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Implementing Mental Model Updating in ACT-R

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Abstract

This paper demonstrates how mental models and updates of mental models due to system changes can be modeled with the cognitive architecture ACT-R using explicit mechanisms. The mental model building and updating is modeled with a representation chunk and a control chunk. The representation chunk holds the strategy, the expected outcome and an evaluation mechanism of the strategy. The control chunk holds information over environmental conditions and the learning history. This modeling approach was developed and tested for smartphone application tasks and then implemented in a dynamic decision-making task investigating strategy development with complex stimuli. The later task used different multi-feature auditory stimuli material. The modeling approach explained data of participants in the smartphone studies very well and met the trends found in the dynamic decision-making task.

Keywords: *ACT-R; mental model updating; general model; learning; dynamic decision-making, applied*

Introduction and Theory

Our behavior is guided by our internal representation of tasks and situations (Norman, 1983). However, such representations or mental models are not static but they change and are adjusted, due to experience gain, environmental changes etc. Understanding how people update or adapt their mental model is relevant in many fields, from updates in technical systems to real-life tasks that require strategy learning and dynamic decision-making. The later investigates serial decisions. Such decisions are dependent on previous decisions and are made under time constraints in a changing environment (Edwards,1962; Gonzalez, 2014). Dynamic decision-making can be seen as a continuous cycle of mental model updating, made up of conceptualization – experimentation – reflection (Li and Maani, 2011). In the conceptualization phase a general concept of the situation is obtained. Hereby, the outcome of potential decisions is mentally simulated. The current situation is compared to information in the decision maker's mental model.

New information obtained from the environment is integrated to develop a set of decisions. In the experimentation phase, these decisions are tested. The outcome (e.g. feedback) of the experimentation phase is evaluated on in the reflection phase. If the expected outcome is achieved (e.g. positive feedback), initial decisions are kept. If, the outcome is unexpected (e.g. negative feedback) the mental model of the decision maker is updated. Thus, alternatives are sought for, such as new sources of information.

In real-life settings adaptations of mental representations of users are required in many different circumstances. Typical situations which require a user to update his or her mental model are situations leading to errors, due to incomplete or wrong representations. For example, if a user repeatedly fails to install the connection settings for the universities Wi-Fi, he or she needs to adjust his or her mental model, about how to install Wi-Fi on phones. Situations in which changes to the system (due to aspects outside of the person) make the current (in the past correct mental model) inadequate also require adjustment to the user´s mental representation. Examples for the later are a) that due to system-upgrades a new version of an application is launched or b) that past-successful strategies used in decision-making tasks are misleading due to environmental changes.

Nevertheless, the core mechanisms of mental model adaptation should be the same for both situations. This paper demonstrates how mental model build-up and adjustment due to environmental can be addressed using the cognitive architecture ACT-R.

Cognitive architectures allow computationally implementing theories about human cognition in a broad spectrum. The cognitive architecture ACT-R has been applied in many applied domains such as smartphone usage (Prezenski, Bruechner and Russwinkel, 2017) or air-traffic control (Raufaste, 2006) but also in more ground-based research (Halbrügge and Russwinkel, 2016).

ACT-R has symbolic and subsymbolic parts which together produce the modeled behavior. The symbolic parts are chunks, production rules, buffers and modules. The modules resemble the architecture of the human brain. are specified, each of them handles different types of information (chunks). The chunks have slots, they store the smallest pieces of information. The different modules interact through their corresponding buffers. For example, visual information is processed by the visual module and its two buffers. Motor movement is controlled by the manual module and buffer. The declarative module is the long-term memory of ACT-R. Information for this module is retrieved via the retrieval buffer. The imaginal module and buffer are important for learning new information and can be seen as ACT-Rs working memory. Model steering is controlled by the goal module and buffer. The procedural module connects the modules and selects (production-) rules. These production rules are the core part of an ACT-R model- they govern the model behavior. Production-rules can be selected and executed, if buffer states are met. The selected production-rule can then change the states of the modules. An example of a subsymbolic process in ACT-R is the activation level. Thus, if a production requests a chunk and more than one chunk matches this request, this results in the selection of the chunk with the highest activation level. The activation level of a chunk is composed of how often it was used when it was last accessed and how long ago the chunk was created. There are many more subsymbolic processes built into the architecture of ACT-R (e.g. blending, partial matching). Subsymbolic processes are used for modeling implicit learning, e.g. usage of activation mechanism to model information that is well- known can be better retrieved than information that is less well-known.

