 point range as shown in Equation 1. More specifically, check-in preference will be increased or decreased by 1 point when sentiment preference is two points higher or less than check-in preference, respectively. For example, when a user has a preference of 3 points from check-in for a venue and left a very negative tip (1 point), the final preference will be 2 points because of the tip.

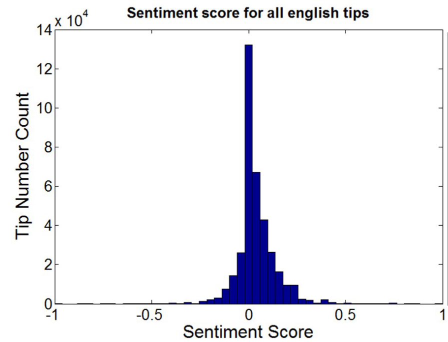
$$P_{final} = P_c - sgn(P_c - P_s) \cdot H(|P_c - P_s| - 2) \quad (1)$$

where P_c and P_s is the check-in and sentiment preference score, respectively. Function $sgn(x)$ is the Sign function and $H(x)$ is the Heaviside step function.

Based on the above two assumptions and the fusion criteria, we construct the hybrid preference matrix which combines both preference extracted from check-ins and tips.

5. LOCATION BASED SOCIAL MATRIX FACTORIZATION MODEL

In this section, we present the proposed Location Based Social Matrix Factorization (LBSMF) approach. First, we explain the basic principle of matrix factorization technique, and then extend it by combining with user social network and venue similarity network for location recommendation.



Sentiment Score	Preference Measure
[-1, -0.05]	1
(-0.05, -0.01]	2
(-0.01, 0.01)	3
[0.01, 0.05)	4
[0.05, 1]	5

Figure 2: Sentiment score distribution for all tips in English and the preference mapping scheme

5.1 Matrix Factorization

Probabilistic matrix factorization (PMF) model [25] is an efficient approach in recommendation systems. It factorizes user-item rating matrix into a user-latent space matrix and an item-latent space matrix which are later used to predict the unknown ratings. Given a user-item rating matrix $R_{m\times n}$ describing m users' ratings on n items, the matrix factorization methods try to approximate $R_{m\times n}$ by a product of two matrices $U_{m\times l}$ and $V_{n\times l}^T$ which represent the user-latent space matrix and item-latent space matrix, respectively. The dimensionality of the latent space is denoted as l.

$$R_{m\times n} \approx U_{m\times l} \times V_{n\times l}^T \quad (2)$$

Since the rating matrix R is usually sparse in the real dataset, only the observed rating in R should be considered. In order to model the latent features of U and V, the conditional probability of the observed ratings are:

$$p(R|U,V,\sigma_R^2) = \prod_{i=1}^{m}\prod_{j=1}^{n} I_{ij}[\mathcal{N}(R_{i,j}|U_i \times V_j^T, \sigma_r^2)] \quad (3)$$

where I_{ij} is the indicator function that equals 1 if user i rated item j and equals 0 otherwise, $\mathcal{N}(x|\mu,\sigma^2)$ is the normal distribution with mean μ and variance σ^2. Gaussian priors are also assumed for U and V.

$$p(U|\sigma_U^2) = \prod_{i=1}^{m}[\mathcal{N}(U_i|0,\sigma_U^2\mathbf{I})] \quad (4)$$

$$p(V|\sigma_V^2) = \prod_{j=1}^{n}[\mathcal{N}(V_j|0,\sigma_V^2\mathbf{I})] \quad (5)$$

Based on Bayesian inference, the posterior probability of U and V are as follows.

$$p(U,V|R,\sigma_R^2,\sigma_U^2,\sigma_V^2) \propto p(R|U,V,\sigma_R^2)p(U|\sigma_U^2)p(V|\sigma_V^2) \quad (6)$$

By maximizing Equation 6, we can obtain the learned U and V for recommendation. Due to the space limit, we don't elaborate the whole derivation process and the details can be found in [25]. The graphical model of probabilistic matrix factorization is shown in Figure 3.

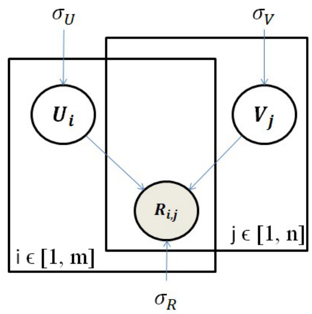


Figure 3: Graphical model of probabilistic matrix factorization.

