Exploiting Dining Preference for Restaurant Recommendation

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ABSTRACT

The wide adoption of location-based services provide the potential to understand people's mobility pattern at an unprecedented level, which can also enable food-service industry to accurately predict consumers' dining behavior. In this paper, based on users' dining implicit feedbacks (restaurant visit via check-ins), explicit feedbacks (restaurant reviews) as well as some meta data (e.g., location, user demographics, restaurant attributes), we aim at recommending each user a list of restaurants for his next dining. Implicit and Explicit feedbacks of dining behavior exhibit different characteristics of user preference. Therefore, in our work, user's dining preference mainly contains two parts: implicit preference coming from check-in data (implicit feedbacks) and explicit preference coming from rating and review data (explicit feedbacks). For implicit preference, we first apply a probabilistic tensor factorization model (PTF) to capture preference in a latent subspace. Then, in order to incorporate contextual signals from meta data, we extend PTF by proposing an Implicit Preference Model (**IPM**), which can simultaneously capture users'/restaurants'/time' preference in the collaborative filtering and dining preference in a specific context (e.g., spatial distance preference, environmental preference). For explicit preference, we propose Explicit Preference Model (**EPM**) by combining matrix factorization with topic modeling to discover the user preference embedded both in rating score and text content. Finally, we design a unified model termed as Collective Implicit Explicit Preference Model (**CIEPM**) to combine implicit and explicit preference together for restaurant recommendation. To evaluate the performance of our system, we conduct extensive experiments with large-scale datasets covering hundreds of thousands of users and restaurants. The results reveal that our system is effective for restaurant recommendation.

Keywords

Implicit Preference, Explicit Preference, Restaurant Recommendation

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1. INTRODUCTION

With the blooming development of smart phones and positioning technology, the emerging location based services (e.g., Foursquare, Facebook Place) can accurately record users' location information, which provide the opportunity to gain insight on users' dining behavior at an unprecedented level.

In this paper, we aim at leveraging users' historical dining implicit feedbacks (restaurant visit via check-ins), explicit feedbacks (restaurant reviews) as well as some meta data (e.g., location, user demographics, restaurant attributes), to recommend each user a list of restaurants for his next dining. This problem can be subsumed into the general location recommendation problem. Most of the previous studies in this field put an emphasis on the exploitation of implicit feedback itself, i.e., the location visit, and the proposed recommendation methods mainly focus on uncovering users' and restaurants' latent interests in factorization models [24, 11]. However, contextual signals such as user demographics and restaurant attributes have not been fully utilized in a single factorization model to enhance the preference related to a specific context. Actually, researchers in consumer research have found that user demographics and restaurant attributes has played a critical role in determining restaurant selection [8, 9, 21]. For example, female consumers place higher importance on restaurant environment and service quality according to the reported results in [13]. In addition, the rating scores and texts description in restaurant reviews are explicit feedbacks user providing for restaurants. These positive or negative opinions directly indicate users' like or dislike for restaurants, and these texts also indicate what kind of restaurants a user like or dislike.

Given above, aiming at solving the restaurant recommendation problem effectively, we present a framework, termed Collective Implicit Explicit Preference Model (**CIEPM**) based on the following motivations:

1. For implicit check-in data, dining behavior can be represented as a binary-valued user-restaurant-time tensor. The value 1 in this tensor represented positive feedback (this user have visited this restaurant at this time), while value 0 represents a mixture of negative feedback and unobserved potential interests. To model a user's dining preference at a time, restaurants with value 1 should rank higher than those with value 0.

2. For explicit review data, the rating scores users providing for restaurants indicate the preference, and the more concrete texts content usually describe the reason of like or dislike.

3. User dining preference is closely related to contextual signals such as spatial distance, user demographics and restaurant attributes. For example, in China, users from Sichuan province prefer to restaurants with spicy taste while users from Hangzhou province prefer to restaurants with light taste.

4. Implicit check-in data and explicit review data provide different perspectives for user's dining preference. The effective integration of these two types of feedbacks provides the potential to boost restaurant recommendation.

According to a collection of users' restaurant visits, user demographics, and restaurant attributes, motivations 1 and 3 lead to a Implicit Preference Model (**IPM**) which integrates collaborative filtering with contextual signals for implicit check-in data. To be specific, on the one hand, the user-restaurant-time visit tensor is factorized into three low-dimensional latent vectors, which represent users'/restaurants'/times' interests in a latent space; on the other hand, since contextual signals such as user demographics and restaurant attributes are closely related to dining behavior, they are designed as contextual features being embedded into the factorization model. Motivations 2 and 3 lead to a Explicit Preference Model (**EPM**) which combines collaborative filtering with topic modeling for explicit review data. By considering motivation 4, our final system **CIEPM** combine implicit preference and explicit preference to form a collective model, which simultaneously factorizes user-restaurant-time visit tensor and user-restaurant rating matrix.

Our evaluation consists of multiple parts. First, we conduct several experiments to evaluate the performance of our implicit preference model **IPM**. Next, we investigate the effectiveness of incorporating contextual signals by comparing different configurations. Finally, we evaluate whether our collective model **CIEPM** can fully leverage implicit and explicit feedback to improve recommendation performance.

To the best of our knowledge, this is the first work focusing on dining recommendation by exploiting implicit feedback, contextual signals and explicit feedback simultaneously. The key contributions of this paper include the following:

- We give a comprehensive analysis on dining behavior exploitation, which contains spatial preference, regional cuisine preference, etc.

- For implicit check-in data, we present a contextual tensor factorization model to simultaneously consider the latent preference in the collaborative filtering and the preference in a specific context. For explicit review data, we combine matrix factorization and topic modeling to model explicit preference. Furthermore, we design a unified collective model to integrate implicit preference and explicit preference.

- Based on a large dataset collected from Dianping, we have conducted extensive experiments to evaluate the effectiveness of our system. The results show that our methods significantly outperform baseline models.

The rest of this paper is organized as follows. In Section 2, we present the framework of our system. In Section 3, we describe the used datasets. In Section 4, we give an analysis of different dining behavior. In Section 5, we delve into the proposed methods for implicit preference modeling, explicit preference modeling and restaurant recommendation. In Section 6, we present the detail of experiment results. Finally, we summarize the related work in Section 7 and give the conclusion in Section 8.

2. OVERVIEW

2.1 Preliminary

We first clarify some terms commonly used in this article, and then explicitly present our problem.

Definition 1: Point of Interest (POI) and Restaurant. A POI refers to a venue in the physical world that someone may find useful or interesting. It is described by a name, address, coordinates, category (such as restaurant, cinema, shopping mall etc.), and other attributes. Note that a restaurant is a particular type of POI with "Restaurant" category, and it is usually further described by price, restaurant type, taste, etc.