However, learning (especially in early phases) is also an explicit process (Tenison, Fincham & Anderson, 2016). Thus, the learner is deliberately processing information and deciding what to do next stepwise. This can be modeled by building of new chunks via specific production rules. They can represent the strategies given to a model by the modeler. For an overview and a discussion of implicit and explicit mechanisms in ACT-R in context of intuitive decision-making see Thomson et al (2016).

Explicit mechanisms seem especially important in mental model updating. According to Li and Maani (2011) mental model updating occurs in the reflection phase when negative feedback (unexpected outcome) is observed. Then new sources of information need to be sought for. Such processes require the modeler to use explicit mechanism.

Cognitive models are useful to make precise predictions about theories on human cognition. Models build with cognitive architectures moreover allow precise prediction about behavior influenced by different cognitive processes. They try to capture cognition as a whole. Enough effort, modeling skills and free parameters make it possible to precisely match behavior of participants with models. But for models to be useful. they should be able to predict data in other situations as well. Therefore, modelers should avoid using many specifications to match the data, but attempt to use broader concepts. A successful example for this are models using instance based learning (Gonzalez, 2005). Instance based learning is used to model intuitive decision-making (Thomson et al, 2016). Hereby problem-solving instances are stored in declarative memory and decisions are made by retrieving these instances. The activation mechanism of ACT-R is used to determine which instances are retrieved. However, in early phases of learning and when previously-learned instances become invalid (due to changes in the environment) explicit mechanisms are needed. Such explicit mechanism should be constructed in a general manner and thus be applicable in a variety of tasks.

Aim and Previous Work

The aim of this paper is to show how the same modeling approaches and mechanisms relevant for mental model building and updating can be used in very different applied tasks. Both tasks have in common that they require the participants to explicitly a) learn and b) notice changes and thus to readjust their mental model. Otherwise the tasks are different, thus two ACT-R models are used. Nevertheless, this paper resembles a general modeling approach, since it demonstrates how the core model mechanisms developed in one study (Prezenski and Russwinkel, 2016) are applied to a different study (Prezenski et al. submitted).

The first study investigated a search-and select task with two different smartphone applications. One application allows users to select items to assemble a shopping list and the other to select search-criteria for real-estates. Initial and repeated usage of these applications was investigated. Furthermore, users' adaptation to changes in the applications due to updates influencing the menu-structure (shopping application) and adaptations (real-estate application) was studied.

The second study examined strategy learning in an auditory dynamic decision-making task. In this task, multi-feature sounds were repeatedly presented to the participants. The task was to decide if the presented sound was a target or a non-target. To solve this task a combination of features had to be chosen as targets. The relevance of feature combinations had to be learned from the feedback given in the experiment. In the middle of the task a uniformed switch of targets and non-targets occurred. The task can be seen as an example for dynamic decision-making, because it requires participants to repeatedly make decisions on whether or not a stimulus is a target or a non-target and learn (e.g. improve their decisions) from feedback of the previous decisions. The decisions have to be made under time-constraints. Other feature-combinations become targets at a given point in the experiment due to changes in the environment.

Methods

The methods section of this paper is structured in the following way: First, the core mechanisms for mental model building and mental model updating are described. Second, the results of the first study on smartphone interaction and the implementation of the mechanisms in the first study is summarized. Third, the second study on dynamic decision-making and the transfer and implementation of the mechanisms is explained.

Mechanisms

Mental model building The core part of the mental model (or abstract representation) of a situation, strategy or solution is stored in the *representation chunk* (see figure 1). The slots of this *representation chunk* hold information on the strategy and the expected outcome of applying this strategy. The information on the strategy consists of a representation of the situation and the action.

