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Response times identification tools for cognitive processes as at the final decision stage

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One central aim of contemporary research in cognitive psychology is the identification of the cognitive mechanisms engaged in judgment and decision making. In contrast, standard economic approaches to decision making have followed an axiomatic approach, according to which people's choice can be described by expected utility models if their choice obey various choice axioms (e.g. von Neumann & Morgenstern, 1954), without aiming for understanding the cognitive process that leads to decisions (cf. Rieskamp, Busemeyer & Mellers, 2006). This research has also been called an *as if* approach, which treats the psychological processes behind decision making as a black box (see Gigerenzer & Selten, 2001). Although the "as if" approach can be quite successful in describing people's choices in various domains it could be limited when making predictions for future and independent behavior not used for fitting a model, because it lacks the understanding of the causal mechanisms of people's behavior. Contrary to the as-if approaches recent approaches in cognitive psychology, behavioral economics and decision neuroscience of studying judgment and decision making have led to advances towards unpacking the black box. Understanding the underlying cognitive processes of human decision making allows to explain when and why people violate important choice axioms and should ultimately lead to better independent, out of sample predictions.

Many models of decision making create strong assumptions about the processes that lead to a decision. Specifically, these models make assumptions about **the fundamental cognitive processes:** (a) type of information search, that is how attribute information is searched for (for example- serial or parallel), (b) scope of information search, that is when this attribute information search is stopped (limited search vs. all information search), and (c) type of information integration, that is how the acquired attribute information is integrated to reach the decision (intendent or dependent analysis of attributes).

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Current Approaches to identification of processes involved in decision making

Perhaps one of the most effective approaches to discovering how decision makers use information is the process-tracing approach, which includes both overt and covert methods. Overt process tracing methods rely on directly observable behavior during the decision making process. Interactive information displays (Payne, 1976), mouslab (Payne, Bettman, & Johnson, 1993), eye tracking (Russo & Rosen, 1975; Lohse & Johnson, 1996) and retrospective verbal protocols (Ericsson & Simon, 1984) are all types of overt process-tracing methods used to investigate information search during decision making (Schulte-Mecklenbeck, Kuhberger, & Ranyard, 2011). These methods can indicate what information people search for, the order in which they search, and the amount of time they devote to each information source. These data can indicate whether assumptions about the fundamental cognitive processes hold and provide strong constraints on models of the decision process (e.g., Bröder, 2000, 2003; Maule, 1994; Newell & Shanks, 2003; Newell, Weston, & Shanks, 2003; Payne, Bettman, & Johnson, 1988, 1993; Rieskamp & Hoffrage, 1999, 2008). Despite the clear value of these overt methods (Svanson, 1979), it is possible that they provide less constraint on how the decision is made once the decision-maker has collected information. Furthermore, some researchers have suggested that these overt methods are particularly vulnerable to participants being aware of the manipulations and adapting their performance accordingly (Reisen, Hoffrage & Mast, 2008).

Covert process tracing methods, in contrast, rely on indirect inferences from the observed behaviors about the cognitive processes. Examples of covert methods are those that rely on collected choice responses, scaled choice preferences, and/or response times (e.g. Busemeyer & Townsend, 1993; Nosofsky & Palmeri, 1997; Ashby, 2000; Glockner 2009). Normally, any of these observations could not be directly connected to underlying cognitive process. However, by using specific experimental designs (input), researcher can collect the appropriate response data (output) to constrain the possible models of the decision making process. The input-output analysis is achieved by the means of model testing. The best model of underlying cognitive processes is inferred from likelihoods of the observed input-output relationship across the candidate models, or within the Bayesian approaches, the posterior probability of a decision making models given the input-output patterns.

Covert and overt methods are in many ways complementary. The main limitation of the covert input-output methods is that they provides minimal information about pre-decision stage (Payne, Braunstein & Carroll,1978; Svenson,1979) where the overt methods are strongest, and covert methods can be informative about the final decision stage, the stage in which overt methods are the least informative. This final decision stage is considered inaccessible to introspection. Importantly at this stage, many cognitive factors could significantly affect the decision, particularly memory storage and retrieval, perceptual context, attention, and others.

