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DISTINGUISHING RECONFIGURATION AND COMPOUND-CUE RETRIEVAL IN TASK SWITCHING

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Many researchers claim that task switching requires reconfiguration of the cognitive system. Others claim that task switching involves cue-based memory retrieval processes and not reconfiguration. We evaluate these competing claims by developing both reconfiguration and cue-based memory models in a common theoretical framework and by fitting the models to *target functions*, which show how performance on individual target stimuli varies depending on the task subjects perform on the targets. Our analyses show that the process of compound-cue retrieval – using the task cue and the target as joint retrieval cues to select a response from memory – is sufficient to explain target functions for parity and magnitude judgments of digits and that reconfiguration does not seem to add anything to the explanation. We address the generality of this conclusion and speculate about the conditions under which reconfiguration may be necessary for task switching.

Introduction

From a computational perspective, we humans are general-purpose processors. We can do many different tasks, often on a moment's notice, and we are often as comfortable with novel tasks as with familiar ones. From the perspective of computational models of cognition, we are special-purpose processors, built to do particular tasks, like the Stroop task or the stop-signal task. Our behaviour can be explained very well by the limited set of processes required for these tasks, as if we had no other capabilities. Research on task switching is intended to bridge the gap between these perspectives, explaining how we can do many different things by reconfiguring ourselves as special-purpose processors designed for the task at hand (Monsell, 2003; Vandierendonck, Liefooghe, & Verbruggen, 2010). How we manage to do

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this is a matter of ongoing debate. Many researchers endorse the idea that we actually reconfigure ourselves, reprogramming our cognitive systems for the specific demands of each particular task (e.g., Meiran, 1996; Monsell & Mizon, 2006; Rogers & Monsell, 1995). Our approach has challenged this idea, arguing that much of cognition – and most cognition in task-switching experiments – relies on cue-based memory retrieval, and task switching often involves nothing more than changing the cues that drive the retrieval process. The purpose of this article is to address this debate with a computational modelling framework that can instantiate both reconfiguration and cue-based retrieval accounts to determine which account best explains the data.

Defining reconfiguration

The concept of reconfiguration is based on the idea that performance of a particular task depends on a special state of preparation called a *task set*. Reconfiguration involves changing task set: abandoning the state of preparation that was appropriate for the previous task and engaging a different state of preparation that is appropriate for the new task (e.g., Meiran, 1996; Monsell & Mizon, 2006; Rogers & Monsell, 1995). A key question for reconfiguration theorists is how task sets are specified: what are the states of preparation that enable task performance? Despite the broad appeal of the concept of reconfiguration, few theorists have been very specific about what task sets consist of and few researchers have investigated changes in specific components of task sets (but see Logan, 2005; Schneider & Logan, 2007a).

Reconfiguration and switch costs

Many researchers have defined reconfiguration operationally in terms of *switch costs*, which are the differences in response time (RT) and accuracy between trials on which tasks repeat and trials on which tasks switch. Switch costs are generally large, and researchers have assumed that such large effects must reflect a qualitative difference in processing. In particular, they have assumed that switch costs reflect the time required for reconfiguration. Reconfiguration is required on task switch trials but not on task repetition trials, so reconfiguration time can be estimated simply by subtracting task repetition RT from task switch RT (Meiran, 1996; Rogers & Monsell, 1995). However, there are alternative interpretations of switch costs that do not attribute them to reconfiguration (Allport, Styles, & Hsieh, 1994; Logan & Bundesen, 2003; Schneider & Logan, 2005), so reconfiguration must be defined in some other way.

Reconfiguration and target functions

Some researchers have argued that task switching must involve reconfiguration because subjects respond appropriately to the new task on task-switch trials. This, too, is subject to alternative interpretations. In our view, changing the retrieval cues changes what is retrieved from memory, so changing task cues can change the responses that are retrieved and enable appropriate responses to the new task (Logan & Bundesen, 2003; Schneider & Logan, 2005, 2009). In this article, we explore a more detailed version of this perspective, analysing *target functions*, which are plots of performance measures for the different target stimuli presented in an experiment when subjects perform different tasks. Figure 1 presents target functions for parity (odd or even) and magnitude (lower or higher than 5) judgments of digits from Schneider and Logan (2005), averaging over all three experiments and plotting RT as a function of the digits that were presented (more details are presented below). The target function changes markedly from one task to another. The target function for the magnitude task is peaked at the middle around the reference point (the digit 5) and decreases monotonically for digits that are progressively lower and higher than the reference point. The target function for the parity task has a very different shape. It is less systematic but appears as a kind of saw-tooth pattern, with longer RTs for odd digits than for even digits.

The target functions in Figure 1 could be interpreted as evidence for reconfiguration. The same digits are responded to very differently under different task sets, as if a special state of preparation was engaged for each task. Since Sternberg (1969), it has been common to define processes in terms of the effects of variables, and these different patterns of effects suggest different processes. However, the target functions may also reflect differences in memory retrieval. The different cues associated with different tasks may retrieve different things from memory. In particular, the strength with which each digit is associated with each task category may differ between tasks, and those differences in associative strength may be sufficient to produce different target functions. We explore this possibility below.

