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A prediction framework based on contextual data to support Mobile Personalized Marketing

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ABSTRACT

Personalized marketing via mobile devices, also known as Mobile Personalized Marketing (MPM), has become an increasingly important marketing tool because the ubiquity, interactivity and localization of mobile devices offers great potential for understanding customers' preferences and quickly advertising customized products or services. A tremendous challenge in MPM is to factor a mobile user's context into the prediction of the user's preferences. This paper proposes a novel framework with a three-stage procedure to discover the correlation between contexts of mobile users and their activities for better predicting customers' preferences. Our framework helps not only to discover sequential rules from contextual data, but also to overcome a common barrier in mining contextual data, i.e. elimination of redundant rules that occur when multiple dimensions of contextual information are used in the prediction. The effectiveness of our framework is evaluated through experiments conducted on a mobile user's context dataset. The results show that our framework can effectively extract patterns from a mobile customer's context information for improving the prediction of his/her activities.

1. Introduction

Personalized Marketing (PM), also known as one-to-one marketing, is the process of delivering targeted products and services to a customer based on the customer's profile [36,41]. The main objective of PM is to identify the needs of a customer and offer products and services that appeal to that particular customer. Recently, with the dazzling proliferation of mobile commerce, personalized marketing via mobile devices (Mobile Personalized Marketing, MPM) has become an increasingly important marketing tool because the ubiquity, interactivity, and localization of mobile devices offers great potential for collecting customers' information, understanding their preferences and quickly advertising customized products [16,37,60]. Recent studies have predicted that the volume of business transactions associated with MPM will soon become the primary contributor to revenue growth in one-to-one marketing [39].

In personalized marketing, it is important to consider the contextual information, i.e. the environment where a customer is located, in order to understand the needs of the customer. Since it is possible to collect mobile device carriers' geographical positions, value-added services can be delivered via mobile devices, based on the location of a customer, which is often referred to as "Location-based Services", or LBS for short [44]. The correlations between a specific location and the actual activities of a customer can be identified by analysis of his/her short-term location log and then used to predict his/her preferences at certain locations [11,24,44]. However, location is only one aspect of a context [9]. In practice, predicting a mobile user's possible activities simply based on "location" may not achieve satisfactory accuracy in many cases. As empirical studies have shown [40], a view of a customer's activities from multiple perspectives can enhance the predictive accuracy of data-based methods of customer analysis. Thus, dimensions other than location, of contextual information, e.g., time of the day and weather, can also be useful in predicting activities of a mobile user. In order to accurately predict customer preferences, we need to take into account multiple dimensions of a customer's context. Let us look at the following example.

Example 1. When a customer is in a shopping mall, there is a 60% possibility of him/her being interested in redeeming a mobile coupon in a shop. The estimation of this possibility can significantly vary with extra contextual information. When it is a rainy weekend, the possibility that the service is preferred by the customer in a shopping mall can increase to 95%, and in other contexts the possibility can be as low as 15% because people tend to be indoors when the weather is not favorable for outdoor activities.

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In the example above, multiple dimensions of the contextual information provide important clues to the customer's preferences under a more specific circumstance (e.g., location, weather and time). As such, accuracy of the prediction whether a customer will likely accept an offer of a service can be improved when such multidimensional information about the customer's context is incorporated into a prediction method for personalized marketing.

The estimation of a customer's preference for a service can be regarded as a mapping from the customer, context, and service to a probability, i.e. $p = f$ (*Customer*, *Context*, *Service*). In recommender systems, the extent to which a customer prefers a service is reflected by the "User Rating" [2]. In this study, the probability of a customer preferring a service is obtained through analyzing the correlation between a sequence of contexts and the activities of a customer based on historical data. Then, for a given context, the service or product with the highest probability of being preferred can be proactively offered to the customer. The correlations between a series of contexts and activities of a customer are represented as sequential rules, often represented as "*x* leads to *y*" indicating *y* happens after *x* has happened [5]. Users' activities, notably, can also be viewed as an important type of contextual information, since they can offer valuable clues for predicting future moves. This sequential rule based solution enables the service provider to not only tailor services for customers, but also deliver the services in advance.

Example 2. A simple sequential rule is given as follows, showing the correlation between the contexts and the activities of the customer in Example 1.

{office, afternoon}, {shopping mall, night} *leads to* "redeeming a mobile coupon for the food court" (probability = 70%).

