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Social Engine for Pattern Mining and Prediction of Mobile Commerce Users

J. Mohabath[1], S. J. Vivekanandan[2]

[1]M.Tech CSE II Year, Department of Computer Science, PRIST University, Thanjavur – 613 403

[2]Research Scholar, Sathyabama University, Chennai
Assistant Professor, Department of Computer Science, PRIST University, Thanjavur – 613 403

Abstract: ***Due to research on social network, mobile commerce has received lot of interests. Mining and prediction of users' mobile commerce behaviors such as their movements and purchase transactions. In this paper, we propose a novel framework, called Social Engine, for mining and prediction of mobile users' movements and purchase transactions under mobile commerce using social networks. The social engine framework consists of major components: Social Engine mainly consists of Location Extractor used to track user movements, events, shops. Social Data Extractor used to extract data from social, Preference Extractor, Consumer Sentiments used to extract customer feedbacks about items, location and Recommender system used to recommend product, travel location, promote offers, discount. It facilitates mining and prediction of mobile users' commerce behaviors in order to recommend stores and items to a user via social network.***

Keywords: Data mining, mobile commerce, social network

1. Introduction

With the rapid advance of wireless communication technology and the increasing popularity of powerful portable devices, mobile users not only can access worldwide information from anywhere at any time [28] but also use their mobile devices to make business transactions easily, e.g., via digital wallet. Meanwhile, the availability of location- acquisition technology, e.g., Global Positioning System (GPS), facilitates easy acquisition of a moving trajectory, which records a user movement history. Thus, we envisage that, in the coming future of Mobile Commerce (M- Commerce) age [27], some m-commerce services will be able to capture the moving trajectories and purchase transactions of users. Take the recent announced Shopkick [20] as an example, it gives mobile users rewards and offers when users check-in in stores and on items. Anticipating that some users may be willing to exchange their locations and transactions for good rewards and discounts, we expect more mobile commerce applications, whether they will bear a business model similar with Shopkick or not, will appear in the future. In this paper, we aim at developing pattern mining and prediction techniques that explore the correlation between the moving behavior and purchasing transactions of mobile users to explore potential M-Commerce features. Social networks and communities like Facebook, Twitter, and MySpace gain increasing importance in people's everyday lives. Companies start to see these platforms as a for communicating to target group and deriving innovation ideas from this group. Introducing new ideas to leaders of communities maximizes their spread to the rest of the population and is an effective way of indirectly reaching individuals that shy away from authorities. Perhaps, one of the most recent IT-based solutions nowadays is social media solution. Many organizations have created their own Facebook and Twitter pages, and employ social media tools to monitor their standing, offers, news update about products and other details about products in the social networks. An online social network is important for various applications in many domains such as advertisement, community health campaigns, administrative science, and even politics. In this, we study identifying leaders and followers in online social networks using user interaction information. Many companies diligently establish their presence on Social Networking Services (SNSs) as they recognize Social Media Marketing (SMM) will be the next "holy grail of marketing". However, yet the true value of SMM remains unclear because marketing based on social networking still defines its best practices and metrics. Owing to the rapid development of the web 2.0 technology, many stores have made their store information, e.g., business hours, location, and features available online, e.g., via mapping services such as Google Map. Additionally, user trajectories can be detected by GPS-enabled devices, when users move around. For example, in [31], [33], the authors discuss how to collect and analyze user trajectories from GPS-enabled devices. When a user enters a building, the user may lose the satellite signal until returning to the outdoors. By matching user trajectories with store location information, a user's moving sequence among stores in some shop areas can be extracted. Fig. 1 shows a scenario, where a user moves among stores while making some purchase transactions (or transactions in short). Fig. 1a shows a moving sequence, where underlined store labels indicate some transactions being made there. Fig. 1b shows the transaction records of a user, where item was purchased when this user is in store. There usually is an entangling relation between moving patterns and purchase patterns since mobile users are moving between stores to shop for desired items [30]. The moving and purchase patterns of a user can be captured together as mobile commerce pattern for mobile users. For example, the user taking the shopping trip shown in Fig. 1 may exhibit a moving pattern ABC and two purchase patterns. This pattern, which can be expressed as, indicates that the user usually purchases item i_1 in store A and then

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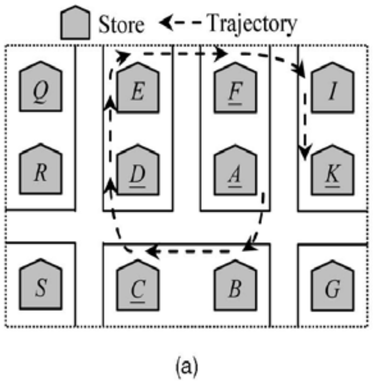
purchases item i_3 in store C on the specific path ABC. Armed with knowledge of this pattern, an m-commerce service could push some discount coupons of item i_3 to the user to boost the sales of store C when the user purchases item i_1 in store A. To provide this mobile ad hoc advertisement, mining



Store	Item
A	i_1
B	
C	i_3
D	i_2
E	
F	i_3, i_4
I	
K	i_5

Figure 1: An example for a mobile transaction sequence. (a) Moving trajectory. (b) Transactions.

