gSCorr: Modeling Geo-Social Correlations for New Check-ins on Location-Based Social Networks

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ABSTRACT

Location-based social networks (LBSNs) have attracted an increasing number of users in recent years. The availability of geographical and social information of online LBSNs provides an unprecedented opportunity to study the human movement from their socio-spatial behavior, enabling a variety of location-based services. Previous work on LBSNs reported limited improvements from using the social network information for location prediction; as users can check-in at new places, traditional work on location prediction that relies on mining a user's historical trajectories is not designed for this "cold start" problem of predicting new check-ins. In this paper, we propose to utilize the social network information for solving the "cold start" location prediction problem, with a geo-social correlation model to capture social correlations on LBSNs considering social networks and geographical distance. The experimental results on a real-world LBSN demonstrate that our approach properly models the social correlations of a user's new check-ins by considering various correlation strengths and correlation measures.

Categories and Subject Descriptors

H.2.8 [**Database Management**]: Database Applications - Data mining

General Terms

Algorithm, experimentation

Keywords

Location-Based Social Networks, Location Prediction, Social Correlation

1. INTRODUCTION

Location-based social media have attracted millions of users. A recent survey from the Pew Internet and American Life Project reports that over 28% of Americans use mobile or social location-based services[1]. Typical online location-based social networking sites such as Foursquare[2] and Facebook places[3] provide location-based services for users to "check-in" at a physical place. The "check-in" posts a user's current geographical location, making known to his friends the information on when and where he is. Compared with many other online activities, "check-in" reflects a user's geographical action in the real world, residing where the online world and real world intersect. Thus, the study of check-ins provides an ideal environment to understand human behavior, and could also benefit a variety of location-based services from mobile marketing [2] to disaster relief [6].

In recent years, with the increasingly available information on LBSNs, researchers began to investigate the role of social networks, and hoped to leverage the social network information in explaining a user's check-in behavior [10, 4]. However, recent work on LBSNs has reported a limited role of social information in improving location prediction performance [5, 7, 3]. In search of the reasons why social information has made limited contribution to the performance of location prediction, we notice the problem of "cold start" check-ins. It is reported in previous research that a user's check-in behavior displays a power-law property on LBSNs [7], indicating that users do visit new places, resulting in the "cold start" check-ins. Traditional research predicts a user's next location relying on sufficient numbers of observations of an individual's check-in history [9, 5, 7]; however, it is difficult to apply them to the "cold start" check-ins.

In this paper, we tackle these two challenging yet important problems in LBSNs, i.e., role of social networks and "cold-start" check-in prediction, propose the concept of geo-social correlations, which considers both effects from social networks and geographical distance, and study user's check-in behavior while taking into account "cold-start" check-ins. To the best of our knowledge, this work presents the first study of social correlations for the "cold start" problem on location-based social networks. The contributions of our work are summarized below:

- We investigate the social correlations in geo-social perspective, and observe that users in different geo-social circles have various correlation strength with corresponding most effective correlation measures.

[1]http://pewinternet.org/Reports/2011/Location.aspx
[2]https://foursquare.com
[3]https://www.facebook.com/about/location

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Table 1: Geo-social correlations

	F	$\bar{F}$
$\bar{D}$	$S_{F\bar{D}}$: Local Friends	$S_{\bar{F}\bar{D}}$: Local Non-friends
D	S_{FD}: Distant Friends	$S_{\bar{F}D}$: Distant Non-friends

- We propose a geo-social correlation model (**gSCorr**) to solve the "clod start" location prediction problem by considering four types of geo-social circles with corresponding correlation strength.

