A Pro-active and Dynamic Prediction Assistance Using BaranC Framework

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ABSTRACT

Monitoring user interaction activities provides the basis for creating a user model that can be used to predict user behaviour and enable user assistant services. The BaranC framework provides components that perform UI monitoring (and collect all associated context data), builds a user model, and supports services that make use of the user model. In this case study, a Next-App prediction service 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; it is dynamic both in responding to the current context, and also 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.

CCS Concepts

•Human-centered computing → User models;

1. INTRODUCTION

The exponential growth in the number of mobile applications available leads to more applications on smart devices. Apple reports about one million apps released[1] and that the number of app downloads has reached 100 billion[2]. Based on the classification of [3], context has two main types, representational (e.g. time, location) and interactional (e.g. clicks, usage). It has been shown that contextual factors strongly influence user recommendations [1]. Most current work [2, 4] seems to focus on recommending an application to install based on the context and only considers representational context such as location, time, etc. Interactional context (e.g. the sequence of applications, music, etc.) has been used, however, for predicting future actions [8]. These approaches do not seem to attempt recommendations based on both interactional and representational context information. Most proposed recommendation services seem to ignore user profile and user habits. This paper describes a light-weight recommender service. This service analyses the data obtained by monitoring a user's interaction with a smartphone, learns how the user uses applications, and makes a predictive model. The recommender service uses the BaranC framework [7] that provides user's interaction data, enriched with the context information. What distinguishes our work from existing work is that we focus on how applications are used by an individual user in context, and we then recommend, based on the user's habits, a list of applications the user is likely to want to use next. For instance, Alice regularly calls Bob at the weekend, between 6-9 P.M., more specifically when she is at home, and not listening to the radio. An intelligent and context-aware service can analyse the user's current situation, predict a possible action the user might want to do next, and prepare some basics (e.g. checking network quality, sufficient credit to call, etc.) for that action.

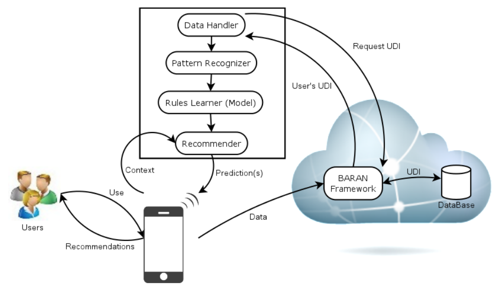

Figure 1: The Overview of How Next-App service Cooperate with the Baran Framework

BaranC [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. 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 personalized assistant services to a user. The current BaranC [7] supports 3rd party services which can use BaranC's monitoring and user model as the basis for providing useful user services. BaranC is based on a user model, the User Digital Imprint (UDI), which is a manageable, flexible, and scalable data structure that holds various types of data and information. The main purpose of the UDI is to record the user's *digital imprint* and by that we mean to record all dynamic user interaction with digital devices. Each user has a UDI model that can be requested by a 3rd party service. BaranC gives the user full control of the data collection and sharing, so it is the user who decides which service can access which data and for how long [7].

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

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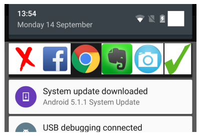

Figure 2: Next-App Notification User Interface Showing a List of Predictions

2. APPLICATION RECOMMENDATION SERVICE (NEXT-APP)

A simple case study demonstrates how a 3rd party service can cooperate with BaranC framework (Figure 1). A service is designed to analyse a user's data and make a predictive model of what application a user is more likely to require next, based on the current context. The service has four components: Data Handler, Pattern Recognizer, Rule Learner, and Recommender components. An Android application (Next-App; Figure 2) 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 application can then request the user model (UDI) from the BaranC framework. The Data Handler component periodically requests an up-to-date data for the user. The Pattern Recognizer component then extracts patterns of frequent use (the user's habits) from the data. The Rule Learner component extracts rules from the history of application usage (taking into consideration the context data as the observers of the classification) using the Association Rule technique, and then creates a predictive model for each user. The predictive model can be used by the Recommender component in order to predict the next N applications the user is likely to use based on the context. The Next-App application is a notification based service. It pro-actively predicts and shows a notification containing a list of recommendations. Our algorithm increases/decreases the frequency of generating predictions based on the device usage pattern in order to save battery life. This avoids unnecessary generation of predictions when the device is unlikely to be in use.

