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Modeling Individual Strategies in Dynamic Decision-making with ACT-R: A Task Toward Decision-making Assistance in HCI

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Abstract

New findings from cognitive science, computer science, and psychology should be used to develop better artificial intelligence (AI). One of the important goals in AI development is the accurate understanding and prediction of the behaviors and decision-making processes of humans. It is especially demanding to achieve this for real dynamic settings, characterized by constant changes. Individual differences in decision-making and behavior make this even more challenging. The area of human-computer interaction looks at a series of decisions and multifactor situations which are influenced by corresponding feedback. Cognitive modeling provides us with a method to understand and explain how such dynamic decisions are made. This work is a demonstration of how cognitive modeling allows to flexible simulate decision-making in dynamic environments for different individual strategies. In this work an empirical study of an improved complex category learning task is presented, the study is based on previous work [8]. The task requires participants to categorize tones (consisting of different features) by applying acoustic strategies to define a target category and adapt to a reversal of feedback. Thus, a model based on the cognitive architecture ACT-R is developed. This model firstly tries out one-feature strategies (e.g. frequency) and then switches to two-feature strategies (e.g. frequency + volume) as a result of negative feedback. However, after comparing the model fit data and analyzing each individual's data and answers, there is a great variance among some individuals and the first model which only considers acoustic feature strategies and cannot predict individuals who consider the uncertain correct button representing target tones. The upgraded second model contains two independent threshold count mechanisms for these two factors' learning process. The result of the second model provides a better approximation of the values with the empirical data of those subjects who prefer to consider multi-factors in the tasks. It proves the extensibility of this ACT-R cognitive modeling approach for the different individual cases. A great potential of our approach is, that it can be applied to other HCI tasks and thus it can contribute to related AI approaches and help build AIs with a better understanding of human decision-making.

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1. Introduction

With the development of technology, people have more powerful tools to deal with universal and challenging issues in broader areas to improve the quality of life and the efficiency of work. These new developments are not limited to the areas of autonomous driving or genome editing technologies, but more and more breakthroughs in computer science, psychology, or cognitive science which motivate people to embrace the world with the help of the well-developed artificial intelligence (AI). For example, one of the inspiring possibilities is the appearance of "smart city". Here AI helps to manage resources and energy to create smarter, safer and more comfortable living and working areas for people. Let's take traffic accident as the example. In the future, smart cities will deploy robust and efficient moving schedules for each active vehicle with collision avoidance guarantee. However, crucial for the success of smart cities is a good understanding of its inhabitants. Understanding and predicting human behavior and the human decision-making process in these dynamic settings and changing environments is a major challenge for AI. The variation of individual differences in humans makes this even more demanding.

To gain a better understanding of the decision-making process on the individual level in order to design such understanding system transfer to AI from fields, it is required to focus on deciphering human behavior and decision-making in complex systems. And some important candidates here are cognitive science, psychology, and HCI.

HCI research is faced with the challenge, that many system-interaction tasks are influenced by multi- factors (such as the uncertain number and quality results for every search, the unpredictable recognition accuracy of Siri, etc.) and need to be adjusted according to changing environments. Here for, possible influenced conditions need to be pre-considered as well as an adequate prediction of various situations and reactions of users, such as intuition or experience based on prior learning, habit or preference, the anticipation of consequences of actions, emotional responses, and social influence. Wouldn't it be great if we could provide a mechanism at the cognitive level which can explain and predict user behaviors for every specific decision?

1.1. Theory

Naturalistic decision-making (NDM) research [2] addresses the complexity of the decision-making process, by looking at all important factors together, such as time pressure, uncertainty, high stakes, etc. However, NDM emphasizes the details and thus relies on ethnographic methods. Thus, the findings are very specific to the subject and the subjects of the study. Thus, for designing intelligent systems that understand and anticipate the users there is little possibility to transfer these findings in a systematic way.

Is it possible to address the complexity of decision-making in a more flexible (thus transfer to other domains) and more effective and finally in a more applicable manner? Dynamic decision making (DDM) research [3] can fill this gap. It looks at decision-making in the sense that the decisions are changeable with different incoming information.

