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Exploiting the roles of aspects in personalized POI recommender systems

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Abstract The evolution of World Wide Web (WWW) and the smart-phone technologies have revolutionized our daily life. This has facilitated the emergence of many useful systems, such as Location-based Social Networks (LBSN) which have provisioned many factors that are crucial for selection of Point-of-Interests (POI). Some of the major factors are: (i) the location attributes, such as geo-coordinates, category, and check-in time, (ii) the user attributes, such as, comments, tips, reviews, and ratings made to the locations, and (iii) other information, such as the distance of the POI from user's house/office, social tie between users, and so forth. Careful selection of such factors can have significant impact on the efficiency of POI recommendation. In this paper, we define and analyze the fusion of different major aspects in POI recommendation. Such a fusion and analysis is barely explored by other researchers. The major contributions of this paper are: (i) it analyzes the role of different aspects (e.g., check-in frequency, social, temporal, spatial, and categorical) in the location recommendation, (ii) it proposes two fused models—a ranking-based, and a matrix factorization-based, that incorporate all the major aspects into a single recommendation model, and (iii) it evaluates the proposed models against two real-world datasets.

Keywords Information retrieval · Context aware recommendation · POI recommendation · Social networks

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1 Introduction

The LBSNs (e.g., Facebook,[1] Foursquare,[2] Gowalla,[3] and so forth) have facilitated users to share many information including their check-in behaviors. Such an information has been exploited to predict the potential check-ins. Due to some similarities with the generic recommendation, the earlier POI recommenders have been heavily influenced by the generic recommendation models [e.g., Collaborative Filtering (CF) (Zheng et al. 2009; Levandoski et al. 2012)], Content-Based Filtering (Yin et al. 2013), and Hybrid approaches (Yang et al. 2013). Most of the generic models have been relying on the user-item rating matrix to predict the user-item preference. This general approach may not always be applicable for POI domain where the users and places can have few check-ins, resulting in sparse rating matrix. As there can be many influential factors (or challenges) governing the selection of POI, the traditional models are either unable to incorporate them or are difficult to model. In the past few years, the community has been exploring the impact of such factors and has been pondering on their incorporation for efficient POI recommendations.

One of the special attributes is variation of the check-in frequency across different users and places. This often arises when users and places have few check-ins. This results in the *sparsity* of the *user-location* frequency matrix, in comparison to the generic *user-item* rating matrix in simple recommenders. The incorporation of different aspects can help to alleviate this problem. The preference to nearby places introduces the *spatial aspect* in the recommendation model. The preference to similar category introduces the *categorical aspect* in LBSN. The temporal check-in trend introduces the *temporal aspect*. The popularity of *bars* in the evenings and nights is an example of the temporal popularity. The tendency of traveling with family and friends and traveling to the places that are already visited by someone in his/her network implies the *social aspect* which also impacts the check-in behavior of users. Though such social-tie (*for instance, friendship*) seems to be interesting, it is not always reliable. Earlier studies have shown that only ∼96% of people share <10% of the commonly visited places and ∼87% of people share nothing at all (Ye et al. 2010). Though some aspects might not be a sole contributor, combining them with other aspects might positively impact the recommendation quality.

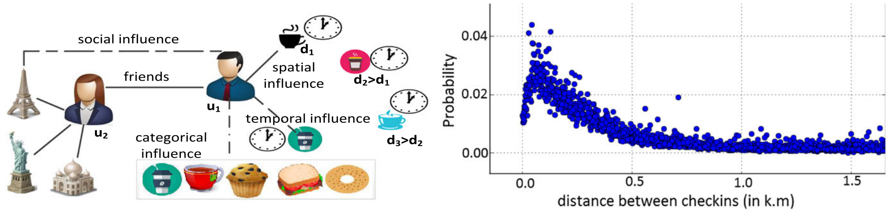
The role of above-mentioned aspects is illustrated in Fig. 1. In the figure, two users u_1 and u_2 are friends. The *social* impact of user u_2 can influence user u_1 to the places that were visited by user u_2. The *spatial* influence can affect user u_1 to select the nearest location among the available options. As shown in the figure, the visit of user u_1 to a *cafe* around the same hour of days is due to *temporal* influence. Similarly, the *categorical* influence is reflected when a coffee lover visits any place that serves coffee.

There can be additional influential factors, for instance, (i) the utility of a POI, regardless of the distance and cost, (ii) the popularity of a POI (due to historical,

[1] www.facebook.com.

[2] www.foursquare.com.

[3] www.gowalla.com.



(a) **(b)**

Fig. 1 Illustration of aspects in LBSN (**a**), and illustration of impact of distance to check-in trends (**b**)

cultural, social or other impacts), (iii) the dynamic mobility of a user (trend to visit new places), (iv) promotional offers, such as coupons, discounts, and so forth. Though it might also be interesting to explore these factors, we defer them for our future studies.

Although the POI recommendation is a well explored topic (Jin et al. 2012; Wang et al. 2013; Ye et al. 2011; Yuan et al. 2013; Zhang and Chow 2015; Baral and Li 2016; Baral et al. 2016), most of the existing studies have fused just few of the major aspects in their model. Based on our knowledge so far, none of the existing studies have explored the detail analysis of major aspects for POI recommendation. This paper attempts to fill the gap by providing the following core contributions: (i) it analyzes the impact of major influential factors for POI domain, (ii) it proposes a personalized ranking-based, and a matrix factorization-based models that fuse the major influential aspects for POI recommendation, and (iii) it evaluates the proposed models with two real-world datasets.

2 Related research

This section provides the insight of relevant studies based on the aspects they have focused.

Social aspect: Cho et al. (2011) claimed that around 10–30% of human movements can be socially influenced. They found that the influence of friendship on user's mobility could be around 61% and the influence of mobility on new friendship could be around 24%. They used the Gaussian distribution with time of a day as a parameter to model the probability distribution over the latent states (work and home place) for a user. Contrary to the claim of Ye et al. (2010) (∼96% of people share <10% of the commonly visited places and ∼87% of people share nothing at all), Gao et al. (2012) assumed that people share their check-in activities among friends. Their model used the Hierarchical Pitman-Yor (HPY) language model to represent the check-in pattern of a user and has shown effective results. Although these models exploited the social aspects, they did not focus on the temporal aspect of check-in activities.

Temporal aspect: Jin et al. (2012) proposed a graph-based model where the following/follower relation was realized as directed edge between user nodes. The nodes were ranked using the topic-sensitive PageRank (Haveliwala 2002). Though they incorporated the temporal aspect, other major aspects, such as geographical, categorical, and the social aspects were not explored. Yuan et al. (2013) incorporated the spatial and temporal aspects. The prediction of a check-in to a location was defined as the aggregate of visits count on that location across all the users. The check-in time constraint was introduced for the temporal similarity measure. Though the model incorporated spatial aspect by considering its impact on the check-in trend, it did not define the social, and categorical aspects for recommendation. Though the matrix factorization model from Gao et al. (2013) achieved exciting results by incorporating the temporal aspects, other aspects were left unexplored.

Categorical aspect: Liu et al. (2013b) introduced the dependency of user's check-in behavior with her current location, and the implicit POI category preference based on the categorical patterns on check-in data. They used K-means clustering algorithm to group the users with similar check-in category and frequency values, and similar check-in time. The HITS (Gibson et al. 1998) based model from Bao et al. (2012) addressed the users' preferences and their social opinions. The users' location history was categorized according to the types (for instance, shopping, restaurants, and so forth). A user-location matrix was used to identify the local experts who have the higher affinity towards a POI category, and the experts' social opinions were used in the recommendation. Their model also did not address the temporal aspect in LBSN.

