GeoTeCS: Exploiting Geographical, Temporal, Categorical and Social aspects for Personalized POI Recommendation

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***Abstract*—The maturity of the smartphone and the World Wide Web (www) technologies have driven many social network applications which have facilitated people to share text and multimedia contents. The social networks that facilitate users to share the check-in (location visit) information are known as the location-based social networks (LBSN)s and provide various information for a recommendation problem that spans beyond the user-location ratings, and comments. For instance, the time of the check-in, the category of the POI, the distance of POI from the user's home, the user's friends' visit to that place, and so forth. It's worthwhile to explore and efficiently integrate such information for the desired purpose. A Point of Interest (POI) recommendation system uses a user's historical check-in information from LBSNs and recommends the list of places that are potential for future visits.**
Many of the existing POI recommendation systems have focused on either of the temporal (time of the check-in), the geographical/spatial (distance between check-in locations), or the social (friendship, and trust based) aspects. Incorporation of all the major aspects (the categorical, the geographical, the social, and the temporal) of check-ins into a single model is barely explored by other studies. In this paper, we propose a fused model termed GeoTeCS (Geographical Temporal Categorical and Social) for personalized location recommendation. GeoTeCS uses the matrix factorization technique to fuse the major check-in aspects into a recommendation model. The contributions of this paper are: (i) it proposes a matrix factorization based location recommender that incorporates all the major aspects -the categorical, the geographical, the social, and the temporal aspects into a single model and (ii) it extensively evaluates the proposed model against two real-world datasets - the Gowalla, and the Weeplaces, to illustrate its effectiveness.

***Keywords*-Information Retrieval; Recommendation system; Matrix Factorization; Point of Interest Recommendation**

I. Introduction

The LBSNs, such as, the Facebook[1], the Foursquare[2], the Gowalla[3], and so forth have facilitated the users to share their check-in behavior accompanied by the multimedia contents. The analysis of such check-in information has been an interest for effective prediction in the location recommendation domain. Though some success has been achieved using the check-in frequency and the generic recommendation approaches, the better results of recent studies have motivated the community towards the incorporation of the major aspects of the check-in behaviors.

The role of multiple aspects makes the POI recommendation domain special than other domains. Unlike the traditional

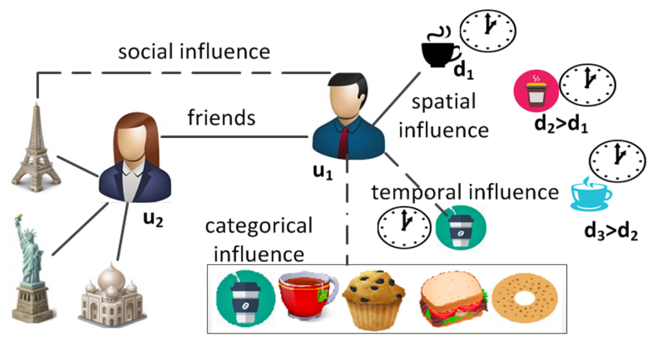

Figure 1: Impact of different aspects in check-in trends

recommendation problems, the visit frequency can vary across different users and places, resulting in the *sparsity* of the *user-location* frequency matrix. The user's affinity towards the nearby locations adds the constraint of the *spatial aspect* in this domain.

Although most of our daily activities are highly influenced by our society, its impact on the check-in trends is not always reliable. For instance, the research [1] has shown that only $\sim$ 96% of people share $<$ 10% of the commonly visited places and $\sim$ 87% of people share nothing at all. This unreliability of check-in information diffusion piles up the challenge for the *social aspect* incorporation. Similarly, the *temporal popularity* (time of the check-in) of a place is also another major aspect. For instance, the bars are more popular in the evenings and the nights. So, relying on just one or two major factors might not be enough for an efficient recommendation.