5.2 Location Based Social MF

As mentioned in the problem definition section, based on PMF approach, we design our location based social MF model considering both user social network and venue similarity network for location recommendation. Note that venue is considered as the item in the location recommendation. Due to social influence, we assume that a user's preference is similar to her friends', i.e. her latent features are similar to her friends'. Similarly, a venue's visiting record is similar to the similar venues (e.g., venues in the same category may probably have similar temporal traffic pattern), i.e. its latent features resemble the similar venues'. For a user i, the social influence of her friends' can be formulated as follows:

$$InfU_i = \frac{\sum_{f \in F_i} SimU_{i,f} \cdot U_f}{\sum_{f \in F_i} SimU_{i,f}} \tag{7}$$

where F_i is the friends set of user i and $SimU_{i,f}$ is the similarity measure between user i and her friend f. We use such similarity to determine how influential a friend is to user i. Similarly, for a venue j, the influence of the similar venues can be formulated as

$$InfV_j = \frac{\sum_{s \in N_j} SimV_{j,s} \cdot V_s}{\sum_{s \in N_j} SimV_{j,s}} \tag{8}$$

where N_j is the similar venues set of venue j and $SimU_{j,s}$ is the similarity measure between venue j and venue s. Note that the non-zero value in $SimU$ and $SimV$ represent the similarity measure. After normalizing each rows of $SimU$ and $SimV$ so that $\sum_{f \in F_i} SimU_{i,f} = 1$ and $\sum_{s \in N_j} SimV_{j,s} = 1$. The influence terms become:

$$\begin{aligned} InfU_i &= \sum_{f \in F_i} SimU_{i,f} \cdot U_f \\ InfV_j &= \sum_{s \in N_j} SimV_{j,s} \cdot V_s \end{aligned} \tag{9}$$

Based on the Gaussian priors of U and V, the latent features of users and venues are directly proportional to the combination of two factors: the zeros-means Gaussian priors as in Equation 4 and 5, and the conditional distribution of $InfU$ and $InfV$ that represent the social and inter-venue influence. Hence, the conditional distribution of the latent features of U and V are:

$$\begin{aligned} & p(U|SimU, \sigma_U^2, \sigma_{SimU}^2) \propto p(U|\sigma_U^2) p(U|SimU, \sigma_{SimU}^2) \\ & = \prod_{i=1}^{m} [\mathcal{N}(U_i|0, \sigma_U^2 \mathbf{I})] \\ & \times \prod_{i=1}^{m} [\mathcal{N}(U_i| \sum_{f \in F_i} SimU_{i,f} \cdot U_f, \sigma_{SimU}^2 \mathbf{I})] \end{aligned} \tag{10}$$

$$\begin{aligned} & p(V|SimV, \sigma_V^2, \sigma_{SimV}^2) \propto p(V|\sigma_V^2) p(V|SimV, \sigma_{SimV}^2) \\ & = \prod_{i=1}^{n} [\mathcal{N}(V_i|0, \sigma_V^2 \mathbf{I})] \\ & \times \prod_{i=1}^{n} [\mathcal{N}(V_i| \sum_{s \in N_j} SimV_{j,s} \cdot V_s, \sigma_{SimV}^2 \mathbf{I})] \end{aligned} \tag{11}$$

Similar to Equation 6, using Bayesian inference the posterior probability of latent features is:

$$\begin{aligned} & p(U, V|R, SimU, SimV, \sigma_R^2, \sigma_U^2, \sigma_V^2, \sigma_{SimU}^2, \sigma_{SimV}^2) \\ & \propto p(R|U, V, \sigma_R^2) p(U|SimU, \sigma_U^2, \sigma_{SimU}^2) p(V|SimV, \sigma_V^2, \sigma_{SimV}^2) \\ & = \prod_{i=1}^{m} \prod_{j=1}^{n} I_{ij} [\mathcal{N}(R_{i,j}|g(U_i \times V_j^T), \sigma_r^2)] \\ & \times \prod_{i=1}^{m} [\mathcal{N}(U_i| \sum_{f \in F_i} SimU_{i,f} \cdot U_f, \sigma_{SimU}^2 \mathbf{I})] \\ & \times \prod_{j=1}^{n} [\mathcal{N}(V_j| \sum_{s \in N_j} SimV_{j,s} \cdot V_s, \sigma_{SimV}^2 \mathbf{I})] \\ & \times \prod_{i=1}^{m} [\mathcal{N}(U_i|0, \sigma_U^2 \mathbf{I})] \times \prod_{j=1}^{n} [\mathcal{N}(V_j|0, \sigma_V^2 \mathbf{I})] \end{aligned} \tag{12}$$

where $g(x)$ is the logistic function that bounds the range of predictions into [0, 1]. In order to keep the generality, the user-venue ratings are mapped to interval [0, 1] using the function $f(x) = (x-1)/(max\_rating - 1)$, and recovered later using $f^{-1}(x)$. Then, the log posterior probability of Equation 12 is:

$$\begin{aligned} & \ln p(U, V|R, SimU, SimV, \sigma_R^2, \sigma_U^2, \sigma_V^2, \sigma_{SimU}^2, \sigma_{SimV}^2) \\ & = -\frac{1}{2\sigma_R^2} \sum_{i=1}^{m} \sum_{j=1}^{n} I_{ij} [R_{i,j} - g(U_i \times V_j^T)] \\ & - \frac{1}{2\sigma_{SimU}^2} \sum_{i=1}^{m} (U_i - \sum_{f \in F_i} SimU_{i,f} U_f)(U_i - \sum_{f \in F_i} SimU_{i,f} U_f)^T \\ & - \frac{1}{2\sigma_{SimV}^2} \sum_{j=1}^{n} (V_j - \sum_{s \in N_j} SimV_{j,s} V_s)(V_j - \sum_{s \in N_j} SimV_{j,s} V_s)^T \\ & - \frac{1}{2} [\frac{1}{\sigma_U^2} \sum_{i=1}^{m} U_i U_i^T + \frac{1}{\sigma_V^2} \sum_{j=1}^{n} V_j V_j^T + (\sum_{i=1}^{m} \sum_{j=1}^{n} I_{ij}) \ln \sigma_R^2] \\ & - \frac{1}{2} [ml(\ln \sigma_U^2 + \ln \sigma_{SimU}^2) + nl(\ln \sigma_V^2 + \ln \sigma_{SimV}^2)] + \mathcal{C} \end{aligned} \tag{13}$$

We aim at maximizing log posterior probability of U and V keeping the variance parameter fixed. Maximizing above term is equivalent to minimizing the following objective func-

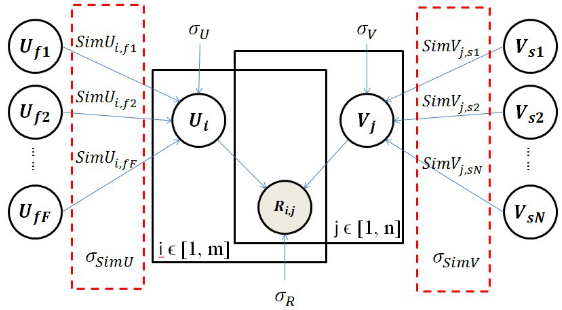


Figure 4: Graphical model of LBSMF.

tion:

$$
\begin{aligned}
&\mathcal{L}(R, SimU, SimV, U, V) \\
&= \frac{1}{2}\sum_{i=1}^{m}\sum_{j=1}^{n} I_{ij}[R_{i,j} - g(U_i \times V_j^T)] \\
&+ \frac{1}{2}[\lambda_U \sum_{i=1}^{m} U_i U_i^T + \lambda_V \sum_{j=1}^{n} V_j V_j^T] \\
&+ \frac{1}{2}\alpha \sum_{i=1}^{m}(U_i - \sum_{f\in F_i} SimU_{i,f}U_f)(U_i - \sum_{f\in F_i} SimU_{i,f}U_f)^T \\
&+ \frac{1}{2}\beta \sum_{j=1}^{n}(V_j - \sum_{s\in N_j} SimV_{j,s}V_s)(V_j - \sum_{s\in N_j} SimV_{j,s}V_s)^T
\end{aligned} \tag{14}
$$

where $\lambda_U = \sigma_R^2/\sigma_U^2$, $\lambda_V = \sigma_R^2/\sigma_V^2$, $\alpha = \sigma_R^2/\sigma_{SimU}^2$ and $\beta = \sigma_R^2/\sigma_{SimV}^2$. Applying the gradient descent approach on each user latent feature vector U_i and venue latent feature vector V_j for above objective function, we have

$$
\begin{aligned}
\frac{\partial \mathcal{L}}{\partial U_i} &= \sum_{j=1}^{n} I_{ij} V_j g'(U_i \times V_j^T)[g(U_i \times V_j^T) - R_{i,j}] \\
&+ \lambda_U U_i + \alpha(U_i - \sum_{f\in F_i} SimU_{i,f}U_f) \\
&- \alpha \sum_{\{f|i\in F_f\}} simU_{f,i}(U_f - \sum_{w\in F_f} SimU_{f,w}U_w)
\end{aligned} \tag{15}
$$

$$
\begin{aligned}
\frac{\partial \mathcal{L}}{\partial V_j} &= \sum_{i=1}^{m} I_{ij} U_i g'(U_i \times V_j^T)[g(U_i \times V_j^T) - R_{i,j}] \\
&+ \lambda_V V_j + \beta(V_j - \sum_{s\in N_j} SimV_{j,s}V_s) \\
&- \beta \sum_{\{s|j\in N_s\}} simV_{s,j}(V_s - \sum_{p\in N_s} SimV_{s,p}V_s)
\end{aligned} \tag{16}
$$

where $g'(x) = e^{-x}/(1+e^{-x})^2$ which is the derivative of the logistic function. Using gradient descent approach, U_i and V_j are updated in each iteration according to Equation 15 and 16, respectively. The graphical model of our proposed location based social matrix factorization method is illustrated in Figure 4. Compared to the PMF model, we introduce the user friendship network and venue similarity network in matrix factorization approach in order to consider the influence of inter-user and inter-venue relationships in location recommendation.

