An Approach to Behavior Modeling Based on Elements of Theories of Planned and Organizational Behavior

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Abstract—**The analysis of human behavior has been attracting the attention of scientists for a long time. Prediction of user intents and actions when interacting with an information system and the corresponding adaptation of the system can significantly increase the efficiency of the joint work of the pair "user - information system". The paper proposes an approach to modeling the behavior of information system users based on the situation analysis with the aim of further behavior analysis via, for example, machine learning methods. The main idea of the approach is to capture and compare the situation described by a context before, at the moment of, and after an action made by the user. The applicability of the proposed approach is confirmed by the presented case study.**

I. Introduction

Analysis of users' behavior, predicting their actions when interacting with an information system, and the corresponding adaptation of the system can significantly increase the efficiency of the joint work of the pair "user – information system".

The analysis of human behavior has been attracting the attention of scientists for a long time all around the world [1]–[3]. Nevertheless, issues related to the analysis of the behavior of users (subjects) of information systems in order to solve the problems of forecasting and improve the quality of service are still not fully resolved and cause significant interest of the scientific community [4], [5].

The classical forecasting methodology, consisting of (a) data preparation, (b) forecast model building, (c) usage of new data to build a forecast, relies on a number of models to function. First of all, one needs to decide how to model the behavior. The proper modeling approach makes a significant impact on the success of the behavior analysis. Despite the significant recent growth of machine learning techniques, it is still necessary to select proper features that would be used for forecasting. The contribution of this paper is the approach to the behavior modeling of information system users based on the situation analysis. It makes it possible to identify features affecting the behavior. The main idea of the approach is capturing the situation described by the context before and after the action made by the user.

The paper is structured as follows. The next section overviews existing research efforts addressing human behavior prediction and modeling. It is followed by a description of the proposed approach. Section 4 presents introductory illustrative scenarios explaining the idea behind the approach. Section 5 presents a case study illustrating the applicability of the developed framework. It is followed by the discussion section. Main results are summarized in the Conclusions.

II. Existing Human Behavior Prediction and Modelling Approaches

There exist a number of approaches to model information system user behavior, the most typical of which are discussed in this section.

Human behavior is generally considered from two points of view:

- an action that is undertaken as a response to certain circumstances [6], [7];
- a sequence of actions [4], [8]–[10].

The approaches from the former group are usually aimed at the analysis of dependencies between the circumstances and actions caused by them. In this regard, human behavior analysis merges with research in the field of recommender systems, in particular, context-sensitive recommender systems. Indeed, one can draw a parallel between the reaction to the situation and the fact of buying or rating an item when the user is in a contact with another item under certain conditions. As a result, the model of such behavior compares descriptions of potential situations with possible actions. Such approaches, for example, make it possible to determine the probability of a particular reaction to a situation. An example of such an approach can be a reply to an e-mail that has certain characteristics with a delay that depends on the e-mail characteristics [6].

The approaches from the latter group are concentrated on the sequence itself, for example, predicting the next action based on the previous ones [4].

The behavior prediction mechanisms can also be different. Some of the main classes of such mechanisms include Markov models, including hidden Markov models (HMM) [11], Gaussian mixtures (GMM) [12], rules (associative, classification) [13], neural network models [4], [14], and reverse reinforcement learning [15].

In this particular work, we concentrate on the first group of approaches that are aimed at forecasting user actions based on the situation analysis.

Since treating the situation and user action depends on how they are understood in relation to time, let us consider three classes of behavior modeling.

In the first class, both the situation and the action are considered momentary so that they do not have any duration. An example of such user behavior modeling is the prediction of CTR (click-through rate, the indicator of the frequency of transitions to other pages, attractiveness to users), which is often used in online digital advertising. Most of the research efforts addressing CTR accuracy are based on data analytics techniques and tools. Hence, the key attributes to be analyzed include landing page address, keywords, ad title, and text that form the context at the moment of the user action and are used for training models for predicting the probability of ad clicks, built using such methods as logistic regression [16], multivariate linear regression, Poisson regression [17], support vector regression (SVR) [18], and others.

