How do information processing systems deal with conflicting information? Differential predictions for serial, parallel and coactive models

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Abstract

In this paper, we analyze how different information-processing architectures deal with conflicting information. A robust finding in psychological research is that response times are slower when processing conflicting sources of information (e.g., naming the color of the word RED when printed in green in the well-known Stroop task) than when processing congruent sources of information (e.g., naming the color of the word GREEN when printed in green). We suggest that the effect of conflicting information depends on the processing architectures and derive a new measure of information processing called the *conflict contrast function,* which is indicative of how different architectures perform with conflicts at different levels of salience. By varying the salience of the conflicting information source, we show that serial, parallel, and coactive information processing architectures predict qualitatively distinct conflict contrast functions. We provide new analyses of three previously-collected data sets: a detection task with Stroop color-word stimuli, and two categorization experiments. Our novel measure provides convergent evidence about the underlying processing architecture in the categorization tasks, and surprising results in the Stroop detection task.

Keywords: Response Time, Information Processing, Serial vs Parallel, Coactivation, Conflict

How do information-processing systems deal with conflicting information? Differential predictions for serial, parallel and coactive models.

When people make decisions they are sometimes confronted with sources that provide conflicting information. A driver must slow down upon detection of a pedestrian crossing the road, yet the traffic light could be green at the same time, signaling to go. Conflicting information can take toll on performance, in terms of error rate, response latencies, or both. Perhaps the most prominent laboratory example of a decision based on conflicting information is the Stroop task (e.g., Stroop, 1935; Eidels, Townsend & Algom, 2010): naming the font color of a word when the color and word are incompatible (e.g., the word RED printed in green) is more difficult and takes more time than if the word and its color match (GREEN printed in green). Here, the word "source" and the color source can provide conflicting information as to the correct response. In general and across many psychological tasks decision making is slower and more error prone when both sources are in conflict than when both sources provide congruent information. In this paper, we examine how the human information processing system resolves situations in which conflicting sources of information point to different decisions.

The term conflict is colloquially used to describe a clash, or disagreement between opposing forces. For scientific rigor, we need a more precise and specific definition for "conflict" between two stimulus dimensions. We draw on Livnat and Pippenger's (2006) game theoretic definition of conflict. The basic idea is that two "agents" are in conflict if the utility resultant from one agent's "behavior" could have been higher if the other agent "acted" differently. In adapting this definition to cognitive process models, we treat each individual stimulus dimension as an agent, with the behavior of that dimension simply reflecting the value of the dimension (e.g., the value red on the word dimension, the value green on the color dimension). Utility is a function of the decision that results from an observer extracting evidence from each dimension. In the present context, this decision depends on how the dimensions are combined with respect to different experimental outcomes. For instance, in the standard Stroop task, the decision to respond “red” to the print color occurs more quickly and accurately given the word RED is printed in red than given the word GREEN printed in red. Hence, the dimensions of word and print color are in conflict in the latter example. Livnat and Pippenger used this definition of conflict to describe many different types of internal and external conflict, making it generalizable to the processing of multiple stimulus dimensions.

Behavioral outcomes of processing conflicting information are well-studied in a variety of tasks. In stimulus-response congruency tasks, such as the Stroop task (MacLeod, 1991), the Simon task (Proctor & Vu, 2006; Simon & Rudell, 1967), or the Flanker task (Eriksen & Eriksen, 1974), one source of information is relevant whereas a to-be-ignored second source of information nonetheless interferes with responding. In the categorization domain, two (or more) sources of information could again be either in conflict or in agreement. For example, a participant could be asked to classify a whale as either a mammal or a fish. Rule-based evidence suggests that the biological properties of a whale make it a mammal whereas similarity-based evidence suggests a whale lives in an environment typically populated by trout, sharks and a like, and is therefore a fish. Thus, while one source of information provides the correct category, the other source interferes with responding in a way which increases errors and slows response time (Allen & Brookes, 1991; Folstein, van Petten & Rose, 2008; Nosofsky, 1991; Nosofsky & Little, 2010).

The present paper aims to show that the nature of this interference can be elucidated by considering how multiple sources of information are integrated. In particular, we systematically examine the intimate relationship between conflicting sources of information and the system's processing architecture (e.g., serial vs parallel processing), focusing on how conflicting sources of information affect response time (RT). For instance, if both sources are processed *independently* and in *parallel*, the processing time of a *correct* decision should only be affected by how long it takes to process the correct source (i.e., the minimum processing time); consequently, the conflicting information should not affect responding. By contrast, if the sources are pooled together (into what we refer to as a *coactive* processing channel), the conflicting information will slow responding. Finally, if processing is *serial*, one attribute at a time, then the interference will depend primarily on which source of information is processed first and how long each source takes to process. Schematic illustrations of the three processing architectures are presented in Figure 1. Several popular models that had been put forth to explain human performance in conflict tasks assume that information from various sources is pooled in a coactive (or similar) fashion. For instance, Logan (1980) proposed that Stroop interference arises due to obligatory automatic processing of words but effortful attentive processing of colors. Each of the components is pooled to drive a common random walk process which is used to generate the model's response time predictions. We show how conflicting information can be used to inform inferences about the underlying processing architecture in conflict (e.g., Stroop) and categorization tasks, thereby allowing to test some of the most fundamental assumptions of current theories of these tasks.

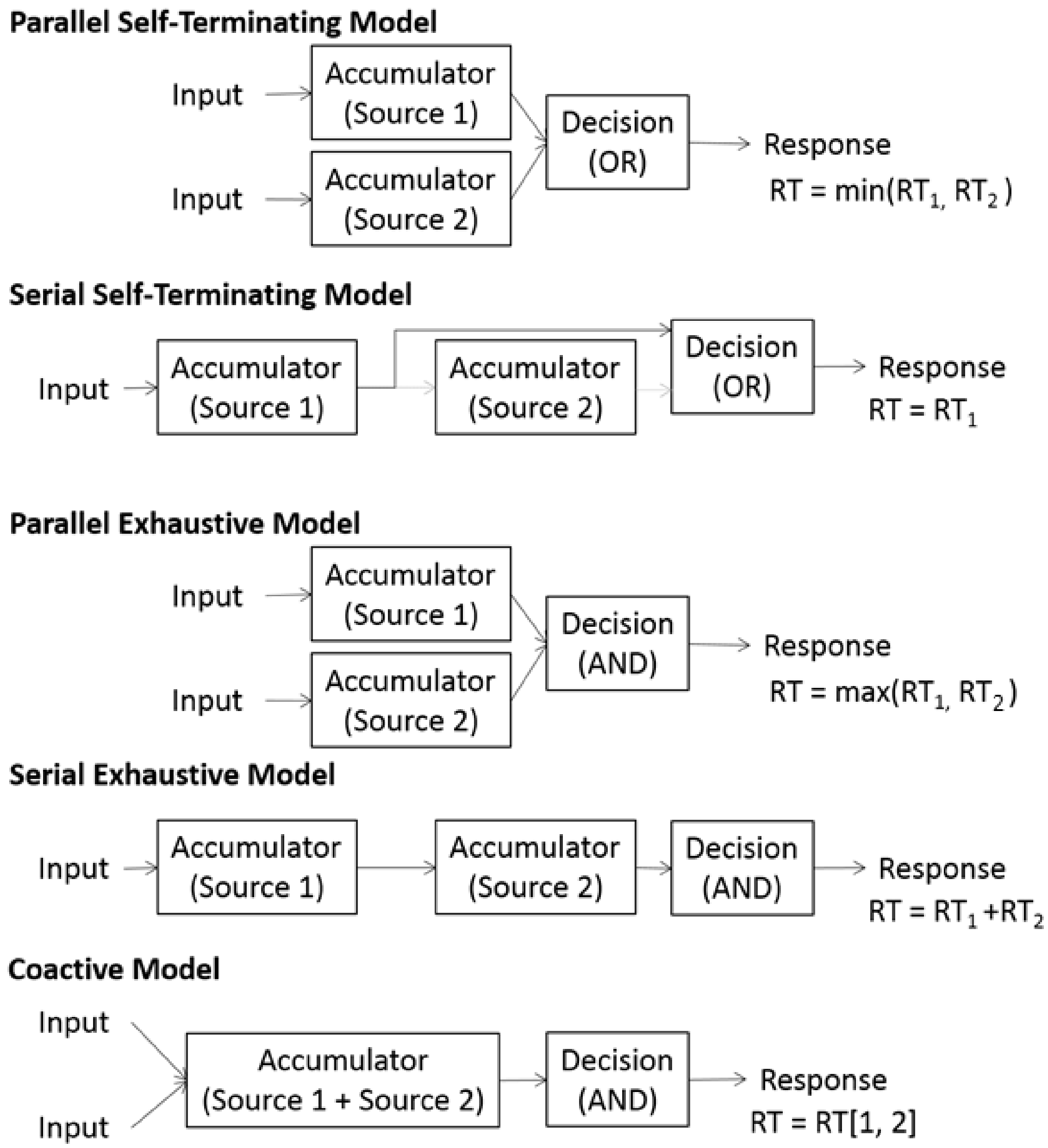

Figure 1. Schematic illustration of the processing models considered in the present work. Generalized predictions for what each of the models predict when self-termination is possible (i.e., an OR task) are shown.

Processing conflicting information is presumably more difficult and requires increased control demands when compared to processing multiple sources of information that are not in conflict. Increased control demands are reported to trigger a shift from parallel to serial processing (e.g., Luria & Meiran, 2005; Fischer & Plessow, 2015; Dosher et al., 2010), yet differentiating serial from parallel processes is a non-trivial feat.

Determining whether multiple sources of information are processed in serial or in parallel or in a coactive fashion is a notoriously difficult problem because these models can mimic the predictions of each other in a variety of tasks (Townsend, 1990a). As a consequence, providing a new tool that can differentiate these models is vital to the study of information processing systems, and human cognition in general. In this paper, we derive a novel measure of information processing, the *Conflict Contrast Function (CCF)*, that can uncover the way conflicting sources of information are processed and integrated. The key insight is this: by contrasting conflicting information at differing interference levels[1] (i.e., an easy conflict and a hard conflict) one can differentiate between parallel, coactive, and serial processing models because each of these models predict a qualitatively different conflict contrast function.

Before presenting the novel *Conflict Contrast Function*, we set up the scene and explain the notation via an example task (a visual target-detection task using Stroop stimuli; Eidels, Townsend, & Algom, 2010). We then briefly survey a set of nonparametric theoretical and methodological analyses known as Systems Factorial Technology (SFT; Little, Altieri, Fifić & Yang, 2017; Townsend & Nozawa, 1995; Townsend & Wenger, 2004). Readers familiar

[1] We use the term "interference" to mean any manipulation that results in a slower response time. This has been alternatively referred to stimulus salience (Townsend & Nozawa, 1995) or stimulus discriminability (Fific, Little & Nosofsky, 2010). Zhang and Dzhafarov (2015) term this assumption *prolongation*. In the context of information conflict, interference or stimulus discriminability are appropriate terms for the strength of the distractor dimension.

with SFT will be able to skip this section. The SFT framework offers RT-based measures that allow inferences about the *architecture* of information processing (e.g., serial or parallel or coactive), decisional *stopping rules*, the *independence* of processing (decisions about each information source are made without influence from the other information sources), and the efficiency of processing (*workload capacity*, or simply *capacity*). Following a brief SFT overview, we present the new conflict contrast function and a summary table with its diagnostic predictions. Like existing SFT measures the CCF is a non-parametric index, meaning it makes no assumptions about the specific distributions of processing times and is thus general and powerful. The novel contrast function provides a useful extension to the SFT set of tools in cases where various information sources could be in conflict. We demonstrate the practical benefits of the CCF by analyzing data sets from two previously published conflict tasks, and conclude by discussing the interpretation of the current results in the context of previous analyses.

