A Model of Flexible Control in Task Switching

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Abstract

The paper presents an ACT-R model of task switching, which implements flexible mechanism of control over task rules, that adapts to the level of task change predictability. In predictable task switching situations, the model loads relevant task rules into an easily accessible focus of attention (simulated with an ACT-R goal buffer). However, when tasks change randomly, such strategy would lead to long recovery from incorrect rules already loaded into the focus. So, during unpredictable task changes the model always retrieves relevant task rules from its declarative memory. Two experiments were administered to test assumptions of the model: one required predictable switching while the other imposed some level of unpredictability. The model aptly simulated the pattern of switch trial RTs from both studies, and it also replicated constant RTs of repeat trials in fully predictable conditions, as well as decreasing RTs of repeat trials in less predictable conditions.

Introduction

Due to the processes of cognitive control humans are able to behave in a goal-driven and not in stimulus-driven way. When the control fails, as in some neuropsychological deficits, people produce numerous lapses and errors (Shallice, 1988). Especially, mechanisms of control seem to be crucial for correct processing in new or highly distracting situations. Several experimental paradigms are used for examination of the nature of executive control processes. For example, task switching is believed to strongly engage cognitive control (Monsell, 2003).

Most of psychological research on task switching is focused on factors influencing *switch costs*: longer latencies (and, often, higher error rates) in trials following changes of a task (*switch trials*) in comparision to trials when a task was repeated (*repeat trials*). Although some researchers (Allport & Wylie, 2000) believe that switch costs do not reflect involvement of cognitive control, and some others even doubt if the control is needed for switching at all (Logan & Bundesen, 2003), analysis of patterns of task switching costs remains one of the main methods for examination of control processes. Thus, the proper estimation of switch cost values seems to be crucial.

However, such an estimation depends strongly on whether a switch was completed during switch trial (i.e., after switch trial a subject is fully prepared for executing a new task) or was not completed (i.e., a subject requires one or more repeat trials to complete the preparation process). In the former case, a difference in RT between a switch trial and a first repeat trial should capture all latency of a switching process and thus RTs of all the consecutive repeat trials should reflect only time (constant on average) needed to execute the very task. In the latter case, the first repeat trial RT reflects in some part a switching process latency as well, so responses in consecutive repeat trials may get shorter. Then, the switch cost may not reflect the full duration of control process.

Closer examination of task switching studies shows that there are significant differences between some studies in respect to how complete a switching process is. These differences strongly depend on experimental paradigms used. When a sequence of tasks is predictable (for example, AABB or AAAABBBB; as in alternating-runs paradigm, Rogers & Monsell, 1995) reactions for all repeat trials following the switch trial usually do not differ in latency. In random task sequences, when each stimulus is cued with information indicating the proper task, second repeat trial is usually faster than the first repeat trial (Milán, Sanabria, Tornay, & González, 2005). This indicates that when tasks change on random, the involvement of control processes in switching may not be limited to switch trials only.

Monsell, Sumner, and Waters (2002), in order to compare task switching paradigms, used in a single experiment both predictable and random task sequences. RTs in consecutive repeat trials were constant in predictable task sequence condition, but they were decreasing in random sequences. Authors explained the observed effect in terms of attenuation of cognitive control in random switching. According to them, “if the next switch is likely, participants to some degree voluntarily attenuate or restrain the increment in readiness that would otherwise result from one performance of a task” (ibidem, p. 340). The attenuation of control is fragile: after two or three task repeat trials in random sequence, even if a subjective probability of switch is high, subjects’ endogenous control of readiness is overwhelmed and they quickly reach its maximal level.

Above mentioned explanation sounds reasonable, but it does not propose any precise mechanism of cognitive control responsible for changing the level of readiness. The aim of this paper is to describe a computational model of task switching, which specifies in detail the operation of cognitive processes in both low and highly predictable task switching situations. The model will be successfully fitted to data gathered from two experiments.

Computational Models of Task Switching

Several mathematical models of task switching have been proposed in literature (e.g., De Jong, 2000; Logan & Bundesen, 2003; Meiran, 2000; Yeung & Monsell, 2003).

Among computational models, which seem to be an especially promising method for understanding cognitive processes involved in task switching (Monsell, 2003), there exist both connectionist (Gilbert & Shallice, 2002) and symbolic models. The latter are mainly implemented within two leading cognitive architectures (EPIC: Kieras, Meyer, Ballas, & Lauber, 2000; ACT-R: Altmann & Gray, 1999; Sohn & Anderson, 2001).

