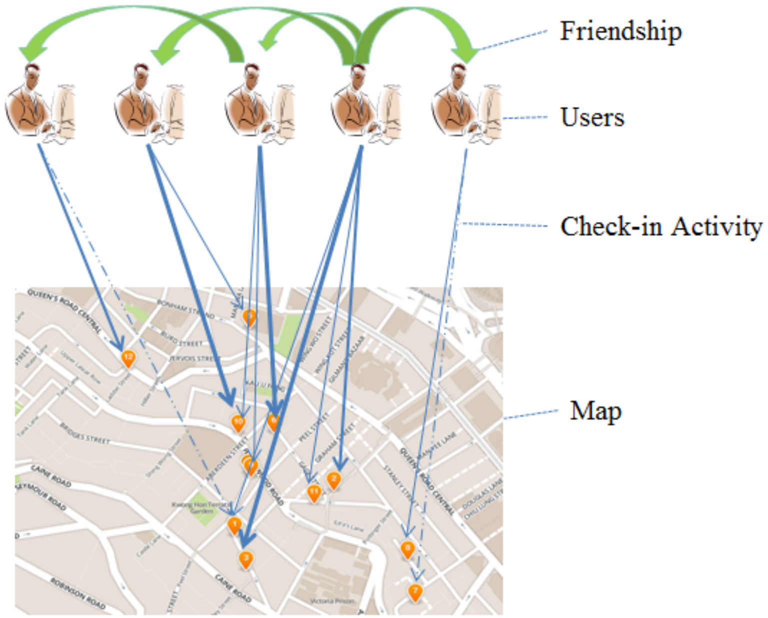
POINT-OF-INTEREST RECOMMENDATION IN LOCATION-BASED SOCIAL NETWORKS

Ludovico Boratto

https://www.ludovicoboratto.com

LOCATION-BASED SOCIAL NETWORKS

- Sharp increase of smart phones led to the massive use of online location-based social networks (LBSNs)
  - E.g., Foursquare, Facebook Places, and Yelp
- LBSNs collect users' check-in information
  - visited locations' geographical information (latitude and longitude)
  - users' tips at the location
- LBSNs also allow users to make friends and share information

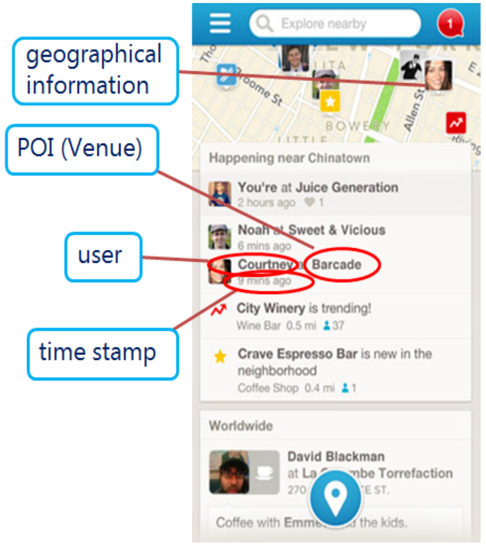


POINT-OF-INTEREST RECOMENDATION

- Point-of-interest (POI) recommendation suggests new places for users to visit
- One of the most important tasks in LBSNs
  - It helps users discover new interesting locations in the LBSNs
- POI recommendation mines:
  - users' check-in records
  - venue information such as categories
  - users' social relationships
- POI recommendation is a branch of recommendation systems
  - It borrows ideas for this task from conventional recommendation systems (e.g., collaborative filtering)

CHALLENGES FOR POI RECOMMENDATION

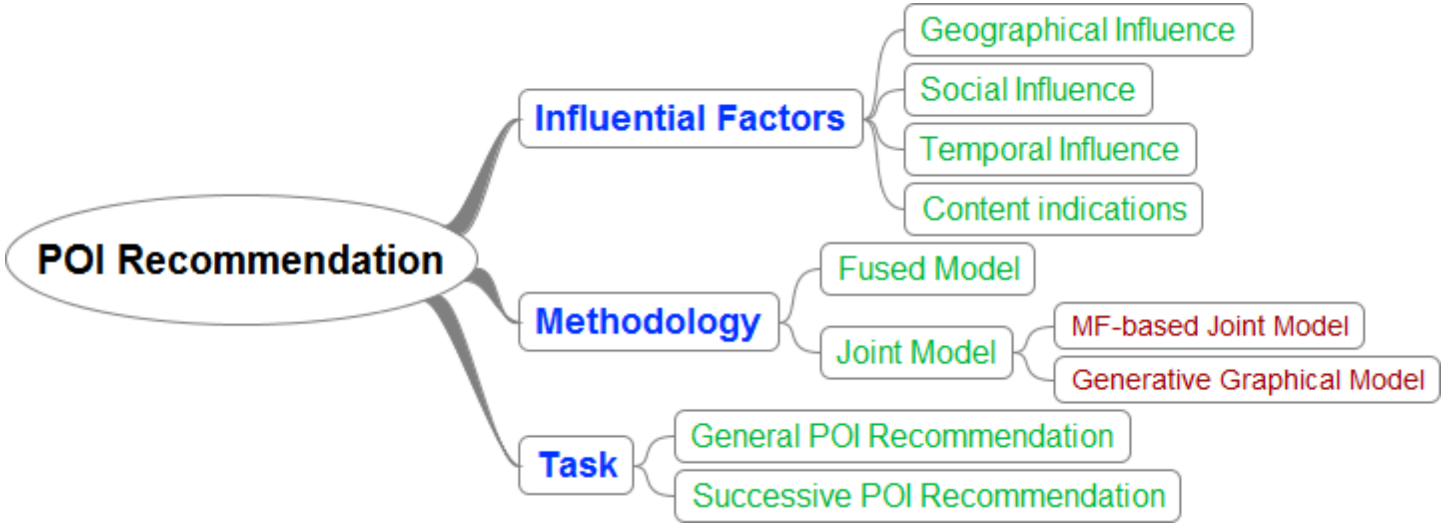
- Physical constraints [2,5,11,12,25,34,39]
  - users in LBSNs check-in at geographically constrained areas (shops open at given times)
  - Physical constraints make the check-in activity in LBSN exhibit significantly spatial and temporal properties
- Complex relations
  - For online social media services such as Twitter and Facebook, location is a new object
  - It creates new relations between locations [41], between users and locations [10,27,37], and between users [28,29]
- Heterogeneous information [19,20,23,26,30,32,31,43,48]
  - LBSNs go beyond check-in records
  - Geographical information of locations
  - Venue descriptions
  - Users' social relation information and media information (e.g., user comments and tweets)



PROBLEM DEFINITION

- **Definition 1 (Check-in)** A check-in is denoted as a triple ⟨u, l, t⟩ that depicts a user u visiting POI l at time t.
- **Definition 2 (Check-in sequence)** A check-in sequence is a set of check-ins of user u, denoted as $S_u = \{\langle l_1, t_1\rangle, \ldots, \langle l_n, t_n\rangle\}$, where t_i is the check-in time stamp. For simplicity, we denote $S_u = \{l_1, \ldots, l_n\}$.
- **Problem 1 (POI recommendation)** Given all users' check-in sequences *S*, POI recommendation aims to recommend a POI list S_N for to each user *u*.

