An Adaptive User Interface That Follows HCI Best Practices While Using Personalities Extracted From Users' Social Media Behaviors

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1 RELATED WORKS

1.1 Recommender Systems

Recommender systems apply knowledge discovery techniques to the problem of making personalized recommendations for information, products, or services during a live interaction. (1) Recommender systems apply data analysis techniques to the problem of helping users find the items they would like. This happened by producing a predicted likeliness score or of *Top-N* recommended items for a given user. Item recommendations can be made using different methods. (1)

1.1.1 Collaborative filtering

Collaborative filtering algorithm is an algorithm which suggests new items or predicts the utility of a certain item for a particular user based on the user's previous likings and the opinions of other like-minded users. Usually, there is a list of users and items which each user has a list of items which user has expressed his/her opinion about them. The end goal of the algorithm is to suggest a list of recommendation to the user, which is also known as *Top-N recommendation.*

Collaborative filtering can be based on model-based user modeling. The model building process can be performed by different machine learning algorithms such as Bayesian network, clustering, and rule-based approaches.

1.2 User Modeling

An ideal user model is a user model that address the needs for ensuring the user's privacy, control, and ability to scrutinize their user model and the process for personalization. (2) At first blush, user modeling appears to be a prime candidate for a straightforward application of standard machine learning technique. Observations of the user's behavior can provide training examples that a machine learning system can use to form a model designed to predict future actions. (3)

1.2.1 Agent-based User Modeling

A network of small active entities which reside on the client side, building an ad-hoc network and deliver requested information on demand. So on each level of system design, there would be a distributed active entities receiving data from and delivering information to other entities. In the context of user modeling, this implies replacing monolithic user modeling by distributed user model fragments. (4)

1.2.2 Bayesian User Modeling

Bayesian models can be effective in diagnosing a user's need and can provide useful enhancement to legacy software applications when embedded within these programs. Additionally, Bayesian user models can provide instruction for building new kinds of services and applications in software. (5)

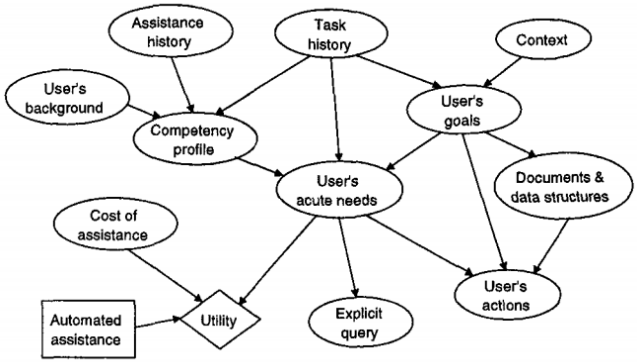

Figure 1: *An influence diagram for providing intelligent assistance given uncertainty in a user's background, goals, and competency in working with a software application.* (5)

The overall goal is to take automated actions to optimize the user's expected utility. A system taking autonomous action to assist users needs to balance the benefits and costs of such actions. The value of actions depend on the nature of the action, the cost of the actions, and the user's needs. Assessing and integration such user models would allow a system to compute a probability distribution over a user's informational needs in real time, given a set of observations about activity and explicit queries when such queries are issued. (5)

1.3 Cross-system User Modeling

Recommendation systems virtually have become as a means of identifying and serving relevant content to any given user. However, three main issues include sparsity (6), cold start (7), and the new user are still unsolved. Several studies (8, 9) show that using Cross-domain user modeling can mitigate the issues above. Using different available social media data to solve this issue is a possible solution.

1.4 HCI

The challenge in the information-rich world is not only to make information available to people at any time, at any place, and in any form, but specifically to say the "right" thing at the "right" time in the "right" way. (10) the new essential challenges are improving the way people use computers to work, think, communicate, learn, critique, explain, argue, debate, observe, decide, calculate, simulate, and design. (10)

1.5 Personalities

A variety of approaches have been recently proposed to automatically infer users' personality from their user-generated

content in social media. Approaches differ in terms of the machine learning algorithms, and the feature sets used, type of utilized footprint and the social media environment used to collect the data. (11)

Research in psychology has suggested that the behavior and preferences of individuals can be explained to a great extent by underlying psychological constructs: personality traits. Knowledge of an individual's personality allows us to make a prediction about preferences across contexts and environments and to enhance recommendation systems. Personality can affect the decision-making process and has been shown to affect preferences for websites, products, brands, and services, and content such as movies, TV shows, and books. (11)

The most widely accepted model of personality, Big Five or Five Factor Model, embrace five traits: Openness, Conscientiousness, Extroversion, Agreeableness, and Emotional Stability (Neuroticism). (11)

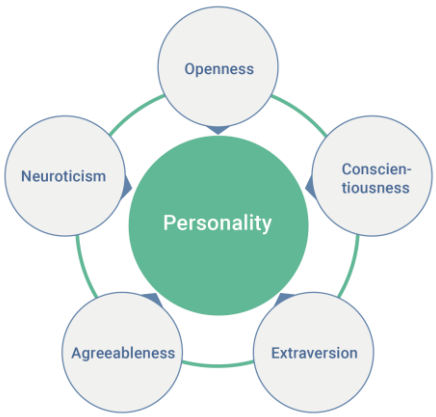

Figure 2: Big 5 personality model

2 Objectives

(a) Extract a comprehensive user model using different available aspect of a user's presence on our software application and the internet, including but not limited to Twitter, YouTube, and Instagram. This user modeling can utilize various subjects above, such as different machine learning techniques, collaborative filtering, and cross-system recommender.

(b) Extract user personality using data extracted from social media and our software application to aggregate with previous user modeling in order to enrich user modeling.

(c) Use all available context at hand, and best practices in designing user interface to build an adaptive user interface that says the "right" thing at the "right" time in the "right" way using more in-depth fetched user modeling.

3 Innovative Aspects

In previous studies, a different aspect of user modelings, HCI methods, Adaptive user interface, and recommendation systems has been discussed but and particular user interface that to its best to "understand" user and suggest not only best items (recommendation systems) but best UI for each particular user (Adaptive UI) in a way that reflect all available data from user on the web and on our software application (Cross-system recommendation) with respect to different user personalities in different context, yet has to be discussed.

In this project, we can improve user modeling by a more comprehensive user modeling in order to enrich the UI and recommender system for each user. Ultimately a better enrich user model can lead to says the "right" thing at the "right" time in the "right" way.

4 Sustainability

The first step of this project can be started with enriching user models by different machine learning techniques and include personalities of each user to their corresponding models. The possible second phase determines how we can improve the user interface with inferred results and how we can improve a cross-system recommendation using the new model. Moreover, the third and final step can be how our results can improve total users experience.

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