In DDM stresses the important role of feedback in the decision-making process. DDM is a feedback loop of consequences and results. New knowledge is built up and influences the following decisions due to feedback learning [4]. For most stages of human-computer interaction, feedback triggers immediate reactions and affects the future behaviors of the user. Therefore, researchers, as well as designers in the industry, pay close attention to when and how to provide useful feedback. As a cognitive scientist, our goals are to explore and explain the mechanism of how people receive, understand and react to different feedback. This explanation on a theory level has the potential to become a useful tool for the designers to predict human-machine interaction and improve their design effectiveness.

Learning from feedback is the experience of accumulating from the previous instances. This is referred to as instance-based learning (IBL) [5]. The decision-related products and operations are obtained by accumulating and refining of the decision instances. IBL can be seen in an exemplar-based and history-based way because the decision instances should have certain accessible instances from the previous experience. This requires the additional buffer to store the collected relevant instances to let people make retrieval decisions. IBL is strongly related to category learning and has been successfully modeled with a cognitive model (CogIBLT) in dynamic decision-making tasks involved auditory process [5]. Other works [6] [7] also provide some physiological explanations about the functional parts of the auditory cortex corresponding to the sensory and cognitive mechanisms. These indicate that we need to consider not only IBL but also different and independent rules for different subtasks.

In our previous work [8], a cognitive model, based on a dynamic decision-making task in which categorization was required, was successfully implemented using both a rule and an instance-based approach. This model is implemented in ACT-R, a cognitive architecture [1], that can simulate the interplay of different cognitive processes, which is very much needed if complex tasks are modeled.

In the modeled task, participants needed to categorize tones (consisting of different features) by applying acoustic strategies to define a target category and adapt to a reversal of feedback. The model firstly tries out strategies using one acoustic feature (frequency) and after learning through (negative) feedback that one feature is insufficient, it switches to strategies using two acoustic features (e.g. frequency + volume). However, the model matched the average data well, but we need to find out if the strategies of this model, were really those of the participants. So, a new empirical study [9] where we used a mix of qualitative interviews and behavior recordings were conducted and the first model was built following the above method. After comparing the model fit data and analyzing each individual's data and answers, we found a great variance among individuals and the first model. Especially, this first model only considers acoustic feature strategies and cannot predict individuals who consider two different strategies together, not only acoustic-features but also the uncertain correct button representing target tones. The first model needs to be extended to capture the different decision-making strategies of specific individuals. So, in this paper we want to shed light on two research questions:

- Can the cognitive modeling mechanism capture dynamic decision-making processes that are relevant for designing future AI systems?
- Are such models expendable in order to address the individual differences in such dynamic decision-making processes?

2. Method

2.1. Empirical study

To get more insight on the strategies of the participants and due to the long-term goal to learn about actual decision-making in complex real-world tasks, the new empirical study changed the auditory category learning task from Prezenski et al [8] and added complexity to the task.

160 frequency-modulated different tones served as stimuli for this tone categorization task. These tones have 6 different acoustic features; the duration, the direction of frequency modulation, the intensity, the basic frequency level, the frequency range (5 low level and 5 high), the speed of modulation. The first two features- duration and the direction of frequency change- have four categories. We set the tones with a short duration and rising character as the target tones (25%). The participants' goal is to find out target tones without any previous knowledge but using the feedback from previous trials. Feedback stimulus consists of 4 positive utterances, 4 negative utterances and 1 time-out utterance taken from MOTI [10] [11]. The whole experiment is implemented by Presentation V18.3.

The experiment consists of 220 trials, in each trial a tone is presented, and participants are required first to decide if the tone is a target or a non-target by pressing one of two buttons (9 or 0) using their right hand and second to rate their confidence (1 to 4) using their left hand. After every 10 trials (10 trials make a block) there is a short pause and retrospective reports are collected. In the experiment, the correct button, which represents the target tones, swaps two times: after Block 10 (100 trials), and after

Block 16 (160 trials). The participants are not informed about these swaps. Two kinds of retrospective reports are used in this experiment; the "middle survey" is applied in each pause; its aim is to investigate how their memory and recognition of the current correct button changes because of some feedback; the "final questionnaire" is applied at the end of the experiment, in order to obtain a more comprehensive understanding of their overall strategies.