Example Task with Conflicting Sources of Information

Eidels et al. (2010; Experiment 2) studied the processing architecture of Stroop-like stimuli made of color-words printed in color. Participants were presented with a single word (either RED or GREEN) printed in color (red or green) and had to respond YES anytime the stimulus contained any “redness” (i.e., if the display contained the word RED, the print color red, or both), and respond NO otherwise (i.e., the target absent display -- word GREEN printed in the color green). The values of the print color and the legibility of the color word were varied to affect their discriminability, as shown in Figure 2. Accordingly, the four stimuli in the bottom right-hand quadrant of the stimulus space contain neither the word RED or red color, so require a NO response. Importantly, both the color *and* the word need to be evaluated to ensure that neither contains any “redness”. Thus, the appropriate decision rule is termed an AND decision rule. Notice this task is not an ordinary Stroop variant; it encourages participants to allocate attention to both color and word dimensions, in contrast to the classic Stroop task in which observers are asked to focus attention exclusively on the color and ignore the printed word.

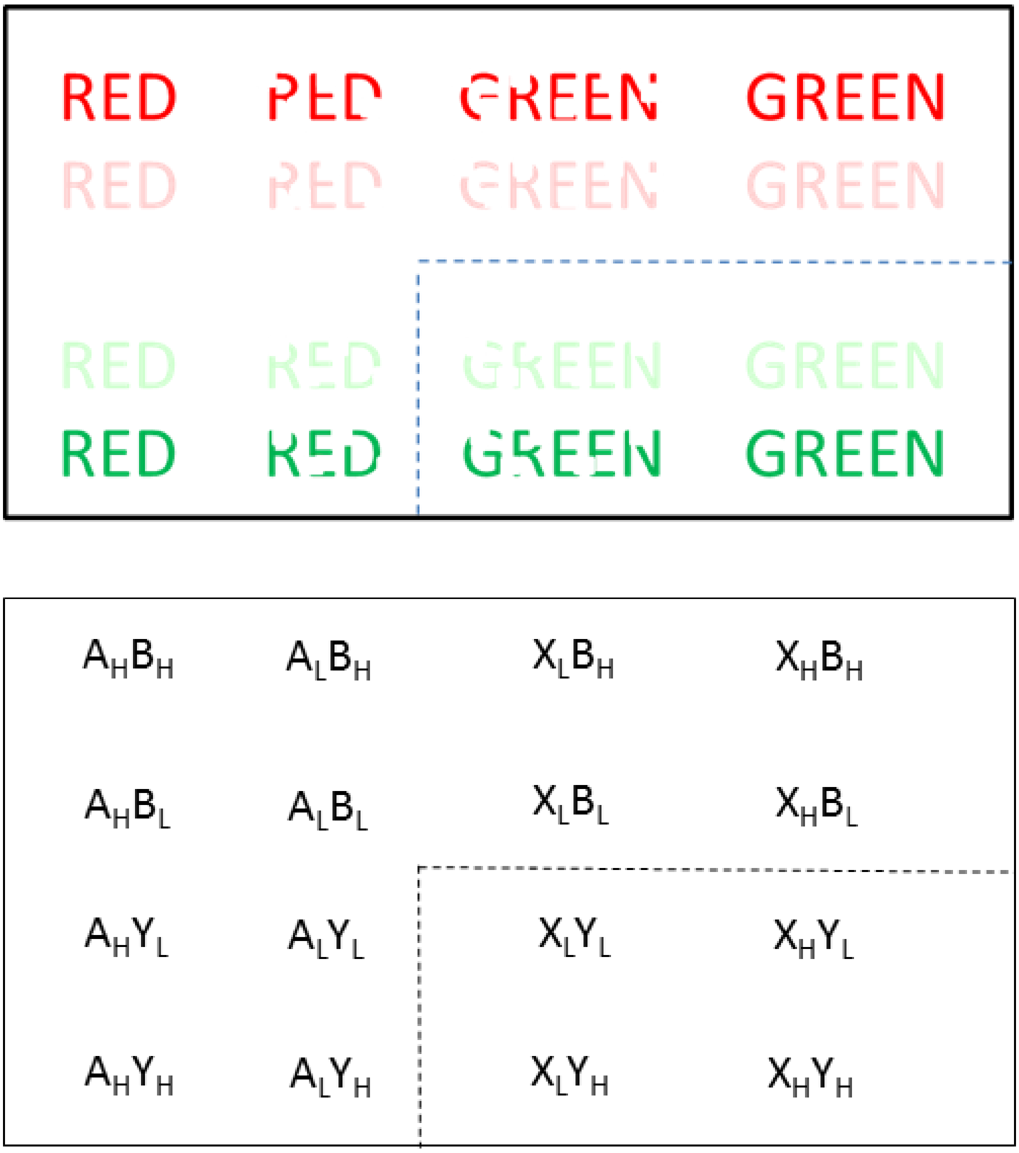

Figure 2. Example of the stimuli and schematic experimental design used in Eidels, Townsend & Algom (2010; Experiment 2). Observers were to respond YES if any "redness" was detected in the stimulus or "NO" otherwise (i.e., for the GREEN in green stimuli). The bottom panel provides the nomenclature that will be used throughout the article. Dimensional values which provide correct evidence for the AND decision response (e.g., in the lower right-hand corner) are labelled X and Y for the word and color dimension, respectively (e.g., X refers to the case when the word green is either a hard-to-read or easy-to-read. Y refers to the color green). The legibility or saturation value is labelled with a subscript L or H for the low and high discriminability values, respectively. Finally, the target information (e.g., redness) is labelled A or B for the word red or the color red, respectively.

Table 1

Glossary of terms

1, 2	Stimulus dimensions; processing channels
AND, OR	Response Sets or Categories
H, L	High interference or discriminability; Low interference or discriminability
A, B	Target information; information sources which provide evidence for the OR set or category response
X, Y	Conflicting information sources which provide evidence for the AND set or category response
AB	Redundant stimulus
AY, XB	Incongruent target stimuli
MIC	Mean Interaction Contrast
SIC	Survivor Interaction Contrast
MRT	Mean Response Time
F(t)	Cumulative Probability Distribution
S(t)	Survivor Function (1 – F(t))
f(t)	Probability density function
CCF	Conflict Contrast Function

The stimuli in the AND set are further distinguished by how easy it is to determine the value of each dimension as either red or green. For the AND set, we use the labels X and Y for the word and color dimensions, respectively. For each item we use the subscripts H and L to indicate the discriminability (High, Low) on each of the dimensions. For instance, the X_HY_H item has high discriminability on both the word and the color dimensions (it this example it would be a highly legible word GREEN and the relatively saturated green color) so they are both easy to tell apart from their (red) 'rivals'. The X_LY_H and X_HY_L stimuli have high discriminability on one dimension and low discriminability on the other dimension. The X_LY_L stimulus has low discriminability on both dimensions (i.e., the word is more difficult to read and the font color is more difficult to determine). Consequently, if both dimensions are processed RTs should be slower for the LL stimulus than the LH or HL stimuli, which in turn should be slower than the HH stimulus.[2] A complete glossary of this terminology is provided in Table 1.

The remaining stimuli can be classified by noting that they contain "redness" either on the word *or* on the color dimension. Thus, they belong to a set defined by an OR decision rule (see Figure 2 again). The *redundant* stimulus set, the word RED printed in red color, contains "redness" on both dimensions. It is also, incidentally, a congruent set (Eidels et al manipulated this contingency in subsequent experiments). The *incongruent* stimuli (GREEN in red, RED in green) contain redness on one dimension but not on the other. In the discussion that follows, we denote the redundant set AB with a subscript specifying the discriminability of the word and the color dimension respectively. Hence, $A_H B_H$ is an easy-to-read RED word presented in a highly saturated red color. The incongruent, *conflict* stimuli are referred to as a mixture of A or B, to indicate the component that satisfies the OR rule (i.e., "redness"), and X or Y, to indicate the component that satisfies the AND rule (i.e., "greenness"). Any AB or XY item in Figure 2 corresponds to a congruent stimulus, whereas AY or XB labels correspond to an incongruent (conflict) stimulus, with the same H and L subscripts indicating the strength of each of the components. For instance, a highly legible (easy-to-read) GREEN word in a highly saturated red font color is termed $X_H B_H$. Hence, in this experiment, the incongruent stimulus, $X_L B_H$ lies on a horizontal (word) continuum between the incongruent stimulus, $X_H B_H$, and the congruent stimulus, $A_H B_H$ (cf. Figure 2). In this sense, the stimulus $X_L B_H$ can be thought of as more "neutral" than $X_H B_H$. Critically, the serial, parallel, and coactive architectures each provide a different set of RT predictions for how stimuli are processed in this space (Fifić, Little & Nosofsky, 2010).

[2] HH could stand for $X_H Y_H$ or $A_H B_H$, LL stands for $X_L Y_L$ or $A_L B_L$, etc. We drop the XY or AB when the stimulus discriminability matters but stimulus content does not.

If processed in *serial*, the decisions concerning each dimension are completed one after the other, and the total RT for items in the AND set is the sum of the RTs on each of the dimensions. If processed in *parallel*, then the total RT for AND set is the maximum of the RTs on each of the independent dimensions. For the coactive model, we assume that rather than making independent decisions on each dimension, the decisions are driven by consideration of information pooled from two dimensions.

A further consideration for serial and parallel models is whether processing can *self-terminate* after processing one of the dimensions or whether both dimensions must be processed *exhaustively*. The stopping rule should be logically determined by the nature of the task; AND task requires both channels to be completed for responses to be correct so naturally calls for exhaustive processing, whereas the OR task can be accomplished based on any one of the channels alone, so self-terminating rule is in place. Empirically, however, that may not necessarily be the case (Bushmakin, Eidels & Heathcote, 2017). For example, conservative observers may process all incoming information in an OR task. Combining the stopping rules with each of the model architectures (except for the coactive architecture for which the self-terminating versus exhaustive distinction has no bearing), allows for qualitatively different predictions for all of the stimuli. The intuitions for these predictions have been described elsewhere (Fifić et al., 2010; Little, 2012; Little, Nosofsky & Denton, 2011; Little, Nosofsky, Donkin & Denton, 2013; Moneer, Wang & Little, 2016; Cheng, McCarthy, Wang, Palmeri & Little, 2017); only a summary of the qualitative predictions is provided here. We outline these known predictions for each of the models in relation to two diagnostic measures developed within the theoretical framework of Systems Factorial Technology. These predictions can be then used in conjunction with the CCF to provide a complete picture of processing.

Systems Factorial Technology: Mean and Survivor Interaction Contrast

Systems factorial technology (SFT) is a model-identification framework developed by Townsend and colleagues (Townsend, 1972, Townsend & Ashby, 1983; Townsend & Nozawa, 1995; see Algom, Eidels, Hawkins, Jefferson & Townsend. 2015, or Altieri, Fifić, Little & Yang, 2017 for an overview). SFT provides a number of measures that can be readily estimated from empirical data. Critically, several models of interest (such as those illustrated in Figure 1) make unique predictions within this framework, so the measures can be conveniently used to tell apart competing accounts. The first measure is best illustrated using Figure 2. Because the stimulus space in the figure contains a factorial combination of stimulus discriminability on each dimension, we can compute the mean interaction contrast (MIC) and the survivor interaction contrast for the AND category stimuli. The MIC is calculated as:

$$MIC = \left(MRT_{LL} - MRT_{LH}\right) - \left(MRT_{HL} - MRT_{HH}\right), \tag{1}$$

where MRT is the mean response time, and the subscripts denote specific stimulus conditions (see Figure 2). In general, serial self-terminating models predict MIC = 0 in both the AND and the OR conditions, parallel self-terminating models predict an *overadditive* MIC (i.e., MIC > 0) in the OR condition and an *underadditive* MIC (MIC < 0) in the AND condition (i.e., because processing is forced to be exhaustive), and coactive models predict and *overadditive* MIC in both conditions.