Spatial aspect: The First Law of Geography from Tobler (1970) which states "everything is related to everything else, but near things are more related than the distant things" is relevant to POI recommendation as well. Ye et al. (2010) incorporated the check-in willingness factor (Tobler 1970), social, and spatial aspects. The spatial influence was modeled using Bayesian CF approach. The social aspect was incorporated by considering a user's friends' check-in behavior rather than finding similarities with all the users in the dataset. Liu et al. (2013a) used the geographical probabilistic factor analysis framework that focused on multiple factors, such as, the user check-in count, geographical influence on POI selection, user mobility nature, and so forth. They modeled the users' mobility behavior by using multinomial distribution over latent regions and different activity regions. The temporal aspect remained unexplored in their model as well.

Other fused models: Wang et al. (2013) defined a heterogeneous graph with user and location nodes and computed the nodes' rank. The unobserved places which have the highest rank and within a threshold distance (e.g., from user's house) were recommended. Yin et al. (2013) exploited the POIs' content information (for instance, item tags or category keywords) to link the content-similar spatial items. Liu and Xiong (2013) incorporated the POIs' content into users' and POIs' profile and utilized the context-aware information through probabilistic matrix factorization. Hu and Ester (2013) used topic modeling to exploit the spatial and textual aspects of user posts. Cheng et al. (2013) considered the users' movement constraint and proposed a successive personalized POI recommendation model using matrix factorization method which embedded the personalized Markov chains and the localized regions. Wang et al.

(2015) used both the users' personal interests and the preference of crowd (with same role, e.g., tourist or local) in the target region along with the co-occurrence pattern of spatial items and the content (for instance, the tags and category keywords) of those spatial items. The probabilistic generative model from Yin et al. (2015) exploited the geographical, temporal, word-of-mouth, and semantic effect. Xie et al. (2016) used the geographical, temporal, and semantic aspects in their heterogeneous graph embedding model that was based on the time decay method and was claimed to be an efficient predictor for the user's latest preferences. Lian et al. (2014) exploited matrix factorization to incorporate users activity area and POIs influence area and used the spatial clustering of users and POIs. Liu et al. (2015) used a geographical probabilistic factor model for POI recommendation. Liu et al. (2016) exploited the user interests and their evolving sequential preferences with temporal interval assessment. Hu et al. (2014) exploited the impact of geographical neighborhood of a place on its rating. Wang et al. (2017) used the visual correlation between the places and the images posted by users. A recent study from Stepan et al. (2016) incorporated the spatial, temporal and the social aspect in their recommendation model.

We can see that most of the existing studies are focused on the check-in frequency and only few of them have exploited additional factors. Though the study from Stepan et al. (2016) looks more relevant to our work, two of the major differences make our study more interesting. First, we incorporate the location category but they did not. Second, we analyze the roles of major aspects by combining different aspects in different fused models but their model analyzed the role of one aspect at a time and only fused the aspects in the final model. Our paper attempts to fill this gap via detailed analysis of impact of different factors (for instance, (i) what might be the impact of using social and temporal factors instead of spatial and temporal factors?, (ii) does the social factor contribute more than categorical factor?, (iii) can we get better results by having more factors?, and so on). To the best of our knowledge, none of the existing recommendation models spanned to incorporate all the major aspects. The exploitation of roles of different aspects and their incorporation into a single model is the novelty of our paper. We present ranking-based and matrix factorization-based fused models in this paper.

3 Ranking-based approach

In this section, we present ranking-based models that fuse the categorical, social, spatial, and temporal aspects.

1. *Single aspect*: (i) check-in frequency (F)— While it might be possible to get several single aspect models, we mainly focus on the check-in frequency because it is the basic criteria to be used for the prediction. The other aspects mainly act like a supplement to this aspect.
2. *Two aspects*: These models use check-in frequency along with some other aspects. The following models are defined in this paper: (i) check-in frequency and temporal (check-in time) (FT), (ii) check-in frequency and social (friends) (FS), (iii) check-in frequency and location category (FC), (iv) check-in frequency and spatial(location distance) (FD).

3. *Three aspects*: We combine three aspects to define following models: (i) the check-in frequency, social, and temporal (FST), (ii) the check-in frequency, categorical, and temporal (FCT), (iii) the check-in frequency, spatial, and temporal (FDT), (iv) the check-in frequency, categorical, and social (FCS), (v) the check-in frequency, spatial, and social (FDS), (vi) the check-in frequency, categorical, and spatial (FCD).
4. *Four aspects*: We define the following models: (i) check-in frequency, categorical, social, and temporal (FCST), (ii) check-in frequency, spatial, social, and temporal (FDST), (iii) check-in frequency, categorical, spatial, and temporal (FCDT), and (iv) check-in frequency, categorical, spatial, and social (FCDS).
5. *Five aspects*: (FCDST) It fuses the check-in frequency, categorical, spatial, social, and temporal aspects.

All of the models proposed in this section are based on the Topic-Sensitive PageRank (Haveliwala 2002) which can introduce some bias to the PageRank (Page et al. 1999) vector. The Topic-Sensitive PageRank (Haveliwala 2002) is a state-of-art ranking method for large graphs. It can incorporate the set of influential or representative (*or additional context relevant attributes*) topics to address the importance of particular topics. For a given context, it can identify the most closely associated (contextual) topics and such relevant topic-sensitive (biased) vectors can be used to rank the documents satisfying the query. It is a good fit for our problem because we can realize the users, locations, check-in relation, and social relation as a graph and use the additional factors of LBSN to achieve the personalized ranking of user and place nodes. Similar to the web graph, we can assure the convergence of ranking of user-location graph by adding the damping factor $(1-\alpha)$ to the rank propagation. This can improve the quality of PageRank not only by limiting the effect of the rank sinks (Brin et al. 1998), but also by assuring the convergence to a unique rank vector (Haveliwala 2002).

We define 16 different recommendation models. The terms used in this paper are defined in Table 1.

3.1 Single aspect

In this model, the check-in frequency of a location is solely used to define the popularity of a location. The rank of a location is then defined using the following relation:

$$\Pi^f(l) = \alpha\beta^f(l) + (1-\alpha)\sum_{\substack{l'\in L\\ l'\neq l}} \Pi^f(l'), \quad \text{and} \quad \beta^f(l) = \frac{\sum\limits_{u\in U} \mid V_u(l) \mid}{\sum\limits_{\substack{u\in U\\ p\in L}} \mid V_u(p) \mid}. \tag{1}$$

where the term $\beta^f(l)$ is the check-in frequency personalization. The highly ranked locations can be recommended to the users. This approach will always recommend the same set of locations to all the users because the rank of a location is only dependent on the frequency of check-ins across all the users. A better approach would be to personalize the recommendation by using similarity of the target location to the locations already visited by the user. The likelihood of a user u to visit a location l

Table 1 Definition of terms used in the paper

Terms	Definition
U	The users in the dataset
L	The locations in the dataset
u_L	Locations visited by the user u
u_f	The friends of the user u
l_U	Visitors to the location l
$l.cat$	Category of the location l
$V_u(l)$	Visit counts of user u to the location l
$V_{u,t_1,t_2}(l)$	Visit counts of user u to the location l, within the time interval t_1, t_2
$dist(l_1, l_2)$	Distance between locations l_1 and l_2
$\Pi^{\mathbf{a}}(l)$	Rank of location l using the aspect **a**
$\Pi^{\mathbf{a}}_{t_1,t_2}(l)$	Rank of location l in the time range t_1, t_2 using the aspect **a**
$\beta_{t_1,t_2}(l)$	Topic sensitive factor of location l in the time range t_1, t_2
$\beta_{a,b}(l)$	Topic sensitive factor of location l using the aspects a and b
$P(u, l, t_1, t_2)$	Likelihood of checkin by user u to location l in the time range t_1, t_2
K_i^a	Constant parameters using aspect a
ψ_+^+	Weight factor estimated by TF-IDF
α	The damping factor
ϵ	The threshold distance

can be then defined as: $P_{u,l}^f = \Pi^f(l) * \psi_f^l$. The term ψ_f^l (defined later) is the weight factor which can be estimated using TF-IDF (Salton and Buckley 1988; Wu et al. 2008). This model favors the locations with common visitors and assigns a non-zero, positive similarity value only to places with common visitors. So, in this case, the likelihood of visiting a location will depend only on its rank. Though the common visitors count might be used to measure the similarity between places, the places with common spatial, temporal, or categorical trend cannot be addressed with this model.