EPIC architecture (Kieras et. al., 2000) is a modular production system that simulates cognition in parallel process of matching productions (representing well-learned knowledge about a task) with contents of working memory (WM, representing knowledge on a current state of the task). Productions change contents of WM, so in a next cycle new productions can be matched to WM. When more than one production may be fired, cognitive control has to be involved: executive productions are run to schedule task-specific productions and/or resolve conflicts among them.

Based on EPIC assumptions, Rubinstein, Meyer, and Evans (2001) proposed two-stage executive control process that appropriately configures contents of WM for an incoming task. First stage consists on goal shifting, i.e. putting into WM the information which task is the proper one. Usually, when a cue precisely indicates the task, the goal shifting process may be fully completed before stimulus identification. Switch costs can be significantly reduced with long cue-stimulus intervals (CSI), because with more time it is easier to switch to the proper goal. Second stage – rule activation process – can be run exogenously only, i.e. after stimulus appearance. It is assumed, that in order to avoid interference caused by the same stimuli used for all tasks, subjects activate proper rules by adding or activating them in WM, while deleting or deactivating incorrect ones. In the first trial of a task, after stimulus identification, adequate rule is activated in time reflected in additional latency of this switch trial. In repeat trials, as there is no change in a task, no rule activation is needed. Therefore, latency of all repeat trials is similar, reflecting only time needed for rule application and movement production. The rule activation process may be responsible for a common observation that although with long CSIs the switch cost is reduced, it is not eliminated (the cost that cannot be further reduced is called *residual*).

Following Rubinstein at al.'s (2001) theoretical proposal, Kieras et al. (2000) implemented an EPIC model of task switching that removed irrelevant and loaded relevant goals and rules from/into WM. Although authors do not present simulation data on repeat trials beyond the first one, it can be deduced that simulated response latencies would be constant for succesive task repetitions, as task rules are loaded into WM and can be accessed in constant time.

ACT-R cognitive architecture is also implemented as a production system (Anderson et al., 2004). It differs from EPIC in two major attributes. First, resolution of conflicts is not based on strategic productions, but on built-in rule selection mechanism, that runs only one (usually optimal) production at a time. Second, ACT-R includes numerical parameters assigned to all symbolic structures, which modulate cognitive processing. For example, in ACT-R declarative memory, an activation level is assigned to each memory chunk. The higher chunk's activation value is, the greater probability and shorter latency of its retrieval are.

Sohn and Anderson (2001) proposed an ACT-R model of task switching. The model can prepare for the task (if it is known in advance) by loading into system's focus of attention (the goal buffer) a representation indicating the task. This is a similar operation to goal shifting in EPIC model. The main difference between both proposals is that ACT-R model does not load any task rules into the goal buffer. At each trial, the proper rule is retrieved from declarative memory. After each retrieval, a level of a rule's activation rises and on the next trial this rule can be retrieved faster. Although the autors did not present data on repeat trials beyond the first one, it may be deduced that latencies would be shorter for successive task repetitions.

A Model of Flexible Control in Task Switching

The model proposed in this paper integrates both presented mechanisms of task rules activation. We assume that, when a task sequence is predictable, it is optimal to load task rules into the focus of attention of WM, i.e. the most active and easily accessible part of WM (Cowan, 1995; Oberauer, 2002). If rules are already in the focus, they become the most active representations within cognitive system and they can be applied very fast. No effects of facilitation will be observed, as their activation is at ceiling. So, if task switches are predictable, the model loads proper rules into its focus of attention, like the model by Kieras et al. (2000).

However, in random task sequence situation, loading rules into the focus of attention may not be the optimal strategy. If the task suddenly changed while inproper rules are in the focus, the cognitive system would not be prepared for a new task. Highly active but inproper rules would probably lead to a slower access to less activated proper rules. So, during unpredictable task changes it is probably better to hold in the focus only information that identifies which task to perform, while keeping all task rules in working memory area outside the focus, at similar activation levels (Meiran, 2000). Although access to these rules will be slower, and they will be subject to decay and interference to a greater extend, the cognitive system will not suffer from unpredictable task changes so much as when focusing on inproper rules. So, if task switches are unpredictable, the model keeps all rules in active part of memory outside a focus, like model by Sohn and Anderson (2001).

