iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 5 **Issue:** III **Month of publication:** March 2017

DOI: http://doi.org/10.22214/ijraset.2017.3179

Volume 5 Issue III, March 2017
ISSN: 2321-9653
International Journal for Research in Applied Science & Engineering Technology (IJRASET)

Service Objective Prediction via Sentimental System on Multi-Source Big Social Network

Mr. B. Aravind[1], Mr. R. Muralidharan[2], Mr. B. Jehan[3], Ms. D. Mahalakshmi[4]
[1,2,3,4]*B.TECH-Information Technology, A.V.C College of Engineering, Mannampandal.*

***Abstract*: We have a vast amount of descriptions, comments, and ratings for local services. The information is valuable for new users to judge whether the services meet their requirements before partaking. In this paper, we propose service objective prediction via sentimental system on multi source big social network. In order to predict service objective, we focus on specific interest of the user and user's recent activities. The recent activities can be mined through their status such as sharing of files, messages. In this proposed system, user interest related advertisements only provided to the respective users. The services can be predicted and mined through Collaborative Filtering (CF) technology**.
Keyword: Collaborative Filtering, Sentimental System.

I. INTRODUCTION

The main goal of this paper is how to provide services (advertisement) to the particular social network users. Recently, advances in intelligent mobile device and positioning techniques have fundamentally enhanced social networks, which allow users to share their experiences, reviews, ratings, photos, check-ins, etc. We refer to these social networks involving geographical information as location-based social networks (LBSNs). Such information brings opportunities and challenges for recommender systems to solve the cold start, sparsest problem of datasets and rating prediction. In this paper, we make full activities of the particular social network users to provide services based on the specific interest of the users. We mine the particular interest of the users at the time of registration. Similarly, we mine the products which are matching with the respective interest of the users. Moreover, the dynamic interests of the users also fetched by focusing on the shared status, files, etc. The recent activities can be mined through their status such as sharing of files, messages. The services can be predicted and mined through Collaborative Filtering (CF) technology. The admin of the particular social network is responsible for adding new product details and its availability which need to be advertised to their registered users. The services can be displayed at the home page of the registered user's profile and user's interest related advertisements only provided to the respective users.

II. RELATED WORK

The first generation of recommender systems [1] with traditional collaborative filtering algorithms [3]-[9] is facing great challenges of cold start for users (new users in the recommender system with little historical records) and the sparsity of datasets. Fortunately, with the popularity and rapid development of social networks, more and more users enjoy sharing their experiences, reviews, ratings, photos, and moods with their friends. Many social-based models [10]-[16], [62] have been proposed to improve the performance of recommender system. Yang *et al.* [17] Propose to use the concept of 'inferred trust circle' based on the domain-obvious of circles of friends on social networks to recommend users favorite items. Jiang *et al.* [18] prove that individual preference is also an important factor in social networks. In their Context Model, user latent features should be similar to his/her friends' according to preference similarity. Hu *et al*. [61] and Lei *et al*. [59] utilize the power of semantic knowledge bases to handle textual messages and recommendations. Our previous works [57], [58] focus on objective evaluation in order to recommend the high-quality services by exploring social users' contextual information.
There is a paper [43] also focusing on observations on ratings combining with geographical location information. They find that geographical neighbourhood has influences on the rating of a business. They perform biases based matrix factorization model with their observations, but there are some differences between us: 1) we focus on the relevance between ratings and user-item geographic distances. They focus on item-item geographic location distances and the impact of items' neighbourhoods. 2) We focus more on exploring social users' rating behaviors and social influence, i.e. the relevance between users' rating differences and user-user geographic distances. 3) They perform biases based matrix factorization model, but we perform our model with constraining user and item latent factor vectors. That is to say, formula of our object function is different with theirs.