2. GEO-SOCIAL CORRELATIONS

When we observe a check-in from a user, there are two scenarios: checking in at a previous visited location, or a new location that the user has never checked in before. In this paper, we define the former one as "existing check-in(s)", and the latter one as "new check-in(s)". As a user's "existing check-in" could be correlated to both of his historical ties and social ties [7], while when a user performs a "new check-in", the effect of this behavior is more likely from his social ties than his historical ties, which indicates the chance to study the correlation between such check-ins and his social networks in a controlled social environment that excludes the effects of users' historical ties, while in turn also provides a feasible perspective of solving the traditional "cold start" location prediction problem. Therefore, we focus on investigating the social correlations with a user's "new check-in" by eliminating the historical tie effect to the largest extent.

Figure 2(a) shows the percentage of "new check-ins" over the total number of observed check-ins in a period of a half year with 11,326 users and 1,171,521 check-ins on Foursquare. The x-axis represents the number of observed check-ins in a chronological order, and the y-axis represents the percentage of "new check-ins". The figure indicates that a user would like to go to a new location when he does not have much check-in history at early time; and then, as time goes by, the user would gradually shift his check-ins from new locations to existing locations.

Social scientists found that geographical distance plays an important role in social connections [8]. Previous work on LBSNs studied the spatial property of social networks, and reported that the probability of having a social connection between two individuals is a function of their distance [10]. Therefore, to study the social correlation of a user's "new check-in" behavior, we divide the social correlations into four sub-correlations, namely geo-social correlations, corresponding to four social circles with respect to the factors of social friendship and geographical distance. The confusing matrix of the four social circles is listed in Table 1, where F indicates observed social friendship, $\bar{F}$ indicates non-friendship, D indicates long geographical distance, and $\bar{D}$ indicates short geographical distance. For example, $S_{F\bar{D}}$ represents a user's social circle consisting of his friends who live close.

We define the four social circles as "**geo-social circles**". In [5], it is reported that the relative influence of a friend who lives 1,000km away is 10 times greater than the influence of a friend who lives 40km away on a user making check-ins. Therefore in this paper, we consider a pair of users within the same state/province as living close with short geographical distance, and a pair of users in different states/provinces as living distant with long geographical distance.

Figure 1 illustrates a user's "new check-in" behavior in different social correlation aspects. User u goes to the airport at t_1, and then the restaurant at t_2 followed by the hospital at t_3. When u performs a "new check-in" at t_4, i.e., the check-in location does not belong to $\{l_1, l_2, l_3\}$, it may be correlated to those users that are from u's different geo-social circles $S_{F\bar{D}}$, S_{FD}, $S_{\bar{F}\bar{D}}$ and $S_{\bar{F}D}$. Investigating these four circles enables us to study a user's check-in behavior in four corresponding aspects: local social correlation, distant social correlation, confounding, and unknown effect.

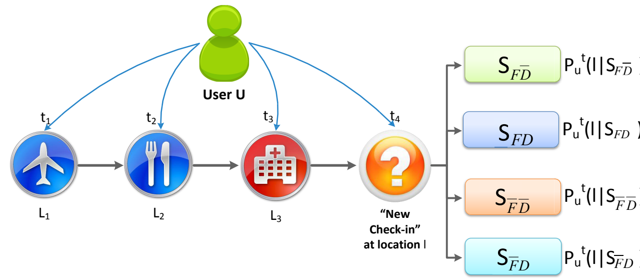


Figure 1: Geo-social correlations of new check-in behavior

3. MODELING GEO-SOCIAL CORRELATIONS

3.1 Problem Formulation

To model the geo-social correlations of "new check-in" behavior, we consider the probability of a user u checking-in at a new location l at time t as $P_u^t(l)$. We define this probability as a combination of the four geo-social correlations,

