Identifying Relationships Between Cognitive Processes Across Tasks, Contexts, and Time

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Abstract

It is commonly assumed that a specific testing occasion (task, design, procedure, etc.) provides insight into psychological phenomena that generalise to other, related testing occasions. However, this assumption is rarely tested in data. When it is tested, the two existing methods of comparison have one of the following two shortcomings: they either correlate summary statistics like mean response time or accuracy, which does not provide insight into relationships between latent psychological processes, or they first assume independence in cognitive processes across tasks and then, in a second step, test whether there is in fact a relationship. Our article develops a statistically principled method to directly estimate the correlation between latent components of cognitive processing across tasks, contexts, and time. Our method simultaneously estimates individual participant parameters of a cognitive model at each testing occasion, group-level parameters representing across-participant parameter averages and variances, and across-task covariances, i.e., correlations. The approach provides a natural way to “borrow” data across testing occasions, which increases the precision of parameter estimates across all testing occasions provided there is a non-zero relationship between some of the latent processes of the model. We illustrate the method in two applications in decision making contexts. The first assesses the effect of the neural scanning environment on model parameters, and the second assesses relationships between latent processes underlying performance of three different tasks. We conclude by highlighting the potential of the parameter-correlation method to provide an “assumption-light” tool for estimating the relatedness of cognitive processes across tasks, contexts, and time.

Keywords: Cognitive model, correlation, covariance, individual differences, latent processes, LBA model.
Introduction

Evidence accumulation models of simple decisions, such as the linear ballistic accumulator (Brown & Heathcote, 2008) and the diffusion model (Ratcliff & Rouder, 1998), began as theoretical tools to understand the cognitive processes of simple decision making. However, these models are now increasingly used as psychometric tools in clinical and applied research. For example, there is extensive research using the diffusion and LBA models showing that older adults perform slower on simple cognitive tasks mostly because of changes in the speed with which motor response actions are executed, and not due to decreased processing speed, as was traditionally theorised (Forstmann et al., 2011; Ratcliff, Spieler, & McKoon, 2004; Ratcliff, Thapar, & McKoon, 2006, 2007). Other investigations have addressed questions about clinical disorders, for example finding differences in decision making processes for people with anxiety (White, Ratcliff, Vasey, & McKoon, 2010), depression (Ho et al., 2014), schizophrenia (Heathcote, Suraev, Curley, Gong, & Love, 2015; Matzke, Hughes, Badcock, Michie, & Heathcote, 2017), and ADHD (Weigard & Huang-Pollock, 2014).

In applied investigations using evidence accumulation models, researchers typically do not emphasise choices about the particular decision making task that is used. The task is typically chosen to be amenable to modelling, allowing many decisions in a session, with clearly-timed events within each one, and to have some validity as a measure of the cognitive process under investigation (e.g. a flanker task to measure attention, or a stopping task to measure inhibitory control). Despite the limitations of every decision task, investigators presumably intend their inferences to generalise beyond the specific task that was chosen. For example, Ho et al. (2014) concluded that people with depression exhibit a general slowdown in the speed of information processing, compared with a control group. This conclusion was based on the analysis of parameters estimated using data from a random dot motion task. Ho et al. assume that parameters estimated from other perceptual decision-making tasks would have led to similar results, for the same sample of participants. The more general assumption here is that there is some consistency in the parameter estimates across tasks for individuals.

Given the extensive use of evidence accumulation models as measurement tools (Ratcliff, Smith, Brown, & McKoon, 2016), there has been some investigation of the psychometric properties of the models, and particularly of the reliability and validity of the estimated parameters. Voss, Rothermund, and Voss (2004) tested the criterion validity of the diffusion model by manipulating aspects of the task which could be expected to selectively influence different model components: manipulating the difficulty of the stimuli selectively influenced parameters related to processing rate, manipulating the cautiousness of the decision makers selectively influenced parameters which balanced urgency vs. caution, and so on. Literally dozens of experiments have confirmed that model parameters related to processing speed are reliably effected by changes in the difficulty of the decision itself – motion coherence, visual contrast, etc.. Other experiments have investigated changes between
people rather than between conditions. Ratcliff, Thapar, and McKoon (2010) investigated the known-groups validity of the diffusion model by showing that individuals with a higher IQ also produce higher drift rate estimates. Using the LBA model, Ho et al. (2014) found that people with depression yield smaller drift rate estimates than controls. Similar studies have shown expected differences in parameters for people with anxiety (White et al., 2010), ADHD (Weigard & Huang-Pollock, 2014), and schizophrenia (Heathcote et al., 2015; Matzke, Love, & Heathcote, 2017).

