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Improve Accuracy of Prediction of User's Future M-Commerce Behaviour

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Abstract

Mobile commerce means "the delivery of electronic commerce capabilities directly into the consumer's hand, anywhere, via wireless technology." In this paper, we consider a system, called Mobile Commerce Predictor (MCP), for mining and prediction of mobile user behaviours under the context of mobile commerce. The main objective of this framework is to predict future m-commerce behaviour of the user on the basis of his current transaction. Predicting future always associated with risk. By improving prediction accuracy, we can minimize that risk. We present efficient strategy to improve accuracy of prediction by introducing confidence as new parameter in existing prediction strategies of MCP framework. We also present results of applying this strategy to transaction data obtained from sample database (i.e. AdventureWorks) which shows effectiveness of the strategy over existing ones.

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*Keywords:*Mobile Commerce Predictor; Pattern Mining; Behavior Prediction

1. Introduction

With the fast expansion of tele-communication technologies mobile devices and wireless applications become more and more popular. We can easily obtain One's present position via a mobile device with GPS service which

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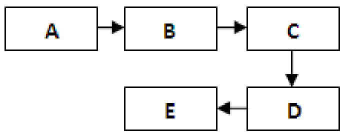
records a user movement history[1]. With a series of users' moving logs, we can know the moving paths of mobile users. Besides, a greater number of people are using mobile devices to purchase items online by credit cards. Combining moving path and transaction records, mobile transaction sequences, which are the sequences of moving paths with transactions, can be obtained[4]. From achieved mobile transaction sequence, we are able to find out frequent transaction of individual user i.e. mining interesting patterns of user transaction. Mined useful patterns are used for predicting user future M-commerce behaviour on the basis of user current transaction. Finding valuable patterns in mobile commerce environments will be helpful in metropolitan planning and maintaining the structure and designing promotions for online shopping websites. Fig. 1 shows a moving sequence of user, where store labels indicate some transactions being made there and transaction records of a user indicate item i1 was purchased when user is in store A. The mobile transaction sequence generated by this user is {(A, {i1}), (B, null), (C, {i3}), (D, {i2}), (E, null).



Store	Item
A	I_1
B	
C	I_3
D	I_2
E	

Fig. 1: Moving Sequence and Transaction Records of a User

There usually some association between moving patterns and purchase patterns since mobile users are moving between stores to shop for desired items. The moving and purchase patterns of a user can be captured jointly as mobile commerce pattern for mobile users. For example, the user taking the shopping trip shown in Fig. 1 shows a moving pattern ABCDE and three purchases patterns (A, i1) → (B, null) → (C, i3) → (D, i2) → (E, null). This pattern indicates that the user generally purchases item i1 in store A and then purchases item i3 in store C on the specific path ABC. Armed with knowledge of this pattern, an m-commerce service could offer some discount coupons of item i3 to the user to increase the sales of store C when the user purchases item i1 in store A[1]. To provide this mobile advertisement, mining mobile commerce patterns of users and accurately predicts their potential mobile commerce behaviours are essential operations which require more research. By considering past transaction records of user we can predict next m-commerce transaction of user in terms of both movement and transaction.

However, in M-commerce behaviour prediction techniques used in existing system not included Confidence parameter. As we deals with prediction of future M-commerce behaviour of user, predicting future always have risk. By improving prediction accuracy, we can minimize that risk. There are n no of ways to improve prediction accuracy. This work aims at improving prediction accuracy by introducing confidence as new parameter in existing prediction method (i.e. Mobile Commerce Behaviours Predictor) of proposed MCP framework. Performance of existing method with addition of this parameter is evaluated by manual simulation method. Experimental result shows that modified technique with confidence parameter has better performance over existing technique used in proposed MCP framework.

The remainder of this paper is organized as follows. We briefly review the related Work in section 2. Section 3 is Existing MCP framework considers for this work. In section 4, we describe Strategies used for prediction in MCP Framework along with proposed technique with new parameter. The experimental evaluation for performance study is made in section 5. The conclusions and future work are given in section 6.

