The following publication Y. Chen, J. Zhang, M. Guo and J. Cao, "Learning User Preference from Heterogeneous Information for Store-Type Recommendation," in IEEE Transactions on Services Computing, vol. 13, no. 6, pp. 1100-1114, 1 Nov.-Dec. 2020 is available at https://doi.org/10.1109/TSC.2017.2755009.

Learning User Preference from Heterogeneous Information for Store-type Recommendation

Yuanyi Chen, Jingyu Zhang, Minyi Guo, *senior member, IEEE,* and Jiannong Cao, *Fellow, IEEE,*

Abstract—Online stores are capable analyzing user preference from click logs and transaction records, while retailers with physical stores still lack effective methods to understand user preference. Traditional ways are predominantly field surveys, which are not effective as they need labor-intensive survey thus limit to small populations. As mobile devices and social media are becoming more and more pervasive, user-generated heterogeneous information (e.g., check-in activities and online reviews) from these platforms are providing rich information to in-depth understand user preference. In this paper, we present a recommendation model for physical stores by learning user's preference from user-generated heterogeneous information. Specifically, the proposed model consists of two phases: 1) offline modeling multi-relation among users, stores and aspects; 2) online graph-based recommendation. The offline modeling phase is designed to learn two kinds of relations: *User-Store* relation and Store-Aspect relation, while the online recommendation phase automatically produces top-k recommended stores based on the learnt relations with a graph-based model. To demonstrate the utility of our proposed model, we have performed a comprehensive experimental evaluation on two real-world datasets, which are collected by more than 120,000 users during 12 months. Experimental results show our method outperforms all baselines significantly in terms of recommendation effectiveness.

Index Terms—Store-type recommendation; User preference; Check-in activity; Online reviews; Heterogeneous Information

1 Introduction

As a driver of local economies, retail business play a significant role in maintaining economic growth, offering employment and providing a better quality of life. Recent years have witnessed a rapid development of retail business, for example, more than 1,650 new shopping malls containing 63.9 million sq.m of gross leasable area were delivered between 2013 and 2014 according to Cushman & Wakefield [1]. Given increasing number of homogeneous physical stores, the retailers who in-depth understand user preference will gain advantages to build excitement with users and facilitate a few valuable services, such as:

- **Targeted Advertising.** Advertisers can efficiently spend their budget in a way that maximizes the expected profit by mining user preference. For instance, if a store owner has to push newly launched products to consumers, the proposed model can help her selecting the best k users that maximizes the expected profit based on user preference.
- **Proactive Retail Assistant.** [23] stated most shopping decisions occur in the store and only 1/3 of shopping decisions is planned beforehand, thus a store assistant can direct to assist the potential customers based on their preference.
- **Space planning and management.** Mall managers can utilize the understanding of major user preference for store relocation, facility management, correlation discovery between stores and consumers, these information is useful for optimizing shopping mall layout and management.

However, user preference in physical stores is little understood due to the following challenges: 1) Nowadays, physical stores not only need to offer shopping experience but also provide various leisure and food facilities (e.g., coffee shop, game center and theatre) for improving comprehensive experience. For instance, some users visit a store for buying products that they need, other users enjoy the store environment and atmosphere. As a result, it is quite challenging to figure out user's real intention; 2) User preference in physical stores is a result of both personality and situational influences [26]. Traditional marketing research has reported various factors that have impact on user preference, such as demographic factors (e.g., gender [11] and age [1]) and mall environment (e.g., background music [33], light and employee [18]). However, these heterogeneous factors that affect user preference cannot be easily represented in a uniform feature space for analysis.

Even though a number of studies on mining user preference in physical stores [7], [17], [22], [25], [32] have been recently proposed (for a review see Section 2), these approaches suffer from a number of limitations. These limitations include data sparsity due to few check-ins in Location Based Social Network (LBSN), the inability to make recommendations for people who are not members of LBSN, the huge cost for collecting user's shopping behaviours with store-deployed infrastructure. Learning user preference in physical stores has also attracted enormous research from traditional marketing research [3], [10], [11], [26], [29], [33], which were based on labor-intensive surveys thus limited to small populations.

Fortunately, user-generated data from mobile devices [22], [25] and social media [2] provide rich information to mine user

- *Yuanyi Chen is the correspondence author and with the Department of Computer Science and Technology, Shanghai Jiao Tong University, Shanghai, China. Email: cyyxz@sjtu.edu.cn.*
- *Jingyu Zhang, and Minyi Guo are with the Department of Computer Science and Engineering, Shanghai Jiao Tong University, Shanghai, China. E-mail: zhangzhang@sjtu.edu.cn, guo-my@cs.sjtu.edu.cn.*
- *Jiannong Cao is with the Department of Computing, Hong Kong Polytechnic University, Hong Kong, China. E-mail: csjcao@comp.polyu.edu.hk.*

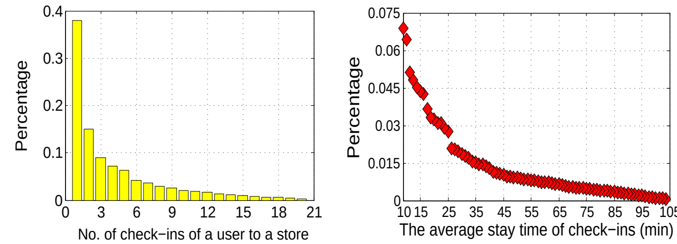
1. http://www.cushmanwakefield.com/en/research-and-insight/2014/global-shopping-center-development-report-spring-2014/

preference. For example, user's check-in activities (e.g., the check-in frequency and stay time in a store) reflect to some extent their preference, and such kind of check-in activities can be extracted from user-generated WiFi logs. Recently, user-generated WiFi logs are ubiquitous as free WiFi service is increasingly available in most physical stores, which implicitly imply user's check-in activities and provide us a new approach to understand user's preference. However, most users usually visit a store only once or twice, for instance, Figure 1a depicts the distribution of the check-in frequency of users to the same store using two real-world datasets, more details of the datasets are reported in Table 5. From Figure 1a, we observe that above 50% stores have been visited only once by the same user. Figure 1b shows that the percentage of check-ins that the stay time in a store is more than 1 hour is only 16%. Therefore for user with few check-in records, only utilizing check-in activities are insufficient to reflect the level of his/her preference to a store. To learn user preference in such cases, our proposed approach exploits not only user's check-in activities but also store's online reviews. Intuitively, a user visits a store by matching personal preferences with the service content of that store. A user would have her/his personal preference for the choice of stores, and the personal preference can be represented by his/her opinion to various aspects of stores (e.g., environment, price and service). For instance, consider a typical review written by a user regarding a restaurant: "both the environment and service are excellent, while the price is little expensive!". This comment shows the user's opinions towards three aspects of the restaurant, like "environment:excellent", "service:excellent" and "price:little expensive". Therefore, we can uncover the aspects of a store that users cared most about by analyzing its online reviews. The check-in activities, imply user's preference towards a store. The textual reviews, provide meaningful semantics about most user's opinion towards various aspects of stores. Thus we can learn user's preference by jointly considering the two kind of heterogeneous information.

In this study, we propose a store-type recommendation model for physical stores by learning user preference from their check-in activities and store's online reviews. The contributions of our research are three-fold:

- We model multi-relation among suers, stores and aspects, i.e., *User-Store* relation from user's check-in activities with a latent variable model and *Store-Aspect* relation from store's online reviews using an Elo-based scheme.
- We construct a tripartite graph model to capture multi-relation among suers, stores and aspects, and generate top-k store recommendation utilizing a random walk-based propagation algorithm
- We evaluate our approach based on two real-world datasets collected by more than 120,000 users. The results show the advantages of our approach beyond multiple baseline algorithms.

The remainder of the paper is organized as follows: Section 2 surveys related work on learning user preference in physical stores and store-type recommendation. Section 3 describes the overview of the proposed store-type recommendation model. Section 4 proposes the offline modeling phase for learning user preference. Section 5 describes the proposed graph-based recommendation model in detail. Section 6 reports and discusses the experimental results. Finally, we present our conclusion and future work in Section 7.



(a) Distribution of check-in frequency (b) Distribution of average stay time

Fig. 1: (a) Above 50% stores have been checked in only once or twice by the same user; (b) the percentage of check-ins that the stay time is more time 25 minutes is less than 12%.

2 Related Work

In this section, we first survey related works on learning user preference in physical stores and store-type recommendation, and then discuss how these works differ from our work.

Learning user preference using intercept surveys. Learning user preference in physical stores has attracted an enormous amount of research from traditional marketing research in view of its great importance to understand the effectiveness of marketing and merchandising efforts. In the marketing domain, it is of great interest to build a satisfactory relation with the user, by assessing her/his preference and intention. The studies [3], [29] focused on distinguishing the consuming style of users based on their shopping behaviours. The work in [11], [33] aimed to analyze the influence of situational factors (e.g., background music, shop brand, and billboard image) on user behaviour in physical stores. [10] surveyed the relation between user's shopping path and their behaviors in terms of the visited zones, elapsed time in each zone and purchased items. However, these studies mine user preference by collecting user's profiles and shopping information with manual intercept surveys, which are labor-intensive and requiring huge cost that cannot be performed frequently at a large scale. Moreover, intercept surveys are powerless to capture information from survey avoiders for understanding their preference.

Learning users preference using check-in activities. A few efforts have been made to learn user preference using their check-in activities. User's check-in activities are regarded and interpreted as a trace of her/his store visits, which are intuitive because users usually hop across stores and enjoy services provided by individual stores while they are hanging around in physical stores. Many pervasive computing technologies (e.g., RFID [25] and smart glasses [22]) are utilized to generate user's check-in activities in physical stores. For example, [13] placed a ubiquitous sensor network in a shopping mall to track user's positions as well as local behaviors. [30] utilized ambient devices (e.g., speakers and electric displays) to detect user's unforced natural behavior to information, and analyzed user's preference on features and their values of commodities. [25] proposed a RFID-based system to infer the aggregated shopper interaction patterns with specific items in a physical clothing store. [21] assumed that a user carries both smart-phone and smart-watch to get insights into the user's behavior inside a retail store. [20] proposed a multi-level framework for the automatic assessment of user's shopping behavior by utilizing a fish-eye camera to track users. However, the methods mentioned above either require densely deployed infrastructure to capture user's check-in activities or collect sensor

TABLE 1: Compare of experimental datasets

Methods	Participants	Stores	Collecting Time
[13]	21817	4	7 days
[30]	10	unknown	7 days
[21]	25	50	unknown
[20]	20	unknown	5 hours
[25]	10+	2	unknown
[15]	195	353	30 days
Our datasets	123,406	342	12 months

data from user's mobile phones thus are lack of scalability due to user involvement (as shown in Table 1). By contrast, our approach takes advantage of existing WLAN infrastructure for generating user's check-in activities by passive crowdsourcing, which is no user involvement and infrastructure-free.