3.2 Two aspects

1. *Categorical (FC)*: This approach ameliorates the recommendation model by incorporating the location category. The rank of a location can be defined using the following relation:

$$\Pi^c(l) = \alpha\beta^c(l) + (1-\alpha) \sum_{l' \in L, l' \neq l, l.cat = l'.cat} \Pi^c(l'), \quad \text{and}$$

$$\beta^c(l) = K_1^c * \frac{\sum_{u \in U} \mid V_u(l) \mid}{\sum_{\substack{l.cat = l'.cat \\ u \in U}} \mid V_u(l') \mid}$$

$$+ K_2^c * \frac{\sum\limits_{\substack{l.cat=l'.cat \\ u\in U}} \mid V_u(l') \mid}{\sum\limits_{\substack{u\in U \\ p\in L}} \mid V_u(p) \mid}. \tag{2}$$

where $\beta^c(l)$ is the categorical personalization, $K_1^c \in [0, 1]$ and $K_2^c \in [0, 1]$ are constants. The likelihood of a user (u) to visit a location (l) is then defined as: $P_{u,l}^c = \Pi^c(l) * \psi_c^l$, where ψ_c^l is estimated using TF-IDF.

2. *Temporal (FT)*: Any two locations that have same check-in hour (or within a threshold time interval) can be more likely similar than the ones having check-in time beyond the threshold. The rank of a location can then be defined using the following relation:

$$\Pi^t(l) = \alpha\beta^t(l) + (1-\alpha) \sum_{l\in L, l'\neq l, l.t=l'.t} \Pi^t(l'), \quad \text{and}$$

$$\beta^t(l) = K_1^t * \frac{\sum\limits_{u\in U} \mid V_{u,t}(l) \mid}{\sum\limits_{\substack{u\in U \\ l'\in L}} \mid V_{u,t}(l') \mid} + K_2^t * \frac{\sum\limits_{\substack{u\in U \\ l'\in L}} \mid V_{u,t}(l') \mid}{\sum\limits_{\substack{u\in U \\ p\in L}} \mid V_u(p) \mid}. \tag{3}$$

where $\beta^t(l)$ is the temporal personalization. The likelihood of check-in for user u, in location l, at time t is then defined as: $P_{u,l}^t = \Pi^t(l) * \psi_t^l$.

3. *Spatial (FD)*: This model is influenced by Tobler's Law (1970) ("everything is related to everything else, but near things are more related than the distant things"). Using this concept, we take into account the distance aspect and define the rank of a location as:

$$\Pi^d(l) = \alpha\beta^d(l) + (1-\alpha) \sum_{l'\in L, l'\neq l, dist(l,l')\leq\epsilon} \Pi^d(l'), \quad \text{and}$$

$$\beta^d(l) = K_1^d * \frac{\sum\limits_{u\in U} \mid V_u(l) \mid}{\sum\limits_{\substack{\text{dist(l,l')}\leq\epsilon \\ u\in U}} \mid V_u(l') \mid} + K_2^d * \frac{\sum\limits_{\substack{\text{dist(l,l')}\leq\epsilon \\ u\in U}} \mid V_u(l') \mid}{\sum\limits_{\substack{u\in U \\ p\in L}} \mid V_u(p) \mid}. \tag{4}$$

where the term $\beta^d(l)$ is the spatial personalization, $K_1^d \in [0, 1]$ and $K_2^d \in [0, 1]$ are constants. The likelihood of a user u to visit a location l is then defined as: $P_{u,l}^d = \Pi^d(l) * \psi_d^l$.

4. *Social (FS)*: Generally, the social networks define the social-tie between users (for instance, friends, followers, and so forth). Using this concept, we formulate the impact of social relation as:

$$\Pi^s(l) = \alpha\beta^s(l) + (1-\alpha) \sum_{u\in l_U, u'\in u_f, l'\in u'_L} \Pi^s(l'), \quad \text{and}$$

$$\beta^{s}(l) = \sum_{u \in U}\left(K_1^{s} * \left(\frac{\sum\limits_{u' \in u_f} \mid V_{u'}(l) \mid}{\sum\limits_{\substack{u' \in u_f \\ l' \in L}} \mid V_{u'}(l') \mid} \right) + K_2^{s} * \left(\frac{\sum\limits_{\substack{u' \in u_f \\ l' \in L}} \mid V_{u'}(l') \mid}{\sum\limits_{\substack{u \in U \\ p \in L}} \mid V_u(p) \mid} \right)\right). \quad (5)$$

where $\beta^{s}(l)$ is the social personalization, $K_1^{s} \in [0, 1]$ and $K_2^{s} \in [0, 1]$ are constants. In this model, the popularity of a location is computed by taking into account the fraction of check-in counts it gets among the check-in counts in the friend circle. The likelihood of a user u to visit a location l is then defined as: $P_{u,l}^{s} = \Pi^{s}(l) * \psi_{s}^{l}$.

3.3 Three aspects

1. *Categoric-Temporal (FCT):* We define the categoric-temporal ranking as:

$$\Pi_{t_1,t_2}^{c}(l) = \alpha * \beta_{t_1,t_2}(l) + (1-\alpha) * \sum_{l' \in L, l' \neq l, l'.cat = l.cat} \Pi_{t_1,t_2}^{c}(l'),$$

$$\beta_{t_1,t_2}(l) = K_1^{ct} * \frac{\sum\limits_{u \in U} \mid V_{u,t_1,t_2}(l) \mid}{\sum\limits_{\substack{l.cat = l'.cat \\ u \in U}} \mid V_{u,t_1,t_2}(l') \mid} + K_2^{ct} * \frac{\sum\limits_{\substack{l.cat = l'.cat \\ u \in U}} \mid V_{u,t_1,t_2}(l') \mid}{\sum\limits_{p \in L, u \in U} \mid V_{u,t_1,t_2}(p) \mid}. \quad (6)$$

   where $\beta_{t_1,t_2}(l)$ is the categoric sensitive factor. The likelihood of a user (u) to visit a location (l) is then defined as: $P_{u,l}^{ct} = \Pi_{t_1,t_2}^{c}(l) * \psi_{ct}^{l}$.
2. *Socio-Temporal (FST)*: This model can be defined by substituting the categorical constraint with social constraint in the Categoric-Temporal (FCT) model.
3. *Spatio-Temporal (FDT)*: This model can be defined by substituting the categorical constraint with the spatial constraint in the Categoric-Temporal (FCT) model.
4. *Categorical-Spatial (FCD)*: This model uses the categorical and spatial factors to rank the locations as:

$$\Pi_{c}^{d}(l) = \alpha * \beta_{cd}(l) + (1-\alpha) * \sum_{l' \in L, l' \neq l, dist(l', l) \leq \epsilon, l'.cat = l.cat} \Pi_{c}^{d}(l'), \quad \text{and}$$

$$\beta_{cd}(l) = K_1^{cd} * \frac{\sum\limits_{u \in U} \mid V_u(l) \mid}{\sum\limits_{\substack{u \in U \\ dist(l,l') \leq \epsilon \\ l.cat = l'.cat}} \mid V_u(l') \mid} + K_2^{cd} * \frac{\sum\limits_{\substack{u \in U \\ dist(l,l') \leq \epsilon \\ l.cat = l'.cat}} \mid V_u(l') \mid}{\sum\limits_{p \in L, u \in U} \mid V_u(p) \mid}. \quad (7)$$

where $\beta_{cd}(l)$ is the categoric-distance sensitive factor, K_1^{cd}, and K_2^{cd} are constant tuning factors. The likelihood of a user to visit a location is then defined as: $P_{u,l}^{cd} = \Pi_{c}^{d}(l) * \psi_{cd}^{l}$.