Except for ratings prediction, there are some systems focusing on location recommendation. Many researchers mine user's interests from the user's location history to make recommendament with consideration of the human mobility features. The location based recommender sys-tem using the user similarity outperforms those using the Cosine similarity. Bao *et al*. Combine user's location and preference to provide effective location recommendations. Jiang *et al*. [56] propose a user topic based collaborative filtering approach for personalized travel recommendation. Gao *et al*. [31] introduce a location recommendation framework with temporal effects based on observed temporal properties. They explore the number of check-ins made by a user at a location to recommend a new location user may prefer. Cheng *et al*. fuse matrix factorization (MF) with geographical and social influence for POI (Point-of-Interest) recommendations on LBSNs, and propose a Multi-center Gaussian Model to model the geographical influence of users' check-in behaviors. Zhang *et al*. propose several location recommendation frame-works by exploiting geographical influence [temporal influence, categorical correlations, spatiotemporal sequential influence [], user opinions [etc. Sang *et al*. [49] conduct an in-depth usage mining on real-world check-in data and present a POI category transition based approach to estimate the visiting probability. For multi-modality datasets, Zheng [60] summarizes existing data fusion methods, classifying them into three major categories to help people to find proper data fusion methods.

III. FEASIBILITY STUDY

Yelp is a local directory service with social networks and user reviews. It is the largest review site in America. Users rate the businesses, submit comments, communicate shopping experience, etc. It combines local reviews and social networking functionality to create a local online community. Moreover, it is proved by the data of Yelp that users are more willing to visit places or to consume items that his/her friends have visited or consumed be-fore. As shown in Table 3, a statistic of rating intersections is given. For each rating of a user, if the item has been rated by his/her friends, we call it rating intersections. It is obvious that the more rating intersections are, the users are more influenced by their friends. In Table 3, it can be discovered that there are many rating intersections be-tween users and their friends. Therefore, it can be concluded that users' mobility and consuming behaviors may be easily influenced by their social relationships.

We have crawled nearly 80 thousand users' social circles and their rated items. Table 2 is the statistic of our dataset which consists of ten categories, 80,050 users, 155,965 items and 1,543,315 ratings. Note that we have items' information including their GPS positions. For a user, the average geographical location of items rated by this user is set as his/her activity center. In other words, for a user *u*, we represent his/her activity center position

The proposed personalized location based rating prediction model (LBRP) has three main steps: 1) obtain three geo- social factors, interpersonal interest similarity, user-user geographical connection, and user-item geographical connection, through smart phone with the Wi-Fi technology and Global Positioning System (GPS); 2) build up personalized rating prediction model combining with the three factors in the cloud; 3) train the model in the cloud to learn user and item latent feature matrices for rating prediction to recommend suitable items of user's interest. In this paper, we focus on the algorithm part: step 2 and step 3. When the geo-social data through smart phone is given by step 1, as shown in Fig. 1, the model is built up combining geo-social factors to learn user and item latent features. User and item latent feature matrices can be calculated by machine learning methods for rating prediction. Once the ratings are predicted, the items can be ranked by the ratings and provided as TopN recommendation.

TABLE 1
STATISTIC OF OUR YELP DATASETS

Dataset	Number of users	Number of items	Number of ratings	Sparsity
Active Life	6152	6390	48803	1.24E-03
Arts & Entertainment	11182	5221	108861	1.86E-03
Automotive	1351	2523	6213	1.82E-03
Beauty & Spas	5529	7323	36845	9.10E-

Volume 5 Issue III, March 2017
ISSN: 2321-9653
International Journal for Research in Applied Science & Engineering Technology (IJRASET)

				04
Event Planning & Services	11447	6028	98491	1.43E-03
Food	9770	21370	341573	1.64E-03
Hotels & Travel	4897	2146	31833	3.03E-03
Restaurants	10,449	67,857	321,551	4.54E-04
Nightlife	11,152	21,647	436,301	1.81E-03
Shopping	8,121	15,460	112,844	8.99E-04

TABLE 2 STATISTIC OF RATING INTERSECTIONS

Category	Ratings count	Intersections count	Proportion
Restaurants	321,551	98,402	30.6%
Nightlife	436,301	306,294	70.2%
Shopping	112,844	63,821	56.6%

IV. DESIGN AND ARCHITECTURE

In this project, we make full activities of the particular social network users to provide services based on the specific interest of the users. We mine the particular interest of the users at the time of registration. Similarly, we mine the products which are matching with the respective interest of the users. Moreover, the dynamic interests of the users also fetched by focusing on the shared status, files, etc. The recent activities can be mined through their status such as sharing of files, messages. The services can be predicted and mined through Collaborative Filtering (CF) technology. The admin of the particular social network is responsible for adding new product details and its availability which need to be advertised to their registered users. The services can be displayed at the home page of the registered user’s profile and user’s interest related advertisements only provided to the respective users.