To our best knowledge, only few studies [7], [17], [32] address the problem of store-type recommendation in physical stores using WiFi logs. For example, the work [17] mined user preference by rating a store using the residence time in the store. [7] further derived user's preference by linearly fusing the residence time and the check-in frequency. The work in [32] aimed to analyze user behaviour using an opt-in WiFi service, which first obtains user's behaviour information using location tracking technology based on WiFi access points (APs) that listen to transmissions from WiFi-enabled devices. Then, they map concepts of user behaviour (e.g., the residence time in a store and check-in frequency) to concepts and key performance indicators commonly used in online store analytics, and finally using some marketing management technologies to learn user preference. However, by analyzing millions of WiFi logs, we find that these studies mentioned above are unsuitable to model the relation between user preference and their check-in activities.

Our proposed approach differs from the above-mentioned works in the following three aspects: 1) We generate various check-in activities (e.g., the check-in frequency and stay time in a store) using user-generated WiFi Logs, which is collected by passive crowdsourcing thus without user involvement; 2) We consider that both the check-in frequency and stay time characterizes users preference and model the *User-Store* relation by a latent variable model; 3) We construct the *Store-Aspect* relation by extracting the aspects that users most concerned about when checking a store from store's online textual reviews, then make recommendation for users by jointly considering the learnt *User-Store* relation and *Store-Aspect* relation.

3 Overview of The Proposed Store-type Recommendation Model

3.1 Preliminary

For ease of the following presentation, we define the key data structures and notations used in the proposed method. Table 2 lists the relevant notations used in this paper.

Definition 1. (**WiFi Log**) A WiFi log consists of a set of WiFi records and denote by $P = \{p_1, ..., p_i, ...\}$, p_i is a triple $< u, t_i, R_i >$ which means the WiFi RSS (radio signal strength) sample R_i is collected by user u at time t_i, where $R_i = (r_i^1, ..., r_i^j, ...r_i^K)$ is a K-dimension vector which means the RSS values collected from surrounding WiFi APs (access points), r_i^j means the collected RSS value from WiFi AP ap_j, K is the number of WiFi APs. An example of WiFi record is shown in Table 3.

TABLE 2: Notations used in the paper

SYMBOL	DESCRIPTION
U,S,A	the set of users, stores, aspects
P	a WiFi logs set and denote by a set of WiFi records $\{p_1,...,p_i,...\}$
p_i	a WiFi records and denote by a triple $< u,t_i,R_i >$
R_i	the RSS samples collected from surrounding WiFi APs at time t_i
r_i^j	the RSS value collected from ap_j at time t_i
a	an attribute or feature of a store, such as "service" for a restaurant
o	the sentiment orientation towards an aspect
$I^{(ij)}$	the relation strength between user u_i and store s_j
$W^{(jk)}$	the relation strength between store s_j and aspect a_k
$e^{(ij)}$	the initial interest of u_i to s_j
$F^{(ij)}$	the check-in frequency of user u_i to store s_j
$T^{(ij)}$	the average stay time of user u_i to store s_j
R_a	Elo point of aspect a that calculated by pairwise aspect preference
G	A graph to capture multi-relation among users, stores and aspects
E_{US}	the edge set between users vertices and stores vertices
E_{SA}	the edge set between stores vertices and aspect vertices
Y,X	the edge weight matrix of E_{US} and E_{SA}
T_U	self transition matrix that allow a user vertex to stay in itself
T_S	self transition matrix that allow a store vertex to stay in itself
T_A	self transition matrix that allow a aspect vertex to stay in itself
$\overline{E}$	transition probability matrix of random walk
H	the vector of visiting probability of all vertices in tripartite graph
V_u,V_a,V_s	the restart vector of user vertices, aspects vertices, store vertices

TABLE 3: An example of WiFi record

User	Timestamp	ap_1	ap_2	...	ap_{121}
u_1	2016/10/15 17:29:41	-48	-69	...	-75

Definition 2. (**Check-in Activity**) A check-in activity is a triple $< u, s, ts >$ that means user u visits store s and the stay time of this visit is ts. For generating user's check-in activity, we first map all elements of WiFi logs ($p_i \in P$) to the corresponding store, then generate a sequence of stores consecutively visited by a user based on chronological order and further extract user's check-in activity.

Definition 3. (**Aspect**) An aspect a is an attribute or feature of a store, e.g., "service", "price", "environment" and "taste" for a restaurant.

Definition 4. (**Aspect-sentiment phase**) An aspect-sentiment phase is defined as a tuple $< a, o >$, where a is an aspect and o is the sentiment orientation towards the aspect. For example, for the piece of review 'the service is perfect, but the taste is terrible!', the extracted aspect-sentiment phases can be "$< service, +1 >$ *and* $< taste, -1 >$".

Definition 5. (**User-Store Relation**) Denote by an adjacent matrix I, where $I^{(ij)}$ is the relation strength that indicates the preference of user u_i for store s_j. The *User-Store* relation is mined from user's check-in activities.

Definition 6. (**Store-Aspect Relation**) Denote by an adjacent matrix W, where $W^{(jk)}$ is the relation strength between store s_j and aspect a_k that indicates the opinion of most users to aspect a_k of store s_j. The *Store-Aspect* relation is derived from store's online reviews.

3.2 Store-type Recommendation Framework

As shown in Figure 2, our proposed model produces top-k recommended stores by two phases: 1) offline learning user preference via heterogeneous information (Details of offline learning user preference will be introduced in Section 4.). The phase aims to model multi-relation among users, stores and aspects, which involves two major pipelines: (i) model *User-Store* relation from user's check-in activities, and (ii) model *Store-Aspect* relation

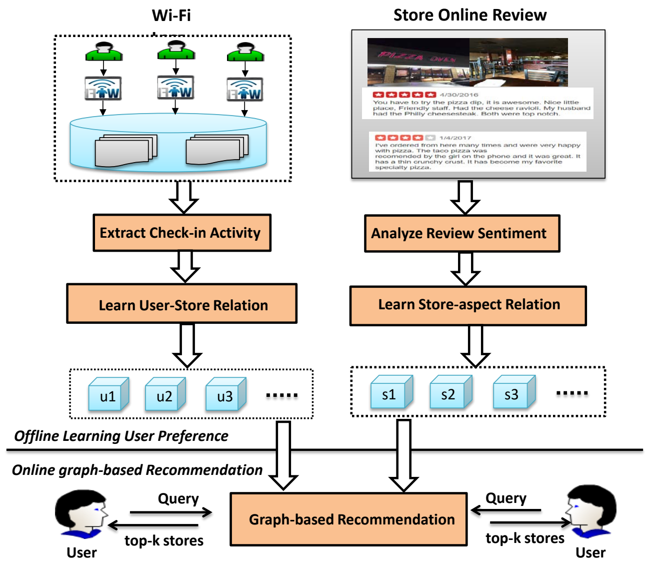


Fig. 2: The framework of the proposed store-type recommendation model

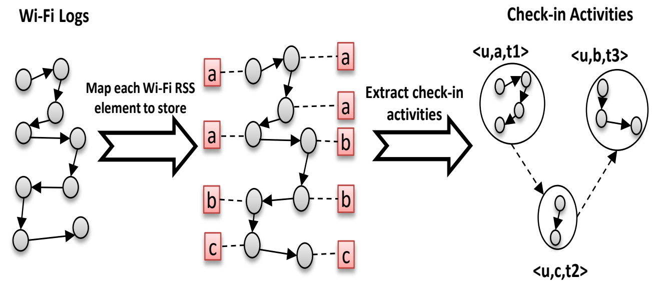


Fig. 3: Extract check-in activities from WiFi logs

from store's online reviews; 2) online store recommendation via graph-based model (Details of online store recommendation will be introduced in Section 5.). The phase produces top-k recommended stores by jointly considering the learnt *User-Store* and *Store-Aspect* relation.

3.2.1 Modeling User-Store relation from User's check-in activities

The idea behind our approach is user's check-in activities imply their preference, as most people have a finite amount of resources (e.g., time and money), they tend to visit a store by matching their personal preference. As shown in Figure 2, we model *User-Store* relation by the following two steps:

(1) Extract check-in activity from WiFi logs. As mentioned above, our approach utilizes existing WLAN infrastructure to generate user's check-in activities from WiFi logs, which is infrastructure-free and no user involvement. To achieve both goals, we utilize WiFi probe requests collect the data with a non-intrusive way. WiFi probe requests are frames that are broadcast by mobile phones to discover nearby WiFi APs, and can be sniffed by WiFi compatible antennas on 802.11b/g/n channels. According to [19], mobile phones will broadcast WiFi probe requests every few seconds. That means collecting data by WiFi probe requests allowed us to track every mobile device that connects to the WiFi infrastructure. In our experiment, every device that connects to WLAN infrastructure at each store has agreed to this data collection as part of the sign-on agreement. For privacy issue, we collect user-generated WiFi logs as hashed entities with no additional knowledge about them, and finish collecting data when user leaves the shopping mall. We believe that this is a privacy-safe application.

For extracting user's check-in activities, we need to map all elements of WiFi logs to the corresponding stores (as shown in Figure 3). The problem can be described as: given a WiFi log $P = \{p_1, ..., p_i, ...\}$, map P to the corresponding check-in stores $S(P) =< s_1 \longrightarrow ... \longrightarrow s_i \longrightarrow ... >$. In a previous work, we presented *GraphLoc* [5], a graph-based method for indoor subarea localization to solve the mapping problem, we refer the readers to the literature for more mapping details. After mapping all elements $p_i \in P$ to the corresponding store, we extract user's check-in activity according to *Definition 2*.

(2) Learn User-Store relation via latent variable model. The idea of learning *User-Store* relation is user's check-in activities can be viewed as a contexture of behaviors that are motivated by their intent and preference, thus we can infer user's preference towards a store from history check-in records. User's preference towards a store directly impacts the check-in frequency and stay time of the store, since people have a finite amount of resources, they tend to visit their favorite stores. Moreover, user's preference towards a store relates positively to her/his check-in frequency and the stay time, which has theoretical foundations and empirical evidence from marketing research [4], [17]. In this way, we model user's preference towards a store as the hidden factor of his/her check-in activities with a latent variable model (Details of the modeling process will be introduced in Section 4.1) .