Thus, our model, which is implemented in ACT-R architecture, assumes that *the control mechanism over task rules may be flexibly adapted to the level of predictability of a task switching situation by changing the mode of access to task rules*. This novel assumption is implemented with two mechanisms:

(1) a monitoring process estimating the level of task change predictability on a basis of both cues and stimuli,

(2) a rule loading process which, if the monitoring process allows (i.e. when the task to come has been identified), loads the proper task rule into the goal buffer and turns off the monitoring process.

Description of the Model

The model is able to switch between two tasks, one that requires responding to two-digit numbers greater than 50 (and witholding responses to numbers less than 50), and the other that requires responding to even numbers (and withholding responses to odd numbers). We used go/no-go methodology in order to keep the model very simple. For example, we did not have to model response choice process.

The representation of both tasks in declarative memory consists of four chunks: two reflecting task names: (task even) and (task greater), and two reflecting the pattern of stimuli that requires manual reaction: (even X0 X2 X4 X6 X8) and (greater 5X 6X 7X 8X 9X), where X stands for any digit. Task names and task rules for the same task are mutually associated (this association is probably acquired by subjects during training). When a task name chunk is loaded into the goal buffer, ACT-R propagates some source activation from the goal to a respective task rule chunk. In a foreknowledge condition (when a cue that identifies an incoming task is being presented before presentation of a first stimulus in a new task), the proper task name chunk may be loaded into the goal buffer, and all source activation is being spread to the associated rule. In a no-foreknowledge condition (when there is no cue), both task names are loaded into the goal buffer, as both tasks are equally probable. Source activation is divided between both task rules. Due to activation decay and noise, in a proportion of trials task rules may not be properly retrieved, causing errors of omission. The model includes also eight productions:

(1) *Encode Stimulus*: if a stimulus is being presented this production makes a memory trace for each of its digits.

(2) *Retrieve Rules*: if the task name(s) is(are) in the goal buffer, it retrieves associated task rule(s). If monitoring production (6) allows, it loads the task rule into the goal buffer and blocks production (6). So, after loading, production (2) does not need to access declarative memory. When the rule is loaded, production (4) is run in a next ACT-R cycle.

(3) *Retrieval Failure*: if no rule can be retrieved it hands control over to the production (1).

(4) *Categorize*: it applies currently retrieved task rule to a stimulus chunk and runs production (5).

(5) *Compare*: it compares in parallel all patterns in task rule to a stimulus chunk, and runs production (7), if a stimulus fills any pattern.

(6) *Monitor*: on a stimulus categorization, it checks whether any task rule may be loaded into the goal buffer and may replace a task name. To allow for loading the proper rule into the goal buffer, it requires any stimulus if there is one task name in the buffer (i.e., in a foreknowledge condition), and it requires a target if there are two task names (i.e., no-foreknowledge).

(7) *Press Button*: it just stores reaction time for a trial.

(8) *Wait*: if there is no stimulus on a screen or a stimulus is already categorized, the model waits for 100 ms.

Productions (2) and (6) are control processes regulating in a feedback loop access to task rules, and blocking each other depending on a perceived level of predictability. Switch cost values generated with the model depend on whether and for how long production (2) accesses declarative memory.

Experiment 1

Experiment was designed to test whether subjects' behavior in predictable task switching situation would be consistent with the model's predictions. Three hypotheses were tested. Most important, a position of a repeat trial in a sequence was manipulated (1 to 3). We expected that RTs in repeat trials on all positions should not differ significantly. Of course, we expected longer RTs for switch trials.

Second, we tested if the switch cost can be reduced or even eliminated. In Gonzáles, Milán, Pereda, and Hochel (2005) if subjects emitted an extra response just before a switch trial the residual switch costs were eliminated. We expected similar effect when presenting to subjects, just before a switch trial, a neutral stimulus that does not require any response, but requires a categorization process. In such a case the model assumes a boost in task rules activation, which should lead to reduction in relevant chunk retrieval latency, and in consequence, in reduced RT.

Third, we manipulated foreknowledge on an incoming task. In a foreknowledge condition, a cue indicated the proper task. In a no-foreknowledge condition there was no cue and the first target stimulus indicated the proper task. The model predicts that in the latter condition switch costs will be higher, as subjects will not load the goal of processing ('task name') before the first target presentation.

Method

Subjects 35 college students (25 men, one excluded due to low accuracy) were examined (subjects were 18-31 yrs old).