To capture and obtain a better understanding of mobile users' mobile commerce behaviors, data mining [7] has been widely used for discovering valuable information from complex data sets. A number of studies have discussed the issue of mobile behavior mining analysis, even though the targeted patterns in these prior works are typically different. For example, Tseng and Tsui, [26] studied the problem of mining associated service patterns in mobile web environments. They also proposed SMAP- Mine [23] for efficient mining of users' sequential mobile access patterns, based on the FP-Tree [8]. Chen et al. [5] proposed the path traversal patterns for mining mobile web user behaviors. Yun and Chen [30] proposed a method for mining mobile sequential pattern (MSP) by taking moving paths of users into consideration. Jeung et al., proposed a prediction approach called Hybrid Prediction Model (HPM) [12] for mining the trajectory pattern of a moving object. While the aforementioned studies have been conducted for discovery of mobile patterns, few of them consider the personalization issue. Since patterns mined in these studies are typically from all users, they do not reflect the personal behaviors of individual users, especially when the mobile behaviors may vary a lot among different mobile users. In this paper, we aim at mining mobile commerce behavior of individual users to support m-commerce services at a personalized level. As mentioned earlier, in addition to mining mobile patterns, predicting the next mobile behaviors of a user is a critical research issue. Existing work on mobile behavior prediction can be roughly divided into two categories. The first category is vector-based prediction [18], [21], [22] and the second category is pattern-based prediction [10], [12], [23], [30]. The idea of vector-based prediction is to predict the next location of an object according to its moving direction and velocity. Vector-based predictions assume that the predictive mobile behaviors of a user can be represented by mathematical models based on his recent movement in the form of geographic information. Pattern- based prediction models, on the other hand, capture semantic patterns that match the user's recent mobile behaviors well. Pattern-based predictions are more precise than vector-based predictions [12]. Hybrid Prediction Model [12] represents the state of the art in the field of movement prediction for moving objects. HPM integrates both ideas of the pattern-based prediction and vector-based prediction. We argue that the vector-based prediction models may not be appropriate for mobile user behavior prediction, since an object's movements are more complicated than what the mathematical formulas can represent [12]. Thus, our study follows the paradigm of pattern-based prediction. Nevertheless, our work is uniquely different from the existing work because we aim at predicting the mobile commerce behavior in terms of both the movement and purchase transaction, while the existing work mostly focus on predict the movement only. A crucial issue for pattern-based prediction is that the predictions fail if there is no existing pattern to match. In the previous pattern-based prediction models, pattern selection is typically based on exact matching, e.g., the similarity between different stores is 0. Take Fig. 1 as an example, the user has never been to store Q, store R, and store S. Since there is no pattern involving these stores, pattern-based predictions do not work when a user first moves to these stores. To overcome this problem, our idea is to incorporate the similarities of stores and items into the mobile commerce behavior prediction. Consider the exam- ple in Fig. 1 again. Since the user has never been to store Q, the mobile patterns mined by this user do not contain any information about store Q. However, if we know that store A (where the user had visited before) is similar with store Q, we can make recommendation to the user based on the patterns exhibited in store A. In other words, we consider that the mobile behaviors of the user in store A may be similar with those in store Q. Thus, we can employ the inferred behaviors in store A to predict next mobile behaviors in store Q even though the user has never been to store Q. Hence, a fundamental issue is to derive the similarities of stores in this paper. Multiple-level hierarchical structures can be defined to measure which stores are similar [6], [15], [26]. However, the method requires the users to set up hierarchical structures. It is difficult to determine suitable structures in a mobile commerce environment. In this paper, we develop a similarity inference model (SIM) to automatically measure the similarities between stores and between items. Based on our observations, we identify two basic heuristics as the bases of our inference model: 1) two stores are similar if the items they sell are similar; 2) two items are dissimilar if the stores which sell them are dissimilar. Accordingly, we infer the store similarity and item similarity from each other. Although a number of similarity measures have been studied to measure the similarity of two vectors in the literature, they are not applicable in this work due to the following factors: 1) most of similarity measures can only process numerical data [13] but not the categorical data considered in this paper; 2) most of similarity measures consider the similarity between two vectors as 0, when their elements are different [13], [29]. It is not true in this work. For example, there are two stores A and

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B which only sell milk and coffee, respectively. The similarity between store A and store B should not be 0 since milk and coffee are both drinks; and 3) most of the similarity measures can only handle one entity type, while we consider both store similarity and item similarity at the same time. In [11], Jeh and Widom, propose an iterative similarity computation method named SimRank. Although SimRank bears with similar ideas as SIM, SimRank is not applicable to our problem. Particularly, SimRank needs to set a decay factor C and a fixed number of iterations K to perform. In mobile commerce environments, it is difficult to determine which parameters are suitable. To provide a high-precision mobile commerce behavior predictor (MCBP), we focus on personal mobile pattern mining. Besides, to overcome the predictions failure problem, we incorporate the similarities of stores and items into the mobile commerce behavior prediction. Hence, in this paper, we propose a novel framework, namely Social Engine, to mine and predict mobile users' movements and transactions using social network. The Social Engine framework consists of three major components: 1) Similarity Inference Model for measuring the similarities among stores and items, which are two basic mobile commerce entities considered in this paper; 2) Personal Mobile Commerce Pattern Mine (PMCP-Mine) algorithm for efficient discovery of mobile users' Personal Mobile Commerce Patterns (PMCPs); and Mobile Commerce Behavior Predictor (MCBP) for prediction of possible mobile user behaviors. To our best knowledge, this is the first work that facilitates mining and prediction of mobile. Users' commerce behaviors that may recommend stores and items previously unknown to a user. Finally, through an extensively experimental evaluation, we show that our proposals deliver an excellent performance in terms of precision, recall, and F-measure.