During mental model building (conceptualisation phase) the *representation chunk* needs to be placed in the imaginal buffer. Only here ACT-R allows chunks to be altered. In the experimentation phase, the expected (or predicted) outcome of this *representation chunk* is tested and then reflected on (reflection phase).

In the reflection phase, mental models can either be revised or strengthened. On the one hand, revision is required, if the outcome is different from what is expected. On the other hand, if the outcome is as expected mechanisms for strengthening the mental model are needed. Here fore, explicit mechanisms are used; namely a slot that notes if a strategy is correct and other slots that keep track (until a threshold) how often a strategy was correct. Other implicit ACT-R strengthening mechanisms are also used, such as that frequently used chunks, are retrieved more often and have a higher activation and this again makes them more likely to be retrieved.

Furthermore, as learning evolves, mental models often become more specific (Gonzalez and Lebiere, 2005). For example, a user experienced in installing Wi-Fi on phones for university networks might have two or more mental models depending on the different types of phones the user installed Wi-Fi for university network in the past. Thus, learners may know that a solution is only applicable for a specific situation (e.g. for one version of an application) such knowledge should also be stored in the *representation chunk*.

Besides a representation of the situation, expected outcome and observed success (core part of the mental model), the building of such a model also requires some form of control over the environmental conditions and the learning history. Such information is stored in the *control chunk* (see Figure 1). This chunk is kept in the goal buffer.

representation chunk	control chunk
specification situation part a) situation part b) ... action predicted outcome unsucessful strengthening mechanism	uncertainty environment change

Figure 1: Main chunks and slots required for mental model building and updating

Mental Model Updating In this paper *mental model updating* refers to the modification of an established *representation chunk,* e.g. a strategy that has been successful in the past.

The mechanism, illustrated in Figure 2 works the following way: First, the strategy of the suggested action of the *representation chunk* leads to unexpected outcome. This unexpected outcome is then encoded in a slot of the *control chunk*. This slot represents the uncertainty of the current strategy that something may have changed. The *representation chunk* is nevertheless kept as mental model and tested again. If following the strategy proposed by the *representation chunk* produces unexpected outcome again, this is noted in a slot of the control chunk. This represents that a change has occurred and that a different strategy needs to be built up from now on.

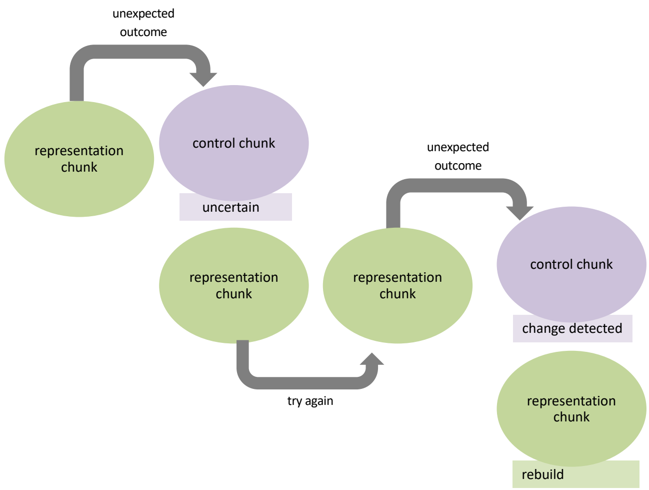

Figure 2: Mental model updating process, governed by specified production rules.

Studies

In the following section the two studies, first the smartphone study and then the decision-making study are presented. Both sections first provide an overview of the tasks and material and then focus on how the core model mechanism from above are implemented respectively.

1) Smartphone Application Study These mechanisms were implemented in a model of users search and select behavior via navigating two smartphone applications. This study has been presented in greater detail elsewhere (Prezenski and Russwinkel, 2016). Thus, only a brief short summary of the applications (material), task, participants, study-design and the implementation of the mental model building and updating mechanism is given.