Definition 2: Dining Check-in. In a location-based social networking service (e.g., Foursquare), a user can mark a POI when the user arrives there, which is known as a check-in. Each check-in is related to a user, a POI and a time stamp. Check-ins record the footprints of users in the physical world. We use the term "dining check-in" to denote a check-in marked in a restaurant. Dining check-in is a kind of implicit feedback data which can indicate implicit preference.

Definition 3: Dining Review. In a crowd-source reviews service for local businesses (e.g., Yelp), a user can explicitly express a positive or negative attitude for a POI by giving a score (e.g., an integer from 1 to 5, where 1 means the most negative and 5 means the most positive) along with some text description. Compared to check-ins, the negative and positive score explicitly express the preference. And these text content describe the dining experience. We use the term "dining review" to denote a review given to a restaurant. Dining review falls into the scope of explicit feedback data which can indicate explicit preference.

Problem formulation: In this study, we consider the restaurant recommendation problem as follows: given a collection of users' check-ins, ratings/reviews in the restaurants, users' demographic characteristics (e.g., gender, age, residence, etc.) and restaurants' attributes (e.g., price, service, environment, etc.), we aim to recommend each user with a list of restaurants for his next dining.

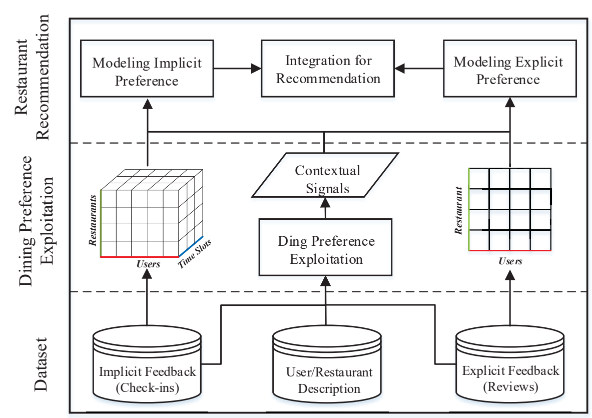


Figure 1: The architecture of our system

2.2 Framework

Figure 1 presents the architecture of our system, which consists of three major components: 1) data collection and analysis, 2) dining preference exploitation, and 3) restaurant recommendation. We will detail these components in the following sections respectively.

City	Shanghai	Beijing	Guangzhou	Nanjing	Tianjin	Hangzhou	Suzhou	Shenzhen	Chengdu
Users	74,266	24,809	5,740	4,188	3,503	2,816	2,812	2,718	2,320
Restaurants	31,839	24,323	12,792	10,765	12,464	8,156	10,050	9,781	8,355
Avg. dining check-ins via user	58.2	75.5	41.3	59.6	88.2	48.4	52.6	49.3	39.7
Avg. dining reviews via user	19.6	17.8	14.3	15.5	23.1	16.9	15.7	17.2	14.2

Table 1: Summarization of collected dataset for different cities (partially presented due to page limit)

Category	%	Category	%	Category	%
Chuan	8.05	HuBei	0.83	Snack	28.20
Foreign	7.76	YunGui	0.41	Dessert	10.96
SuZhe	6.37	Min	0.35	Hot Pot	6.50
Yue	5.78	Lu	0.28	Barbecue	1.65
Xiang	2.52	Hui	0.09	Buffet	1.18
DongBei	1.87	Yu	0.77	Seafood	1.11
Jing	1.85	JiangXi	0.03	Fastfood	0.31
QingZhen	1.22	Other Regions	2.09	Vegetables	0.14
XiBei	0.90			Others	9.47

Table 2: Categories of restaurant and their proportions

	Attribute	Completion Rating
Restaurant	category	72.6%
	rating	32.7%
	price	31.6%
	taste	33.1%
	environment	33.1%
	service	33.1%
	located city	100%
User	gender	81.1%
	age	73.8%
	residence city	97.6%

Table 3: Restaurant attributes, user demographics, and completion rate

3. DATA COLLECTION

In this section, we introduce the collected dataset of check-ins, reviews, and meta data (including demographics and restaurant attributes) for our system.

3.1 Check-in and Review Data

In order to investigate and evaluate users' preference for restaurants, we crawled 48,457,261 check-ins and 7,275,443 restaurant reviews from 1,123,285 users on Dianping (the largest crowd-sourced review website for local business in China, which also provides location-based check-in service) using the LifeSpec data crawling platform [43]. The reason we choose Dianping instead of others is that Dianping specially concentrates on catering industry in China and covers most of restaurants in the city region, and the digital footprints there such as check-ins and reviews can typically represent user's preference for restaurants.

To clean the dataset, we first filtered the noisy data, e.g., repeated check-ins at the same place in quite a short interval (1hr is adopted in our setting) and repeated reviews in the same restaurant. Next, since our system focuses on the dining check-ins of a user, we need sufficient restaurant visits. On top of this, we adopt the following strategies to further filter the check-in dataset and rating dataset: 1) even though "bar", "coffee shop", and "tea house" are categorized into "restaurant" by Dianping, we removed these related check-ins from dining check-ins because the activities there reveal the entertainment rather than dining behavior. 2) we removed those users who have fewer than 5 dining check-ins, which is to ensure sufficient dining observation for training and validating the performance of our system. 3) we removed reviews which are not given to the restaurants covered by the check-in dataset.

After the filtering procedure, we eventually obtained a collection of 140,671 unique users, with totally 7,892,360 dining check-ins and 1,808,107 dining reviews. In addition, we obtained 157,283 restaurants from 356 cities. Table 1 summarizes the statistics of the final check-in and reviews datasets for different cities.

3.2 Meta Data

For each restaurant, we crawled the meta information including restaurant name, latitude, longitude, province, city, category, price and various scores (overall rating, taste, environment and service). Since Chinese food exhibits strong regional characteristics, we clear up the restaurant category description on Dianping by reducing the original 82 restaurant categories into 17 regional cuisine categories according to the regional cuisine segmentation in China [49] (e.g., Beijing style, Chuan style, Foreign style, etc.) as well as 9 other dining types (e.g., barbecue, fast-food, hot pot, etc.). Table 2 shows the restaurant categories and their proportions in the total number of restaurants. To be more specific, Figure 2 paints the map of regional cuisine categories in China.

Figure 2: Map of regional cuisine categories in China

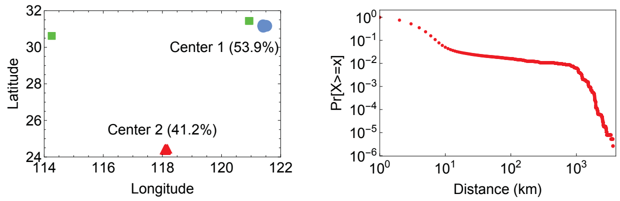
Additionally, for each user, we crawled the meta information including gender, age and residence city. The summary of completion rates (ratio of effective restaurant/user) for restaurant attributes and user demographics are listed in Table 3.