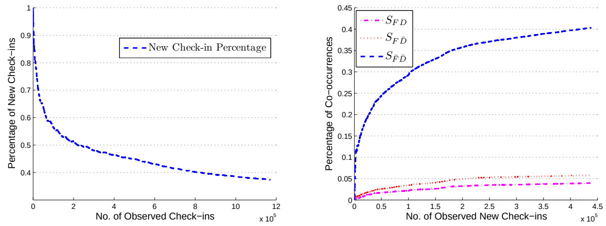
$$P_u^t(l) = \Phi_1 P_u^t(l|S_{\bar{F}\bar{D}}) + \Phi_2 P_u^t(l|S_{F\bar{D}}) + \Phi_3 P_u^t(l|S_{FD}) + \Phi_4 P_u^t(l|S_{\bar{F}D}). \quad (1)$$

where Φ_1, Φ_2 and Φ_3 and Φ_4 are four distributions that govern the strength of different geo-social correlations, $P_u^t(l|S_x)$ indicates the geo-social correlation probability, which is the probability of user u checking-in at location l that is correlated to u's geo-social circle S_x. In the following sections, we will further discuss how to model the geo-social correlation strength and measuring the correlation probabilities.

3.2 Modeling Geo-Social Correlation Strength

To explicitly model the distribution Φ_1, Φ_2, Φ_3 and Φ_4, we investigate the intrinsic patterns of correlations between a user's check-ins and his geo-social circles. We plot the percentage of "new check-ins" that can be found from the different geo-social circles in Figure 2(b). The x-axis represents the number of observed "new check-ins" in a chronological order, and the y-axis represents the percentage of "new check-in" locations that have been checked-in before by users from that specific geo-social circle. The percentage of "new check-ins" from $S_{\bar{F}D}$ is not presented, since it can be deduced from the other three. Note that the geo-social correlations of the four geo-social circles may overlap. For example, a user may visit a new location l where both of his local friends and distant friends have visited before.

Eq. (1) indicates that with probability Φ_1, the current "new check-in" is correlated to $S_{\bar{F}\bar{D}}$. According to the observation in Figure 2(b), the correlation between "new check-ins" and the geo-social circle $S_{\bar{F}\bar{D}}$ (blue line) increases with the increment of the number of observed "new check-ins". It keeps increasing rapidly early on, and then gradually becomes stable. Therefore, we set Φ_1 as an active function to



(a) Ratio of new check-ins. (b) Observed social correlations on new check-ins.

Figure 2: New check-in rate and social correlation on Foursquare data.

Table 2: Check-in and social features

Features	Description
N^c	Number of check-ins in u's history
N^{nc}	Number of new check-ins in u's history
$N_{F\bar{D}}$	Number of friends in $S_{F\bar{D}}$
$N^c_{F\bar{D}}$	Number of check-ins from $S_{F\bar{D}}$
$N^{uc}_{F\bar{D}}$	Number of unique check-ins from $S_{F\bar{D}}$
$N^{vc}_{F\bar{D}}$	Number of visited check-ins from $S_{F\bar{D}}$
$N^{uvc}_{F\bar{D}}$	Number of visited unique check-ins from $S_{F\bar{D}}$
N_{FD}	Number of friends in S_{FD}
N^c_{FD}	Number of check-ins from S_{FD}
N^{uc}_{FD}	Number of unique check-ins from S_{FD}
N^{vc}_{FD}	Number of visited check-ins from S_{FD}
N^{uvc}_{FD}	Number of visited unique check-ins from S_{FD}
$N_{\bar{F}\bar{D}}$	Number of users in $S_{\bar{F}\bar{D}}$
$N^c_{\bar{F}\bar{D}}$	Number of check-ins from $S_{\bar{F}\bar{D}}$
$N^{uc}_{\bar{F}\bar{D}}$	Number of unique check-ins from $S_{\bar{F}\bar{D}}$
$N^{vc}_{\bar{F}\bar{D}}$	Number of visited check-ins from $S_{\bar{F}\bar{D}}$
$N^{uvc}_{\bar{F}\bar{D}}$	Number of visited unique check-ins from $S_{\bar{F}\bar{D}}$

control the social correlation strength from local non-friend users, which considers a set of features capturing u's historical check-in behavior and his different geo-social circles.

$$\Phi_1 = f(\mathbf{w}^T \mathbf{f}_u^t + b),\ 0 \leq \Phi_1 \leq 1, \tag{2}$$

where $\mathbf{f}_u^t$ is a check-in feature vector of a single user u at time t, $\mathbf{w}$ is a vector of the weights of $\mathbf{f}_u^t$, and b controls the bias. In this work, we define a user's check-in and social features $\mathbf{f}_u^t$ in Table 2. Note that $\mathbf{f}_u^t$ is time sensitive, where all the features in $\mathbf{f}_u^t$ are computed at time t.