Many researchers have applied the input-output model analyses of choices to examine this final decision stage. Although there have been notable successes progress has been stymied by the problems with model identifiability: several classes of different models predict the exact same choice patterns. The strategic plan to avoid choice model mimicking has been consider in several publications (e.g. Rieskamp & Hoffrage 1999, 2008; Broder 2000; Lee & Cummins 2004)

In addition to choice patterns, response time analysis is another covert approach that can offer insight into the cognitive processes underlying decision making (e.g., Busemeyer &

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Townsend, 1993). Sophisticated modeling based on response times dates back to the early days of experimental psychology in the latter half of the 19th century starting with the work of Donders (1868) and Wundt (1880), and flourished with the development of the information-processing approach (e.g., Sternberg, 1966, 1969). When combined with choice patterns, response times have led to a number of important advances in cognitive psychology (e.g., Ashby, 2000; Ashby & Maddox, 1994; Heath, 1992; Lamberts, 1998, 2000; Link, 1992; Nosofsky & Palmeri, 1997; Ratcliff, 1978; Smith, 1995, Donkin, Nosofsky, Gold, & Shiffrin, 2013; Little, Nosofsky, Donkin, & Denton, 2013; Starns & Ratcliff, 2010; Bogacz, Wagenmakers, Forstmann, & Nieuwenhuis, 2010).

In the present chapter, we will not discuss the response time predictions that can be derived from all the models mentioned above. Instead, for illustration purposes we will only focus on how response times can be used to test two prototypical inference strategies suggested by *the strategy approach* (Gigerenzer, Todd, & the ABC Research Group, 1999; Payne et al., 1993). This illustration, however, can be generalized to a variety of decision making models. The strategy approach assumes that people are equipped with a repertoire of different strategies to make inferences.

Response time analysis for testing process model of probabilistic inferences

Several research publications used the analysis of response times in examining probabilistic inferences. Bergert and Nosofsky tested a generalized, lexicographic take-the-best and a generalized weighted-additive (WADD) model (see Bergert & Nosofsky, 2007, for details). As demonstrated by Bergert and Nosofsky (2007), the resulting generalized model was able to

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make identical choice predictions, so that choice behavior alone does not allow to differentiate between the two models. Choice data was not sufficient to discriminate between the two models. However, response time data provided an additional source of information for testing the models; indeed, results of response time analysis largely supported take-the-best over WADD.

Bröder and Gaissmaier (2007) re-examined five of Bröder and Schiffer's (2003) experiments. They split the participants into four groups with identical strategy classifications on the basis of their observed inferences. Bröder and Gaissmaier computed the median response time[1] and found that the response times followed the predicted pattern and supported the assumption of sequential search: Participants classified as using take-the-best showed an increase in response time depending on the position of the best discriminating cue, while this increase was much less pronounced for participants who were classified as using WADD or Tally. In sum, the response time analysis results converged to the previous conclusions of the previous choice behavior analyses, and strongly supported the main results.

Persson and Rieskamp (2009) performed a response time analysis to confirm the results of their strategy classification analysis, similar to Bröder and Gaissmaier (2007). Overall their results supported the strategy-based approach in decision making, in which decision maker adapts to the constraints in the environment, including the factors such are: time pressure, information search costs, the nature of feedback, and presentation format of information.

One of the main questions posed by this research was whether the prevalence of take-the-best in Bröder and Schiffer (2003) was induced by the experimental requirements. For instance, in Bröder and Schiffer's (2003) experiments, participants were given the rank order of cue validities,

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[1] Analysis of median RT rather than mean RT can offer more robust results because RTs are often skewed. Extreme outliers may also be an issue for RT analysis, which is to some degree mitigated by the use of medians. For distributional analyses, such at the SIC described below, outliers are even less of an issue than for median based approaches. When mean RT is the statistic of interest, we recommend a contaminant model such as that presented in Craigmile, Peruggia, & Van Zandt (2010).

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which may have fostered the selection of take-the-best. In contrast, if participants had to learn the validities of the cues, this might lead them to use other inference strategies, such as Tally, which does not require any cue validities. This issues was addressed in the later study (Perssson & Rieskamp, 2009) using response time analysis: the results indicated that the non-compensatory TTB strategy and compensatory (WADD) strategy are dependent on the type of decision feedback provided.

The reported studies illustrate how a response time analysis can be used to validate the inference that had been made on a pure analysis of people's choices. The goal of the reported response time analyses was to find convergent evidence for the processes assumed to underlie memory-based probabilistic inferences. For memory-based decisions monitoring external information search processes cannot be applied. Therefore, response times were analyzed to validate the idea of sequential cue search in inference processes and as an independent source of support for the outcome-based strategy classification method. In this manner, Bergert and Nosofsky (2007), Bröder and Gaissmaier (2007), and Persson and Rieskamp (2009) tried to achieve the goal that models should be testable with different kinds of data (e.g., Jacobs & Grainger, 1994).

