Expert Systems With Applications 83 (2017) 18–29

Contents lists available at ScienceDirect

Expert Systems With Applications

journal homepage: www.elsevier.com/locate/eswa

VRer: Context-Based Venue Recommendation using embedded space ranking SVM in location-based social network

Bin Xia[a], Zhen Ni[a], Tao Li[b,c], Qianmu Li[a,*], Qifeng Zhou[d]

[a] School of Computer Science and Engineer, Nanjing University of Science and Technology, Nanjing, China
[b] Jiangsu Key Lab of BDSIP, School of Computer Science, Nanjing University of Posts and Telecommunications, Nanjing, China
[c] School of Computer and Information Sciences, Florida International University, Miami, FL, USA
[d] Automation Department, Xiamen University, Xiamen, China

A R T I C L E I N F O

Article history:
Received 17 September 2016
Revised 6 April 2017
Accepted 7 April 2017
Available online 14 April 2017

MSC:
00-01
99-00

Keywords:
LBSNs
Preference
Check-in
Context-based
Ranking SVM

A B S T R A C T

Venue recommendation has attracted a lot of research attention with the rapid development of Location-Based Social Networks. The effectiveness of venue recommendation largely depends on how well it captures users' contexts or preferences. However, it is quite difficult, if not impossible, to capture the whole information about users' preferences. In addition, users' preferences are often heterogeneous (i.e., some preferences are static and common to all users while some preferences are dynamic and diverse). Existing venue recommendation does not well address the aforementioned issues and often recommends the most popular, the cheapest, or the closest venues based on simple contexts.

In this paper, we cast the venue recommendation as a ranking problem and propose a recommendation framework named VRer (Context-Based Venue Recommendation using embedded space ranking SVM) employing an embedded space ranking SVM model to separate the venues in terms of different characteristics. Our proposed approach makes use of 'check-in' data to capture users' preferences and utilizes a machine learning model to tune the importance of different factors in ranking. The major contribution of this paper are: (1) VRer combines various contexts (e.g., the temporal influence and the category of locations) with the check-in records to capture individual heterogeneous preferences; (2) we propose an embedded space ranking SVM optimizing the learning function to reduce the time consumption of training the personalized recommendation model for each group or user; (3) we evaluate our proposed approach against a real world LBSN and compare it with other baseline methods. Experimental results demonstrate the benefits of our proposed approach.

1. Introduction

With the rapid growth of Location-Based Social Networks (LBSNs), venue recommender systems have become increasingly prevalent. Users can benefit from the venue recommendation, and enjoy the personalized services. However, the effectiveness of venue recommendation largely depends on how well it captures users' contexts or preferences. A typical characteristic of Location-Based Social Networks is 'check-in', which allows the services to access geo-spatial information of users from their posts.

In real applications, users' preferences are often heterogeneous in nature. On one hand, some preferences are static and common to all users. For example, consumers always prefer closest and most cost-effective venues if everything else is equal or comparable. On the other hand, some references are dynamic and diverse. For example, customers who prefer luxury hotels are often less sensitive to meal prices when choosing restaurants. Even the same users' preferences may change under different contexts. e.g., users, who like cheap fast foods when they are eating alone, might prefer fine expensive restaurants when they are meeting friends. Due to the complexity of users' preferences, with the Location-Based Social Networks, it is quite difficult to capture the whole information about users' preferences.

In this paper, we formulate the venue recommendation as a ranking problem based on the ordered 'beenHere', which represents how many 'check-in' people have in the venues. Our proposed approach makes use of 'check-in' data to capture users' preferences and utilizes a machine learning model to tune the importance of different factors in ranking (Chen, Li, & Sun, 2013). As

* Corresponding author.
E-mail addresses: bxia@cs.fiu.edu (B. Xia), nizhen0523@189.cn (Z. Ni), taoli@cs.fiu.edu (T. Li), qianmu@njust.edu.cn (Q. Li), zhouqf@xmu.edu.cn (Q. Zhou).

http://dx.doi.org/10.1016/j.eswa.2017.04.020

the popular learning to rank method in Information Retrieval (IR) community, the basic idea of Ranking SVM (RSVM) is to formalize the ranking problem as a binary classification problem on instance pairs and then to solve the problem using Support Vector Machines (SVM) (Joachims, 2002). However, RSVM is often time-consuming and requires many ranked pairs as training examples. To address the limitation of RSVM, we propose the Embedded Space ranking SVM (ESSVM) model to learn the ranking function that separates the venues. ESSVM formulates the ranking problem as a binary classification problem by exploiting the inherent structure in the data with feature transformation. The contribution of this paper can be summarized in the following:

- Existing venue recommendations often recommend the most popular, the cheapest, or the closest venues, and those methods do not consider heterogeneous users' preferences. Different with previous methods, the context-based venue recommendation combines the time and category information with users' check-in records to capture the user's preference, which effectively improve the recommendation precision;
- The main idea of context-based venue recommendation is ranking the recommendation for each user. However, the traditional ranking method Ranking SVM (RSVM) is time-consuming with the increasing quantity of venues, and the precision is not outstanding. To address this issue, we propose the Embedded Space ranking SVM (ESSVM) to optimize the leaning function, and both the efficiency and effectiveness are improving in our work;
- To validate the context-based venue recommendation, we firstly use SVMRFE, which is the effective method in the feature selection, to rank the venue attributes for understanding the user's preference. Then we compare ESSVM with several baseline methods and also compare the actual check-ins with our recommendations during different periods in different categories. Results proof that our proposed strategy has better performance in precision while maintaining the high location coverage.

The rest of this paper is organized as follows: Section 2 introduces the related work in Recommender System; Section 3 shows the details of our proposed ESSVM; Section 4 introduces our 'check-in' dataset and related baseline strategies; Section 5 presents the setup of our experiments and discusses the results.

2. Related work

The rapid development of the Internet technology brings an era of information explosion. The online servers and websites are growing exponentially, and people are facing a lot of information according to the progress of information science. Recommender System, which is the technology of information filtering, is widely acknowledged as the effective tool to address the information explosion. In Amazon, which is one of the most famous Electronic Commerce platform, it is difficult to make a choice from millions of commodities. In order to address the trouble of selection, Amazon proposed the item-to-item collaborative filtering, which is the most early and efficient method in Recommender System (Deshpande & Karypis, 2004; Linden, Smith, & York, 2003; Sarwar, Karypis, Konstan, & Riedl, 2001). However, the collaborative filtering is time-consuming with millions of items, and the recommender model has to be updated while new users or items are added (Breese, Heckerman, & Kadie, 1998; Herlocker, Konstan, Terveen, & Riedl, 2004; Sarwar et al., 2001).

A few years later, the number of venues is sharply increasing according to the development of cities. When people prefer to have meals outside, we become rely on the location recommendations from social networks such as Yelp and Foursquare. Traditionally, in these platforms, the venue is recommended using collaborative filtering where Recommender System treats 'venue' as 'item'. In order to solve the consumption of huge calculation about the collaborative filtering, researchers proposed many strategies such as content-based and sentiment-based (Ganu, Elhadad, & Marian, 2009; Pazzani & Billsus, 2007; Singh, Mukherjee, & Mehta, 2011). However, the review data is insufficient due to the cold start, and it is difficult to represent.

Recently, the popularity of smart phones promoted the growth of Location-Based Social Networks. Plenty of useful information, such as the venue information and user geo-trajectory, can be obtained. Especially, the check-in information, which is the simple and accurate location data, show venues where people have been. Based on check-in information, many effective methods have been developed for venue recommendation (Baral & Li, 2016; Li, Peng, Kataria, Sun, & Li, 2013; 2015). Noulas et al. found that the majority people did not visit the venues where they have been in the past 30 days. Then they proposed a model using the frequency visiting data based on the individual random walk over a user-venue graph (Noulas, Scellato, Lathia, & Mascolo, 2012). Bao et al. presented a recommender system combining user's location history and the social influence (Bao, Zheng, & Mokbel, 2012). Cheng et al. developed a UPOI-Mine(Urban Points-Of-Interesting) system considering the users' preferences and the venue information based on the normalized check-in space using a regression-tree-based predictor (Cheng, Yang, King, & Lyu, 2012). Zhu et al. collected the context-rich logs from mobile devices and proposed a context-aware recommender system that exploited the individual preferences from the context logs (Zhu et al., 2015). In Yao et al. (2015), Yao et al. proposed a collaborative filtering approach based on the nonnegative tensor factorization using the constraint of users' social relationships as regularization. Ying et al. proposed a POI recommender system that applies the context-aware tensor decomposition to model users' preferences and incorporates the influence of social opinions about the rate of each POI (Ying, Chen, & Chen, 2017). We summarize the advantages and the disadvantages of each aforementioned approaches in the Table 1:

3. The proposed method

RSVM formalizes the ranking problem as a binary classification problem on instance pairs and then to solve the problem using Support Vector Machines (SVM) (Joachims, 2002). However, RSVM requires many ranked pairs as training examples and is often time-consuming with the exponential increasing training samples.