The psychometric reliability of parameter estimates has been less carefully investigated than validity. Using the LBA model, Lerche and Voss (2017) examined correlations between parameters estimated from two different tasks: lexical decisions and recognition memory for pictures. Subjects in that experiment participated in two different sessions, and Lerche and Voss observed very weak correlations in parameters across tasks for data from the first session. Data from the second session, however, provided stronger correlations. Ratcliff et al. (2010) used two similar tasks (lexical decision, and recognition memory for words) and observed reliable correlations in almost all parameters of the diffusion model. Ratcliff, Thompson, and McKoon (2015) investigated numeracy using four different decision-making tasks. In that investigation, parameters of the diffusion model related to processing speed correlated across tasks, but the other model parameters did not. Mueller, White, and Kuchinke (2019) also used the diffusion model, and analysed data from an experiment in which one group of participants completed two tasks related to emotion perception: one task used word-based stimuli, the other used faces. Mueller et al. found that parameters of the diffusion model related to response style and non-decision time were more strongly correlated across tasks than drift-related parameters, on average. Similarly, Hedge, Vivian-Griffiths, Powell, Bompas, and Sumner (2019) found moderate-to-good correlations between response caution parameters of the diffusion model across Flanker, Stroop and random dot motion tasks.

Clearly, the properties of the decision making task influence parameter estimates – this is sometimes expected and desired, such as when stimulus properties related to decision difficulty influence drift rate estimates. However, it is important to establish that there is some reliable correlation in parameter estimates across tasks, in order to support the assumption that results observed using one particular decision making task can generalise to other, related, decisions.

We investigate correlations in latent cognitive processes across tasks, using the LBA model. An important theoretical contribution of our work is that we directly estimate between-task parameter correlations as part of the model. Previous investigations have always estimated parameters for different tasks independently, and then examined correlations in those estimated parameters afterwards. Instead, our approach involves estimating parameters for multiple tasks simultaneously, while also estimating the correlations between those parameters. This approach has important statistical and methodological benefits, as well as scientific advantages. Estimating parameters using data from multiple tasks allows for “borrowing” of information across the tasks, analogous to the borrowing that takes place between participants in a repeated measures design. This opens up exciting new possibilities. For example, some data collection procedures have subjects participate in several different decision-making tasks, such as those in a psychological test battery. This approach naturally restricts the amount of data collected for each individual task, making cognitive
modelling of those tasks difficult or impossible. However, modelling the tasks jointly, and estimating the correlation in parameters across tasks, allows for information from one task to inform parameter estimates for other tasks. As long as some consistency in parameter estimates can be expected across tasks, this approach can allow analysis of data not previously possible.

Applications

We apply our methods to data from two decision-making experiments: one first reported by Forstmann et al. (2008), and one new experiment. Forstmann et al.’s experiment had $n = 19$ participants repeatedly judge the direction of motion of a cloud of moving dots. On some decisions, participants were encouraged to be very urgent (“speed emphasis”), on other decisions they were encouraged to be very careful (“accuracy emphasis”), and on still others to balance speed and accuracy (“neutral emphasis”). Each participant practised the task for more than an hour, in a regular lab environment, and then later also performed the task while in a magnetic resonance imaging (MRI) scanner. See p.17541 of the original article for full details of the method.

Van Maanen, Forstmann, Keuken, Wagenmakers, and Heathcote (2016) investigated differences in performance between decisions made in and out of the scanner, using the LBA model, and found differences in parameter estimates from the two sessions. Our interest here is in the parameter correlations between sessions. Except for the differences induced by the scanner environment, Forstmann et al.’s experiment provides an opportunity to examine the reliability of the model parameters. There are several possible reasons why parameters estimated in and out of the scanner may differ: sampling error from the finite number of trials per person; different effects of the scanner environment on different people; and actual changes in the latent cognitive processing of the participants across time. Our investigation uncovers what commonality remains in parameter estimates beyond these effects.