3.2.2 Modeling Store-Aspect relation from store's online reviews

For users with few check-ins, merely utilizing check-in activities are insufficient to reflect their preference level towards stores. To model a target user's preference in such cases, additional information about store aspects (e.g. service, taste and price) must be used due to their explainable property for store's latent features [8]. In this way, we model *Store-Aspect* relation from store's online reviews to identify what aspects of the store users cared most about. As shown in Figure 2, we model *Store-Aspect* relation by the following two steps:

(1) Analyze aspect sentiment from online reviews. As our focus is to model *Store-Aspect* relation for identifying what aspects users cared most about when they check in stores, we do not contribute to analyze aspect-sentiment phase from reviews, but instead exploit ASUM model, a state-of-art optimization approach described in [12] due to its high accuracy. ASUM supposes each word of user's review correspond to a specific pair of aspect-sentiment phase, and models the generative process of writing a review as: the user first decides to write a review of a clothes that expresses the distribution of sentiments, for example, 80% satisfied and 20% unsatisfied. And he decides the distribution of the aspects of each sentiment, say 50% about the "style", 25% about the "service", and 25% about the "price" for the positive sentiment. Then he decides, for each sentence, a sentiment to express and an aspect for which he feels that sentiment.

For a given piece of review, we generate a set of aspect-sentiment phases (A, O) using ASUM model to represent this

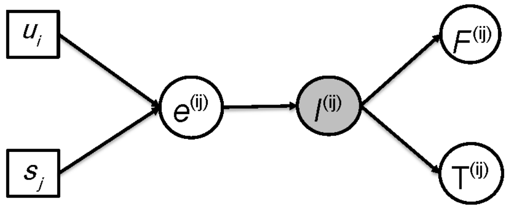
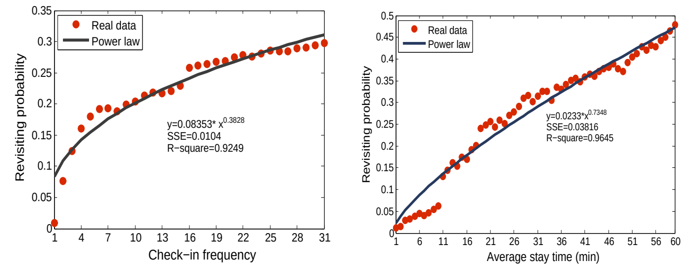


Fig. 4: Graphical model representation of learning *User-Store* relation



(a) Check-in frequency

(b) Average stay time

Fig. 5: Fraction of revisiting probability as a function of check-in frequency(a) and average stay time(b)

review, where O is assigned as 1 or -1 according to the sentiment polarity that the user expressed on this aspect. For example, an entry such as $< taste, -1 >, < service, 1 >$ might be extracted from a restaurant review.

(2) Learn Store-Aspect relation. This step aims to infer the aspects of a store that are most interesting to users based on aspect-level sentiment analysis. Firstly, we extract pairwise preferences of aspects from the generated aspect-sentiment phases from store's online reviews. Then we utilize an Elo rating-based method [24] to estimate the relation strength between aspects and stores based on aspect's pairwise preferences. (Details of the method for learning *store-aspect* relation will be introduced in Section 4.2)

3.2.3 Online store recommendation via graph-based model

After modeling the *User-Store* relation and Store-Aspect relation, we combine the two kinds of relations among users, stores and aspects to build a tripartite graph. Then we formulate the top-k store recommendation as one of vertex ranking in the tripartite graph, and further propose a vertex ranking algorithm by iterative propagating over the tripartite graph. The basic idea of the proposed iterative propagating scheme is to recommend a list of stores according to the edge weight that are reachable from a user node on the tripartite graph. (Details of the graph-based recommendation model will be introduced in Section 5).

4 Offline Learning User Preference via Heterogeneous Information

In this section, we learn user preference by modeling two kinds of relations among users, stores and aspects: (i) *User-Store* relation from their check-in activities, and (ii) *Store-Aspect* relation from store's online reviews.

4.1 Modeling User-Store Relation from Check-in Activities

In this subsection, we first describe the modeling part of the proposed approach a latent variable model to learn *User-Store* relation from user's check-in activities, and then present its inference process.

Model Description. Formally, let $F^{(ij)}$ and $T^{(ij)}$ denote the check-in frequency and average stay time of user u_i to store s_j, $I^{(ij)}$ is the relation strength between user u_i and store s_j (denote the preference of u_i towards s_j). Then, we utilize a graphical model to combine the influence of u_i and s_j to $I^{(ij)}$, as well as the influence of $I^{(ij)}$ to $F^{(ij)}$ and $T^{(ij)}$, as shown in Figure 4. The detailed description of variables in this figure is explained as follows:

- $e^{(ij)}$ denote the initial interest of u_i to s_j, which is a result of both personality and situational factors [27]. Since the initial preference is implicit and influenced by various factors, we estimate the initial interest based on the check-in frequency and average stay time. Let $max(F^{u_i})$ denotes the maximum value of check-in frequency for u_i, $max(T^{u_i})$ denotes the maximum value of average stay time for u_i to all stores. Then the initial interest $e^{(ij)}$ between u_i and s_j can be calculated by:

$$e^{(ij)} = \theta \frac{F^{(ij)}}{max(F^{u_i})} + (1-\theta)\frac{T^{(ij)}}{max(T^{u_i})} \tag{1}$$

where θ is the weight for moderating the check-in frequency and stay time, which is set to 0.5 in our experiment.
- $I^{(ij)}$ is the relation strength between user u_i and store s_j, which is modelled as a hidden factor for user's check-in activities and influenced by the initial interest $e^{(ij)}$.

Our model represents the relationships among these variables by modeling the conditional dependencies as shown in Figure 4, so the joint distribution decomposes as follows:

$$P(I^{(ij)}, F^{(ij)}, T^{(ij)}|u_i, s_j) = P(I^{(ij)}|u_i, s_j)P(F^{(ij)}|I^{(ij)})P(T^{(ij)}|I^{(ij)}) \tag{2}$$

Given the initial interest $e^{(ij)}$, we model the conditional probabilities $P(I^{(ij)}|u_i, s_j)$ with the widely-used Gaussian distribution:

$$P(I^{(ij)}|u_i, s_j) = (\eta e^{(ij)}, \sigma^2) \tag{3}$$

where η is a coefficient to be estimated, σ^2 is the variance of Gaussian model and is set to 0.5 suggested by [39] in our experiments.

For modeling the dependency between $F^{(ij)}, T^{(ij)}$ and $I^{(ij)}$, we study two anonymized datasets collected by registered users in two urban shopping malls during 12 months, which consists of more than 3 million check-ins from 123,406 users on 342 stores, more details of the dataset are shown in Table 5. Figure 5a shows user's revisiting probability to a store as a function of the check-in frequency. From this figure, we observe that: 1) over 16% of users will revisit a store if they have visited the store more than 4 times; 2) the distribution follows a roughly power-law form. Figure 5b shows user's revisiting probability to a store as a function of the average stay time of the store. From this figure, we also observe the distribution follows a roughly power-law form.

In this way, we model the dependency between $F^{(ij)}, T^{(ij)}$ and $I^{(ij)}$ as follows:

$$P(F^{(ij)}|I^{(ij)}) = (\alpha_1 I^{(ij)})^{\beta_1}, \qquad P(T^{(ij)}|I^{(ij)}) = (\alpha_2 I^{(ij)})^{\beta_2} \tag{4}$$

where α_1, β_1, α_2, β_2 are the parameters to be estimated.

We further add L_2 regularizes on these parameters (e.g., α_1, β_1, η) to avoid over-fitting, which can be regarded as Gaussian priors:

$$\begin{aligned} &P(\eta) \propto e^{-(\lambda_\eta/2)\eta^2} \\ &P(\alpha_l) \propto e^{-(\lambda_{\alpha_l}/2)\alpha_l^2}, P(\beta_l) \propto e^{-(\lambda_{\beta_l}/2)\beta_l^2}, l = 1,2. \end{aligned} \tag{5}$$

The data are represented as $\Phi = U \times S$ samples of *user-store* pairs, denoted as $D = \{(i_1, j_1), ..., (i_{|U|}, j_{|S|})\}$. During the training phase, the variables $e^{(ij)}, F^{(ij)}, T^{(ij)}$ are all visible, $(i, j) \in \Phi$. According to Equation 2, given all the observed variables, the joint probability is shown as:

$$\begin{aligned} &\prod_{l=1}^{2} P(\Phi|\eta, \alpha_l, \beta_l) P(\eta, \alpha_l, \beta_l) \\ &= \prod_{l=1}^{2} \prod_{(i,j)\in D} P(D|I^{(ij)}, \alpha_l, \beta_l) P(I^{(ij)}|e^{(ij)}, \eta) P(\eta, \alpha_l, \beta_l) \\ &\propto \prod_{l=1}^{2} \prod_{(i,j)\in D} (\alpha_l I^{(ij)})^{\beta_l} e^{-(1/2\delta^2)(\eta e^{(ij)} - I^{(ij)})^2} e^{-(\lambda_\eta/2)\eta^2} \\ &e^{-(\lambda_{\beta_l}/2)(\beta_l)^2} e^{-(\lambda_{\alpha_l}/2)(\alpha_l^2)} \end{aligned} \tag{6}$$

Model Inference. We estimate the unknown model parameters $\Sigma = \{\eta, \alpha_l, \beta_l | l = 1,2\}$ by maximizing the likelihood function in Equation 6. As for the regularization parameters $\lambda_\eta, \lambda_{\alpha_l} and \lambda_{\beta_l}$, for simplicity , we take a fixed value ($\lambda_\eta = \lambda_{\alpha_l} = \lambda_{\beta_l} = 0.01$). Applying a logarithmic transformation to both sides of Equation 6, we obtain the following expression:

$$\begin{aligned} &L((i,j) \in D, \eta, \alpha_l, \beta_l) \\ &= -\frac{1}{2\sigma^2} \sum_{(i,j)\in D} (\eta e^{(ij)} - I^{(ij)})^2 + \sum_{l=1}^{2} \beta_l log(\alpha_l I^{(ij)}) \\ &- \sum_{l=1}^{2} \frac{\lambda_{\beta_l}}{2} \beta_l^2 - \frac{\lambda_\eta}{2} \eta^2 - \sum_{l=1}^{2} \frac{\lambda_{\alpha_l}}{2} (\alpha_l^2) \end{aligned} \tag{7}$$