4. DINING PREFERENCE EXPLOITATION

The object of dining preference studies generally fits into a two-stage schema of targeting (finding out what a particular group of consumers will come to dine) and positioning (identifying what a particular restaurant style offers the market) [17]. The collected datasets provide rich information for understanding users' dining preference in real-world daily life. In this section, we use check-in data to first study user's spatial preference in dining behavior and then investigate how dining preference is related to user demographics and restaurant attributes. Note that review data show similar pattern with check-in data and the related exploitation is not listed here.

4.1 Individual Spatial Preference

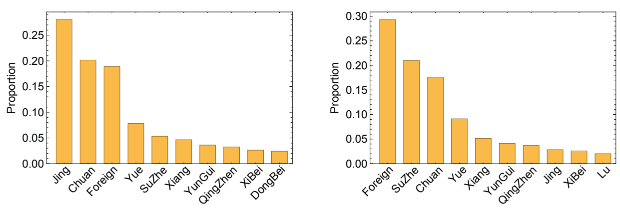
Human mobility is limited to geographic distance [6] and researchers in location recommendation area have pay great atten-



(a) Distributions of an individual's dining check-ins.

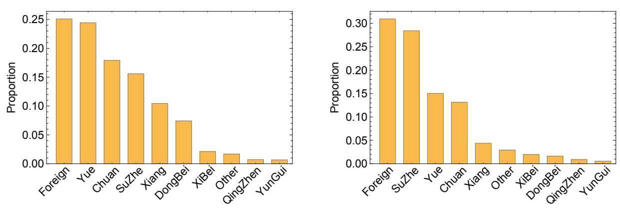
(b) all users' dining probabilities over spatial distances

Figure 3: Spatial preference in dining behavior



(a) Beijing citizens in Beijing

(b) Shanghai citizens in Beijing

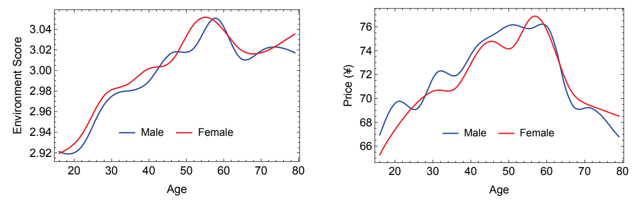


(c) Beijing citizens in Shanghai

(d) Shanghai citizens in Shanghai

Figure 4: Regional-cuisine preference of Beijing citizens and Shanghai citizens in Beijing and Shanghai, respectively. Note that the proportion is calculated on these regional-cuisine categories.

tions to the geographical factors [45]. Dining behavior, as a particular kind of location visit, should certainly be influenced by the spatial distance. To exhibit the spatial distribution of dining behavior, we paint an individual's dining check-ins in Figure 3(a). The blue points and red triangles refer to two centers respectively, and the green squares refer to outliers, which mean dining in unfamiliar places. It indicates that users frequently dine in some familiar areas and occasionally dine far away (e.g., dine when being on business or dine in a distant local restaurant for delicacy). To summarize the overall spatial preference at the individual level, we adopt the following strategies: 1) First, we apply DBSCAN [10] (a clustering algorithm, the maximum distance parameter is set as 5 km and the neighbor number parameter for a core point is set as 10 in our setting) on dining check-ins to find out regional centers for each user. If an individual does not have any centers, we randomly select a dining check-in as a center for her. 2) Next, for each dining check-in of an individual, we calculate the distance to dine out as the geographical distance between this dining check-in and its nearest center. The overall check-in probability over spatial distance is shown in Figure 3, which indicates that nearly 75% dining check-ins travel no more than 2 kilometers and almost 95% dining check-ins are located in a 10-kilometer area.



(a) Environmental preference

(b) Price preference

Figure 5: Dining preference w.r.t. gender and age

4.2 Demographics and Ding Preference

4.2.1 Residence and Dining Preference

The dining preferences of users reside in different cities are distinctive from one another due to factors such as availability of food supply, climate, geography, cooking techniques and lifestyle [19]. In China, due to the vast territory and diverse resources, the regional variance of dining preference is especially obvious and has been extensively studied in hospitality research [7].

As an example, Figure 4 presents the proportions of dining check-ins in different regional categories by Beijing citizens and Shanghai citizens in Beijing and Shanghai, respectively. Figure 4(a) and Figure 4(d) clearly indicate that citizens prefer local cuisine much more than other regional categories (as expected, Beijing citizens prefer Jing-style restaurants, Shanghai citizens prefer Suzhe-style restaurants). Figure 4(b) tells that Suzhe-style restaurants are still selected the second most frequently while Jing-style restaurants are rarely visited (less than 5%) when Shanghai citizens travel in or move to Beijing, which implies that Shanghai citizens still pay more attention to their hometown taste. In Figure 4(c), it shows that when Beijing citizens dine out in Shanghai, the proportion of Suzhe-style restaurants' visit rises up to about 16% (note that the proportion is only nearly 5% in Figure 4(a)), which shows that Beijing citizens are more likely to accept restaurants of unfamiliar categories when they are away from home.

4.2.2 Gender, Age and Dining Preference

Gender and age are usually used as segmentation variables to examine whether there are differences in the perceptions of environment, service, and satisfaction in dining behavior analysis [40, 1].

We use spline regression [27] to fit the average environmental score for male users and female users with different ages, respectively. As shown in Figure 5(a), it indicates that when dine out, female users are slightly more concerned with environmental factor than male users. However, the difference is not significant here. For users under 56, older users are more concerned with environment. Due to space limitation, the trends for taste and service are similar to environment score and are not painted here. Figure 5(b) also shows that for users under 60, older users are willing to pay more for dining, and male users usually spend a little more than female users.

5. RESTAURANT RECOMMENDATION

In this section, we first describe for dining behavior, how to model implicit preference and explicit preference from check-in data and review data respectively. Next, we will show how to integrate them into a unified collective model for restaurant recommendation.

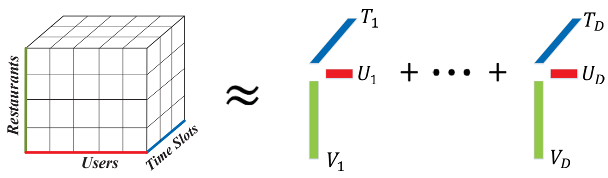


Figure 6: The CP decomposition of the dining check-in tensor

5.1 Modeling Implicit Preference

Check-ins are usually regarded as users' implicit feedbacks for the marked POIs, where the visit at a particular POI indicate the preference [24]. Therefore, the check-in data implicitly express user's preference for restaurants.

Considering in our scenario, the dining check-in data, which is a kind of implicit feedback, can be denoted as a three-dimensional binary tensor $C \in \{0,1\}^{I\times J\times S}$, where I is number of users, J is the number of restaurants, and S is the number of time slots (for the time dimension, we divide a day equally into 24 time slots). If user i has visited the restaurant j at the time slot s, the value of that entry is 1, which represents positive feedback (user i is interested in restaurant j at time slot s). Otherwise, the value of a missing entry is 0, which represents a mixture of negative feedback (user i is not interested in restaurant j at that time slot s) and unobserved potential preference (user i is not aware of restaurant j at time slot s).

