Conceptual framework of intelligent decision support based on user digital life traces and ontology-based user categorisation

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Abstract. The paper presents conceptual framework and information model of intelligent decision support based on traces of user digital lives and ontology-based user categorisation. The conceptual framework defines components that provide information revealed from the traces of user digital lives, generalize this information, and make ontology inference. The information model defines information flows between the components of the conceptual framework. The novelties of this research are grouping users with common preferences and decision making behaviours based on the user digital traces, and context-sensitive ontology-based categorization of users into the user groups.

1. Introduction

The digital revolution that has been occurring since the middle of the last century is blurring the lines between the physical, digital, and biological spheres [1]. This revolution is impacting everything, from economy, science and education, to health, sustainability, governance, and lifestyles. Digital technologies have fundamentally change business models, institutions and society as a whole [2] and gave birth to digital lifestyle that is tightly related to the overall need of "liveability" [3]. Living digital style and interacting with various applications and Web sites, humans leave digital traces of their online activities [4,5]. These trace are referred to as human digital life.

In decision support, the user digital lives are sources for recommending preventive and predictive decisions [6–8]. The present research aims at the development of a conceptual framework that addresses user digital life as a source of historical data for recommending decisions. The conceptual framework defines components that provide information revealed from the traces of user digital lives, generalize this information, and make ontology inference. Intelligent decision support according to the proposed framework consists in recommending to the user a decision that users whose preferences and decision making behaviour close to the active user, would make in the context of this user. Ontology-based user categorization supports inference of a user type as a decision maker to identify a group of users having common preferences and decision making behaviour to which the active user belongs. An information model defines information relationships between the components of the conceptual framework.
The rest of the paper is as follows. Section 2 introduces the conceptual framework for intelligent decision support based on user digital life traces and ontology-based user categorization. Section 3 outlines the information model of the developed conceptual framework. Main research results are discussed in the conclusion.

2. Conceptual framework for intelligent decision support based on user digital life traces and ontology-based user categorization

The conceptual framework for intelligent decision support based on user digital life traces and ontology-based user categorization (figure 1) is intended to recommend decisions that a user would make in the current situation. The main components of this framework are user profile, model of user digital life, group pattern, and decision maker ontology.

2.1. User profile

A user profile represents information that can be used to characterize this user or build his/her descriptive portrait. Usually, a user has several profiles created in different domains. Characteristics of two types comprise a user profile. They are context-independent and context-dependent. The context-independent characteristics (e.g., the user’s birth name, his/her age, the education, etc.) can be introduced by users themselves when creating their profile or filling in questionnaires during the registration process. As well, such characteristics can be reused if the users made them available for certain domains or can be revealed from traces of user digital life [9].

Special techniques and procedures are applied to capture context-dependent user characteristics. For instance, procedures processing sensor data identify typical context-dependent characteristics as the user’s location and time. In addition to typical context-dependent characteristics, specific user preferences come from user digital life model.

Figure 1. Conceptual framework for intelligent decision support based on user digital life traces and ontology-based user categorization.
characteristics that are of interest to particular domains are revealed. Relation of these characteristics to domains make them context-dependent. For example, in the Internet banking, such characteristics are the integrity / unreliability of the customer-borrower, the customer segment (a group of customers with the same needs and behavioral responses to the product), how the customer is “advanced”, and others. One of the ways to capture context-dependent characteristics is to analyse traces of user digital life.

Besides of all the above, an important piece of the user profiles are user preferences. In decision support, the preferences are criteria that a user prefers for evaluating alternatives. In the conceptual framework, it is taken that the user preferences can change depending on the context, so they are considered to belong to the set of context-dependent characteristics. Revealing user preferences is a focus of numerous methods and techniques [10].

Below, the user profile model \(P\) (1) is given.

\[
P = \langle \text{User\_ID}, \ P\_\text{out}, P\_\text{in}(C) \rangle,
\]

where \(\text{User\_ID}\) – unique user identifier, \(P\_\text{out}\) – set of context-independent user characteristics, \(P\_\text{in}\) – set of context-dependent user characteristics in the context \(C\).