2. Related Work

In this section, we review and classify relevant previous studies into three categories: similarity measures, mobile pattern mining techniques, and mobile behavior predictions. Similarity Measure. There have been many studies on measuring the similarity between two objects. The first one is based on multiple-level hierarchical structures. In [15], Lu first proposes the concept of multiple-level hierarchical structure in data mining. In [6], Han and Fu, propose the multiple-level association rules mining. In this study, taxonomy is incorporated for representing the hierarchical relations of items. In [26], Tseng and Tsui, first applies the multiple-level hierarchical concept to mine associated service patterns in mobile web environments. Based on the structure, the items in the same level are regarded as similar items. However, we do not know the relations between the items in the different levels. The second one is sequence alignments. In [11], Jeh and Widom, propose the SimRank to iteratively compute the similarities between objects. The idea is that two objects are similar if they are related to similar objects. To improve the efficiency of SimRank, in [32], Yin et al., develop the hierarchical structure named SimTree to reduce the computation cost and the storage of object similarities but still discover the relationships between objects. In [29], Xin et al., propose a pattern distance measure based on set similarity (SET) between two association patterns. The concept of set similarity is to apply Jaccard Measure to calculate the similarity of two sets. Let S1 and S2 be two sets, the set similarity set_similarity(S1 ; S2) is defined as (1). However, set similarity is not applicable to store similarity in mobile commerce. For example, there are two stores A and B which only provides milk and coffee, respectively. The similarity of store A and store B should not be 0, since milk and coffee belong to the same drink category. Mobile Pattern Mining. In recent years, a number of studies have discussed the usage of data mining techniques to discover useful rules/patterns from WWW [19], transaction databases [1], [2], [3], [8], [17] and mobility data [14], [23], [26], [30]. Mining association rules [1] are proposed to find important items in a transaction database. In [2], Agrawal and Srikant, propose the Apriori algorithm to mine the association rules. In [17], Park et al., propose the DHP algorithm to improve the performance of an association rule mining. In [19], Pei et al., propose an algorithm named WAP-Mine to efficiently discover web access patterns in web logs, using a tree-based data structure without candidate generation. Sequential pattern mining has been first introduced in [3] to search for time-ordered patterns, known as sequential patterns within transaction databases. For the studies considering the relation between location and service, in [5], Chen et al., propose the path traversal patterns for mining web user behaviors. Tseng and Tsui, [26] first study the problem of mining associated service patterns in mobile web environments. SMAP-Mine [23] has been proposed by Tseng et al., for efficiently mining users' sequential mobile access patterns, based on the FP-Tree [8]. Lee et al., propose T-MAP [14] to efficiently find the mobile users' mobile access patterns in distinct time intervals. Yun and Chen, propose the Mobile Sequential Pattern [30] to take moving paths into consideration and add the moving path between the left hand and the right hand in the content of rules. In [25], Tseng et al., propose the TMSP-Mine for discovering the temporal mobile sequence patterns in a location-based service environment. Jeung et al., propose a prediction approach called Hybrid Prediction Model [12] for estimating an object's future locations based on its pattern information. This paper considers that an object's move- ments are more complicated than what the mathematical formulas can represent. However, there is no work consider user relations in the mobile pattern mining.Mobile Behavior Prediction. The studies on mobile behavior predictions can be roughly divided into two categories. The first category is a vector-based prediction that can be further divided into two types: 1) linear models [18], [22] and 2) nonlinear models [21]. The nonlinear models capture objects' movements with sophisticate regression functions. Thus, their prediction accuracies are higher than those of the linear models. Recursive Motion Function (RMF) [21] is the most accurate prediction method in the literature based on regression functions. The second category is a pattern-based prediction. In [10], Ishikawa et al., derive a Markov Model (MM) that generates Markov transition probabilities from one cell to another for predicting the next cell of the object. However, these methods can only predict the next spatial locations of objects. SMAP-Mine [23] has been proposed to discover sequential mobile access rules and predict the user's next locations and services.

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3. Proposed Method

In this section, we describe our design of a personal mobile commerce mining and prediction framework, called MCE, which incorporates three innovative techniques, including 1) Similarity Inference Model for measuring the similarities among stores and items, which are two basic mobile commerce entities considered in this paper; 2) Personal Mobile Commerce Pattern Mine algorithm for efficient discovery of mobile users' Personal Mobile Commerce Patterns; and 3) Mobile Commerce Behavior Predictor for prediction of possible mobile user behaviors.

