A Next Application Prediction Service Using The BaranC Framework

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***Abstract*—Predicting user behaviour enables user assistant services provide personalized services to the users. This requires a comprehensive user model that can be created by monitoring user interactions and activities. BaranC is a framework that performs user interface (UI) monitoring (and collects all associated context data), builds a user model, and supports services that make use of the user model. A prediction service, Next-App, is built to demonstrate the use of the framework and to evaluate the usefulness of such a prediction service. Next-App analyses a user's data, learns patterns, makes a model for a user, and finally predicts, based on the user model and current context, what application(s) the user is likely to want to use. The prediction is pro-active and dynamic, reflecting the current context, and is also dynamic in that it responds to changes in the user model, as might occur over time as a user's habits change. Initial evaluation of Next-App indicates a high-level of satisfaction with the service.**

I. Introduction

Exponentially growing the number of mobile applications leads users to install many applications on their smart devices. Apple has reported to have about one million apps released[1] and the number of app downloads has reached 100 billion[2]. Context-aware recommender services [1], [2] have been proposed to make it easier to find an application based on a specific location or time. These framework do not seem to focus on recommendations based on the user's habit of using an application. For instance a recommender system (RS) [2] is proposed ro recommend an application to a user based on the context for buying/installing. The recommendation seems to be objective regardless of the user profile and habits.

An intelligent service enables data to flow across an enterprise system, spanning the devices where valuable data is gathered from artefacts, to the back-end systems where that data can be translated into insights and actions. These insights and actions are the key to constructing a predictive model to improve User Experience (UX). A comprehensive model of a user including the corresponding context descriptions enables adaptive systems to learn about the user [3]. This paper describes a light-weight recommender service that analyses a user's interaction data of using a smartphone, learns how the user is using applications, and makes a predictive model. The model can be used to recommend what application(s) might be used next based on the current context and situations. The service relies on the BaranC framework [4], [5], [6] that is responsible for collecting a user's data from digitally controlled internet-enabled devices (e.g. smartphone), storing it to be shared to a 3rd party service (e.g. our recommender service) under the user's control. BaranC provides APIs that allow a 3rd party service to request a user's data, and access it if the permission is granted by the user. In this case our service does not need to care about data collection for a user. This service receives the data from the BaranC framework and uses it to make a predictive model for each user.

What distinguishes our work to the existing works is that we focus on how applications are used by a user and we recommend subjectively a list of applications a user likely want to use next based on the user's habits.

For instance, Alice regularly calls Bob on the weekend, between 6-9 P.M., more specifically when she is home, and she is not engaged any other activity. An intelligent and context-aware service could look for a match with the current situation by looking at the frequent patterns in order to predict and do preparation for a possible action that best suites the current context. The action could be providing the contact information of Bob on all Alice's devices, making sure she has sufficient credit to call, or checking the network quality to find the best and reliable way of making contact.

II. Related Work

Context-aware recommender systems (CARS) [1] proposed a method of considering context factors (e.g. time, location, etc.) in recommending an application to a user. It has been shown that contextual factors strongly influence the recommendations [7]. A hybrid RS is proposed [8] to recommend what application to install based on what other users installed for the same context. Based on the classification of [9], context has two main types, representational (e.g. time, location) and interactional (e.g. clicks, usage). Most of the current proposed works [10], [11] seem to focus on recommending an application to install based on the context and only consider representational context such as location, time, etc. Nagarajan et al. [12] present an algorithm, iConRank, in order to rank the applications based on the recent app sequences. They believe that the sequence of recent applications is related to the next application. For instance, if a user uses a "Contact" application, he/she is likely to use "Message" or "Email" application. They consider interactional context as the foundation of their algorithm. Another example of a recommender considering interactional context is a music recommender system to provide