POI RECOMMENDATION



INFLUENTIAL FACTORS

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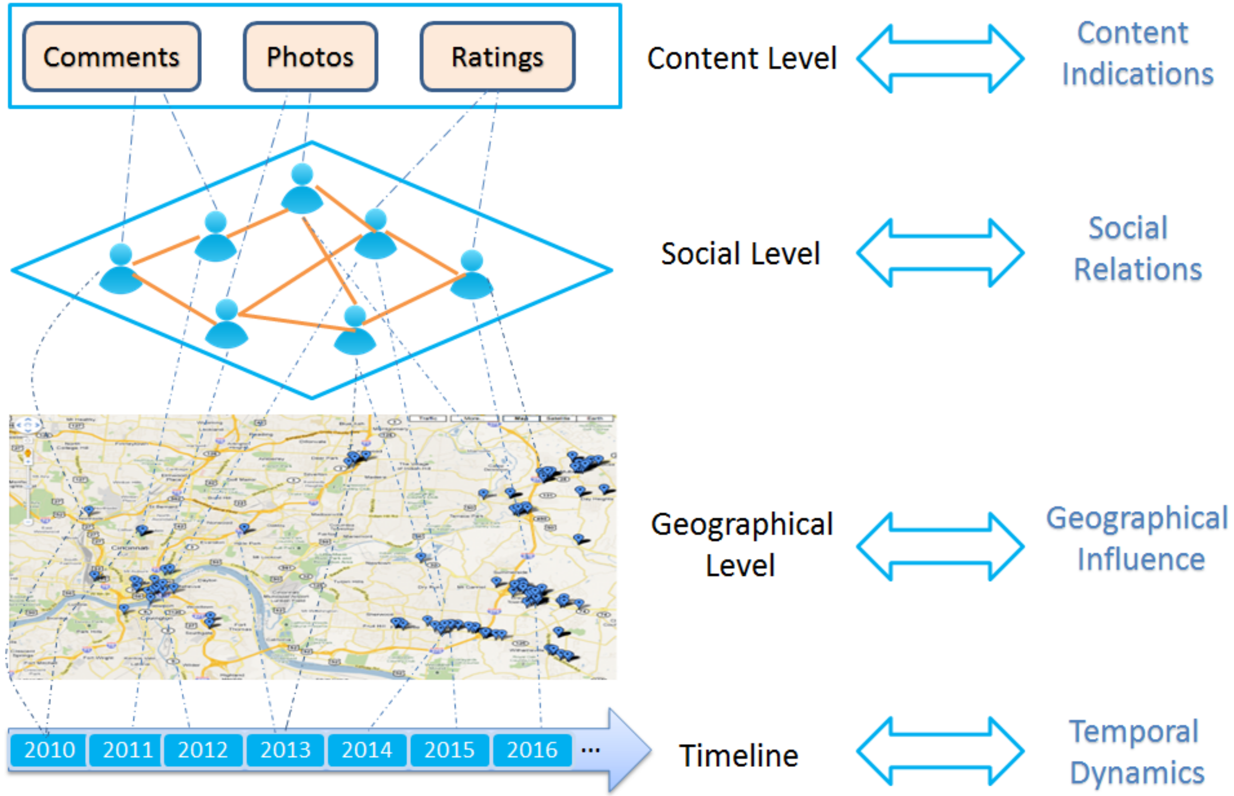
- Check-in activity is a synthesized decision from a variety of factors

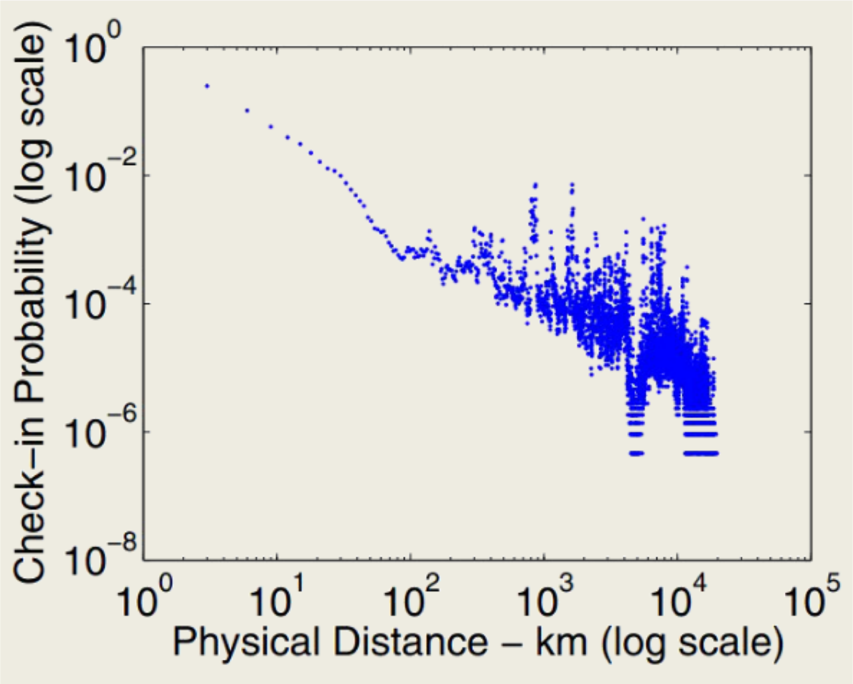


GEOGRAPHICAL INFLUENCE

- It's an important factor that distinguishes the POI recommendation from traditional item recommendation
  - Check-in behavior depends on locations' geographical features
  - A user acts in geographically constrained areas and prefers to visiting POIs nearby those where the user has checked-in
- We can employ the geographical influence to improve POI recommendation systems [3,17,22,36,42,44,45,50]