Reconfiguration and computational modelling

In our view, the best way to define reconfiguration is theoretical. If reconfiguration involves changing the states of the cognitive system, then those states must be defined in a way that allows them to be measured, so changes in states can be detected. This is difficult because the states of the cognitive system are not directly observable. They must be inferred somehow, and in our view, the best way to make inferences is to model the tasks computationally and define the states of the cognitive system in terms of the states of the computational model (Logan & Gordon, 2001). Computational models of specific tasks are tractable because their inputs and outputs are grounded in states of the environment. We know what stimuli drive performance and we know what responses are produced at what times, and these constraints allow us to distinguish between alternative models. Models of reconfiguration cannot be grounded directly in the environment because their inputs are states of the cognitive system and their outputs are changes in the states of the cognitive system. However, they can be grounded in computational models of the specific tasks subjects switch between. Thus, a task set may be defined as a set of parameters in a computational model that is sufficient to program the model to perform particular task-relevant computations (Logan & Gordon, 2001; Schneider & Logan, 2007a; Vandierendonck et al., 2010). In this definition, reconfiguration involves changing model parameters to reprogram the model to perform different computations. We can measure the parameters by fitting models to data and we can evaluate changes in parameters across experimental conditions (Logan & Gordon, 2001). This is the approach we adopt in the present article in modelling target functions. We define reconfiguration and memory retrieval in terms of the same computational model, which sharpens the contrast between them and focuses the argument on essential differences.

ITAM, ECTVA, and compound-cue retrieval

We chose to model task switching with the instance theory of attention and memory (ITAM; Logan, 2002). ITAM is a generalisation of several previous models, including Bundesen's (1990) theory of visual attention (TVA), Logan and Gordon's (2001) executive control of TVA model, Nosofsky's (1986) generalised context model (GCM), Logan's (1988) instance theory of automaticity, and Nosofsky and Palmeri's (1997) exemplar-based random walk model (EBRW). ITAM incorporates each of its ancestors as a special case and so inherits their successes in applications to many different phenomena of attention, categorisation, and memory.

ITAM assumes that performance of all of the tasks it addresses relies on a biased choice process that depends on similarities and associations between stimuli. Attention involves choice among display elements, which is modulated by priorities and response biases. Categorisation and memory retrieval involve choice among memory representations, which is modulated by response biases. Similarities are represented as distances in multidimensional similarity space, denoted as $\eta(i|x)$, indicating the similarity between object x and category i. Biases are represented as β_i, indicating the bias to categorise objects as members of category i. Priorities are represented as π_k, indicating the importance of objects in category k. Our analysis focuses on single-target displays, which are prevalent in task-switching experiments, so we focus on βs and ignore πs, although πs and βs work in the same manner, multiplying η values (see Logan, 2002).

In ITAM, the tendency to categorise object x as a member of category i, $v(i|x)$, depends on the product of η and β values, i.e., $v(i|x) = \eta(i|x)\beta_i$. The probability of choosing object x and categorising it as a member of category i is the ratio of $\eta(i|x)\beta_i$ and the sum of the $\eta\beta$ products that represent all possible categorisations for the current display:

$$p(i \mid x) = \frac{v(i \mid x)}{\sum_{j \in R} v(j \mid x)} = \frac{\eta(i \mid x)\beta_i}{\sum_{j \in R} \eta(j \mid x)\beta_j} \tag{1}$$

This is the familiar Luce choice ratio, which is common to all models subsumed in ITAM. If there is a single choice, as in Bundesen's (1990) applications of TVA to attention and Nosofsky's (1986) applications of GCM to categorisation, then Equation 1 gives the choice probability. If choices are aggregated over time in a stochastic accumulator, as in Nosofsky and Palmeri's (1997) applications of EBRW to RT and choice probabilities and Logan and Gordon's (2001) applications of ECTVA to dual-task performance, then Equation 1 gives the drift rate of a random-walk process. RTs and accuracies for the random walk are functions of the drift rate in Equation 1 (the functions are given below).

ECTVA and reconfiguration

Logan and Gordon (2001) applied ITAM to task switching in dual-task experiments, defining a task set in terms of the ITAM parameters that are assumed to be controlled by executive processes (i.e., β and π, as discussed previously, and K, the response threshold for the random walk). They assumed the η parameters were not subject to online executive control, being determined by the quality of the current stimulus and the subject's history with members of the relevant categories. In their model, switching task set involved changing the parameters that the executive controlled. To illustrate, consider magnitude and parity judgments of the digit 7, which is higher than 5 and odd. Thus, $\eta(Odd|7)$ and $\eta(High|7)$ would have high values and $\eta(Even|7)$ and $\eta(Low|7)$ would have low values. The digit would likely be categorised as odd or high. If the task was to categorise parity, then β_{Parity} would be greater than $\beta_{Magnitude}$, so the product $\eta(Odd|7)\beta_{Parity}$ would be greater than the products $\eta(High|7)\beta_{Magnitude}$, $\eta(even|7)\beta_{Parity}$, and $\eta(Low|7)\beta_{Magnitude}$, so Equation 1 would dictate that the probability of choosing "odd" would be greater than the probability of choosing "high," "even," or "low." If the task was to categorise magnitude, then $\beta_{Magnitude}$ would be greater than β_{Parity}, so $\eta(High|7)\beta_{Magnitude}$ would be greater than $\eta(Odd|7)\beta_{Parity}$, etc., so the probability of choosing "high" would be greater than the probability of choosing "odd," etc. The key point here is that β acts as a gain control, implementing cognitive control by increasing the gain on desired categorisations and decreasing the gain on undesired categorisations, gating the response to the target. Another key point is that changing β, like changing other executive-controlled parameters (π and *K*), reconfigures the cognitive system so that it responds differently to the same input. This is the central idea in reconfiguration theories of task switching.