Greater diagnostic power is afforded by the survivor interaction contrast (SIC), which is computed the same way as the MIC, except using the survivor functions, S(t), for each factorial stimulus instead of mean RT:

$$SIC = \left(S_{LL}(t) - S_{LH}(t)\right) - \left(S_{HL}(t) - S_{HH}(t)\right) \tag{2}$$

The survivor function is one minus the cumulative response-time distribution function (cdf), $S(t)=1-F(t)$, and the subscripts again denote the experimental condition (see Figure 2). SIC is a function over time, and SICs for each of the models take on qualitatively different functional forms. As evident in Figure 3, the SIC can differentiate between self-terminating and exhaustive stopping rules in addition to the different architectures (Townsend & Nozawa, 1995).

In summary, using the design shown in Figure 2, Eidels et al. (2010) applied the diagnostic analyses of Systems Factorial Technology to make inferences about the type of architecture that underlies processing of Stroop color-word stimuli. However, the application of the MIC and SIC measures was limited to the *congruent* AB and XY cases (RED in red and GREEN in green; Figure 2). The current paper extends the analysis to the AY and XB *incongruent* cases (GREEN in red, and RED in green). More broadly, we develop and present the conflict contrast function as a general tool for diagnosing systems that process conflicting sources of information, Stroop and non-Stroop alike. In this example data, we also use the SIC to provide independent, converging evidence to our novel CCF, which we introduce next.

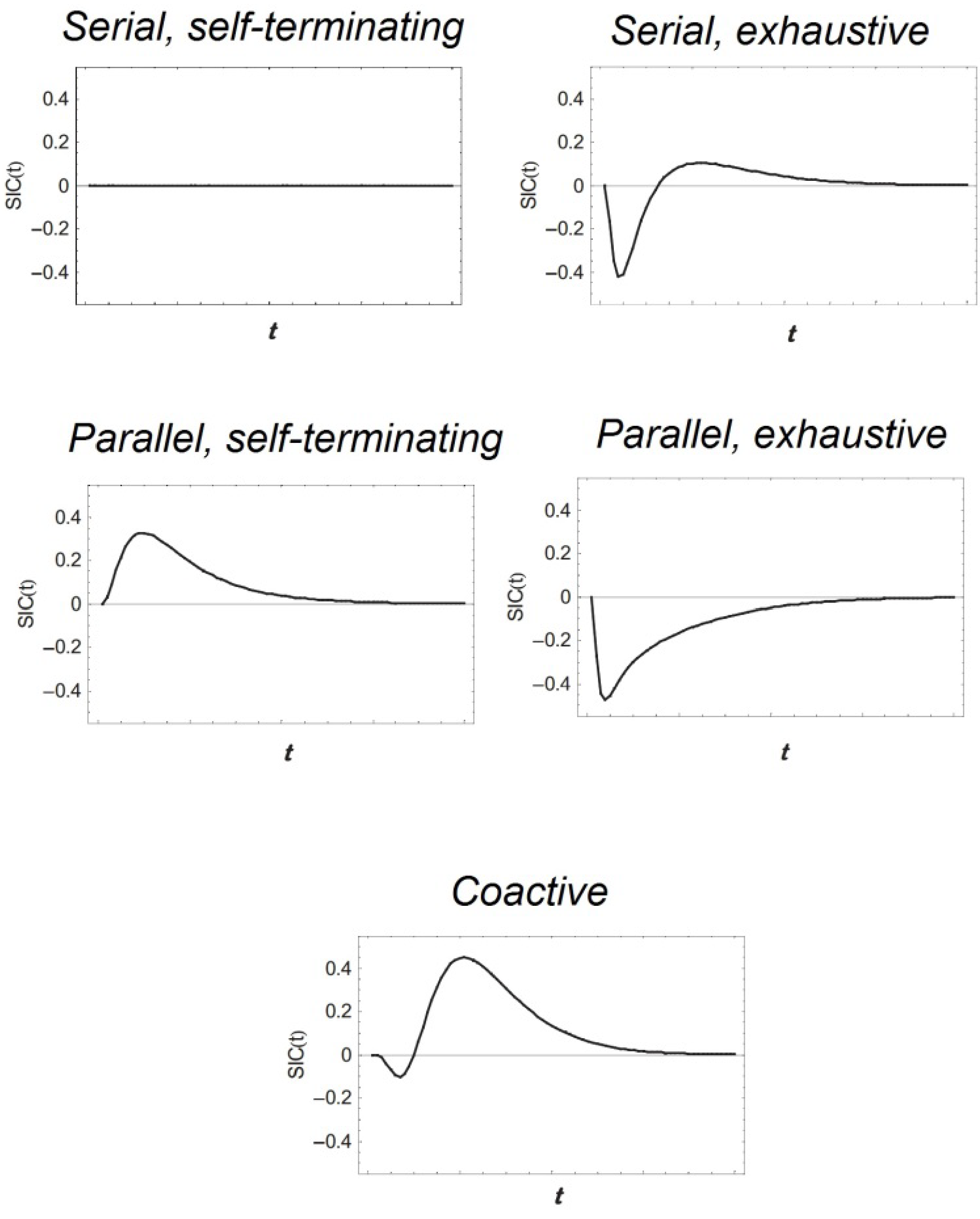

Figure 3. Survivor interaction contrast (SIC) predictions for each of the candidate architectures.

Table 2

Important processing models and their conflict contrast function predictions.

Model	Conflict contrast function (CCF) prediction
Coactive	CCF(t) > 0
Parallel, self-terminating	CCF(t) = 0
Parallel exhaustive	CCF(t) < 0
Serial self-terminating	CCF(t) < 0
Serial exhaustive	CCF(t) < 0

Conflict Contrast Function

Much like the survivor interaction contrast (SIC), the Conflict Contrast Function (CCF) is a contrast between two sets of stimuli (in the Stroop example, combinations of words and colors) that have components which vary in their consequences for response times. For the CCF, the target information (i.e., information that provides evidence for the correct response) is held constant and the conflicting information is varied from low to high discriminability on both stimulus dimensions. The conflict contrast function is expressed as the sum of the differences between log survivor functions of the high and low conflicting information on each stimulus dimension, as follows[3]:

$$CCF(t) = \left(\log\left(S_{AY_H}(t)\right) - \log\left(S_{AY_L}(t)\right)\right) + \left(\log\left(S_{X_H B}(t)\right) - \log\left(S_{X_L B}(t)\right)\right). \qquad (3)$$

S_{AY_H}, S_{AY_L}, $S_{X_H B}$, and $S_{X_L B}$ are the survivor functions for the AY_H, AY_L, $X_H B$, and $X_L B$ item conditions, respectively (see Figure 2). As shown in the Appendices, the CCF is a useful tool

[3] We drop the subscript on A and B because the level of this dimension does not matter so long as it is consistent across both A and B.

for model diagnosis: the conflict contrast function predicts a value of 0 for all *t* for a parallel, self-terminating model; a value greater than 0 for a coactive model; and a value less than 0 for serial self-terminating, serial exhaustive, and parallel exhaustive models. These predictions are summarized in Table 2. Thus, the conflict contrast function is a novel tool that allows differentiation of an important class of processing models. The formal derivation of this function is provided in Appendix A; Appendix B provides a more intuitive explanation for why these predictions hold. Appendix C shows how to implement the CCF (in pseudocode) along with a diagram showing precisely how the item conditions map to the equation in our first application. These predictions follow from similar considerations to the theory of capacity with distractors, termed *resilience,* and the *resilience difference function,* introduced by Little, Eidels, Fifić & Wang (2015; Houpt & Little, 2016; see also Cheng, Moneer, Christie & Little, 2017, for a review).

To illustrate the usefulness of the conflict contrast function, consider the OR set of the Stroop detection task in Figure 2. To respond correctly, an item needs to be perceived as either consisting of the word RED, or the color red, or both. When presented with, say, stimulus AY_L -- the word RED printed in an unsaturated green color -- the color in this stimulus conflicts with the word. Importantly, for item AY_L, analyzing source Y (i.e., the color) alone does not allow an observer to respond accurately; however, under certain models source Y can influence how quickly the correct decision can be made. For an intuitive example, a serial system attempting to detect the presence of redness (e.g., in the word RED in green) that processes color first and then word *cannot* finish as soon as the processing of the low-quality green color was completed, but rather must await the processing of the RED word to respond. Thus, although the green color attribute does not determine the response, it has a direct effect on its time course (namely, slow down). A serial system that starts with the word and then moves on to process color, on the other hand, can yield a quick (and correct) "yes" response as soon as the processing of the RED word is accomplished. The conflict contrast function is sensitive to such processing differences.

Armed with our novel theoretical analyses, demonstrating how conflicting dimensions affect the CCF differentially for each of our candidate processing models (see Table 2 for a summary of models' predictions), in the remainder of this article we compute the CCF for published data from (a) target-detection Stroop task previously reported in Eidels et al. (2010) and (b) a number of previously published categorization studies that all utilized stimulus space akin to that shown in Figure 2 (but with different stimulus dimensions and instructions: Little et al., 2011, Experiment 1; Little et al., 2013, Experiment 1).

In each of the tasks, the original report presented evidence concerning the information processing architecture using the MIC or SIC measure (along with computational modelling confirming that evidence). The original measures were calculated from one set of items (for instance, the AND set in Figure 2); here, we show that the CCF provides complementary evidence using a completely different set of items (e.g., the OR category). In the Stroop detection task, where processing appears to be serial, the CCF is less than 0. In the categorization tasks, we demonstrate that when the dimensions are separable (i.e., dimensions which can be analysed individually; Garner, 1974) and the results are well-described by a serial self-terminating model (or a mixture of serial and parallel self-terminating models in the case of spatially overlapped stimuli), the CCF is less than 0 as predicted. By contrast, when the dimensions are integral (i.e., dimensions which are thought to be processed holistically; Garner, 1974) and the results are well-described by a coactive processing model, the CCF is greater than 0.

Application I. Conflict Contrast Function analysis of a Stroop detection task

Consider the opening example again: a driver approaching an intersection must monitor the traffic lights as well as any crossing vehicles or pedestrians. Either signal (red light, pedestrian crossing) is sufficient to propel a breaking response. Attention thus needs to be split, or divided, across multiple sources of information and a suitable laboratory demonstration should reflect this requirement, while presenting observers with signals that could conflict or not. Eidels et al (2010) tested participants' performance in a standard Stroop task and a divided-attention Stroop detection task. The stimulus set for both tasks was the same, the words RED and GREEN printed in *red* or *green* color. In the standard Stroop task, participants were asked to focus exclusively on one source of information (print color) and ignore the other (content of word), as is the case in scores of Stroop studies. In a separate session participants were again presented with Stroop color-word stimuli, but instructed to divide their attention ("respond YES if you detect the word RED or the color *red*"). This task is an ideal testbed for the CCF as (i) it presents observers with two sources of information that are both relevant, and hence requires divided attention, and (ii) the sources could be in conflict (e.g., RED in *green*) or not (RED in *red*). We used this task in a previous section to illustrate how to compute the new CCF. We use it again now to compute CCF from empirical data. Specifically, we calculate CCF from data previously collected by Eidels et al. (Exp 2).

The CCF is a new development that was not available to Eidels and colleagues. However, as shown in Figure 2, which depicts their original design, there are high-discriminability and low-discriminability conflict items in each condition. This allows us to compute the CCF function at each level of target salience.

First, we calculated whether there is a Stroop effect present in this task. Since the task required detecting the presence of redness of any kind, the congruent stimulus would be one in which the observer had to detect redness in the word RED printed in red color, and the incongruent stimulus would be the word GREEN printed in red. If we average the means of the highly saturated and fully visible combinations (e.g., A_HB_H and X_HB_H, see Figure 2) across the five observers in this task, the congruent stimulus (M = 355.38 ms, SD = 54.90) is faster than the incongruent stimulus (M = 396.7 ms, SD = 96.18), as expected. The means of each observer are also in the same direction. As discussed by Eidels and colleagues (2010; 2012), this difference could be driven by congruency (e.g., as expected by many Stroop models that assume cross-channel interference; the coactive model is an extreme example; Eidels et al., 2011) but could also be driven by statistical facilitation or redundancy, in a system with completely separate channels for color and word processing (e.g., as in a parallel race model). The remaining analyses speak to this theoretical question.