Different from RSVM, ESSVM extends the feature space instead of the exponential growth of the sample space, and each training sample consists of a pair of raw training instances with different ranks. In ESSVM, we assume that a 1-dimension coordinate axis exists, and each point, which represents the data in the feature-space, is projected onto this axis. The distances among the projected points on the 1-dimension coordinate axis capture the differences of samples (Zhou, Hong, Shao, & Cai, 2009). Based on this assumption, we can utilize the set of points to learn a rank function $\boldsymbol{f}$: $X \rightarrow Y$ for addressing the ranking problem. In the feature-space, we suppose there exists a hyperplane $\boldsymbol{h}$, then the distance from the data points to $\boldsymbol{h}$ captures the relative order of each point. Then we propose $\boldsymbol{f}(\boldsymbol{x_e}) = \boldsymbol{h^T x_e}$ as the linear function to represent the distance, and the thresholds satisfying $\theta_1 < \theta_2 < \ldots < \theta_{k-1}$ are learned to divide the data into different ranks:

$$\boldsymbol{f}(\boldsymbol{x}) = \begin{cases} 1 & \boldsymbol{h^T x_e} < \theta_1 \\ i & \theta_{i-1} < \boldsymbol{h^T x_e} < \theta_i, i \neq 1, k \\ k & \theta_{k-1} < \boldsymbol{h^T x_e} \end{cases} \quad (1)$$

Table 1
The advantages and the disadvantages of related approaches.

Approach	Pros	Cons
Random Walk (Noulas et al., 2012)	1. Focus on the locations users previously unvisited 2. Consider both social ties and venue-visit data	1. Limited context information 2. Based on a strong assumption
Geo-Social Network (Bao et al., 2012)	1. Make use of the specified geo-position 2. Effective recommendation of unvisited venues	1. Cold start problem 2. Lack of temporal context
MGM (Cheng et al., 2012)	1. Model the geographical influence of users' check-in behavior 2. Combine users' social information and geographical influence	1. Weak in extremely sparse frequency data 2. Simple contextual information 3. Ignore changes of users' preference based on temporal effect
CIAP (Zhu et al., 2015)	1. Exploit context-aware preference using context logs from individual devices 2. Combine the common and individual preferences	1. Consume much time to process and analyze huge context logs 2. Ignore the protect of individual privacy
TenInt (Yao et al., 2015)	1. Focus on the personalized recommendation 2. Combine users' social information and temporal contexts	1. Weak in extremely sparse contextual data 2. The unexplainable recommendation
TAP-F (Ying et al., 2017)	1. Overcome the problem of check-in data sparsity 2. Capture the changes of users' preference due to the temporal influence	1. Limited context information 2. Based on a strong assumption

Define $\boldsymbol{a}_i = \theta_{i+1} - \theta_i (1 \le i \le k-2), \theta_0 = -\infty,$ and $\theta_k = +\infty$. Assuming $\boldsymbol{a}_0 = 0$, sample $\boldsymbol{x}_e \in class_i (1 < i < k)$ satisfies:

$$\begin{aligned} \boldsymbol{h}^T \boldsymbol{x}_e &> \theta_{i-1} \\ \boldsymbol{h}^T \boldsymbol{x}_e + \boldsymbol{a}_{i-1} &> \theta_i \\ \boldsymbol{h}^T \boldsymbol{x}_e + \sum_{k=i-1}^{k-2} \boldsymbol{a}_k &> \theta_{k-1} \end{aligned} \tag{2}$$

With the assumption $\boldsymbol{a}_{k-1} = 0$, sample $\boldsymbol{x}_e \in class_i$ also satisfies:

$$\begin{aligned} \boldsymbol{h}^T \boldsymbol{x}_e &< \theta_i \\ \boldsymbol{h}^T \boldsymbol{x}_e + \boldsymbol{a}_{i-1} &< \theta_{i+1} \\ \boldsymbol{h}^T \boldsymbol{x}_e + \sum_{k=i}^{k-2} \boldsymbol{a}_{k-1} &< \theta_{k-1} \end{aligned} \tag{3}$$

The essence of ESSVM is to extend features of each sample instead of boosting the sample-space phenomenally, and the thresholds $\theta_1, \theta_2, \ldots, \theta_{k-1}$ are presented by the weight of k-2 dimensions $a_1, a_2, \ldots, a_{k-2}$. For sample $\boldsymbol{x}_e \in class_i$, the extended features comply with the following rules:

$$\boldsymbol{x}_e^{neg}[l] = \begin{cases} \boldsymbol{x}_e[l] & 1 \le l \le n \\ 0 & n < l < n+i \\ 1 & n+i \le l \le n+k-2 \end{cases} \tag{4}$$

$$\boldsymbol{x}_e^{pos}[l] = \begin{cases} \boldsymbol{x}_e[l] & 1 \le l \le n \\ 0 & n < l < n+i-1 \\ 1 & n+i-1 \le l \le n+k-2 \end{cases} \tag{5}$$

where l donates the index of extended feature vector, n is the length of original feature, and $\boldsymbol{x}_e^{pos}, \boldsymbol{x}_e^{neg}$ represent the positive and negative samples which are generated from $\boldsymbol{x}_e$ respectively. For $i = 1$ or $i = k$, only $\boldsymbol{x}_e^{neg}$ or $\boldsymbol{x}_e^{pos}$ is defined. With the assumption of $\theta_{k-1} = 0$, the classifier $\bar{h}$ which satisfies $\bar{h}^T x_e^{neg} > 0$ and $\bar{h}^T x_e^{pos} < 0$ is trained in the $(n+k-2)$-dimension feature space. Therefore, if $\boldsymbol{x}_e^{neg}$ and $\boldsymbol{x}_e^{pos}$ are defined as the class -1 and +1, then the multi-classification problem is converted into a binary classification case.

For example(see Fig. 1), we have a dataset $\boldsymbol{D} = \{X_1, X_2, \ldots, X_n\}$. Define:

$$X_e = \{x_{e,1}, x_{e,2}, \ldots, x_{e,n}, Y_e\}, \tag{6}$$

where $\{x_{e,1}, x_{e,2}, \ldots, x_{e,n}\}$ are the features of X_e, and $Y_e \in \{i | 1 \le i \le 3\}$ represents the corresponding ordered label. In order to explain our method, we consider:

$$\begin{aligned} X_1 &= \{x_{1,1}, x_{1,2}, \ldots, x_{1,n}, 1\}, \\ X_2 &= \{x_{2,1}, x_{2,2}, \ldots, x_{2,n}, 2\}, \\ X_3 &= \{x_{3,1}, x_{3,2}, \ldots, x_{3,n}, 3\}, \end{aligned} \tag{7}$$

where $Y_1 = 1$, $Y_2 = 2$, and $Y_3 = 3$. In this problem, there are three classes, so we only need to extend the n-dimensional feature space to $n+1$ dimensions. For each instance, X_1 belongs to Class 1, which represents the minimum, so we only need to convert X_1 into $\boldsymbol{x}_1^{neg}$. Based on Eq. 4:

$$\begin{aligned} X_1 &= \{x_{1,1}, x_{1,2}, \ldots, x_{1,n}, Y_1\} \Rightarrow \\ X_1^{neg} &= \{x_{1,1}, x_{1,2}, \ldots, x_{1,n}, x_{1,n+1^{neg}}, Y_1^{neg}\}, \end{aligned} \tag{8}$$

where $x_{1,n+1^{neg}} = 1$ and $Y_1^{neg} = -1$. Meanwhile, X_3, which belongs to the maximal class, is converted to:

$$X_3^{pos} = \{x_{3,1}, x_{3,2}, \ldots, x_{3,n}, x_{3,n+1^{pos}}, Y_3^{pos}\}, \tag{9}$$

where $x_{3,n+1^{pos}} = 0$ and $Y_3^{pos} = +1$. Different with X_1 and X_3, X_2, which is the medium, is going to separate into two instances:

$$\begin{aligned} X_2^{neg} &= \{x_{2,1}, x_{2,2}, \ldots, x_{2,n}, x_{2,n+1^{neg}}, Y_2^{neg}\}, \\ X_2^{pos} &= \{x_{2,1}, x_{2,2}, \ldots, x_{2,n}, x_{2,n+1^{pos}}, Y_2^{pos}\}, \end{aligned} \tag{10}$$