Compound-cue retrieval and task switching

Schneider and Logan (2005) applied ITAM to task switching as well, but focused their analysis on the explicit task-cuing procedure, in which the target stimulus is preceded by a cue that indicates the task to perform on it. For example, *PARITY* would indicate that an odd-even judgment was required and *MAGNITUDE* would indicate that a high-low judgment was required. The explicit task-cuing procedure involves two stimuli, so two η values have to be considered, one for the cue and one for the target. The key question Schneider and Logan had to address was how to combine the η values for the cue and the target. They chose multiplication:

$$\eta(i \mid x,y) = \eta(i \mid x)\,\eta(i \mid y), \tag{2}$$

where y is the cue, x is the target, and i is the category. They assumed that these products act as *compound cues* (joint retrieval cues) that drive the memory retrieval processes on which performance depends. Multiplication is justified in ITAM's mathematics and its assumptions about similarity. According to ITAM, similarity is an exponential function of distance in multidimensional space, so

$$\eta(i \mid x) = \exp(d_{xi}) \text{ and } \eta(i \mid y) = \exp(d_{yi})$$

The cue and the target are separate objects and so constitute separable dimensions. For separable dimensions, distances simply add (Logan, 2002), so

$$\begin{aligned}\eta(i \mid x,y) &= \exp(d_{xi} + d_{yi})\\ &= \exp(d_{xi})\exp(d_{yi})\\ &= \eta(i \mid x)\,\eta(i \mid y)\end{aligned}$$

Because of the multiplication in Equation two, the ηs for the cues act as gain controls for the ηs for the targets, increasing the gain on cued categorisations and decreasing the gain on uncued categorisations, gating the response to the target. If the target was the digit 7, then η(*Odd*|*7*) and η(*High*|*7*) would have high values. If the cue was PARITY, then η(*Odd*|*PARITY*) and η(*Even*|*PARITY*) would be high and η(*High*|*PARITY*) and η(*Low*|*PARITY*) would be low. Consequently, η(*Odd*|*7*)η(*Odd*|*PARITY*) would be greater than η(*High*|*7*)η(*High*|*PARITY*), so Equation 1 would dictate that the probability of choosing "odd" would be greater than the probability of choosing "high." Thus, cue-based gating has the same effect as bias-based gating. Compound-cue retrieval can accomplish task switching in the same way as reconfiguration. Both approaches assume that target processing is modulated by gain control, instantiated as multiplication of target η values in ITAM. To express this idea formally, the strength, $v(i|x,y)$, of the tendency to respond with category i given the target x and the cue y, is:

$$v(i \mid x,y) = \eta(i \mid x)\,\eta(i \mid y)\,\beta_i \tag{3}$$

The effect of the target representation, $\eta(i|x)$, can be modulated by changing either the cue representation, $\eta(i|y)$, or the bias, β_i. Thus, compound-cue retrieval and reconfiguration accounts of task switching may mimic each other. Our applications of the models to target functions address the possibility of mimicry.

Compound-cue retrieval, reconfiguration, and target functions

Schneider and Logan (2005) reported three explicit task-cuing experiments in which subjects switched between magnitude (lower or higher than 5) and parity (odd or even) judgments of single-digit targets (1-9, excluding 5). Mean RTs for all combinations of task and target were not reported in the original article, so we calculated them for each subject in each experiment, collapsing across task transition and cue-target interval to obtain an adequate number of observations per condition. These data were submitted to a 3 (experiment) x 2 (task) x 8 (target) mixed-factors analysis of variance, with experiment as a between-subjects factor and task and target as within-subjects factors. There were significant main effects of task, $F(1, 81) = 20.45$, MS_e = 24,493.21, $p < .001$, $\eta_p^2 = .20$, and target, $F(7, 567) = 4.42$, MS_e = 8,760.28, $p < .001$, $\eta_p^2 = .05$, as well as a significant task x target interaction, $F(7, 567) = 15.22$, MS_e = 4,755.60, $p < .001$, $\eta_p 2 = .16$. The main effect of experiment and all interactions involving experiment were non-significant (all *p*s > .10), so we collapsed across experiments to obtain the target functions in Figure 1.

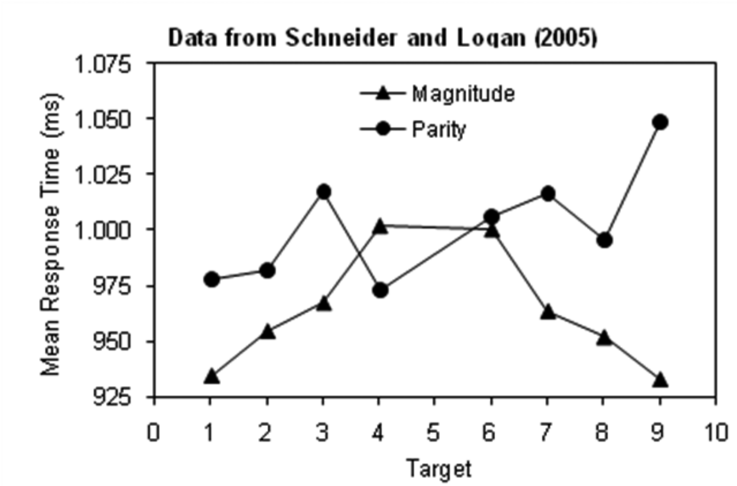

Figure 1

Mean response time for each digit as a function of judgment (magnitude versus parity) in Experiments 1-3 of Schneider and Logan (2005)

The target functions were clearly different for magnitude and parity judgments, consistent with the significant task x target interaction. For magnitude judgments, RT became shorter as the distance between the target and the reference point (5) increased. A contrast with weights representing a linear decline in RT with distance from 5 was highly significant, $F(1, 567) = 76.60$, $MS_e = 4{,}755.60$, $p < .001$, $\eta_p^2 = .12$. For parity judgments, no such distance effect was present, but RT was longer for odd targets ($M = 1{,}015$ ms) than for even targets ($M = 989$ ms), $F(1, 567) = 23.91$, $MS_e = 4{,}755.60$, $p < .001$, $\eta_p^2 = .04$. The question of interest is how well these different target functions can be accounted for with compound-cue retrieval and reconfiguration models articulated in the language of ITAM.

