A STRUCTURAL PLAN FOR MOBILE COMMERCE IN PERTAINING WIRELESS SENSOR NETWORKS

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Abstract : Nowadays, mobile commerce has received a lot of interests and, one of the active topic areas in mining and prediction of users' behaviors such as their movements and purchase transactions. In this paper, we suggest a great framework, called Mobile Commerce Explorer (MCE), for mining and prediction of mobile users' movements and buy using mobile commerce. The MCE framework consists of three major components: 1) Similarity Inference Model (SIM) for measuring the similarities among stores and items 2) Personal Mobile Commerce Pattern Mine (PMCP-Mine) algorithm for efficient discovery of mobile users' Personal Mobile Commerce Patterns (PMCPs); and 3) Mobile Commerce Behavior Predictor (MCBP) for prediction of possible mobile user behaviors. This is one of the mining and prediction of mobile users' commerce behaviors in order to recommend stores and items previously unknown to a user.

Keywords : Data mining, mobile commerce.

1. INTRODUCTION

With the rapid advance of wireless communication technology and the increasing popularity of powerful portable devices, mobile users 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... 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. Owing to the rapid development of the web 2.0technology,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 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 easily.

2. EXISTING SYSTEM

2.1. Similarity Measure

2.1.1 Multiple-level hierarchical structures

Lu proposes the concept of multiple-level hierarchical structure in data mining. Han and Fu, propose the multiple- level association rules mining. The taxonomy is incorporated for representing the hierarchical relations of items. Tseng and Tsui, 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.

2.1.2 Sequence alignments

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 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

$$set\_similarity(S_1, S_2) = \frac{S_1 \cap S_2}{S_1 \cup S_2}.$$

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.

2.2 Mobile Pattern Mining

Agrawal and Srikant, propose the Apriori algorithm to mine the association rules. In Park et al., propose the DHP algorithm to improve the performance of an association rule mining. In 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 to search for time-ordered patterns, known as sequential patterns within transaction databases. Chen et al., propose the path traversal patterns for mining web user behaviors. Tseng and Tsui, first study the problem of mining associated service patterns in mobile web environments.

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 for estimating an object's future locations based on its pattern information.

2.3. Mobile Behavior Prediction

2.3.1 A vector-based prediction

A vector-based prediction that can be divided into two types:

a) Linear models

b) Nonlinear models

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) is the most accurate prediction method in the literature based on regression functions.

2.3.2 Pattern-based prediction

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. SMAP-Mine has been proposed to discover sequential mobile access rules and predict the user's next locations and services. Yun and Chen, propose the Mobile Sequential Pattern to predict the next mobile behaviors. The form of the pattern is {(ri, si); (r1),(r2), (r3) ,(rj; sj)}, where item (ri, si) indicates a user request service si at location ri. The pattern above means that a user requests service si in location ri and then requests service sj in location rj via a specific path r1r2r3.

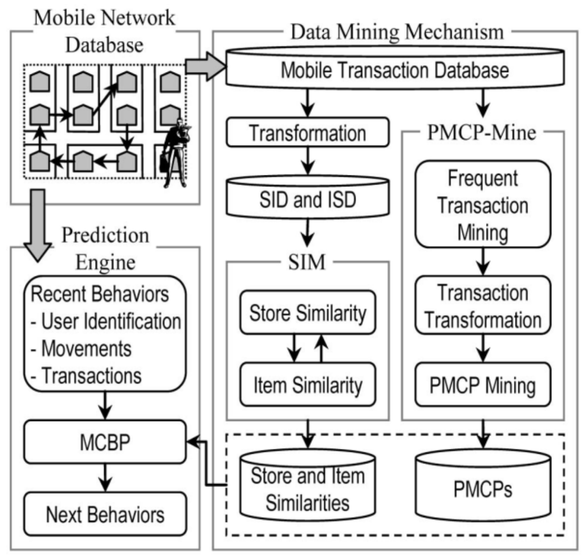
Disadvantages:

1. Multiple-level hierarchical structure was implemented for similarity measure, in this bases on the structure the items in same level are regarded as similar item.
2. In the existing system the similarity of store r measured based on sim rank when two stores r not be 0
3. Prediction was completely based on vector based ie using mathematically calculation and sequential pattern for specific path.
4. No Accuracy of Prediction because its based on the profile or preference of the user.
5.No accuracy of prediction because based on item categories or properties

2. Proposed System

We propose 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;
2) Personal Mobile Commerce Pattern Mine algorithm for efficient discovery of mobile users' Personal Mobile Commerce Patterns;
3) Mobile Commerce Behavior Predictor for prediction of possible mobile user behaviors.

System Architecture



In this architecture there are 3 different modules
1. Mobile network database
2. Data mining mechanism
3. Behavior prediction engine

3.1. Mobile Network Database:

The mobile network database maintains detailed store information which includes locations. 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.