Potential limitations of the traditional RT analysis and the solution

Although response times analysis improves inferences over the analysis of choice responses alone, there can still be significant model identifiability problems, even with simple decision making systems. For example, one fundamental question in understanding the decision stage is whether individuals consider each piece of evidence one-at-a-time (in series) or all at once

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(in parallel). Despite a clear conceptual distinction between serial and parallel processing, serial and parallel systems can exactly mimic each other across a wide range of empirical settings (Townsend & Ashby, 1983; Townsend & Wenger, 2004, p. 1011). One reason this mimicking can occur is that slow-downs or speed-ups across conditions can be explained equally well by differences in temporal structure (i.e., parallel versus serial) as by differences in processing efficiency (e.g., Townsend, 1969, 1971, 1972; Townsend & Ashby, 1983).

In sum, several approaches have been employed created to answer the questions about the organization of cognitive processes in decision making. One of the most challenging issues faced was model mimicking. Different models are able to predict the same outcomes either at the choice levels or at the response time levels. This poses a serious challenges to discriminating among candidate descriptions of the decision making process.

To overcome the model mimicking, and to unlock more powerful ways of decision making model identification, we propose a synthesis between the *systems factorial technology* (SFT) with the traditional decision making analysis.

As a preview, to show how SFT deals with the response time mimicking a simulations study was conducted using two different decision strategies. First we simulated a response time output of TTB decision making model in a situation in which stopping can occur on the first discriminating cue. Second, we simulated the coactive model – one of the possible candidate variants for the cognitive model underlying WADD decision strategy. In the coactive model information from all cue attributes is processed in parallel fashion. The two simulated models differ critically on all the three fundamental cognitive properties. However, the simulation results showed that the two models can perfectly mimic each others response times (Figure 1 A). The TTB and coactive models are able to generate the identical outputs – showing that the response times distributions of the two model predictions completely overlap (Figure 1 A). Nonetheless, we see that data from the same models with the same parameterization reveals quite distinct diagnostic patterns of response times when analyzed using SFT (shown on the right Figure 1 B). The response time data function for the TTB model shows almost flat – randomly hovering around zero value, while the coactive WADD model shows an S-shaped function. The SFT approach thus avoids the response time mimicking problem and provides a sufficient model discriminability power to distinguish between the two different decision making strategies.

In the following section the SFT methods will be described with more details, and information would be provide about how SFT could be applied in the classical probabilistic inference task.

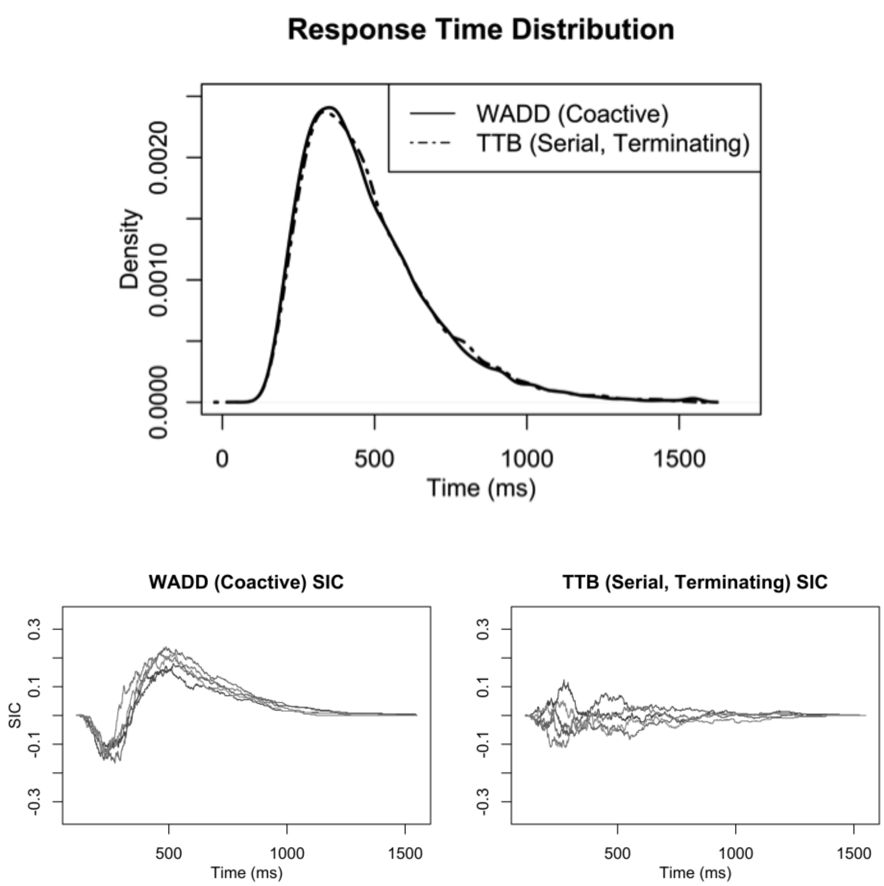

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Figure 1: (A) A simulated response time distributions for two different models WADD and TTB. The two distributions almost perfect overlap, implying that at this level two models can't be differentiate in the output. Both models' choice accuracies were also equal (p=.999) meaning that both models achieved high decision accuracy. (B) When the SFT analyses was applied on the same data from A, we can see that the two models generated clearly distinct SIC signatures, thus implying that the models can be now differentiate in the output.