2.2. User digital life model
User digital life model \(DFM\) (2) is a structured representation of weekly systematized and poorly curated content of digital life. Among many other things, digital life incorporates traces of user activity on making decisions in problem situations. These traces are a source of knowledge to reveal a problem profile. Such a profile is a complex formalized description of the user interactions with a digital platform when making a decision on the problem this user deals with. The present framework considers the problem profile, the kinds of problems that the user has ever dealt with, and the decisions made as the structural components of the model of the user digital life. At that, the problems are described with relations to the domains where these problems occur.

\[
DFM = \langle \text{User\_ID}, PP \rangle,
\]

where \(PP\) – unique reference to problem profile \(PP\).

\[
PP = \langle PP, Problem, Domain, Decision, R_s \subseteq Problem \times Domain, R_s \subseteq Problem \times Decision \rangle
\]

where, \(Problem\) – set of problems the user dealt with, \(Domain\) – set of domains where problems \(Problem\) take place, \(Decision\) – set of decisions that the user made for problems \(Problem\).

2.3. Group pattern
The user preferences and the models of user digital lives are sources to reveal groups of users \((UG)\) with similar preferences and decision making behaviours. Group pattern \((GP)\) (3) represents these groups. It generalizes preferences and decision making behaviours of the users belonging to the group. The kinds of groups depend on the domains. In each domain, own techniques of user grouping are applied [11]. For e-Commerce, kinds of groups can correspond to the types of customer segments (for example, smart buyers, dependent buyers, non-demanding buyers, and others); for tourism, a kind of group can be, for instance, a group of tourists who have psychophysical barriers (for example, communication problems, economic difficulties, cultural barriers).

\[
GP = \langle \text{Group}, Domain, Problem, Beh\_\text{type}_s, Pref\_s \rangle,
\]

where \(Group\) – unique name for the group of users with similar preferences \(Pref\_s\) and decision making behaviour \(Beh\_\text{type}_s\) in the domain \(Domain\) when dealing with the problem \(Problem\); \(Beh\_\text{type}_s\) – kind of decision making behaviour distinguished in the domain \(Domain\) that corresponds to the behaviour pattern of the users belonging to the group \(Group\).
2.4. Decision maker ontology
From the decision support perspective, the users of a decision support system play the role of decision makers. The decision maker ontology specifies knowledge based on that the users can be categorized into the user groups $UG$. In this ontology, a decision maker belongs to a type. The class “type” represents types of decision makers. This class can be matched to the revealed kinds of user groups $UG$. Axioms define conditions for the classification of the users into the decision maker types and the information from the user profiles produces assertions for this. Here the convention that axioms are statements that describe the domain being modelled, and assertions are axioms describing individuals is used [12]. Context-dependent user characteristics make the decision maker type context-sensitive. Therefore, the same user in different contexts can be inferred belonging to different decision making types.

2.5. Decision support
The decision support according to the proposed conceptual framework is as follows. When a user faces a problem requiring a decision, the information from the profile of this user is introduced to the axioms of the ontology. The ontology reasoner solves the classification problem to define to which decision maker type this user belongs. The inferred type is related to a user group $UG_{user}, UG_{user} \in UG$. A group pattern specifies preferences and decision making behaviours of the users belonging to the group $UG_{user}$. This pattern is the basis to predict preferences of the user. For the prediction, methods of collaborative filtering are applied. The methods enable to make predictions about preferences of a user based on the collected information about preferences of other users. Here the users belonging to the group $UG_{user}$ serve as users who share their preferences and decision making behaviours with the active user.

Commonly accepted that a problem requiring a decision occurs in some context. In the context-aware environments, context is defined as “any information that can be used to characterize the situation of an entity” [13]. The conceptual framework uses information about the decision maker type of the user, the decision problem, the problem domain, and the user preferences to characterise the situation of the user. This information specifies context $C$ (4). Contextual information is used to recommend to the user a decision that the users from the group $UG_{user}$ would make in the context $C$.

\[
C = \{User\_ID, User\_type, Domain, Problem, Pref\_c\},
\]  

(4)

where $User\_type\_c$ – the type of the user as a decision maker in the context $C$, $Domain\_c$ – the domain to which the problem $Problem\_c$ belongs, $Problem\_c$ – the problem that the user is dealing with in the context $C$, $Pref\_c$ – the set of user preferences in the context $C$.