$f(\bullet)$ is a real-valued and differentiable function that guarantees the range of Φ_1 limited in [0, 1]. In this case, a sigmoid function is often used [1], which can approximately capture the observations about $S_{\bar{F}\bar{D}}$ in Figure 2(b). Similarly, we observe that the social correlations of S_{FD} and $S_{F\bar{D}}$ are fairly constant in Figure 2(b), therefore we define,

$$\begin{aligned}
&\Phi_2 = (1-\Phi_1)\phi_1\\
&\Phi_3 = (1-\Phi_1)(1-\phi_1)\phi_2\\
&\Phi_4 = (1-\Phi_1)(1-\phi_1)(1-\phi_2),
\end{aligned} \tag{3}$$

where $\phi_1 \in [0,1]$, $\phi_2 \in [0,1]$ are two constants to govern the social correlation strength of local friends and distant friends respectively.

Based on above definitions, we can rewrite the probability $P_u^t(l)$ in Eq. (1) as below,

$$\begin{aligned}
&P_u^t(l) = f(\mathbf{w}^T \mathbf{f}_u^t + b) P_u^t(l|S_{\bar{F}\bar{D}})\\
&+ \big(1 - f(\mathbf{w}^T \mathbf{f}_u^t + b)\big)\phi_1 P_u^t(l|S_{F\bar{D}})\\
&+ \big(1 - f(\mathbf{w}^T \mathbf{f}_u^t + b)\big)(1-\phi_1)\phi_2 P_u^t(l|S_{FD})\\
&+ \big(1 - f(\mathbf{w}^T \mathbf{f}_u^t + b)\big)(1-\phi_1)(1-\phi_2) P_u^t(l|S_{\bar{F}D}).
\end{aligned} \tag{4}$$

We define (u, l, t) as a check-in action at location l performed by user u at time t, and learn the parameters $\mathbf{w}$, b, ϕ_1, and ϕ_2 through maximum likelihood over all the (u, l, t) actions in whole dataset. We take the projected gradient method to solve the maximum likelihood problem.

3.3 Measuring Geo-Social Correlation Probabilities

In this section, we discuss the measurement of geo-social correlation probabilities, i.e., $P_u^t(l|S_x)$, representing the probability of user u checking in at location l at time t that is correlated to u's S_x, $S_x = \{S_{FD}, S_{F\bar{D}}, S_{\bar{F}D}, S_{\bar{F}\bar{D}}\}$. We propose 3 geo-social correlation measures to examine the probability $P_u^t(l|S_x)$, considering the factors of location frequency, user frequency and user similarity, as described below,

- **Sim-Location Frequency (S.Lf)**

$$P_u^t(l|\mathcal{S}_x) = \frac{\sum_{v\in\mathcal{S}_x} s(u,v) N_v^t(l)}{\sum_{v\in\mathcal{S}_x} s(u,v) N_v^t}, \tag{5}$$

where $s(u, v)$ represents the user similarity between user u and user v. $N_v^t(l)$ represents the number of check-ins at location l by user v before time t, and N_v^t the total number of locations visited by user v that user u has not visited before time t .

- **Sim-User Frequency (S.Uf)**

$$P_u^t(l|\mathcal{S}_x) = \frac{\sum_{v\in\mathcal{S}_x} \delta_v^t(l) s(u,v)}{\sum_{v\in\mathcal{S}_x} s(u,v)}, \tag{6}$$

where $\delta_v^t(l)$ equals to 1 if user v has check-in in at l before t, and 0 otherwise.