2. Related Work

The studies on mobile behaviour predictions can be generally categorized into two classes. The first class is a vector-based prediction that can be further divided into two types: 1) linear models [10, 12] and 2) Nonlinear models [11]. The nonlinear models used regression functions to capture objects' movements. Thus, their prediction accuracies are higher than those of the linear models. The second class is a pattern-based prediction which used existing patterns (user behaviour) for prediction. In[8], Ishikawa etal., derive a Markov Model (MM) that generates Markov transition probabilities from one cell to another for predicting the next cell of the object. In HPM [9], when the premise of the pattern occurs, the consequence will also occur with probability c. However, these methods can only predict the next spatial locations of objects. SMAP-Mine[13] has been proposed to find out 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 behaviours.

The idea of Collaborative Filtering (CF)[7] may be applied to the prediction of user's behaviour. Collaborative filtering is a method of making automatic predictions (filtering) about the interests of a user by collecting preferences information from many users. Collaborative filtering can be divided into two types: 1) user-based collaborative filtering and 2) item-based collaborative filtering. The user-based collaborative filtering is based on the behaviours of other similar users. For example, suppose that John and Smith are similar based on their profiles or preferences. We may refer to the behaviours of Smith to predict the next behaviour of John. However, the behaviours of two users are not always similar even if the two users are very similar. For the item-based collaborative filtering, the prediction concept is based on user behaviour associated with similar items. Generally speaking, collaborative filtering techniques are not suitable for our study as it is based on user ratings on items to predict user purchase behaviour [1].

To capture and obtain a better understanding of mobile users' mobile commerce behaviours, data mining [5] has been widely used for discovering valuable information from large and complex data sets. Tseng and Tsui, proposed SMAP Mine[13] for efficient mining of users' sequential mobile access patterns, based on the FP-Tree[6]. Jeung et al., proposed a prediction approach named Hybrid Prediction Model (HPM)[9] for mining the trajectory pattern of a moving object. In vector based prediction predictive mobile behaviours 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 behaviours well. Pattern-based predictions are more precise than vector-based predictions[9]. Hybrid Prediction Model[9] 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. The vector-based prediction models may not be suitable for mobile user behaviour prediction, as an object's movements are more complex than what the mathematical formulas can represent[9]. Thus, our study follows the paradigm of pattern-based prediction.

3. Mobile Commerce Predictor Framework

In this section, we describe design of a personal mobile commerce mining and prediction framework, called MCP, which consist of innovative techniques, including 1) Personal Mobile Commerce Pattern Mine algorithm for efficient discovery of mobile users' Personal Mobile Commerce Patterns; and 2) Mobile Commerce Behaviour Predictor for prediction of possible mobile user behaviours[1].

The proposed MCP framework consists of three modules, 1) Mobile network database, 2) data mining mechanism, and 3) a behaviour prediction engine (See Fig. 2)[1]. The detailed information of store including its location will be store into mobile network database. System has an "offline" mechanism for PMCPs mining, and an "online" engine for mobile commerce behaviour 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 algorithm named as PMCP Mine to find out user's m-commerce patterns. 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.

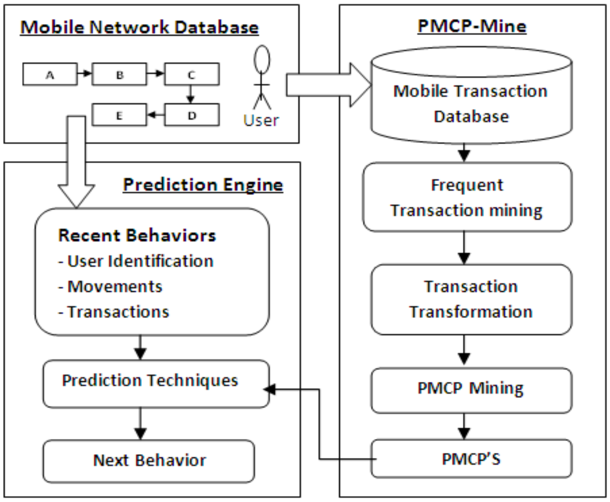


Fig 2: The Mobile Commerce Predictor Framework

4. Prediction Strategies Used In MCP Framework

In this section, we describe strategies used for prediction in MCP framework. Before making prediction, first use Mobile Commerce Pattern Mine (PCMP-mine) algorithm for efficient discovery of Frequent pattern of mobile users from his past transaction history & from that discovered frequent patterns, we find out interesting pattern matches with user current transaction which is called as Mobile commerce pattern (MCPs)[1]. Mined MCPs are used to predict the users' future mobile commerce behaviours which include movements and transactions. MCP framework used following Strategies for prediction