Eidels et al. (2010) calculated SICs for the redundant-target and no-target conditions (RED in red and GREEN in green, respectively; both incidentally congruent). Their primary finding was that word and color of congruent displays (the redundant RED in red) were processed in parallel. They could not, however, examine processing on conflicting conditions (the single-target, incongruent displays: RED in green and GREEN in red) since the SIC is not suitable for this purpose. Processing conflicting information is presumably more difficult and requires increased control demands, which in turn trigger a shift from parallel to serial processing (e.g., Luria & Meiran, 2005). By applying the novel CCF to a set of target-present items containing conflicting information, we can uncover the time course of processing conflicting word and colors. As summarized in Table 2, parallel processing implies CCF=0 whereas serial processing implies CCF<0.

Method and Results

Eidels et al. (2010; Experiment 2) tested five observers in the task illustrated in Figure 2. On each trial, a single word printed in color was displayed on the screen and the observer had to press a designated “yes” key if she detected the word RED, the color red, or both.

Otherwise, if no ‘redness’ was detected (i.e., GREEN in green) the observer had to press the “no” key. The stimulus set comprised 16 items -- the factorial combinations of the words RED and GREEN in high and low discriminability (i.e., each printed in high and low level of legibility) crossed with the print colors red and green in high and low discriminability (saturation). Dimensional discriminability was matched after extensive pilot testing, such that the difference in response latencies between high and low quality of the word was about the same as that between high and low color salience. Each stimulus was presented 400 times over five successive 1.5 hours sessions. Full details of the method are provided in that paper.

Figure 4 shows the CCF(t) functions at each level of target discriminability. Regardless of whether target discriminability was high or low, the contrast of the conflicting dimension resulted in a CCF(t) function less than zero. This indicates that the color and word attributes on incongruent, conflict displays were processed in serial (with either self-terminating or exhaustive stopping) or parallel (exhaustive) processing (cf. Table 2). Either way, the immediate implication is that the redundant, non-conflict trials (i.e., RED in red) enjoy a privileged status: they afford a benefit to processing by allowing independent parallel, self-terminating processing (as reported in Eidels et al.), whereas the presence of conflict information in the incongruent trials (‘greenness’, in this case) results in inefficient processing, regardless of whether it appears in the word or the print color, and regardless of the response associated with the item.

We highlight the value of the CCF analysis by pointing out that one could observe behaviorally that congruent stimuli were processed faster than incongruent stimuli (355 vs 397 ms, as we reported above), but this observation affords little information about the reasons for this difference. The CCF(t) function allows researchers to assess the latent processing characteristics (architecture, stopping rule) of incongruent, conflict items.

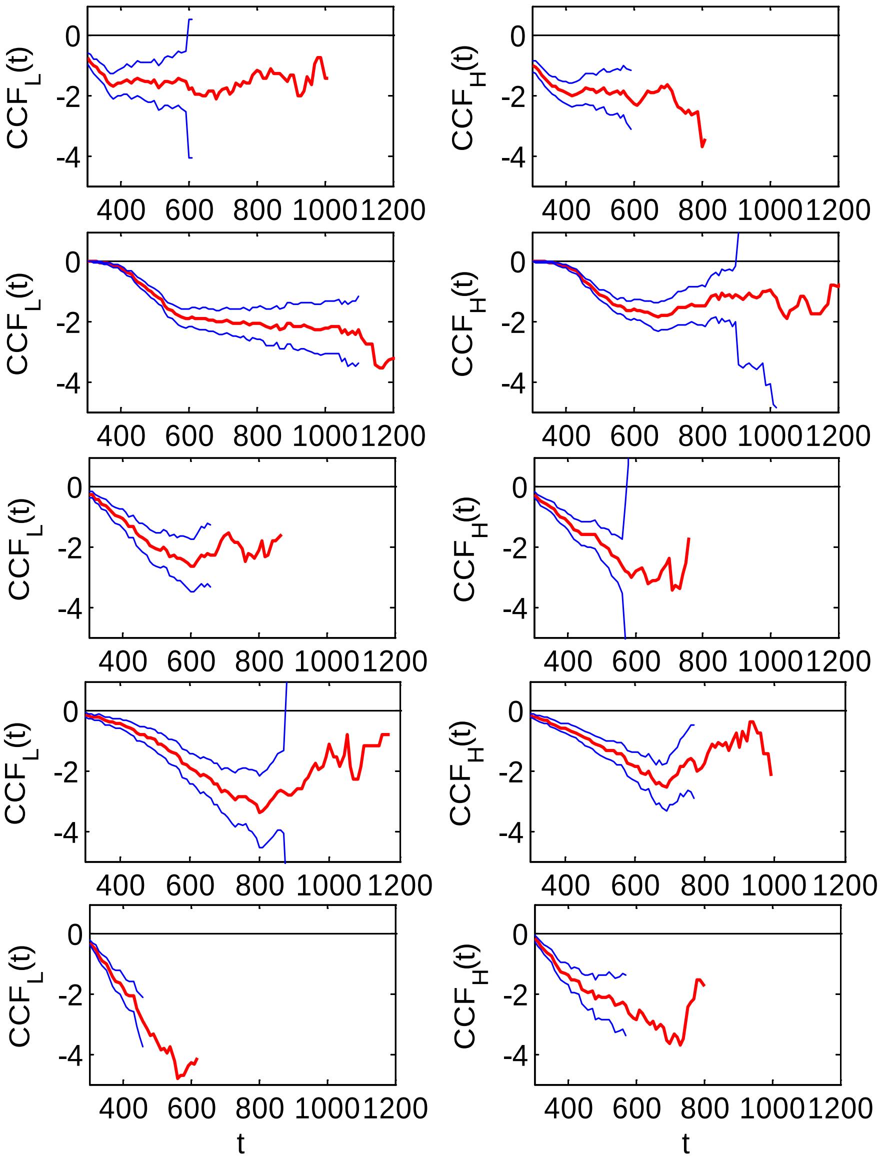

Figure 4. The red lines show the conflict contrast function (CCF) results for five observers from Eidels, Townsend and Algom (2010; Experiment 2). The blue lines above and below are two standard errors. The left-hand panels show the CCF(t) results when the target information was of high salience and the right-hand panels show the CCF(t) results when the target information was of low salience.

Summary

The new analyses of the Eidels et al. (2010) Stroop data provide insight into how architecture varies across different item-types in a Stroop detection task (see Figure 2). The CCF allows us to uncover the processing characteristics of incongruent conflict trials. We found that a complex pattern of architecture that shifts from (i) parallel self-terminating with redundant OR information to (ii) serial self-terminating, serial exhaustive or parallel exhaustive processing with incongruent information to (iii) serial exhaustive processing with the target-absent AND items. The nuanced and subtle interaction between the response rule and the combination of stimulus dimensions is inconsistent with most existing models (see our Discussion below).

The conflict contrast function can be used with a variety of tasks and stimuli. In the next section, we analyse data from a categorization task that uses a similar AND-OR design as the Stroop detection task. In these experiments, computational modelling reported in the original papers indicated that processing was consistent across all of the items. The aims of the CCF analysis of these data are threefold: (a) to provide convergent nonparametric evidence to the existing parametric results, (b) to provide a counterpoint to the Stroop detection task, demonstrating a case where the interaction of stimulus components and response rules is more straightforward, and finally (c) to further demonstrate how the CCF complements existing measures such as the SIC.

Application II. Conflict Contrast Function analysis of Logical Rule Studies of Categorization

We indicated earlier that some psychological tasks, as well as everyday life decisions, require processing of several stimulus attributes or dimensions at the same time (*divided attention*, e.g., ‘is my date both clever and good looking?’), whereas others require processing of certain dimension(s) but not others (*selective attention*, e.g., 'is car A more reliable than car B irrespective of their color?'). If only one target dimension is relevant, then in theory attention can shift away from the distracting dimension and ignore the conflicting information (empirical data suggests differently; slower responses to the incongruent displays on the classic Stroop task imply selective attention could fail). But on those instances where the conflicting information is relevant, successful models of categorization, such as Nosofsky and Palmeri's (1997) Exemplar-based Random Walk model (EBRW) assumes that some attention is given to the conflicting information. A key feature of models like EBRW, and the other primary categorization models of RT, such as stochastic General Recognition Theory (Ashby, 2000), distance-from-boundary models (Ashby & Gott, 1988), and simple diffusion models (Ratcliff, 1978), is that all of the attention-weighted information is pooled into a single processing channel, which is often termed coactive (see Figure 1 again for an illustration of a coactive architecture). Recently, across a number of studies, it has been demonstrated that a dichotomous characterization is more appropriate; stimuli comprised of integral-dimensioned stimuli were well-described by the assumption of coactivity, whereas stimuli comprised of separable dimensions were not (Fifić et al., 2010; Little et al., 2011; Little et al., 2013).

Little et al. (2011; Experiment 1; see also Fifić et al., 2010; Experiment 1) instructed observers to classify stimuli made of separable dimensions that were presented in different spatial locations. The category space was similar to the Stroop detection design with the exception that fewer stimuli were presented in the OR set (see Figure 5). The dimensions for judgment were presented as part of the same object (e.g., base-width and top-curvature of lamp silhouettes, see Figure 6). In this experiment, processing was best explained by a serial, self-terminating model. In another study observers classified stimuli comprised of integral dimensions (Little et al., 2013; Experiment 1; see also Fifić et al., 2008). Contrary to the separable-dimensions study, processing was best explained as a coactive process. Here we calculate the new CCF(t) measure to two distinct data sets, a separable data set (Little et al., 2011) and an integral set (Little et al., 2013); we expect the CCF(t) to be a sensitive measure and uncover different architectures for the different sets – serial for the former and coactive for the latter, as identified previously (see right-most column of Figure 6). Extensive model comparisons conducted in the original papers indicated that both the AND category and the OR category could be handled by the same underlying architecture (serial self-terminating for the separable set, and coactive for the integral set). Consequently, we expect the CCF(t) to lead to the same inference as the SIC, unlike our application to the Stroop stimulus data.

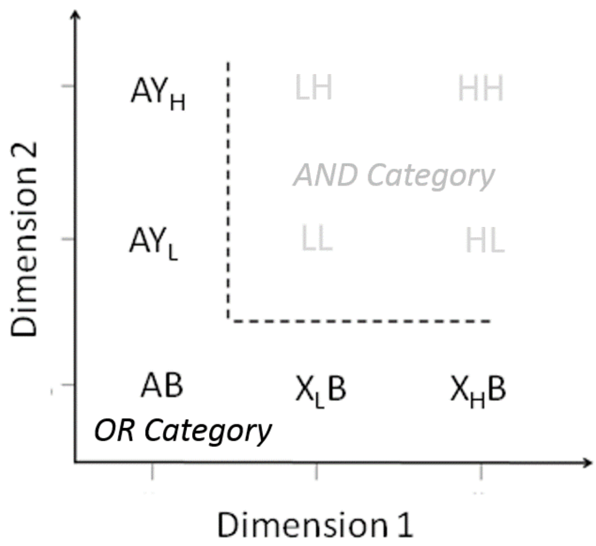

Figure 5. Schematic illustration of the category structure used in the categorization experiments. There are three values for each dimension 1 and 2, combined orthogonally to produce the nine members of the stimulus set. The stimuli in the upper right quadrant of the space are the members of the AND category, whereas the remaining stimuli are the members of the OR category. For the AND category, H and L refer to the high- and low-discriminability dimension values, respectively. The OR category stimulus that satisfies the disjunctive OR rule on both dimensions is denoted as the redundant (AB) stimulus. The remaining OR stimuli are indexed as a combination of one dimension value which satisfies one of the OR rules (either A for dimension 1 or B for dimension 2) and a dimension value which provides evidence for the AND category (X for dimension 1 and Y for dimension 2). The subscripts H and L for the OR category stimuli reflect whether the conflicting information provides evidence for the AND category of high or low salience, respectively. For example, the OR stimulus AY_L provides only weak evidence for the AND category on dimension 2 (i.e., because this dimension is close to the horizontal boundary on dimension 2).