In the second class, the action is considered momentary, but the situation is considered as having a duration (temporal). Usually, such methods are oriented to human state analysis based on a history of measurements. As an example, a method for vehicle driver’s drowsy state detection can be considered [19]. The developed method is based on determining the percentage of time during which the driver's eyes are closed (PERCLOS), which forms the temporal context. And the driver’s state is evaluated at the moment of the last measurement based on machine learning techniques.

In this paper, we will consider the third class when both the user action and the context are temporal (in other words, have a certain non-zero length duration) since this consideration better matches the purposes of improving the interaction between the user and an information system.

Despite the availability of the variety of the prediction mechanisms, it is still necessary for one to understand which features (for example, elements of the state of the information system) actually may trigger this or that action. With the increased power of machine learning, it is now possible to put the entire information system state so that the machine learning model would sort out those affecting certain actions. However, having an additional continuous dimension of time complicates this process since the action doesn’t necessarily directly follows the change of the state, but can follow it with some delay. The proposed approach is aimed at behavior modeling with the possibility to monitor the context before, at the moment of, and after the action made by the user.

III. Formal Behavior Model Using Elements of Planned and Organizational Behavior Theories

According to the theories of planned and organizational behavior [20], behavior can be defined as a set of conscious actions of a subject with specific features that are repeated in different situations. Behavior is mainly determined by the following factors that must be taken into account when analyzing and predicting it:

- Action.

The action determines what kind of behavior is performed. It can be specific social or economic behavior, some kind of interaction, etc.

- Object.

The object determines what the behavior is directed to: a certain service, to object, another person, etc.

- Context.

The context defines the conditions in which the behavior occurs.

- Time factor.

The time factor indicates a specific time of the behavior: for example, immediately, after an hour, within a few minutes, on a specific day.

The functional analysis of the behavior, also known as ABC analysis (Antecedent, Behavior, Consequence), is aimed at the identification of both prerequisites A and the results C of the behavioral event B. To improve the quality of an information system, it is proposed to reveal such behavior patterns.

Let us describe the behavior as a triple in accordance with ABC:

$$\langle a, b, c \rangle, \text{ where}$$

a – antecedent. In functional analysis, the antecedent is usually understood as something that caused the subject's behavior, the trigger of the behavior;

b – behavior. The behavior is understood as the performance of certain actions of the subject to change both his/her own state and the state of the environment from the current one to the desired one, which in turn is defined by subject’s preferences and strategies.

c – consequence. The consequence defines what has changed after the performed actions.

Let us consider the timescale (Fig. 1):
τ_a – some point in time before the subject starts the behavior,
τ_b – the point in time at which the subject starts the behavior,
τ_c – the point in time when the behavior has ended, and the consequences have taken effect.

Let $context_\tau$ to denote the context at some moment of time

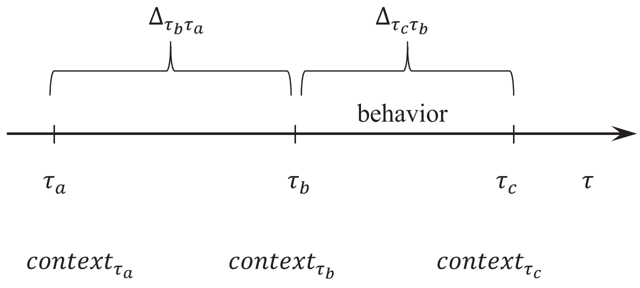

Fig. 1. The timescale of user behavior

τ. The context describes the state of the subject him/herself, as well as the state of the environment. Thus, $context_{\tau_a}$ describes the state in which the subject does not yet perform the behavior in question. In turn, $context_{\tau_b}$ describes the state in which the subject starts the behavior. That is, it can be stated that the change of the state from $context_{\tau_a}$ to $context_{\tau_b}$ is the trigger of the behavior. The difference between the contexts $context_{\tau_b}$ and $context_{\tau_a}$ (the trigger) is denoted as $\Delta_{\tau_b\tau_a}$.