The Figure-1 illustrates the influence of the categorical, the

[1]https://www.facebook.com
[2]https://www.foursquare.com
[3]https://www.gowalla.com

social, the spatial and the temporal influences in the check-in trend of the users. The figure shows a friendship relation between the users u_1 and u_2. The *social aspect* can influence the user u_1 to visit the places that were already visited (or recommended) by his friend (u_2). The user (u_1) has check-in(s) at the coffee shop at 1 pm. The *temporal aspect* may influence the user to visit the same (or other) coffee shop(s) at the same time (of a day). The *categorical aspect* is reflected if the user visits other places that serve coffee. For instance, most of the shops that serve a breakfast serve the coffee too. The users have preference to the nearest locations [2]. There are many shops that serve coffee in the afternoon, but the user prefers the nearest one (*spatial influence*) (for instance, the shop at distance d_1 is preferred than the farthest ones (at distance d_2, and d_3)).

There are many other relevant factors, such as, (i) the utility of a POI, (ii) the popularity of the POI (due to the social or other impacts), (iii) the trend of visiting new places, and so forth, which can influence the check-in trend. For instance, users might plan to visit popular places regardless of their distance. The utility of a service is defined in terms of preference of attributes of a service. For instance, if a user is a hiking enthusiast, then she may hike places that are far from her house. The trend to visit new places can influence a user to visit places that might be far, might not have been visited by her friends, and might be of different location type than her past visits. An efficient incorporation of all such major aspects can be challenging as well as beneficial for a good POI recommendation system.

Though the POI recommendation problem is a special area, the techniques used in generic recommendation systems have been explored for POI domain too. For instance, many of them are based on the popular concepts such as, the Collaborative Filtering (CF) ([3], [4]), the Content Based Filtering ([5]), and the Hybrid ([6]) approaches. Albeit, the POI recommendation is a well explored topic (temporal ([7], [8], [9], [10], [11]), geographical ([2], [12], [9], [13], [14], [15], [16], [17], [11]), social ([2], [18], [13], [9], [17], [11]), categorical ([12], [16], [19], [20], [17], [11]), sentiment ([6]), popularity ([19], [20])), to our knowledge, the incorporation of all the major aspects (*the categorical, the social, the spatial, and the temporal*) into a single model is not well explored. The main beauty of GeoTeCS is the fusion of all those major aspects into a single efficient recommendation model.

The rest of the paper is organized as follows: the section (II) describes the relevant studies in this area, the section (III) describes the methodology of GeoTeCS, the section (IV) presents the evaluation of the proposed model, and the section (V) concludes the paper.

II. Related Research

A. Simple similarity based approaches

The spatial aspect has been defined in Tobler's First Law of Geography [21], ("everything is related to everything else, but the near things are more related than the distant things"). Based on this, Yuan et al. [7] designed a model with the spatial and the temporal aspect. They used the cosine similarity measure to identify the users' with similar check-in profiles. They defined the recommendation score for a user-location tuple in terms of the aggregate of the visits count on that location over all the users in the dataset. This was further time constrained by considering only the check-ins that were made in the same location and at the same check-in time. They experimentally claimed that the willingness of a user to visit a location has an inverse relation to the distance from the user's current location. Though their evaluation favored their model, their research didn't address the social, and the categorical aspects.

The social and the spatial aspects were fused in the study from Ye et al. [2]. They also used the willingness factor and the weighted cosine similarity measure to compare the user profiles for the recommendation. The categorical and the temporal aspects were not explored in their proposed model.

B. Graph based approaches

The usage of link analysis has been proposed by Jin et al. [8] in their personalized PageRank [22] based model. They realized the LBSN as a graph with the users as the nodes, and the users' following/followers link as the directed edges. The model used the personalized PageRank algorithm to compute the rank of the users with respect to a location and a time range. The personalized factor for the (user, location (p), time $(\mathrm{t}_1 : \mathrm{t}_2)$) tuple was defined as the ratio of the number of check-ins for the tuple to the number of check-ins for the (location (p), time $(\mathrm{t}_1 : \mathrm{t}_2)$) tuple across all the users. They also used similar approach to define the rank of a location within a time range. Though they incorporated the temporal aspect, they left the space for the geographical, categorical and the social aspects.