3.1 System Framework

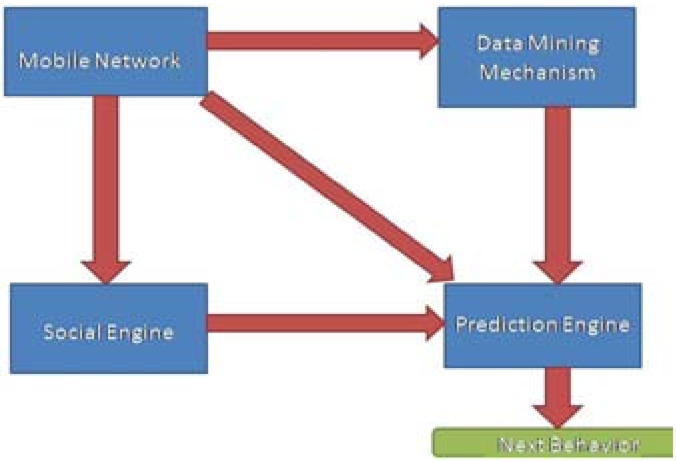
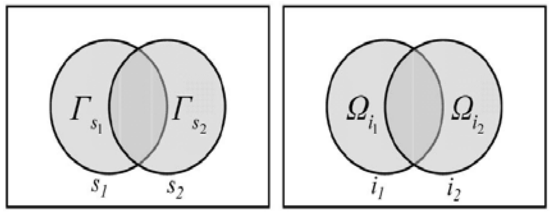


Figure 2: Proposed Framework.

The proposed Social Engine framework consists of three modules, 1) a mobile network database, 2) a data mining mechanism, and 3) a behavior prediction engine and social engine. The mobile network database maintains detailed store information which includes locations. Our system has an "offline" mechanism for similarity inference and PMCPs mining, and an "online" engine for mobile commerce behavior prediction. When mobile users move between the stores, the mobile information which includes user identification, stores, and item purchased are stored in the mobile transaction database. In the offline data mining mechanism, we develop the SIM model and the PMCPMine algorithm to discover the store/item similarities and the PMCPs, respectively. In the online prediction engine, we propose a MCBP based on the store and item similarities as well as the mined PMCPs. When a mobile user moves and purchases items among the stores, the next steps will be predicted according to the mobile user's identification and recent mobile transactions. The framework is to support the prediction of next movement and transaction.

3.2 Similarity Inference Model

An essential task in our framework is to determine the similarities of stores and items. The problem may be solved by using store and item category ontology. However, the store or item ontology may not match with the mobile transaction database. Our goal is to automatically compute the store and item similarities from the mobile transaction database, which captures mobile users' moving and transactional behaviors (in terms of movement among stores and purchased items). From the database, we have the following information available: 1) for a given store, we know which items are available for sale; 2) for a given item, we know which stores sell this item. The information can help us to infer which stores or items are similar.



(a) (b)

Figure 3: The basic concept of SIM. (a) Store similarity inference. (b) Item similarity inference.

We propose a parameter-less data mining model, named Similarity Inference Model, to tackle this task of computing store and item similarities. Before computing the SIM, we derive two databases, namely, SID and ISD, from the mobile transaction database. An entry SIDpq in database SID represents that a user has purchased item q in store p, while an entry ISDxy in database ISD represents that a user has purchased item x in store y. Table 3 shows the transformed SID and ISD from mobile transaction database in Table 2. There are eight stores and eight items in this database. After obtaining SID and ISD, the major challenge we have to tackle on is to automatically compute the similarities between stores and items. We derive the SIM to capture the similarity score between stores/items. For every pair of stores or items, SIM assigns them a similarity score. As shown in Fig. 3a, s1 and s2 are two stores and _s1 and _s2 are two item sets which are sold in stores s1 and s2, respectively. In Fig. 3b, i1 and i2 are two items and _i1 and _i2 are two store sets where users have purchased i1 and i2, respectively. Based on our observations, we identify two basic heuristics to serve as the basis of our similarity inference model: 1) s1 and s2 are more similar, if _s1 and _s2 are more similar.

3.3 Discovery of PMCPs

In this section, we describe the PMCP-Mine algorithm to mine the personal mobile commerce patterns efficiently. The PMCP-Mine algorithm is inspired by the TJPF algorithm [30] which is an Apriori-like algorithm. However, we observe that the TJPF algorithm does not consider user identification, which is essential for discovering personal mobile behaviors. In other words, the TJPF algorithm cannot be employed in our framework. The PMCP-Mine algorithm is performed in a bottom-up manner. The PMCP-Mine algorithm is divided into three main phases: 1) Frequent-Transaction Mining. A Frequent- Transaction is a pair of store and items indicating frequently made purchasing transactions. In this phase, we first discover all Frequent-Transactions for each user. 2) Mobile Transaction Database Transformation. Based on the all Frequent-Transactions, the original mobile transaction database can be reduced by deleting infrequent items. The main purpose is to increase the database scan efficiency for pattern support counting. 3) PMCP Mining. This phase is mining all patterns of length k from patterns of length k _ 1 in a bottom-up fashion.