[1]http://goo.gl/yMySLB
[2]http://goo.gl/rTNE80

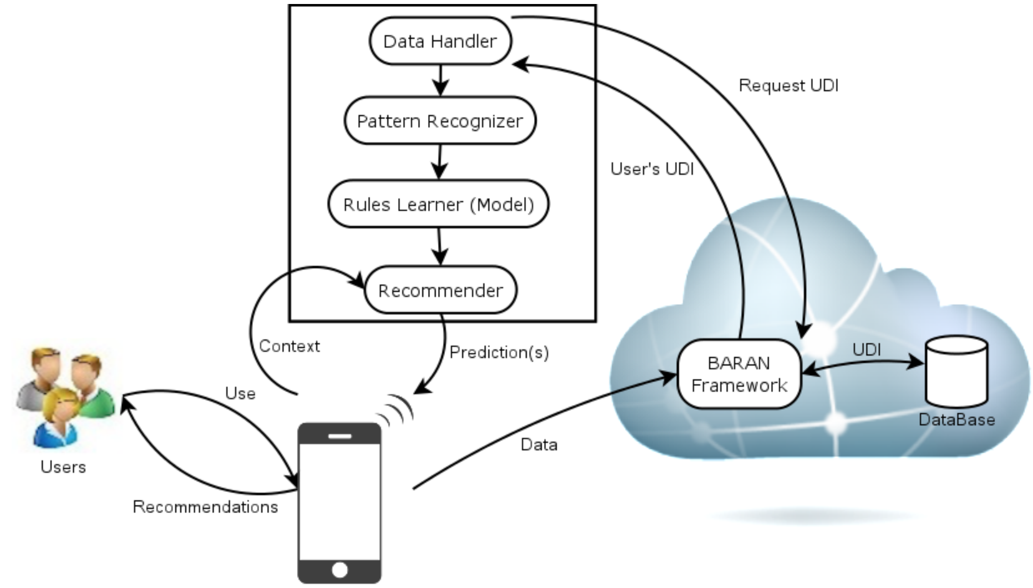

Fig. 1. The Overview of How Next-App service Cooperate with the BaranC Framework

a personalized next track based on a history of music tracks listened by users [13].

A. *BaranC Framework*

BaranC [4], [5], [6] is a cloud-based, service-oriented, user monitoring and data analysis framework. It transparently, efficiently, and implicitly records a user's activities (interactional context) and representational context data. It analyses the collected data, extracts information and knowledge from the raw data, and enables other IT systems to use the information in order to provide a better (e.g. personalized) service to a user. BaranC is constructed as a service-oriented framework and 3rd party services can be built on the top of it.

Each user has a model that holds user digital activities including context data. The User Digital Imprint (UDI) is the user model that underlies BaranC. It is a model with a manageable, flexible, and scalable data structure that holds various types of data and information. The main focus of the UDI is to record the user's *digital imprint* and by that we mean to record dynamic user interaction with digital devices. Analysing the UDI enables better understanding of a user [3] and provides the basis for personalized services [14], [15]. We can use a user model or presence in order to change our services and systems behaviour.

Third party services can request a user's model. BaranC provides the user with a full control on the data collection and sharing, so that it is the user who permits a service (Figure 2) to access what data and for how long.

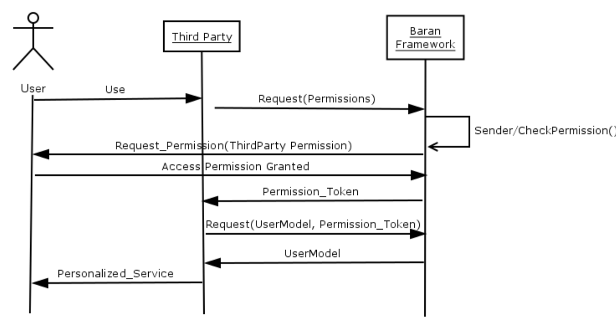

Fig. 2. The Sequence Diagram of How a User Permit a 3rd Party Service Accessing the Data

III. Application Recommendation Service (Next-App)

A demonstrator is implemented to demonstrate how a 3rd party service can cooperate with the BaranC framework (Figure 1). A service is designed to collect a user's data, and make a predictive model of what application is more likely to be used based on the current context. The service has four components, Data Handler, Pattern Recognizer, Rule Learner,