Similarly, let $\Delta_{\tau_c\tau_b}$ to denote the difference between the contexts $context_{\tau_b}$ and $context_{\tau_c}$. In this case (assuming no context changes caused by external factors other than time) $\Delta_{\tau_c\tau_b}$ describes the result of the behavior.

Thus, the behavior can be described as the triple: $\langle\Delta_{\tau_b\tau_a}, b, \Delta_{\tau_c\tau_b}\rangle$. However, since the behavior trigger depends on the context, the latter has also to be introduced into the model. As a result, the final behavior model is described as:

$$\langle\Delta_{\tau_b\tau_a}, b, \Delta_{\tau_c\tau_b}, context_{\tau_b}\rangle$$

One can make some observations based on the model:

- $\Delta_{\tau_b\tau_a}$ cannot be equal $\emptyset$, since at least the time has changed. Therefore, if all parameters (except for time) in a given trigger are equal, then the reason for the behavior was exactly the time.
- If $\Delta_{\tau_b\tau_a} = -\Delta_{\tau_c\tau_b}$ (except for time), then the subject has just returned the situation to its original state, in other words, the trigger can be considered as not desirable in this context.

This representation is very close to that considered by hidden Markov models (for example, [21]), what makes it possible to use appropriate mathematical apparatus for analyzing behavior and identifying patterns.

The main advantage of this model is the possibility of a comprehensive analysis of the behavior depending on the prerequisites (the trigger) in the presence of historical data to identify which elements of the context affect triggers and which do not, determine the preferences of the subject, etc.

The following classes of the forecasting models can be identified:

- Statistical models make it possible to find the most common patterns that cause a certain behavior or which are the objectives for the subject. In other words, they make it possible to identify which changes in which parameters of the context cause this or that behavior, changes in which parameters do not affect the behavior, and which values of which parameters the subject prefers when performing certain actions.
- Similarity models (both between states and between subjects) from the area of collaborative filtering. With the accumulation of sufficient statistics, it is possible to use these methods to identify subjects with similar preferences (for example, based on a comparison of trigger vectors and behavior results, cf. [22]) to apply, for example, collaborative filtering techniques.
- Use of data mining methods to identify tacit patterns between trigger parameters, behavior, and behavior outcomes (for example, using Bayesian classifier, neural networks, etc.).
- Use of the methods of hidden Markov models. These methods are focused on searching for patterns similar to those mentioned above, calculating the probability of a sequence of actions, as well as searching for actions that could lead to a certain state of the system.

IV. Introductory Examples Illustrating the Idea Behind the Approach

In the below examples an information system is considered that provides for information support of problem-solving [23]. Users get an assignment ("task") to solve in accordance with preferences captured in their profiles. The system provides possibilities for information search during task solving and message exchange between users.

A. Checking Own Profile

In this example, the user checks his/her profile in the information system.

Behavior: $\langle\Delta_{\tau_b\tau_a}, b, \Delta_{\tau_c\tau_b}, context_{\tau_b}\rangle$

$\Delta_{\tau_b\tau_a}$ – only time has changed.

b – profile opening.

$\Delta_{\tau_c\tau_b}$ – time has changed, the profile page has been opened.

The analysis can show that, for example, the user checks the profile weekly and move the control associated with the profile opening closer to the user at the corresponding time. Besides, if the currently executing by the user scenario is captured as well, it can be noted that, for example, the profile is not opened when the user is working on a task (task solving scenario is activated), so in this case, the corresponding control can be moved out of the screen in order not to occupy space and distract the user from task solving activities.

B. Search for Information Related to Task Solving

In this example, the user searches for information required for task-solving.