The systems factorial technology methodology

Systems factorial technology (SFT) is a suite of methodological tools aimed at discovering the fundamental properties of cognitive operations by the decomposition of output response time (Townsend & Ashby, 1983; Townsend & Nozawa, 1995; also see the related approach Schweickert, Fisher & Sung, 2012; Schweickert, Giorgini, & Dzhafarov, 2000). The SFT analysis provides rigorous tests and mathematical tools for discerning the fundamental properties of the cognitive processes underlying many decision making models:

1) Type of information search: (serial, parallel or coactive)
2) Scope of information search (limited vs. total, that is self-terminating vs. exhaustive)
3) Type of information integration (Process (in)dependence, whether cognitive processes are independent or dependent of each other)
4) Capacity of the system under investigation, that is, amount of work done by the decision making system, when information load increases (limited, unlimited or supercapacity).

We include a necessarily brief overview of the approach below. For additional details, there are several tutorials on SFT (Fific & Little, 2016; Altieri, Fific, Little & Young, 2016; Harding et al. 2016; Houpt, et al. 2014). In a nutshell, SFT requires the factorial manipulation of the time spent considering each of the sources of information available. We refer to the manipulations that

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slow down or speed up the processing of each source as “stretching factors”. Critically, each stretching factor should influence the processing of a specific a target source of information and not others (selective influence).

Consider a generic study in which a choice must be made between two options based on two attributes. One stretching factor should influence the speed of with which an individual evaluates attribute 1, with the two levels: Fast (F) for faster evaluation and Slow (S) for slower evaluation. The second stretching factor is the same for attribute 2. Stretching factor 1 should not affect the processing of attribute 2 and stretching factor 2 should not affect the processing of attribute 1. A factorial combination of the levels of each stretching factor, yields four experimental conditions: SS, SF, FS, and FF. Here, each letter indicates whether the evaluation process was stretched in time or not. For example, SF means that the first attribute evaluation was stretched thus slow, and the second attribute evaluation was not stretched - thus fast. We denote the collection of response times in each factorial condition with RT_{SS}, RT_{SF}, RT_{FS} and RT_{SS}.

The factorial design uses the stretching effects that are conducted on at least two (decision) processes of interest, to investigate the interaction of the stretching effects. In the SFT approach the interaction analysis provides the most diagnostic information about the organization of underlying processes. Two SFT statistics are generated from the interaction test analysis.

Double factor manipulation: Stretching two processes.

The orthogonal factors can be used to calculate the interaction contrast, much like in factorial ANOVA. The first interaction test can be expressed as the difference between stretching effects on response times. Using the M.. to indicate the mean time across the collection RT.., the mean interaction contrast (MIC) is given by:

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$MIC = (M_{SS} – M_{SF}) – (M_{FS} – M_{FF})$.

Additional diagnostic information can be gleaned using survivor functions. Completely analogous to deriving the mean interaction contrast (MIC), one can compute the survivor interaction contrast (SIC). The survivor function describes the probability that a response time will occur after a given time and is one minus the more familiar cumulative distribution function. By replacing the mean RTs for each condition by the survivor function, at each value of *t*, one computes:

$SIC(t) = [S_{SS}(t) – S_{SF}(t)] – [S_{FS}(t) – S_{FF}(t)]$.

Both the MIC and SIC provide powerful information for exploring the fundamental properties of the decision making process. Figure 2 shows the correspondence between MIC and SIC signatures (middle), and cognitive processes that could be used to make a decision model (left-hand side), and the interpretation of the signatures in terms of decision making model properties (right-hand side).

SFT has been used in the context of various cognitive tasks and domains: perceptual processes (e.g., Eidels, Townsend, & Pomerantz, 2008; Fific, Nosofsky, & Townsend, 2008; Johnson, Blaha, Houpt, & Townsend, 2010; Townsend & Nozawa, 1995; Yang, 2011; Yang, Chang, & Wu, 2013), visual and memory search tasks (Egeth & Dagenbach, 1991; Fific, Townsend, & Eidels, 2008; Sung, 2008; Townsend & Fific, 2004; Wenger & Townsend, 2001; 2006), face perception tasks (Fific & Townsend, 2010; Ingvalson & Wenger, 2005; Blunden, Wang, Griffiths, & Little, 2014), and classification and categorization (e.g., Fific, Little, &

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Nosofsky, 2010; Little, Nosofsky, & Denton 2011; Little, Nosofsky, Donkin, & Denton, 2013). The SFT tools were recognized as potentially the most important and promising methodology in understanding cognitive processes (Greenwald, 2012), and also invited to the domain of decision making as a promising new direction in model testing (Busemeyer, 2017; Gaissmaier, Fific, & Rieskamp, 2011).

