User Interface Adaptation based on User Feedback and Machine Learning

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ABSTRACT

With the growing need for intelligent software, exploring the potential of Machine Learning (ML) algorithms for User Interface (UI) adaptation becomes an ultimate requirement. The work reported in this paper aims at enhancing the UI interaction by using a Rule Management Engine (RME) in order to handle a training phase for personalization. This phase is intended to teach to the system novel adaptation strategies based on the end-user feedback concerning his interaction (history, preferences…). The goal is also to ensure an adaptation learning by capitalizing on the user feedbacks via a promoting/demoting technique, and then to employ it later in different levels of the UI development.

Author Keywords

User Interfaces; Adaptation based on machine learning algorithms.

ACM Classification Keywords

H.5.m. Information interfaces and presentation

General Terms

User Interface; Adaptation Learning; User Experience.

Context And Motivations

Nowadays, in order to ensure a high quality UI, systems often focus their adaptation as a key point in the development cycle of UIs. Given that, the more the system is adapted, the less the time for accomplishing tasks is needed. By consequence, the UI specification needs to be founded on a user-centred design and intelligently adapted to increase the usability level. Machine Learning (ML) techniques provide a significant potential to convey the UI adaptation. Through its several algorithms, it is suitable to manage several adaptation approaches and support systems in learning new adaptation rules with the main purpose of increasing the user satisfaction.

To perform user-centred adaptation, interaction should be considered as well as different user backgrounds. In fact several works investigate the user profiles in term of their interests, culture, expertise [2]. In this way, considering the user profiles allows the system to benefit from their characteristics as a supplemental user-related fact, which seems promising to enhance the end users' influence in the UI definition.

Within this context, Machine Learning techniques seems appropriate to give the system the opportunity of adapting the UI according to user preferences and interventions. Furthermore, ML techniques are intended to ensure a high predictability precision among systems.

Background And Related Works

The development of Intelligent Interactive Systems, which have the ability to offer valuable guidance for users, is still one of the main challenges targeted by several modern researches [16]. Thus several works converge into the user-centered adaptation. Broad investigated categories of applications provide the adaptation regarding the user interaction. Thus the first challenge is to gather useful knowledge based on the user interaction, to increase the performance of the system in the adaptation process.

Given that the most commonly cited issues with adaptive UI are the lack of predictability, control, and privacy [7], because that UI adaptation consider prior interaction knowledge. Several studies investigate the user behavior in terms of implicit and explicit user feedback, such studies also investigate which data to gather and respective approaches.

As every user interaction can contribute to an implicit interest-indicator [5], many researches give intention to the unconscious interaction as useful data for adaptation [1],[6],[15]. However as [8] and [11] remark the implicit feedback does not illustrate a dislike-attitude as well the high inherent noise.

Furthermore, knowledge can be acquired by asking user during the interaction in an explicit way, which shows generally more expressivity than implicit feedback [12]. Equally, [11] recommend the use of satisfaction analysis techniques as the most accurate ones for taking decisions. The literature presents several techniques to gather explicit feedback [2].

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The second challenge is to execute adaptation based on the observation of user interaction, where Machine Learning (ML) technique shows their potential to meet this need [13]. The conducted researches in learning-based adaptation focus mainly on investigating Machine Learning (ML) techniques for recognizing patterns from the user behavior and making valuable recommendations. Liu [14] defined a personalized learning approach as of “Windows Episode and Minimal Occurrence Episode”, which consists of learning individual user’s behavior patterns to put forward assistance and recommendations. Likewise, websites design adaptation is an application field of learning based on the user interaction. Ivory [11] utilizes a learned statistical profile of valuable websites to suggest enhancements for existing designs. Further works apply collaborative filtering algorithms to recommend adaptation; this technique is mainly used for e-commerce and search engines, for instance syskill&webert [6], FilmFinder [13].