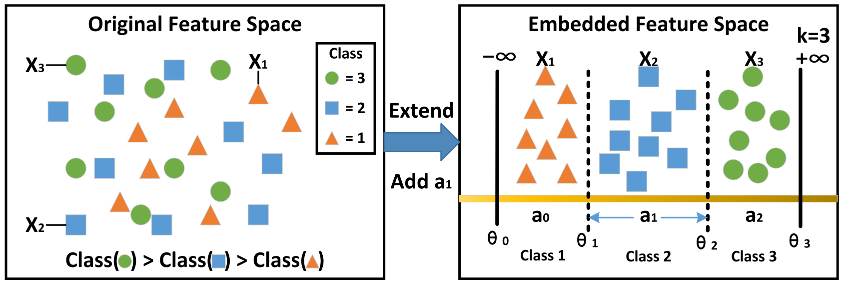


Fig. 1. The embedded space in ESSVM.

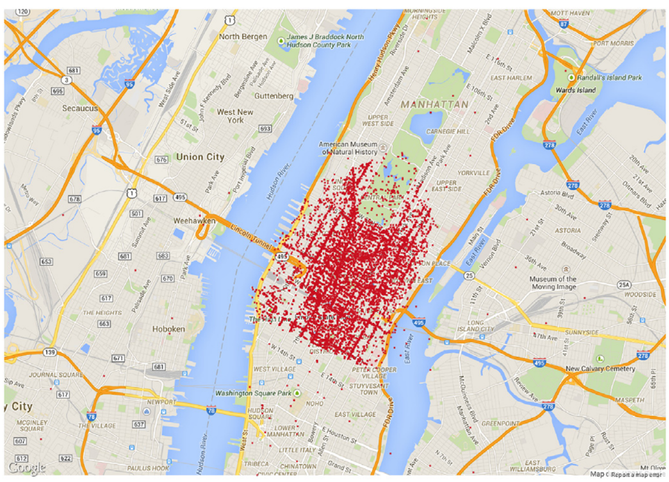


Fig. 2. The check-in venues in Manhattan.

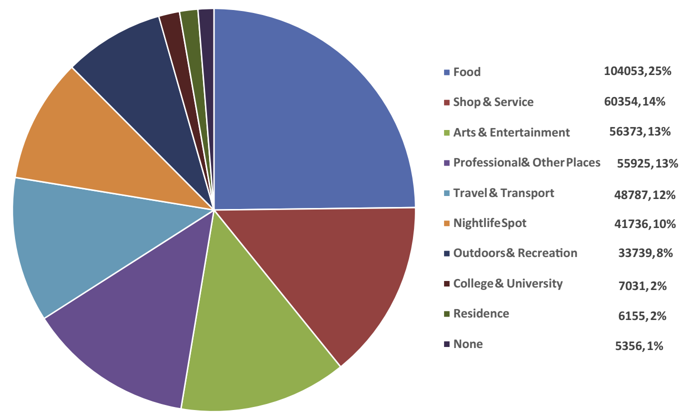


Fig. 3. The check-in popularity among different categories.

where $x_{2,n+1^{neg}} = 0$, $x_{2,n+1^{pos}} = 1$, $Y_2^{neg} = -1$, and $Y_2^{pos} = +1$. Finally, $\boldsymbol{D} = \{X_1, X_2, \dots, X_n\}$ will be updated to:

$$\boldsymbol{D_{ESSVM}} = \{X_1^{neg}, X_2^{neg}, X_2^{pos}, \dots, X_n^{pos}\}, \tag{11}$$

where the class of $\boldsymbol{D_{ESSVM}}$, $Y_e^{ESSVM} \in \{-1, +1\}$. After training $\boldsymbol{D_{ESSVM}}$, the weights of $x_{e,\,j} (1 \le j \le n)$ are used to fit the

Different from RSVM, in ESSVM: (a) the number of samples is extended to $2l - l_1 - l_k$ where l_1 and l_k represent the samples of the class 1 and the class k; (b) the vector of weight is extended by $k - 2$ dimensions, and the relationships between the ordered classes are presented using the extending information (Rajaram, Garg, Zhou, & Huang, 2003).

4. Check-ins information

4.1. Data

The dataset, in this paper, is collected from two famous social media—Twitter and Foursquare. Twitter is a popular social network service, and the API (https://dev.twitter.com/) is used to collect the public tweets. With the keyword filtering, we only collect the tweets, which are generated from Foursquare APP. Finally, 419,509 tweets, which are published by 49,823 users from August 2012 to July 2013 in Manhattan, are used to construct our database (see Fig. 2). In addition, we collect the detailed information of each venue such as checkinsCount (total check-ins ever here) and likes (a count of users who have liked this venue) using the Foursquare API (https://developer.foursquare.com/).

Fig. 3 presents the categories, which are the statistics of our database. The category is the representative attribute to distinguish different kinds of venues. For example, the restaurant, which is categorized as 'Food', is a place for having meals, and the mall classified as 'Shop & Service' is for shopping.

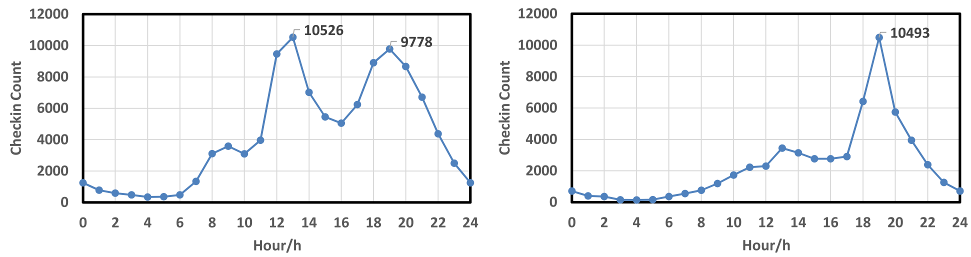
Fig. 4 demonstrates the sum of check-in information from two categories everyday. From Fig. 4a, we can see that, the majority of people would like have meals during 11:00–13:00 and 18:00–20:00. Although, there is a check-in peak during 8:00–10:00 which is the time for breakfast, people prefer to having breakfast at home. Fig. 4b shows us that, about 19:00, the majority of people go to 'Arts & Entertainment' which includes venues such as theaters and stadiums. Compared with Fig. 4a and b, the consumption custom of people can be obviously captured from the period when people check in.

If the observed period is changed from hours to days, in Fig. 5, we can see the check-in information each day of weeks. Obviously, the check-in records in Friday and Saturday are more than any other day except 'Professional & Other Places'. Specially, people prefer to visiting 'Nightlife Spot' and 'Arts & Entertainment' at weekends. This phenomenon totally meets the consumption custom of people in our daily lives.

In addition, we randomly select four users who have lots of check-in records. From Fig. 6 we can find that, the consumption custom of each user is more diverse with more check-in records. Combined Figs. 4 and 6, we can know the time that the categories are mostly checked in and the categories that the user mostly visits, then the corresponding venues can be recommended at the specific time to users respectively.

4.2. Baseline venue recommender strategies

In this paper, we compare our proposed approach with some effective recommender algorithms including User-based Collaborative Filtering(UserCF (Ricci, Rokach, & Shapira, 2011a)), Venue-based Collaborative Filtering(VenueCF (Ricci et al., 2011a)), Popularity of Venues(PoV), and Nearest Neighbor Recommenda-



(a) Food (b) Arts & Entertainment

Fig. 4. The distribution of each time period under different categories.