Target representations and target functions

To account for target functions, we assume that the presented target is encoded to a level that results in a semantic, categorical representation (Schneider & Logan, 2010). The nature of this representation depends on the associations between particular digits and the target categories *High, Low, Odd*, and *Even*. For magnitudes, we assumed that associations between the digits and the category *Low* were strong for the lower digits and became weaker for the higher digits. We assumed that associations between the digits and the category *High* were strong for the higher digits and became weaker for lower digits. For simplicity, we assumed that association strength varied linearly with the value of the digits, with association strengths decreasing from 1-9 for the category *Low* and increasing from 1-9 for the category *High* (Choplin & Logan, 2005; Miller & Gelman, 1983; Shepard, Kilpatric, & Cunningham, 1975). We assumed a common slope, m, for both linear functions (formally, $-m$ and m). More complex monotonic functions (e.g., logarithmic) with different derivatives may yield better fits, but simple linear functions were sufficient for our purposes.

The top panel in Figure 2 shows the linear functions specifying the strength of association between each digit and the response categories *Low* and *High*, that is, $\eta(Low|x)$ and $\eta(High|x)$ as a function of digit x. The lower left panel shows the effective association strength when the magnitude task is cued. The effective association strengths are the products of η values for targets and cues, that is, $\eta(Low|x)\eta(Low|MAGNITUDE)$ and $\eta(High|x)\eta(High|MAGNITUDE)$ (see Equation 2). We assume that the target retrieves all responses associated with it (e.g., *7* retrieves both *High* and *Odd*), so the $\eta(Low|x)$ and $\eta(High|x)$ values remain the same regardless of the cue. The cue signals the magnitude task, so $\eta(High|MAGNITUDE)$ and $\eta(Low|MAGNITUDE)$ are high and the products $\eta(Low|x)\eta(Low|MAGNITUDE)$ and $\eta(High|x)\eta(High|MAGNITUDE)$ will be high, depending on the value of the digit. Subjects would be likely to respond "high" or "low" depending on the value of the digit. The lower right panel shows the effective association strength when the parity task is cued. Again, the $\eta(Low|x)$ and $\eta(High|x)$ values remain the same and the effective association strengths are the products $\eta(Low|x)\eta(Low|PARITY)$ and $\eta(High|x)\eta(High|PARITY)$. However, this time, the cue signals parity, so $\eta(High|PARITY)$ and $\eta(Low|PARITY)$ are low and the products are low. Subjects would be unlikely to respond "high" or "low" regardless of the value of the digit.

Figure 3 shows the functions specifying the strength of association between each digit and the response categories *Odd* and *Even* for the parity task. Following previous research (Dehaene, Bossini, & Giraux, 1993; Hines, 1990) and the data in Figure 1, we assumed the strength of association between even digits and the category *Even* was greater than the strength of association between odd digits and the category *Odd*. That is, $\eta(Even|x) > \eta(Odd|x)$. In addition, we assumed that associations between even digits and the category *Odd* and associations between odd digits and the category *Even* were very weak. These assumptions resulted in the saw-tooth patterns shown in the top panel of Figure 3.

The lower panels of Figure 3 show the effective association strengths when target information is combined with cue information, following Equation 2. As before, we assume that the targets retrieve parity information regardless of the cue, so $\eta(Even|x)$ and $\eta(Odd|x)$ remain high for both cues. When the parity task is cued, $\eta(Even|PARITY)$ and $\eta(Odd|PARITY)$ are high, so the products

$\eta(Even|x)\eta(Even|PARITY)$ and $\eta(Odd|x)\eta(Odd|PARITY)$ are high, and subjects are likely to respond "odd" or "even," depending on the value of the digit. When the magnitude task is cued, $\eta(Even|MAGNITUDE)$ and $\eta(Odd|MAGNITUDE)$ are low, so the products $\eta(Even|x)\eta(Even|MAGNITUDE)$ and $\eta(Odd|x)$ $\eta(Odd|MAGNITUDE)$ are low and subjects are unlikely to respond "odd" or "even" regardless of the value of the digit.

Modelling compound-cue retrieval

We modelled compound-cue retrieval by adapting Schneider and Logan's (2005, 2009) random-walk model of task switching, which was written in the language of ITAM (Logan, 2002). The model was implemented as a set of equations in Microsoft Excel. For each combination of task and target, Equation 3 was computed for each response category (*Low, High, Odd*, and *Even*). The η value for the cue, $\eta(i|y)$, was η_P if the cue was associated with the relevant task and η_U if the cue was associated with the irrelevant task, with $\eta_P > \eta_U$. The η value for the target, $\eta(i|x)$, was taken from the magnitude or parity representations depicted in Figures 2 and 3.