5. *Spatio-Social (FDS)*: The ranking of a location in terms of spatial and social factors is defined as:

$$\Pi_s^d(l) = \alpha * \beta_{sd}(l) + (1-\alpha) * \sum_{l' \in L, dist(l',l) \leq \epsilon, u' \in l_U, l' \in u'_{f_L}} \Pi_s^d(l'), \quad \text{and}$$

$$\beta_{sd}(l) = \sum_{u \in U} \left(K_1^{sd} * \frac{\sum\limits_{u' \in u_f} | V_{u'}(l) |}{\sum\limits_{\substack{u' \in u_f \\ dist(l,l') \leq \epsilon}} | V_{u'}(l') |} + K_2^{sd} * \frac{\sum\limits_{\substack{dist(l,l') \leq \epsilon \\ u' \in u_f}} | V_{u'}(l') |}{\sum\limits_{\substack{p \in L \\ u' \in u_f}} | V_u(p) |} \right). \tag{8}$$

where $\beta_{sd}(l)$ is the spatio-social sensitive factor, K_1^{sd}, and K_2^{sd} are constant tuning factors. The likelihood of a user to visit a location is then defined as: $P_{u,l}^{sd} = \Pi_s^d(l) * \psi_{ds}^l$.
6. *Categorical-Social (FCS)*: This model can be defined by substituting the spatial constraint with categorical constraint in the definition of Spatio-Social (FDS) model.

3.4 Four aspects

These recommendation models have three other aspects along with the check-in frequency.

1. *Categoric-Spatial-Temporal (FCDT)*: In this model, the categorical, spatial, and temporal aspects are incorporated into a single recommendation model. The rank of a location can then be defined as:

$$\Pi_{t_1,t_2}^{cd}(l) = \alpha * \beta_{cdt}(l) + (1-\alpha) * \sum_{dist(l',l) \leq \epsilon, l'.cat = l.cat} \Pi_{t_1,t_2}^{cs}(l'),$$

$$\beta_{cdt}(l) = K_{cdt}^1 * \frac{\sum\limits_{u \in U} | V_{u,t_1,t_2}(l) |}{\sum\limits_{\substack{l.cat = l'.cat \\ dist(l,l') \leq \epsilon \\ u \in U}} | V_{u,t_1,t_2}(l') |} + K_{cdt}^2 * \frac{\sum\limits_{\substack{l.cat = l'.cat \\ dist(l,l') \leq \epsilon \\ u \in U}} | V_{u,t_1,t_2}(l') |}{\sum\limits_{p \in L, u \in U} | V_{u,t_1,t_2}(p) |}, \tag{9}$$

where $\beta_{cdt}(l)$ is the categoric-spatial-temporal sensitive factor, K_{cdt}^1 and K_{cdt}^2 are constant tuning factors. The likelihood of a user to visit a location is then defined as: $P_{u,l}^{cdt} = \Pi_{t_1,t_2}^{cd}(l) * \psi_{cdt}^l$.
2. *Categoric-Spatial-Social (FCDS)*: In this model, the categorical, spatial, and social aspects are incorporated into a single recommendation model. The rank of a location can then be defined as:

$$\Pi_d^{cs}(l) = \alpha * \beta_{cds}(l) + (1-\alpha) * \sum_{dist(l',l) \leq \epsilon, l'.cat = l.cat, u \in l_U, l' \in u_{f_L}} \Pi_d^{cs}(l'),$$

$$\beta_{cds}(l) = \sum_{u\in U}\left(K_1^{cds} * \frac{\sum\limits_{u'\in u_f} | V_{u'}(l) |}{\sum\limits_{\substack{l.cat=l'.cat\\ dist(l,l')\le\epsilon\\ u'\in u_f\\ l'\in L}} | V_{u'}(l') |} + K_2^{cds} * \frac{\sum\limits_{\substack{l.cat=l'.cat\\ dist(l,l')\le\epsilon\\ u'\in u_f\\ l'\in L}} | V_{u'}(l') |}{\sum\limits_{\substack{p\in L\\ u\in U}} | V_u(p) |} \right). \quad (10)$$

where $\beta_{cds}(l)$ is the categoric-spatial-social sensitive factor, K_1^{cds} and K_2^{cds} are constant tuning factors.

3. *Categoric-Social-Temporal (FCST)*: In this model, the categorical, social, and temporal aspects are incorporated into a single recommendation model. The rank of a location can then be defined as:

$$\Pi_{t_1,t_2}^{cs}(l) = \alpha * \beta_{cst}(l) + (1-\alpha) * \sum_{l'.cat=l.cat, u\in l_U, l'\in u_{f_L}, l'\in L} \Pi_{t_1,t_2}^{cs}(l'),$$

$$\beta_{cst}(l) = \sum_{u\in U}\left(K_1^{cst} * \frac{\sum\limits_{u'\in u_f} | V_{u',t_1,t_2}(l) |}{\sum\limits_{\substack{l.cat=l'.cat\\ u'\in u_f}} | V_{u',t_1,t_2}(l') |} + K_2^{cst} * \frac{\sum\limits_{\substack{l.cat=l'.cat\\ u'\in u_f}} | V_{u',t_1,t_2}(l') |}{\sum\limits_{\substack{p\in L\\ u\in U}} | V_{u,t_1,t_2}(p) |} \right). \quad (11)$$

where $\beta_{cst}(l)$ is the categoric-social-temporal sensitive factor, K_1^{cst} and K_2^{cst} are constant tuning factors, and $t_1 \le t \le t_2$. The likelihood of a user to visit a location is then defined as: $P_{u,l}^{cst} = \Pi_{t_1,t_2}^{cs}(l) * \psi_{cst}^{l}$.

4. *Spatial-Social-Temporal (FDST)*: This model can be defined by substituting the categorical constraint with spatial constraint in the definition of Categoric-Social-Temporal (FCST) model.

3.5 Five aspects

In this model (FCDST), all the major aspects (e.g., categorical, social, spatial, and temporal) along with the check-in frequency are incorporated into a single model. The categorical sensitive ranking is defined as:

$$\Pi_{t_1,t_2}^{c}(l) = \alpha * \beta_{t_1,t_2}(l) + (1-\alpha) * \sum_{l'.cat=l.cat, l'\in L, l'\neq l} \Pi_{t_1,t_2}^{c}(l'),$$

$$\beta_{t_1,t_2}(l) = K_1^{c} * \frac{\sum\limits_{u\in U} | V_{u,t_1,t_2}(l) |}{\sum\limits_{\substack{l.cat=l'.cat\\ u\in U}} | V_{u,t_1,t_2}(l') |} + K_2^{c} * \frac{\sum\limits_{\substack{l.cat=l'.cat\\ u\in U}} | V_{u,t_1,t_2}(l') |}{\sum\limits_{\substack{p\in L\\ u\in U}} | V_{u,t_1,t_2}(p) |}. \quad (12)$$

where $\beta_{t_1,t_2}(l)$ is the categoric sensitive factor, K_1^{c}, and K_2^{c} are constant tuning factors.