The collaborative filtering systems are divided into two categories, i.e., memory-based and model-based. Memory based systems can be further classified into user-based and item-based systems. For user-based systems, the similarity between all pairs of users is computed based on their ratings on associated items using some selected similarity measurement such as cosine similarity or Pearson correlation.

Meanwhile, by understanding the profile of a geospatial region, a content-based method is integrated into the location recommender to reduce the cold start problem. Point-of-Interest (POI) recommender system plays an important role in LBSNs since it can help users explore attractive locations as well as help social network service providers design location aware advertisements for Point-of-Interest. This information may concern demographic data preferences about user's domain of interest, quality and delivery requirements as well as the time of the interaction, the location, the media, the cognitive status of the user and his availability.

Volume 5 Issue III, March 2017
ISSN: 2321-9653

Hence, unwanted advertisements are avoided. Marketing costs are reduced. User's personal information are secured using cryptography. Particular social network user's time, effort can be minimized.

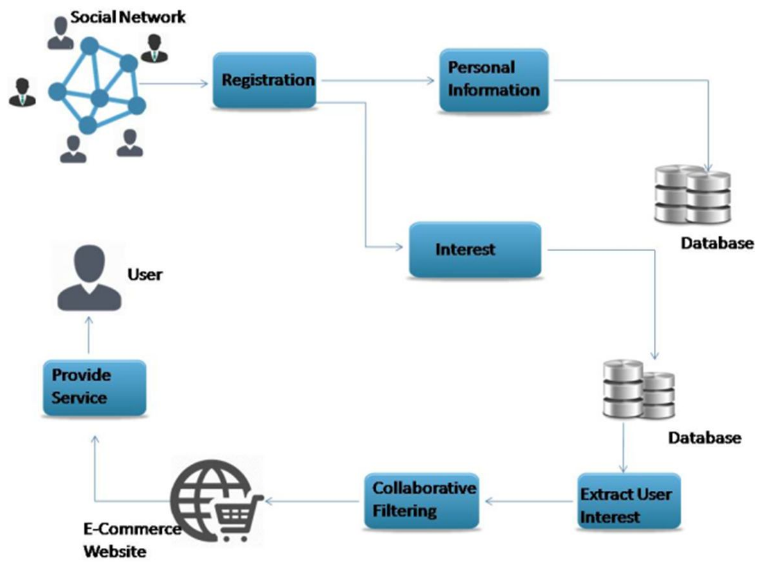


Fig.1. Proposed Architecture

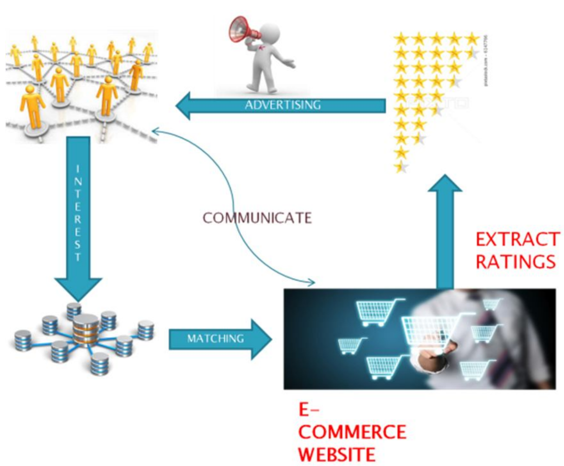


Fig.2. Proposed Architecture

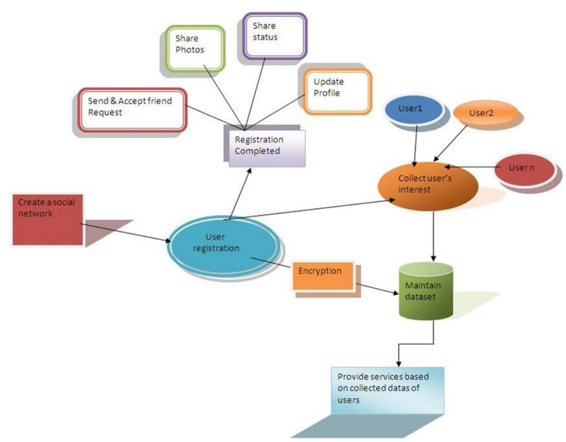
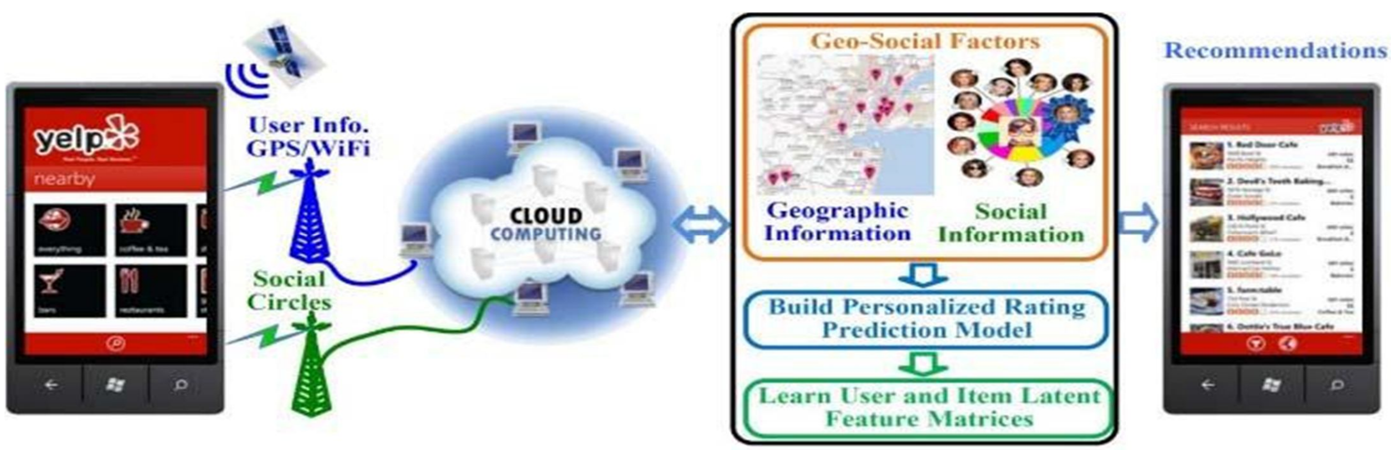


Fig.3. Usecase Diagram



Volume 5 Issue III, March 2017
ISSN: 2321-9653
International Journal for Research in Applied Science & Engineering Technology (IJRASET)