Note the function L (see in Equation 7) is concave, then we optimize the parameters η, α_l, β_l and variable $I^{(ij)}$ with a stochastic gradient descent algorithm. The coordinate-wise gradients are:

$$\begin{aligned} &\frac{\partial L}{\partial I^{(ij)}} = \frac{1}{\sigma^2}(\eta e^{(ij)} - I^{(ij)}) + \sum_{l=1}^{2} \frac{\beta_l}{I^{(ij)}} \\ &\frac{\partial L}{\partial \eta} = -\frac{1}{\sigma^2} \sum_{(i,j)\in D} e^{(ij)}(\eta e^{(ij)} - I^{(ij)}) - \lambda_\eta \alpha_\eta \\ &\frac{\partial L}{\partial \alpha_l} = \frac{\beta_l}{\alpha_l} - \lambda_{\alpha_l}\alpha_l, \quad \frac{\partial L}{\partial \beta_l} = log(\alpha_l I^{(ij)}) - \lambda_{\beta_l}\beta_l \end{aligned} \tag{8}$$

We use Netwton-Raphson algorithm to update η, α_l, β_l and $I^{(ij)}$ in each iteration:

$$I^{(ij)new} = I^{(ij)old} - \frac{\partial L}{\partial I^{(ij)}} / \frac{\partial^2 L}{\partial((I^{(ij)})^2} \tag{9}$$

$$\eta^{new} = \eta^{old} - \frac{\partial L}{\partial \eta} / \frac{\partial^2 L}{\partial(\eta)^2} \tag{10}$$

$$\alpha_l^{new} = \alpha_l^{old} - \frac{\partial L}{\partial \alpha_l} / \frac{\partial^2 L}{\partial(\alpha_l)^2} \tag{11}$$

$$\beta_l^{new} = \beta_l^{old} - \frac{\partial L}{\partial \beta_l} / \frac{\partial^2 L}{\partial(\beta_l)^2} \tag{12}$$

where the second order derivatives are given by:

$$\begin{aligned} &\frac{\partial^2 L}{\partial(I^{ij})^2} = -\frac{1}{\sigma^2} - \sum_{i=1}^{2} \frac{\beta_i}{(I^{ij})^2}, \quad \frac{\partial^2 L}{\partial(\alpha_l)^2} = -\lambda_{\alpha_l} - \frac{\beta_l}{(\alpha_l)^2} \\ &\frac{\partial^2 L}{\partial(\beta_i)^2} = \lambda_{\beta_l}, \quad \frac{\partial^2 L}{\partial(\eta)^2} = -\frac{1}{\sigma^2} \sum_{(i,j)\in D} (e^{ij})^2 \end{aligned} \tag{13}$$

Algorithm 1 shows the learning procedure for optimizing the parameters. First, as shown in Line 1, we calculate the initial interest between users and stores using check-in records. Then, as depicted in Line 3 $\sim$ 13, we optimize model parameters $\Sigma = \{\eta, \alpha_l, \beta_l | l = 1,2\}$ using Newton-Raphson until converged.

Algorithm 1 The algorithm for optimizing parameters

Require: Data samples $D = \{(u_1, s_1), ..., ..., (u_{|U|}, s_{|S|})\}$.
Ensure: Model parameters $\Sigma = \{\eta, \alpha_l, \beta_l | l = 1,2\}$.
1: Calculate the initial interest between users and stores according to Equation 1.
2: **while** not converged **do**
3: **for** each Newton-Raphson step **do**
4:   **for** $(i, j) \in D$ **do**
5:     Update $I^{(ij)}$ according to Equation 9.
6:   **end for**
7:   **for** $l = 1,2$ **do**
8:     Update α_l, β_l according to Equation 11 $\sim$ 12.
9:   **end for**
10: **end for**
11: Update η according to Equation 10.
12: **endwhile**
13: **return** $\Sigma = \{\eta, \alpha_l, \beta_l | l = 1,2\}$.

Once the model is learned, for new data the relation strength $I^{(ij)}$ between u_i and s_j can be inferred using only the upper level of variables (the check-in frequency and the average stay time) in the model.

4.2 Modeling Store-Aspect Relation from Online Reviews

In this subsection, we first present the problem statement of modeling *store-aspect relation*. Then we detail the proposed solution, an Elo rating-based method to estimate the relation strength between store and its aspects based on the extracted aspect-sentiment phases from online reviews.

Problem Statement. Let $A_s = \{a_1, a_2, ...a_{|A_s|}\}$ denote a finite aspect set of store s, (A_s, O_s) denote a set of aspect-sentiment phases extracted from the online reviews of s, the problem of modeling *store-aspect relation* is estimating the relation strength between aspect $a_i \in A_s$ and store s.

Problem Solution. Our solution for this problem consists of two phases:

(1) Extract pairwise preference of aspects: Given two aspects $a_i, a_j \in A_s$, a pairwise preference label is extracted as a response from user's online reviews. Either a_i is preferred to a_j (denoted

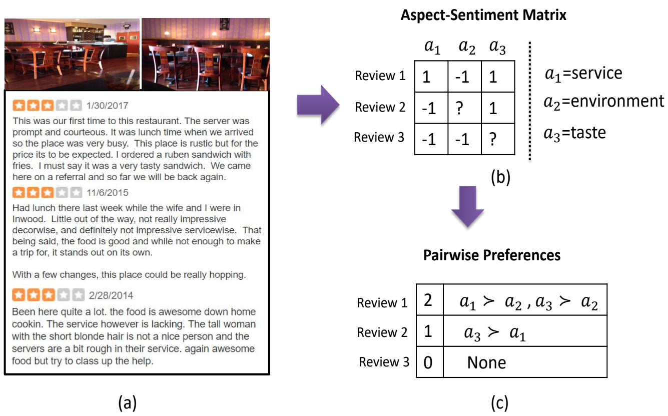


Fig. 6: Example of extracting aspect's pairwise preferences

$a_i \succ a_j$) or the other way around. Note pairwise preference labels may be non-transitive (due to irrationality or different personal preference), which means $a_i \prec a_k$ and $a_k \prec a_j$ cannot deduce $a_i \prec a_j$.

Example 1: Suppose we have three online reviews about one restaurant (as shown in Figure 6a), then we generate 7 aspect-sentiment phases from the three reviews and create an aspect-sentiment matrix (as shown in Figure 6b). Finally, we can extract 3 pairwise preferences(as shown in Figure 6c).

(2) Estimate relation strength of aspects based on pairwise preferences: We utilize a linear score function based on Elo rating-based scheme to estimate relation strength of aspects. Specifically, the Elo rating-based scheme is shown in Algorithm 2. First, as shown in Line 2, we calculate the winning expectation of aspects according to pairwise preference. Then, as depicted in Line 3, we update the Elo point of aspects according to their winning expectation. Finally, we utilize the ultimate Elo points as aspect's relation strength after all updates.

Algorithm 2 The Elo rating-based scheme for estimating relation strength

Require: 1) Store aspects $\{a_1,...,a_i,...,a_{|A|}\}$; 2) Pairwise preferences:$\Gamma = \{...,a_i \prec a_j,...\}$; 3) The starting Elo points of aspects: $\{R_1^0,...,R_i^0,...,R_{|A|}^0\}$; 4) Elo parameters: $\sum_E = \{\alpha_E, \beta_E, K_E\}$.

Ensure: Relation strength of aspects: $\{R_1,...,R_i,...,R_{|A|}\}$

1: **for** each pairwise preference $a_i \prec a_j \in \Gamma$ **do**

2: Calculate winning expectation of a_i, a_j:

$$E_i = \frac{1}{1+\alpha_E^{(R_j - R_i)/\beta_E}}, \quad E_j = \frac{1}{1+\alpha_E^{(R_i - R_j)/\beta_E}}$$

3: Update the Elo point of a_i, a_j:

$$R_i \leftarrow R_i - K_E * E_i, \quad R_j \leftarrow R_j + K_E * (1 - E_j)$$

4: **end for**

5: **return** The ultimate Elo ratings: $\{R_1,...,R_i,...,R_{|A|}\}$.

Example 2: Suppose we have three pairwise preferences $\{a_2 \prec a_1, a_2 \prec a_3, a_1 \prec a_1\}$ and the starting Elo points of all aspects are 1000, we set the Elo parameters as $\sum_E = \{\alpha_E = 10, \beta_E = 400, K_E = 32\}$ suggested by [37]. The estimating process using Elo rating-based scheme is shown Figure 7, thus we can rank the three aspects in descending order as $\{a_3, a_1, a_2\}$ according to their

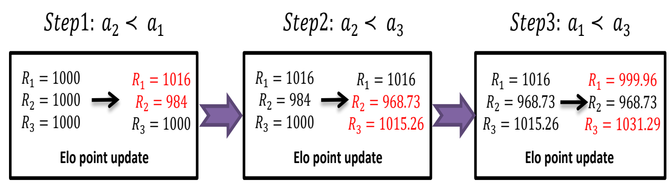


Fig. 7: Example of estimating relation strength using Elo rating-based scheme (the red value are the new Elo points after each update)

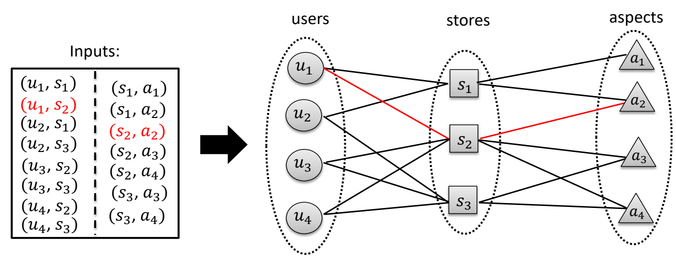


Fig. 8: Example of tripartite graph of the given inputs (the red line illustrates the additional input $\{(u_1, s_2), (s_2, a_2)\}$

Elo points. Finally, we obtain the relation strength between the three aspects and the store: $\{999.96, 968.73, 1031.29\}$.

5 Online Graph-based Recommendation

In this section, we present the proposed graph-based model for top-k store recommendation, by firstly constructing a tripartite graph to capture multi-relation among users, stores and aspects (i.e., *User-Store* relation and *Store-Aspect* relation). We then regard top-k store recommendation as one of vertex ranking in the tripartite graph, and solve the problem by utilizing a random walk-based propagation algorithm.