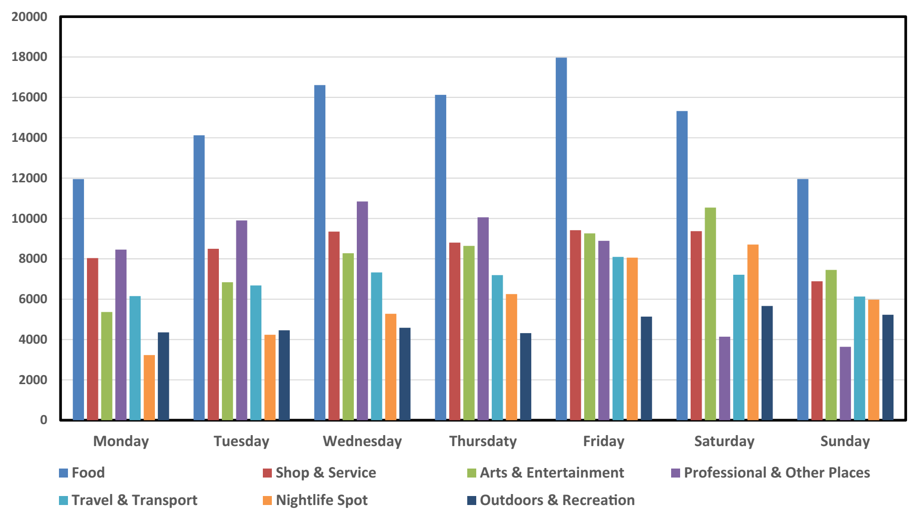


Fig. 5. The check-ins under different categories in each day of a week.

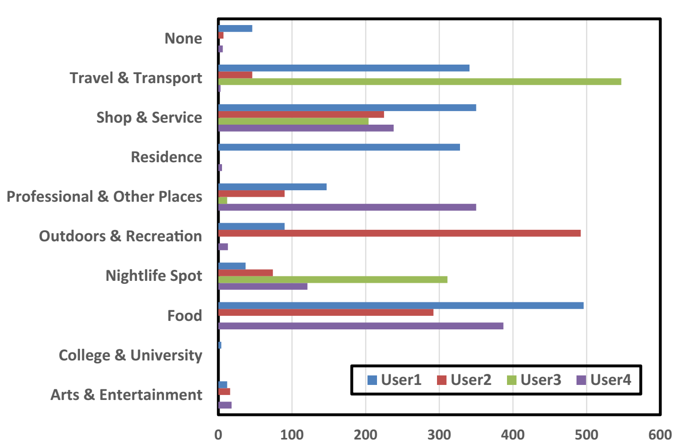


Fig. 6. The check-ins of 4 individuals under different categories.

tion(NNR (Samworth, 2012)). In this section, we briefly introduce these baseline methods.

4.2.1. User-based Collaborative Filtering(UserCF)

The assumption of User-based Collaborative Filtering(UserCF) is *people who have similar preferences visit similar venues*. The idea of UserCF is comparing user u_i with similar users $u_1, u_2, \dots, u_m$ who visit or have similar preferences with venues. For example, to recommend user u_i a venue, the set of venues u_i has been to $V_{u_i} = \{v_1, v_2, \dots, v_n\}$ are compared with the sets $\overline{\mathbf{V}} = \{V_{u_1}, V_{u_2}, \dots, V_{u_m}\}$ of other users $u_1, u_2, \dots, u_m$. The venues, which the similar users $u_j (j \in [1, m]$ and $j \neq i)$ have been to and user u_i does not visit, will be recommended to user u_i. UserCF is efficient, however, it is limited in the User Cold-Start problem and the sharply increasing datasets.

4.2.2. Venue-based Collaborative Filtering(VenueCF)

Different from UserCF which is based on similar users, Venue-based Collaborative Filtering(VenueCF) focuses on the similar custom of visiting. The assumption of VenueCF is *people will visit similar venues*. For example, to recommend user u_i a venue, we select a venue v_k from the u_i's visited history $V_{u_i} = \{v_1, v_2, \dots, v_n\}$, and combine the venues V_{v_k} from the visited histories of people U_{v_k} who have been to v_k. Then the mostly visited venue in V_{v_k} will be recommended to u_i. VenueCF addresses the User Cold-Start problem and improves the scalability, however, it is limited in the Venue Cold-Start Problem.

4.2.3. Popularity of Venues(PoV)

Besides Collaborative Filtering strategies, recommending the most popular venues is also a simple and efficient method in the venue recommendation. The assumption of this strategy is *the venue is not bad and worth visiting if many other people have been to*. For example, from all venues $\mathbf{V}$, we select the venues which have the most check-in records as the recommendation. However, this strategy is also limited by the Cold-Start problem and ignore the users' preferences.

4.2.4. Nearest Neighbor Recommendation(NNR)

The assumption of Nearest Neighbor venue recommendation is *people prefer to visiting the venues nearby if they have obvious life patterns*. Based on the available location information, we can easily know the region where the user often has the consumption. Then,

Table 2
The description of attributes.

Field	Description
checkinsCount	Total check-ins ever here.
usersCount	Total users who have ever checked in here.
tips	The number of tips here.
likes	A count of users who have liked this venue.
rating	Numerical rating of the venue (0 through 10).
photos	A count of photos for this venue.
price	The price tier from 1 (least pricey) - 4 (most pricey).
verified	Boolean indicating whether the owner of this business has claimed it and verified the information.
createdAt	The timestamp when the venue was created.
beenHere[a]	Times of the user has been here.

[a] 'beenHere' here is not the field in the venue response, that is the statistics which is from the database constructed by the tweets.

the venues, which is located in the region and the user has never been to, will be recommended. This strategy can recommend the venues which is suitable for users' life patterns, however, sometimes it does not work if people want a new experiment long distance from the region at weekend.

5. Experiments

5.1. Setup

We first extract the attributes using the venue response from Foursquare. The venue response, which contains the detailed information of the venue, is returned using the Foursquare API. In Table 2, the representative attributes used in our experiments, are described in detail. To capture each user's preference, the check-in venue of user are used to construct the model. Based on different contexts, the model(user's preference) are trained using the features of corresponding venues. For training the accurate model, 'beenHere', which represents the popularity of the venue, is used to determine the data label. The venues are divided into three classes: General(0), Okay(1), and Recommended(2) where the top 25% venues with the largest 'beenHere' are treated as Recommended(2), the next 25% venues are viewed as Okay(1), and the remaining ones are classified as General(0).

In this paper, we present the experimental studies with the following aims: (1) to understand the diverse users' preferences and categories in venue recommendation; (2) to evaluate the effectiveness of our proposed ESSVM in ranking venues; and (3) to validate the context-based venue recommendation. For the first aim, we compare the models built for all the users and the model built for different user groups where users in each group have similar preferences. For the second aim, we compare our strategy with the aforementioned baseline venue recommender methods. For the third aim, we compare RSVM and ESSVM in ranking venues and also select the important attributes using SVMRFE (Guyon, Weston, Barnhill, & Vapnik, 2002).

5.2. Metrics

Assume that, there are U active users during the testing period P, which includes K valid check-in records, then, venues $v_{(u,1)}, v_{(u,2)}, \ldots, v_{(u,n)}$ are recommended to user u using the algorithm $\mathfrak{A}$ (e.g., UserCF or ESSVM). Define the recommendation and the venues which user u actually visited in $[t, t+P]$ as $R_u = \{v_{(u,i)}\}_{i=1,2,\ldots,n}$ and $A_u = \{v_j\}_{j=1,2,\ldots,m}$, respectively. Then, the count of valid recommendations in $[t, t+P]$ is represented by:

$$C_u = |\{R_u \cap A_u\}|. \tag{12}$$

To evaluate the recommender algorithm $\mathfrak{A}$, several criteria which contain C_u are represented as:

$$\begin{aligned} Coverage_n(\mathfrak{A}) &= \frac{|\cup_{u\in U} R_u|}{|I|}, \\ Precision_n(\mathfrak{A}) &= \frac{\sum_{u\in U} C_u}{\sum_{u\in U} |A_u|}, \\ Recall_n(\mathfrak{A}) &= \frac{\sum_{u\in U} C_u}{\sum_{u\in U} |R_u|}, \\ Popularity_n(\mathfrak{A}) &= \frac{\sum_{u\in U}\sum_{v\in R_u} log(1+|v|)}{\sum_{u\in U} |R_u|}, \end{aligned} \tag{13}$$

where $|v|$ means the times user u has been to the venue v (Ricci, Rokach, Shapira, & Kantor, 2011b; Wang, Terrovitis, & Mamoulis, 2013). Beside $Coverage_n$, $Precision_n$, and $Recall_n$ which are well known in Recommender Systems, $Popularity_n$ is the criterion which describes the popularity of recommended venues. In other words, the smaller $Popularity_n$ means that the recommended venues are more infrequent.

5.3. Diverse users' preferences and venue categories

To understand the diversity of users' preferences in venue recommendation, we construct different models for users with different granularities. In this set of experiments, we build three types of data sets with different granularities: (1) all users, (2) groups of users who have the similar preferences, and (3) individual user.