Fig.4. System overview of our personalized recommendation via geographical social networking, including smart phone user of mobile social network services, cloud computing, rating prediction, and the recommendation lists.

V. SCHEDULING

On this phase, we element how tasks are scheduled in CWC. We are given a fixed J of jobs and a set P of smartphones. as mentioned in advance, each job j ∈ J and speak to i ∈ p. the time it takes i to manner x kb of j's enter is given through

$$Ej * bi + x * (bi + cij) \qquad (1)$$

where, Ej is the size (in kb) of process j's executable, bi is the time (in milliseconds) that it takes cellphone i to receive 1 kb of facts from the server, and cij is the time that it takes for cell phone i to execute the process j on 1 kb of enter statistics. Our goal is to time table the obligations across the phones such that the time it takes for the ultimate phone to complete, T, (the makespan) is minimized. in the agenda, each activity j's enter can be split into portions and every piece can be assigned to a smartphone. lij denotes the dimensions (in kb) of job j's enter partition assigned to phone i. lij = 0 definitely shows that phone i is not assigned any input partition of job j. uij is a hallmark variable that denotes whether or not or no longer a partition of job j's enter is scheduled to run on telephone i. the scheduling problem (SCH) is then captured by using the following quadratic integer program

A. SCH Minimize T

1) s.t $\sum_j uij *(E_j*b_i+l_{ij}*(b_i+c_{ij})\leq T,\forall_i€$ P
2) $\sum_i lij=L_j,\forall_j€J$
3) $u_{ij}\in\{0,1\}\ \forall_i\in P, \forall_j\in J$
4) $\sum_i uij=1\ \forall$ atomic $j\in J$