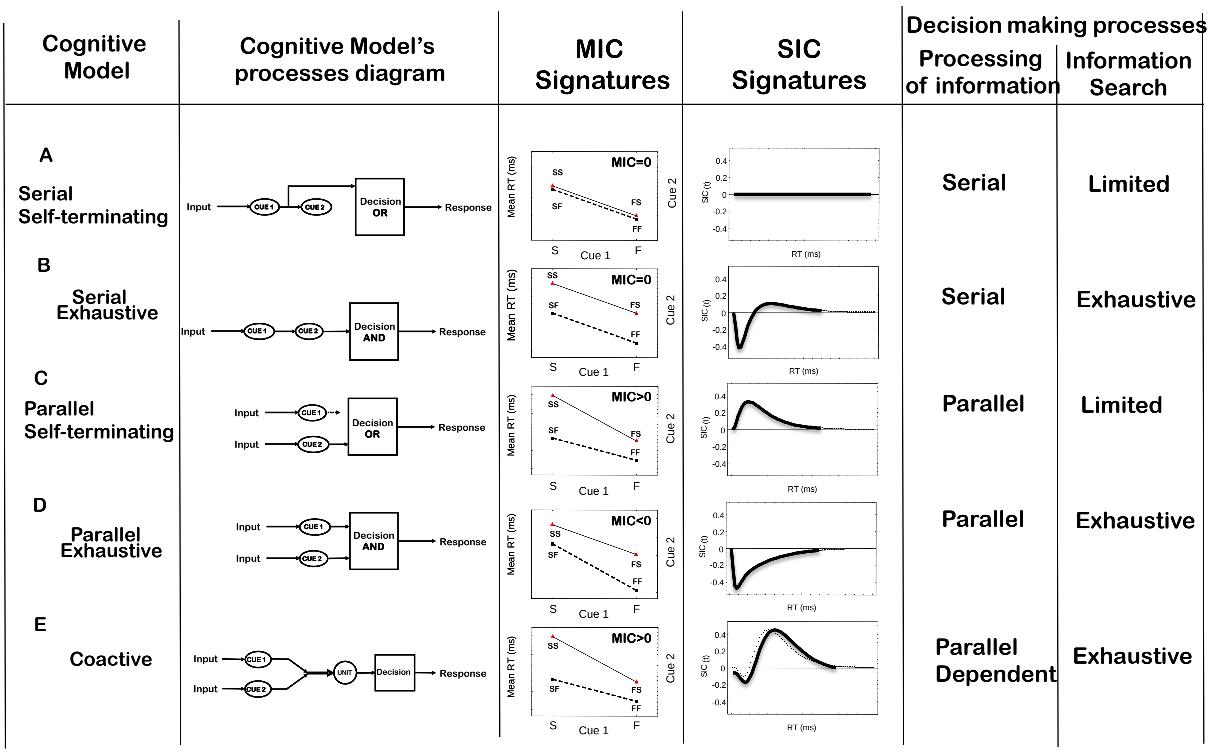

Figure 2: The correspondence among cognitive models (left), SFT signatures (middle) and the inferred decision process structure (right).

Applying Systems Factorial Technology to the probabilistic inference task

In order to apply SFT we follow the three-step instructions described in (Fific & Little, 2016):

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(1) Identify a processing model(s) of interest that will be tested in terms of its fundamental cognitive processes: processing order, stopping rule, and process interdependency.

(2) Determine the task structure, particularly the stretching manipulations.

(3) Collecting RT data, analyze the corresponding response distributions using MIC and SIC, and interpret.