2.2. Modeling Approach

First Model. 50 participants took part in this study (31 females and 19 males, with the age range between 20 and 49 years old, 90% right - handed. No one has a hearing impairment and 86% of them do not have professional training or experience in subjects related to sounds or tones). The modeling approach of Prezenski [8] was applied to the new empirical study firstly. This model (Smodel) considers one main factor for this learning process: the acoustic features. The Smodel uses two chunks: "Strategy chunk" and "Control chunk". The "Strategy chunk" contains the acoustic strategies including examples of feature-value pairs and responses, which are stored in and retrieved from long-term memory (declarative module). All processes of the current strategy are held in working memory (imaginal module). The "control chunk" which is kept in the goal buffer of the model includes the information involving meta-cognitive aspects: the level of feature-complexity of the strategy (one/two-feature), the uncertainty and accuracy of the current strategy (The success or failure times of a strategy. The evaluation of a strategy is based on the feedback. A negative feedback will not cause strategies to change immediately, but there is a count threshold evaluation mechanism of the strategies. The Smodel always begins with a one-feature strategy randomly and then switches to another one-feature strategy which has not been used recently, and if one-feature strategies are unsuccessful, then two feature strategies are used. The switching moment depends on the value of how often the current strategy is successful. The fit of the Smodel with the average data from this experiment was computed. The correlation coefficient (r) is 0.732 and the root-mean-square deviation (RMSE) is 0.067.

Although r and RMSE of average data are reasonable, after calculating them for each subject, we found that they have a great variance. This is a strong indication that individuals have a very different way to deal with such a task, even if on the surface it seems like a very simple tone discrimination task.

Second Model. The retrospective reports were used to gain more insight into the methods and strategies the participants used during the different periods of the experiment. The analysis of these reports shows that for some subjects, the uncertain correct button representing target tones is an important factor they considered each time they make a decision. Participants reported, that when receiving negative feedback, they hesitate and ask themselves whether the correct button has changed rather than assuming that the acoustic strategy is different. Thus, in the next trial, they would first attempt to press the other button. Thus, the Smodel cannot describe the data of every individual because it lacks this factor. This finding motivated us to enhance the Smodel. Thus, to consider this individual difference, we designed a second model (Zmodel). This model extends the first model, by integrating a strategy about button changes into the model. So, if the Zmodel goes through a trial (adding the correct button change), there needs to be the process of loading the current status of the correct button and updating this status after receiving feedback. In each trial, the model first loads its current knowledge about the correct button, and then listens to the tone and makes a judgment relying on the acoustic strategies, then presses the assumed correct button. After the button-press, feedback is received, and the model updates the acoustic strategies according to the feedback, and it also updates its knowledge about the correct button.

The cognitive processes happening in a trial can be separated into two sub-processes: first listening to the tone and second hearing and reacting to feedback. When we consider the mechanism of the correct button update during these two sub-processes, the simple way is to assume it as an independent changing process influenced by feedback. It is different from the change of acoustic strategies and without any interaction with it. In Zmodel the acoustic strategy follows the same rules as the previous model, however, their knowledge about the correct button follows its own rules and to updates independently from the acoustic strategy.

The evaluation mechanism of the button change strategy is built in a similar manner as the evaluation mechanism of the acoustic strategy. Both have a meta- cognitive count mechanism that uses a threshold count for negative Feedback before strategies are changed. For an example of the threshold count for the acoustic strategy see Prezenski et al [8]. The threshold count mechanism for the new strategy works in the following manner: we set the exact count using the answers from the subjective questionnaires to 3. This means, that if continuous negative feedback accumulates to 3, the correct button representing target tones in the subject's memory will switch to another button, and the count of it is reset to be 0.