6. EXPERIMENTAL ANALYSIS

In this section, using two datasets extracted from Foursquare, we evaluate the proposed preference model and algorithm for location recommendation, and compare it with other state-of-the-art methods. Our evaluation tries to address the following questions:

1. How does the proposed hybrid preference model capture users' preference? Can it maintain the consistency of the preference extracted from check-ins and tips?
2. Comparing with other methods, does LBSMF achieve better performance?
3. How do social network and venue similarity network affect recommendation performance and to what extent?
4. Considering both social and inter-venue influence, how does our approach perform in runtime evaluation?

6.1 Dataset Description

In this work, we use a collection of Foursquare check-ins lasting for 4 months (from 24 October 2011 to 20 February 2012). We firstly filter noise and invalid check-in data, and then extract tips corresponding to the refined check-ins. The detailed procedure of data processing is as follows.

Since personal check-in information can only be accessed from one's own social circle, they are not available publicly. Foursquare user can choose to post their check-ins via Twitter when they visited a place. Hence, we captured check-ins by crawling foursquare-tagged tweets from Twitter Public Stream[7], resulting in a total collection of 762,315 users and 31,920,144 check-ins. We only select users who have performed at least one check-in per week (these users are regarded as active users). Even though Foursquare is able to verify whether a user is actually near the place when they check in, fake check-in data is still inevitable in large dataset. We observed a total of 9,276 users (1.2%) who had performed "sudden-move" check-ins (consecutive check-ins with a speed faster than 1200 km/h: the common airplane speed). All the check-ins from these "sudden-move" users are eliminated. In addition, some of the venues in our dataset cannot be resolved by Foursquare venue API, causing the category information of these venues unavailable. As venue category is necessary for the semantic tagging of check-ins, we also excluded check-ins which were performed over these venues (about 7.52% of the total dataset). After noise filtering, our dataset includes 311,475 users and 21,920,144 check-ins which were performed over 3,715,092 venues globally.

Since we only process venue tips written in English for sentiment analysis, we select two big cities in English-speaking countries, i.e. New York and London, and then extract tips of the venues in these two cities. Note that we only extract check-in data for 4 months from foursquare-tagged tweets but the tips are extracted from Foursquare API without time limitation. Currently, the Foursquare API can return a maximum of 500 tips for each venue. This indicates that in our dataset, tips maybe observed even user didn't check in at that venue within these four months.

In Foursquare, user relationship is not public available. We indirectly build social network via twitter follower and

[7]https://dev.twitter.com/docs/streaming-apis/streams/public

Table 1: Dataset Statistic

Dataset	New York Restaurant	London
Users	2601	1233
Venues	2392	1623
Density using check-in	0.0042	0.0048
Density using HPM	0.0053	0.0058
Social network density	0.0007	0.0029

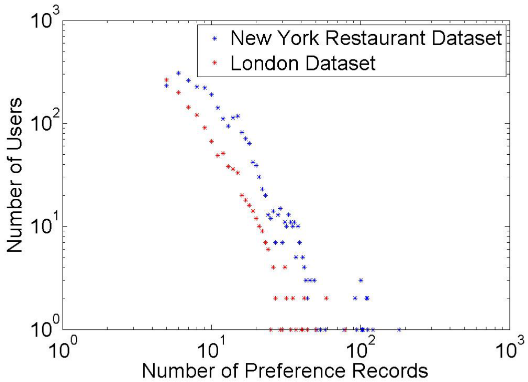


Figure 5: Distribution of the number of preference records.

following relationship, i.e. we assume that the friendship exists if two users follow each other in Twitter. Venues in Foursquare are classified into 9 parent categories (i.e. Arts & Entertainment, College & University, Food, Great Outdoors, Nightlife Spot, Professional & Other Places, Residence, Shop & Service, Travel & Transport) and 400 sub-categories[8]. We manually merge the similar venue categories together, resulting in a total of 274 venue sub-categories. In order to validate that our approach is not dataset dependent, we choose the food related venue check-ins ("Food" parent category, containing 86 sub-categories such as French restaurant, Italian restaurant, etc.) in New York (denoted as New York Restaurant) and keep all categories in London.

When we construct the final hybrid preference model, we only choose users who have at least 5 records in the user-venue matrix. The data statistics is shown in Table 1. The distribution of user's number of preference records is shown in Figure 5. Both New York and London datasets have a power-law distribution [9] in terms of preference record numbers.

6.2 Social and Inter-venue Influence Modeling

As inputs to LBSMF, social network and venue similarity network need to be built properly. As mentioned previously, social network is extracted based on user follower/following relationship. Since we have the preference of all the users, the evaluation of similarity between two users can then be calculated by measuring the preference vectors of these two users. Similar to [20], Pearson Correlation Coefficient is used as similarity measure in this study.

With regard to venue similarity network, we extract venue category information from Foursquare to build a 0/1 based venue similarity network. For two venues, the similarity score is set to 1 if both venues have the same sub-category in Foursquare, it is set to 0 if there is no overlapping sub-category. Since our experiment dataset is constrained to these two cities, the geographical influence is omitted in this experiment. It will be considered in the future work combining with venue semantic similarity from tips. For New York restaurant and London dataset, the density of venue similarity network is 0.0353 and 0.0339, respectively.