Wang et al. [9] defined the problem as a graph with the users and the locations as the graph nodes, the friendship relation as the user-user edges, and the user-location relation as the user-location check-in edges. The friendship based similarity was computed by starting from the target user and by ranking all the users (that formed the user-user link). This was followed by the ranking of all the places visited by those users. The locations with the highest rank value and within a given distance from the past visits of the users were recommended. Their model also had no provision for the location category aspect.

C. Matrix Approximation based approaches

Ding et al. [23] explored the user-item recommendation problem using the label information propagation. The label propagation is similar to the random walk [24]. They proposed a learning framework based on the Green's function and applied that to estimate the missing ratings in the user-item rating matrix. In the case of a graph of pairwise similarities, the Green's function can be realized as the inverse of the combinatorial Laplacian. Given the item similarity matrix $\mathbf{W}$, the propagation takes from the labeled data (i.e., items with ratings) to the unlabeled data. The computation of the missing rating was realized as the linear influence propagation. For instance, given the rating from a user as $\mathbf{y}_0^T = (1, 4, ?, ?, ?, 7)$, the estimation of the missing values was made using the influence propagation and was defined as $\mathbf{y} = G\mathbf{y}_0$, where the term G was the Green's function that was obtained from the user-item graph. The rating prediction was then defined as $\mathbf{R}^T = G\mathbf{R}_0^T$, where $\mathbf{R}_0$, is the incomplete user-item rating matrix.

Shao et al. [25] also used the Green's function as the basis for the linear influence propagation to compute the missing values in the user-music preference matrix for their music recommendation system.

Recently, the matrix factorization models have caught considerable attention due to their scalability and accuracy, which was demonstrated in the seminal research from Koren et al. [26]. Generally, such models learn the low-rank representations (also referred as latent factors) of the users and the items from the user-item rating matrix, which are further used to predict new scores between the users and the items. The non-negative matrix factorization (NMF) approach has attracted the attention of many research areas. Li et al. [27] have defined the usage of NMF methods for clustering (for instance, co-clustering, semi-supervised clustering, consensus clustering) and have explained the potential directions of NMF.

Recently, some notable studies in POI recommendation have exploited the fused matrix factorization. Cheng et al. [18] proposed FMMGM (fused matrix factorization with MultiCenter Gaussian model) that used the Multi-center Gaussian model (MGM) to fuse the geographical and the social aspects of POI recommendation. The MGM relied on the following assumptions: (i) the check-in locations usually clutter around several centers, and (ii) the probability of a user's visit to a location is inversely proportional to the distance from its nearest center. The FMMGM adopted the Gaussian distribution to model the users' check-in behavior. The users' check-ins to a location were sorted based on the check-in frequency and then clustered into centers or regions. All other visited locations within a threshold distance from such centers were considered in the model. If the ratio of the total check-ins (by all the users) in such a region to the total check-ins (from all users to all the places) was greater than a threshold, then those check-ins locations were assumed as a valid region. The likelihood of a user visiting a location was then defined in terms of the aggregated normalized check-in frequency in each center and the normalized probability of the location belonging to that center.

Their fusion framework was a combination of the likelihood of a location belonging to a center (region), and the preference of the user (*u*) to that location (*l*). This was defined as: $P_{ul} = P(F_{ul}).P(l \mid C_u)$, where the term $P(F_{ul}) \propto \mathbf{U}_u^T \mathbf{L}_l$ was obtained by using the user topic matrix $\mathbf{U}$ and the location topic matrix $\mathbf{L}$ obtained from the factorization of the *user-location* frequency matrix. Though the experimental results were in favor of the fused social and spatial aspects, the model didn't incorporate the categorical and the temporal aspects.

Lian et al. [15] proposed the GeoMF which used the factorization model along with the spatial clustering with the two-dimensional kernel density estimation. The locations were divided into grids and the influence of the users and the locations on those grids were computed. A user's activity or influence area was determined by the grid locations $l \in L$ where the user had check-ins. The POI influence area was defined in terms of the collection of locations in the grid $l \in L$ to which the influence of this POI could be propagated. The prediction model used the factorized user topic matrix, the location topic matrix, the user activity matrix and the location influence matrix. The fused model was claimed efficient but the impact of the categorical, the temporal and the social aspects remained unexplored.