Material/Applications Two self-designed Android applications (a shopping list application and a real-estate application) each with two different versions were used. The shopping list applications differed in overall menu-depth (three layers vs. four layers). The real-estate application adapted to prior selection, this affected the menu-depth and the positions of some items. These applications were installed on Google Nexus 4.

They are hierarchical-list style applications that support search and select task. Targets and subtargets are spread out over different pages of the applications. See Figure 3 for an impression of the applications.

Task In the shopping-list application participants had to search and select shopping items via navigating through different pages of the application. The participants had to search and select targets (shopping items) via selecting subtargets (e.g. categories, shops) placed on different layers of the application.

Figure 3: Application layout, reprinted from (Prezenski et al, 2017, p. 170)

In the real-estate application participants had to search and select search criteria for real-estates via selecting different subcategories which were again placed on different layers of the application.

Study-Design The design in the four substudies was similar. In the shopping-list study the participants were required to search for the same nine items for four times. In the first two blocks, they used one version of the application (either three or four layers) in the last two blocks the version "updated" and they had to use the other version. They were not informed about the occurrence of a version switch. In the real-estate study the participants were required to search for either a house or an apartment with six or seven other criteria (e.g. specific size, rent) and after two blocks they had to search for the other one twice (e.g. those who searched for a house twice had to search for an apartment and vice versa). Depending on the pre-selection of house or apartment the position and the menu-depth of other search-criteria could differ (e.g. if house was pre-selected the search-criteria 60qm was positioned higher in the list then if apartment was pre-selected).

The dependent variable is the average target selection time per block. Each block consists of the selection of all items (eight items per block for the shopping list studies and six or seven items for the real-estate studies). Thus, four blocks per study existed.

The four sub studies were conducted with student participants**.** 10 participants took part in the real-estate study where apartment was selected first, and 12 in the one where house was selected first. 17 took part in the shopping list study that used the three-layer version first and 12 in the one that used the four layer version first.

Model implementation The apps were implemented in Lisp and the model was run with ACT-R 7.1. 10 model runs per study were implemented[1]. In the following the modeling principles are summarized. This section focuses on how the mechanism for mental model building and updating are implemented. Other supplemental mechanisms will be briefly introduced in the following section, as well.

Mental model building in smartphone studies The task is to find a target via navigating through different layers of the application. In the beginning of the task, a mental representation of the application is not inherent to the model. Thus, navigation of the application if achieved using *knowledge of the world chunks*. These are made up of associations between different words (e.g. the target-word *alcohol-free beer* is related to the word *bottle shop).* Thus, each item of the application is read and a request for a *knowledge of the world chunk* linking the current processed item and the target, is made. If such a *knowledge of the world chunk* can be found the item is selected, otherwise the next item is processed. The *knowledge of the world chunk* is used to build up a r*epresentation chunk* in the imaginal buffer. If *a representation chunk* is available, it will be used to navigate to the target. This chunk contains the path leading to the target, e.g. which item needs to be selected in order to reach the target. Thus, the items are the *situation* and the target is the *expected outcome*. There is no strengthening mechanism used in this model. But a *specification* mechanism that clarifies when a *representation chunk* is adequate to be used, e.g. use *representation chunk* for a menu-depth of three. However, this is part of the *control chunk* held in the goal buffer. The control chunk of this model also holds information about *uncertainty* of the current strategy (or path chunk) and on *detected changes* (e.g. updates).

Mental model updates in smartphone studies After the second block a change (either a version update or an adaptation due to prior selection) is made to the application. Thus, the established *representation chunk*s will not lead to the expected outcome anymore. So, targets, or subtargets cannot be found with these *representation chunks*. This *uncertainty* is noted in the *control chunk.* Another attempt to find the target using this *representation chunk* is made. If it again does not lead to the target, then a change in the environment is noted. Thus, a strategy change is initiated and the *knowledge-of the world* chunks are used to build a different *representation chunk*. For the next target, a new *representation chunk* is built directly. If the model is required to search for a target with a new version a second time it can retrieve the correct *representation chunk* using the specification (see Figure 4).