GEOGRAPHICAL INFLUENCE

- Three main models:
  - Power law distribution [35,36]



GEOGRAPHICAL INFLUENCE

- Three main models:
  - Power law distribution [35,36]
  - Gaussian distribution [3,6]

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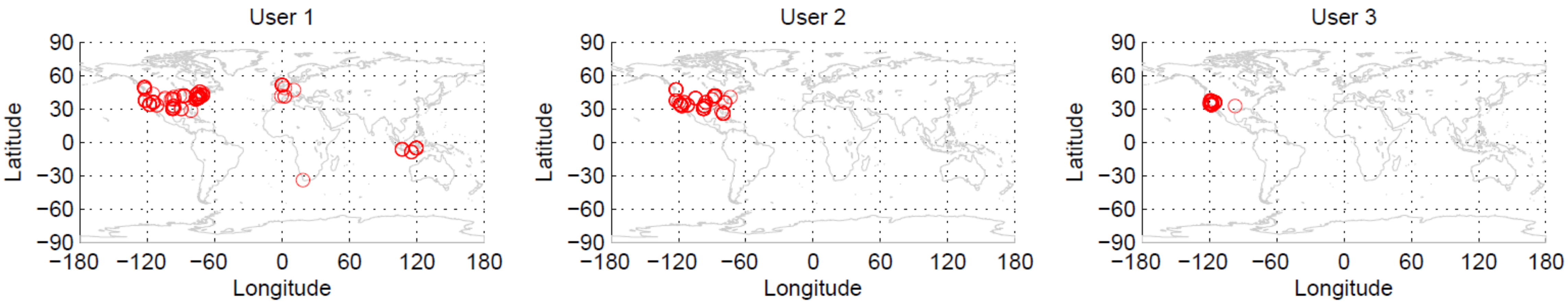
  - Gaussian distribution [3,6]
  - Kernel density estimation (KDE) [44]



SOCIAL INFLUENCE

- Intuition: friends in LBSNs share more common interests than non-friends [3,10,11,13,35,33,45,47]
- Friend-based Collaborative Filtering (FCF) [35]: preference r_{ij} of user u_i for l_j

$$r_{ij} = \frac{\sum_{u_k \in F_i} r_{kj} w_{ik}}{\sum_{u_k \in F_i} r_{kj}}$$

- where F_i is the set of friends with top-n similarity, w_{ik} is similarity weight between u_i and u_k
- FCF enhances the efficiency by reducing the computation cost of finding top similar users
  - However, it overlooks the non-friends who share many common check-ins with the target user

Result: very limited improvements over user-based POI recommendation in terms of precision

SOCIAL INFLUENCE

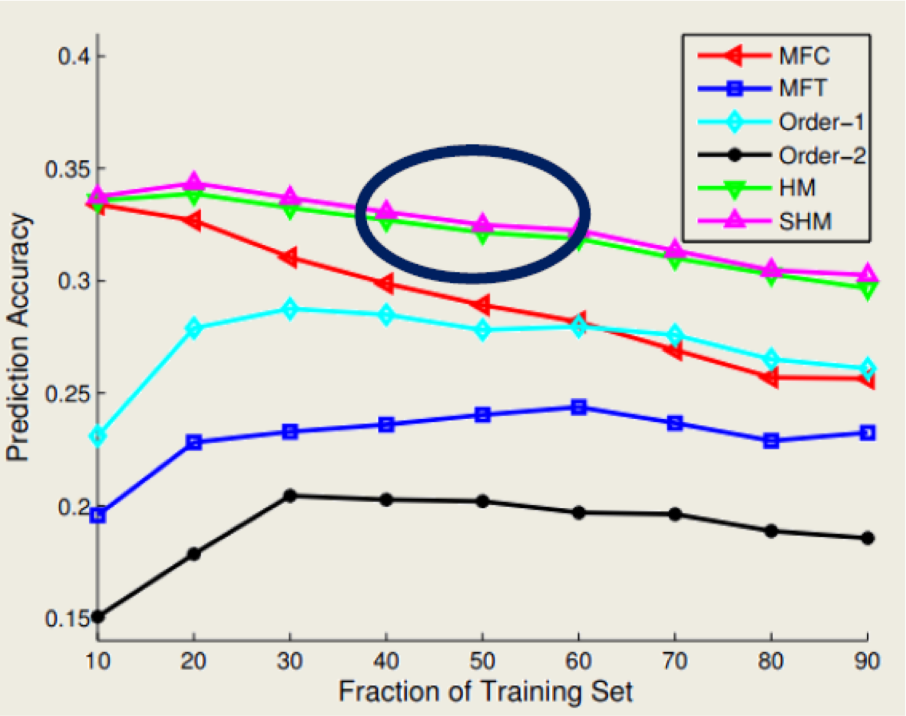
- Cheng et al. [3] apply the probabilistic matrix factorization with social regularization (PMFSR)

$$\arg\min_{U,L} \sum_{i=1}^{|\mathcal{U}|} \sum_{j=1}^{|\mathcal{L}|} I_{ij}(g(c_{ij}) - g(U_i^T L_j))^2 + \lambda_1 ||U||_F^2 + \lambda_2 ||V||_F^2 + \boxed{\beta \sum_{i=1}^{N} \sum_{u_f \in F_i} sim(i,f) ||U_i - U_f||^2}$$

- Social influence is incorporated by the social constraints that ensure latent features of friends keep in close distance at the latent subspace