5.1.1 *Probabilistic Tensor Factorization*

Given users' implicit feedbacks in a domain, e.g., POI visits on location based social network or product purchases on e-commerce website, collaborative filtering methods are usually used for modeling users' preference for items. Thus, we apply CANDECOMP/PARAFAC (CP) tensor decomposition, which is the state-of-the-art method used for collaborative filtering in the high dimensional situation [20]. As shown in Figure 6, CP decomposition factorizes the check-in tensor C into a summation of vectors, where U, V and T are the latent factors corresponding to users, restaurants and time slots, respectively. These latent factors can be regarded as users'/restaurants'/time slots' preference in a latent subspace. In particular, we apply probabilistic tensor factorization (**PTF**) [32], which is a special instance of CP, to model the implicit preference for dining check-in data. To be more specific, we assume that there is D-dimensional latent factors U_i^C, V_j^C, T_s^C corresponding to each user i, restaurant j and time slot s respectively. In other words, for each dimension of the check-in tensor C, we have a latent factor matrix $U^C_{I\times D}$, $V^C_{J\times D}$ and $T^C_{S\times D}$ respectively. In **PTF**, these latent factors are assumed to be generated from multi-variate Gaussian distributions, and each entry C_{ijs} is generated from a univariate Gaussian, whose mean is determined by the corresponding latent factors on user i, restaurant j and time slot s. As shown in Figure 7, the generative process of **PTF** is given as follows:

1. For a user i, sample a vector: $U_i^C \sim \mathcal{N}(\mathbf{0}, \frac{1}{\lambda^C}\mathbf{I})$.
2. For a restaurant j, sample a vector: $V_j^C \sim \mathcal{N}(\mathbf{0}, \frac{1}{\lambda^C}\mathbf{I})$.
3. For a time slot s, sample a vector: $T_s^C \sim \mathcal{N}(\mathbf{0}, \frac{1}{\lambda^C}\mathbf{I})$.
4. For each entry, generate $C_{ijs} \sim \mathcal{N}(U_i^C \cdot V_j^C \cdot T_s^C, \frac{1}{\lambda^C})$, where $U_i^C \cdot V_j^C \cdot T_s^C = \sum_{d=1}^{D} U_{id}^C V_{jd}^C T_{sd}^C$.

Note that for convenience, we assume all the Gaussian distribution with the same variance parameter $\frac{1}{\lambda^C}$ for check-in data.

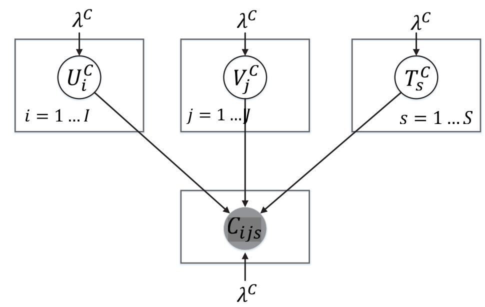


Figure 7: The graphical representation for probabilistic tensor factorization (PTF)

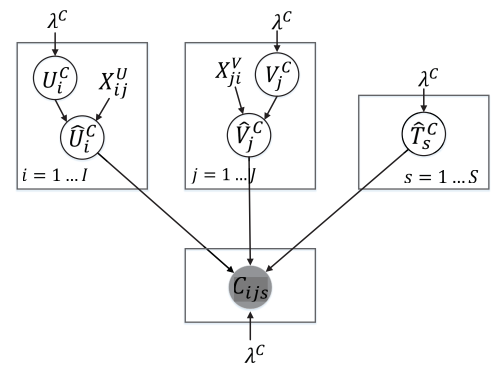


Figure 8: The graphical representation for implicit preference model (IPM).

5.1.2 *Implicit Preference Model*

Actually, the single **PTF** model only replies on historical check-in behavior to reveal the user-restaurant-time's intrinsic relationship. However, as shown in Section 4, contextual signals such as spatial distance, user demographics and restaurant attributes are also closely connected to dining preference. Thus we would prefer a model that can incorporate these signals into the factorization procedure.

Instead of just generating a feedback estimation from the latent factors U_i^C, V_j^C and T_s^C, we show how it is possible to extend **PTF** to include the contextual signals with respect to users and restaurants. We propose the implicit preference model (**IPM**), to augment U_i^C, V_j^C with additional terms that contain information about the user, restaurant and user-restaurant pair. As shown in Figure 8, the augmented version of $\hat{U}_{ij}^C$ is now specific to a user-restaurant pair, $\hat{U}_{ij}^C = \{U_i^C, \mathrm{X}_{ij}^U\}$. The part U_i^C contains the free parameters that will be learned for user i and X_{ij}^U contains additional contextual signals about this user (e.g., age, gender, etc.) or this user-restaurant pair (e.g., spatial distance between this user's dining center and this restaurant). The restaurant vector $\hat{V}_{ji}^C$ is similarly augmented. To clearly differentiate the changes with **PTF**, we further segment the augmented latent factors into three parts respectively as shown in Figure 9, where gray part X_{ij}^U and X_{ji}^V are observed contextual signals and others are free parameters. Then, the mean preference estimate from user i, restaurant j and time slot s is changed as follows:

$$\begin{aligned}\mu_{ijs}^C &= \hat{U}_i^C \cdot \hat{V}_j^C \cdot \hat{T}_s^C \\ &= U_{ia}^C \cdot V_{ja}^C \cdot T_{sa}^C + U_{ib}^C \cdot X_{ji}^V \cdot T_{sb}^C + X_{ij}^U \cdot V_{jc}^C \cdot T_{sc}^C,\end{aligned} \quad (1)$$

The first term, $U_{ia}^C \cdot V_{ja}^C \cdot T_{sa}^C$, is the tensor factorization term. The second term, $U_{ib}^C \cdot X_{ji}^V \cdot T_{sb}^C$ is the result of user i's and time slot

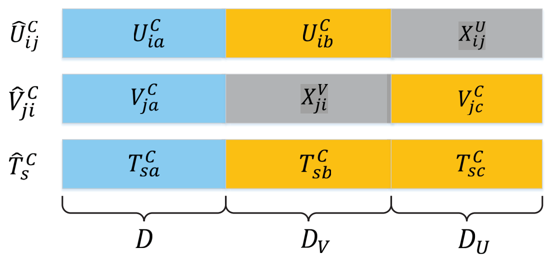


Figure 9: The description of augmented latent vectors, where gray parts indicate observed contextual signals and colored parts indicates free parameters to learn.

s's linear regression against the attributes of the restaurants they have visited or user-restaurant paired features such as spatial distance. For example, if X_{ji}^{V} contains a flag indicating the category of a restaurant, then the corresponding variable U_{ib}^{C} and T_{sb}^{C} indicates the user's bias towards different categories at a particular time slot. Similarly, $X_{ij}^{U} \cdot V_{jc}^{C} \cdot T_{sc}^{C}$ is the result of the restaurant j's and time slot s's linear regression against user demographics or user-restaurant paired features. Note that the user-restaurant paired features can be contained in either X_{ij}^{U} or X_{ji}^{V}. Similar to **PTF**, the generative procedure of **IPM** is as follows:

1. For a user i, sample two vectors U_{ia}^{C}, U_{ib}^{C} according to $U_{i}^{C} \sim \mathcal{N}(\mathbf{0}, \frac{1}{\lambda^C}\mathbf{I})$, respectively.