3. EVALUATION

Six users were enlisted as users of the Next-App service in order to evaluate the prediction accuracy of the service. As the service is designed to use the user's model (UDI) for prediction, an assumption is that each participant already has a UDI model in the BaranC framework. The six evaluation users have two months data recorded in the BaranC framework, and the prediction is based on analysing this data. Next-App pro-actively predicts the next application, based on the current context, and provides the recommendation in the notification bar (Figure 2). We count how many times a user uses our prediction(s) to open an application. Next-App provides an in-app rating service that lets a user indicates a like or dislike for the list of recommendations. Figure 3 presents the acceptance rate of the predictions, the positive (number of likes) and negative (number of dislikes) ratings recorded by the in in-app rating. This shows that, on average, the users take approximately 30% of the predictions. It also shows that the service gets a good positive rating versus negative rating. In addition, we provided a questionnaire to each user in order to get their opinion about the service presentation and its usefulness. Figure 4 shows a summary of the questionnaire feedback. It indicates positive feedback for the service's presentation, usefulness, and prediction accuracy.

4. CONCLUSION

Next-App is a 3rd party service that predicts the next application(s) a user is likely to use based on the current context. The Next-App service demonstrates the ease of implementing a 3rd party service based on the BaranC framework, and shows how analysing a user's device interaction data can produce a useful user model that can be the basis for a personalized dynamic prediction service. The Next-App service has been implemented, evaluated by users and found to be a useful service.

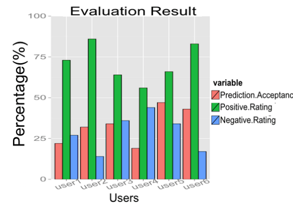

Figure 3: Service Evaluation Result

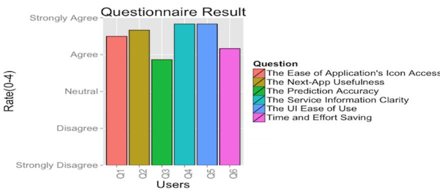

Figure 4: Service Evaluation Result

5. ACKNOWLEDGEMENTS

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6. REFERENCES

[1] L. Baltrunas, B. Ludwig, S. Peer, and F. Ricci. Context relevance assessment and exploitation in mobile recommender systems. *Personal and Ubiquitous Computing*, 16(5):507–526, jun 2011.

[2] C. Davidsson and S. Moritz. Utilizing implicit feedback and context to recommend mobile applications from first use. In *Proceedings of the 2011 Workshop on Context-awareness in Retrieval and Recommendation - CaRR '11*, pages 19–22. ACM, 2011.

[3] P. Dourish. What we talk about when we talk about context. *Personal and Ubiquitous Computing*, 8(1):19–30, 2004.

[4] A. Girardello and F. Michahelles. AppAware: Which Mobile Applications Are Hot? In *Proceedings of the 12th international conference on Human computer interaction with mobile devices and services - MobileHCI '10*, page 431. ACM, 2010.

[5] M. Hashemi and J. Herbert. {UIXSim:} A User Interface Experience Analysis Framework. In *5th International Conference on Intelligent Systems, Modelling and Simulation, ISMS2014*, pages 29–34. IEEE, 2014.

[6] M. Hashemi and J. Herbert. Baran: An Interaction-Centred User Monitoring Framework. In *International Conference on Physiological Computing Systems 2015*, pages 52–60, 2015.

[7] M. Hashemi and J. Herbert. User interaction monitoring and analysis framework. In *MobileSoft'16:IEEE/ACM International Conference on Mobile Software Engineering and Systems*. ACM, 2016.

[8] N. Natarajan, D. Shin, and I. S. Dhillon. Which app will you use next? In *Proceedings of the 7th ACM Conference on Recommender Systems*, pages 201–208, 2013.