The experiment reported by Forstmann et al. (2008) uses an identical decision-making task in the two sessions. What changes between sessions is the environmental context (the MRI scanner vs. the lab) and also the amount of practice (the lab session always came before the MRI session). The second data set we analyse had participants undertake three tasks. The order of task administration was randomised across participants, to avoid the practise effect present in Forstmann et al.’s experiment. The three tasks were chosen to share some common elements, including the basic visual properties of the stimulus, but to differ in their cognitive demands. One task used visual search – finding a feature conjunction amongst distractors that shared the same features in different combinations. The difficulty of the visual search task was manipulated by changing the number of distractor items. Every display always included a target item, and the participant’s task was to subsequently report the location of a search-irrelevant feature on that target.

Another task was identical to the visual search task, but with an added component of response inhibition. In the “stop” task, a random 25% of trials were interrupted by a signal which instructed the participant to withhold their response. The stop-signal task has become important for measuring and understanding inhibitory control in basic and applied investigations (Logan & Cowan, 1984), but it is also not easily amenable to cognitive modelling (Matzke, Hughes, et al., 2017; Matzke, Love, & Heathcote, 2017). As such, we analysed data from trials which were not interrupted by a stop signal. The third task used
the same visual stimuli, but tested participants’ short term memory. This “match” task required participants to decide whether the stimulus array shown on one trial had the same set of stimuli (perhaps in different locations) as the stimulus array shown on the preceding trial. The match task is a variant of the “n-back” task, which is a widely used and very difficult memory test. We manipulated the difficulty of the match task by changing the number of items in the stimulus array. See Appendix A for full details of the experiment.

Modelling Correlations in Latent Cognitive Processes Across Tasks

We develop an approach to modelling across-task correlations in the latent processes by linking the parameters of evidence accumulation models of decision making across those tasks. Evidence accumulation models are named by their shared premise that when making a decision, evidence is accumulated for each choice alternative until a threshold amount is reached, which triggers a decision. For an LBA model of a two-choice decision, there are two accumulators, one corresponding to each response (see Figure 1). The speed of evidence accumulation is called the “drift rate”, and this randomly varies from decision-to-decision, reflecting changes in attention and internal states (Ratcliff, 1978). In the LBA model, the distribution of drift rates is usually assumed to follow a normal distribution truncated to positive values, although other distributions are also possible (Terry et al., 2015). The mean of the drift rate distribution is usually larger in an accumulator for a response alternative which matches the stimulus (a “correct” response) than one that does not, but on any particular trial, sample drift rates maybe be quite different. We use \( v_c \) and \( v_e \) to denote the means of the drift rate distributions in the correct and error accumulators, respectively, and assume a variance of \( s^2 = 1 \) for all drift rate distributions. The other source of random variability in the LBA model concerns the amount of evidence with which each accumulator begins. This “starting point” is randomly sampled for each accumulator and each decision, from a uniform distribution of width \( A \). Evidence accumulation continues until the first accumulator reaches a threshold value, which is \( b \) units larger than the maximum starting point. Threshold crossing triggers a response, which is delayed by some fixed constant \( t_0 \), representing the time taken for processes outside of decision-making, such as stimulus encoding and the execution of the motor response.

Reflecting the reality of inter-twined cognitive systems, and like all cognitive models, the parameters of the LBA model are correlated. For example, increases in the decision threshold lead to slower and more variable predicted response times, and more errors. Similar (but not identical) predictions can also arise from decreased mean drift rates. Parameter correlations can cause estimation difficulty, for example requiring more sophisticated sampling or search algorithms (Turner, Sederberg, Brown, & Steyvers, 2013). We begin our work by building on a recent advance (Gunawan, Hawkins, Tran, Kohn, & Brown, 2019) which directly estimates the correlations between parameters, which improves statistical efficiency. Gunawan et al.’s method involves first log-transforming the parameters of the LBA model (so that they have support on the entire real line) and then assuming that the distribution of parameters across participants is multivariate normal. The correlation matrix implied by that multivariate normal distribution describes the correlation between parameters within a task.

Our article extends the method of Gunawan et al. (2019) to model correlations between tasks. The basic idea is to extend the vector of parameters for each person to
Figure 1. The linear ballistic accumulator: On each trial, evidence for each response option begins randomly between 0 and A (the upper value of the start point variability). The speed of the linear evidence accumulation is called the “drift rate”, which is sampled from a normal distribution with mean \( v \), unit standard deviation, truncated to positive values. Accumulation continues until a response threshold (\( b \) units above A) is reached. The accumulator which reaches the threshold first (the left accumulator in this example) determines the response.