1) Support Only (SO)
2) Integrated Support & Matching Length (ISM)

4.1 Support Only (SO)

It is most basic pattern based prediction strategy. In this strategy, we select patterns having highest support value from all the patterns whose premise matches the user's recent mobile commerce behaviour. It is called Support Only (SO) as only support factor take into consideration for prediction. Support can be defined as occurrence frequency of pattern in transaction database. Support reflects usefulness of selected pattern. We first define the premise and consequence of a mobile commerce pattern (MCP).

Let $P = (S_1,I_1) \rightarrow (S_2,I_2) \ldots .(S_m,I_m) \rightarrow (S_{m+1},I_{m+1})$ be MCP of length m+1 and support of P is sup(p). We call $(S_1,I_1) \rightarrow (S_2,I_2) \ldots .(S_m,I_m)$ as premise and (S_{m+1},I_{m+1}) the consequence.

For example,

P1 = {(A, I1)→(C, I2)→(F, I3)} & SUP (P1) = 5

P2 = {(C, I2)→(I, I4)} & SUP (P2) = 8

P3 = {(D, I1),→(F, I2)→(C, I5)} & SUP (P3) = 10

Let user's current transaction is P' = {(A, I1),(C, I2)}

P' is user's recent mobile commerce behaviour. Since the premise of P3, i.e. {(D, I1)→(F, I2)→} does not match with P', P3 is not used for predicting the user next behaviours. Since P1 and P2 both match P', they are thus two candidates for behaviour prediction. Since P2 has a larger support than P1, the consequence of P2, i.e. (I, I4)} is used to predict the user's next behaviours. However, the SO strategy does not take into account the lengths of pattern matches. For instance, in the above example, although the support of P2 is larger than that of P1, the matching length of P1 is longer than P2 for user's recent mobile behaviours. In the mobile commerce behaviour prediction, a longer pattern match may represent that this pattern is better matched for recent mobile commerce behaviours[1]. Based on the above discussion, the second prediction strategy named Integration of Support and matching length (ISM) was proposed.

4.2 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 behaviour prediction. In ISM[1], we design a scoring function SF (P, P') to compute the matching score between the premise of MCP (P) and user's recent mobile commerce behaviour (P'). The consequence of MCP with the highest score is used to predict the next mobile commerce behaviour. The scoring function SF (P, P') is defined as (1), where the function matching length (P, P') represents the length of pattern matching.

SF (P, P') = Matching Length (P, P') × Sup (P) (1)

For example,
P1 = {(A, I1→(C, I2) →(F, I3)} and SUP (P1) = 5
P2 = {(C, I2)→(I, I4)} and SUP (P2) = 8 be two MCPs

Let P' = {(A, I1)→(C, I2)} be the user's recent mobile commerce behaviour. The matching lengths are 2 between P1 and P' and 1 between P2 and P' Hence, the consequence of P1, i.e. (A1, I1→(C, I2)→ is used to predict the user's next behaviour, since the pattern score of P1 is 2 × 5 = 10 which is larger than that of P2 (1 × 8 = 8)

In the ISM strategy, suppose if there are two or more patterns having similar premise with different consequences then question arises which pattern should be selected for prediction, because in above condition matching length will be same for both patterns. Single support parameter will not sufficiently work in mentioned case. To solve above discussed problem, pattern having high confidence should be consider for prediction.ISM strategy does not take into account the confidence of pattern matches. Based on the above discussion, we propose the new prediction strategy named Integration of Support and Confidence (ISC).

4.3 Integration of Support & Confidence (ISC)

The idea of ISC is to incorporate the pattern support and confidence into the mobile commerce behaviour prediction. Confidence reflects the certainty of discovered M-commerce patterns. For example the pattern (A, I1) →(B, I2) has confidence c in the transaction database where c percentage of transaction s in D containing (A, I1) also contain (B I2)[5]. In Integration of Support and Confidence (ISC), we consider a scoring function SF (P, P') to compute the matching score between the premise of a MCP (i.e. P) and user's recent mobile commerce behaviour (i.e. P'). The consequence of MCP with the highest score is used to predict the next mobile commerce behaviour. The scoring function SF (P, P') is defined as (2), where the Confidence (P) represents certainty of discovered M-commerce patterns.