3. Information model of conceptual framework for intelligent decision support based on user digital life traces and ontology-based user categorization
Information model of the conceptual framework for intelligent decision support based on user digital life traces and ontology-based user categorization (figure 2) defines information relationships between the main components of the proposed framework. The model distinguishes external and internal sources. External sources are information sources that exist and maintained outside the conceptual framework. They are user profiles, user digital life models, user segments (S), and outcomes of segmentation and profiling techniques. Internal sources are integral components of the framework. The group patterns and the decision maker ontology fall into this kind of sources.

In the information model, the set of context-dependent characteristics represented in the user profile model (1) comprises the set of user preferences in the context $C$, and the set of segments into which this user is bucketed in different domains (S). The sources for the user characteristics included in the model (5) except the user segments are described in Section 2.1. Group patterns provide information on the user segments. The user profiles are sources of information on user preferences for the group patterns, and sources of information on various user characteristics for the decision maker ontology.
\[ P = ( \text{User\_ID, } P_{\text{out}}, \text{Pref}_C, S_c, R_3 \subseteq S_c \times \text{Domain}) \]  

where \( S_c \) – the user segment in the context \( C \).

Group patterns use information on the user preferences from the user profiles and on the user behaviours from domains. In domains, segmentation techniques define segments of users with common characteristics. Here it should mention that the conceptual framework suggests grouping users with similar decision making behaviours. Because of this, user segments obtained as a result of behavioural segmentation are taken into account only. Traces of user digital lives and user digital life models are considered as sources providing the domains with information based on that the user behaviours are revealed. The group patterns are sources of information on the user segments for the user profiles and for the decision maker ontology.

Sources of information for the user digital life models are traces of user digital lives. Special methods are needed to retrieve values from these contents and particularly, to identify problems and decisions in them. Methods of content analysis of social media (e.g., [14–16]) may be suitable for this purpose. The user digital lives are sources for the user segmentation techniques.

User digital life models get information on problems and decisions from traces of user digital lives or, more precisely, from the methods intended for their reveal. The digital life models themselves are sources of information on problem profiles for the group patterns.

The decision maker ontology is developed by ontology engineers. They use information on segmentation rules to specify the axioms for the classification of users into the decision maker types. The ontology developers extract these rules from the segmentation techniques when it is possible and represent as axioms. Mandatory elements of the axioms are concepts that represent the problems and their domains. The user digital life models are sources of information on these elements. The group patterns are sources of information on the groups of users characterized by common preferences and behaviours \( (UG) \). The names of these groups can be used to naming the decision maker types in the ontology. Regardless of the chosen naming method, each user group from \( UG \) is related to a corresponding decision maker type. User profiles provide the kinds of segments to which the users are bucketed in the domains, and the user characteristics applied in the segmentation rules. In context, this information instantiates the axioms. The decision maker ontology provides information on the user type as a decision maker to the decision support environment.
4. Conclusion
The paper proposes the conceptual framework of intelligent decision support based on traces of user digital lives and ontology-based user categorisation and the information model for this framework.

The main components of the conceptual framework are user profile, model of user digital life, group pattern, and decision maker ontology. The user profiles represent context-dependent and context-independent user characteristics. The group patterns describe preferences and decision making behaviours of the user groups organized from the users having common preferences and decision making behaviour. The user digital life model represents problems the user have ever dealt with and decisions this user made. The decision maker ontology represents types of decision makers into which the users are classified. The user type is context-sensitive; in a context, it determines the user group to which the user of this type belongs. Traces of user digital lives are primary sources of information for the framework components. The proposed framework enables to recommend context-aware decisions based on the knowledge about the user type and about preferences and decision making behaviours of other users of this type.

The information model defines information flows between the components of the conceptual framework and introduces techniques that can provide valuable information retrieved from the digital traces to these components.

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