The GeoMFTD [28] extended the GeoMF [15] to fuse the spatial and the temporal influence but still didn't incorporate other major aspects for the recommendation. For the temporal aspect, on each POI *i*, they computed the average time spent by each user to reach the POI *j* ($j \in g_l$, where g_l is the l^{th} geographical grid/region) from the POI *i*. This was computed for every user who had at least one check-in at POI *i* and another (more recent) check-in at the POI *j* into g_l. The average of such time (t_i^{gl}) for the POI *i* and all the collocated POIs in the grid g_l for each of the users was computed. The temporal aspect was addressed by incorporating the temporal coefficients to the POI influence.

Although this model outperformed the traditional ones, it also didn't incorporate the social and the categorical aspects. Furthermore, we think that the check-in time to a POI is as important and relevant as the time that one spends traveling to that POI or the time that was spent in that particular POI. So, GeoTeCS defines the temporal aspect as the check-in time to a location and uses this as the basis of the temporal popularity of a location.

III. METHODOLOGY

The matrix factorization method is one of the most popular methods in the recommender systems. It characterizes both items and users by vectors of factors inferred from the user-item rating matrix. The high correspondence between the item and the user factors leads to a recommendation. The basic idea is to map both the users and the items to a joint latent factor space of dimensionality *f*, which gives the way to model or define the *user-item* interactions in terms of the inner products in that space. The factor matrices are approximated (for instance by using the gradient descent or by other relevant approaches) to have minimal reconstruction error.

Given the user factor matrix $\mathbf{U}$ $=[\mathbf{u}_1, \mathbf{u}_2 ..., \mathbf{u}_m]$ $\in$ $\mathbb{R}^{lxm}$, and the item factor matrix $\mathbf{V}=$ $[\mathbf{v}_1, \mathbf{v}_2 ...., \mathbf{v}_n]$ $\in \mathbb{R}^{lxn}$, the approximation of the rating matrix $\mathbf{R}$ can be achieved by the multiplication of the low rank factors and can be defined as: $\mathbf{R} \approx \mathbf{U}^T\mathbf{V}$. Due to the sparseness of the rating matrix $\mathbf{R}$, only the observed ratings in the matrix $\mathbf{R}$ can be factorized to define the objective function of the form:

$$\min_{U,V} \frac{1}{2} \sum_{i=1}^{m} \sum_{j=1}^{n} I_{ij} (\mathbf{R}_{ij} - \mathbf{U}_i^T \mathbf{V}_j)^2 \tag{1}$$

where the term $I_{ij} \in [0, 1]$ is an indicator function where $I_{ij} = 1$ only if the user u_i has a rating for the item v_j. The problem of overfitting can be addressed by regularizing Eqn. (1) as:

$$\min_{\mathbf{U}, \mathbf{V}} \frac{1}{2} \sum_{i=1}^{m} \sum_{j=1}^{n} I_{ij} (\mathbf{R}_{ij} - \mathbf{U}_i^T \mathbf{V}_j)^2 + \frac{\lambda_1}{2} \parallel \mathbf{U} \parallel_F^2 + \frac{\lambda_2}{2} \parallel \mathbf{V} \parallel_F^2 \tag{2}$$

where the constants $\lambda_1 > 0, \lambda_2 > 0$ and $\| \,.\, \|_F$ is the Frobenius norm.

According to this concept, each item *i* is associated with a vector $\mathbf{q}_i \in \mathbb{R}^f$ and each user *u* is associated with a vector $\mathbf{p}_u \in \mathbb{R}^f$. The resulting dot product ($\mathbf{q}_i^T . \mathbf{p}_u$) defines the preference of the user *u* to the item *i*. This gives the approximation of the user *u*'s rating on the item *i*, which is denoted by r_{ui}, and the estimate is defined as: $\hat{r}_{ui} = \mathbf{q}_i^T . \mathbf{p}_u$. Often, such model is related to the singular value decomposition (SVD), whose conventional variant is undefined when the knowledge about the matrix is incomplete and is highly prone to over-fitting, if only few known entries are incorporated. Usually, the factor vectors ($\mathbf{p}_\mathrm{u}$ and $\mathbf{q}_\mathrm{i}$) are learned from some objective function by minimizing the regularized squared error on the set of the known ratings. The generic objective function can then be defined as:

$$\min_{\mathbf{q}, \mathbf{p}} \sum_{(u,i) \in k} (r_{ui} - \mathbf{q}_i^T \mathbf{p}_u)^2 + \lambda (\parallel \mathbf{q}_i \parallel^2 + \parallel \mathbf{p}_u \parallel^2) \tag{3}$$

where, k is the set of the user-item (*u,i*) pairs for which the rating/score (r_{ui}) is known and the constant λ is used to control the extent of the regularization.