Similarly, the distance sensitive rank of a location is defined using the following relation:

$$\Pi^d_{t_1,t_2}(l) = \alpha * \theta_{t_1,t_2}(l) + (1-\alpha) * \sum_{\substack{dist(l',l)\le\epsilon \\ l'\in L \\ l'\neq l}} \Pi^d_{t_1,t_2}(l'),$$

$$\theta_{t_1,t_2}(l) = K^d_1 * \frac{\sum_{u\in U} | V_{u,t_1,t_2}(l) |}{\sum_{\substack{dist(l,l')\le\epsilon \\ u\in U}} | V_{u,t_1,t_2}(l') |} + K^d_2 * \frac{\sum_{\substack{dist(l,l')\le\epsilon \\ u\in U}} | V_{u,t_1,t_2}(l') |}{\sum_{\substack{p\in L \\ u\in U}} | V_{u,t_1,t_2}(p) |}. \tag{13}$$

where $\theta_{t_1,t_2}(l)$ is the distance sensitive factor, K^d_1, and K^d_2 are constant tuning factors. The unified rank is the fusion of the two ranks and is defined as:

$$\Pi_{t_1,t_2}(l) = \xi_1 * \Pi^c_{t_1,t_2}(l) + \xi_2 * \Pi^d_{t_1,t_2}(l). \tag{14}$$

where ξ_1, ξ_2 are tuning parameters for the two aspects. The likelihood of the check-in for the user i at the location l within the time frame t_1,t_2 is defined as:

$$\begin{aligned} P(u,l,t_1,t_2) = &\Pi_{t_1,t_2}(l) * \Bigg(\psi_d * \sum_{\substack{l'\in L, \\ dist(l,l')\le\epsilon}} | V_{u,t_1,t_2}(l') | + \psi_c * \sum_{\substack{l'\in L, \\ l.cat=l'.cat}} | V_{u,t_1,t_2}(l') | \\ &+ \psi_s * \sum_{(u',u)\in friend} | V_{u',t_1,t_2}(l) | \Bigg). \end{aligned} \tag{15}$$

where the terms ψ_* are estimated using TF-IDF.

Parameters estimation: The parameters used in the likelihood relations are defined using TF-IDF (Salton and Buckley 1988; Wu et al. 2008) for each user. For a user u, $\psi_d = \frac{n_d}{n}.\log(1+\frac{N}{N_d})$, where n_d is the number of visits by user u that are within the threshold distance ϵ, and N_d is the number of POIs that are within the threshold distance ϵ from the user's check-in history, n is the total visits made by user u, and N is the number of POIs. For the categorical factor, we use the relation: $\psi_c = \frac{n_c}{n}.\log(1+\frac{N}{N_c})$, where n_c is the number of visits by user u to category c, and N_c is the number of POIs with the category c. Similarly, $\psi_s = \frac{n_s}{n}.\log(1+\frac{N}{N_s})$, where n_s is the number of visits by a user u in common to her friends, and N_s is the number of visits in common to the friends for all the users $u \in U$. The other parameters are defined accordingly.

4 Matrix factorization-based approach

After demonstrating its effectiveness in the Netflix Prize competition,[4] the Matrix Factorization (Koren et al. 2009) technique has been widely renowned in recommendation domain. The basic factorization model attempts to predict the user-item rating by mapping the original rating matrix into low dimensional latent factor matrices. Given r_{ui} as the rating of a user u to the item i, the basic idea is to approximate the rating by using the lower order latent user matrix **p** and latent item matrix **q** which can be realized as: $\hat{r}_{ui} = q_i^T.p_u$. Basically, the entries at q_i represent the extent to which the item i possesses these factors, and the entries at p_u represent the extent of preference of user u on the items that are high on these factors. The main intuition is to minimize the following objective function by regularizing the above relation as:

$$\min_{q,p} \sum_{(u,i)\in k} \left(r_{ui} - q_i^T p_u\right)^2 + \lambda \left(|| q_i ||^2 + || p_u ||^2\right). \tag{16}$$

where k is the number of user-item pairs whose rating is known in the training set, and λ is a regularization constant. For the POI domain, the check-in frequency can be taken as an implicit rating. Inspired from Koren et al. (2009), we extend the above relation to incorporate additional factors as mentioned below:

$$\hat{r}_{ui}(t) = \mu + b_i(t) + b_u(t) + q_i^T \left[p_u(t) + \sum_{a\in A(u)} y_a + \sum_{l\in u_L} x_l \right], \tag{17}$$

where $\hat{r}_{ui}(t)$ is the estimated rating of a user u to the item i at time t, μ is the global average rating of all places, $b_i(t)$ is the location bias at time t (the difference of rating of location i to the average rating μ of all locations for the visits made at time t), $b_u(t)$ is the user bias, $A(u)$ is the set of user attributes, and x_l represent the factors of locations visited by the user. For user attributes, we use the vector $<r_{cat_1}, r_{cat_2}, \ldots, r_{cat_k}, r_{soc}, r_{dist}>$, where for a user u, $r_{cat_1} = \frac{\sum_{l.cat=cat_1} V_u(l)}{\sum_{l'\in u_L} V_u(l)}$ is the ratio of total check-ins made to the places with category cat_1 to that of total check-ins made on all places, $r_{soc} = \frac{\sum_{l\in u_{f_L}} V_u(l)}{\sum_{l'\in u_L} V_u(l')}$ is the ratio of total check-ins made on the places visited due to social influence to that of total check-ins on all places, and $r_{dist} = \frac{\sum_{dist(l)\le\epsilon} V_u(l)}{\sum_{l'\in u_L} V_u(l')}$ is the ratio of total check-ins on the places within a threshold distance ϵ (from users home or work place) to that of total check-ins on all places. Similarly, we use the vector $<r_{cat}, r_{soc}, r_{dist}>$ for places, where r_{cat} is the ratio of number of check-ins made to this place to that of check-ins made to places with the same category, r_{dist} is the ratio

[4] http://www.netflixprize.com/.

Table 2 Statistics of the dataset

Dataset	Check-ins	Users	Locations	Links	Location categories
Gowalla	36,001,959	319,063	2,844,076	337,545	629
Weeplace	7,658,368	15,799	971,309	59,970	96

of number of check-ins made to this place to that of check-ins made in its nearby places, and r_{soc} is the fraction of check-ins due to social influence of the visitors of this place. Furthermore, these attributes can be time constrained by accounting only the check-ins within a time interval.

5 Evaluation

This section defines the dataset, analysis of the aspects, and the performance of different models. We evaluated the ranking-based models as defined earlier, Non-negative Matrix Factorization (simple) that just used the check-in frequency, Non-negative Matrix Factorization (fused) that incorporated additional factors (see Eq. 17), and three relevant models (Ye et al. 2011; Jin et al. 2012; Wang et al. 2013). For Matrix Factorization, the check-in count of every user to a place was normalized in the range (0,10), the non-negative singular value decomposition (Boutsidis and Gallopoulos 2008) was used for initialization, and up to 5000 iterations were observed. The hour of a day was used to analyze the temporal trend.

5.1 Dataset

The Weeplaces and the Gowalla datasets were collected from the popular LBSNs—Gowalla and the Weeplaces (Liu et al. 2013b). We found that the datasets were well-defined and also had all the attributes (the location category, geo-spatial coordinates, friendship information, and the check-in time) relevant to our model. The incomplete records were eliminated in the analysis and evaluation. The Gowalla dataset had records from November 2010 to June 1, 2011, and had only 7 main location categories, so we used the well defined subcategories instead. The statistics of the datasets is defined in Table 2.