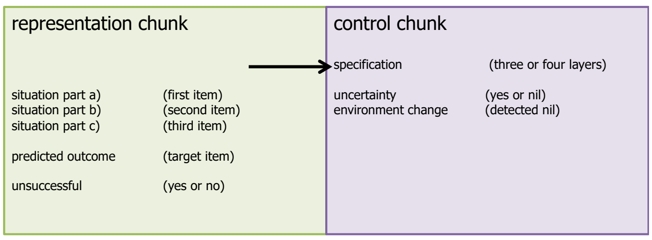

Figure 4: Two chunks which are implemented in the Smartphone application study

2) Dynamic Decision-Making Study Mental model building and updating should be the same process even in very different tasks. Thus, it should be modeled in the same way

[1] The data of the model did not show much variance. Thus, additional model runs were not necessary.

as other tasks that require mental model building and updating. Such another task was investigated in the second study. It required the participants to make sense of multi-feature auditory stimuli. The experiment and the model are presented in more detail in Prezenski et al (submitted). In the following section, a short overview of material, task, participants will be given. Followed by a more description of how the mental model building and updating mechanisms were implemented.

The stimuli were 160 different tones. These were made up of a combination of different category features, namely duration (short vs. long), direction of frequency modulation (rising vs. falling) and intensity (quiet vs. loud) and frequency (high vs. low). Tones which included a combination of specific category feature (e.g. loud and falling) were the target stimuli (25%), while the other where the non-targets (75%). Different category-feature combinations were the target for different participants.

In each trial (there were 240 altogether), a tone was presented to the participant and he or she was required to press one of two buttons to classify if the tone was a target or a non-target. After the button-press auditory feedback was presented ("wrong" or "correct") and then after a pseudo-random time of six, eight or ten seconds the next trial began. After 120 trials, there was a switch of the button allocations, the participants were not informed about this. There were four different randomizations of the experiment; each had different category features as targets.

The dependent variable was the average percentage of correct responses per block. 20 trials were always grouped together as a block. Thus, the experiment consisted of 12 blocks.

55 student participants took part in the experiment.

Model implementation The experiment for the model was implemented in Lisp using the new-other-sound command for the tones and using 16 tones (all possible combinations of the category-feature) pairs as auditory stimuli. The model was written with ACT-R 7.1.

Mental model building The task is to find the correct strategy to classify tones into targets and non-targets. The fact, that a combination of feature-value pairs is the correct solution is unknown to model. Thus, first a single feature-value-pair strategy is used and this is changed to a two feature-value-pair strategy in the course of the experiment.

Two main chunks are part of the model (see Figure 5). The first is a *representation chunk* which holds the current strategy in the imaginal buffer. The second is a *control chunk* in the goal buffer. In the beginning of a trial a tone is heard and a decision has to be made if the tone is a target or not.

The *representation chunk* holds the current strategy the in the imaginal buffer. It contains information about the relevant feature(s) and value(s) (e.g., *the sound is quiet* or the *sound is quiet and its frequency range is high*) and the proposed response (0 or 1). This can be seen as the *situation* and the *predicted action*. Furthermore, the *specification slot* of the *representation chunk* holds information on the degree of complexity of the strategy (e.g. one or two-feature strategy). An evaluation mechanism is part of the representation chunk as well. The evaluation's result determines if a strategy was unsuccessful and keeps record of how many times a strategy was successful. It marks if the first attempt to use this strategy is successful. Furthermore, the number of successful strategy uses are counted until a certain value is reached. This is meant to reflect the subjective feeling that a strategy was useful often. If a strategy was useful often, then is well-established. The same representation chunk is held in the imaginal buffer as long as feedback is positive. If feedback is negative a different *representation chunk* will be retrieved from memory.