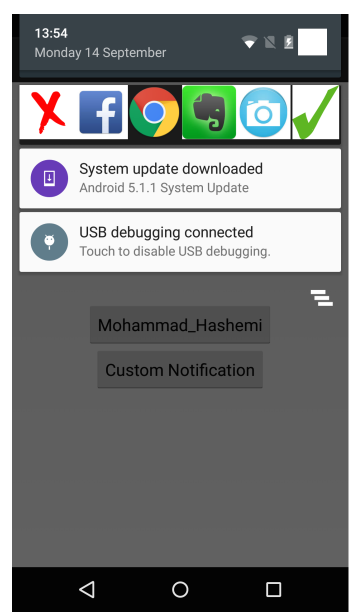

Fig. 3. Next-App Notification User Interface Showing Four Predictions

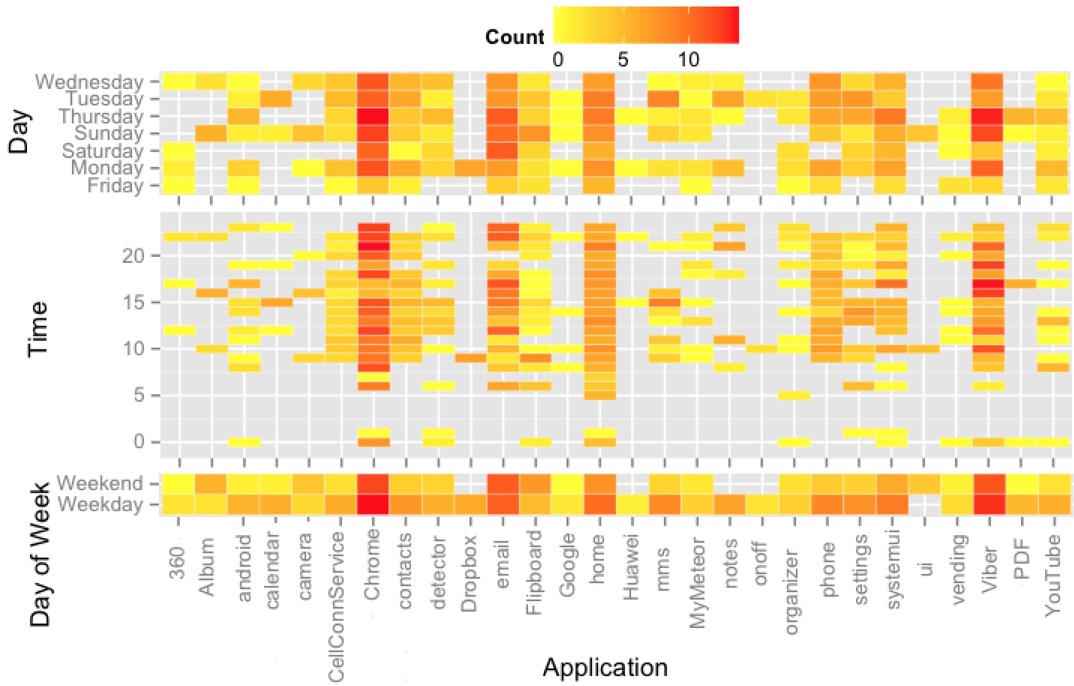

Fig. 4. Frequency: Application Category Pattern of a User

and Recommender. There are various work show why and where the next application prediction is important [16], [12]. The recommender systems, adaptive services, and context-aware applications are examples that use next user action's prediction [14].

An android application (Next-App; Figure 3) is implemented to use this service. Once a user starts using Next-App, and provides it the required permissions to access his/her data, the Next-App can start requesting the user data (UDI) from the BaranC framework. The Data Handler component periodically requests a user's up-to-date data/model. The Pattern Recognizer component, then, extracts frequent patterns (User's habits) from the data. Machine learning is used for prediction. The Association Rule technique [17], [18] is selected in order to make a predictive model in this work. This technique takes advantage of a sets of rules and a predictive class for a set of rules. The Rule learner component uses the extracted patterns (a set of rules from the history of application usage of the user by considering the context data as the observers of the classification) and creates a predictive model for each user. The predictive model can then be used by the Recommender component in order to predict the next N applications the user is likely to use based on his/her habits and also the context. For instance, if a user regularly uses an application between 8.00 PM to 11.00 PM, then the Next-App application recommends that application to the user at that time. The Next-App application is a notification based service. It pro-actively predicts and shows a notification containing a list of recommendations. The user can select one of the recommendations to open and use the application. The same scenario can be used to predict the next person to contact.

Figure 4 shows a graphical representation of the frequent patterns of a user that the Pattern Recognizer component extracts from the user's data(received from the BaranC framework). It shows the patterns and user's habits by considering time of day, day of week, or day-type(weekdays, weekend) as an observer. This figure shows how many times an application is used a specific time. Figure 5 also shows the patterns of duration a user spends on an application at a specific time. These patterns provide the basis of making rules for a predictive model. Time is one part of the context that is used in our prediction model. Any sensor data (e.g. Accelerometer, Gyroscope, Light) and any information extract from the sensor data (e.g. movement status) could be a part of the context in our predictive model. The predictive model is dynamic and will be updated based on the user's changes in behaviour.