5.1.1 Impact of distance to the check-ins

For every user, the check-ins were chronologically sorted and the distance between consecutive check-ins of each user was computed. The likelihood of a user to check-in at a particular distance (for convenience, the distance was arbitrarily rounded to four decimals) was estimated by her visit history. The inverse relation of check-in trend to the distance of POI in Weeplaces dataset[5] is illustrated in Fig. 1b. We can see that

[5] Though the trend on Gowalla dataset is not shown, it also had similar trend.

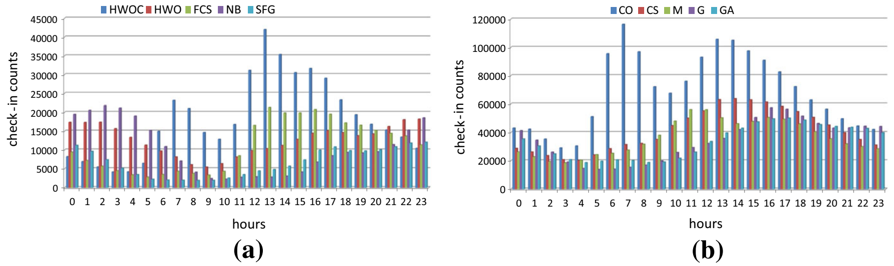


Fig. 2 Distribution of categorical check-ins with hours for top-5 categories in Weeplace (**a**) and Gowalla (**b**) datasets. HWOC = Home/Work/Other: Corporate/Office, HWO = Home/Work/Other: Home, FCS = Food: coffee: Shop, NB = Nightlife: Bar, SFG = Shops: Food & Drink: Grocery/Supermarket, CO = Corporate Office, CS = Coffee Shop, M = Mall, G = Grocery, G&A = Gas & Automotive

most of the users' check-ins are centralized within some distance (the dense patches within 0.5 km indicate that most of the users' had the check-ins to the near places). The figure also shows that the willingness of check-in decreases with the increasing distance of the location.

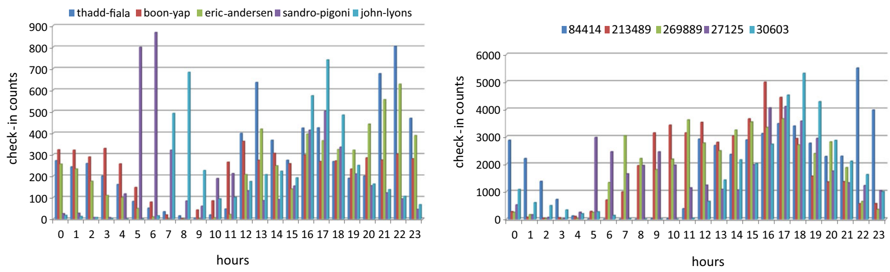
5.1.2 Distribution of check-ins based on location category and check-in time

The top-10 visited location categories (and their check-in counts) for Weeplace were: (i) Home/Work/Other: Corporate/Office (437,730), (ii) Home/Work/Other:Home (306,105), (iii) Food:Coffee Shop (267,572), (iv) Nightlife:Bar (248,563), (v) Shops:Food&Drink:Grocery Supermarket (160,913), (vi) Travel:Train Station (152,104), (vii) Food:Cafe (129,205), (viii) Travel:Subway (107,879), (ix) Food: American (100,174), and (x) Travel:Airport (98,183). Similarly, for Gowalla, we had: (i) Corporate Office(1,660,159), (ii) Coffee Shop (988,999), (iii) Mall (872,873), (iv) Grocery (820,326), (v) Gas&Automotive (806,916), (vi) Apartment (753,547), (vii) Asian (735,453), (viii) Train Station (680,612), (ix) Other—Food (665,229), and (x) American (634,031).

The *work* or *home* related category (Home/Work/Other: Corporate/Office) was popular from 6 am to 6 pm, with the highest check-ins (42,019) made at 1 pm. Similarly, the **bars** had highest of 21,806 check-ins at 2 am and the lowest check-ins (15,209) at 5 am. Most of the check-ins were made between 12 pm–6 pm and were in either **Home** or **Work** related categories. Figure 2 illustrates the hourly distribution of top-5 categories.

5.1.3 Distribution of check-ins based on place

The top 10 places (and check-in counts) for Weeplace dataset were: (1) jr (13,769), (2) seoul (10,973), (3) san-francisco-international- airport-sfo-san-franci (10,658), (4) starbucks -new-york (10,329), (5) new-york-penn-station-new-york (7809), (6) los-angeles-international- airport-lax-los-angeles (5859), (7) grand-central-terminal-new-york (5668), (8) john-f-kennedy-international-airport-jfk-queens (5360), (9) whole-



(a) **(b)**

Fig. 3 Distribution of check-ins of top-5 users with time. **a** Weeplace dataset. **b** Gowalla dataset

foods-new-york (4562), and (10) station-utrecht-centraal-utrecht (4227). Similarly the top 10 places (and check-in counts) for Gowalla[6] dataset were: (1) 55033 (28,414), (2) 19542 (19,996), (3) 66171 (19,186), (4) 9410 (18,542), (5) 58725 (18,457), (6) 23519 (18,136), (7) 10259 (17,397), (8) 9246 (15,909), (9) 155746 (15,640), and (10) 10190 (14,127).

5.1.4 Distribution of check-ins based on user

The check-in count of top 10 users in Weeplace dataset were: (1) thadd-fiala (6517), (2) boon-yap (5573), (3) eric-andersen (5394), (4) sandro-pigoni (5055), (5) john-lyons (4963), (6) bob-boles (4560), (7) hillary-lannan (4342), (8) nate-folkert (4289), (9) jason-allen (4279), and (10) rue (4237). Similarly, for the Gowalla dataset, the top 10 users were: 1) 84414 (45,375), (2) 213489 (44,960), (3) 269889 (44,726), (4) 27125 (41,017), (5) 30603 (33,851), (6)9298 (32,791), (7) 114774 (32,347), (8) 5153 (29,075), (9) 76390 (28,636), and (10) 28509 (28,194). The hourly check-in distribution of top-5 visitors is illustrated in Fig. 3.[7]

5.1.5 Distribution of check-ins based on hour of a day

The hourly distribution of check-in counts are listed in Table 3.

5.2 Experimental results

We used a 5-fold cross validation and considered top N (5, 10, 15 and 20) recommendation scores to compute the precision ($P = \frac{|\text{true positive}|}{|\text{true positive}|+|\text{false positive}|}$), recall ($R = \frac{|\text{true positive}|}{|\text{true positive}|+|\text{false negative}|}$), and F-score (2*P*R/(P+R)) metrics. Though the goal of this paper is just to exploit the role of different aspects and not to compare the ranking based models with matrix factorization based models, we still illustrate the

[6] The Gowalla place id is numeric.

[7] The Gowalla user id is numeric.