Behavior: $\langle\Delta_{\tau_b\tau_a}, b, \Delta_{\tau_c\tau_b}, context_{\tau_b}\rangle$

$\Delta_{\tau_b\tau_a}$ – changes include time and activation of the task-solving scenario.

b – submitting an information search query.

$\Delta_{\tau_c\tau_b}$ – changes include time, deactivation of the task-solving scenario, absence of unsolved tasks.

In this case, the analysis might show that whenever the user starts solving a task, he/she searches for information. As a result, controls associated with information search can be put forward when the user starts solving a task.

C. Reading an Incoming Message

In this example, the user reads an incoming message (cf. [6]).

Behavior: $\langle\Delta_{\tau_b\tau_a}, b, \Delta_{\tau_c\tau_b}, context_{\tau_b}\rangle$

$\Delta_{\tau_b\tau_a}$ – changes include the time and appearance of an unread message.

	time	ring_volume	time_dt	prev_ring_volume
6852	1523456760000	0.0	2018-04-11 14:26:00	0.714286
7954	1523522880000	0.0	2018-04-12 08:48:00	1.000000
21202	1525331400000	0.0	2018-05-03 07:10:00	1.000000
37220	1526634780000	0.0	2018-05-18 09:13:00	1.000000

Fig. 2. Time instances when the user changed the ring volume from a non-zero value to the zero value (*time_dt* is a human-readable copy of the time column, which is a timestamp)

b – unread message opening.

$\Delta_{\tau_c\tau_b}$ – changes include time and absence of unread messages.

In this case, the analysis might show that whenever the user has an unread message (or receives a message) he/she tries to return the situation to the original state (without unread messages) via reading the message. As a result, the system can pop up a notification when a new message arrives with the possibility to open it. This scenario can be made more complex including properties of the messages into the context. In this case, it can be potentially found that, for example, the user tends to urgently open messages only from a certain address or with certain keywords only when he/she is not in the scenario of task-solving.

V. Case Study

To check the applicability of the developed approach to behavior analysis, an experiment has been conducted. For this purpose, a search for a dataset that describes the state of some system before and after user actions has been done. The most appropriate found dataset was the MDF ("MyDigitalFootprint") dataset [24]. This dataset includes various information about the state of a mobile phone of 31 users captured for several days approximately once a second. It covers such parameters as installed applications and their activities, audio settings, connectivity functions, calendar events, calls, sensor data, localization data, and others.

In this case study, we were trying to identify which context changes cause a user to switch off the ringer of the mobile phone, so the behavior (b) in this case is "switching off the ringer of the mobile phone". For this purpose, we selected the user with the biggest dataset (user 27) without any preliminary investigation of the associated data. For finding τ_b (the point in time at which the subject starts the behavior), we selected those time instants (rounded to minutes) where the ringer volume ("*ring_volume*") changed from a non-zero value to the zero value. This was done via copying the "*ring_volume*" data series shifted to 1 back naming it as "*prev_ring_volume*", and then selecting only those records where these two parameters are not equal, and the "*ring_volume*" is equal "0":

Algorithm 1

for *i* **in** range(1, len(*dataset_audio*)):
    dataset_audio.loc[*i*, 'prev_ring_volume'] =
        dataset_audio.loc[*i*-1, 'ring_volume']

dataset_audio =
    dataset_audio[*dataset_audio*['ring_volume'] !=
    dataset_audio['prev_ring_volume']]

dataset_audio =
    dataset_audio[*dataset_audio*['ring_volume'] == 0]

Out of 44235 records, only 4 meet the above criteria (Fig. 2).