6.3 Metrics

Two common metrics are used for evaluation: Mean Absolute Error (MAE) and Root Mean Square Error (RMSE).

$$MAE = \frac{1}{|T|} \sum_{R_{i,j} \in T} |R_{i,j} - \hat{R}_{i,j}| \tag{17}$$

$$RMSE = \sqrt{\frac{1}{|T|} \sum_{R_{i,j} \in T} (R_{i,j} - \hat{R}_{i,j})^2} \tag{18}$$

where T is the test dataset. $R_{i,j}$ and $\hat{R}_{i,j}$ represent the observed preference and the predicted preference measure of user i on venue j, respectively. Smaller MAE and RMSE imply better performance. The greater difference between them, the greater the variance in the individual errors in the test set.

6.4 Hybrid Preference Model Evaluation

In order to evaluate the proposed hybrid preference model using both check-ins and tips, we compare the performance of LBSMF with different preference models. A model built from only user's check-in behavior is used as baseline. Obviously, considering tip data can increase the density of the preference matrix. In order to prove that the hybrid preference model outperforms other models not merely because it alleviates the sparsity problem, we proposed a null model with the same density and same distribution of the preference record numbers. Hence, the models used and tested in this experiment are as follows:

1. Basic model (BM) that only uses *check-in preference matrix.*
2. Tip null model (TNM) that considers tips influence in a random way. It shuffles the preference measure in *sentiment preference matrix* and then fuses it with *check-in preference matrix.* In this way, it preserves the same distribution of the number of preference records as shown in Figure 5.
3. Hybrid preference model (HPM) that uses our proposed *hybrid preference matrix.*

We fixed $\lambda_U = \lambda_V = 0.005$, *learning rate* $= 0.02$ for all the evaluations conducted in the following section. The social and inter-venue influence parameters are set as $\alpha = 0.001$ and $\beta = 0.01$ for New York Restaurant dataset, $\alpha = 0.002$ and $\beta = 0.02$ for London dataset because they result in the best performance (the detailed study about parameter tuning is presented in evaluation of social and inter-venue influence). We use different percentage of data (i.e. 90%, 80%) for training. For example, training data 90% means that we randomly select 90% of the preference records as the training set, and the rest 10% as the test set. The latent space dimension is set to 10 in this experiments. The results are shown in Table 2. Each result is the mean value of five repeated trials.

[8]https://developer.foursquare.com/docs/venues/categories

Table 3: Performance Comparisons with Other Approaches

Dataset	Training	Metric	Dimension = 5					Dimension = 10				
			CF	PMF	SocialMF	SRMF	LBSMF	CF	PMF	SocialMF	SRMF	LBSMF
New York Restaurant	90%	RMSE	1.2463	0.9440	0.9364	0.9342	0.9184	1.2463	0.9136	0.8889	0.8755	0.8524
		Improve	26.31%	2.71%	1.92%	1.69%		31.61%	6.70%	4.11%	2.64%	
		MAE	0.7190	0.7182	0.7074	0.7034	0.6949	0.7190	0.7047	0.6429	0.6238	0.6204
		Improve	3.35%	3.24%	1.77%	1.21%		13.71%	11.96%	3.50%	0.55%	
	80%	RMSE	1.4887	1.0209	1.0279	1.0206	1.0040	1.4887	0.9942	0.9748	0.9713	0.9580
		Improve	32.56%	1.66%	2.33%	1.63%		35.65%	3.64%	1.72%	1.37%	
		MAE	0.8435	0.8262	0.8204	0.7959	0.7916	0.8435	0.8101	0.7585	0.7425	0.7345
		Improve	6.15%	4.19%	3.51%	0.54%		12.92%	9.33%	3.16%	1.08%	
London	90%	RMSE	1.3787	0.9758	0.9651	0.9519	0.9328	1.3787	0.9763	0.9125	0.9382	0.8929
		Improve	32.34%	4.41%	3.35%	2.01%		35.24%	8.54%	2.15%	4.83%	
		MAE	0.8687	0.7719	0.7682	0.7568	0.7315	0.8687	0.7882	0.7203	0.7379	0.7022
		Improve	15.79%	5.23%	4.78%	3.34%		19.17%	10.91%	2.51%	4.84%	
	80%	RMSE	1.6222	1.0733	1.0497	1.0547	1.0273	1.6222	1.0496	1.0358	1.0440	1.0119
		Improve	36.67%	4.29%	2.13%	2.60%		37.62%	3.59%	2.31%	3.07%	
		MAE	1.0441	0.8682	0.8539	0.8520	0.8266	1.0441	0.8508	0.8246	0.8441	0.8075
		Improve	20.83%	4.79%	3.20%	2.98%		22.66%	5.09%	2.07%	4.34%	