Thus, the new cognitive process considering the correct button memory mainly does two things. One is to add a new step before the start of strategy comparison in the sub-process of listening tones. It helps to load the current correct button memory and the status of the control condition. And the other one is to add a step after the end of strategy parts in the listening feedback sub-process, which updates the control condition status via current feedback and decide whether the correct button memory change or not via the status. The whole cognitive process can be checked in Figure 1.

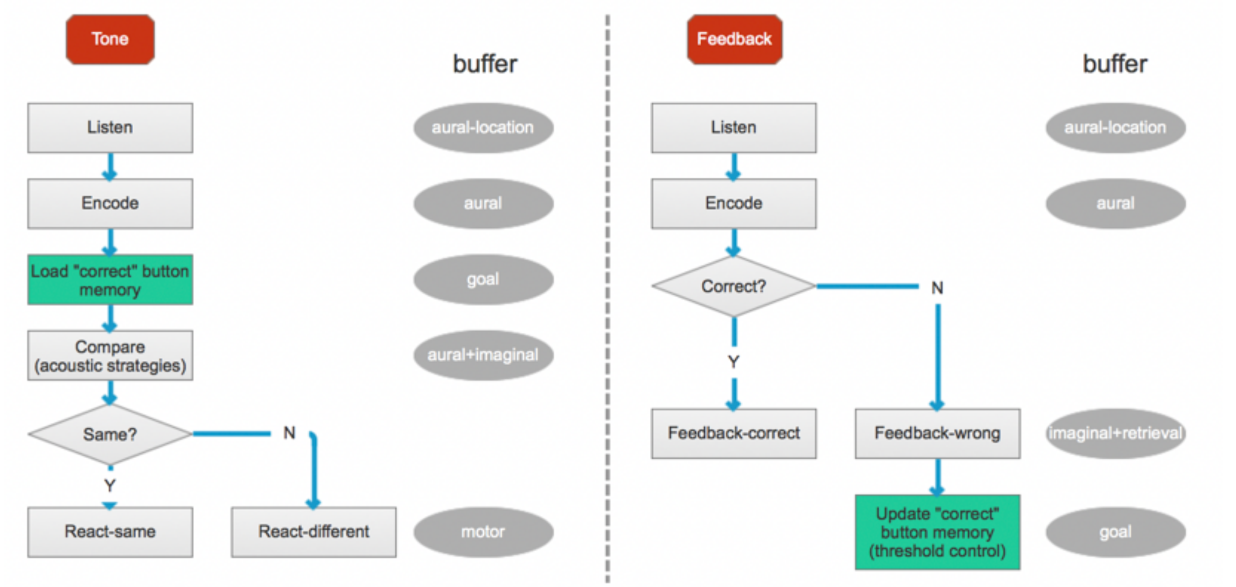

Fig. 1. The cognitive process after listening to the tones and feedback. The boxes on the left represent the main productions, the ellipses on the right mean the main buffers involved.

3. Result

The two model fit results with average empirical data can be checked in Figure 2. The r of Zmodel (new) is 0.663, while the Smodel (old) is 0.732. The RMSE of Zmodel and Smodel is 0.045 and 0.067. The Zmodel has a lower r but a smaller RMSE. Considering the Fig 2 showing, for the average data of all subjects, the Smodel is better in the trend prediction but the new Zmodel is closer to the real values.

To evaluate how useful the models are for predicting individuals whose retrospective reports indicate that they always consider the correct button change firstly, we calculated fit indices of two subjects which reported this (Subject p1_g2, Subject p4_g4). For Subject p1_g2, the r and the RMSE for Smodel are 0.524 and 0.154, for Zmodel are 0.621 and 0.123. Another Subject p4_g4 has 0.465 and 0.122 in the r and the RMSE with Smodel, while for Zmodel the r and the RMSE are 0.490 and 0.129. The larger value of r and the smaller RMSE of Zmodel indicates that the model performs better to predict these individuals' behaviors for this task. So, for such participants, who report to always consider the possibility that the correct button might change, the Zmodel is somewhat more plausible.