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3.4 Mobile Commerce Behavior Predictor

In this sub module, we describe how to use the discovered PMCPs to predict the users' future mobile commerce behaviors which include movements and transactions. In existing pattern-based prediction models, the pattern selection strategy is based on exact matching, i.e., the similarity between different locations is treated as 0. Such prediction strategy may lead to prediction failures if there is no existing pattern to match. To overcome this problem, we integrate the similarities of stores and items which are obtained from SIM into the mobile commerce behavior prediction. The most basic pattern-based prediction strategy is to choose the pattern with highest support from all the patterns whose premise matches the user's recent mobile commerce behavior. In mobile commerce behavior prediction, a longer pattern match may represent that this pattern is better matched for recent mobile commerce behaviors. Based on that, we propose the second prediction strategy named Integration of Support and Matching length (ISM). The idea of ISM is to incorporate both the pattern support and matching length into the mobile commerce behavior prediction. In ISM, we design a scoring function to compute the matching score between the premise of a PMCP and user's recent mobile commerce behavior. The significance of PMCP with the maximum score is used to calculate the next mobile commerce behavior. The scoring function, the function matching length represents the length of pattern matching. However, the predictions fail if there is no pattern to match in pattern-based predictions. To overcome this problem, we incorporate the store and item similarities into the mobile commerce behavior prediction. Accordingly, we propose MCBP, which measures the similarity score of every PMCP with a user's recent mobile commerce behavior by taking store and item similarities into account. In MCBP, three ideas are considered: 1) the premises of PMCPs with high similarity to the user's recent mobile commerce behavior are considered as prediction knowledge; 2) more recent mobile commerce behaviors potentially have a greater effect on next mobile commerce behavior predictions; and 3) PMCPs with higher support provide greater confidence for predicting users' next mobile commerce behavior. We propose a weighted scoring function to evaluate the scores of PMCPs. For all PMCPs, we can calculate their pattern score by the weighted scoring function. The consequence of PMCP with the highest score is used to predict the next mobile commerce behavior.

3.5 Location Extractor

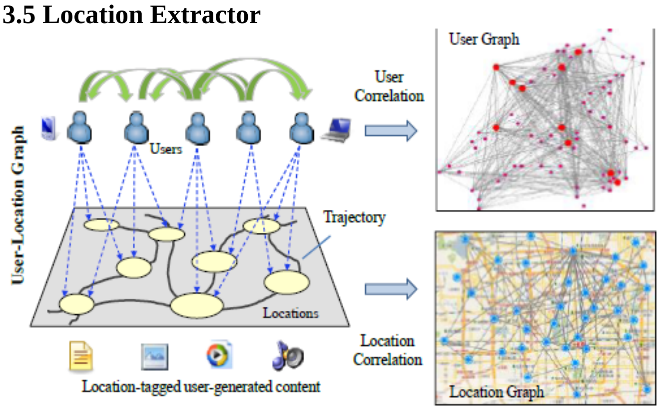

Figure 4: Research philosophy of a location-based social network

We propose a location-based social network extractor so that people in the social structure can share location embedded information, consists of the new social structure made up of individuals connected by the interdependency derived from their locations in the physical world as well as their location-tagged media content. Here, the physical location consists of the instant location of an individual at a given timestamp and the location history that an individual has accumulated in a certain period. Further, the interdependency includes not only that two persons co-occur in the same physical location or share similar location histories e.g., common interests, behavior, and activities, inferred from an individual's location history and location-tagged data. In a location-based social network, people can not only track and share the location-related information of an individual via mobile devices, but also collaborative social knowledge learned from user generated and location-related content, GPS trajectories and geo-tagged photos. *Geo-tagged-media-based*. Quite a few geo-tagging services enable users to add location label to media content generated in the physical world. *Point-location-driven*. Applications like Google Latitude encourage people to share their current locations. *Trajectory-centric*. In a trajectory-centric social networking service, such as Microsoft GeoLife, users pay attention to both point locations and the detailed route connecting these point locations. These services do not only tell users basic information, such as distance, duration, and velocity, about a particular trajectory, but also show a user's experiences represented by tags, tips, and photos for the trajectory. User and location are two major subjects closely associated with each other in a location-based social network. As illustrated in Fig 3, users visit some locations in the physical world, leaving their location histories and generating location-tagged content. We sequentially connect these locations in terms of time; a trajectory will be formulated for each user. Based trajectories, we can build three graphs: a location-location graph, a user-location graph, and a user-user graph. In Proposed system we can understand users based

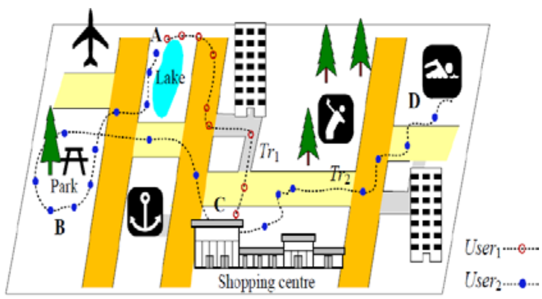

Figure 5: Modeling the location history of a user from sensor data

upon their location via user mobility, Events discovery from social media, for instance, anomalous events like a natural disaster or a celebration. location history of an individual using the individual's geo-data such as GPS trajectories following the paradigm of "sensor data → geospatial locations (significant places) →semantic meanings (e.g., restaurants)". First is mining the most interesting locations, travel experts, and travel sequences in a city using user-generated GPS trajectories. The second is some trip planning and itinerary recommendation literatures. The third is a location-activity recommender that provides a user with two types of recommendations. The most popular activities that

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can be performed in a given location and the most popular locations for conducting a given activity. The above three types of work are generic recommendations.