Terms	**Definition**
$\mathbf{R}$	user-location checkin frequency matrix $\mathbf{R} \in \mathbb{R}^{M \times N}$
$\mathbf{P}$	user's latent matrix, $\mathbf{P} \in \mathbb{R}^{M\mathrm{x}K}$
$\mathbf{Q}$	location's latent matrix $\mathbf{Q} \in \mathbb{R}^{N\mathrm{x}K}$
$\mathbf{A}^T$	the transpose of the matrix $\mathbf{A}$
$\| \,.\, \|_F$	Frobenius norm
g_l	a location grid
F_u	the friends of the user *u*
$r_{u,i}$	rating from user *u* to item *i*
$x_{u,i}^{lt}$	activity/influence of the user *u* in the location *i* at time *t*, given the grid g_l
P_u	the set of locations visited by the user u
P_{ut}	the set of locations visited by the user u at time t
$\mathbb{L}_u$	the POIs P_u mapped to the visited areas on the grids; $\mathbb{L}_u \in \mathbb{L}$
y_i^l	the influence of the location *i* to the grid g_l
y_i^{lt}	the influence of the location *i* to the grid g_l at time *t*
n_u^{lt}	the visit frequency of the user u to the grid g_l at time t
σ	the standard deviation
$K(.)$	the standard normal distribution
$d(l_1, l_2)$	the geographical distance function between the two locations l_1 and l_2
λ	the regularization constant
α, β	tuning parameters

Table I: Terms used in the paper

Many recommendation systems have used the matrix factorization on top of the collaborative filtering because the matrix factorization provides flexibility in terms of bias (for instance, the various data aspects and other application-specific requirements). This facilitates GeoTeCS to incorporate this approach to fuse the major aspects into a single recommendation model.

GeoTeCS is a weighted matrix factorization based model and is inspired from the relevant studies ([15], [26], [28], [29], [30]). The incorporation of major aspects makes our model advanced than the studies from Lian et al. [15] and Griesner et al. [28]. The terms used in this paper are defined in the Table- I. Given a user-location check-in frequency matrix ($\mathbf{R}$) of dimension $M \times N$, it maps the users and the locations into a joint latent space of dimension K $\ll \min(M,N)$ in a way that a user's preference to a location can be defined as the inner product between them in the latent space. The approximation of the frequency matrix can be achieved by solving the following optimization problem:

$$\min_{\mathbf{P},\mathbf{Q}} \parallel \mathbf{R} - \mathbf{P}\mathbf{Q}^T \parallel_F^2 \tag{4}$$

, where the terms $\mathbf{P}$ and $\mathbf{Q}$ are the user and location latent matrices. The generalization error can be reduced by using the following variant of the optimization function:

$$\min_{\mathbf{P},\mathbf{Q}} \parallel \mathbf{W} \odot (\mathbf{R} - \mathbf{P}\mathbf{Q}^T) \parallel_F^2 + \lambda(\parallel \mathbf{P} \parallel_F^2 + \parallel \mathbf{Q} \parallel_F^2) \tag{5}$$

where the Hadamard operator ($\odot$) represents the element wise matrix multiplication and $\mathbf{W}$ is a binary weighted matrix with $w_{ui} \in \{0,1\}$, and is 1 only if there is at least one check-in by the user *u* to the location *i*.