- **Sim-Location Frequency & User Frequency (S.Lf.Uf)**

$$P_u^t(l|\mathcal{S}_x) = \frac{\sum_{v\in\mathcal{S}_x} s(u,v) N_v^t(l)}{\sum_{v\in\mathcal{S}_x} s(u,v) N_v^t} \frac{\sum_{v\in\mathcal{S}_x} \delta_v^t(l)}{N_{\mathcal{S}_x}}, \tag{7}$$

We adopt *S.Lf.Uf*, *S.Lf* and *S.Uf* to compute $P_u^t(l|S_{F\bar{D}})$, $P_u^t(l|S_{FD})$ and $P_u^t(l|S_{\bar{F}\bar{D}})$ respectively, based on our observation of their good performance on corresponding geo-social circles. To reduce time complexity, we consider $P_u^t(l|S_{\bar{F}D})$ as a probability of random jump to a location in current location vocabulary that u has not checked-in before.

4. EXPERIMENTS

In this work, we use location prediction to evaluate our proposed geo-social correlation model (**gSCorr**). In particular, we evaluate the following: (1) How the geo-social correlation strength and measures affect the "new check-in"' behavior; and (2) whether social correlations help "new check-in" prediction. Before we delve into experiment details, we first discuss an LBSN dataset and evaluation metrics.

Table 3: Statistical information of the dataset

duration	Jan 1, 2011-July 31, 2011
No. of users	11,326
No. of check-ins	1,385,223
No. of unique locations	182,968
No. of links	47,164

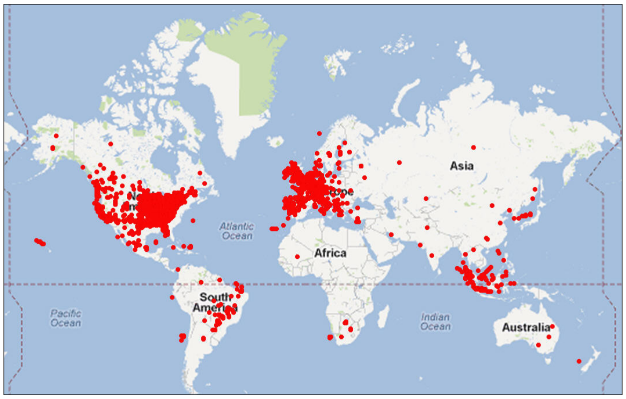


Figure 3: User distribution over the world.

4.1 Data Collection and Experiment Setup

We use Foursquare dataset to study the geo-social correlations of check-in behavior on location-based social networks. Foursquare is one of the most popular online LBSNs. It has more than 20 million users and 2 billion check-ins as of April, 2012[4]. We collected public Foursquare check-in data from January 2011 to July 2011 through Twitter with the same crawling strategy as proposed in [10, 7]. We also collected the user friendships and hometown information through Foursquare.

We use the check-in data ranging from January 1 to June 30 as the **training set** to learn our model parameters, and construct the **testing set** (to discuss later) from the check-in data in July to predict the check-in probability. We select the users who have checked in on both training and testing. The statistics of the final dataset are shown in Table 3. The user distributions w.r.t. the world is given in Figure 3.

Table 4 lists detailed statistical information of the observed "new check-in" distribution in four geo-social circles on the check-in data in July. We define ***"Social Co-occurrence Check-ins" (SCCs)*** as the "new check-ins" whose check-in locations can be found from the user's different social circles before its checking in time. The check-in data in the July contains 213,702 check-ins, with 77,581 "new check-ins" performed at the locations that have never been visited before (the July testing data is a closed set in the sense that it does not consider the historical check-ins before July). Among the 77,581 "new check-ins", around 44.5% SCCs can be found from the $S_{\bar{F}\bar{D}}$, 7.26% from $S_{F\bar{D}}$, 4.62% from S_{FD} and 50.82% from $S_{\bar{F}D}$. Note that there are 2.2% "Others" can not be found from any of the four social circles. We consider this as an unknown effect and merge it into $S_{\bar{F}D}$.