3.6 Consumer Sentiment Extractor

Consumer sentiment Extractor used to extract customer feedbacks, rating about products and location from social media. It collecting texts from Twitter, we do a preliminary screening for the most commonly used words in the Internet searches regarding the study area. Two specialists were sought to cite most commonly used words concerning about products with a suggestion of values from -10 to +10. These words were added to the dictionary. Their final values were chosen according to an average of the Specialists' suggestion and similar existing words in list. The most mentioned words by Specialists were adjectives, verbs and some negative words. Hundreds of texts extracted from Twitter and facebook were studied. Some words were also added to the dictionary. The most mentioned by tweets were slangs and some negative words. For other contexts, it will be studied if only five-hundred texts extracted from social networks are necessary or if more texts have to be extracted to make a good classification of polarity. The Sentimeter dictionary contains 2596 words among which 700 words are tenses, 1600 are adjectives (positive and negative adjectives), 130 are slangs, 116 are emotions and 50 are negatives words (e.g., not, never). The texts from Twitter that helped to build the dictionary were not used as a test. Three other Specialists validated the dictionary in order not to influence the results. Two thousand more tweets were captured to be classified by the Sentimeter and to have their polarity represented in a numeric value. The results of sentiment strength can be seen in which each word has a scale from −1 to −10 for negative sentiments and from +1 to +10 for positive sentiments. It includes emotions with value −1 or +1, slang and strong obscene words with values +10 or −10. There are separate files for slangs, negative words, negative adjectives, positive adjectives, emotions and tenses (past tense is in a separate file from present tense) in order to facilitate the application of some exceptions, such as the negative rule and the tense rule. A friendly message search framework was used to see the texts extracted from Twitter an Facebook. The users can have access to similar preferences and characteristics by using this framework in order to find promotion products in social web. Finally it fetches rating, comments, shares about the product, travel location and etc from social media users used to recommend to users for better purchase.

3.7 Social Recommender System

Using social network information to recommend items has become hot in the area of recommender systems. Social contextual information which can be derived from links and data on social networks. Users typically examine items' content and information on senders. For example, in Twitter, when a user receives a tweet that is posted by one of his friends (the sender), he usually reads its content to see whether the item is interesting.

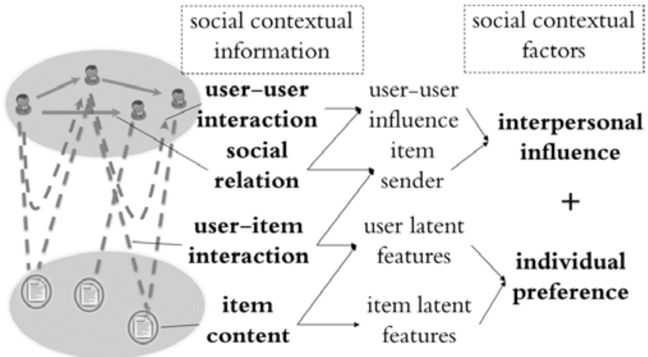

Figure 6: A novel framework for social recommendation

We can get this knowledge from item content and user-item interaction information. In this case, the user cares about who the sender is and whether the sender is a close friend or authoritative. If more than one friend sends him the same tweet, he may read it more attentively. This knowledge can be learnt from social relation and user-user interaction information. Both of these aspects are important for the user to decide whether to adopt (e.g., share, retweet) the item. Social Recommender System incorporates a variety of contextual information without the restriction on information type from two aspects: (i) contexts are explicitly considered to partition the rating matrix, (ii) a context-aware Pearson Correlation Coefficient is proposed to improve the accuracy of user similarity measure. In this section, we present a social network aided context-aware recommender system. We first formalize the context-aware social recommendation problem. Probabilistic matrix factorization based approach to fuse user-item-rating matrix and users' social network information. In, a neighborhood- based approach is developed to generate social recommendations. Social regularization on the basis of matrix factorization to constrain the taste difference between a user and his/her friends. Two variants are proposed: (1) average-based regularization that targets to minimize the difference between a user's latent factors and average of that of his/her friends; (2) individual-based regularization that focuses on latent factor difference between a user and each of his/her friends. For instance, even if a friend has very similar tastes with a user, her rating on a movie may be greatly influenced by other factors, for instance, her mood, or with whom she watched the movie. Proposed to cluster users and items such that like-minded users and their items are grouped. Subgroup information is then utilized by applying collaborative filtering to improve top-N recommendation quality. user may trust different subsets of friends regarding different domains, and then proposed a category specific circle-based model to make context-aware recommendation. However, these works only consider very basic contextual information (e.g., category/group). proposed an architecture to collect contexts and social network information for personalized recommender systems. Focused on how relevant data is collected and stored but ignored how such data is efficiently combined from an algorithmic perspective. Integrate social contexts (individual preference and interpersonal influence) into a matrix factorization model. In proposed system social aided recommender system suggestion best products, travel location, investments, offers, discounts, and other related to shops etc according to the social network user's ratings, likes, comments and preferences.

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4. Future Work

For the future work, we plan to explore more efficient mobile commerce pattern mining algorithm, design more efficient similarity inference models, and develop profound prediction strategies to further enhance the Social Engine framework. In addition, we plan to apply the Social Engine framework to other applications, such as object tracking sensor networks and location-based services, aiming to achieve high precision in predicting object behaviors. We plan to use Bluetooth 3.0 and NFC (Near Field Communication) technologies for more efficient transaction tracking and movements' acquisition of the mobile users. In near future we plan to enhanced depth analysis and prediction of mobile users' transactional behavior and movements. Next we are planning to use efficient wireless technologies like AGPS, 4G, 5G and etc for better results.

