

Adaptive User Interfaces for Mobile Computing Devices

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Except where otherwise indicated, this thesis is my own original work.

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Abstract

This thesis examines the use of adaptive user interface elements on a mobile phone and presents two adaptive user interface approaches. The approaches attempt to increase the efficiency with which a user interacts with a mobile phone, while ensuring the interface remains predictable to a user.

An adaptive user interface approach is presented that predicts the menu item a user will select. When a menu is opened, the predicted menu item is highlighted instead of the top-most menu item. The aim is to maintain the layout of the menu and to save the user from performing scrolling key presses. A machine learning approach is used to accomplish the prediction task. However, learning in the mobile phone environment produces several difficulties. These are limited availability of training examples, concept drift and limited computational resources. A novel learning approach is presented that addresses these difficulties. This learning approach addresses limited training examples and limited computational resources by employing a highly restricted hypothesis space. Furthermore, the approach addresses concept drift by determining the hypothesis that has been consistent for the longest run of training examples into the past. Under certain concept drift restrictions, an analysis of this approach shows it to be superior to approaches that use a fixed window of training examples. An experimental evaluation on data collected from several users interacting with a mobile phone was used to assess this learning approach in practice. The results of this evaluation are reported in terms of the average number of key presses saved. The benefit of menu-item prediction can clearly be seen, with savings of up to three key presses on every menu interaction.

An extension of the menu-item prediction approach is presented that removes the need to manually specify a restricted hypothesis space. The ap-

proach uses a decision-tree learner to generate hypotheses online and uses the minimum description length principle to identify the occurrence of concept shifts. The identification of concept shifts is used to guide the hypothesis generation process. The approach is compared with the original menu-item prediction approach in which hypotheses are manually specified. Experimental results using the same datasets are reported.

Another adaptive user interface approach is presented that induces shortcuts on a mobile phone interface. The approach is based on identifying shortcuts in the form of macros, which can automate a sequence of actions. A means of specifying relevant action sequences is presented, together with several learning approaches for predicting which shortcut to present to a user. A small subset of the possible shortcuts on a mobile phone was considered. This subset consisted of shortcuts that automated the actions of making a phone call or sending a text message. The results of an experimental evaluation of the shortcut prediction approaches are presented. The shortcut prediction process was evaluated in terms of predictive accuracy and stability, where stability was defined as the rate at which predicted shortcuts changed over time. The importance of stability is discussed, and is used to question the advantages of using sophisticated learning approaches for achieving adaptive user interfaces on mobile phones. Finally, several methods for combining accuracy and stability measures are presented, and the learning approaches are compared with these methods.

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