STEP1: Identify processing models of interest, and the SFT model predictions

A first prototypical strategy that we consider is a noncompensatory lexicographic one, of which the take-the-best (TTB) heuristic (Gigerenzer & Goldstein, 1996) is an example. The strategy predicts limited and serial processing of information. Take-the-best assumes that people compare objects cue-wise (cue=attribute), starting with the most valid cue with regard to predicting the criterion, and stop as soon as one cue is found that discriminates between the two objects. That is, a person using take-the-best first searches for the most valid cue, which is the best discriminating cue between two objects on a criterion. If this cue discriminates, the person does not search further and makes a decision. Otherwise, searching for cues continues until a discriminating cue is found. Therefore, when take-the-best finds the first (i.e., most valid) discriminating cue, it stops searching and makes a decision based on that cue alone, while all the remaining cues are ignored. If TTB stops on processing of the first discriminating attribute then one can expect to observe MIC=0 and flat SIC, as shown in Figure 2 A (serial self-terminating model). If TTB stops on the second discriminating attribute, after processing the first non-discriminative, then one can expect MIC=0 and S-shaped SIC, as shown in Figure 2 B (serial exhaustive model). In contrast, compensatory strategies, such as the weighted additive strategy (WADD), assume that all available information is processed in series (e.g., Gigerenzer & Goldstein, 1996; Payne et al., 1988). WADD assumes that each cue is weighted (usually by the validity of the cue), and that a decision maker calculates the sum of all weighted cue values when choosing between two alternatives. A decision maker chooses the alternative with the largest weighted sum. WADD needs to process all attributes, so it could be expected that MIC=0 and SIC function should be the form of Figure 2 B (serial exhaustive model), regardless of the position of the discriminating cue attribute. Another variants of compensatory strategies are Bayesian inference models (Naïve Bayes or NB). A Bayesian inference that is built into a connectionist processing model assumes that all available information is processed in parallel (cf. Griffiths, Chater, Kemp, Perfors, Tenenbaum, 2010, Glöckner, Hilbig & Jekel, 2014). In these cases one can expect to observe MIC<0 and negative SIC function, as shown in Figure 2 D. However if the processing of cue attributes are dependent of each other, then one can expect to observe the coactive signature that is MIC>0 and SIC has a mainly positive shape with a small negative initial blip, Figure 2 E (the exemplar model e.g. Fific, Little, Nosofsky, 2010; Fifić & Townsend, 2010). The attribute dependencies can formed either by creating a learning environment in which a decision maker learns statistically dependencies between the options' attributes; and/or could be created in the parallel network systems which assigns conjoint weights to the attribute representations. Finally, some decision making systems can benefit from parallel self-terminating processing, so called horse-race models (Marley & Colonius, 1992; Pike, 1973; Townsend & Ashby, 1983; Van Zandt, Colonius, & Proctor, 2000), in which the first discriminating attribute can terminate the parallel information search and lead to final decision, as shown in Figure 2 C. Taking altogether, we could see that among several dominant decision making models the critical distinguishing cognitive properties are the processing order, the extent of processing, and processing integration structure, all of which could be diagnosed using SFT.

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STEP 2. Task selection and stretching manipulation

Task selection: In a probabilistic inference task, participants have to compare objects and decide which objects scores higher based on several attributes (cues) of the objects. For example, assume that participants must decide which of two bugs is more poisonous based on their legs and body texture (Bergert & Nosofsky, 2007). Many researchers have modeled this choice process as probabilistic inference (e.g. Dougherty, Gettys, & Ogden, 1999; Gigerenzer & Goldstein, 1996; Hammond, 1990; Juslin & Persson, 2002; Lee & Cummins, 2004; Rieskamp, 2006; Rieskamp & Hoffrage, 1999, 2008; Payne et al., 1988; Rieskamp & Otto, 2006). These include, among others, connectionist models (Gluck & Bower, 1988), exemplar models (Juslin & Persson, 2002), sequential sampling models (Lee & Cummins, 2004; Wallsten & Barton, 1982), and procedural strategies (Gigerenzer, Todd, & the ABC Research Group, 1999; Payne et al., 1993). Furthermore, people may use different strategies based on whether both attributes are necessary for decision making (compensatory environment) or a single attribute is sufficient (non-compensatory environment).

Generally speaking, when viewers approach this task they could check the attributes in series (e.g., legs, then bodies) or examine all attributes of a bug before moving on to the other. At this point, we focus our description on testing attribute-wise search, although the design and analysis also apply to option-wise search. Hence, our question can be framed as how a decision maker processes the attributes and combines them to make a decision? To answer the question we can design the experiment in two phases: the first phase was a learning phase, with two environments: Compensatory and non-compensatory, and three cues legs, antenna and body. On

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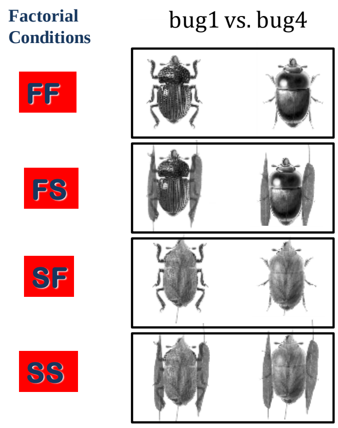
each trial two randomly selected bugs were displayed simultaneously next to each other, separated by a fixation point. The task was to decide which bug was more poisonous as quickly as possible without making errors. Bug images were created by combining three cue attributes (legs, antenna and body). Probabilistic feedback was provided and participants were informed that the feedback would help them to learn to recognize poison levels of bugs.