The basic idea behind GeoTeCS is to divide the check-in locations into L grids or regions (g_l such that $\mathbb{L} = \{g_1, g_2, ..., g_L\}$). The division can be done either by using the Haversine Formula (*which gives the great circle distances between two points using their geo-co-ordinates*) or simply by dividing the distance into equal regions (based on the latitude value or based on the density of the check-ins). GeoTeCS realizes the locations as the sequential grids of equal area ensuring each area has location with some check-ins. Along with the two-factor matrices, the users' influence and the POIs' influence are also incorporated into the grids. The user's influence area or activity area is defined as the region/area which depicts high possibility of the appearance of the user. The POI influence area is defined as the popularity of a POI within a grid.

We assume that the influence areas of the POIs have the normal distribution centered at them. The POI influence area is represented by a non-negative vector $\mathbf{y} \in \mathbb{R}_+^L$, where the term y_i^l is the influence of the location *i* to the grid g_l and is defined as:

$$y_i^l = \frac{1}{\sigma} K(\frac{d(i,l)}{\sigma}) \tag{6}$$

where *K(.)* is the standard normal distribution and the term σ is the standard deviation of the distance between the locations in the grid.

There can be some locations with the same category as the location *i* and still not explored in the past. This may not necessarily indicate the negative preference to this location. As already explained in the Figure -1, the locations with the same category might have potential visits. Similarly, if there are some locations in the vicinity that have a check-in time similar to the location *i*, then their temporal popularity might make them potential POIs too. Such temporal and the categorical bias can be incorporated by extending the POI influence relation (of Eqn. (6)) and can be defined as:

$$y_i^{lt} = y_i^l + \frac{1}{\mid g_l \mid} \sum_{l' \in g_l} (\mathcal{C}\alpha * y_i^{l'} + \mathcal{T}\beta * y_i^{l'}) \tag{7}$$

where $\mathcal{C} \in \{1,0\}$ and is 1 only if the two locations (*l, l'*) are of the same category, $\mathcal{T} \in \{1,0\}$ and is 1 only if the check-in time of the two locations are within some threshold ($\triangle T$, we assume the same hour of a day). When none of these is satisfied, we have $y_i^{lt} = y_i^l$ (*only the spatial aspect*). The terms α and β are tuning parameters. This relation defines the integration of the categorical and the temporal aspect in the popularity of a location. The location's influence area can then be defined in terms of a non-negative vector $\mathbf{y} \in \mathbb{R}_+^L$, where the term $y_i^{l,t} \in \mathbf{y}$ is the influence of a location *i* at the time *t*, to the location grid $g_l \in \mathbb{L}$.

Similarly, the activity of a user in a given location can be defined using the location grids. The basic idea is to dissipate the check-in history among the grids and to find the activity of the user in those grids. The estimated density of a user *u* at a POI *i* can be defined as:

$$\frac{1}{\mid P_u \mid \sigma} \sum_{j \in P_u} K(\frac{d(i,j)}{\sigma}) \tag{8}$$

where, P_u is the set of locations visited by the user *u* and the σ is the standard deviation of the distances previously visited by the user.

The user's activity can then be defined in terms of a non-negative vector $\mathbf{x} \in \mathbb{R}_+^L$, where the term $x_{u,i}^{l,t} \in \mathbf{x}$ is the influence of a user *u* to the location *i* at the time *t*, with respect to the locations belonging to the grid/region $g_l \in \mathbb{L}$. As the user's visit is influenced by the social aspect, we integrate the influence of all the friends while computing the influence of a user. The user's activity vector $\mathbf{x}$ can then be defined as:

$$\begin{aligned} x_{u,i}^t &= \frac{1}{\mid P_{ut} \mid} \sum_{l \in \mathbb{L}_u} \frac{n_u^{lt}}{\sigma} K(\frac{d(i,l)}{\sigma}) \\ &+ \sum_{u' \in F_u} \frac{1}{\mid P_{u't} \mid} \sum_{l' \in \mathbb{L}'_u} \frac{n_{u'}^{lt}}{\sigma'} K(\frac{d(i,l')}{\sigma'}) \end{aligned} \tag{9}$$