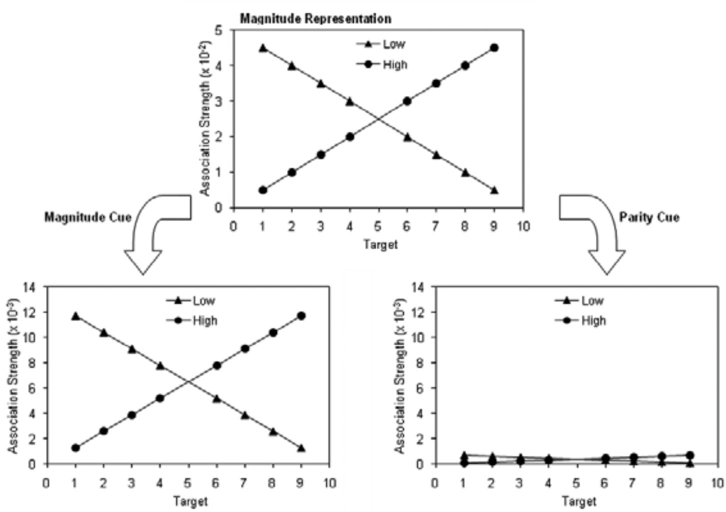

Figure 2
Cue-based gating of the magnitude representation. The top panel shows the magnitude representation, which is based on $\eta(i|x)$ values, where i is Low or High and x is a digit from 1-9, excluding 5. The bottom-left and bottom-right panels show the effective association strengths obtained with magnitude and parity cues, respectively (i.e., $\eta(i|x)\eta(i|y)$ products in Equation 2). Note that the y-axis scales differ for the top and bottom panels

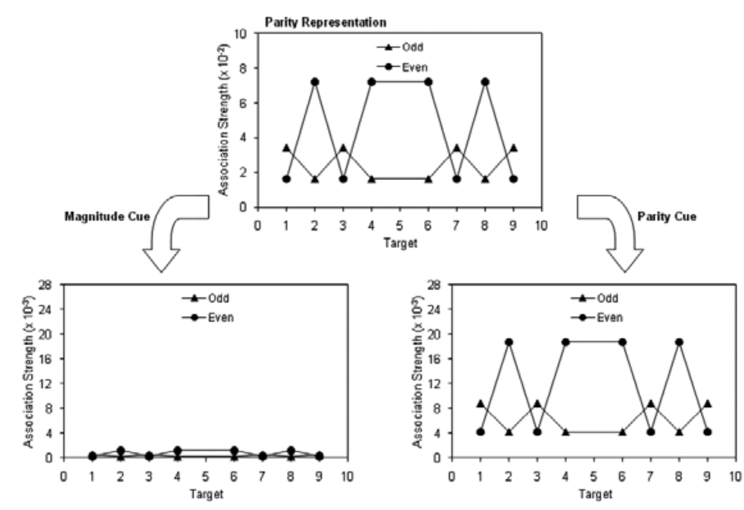

Figure 3
Cue-based gating of the parity representation. The top panel shows the parity representation, which is based on $\eta(i|x)$ values, where i is Odd or Even and x is a digit from 1-9, excluding 5. The bottom-left and bottom-right panels show the effective association strengths obtained with magnitude and parity cues, respectively (i.e., $\eta(i|x)\eta(i|y)$ products in Equation 2). Note that the y-axis scales differ for the top and bottom panels

The β value was either $\beta_{Relevant}$ or $\beta_{Irrelevant}$, where $\beta_{Relevant}$ represents the bias associated with the relevant response categories (i.e., for the cued task) and $\beta_{Irrelevant}$ represents the bias associated with the irrelevant response categories (i.e., for the uncued task). For example, if the magnitude task was to be performed, $\beta_{Relevant}$ would be associated with the *Low* and *High* response categories and $\beta_{Irrelevant}$ would be associated with the *Odd* and *Even* response categories. We assume that β values are associated with task-specific response categories based on the presented cue being encoded to a level that results in a semantic, categorical representation of the task to be performed (Arrington, Logan, & Schneider, 2007).

The resultant v values from Equation 3 were used in Equation 1 to compute drift rates for the random walk. Given that two response categories were mapped onto each response key, a composite drift rate ($P(A_n|x,y)$) was calculated for each response key (n = 1 for the correct response key and n = 2 for the incorrect response key) by summing the drift rates for the two response categories assigned to that key; this was done for each possible response-key mapping. The composite drift rates were then used in conjunction with the random-walk criterion K to compute the number of steps (N_{Step}) for the random walk to finish, given target x and cue y, using the following equations (derived by Busemeyer, 1982, and adapted from Nosofsky & Palmeri, 1997, by assuming symmetrical random-walk boundaries):

$$N_{Step}(x,y) = \frac{1}{P(A_1 \mid x,y) - P(A_2 \mid x,y)}[\theta_1(2K) - \theta_2(K)],$$

$$\text{if } P(A_1 \mid x,y) \neq P(A_2 \mid x,y), \tag{4a}$$

and

$$N_{Step}(x,y) = K^2,$$

$$\text{if } P(A_1 \mid x,y) = P(A_2 \mid x,y), \tag{4b}$$

$$\theta_1 = \frac{(P(A_1 \mid x,y)/P(A_2 \mid x,y))^{2K} + 1}{(P(A_1 \mid x,y)/P(A_2 \mid x,y))^{2K} - 1}, \text{ and } \theta_2 = \frac{(P(A_1 \mid x,y)/P(A_2 \mid x,y))^{K} + 1}{(P(A_1 \mid x,y)/P(A_2 \mid x,y))^{K} - 1}. \tag{5}$$

