Detecting Real User Tasks by Training on Laboratory Contextual Attention Metadata

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Detecting the current task of a user is essential for providing her with contextualized and personalized support, and using Contextual Attention Metadata (CAM) can help doing so. Some recent approaches have proposed to perform automatic user task detection by means of task classifiers using such metadata.

In this paper, while going in the same direction as these approaches, we focus more specifically on the following research questions: (i) How good can the performance of a task classifier be when used in a real work environment, while being trained with CAM gathered in laboratory settings? (ii) Which are the automatically observable CAM features that allow for good task detection performance? Both questions are concerned with work efficiency. The goal of the first one is to determine whether a task classifier can be trained offline, thus saving the user from the burden of manual training. The second one aims at finding the most discriminative features for achieving a good balance between task detection accuracy and classification workload.

To study these questions we designed a large-scale experiment in which users performed a set of tasks both on a single laboratory computer and on their personal workstations. We gathered 203 task instances from 14 employees: 106 tasks from the laboratory computer and 97 from personal workstations. For capturing the users' CAM, we used multiple sensors recording the user interactions with resources and applications on the computer desktop. The captured usage data was used to automatically populate our *User Interaction Context Ontology* (UICO) which constitutes an ontology-based user context model. Based on the populated ontology, training instances for the machine learning algorithms were constructed at the task level, which resulted in a *multi-class* classification problem.

Results of our experiment are manifold. First, it shows that a reliable detection of real tasks via offline training is possible: several of the classification settings we defined have correctly identified more than 80% of the real tasks. Second, the good discriminative power of the classical *window title* feature has been confirmed: it obtained an accuracy of 85.57% (with a precision of 0.95 and a recall of 0.87). Finally, we have even improved classification accuracy by using a combination of 6 features specific to our approach. This specific setting obtained the highest accuracy (94.85%), precision (0.98) and recall (0.95), among all studied settings. This was an accuracy increase of 9.28%, a precision increase of 0.03 and a recall increase of 0.08 compared to the performance of the window title feature.