Using the POI influence area and the user's influence area, the optimization problem can be redefined as:

$$\begin{aligned} \min_{\mathbf{P},\mathbf{Q},\,\mathbf{X}} &\parallel \mathbf{W} \odot (\mathbf{R} - \mathbf{P}\mathbf{Q}^T) - \mathbf{X}\mathbf{Y}^T \parallel_F^2 \\ &+ \lambda(\parallel \mathbf{P} \parallel_F^2 + \parallel \mathbf{Q} \parallel_F^2) + \gamma \parallel \mathbf{X} \parallel_F^2 \end{aligned} \tag{10}$$

The term γ is used to control the sparsity across the user-location-grids. The dimension of $\mathbf{X}$ and $\mathbf{Y}$ matrices is dependent on the number of location grids L $\ll \min(M,N)$, so we have $\mathbf{X} \in \mathbb{R}^{M \times L}$ and $\mathbf{Y} \in \mathbb{R}^{N \times L}$. We have $\mid T \mid$ copies of $\mathbf{X}$ and $\mathbf{Y}$ matrices, where each copy represents one of the time slot $t \in T$.

The preference matrix can then be defined by integrating these factor matrices and can be defined as:

$$\hat{\mathbf{R}} = \mathbf{P}\mathbf{Q}^T + \mathbf{X}\mathbf{Y}^T \tag{11}$$

where $\mathbf{P}$ and $\mathbf{Q}$ are the user topic and the location topic matrices, and $\mathbf{X}$ and $\mathbf{Y}$ are the user's activity and the location

Attributes	Gowalla	Weeplaces
Checkins	36,001,959	7,658,368
Users	319,063	15,799
Locations	2,844,076	971,309
Social links (*undirected*)	337,545	59,970
Location Categories	629	96

Table II: Statistics of the dataset

Gowalla	Weeplaces
Corporate Office (1,750,707)	Home / Work / Other: Corporate / Office (437,824)
Coffee Shop (1,063,961)	Home / Work / Other:Home (306,126)
Mall (958,285)	Food:Coffee Shop (267,589)
Grocery (884,557)	Nightlife:Bar (248,565)
Gas & Automotive (863,199)	Shops:Food & Drink:Grocery Supermarket (161,016)

Table III: Top -5 visited location categories (and their check-ins count)

influence matrices respectively.
Using the factorized matrices **P**, **Q** and the influential matrices **X** and **Y**, the estimated preference of a user u, to the location i at the time t is then defined as:

$$p_{u,i,t} = \mathbf{P}_u \mathbf{Q}_i^T + \mathbf{X}_{u,t} \mathbf{Y}_{i,t}^T \quad (12)$$

IV. Evaluation

A. DataSet

The Weeplaces and the Gowalla dataset [20], which was collected from the popular LBSNs - Gowalla and the Weeplaces was used for evaluation. These datasets are well defined and had all the attributes (the location category, the geo-spatial co-ordinates, the friendship information, and the check-in time) relevant to the model. The incomplete records were eliminated in the evaluation. The statistics of the dataset is defined in the Table -II. The Gowalla dataset had only 7 main location categories, so we used the well defined subcategories instead.
The 5 most checked-in location categories are listed in Table -III. 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 at 12 pm to 6 pm and were in either **Home** or **Work** related categories.

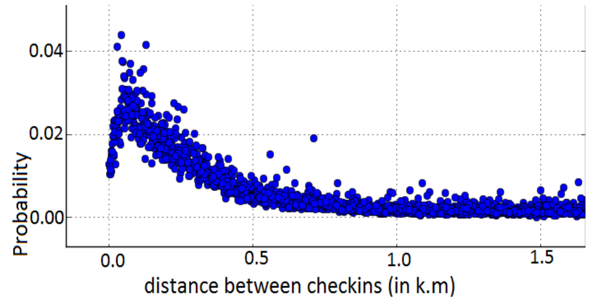

Figure 2: Impact of distance to check-in trend in Weeplaces dataset

Models	Precision	Recall	F-Score
Weeplaces Dataset			
Ye et al. [2]	0.02417	0.00095	0.00183
LBSNRank [8]	0.08496	0.00063	0.00125
Wang et al. [9]	0.01818	0.00052	0.00100
FMFMGM	0.06549	0.00487	0.00906
GeoMFTD	0.09415	0.00676	0.01261
GeoTeCS	0.29800	0.01546	**0.02939***
Gowalla Dataset			
Ye et al. [2]	0.03000	0.00120	0.00230
LBSNRank [8]	0.40900	0.00300	0.00600
Wang et al. [9]	0.10600	0.00200	0.00392
FMFMGM	0.07220	0.00800	0.01440
GeoMFTD	0.09900	0.01570	0.02710
GeoTeCS	0.38477	0.03410	**0.06264***