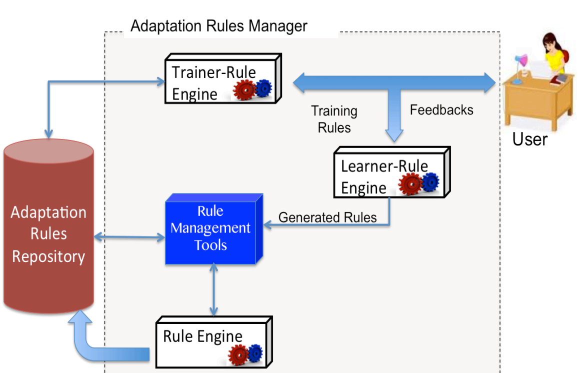
Research Goal And Methods

This work aims mainly to ensure an UI adaptation based on Machine Learning and user intervention. It is based on taking advantage from users feedbacks during the interaction to reinforce existing adaptation rules, besides the extraction of new supplied acquaintance for the UI personalization.

The major purpose is to investigate how ML algorithms manifest themselves to ensure an adaptive learning during user interaction. According to this perspective, performing the adaptation learning among the software requires an enhancement via an Adaptation Rule Management Module (ARM).

The ARM module (figure1.a) is intended to handle a training phase, which involves an upgrading the pre-existing set of adaptation rules according to the user experience with the system.

(a)



(b)

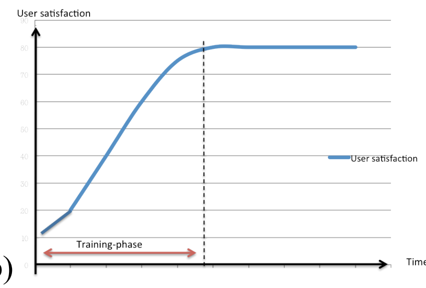
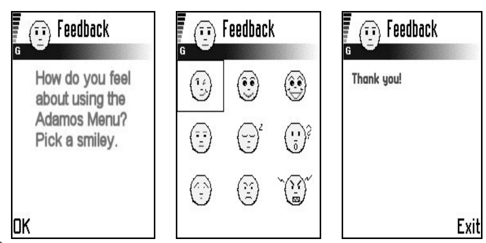


Figure 1. a. The Adaptation Rule Manager b. Estimation of user-satisfaction degrees by time

In fact, the user experience recapitulates the end user preferences, which need to be explicitly transmitted to the Rule Learner Engine by means of his intervention and feedbacks.

As mentioned above, several techniques exist in the literature referring to users able to evaluate and reinforce the adaptation of the UI.

(a)



(b)

Figure2. (a) Answering to feedback question with emoticons (Arhippainen et al. 2004). (b) Various recommendation interfaces

In our case, Intention is agreed to the explicit feedback acquired from the end-user interaction. Two possible implementations can be considered;

- Emoticons based feedback: aiming at expressing the satisfaction degrees among end-user via picking an emoticon judging his user experience. Arhippainen [2] give an instance application of an answering to feedback question with emoticons (figure2.a).
- Recommendation frames: a simple interaction illustrated differently (e.g. pop-up window, Sliding area), which is mainly used in e-commerce to provide client recommendations (figure2.b). Likewise, they may allow end users to express their preference by accepting or cancelling the system recommendation.

A Rule learner RL is responsible for analyzing collected user judgments. Gathered data are intended to serve in a promoting/demoting ranking, which assigns a priority to the executed rule in order to promote or demote rules and to try to resolve conflicting ones. The Rules learner is based on a supervised learning approach requiring a Trainer-Rule Engine (TRE).

The TRE module is responsible for ensuring the training phase through the following accomplishments;

(1) Executing pre-existed adaptation rules, which serve by way of a training set to (2) detect a pattern of user behavior throughout his interaction and feedbacks. Besides, (3) coming up with statistics and (promote/demote) ranking for the Learner Rule Engine (RLE).

The mentioned training phase is intended to outline a monotonic function drawing up the increase of user satisfaction degrees by time (figure1.b). The variance should show a system jump from the adaptive mode to proactive one by the end of the training phase.

The second main point of this research is to avail adaptation based on learning in different levels of UI generation according to the CAMELEON reference framework [4]. The focus of this point is to capitalize on learning based adaptation to improve the validity of the Abstract User Interface. Several algorithms were defined for the AUI definition however a lack of validity and consistency control still arise (figure3).