5.1 Tripartite Graph Model and Notation

To model the multi-relation among users, stores and aspects, we construct a tripartite graph: $G = (U \cup S \cup A, E_{US} \cup E_{SA})$, where U, S and A are vertex sets that represent users, stores and aspects, respectively. Let E_{US} and E_{SA} be edges that represent *User-Store* relation and *Store-Aspect* relation, respectively. Each edge carries a weight to denote the relation strength of two connected vertices, edges with higher weight denote more significant relations between vertices. For instance, we can model user the preference of u_i towards store s_j as an edge with weight of $e_{ij} \in E_{US}$ (as in Figure 8). Without loss of generality, we use the symbol Y and X to denote the edge weight matrix of E_{US} and E_{SA}, where $Y_{ij} = I^{(ij)}$ if user u_i have check-in records on store s_j, 0 otherwise, X_{pq} reflects the relation strength between store s_p and aspect a_q that estimated based on store's online reviews.

5.2 Random Walk-based Propagation Algorithm

Given the tripartite graph, the problem of store recommendation is to firstly predict the strengths of the unknown relations between users and stores, then result in a personalized store ranking for each user by sorting the stores in descending order of relation strengths. We utilize a random walk-based propagation algorithm to predict the strengths of the unknown relations by updating user's

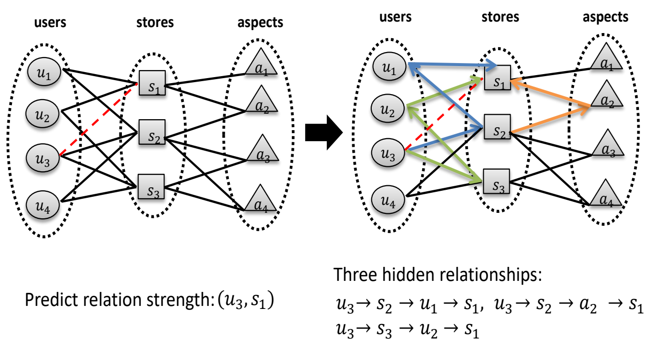


Fig. 9: Example of predicting the relation strengths between two vertices by hidden relationships

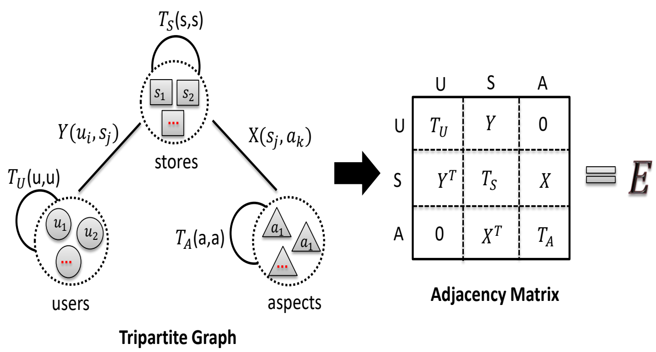


Fig. 10: Adjacency matrix of tripartite graph

relation strength with stores iteratively through the graph with random walk.

Random walk on graph can alleviate the sparsity problem in store recommendation by utilizing both *User-Store* relation and *Store-Aspect* relation. Typically, most users have few check-ins and tend to review a small number of stores, thus the data of directly connected vertices (e.g., User-Store vertex pairs and Store-Aspect vertex pairs) are sparse. Fortunately, one vertex can reach another vertex through intermediate vertices (denote as hidden propagation path), which can better estimate the relation strengths between two vertices that are not directly connected with these hidden propagation paths. The intuition on how hidden propagation paths can alleviate sparsity can be explained by the following example.

Example 3: Suppose we need to predict the relation strength between two vertices: u_3 and s_1 (as shown in Figure 9), which are not directly connected in the tripartite graph. Since u_3 has an edge with s_2 and s_3 respectively, we can find some hidden relations between u_3 and s_1 through intermediate vertices (s_2 and s_3). More exactly, we can find one hidden propagation path $< u_3 \rightarrow s_2 \rightarrow a_2 \rightarrow s_1 >$ from the *Store-Aspect* relation, and two hidden propagation paths $< u_3 \rightarrow s_3 \rightarrow u_2 \rightarrow s_1 >$ and $< u_3 \rightarrow s_2 \rightarrow u_1 \rightarrow s_1 >$ from the *User-Store* relation. Such hidden propagation paths are beneficial to predict the relation strength of two vertices that are not connected directly, thus alleviating the data sparsity problem.

As mentioned earlier, we utilize a tripartite graph to capture multi-relations among users, stores and aspects. The edges weight between these entities are determined by check-in activities (Y) or online reviews (X). Additionally, self transition matrices (T_U, T_S, T_A) allow the random walk to stay in the same vertex with a certain probability, these self transition matrices are represented in diagonal matrix of ones: $diag(1, \dots, 1)$. Finally, these edges constitute the adjacency matrix (E) of tripartite graph, $E(i, j)$ denote the probability from vertex i to vertex j, as shown in Figure 10.

To perform random walk-based propagation on the tripartite graph, we generate transition probability matrix by normalizing each column of adjacency matrix E (due to all entries in E are in different ranges):

$$\overline{E} = \begin{bmatrix} T_U Z_U^{-1} & Y Z_S^{-1} & 0 \\ Y^T Z_U^{-1} & T_S Z_S^{-1} & X Z_A^{-1} \\ 0 & X^T Z_S^{-1} & T_A Z_A^{-1} \end{bmatrix} \tag{14}$$

where Z_U, Z_S and Z_A are diagonal matrices. The i-th entry in the diagonal of Z_U is the sum of column i in matrix E, the $Z_U^{-1}(i,i)$ is computed as follows (Z_S^{-1} and Z_A^{-1} are defined similarly):

$$Z_U^{-1}(i,i) = \frac{1}{\sum_j T_U(j,i) + \sum_j Y^T(j,i)} \tag{15}$$

Let $H = (H_U^T, H_S^T, H_A^T)^T$ denote a vector of visiting probability of all vertices, we make top-k store recommendation by random walk-based propagation based on the transition probability matrix with three phases (as shown in Figure 11):

(1) Random walk-based propagation from store to user: let V_u denotes the restart vector with all its entries initialized to be 0 except a 1 for the entry denoted by starting vertex $u \in U$, the random walk with restart process from store to user can be represented as:

$$H_U^{(n+1)} = (1 - \alpha_u)(T_U Z_U^{-1} H_U^{(n)} + Y Z_S^{-1} H_S^{(n)}) + \alpha_u V_u \tag{16}$$

Where $H_U^{(0)}$ is initialized with V_u.

(2) Random walk-based propagation from store to aspect: let V_a denotes the restart vector with all its entries initialized to be 0 except a 1 for the entry denoted by starting vertex $a \in A$, the random walk with restart process from store to aspect can be represented as:

$$H_A^{(n+1)} = (1 - \alpha_a)(X^T Z_S^{-1} H_S^{(n)} + T_A Z_A^{-1} H_A^{(n)}) + \alpha_a V_a \tag{17}$$

Where $H_A^{(0)}$ is initialized with V_a.

(3) Random walk-based propagation from user and aspect to store: let V_s denotes the restart vector with all its entries initialized to be 0 except a 1 for the entry denoted by starting vertex $s \in S$, the random walk with restart process from user and aspect to store can be represented as:

$$H_S^{(n+1)} = (1 - \alpha_s)(Y^T Z_U^{-1} H_U^{(n)} + T_S Z_S^{-1} H_S^{(n)} + X Z_A^{-1} H_A^{(n)}) + \alpha_s V_s \tag{18}$$

Where $H_S^{(0)}$ is initialized with V_s.

After the random walk-based propagation converging or reaching the number of iterations, we regard $H_S^{(final)}$ as the ranked recommendation scores of stores for each target user, and select the unvisited stores with top-k ranked scores as the recommended stores. α_u, α_a and α_s are restart probabilities (we set $\alpha_u = \alpha_a = \alpha_s = 0.05$ in the experiment suggested by [28], [31]), controlling the walker jumping back to its initial state from the current state randomly.

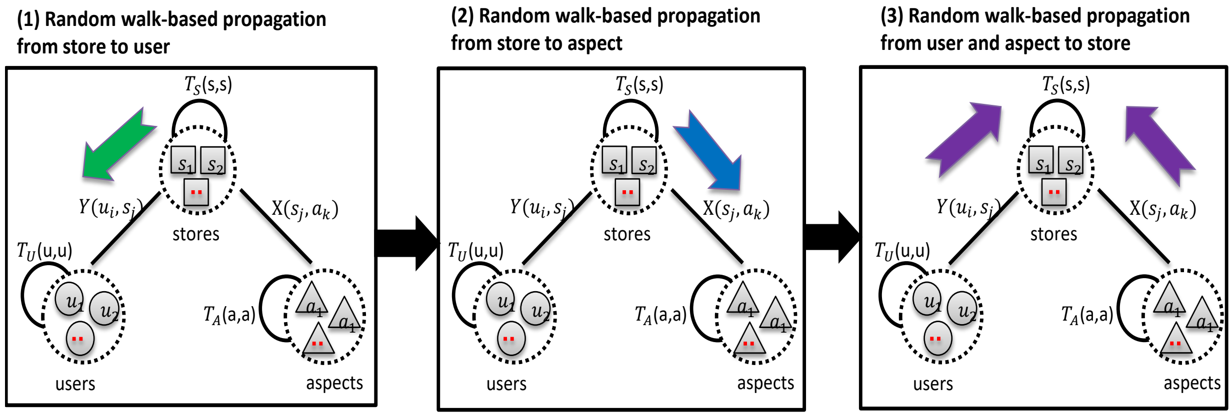


Fig. 11: Random walk-based propagation algorithm for top-k store recommendation

TABLE 5: Statistics of user's check-in activities

Dataset	Mall 1	Mall 2
Number of Stores	208	134
Number of Users	75,541	47,865
Number of Check-ins	2,568,394	1,292,355
Average No. of check-ins per user	34	27
Average No. of check-ins per store	12348	9644

6 Experiment Evaluation

In this section, we report on the results of a series of experiments conducted to evaluate the performance of the proposed recommendation model. We first describe the settings of experiments including data sets, comparative methods and evaluation metric. Then, we report and discuss the experimental results.

6.1 Experimental Settings

6.1.1 Data sets

Check-ins of users. Our experimental environment includes two inner-city shopping malls: one is with 5 floors and covered over 300,000 m^2, which contains 208 stores and these stores belong to 6 categories given by the mall owner; another contains 3 floors with 134 stores, which also consists of 6 categories of stores. More details of the two shopping malls are shown in Table 4.