2. For a restaurant j, sample two vectors V_{ja}^{C}, V_{jb}^{C} according to $V_{j}^{C} \sim \mathcal{N}(\mathbf{0}, \frac{1}{\lambda^C}\mathbf{I})$, respectively.

3. For a time slot s, sample three vectors $T_{sa}^{C}, T_{sb}^{C}, T_{sc}^{C}$ according to $T_{s}^{C} \sim \mathcal{N}(\mathbf{0}, \frac{1}{\lambda^C}\mathbf{I})$, respectively.

4. For each entry, generate $C_{ijs} \sim \mathcal{N}(\mu_{ijs}^{C}, \frac{1}{\lambda^C})$, where μ_{ijs}^{C} is calculated in Eq. (1).

We consider three types of contextual signals for **IPM** as follows: 1) User features include user residence city, gender and age. 2) Restaurant features include restaurant category, overall rating, taste, environment, service, price and the city a restaurant locates in. 3) For a user-restaurant pair (i, j), we first consider the geographical distance between restaurant j and user i's nearest dining centers (note that we have used DBSCAN algorithm to find out individual dining centers in Section 4.1) as the spatial feature. Next, we consider whether user i's residence city is the same as the city restaurant j locates as another feature. Furthermore, we impute a missing value using the mean if it is continuous.

5.1.3 *Bayesian Ranking-Based Optimization*

Motivated by [31], we consider the pair-wise ranking between entries for the learning approach, which is especially effective for implicit feedback data. To be more specific, we use $p(j > j'; i, s|\theta)$ to denote the probability that user i prefers restaurant j over j' at time slot s, where $\theta = \{\hat{U}^C, \hat{V}^C, \hat{T}^C\}$ represent the model parameters. The Bayesian formulation of the optimization criterion is to maximize the posterior probability as follows:

$$p(\theta|\mathcal{R}) \propto p(\mathcal{R}|\theta)p(\theta), \tag{2}$$

where $p(\mathcal{R}|\theta)$ represents the probability that all entry pairs can be ranked correctly according to pair-wise rank $\mathcal{R}$, i.e., for each entry with feedback 1 can be ranked higher than entries with feedback 0.

With the assumption that entry pairs are independent, we can expand the likelihood function $p(\mathcal{R}|\theta)$ as follows:

$$\begin{aligned} p(\mathcal{R}|\theta) &= \prod_i \prod_s p(\mathcal{R}_{is}|\theta) \\ &\prod_i \prod_s \prod_{(j>j')\in\mathcal{R}_{is}} p(j > j'; i, s|\theta), \end{aligned} \tag{3}$$

where $(j > j') \in \mathcal{R}_{is}$ represent all restaurant pairs with the correct orders in the observed implicit feedback of user i at time slot s.

We define $p(j > j'; i, s|\theta)$ as:

$$p(j > j'; i, s|\theta) = \sigma(\mu_{ijs}^{C} - \mu_{ij's}^{C}), \tag{4}$$

where σ is the logistic sigmoid function $\sigma(x) = \frac{1}{1+e^{-x}}$.

With the likelihood and the Gaussian distribution $p(\theta)$, we can derive the objective function as follows:

$$\begin{aligned} O^C &= -\ln p(\theta|\mathcal{R}) = -\ln p(\mathcal{R}|\theta)p(\theta) \\ &= \sum_i \sum_s \sum_{(j>j')\in\mathcal{R}_{is}} \ln p(j > j'; i, s|\theta) + \lambda^C ||\theta||_2^2 \\ &= \sum_i \sum_s \sum_{(j>j')\in\mathcal{R}_{is}} \ln \sigma(\mu_{ijs} - \mu_{ij's})) + \lambda^C ||\theta||_2^2 \end{aligned} \tag{5}$$

Considering the data size of the check-in data, we use stochastic gradient descent [46] to update parameters $\hat{U}^C$, $\hat{V}^C$, and $\hat{T}^C$. Note that the time complexity of this proposed learning process is $O(IJ^2S)$, which can be overwhelming for our check-in data. Thus, we only need to estimate the gradient with a very small subset (10^{-4} sample rate is adopted in our method) of training pairs sampled from $\mathcal{R}$ at each iteration.

5.2 Modeling Explicit Preference

Considering in our scenario, the explicit feedback of dining review for restaurants contains both ratings and review texts. Since rating behavior usually lags behind the actually dining experience, we ignore the temporal information and use a matrix $R \in \mathbb{R}^{I\times J}$ to represent rating data. For each user i, we merge all the review texts pertaining to this user to build a review document d_i. Similarly, we build a review document d_j for each restaurant j.

5.2.1 *Probabilistic Topic Models*

An intuitive way to model review texts is to use the word vector features as contextual signals. However, there are usually some latent structures among different documents and word vector features usually give an unsatisfied performance in document analysis [36]. Topic modeling algorithms [35] are usually used to discover a set of "topics" from a large collection of documents, where a topic is a distribution over terms that is biased around those associated under a single theme. Topic models can provide an interpretable low-dimensional representation of the documents. They have been widely used for tasks like corpus exploration, document classification, and information retrieval. Here we will apply topic modeling to exploit the discovered topic structure for these review texts.

Here, we apply latent Dirichlet allocation (LDA) [4], which is the simplest topic model. Assume that there are K topics $\beta = \beta_{1:K}$, each of which is a multinomial distribution over a fixed vocabulary. The generative process LDA is as follows, For each document d in the corpus,

1. Sample topic proportions $\phi \sim \text{Dirichlet}(\alpha)$.

2. For each word n,

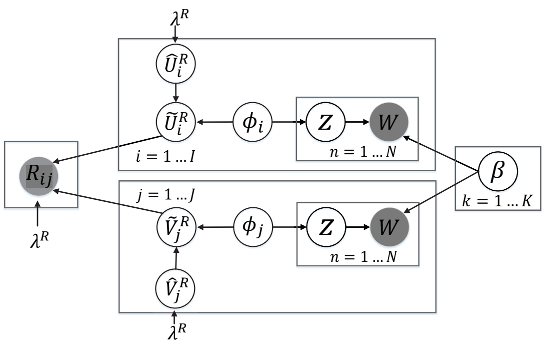


Figure 10: The graphical representation for explicit preference model (EPM)

(a) Sample topic assignment $z_n \sim \mathrm{Mult}(\phi)$.