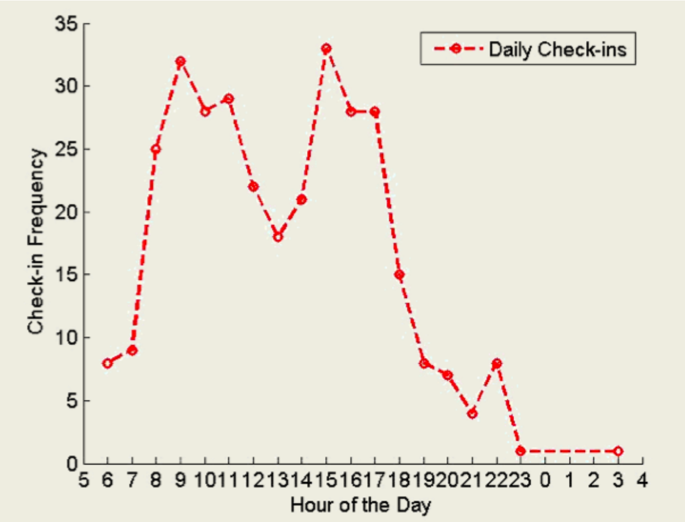
SOCIAL INFLUENCE

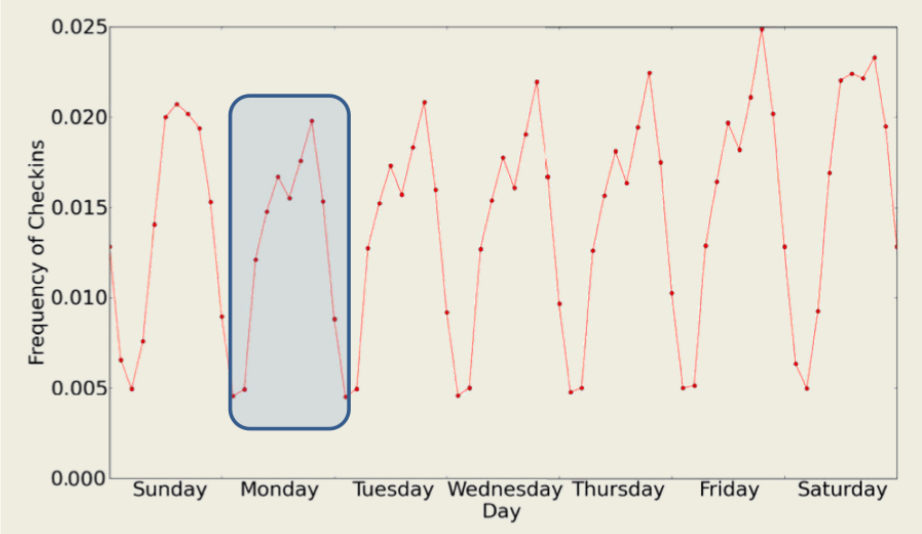
- Also in this case, limited improvements w.r.t. classic POI recommendation
- Users in LBSNs make friends online without any limitation;
  - The check-in activity requires physical interactions between users and POIs
- Friends in LBSNs may share common interest but may not visit common locations
  - Friends in favor of Italian food from different cities will visit their own local Italian food restaurants



TEMPORAL INFLUENCE

- Physical constraints on the check-in activity result in specific temporal patterns
- Three main aspects: periodicity, consecutiveness, and non-uniformness
- **Periodicity**: users' check-in behaviors in LBSNs exhibit periodic pattern [6,8,42,46]





TEMPORAL INFLUENCE

- Physical constraints on the check-in activity result in specific temporal patterns
- Three main aspects: periodicity, consecutiveness, and non-uniformness
- **Consecutiveness**: Successive check-ins are usually correlated [4,7,14,24,47,28]
  - Users may have fun in a nightclub after diner in a restaurant
  - The nightclub and the restaurant are geographically adjacent and correlated from the perspective of venue function

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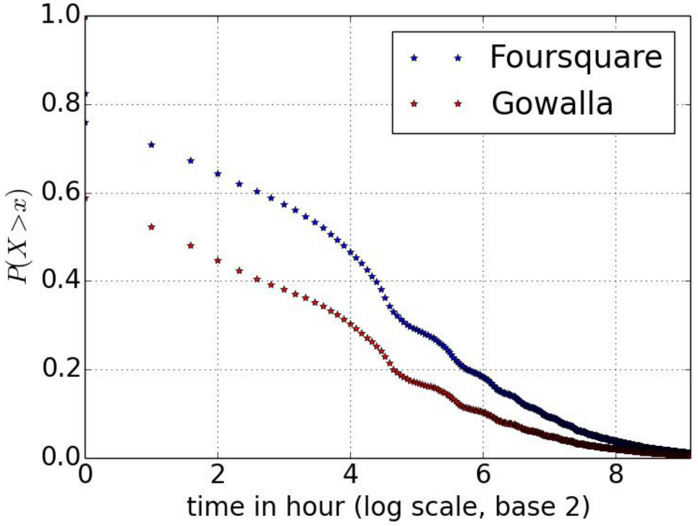
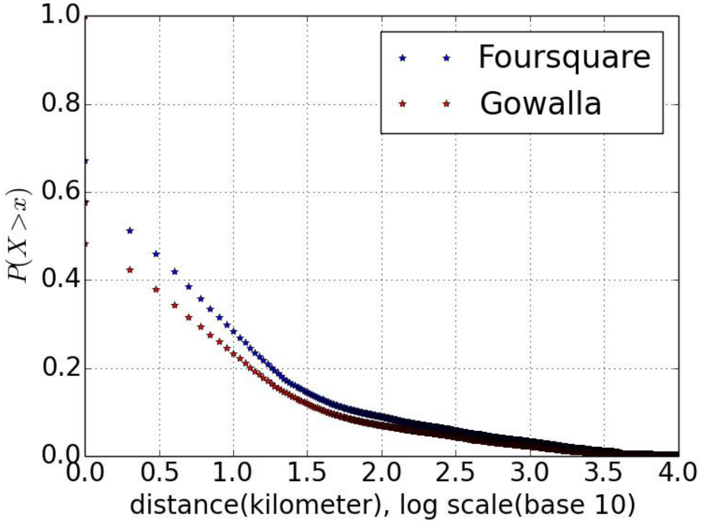