Stretching manipulation: In the second test phase, the SFT methodology was applied. The third cue (antennae) was covered using a non-transparent mask leaving two cue attributes for inspection (body and legs). The stretching manipulation, that is speeding up or slowing down the processes of interest (S=slow, F=fast), was achieved by visually masking attributes: In this case, we used semi-transparent leaves to occlude attributes (see Figure 3). Cue stretching (S, F) was factorially combined across the factor cues (factor cue 1 body and factor cue 2 legs), leading to the four conditions: SS, SF, FS and FF (Figure 3). The indices on the left indicate saliency level of cue 1 (body) and the indices on the right indicate saliency of cue 2 (legs). Thus, "SF" indicates a condition in which two simultaneously displayed bugs had their cue 1 (body) semi-transparently masked, and the cue 2 unmasked (legs). No feedback was provided in the test phase. Otherwise, the task instructions were the same as the training phase; decide which bug is more poisonous as rapidly as possible without making errors.



	c1	c2	Criterion (poisonous)
bug1	1	1	4
bug2	1	0	3
bug3	0	1	2
bug4	0	0	1

Figure 3: Demonstration of SFT stretching when the most poisonous bug1 is compared to the least poisons bug4. The left column processing. F stands for “fast” and S stands for “slow”. The mask is used to slow processing.

STEP 3. Face Validity of the SFT in testing probabilistic inference task: Simulation study.

We use results from the two subjects in a probabilistic inference task to demonstrate the application of SFT. One subject is tested in a non-compensatory condition and another one in a compensatory condition. Recall that the Naïve Bayes and WADD predict that participants will use an exhaustive strategy, with Naïve Bayes normally being not so strongly associated with parallel or coactive processing and WADD associated with serial processing, in both environments. In contrast, the TTB strategy predicts a serial first-terminating process in the non-compensatory environment and a serial exhaustive process in the compensatory condition. A non-zero MIC would rule out serial processing, hence a non-zero MIC in either environment would rule out TTB. A change in MIC sign between the compensatory and non-compensatory conditions, indicating a switch between exhaustive and first-terminating decision-making, would rule out standard versions of Naïve Bayes and WADD models.

For both subjects (in the compensatory, and the non-compensatory conditions) the posterior probabilities favored an MIC equal to zero (p>.75). We applied follow-up SIC analysis at the individual level: In the compensatory condition three participants had significantly negative SIC values, which along with the MIC result indicates serial-exhaustive processing (Figure 4). In the non-compensatory condition the subjects had no significant deviations from zero in the SIC, indicating serial first-terminating processing (Figure 4) The pattern of results is exactly that predicted by TTB and the zero MIC with a lack of SIC deviations from zero in rule out WADD and Naïve Bayes models. Thus, this approach has allowed us to conclude that these participants were using a one-at-a-time (serial) strategy and stopped assessing information once they had enough to make a decision (self-terminating).

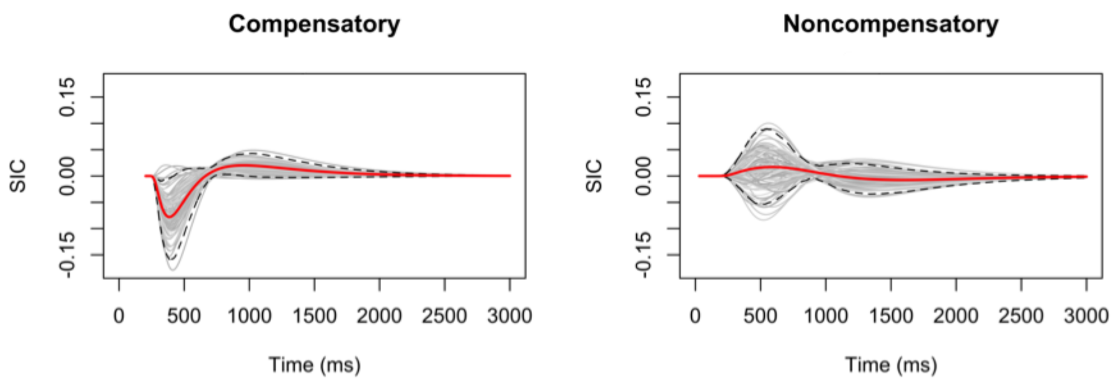


Figure 4: The two selected SIC functions (bottom row). The left compensatory SIC function indicates serial exhaustive processing across attributes (for comparison see Figure 2 B); the right non-compensatory SIC function indicates serial self-terminating processing, and is statistically “flat” (for comparison see Figure 2 A).