Wherein we minimize the makespan, t. The primary constraint requires that everyone phones end executing their assigned tasks before t. The second constraint ensures that for every task, all of its input is processed. The ultimate constraint ensures that atomic jobs are allotted to a single telephone four. SCH reflects the general case for the minimum makespan scheduling (MMS) problem, which is known to be NP-hard. MMS is defined as: "given a set of jobs and a hard and fast of identical machines, assign the roles to the machines such that the makespan is minimized" [37]. a extra preferred model of mms is scheduling the use of unrelated machines (u-mms), wherein each system has one-of-a-kind capabilities and as a consequence, can execute obligations in specific instances. In each of those issues, handiest atomic jobs are considered. In different phrases, the goal is to assign each job to precisely one of the machines such that the makespan is minimized. SCH is a standard case of u-mms. We don't forget both atomic and breakable duties and the gadget abilities are exclusive. Since the unique case of SCH (u-mms) is NP-hard, the hardness consists of over to SCH as well.

Our solution: we address the SCH hassle via fixing the complementary bin packing trouble (CBP), much like the method in [38]. In CBP, the objective is to percent objects the use of at maximum ||P|| packing containers (with capacity C) such that the most peak throughout packing containers is minimized. Here, the objects correspond to the obligations and the packing containers correspond to the phones. The correlation among CBP and SCH may be drawn as follows. Allow us to anticipate that there is an premiere strategy to CBP in which the most top throughout the bins is m. if one rotates every bin ninety◦ to the proper, each bin visually seems as a cell phone in make span scheduling. Items packed on pinnacle of each other in a bin correspond to enter partitions assigned to a phone one after the other. Without a doubt, m corresponds to the most finishing touch time throughout the set of phones in the rotated visualization. As a consequence, packing all gadgets (tasks) the usage of at maximum ||P|| packing containers (phones) and minimizing the most peak throughout packing containers will minimize the makespan .

The pseudo code of our greedy algorithm to solve CBP is given in algorithm 1. The idea is to first sort the tasks in decreasing order of neighbourhood execution time. The primary object within the sorted list is the only wherein Rj ∗ csj is the largest; s is the slowest CPU cell phone in the machine and Rj is the ultimate enter length (in kb) of item (process) j this is but to be assigned to a few cell phone. To start with Rj = Lj.

In every generation, we look for the primary object in the listing that can be packed in any of the previously opened bins (an open bin represents a smartphone that has previously been assigned some enter partition). word that determining whether or not an object can be packed in a bin depends on whether or not the contemporary height of the bin plus the execution fee of that item within the unique bin is much less than the bin capability. if we will discover such an item, we percent it inside the bin with the minimal top at that point (i.e., the telephone with the least general execution time). While packing such an object (line 6), we pack its largest input partition that can fit. If the item can fit without partitioning it, we prefer packing it as a whole.

VI. IMPLEMENTATION AND EVALUATION

Here we focus on parameter settings. First, the meaning of each parameter is explained as follows.

K: The dimension of the latent vector. If *k* is too small, it is difficult for the model to make a distinction among users or items. If *k* is too large, the complexity wills considerably increase. Previous works [10], [33], [62] have investigated the changes of performance with different *k*. But whatever the *k* is, it is fair for all compared algorithms when we set it as an invariant. Here we set $k = 10$ as in [13], [15] and [17].

$\lambda 1$ and $\lambda 2$: The parameters of trading-off over-fitting factor in (11).

β: The weight of the inferred interest similarity in (11).

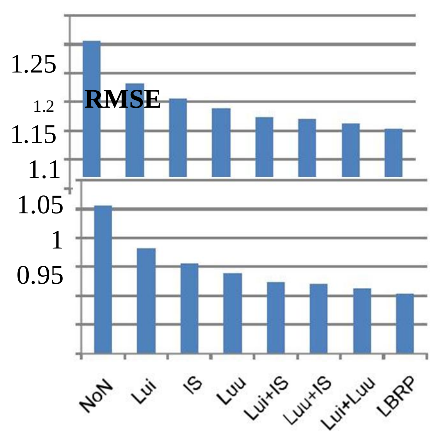
δ: The weight of user-user geographical connection in the third term of (11).

η: The weight of the user-item geographical connection in the last term of (11).

These parameters play the roles of balancing factors. As in [18], to balance the components in each algorithm, these parameters are proportional

A. Performance Comparison

In this section, we compare the performance of LBRP algorithm with the existing models, including BaseMF [33], CircleCon [17], Context MF [18], PRM [13], [15], and NCPD [43] on our Yelp datasets. In a series of experiments, the effectiveness and reliability of the proposed model are demonstrated according to the experimental results in Table 5. We implement performance comparison with performing 5-fold cross-validation. It can be seen that LBRP is better than other existing approaches on most of Yelp datasets.