Table 2: Comparison between Different Preference Models

Dataset	Training	Metric	BM	TNM	HPM
New York Restaurant	90%	RMSE	1.0137	0.8887	0.8524
		MAE	0.8072	0.7032	0.6204
	80%	RMSE	1.0386	**1.0506**	0.9580
		MAE	0.8103	**0.8306**	0.7345
London	90%	RMSE	1.1045	0.9864	0.8929
		MAE	0.9031	0.7889	0.7022
	80%	RMSE	1.1245	1.0895	1.0119
		MAE	0.9147	0.8828	0.8075

We can observe clearly that HPM achieves the best performance for both dataset. The BM which only considers check-in data yields the worst performance among the three models. Although TNM model has the same density and the same distribution of the preference record numbers as HPM, the performance is still poorer than HPM. An interesting observation is that TNM model is even worse than BM when using New York Restaurant dataset with 80% of data as training set. We can see even if TNM increases the density of the preference matrix but it impacts dramatically on user's real preference due to the random assignment of sentiment preference measure.

These observations strongly support that the proposed HPM is able to characterize users' preference and maintain the consistency of user preference modeled from both check-in and tip data.

6.5 Location Recommendation Evaluation

In this section, we compare our proposed LBSMF with the following approaches to show its effectiveness in location recommendation.

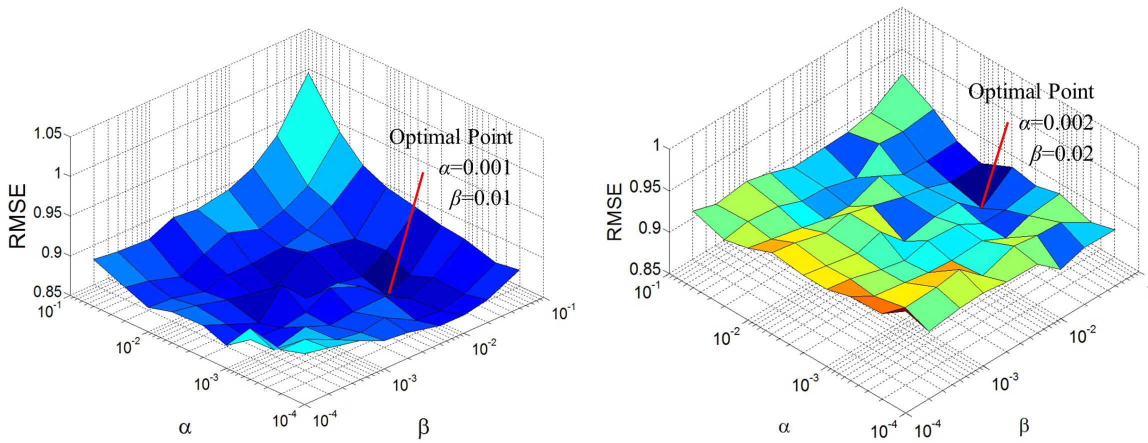
1. Collaborative filtering (CF) is used as baseline.
2. Probabilistic matrix factorization (PMF) [25]: one classical matrix factorization approach. Our approach extends PMF by introducing social and inter-venue influence.
3. SocialMF [13]: this approach considers social network influence in recommendation problem and treats friend's impact equally. After a series of experiments, the social influence parameter is set to 0.01 since it achieves best results on both of our datasets.
4. Social Regularized MF (SRMF) [20]: it considers not only social network connection, but also the similarity measure between friends. We implement the individual-based regularization model using Pearson Correlation Coefficient as similarity measure in the experiment since it reports the best results. Note that the social regularization term is added in a different way from that of SocialMF. Similar to SocialMF, the social influence parameter is set to 10^{-6} for the best performance.

The dimension of latent space is set to 5 and 10, respectively. Other parameters are set as the same as in section 6.4. The results are reported in Table 3. Each result is the average value of five repeated experiments. No matter 5-dimension or 10-dimension representation of latent space is used, the gain of LBSMF is significant comparing to other approaches. Considering inter-venue influence, both datasets achieve better RMSE and MAE. Besides the RMSE and MAE value, the rate of improvement over other approaches is also indicated in Table 3.

As can be seen from Table 3, the traditional CF performs the worst. The PMF method achieves better results comparing to CF. Considering social influence, both SocialMF and Social Regularized MF perform better than those methods that ignore social influence, which confirms that social influence is able to impact user preference behavior to some extent. LBSMF that takes both social and inter-venue relationship into account achieves the best results comparing to the state-of-the-art approaches. The results also imply that inter-venue influence such as category in this experiment has strong influence on location recommendation.

6.6 Social and Inter-venue Influence

LBSMF approach leverages the parameters α and β to control the influence from social network and venue similarity network, respectively. In this section, we investigate the impact of parameters α and β. Keeping latent space dimension as 10, training data 90%, we set parameters α and β varying within [0.0001, 0.0002, 0.0005, 0.001, 0.002, 0.005,



(a) New York restaurant dataset.

(b) London dataset.

Figure 6: Impact of parameters α and β (Dimension=10, Training data 90%)

0.01, 0.02, 0.05], and use RMSE as metric. Smaller value of α or β implies that we consider less social or inter-venue influence, and vice versa. In the extreme case that we set α and β to zero, LBSMF approach becomes PMF because it only uses users' preference for recommendation. On the contrary, a large value for α or β implies that social network or venue similarity dominates the latent feature learning process.