(b) Sample word $w_n \sim \mathrm{Mult}(\beta_{z_n})$.

The process reveals that how the words of each document are assumed to come from a mixture of topics: the topic proportions are document-specific, but the set of topics is shared by the corpus.

5.2.2 *Explicit Preference Model*

We combine factorization with topic models for modeling explicit preference. To be specific, we use topic distribution ϕ_i to represent user i's topic interest and topic distribution ϕ_j to represent restaurant j's topic structure. Therefore, a user's latent vector can be expressed as $\tilde{U}_i^R = \hat{U}_i^R + \phi_i$, where $\hat{U}_i^R$ is the augmented user latent vector which is similar to $\hat{U}_i^C$ mentioned in Section 5.1.2. Similarly, a restaurant's latent vector can be expressed as $\tilde{V}_j^R = \hat{V}_j^R + \phi_j$. Then, the mean explicit preference estimate from user i and restaurant j is given as follows:

$$\mu_{ij}^R = \tilde{U}_i^R \cdot \tilde{V}_j^R = \hat{U}_i^R \cdot \hat{V}_j^R + \hat{U}_i^R \cdot \phi_j^R + \hat{V}_j^R \cdot \phi_i^R + \phi_i^R \cdot \phi_j^R \tag{6}$$

Figure 10 shows the graphical representation of our explicit preference model (**EPM**). Again, assume there are K topics $\beta = \beta_{1:K}$, the generative process of **EPM** is as follows,

1. For a user i,
   (a) sample a user topic proportions $\phi_i \sim \mathrm{Dirichlet}(\alpha)$.
   (b) For each word w_{in} in d_i,
      i. Sample topic assignment $z_{in} \sim \mathrm{Mult}(\phi_i)$.
      ii. Sample word $w_{in} \sim \beta_{z_{in}}$.
   (c) Sample user augmented vector $\hat{U}_i^R$ similar to $\hat{U}_i^C$, and set the user latent vector as $\tilde{U}_i^R = \hat{U}_i^R + \phi_i$.
2. For a restaurant j,
   (a) sample a restaurant topic proportions $\phi_j \sim \mathrm{Dirichlet}(\alpha)$.
   (b) For each word w_{jn} in d_j,
      i. Sample topic assignment $z_{jn} \sim \mathrm{Mult}(\phi_j)$.
      ii. Sample word $w_{jn} \sim \beta_{z_{jn}}$.
   (c) Sample restaurant augmented vector $\hat{V}_j^R$ similar to $\hat{V}_j^C$, and set the restaurant latent vector as $\tilde{V}_j^R = \hat{V}_j^R + \phi_j$
3. For each user-restaurant pair (i, j), generate the rating $R_{ij} \sim \mathcal{N}(\mu_{ij}^R, \frac{1}{\lambda^R})$, where μ_{ij}^R is calculated in Eq. (6).

Maximization of the posterior of these parameters is equivalent to maximizing the following objective function:

$$\begin{aligned} O^R = &\sum_i \sum_n \log(\sum_k \phi_{ik}\beta_{k,w_{in}}) + \sum_j \sum_n \log(\sum_k \phi_{jk}\beta_{k,w_{jn}}) \\ &- \frac{\lambda^R}{2} \sum_{i,j} (R_{ij} - (\hat{U}_i^R + \phi_i) \cdot (\hat{V}_j^R + \phi_j)) \\ &- \frac{\lambda^R}{2} \sum_i \hat{U}_i^R \cdot \hat{U}_i^R - \frac{\lambda^R}{2} \sum_j \hat{V}_j^R \cdot \hat{V}_j^R \end{aligned} \tag{7}$$

Note that we have omitted a constant and set $\alpha = 1$.

5.3 Integration for Recommendation

Given both check-in tensor C, review matrix R and contextual signals, according to the assumption that users/items across different data sources share some common latent interests [26], we integrate implicit preference model and explicit preference model to propose a unified model termed Collective Implicit Explicit Preference Model (**CIEPM**). **CIEPM** assumes that check-in data and review data have a shared user latent vector $\hat{U}_i^{shared}$ and a shared restaurant latent vector $\hat{V}_j^{shared}$. Therefore, $\hat{U}_i^C$, $\hat{V}_j^C$, $\hat{U}_i^R$, and $\hat{V}_j^R$ can be re-expressed as:

$$\begin{aligned} \hat{U}_i^C &= \hat{U}_i^{shared} + \triangle\hat{U}_i^C, \qquad & \hat{U}_i^R &= \hat{U}_i^{shared} + \triangle\hat{U}_i^R, \\ \hat{V}_j^C &= \hat{V}_j^{shared} + \triangle\hat{V}_j^C, \qquad & \hat{V}_j^R &= \hat{V}_j^{shared} + \triangle\hat{V}_j^R, \end{aligned} \tag{8}$$

where, $\hat{U}_i^{shared}$, $\triangle\hat{U}_i^C$, $\triangle\hat{U}_i^R$, $\triangle\hat{V}_j^C$ and $\triangle\hat{V}_j^R$ come from Gaussian distribution as introduced before.

The final objective function can be given as:

$$O = O^C + \eta \cdot O^R \tag{9}$$

where O^C indicate the objective function calculated in Eq. (5) with the new formation of $\hat{U}_i^C$ and $\hat{V}_j^C$, and O^R indicate the objective function calculated in Eq. (7) with the new formation of $\hat{U}_i^R$ and $\hat{V}_j^R$. η is a scale factor since implicit feedback and explicit feedback have different value scales (C_{ijs} is $0/1$ valued and R_{ij} ranges from 1 to 5).

Again, we use stochastic gradient descent to update parameters $\hat{U}^C, \hat{V}^C, \hat{T}^C, \hat{U}^R, \hat{V}^R, \phi$ and β. To be specific, in each iteration, we first update parameters $\hat{U}^C, \hat{V}^C, \hat{T}^C$ by sampling a mini-batch instances from check-in data, and next update parameters $\hat{U}^R$, $\hat{V}^R$, ϕ and β by sampling a mini-batch instances from review data.

Finally, the integrated implicit and explicit dining preference a user i providing for a restaurant j at time slot s is given as:

$$\mu_{ijs} = \mu_{ijs}^C + \eta \cdot \mu_{ij}^R \tag{10}$$

where μ_{ijs}^C is calculated in Eq. (1) and μ_{ij}^R is calculated in Eq. (6).