We use location prediction as a prediction task and utilize the prediction accuracy to evaluate our model performance. The user similarities are computed based on the training set by cosine similarity, while each user is represented by a check-in vector, and the entry in the vector indicates the visiting frequency of the user at the location. The **testing set** is selected as the SCCs of $S_{\bar{F}\bar{D}} \cup S_{F\bar{D}} \cup S_{FD}$ listed in Table 4, and the **ground truth** is the corresponding check-in locations. We do not consider $S_{\bar{F}D}$ because from a user's perspective, friends and local non-friends are the ones that are reachable, while the distant non-friend users are too weak in relation for the user to correlate.

[4]https://foursquare.com/about/

Table 4: Statistical information of the July data

Social Circle	No. of SCCs	Ratio
$S_{\bar{F}\bar{D}}$	34,523	44.50%
$S_{F\bar{D}}$	5,636	7.26%
S_{FD}	3,588	4.62%
$S_{\bar{F}D}$	39,423	50.82%
Others	1,672	2.2%
$S_{\bar{F}\bar{D}} \cup S_{F\bar{D}}$	35,277	45.47%
$S_{\bar{F}\bar{D}} \cup S_{FD}$	35,784	46.12%
$S_{F\bar{D}} \cup S_{FD}$	8,235	10.61%
$S_{\bar{F}\bar{D}} \cup S_{F\bar{D}} \cup S_{FD}$	36,486	47.03%

Table 5: Evaluation metrics

	Single Metric	Various Metrics
Equal Strength	EsSm	EsVm
Random Strength	RsSm	RsVm
Various Strength	VsSm	gSCorr

4.2 Effect of Geo-Social Correlation Strength and Measures

To evaluate gSCorr, we consider the effect of both geo-social correlation strength and measures in capturing the user's "new check-in" behavior. Therefore, we set up five baselines to compare the location prediction performance with gSCorr, as shown in Table 5. Each baseline adopts a different combination of correlation strength and measures, where "Es", "Rs", "Vs", "Sm", "Vm" represent "Equal Strength" (set all the geo-social correlation strength as 1), "Random Strength" (randomly assign the geo-social correlation strength), "Various Strength" (the same as gScorr), "Single Measure" (use $S.Lf.Uf$ to measure the correlation probabilities for all the geo-social circles) and "Various Measures" (the same as gScorr) respectively. Note that gSCorr is a various strength and various metrics approach. Following the evaluation metrics of recommendation system, we return top-k locations as prediction, and treat the prediction as correct as long as the ground truth location is among the top-k returned locations. We set $k = 1, 2, 3$ in the experiment. For each random strength approach (RsSm and RsVm), we run 30 times and report the average accuracy.

Table 6 shows the detailed prediction accuracy of each method for further comparison. We summarize the essential observations below:

- The geo-social correlations from different geo-social circles contribute variously to a user's check-in behavior. Both ***VsSm*** and ***gSCorr*** perform better than their equal strength versions (i.e., ***EsSm*** and ***EsSm***), respectively, indicating that the geo-social correlations are not equally weighted.

- The randomly assigned strength approaches (***RsSm*** and ***RsVm***) perform the worst comparing to the other approaches, where the performance of ***VsSm*** has a 10.50% relative improvement over ***RsSm***, and ***gSCorr*** has a 26.11% relative improvement over ***RsVm***, in-

Table 6: Location Prediction with Various Geo-Social Correlation Strength and Metrics

Methods	**Top-1**	**Top-2**	**Top-3**
EwVm	17.88%	24.06%	27.86%
EwSm	16.20%	21.92%	25.43%
VwSm	16.49%	22.28%	25.92%
RwSm	14.93%	20.30%	23.70%
RwVm	15.23%	20.85%	24.50%
gSCorr	**19.21%**	**25.19%**	**28.69%**

dicating that social correlation strength do affect the check-in behavior.