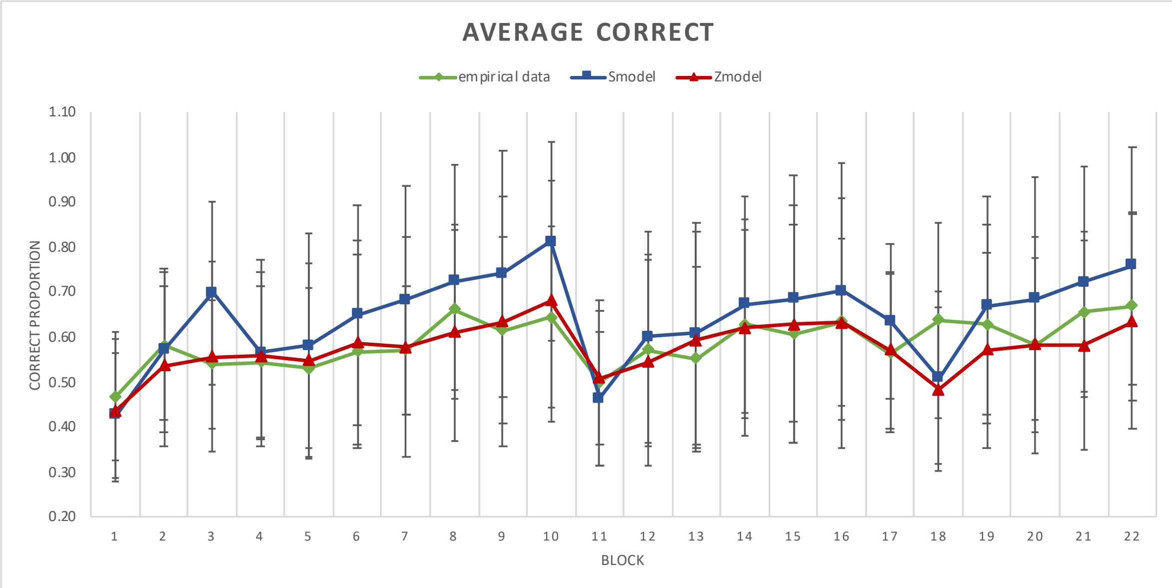

Fig. 2. Two model fit results in the average correct percentage of each block.

4. Conclusion and discussion

The ACT-R modeling approach of Prezenski's previous work [8] shows a good scalability and adaptability for a more modified version of this task. However, the modified task adds complexity to the setup. The modified version of the task makes it more similar to real-life tasks, such as tasks in HCI. This added complexity is somewhat problematic for the old modeling approach. It cannot resemble individuals with more complex decision-making strategies. To address this, the modified version added a new factor. It shows a better performance in simulating such individuals. Furthermore, its assumption that the two factors recognition of acoustic feature and the correct button memory, are dealt with by our brain independently is plausible from a biological point of view.

Two aspects can be extracted from our work. The first one is, that for dynamic tasks which rely on continuous feedback and very common in HCI, our modeling approach (combining instance- based learning and rule-based learning) can predict users' behavior. The second aspect is, that if decisions in such as task are influenced by many factors and the environment is unstable, models can and should be modified, by treating all changing factors as independently. We can modify, existing models to address this complexity and individual differences in human decision-making. We can do this in a feasible manner. With- out having to remodel the complete task, So, we can have, different variations of a model, which can contain different factors and they can predict the diversity of users.

These two aspects have the potential to benefit many ordinary tasks in HCI. For example, when designers or researchers do a pre-investigation of users to find out more about a feature or function,

which requires category learning, a cognitive modeling similar to the one presented above can be used. This can be done, by coding the main influencing factor (in our model this corresponds to coding the acoustic features) and other factors which might be strongly influenced by individual difference can be added extra (such as the correct button memory in our modified model). This will improve the correctness of the capability of predicting individuals' strategies. Finally, our approach is a step towards developing more accurate AIs that can better understand and predict the individual decision-making process of humans.

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