CCDF of intervals in check-ins

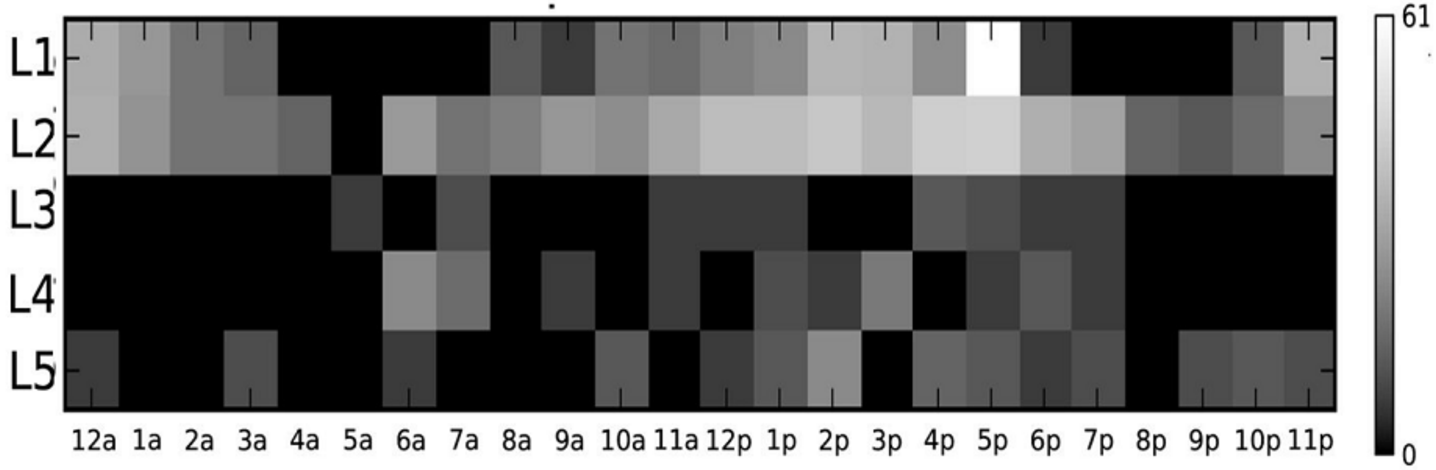


CCDF of distances in successive check-ins

- 40%-60% successive check-in behaviors happen in less than 4 hours since last check-in in Foursquare and Gowalla
- 90% successive check-ins happen in less than 32 kilometers (half an hour driving distance) in Foursquare and Gowalla

TEMPORAL INFLUENCE

- Physical constraints on the check-in activity result in specific temporal patterns
- Three main aspects: periodicity, consecutiveness, and non-uniformness
- **Non-uniformness**: a user's check-in preference variance at different hours of a day, or at different months of a year, or at different days of a week [8]
  - a user's check-in preference changes at different hours of a day
  - The most frequent checked-in POI alters at different hours

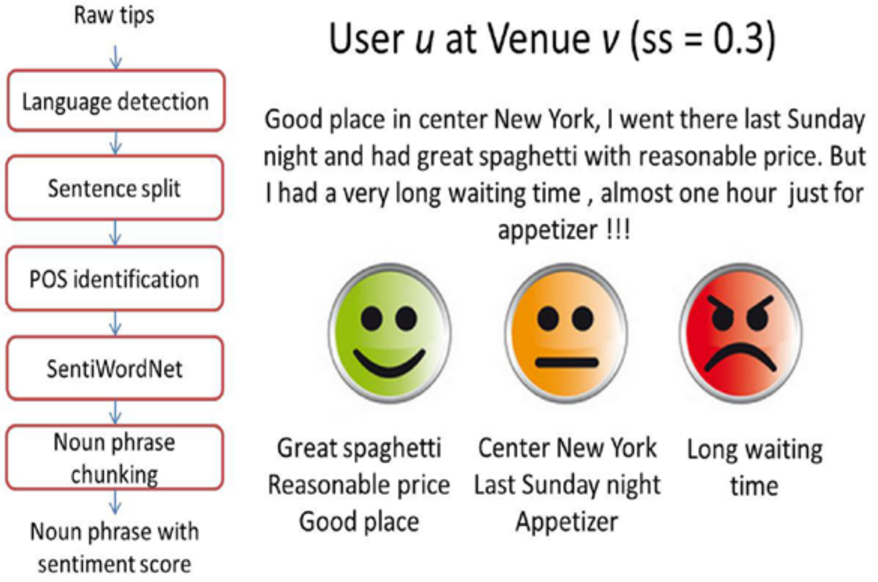


TEMPORAL INFLUENCE

- Physical constraints on the check-in activity result in specific temporal patterns
- Three main aspects: periodicity, consecutiveness, and non-uniformness
- These distinct temporal characteristics mentioned above make the previous temporal models unsatisfactory for POI recommendation
- A variety of systems are proposed to enhance POI recommendation performance [4,8,23,51]

CONTENT INDICATION

- In LBSNs, users generate contents including tips and ratings for POIs and also photos about the POIs [9,21,30,33,38]
  - They can be used to enhance the POI recommendation
- Comments provide extra information from the shared tips beyond the check-in behavior
- Yang et al. [33] propose a sentiment-enhanced location recommendation method



Sentiment Score	Preference Measure
[-1, -0.05]	1
(-0.05, -0.01]	2
(-0.01, 0.01)	3
[0.01, 0.05)	4
[0.05, 1]	5

- $\hat{C}_{ij}$ measures the preference of user u_i at a POI l_j
- Traditional matrix factorization method can be employed to recommend POIs through the following objective

$$\arg\min_{U,L} \sum_{(i,j)\in\Omega} (\hat{C}_{i,j} - U_i L_j^T)^2 + \alpha ||U||_F^2 + \beta ||L||_F^2$$

METHODOLOGY

METHODOLOGY

- We discussed four general influential factors for POI recommendation
- A POI recommendation system requires to construct a model incorporating those influential factors
- The **fused model** fuses recommended results from collaborative filtering and recommended results from models capturing geographical influence, social influence, and temporal influence [3,36,45]
- The **joint model** establishes a joint model to learn the user preference and the influential factors together [8,9,15,17,18,22,33,40]

FUSED MODEL

- It establishes **a model for each influential facto**r and combines their recommended results with **suggestions from the collaborative filtering model**
- Social influence provides limited improvements in POI recommendation and user comments are usually missing in users' check-ins
- Geographical influence and temporal influence constitute two important factors for POI recommendation
- In [5], Cheng et al. employ probabilistic matrix factorization (PMF) and probabilistic factor model (PFM) to learn user preference for recommending POIs

$$P_{ul} = P(F_{ul}) \cdot P(l|C_u)$$

- $P(F_{ul})$ encodes a users preference on a location
- $P(l|C_u)$ is calculated via the Multi-center Gaussian Model

JOINT MODEL

- The joint model learns several influential factors together, and then recommends POIs from the jointly learned model
- The check-in behavior as a synchronized decision influenced by several factors together
- Two types of joint models:
  - **Incorporating factors** (e.g., geographical influence and temporal influence) into traditional collaborative filtering, like matrix factorization [8,9,17,22,33]
  - **Generating a graphical model** according to the check-ins and extra influences like geographical information [18,15,40]

JOINT MODEL

- In [17], Lian et al. propose the GeoMF model to incorporate geographical influence into a weighted regularized matrix factorization model (WRMF)