Experiment	Stimulus	X	Y	Best Model
Fifić, Little & Nosofsky (2010; Experiment 2); Little, Nosofsky & Denton (2011; Experiment 1)		Curvature of Top	Base Width	Serial, Self-Terminating
Little, Nosofsky, Donkin & Denton (2013)		Brightness	Saturation	Coactive

Figure 6. Example of the stimuli used in the presently-examined categorization experiments.

Method and Results

The results reported in this section are based on new analyses of data collected in previous studies by Little et al. (2011, 2013). Specific details about the method, as well as mean RT results and error rates are presented in the original papers. The pertinent stimulus space is presented in Figure 5.

In order to investigate how the conflict contrast function is related to architecture in categorization tasks, we present in Figures 7 and 8 the previously-developed SIC(t) along with our newly-developed CCF(t). The SICs are diagnostic of architecture and decisional stopping-rule, and consequently can be used to relate architecture across performance on both the AND and OR category items.

Separable dimensions. The results in Figure 7 show that participants clearly demonstrated serial SIC functions. Further analyses and modeling reported in Little et al. (2011) were also consistent with serial, self-terminating processing. Examination of the CCF(t) functions in Figure 7 reveals that the CCF(t) are less than zero in all cases, commensurate with serial self-terminating, serial exhaustive, and parallel exhaustive models (thus allowing to reject parallel self-terminating and coactive models). In at least one of the cases, the bootstrapped 95% confidence intervals overlap 0 for the CCF(t) indicating larger variability for that observer.

Integral dimensions. For the integral dimensions studied in Little et al. (2013; Experiment 1), the SIC functions consistently support coactive processing in agreement with the analyses and modeling reported in that paper (see Figure 8).[4] All of the reported analyses indicated coactivity for all participants in this experiment (see Little et al., 2013). Likewise, the CCF(t) in Figure 8 are greater than 0 for all subjects, providing converging evidence for coactive processing of these stimuli.

[4] The two exceptions are the negative deflection in the SIC at longer *t*'s for observer 3 and the lack of a small initial deflection for observer 4. For observer 3, we note that examination of the cdfs indicated a violation of stochastic dominance at the same time, *t*, as the negative deflection in the SIC. That is, for observer 3, at around 800 ms, the cdf for the LL stimulus crosses over the cdf for the LH stimulus, thereby violating the assumed ordering of RT distributions. This violation of stochastic dominance renders the latter part of the SIC function uninformative for this subject. Nonetheless, the early part of the SIC function is consistent with coactivity. For observer 4, the lack of an initial small negative deflection might tempt one to conclude that processing is in fact parallel and self-terminating. A parallel, self-terminating model would exhibit a completely positive SIC function (see Figure 3); however, we note that this is unlikely because the target category requires exhaustive processing. Consequently, we suspect that the lack of an initial negative deflection is due to the lack of differentiation between the response time cdfs for fast RTs.

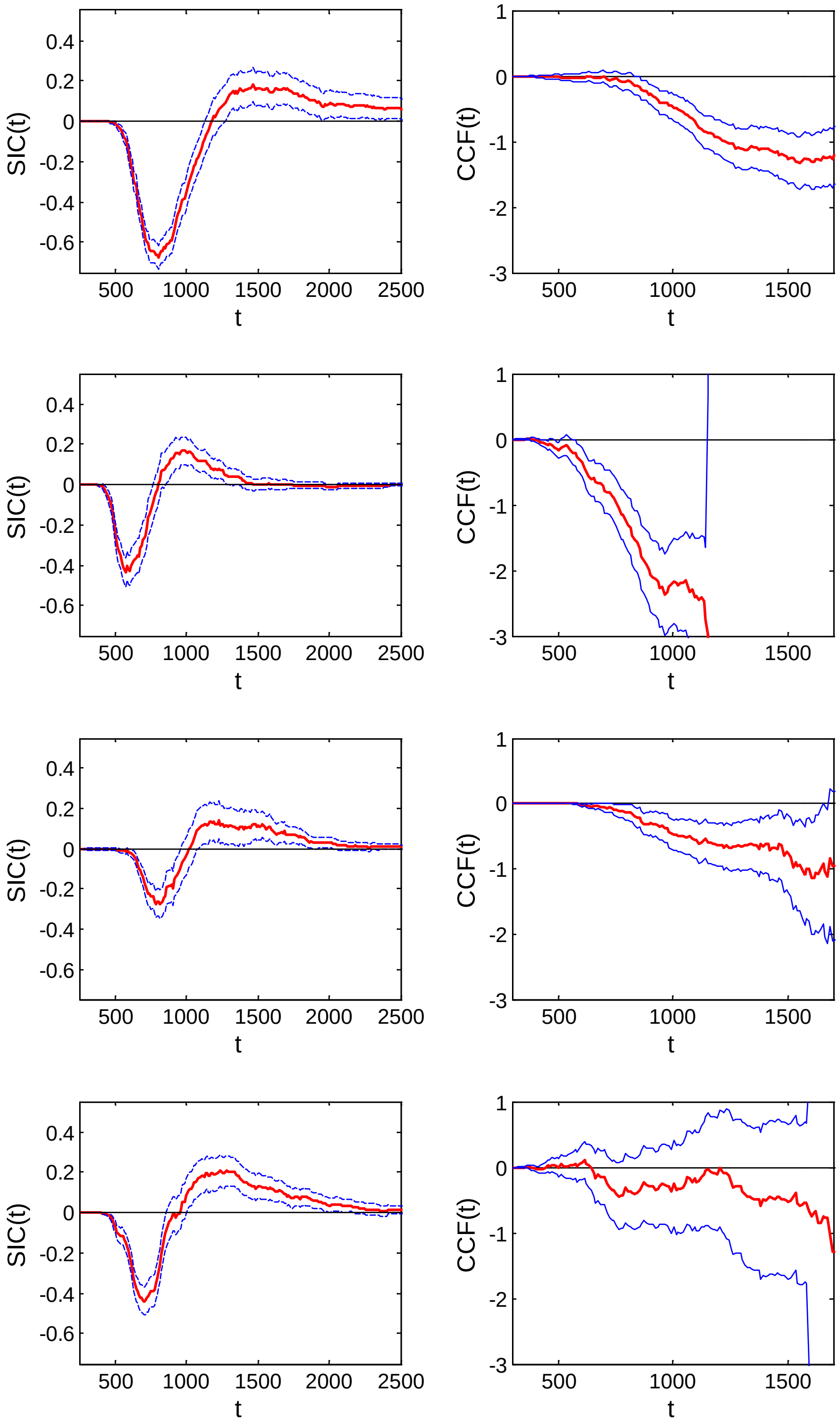

Figure 7. Results from Little, Nosofsky & Denton (2011; Experiment 1). Each row shows the results for a single observer. The first column shows the SIC (the red line is the SIC; the solid horizontal line marks the zero point for all t), and the second column shows the CCF(t) function. In the SIC and CCF(t) panels, the blue lines show two standard error nonparametric bootstrapped confidence intervals. The solid horizontal line in the CCF(t) panel shows the predictions of the baseline unlimited capacity independent parallel model (e.g., CCF(t) = 0).

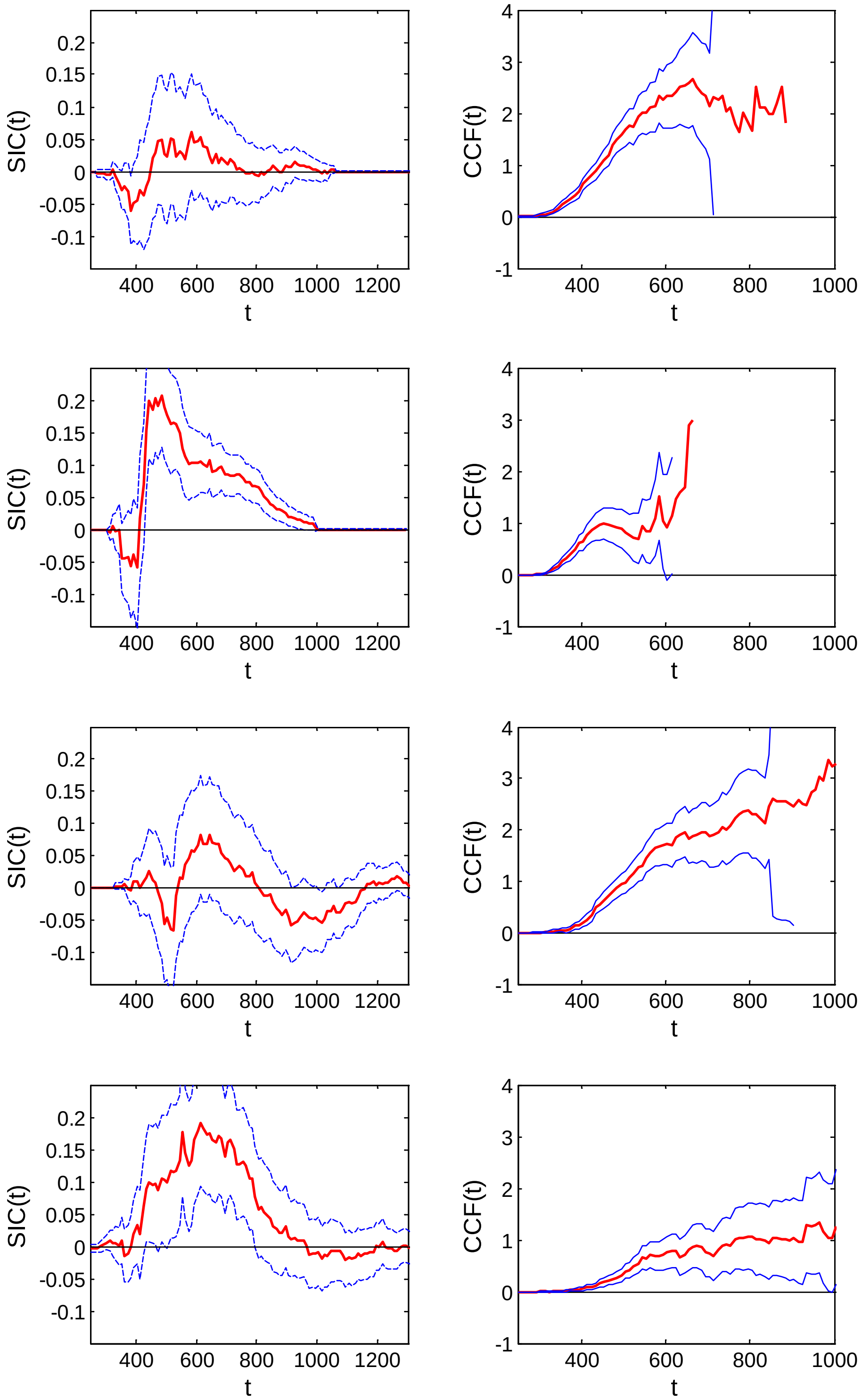

Figure 8. Results from Little, Nosofsky, Donkin & Denton (2013; Experiment 1). Each row shows the results for a single observer. The first column shows the SIC (the red line is the SIC; the solid horizontal line marks the zero point for all t), and the second column shows the CCF(t) function. In the SIC and CCF(t) panels, the blue lines show two standard error nonparametric bootstrapped confidence intervals. The solid horizontal line in the CCF(t) panel shows the predictions of the baseline unlimited capacity independent parallel model (e.g., CCF(t) = 0).

Summary. The results confirm that the CCF(t) provides a novel contrast between serial, parallel, and coactive models. The results provide evidence against a coactive processing model as a viable explanation for the processing of separable stimulus dimensions (Figure 7). As discussed in Fifić et al. (2010), this result effectively rules out most of the prominent models of categorization RT as explanations for the processing of separable dimensions. For instance, models such as the EBRW (Nosofsky & Palmeri, 1997), stochastic General Recognition Theory (Ashby, 2000), and the extended Generalized Context Model (Lamberts, 2000) each assume that the stimulus dimensions are pooled into a single processing channel. While our results show that this explanation works for integral-dimensions stimuli (Figure 8), it is not appropriate for separable dimensions.