Parameter labels and descriptions.

| Symbol | Name                          | Psychological Interpretation                                      |
|--------|-------------------------------|------------------------------------------------------------------|
| \( v \) | Mean Drift Rate               | Speed of information processing                                   |
| \( b \) | Response Threshold            | Evidence required to make decision                               |
| \( A \) | Starting Point Variability    | Variability in the initial evidence across trials                |
| \( s \) | Drift Rate Variability        | Variability in the speed of processing across trials             |
| \( t_0 \) | Non-Decision Time             | Time for processes other than decision processing                |

Results

Application 1: Correlations in Latent Processes In and Out of the Scanner

To model the decisions in each session, we followed the same LBA specification as used in the original article (Forstmann et al., 2008) and confirmed subsequently by Gunawan et
al. (2019). We collapsed across left- and right-moving stimuli, forcing the same mean drift rate for the accumulator corresponding to a “right” response to a right-moving stimulus as for the accumulator corresponding to a “left” response to a left-moving stimulus; we denote this mean drift rate by \( v^{(c)} \). Similarly, drift rates for the accumulators corresponding to the wrong direction of motion are constrained to be equal and denoted by \( v^{(e)} \). Three different response thresholds were estimated, for the speed, neutral, and accuracy conditions: \( b^{(s)} \), \( b^{(n)} \), and \( b^{(a)} \) respectively. Two other parameters were also estimated: the time taken by non-decision process (\( \tau \)) and the width of the uniform distribution for start points in evidence accumulation (\( A \)).

These assumptions result in seven parameters that need to be estimated: \( \{ A, v^{(c)}, v^{(e)}, b^{(s)}, b^{(n)}, b^{(a)}, \tau \} \). Different parameters were estimated for the in-scanner and out-of-scanner sessions. The full vector of 14 (log-transformed) parameters was estimated as a random effect for each participant, with a multivariate normal prior distribution assumed across participants. The prior for the mean vector of the multivariate normal distribution is another multivariate normal distribution with zero mean, whose covariance matrix is the identity matrix. The prior for the covariance matrix of the group distribution was a random mixture of inverse Wishart distributions, with mixture weights according to an inverse Gaussian distribution. We chose settings of \( v_a = 2 \) and \( A_d = 1 \), which Huang and Wand (2013) show leads to marginally non-informative (uniform) priors on all correlation coefficients, and half-t distributed priors on the standard deviations. All other sampling details are identical to those reported by Gunawan et al. (2019).

Since the data from this experiment were used to estimate the LBA model previously, several times, our article does not report the usual summaries of the model’s goodness-of-fit; see Figures 6 and 7 of Van Maanen et al. (2016) for details. Our focus is on the estimated parameters. Table 1 shows the estimated parameters separately for the two sessions. Compared with the out-of-scanner session, when participants were tested in the MRI scanner, the group average parameters changed in ways consistent with those reported by Van Maanen et al.: participants made much more cautious decisions (higher thresholds, \( b \), and larger start point variability, \( A \)), but there was little difference in drift rate or non-decision time parameters.

Table 1

| Parameter | Out of Scanner | In Scanner |
|-----------|----------------|------------|
| \( b^{(a)} \) | 1.33 (.11) | 1.63 (.13) |
| \( b^{(n)} \) | 1.39 (.11) | 1.80 (.14) |
| \( b^{(s)} \) | 1.05 (.10) | 1.25 (.11) |
| \( A \) | 0.73 (.06) | 0.92 (.10) |
| \( v^{(e)} \) | 1.50 (.27) | 1.69 (.19) |
| \( v^{(c)} \) | 3.12 (.26) | 3.24 (.12) |
| \( \tau \) | 0.19 (.02) | 0.18 (.02) |

Our main focus, however, is on the correlations between the parameters estimated
Figure 2. Posterior means for the correlation matrix between parameters estimated for the out-of-scanner and in-scanner sessions of Forstmann et al.’s (2008) experiment. Correlations near zero are shown as white squares. Positive and negative correlations are shown by green and red shades, respectively. Cells enclosed by black borders are strongly reliable correlations, as indicated by having a posterior mean ±3 or more standard deviations away from zero.