TASKS

TASKS

- We categorize the POI recommendation task in two ways
- **General POI recommendation**: it recommends the top-N POIs for users, similar to movie recommendation task in Netflix competition [8,16,18,36]
- **Successive POI recommendation**: it generates to list sensitive to their recent check-ins [3,7,49,51]
  - It takes advantage of the recent check-in information → recall improves

SUCCESSIVE POI RECOMMENDATION

- POI recommendation provides satisfied recommendations promptly based on users most recent checked-in location
- It requires not only the preference modeling from users but also the accurate correlation analysis between POIs
- In [51], Zhao et al. propose the STELLAR system, which aims to provide time-aware successive POI recommendations
- Rank the POIs via a score function $f: U \times L \times T \times L \rightarrow R$
- The score function $f(u,l_q,t,l_c)$ that represents the "successive check-in possibility", is defined for user *u* to a candidate POI l_c at the time stamp *t* given the user's last check-in as a query POI l_q

EVALUATION

Data source

Metrics

DATA SOURCE

- Gowalla, Brightkite, and Foursquare are famous benchmark datasets available for evaluating a POI recommendation model

Name	Statistics
Brightkite [6]	4,491,143 check-ins from 58,228 users
Gowalla 1 [6]	6,442,890 check-ins from 196,591 users
Gowalla 2 [3]	4,128,714 check-ins from 53,944 users
Foursquare 1 [10]	2,073,740 check-ins from 18,107 users
Foursquare 2 [11]	1,385,223 check-ins from 11,326 users
Foursquare 3 [1]	325,606 check-ins from 80,606 users
Foursquare (NYC restaurants) [52]	27,149 check-ins and 10377 tips from 3,112 users
Foursquare (NYC and Tokio) [53]	227,428 check-ins in New York city and 573,703 check-ins in Tokyo
Foursquare (Global scale) [54]	33,278,683 check-ins by 266,909 users
Foursquare (Global scale + Social network) [55]	22,809,624 checkins by 114,324 users

METRICS

- Most of POI recommendation systems utilize metrics of *precision* and *recall*
  - F-score is also introduced in some work
- The precision and recall in the top-N recommendation system are denoted as P@N and R@N
- P@N measures the ratio of recovered POIs to the N recommended POIs
- R@N is the ratio of recovered POIs to the set of POIs in the testing data

- L^T_u denotes the set of POIs visited by user *u* in the test data
- L^R_u denotes the set of POIs recommended to user *u*

$$P@N = \frac{1}{|U|} \sum_{u \in N} \frac{|L_u^R \cap L_u^T|}{N}$$

$$R@N = \frac{1}{|U|} \sum_{u \in N} \frac{|L_u^R \cap L_u^T|}{|L_u^T|}$$

$$F - score@N = \frac{2 * P@N * R@N}{P@N + R@N}$$

METRICS

- Relative precision@N and recall@N (r-P@N and r-R@N) have been introduced in [18,35]
- Let L^C_u denote the candidate POIs for each user u, namely POIs the user has not checked-in
- Precision of a random recommender would be $\frac{|L_u^T|}{|L_u^C|}$
- Recall of a random recommender would be $\frac{|N|}{|L_u^C|}$

- Then:

$$r - P@N = \frac{P@N}{|L_u^T|/|L_u^C|}$$

$$r - R@N = \frac{R@N}{|N|/|L_u^C|}$$

TRENDS AND NEW DIRECTIONS

RANKING-BASED MODELS

- Most of previous methods generally attempt to estimate the user check-in probability over POIs
- We do not really care about the predicted check-in possibility value but the preference order
- Recent advances in recommender systems who optimize for ranking quality may be applied to POI recommendation:
  - Bayesian personalized ranking (BPR)
  - Weighted approximate rank pairwise (WARP)

ONLINE RECOMMENDATION

- The existing approaches work with pre-trained offline methods
- This suffers two problems:
  - **Cold start**: the offline model performs not satisfying for new users or users who have only a few check-ins
  - **User behavior variance**: the offline model may perform awfully if a users behavior changes since it learns user behavior according to history records
- No work using online model for POI recommendation exists

USER PRIVACY AND DATA SOURCES

- Due to recent scandals and recent regulations (GDPR) collecting real data is becoming more and more challenging
- However, algorithms are becoming more and more thirsty for data (e.g., Deep Learning approaches)
- Balancing these two challenges is not trivial

BIASES AND DISCRIMINATION

- Recommendation algorithms learn patterns from data
- But no perfect data exists!
- Several biases affect the data (popularity, gender unbalance)
- This is very likely to lead to **biased recommendations**!
  - Only popular venues get recommended (places get too crowded, owners of unpopular venues are affected)
  - Minorities get systematically worse recommendations, thus affecting their experience

REFERENCES

[1] Jie Bao, Yu Zheng, and Mohamed F. Mokbel. Location-based and preference-aware recommendation using sparse geo-social networking data. In Proceedings of the 21st ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems, pages 199–208, 2012.

[2] Preeti Bhargava, Thomas Phan, Jiayu Zhou, and Juhan Lee. Who, what, when, and where: Multi-dimensional collaborative recommendations using tensor factorization on sparse user-generated data. In Proceedings of the 24th International Conference on World Wide Web, pages 130–140. ACM, 2015.

[3] Chen Cheng, Haiqin Yang, Irwin King, and Michael R Lyu. Fused matrix factorization with geographical and social influence in location-based social networks. In Proceedings of the Twenty-Sixth AAAI Conference on Artificial Intelligence, pages 17–23. AAAI Press, 2012.

[4] Chen Cheng, Haiqin Yang, Michael R Lyu, and Irwin King. Where you like to go next: successive point-of-interest recommendation. In Proceedings of the Twenty-Third international joint conference on Artificial Intelligence, pages 2605–2611. AAAI Press, 2013.

[5] Zhiyuan Cheng, James Caverlee, Kyumin Lee, and Daniel Z Sui. Exploring millions of footprints in location sharing services. In Fifth International AAAI Conference on Weblogs and Social Media, pages 81–88. AAAI, 2011.

[6] Eunjoon Cho, Seth A Myers, and Jure Leskovec. Friendship and mobility: user movement in location-based social networks. In Proceedings of the 17th ACM SIGKDD international conference on Knowledge discovery and data mining, pages 1082–1090. ACM, 2011.

[7] Shanshan Feng, Xutao Li, Yifeng Zeng, Gao Cong, Yeow Meng Chee, and Quan Yuan. Personalized ranking metric embedding for next new poi recommendation. In Proceed- ings of the 24th International Conference on Artificial Intelligence, pages 2069–2075. AAAI Press, 2015.