Taken together with other qualitative contrasts, such as the SIC, the CCF measure provides a powerful, nonparametric diagnostic tool for analyzing information-processing systems. This inference would not be available without the development of the CCF. The CCF complements the existing SIC-based inference and expands it. It is not a different transformation of the same data, but is rather calculated from different conditions of the experimental design that have been underutilized to date.

General Discussion

In this paper, we developed and applied a novel modeling tool to uncover how conflicting sources of information are processed in the cognitive system. Conflict between various sources of information is a common aspect of many psychological tasks, although it is more obvious in some tasks than in others. For instance, in the Stroop task, the notion of congruency and conflict is obvious due to the matching and mismatching nature of the color and word attributes. More generally conflict arises whenever two sources of information provide evidence supporting two (or more) opposing responses. This can occur in psychological tasks where, for example, a category judgment requires integration of multiple stimulus-dimensions, each governed by different rules or different types of similarity, or it can happen in real world judgments where the validity of a given source may be uncertain.

We demonstrated that different architectures (serial, parallel, and coactive, with an associated stopping rule) differ in the way they are affected by conflicting information. Namely, the correct RT predictions of parallel models are unaffected by conflicting information, serial models are slowed more by weaker conflicting evidence, and coactive models are slowed more by strongly conflicting evidence. We derived a novel measure of information processing, the CCF(t), that makes qualitatively different predictions for standard versions of these models, and thus serves as a useful diagnostic tool for cognitive models.

We reported two applications of the CCF to existing data sets, one that served for validation purposes, and the other analyzing conditions that could not have been utilized before, revealing surprising results. We validated the CCF(t) by comparing it to previous categorization studies that used other non-parametric measures of information processing (Little et al. 2011, 2013; described in Application II). The agreement between these measures indicates that the CCF(t) complements the set of existing tools (Townsend & Nozawa's, 1995, mean and survivor interaction contrasts), which were also capable to differentiate the standard models. In addition, we extended the investigation of the underlying properties of the cognitive system to cases that could not be studied using existing non-parametric contrasts. Specifically, we showed how the CCF(t) could be applied to previously unharvested data cells in a conflict task. In the Stroop detection task developed by Eidels et al (2010) subjects were presented with color names printed in color and had to detect the presence of 'redness' in either the word or color dimensions. The existing contrasts, MIC and SIC, delivered evidence in favor of parallel self-terminating processing of color and word information, but could not be applied to the conflict conditions (i.e., RED in green and GREEN in red displays). The surprising result that the CCF and the SIC disagree leads us to conclude that the architecture or stopping rule changes when conflict is detected. That is, application of the new CCF to the conflict conditions revealed an architecture that is either serial or parallel-exhaustive, suggesting a staggering architecture change when moving from the processing of non-conflict to conflict displays (possibly due to increased control demands, Luria and Meiran, 2005). Some caution should be taken since this inference is post-hoc, and future work should consider what processes allow for this type of switching to occur.

The key benefit of the CCF(t) over existing measures is that it requires only varying the salience of one of the experimental factors at a time rather than both factors simultaneously as for the MIC and SIC. This constrained variation, of one factor at a time, is typical in many experimental situations. For instance, in stimulus-response congruency like the Simon task, it is common to systematically vary the degree of conflict by altering the location of the stimulus (which is irrelevant to determining the response), but holding the cue to response (e.g., the color of the cue) constant. Future research could apply the CCF to divided attention versions of Simon task or and other conflict tasks.

The additional analyses conducted here allowed a more detailed understanding of performance in conflict tasks and provided additional constraints for theoretical explanations of these tasks. In the remainder of the article, we briefly discuss the theoretical implications of the CCF for models of various conflict tasks. We then discuss the relation of the new CCF measure to two other related applications: the mean RT predictions for the OR category items in the logical rule tasks reported by Fifić et al. (2010), and the workload capacity coefficient developed by Townsend and Nozawa (1995). We conclude by discussing potential limitations of the CCF and possible remedies.

Models of Conflict Tasks

Many models of conflict tasks are best characterized as coactive in that they assume information is pooled across sources to some degree (though see Teodorescu & Usher, 2013, for an alternative conception of conflict and competition between sources of information). We have mentioned Logan's (1980) theory of Stroop interference, but this is also true of other theories of Stroop performance. For instance, Cattell's (1886, as cited in MacLeod, 1991) *relative speed of processing theory* assumes that words are read faster than colors are named and interference arises because the word and color compete for the response (see also Posner & Snyder, 1975; Treisman, 1969). Cohen, Dunbar, and McClelland (1990) developed a parallel distributed processing model in which the activation of the font color and the color word are differentially weighted by the task demands (i.e., selectively attending to the color dimension) and summed to determine the activation of each of the possible responses (e.g., red or green), which in turn drives evidence accumulation in competing response accumulators. Melara and Algom (2003) introduce an information-based theory of Stroop interference in which variable perceptions are filtered through short-term memory and attention to activate long-term memory representations, which in turn drive accumulation of evidence to a threshold. By contrast, our analysis suggests that the task demands of processing incongruent stimuli lead to a shift from parallel (when congruent) to serial processing (when incongruent) of Stroop stimuli.

Models of other tasks, such as the Simon task, can also be characterized as coactive. For example, in Yamaguchi and Proctor's (2012) Multidimensional Vector model of the Simon task, stimuli are coded as points representing the values of the relevant color information and the irrelevant position information compared projected onto a variable decision axis. Due to variability in the decision axis orientation, this representation is equivalent to signal detection theory (Green & Swets, 1966). The integral of the distribution function (area under the curve) up to a criterion is used to drive a counting process which is used to predict the response times. The model predicts slower response times for incongruent information than congruent information because the former has a smaller probability of accumulating evidence for the correct response than the latter. Hence, like models of the Stroop task, information in the multi-dimensional vector model is pooled into a single decision process and can be classified as coactive (see e.g., Fifić et al., 2010).

Models of the flanker task are also best characterized as coactive. For instance, Logan (1996; see also Logan, 2002) examined the predictions of Bundesen's TVA model ('Theory of Visual Attention', an independent parallel race model; Bundesen, 1991) on the flanker task and showed the model predicted increased error rate but no effect of conflicting flankers on RT. To deal with the discrepancy between TVA's predictions and the empirical results, Logan modified TVA by allowing stimulus information to drive a single counter process (Logan, 1996) or a random walk process (Logan, 2002). More complex information-accumulation models have been developed since, yet these models also involve pooling of information into a single channel. For example, White, Ratcliff, and Starns (2011) proposed a shrinking-spotlight model in which the information driving the evidence accumulation processes includes the conflicting information at the start of the trial, but the influence of the distracting information is gradually reduced as attention focuses on the target.

To summarize, these different models characterize information-processing towards a decision in different ways, but all of the models assume that information is pooled into a common decision mechanism. Consequently, these models can all be classed as coactive processing models. Whereas most models of the conflict tasks have focused on the detailed specification of mechanisms that produce certain patterns of RTs, an alternative approach, which we adopt here, is to consider the fundamental predictions for whole classes of models (Logan, 2007; Townsend & Nozawa, 1995; Townsend & Wenger, 2004). This meta-theoretical approach can then be used to derive nonparametric predictions allowing some model classes to be ruled out. For instance, our analysis of the Stroop data rules out pure coactive processing since the processing of incongruent stimuli is best captured by serial processing. One interpretation of this result is that the divided attention task leads to different types of processing than in the standard selective attention Stroop task. Alternatively, fast detection of conflict might trigger the initiation of control processes that result in a different strategy for categorizing incongruent stimuli compared to congruent stimuli.

Relation to Mean RT predictions

Fifić et al. (2010) introduced the mean RT predictions for the OR category items in the categorization design shown in Figure 5. These predictions follow the basic logic of the CCF(t) model predictions that we derive here. Using simulations and intuitive explanations of the models, Fifić et al. showed that parallel self-terminating models predict no difference in the mean RTs between the conflicting stimuli for any level of conflict salience, whereas serial models predict that low levels of conflict salience will be slower than high levels of conflict salience.[5] Coactive models predict that low levels of conflict salience will be faster than high levels of conflict salience. It is not clear from their paper, however, whether these predictions are contingent on specific parameter settings of the models. It therefore useful to consider how we might relate the mean RT predictions to the CCF's predictions. Townsend (1990b) showed that if $H_A(t) > H_B(t)$ for all t then $F_A(t) > F_B(t)$ for all t, where H(t) is the

[5] These predictions may not be generally true but apply to the categorization design in Figure 5. For instance, Teodorescu and Usher (2013) studied competition between dynamically varying luminance patches where the decision was to determine which patch had on average the higher brightness. In their task, varying the level of competition could change the RT predictions of the parallel model. To make their task commensurate with ours, one would need to examine two *pairs* of patches with the outcome of the brightness decision on each pair being combined using a logical decision gate.

integrated hazard function (i.e., -ln(S(t))) and F(t) is the cumulative distribution function of response times. This in turn implies that Mean(T_A) < Mean (T_B), where T is the random variable for response times and the subscript indicates the condition. We note that $F_A(t) > F_B(t)$ also implies that: $S_A(t) < S_B(t)$, and taking the logarithm of the survivor function does not change the ordering (for any 0<S(t)<1) so $\log\left[S_A(t)\right] < \log\left[S_B(t)\right]$. Likewise, $\log\left[S_A(t)\right] < \log\left[S_B(t)\right]$ implies that $F_A(t) > F_B(t)$ and, consequently, Mean(T_A) < Mean (T_B). Hence, if $\log\left[S_H(t)\right] > \log\left[S_L(t)\right]$ then Mean(T_H) > Mean (T_L) and vice versa. We can then write a mean conflict contrast function, MCCF(t), as:

$$MCCF(t) = \left(M_{AY_H} - M_{AY_L}\right) + \left(M_{X_H B} - M_{X_L B}\right),$$

where M_{AY_H} is the mean RT for stimulus condition AY_H.

Of course, averaging the two high-salience conflict items and the two low salience conflict items does not change the qualitative direction of the difference so finding the mean RTs and testing whether the MCCF is different from zero, by using an independent samples t-test, would allow a simple method of statistically evaluating the contrast. Such an approach was employed by Little et al. (2013) to argue that integral stimulus dimensions are processed coactively but separable dimensions are processed independently. The CCF generalizes this approach to the entire response time distribution and relevant statistical tests can be generalized from the related capacity and resilience functions (Houpt & Little, 2016).

Relation to Workload Capacity

As detailed in the Appendix A, our derivation of the CCF starts from the assumption that parallel, self-terminating models predict that the observed RT for a redundant target stimulus (e.g., AB) should be equal to the minimum derived from two single targets (e.g., AY and XB). Townsend and Nozawa (1995) used this property as a baseline in their derivation of a measure of the workload capacity of an information-processing system. Their measure assesses how processing efficiency changes between cases where the system is processing one target (e.g., A or B alone) compared to cases where the system is processing two or more target signals (e.g., AB). Unlike the traditional approach to understanding capacity, which operationally defines capacity as a single number capturing the amount of information that can be stored in or manipulated by the cognitive system (e.g., Kahneman, 1973), Townsend and Nozawa's capacity coefficient is a function that describes the efficiency of the processing system over the entire time course of processing.

Like the CCF, the capacity function of a parallel, independent self-terminating model is unaffected by the number of targets to process; this property is termed unlimited capacity. Under certain assumptions, serial models, which process information sequentially, predict limited capacity because increasing the number of the to-be-processed items slows down the overall processing time of the system (e.g., Townsend & Ashby, 1983). By contrast, coactive models, which pool together information from multiple processing channels, predict super-capacity because increasing the number of items to be processed speeds up the overall processing time beyond what is expected by independent-parallel processing (Townsend & Nozawa, 1995; Townsend & Wenger, 2004).