The control chunk holds information on the *uncertainty* about a current strategy and on detected *environmental changes*.

representation chunk		control chunk	
specification	one or two feature strategy	uncertainty	(yes or nil)
situation part a)	1.feature-value-pair (e.g. duration short)	environment change	(detected nil)
situation part b)	2.feature-value-pair (e.g.volume high)		
predicted outcome	response (0 or 1)		
Unsucessful	(nil-yes)		
First attempt	(nil- yes)		
1.count	(nil, 1,2… threshold)		
2.Count	(nil, 1,2…threshold)		

Figure 5: Two chunks which are implemented in the dynamic decision-making study

Mental model updating If an established strategy (in other words representation chunk) causes unexpected negative feedback uncertainty about this current strategy is noted in the control chunk. Nevertheless, this strategy is used a second time. If again unexpected outcome occurs, the strategy will be changed using the mechanism seen in figure 2. In the course of the experiment, this can occur in two different situations. The first situation is, when a one-feature strategy (e.g. volume loudness is 1) is successful often but after repeated unexpected outcome (negative feedback) it is changed into a two-feature strategy. Thereby, the first feature-value pair (volume loudness is 1) is kept as part of the strategy and complemented by another feature-value pair.

The second situation is, after the environment changed when a past establish two-feature strategy repeatedly leads to unexpected outcome. Then different two-feature strategies are sought for.

To sum up, both the smartphone and the decision task implemented mental model building and updating in the same way. Mental model building and updating is modeled using a representation and a control chunk. The followed strategy is held in the representation chunk. This chunk is retrieved from declarative memory and altered using working memory. Information over environmental conditions and the learning history is encoded in the control chunk which is held in the goal buffer. In both models, well-established strategies are not discarded directly in case of unexpected outcome, but tested once more. If they lead to failure again, they are partly revised and rebuilt.

However, the type of behavioral data that the models´ performance was compared to, differed: average item selection time was used for the smartphone studies and percentage of correct responses for the dynamic decision-making experiment.

Results

The results section briefly presents the results of the empirical data together with the modeled data. The results of the smartphone studies are presented in greater detail in Prezenski & Russwinkel, 2016. The results of the decision-making experiment in Prezenski et al (submitted).

Study 1: Smartphone Interaction

In all smartphone sub studies, the model captured the trends found in the empirical data. The trends show a decrease in item selection time from the first to the second block in all four studies. An increase from the second to the third block found in three studies (both real-estate app studies and the shopping-list app, that added an additional layer (shopping 3-4), see Figure 6). In the other shopping-list app study the model also captured the decrease found between the second and the third block. Finally, in all four studies there is a decrease in the mean item-selection time this was again captured by the model.

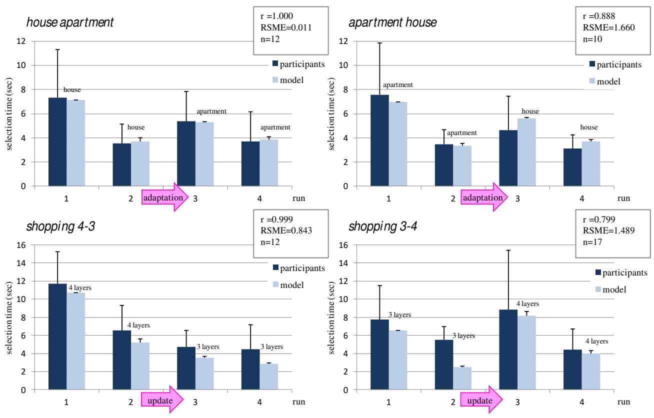

Figure 6: Mean target selection time, reprinted from (Prezenski and Russwinkel, 2016, p. 205)

In the other shopping-list app study the model also captured the decrease found between the second and the third block. Finally, in all four studies there is a decrease in the mean item-selection time this was again captured by the model.

To sum up, the model captured learning and relearning (update detection and new learning). It matched the participant's behavior in mean item selection time very well for all four studies ($r^2 > 0.799$).