[8] Huiji Gao, Jiliang Tang, Xia Hu, and Huan Liu. Exploring temporal effects for location recommendation on location-based social networks. In Proceedings of the 7th ACM conference on Recommender systems, pages 93–100. ACM, 2013.

[9] Huiji Gao, Jiliang Tang, Xia Hu, and Huan Liu. Content-aware point of interest recommendation on location-based social networks. In Proceedings of the Twenty-Ninth AAAI Conference on Artificial Intelligence, pages 1721–1727. AAAI Press, 2015.

[10] Huiji Gao, Jiliang Tang, and Huan Liu. Exploring social-historical ties on location-based social networks. In Sixth International AAAI Conference on Weblogs and Social Media. AAAI, 2012.

[11] Huiji Gao, Jiliang Tang, and Huan Liu. gscorr: modeling geo-social correlations for new check-ins on location-based social networks. In Proceedings of the 21st ACM interna- tional conference on Information and knowledge management, pages 1582–1586. ACM, 2012.

[12] Huiji Gao, Jiliang Tang, and Huan Liu. Addressing the cold-start problem in location recommendation using geo-social correlations. Data Mining & Knowledge Discovery, 29(2):299–323, 2015.

[13] Yong Ge, Huayu Li, and Hengshu Zhu. Point-of-interest recommendations: Learning potential check-ins from friends. 2016.

[14] Jing He, Xin Li, Lejian Liao, Dandan Song, and William K Cheung. Inferring a per- sonalized next point-of-interest recommendation model with latent behavior patterns. In Thirtieth AAAI Conference on Artificial Intelligence, 2016. [21] Bo Hu and Martin Ester. Social topic modeling for point-of-interest recommendation in location-based social networks. In 2014 IEEE International Conference on Data Mining, pages 845–850. IEEE, 2014.

[15] Takeshi Kurashima, Tomoharu Iwata, Takahide Hoshide, Noriko Takaya, and Ko Fujimura. Geo topic model: joint modeling of user's activity area and interests for location recommendation. In Proceedings of the sixth ACM international conference on Web search and data mining, pages 375–384. ACM, 2013.

[16] Xutao Li, Gao Cong, Xiao-Li Li, Tuan-Anh Nguyen Pham, and Shonali Krishnaswamy. Rank-geofm: A ranking based geographical factorization method for point of interest recommendation. In Proceedings of the 38th International ACM SIGIR Conference on Research and Development in Information Retrieval, pages 433–442. ACM, 2015.

[17] Defu Lian, Cong Zhao, Xing Xie, Guangzhong Sun, Enhong Chen, and Yong Rui. Ge- oMF: Joint geographical modeling and matrix factorization for point-of-interest recom- mendation. In ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, pages 831–840. ACM, 2014.

[18] Bin Liu, Yanjie Fu, Zijun Yao, and Hui Xiong. Learning geographical preferences for point-of-interest recommendation. In Proceedings of the 19th ACM SIGKDD interna- tional conference on Knowledge discovery and data mining, pages 1043–1051. ACM, 2013.

[19] Bin Liu and Hui Xiong. Point-of-Interest recommendation in location based social networks with topic and location awareness. In Siam International Conference on Data Mining, pages 396–404. SIAM, 2013.

[20] Bin Liu, Hui Xiong, Spiros Papadimitriou, Yanjie Fu, and Zijun Yao. A general geo-graphical probabilistic factor model for point of interest recommendation. IEEE Trans- actions on Knowledge and Data Engineering, 27(5):1167–1179, 2015.

[21] Yanchi Liu, Chuanren Liu, Bin Liu, Meng Qu, and Hui Xiong. Unified point-of-interest recommendation with temporal interval assessment. 2016.

[22] Yong Liu, Wei Wei, Aixin Sun, and Chunyan Miao. Exploiting geographical neighbor- hood characteristics for location recommendation. In ACM International Conference on Conference on Information and Knowledge Management, pages 739–748, 2014.

[23] Anastasios Noulas, Salvatore Scellato, Neal Lathia, and Cecilia Mascolo. Mining user mobility features for next place prediction in location-based services. In 2012 IEEE 12th International Conference on Data Mining, pages 1038–1043. IEEE, 2012.

[24] Steffen Rendle, Christoph Freudenthaler, and Lars Schmidt-Thieme. Factorizing per- sonalized markov chains for next-basket recommendation. In Proceedings of the 19th international conference on World wide web, pages 811–820. ACM, 2010.

[25] Injong Rhee, Minsu Shin, Seongik Hong, Kyunghan Lee, Seong Joon Kim, and Song Chong. On the levy-walk nature of human mobility. IEEE/ACM transactions on networking (TON), 19(3):630–643, 2011.

[26] Jitao Sang, Tao Mei, and Changsheng Xu. Activity sensor: Check-in usage mining for local recommendation. ACM Transactions on Intelligent Systems and Technology (TIST), 6(3):41, 2015.

[27] Masoud Sattari, Murat Manguoglu, Ismail H Toroslu, Panagiotis Symeonidis, Pinar Senkul, and Yannis Manolopoulos. Geo-activity recommendations by using improved feature combination. In Proceedings of the 2012 ACM Conference on Ubiquitous Computing, pages 996–1003. ACM, 2012.

[28] Salvatore Scellato, Cecilia Mascolo, Mirco Musolesi, and Vito Latora. Distance matters: geo-social metrics for online social networks. In Wonference on Online Social Networks, pages 8–8, 2010.

[29] Salvatore Scellato, Anastasios Noulas, and Cecilia Mascolo. Exploiting place features in link prediction on location-based social networks. In ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, San Diego, Ca, Usa, August, pages 1046–1054, 2011.

[30] Xiangyu Wang, Yi-Liang Zhao, Liqiang Nie, Yue Gao, Weizhi Nie, Zheng-Jun Zha, and Tat-Seng Chua. Semantic-based location recommendation with multimodal venue semantics. IEEE Transactions on Multimedia, 17(3):409–419, 2015.

[31] Yingzi Wang, Nicholas Jing Yuan, Defu Lian, Linli Xu, Xing Xie, Enhong Chen, and Yong Rui. Regularity and conformity: Location prediction using heterogeneous mobility data. In ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, pages 1275–1284, 2015.