Table 3 Distribution of check-ins count by hour of a day for D_1 = Weeplaces and D_2 = Gowalla dataset

Hours	00	01	02	03	04	05	06	07
D_1	396,066	353,423	316,200	274,667	224,824	199,217	206,555	210,419
D_2	1,593,460	1,404,780	1,178,790	981,032	870,534	896,153	932,948	941,970
Hours	08	09	10	11	12	13	14	15
D_1	185,940	170,621	196,994	240,939	305,864	332,520	328,622	362,591
D_2	887,360	925,178	1,116,408	1,294,830	1,445,426	1,569,247	1,691,046	1,886,372
Hours	16	17	18	19	20	21	22	23
D_1	448,212	469,033	428,219	404,414	380,106	378,907	416,496	430,522
D_2	2,143,873	2,260,887	2,153,428	1,971,677	1,808,640	1,691,609	1,677,072	1,682,730

Table 4 Average performance of fused models in Weeplaces and Gowalla dataset

Models	Weeplace			Gowalla		
	Precision	Recall	F-Score	Precision	Recall	F-Score
F	0.067110	0.001175	0.002308	0.099857	0.001523	0.003000
FC	0.003000	0.002140	0.002498	0.006370	0.001970	0.003009
FS	0.064100	0.001900	*0.003690*	0.100708	0.004261	*0.008176*
FT	0.026957	0.001804	0.003381	0.032011	0.002529	0.004687
FD	0.035578	0.001100	0.002134	0.047063	0.001446	0.002806
FCT	0.050933	0.000993	0.001948	0.061397	0.001591	0.003102
FDT	0.091116	0.008065	*0.014818*	0.102230	0.009005	*0.016552*
FCD	0.046334	0.001258	0.002449	0.048900	0.002438	0.004644
FCS	0.079333	0.001683	0.003297	0.083138	0.003764	0.007202
FDS	0.078166	0.002966	0.005716	0.078144	0.003884	0.007401
FST	0.066260	0.007533	0.013528	0.078210	0.007611	0.013872
FCST	0.094066	0.007700	0.014234	0.107462	0.008802	0.016271
FDST	0.090636	0.006667	0.012420	0.124064	0.010270	0.018970
FCDT	0.094166	0.008556	0.015687	0.129663	0.021236	*0.036495*
FCDS	0.094166	0.008566	*0.015704*	0.106753	0.009580	0.017582
FCDST	0.297690	0.010390	*0.020080*	0.354013	0.031066	*0.057120*
Ye et al. (2011)	0.024170	0.000950	0.001834	0.030000	0.001200	0.002307
Jin et al. (2012)	0.084969	0.000639	0.001268	0.409000	0.003000	0.005956
Wang et al. (2013)	0.018180	0.000520	0.001010	0.106000	0.002000	0.003925
Matrix factorization (simple)	0.012747	0.044715	0.019838	0.014614	0.042218	0.021712
Matrix factorization (fused)	0.330390	0.021793	**0.040888***	0.392227	0.038130	**0.069503***

Bold and italic values indicate outperforming model among the relevant counterparts
* indicates statistically significant

performance of these models in this section. The average performance of different models is illustrated in Table 4. The average metrics across the top@N recommendations are illustrated in Tables 5 and 6.

5.2.1 Experimental setup

We used Python 2.7,[8] Pandas 0.19.1,[9] and Networkx 2.0[10] in a 24 core 2.40 GHz Intel(R) Xeon(R) CPU E5-2430L v2 CPU, 32 GB RAM, and a Scientific Linux release 6.5 (Carbon) for development and evaluation.

8 https://www.python.org.

9 http://www.pandas.pydata.org.

10 https://www.networkx.github.io.

Table 5 Precision@N, Recall@N of different models in Weeplace dataset

F	**FC**	**FS**	**FT**	**FD**
Precision@N	*Precision@N*	*Precision@N*	*Precision@N*	*Precision@N*
@5= 0.100573	@5= 0.002380	@5= 0.044900	@5= 0.029053	@5= 0.025729
@10= 0.055769	@10= 0.002441	@10= 0.041400	@10= 0.029693	@10= 0.030010
@15= 0.044989	@15= 0.004200	@15= 0.106000	@15= 0.022126	@15= 0.051000
Recall@N	*Recall@N*	*Recall@N*	*Recall@N*	*Recall@N*
@5= 0.002856	@5= 0.001790	@5= 0.001400	@5= 0.001052	@5= 0.000890
@10= 0.000304	@10= 0.001635	@10= 0.002000	@10= 0.002170	@10= 0.000982
@15= 0.000364	@15= 0.003000	@15= 0.002300	@15= 0.002190	@15= 0.001340
FCT	**FDT**	**FCD**	**FCS**	**FDS**
Precision@N	*Precision@N*	*Precision@N*	*Precision@N*	*Precision@N*
@5= 0.042800	@5= 0.090850	@5= 0.037000	@5= 0.077000	@5= 0.067500
@10= 0.045000	@10= 0.091100	@10= 0.045000	@10= 0.079000	@10= 0.079000
@15= 0.065000	@15= 0.091400	@15= 0.057000	@15= 0.082000	@15= 0.088000
Recall@N	*Recall@N*	*Recall@N*	*Recall@N*	*Recall@N*
@5= 0.000840	@5= 0.007990	@5= 0.000824	@5= 0.001700	@5= 0.001500
@10= 0.000860	@10= 0.008100	@10= 0.000950	@10= 0.001100	@10= 0.003500
@15= 0.001279	@15= 0.008106	@15= 0.002000	@15= 0.002251	@15= 0.003900
FST	**FCST**	**FDST**	**FCDT**	**FCDS**
Precision@N	*Precision@N*	*Precision@N*	*Precision@N*	*Precision@N*
@5= 0.052100	@5= 0.091200	@5= 0.090330	@5= 0.091100	@5= 0.091100
@10= 0.067790	@10= 0.094000	@10= 0.090700	@10= 0.093500	@10= 0.093500
@15= 0.078880	@15= 0.097000	@15= 0.090880	@15= 0.097900	@15= 0.097900
Recall@N	*Recall@N*	*Recall@N*	*Recall@N*	*Recall@N*
@5= 0.005910	@5= 0.007600	@5= 0.006560	@5= 0.008210	@5= 0.008227
@10= 0.007990	@10= 0.007600	@10= 0.006660	@10= 0.008490	@10= 0.008493
@15= 0.008700	@15= 0.007900	@15= 0.006760	@15= 0.008970	@15= 0.008980
FCDST	Ye et al. (2011)	Jin et al. (2012)	Wang et al. (2013)	Matrix factorization (fused)
Precision@N	*Precision@N*	*Precision@N*	*Precision@N*	*Precision@N*
@5= 0.244000	@5= 0.030300	@5= 0.085300	@5= 0.0449	@5= 0.291260
@10= 0.305000	@10= 0.023020	@10= 0.084800	@10= 0.0414	@10= 0.31995
@15= 0.336000	@15= 0.019180	@15= 0.409000	@15= 0.1060	@15= 0.375890
Recall@N	*Recall@N*	*Recall@N*	*Recall@N*	*Recall@N*
@5= 0.004500	@5= 0.000800	@5= 0.000610	@5= 0.0014	@5= 0.019793
@10= 0.009200	@10= 0.000900	@10= 0.000610	@10= 0.0020	@10= 0.021992
@15= 0.031000	@15= 0.001160	@15= 0.003000	@15= 0.0022	@15= 0.022651