T_{id}	U_{id}	Mobile Transaction Sequence
1	1	$(A,\{i_1\}), (B,\emptyset), (C,\{i_3\}),(D,\{i_2\}), (E,\emptyset), (F,\{i_3,i_4\}), (I,\emptyset), (K,\{i_5\})$
2	1	$(A,\{i_1\}), (B,\emptyset), (C,\emptyset), (D,\{i_2\})$
3	1	$(A,\{i_1\}), (B,\emptyset), (C,\emptyset), (D,\{i_2\}), (E,\emptyset), (F,\{i_3,i_4\}), (I,\emptyset), (K,\{i_5\})$
4	1	$(A,\{i_1\}), (D,\{i_6\}), (C,\{i_5\})$
5	2	$(A,\{i_1\}), (E,\emptyset), (F,\emptyset), (K,\{i_2\}), (I,\{i_2\})$
6	2	$(B,\{i_5\}), (A,\{i_1\}), (E,\emptyset), (F,\emptyset), (K,\{i_2\})$
7	2	$(A,\{i_1\}), (E,\emptyset), (F,\emptyset), (K,\{i_2\}), (I,\emptyset)$
8	2	$(A,\{i_1\}), (E,\emptyset), (F,\{i_3\}), (K,\{i_2\}), (I,\{i_8\})$
9	3	$(B,\{i_1\}), (A,\emptyset), (E,\{i_3\}), (D,\emptyset), (E,\emptyset)$
10	3	$(B,\emptyset), (A,\emptyset), (E,\emptyset), (D,\emptyset), (B,\{i_1\}), (D,\{i_7\})$
11	3	$(B,\{i_1\}), (A,\emptyset), (E,\{i_3\}), (D,\emptyset)$
12	4	$(D,\{i_4\}), (B,\emptyset), (A,\{i_3\})$
13	4	$(I,\{i_5\}), (F,\emptyset), (E,\emptyset), (D,\{i_4\})$
14	4	$(I,\{i_6\}), (F,\emptyset), (E,\{i_1\}), (D,\{i_4\})$

3.2. Data Mining Mechanism

In data mining mechanism, we develop the SIM model and the PMCP Mine algorithm to discover the store/item similarities and the PMCPs, respectively.

3.2.1 Similar Inference Model

We 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).

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.

Store	Items
A	i_1, i_3
B	i_1, i_5
C	i_3, i_5
D	i_2, i_4, i_6, i_7
E	i_1, i_3
F	i_3, i_4
I	i_2, i_5, i_6, i_8
K	i_2, i_5

Item	Stores
i_1	A, B, E
i_2	D, I, K
i_3	A, C, E, F
i_4	D, F
i_5	B, C, I, K
i_6	D, I
i_7	D
i_8	I

Table shows the transformed SID and ISD from mobile transaction database. 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.

	A	*B*	*C*	*D*	*E*	*F*	*I*	*K*
A	1	0.6	0.653	0.185	1	0.656	0.173	0.253
B	0.6	1	0.739	0.281	0.6	0.303	0.52	0.764
C	0.653	0.739	1	0.326	0.653	0.563	0.517	0.759
D	0.185	0.281	0.326	1	0.185	0.494	0.649	0.461
E	1	0.6	0.653	0.185	1	0.656	0.173	0.253
F	0.656	0.303	0.563	0.494	0.656	1	0.202	0.243
I	0.173	0.52	0.517	0.649	0.173	0.202	1	0.68
K	0.253	0.764	0.759	0.461	0.253	0.243	0.68	1

	i_1	i_2	i_3	i_4	i_5	i_6	i_7	i_8
i_1	1	0.19	0.584	0.276	0.39	0.164	0.124	0.168
i_2	0.19	1	0.222	0.346	0.665	0.608	0.387	0.505
i_3	0.584	0.222	1	0.549	0.372	0.201	0.156	0.164
i_4	0.276	0.346	0.549	1	0.227	0.421	0.509	0.221
i_5	0.39	0.665	0.372	0.227	1	0.467	0.197	0.463
i_6	0.164	0.608	0.201	0.421	0.467	1	0.51	0.666
i_7	0.124	0.387	0.156	0.509	0.197	0.51	1	0.256
i_8	0.168	0.505	0.164	0.221	0.463	0.666	0.256	1

3.2.2. The PMCP-Mine algorithm

It 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.

3.3. Behavior prediction engine

In this module we predict the users' future mobile commerce behaviors which include movements and transactions. MCBP (Mobile Commerce Behavior prediction) 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:

i) The premises of PMCPs with high similarity to the user's recent mobile commerce behavior are considered as prediction knowledge;

ii) More recent mobile commerce behaviors potentially have a greater effect on next mobile commerce behavior predictions;

iii) PMCPs with higher support provide greater confidence for predicting users' next mobile commerce behavior

4. CONCLUSION & FUTURE WORK

In this paper, we have proposed a great framework, namely MCE, for mining and prediction of mobile users' movements and transactions in mobile commerce environments. In the MCE framework, we have proposed three 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.

The experimental results show that the framework MCE achieves a very high precision in mobile commerce behavior predictions. Besides, the prediction technique MCBP in our MCE 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. 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 MCE framework

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