[32] Zih-Syuan Wang, Jing-Fu Juang, and Wei-Guang Teng. Predicting poi visits with a het- erogeneous information network. In 2015 Conference on Technologies and Applications of Artificial Intelligence (TAAI), pages 388–395. IEEE, 2015.

[33] Dingqi Yang, Daqing Zhang, Zhiyong Yu, and Zhu Wang. A sentiment-enhanced per- sonalized location recommendation system. In Proceedings of the 24th ACM Conference on Hypertext and Social Media, pages 119–128. ACM, 2013.

[34] Dingqi Yang, Daqing Zhang, Vincent W Zheng, and Zhiyong Yu. Modeling user ac- tivity preference by leveraging user spatial temporal characteristics in lbsns. IEEE Transactions on Systems, Man, and Cybernetics: Systems, 45(1):129–142, 2015.

[35] Mao Ye, Peifeng Yin, and Wang-Chien Lee. Location recommendation for location-based social networks. In Proceedings of the 18th SIGSPATIAL international conference on advances in geographic information systems, pages 458–461. ACM, 2010.

[36] Mao Ye, Peifeng Yin, Wang-Chien Lee, and Dik-Lun Lee. Exploiting geographical influence for collaborative point-of-interest recommendation. In Proceedings of the 34th international ACM SIGIR conference on Research and development in Information Retrieval, pages 325–334. ACM, 2011.

[37] Hongzhi Yin, Bin Cui, Ling Chen, Zhiting Hu, and Xiaofang Zhou. Dynamic user modeling in social media systems. ACM Transactions on Information Systems (TOIS), 33(3):10, 2015.

[38] Hongzhi Yin, Bin Cui, Yizhou Sun, Zhiting Hu, and Ling Chen. Lcars: A spatial item recommender system. ACM Transactions on Information Systems (TOIS), 32(3):11, 2014.

[39] Hongzhi Yin, Zhiting Hu, Xiaofang Zhou, Hao Wang, Kai Zheng, Quoc Viet Hung Nguyen, and Shazia Sadiq. Discovering interpretable geo-social communities for user behavior prediction. In The 32nd IEEE International Conference on Data Engineering, 2016.

[40] Hongzhi Yin, Yizhou Sun, Bin Cui, Zhiting Hu, and Ling Chen. Lcars: A location-content-aware recommender system. In ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, pages 221–229, 2013.

[41] Jing Yuan, Yu Zheng, and Xing Xie. Discovering regions of different functions in a city using human mobility and pois. In Proceedings of the 18th ACM SIGKDD international conference on Knowledge discovery and data mining, pages 186–194. ACM, 2012.

[42] Quan Yuan, Gao Cong, Zongyang Ma, Aixin Sun, and Nadia Magnenat Thalmann. Time-aware point-of-interest recommendation. In Proceedings of the 36th international ACM SIGIR conference on Research and development in information retrieval, pages 363–372. ACM, 2013.

[43] Quan Yuan, Gao Cong, and Aixin Sun. Graph-based point-of-interest recommendation with geographical and temporal influences. In Proceedings of the 23rd ACM Interna- tional Conference on Conference on Information and Knowledge Management, pages 659–668. ACM, 2014.

[44] Jia-Dong Zhang and Chi-Yin Chow. igslr: personalized geo-social location recommen-dation: a kernel density estimation approach. In Proceedings of the 21st ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems, pages 334–343. ACM, 2013.

[45] Jia-Dong Zhang and Chi-Yin Chow. Geosoca: Exploiting geographical, social and cat-egorical correlations for point-of-interest recommendations. In Proceedings of the 38th International ACM SIGIR Conference on Research and Development in Information Retrieval, pages 443–452. ACM, 2015.

[46] Jia Dong Zhang and Chi Yin Chow. Ticrec: A probabilistic framework to utilize tempo- ral influence correlations for time-aware location recommendations. IEEE Transactions on Services Computing, (1):1–1, 2015.

[47] Jia-Dong Zhang, Chi-Yin Chow, and Yanhua Li. Lore: exploiting sequential influence for location recommendations. In Proceedings of the 22nd ACM SIGSPATIAL Inter- national Conference on Advances in Geographic Information Systems, pages 103–112. ACM, 2014.

[48] JiaweiZhang,XiangnanKong,andPhilipS.Yu.Transferringheterogeneouslinksacross location-based social networks. In ACM International Conference on Web Search and Data Mining, pages 303–312, 2014.

[49] Wei Zhang and Jianyong Wang. Location and time aware social collaborative retrieval for new successive point-of-interest recommendation. In Proceedings of the 24th ACM International on Conference on Information and Knowledge Management, pages 1221– 1230. ACM, 2015.

[50] Shenglin Zhao, Irwin King, and Michael R Lyu. Capturing geographical influence in poi recommendations. In International Conference on Neural Information Processing, pages 530–537. Springer, 2013.

[51] Shenglin Zhao, Tong Zhao, Haiqin Yang, Michael R Lyu, and Irwin King. Stellar: Spatial-temporal latent ranking for successive point-of-interest recommendation. In Thirtieth AAAI Conference on Artificial Intelligence, 2016.

[52] Dingqi Yang, Daqing Zhang, Zhiyong Yu and Zhiwen Yu, Fine-Grained Preference-Aware Location Search Leveraging Crowdsourced Digital Footprints from LBSNs. In Proceeding of the 2013 ACM International Joint Conference on Pervasive and Ubiquitous Computing (UbiComp 2013), September 8-12, 2013, in Zurich, Switzerland.

[53] Dingqi Yang, Daqing Zhang, Vincent W. Zheng, Zhiyong Yu. Modeling User Activity Preference by Leveraging User Spatial Temporal Characteristics in LBSNs. IEEE Trans. on Systems, Man, and Cybernetics: Systems, (TSMC), 45(1), 129-142, 2015.

[54] Dingqi Yang, Daqing Zhang, Bingqing Qu. Participatory Cultural Mapping Based on Collective Behavior Data in Location Based Social Networks. ACM Trans. on Intelligent Systems and Technology (*TIST*), 2015.

[55] Dingqi Yang, Bingqing Qu, Jie Yang, Philippe Cudre-Mauroux, Revisiting User Mobility and Social Relationships in LBSNs: A Hypergraph Embedding Approach, In Proc. of The Web Conference (*WWW'19*). May. 2019, San Francisco, USA.[50] Shenglin Zhao, Irwin King, and Michael R Lyu. Capturing geographical influence in poi recommendations. In International Conference on Neural Information Processing, pages 530–537. Springer, 2013.