Study 2: Dynamic Decision-Making

In this study, the empirical data show an increase in the proportion of the correct response from the first to the sixth block (see Figure 7). This is followed by a drop in correct responses in the seventh block, which is pursued by a performance increase until the twelfth block. The model resembles these trends. The overall r^2 is at 0.672. Nevertheless, the descriptive data indicates that the participants have almost "recovered" from the change in the eighth block, while the model takes longer.

In summary, the model captured the empirical data well; an improvement in performance in the first half of the experiment, the performance drop after the strategy changed and the recovering in performance in the second half of the experiment.

The overall fit of the dynamic decision-making task is not as precise as the fit of the model in the smartphone studies. One explanation hereof is that more measurement points in the decision-making study (12) then in the smartphone study (4) make it less likely to achieve a good fit.

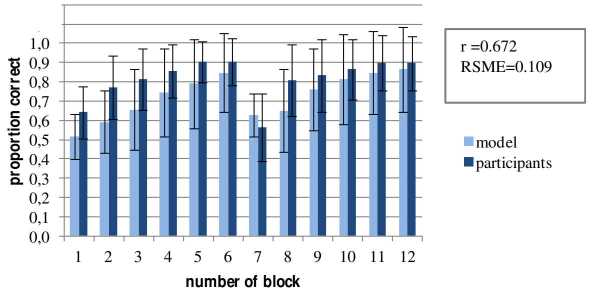

Figure 7: Proportions of correct responses of the model and participants

Another explanation could be that the participants need less long to find an adequate strategy (adequate update of their mental model) after the switch, because they tried the strategy of pressing the other button for the same strategy. Such an explicit strategy was not modeled to keep the model simple and more general.

Discussion

Two very different real-life tasks were modeled with ACT-R using the same explicit mechanisms for mental model building and updating.

The building process of a mental model involves implementing a preliminary version of a mental model and a subsequent testing of this model or strategy. If the strategy performs as expected, it is strengthened, if not it will be updated with a different strategy. Established strategies are not changed immediately in case of unexpected outcome but tested another time before they are changed. Changes to the strategy are gradual; a strategy is not completely discarded; some aspects are kept.

Explicit mechanisms were used, because the changes investigated are registered by the humans. Such distinct noticed changes lead to changes in behavior. Examples for these kinds of changes in real-life settings are software-updates or changes in environmental conditions during outdoor activity (e.g. sudden rain while climbing).

The scope of the presented model mechanisms is not mental model updating during highly automated processes for very skilled users. However, the presented mechanisms can reproduce initial learning, usage and relearning of strategies. Implicit mechanisms are nevertheless part of the models. For example, the previous activation of chunks, as well as if a chunk has been retrieved recently, influence the course of the model.

Modeling the change in strategy and the relatively fast occurring relearning of the participants using solely implicit mechanism with ACT-R is a challenge.

From a cognitive psychological point of view, explicit mechanisms are superior to data driven machine learning approaches, such as deep neural networks because they provide explanations of the underlying mechanisms of participants. Knowledge about explicit strategies of participants is valuable for the design and testing of interactive systems because such knowledge does not only provide summative performance metrics of an interface but also gives hints towards the causes of usability shortcomings and possible solutions.

The examples that have been demonstrated assume specific mental models and provide mechanisms on how such mental models might be updated in human cognition. There is of course no guarantee that such strategies and mental models closely resemble the real strategies, this is not at last grounded on the fact that the human brain does not employ explicit symbol manipulation mechanisms, such as the explained process of building and updating of mental models does. However, the studies that were presented here show that such models provide a reasonable approximation of participant performance.

Potential next steps are investigating the proposed mental model building and switching strategies empirical, with studies targeting these mechanisms.

Summary

This paper demonstrates how mental models updating due to system changes can be modeled using explicit mechanism. This explicit mental model updating mechanism was first implemented in a model of smartphone application usage (Prezenski & Russwinkel, 2016). The mechanism was then applied to a dynamic decision-making task, where participants were presented with different multi-feature auditory stimuli material (Prezenski, Brechmann, Wolff & Russwinkel, submitted). While the model explained data of participants in the smartphone studies very well, the data in the dynamic decision-making task was not explained to such extend.

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