As mentioned in Section 3.2.1 , We gather two anonymized WiFi logs datasets from registered users using an opt-in WiFi network in urban shopping malls during 12 months. For removing noise data, we perform two preprocessing steps: (1) we filter out the mall workers and store employees based on the check-in frequency. Empirically, we consider a user as a mall worker or store employee if her/his check-ins are more than 100 during 12 months; (2) we remove the abnormal check-ins that the residence time is less than 1 minute. After preprocessing, the two datasets consist of 3,860,749 check-ins from 123,406 users, more details of the two datasets are shown in Table 5.

Online reviews of stores. Dianping [2] is China's largest store review site (similar to Yelp [3]) where users can freely write their comments on physical stores. We crawl textual reviews about these stores of two shopping malls from Dianping site. We pre-process store reviews by removing web URLs and non-Chinese words, and utilize ICTCLAS [38] for parsing and stemming.

2. http://www.dianping.com/
3. https://www.yelp.com/

TABLE 6: Statistics of store's online reviews(#Avg reviews, i.e., average reviews per store)

Dataset	**Mall 1**		**Mall 2**	
	# of reviews	#Avg reviews	# of reviews	#Avg reviews
Restaurant	91,011	1319	43,845	1185
Fashion	15,568	278	13,478	293
Kids store	7,722	297	3,536	272
Leisure	3,174	138	2,610	145
Education	2,760	184	1,956	163
Jewelry	969	51	304	38

This data set consists of 186,933 reviews, where 72% of the reviews are about restaurant stores, as shown in Table 6. The sentiment seed words of ASUM model should not be aspect-specfic evaluative words because they are assumed to be unknown. In this experiment, we use two sets of sentiment seed words: HowNet [6] and NTUSD [14].

6.1.2 Comparative Methods

We compare the proposed recommendation model with the following five methods, where the first four methods are well-known existing methods for store recommendation, and the last method corresponds to our proposed method without considering store's online textual reviews.

- **User-based Collaborative Filtering based on Location Co-occurrence (UCF-LC).** UCF-LC [34] was originally proposed to perform location recommendation in LBSN. We follow this work to predict the recommendation score of a unvisited store by considering other user's check-ins on the store. Let $c < u,s >= 1$ if u has visited store s, and $c < u,s >= 0$ otherwise; $c(u) = \{c < u,s_1 >,...,c < u,s_N >\}$ is the check-in vector of user u. Then, the recommendation score between u and a unvisited store $\hat{s}$ is calculated by

$$score(u,\hat{s}) = \frac{\sum_{v\in U} sim(u,v) * c < v,s >}{\sum_{v\in U} sim(u,v)} \qquad (19)$$

where $sim(u,v)$ is the similarity between u and v, and is calculated using the cosine similarity between $c(u)$ and $c(v)$.

TABLE 4: Statistics of store categories

	Restaurant	Fashion	Kids store	Leisure	Education	Jewelery	Total
Mall 1	69	56	26	23	15	19	208
Mall 2	37	46	13	18	12	8	134

- **Matrix Factorization based Recommendation Algorithm (MFRA).** MFRA [9] was originally proposed to perform POI recommendation in LBSN, we follow this work to construct *User-Store* frequency matrix from user's check-in frequency for performing matrix factorization based store recommendation.
- **Rule-based recommendation method (RBCA).** RBCA [7] estimates user's preference towards a store by linearly fusing three factors: the stay time, the check-in frequency, and the matching degree between promotional activities and user preference.
- **Time-based Slope One (TSO).** In [17], user preference is evaluated directly from the stay time. More exactly, user preference is generated by using a logarithmic function to map the stay time to recommendation score, then using Slope-One [16] to make recommendation.
- **User-based Collaborative Filtering using Check-in Activities (UCF-CA)**. As a component of the proposed recommendation method, UCF-CA means our model without fusing online textual reviews for store recommendation. Given a user u and a unvisited store $\widehat{s}$, UCF-CA calculate the recommendation score as:

$$score(u,\widehat{s}) = \frac{\sum_{v\in U} sim(u,v) * I^{v\widehat{s}}}{\sum_{v\in U} sim(u,v)} \tag{20}$$

where $I^{v\widehat{s}}$ is the preference of user v to $\widehat{s}$, $sim(u,v)$ is the similarity between user u and v, calculated as:

$$sim(u,v) = \frac{\sum_{i\in S_{uv}} (I^{ui} - \overline{I_u})(I^{vi} - \overline{I_v})}{\sqrt{\sum_{i\in S_{uv}} (I^{ui} - \overline{I_u})^2 \sum_{i\in S_{uv}} (I^{ui} - \overline{I_u})^2}} \tag{21}$$

where S_{uv} is the stores that have been checked by both u and v.

6.1.3 Evaluation Metric

For each user, we randomly select 30% of check-ins as the test set D_{te}, and use the rest check-ins as the training set D_{tr}. Following the work [36] [35], we adopt Recall@k as the measurement metric to evaluate recommendation effectiveness, where k is the number of the recommendation results. For each test case $(u,s_i) \in D_{te}$:

(1). We randomly select 100 stores that unvisited by user u, and compute the recommendation score for s_i and the additional selected 100 stores;

(2). We form a ranked list by ordering all the 101 stores according to their recommendation scores. Let *ind* denote the rank of the test store s_i within this list;

(3). We form a top-k recommendation list by picking the k top ranked stores from the list. If $ind < k$ we have a hit (i.e., the test store s_i is recommended to the user). Otherwise we have a miss. Clearly, the probability of a hit increases with the increasing value of k. When $k = 101$ we always have a hit.

Let $\#hit@k$ denotes a single test case as either the value 1 if the test item s_i appears in the top-k results, or else the value 0. The overall $Recall@k$ are defined by averaging all test cases:

$$Recall@k = \frac{\#hit@k}{|D_{te}|} \tag{22}$$

where $\#hit@k$ denotes the number of hits in the test set, and $|D_{te}|$ is the number of all test cases.

6.2 Experimental Results

In this subsection, we first study the impact of model parameters of the proposed recommendation model. Then we conduct two groups of experiments and report their performance with the well-tuned parameters. The first group is to evaluate the recommendation performance for all users while the second group is to evaluate the recommendation performance for cold-start users. For the two groups of experiments, we show only the performance where the number (k) of recommendation results is in the range [1...15], because a greater value of k is usually ignored for a top-k recommendation task.

6.2.1 Impact of Model Parameters

Tuning model parameters, such as the number of aspects per sentiment, is critical to the recommendation performance of utilizing online reviews. As for the hyper parameters of ASUM model, following existing work [12], we empirically set $\phi = 0$ for the negative seed words and 0.001 for all the other words. Similarly, for negative aspect-sentiment, we set $phi = 0$ for the positive seed words and 0.001 for all the other words. We tried different setups and found that the recommendation performance are not sensitive to the hyper parameters, but the recommendation performance of different store categories are slightly sensitive to the number of aspects per sentiment.

Thus we tested the performance of the proposed method by varying the number of aspects per sentiment, and reported the results in Table 7 and Table 8. For each kind of store, we randomly select 30% of check-ins as test set, and use the rest of check-ins as the training set. ASUM model converges after 5000 iterations for all store categories. From the two tables, we observe: 1) the $Recall@8$ are maintained in a certain range for all store categories with different number of aspects per sentiment (e.g., the maximum range of variation is about 11.2% for *Restaurant* on Mall 1), showing ASUM model is relative robust with different aspects per sentiment; 2) the best performance for different store categories are achieved with different number of aspects per sentiment. Roughly speaking, the optimal value of aspects per sentiment for different categories have a correlation with the number of reviews: the more the reviews, the bigger the optimal value of aspects per sentiment. For instance, the optimal value of aspects per sentiment is 120 for *Restaurant* for both Mall 1 and Mall 2, while 30 for *Jewelry*.

6.2.2 Recommendation effectiveness for all users

Figure 12 reports the performance of the recommendation algorithms on Mall 1 and Mall 2. It is apparent that these algorithms have significant performance disparity in terms of top-k recall.

TABLE 7: Top-k recommendation performance on Mall 1 with different number of aspects per sentiment ($k = 8$, # *of avgA* denote the number of aspects per sentiment)

Category \ # of avgA	10	30	50	80	120	160
Restaurant	0.235	0.267	0.291	0.328	**0.347**	0.331
Fashion	0.201	0.228	0.255	**0.279**	0.267	0.261
Kids store	0.218	0.241	0.275	**0.282**	0.275	0.268
Leisure	0.207	0.225	**0.241**	0.232	0.22	0.208
Education	0.192	0.208	**0.23**	0.217	0.204	0.183
Jewelry	0.184	**0.197**	0.183	0.175	0.169	0.157

TABLE 8: Top-k recommendation performance on Mall 2 with different number of aspects per sentiment ($k = 8$, # *of avgA* denote the number of aspects per sentiment)

Category \ # of avgA	10	30	50	80	120	160
Restaurant	0.248	0.279	0.301	0.337	**0.351**	0.342
Fashion	0.215	0.236	0.268	**0.291**	0.284	0.271
Kids store	0.223	0.248	0.271	**0.288**	0.275	0.271
Leisure	0.195	0.218	**0.236**	0.228	0.219	0.203
Education	0.204	0.217	**0.241**	0.228	0.219	0.212
Jewelry	0.165	**0.182**	0.179	0.172	0.163	0.151

From this figure, we observe: 1) the performance of all recommendation methods increases as the number of recommendation results increases. The reason for better performance is, increasing the number of recommendation results makes the data denser, leading to better recommendation; 2) Our method outperforms other competitor recommendation models (TSO, RBCA, MFRA, UCF-LC and UCF-CA) significantly, showing the advantages of jointly considering check-in activities and online reviews for learning user's preference. For example, the Recall@k of our method is about 32.3% when $k = 10$ on Mall 1, and the performance is improved by 15.3% and 12.62% compare with TSO and RBCA respectively. Similar results are also observed in top-k recommendation for Mall 2 (for example, the Recall@10 of other baseline methods are 16%(TSO), 18.87%(RBCA), 23.2%(MFRA), 20.4%(UCF-LC) and 24.43%(UCF-CA)), showing again our proposed method performs better than other competitor recommendation models; 3) For recommendation algorithms merely based on check-in activities (TSO, RBCA, MFRA, UCF-LC and UCF-CA), UCF-CA achieves the best performance, showing the advantage of using latent variable model to learn user's preference. For instance, the recall of UCF-CA is about 28.4% for top-12 store recommendation in Mall 1, (i.e., the UCF-CA model has a probability of 28.4% of placing a store within target user's check-in list in the top-12), while 18.3% for TSO, 21.2% for RBCA, 27.2% for MFRA and 23.2% for UCF-LC; 4) TSO performs worst among all recommendation algorithms, which suggests that only utilizing the residence time in a store is insufficient to reflect the level of user's preference. Similarly, the results of UCF-LC and MFRA suggest that only utilizing the check-in frequency is insufficient to reflect the level of user's preference.