Fig. 7 shows the ranks of important attributes under different users' preferences. User1 and User2, who have sufficient check-in records, are randomly selected from all the involved users. The '+' and '−' signs present the positive and the negative correlations with the venue labels, respectively. From Fig. 7, we observe that, the ranks of the important attributes are quite different for different types of datasets. For example, we find that, the 'createdAt' attribute is positively correlated with the venue labels, while other attributes are negatively correlated. In other words, User1 prefers to the new venues while the traditional venue recommendation often recommends the most popular venues. This experimental results demonstrate that the ranks of important attributes are different based on the diversity of the user granularities.

To evaluate the effects of venue categories on users' preferences, we select six representative categories such as 'Arts & Entertainment' and 'Food'.

Fig. 8 presents the ranks of important attributes under the different venue categories based on the common preference (i.e., entire users). The experimental result shows that, (1) in 'Travel & Transport' category, the top three important attributes from ESSVM are 'tips', 'photos', and 'createdAt'. For instance, NYMM(New York Marriott Marquis) and DHH(DoubleTree by Hilton Hotel New York City - Chelsea) have the similar 'checkinsCount' value, while NYMM's 'tips' value is much larger than DHH's. Based on the 'tips' attributes, our model suggests that NYMM is more popular than DHH, and this is consistent with the ground truth. However, RSVM has the opposite results with ESSVM. (2) In the 'Nightspot' category, the ranks of important attributes from ESSVM are 'checkinsCount' > 'usersCount' > 'photos'. For example, 'Pacha NYC' and 'The Pony Bar' have the similar values in 'checkinsCount' and 'usersCount' attributes, while 'Pacha NYC' has the larger counts of 'photos' than 'The Pony Bar'. Therefore, our ESSVM model suggests that 'Pacha NYC' is more popular than 'The Pony Bar', and it is also consistent with the real data. From the aforementioned observation, we find that users' preferences are diverse under different venue categories.

Furthermore, the 'rating' attribute is not as important as originally expected. It can be easily seen that, the rating is dependent on the count of the check-ins. For example, Bareburger, which is

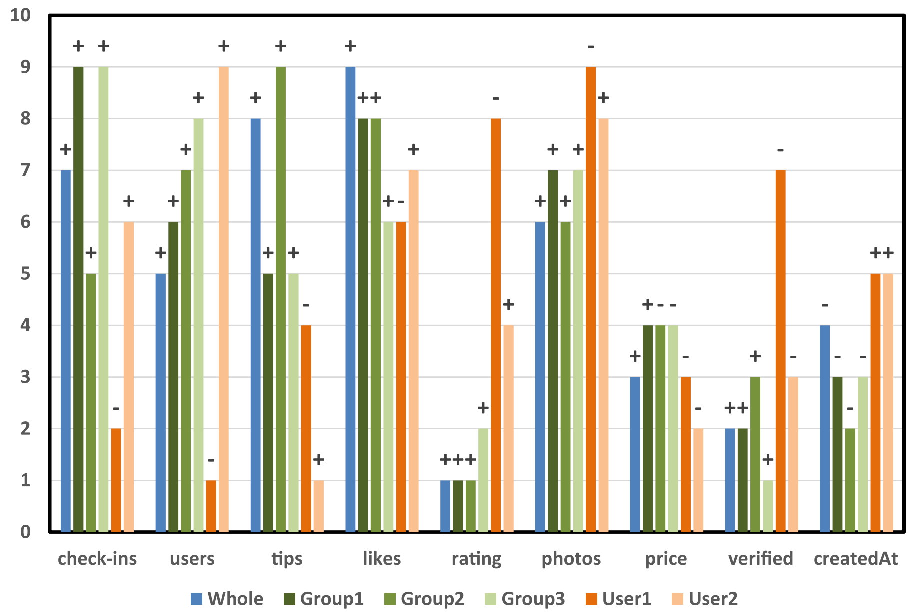


Fig. 7. Users' preferences in different granularities.

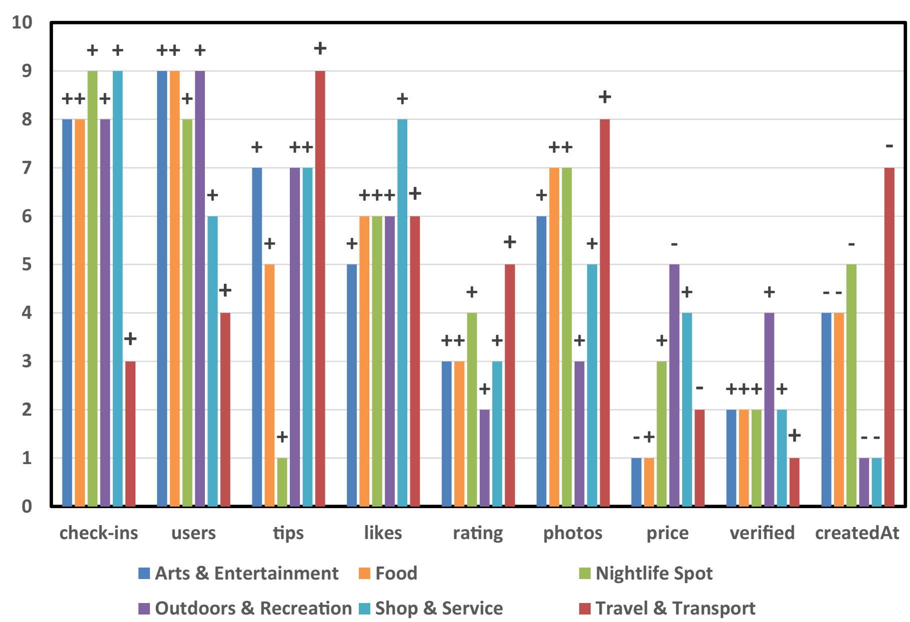


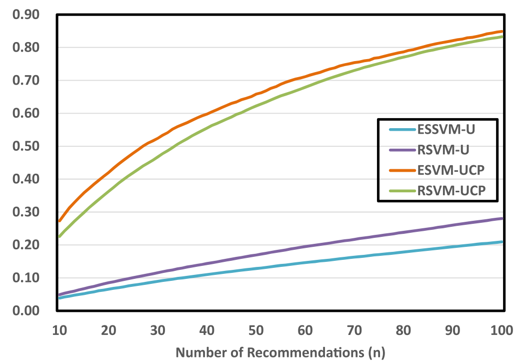
Fig. 8. Users' common preferences in different categories.

an American restaurant has 3813 'checkinsCount' values, and Shake Shack, which is the Burger Joint has 60,441 'checkinsCount' value. Both restaurants have the 9 stars rating; however, the latter one is much more popular than the former venue (e.g., the former one has been only visited twice while the latter one has been visited about one thousand times).

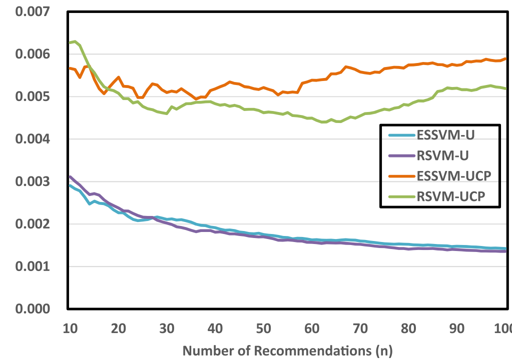
5.4. The comparison of ESSVM and RSVM

In this paper, we propose an embedded space ranking SVM (ESSVM) model to learn hyperplanes that can separate the venues of different characteristics. Compared with RSVM which is the well known method in Information Retrieval, ESSVM maintains the ranking accuracy while decreasing the time consumption. Figs. 9 and 10 present the comparison between ESSVM and RSVM in our proposed context-based venue recommendation strategy(CBVRS). ESSVM-U(User) and RSVM-U(User) are the methods based on users" preferences respectively using ESSVM and RSVM. Different with ESSVM-U and RSVM-U, our proposed ESSVM-UCP(User-Category-Period) and RSVM-UCP(User-Category-Period), which is containing the category and the time period information besides users" preferences, are concerned with the context(e.g., the time period and category) guiding users' selections. For example, people often have fast-food lunches on workdays, however, they prefer to enjoying luxury meals after work or on weekends. Meanwhile, the bars are always open at midnight, thus, recommending a night club in daytime cannot meet demands when people are confused where to go. Thus, both the time period and category are important contexts.