Although the CCF and Townsend's workload capacity function may look close in form, the capacity coefficient cannot be applied directly to the example data in the studies examined here since the "single targets" are 'contaminated' by conflicting information. The predictions of the capacity coefficient take into account only the change in load, from one target to two (or more) targets. One would need to consider the properties of the capacity coefficient when the single targets are not presented in isolation but rather contain additional information. In general, the presence of conflicting information could change the derived minimum-time predictions of a system, making it either easier or harder for the redundant targets to exceed it. Consequently, the diagnosticity of the capacity coefficient for architecture would likely break down in the presence of conflicting information. Nonetheless, one could "salvage" the function by contrasting the capacity function when the nontarget dimension was of high and low salience in the same manner that we apply here. Such an approach is described in Little, Eidels, Fifić & Wang (2015; Houpt & Little, 2016) in their derivation of the resilience function. Cheng et al. (2017) present converging results to our Application II using the resilience difference function.

Limitations of the CCF(t)

Like all modeling exercises, our present analysis relies on a number of key assumptions which may not hold in all situations. For instance, like the capacity coefficient (Townsend & Nozawa, 1995) or the related race model inequality (Miller, 1982; Townsend & Eidels, 2011), the CCF requires context invariance (i.e., that the target information - A or B - does not change its processing rate depending on the other information that is presented with it; see Colonius, 1990; Townsend & Eidels, 2011). This assumption may be easily violated in many situations (see Yang, Altieri & Little, 2017). To take one pertinent example: for the categorization tasks that have been studied in the present article, Fifić et al. previously developed a set of cognitive process models in which the rate of processing is determined by the volume of a perceptual distribution which lies in each category region (i.e., as in multivariate signal detection theory; Ashby & Gott, 1989). The assumption of context invariance would imply that the marginal distributions for, say, dimension A were equal across all levels of the other dimension. This assumption is known as perceptual separability. Violations of this assumption via either mean shift (i.e., a change in the mean location of A with levels of the other dimension) or variance shift (i.e., a change in the variance of A with levels of the other dimension) would result in different rates of processing for A at different levels of the other dimension (Cheng et al, 2017). Consequently, the CCF(t) function can also reflect violation of context invariance in this way.

We also require *selective influence* (Schweickert, Fisher & Sung, 2009; Townsend & Nozawa, 1995) of the different levels of salience of the conflicting dimensions. This means that, when tested alone, the high salience conflict dimension should elicit faster RTs than the low salience conflict dimension such that the survivor functions are ordered for all t (i.e., $S_H(t) < S_L(t)$). Of course, this property cannot be readily assessed from performance on the incongruent target stimuli (i.e., containing target information and conflicting information) because the ordering of these stimuli will depend on the processing architecture. This is, of course, what determines the diagnosticity of the conflict contrast function. This means that assessing this assumption would require independent evidence of the speed at which individual dimensions are processed. However, we feel this assumption is relatively mild since varying the discriminability of any dimension will change the RT as has been demonstrated empirically many times (Link,1992; Luce, 1986; Johnson, 1939; Piéron, 1914, 1952).

Finally, we apply the present analyses only to data from correct responses. The reason for this is two-fold: First, in the tasks presented here, error rates are often unaffected by conflict whereas RTs are substantially slower. Consequently, our presentation of the CCF mirrors the initial development of the workload capacity coefficient, which was initially developed to account for correct RTs (Townsend & Nozawa, 1995) and only later extended to error RTs (Donkin, Little, & Houpt, 2014; Townsend & Altieri, 2012). Second, considerations for how a serial or a parallel model predict error responses is complicated by the fact that the failure of a single decision process may or may not lead to an error response. For instance, if one's task is to respond "mammal" to the question of whether a whale is a mammal or a fish, if ANY of the sources of information (e.g., biological or similarity-based) leads to a mammal outcome, then the response will terminate incorrectly only if the biological-based source fails but the similarity-based source does not. Other combinations of failures will still result in a correct response. Consequently, predicting errors for information processing models with more than one decision component is more complex than in simpler decisions (e.g., Laming, 1968; Ratcliff, 1978; Ratcliff & Rouder, 1998). In fact, redundancy of information allows for complicated error-recovery processes which we are trying to model in a different line of work. Nonetheless, the types of conflict that we examine in this paper are likely to increase error rates in many situations, particularly in cases where there are speed and accuracy tradeoffs.[6] We consider the development of error RT predictions for more complex mental architectures to be of paramount importance; however, we leave this development as a challenge for future research.

[6] We thank Philip Smith for highlighting this issue.

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Appendix A

Derivation of Conflict Contrast Function

Starting from the minimum time relationship implied by the parallel processing model:

$$S_{AB}(t) = S_{AY}(t) \times S_{XB}(t)$$

where *S(t)* is the survivor function for stimulus conditions AB (congruent target) or AY or XB (incongruent target), one can take the negative logarithm to convert these functions to integrated hazard functions (see e.g., Luce, 1986; Townsend & Nozawa, 1995). Rearranging the function then gives for an unlimited capacity, independent, parallel self-terminating model:

$$1 = \frac{-\log\left[S_{AY}(t) \times S_{XB}(t)\right]}{-\log\left[S_{AB}(t)\right]}$$

In the present case, we term this function the *inverse OR capacity plus distractors function* (ICPD) and note that the relationship between the derived minimum time and the observed redundant target time is exactly the opposite of what is expected under Townsend & Nozawa's (1995) capacity function. That is, if the derived minimum time is slower than the observed redundant target time, then the ratio on the right will be less than 1, but if the derived minimum time is faster than the observed redundant target time, then the ratio on the right will be greater than 1.

The key diagnostic contrast occurs when the distractor is high salience and when the distractor is low salience.

$$ICPD^{diff}(t) = ICPD_H(t) - ICPD_L(t)$$
$$= \frac{-\log\left[S_{AY_H}(t)\times S_{X_H B}(t)\right]}{-\log\left[S_{AB}(t)\right]} - \frac{-\log\left[S_{AY_L}(t)\times S_{X_L B}(t)\right]}{-\log\left[S_{AB}(t)\right]}$$

If we allow the negative sign to cancel out and multiply through by $\log\left[S_{AB}(t)\right]$, then this leaves us with the difference between the log product of the survivor functions for the high and low salience single targets plus conflict sources.

$$\begin{aligned}\log\left[S_{AB}(t)\right]\times ICPD_{diff} &= \log\left[S_{AY_H}(t)\times S_{X_H B}(t)\right] - \log\left[S_{AY_L}(t)\times S_{X_L B}(t)\right]\\ &= \log\left(S_{AY_H}(t)\right) + \log\left(S_{X_H B}(t)\right) - \log\left(S_{AY_L}(t)\right) - \log\left(S_{X_L B}(t)\right)\\ &= \left(\log\left(S_{AY_H}(t)\right) - \log\left(S_{AY_L}(t)\right)\right) + \left(\log\left(S_{X_H B}(t)\right) - \log\left(S_{X_L B}(t)\right)\right)\end{aligned}$$

Hence, the diagnostic predictions are given by the sum of the difference between the high and low salience distractors on each dimension.

We term this function the *conflict contrast function*:

$$CCF(t) = \left(\log\left(S_{AY_H}(t)\right) - \log\left(S_{AY_L}(t)\right)\right) + \left(\log\left(S_{X_H B}(t)\right) - \log\left(S_{X_L B}(t)\right)\right)$$

The properties of this function provide qualitative distinctions between serial, parallel and coactive processing models if the following assumptions hold:

1. The processing rate of stimulus dimension A and B do not vary as a function of the other dimensional value. This assumption is known as context invariance (Colonius, 1990; Townsend & Eidels, 2011).

2. The RT of the high salience conflict dimension is faster than the low salience conflict dimension for all t. This assumption is known as stochastic dominance (Schweickert, Fisher & Sung, 2009; Townsend & Nozawa, 1995).

Appendix B

Intuitive predictions for each of the processing models

Parallel, independent, self-terminating model

If processing is parallel self-terminating and each channel (e.g., 1 or 2) is processed independently, then the RT is determined by the minimum channel processing time. That is,

$$F_{12}^{parallel}(t) = 1 - \left(\left[1 - F_1(t)\right] \times \left[1 - F_2(t)\right]\right), \tag{4}$$

which gives the cumulative distribution function for the minimum time distribution (or alternatively, in terms of the survivor functions, $S_{12}^{parallel}(t) = S_1(t) \times S_2(t)$). Note, that for stimuli containing conflicting information, processing the conflict sources X and Y does not allow one to make a correct response; only the target sources A and B allow one to correctly respond (e.g., in the categorization task shown in Figure 2). In other words, the independent, parallel self-terminating model is unperturbed by the presence of conflicting information. Hence, the above equation when applied to stimulus AY_L (or AY_H) reduces to:

$$\begin{aligned} F_{AY_L}^{parallel}(t) &= 1 - \left(\left[1 - F_A(t)\right] \times \left[1 - F_{Y_L}(t)\right]\right) \\ &= 1 - \left[1 - F_A(t)\right] \\ 1 - F_{AY_L}^{parallel}(t) &= 1 - F_A(t) \\ S_{AY_L}^{parallel}(t) &= S_A(t) \end{aligned} \quad . \tag{5}$$

In words, this means that the survivor function for a given dimension A, $S_A(t)$, is the same irrespective of the value or presence of the distractor in the other dimension. The same relationship holds for stimuli X_LB and X_HB. Hence, the discriminability of the conflicting source does not matter, and the CCF function equals 0:

$$
\begin{aligned}
CCF^{parallel}(t) &= \left(\log\left(S_{AY_H}(t)\right) - \log\left(S_{AY_L}(t)\right)\right) + \left(\log\left(S_{X_H B}(t)\right) - \log\left(S_{X_L B}(t)\right)\right) \\
&= \left(\log\left(S_A(t)\right) - \log\left(S_A(t)\right)\right) + \left(\log\left(S_B(t)\right) - \log\left(S_B(t)\right)\right) \\
&= 0
\end{aligned}
$$

Serial, self-terminating model

The RT probability density function (pdf) of a serial, self-terminating model for the *incongruent target* stimuli are:

$$f_{AY}^{serial}(t) = p\left[f_A(t)\right] + (1-p)\left[f_Y(t) * f_A(t)\right] \tag{6}$$

and

$$f_{XB}^{serial}(t) = p\left[f_X(t) * f_B(t)\right] + (1-p)\left[f_B(t)\right], \tag{7}$$

where $f_A(t)$ and $f_B(t)$ are the pdf's associated with processing correct sources A and B, and $f_X(t)$ and $f_Y(t)$ are the pdf's associated with processing the conflicting sources X and Y. AY and XB are the stimuli comprising one correct source and one conflicting source. Under a serial, self-terminating model, the pdf for these stimuli is a mixture of trials on which one dimension is processed first (with probability p) and other trials in which the other dimension is processed first (with probability $1 - p$). On some of these trials, the first processed dimension will provide evidence for the OR set response (i.e., when A or B is processed first) allowing the decision to terminate. On other trials, the conflict information (i.e., X or Y) will be processed first requiring the remaining dimension to be processed before the decision can be terminated accurately. For instance, if one processes the environmental properties of whales first, then the decision will not be able to terminate accurately until the second dimension, biological properties, is processed.

For a serial self-terminating model, the discriminability of the conflicting information matters. The high discriminability conflict dimension should not slow down the stimulus as much as the low discriminability conflict dimension. To explain, in the *conflict* conditions (i.e., the incongruent stimuli), if the high discriminability distractor is faster than the low discriminability distractor (i.e., $S_{Y_H} < S_{Y_L}$) and if the processing rate of A (or B) does not depend on the other dimension, then $S_{AY_H}(t) = S_{AY_L}(t)$ if p = 1 and $S_{AY_H}(t) < S_{AY_L}(t)$ if p < 1 because $1 - \int\left[f_{Y_H}(t) * f_A(t)\right]dt < 1 - \int\left[f_{Y_L}(t) * f_A(t)\right]dt$; and analogously for stimuli $X_H B$ and $X_L B$. Hence, since $S_{AY_H}(t) <= S_{AY_L}(t)$ and $S_{X_H B}(t) <= S_{X_L B}(t)$, then the inequalities also hold for the log of the survivor function and $CCF^{serial}(t) < 0$.