In order to evaluate the performance for different store categories in detail, we also report the Recall@k of different recommendation algorithms in Table 9 and Table 10 (we only show the top-8 recommendation due to space limitations). From the two tables, we can observe: 1) the proposed method achieves the best performance in terms of all store categories, showing again the advantage of learning user's preference by fusing their check-in activities and store's online textual reviews; 2) the performance improvement by online text reviews is diverse for different store categories. For instance, the improvement for *Restaurant* is about 17.9% compare with TSO on Mall 1, while the improvement for *Jewelry* is very slight (only 5.5%). This is no surprising since there are few reviews about *Jewelry* (the average reviews for each store are only 51), leading the advantage by fusing store's reviews can be ignored. We expect that the proposed method can improve the performance as more online reviews are recorded; 3) For recommendation algorithms merely using check-in activities, the performance for two store categories (*Restaurant* and *Education*) are better than other categories. The results suggest that, user's check-in activities for stores that belong to *Restaurant* and *Education* have a stronger pattern with user's preference than the other kinds of stores. We further find the average check-in time of *Restaurant* and *Education* are much higher than other kinds of stores, justifying that there is a positive correlation between the revisit probability and the average check-in time, which is also reported in [4].

TABLE 9: Top-k recommendation performance for all users on Mall 1 ($k = 8$)

Category \ Method	TSO	UCF-LC	MFRA	UCF-CA	RBCA	Our method
Restaurant	0.168	0.186	0.217	0.231	0.213	0.347
Fashion	0.142	0.168	0.208	0.205	0.189	0.279
Kids store	0.138	0.174	0.221	0.218	0.175	0.282
Leisure	0.157	0.181	0.217	0.193	0.169	0.241
Education	0.172	0.188	0.231	0.218	0.204	0.23
Jewelry	0.142	0.182	0.189	0.188	0.173	0.197

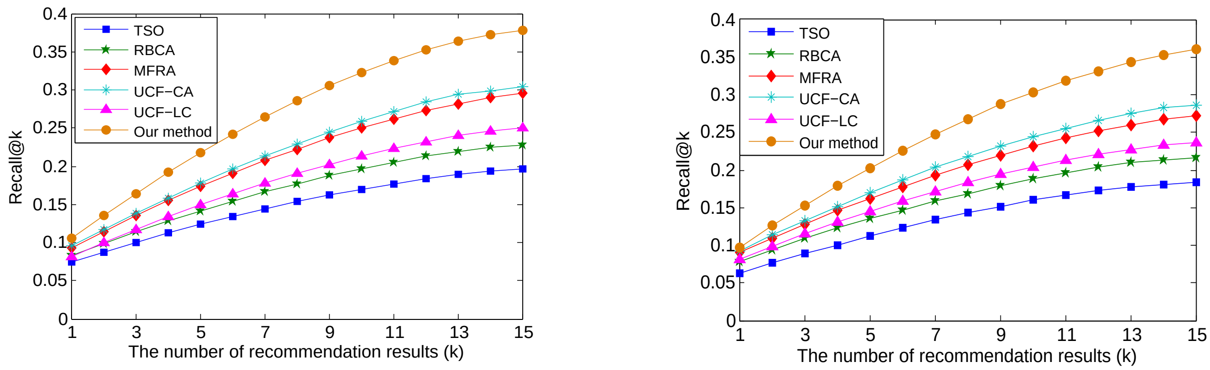
TABLE 10: Top-k recommendation performance for all users on Mall 2 ($k = 8$)

Category \ Method	TSO	UCF-LC	MFRA	UCF-CA	RBCA	Our method
Restaurant	0.152	0.179	0.212	0.224	0.205	0.351
Fashion	0.138	0.158	0.195	0.194	0.176	0.291
Kids store	0.132	0.167	0.206	0.207	0.169	0.288
Leisure	0.142	0.173	0.202	0.185	0.173	0.236
Education	0.15	0.182	0.216	0.207	0.197	0.241
Jewelry	0.138	0.157	0.197	0.175	0.169	0.182

6.2.3 Recommendation effectiveness for cold-start users

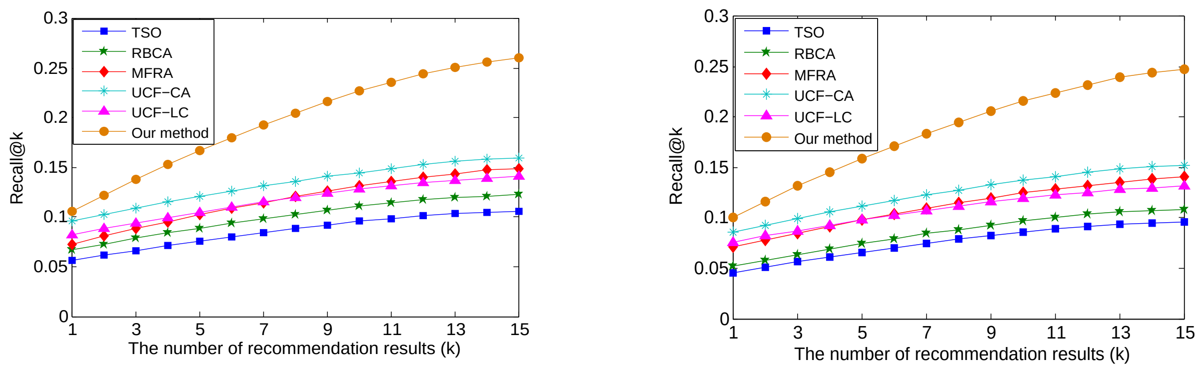
To investigate the advantage of fusing online reviews for store recommendation, we further compare the recommendation performance of different algorithms for "cold-start" users in Figure 13. In this experiment, we regard users whose check-in stores are less than 10 as "cold-start" users. From the figure, we observe: 1) the performance of different recommendation algorithms for cold-start users degrades significantly compares to all users, showing data sparsity caused by few check-ins bring serious challenge for learning user's preference. For instance, the Recall@8 of UCF-CA for "cold-start" users drops 8.98% compare with all users on Mall 2; 2) the proposed method performs much better than baseline algorithms (i.e., TSO, RBCA, MFRA, UCF-LC and UCF-CA), showing the advantage of learning user's preference by modeling multi-relation among users, stores and aspects from heterogeneous information. For instance, our method doubles the Recall@k compare with RBCA when k = 10; 3) the performance improvement is more obvious for "cold-start" users than for all users. For instance, the performance improvement is 11.94% of our method compare with UCF-LC for cold-start users, while 8.79% of our method compare with UCF-LC for all users.

We further report the top-8 recommendation performance of different store categories for "cold-start" users in Table 11 and



(a) Mall 1 (b) Mall 2

Fig. 12: Top-k recommendation performance for all users



(a) Mall 1 (b) Mall 2

Fig. 13: Top-k recommendation performance cold-start users

TABLE 11: Top-k recommendation performance for cold-start users on Mall 1 ($k = 8$)

Method / Category	TSO	UCF-LC	MFRA	UCF-CA	RBCA	Our method
Restaurant	0.089	0.096	0.128	0.137	0.126	0.213
Fashion	0.075	0.079	0.107	0.124	0.109	0.185
Kids store	0.071	0.083	0.122	0.116	0.115	0.196
Leisure	0.078	0.091	0.108	0.128	0.106	0.178
Education	0.083	0.097	0.131	0.133	0.132	0.207
Jewelry	0.075	0.076	0.109	0.129	0.102	0.179

TABLE 12: Top-k recommendation performance for cold-start users on Mall 2 ($k = 8$)

Method / Category	TSO	UCF-LC	MFRA	UCF-CA	RBCA	Our method
Restaurant	0.062	0.092	0.117	0.127	0.115	0.207
Fashion	0.047	0.081	0.112	0.118	0.103	0.176
Kids store	0.068	0.076	0.115	0.109	0.108	0.182
Leisure	0.049	0.085	0.102	0.117	0.104	0.179
Education	0.092	0.092	0.123	0.125	0.123	0.193
Jewelry	0.052	0.073	0.098	0.107	0.094	0.173

Table 12. Clearly, the proposed method outperforms other baseline algorithms significantly, showing the advantage of taking into account hidden propagation paths can allow more accurate estimation of relation strength between two vertices (e.g., user-store and store-aspect). The results suggest that, hidden propagation paths can be explored to alleviate the sparsity problem in store recommendation. We further observe the performance improvement of our method for different store categories is positively related to the number of online reviews. Specifically, the Recall@8 of our method for *Restaurant* is 20.7% on Mall 2, while 6.2% for TSO, 11.5% for RBCA, 11.7% for MFRA, 9.2% for UCF-LC and 12.7% for UCF-CA.

7 Conclusion

This paper proposed a recommendation model for physical stores by learning user's preference from heterogeneous information (i.e., user-generated check-in activities and online reviews). The proposed method aims to overcome the two challenges of existing methods: the inability to make recommendations for people who are not members of the LBSN and data sparsity due to few check-ins in LBSN. Firstly, we model multi-relation among users, stores and aspects (i.e., *User-Store* relation from user's check-in activities with a latent variable model and *Store-Aspect* relation from store's online reviews using an Elo-based scheme). Then, we construct a tripartite graph to capture the two kinds of relations and generate top-k store recommendation utilizing a random walk-based propagation algorithm. Experimental results show that the proposed method achieves much better performance than the state-of-the-art baseline methods for physical stores.

As future work, we plan to facilitate more personal services (such as detecting target customers and making promotion strategy) based on the learnt multi-relations among users, stores and aspects from heterogeneous information.

ACKNOWLEDGE

This work is sponsored by the National Basic Research 973 Program of China (No. 2015CB352403), the Program for National Natural Science Foundation of China / Research Grants Council (NSFC/RGC)(612191030), the Program for Changjiang Scholars and Innovative Research Team in University (IRT1158, PCSIRT).

REFERENCES

[1] Z. U. Ahmed, M. Ghingold, and Z. Dahari. Malaysian shopping mall behavior: an exploratory study. *Asia Pacific Journal of Marketing and Logistics*, 19(4):331–348, 2007.

[2] J. Bernabé-Moreno, A. Tejeda-Lorente, C. Porcel, H. Fujita, and E. Herrera-Viedma. Caresome: A system to enrich marketing customers acquisition and retention campaigns using social media information. *Knowledge-Based Systems*, 80:163–179, 2015.