The correlations between “like” parameters from different sessions are mostly as hypothesised and easy to interpret. For example, all of the threshold-related parameters (b(a), b(n), b(s), and A) are positively correlated with one-another between sessions. This indicates that participants who made cautious decisions out of the scanner (high thresholds) also tended to make cautious decisions inside the scanner, and vice versa. The average magnitude of the correlations for threshold parameters ($r = .33$) is very similar to that reported by Mueller et al. (2019) ($r = .39$).

The drift rate parameters ($v(e)$ and $v(c)$) were quite strongly correlated between sessions, with the exception of error drift rate in-scanner paired with correct drift rate out of scanner. The average correlation between drift rates between sessions ($r = .42$) was almost double that reported by Mueller et al. (2019), which makes sense given that Forstmann et
al.’s experiment was identical between sessions – only the context changed. Non-decision time ($\tau$) was uncorrelated between sessions.

The other correlations summarised in Figure 2 are between “unlike” parameters, such as drift rates estimated out of the scanner correlated with thresholds measured in the scanner. These correlations are not always easy to interpret. For example, the non-decision time ($\tau$) and correct accumulator drift rate ($v^c$) parameters estimated outside of the scanner correlate negatively with almost all the other parameters estimated inside the scanner. This implies that people who were fast at the non-decision components of responding out of the scanner also tended to have high caution and large drift rates, when in the scanner. Others of the “unlike” correlations are easier to interpret, though. For example, participants who made cautious decisions outside the scanner (high $b(a)$, $b(n)$, $b(s)$, and $A$) tended to perform the task well when inside the scanner (high $v(e)$ and $v(c)$).

Only $n = 19$ people participated in the experiment reported by Forstmann et al. (2008), and it can be difficult to estimate correlation parameters with relatively small sample sizes – despite the quite large number of data collected per person. The effect of this is clearly visible in Figure 2, where there are several cells with strong mean correlation (dark colours) that are not strongly statistically reliable (no bounding boxes, which indicates that the mean posterior correlation was less than 3 standard deviations from zero). Figure 3 shows scatter plots corresponding to the correlations from Figure 2. Each panel in Figure 3 has a symbol for each person in the experiment. Each symbol plots a point estimate for an in-scanner parameter vs. a point estimate for an out-of-scanner parameter. The point estimates are the means of the posterior distributions. Figure 3 reveals that the relatively small number of participants contributed to the unstable correlations. For example, the negative correlations previously discussed, for out-of-scanner $\tau$ and $v^c$ with almost all in-scanner parameters, appear to be caused by an outlier (left-hand side of each panel in the top two rows of Figure 3). Similar effects are also apparent for other parameters. The next experiment alleviates this difficulty by drawing a much larger sample of participants.

**Implications for model-based cognitive neuroscience.** Beyond this application, our method has the potential to enhance the reliability of model-based cognitive neuroscience research. A shortcoming of the field is that relatively few data can be collected while participants are inside a scanner, or while other neurophysiological recordings are taken. Given two testing sessions, one inside the scanner and another outside of the scanner, our method can improve the precision of the parameter estimates in both sessions, due to the borrowing of strength between and within tasks.

We consider this a generalisation of the so-called joint-modelling framework that simultaneously estimates parameters of a cognitive model (such as the LBA) and a neural model (typically a GLM; Turner, Forstmann, et al., 2013). Joint modelling allows parameters estimated from one source (say, behavioural data) to influence parameters estimated from the other source (the neural data). Our approach tackles a trickier statistical problem, estimating the correlation between vectors of latent variables (parameters of cognitive models in different tasks, sessions, etc.) whereas to date joint modelling has been used to estimate the covariation between a set of latent variables (cognitive model parameters in one task) with a vector of data-transformed variables (beta-values in a GLM of the neural data). In this sense, our method is a generalisation of the joint modelling framework. It provides an avenue to estimate parameters of cognitive models from two behavioural sessions, which
Figure 3. Scatter plots of maximum posterior probability estimates for the random effects parameters inside vs. outside of scanner.
reduces uncertainty in the parameter estimates from the few-data scanner session, while jointly modelling the in-scanner session with neural recordings, improving precision of the across-task covariation parameters.

**Application 2: Correlations in Latent Processes Across Different Cognitive Tasks**

The second experiment we analysed had participants complete three decision-making tasks in a single session. Compared with the experiment by Forstmann et al. (2008), our experiment kept a constant context and environment for the participants, while the nature of the task varied. We also gathered data from many more participants \((n = 110\) used here). The differences between the three tasks means that lower correlations might be expected for parameters that are strongly dependent on the task; particularly drift rates.

