Chapter 12

Reinforcement and Non-Reinforcement Machine Learning Classifiers for User Movement Prediction

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ABSTRACT

Mobile context-aware applications are required to sense and react to changing environment conditions. Such applications, usually, need to recognize, classify, and predict context in order to act efficiently, beforehand, for the benefit of the user. In this chapter, the authors propose a mobility prediction model, which deals with context representation and location prediction of moving users. Machine Learning (ML) techniques are used for trajectory classification. Spatial and temporal on-line clustering is adopted. They rely on Adaptive Resonance Theory (ART) for location prediction. Location prediction is treated as a context classification problem. The authors introduce a novel classifier that applies a Hausdorff-like distance over the extracted trajectories handling location prediction. Two learning methods (non-reinforcement and reinforcement learning) are presented and evaluated. They compare ART with Self-Organizing Maps (SOM), Offline kMeans, and Online kMeans algorithms. Their findings are very promising for the use of the proposed model in mobile context aware applications.

INTRODUCTION

In order to render mobile context-aware applications intelligent enough to support users everywhere/anytime and materialize the so-called ambient intelligence, information on the present context of the user has to be captured and processed accordingly. A well-known definition of context is the following: “context is any information that can be used to characterize the situation of an entity. An entity is a person, place or object that is considered relevant to the integration between
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a user and an application, including the user and the application themselves” (Dey, 2001). Context refers to the current values of specific ingredients that represent the activity of an entity/situation and environmental state (e.g., attendance of a meeting, location, temperature).

One of the more intuitive capabilities of the mobile context-aware applications is their pro-activity. Predicting user actions and contextual ingredients enables a new class of applications to be developed along with the improvement of existing ones. One very important ingredient is location. Estimating and predicting the future location of a mobile user enables the development of innovative, location-based services/applications (Hightower & Borielo, 2001; Priggouris et al., 2006). For instance, location prediction can be used to improve resource reservation in wireless networks and facilitate the provision of location-based services by preparing and feeding them with the appropriate information well in advance. The accurate determination of the context of users and devices is the basis for context-aware applications. In order to adapt to changing demands, such applications need to reason based on basic context ingredients (e.g., time, location) to determine knowledge of higher-level situation.

Prediction of context is quite similar to information classification/prediction (offline and online). In this paper, we adopt ML techniques for predicting location through an adaptive model. ML is the study of algorithms that improve automatically through experience. ML provides algorithms for learning a system to cluster pre-existing knowledge, classify observations, predict unknown situations based on a history of patterns and adapt to situation changes. Therefore, ML can provide solutions that are suitable for the location prediction problem. Context-aware applications have a set of pivotal requirements (e.g., flexibility and adaptation), which would strongly benefit if the learning and prediction process could be performed in real time. We argue that the most appropriate solutions for location prediction are offline and online clustering and classification. Offline clustering is performed through the Offline kMeans algorithm while online clustering is accomplished through the Self-Organizing Maps (SOM), Online kMeans and Adaptive Resonance Theory (ART). Offline learners typically perform complete model building, which can be very costly, if the amount of samples rises. Online learning algorithms are able to detect changes and adapt/update only parts of the model thus providing for fast adaptation of the model. Both forms of algorithms extract a subset of patterns/clusters (i.e., a knowledge base) from an initial dataset (i.e., a database of user itineraries). Moreover, online learning is more suited for the task of classification/prediction of the user mobility behavior as in the real life user movement data often needs to be processed in an online manner, each time after a new portion of the data arrives. This is caused by the fact that such data is organized in the form of a data stream (e.g., a sequence of time-stamped visited locations) rather than a static data repository, reflecting the natural flow of data. Classification involves the matching of an unseen pattern with existing clusters in the knowledge base. We rely on a Hausdorff-like distance (Belogay et al., 1997) for matching unseen itineraries to clusters (such metric applies to convex patterns and is considered ideal for user itineraries). Finally, location prediction boils down to location classification w.r.t. Hausdorff-like distance.

We assess two training methods for training an algorithm: (1) the “nearly” zero-knowledge method in which an algorithm is incrementally trained starting with a little knowledge on the user mobility behavior and the (2) supervised method in which sets of known itineraries are fed to the classifier. Moreover, we assess two learning methods for the online algorithms regarding the success of location prediction: (1) the non-Reinforcement Learning (nRL), in which a misclassified instance is no further used in the model-training phase,