

# Recurrent Neural Networks for Predicting Mobile Device State

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## INTRODUCTION

Smartphones have become a key part of everyday life as an essential tool for their users. People have fully integrated mobile devices into their lives by using them to communicate with friends, check e-mails, play games, record physical activities and take pictures, among other possible uses. Moreover, smartphones are equipped with several features (WiFi, GPS, and Bluetooth among others) that can record activities and contextual information, such as location, application usage, and even messaging and calling behaviour. Hence, smartphones are interesting options for tracking and mining user behaviour in daily life (Do and Gatica-Perez, 2014). This information offers new opportunities to analyse human behaviour aiming at enhancing the user experience with mobile devices and, at the same time, helping to ease the use of smartphones' services (Rios et al., 2014).

Several domains leverage on the prediction of mobile devices' states (Pejovic and Musolesi, 2015; Niroshinie et al., 2013; Ravi et al., 2008). For example, in the development of context aware applications, the predictions could be useful for determining the context in which applications

are running. Such context aware applications are encompassed in a concept called "Anticipatory Mobile Computing" (AMC) (Pejovic and Musolesi, 2015). The goal of AMC is deciding which actions should be taken based on predicted future states to improve the outcome. AMC concepts are present in personal assistance technology (such as Google Now, Microsoft Cortana or Siri), healthcare applications and smart cities. Personal assistance technology uses state prediction to provide relevant information to the user before such information is requested. For example, predicting that the hour in which the user goes to work allows personal assistance technology to provide information about traffic and weather, which might be relevant to the user.

Other use of predictions can be found in mobile cloud computing (Niroshinie et al., 2013). One of its key proposals is moving computing from mobile devices to the cloud to reduce battery consumption. However, to effectively reduce battery consumption, it is necessary to predict whether the energy requirements for communicating are lower than those of processing. In addition, if the mobile device is not going to be connected to the Internet when the cloud finishes its work,

computation results will be unavailable. This might lead to the repetition of the computation in the mobile device, which would waste more energy than if the mobile device had performed the computation in the first place. These are just a few examples of the developing mobile device state prediction techniques' importance.

The current state of mobile devices can be regarded as the consequence of the previous states. Consequently, future behaviour can be predicted based on how a user has been using his/her device. The generation of predictive models of human behaviour has emerged as a topic of interest in several areas, such as recommendation systems, context-aware services, and personalised and adaptive interfaces. For example, several studies have focused on predicting the probability of users to be at a particular place at a given time. Also, Do and Gatica-Perez (2014) and Liao et al. (2012) aimed at predicting which application the user will use next based on contextual information to reduce the time users spend on searching for a specific application.

Although mobile devices constantly evolve as they provide increasing functionality due to the improvements in processing power, storage capabilities, graphics and connectivity; battery capacities do not experience the same growth (Ravi et al., 2008). Power emerges as a critical resource for battery-powered systems as mobile devices. Hence, battery management becomes a crucial requirement to users. Providing battery management information requires the ability to accurately predict remaining battery life in a dynamically changing system. Interestingly, most of the studies in the literature focus on offering location prediction, or application personalisation, instead of analysing the impact of user behaviour in battery level and life. In this context, this work evaluates the suitability of Recurrent Neural Networks (RNN) for predicting future battery levels of mobile devices based on the users' usage pattern of different features, such as the WiFi connection or screen status, among others.

## BACKGROUND

The analysis of human behaviour through smartphone usage has attracted considerable interest in recent years. Works on smartphone mining include physical activity recognition by applying learning techniques to accelerometer data, and personalisation of content and user interface. For example, Do and Gatica-Perez (2014) predicted human behaviour based on smartphone sensors using statistical methods commonly used in signal processing for forecasting time series. Particularly, user location within a ten-minute window was predicted along with the applications users were more likely to use based on the location, time, Bluetooth proximity and communication logs. The approach linearly combined least-squares linear regression, logistic regression and Markov models. Location prediction results showed that the most important predictors were Bluetooth proximity, location and time, and confirmed the dependency between human mobility and social interactions.

Application usage prediction was also studied in (Shin et al., 2012; Liao et al., 2012). Both approaches aimed at presenting users with the most probable applications to be used aiming at reducing the time spent searching for a desired application. Shin et al. (2012) based the prediction on a probabilistic Naïve Bayes model that was personalised to each user according to his/her application usage pattern. Prediction was based on information from GPS, cellular network, accelerometer, calls, WiFi, Bluetooth, screen status, battery status, illumination and running applications. Results showed that the previously used applications, location and hour of day were useful predictors.

Liao et al. (2012) created temporal profiles of application usage and proposed a three step probability-based scoring model to compute the probability of using an application. First, the periodicity of application usage was detected by a Discrete Fourier Transform. Second, captured periodicities were hierarchically clustered to

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