Collecting more subjects’ data would allow for making inference about decision-making strategies both at the group and individual levels.

Conclusions

In this chapter, we argued that response times are a valuable resource for testing process models of judgment and decision making. Cognitive models of decision making imply different types of information processing that can lead to a decision. One can differentiate three very general aspects of information processing: the scope of information search (self-terminating vs. exhaustive) and the type of information processing (serial vs. parallel), and the type of information integration. These three aspects can be found in different combinations in a variety of models. Despite different processing assumptions, however, these models often cannot be distinguished by the decisions they predict, leading to an identification problem (cf. Anderson, 1990).

Bergert and Nosofsky (2007) were able to distinguish between two different models based on mean response time analyses. These models were identical in their choice predictions but very different in the spirit of the underlying process assumptions. Moreover, the response time analyses of both Bröder and Gaissmaier (2007) and Persson and Rieskamp (2009) supported the assumption of self-terminating, serial cue search in memory-based decision making, for a substantial proportion of their participants. The results demonstrate the usefulness of response time analyses as a method for tracing processes that are not directly observable. The analysis of response times can therefore provide valuable information on whether the interpretations drawn from an analysis of participants' decisions alone appear valid.

Unfortunately, even response time analysis is prone to model mimicking. We showed two very distinct decision making models could predict identical response time distributions. This illustrates that under certain conditions, models under investigation cannot be clearly identified even using both choice accuracy and response time analyses. To address these limitations we demonstrated the SFT methodology which provides an assessment of the type of information processing (serial vs. parallel), the scope of information search (self-terminating vs. exhaustive), and type of information integration (process dependency). SFT could be used to identify different decision-making strategies, such as non-compensatory strategies and compensatory strategies. As we could see, the SFT approach requires adding more experimental conditions to the original decision task (such as in the example above in a probabilistic inference task). The experimental manipulation required using response time stretching manipulations, so that researchers can selectively influence a processing time of each decision attribute. As we could see the SFT stretching manipulation, would lead to the output analysis in terms of patterns of either mean response times (MIC) or survivor function (SIC), so that a distinct decision making model would leave different output patterns of both MICs and SICs. These diagnostic patterns could provide needed diagnostic edge to distinguishing between the models of interest. Thus the SFT approach can be seen as a methodological extension to standard task (Greenwald, 2012).

The key to SFT is the selective influence of the different information sources. Other traditional approaches to decision model testing might also benefit from these manipulations and be combined with the stretching manipulations. For example, the typical approach to examining decision making processes is to manipulate the distribution of attribute validities for options that are considered in decision making. Researchers typically create two different environments, hoping to encourage different decision strategies. In a compensatory environment, compensatory strategies would be appropriate, in which a low value of an attribute of an option can be compensated by a high value on a different attribute. A typical representative would be weighted additive strategy (WADD). In a non-compensatory environment, strategies that do not allow attribute values on one attribute to compensate for low values on another attribute could be sufficient. Take-the-best strategy (TTB) is a typical example of non-compensatory strategy. In practice, to identify TTB and WADD decision making models, one has to compare the response outcomes between the two environments. So in the traditional approach analyzing response data from only one environment doesn't provide sufficient and necessary conditions for decision model comparison.

The required SFT application can be done orthogonal to the manipulation of attributes validities. Selective stretching of the cognitive processes are all that is required for SFT. The time stretching manipulation (Fific & Little, 2016) could be defined completely independent from the attribute validities, which in turn gives more degrees of freedom for SFT application.

Response time analysis is a fruitful endeavor that can increase understanding of cognitive processes underlying peoples' judgments and decisions. Researcher are encouraged to take advantage of the converging principal in process tracing, by employing not only different analyses but also complementary approaches to analysis underlying cognitive process in decision making. One such an approach could be SFT that could add to the informativeness of other process tracing methods such as eye tracking, mouslab, and/or interactive information displays methods.

RECOMMENDED READING

Bröder & Gaissmaier (2007) showed how response time analyses can provide convergent evidence for assumptions about information search in memory-based decision making.

Persson & Rieskamp (2009) tested an exemplar-based approach to predicting people's inferences from memory against the strategy-based approach and used response time analyses to confirm strategy classifications.

Houpt & Fifić (2017) defined the mathematical tools for combining SFT technology with the hierarchical Bayesian inference.

Fifić & Little (2017) provided a tutorial how SFT methodology can be applied to different experimental paradigms and research domains.

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