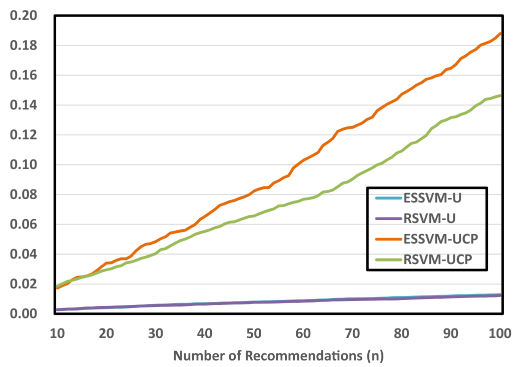
On the one hand, we compare the effectiveness based on the length of recommendation list. As Fig. 9 shown, the performance of UCP(User-Category-Period) is much better than U(User). Further-



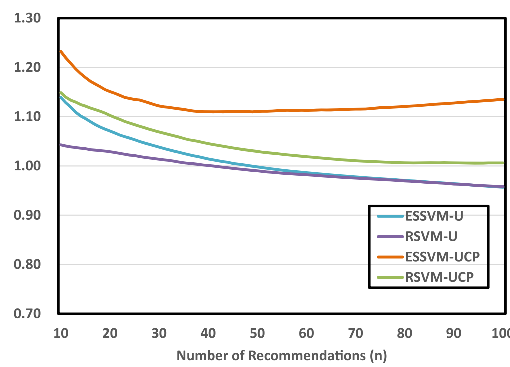
(a) Coverage



(b) Precision

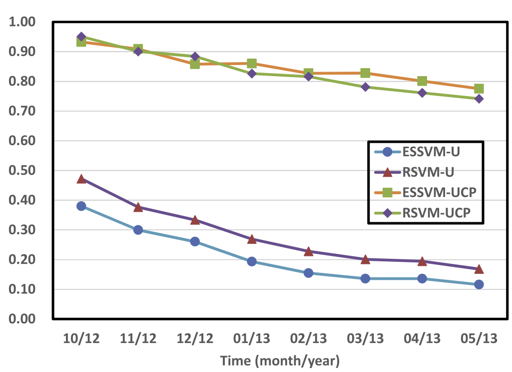


(c) Recall

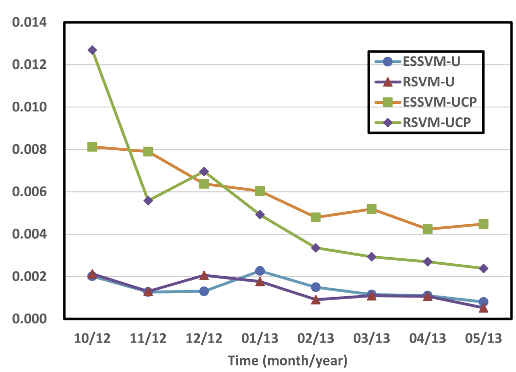


(d) Popularity

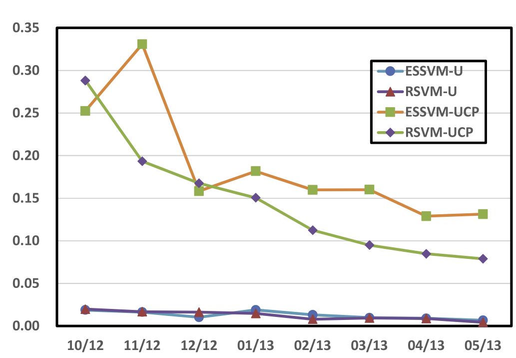
Fig. 9. Results for ESSVM and RSVM with different lengths of recommendation list.



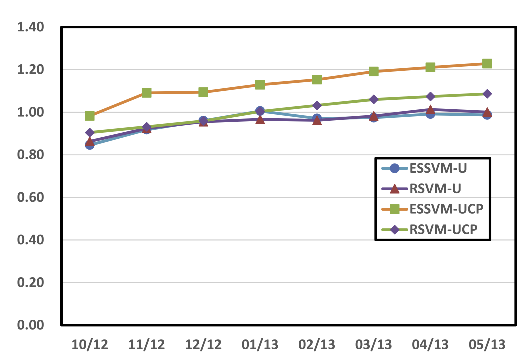
(a) Coverage



(b) Precision



(c) Recall



(d) Popularity

Fig. 10. Results for ESSVM and RSVM during different time periods.

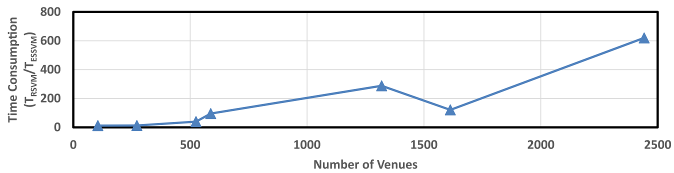


Fig. 11. The comparison of time consumption between ESSVM and RSVM.

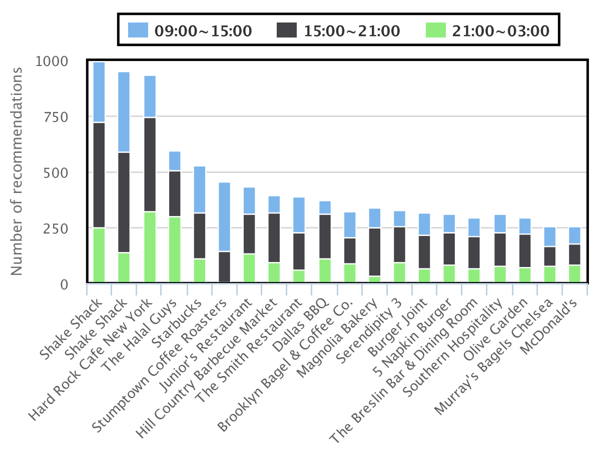
more, ESSVM-UCP outperforms other strategies including RSVM-UCP. On the other hand, we also compare the recommendation performance during different periods. Obviously, in Fig. 10, our proposed method is much more effective than the strategies only considering the users' preferences. In addition, the performance of ESSVM-UCP and RSVM-UCP is unstable in the first three months according to 'Cold Start' problem. If we have more information about users and venues, as the following months shown, ESSVM-UCP outperforms RSVM-UCP well.

To evaluate the efficiency, we cluster venues based on the category and label each venue with corresponding check-in records. Fig. 11 shows the comparison of time consumption using ESSVM and RSVM respectively. Obviously, our proposed method is more efficient than the traditional RSVM. The trough point at about 1600 shows that, the number of instances is not the only reason increasing RSVM's time consumption, but also the label proportion is one of major factors (details can be found in Section 3).

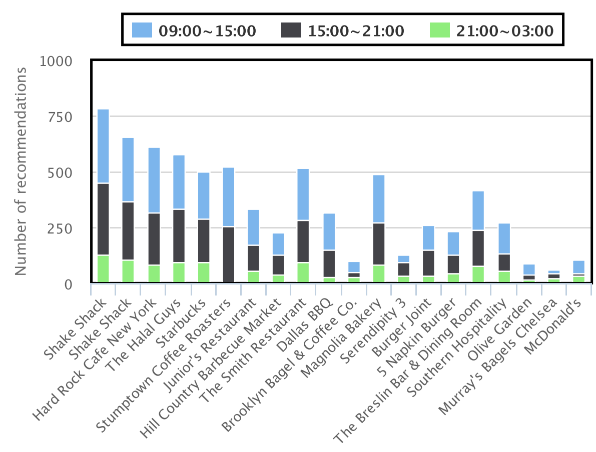
5.5. Context-based venue recommendation

To realize the characteristic of our proposed method intuitively, Fig. 12 shows the comparison between actual check-ins and recommendations during different periods in category Food and Nightlife.