This sequential rule indicates that the customer is likely to accept a mobile coupon when going from office to shopping mall at night. Location and time are the involved dimensions of the two contexts in sequence. As this rule has a comparatively high probability, it can be used to make predictions. Then, whenever the antecedent, i.e. the contexts {office, afternoon} and {shopping mall, night}, occur again, a prediction can be made that a mobile coupon for the food court will be preferred by the customer.

Given that in practice, a huge amount of contextual information with various dimensions can be collected using mobile devices, it is a great challenge to effectively identify the sequential rules that are most useful for prediction of customer preferences. Moreover, in order to proactively address customers' needs, it is also critical to quickly identify situations where a sequential rule is applicable.

As different combinations of dimensions of a context can be used for prediction of customer preferences, accuracy of the prediction undoubtedly depends on the set of dimensions for various contexts. Rather than enhancing the predictiveness, incorporation of additional contextual dimensions sometimes results in redundancy [63], which is generally known as a phenomenon wherein "parts of knowledge are in fact corollaries of other parts of knowledge" [38].

Example 3. Seven sequential rules shown as follows are derived from the sequential rule in Example 2 but incorporate one new dimension, i.e. day of the week:

(1) {office, afternoon, Monday}, {shopping mall, night, Monday} *leads to* "redeeming a mobile coupon", and
(2) {office, afternoon, Tuesday}, {shopping mall, night, Tuesday} *leads to* "redeeming a mobile coupon".
…
(7) {office, afternoon, Sunday}, {shopping mall, night, Sunday} *leads to* "redeeming a mobile coupon".

The probabilities of these rules are found to be very close to each other. Thus, the additional dimension, day of the week, does not introduce new knowledge to the original rule.

As illustrated in Example 3, redundancy of sequential rules needs to be taken into account. It is worth noting that the number of sequential rules may increase dramatically after adding a new dimension. Thus, in order to reduce the complexity of the rule base and optimize prediction efficiency, the redundancy issue needs to be addressed.

In summary, the following problems are important and need to be addressed when mining multidimensional contextual data; these problems have motivated the work reported in this paper. First, how can we efficiently discover sequential rules that can achieve high prediction accuracy from multidimensional data? Second, how can we reduce knowledge redundancy in identified rules and, moreover, using those rules, how can a prediction be made based on the context about a customer?

In this study, we propose a data mining based framework to extract and apply sequential rules for a proactive MPM solution. This framework enables incorporation of multidimensional contextual information into sequential rule mining; a new concept, i.e. snapshot, is proposed to capture contextual information. Under our framework, the existing Apriori-like mining methods [4] can be easily applied to predict the activities of mobile users. Moreover, we propose a post-pruning method to help reduce rule redundancy, based on the multidimensional nature of contextual information. In addition, we propose an online mining algorithm that detects the situations where certain services can be delivered according to the probability of being preferred by a customer, thus enabling real-time predictions based on the extracted rules. The proposed framework follows a 3-stage process comprising rule learning, selection and matching, as summarized in Fig. 1.

The learning stage starts with analysis of contextual data to extract sequential rules. The proposed rule-learning algorithm is underpinned by the classical Apriori method [5], which generates candidate rules in a level-wise manner and then eliminates unqualified candidates using "support" as the criterion. The purpose of the rule reduction stage is to screen out rules conveying redundant dimensional knowledge from the generated rule base. This stage helps diminish the number of rules so as to optimize the efficiency of the matching process. The rule matching process monitors the ongoing context changes, evaluates the probability of a user event to occur, based on previously extracted rules, and identifies events with a high probability of being preferred.

The multidimensionality of contextual data has posed many challenges for mining useful rules. The first challenge is to consider the multidimensional setting in the mining algorithms [25]. In this paper, in order to handle the multidimensional data, we propose to take "snapshots" along a continuous dimension (such as *time*), and then identify the co-occurrence relation between the snapshots and the user's actions. With our formulation of the problem, the data mining algorithm handling single-dimension mining, i.e. WINEPI [33], is extended for multidimensional sequential rule mining. Another challenge is to alleviate the rule base complexity, for which we propose an information-entropy-based post-pruning method to identify redundant rules. Our framework can be applied in proactive MPM, and throughout the rest of the paper, we use the MPM scenario as a running example to demonstrate the efficacy of our proposed methods. This framework, however, is generalizable to many other business applications characterized by multidimensional data.

Overall, the main contributions of this paper include:

- Presenting a generic framework with detailed procedures to take into account contextual information in predicting activities of customers;

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