For the context description, the following parameters were considered: time, the presence of an event in the calendar, and music listening mode. The τ_a (the point in time before the subject starts the behavior) was defined as 15 minutes before τ_b, and τ_c (the point in time when the behavior has ended, and the consequences have taken effect) was defined as 15 minutes after τ_b. Since records in different files of the dataset are not perfectly synchronized, time windows of 5 minutes were used to capture the matching records for τ_a and τ_c, and a 10-minute time window was used for τ_b (Fig. 3). The captured data is shown in Fig. 4 and Fig. 5 and summarized in Table I (for *event*, 1 means that there is an appointment in the user's calendar at the considered time instant, and 0 otherwise; and for

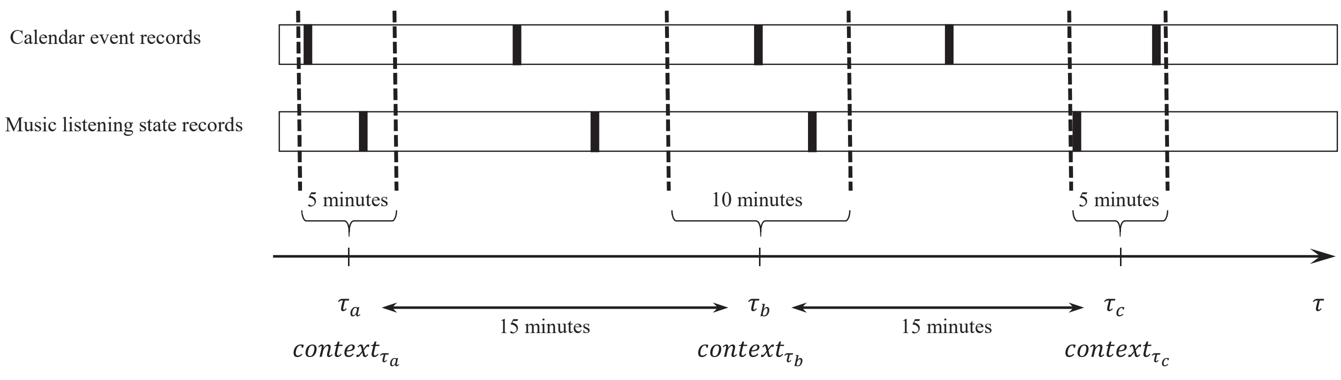

Fig. 3. Capturing context information

	ring_volume	time_dt	prev_ring_volume	time_before_dt	time_after_dt
0	0.0	2018-04-11 14:26:00	0.714286	2018-04-11 14:11:00	2018-04-11 14:41:00
1	0.0	2018-04-12 08:48:00	1.000000	2018-04-12 08:33:00	2018-04-12 09:03:00
2	0.0	2018-05-03 07:10:00	1.000000	2018-05-03 06:55:00	2018-05-03 07:25:00
3	0.0	2018-05-18 09:13:00	1.000000	2018-05-18 08:58:00	2018-05-18 09:28:00

Fig. 4. Time instances when the user changed the ring volume from a non-zero value to the zero value (τ_b – *time_dt*) and corresponding τ_a (*time_before_dt*) and τ_c (*time_after_dt*).

	event_before	event	event_after	music_before	music	music_after
0	0	0	0	0	1	1
1	0	0	0	0	1	1
2	0	1	1	0	1	1
3	1	1	1	0	1	1

Fig. 5. Context parameters for switching the ringer off by the user (labels "*event_brefore*", "*event*", "*event_after*" and "*music_before*", "*music*", "*music_after*" denote values of the parameters of occurring event and music listening mode at times τ_a, τ_b, and τ_c respectively)

TABLE I. SOURCE DATA FOR BEHAVIOR REPRESENTATION

Sample #	$context_{\tau_a}$				$context_{\tau_b}$				$context_{\tau_c}$			
	τ_a	Ring volume	Music is on	Event is present	τ_b	Ring volume	Music is on	Event is present	τ_c	Ring volume	Music is on	Event is present
1	2018-04-11 14:11:00	0.714	0	0	2018-04-11 14:26:00	0.000	1	0	2018-04-11 14:41:00	0.000	1	0
2	2018-04-12 08:33:00	1.000	0	0	2018-04-12 08:48:00	0.000	1	0	2018-04-12 09:03:00	0.000	1	0
3	2018-05-03 06:55:00	1.000	0	0	2018-05-03 07:10:00	0.000	1	1	2018-05-03 07:25:00	0.000	1	1
4	2018-05-18 08:58:00	1.000	0	1	2018-05-18 09:13:00	0.000	1	1	2018-05-18 09:28:00	0.000	1	1

music, 1 means that the smartphone is playing music at the considered time instant, and 0 otherwise). Table II presents the data in accordance with the proposed behavior modeling approach.