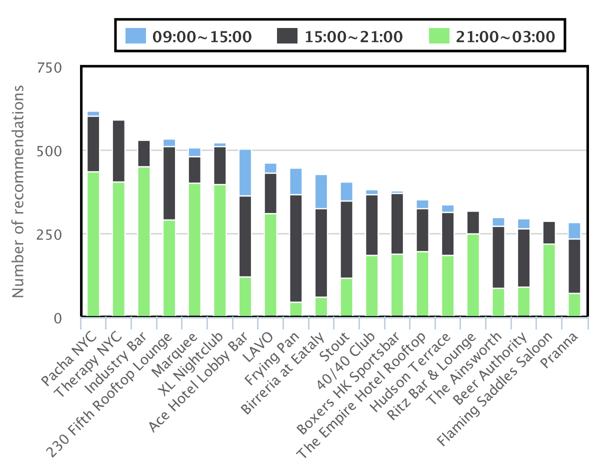
In the experiments of Fig. 12, we select the top-20 venues respectively in the category Food and Nightlife, which have more check-in records, and separate the check-in records based on the time periods of 9:00–15:00, 15:00–21:00, and 21:00–3:00. In Fig. 12a, the check-in records averagely happen in each time period, and our recommendation are against this rule. Meanwhile, from Fig. 12c, we find that check-ins mainly happen from the evening to midnight. Based on this phenomenon, our proposed strategy (Fig. 12d) recommends the corresponding locations during 15:00–21:00. This means, people often visit some locations in the specified time, and ESSVM-UCP recommends the locations based on this phenomenon. In addition, from Fig. 12b and d, we find that,



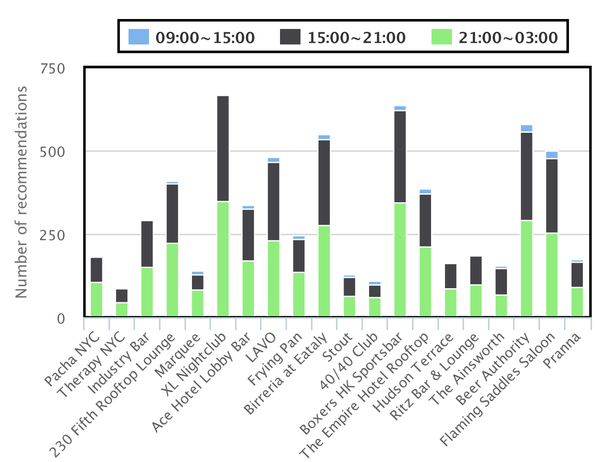
(a) Statistics of check-in records-Food



(b) Recommendations-Food



(c) Statistics of check-in records-Nightlife



(d) Recommendations-Nightlife

Fig. 12. The comparison between actual check-ins and recommendations during different periods.

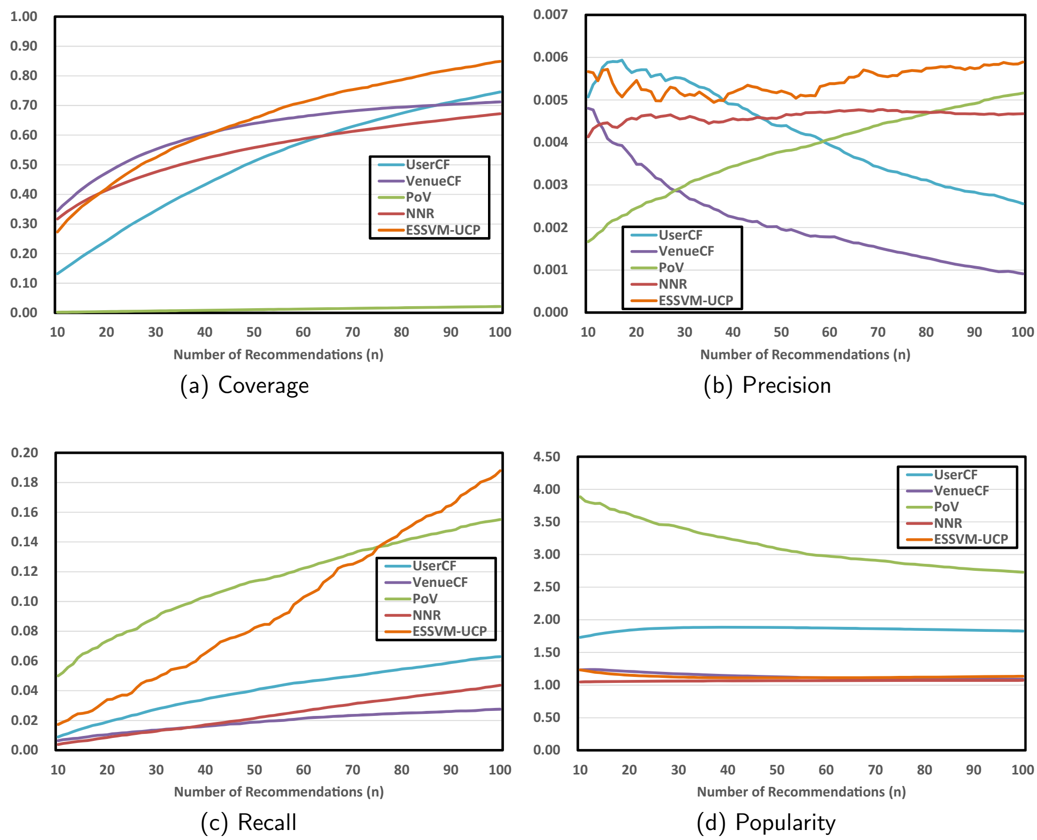


Fig. 13. Results for ESSVM and baseline methods with different lengths of recommendation list.

the times of recommendation for each location and the popularity of locations are not totally relative, which shows that our recommendations include those new venues.

To evaluate our context-based venue recommendation strategy ESSVM-UCP, we compare ESSVM-UCP with aforementioned baseline methods (UserCF, VenueCF, PoV, and NNR) which are well known in Recommender System. Same as the comparison of ESSVM and RSVM, in this section, we also evaluate our proposed method based on: the length of recommendation list (Fig. 13) and different periods (Fig. 14).

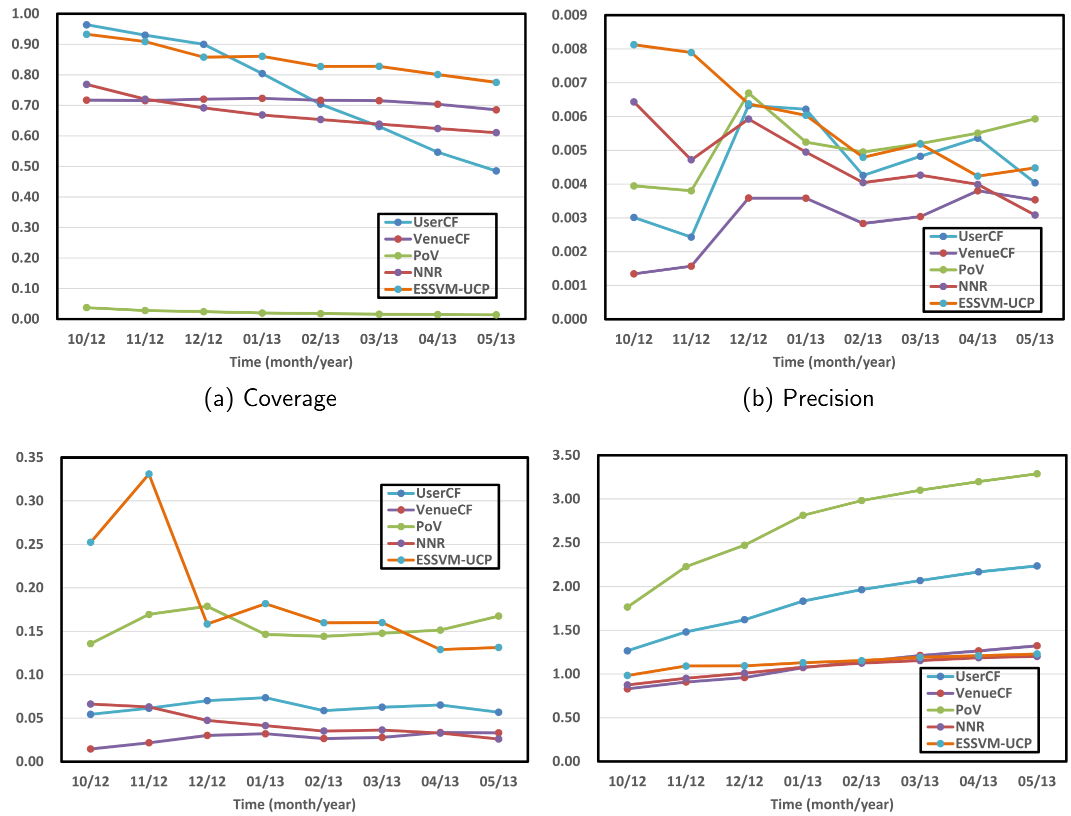
As Figs. 13 and 14 shown, our proposed method has better performance than other baseline strategies. Note that, PoV (Popularity of Venues) has the similar performance with ESSVM-UCP in $Precision_n$ and $Recall_n$, however, $Coverage_n$ and $Popularity_n$ show the drawbacks of PoV. The low $Coverage_n$ represents that, the recommendation of PoV cannot cover most of locations, and the high $Popularity_n$ means that PoV recommends the most popular locations and ignores those venues which are newly open or not famous. According to these drawbacks, if we use PoV to recommend the venues for users, the popular venues will be more famous, and the locations which have little visitors won't be recommended. Different with PoV, based on users' preferences, our proposed ESSVM-UCP shows that the personalized recommendation which covers most of venues in the system, while maintaining the effective recommendation.