In this work we used the patterns of the Pattern Recognizer component to pro-actively predict the next application(s) a user will probably use. At the time that a user is expected to be using the device, the algorithm predicts in a more frequent cycle, and predict less frequently when the device is not expected to be used to save the battery life.

This work also uses a predictive Markov model in order to improve the prediction(s) accuracy. Using the extracted patterns, a Markov chain model is created for each user. Figure 6 shows a partial Markov chain for a user. It shows the probabilities of the sequence of application(s) to be used after each other. For instance, the Google+ app is (4%) likely to be used after AccuWeather app. The model provides an overview of application(s) chain regardless of the context data. We create a Hidden Markov chain model using the context data as observers to validate our predictions.

IV. Evaluation

Six users were requested to use Next-App service in order to evaluate the prediction accuracy. As the service is designed to use a user's model (UDI) for prediction, an assumption

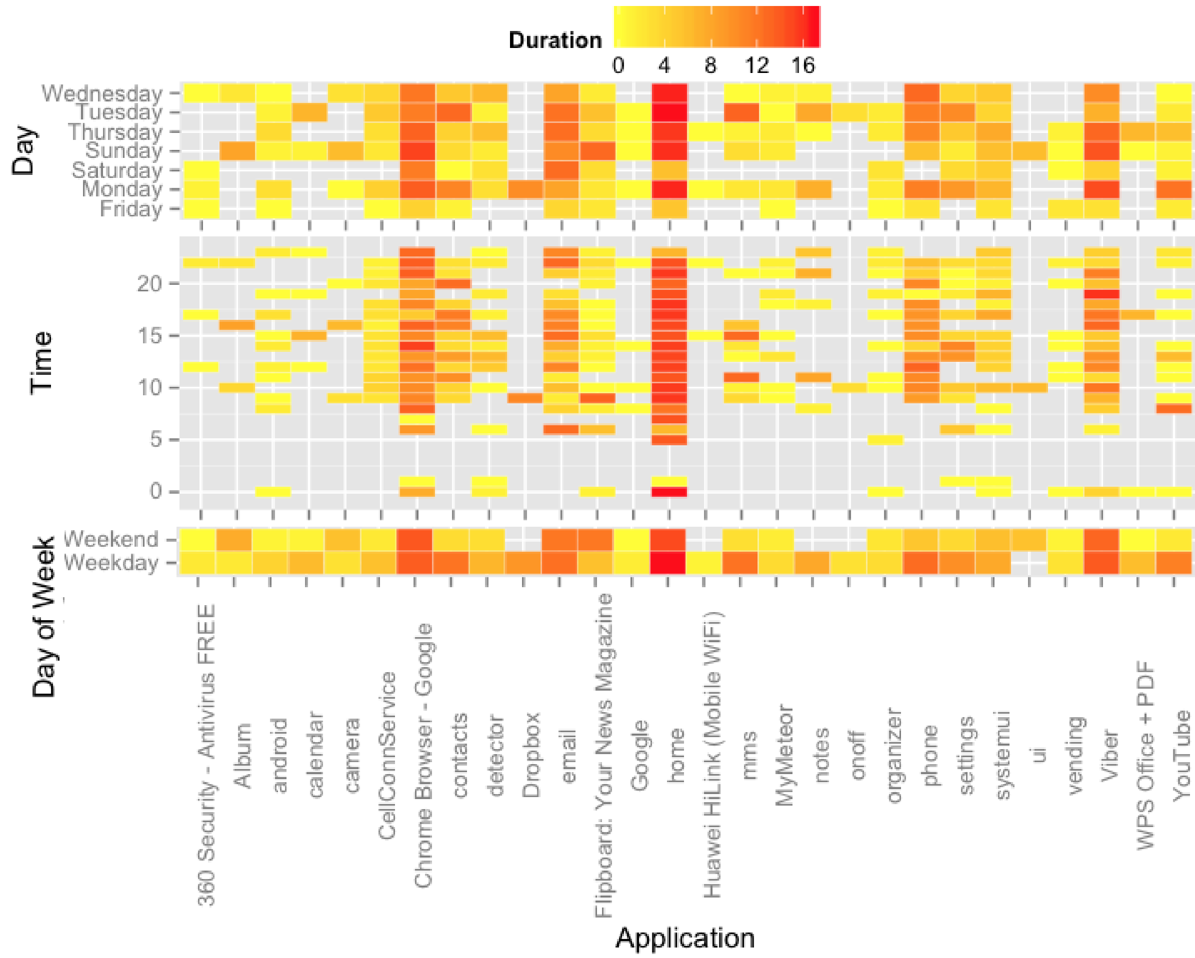

Fig. 5. Duration: Application Category Pattern of a User

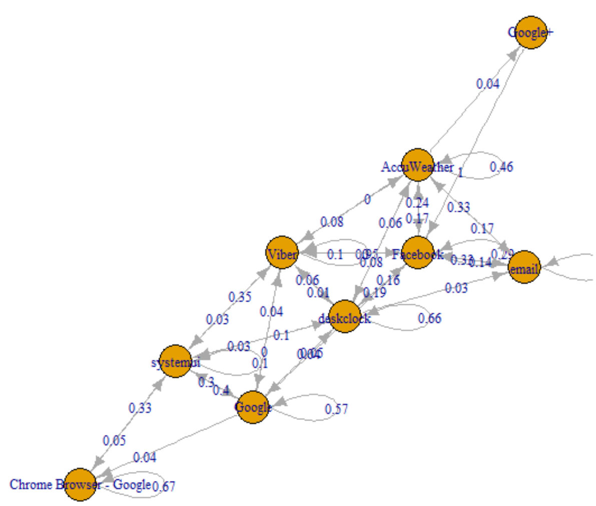

Fig. 6. An Example of Markov Chain Model

is that the participants already have a UDI model in BaranC framework. Our users have two months collected data in the BaranC framework. The application pro-actively predicts based on the current context and provides the recommendation in the notification