- The single metric approaches (***EsSm***, ***RsSm***, ***VsSm***) always perform worse than the various metrics approaches (***EsVm***, ***RsVm***, ***gSCorr***), which suggests that for different social circles, there are different suitable correlation metrics.

gSCorr performs the best among all the approaches. To demonstrate the significance of its improvement over other baseline methods, we launch a random guess approach to predict the "new check-ins". The prediction accuracy of the random guess is always below 0.005% for top-1 prediction, and below 0.01% for top-2 and top-3 prediction, indicating that gSCorr significantly improves the baseline methods, suggesting the advantage of gSCorr as considering different geo-social correlation strength and metrics for each geo-social circle.

4.3 Effect of Different Geo-Social Circles

To further investigate the contribution of different geo-social circles, we compare the prediction results by utilizing various combinations of geo-social circles, as shown in Table 7. The geo-social correlation metrics are all selected as the best one for the corresponding social circles, and the geo-social correlation strength is learned in the previous section through gSCorr.

The results show that the social correlations of user's direct friendships S_{FD} and $S_{F\bar{D}}$ are significantly lower than the local non-friend users $S_{\bar{F}\bar{D}}$. The latter contributes more than 95% of accurate prediction, which indicates that there is a big overlap of check-in locations between local non-friend users and direct friends. On the other hand, the correlations of S_{FD} and $S_{F\bar{D}}$ do not overlap much, where the combination of them has significant improvement over S_{FD} and $S_{F\bar{D}}$ individually. This is due to the diversity of friends distribution since local friends and distant friends do not share much common geographical environment. Furthermore, the combination of $S_{\bar{F}D} \cup S_{F\bar{D}}$ performs much better than $S_{\bar{F}D} \cup S_{FD}$, indicating that local non-friend users share more common check-in locations with local friends than distant friends. Finally, gSCorr always performs the best among all the combinations of social circles, demonstrating that by taking advantage of both social networks and geographical distance, our approach properly captures the user's "new check-in" behavior on LBSNs, and could be utilized to benefit location-based services such as new location recommendation.

5. CONCLUSIONS AND FUTURE WORK

In this paper, we propose a geo-social correlation model to capture the social correlations of check-in behavior on LBSNs. We investigate the correlations in context of social networks and geographical distance. We observe that social correlations do exist on LBSNs and it can be leveraged to solve the "cold start" problem to a certain extent. We also find the correlation is more relevant to a user's local non-friends than direct social friends. The geographical separation of social relationships in this work is binary, it would be interesting to consider a continuous function of social correlations with the changing of geographical distance. In the future we will continue to study how to take advantage of both social correlations and historical check-ins, and achieve a suitable usage of such information.

Table 7: Location Prediction with Various Social Circle Combinations

Methods	**Top-1**	**Top-2**	**Top-3**
$S_{F\bar{D}}$	6.51%	8.31%	9.32%
S_{FD}	3.65%	4.75%	5.34%
$S_{\bar{F}\bar{D}}$	18.37%	24.10%	27.34%
$S_{\bar{F}\bar{D}} \cup S_{F\bar{D}}$	18.62%	24.44%	27.79%
$S_{\bar{F}\bar{D}} \cup S_{FD}$	19.01%	24.95%	28.35%
$S_{F\bar{D}} \cup S_{FD}$	8.33%	10.79%	12.23%
$S_{\bar{F}\bar{D}} \cup S_{F\bar{D}} \cup S_{FD}$	**19.21%**	**25.19%**	**28.69%**

6. ACKNOWLEDGMENTS

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