5. Conclusion

We have proposed a novel framework, namely Social Engine, for mining and prediction of mobile users' movements and preferences in social media. In the Social Engine framework, we have proposed major techniques: 1) SIM for measuring the similarities among stores and items; 2) PMCP-Mine algorithm for efficiently discovering mobile users' PMCPs; and 3) MCBP for predicting possible mobile user behaviors. To our best knowledge, this is the first work that facilitates mining and prediction of personal mobile commerce behaviors that may recommend stores and items previously unknown to a user. To evaluate the performance of the proposed framework and three proposed techniques, we conducted a series of experiments. The experimental results show that the framework Social Engine achieves a very high precision rate in mobile user behavior predictions. Besides, the prediction technique MCBP in our Social Engine framework integrates the mined PMCPs and the similarity information from SIM to achieve superior performs in terms of precision, recall, and F-measure. The experimental results show that our proposed framework and three components are highly accurate under various conditions.

References

[1] R. Agrawal, T. Imielinski, and A. Swami, "Mining Association Rule between Sets of Items in Large Databases," *Proc. ACM SIGMOD Conf. Management of Data*, pp. 207-216, May 1993.
[2] R. Agrawal and R. Srikant, "Fast Algorithm for Mining Association Rules," *Proc. Int'l Conf. Very Large Databases*, pp. 478-499, Sept. 1994.
[3] R. Agrawal and R. Srikant, "Mining Sequential Patterns," *Proc. Int'l Conf. Data Eng.*, Mar. 1995.
[4] S.F. Altschul, W. Gish, W. Miller, E.W. Myers, and D.J. Lipman, "Basic Local Alignment Search Tool," *J. Molecular Biology*, vol. 215, no. 3, pp. 403-410, Oct. 1990.
[5] M.-S. Chen, J.-S. Park, and P.S. Yu, "Efficient Data Mining for Path Traversal Patterns," *IEEE Trans. Knowledge and Data Eng.*, vol. 10, no. 2, pp. 209-221, Apr. 1998.
[6] J. Han and Y. Fu, "Discovery of Multiple-Level Association Rules in Large Database," *Proc. Int'l Conf. Very Large Data Bases*, pp. 420-431, Sept. 1995.
[7] J. Han and M. Kamber, *Data Mining: Concepts and Techniques*, second ed. Morgan Kaufmann, Sept. 2000.
[8] J. Han, J. Pei, and Y. Yin, "Mining Frequent Patterns without Candidate Generation," *Proc. ACM SIGMOD Conf. Management of Data*, pp. 1-12, May 2000.
[9] J.L. Herlocker, J.A. Konstan, A. Brochers, and J. Riedl, "An Algorithm Framework for Performing Collaborative Filtering," *Proc. Int'l ACM SIGIR Conf. Research and Development in Information Retrieval*, pp. 230-237, Aug. 1999.
[10] Y. Ishikawa, Y. Tsukamoto, and H. Kitagawa, "Extracting Mobility Statistics from Indexed Spatio-Temporal DataSets," *Proc. Workshop Spatio-Temporal Database Management*, pp. 9-16, Aug. 2004.
[11] G. Jeh and J. Widom, "SimRank: A Measure of Structural-Context Similarity," *Proc. Int'l Conf. Knowledge Discovery and Data Mining*, pp. 538-543, July 2002.
[12] H. Jeung, Q. Liu, H.T. Shen, and X. Zhou, "A Hybrid Prediction Model for Moving Objects," *Proc. Int'l Conf. Data Eng.*, pp. 70-79, Apr. 2008.
[13] L. Kaufman and P.J. Rousseeuw, *Finding Groups in Data: An Introduction to Cluster Analysis.* Wiley, Mar. 1990.
[14] S.C. Lee, J. Paik, J. Ok, I. Song, and U.M. Kim, "Efficient Mining of User Behaviors by Temporal Mobile Access Patterns," *Int'l J. Computer Science Security*, vol. 7, no. 2, pp. 285-291, Feb. 2007.
[15] Y. Lu, "Concept Hierarchy in Data Mining: Specification, Generation and Implementation," master's thesis, Simon Fraser Univ., 1997.
[16] E. Modiano and A. Ephremides, "Efficient Algorithms for Performing Packet Broadcasts in a Mesh Network," *IEEE/ACM Trans. Networking*,vol. 4, no. 4, pp. 639-648, Aug. 1996.
[17] J.-S. Park, M.-S. Chan, and P.S. Yu, "An Effective Hash Based Algorithm for Mining Association Rules," *Proc. ACM SIGMOD Conf. Management of Data*, pp. 175-186, May 1995.
[18] J.M. Patel, Y. Chen, and V.P. Chakka, "Stripes: An Efficient Index for Predicted Trajectories," *Proc. ACM SIGMOD Conf. Management of Data*, pp. 635-646, June 2004.
[19] J. Pei, J. Han, B. Mortazavi-Asl, and H. Zhu, "Mining Access Patterns Efficiently from Web Logs," *Proc.Knowledge Discovery and Data Mining*, pp. 396-407, Apr. 2000.
[20] ShopKick, http://www.shopkick.com, 2010.
[21] Y. Tao, C. Faloutsos, D. Papadias, and B. Liu, "Prediction and Indexing of Moving Objects with Unknown motion patterns," *Proc. ACM SIGMOD Conf. Mgmt of Data*, pp. 611-622, June 2004.
[22] Y. Tao, D. Papadias, and J. Sun, "The tpr∗-tree: An Optimized Spatio-Temporal Access Method for Predictive Queries," *Proc. Int'l Conf. Very Large Data Bases*, pp. 790-801, Sept. 2003.
[23] V.S. Tseng and W.C. Lin, "Mining Sequential Mobile Access Patterns Efficiently in Mobile Web Systems," *Proc. Int'l Conf. Advanced Information Networking/ Applications*, pp. 867-871, Mar. 2005.