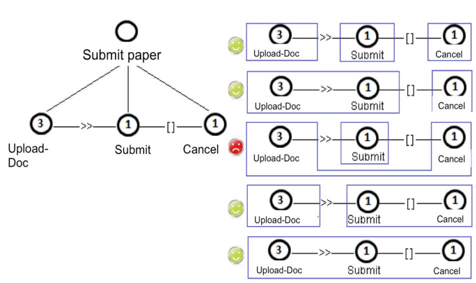


Figure 3. A tasks grouping sample

Moreover, an intended reward of ML technique's potential to be envisaged for the concrete user interfaces. Although some ML techniques were already explored [6], ML is consistently promising to emphasize new scenarios for the adaptation in the concrete UI level, for instance for the widget selection ML techniques seems great to manage all adaptation rules and guideline. In figure 4 we show a sample for considering adaptation guidelines to select a multiple-choice widget selection.

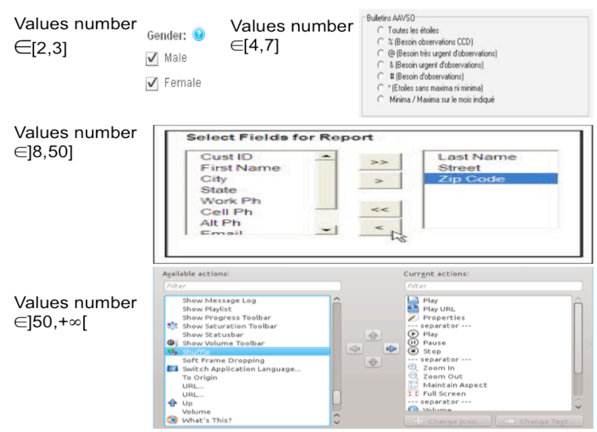


Figure 4. A Multiple-choice widgets definition for a known domain

Dissertation Status

Initially a review of the related literature is done, we did an extensive literature research about UI adaptation based on human interaction and on Machine Learning algorithms, with a focus on ML techniques behaved for UI adaptation to derive adaptive learning patterns to be improved. We proposed a theoretical architecture (figure5), which is intended to establish different included modules relaying to the adaptation based on ML techniques. It aims at illustrating the fundamental purposes and contributing with a unified description for the full adaptation process as well for ML based UI.

In fact, adaptive learning is based mainly on user interaction and feedbacks, which provide user beneficial information to afford reasonable critics explaining his preferences. By gathering those communication flows, the system extracts a set of critics subsequently analyzed in the Perception Layer (PL). Several tracking and analytic tools were retained at this level [1], [6] and [11]. Analyzed data are conveyed to the Adaptation Management Layer (AML), where data will be treated to upgrade the Adaptation Rule Repository (ARR) according to gathered data. Moreover, an evaluation is foreseen for the different layers described above.

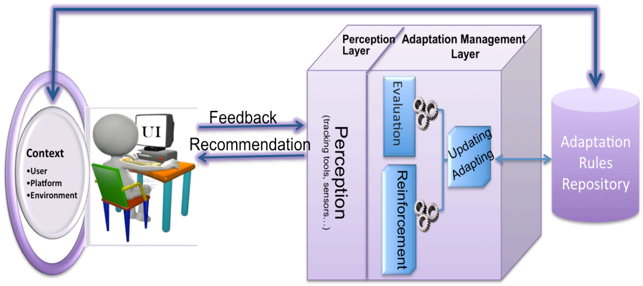


Figure 5. Unified theoretical architecture for adaptation based on machine learning

Given that, instantiated systems practice several ML algorithms for adaptation. A technical evaluation is foreseen. This last consists in an evaluation regarding a set of internal criteria that are relevant for measuring learnability among systems. This evaluation regards the system learnability criterion, which is based on a set of sub-criteria measuring the effectiveness of ML used algorithms. The next paragraph gives a more detailed description.

Evaluation and Anticipated Contribution

To evaluate the ARM and different existing approaches, which are instances of the theoretical architecture, we aim to define an evaluation approach regarding a set of measures for evaluating the learning performance and effectiveness of adapting systems. In the literature, a number of technical metrics was already proved as relevant for evaluating interactive systems [5]. The intended technical evaluation will be about the learnability of systems; the expected tool will be based on objective metrics that can be consistently computed to evaluate learnability among instantiated systems and compare them. Furthermore, the evaluation is intended to appraise learnability according to the general proposed architecture. Accordingly evaluation must regard several aspects as; the accurateness of recommendation, expressing the gap between system recommendation and user requirements, the confidence of feedbacks, which denote the expressiveness and the clarity of considered feedback, and the learning phase in term of training time and user satisfaction level.

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