bar (Figure 3). We count how many times a user uses our prediction(s) to open an application. The application provides an In-App rating service that lets a user to like or dislike a list of recommendations. Figure 7 reports the acceptance rate of the predictions, the positive (number of likes) and negative (number of dislikes) rating that were recorded in In-App rating. It shows that the users take 30% of the predictions in average. It also reports a good positive rating versus the negative rating. Finally we provided a questionnaire to each user in order to ask their opinions about the service and its usefulness. Figure 8 shows a summary of the questionnaire. It shows a positive feedback to the service's presentation, usefulness, and prediction accuracy.

V. Conclusion

An interaction-centred user monitoring framework, BaranC, is introduced. A 3rd party service, Next-App, a service to predict the next application(s) a user is likely to use based on the current context is presented. The UDI is a digital record of the user's digital life that is used as a data model and the basis of our predictive model. This work shows

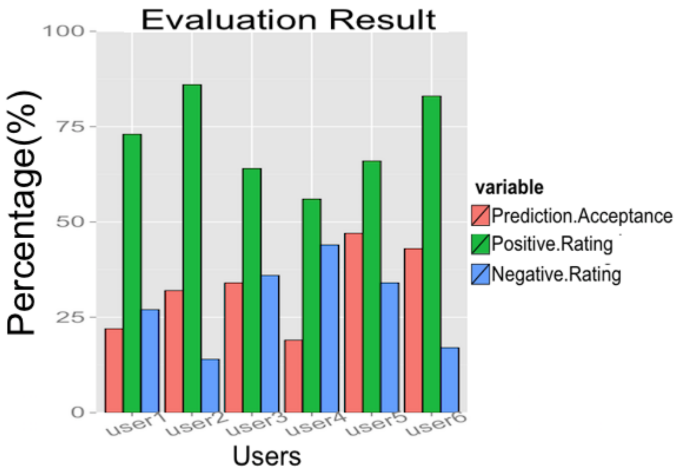

Fig. 7. Service Evaluation Result

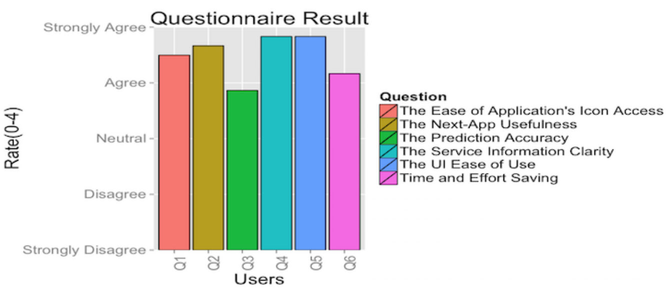

Fig. 8. Service Evaluation Result

that a user's data and a subjective analysis can be used to understand the user better and act accordingly to conveniently provide personalized services, providing the right service at the right time to the right user.

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