Tasks Two-digit numbers were used as stimuli for both tasks. Two tasks were used: "greater than 50" and "even". Odd numbers above 52 were used as targets for the former, while even numbers below 50 were used as targets for the latter. Odd numbers below 50 were non-targets for both tasks. Even numbers above 50 were not used at all. In a single sequence of stimuli, all targets belonged to the same category. Subjects were to press a button if they identified a target, and withhold it when a non-target was presented.

Design A position of a target in the sequence was the first manipulated variable: always four targets were presented in the sequence. The first target trial was considered as a switch trial, next target trials were repeat trials. In one half of the trials, fifth target was also shown, but responses to it were not analysed. It was only aimed to keep subjects vigilant during the fourth target trial. Between each pair of targets, one or two (on random) non-targets were presented.

Priming with a neutral stimulus constituted the second independent variable: in one half of sequences a non-target number was presented before the first target. The non-target did not carry any information on the proper task, and thus served as a neutral prime.

A foreknowledge on an incoming task was the third manipulated variable. In one half of sequences a cue informed which task is the proper one for an incoming sequence of stimuli ("EVEN" or "GREATER", in Polish). In the other half of sequences (i.e., in no-foreknowledge condition), the cue just reminded that one of two tasks may occur ("EVEN or GREATER" or "GREATER or EVEN", on random, in Polish). Subjects were informed that in no-foreknowledge condition the first target indicates the proper task to be performed (i.e., three or four targets following the first one would belong to the same number category).

Apparatus and Stimuli Stimuli (37 × 50 mm in size) were presented on a screen of a laptop computer. Each sequence started with a cue presented for 500 ms. After the cue, "**" stimulus was presented for 2000 ms in no-priming condition. In the priming condition, "**" was presented for 1000 ms, and then a non-target prime was presented for 900 ms, followed by the mask ("##") shown for 100 ms. Then the first target was presented, followed by non-targets and repeat trial targets, each one presented for 900 ms + 100 ms for the mask (see Fig.1). Subjects switched on random to one of two tasks from another task: "greater than 50 and even", that inluded even numbers above 50 as targets.

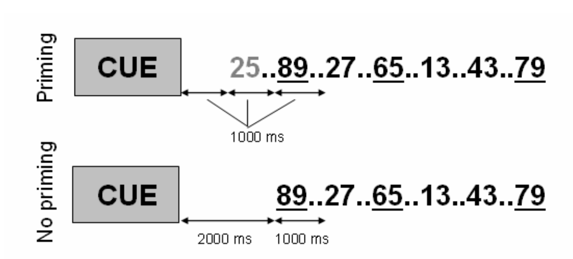

Figure 1: Sample sequences of stimuli in both priming and no-priming conditions. Targets underlined, prime in gray.

Procedure Subjects were examined in groups of two or three. Several training and 80 experimental sequences were presented to each subject (conditions randomly intermixed).

Data Collection Subjects responded with an index finger, pressing a mouse button. Not pressing the button during a target or a mask presentation was recorded as an error of omission. Responding during non-target presentation was taken as a false alarm error and signaled with a beep. We were mainly interested in mean latency of correct responses dependent variable. With task requirement to respond within presentation time of a target and a mask (1000 ms on total) very long responses (outliers) were naturally eliminated.

Results and Discussion

Foreknowledge and priming influenced accuracy only for switch trials: $F(3,32) = 20.74$, $p < 0.001$; $F(3,32) = 6.95$, $p < 0.001$, respectively (Figure 2, dashed lines). Mean false alarms rate was low (6.92%) and is not analysed here.

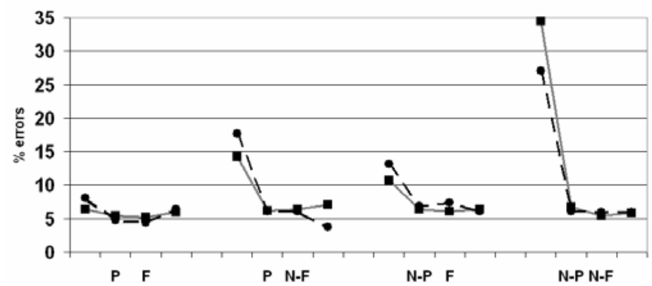

Figure 2: Observed (black dashed lines) and simulated (grey solid lines) error rates (%) in four experimental conditions (P stands for priming, F – for foreknowledge, N- for "no-").