The time for the random walk to finish was then computed by multiplying N_{Step} by α (the time per step). The probability that the correct response was selected by the random walk was computed using the following equations (Nosofsky & Palmeri, 1997):

$$P(A_1 \mid x,y) = \frac{1-(P(A_2 \mid x,y)/P(A_1 \mid x,y))^{K}}{1-(P(A_2 \mid x,y)/P(A_1 \mid x,y))^{2K}},$$

$$\text{if } P(A_1 \mid x,y) \neq P(A_2 \mid x,y), \tag{6a}$$

and

$$P(A_1 \mid x,y) = \frac{1}{2},$$

$$\text{if } P(A_1 \mid x,y) = P(A_2 \mid x,y). \tag{6b}$$

For each combination of task and target, mean random-walk time and accuracy were calculated by averaging across the values for the different response-key mappings. Mean random-walk time was then added to an RT_{Base} value, which represents the time for non-decision processes, to obtain predicted RTs. In the fits reported below, the model was fit to the 16 data points shown in Figure 1, using the Solver function in Excel to minimise the root mean-squared deviation (RMSD) between observed and predicted RTs (the product-moment correlation, *r*, was also computed), with the constraint that the predicted accuracies be greater than or equal to the observed accuracies (Ms = 96.7% and 95.3% for magnitude and parity judgments, respectively).

The model was fit to the data with five free parameters: η_{Odd}, η_{Even}, α, $RT_{Base\text{-}Magnitude}$, and $RT_{Base\text{-}Parity}$. The only constraint was that η_{Odd} and η_{Even} had to be greater than 0. Other parameters in the model were set to values derived from past model fits or set to arbitrary values. Specifically, $\eta_U = .016$ and $\eta_P = .260$, which are the means of the best-fitting η_U and η_P values from Schneider and Logan's (2005) fits to their data collapsed across tasks and targets (see their Table 2). The slope of the magnitude function was $m = .005$ (many other values yielded equivalent results) and the random-walk criterion was $K = 6$ (which yielded an acceptable level of accuracy). Since we assumed there was no reconfiguration in this version of the model, we fixed $\beta_{Relevant} = \beta_{Irrelevant} = 1$, meaning that the bias toward each response category was the same regardless of whether parity or magnitude was the cued task.

This five-parameter model yielded the predictions shown in Figure 4; the best-fitting parameter values are provided in Table 1.

The model produced a satisfactory fit to the data, with RMSD = 14 ms and $r = .890$, capturing the basic shapes of the different target functions. The fit was almost perfect for the magnitude data (RMSD = 3 ms, $r = .991$), but less optimal for the parity data (RMSD = 20 ms, $r = .551$), which were characterised by a much more irregular target function (see Figure 1).

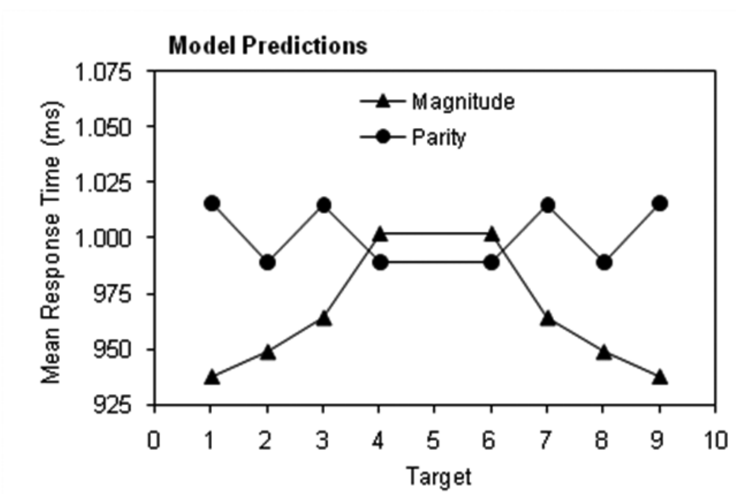

Figure 4
Predicted mean response times for each digit as a function of judgment (magnitude versus parity) in Experiments 1-3 of Schneider and Logan (2005)

Table 1
Best-fitting parameter values and measures of goodness of fit for the fits of the compound-cue retrieval model with and without reconfiguration to Schneider and Logan's (2005) data

Variable	Without Reconfiguration	With Reconfiguration
Parameter		
η_U	.016	.016
η_P	.260	.260
η_{Odd}	**.034**	**.038**
η_{Even}	**.072**	**.072**
α	**3.436**	**3.424**
β_{Relevant}	1.000	1.000
$\beta_{\text{Irrelevant}}$	1.000	**.386**
m	.005	.005
K	6.000	6.000
$RT_{Base\text{-}Magnitude}$	**910.588**	**911.681**
$RT_{Base\text{-}Parity}$	**955.641**	**964.370**
Measure of goodness of fit		
RMSD	14.057	14.048
r	.890	.890

Note: RMSD = root mean-squared deviation between observed and predicted values; r = product-moment correlation. Free parameters in each model fit are denoted in bold font.