Figure 6 plots the RMSE metric under different α and β setting for both New York Restaurant and London datasets. Obviously, there is a concave surface of RMSE values for each dataset. Take the evaluation results with New York restaurant dataset as example, considering the most social influence and the least inter-venue influence corresponds to the left corner ($\alpha = 0.05$ and $\beta = 10^{-4}$) of the Figure 6 (a), which has a relatively high RMSE measure. Similar situation is observed for the right corner ($\alpha = 10^{-4}$ and $\beta = 0.05$) when considering the most inter-venue influence and the least social influence. Moreover, if the recommendation is mainly based on social and inter-venue influence while considering the least user's own preference, the result becomes the worst ($\alpha = 0.05$ and $\beta = 0.05$). On the other hand, when considering little social and venue impact, the RMSE achieves almost the same result as PMF ($\alpha = 10^{-4}$ and $\beta = 10^{-4}$).

The optimal point can then be found when the lowest RMSE value achieved. For New York restaurant dataset, the optimal point (RMSE = 0.8524) is achieved at $\alpha = 0.001$ and $\beta = 0.01$. For London dataset, it achieved at $\alpha = 0.002$ and $\beta = 0.02$ (RMSE = 0.8929).

6.7 Runtime Performance

In this section we evaluate the runtime performance of LBSMF. Since the CF method is a memory based approach without learning step [1], we compare our algorithm only with the matrix factorization based approaches, i.e. PMF, SocialMF, SRMF. The results are shown in Table 4. For both datasets, setting latent space dimension as 10 and training data percentage as 90%, LBSMF converges after around 1500 iterations, which takes about 1400 seconds on a Core2 Duo 2.4GHz PC with Windows 7 and 4BG DDR2 memory. PMF has the shortest running time per iteration (0.1 second) since it only uses user-venue matrix. When considering social influence, SocialMF and SRMF take 0.75 s and 0.8 s per iteration, respectively. However, LBSMF needs 0.9 s considering both social and inter-venue influence. Comparing to other methods, the LBSMF approach increases the performance with an acceptable increasing of learning time.

Table 4: Runtime Performance Comparison

Methods	PMF	SocialMF	SRMF	LBSMF
Number of iteration to converge	1800	1600	1000	1500
Time per iteration	0.1 sec	0.75 sec	0.8 sec	0.9 sec

7. CONCLUSION AND FUTURE WORK

With the increasing popularity of GPS equipped smart phones, location based social networking services attract more and more users. With this trend, personalized services like location recommendation need to be further studied. In contrast to classical recommendation problems, users' preference is not explicitly given in location based social networking services. Although check-in behavior can imply users' preference to a certain extent, we argue that considering both check-in and tips in LBSNs can better model user preference. Furthermore, both user social similarity and inter venue similarity influence user preference model and location recommendation performance.

In this paper, we first propose a hybrid preference model based on check-in and tip data under the assumption that user's comments of a venue can help to better characterize her preference. We then extend the matrix factorization approach considering the impact of both user social similarity and inter venue similarity on location recommendation, named as location based social matrix factorization (LBSMF) approach. Evaluation results confirm that the proposed hybrid preference model can better characterize users' preference, and further verify the effectiveness and efficiency of proposed LBSMF approach.

For future work, we plan to exploit other information in tip data for user modeling and location recommendation. We also intend to consider the venue geographical association to further improve the location recommendation performance.

8. ACKNOWLEDGMENTS

This work was supported by the EU FP7 Project SOCIETIES (No. 257493) and partially supported by the National Basic Research Program of China (No. 2012CB316400) and the National Natural Science Foundation of China (No. 61222209). The authors would like to thank all colleagues for their helpful discussion.

9. REFERENCES

[1] G. Adomavicius and A. Tuzhilin. Toward the next generation of recommender systems: A survey of the state-of-the-art and possible extensions. *IEEE Trans. on Knowl. and Data Eng.*, 17(6):734–749, June 2005.

[2] P. Bedi, H. Kaur, and S. Marwaha. Trust based recommender system for the semantic web. In *IJCAI'07*, pages 2677–2682, San Francisco, CA, USA, 2007. Morgan Kaufmann Publishers Inc.

[3] B. Berjani and T. Strufe. A recommendation system for spots in location-based online social networks. In *SNS '11*, pages 4:1–4:6. ACM, 2011.

[4] A. Bifet and E. Frank. Sentiment knowledge discovery in twitter streaming data. In *DS'10*, pages 1–15, Berlin, Heidelberg, 2010. Springer-Verlag.

[5] J. Bollen, H. Mao, and A. Pepe. Modeling public mood and emotion: Twitter sentiment and socio-economic phenomena. In *ICWSM '11*, 2011.

[6] X. Cao, G. Cong, and C. S. Jensen. Mining significant semantic locations from gps data. *Proc. VLDB Endow.*, 3(1-2):1009–1020, Sept. 2010.