The final restaurant recommendation for a user i at time slot s is given according to the following ranking criterion:

$$i, s : j_1 > j_2 > \cdots > j_J \longrightarrow \mu_{ij_1s} > \mu_{ij_2s} > \cdots > \mu_{ij_Js} \tag{11}$$

6. EXPERIMENTS

In this section, we first introduce the experiment settings and evaluation measurements. Next, we conducted extensive experiments to validate the performance of our implicit preference model (**IPM**) for restaurant recommendation. Finally, we evaluate whether our final collective model (**CIEPM**) is effective in leveraging implicit and explicit preference. Note that explicit preference model

(**EPM**) does not include time information which is needed for our next dining recommendation task. So **EPM** are only evaluated as a part of **CIEPM**.

6.1 Settings

We take a user's last dining check-in as the testing data, and all other check-ins as well as all dining reviews before the last dining check-in as training data. We apply grid search for the parameter setting. Finally, we obtain that the following setting achieves the best performance: latent dimension $D = 64$, variance parameter $\lambda^C = \lambda^R = 0.01$, number of topics $K = 50$, scale factor $\eta = 0.15$.

After learning the parameters of the proposed models, for each user, we generate the recommendation according to the criterion in Eq. (11).

As discussed in [30], precision is not a suitable performance measure for implicit feedback recommendation. Thus, in our experiments, we adopt Recall@k [37] to evaluate the performance of the top k recommendation.

6.2 The Study of Implicit Preference Model

To study the performance of our implicit preference model (**IPM**), we compare it with the following models widely adopted in POI recommendation by using implicit feedback:

- Logistic Regression (**LR**): This method uses a logistic regression with all the contextual signals as well as time slot information in our **IPM** model. For each user, the estimated preference is represented as the predicted probability.
- User-Based Temporal Collaborative Filtering (**UTCF**): This algorithm first computes the similarity between users according to the dynamic common visited restaurants, and then estimate a user's interest in a restaurant based on similar users' interests in that restaurant [3].
- Non-negative Tensor Factorization (**NTF**): This method computes non-negative users', restaurants' and time slots' latent preference under the dining check-in tensor C [33].
- Geographic Bayesian Co-Nonnegative Matrix Factorization (**GC-BCoNMF**): This factorization model is especially designed for restaurant recommendation, which considers both users' preference learning and multiple information fusion [11]. Note that the shared features in GC-BCoNMF correspond to user-restaurant paired features in our **IPM** model.

Figure 11(a) reports the comparison results of **IPM** with the proposed baselines. The results precipitate several observations, which we summarize as: 1) LR performs the worst among all the approaches. This is because LR only considers the contextual signals including time slot, user demographics, restaurant attributes and the paired features, which can represent the observable dining preference but fails to capture the dining interests embodied in the check-in tensor. 2) UTCF performs worse than NTF, GC-BCoNMF and our **IPM**. This is because that among these, UTCF is the only one which does not leverage tensor factorization. Due to the sparseness of the dining check-in tensor, this collaborative filtering approach fails to accurately capture the latent low-rank approximation of users'/restaurants'/time slots' interests. 3) GC-BCoNMF and our model **IPM** both outperform NTF, which demonstrates the effectiveness of leveraging contextual signals to embody the dining preference that can not be captured by individual's latent structure in factorization model. 4) Our model **IPM** also performs better than GC-BCoNMF. This is because that GC-BCoNMF directly incorporates user/restaurant similarity and geographic proximity to estimate preference, while our model considers the interaction of these contextual signals and latent structure, which can help to learn these parameters to achieve a better performance. In summary, since our model **IPM** simultaneously captures individual's latent dining interest in the factorization procedure and dining preference embodied in contextual signals, it gives the best performance for implicit feedback among all the compared approaches.

Note that the performance of each method is usually low, which is actually due to the difficulty of the recommendation task (the data is very sparse and there are hundreds of thousands of candidate restaurants). Therefore, the absolute performance on Recall@k of **IPM** is small but still reasonable. What is more, the improvement of **IPM** over other baselines is significant, which demonstrates the effectiveness of our method.

6.3 The Study of Contextual Signals

To further investigate the influence of different types of contextual signals for restaurant recommendation performance, we compare our method **IPM** leveraging all the contextual signals against the following methods,

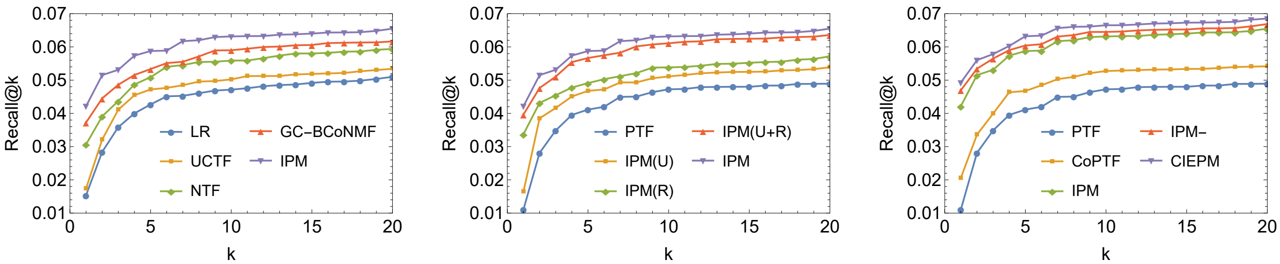
- **PTF**: This method only conduct factorization and ignore all the contextual signals used in **IPM**.
- **IPM(U)**: This method uses the same settings as **IPM**, except that it only use demographics as contextual signals.
- **IPM(R)**: This method uses the same settings as **IPM**, except that it only use restaurant attributes as contextual signals.
- **IPM(U+R)**: This method uses the same settings as **IPM**, except that it considers user demographics and restaurant attributes, while ignores the paired features.

As shown in Figure 11(b), the comparison of the results presents the following observations: 1) PTF performs worst since it does not leverage any contextual signals. 2) IPM(R) performs better than IPM(U), it may be reasoned that user demographics only contain three features while the restaurant attributes are much more rich. In addition, compared to age or gender, the restaurants attributes such as price or taste will probably give more influence on user's dining decision. 3) IPM(U+R) outperforms both IPM(U) and IPM(R), this is because that the interaction of user demographics and restaurant attributes can accurately capture users' dining preference, e.g., Beijing citizens prefer Jing-Style restaurants as described in Section 4.2. In addition, the interaction of user residence and restaurant's located city can generate a higher preference for restaurants locating in a user's hometown or the cities covered by her historical dining check-ins. 4) Compared to IPM(U+R), **IPM** can still improve the performance, which reveals the effectiveness of incorporating spatial preference and residential/non-residential preference in the paired features. In summary, our **IPM** demonstrates that by incorporating various contextual signals, the dining preference can be leveraged into factorization to greatly improve the dining recommendation performance.