SF (P, P') = Confidence (P) × Sup (P) (2)

Table 1. Example for ISC

Sr No.	Patterns	Support	Confidence
1	P1={(A1,I1)→(C,I2)→(F,I3)}	5	60
2	P2={(A1,I1)→(C,I2)→(D,I3)}	7	40

Let P' = {(A, I1), (C, I2)} be the user's recent mobile commerce behaviour.
S.F (P1, P') = 5× 60 = 300
S.F (P2, P') = 7× 40 = 280

In above example both patterns have similar premises (i.e. same matching length) with different consequences, so which pattern to be selected for prediction is difficult. So in this case ISM works similar as SO only. Therefore ISM is not useful when two pattern has same matching length and different consequences .To solve this, we introduce confidence factor into existing strategy (i.e. ISM).This prediction strategy is to choose the pattern with highest confidence from all the patterns whose premise matches the user's recent mobile commerce behaviour.

As matching score of pattern P1 is higher than P2, so P2 is selected for prediction whereas according to ISM pattern P1 will be selected as P1 having higher support, which is incorrect prediction. User next m-Commerce behaviour by ISC strategy will be (F, I3). ISM Strategy will not be work for above case when premise of pattern is similar (i.e. Matching length is similar). We overcome this drawback of ISM strategy by proposed strategy ISC considering Confidence of pattern. By this strategy, we can predict Future M-commerce behaviour accurately.

5. Experimental Evaluation

In this section, we evaluate the performance of the proposed Strategy named as ISC by manual simulation system. We experimented with proposed strategy by using online sample database as AdventureWorks which supports standard online transaction processing. The experiments were performed on sales data obtained from AdventureWorks. For given data, frequent transactions of individual user along with support and confidence factor have been found out. Association rules has been discovered from frequent transactions which satisfy criteria of minimum support and confidence. We made prediction of user next M-commerce behaviour by applying all 3 strategies discussed above (i.e. SO, ISM, ISC). Among them Proposed ISC strategy has better results over SO and ISM.

For experiment, 10 association rules have been discovered for minimum support of 1% and minimum confidence of 50%. On the basis of derived association rules and user's current M-commerce behaviour, 20 predictions has been made by applying all 3 strategies Result has shown that Out of 20 predictions SO strategy predicts 10 predictions accurately, ISM strategy predicts 13 predictions accurately whereas ISC strategy predicts 16 predictions accurately.

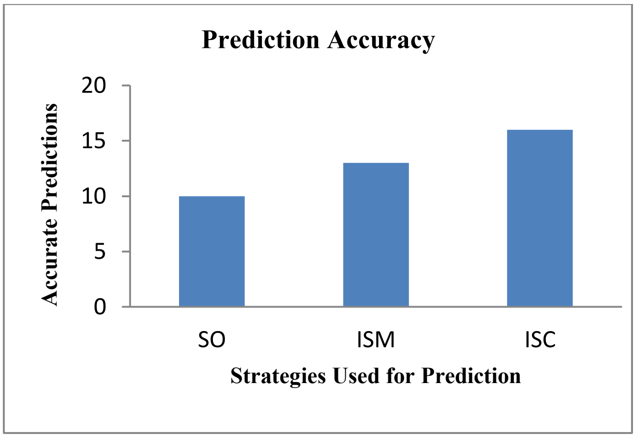


Fig: 3. Performance of Proposed Strategies in Terms of Accuracy

6. Conclusion

In this work, we consider Mobile commerce predictor framework (MCP) and its prediction strategies. To improve accuracy of prediction of user's next M-commerce behaviour, new strategy as Integrated Support and Confidence (ISC) has been proposed. Experimental result shows that proposed strategy has better performance over existing strategies (i.e. SO, ISM) in terms of prediction accuracy. For future work, additional experiments under more conditions of mobile commerce environments will be conducted for further evaluating the Strategies. Moreover, new Method which improves the prediction performance will be designed.

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