This information then can be used by a data mining model (e.g., a neural network), but due to the small number of parameters and for illustrative reasons we will study it manually. From Table II one can easily conclude that:

- there is no dependency between switching off the ringer and time;
- the user switched the ringer off because of an event only once;
- the user switched off the ringer each time because he/she started listening to the music.

So, as the final conclusion it can be said that for the analyzed user, the factor causing switching off the ringer is starting listening the music.

VI. DISCUSSION

The paper presents an approach to behavior modeling. Unlike other existing approaches, the proposed one is aimed to capture the context of the user environment before, at the time of and after the action. As a result, this makes it possible to use the modeling approach for the identification of the features and time that can affect the user actions. The carried out case study has shown its applicability and efficiency.

However, the approach has some limitations that are subject of future research:

- This model does not allow an analysis of a sequence of actions. Behavior history can be added to the context, but this can significantly complicate the model what requires additional research.
- The non-redundancy and (even more important) completeness of the context play an essential (if not decisive) role in the analysis of behavior so one should carefully identify what should be captured. However, as it was mentioned at the introduction of the paper, modern machine learning pipelines can deal with a large

TABLE II. BEHAVIOR REPRESENTATION IN ACCORDANCE WITH THE PROPOSED BEHAVIOR MODELING APPROACH

Sample #	$\Delta_{\tau_b\tau_a}$			$\Delta_{\tau_c\tau_b}$			$context_{\tau_b}$			
	τ_a	Δ_{music}	Δ_{event}	τ_c	Δ_{music}	Δ_{event}	τ_b	Ring volume	Music is on	Event is present
1	2018-04-11 14:11:00	1	-	2018-04-11 14:41:00	-	-	2018-04-11 14:26:00	0.000	1	0
	{Δ_τ= 00:15; Δ_{music}= 1}			{Δ_τ= 00:15 }						
2	2018-04-12 08:33:00	1	0		-	-	2018-04-12 08:48:00	0.000	1	0
	{Δ_τ= 00:15; Δ_{music}= 1}			{Δ_τ= 00:15 }						
3	2018-05-03 06:55:00	1	1		-	-	2018-05-03 07:10:00	0.000	1	1
	{Δ_τ= 00:15; Δ_{music}= 1; Δ_{event}= 1}			{Δ_τ= 00:15 }v						
4	2018-05-18 08:58:00	1	-		-	-	2018-05-18 09:13:00	0.000	1	1
	{Δ_τ= 00:15; Δ_{music}= 1}			{Δ_τ= 00:15 }						

number of features, so redundancy may not be an issue when enough training data is available.

VII. CONCLUSION

The paper describes an approach to user behavior modeling that enables the application of various algorithms for behavior analysis and forecast, which, in turn, can improve the user experience when interacting with an information system. The approach is based on elements of planned and organizational behavior theories and close to Markov models. Its idea is in capturing contexts before the user undertakes an action, at the moment of undertaking the action, and after the behavior is finished. The carried out illustrative case study has confirmed the applicability and the efficiency of the approach. It significantly reduces the search space when an analysis of factors affecting the behavior is carried out.

The approach still has some limitations that are subject of future research, namely: it does not support the analysis of a sequence of actions; and its efficiency strongly depends on the completeness of the captured contexts. Nevertheless, the approach in its present form is applicable what is confirmed by the presented case study.

ACKNOWLEDGMENTS.

The research is due to State Research, project number 0073-2019-0005.

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