6.4 The Study of Explicit Feedback Enrichment

To evaluate how explicit preference can help to improve the recommendation performance in our enhanced collective model **CIEPM**, we compare it with **PTF**, **IPM** and the following methods,

- **CoPTF**: This method uses the same settings as **CIEPM**, except that it does not incorporate any contextual signals and



(a) recommendation performance of implicit check-in data w.r.t various recommendation models

(b) recommendation performance of implicit preference model w.r.t different contextual signals

(c) recommendation performance w.r.t explicit feedback usage

Figure 11: Results comparison. Figures (a) compares the performance of various recommendation models for implicit check-in data. Figures (b) compares the performance of IPM with different configurations of contextual signals. Figures (c) compares our unified model CIEPM with selected baselines to investigate the performance improvement by combing implicit and explicit preference.

review texts. Actually, it extends PTF to a collective model by utilizing the rating matrix R.

- **IPM+**: This method uses the same settings as **IPM**, except that it treats the explicit feedback, i.e., each user-restaurant rating and review text's word vector, as paired features in the contextual signals.

The comparison results of different approaches are shown in Figure 11(c), which provide us the following observations: 1) CoPTF performs better than PTF, which implies that incorporating explicit feedback into a collective factorization model can significantly improve the performance of factorization model when contextual signals are not leveraged. 2) Both **CoPTF** and IPM+ outperform IPM due to the fact that the additional usage of explicit feedback information in the review data. More importantly, the results show that our unified model **CIEPM** can still perform better than IPM+, which indicates that designing a collective model to leverage this additional explicit feedback is more effective. In summary, the results demonstrate that compared to other approaches, our proposed **CIEPM** integrates individual's latent interest, dining preference and explicit feedback to achieve the best performance for dining recommendation.

7. RELATED WORK

7.1 Dining Preference Research

Dining preference is a critical determinant in sustaining the food industry's existence and development [8]. Thus, restaurateurs should identify and take into account consumers' dining preferences in order to ensure successful business [9, 21]. Dining preference can be examined from different perspectives in the past studies.

From the consumer's perspective, different groups of people have distinct dining preference and customer segmentation plays a key role in the competitive restaurant business [28]. Lewis [23] adopted discriminant analysis to examine dining preference to segment groups he termed "goers" and "non-goers". Statistical differences between "goers" and "non-goers" were found for the following factors: food quality, menu variety, price, atmosphere, and convenience. According to Yüksel [44], consumers are partitioned into five groups by distinct dining preferences: value seekers, adventurous food seekers, atmosphere seekers, healthy food seekers, and service seekers. For example, adventurous food seekers consider availability of local, new and interesting food an important factor while atmosphere seekers attach a great deal of importance to convivial dining atmosphere.

From the restaurant's perspective, dining preference research mainly focuses on the most important attributes that customers use in deciding where to dine out. Kivela [15] examined dining preference by investigating fine dining/gourmet, theme/atmosphere, family/popular, and convenience/fast-food restaurants in Hong Kong. The results showed that consumers' dining preferences varied considerably by restaurant type, dining-out occasion, age, and occupation. This study also suggests that food quality and type of food were not the only important attributes affecting marketing strategies. Jian and Namkung [16] suggest three factors: service quality, product quality and atmospherics as main restaurant attributes affecting perceived quality of restaurant experiences. Han et al. [22] examined how negative reviews would generate an effect on consumers' dining decision. Bakhshi et al. [2] revealed that besides endogenous factors such as restaurant attributes, exogenous factors such as demographics (e.g., neighborhood diversity, education) and weather also exert a significant effect on restaurant selection.

Compared to previous works which investigated this problem mainly by surveys or interviews [5, 34], we present a computational framework to integrate contextual signals, implicit feedback and explicit feedback for modeling dining preference.

7.2 POI Recommendation

POI recommendation, also referred to as location recommendation, has been recognized as an essential topic on recommender system. It was firstly studied on GPS trajectory, e.g., Zheng and Xie [48] performed two types of travel recommendations by mining multiple users' GPS traces, where the first one recommends a user with popular interesting locations and travel sequence in a given geospatial region and the second one provides an individual with locations matching her personal travel preference. Zheng et al. [47] leverage GPS data and users' comments at various locations to discover interesting locations and possible activities that can be performed there for recommendation. The presented framework constructs a location-activity matrix for collaborative filtering and uses knowledge such as location features and activity-activity correlations to enhance the recommendation performance.

In recent years, with the rapid accumulation of spatial-temporal check-in records in the location based social networks (LBSNs) and the prevalence of various interesting real-world applications [42], the POI recommendation problem has received much attention once more. A pioneer work of POI recommendation in LBSNs is proposed by Ye et al. [38]. The work has been extended and further studied in [39]. To be more specific, they considered geographic influence by assuming a power-law distribution between check-in probability and leverage social influence to generate the next location recommendation. Liu et al. [25] propose a geographic probabilistic factor analysis framework which strategically considers joint effect of multiple factors into POI recommendation. In Lian et al. [24], mobility records in LBSNs are viewed as implicit feedback for POI recommendation and a weighted matrix factorization is presented for the task. Besides, they also incorporate the spatial clustering phenomenon in human mobility into the factorization model to improve the performance. In addition to social and spatial effects, the impact of contextual signals such as time, the textual description of location has also been investigated. For example, Yin et al. [41] leveraged content information of location via topic modeling to boost POI recommendation. Gao et al. [12] exploited several strategies to aggregate an individual's time-dependent latent factors to improve location recommendation performance.

Restaurant, as a particular type of POI, has also been specially studied in POI recommendation. Kitamura et al. [18] proposed a competitive information recommendation system consisting of multiple animated agents to recommend restaurants competitively. Park et al. [29] presented a system according to Bayesian learning in consideration of both users' preferences and restaurant contexts (such as restaurant type, price, etc.) to recommend restaurants. Horozov et al. [14] designed a user-based collaborative filtering system to recommend restaurants by finding which restaurants similar users have visited before.

Our proposed restaurant recommendation system **CIEPM** distinguishes itself from the above-mentioned works in the following two aspects: 1) We first develop a contextual probabilistic tensor factorization model to infer user's implicit restaurant preference by exploiting multi-aspect dining preferences, such as spatial distance, user demographics, and restaurant attributes. 2) We next integrate implicit preference and explicit preference by a collective model to boost the performance of dining recommendation.

8. CONCLUSION

In this paper, we propose a restaurant recommender system termed **CIEMP**, which embodies both dining preference, implicit feedback and explicit feedback for a user's next dining. Following this framework, we first present a contextual probabilistic tensor factorization model termed **IPM** to model the implicit dining preference. **IPM** can simultaneously capture users'/restaurants'/time slots' interests in a latent space and dining preference related to specific contexts such as spatial distance, demographics and restaurant attributes. Next, we combine matrix factorization and topic modeling to model the preference from explicit review data. Finally, we design a unified collective model (**CIEPM**) to combine implicit and explicit preference together for restaurant recommendation. We evaluated our system with large-scale datasets covering hundreds of thousands of users and restaurants, and the results validated the effectiveness of our dining recommender system.

In the further study, we will investigate a user's pre-dining activities such as going to the cinema or sharing food-related content on social media, which might imply his following dining choice.

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