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[24] V.S. Tseng and K.W. Lin, "Efficient Mining and Prediction of User Behavior Patterns in Mobile Web Systems," *Information and Software Technology*, vol. 48, pp. 357-369, June 2006.
[25] V.S. Tseng, H.C. Lu, and C.H. Huang, "Mining Temporal Mobile Sequential Patterns in Location-Based Service Environments," *Proc. Int'l Conf. Parallel/Distributed Systems*, pp. 1-8.
[26] V.S. Tseng and C.F. Tsui, "Mining Multi-Level and Location-Aware Associated Service Patterns in Mobile Environments," *IEEE Trans. Systems, Man and Cybernetics: Part B*, vol. 34, no. 6, pp. 2480-2485, Dec. 2004.
[27] U. Varshney, R.J. Vetter, and R. Kalakota, "Mobile Commerce: A New Front" *Computer*, vol. 33, no. 10, pp. 32-38, Oct. 2000.
[28] J. Veijalainen, "Transaction in Mobile Electronic Commerce," *Proc. Int'l Workshop Foundations of Models and Languages for Data and Objects*, pp. 203-227, Sept. 1999.
[29] D. Xin, J. Han, X. Yan, and H. Cheng, "Mining Compressed Frequent-Pattern Sets," *Proc. Int'l Conf. Very Large Data Bases*, Aug. 2005.
[30] C.H. Yun and M.S. Chen, "Mining Mobile Sequential Patterns in a Mobile Commerce Environment," *IEEE Trans. Systems, Man, and Cybernetics, Part C*, vol. 37, no. 2, pp. 278-295, Mar. 2007.
[31] Y. Ye, Y. Zheng, Y. Chen, J. Feng, and X. Xie, "Mining Individual Life Pattern Based on Location History," *Proc. Int'l Conf. Mobile Data Management Systems, Services and Middleware*, pp. 1-10, May 2009.
[32] X. Yin, J. Han, and P.S. Yu, "LinkClus: Efficient Clustering via Heterogeneous Semantic Links," *Proc. Int'l Conf. Very Large Data Base*, Aug. 2006.
[33] Y. Zheng, L. Zhang, X. Xie, and W.-Y. Ma, "Mining Interesting Location and Travel Sequences from GPS Trajectories," *Proc. Int'l World Wide Web Conf.*, pp. 791-800, Apr. 2009.
[34] Vedran Podobnik, “An Analysis of Facebook Social Media Marketing Key Performance Indicators," Proceedings of the 12th International Conference on Telecommunications,, June 2013.
[35] Xin Liu, Karl Aberer, " SoCo: A Social Network Aided Context-Aware Recommender System," WWW 2013, pp. 781-791, May , 2013.
[36] Renata Lopes Rosa, Demostenes Zegarra Rodriguez, Graca Bressan , " SentiMeter: Facebook & Twitter Analysis Tool to Discover Consumers Sentiment," AICT 2013 : The Ninth Advanced International Conference on Telecommunications, pp. 511-516, March 2013.
[37] Yiying Cheng, Yangru Fang, Yongqing Yuan, “Recommendation System for Location-based Social Network," *ACM SIGMOD Conf. mgmt of Data*, pp. 611-622, June 2013.
[38] Meng Jiang,Peng Cui, Fei Wang, Wenwu Zhu and Shiqiang Yang , “Recommendation with Social Contextual Information," IEEE TRANSACTIONS ON KNOWLEDGE & DATA ENGG, pp, 16 January 2014.
[39] Md Sarwat, Jie Bao, Amr Magdy, Md F. Mokbel , “Sindbad: A Location-based Social Networking System," SIGMOD ’12, pp. 601-605, May 20–24, 2012.
[40] M. Zubair Shafiq, Muhammad U. Ilyas, Alex X. Liu, and Hayder Radha , “Identifying Leaders and Followers in Online Social Networks," IEEE JOURNAL ON SELECTED AREAS IN COMMUNICATIONS/SUPPLEMENT, VOL. 31, NO. 9, pp. 618-628, September, 2013

Author Profile

Mr. J. Mohabath received B.Tech in Computer Science from PRIST University, Thanjavur in 2013, and Diploma in Computer Science and Engineering from Directorate of Technical Education in 2010; He is currently doing M.Tech in Computer Science and Engineering from PRIST University, Thanjavur, India. He has presented papers in international conferences and published papers in international journals.

S. J. Vivekanandan, pursuing PhD in Sathyabama University Chennai, Tamilnadu., India. He received B.Tech in Information Technology in 2008 and Management from SASTRA University and M.Tech in Computer Science and Engineering from SASTRA University in 2010. He is currently working as Assistant professor in PRIST University Thanjavur, India. His research interests are Data Mining and Utility Mining, Data Structures and Database.

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