Table IV: Average Performance of GeoTeCS and other models

We also analyzed the impact of distance on the check-in behavior. 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 particular distance (for convenience, the distance was arbitrarily rounded to four decimals) was estimated by her visit history. The Figure -2 illustrates the inverse relation of check-in trend to the distance of the POI in Weeplaces dataset [4]. We can see that 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 in the near places). The figure shows that the willingness of check-in decreases with the increasing distance of the location.

B. Results

GeoTeCS was evaluated using 5-fold cross-validation. The precision (P), the recall (R) and the F-score (2*P*R/(P+R))) metrics for the top N recommended items (we considered four cases, (i) top 5, (ii) top 10, (iii) top 15, and (iv) top 20 items with the highest recommendation score) were used. The process was repeated with three sets of values for α:β (0.25:0.75, 0.5:0.5, 0.75:0.25). When computing the POI influence region (refer Eqn. (7)), the best

[4]though the trend on Gowalla dataset is not shown, it also had similar trend

Models	Precision@N	Recall@N
Ye et al. [2]	@5= 0.03030 @10= 0.02300 @15= 0.01910	@5= 0.00080 @10= 0.00090 @15= 0.00100
LBSNRank [8]	@5= 0.08530 @10= 0.08480 @15= 0.40900	@5= 0.00060 @10= 0.00060 @15= 0.00300
Wang et al. [9]	@5= 0.04490 @10= 0.04140 @15= 0.04070	@5= 0.00140 @10= 0.00207 @15= 0.00220
FMFMGM	@5= 0.05900 @10= 0.06800 @15= 0.08700	@5= 0.00489 @10= 0.00687 @15= 0.00873
GeoMFTD	@5= 0.07719 @10= 0.08947 @15= 0.11578	@5= 0.00641 @10= 0.00824 @15= 0.00924
GeoTeCS	@5= **0.28400** @10= **0.36500** @15= **0.38800**	@5= **0.00950** @10= **0.00920** @15= **0.02770**

Table V: Precision@N, Recall@N of GeoTeCS against other studies

result was achieved when the categorical factor (α) was set to 0.25 and the temporal factor (β) was set to 0.75. The hourly time slot was used to compare the check-in hours.

We compared the performance of the following fused models: (i) model from Ye et al. [2], (ii) LBSNRank [8] (iii) the model from Wang et al. [9], (iv) FMMGM, (v) GeoMFTD, and (vi) GeoTeCS. The comparative performance of the different models is illustrated in the Table -IV. The comparison of average precision, recall measure across top 5, 10, 15 recommendation scores for Weeplaces dataset is illustrated in Table -V.

From the evaluation, we can see that **GeoTeCS** consistently outperforms the relevant models. Based on this evaluation, we claim that the efficient integration of the major aspects of check-in behavior results in a more accurate recommendation.

V. Conclusion and Future Work

We explored the check-in data based on (a) the geographical/spatial, (b) the categorical, (c) the temporal and (d) the social aspects and applied the fused matrix factorization model for the POI recommendation. The evaluation results illustrate the efficiency of the proposed model against the relevant models. There are many future directions that can be followed from this study. One direction can be the fusion of other aspects in the recommendation model. The another direction can be to use such fused model for the context (for instance weather, traffic status, and so forth) based location and event recommendation. Similarly, the models can be analyzed against different problem domains.

Acknowledgment

The work was supported in part by the National Science Foundation under grants CNS-1126619, IIS-1213026, and CNS-1461926, the U.S. Department of Homeland Securitys VACCINE Center under Award Number 2009-ST-061-CI0001, and a gift award from Huawei Technologies Co. Ltd.

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