Two important consequences for task performance can be inferred from Figure 4. First, task performance is driven primarily by the target representation that is associated with the same response categories as the cue (the magnitude representation for a magnitude cue – see Figure 2; the parity representation for a parity cue – see Figure 3). Second, task performance is relatively unaffected by the target representation that is not associated with the same response categories as the cue (the magnitude representation for a parity cue – see Figure 2; the parity representation for a magnitude cue – see Figure 3). Thus, cue-based gating of each target representation results in a random walk that chooses between the two task-relevant response categories (*Low* and *High* for magnitude judgments; *Odd* and *Even* for parity judgments)

A corollary of this cue-based gating is that differences in association strength in the task-relevant target representation will dominate task performance and determine the predicted target function. Given that each task is associated with a different target representation, different target functions will emerge. For magnitude judgments, distance effects are predicted because cue-based gating allows the magnitude representation to dominate task performance (see Figure 2). Because the difference in association strength for the *Low* and *High* response categories increases in each direction as one moves away from 5 (see Figure 2), drift rate increases (Equation 1), and the number of steps it takes the random walk to select a response decreases (Equation 4a), resulting in a shorter RT and a distance effect (see Figure 4). For parity judgments, even though the same magnitude representation is accessed, there are no distance effects because cue-based gating quashes the contribution of the magnitude representation to task performance (see Figure 2). Instead, the parity representation dominates task performance (see Figure 3). Because there is a difference in association strength for the *Even* and *Odd* response categories, with $\eta_{Even} > \eta_{Odd}$ (see Table 1; see also Figure 3), drift rate is higher for even targets than for odd targets (Equation 1), and the random walk has to take fewer steps to select a response for even targets (Equation 4a), resulting in shorter RTs for even targets (see Figure 4). As with the distance effect for parity judgments, this parity effect does not occur for magnitude judgments because cue-based gating quashes the contribution of the parity representation to task performance (see Figure 2). Consequently, compound-cue retrieval allows the model to produce different target functions for different tasks and to capture Schneider and Logan's (2005) task-switching data without assuming reconfiguration.

But what if we allow reconfiguration to occur? We added reconfiguration to compound-cue retrieval by allowing $\beta_{Irrelevant}$ to be a free parameter while $\beta_{Relevant}$ was fixed to equal 1, so β values could be different for each task. This six-parameter model yielded predictions that were practically identical to those obtained without reconfiguration; the best-fitting parameter values are provided in Table 1 and the measures of goodness of fit were RMSD = 14 ms and $r = .890$. We tested whether the slight improvement in goodness of fit (at the fourth decimal place of r) was significant and found that it was not, $F(1, 10) < 1$, indicating that reconfiguration is not necessary to account for Schneider and Logan's (2005) data. Compound-cue retrieval is sufficient.

Modelling reconfiguration

Despite our findings, it is tempting to model the target function data in terms of reconfiguration. Reconfiguration is possible in ITAM (Logan, 2002) and it was a core idea in ECTVA (Logan & Gordon, 2001). Indeed, the symmetry of effects of cue-based gating in compound-cue retrieval and bias-based gating in reconfiguration (see Equation 3) suggests that it should be possible to model the target function data simply by reversing the roles of the cues and biases in the models that were fit to the data. Multiplication is multiplication, and the equations work the same whether the multiplier that is modulated is interpreted as a cue (i.e., $\eta(i|y)$) or a bias (i.e., β_i). If this possibility were feasible, then the model fits would indicate that reconfiguration is sufficient to account for the data and compound-cue retrieval does not add anything to the fits beyond reconfiguration.

However, there is a major problem with this account of the data: it would require $\eta(Odd|cue)$ and $\eta(Even|cue)$ to equal $\eta(Low|cue)$ and $\eta(High|cue)$ on each trial, regardless of the presented cue, to mimic the fact that $\beta_{Irrelevant}$ equalled $\beta_{Relevant}$ on each trial. This is not plausible. The η values for categories associated with the presented cue should be higher than the η values for categories that are not associated with the presented cue. Otherwise, η values for the cues are not meaningful psychologically. Schneider and Logan (2005) argued that a presented cue could activate an associated cue that was not presented (so ODD could activate EVEN), but that was plausible only for related cues that signalled the same task (see also Logan & Schneider, 2006b). A cue for one task should not activate a cue for an unrelated task. Even if it did, the activation for the unpresented cue should be much less than the activation of the cue that was actually presented. Note that the ηs for the targets implement the assumption that η values are greater for presented than for unpresented targets. Otherwise, the model could not respond appropriately. We suggest that ηs for cues and targets should follow the same rules in the model, which means that ηs for presented cues should be greater than ηs for unpresented cues. Thus, it is not possible to simply reverse the roles for ηs and βs.

Another possibility for implementing reconfiguration is to reinterpret the fits in which β was allowed to vary between tasks, letting β play the role of the cue and η play the role of β. The problem with this possibility is that the model does not fit the data any better than the original model, in which only the ηs for the cues varied. The variation in η (or β) is redundant. Only one multiplier needs to vary to change the target functions (see Equation 3). The argument against this redundant reconfiguration model is essentially an argument for parsimony, and arguments for parsimony are often weak. They are stronger when the specific models are embedded in a larger family of models with broad scope and a wide range of applicability. The compound-cue retrieval and reconfiguration models are embedded in the ITAM family of models, which has many members (Logan, 2002), and that makes the case for parsimony stronger.

We have argued that reconfiguration is not necessary to explain the data, but that argument rests on the assumption that βs are the same for both tasks (i.e., $\beta_{Irrelevant} = \beta_{Relevant}$). How plausible is that assumption? One way to answer this question is to consider the consequences of allowing all βs to be high (and equal) for all tasks, as we did when we modelled the data with compound-cue retrieval. According to Equation 3, the consequences should be minimal, provided that the ηs for the cues vary. When several terms are multiplied together, one small multiplier can decimate the product even if the other multipliers are large. This was the key insight in Medin and Schaffer's (1978) context model of classification, which is the great-grandparent of ITAM. Allowing all βs to be high will have some effect on performance, however. The ηηβ products for irrelevant categorisations (Equation 3) add a small amount to the denominator of the choice ratio in Equation 1, decreasing drift rate and increasing RT and error rate. These effects will be small, however.