5.6. Discussion

In the above sections, we describe the diverse users' preferences under different contexts (i.e., the temporal influence and the category of location) and compare our proposed approach with other traditional recommender strategies. As observed in the experimental results, the contextual information is meaningful and useful to improve the performance of personalized recommender system. Our proposed approach outperforms other baseline methods and largely reduce the time consumption of traditional ranking SVM. Compared with other traditional recommender algorithms and context-aware methods, in the one hand, VRer is capable of providing personalized recommendations assisted by the combination of some useful contextual information with the check-in records. Unlike the traditional strategies, we consider the time influence on the changes users' preference and the categories of location that users would visit in different periods of a day. In the other hand, competed with other context-aware approaches, VRer takes some extra contextual information (e.g., photos, tips, and price) into account and provides explainable recommendations. In addition, compared with the traditional ranking function (i.e., Ranking SVM), VRer applies the embedded space ranking SVM which is capable of improving the performance of recommender system while decreasing the time consumption of training the recommender model. However, there are some limitations in our proposed recommender system: (1) it is non-trivial to collect and integrate various contextual information from different LBSNs, and the contexts sometimes are unavailable; (2) the problem of data sparsity would bring big challenges if we reduce the granularity of time and category.

6. Conclusions

In this paper, we formulate the venue recommendation as a ranking problem based on the ordered 'beenHere', which represents how many times people have been to the venues, and propose an embedded space ranking SVM (ESSVM) model to learn hyperplanes that can separate the venues of different characteristics. Our presented approach makes use of check-in data to capture



(a) Coverage (b) Precision
(c) Recall (d) Popularity

Fig. 14. Results for ESSVM and baseline methods during different time periods.

users' preferences and utilizes a machine learning model to tune the importance of different attributes in ranking.

There are some research questions. First, based on different scales and categories, the ranking attributes are totally diverse. Can different time periods of each day have the same phenomenon? Second, can a algorithm divide the groups effectively and efficiently? Finally, can some methods classify the new users into the corresponding local model accurately and effectively?

Acknowledgements

The project is supported in part by the Fundamental Research Funds for the Central Universities of China under grant No. 30916015104; the National key research and development program: key projects of international scientific and technological innovation cooperation between governments, grant No. S2016G9070, Scientific and Technological Support Project (Society) of Jiangsu Province (No. BE2016776), Chinese NSF Grant under No. 91646116 and 61503313, and the Natural Science Foundation of Fujian Province of China (No. 2017J01118).

References

Bao, J., Zheng, Y., & Mokbel, M. F. (2012). Location-based and preference-aware recommendation using sparse geo-social networking data. In *Proceedings of the 20th international conference on advances in geographic information systems* (pp. 199–208). ACM.

Baral, R., & Li, T. (2016). Maps: A multi aspect personalized poi recommender system. In *Proceedings of the 10th ACM conference on recommender systems* (pp. 281–284). ACM.

Breese, J. S., Heckerman, D., & Kadie, C. (1998). Empirical analysis of predictive algorithms for collaborative filtering. In *Proceedings of the fourteenth conference on uncertainty in artificial intelligence* (pp. 43–52). Morgan Kaufmann Publishers Inc.

Chen, Z., Li, T., & Sun, Y. (2013). A learning approach to sql query results ranking using skyline and users' current navigational behavior. *IEEE Transactions on Knowledge and Data Engineering, 25*, 2683–2693.

Cheng, C., Yang, H., King, I., & Lyu, M. R. (2012). Fused matrix factorization with geographical and social influence in location-based social networks. *Twenty-sixth AAAI conference on artificial intelligence*.

Deshpande, M., & Karypis, G. (2004). Item-based top-n recommendation algorithms. *ACM Transactions on Information Systems (TOIS), 22*, 143–177.

Ganu, G., Elhadad, N., & Marian, A. (2009). Beyond the stars: Improving rating predictions using review text content.. In *WebDB: vol. 9* (pp. 1–6).

Guyon, I., Weston, J., Barnhill, S., & Vapnik, V. (2002). Gene selection for cancer classification using support vector machines. *Machine Learning, 46*, 389–422.

Herlocker, J. L., Konstan, J. A., Terveen, L. G., & Riedl, J. T. (2004). Evaluating collaborative filtering recommender systems. *ACM Transactions on Information Systems (TOIS), 22*, 5–53.

Joachims, T. (2002). Optimizing search engines using clickthrough data. In *Proceedings of the eighth ACM SIGKDD international conference on knowledge discovery and data mining* (pp. 133–142). ACM.

Li, L., Peng, W., Kataria, S., Sun, T., & Li, T. (2013). Frec: A novel framework of recommending users and communities in social media. In *Proceedings of the 22nd ACM international conference on conference on information & knowledge management* (pp. 1765–1770). ACM.

Li, L., Peng, W., Kataria, S., Sun, T., & Li, T. (2015). Recommending users and communities in social media. *ACM Transactions on Knowledge Discovery from Data (TKDD), 10*, 17.

Linden, G., Smith, B., & York, J. (2003). Amazon. com recommendations: Item–to-item collaborative filtering. *Internet Computing, IEEE, 7*, 76–80.

Noulas, A., Scellato, S., Lathia, N., & Mascolo, C. (2012). A random walk around the city: New venue recommendation in location-based social networks. In *Privacy, security, risk and trust (PASSAT), 2012 international conference on and 2012 international conference on social computing (SocialCom)* (pp. 144–153). IEEE.

Pazzani, M. J., & Billsus, D. (2007). Content-based recommendation systems. In *The adaptive web* (pp. 325–341). Springer.

Rajaram, S., Garg, A., Zhou, X. S., & Huang, T. S. (2003). Classification approach towards ranking and sorting problems. In *Machine learning: ECML 2003* (pp. 301–312). Springer.

Ricci, F., Rokach, L., & Shapira, B. (2011a). *Introduction to recommender systems handbook*. Springer.

Ricci, F., Rokach, L., Shapira, B., & Kantor, P. B. (2011b). *Recommender systems handbook*: 1. Springer.

Samworth, R. J., et al. (2012). Optimal weighted nearest neighbour classifiers. *The Annals of Statistics, 40*, 2733–2763.

Sarwar, B., Karypis, G., Konstan, J., & Riedl, J. (2001). Item-based collaborative filtering recommendation algorithms. In *Proceedings of the 10th international conference on world wide web* (pp. 285–295). ACM.

Singh, V. K., Mukherjee, M., & Mehta, G. K. (2011). Combining collaborative filtering and sentiment classification for improved movie recommendations. In *Multi-disciplinary trends in artificial intelligence* (pp. 38–50). Springer.

Wang, H., Terrovitis, M., & Mamoulis, N. (2013). Location recommendation in location-based social networks using user check-in data. In *Proceedings of the 21st ACM SIGSPATIAL international conference on advances in geographic information systems* (pp. 374–383). ACM.

Yao, L., Sheng, Q. Z., Qin, Y., Wang, X., Shemshadi, A., & He, Q. (2015). Context-aware point-of-interest recommendation using tensor factorization with social regularization. In *Proceedings of the 38th international ACM SIGIR conference on research and development in information retrieval* (pp. 1007–1010). ACM.

Ying, Y., Chen, L., & Chen, G. (2017). A temporal-aware poi recommendation system using context-aware tensor decomposition and weighted hits. *Neurocomputing, 242*, 195–205.

Zhou, Q., Hong, W., Shao, G., & Cai, W. (2009). A new svm-rfe approach towards ranking problem. In *Intelligent computing and intelligent systems, 2009. ICIS 2009. IEEE international conference on: vol. 4* (pp. 270–273). IEEE.

Zhu, H., Chen, E., Xiong, H., Yu, K., Cao, H., & Tian, J. (2015). Mining mobile user preferences for personalized context-aware recommendation. *ACM Transactions on Intelligent Systems and Technology (TIST), 5*, 58.