Response latency data are presented in Figure 3 (dashed lines). There is switch versus repeat trial main effect, $F(3,31) = 69.19$, $p < 0.001$, but no significant difference in latency of consecutive repetitions ($p > 0.1$; 453, 451, 457 ms, respectively). Thus, at least within the paradigm used here, no effect of speeding up repeat trials was observed.

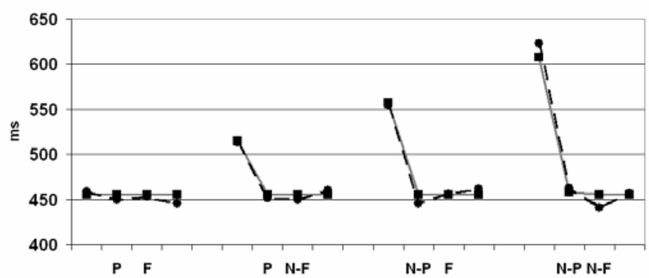

Figure 3: Observed (black dashed lines) and simulated (grey solid lines) latencies (ms) in four experimental conditions.

Both factors of foreknowledge and priming interacted with target position: informative cues as well as primes decreased response latency exclusively in the first trial, $F(3,32) = 20.74$, $p < 0.001$; $F(3,32) = 6.95$, $p < 0.001$, respectively. These two factors additively influenced switch cost: no significant three-way interaction was observed ($p = 0.090$). Priming facilitated cognitive processing, no matter whether subjects did or did not know which task to perform. In foreknowledge-priming condition, the switch cost was practically eliminated (9 ms), switch and repeat trial latencies did not differ significantly ($p > 0.1$). Lack of priming added ~100 ms to the switch cost, lack of foreknowledge added another ~50 ms. Mean latencies in each experimental condition, compared to average repeat trial RT (each compared difference constitutes a respective switch cost), are presented in Figure 4.

All hypotheses were confirmed: we observed switch cost, but limited only to the first trial in a sequence. This cost was eliminated with priming, but only in foreknowledge condition. Lack of foreknowledge on an incoming task made switch costs significantly longer.

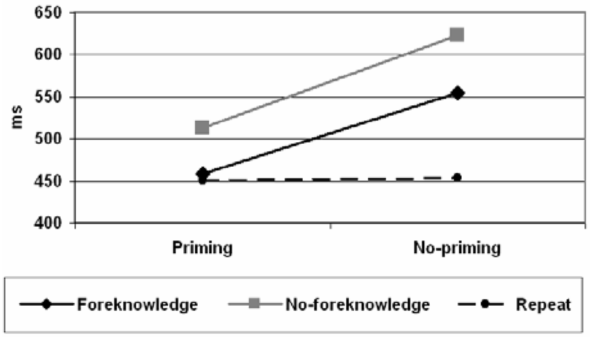

Figure 4: Response latency (ms) in switch trials in four experimental conditions compared to repeat trials.

Data Simulation

To test the model, data from the experiment presented above were simulated in 2000 Monte Carlo runs for each condition. Five parameters influencing model's simulated accuracy were set. Two were optimized to get the best fit: declarative memory activation noise (0.12) and chunk retrieval threshold (0.15). Three parameters were set to arbitrary but reasonable values: strength of associations between task names and task rules (0.5), probability of failed loading of a task rule into the goal buffer (0.12), and a probability of failed categorization of a stimulus (0.12). The fit (presented in Figure 2) was good, R^2 equaled to 0.897.

The crucial test of the model was fitting of response latencies. Values of two additional parameters that are used by ACT-R to translate chunk activation units into latency of chunk retrieval were optimized: latency factor (0.38) and latency exponent (2.8). Standard ACT-R value of productions latency was used (50 ms). Summary duration of perception processes and motor response, not influencing R^2, was set to a reasonable value of 300 ms. The fit of observed and simulated latency patterns was very good (R^2 = 0.983). The model replicated non-trivial effect of error-latency asymmetry in no-priming-foreknowledge, and priming-no-foreknowledge conditions: error rate in switch trials was higher in the former than in the latter condition, but the reverse is true for latencies (see: Fig. 3).