Discussion

Our comparison between reconfiguration and compound-cue retrieval accounts of task switching focused on their ability to account for target functions, which are plots of performance on individual target stimuli while subjects perform different tasks. Empirically, the target functions for parity and magnitude judgments of digits are quite distinct (see Figure 1), but our model fits showed that they could be accounted for very well by compound-cue retrieval without reconfiguration. We believe it is significant that our comparisons of reconfiguration and compound-cue retrieval were done in the context of the same formal theory (i.e., ITAM; Logan, 2002), so the alternative models had an equal footing on a level playing ground. In this respect, our evaluation of response selection in task switching is similar to Logan and Bundesen's (2003) evaluation of preparation and the reduction of switch costs in task switching. Logan and Bundesen also compared reconfiguration and compound-cue models in the same mathematical framework and, like us, found that compound-cue retrieval provided a better account of the data.

The scope of compound-cue retrieval

A major strength of our compound-cue retrieval model is that it accounts for the role of cues in task switching, both in preparation for an impending task and in selecting responses in an ongoing task. Before 2003, few researchers paid any attention to the cues, even in explicit task-cuing experiments. They concerned themselves with the consequences of having encoded the cue rather than with the act of encoding the cue itself, typically assuming that the consequences involved reconfiguration on task-switch trials. Then, Mayr and Kliegl (2003) and Logan and Bundesen (2003) noted a confound between cue repetition and task repetition in explicit task-cuing experiments that used one cue for each task and they presented a method for removing the confound that involved using two cues for each task (e.g., MAGNITUDE and HIGH-LOW for a magnitude task). Their research focused attention on the processes by which cues were encoded and the contribution of cue encoding to switch costs (also see Logan & Schneider, 2006a, 2006b; Logan, Schneider, & Bundesen, 2007; Schneider & Logan, 2006b, 2007c). Shortly afterward, Schneider and Logan (2005) addressed the role of cues in retrieving responses in task switching, proposing a computational model of compound-cue retrieval that accounted for cue encoding and response selection (also see Schneider & Logan, 2009). As a result, the role of cues in task switching is better understood theoretically and empirically.

Compound-cue retrieval may play a role in task-switching situations beyond explicit task cuing, in which no explicit cues are presented. For example, in the task span procedure (Logan, 2004) and the repeating lists procedure (Schneider, 2007; Schneider & Logan, 2006a; see also Schneider & Logan, 2007b), subjects memorise a list of tasks to perform and then respond to a series of targets by successively retrieving tasks on the list. We suggest they retrieve cue-like representations from the list and combine them with the targets to form compound cues, which they use to retrieve appropriate responses from memory. Recently, Mayr (in press) found cue repetition effects in the task span procedure, which suggested that subjects use relatively low-level phonological representations to drive performance.

As another example, the voluntary task switching procedure (Arrington & Logan, 2004) presents no cues and requires subjects to decide for themselves which task to perform. Subjects may generate internal cue-like representations, which they combine with the targets to form compound cues, and retrieve task-relevant responses from memory. Indeed, voluntary switch costs are about the same as explicitly cued switch costs (Arrington & Logan, 2005).

More generally, we might expect to find evidence of compound-cue retrieval whenever tasks can be performed by memory retrieval (and many tasks can be performed by memory retrieval; Logan, 1988). Memory retrieval is cue dependent, so that different things can be retrieved by changing retrieval cues (Tulving & Thompson, 1973). The idea that responses appropriate to different tasks can be retrieved by changing the retrieval cues sits well with a large body of memory research. Our position has been that such changes in retrieval cues do not constitute a change in task set (Logan & Bundesen, 2003; Schneider & Logan, 2005). The task set is “respond with what you retrieve from memory” and the same task set is used on all trials, without any need to reconfigure the cognitive system. People would not normally think they switched tasks when they were asked for their names and then their addresses or when they were asked to name the capital city in Belgium and then to name a prominent Belgian university. These are just different acts of retrieval. Similarly, we do not think people switch tasks when they are asked whether a digit is odd or even and then whether it is lower or higher than 5. These, too, are just different acts of retrieval, in our view.

Where might we find reconfiguration?

Like many researchers, we remain intrigued by the idea that people may reconfigure their cognitive systems to perform different tasks. We think it is unlikely that we will find evidence of reconfiguration in tasks that can be solved by memory retrieval because compound-cue retrieval seems sufficient for those tasks. However, we think it may be possible to find evidence of reconfiguration in tasks that require changes in specific parameters of models like ITAM that are associated with executive processing. Switching attention from one location to another is one example of such a task. Indeed, Logan and Gordon (2001) proposed ECTVA largely to explain switches in spatial attention in dual-task situations, which required changes in π rather than β. Logan (2005) applied Logan and Bundesen's (2003) reconfiguration model and compound-cue retrieval model to a task that required switching attention from one location to another and found that the reconfiguration model fit the data better. Schneider and Logan (2007a) had subjects switch between two reference points in magnitude judgments of digits and found reference-point switching effects that they interpreted as reconfiguration. In terms of ITAM, their data could be modelled by changing β values for *High* and *Low* response categories, which would meet the ECTVA definition of reconfiguration (Logan & Gordon, 2001; Vandierendonck et al., 2010).

In the end, we believe that the search for reconfiguration must be done with the aid of a computational model in which model parameters can be identified with task sets, and alternative hypotheses, like compound-cue retrieval, can be articulated and potentially ruled out. This article has shown, like much of our research before it, that we must go beyond simple operational definitions of reconfiguration in terms of switch costs, target functions, and other empirical results. Without a rigorous model-based analysis, we cannot rule out plausible alternative hypotheses.

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