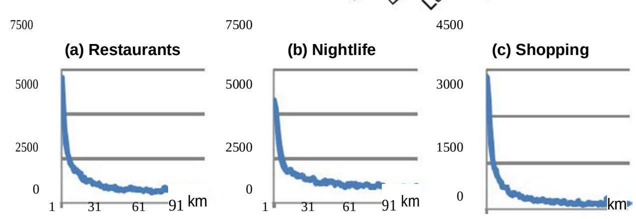


Fig. 5. The distributions of the number of ratings in different dis-tances (km).

B. Parameter Settings

Here we focus on parameter settings. First, the meaning of each parameter is explained as follows.

1) *k*: The dimension of the latent vector. If *k* is too small, it is difficult for the model to make a distinction among users or items. If *k* is too large, the complexity wills con-siderably increase. Previous works [10], [33], [62] have investigated the changes of performance with different *k*. But whatever the *k* is, it is fair for all compared algo-rithms when we set it as an invariant. Here we set $k = 10$ as in [13], [15] and [17].
2) $\lambda 1$ and $\lambda 2$: The parameters of trading-off over-fitting factor in (11).
3) β: The weight of the inferred interest similarity in (11).

4) δ: The weight of user-user geographical connection in the third term of (11).
5) η: The weight of the user-item geographical connection in the last term of (11).

These parameters play the roles of balancing factors. As in [18], to balance the components in each algorithm, these parameters are proportional.

VII. CONCLUSIONS

In this project, Capable to provide services (advertisement) for the users based on their specific interest. Also able to send and accept the friend request. Sharing of photos, status in two modes (Public/Private).User can update their personal information. The ratings of the specific users are analysed and subsequently the services can be provided based on the collected ratings. The security can be done using cryptographic algorithms. The dynamic interests of the users also fetched by focusing on the shared status, files, etc. The recent activities can be mined through their status such as sharing of files, messages. Advertisement costs can be reduced. Particular social network user's time, effort can be minimized.

VIII. ACKNOWLEDGMENT

We would love to thank Ms. D. Mahalakshmi, assistant professor of our department for her helpful hints in the direction of improving the paper.

REFERENCES

[1] G. Adomavicius, and A. Tuzhilin, "Toward the next generation of recommender systems: a survey of the state-of-the-art and possible extensions," *IEEE Transactions on Knowledge and Data Engineering*, pp. 734-749, Jun. 2005.
[2] B. Sarwar, G. Karypis, J. Konstan, and J. Reidl, "Item-based collaborative filtering recommendation algorithms," *World Wide Web*, pp. 285-295, 2001.
[3] J. Ying, E. Lu, W. Kuo, and V. Tseng, "Mining User Check-InBehavior with a Random Walk for Urban Point-of-Interest Recommendations,"*ACM TIST, 2014.*
[4] M. Ye, P. Yin, W. C. Lee, and D. L. Lee, "Exploiting geographical influence for collaborative point-of-interest recommendation, "*ACM SIGIR, pp. 325–334, 2011.*
[5] V. W. Zheng, Y. Zheng, X. Xie, and Q. Yang, "Collaborative location and activity recommendations with gps history data,"*WWW, pp. 1029–1038, 2010.*
[6] Y.-C. Hu, A. Perrig, and D. B. Johnson, "Wormhole attacks in wireless networks," IEEE J. Sel. Areas Commun., vol. 24, no. 2, pp. 370–380, 2006.
[7] D. Dong, Y. Liu, X. Li, and X. Liao, "Topological detection on wormholes in wireless ad hoc and sensor networks," IEEE Trans. Netw., vol. 19, no. 6, pp. 1787–1796, Dec. 2011.
[8] M. Jamali, and M. Ester, "A matrix factorization technique with trust propagation for recommendation in social networks,"*ACM RecSys*, 2010.
[9] J. Bao, Y. Zheng, and M. F. Mokbel, "Location-based and Pref-erence-Aware Recommendation Using Sparse Geo-Social Net-working Data," *ACM SIGSPATIAL GIS'12*, Nov. 2012.
[10] http://www.ieee.org/publications_standards/publications/rights/index.html