Experiment 2

In the simulation presented above, the model always produced answers for repeat trials with the proper task rule loaded into the goal buffer, as always task sequence became predictable after presentation of the first target. It is interesting to test the model against data acquired in less predictable conditions, when we may expect faster consecutive repeat trials. The computerized switching test from Experiment 1 was used, but only in the no-foreknowledge condition, and with several alterations. The main change consisted on not informing subjects that the first target indicated the task in the whole sequence (although the first and consecutive targets indeed belonged to the same task). As the change made the test more difficult, both stimulus' and mask's presentation times were prolonged, as well as a cue presentation time. In consequence of longer stimulus presentation time, the cue-stimulus interval was made longer. Trial's length was shortened, now each trial included three targets. All other experimental conditions were the same as in Experiment 1.

Method

Subjects 73 college students were examined (their demographic data are lost, unfortunately).

Tasks The same tasks and response rules were used as in Experiment 1.

Design A position of the target in a sequence was the first manipulated variable: this time three targets were presented in each sequence. Priming was the second independent variable: in one half of sequences a non-target stimulus was presented before the first target.

Apparatus and Stimuli They were identical as in Experiment 1, except for the following. Each sequence started with a cue ("EVEN or GREATER"/"GREATER or EVEN", in Polish) presented for 3000 ms. After the cue, stimulus "**" was presented for 2400 ms in no-priming condition, and for 1200 ms in priming condition. Stimuli were presented in 1000 ms pace (and each one was followed by a 200 ms mask).

Procedure and Data Collection They were indentical as in Experiment 1.

Results and Discussion

Due to very low error rates, only latency data are presented. Again, an interactive effect of priming and target position occured: a non-target reduced a mean latency only for the switch trial, $F(2,71) = 167.97$; $p < 0.001$, but it did not eliminate residual switch cost. The main hypothesis was confirmed: response latency for the third target position in a sequence was significantly shorter (22 ms) than for the second one, $F(1,72) = 47.92$; $p < 0.001$.

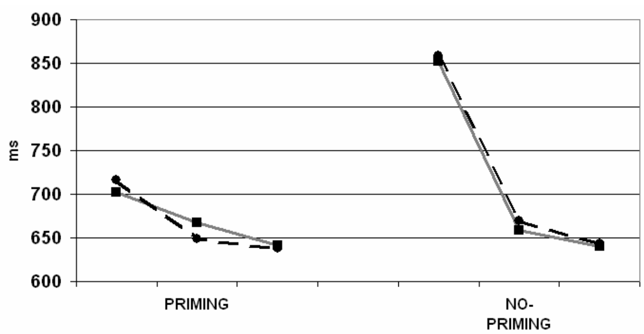

Figure 5: Latencies (ms) observed in Experiment 2 (black dashed lines) and simulated (grey solid lines).

Data Simulation

Because neither cues nor targets yielded any information on a task, the monitoring process never allowed for loading task rules into the goal buffer. In comparision to

Experiment 1 data simulation, we changed two parameters: latency factor (0.55) and the intercept value (480 ms). This was nessesary due to longer cue and stimuli presentation times used in Experiment 2. The simulated data fitted observed data very well (R^2 = 0.982). Most important, an effect of repetition facilitation was replicated, as shown in solid lines in Figure 5.

Summary and Conclusions

The presented model is a preliminary proposal of the cognitive control mechanism responsible for different behavior in task switching situations with low and high levels of task changes predictability. The model integrates assumptions of two leading (ACT-R and EPIC) task switching models. It is based on the hypothesis, that the control mechanism over task rules may be flexibly adapted to the level of predictability of a task switching situation by changing the mode of access to task rules. If the task changes are predictable, the model loads relevant task rules into its easily accessible focus of attention. When the changes are less predictable, it always retrieves these rules from declarative memory outside the focus. Although such an access mode is slower, it grants that rules for all (equally possible) tasks are available to the same extend. With nine free parameters set, the model aptly predicted 38 data points (16 for accuracy + 22 for latency), that were gathered in two experiments, which probably differed in subjects' perception of task changes predictability level (in case of latency R^2 = .982 and .983, respectively).

The hypothesis on flexible nature of cognitive control engaged in task switching allows for integration of data observed in two most popular task switching experimental paradigms (namely, alternating-runs and explicit cueing), and sheds light on cognitive mechanisms of control processes involved in switching. However, the model is still very simple, and it certainly has to be developed and tested in more complex task switching situations than those presented in this paper, especially in the experimental situations involving two or more possible reactions, univalent stimuli, and tasks more mutually differing than the ones exploited in this research.

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