Table 6 Precision@N, Recall@N of different models in Gowalla dataset

F	**FC**	**FS**	**FT**	**FD**
Precision@N	*Precision@N*	*Precision@N*	*Precision@N*	*Precision@N*
@5= 0.176573	@5= 0.004897	@5= 0.044595	@5= 0.029820	@5= 0.037864
@10= 0.057000	@10= 0.005972	@10= 0.05771	@10= 0.031877	@10= 0.038882
@15= 0.066000	@15= 0.008231	@15= 0.19982	@15= 0.034337	@15= 0.064443
Recall@N	*Recall@N*	*Recall@N*	*Recall@N*	*Recall@N*
@5= 0.003721	@5= 0.000993	@5= 0.003542	@5= 0.001577	@5= 0.000721
@10= 0.000462	@10= 0.001940	@10= 0.003820	@10= 0.002878	@10= 0.000858
@15= 0.000387	@15= 0.002970	@15= 0.005422	@15= 0.003133	@15= 0.00276
FCT	**FDT**	**FCD**	**FCS**	**FDS**
Precision@N	*Precision@N*	*Precision@N*	*Precision@N*	*Precision@N*
@5= 0.041983	@5= 0.081100	@5= 0.04470	@5= 0.069971	@5= 0.063310
@10= 0.05121	@10= 0.09335	@10= 0.045000	@10= 0.088221	@10= 0.081130
@15= 0.091000	@15= 0.13224	@15= 0.057000	@15= 0.091223	@15= 0.089993
Recall@N	*Recall@N*	*Recall@N*	*Recall@N*	*Recall@N*
@5= 0.000899	@5= 0.006998	@5= 0.001556	@5= 0.003349	@5= 0.002331
@10= 0.001776	@10= 0.007763	@10= 0.0019823	@10= 0.003622	@10= 0.004112
@15= 0.002100	@15= 0.012254	@15= 0.003776	@15= 0.004322	@15= 0.005211
FST	**FCST**	**FDST**	**FCDT**	**FCDS**
Precision@N	*Precision@N*	*Precision@N*	*Precision@N*	*Precision@N*
@5= 0.070000	@5= 0.093117	@5= 0.098883	@5= 0.083621	@5= 0.086640
@10= 0.075510	@10= 0.113750	@10= 0.110020	@10= 0.11713	@10= 0.099910
@15= 0.089110	@15= 0.115520	@15= 0.163290	@15= 0.18824	@15= 0.133710
Recall@N	*Recall@N*	*Recall@N*	*Recall@N*	*Recall@N*
@5= 0.007100	@5= 0.008001	@5= 0.009921	@5= 0.008114	@5= 0.007763
@10= 0.007137	@10= 0.008773	@10= 0.009631	@10= 0.013361	@10= 0.009977
@15= 0.008598	@15= 0.009633	@15= 0.011260	@15= 0.042235	@15= 0.011001
FCDST	Ye et al. (2011)	Jin et al. (2012)	Wang et al. (2013)	Matrix factorization (fused)
Precision@N	*Precision@N*	*Precision@N*	*Precision@N*	*Precision@N*
@5= 0.199120	@5= 0.029000	@5= 0.403000	@5= 0.091000	@5= 0.339992
@10= 0.34181	@10= 0.029000	@10= 0.405000	@10= 0.109100	@10= 0.399227
@15= 0.521000	@15= 0.033000	@15= 0.419000	@15= 0.117900	@15= 0.435961
Recall@N	*Recall@N*	*Recall@N*	*Recall@N*	*Recall@N*
@5= 0.030000	@5= 0.001277	@5= 0.002900	@5= 0.001970	@5= 0.032054
@10= 0.03101	@10= 0.001190	@10= 0.003000	@10= 0.001900	@10= 0.037000
@15= 0.031992	@15= 0.001198	@15= 0.003100	@15= 0.002200	@15= 0.045000

5.2.2 Parameter analysis

We observed that the greater value of α resulted in slow convergence, had more impact from the inbound links, and had more evenly distributed impact to the nodes on outgoing links. This means the places with more visitors could be impacted with the higher value of α. We used $\alpha = 0.85$ which is a standard value for most graphs. The convergence was detected when the rank scores of the nodes were not changing anymore. The distance threshold ϵ was set to 1 km, which was simply based on the observation of the spatial check-in pattern of the users. For each model, the tuning parameters were selected from random trials conducted with three set of parameters ((0.25:0.75), (0.5:0.5), and (0.75:0.25)). The categorical module performed best when K_1^c was 0.75. This implies the higher importance of the categorical popularity of a place than that of the popularity of the category. In other words, though the categorical factor can be influential, places with same category might have different popularity. For instance, one coffee shop might dominate the coffee business of a community. The spatial module performed best when K_1^d was 0.75. This implies the popularity of a location in its locality is of higher importance than the popularity of the whole locality itself. In other words, all places within a community may not have similar popularity. The five aspect model performed best when ξ_1 was 0.25. The weights for other modules were selected accordingly. The observed difference was statistically significant at 95% confidence level.

5.2.3 Discussion

- We compared the performance of different models using the Precision, Recall, and F-Score metrics. From the evaluation (see Tables 4, 5 and 6), we observed that the fused models performed better than just the simple check-in frequency-based model. We can see that the quality of recommendation not only relied on the number of aspects fused, but also on the importance of the aspects fused.
- The **frequency**-based model had good precision in both datasets but the recall was quite low. This is because it relied on the common visitors to the locations. Besides the common visitors, other aspects also play a major role in the check-in behavior. As this model ignored those aspects, it had many false negatives.
- The **categorical** model could not do as expected. This might be due to the avoidance of the spatial aspect. Though places are of same category, the farther location would be less likely to be visited. The **spatial** model also could not perform well. The evaluation shows that the combination of categorical and social or the categorical and spatial gives better result.
- The **social** model was found to be best among the models with two aspects. It's performance was better in Gowalla dataset because it is bigger and has lots of friendship relation.
- It is better to select the **social** or **temporal** model if an additional aspect beyond check-in frequency is to be incorporated.
- The combination of the **spatial and temporal** (FDT) aspects was found to be the outperforming among the counterparts. The combination of **categorical and**

social aspects (FCS) were found to be better than the combination of **categorical and the spatial** (FCD) aspects.
- The combination of **categorical and the temporal** aspect (FCT) performed worse than the combination of the **social and the temporal** aspect (FST).
- Based on the evaluation, we can see that it is better to select the **spatio-temporal** (DT) model if we need to incorporate just two aspects. Though the *categoric-spatio-social* (CDS) slightly outperformed the *categoric-spatio-temporal* (CDT) in Weeplace dataset, the case was opposite with Gowalla dataset. It is better to select the **categoric-spatio-temporal** (CDT) or *categoric-spatio-social* (CDS) model if we need to incorporate just three aspects. The inconsistent performance of FDST among two datasets also indicates that the social relation may not always be a reliable factor for recommendation. This can also be due to the noisy social links (people with non-matching preferences being in a social tie).
- The category aspect only works as a good supplement to the other models (FCD performs better than FD, FCST performs better than FST, FCDS performs better than FDS, and FCDST performs better than FDST) but is not a sole contributor for the good result. So, if we have to opt out an aspect, then the category aspect could be the right choice.
- The FCDST model not only outperformed all of our ranking-based fused models, but also outperformed the relevant fused models proposed in other studies. It also bet the normal matrix factorization-based model (with five latent factors). This is because we had rating matrices of $\sim 98.5\%$ sparsity. FCDST model incorporated more aspects than all of those fused models. This implies that an efficient fusion of the major aspects can improve the recommendation quality.
- The performance of simple matrix factorization-based model was better when more latent factors were used (we found the model with latent factor 5 performed better than the models with latent factor of 2, and 3). The performance improvement was not that significant with more than 5 factors. The matrix factorization-based fused model (see Eq. 16) performed better with the increasing latent factors (performance with 5 latent factors was better than 2, and 3 latent factors) and also slightly outperformed the FCDST model.
- The single aspect model has better execution time because of the simple graph and rank formulation. The FCDST model's better result costs the execution time because unlike other models, it needs to separately compute the spatial and the categorical based ranking to get the unified rank. The computational cost of matrix factorization-based fused model increased with the number of latent factors.

6 Conclusion and future work

We analyzed the impacts of different aspects (the categorical, spatial, social, and temporal) in POI recommendation. We fused different major aspects to get different recommendation models and analyzed the impact of the major aspects. We also fused all the major aspects into a single recommendation model and demonstrated that it can perform better than other fused models. The analysis of the combination of the aspects and the multi-aspect recommendation model with reasonable performance gain is a novel touch in the relevant area. There are certain limitations of the linearly fused models, for instance, the selected weights of different factors in the linear fusion may be inconsistent across different sets of training, validation, and testing data sets. Inappropriate selection of weights might introduce unnecessary bias in the model. There are many interesting directions to explore, for instance, the analysis of different other factors (for instance, the utility of POI), other datasets, and different other models.

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