For the latter inequality to hold, we require that the assumptions stated above hold for all *t*. Namely, we require that $S_{Y_H}(t) < S_{Y_L}(t)$ and $S_{X_H}(t) < S_{X_L}(t)$ indicating an effective manipulation of conflict discriminability (i.e., the high discriminability conflict presented alone provides stronger evidence for AND category than the low discriminability conflict presented alone). Note that we only require the ordering of survivor functions for the conflicting information (i.e., the high conflict on its own should be faster than the low conflict on its own; this may generally not be true if the high or low conflict is paired with the target information source, A or B). This assumption is typically termed *stochastic dominance* and is a crucial underlying assumptions of techniques based on the manipulation of salience to uncover information processing architecture (Schweickert, Fisher & Sung, 2009; Townsend & Nozawa, 1995). The second assumption is that the processing rate of the target information (i.e., the A component of AY_H and AY_L and the B component of $X_H B$ and $X_L B$) does not vary as a function of the salience of the conflicting information. This assumption is termed *context invariance* (Colonius, 1990; Townsend & Eidels, 2011) and plays an important role in techniques aimed at uncovering the capacity of information processing. Here we combine both of these assumptions.

Coactive processing model

The intuition for the prediction of a coactive model when dealing with conflicting information is that the rate of processing will be slowed down more by high discriminability target than by a low discriminability target; consequently, $S_{AY_H}(t) > S_{AY_L}(t)$ and $S_{X_H B}(t) > S_{X_L B}(t)$ and CCF > 0. To explain, consider the effect of pooling together two conflicting information sources. The final rate of processing will depend on the relative strengths of each of these sources of information. The higher the discriminability of the conflicting source, the slower the rate of accumulation of evidence for the correct OR category response. Different versions of this pooling process have been proposed. Townsend and Nozawa (1995) applied their proofs to a version of a counter model which pooled counts from different sources into a single decision process. Houpt and Townsend (2012) proved that the same diagnostic measures held for a coactive model based on the Weiner diffusion model (e.g., Ratcliff, 1978). Likewise, Fifić et al. (2010; see also Ashby, 2000) proposed a process model in which the area under a bivariate normal distribution in the OR category region provided evidence for a sequential sampling model which determined the RT associated with each stimulus. (This is contrasted with serial and parallel models in which independent sequential sampling models are driven by the marginal normal distributions along each dimension). The high discriminability incongruent stimuli were predicted to be slower for the coactive model because more of the bivariate normal distribution overlapped with the AND category and not the OR category compared to the low discriminability incongruent stimuli. The CCF function shows that this relationship will hold for any coactive model so long as the assumptions of stochastic dominance and context invariance are met.

Exhaustive processing models

In a parallel exhaustive model, all sources must be processed to completion regardless of whether the target source has finished processing. The cumulative density functions of the incongruent targets are $F_{AY}(t) = F_A(t) \times F_Y(t)$ and $F_{XB}(t) = F_X(t) \times F_B(t)$.

In a serial exhaustive model, like a parallel exhaustive model, all sources must be processed regardless of whether the target source is processed first or not. The RT density functions for the incongruent targets are, $f_{AY}(t) = f_A(t) * f_Y(t)$ and $f_{XB}(t) = f_X(t) * f_B(t)$. $f_{AB}(t) = f_A(t) * f_B(t)$, where the * symbol indicates the convolution integral of the two target densities.

For both exhaustive models, because of the stochastic dominance relationship between the high and low salience conflicting sources, the low discriminability conflict source will slow down the incongruent targets more than the high discriminability conflict source. Hence, in both cases, $S_{AY_H}(t) < S_{AY_L}(t)$ and $S_{X_H B}(t) < S_{X_L B}(t)$ and CCF < 0.

Appendix C

Tutorial on using the Conflict Contrast Function

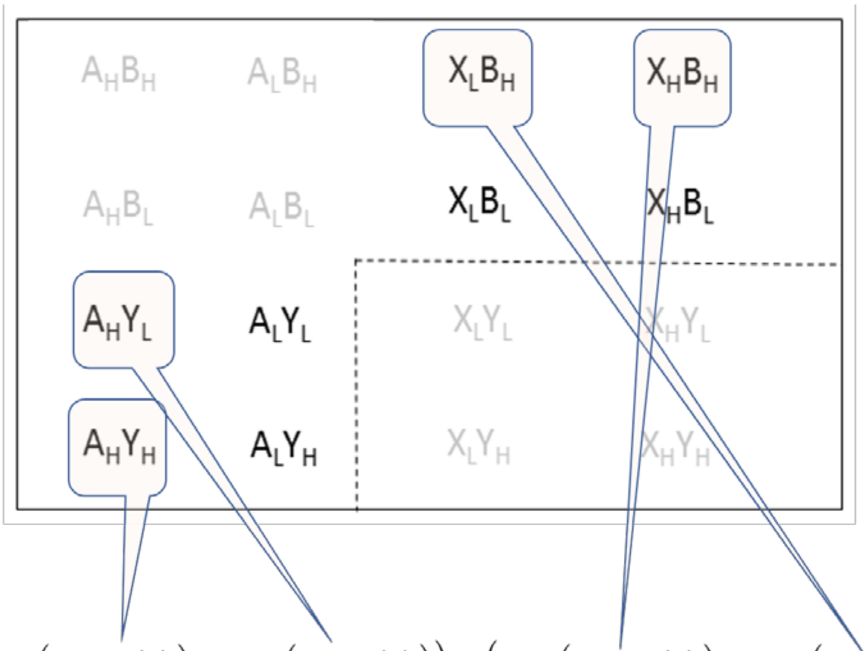
A number of good tutorials have been recently published on the application and use of Systems Factorial Technology (SFT). We direct the reader to chapters by Algom et al. (2015), Altieri et al. (2017), and Harding, Goulet, Jolin, Tremblay, Villeneuve and Durand (2016) along with the comprehensive volume on SFT (Little et al., 2017). Along with the original theorems (Townend & Nozawa, 1995; Townsend & Wenger, 2004), these papers cover the underlying theory along with updated developments in SFT. However, they do not necessarily address hands-on use of the analyses. Houpt, Blaha, McIntire, Havig & Townsend (2014) have released an [R] package (sft) and comprehensive tutorial on using SFT. The sft library includes commands for computing the SIC (`sic`) and the CCF (`conflict.contrast`), along with associated statistical tests for these measures and others (see Houpt & Townsend, 2010, 2012; Houpt & Little, 2016). In this appendix, we provide pseudocode to illustrate the processing pipeline using pre-processed data to plot the SIC and CCF functions to create the figures for Application 2. Our GitHub page contains the full data and analysis code (in MATLAB) for all of the analyses in this paper: https://github.com/knowlabUnimelb/CONFLICT_FUNCTION.

In the following Figure C1, we analyze a datafile that has been preprocessed to remove outlying RTs and error RTs. We assume a data file with two columns: one indexing the relevant condition (i.e., HH, HL, LH, LL, AY_H, AY_L, X_HB, X_LB, AB; see Figure 5 for reference) and another with the response time (RT). We demonstrate the calculation of the empirical survivor function using a histogram method, although other estimation methods are possible (e.g., ecdf, kernel density estimation, censored survivor functions). Figure C2 shows a schematic of how the item conditions from the design correspond to the CCF analysis.

```
% Data matrix
data = [item, rt]

% Create separate vectors for each item condition
HH = rt[item == ‘HH’]
HL = rt[item == ‘HL’]
LH = rt[item == ‘LH’]
LL = rt[item == ‘LL’]
AYH = rt[item == ‘AYH’]
AYL = rt[item == ‘AYL’]
XHB = rt[item == ‘XHB’]
XLB = rt[item == ‘XLB’]
AB = rt[item == ‘AB’]

% Set up a vector of time bins
mint = min(min(rt), 5)
maxt = max(rt) + 100
t = mint:10:maxt

% Compute CDF for each target item condition
%     hist is a function which counts the rts in each bin of t
cdf.HH = cumsum(hist(HH, t))/length(HH)
cdf.HL = cumsum(hist(HL, t))/length(HL)
cdf.LH = cumsum(hist(LH, t))/length(LH)
cdf.LL = cumsum(hist(LL, t))/length(LL)

% Compute the survivor function for each target item
S.HH = 1 – cdf.HH
S.HL = 1 – cdf.HL
S.LH = 1 – cdf.LH
S.LL = 1 – cdf.LL

% Compute SIC
SIC = S.LL – S.HL – S.LH + S.HH

% Bootstrap confidence intervals for SIC
for i = 1:nBootStrapSamples
      % Randomly sample with replacement a new set of rts for
        each item
      boot.HH = sampleWithReplacement(HH, length(HH))
      boot.HL = sampleWithReplacement(HL, length(HL))
      boot.LH = sampleWithReplacement(LH, length(LH))
      boot.LL = sampleWithReplacement(LL, length(LL))

      % Compute S for new bootstrapped data
      Sboot.HH = 1-cumsum(hist(boot.HH, t))/length(boot.HH)
      Sboot.HL = 1-cumsum(hist(boot.HL, t))/length(boot.HL)
      Sboot.LH = 1-cumsum(hist(boot.LH, t))/length(boot.LH)
      Sboot.LL = 1-cumsum(hist(boot.LL, t))/length(boot.LL)

      SICboot[:,i] = Sboot.LL – Sboot.HL – Sboot.LH + Sboot.HH
end

% Compute standard deviation of bootstrapped samples [along the columns]
stdSIC = std(SIC, 2)

plot(t, sic)
plot(t, 2 * stdSIC + SIC)

% Compute CCF
% Compute CDF for each conflict item condition
```

```
%     hist is a function which counts the rts in each bin of t
cdf.AYH = cumsum(hist(AYH, t))/length(AYH)
cdf.AYL = cumsum(hist(AYL, t))/length(AYH)
cdf.XHB = cumsum(hist(XHB, t))/length(XHB)
cdf.XLB = cumsum(hist(XLB, t))/length(XLB)

% Compute the survivor function for each target item condition
S.AYH = 1 – cdf.AYH
S.AYL = 1 – cdf.AYL
S.XHB = 1 – cdf.XHB
S.XLB = 1 – cdf.XLB

% Compute SIC
CCF = (log(S.AYH) – log(S.AYL)) + (log(S.XHB) – log(S.XLB))


% Bootstrap confidence intervals for CCF
for i = 1:nBootStrapSamples
      % Randomly sample with replacement a new set of rts for
       each item
      boot.AYH = sampleWithReplacement(AYH, length(AYH))
      boot.AYL = sampleWithReplacement(AYL, length(AYL))
      boot.XHB = sampleWithReplacement(XHB, length(XHB))
      boot.XLB = sampleWithReplacement(XLB, length(XLB))

      % Compute S for new bootstrapped data
      Sboot.AYH = 1-cumsum(hist(boot.AYH, t))/length(boot.AYH)
      Sboot.AYL = 1-cumsum(hist(boot.AYL, t))/length(boot.AYL)
      Sboot.XHB = 1-cumsum(hist(boot.XHB, t))/length(boot.XHB)
      Sboot.XLB = 1-cumsum(hist(boot.XLB, t))/length(boot.XLB)

      CCFboot[:,i] = (log(Sboot.AYH) – log(Sboot.AYL)) +
                    (log(Sboot.XHB) – log(Sboot.XLB))
end

% Compute standard deviation of bootstrapped samples [along the columns]
stdCCF = std(CCF, 2)

plot(t, CCF)
plot(t, 2 * stdCCF + CCF)
```

Figure C1. Psuedocode implementation of the SIC and CCF.



$$CCF(t) = \left(\log\left(S_{AY_H}(t)\right) - \log\left(S_{AY_L}(t)\right)\right) + \left(\log\left(S_{X_HB}(t)\right) - \log\left(S_{X_LB}(t)\right)\right)$$

Figure C2. Illustration of how different item conditions contribute to the computation of the CCF for the high target salience level (A_H and B_H). An analogous assignment of item conditions to the equation is used for the low target salience level (A_L and B_L).