[3] P. H. Bloch, N. M. Ridgway, and S. A. Dawson. The shopping mall as consumer habitat. *Journal of retailing*, 70(1):23–42, 1994.

[4] Y. Cai and R. Shannon. Personal values and mall shopping behaviour: The mediating role of intention among chinese consumers. *International Journal of Retail & Distribution Management*, 40(4):290–318, 2012.

[5] Y. Chen, M. Guo, J. Shen, and J. Cao. Graphloc: a graph-based method for indoor subarea localization with zero-configuration. *Personal and Ubiquitous Computing*, pages 1–17, 2017.

[6] Z. Dong and Q. Dong. Hownet-a hybrid language and knowledge resource. In *Natural Language Processing and Knowledge Engineering, 2003. Proceedings. 2003 International Conference on*, pages 820–824. IEEE, 2003.

[7] B. Fang, S. Liao, K. Xu, H. Cheng, C. Zhu, and H. Chen. A novel mobile recommender system for indoor shopping. *Expert Systems with Applications*, 39(15):11992–12000, 2012.

[8] Z. Gantner, L. Drumond, C. Freudenthaler, S. Rendle, and L. Schmidt-Thieme. Learning attribute-to-feature mappings for cold-start recommendations. In *Data Mining (ICDM), 2010 IEEE 10th International Conference on*, pages 176–185. IEEE, 2010.

[9] H. Gao, J. Tang, X. Hu, and H. Liu. Exploring temporal effects for location recommendation on location-based social networks. In *Proceedings of the 7th ACM conference on Recommender systems*, pages 93–100. ACM, 2013.

[10] S. K. Hui, E. Bradlow, and P. Fader. An integrated model of grocery store shopping path and purchase behavior. *Available at SSRN 960960*, 2007.

[11] V. Jackson, L. Stoel, and A. Brantley. Mall attributes and shopping value: Differences by gender and generational cohort. *Journal of retailing and consumer services*, 18(1):1–9, 2011.

[12] Y. Jo and A. H. Oh. Aspect and sentiment unification model for online review analysis. In *Proceedings of the fourth ACM international conference on Web search and data mining*, pages 815–824. ACM, 2011.

[13] T. Kanda, D. F. Glas, M. Shiomi, H. Ishiguro, and N. Hagita. Who will be the customer?: a social robot that anticipates people's behavior from their trajectories. In *Proceedings of the 10th international conference on Ubiquitous computing*, pages 380–389. ACM, 2008.

[14] L.-W. Ku, Y.-T. Liang, H.-H. Chen, et al. Opinion extraction, summarization and tracking in news and blog corpora. In *AAAI spring symposium: Computational approaches to analyzing weblogs*, volume 100107, 2006.

[15] S. Lee, C. Min, C. Yoo, and J. Song. Understanding customer malling behavior in an urban shopping mall using smartphones. In *Proceedings of the 2013 ACM conference on Pervasive and ubiquitous computing adjunct publication*, pages 901–910.

[16] D. Lemire and A. Maclachlan. Slope one predictors for online rating-based collaborative filtering. In *SDM*, volume 5, pages 1–5. SIAM, 2005.

[17] Z. Lin. *Indoor Location-based Recommender System*. PhD thesis, University of Toronto, 2013.

[18] G. Mohan, B. Sivakumaran, and P. Sharma. Impact of store environment on impulse buying behavior. *European Journal of Marketing*, 47(10):1711–1732, 2013.

[19] A. Musa and J. Eriksson. Tracking unmodified smartphones using wi-fi monitors. In *Proceedings of the 10th ACM conference on embedded network sensor systems*, pages 281–294. ACM, 2012.

[20] M. C. Popa, L. J. Rothkrantz, C. Shan, T. Gritti, and P. Wiggers. Semantic assessment of shopping behavior using trajectories, shopping related actions, and context information. *Pattern Recognition Letters*, 34(7):809–819, 2013.

[21] M. Radhakrishnan, S. Eswaran, A. Misra, D. Chander, and K. Dasgupta. Iris: Tapping wearable sensing to capture in-store retail insights on shoppers. In *2016 IEEE International Conference on Pervasive Computing and Communications (PerCom)*, pages 1–8. IEEE, 2016.

[22] S. Rallapalli, A. Ganesan, K. Chintalapudi, V. N. Padmanabhan, and L. Qiu. Enabling physical analytics in retail stores using smart glasses. In *Proceedings of the 20th annual international conference on Mobile computing and networking*, pages 115–126. ACM, 2014.

[23] P. M. Reyes and G. V. Frazier. Goal programming model for grocery shelf space allocation. *European Journal of Operational Research*, 181(2):634–644, 2007.

[24] S. Samothrakis, D. Perez, S. M. Lucas, and P. Rohlfshagen. Predicting dominance rankings for score-based games. *IEEE Transactions on Computational Intelligence and AI in Games*, 8(1):1–12, 2016.

[25] L. Shangguan, Z. Zhou, X. Zheng, L. Yang, Y. Liu, and J. Han. Shopminer: Mining customer shopping behavior in physical clothing stores with cots rfid devices. In *Proceedings of the 13th ACM Conference on Embedded Networked Sensor Systems*, pages 113–125. ACM, 2015.

[26] S. Shim and M. A. Eastlick. The hierarchical influence of personal values on mall shopping attitute and behavior. *Journal of Retailing*, 74(1):139–160, 1998.

[27] S. Shim and M. A. Eastlick. The hierarchical influence of personal values on mall shopping attitute and behavior. *Journal of Retailing*, 74(1):139–160, 1998.

[28] K. Shin, J. Jung, S. Lee, and U. Kang. Bear: Block elimination approach for random walk with restart on large graphs. In *Proceedings of the 2015 ACM SIGMOD International Conference on Management of Data*, pages 1571–1585. ACM, 2015.

[29] J. Sit, H. Y. Wong, and D. Birch. An exploratory study on service dimensions of regional shopping centres: A segmentation approach. In *Proceedings of the 2002 Australian and New Zealand Marketing Academy Conference (ANZMAC 2002)*. Australian and New Zealand Marketing Academy (ANZMAC), 2002.

[30] T. Tajima, Y. Iida, and T. Kato. Analysis of customer preference through unforced natural passive observation. In *International Conference on Human-Computer Interaction*, pages 466–474. Springer, 2013.

[31] H. Tong, C. Faloutsos, and J.-Y. Pan. Random walk with restart: fast solutions and applications. *Knowledge and Information Systems*, 14(3):327–346, 2008.

[32] A. Yaeli, P. Bak, G. Feigenblat, S. Nadler, H. Roitman, G. Saadoun, H. J. Ship, D. Cohen, O. Fuchs, S. Ofek-Koifman, et al. Understanding customer behavior using indoor location analysis and visualization. *IBM Journal of Research and Development*, 58(5/6):3–1, 2014.

[33] R. Yalch and E. Spangenberg. Effects of store music on shopping behavior. *Journal of Consumer Marketing*, 7(2):55–63, 1990.

[34] M. Ye, P. Yin, and W.-C. Lee. Location recommendation for location-based social networks. In *Proceedings of the 18th SIGSPATIAL International Conference on Advances in Geographic Information Systems*, pages 458–461. ACM, 2010.

[35] H. Yin, B. Cui, Z. Huang, W. Wang, X. Wu, and X. Zhou. Joint modeling of users' interests and mobility patterns for point-of-interest recommendation. In *Proceedings of the 23rd ACM international conference on Multimedia*, pages 819–822. ACM, 2015.

[36] H. Yin, Y. Sun, B. Cui, Z. Hu, and L. Chen. Lcars: a location-content-aware recommender system. In *Proceedings of the 19th ACM SIGKDD international conference on Knowledge discovery and data mining*, pages 221–229. ACM, 2013.

[37] L. M. Yliniemi and K. Tumer. Elo ratings for structural credit assignment in multiagent systems. In *AAAI (Late-Breaking Developments)*, 2013.

[38] H.-P. Zhang, H.-K. Yu, D.-Y. Xiong, and Q. Liu. Hhmm-based chinese lexical analyzer ictclas. In *Proceedings of the second SIGHAN workshop on Chinese language processing-Volume 17*, pages 184–187. Association for Computational Linguistics, 2003.

[39] X. Zhao, J. Yuan, G. Li, X. Chen, and Z. Li. Relationship strength estimation for online social networks with the study on facebook. *Neurocomputing*, 95:89–97, 2012.

Yuanyi Chen received his BSc degree from Sichuan University in 2010, the master's degree from Zhejiang University in 2013. From September 2014 to September 2015, he was a jointly-supervised PhD candidate at Hong Kong Polytechnic University. He is currently a PhD candidate at Department of Computer Science and Engineering, Shanghai Jiao Tong University. His research topic includes the Internet of Things and mobile computing.

Jingyu Zhang received the BSc degree from Hunan Normal University in 2008 and the ME degree from Chongqing Jiaotong University in 2011. He is currently a PhD candidate at the Department of Computer Science and Engineering, Shanghai Jiao Tong University. His research interests include mobile computing, computer architecture, cache optimization, and adaptive video streaming.

Minyi Guo received the B.S. and M.E. degrees in Computer Science from Nanjing University, China in 1982 and 1986, respectively. From 1986 to 1994, he had been an assistant professor of the Department of Computer Science at Nanjing University. He received the Ph.D.degree in information science from University of Tsukuba, Japan in 1998. He is currently a chair professor and the head of the Department of Computer Science and Engineering at Shanghai Jiao Tong University. His research interests include parallel computing, distributed computing and mobile computing. He has more than 300 publications in major journals and international conferences in these areas. He is on the editorial board of the journals IEEE Transactions on Parallel and Distributed Systems and IEEE Transactions on Computers. He is a senior member of the IEEE, a member of the ACM, IEICE IPSJ, and CCF.

Jiannong Cao received the BSc degree from Nanjing University, China, in 1982, and the MSc and PhD degrees from Washington State University, USA, in 1986 and 1990, all in computer science. He is currently a chair professor and the head of the Department of Computing at Hong Kong Polytechnic University. His research interests include parallel and distributed computing, computer networks, mobile and pervasive computing, fault tolerance, and middle-ware. He co-authored four books, coedited nine books, and published more than 300 technical papers in major international journals and conference proceedings. He has directed and participated in numerous research and development projects and, as a principal investigator, obtained over HK$25 million grants. He is the chair in Technical Committee on Distributed Computing, IEEE Computer Society. He has served as an associate editor and a member of editorial boards of many international journals, and a chair and a member of organizing/program committees for many international conferences. He is a fellow of the IEEE, a member of the ACM, and a senior member of China Computer Federation.