[7] C. Cheng, H. Yang, I. King, and M. Lyu. Fused matrix factorization with geographical and social influence in location-based social networks. In *AAAI '12*, 2012.

[8] Z. Cheng, J. Caverlee, K. Lee, and D. Z. Sui. Exploring millions of footprints in location sharing services. In *ICWSM '11*, 2011.

[9] A. Clauset, C. R. Shalizi, and M. E. J. Newman. Power-law distributions in empirical data. *SIAM Rev.*, 51(4):661–703, Nov. 2009.

[10] A. Culotta. Towards detecting influenza epidemics by analyzing twitter messages. In *SOMA '10*, pages 115–122. ACM, 2010.

[11] N. A. Diakopoulos and D. A. Shamma. Characterizing debate performance via aggregated twitter sentiment. In *CHI '10*, pages 1195–1198. ACM, 2010.

[12] M. Jamali and M. Ester. Trustwalker: a random walk model for combining trust-based and item-based recommendation. In *KDD '09*, pages 397–406. ACM, 2009.

[13] M. Jamali and M. Ester. A matrix factorization technique with trust propagation for recommendation in social networks. In *RecSys '10*, pages 135–142. ACM, 2010.

[14] M. Jamali and M. Ester. A transitivity aware matrix factorization model for recommendation in social networks. In T. Walsh, editor, *IJCAI '11*, pages 2644–2649. IJCAI/AAAI, 2011.

[15] B. J. Jansen, M. Zhang, K. Sobel, and A. Chowdury. Twitter power: Tweets as electronic word of mouth. *J. Am. Soc. Inf. Sci. Technol.*, 60(11):2169–2188, Nov. 2009.

[16] B. Jie, Z. Yu, and F. M. Mohamed. Location-based and preference-aware recommendation using sparse geo-social networking data. In *SIGSPATIAL GIS '12*. ACM, 2012.

[17] S. D. Kamvar and J. Harris. We feel fine and searching the emotional web. In *WSDM '11*, pages 117–126. ACM, 2011.

[18] E. Loper and S. Bird. Nltk: The natural language toolkit. *CoRR*, cs.CL/0205028, 2002.

[19] H. Ma, I. King, and M. R. Lyu. Learning to recommend with social trust ensemble. In *SIGIR '09*, pages 203–210. ACM, 2009.

[20] H. Ma, D. Zhou, C. Liu, M. R. Lyu, and I. King. Recommender systems with social regularization. In *WSDM '11*, pages 287–296. ACM, 2011.

[21] P. Massa and P. Avesani. Trust-aware recommender systems. In *RecSys '07*, pages 17–24. ACM, 2007.

[22] A. Noulas, S. Scellato, N. Lathia, and C. Mascolo. A random walk around the city: New venue recommendation in location-based social networks. In *SocialCom '12*, 2012.

[23] B. O'Connor, R. Balasubramanyan, B. R. Routledge, and N. A. Smith. From Tweets to Polls: Linking Text Sentiment to Public Opinion Time Series. In *ICWSM '10*, 2010.

[24] J. O'Donovan and B. Smyth. Trust in recommender systems. In *IUI '05*, pages 167–174. ACM, 2005.

[25] S. Ruslan and M. Andriy. Probabilistic matrix factorization. In *Advances in Neural Information Processing Systems*, volume 20, 2008.

[26] B. Stefano, E. Andrea, and S. Fabrizio. Sentiwordnet 3.0: An enhanced lexical resource for sentiment analysis and opinion mining. In *LREC'10*, Valletta, Malta, may 2010.

[27] M. Thelwall, K. Buckley, and G. Paltoglou. Sentiment in twitter events. *Journal of the American Society for Information Science and Technology*, 2011.

[28] M. Thelwall, K. Buckley, and G. Paltoglou. Sentiment strength detection for the social web. *JASIST*, 63(1):163–173, 2012.

[29] A. Tumasjan, T. O. Sprenger, P. G. Sandner, and I. M. Welpe. Predicting elections with twitter: What 140 characters reveal about political sentiment. In *ICWSM '10*, pages 178–185, 2010.

[30] M. Ye, P. Yin, and W.-C. Lee. Location recommendation for location-based social networks. In *SIGSPATIAL GIS '10*, pages 458–461. ACM, 2010.

[31] M. Ye, P. Yin, W.-C. Lee, and D.-L. Lee. Exploiting geographical influence for collaborative point-of-interest recommendation. In *SIGIR '11*, pages 325–334. ACM, 2011.

[32] V. W. Zheng, Y. Zheng, X. Xie, and Q. Yang. Collaborative location and activity recommendations with gps history data. In *WWW '10*, pages 1029–1038. ACM, 2010.

[33] Y. Zheng, L. Zhang, Z. Ma, X. Xie, and W.-Y. Ma. Recommending friends and locations based on individual location history. *ACM Trans. Web*, 5(1):5:1–5:44, Feb. 2011.