The tasks were a visual search task, a stop-signal task, and a match-to-memory task, which we abbreviate as “search”, “stop”, and “match”. For the match task, we manipulated difficulty by changing the number of stimuli per trial (set sizes of 1, 2, or 3 objects). This manipulation was intended to change the speed and accuracy of decision-making, and to alter drift rates in the LBA model. The search and stop tasks had participants find a target stimulus, defined by a conjunction of colour and shape features, and then report the location of a small visual feature from the target. We manipulated difficulty in the search and stop tasks by changing the properties of the distractor items. On some trials the target stimulus included a feature which was not present in any distractor stimulus (e.g., the target may have been red, while all distractors were green). These “feature” trials were the easiest for participants, and, by definition, all trials with just one distractor item were of this sort. For the trials with 3 or 7 distractor items, some were “feature” trials, but others were more difficult. The difficult trials are ones in which both the features of the target were present in the distractors, for example searching for a red square amongst distractors that include a red circle and a green square.

Figure 4 demonstrates that there was some association in the observed performance across tasks. In the figure, each dot represents one participant’s mean response time (RT; lower triangle panels) or mean accuracy (upper triangle panels). These means are plotted for one task (search, stop, or match) vs. another. For example, the lower-left panel plots mean RT in the match task on the \(x\)-axis against mean RT on the stop task on the \(y\)-axis. The correlations between tasks in RT were between \(r = .40\) and \(r = .51\), and for accuracy between \(r = .21\) and \(r = .40\). These correlations provide evidence that there is some commonality in performance between tasks which the cognitive modeling can strive to uncover and explain.

Since the three tasks are different, the specification of the LBA model is not identical across them. For each of the three tasks, we constrained the model to use a single value for non-decision time (\(\tau\)) across all conditions, and likewise a single value for the start-point variability (\(A\)) across all conditions. Decision thresholds were allowed to vary with display size in all tasks. We denote these parameters \(b\), with superscripts to indicate the display size, so \(\{b^{(2)}, b^{(4)}, b^{(8)}\}\) for the stop and search tasks, and \(\{b^{(1)}, b^{(2)}, b^{(3)}\}\) for the match task. In most applications of evidence accumulation models, response thresholds are typically not allowed to vary with stimulus manipulations, such as display size. This is because it is
Figure 4. Scatter plots of mean response time (RT; lower triangle) and accuracy (upper triangle) showing associations between performance in the three different tasks of the experiment. Accuracy is probit transformed. Red lines are regressions corresponding to the Pearson correlation coefficients shown in each panel.
implausible to imagine that decision-makers can adjust a response threshold contingent on some stimulus property, prior to making their decision about that stimulus. However, our experiment’s procedure provided participants with sufficient advance notice of the display size that thresholds could be plausibly adjusted. Finally, for the drift rates, we constrained the model to have just one parameter across all conditions to set the mean drift rate of the accumulator corresponding to the incorrect response, $v(e)$, and one parameter for the mean of the correct accumulator’s drift rate in each of the different display size conditions: \{ $v(2)$, $v(4)$, $v(8)$ \} for the stop and search tasks, and \{ $v(1)$, $v(2)$, $v(3)$ \} for the match task. These model assumptions were the product of testing several other models, which were either simpler or more complex, and which either failed to capture important effects in the data or did not fit sufficiently better to justify the extra complexity. Appendix B reports analyses illustrating that the model does a good job of capturing the important trends in the data, without over-fitting, and that the estimated model parameters are sensible.

The model assumptions result in 9 parameters to estimate for each participant, for each of the three different tasks. We estimated these parameters simultaneously. The vector of 27 log-transformed random effects was constrained to follow a multivariate normal distribution at the group level. Uninformed priors were assumed for the mean and covariance matrix of the multivariate normal, using the same settings as the application to Forstmann et al.’s (2008) data.

Table 2 shows the estimated group-level parameters. Each entry gives the mean (with standard deviation in parentheses) for the posterior distribution over a group-level parameter, for one of the three tasks. For all three tasks, participants made more cautious and less efficient decisions, as display size increased. That is, the estimated thresholds ($b$) increased, and the estimated drift rates for the correct-response accumulator ($v(c)$) decreased, though the pattern for the correct drift rates was less clear for the match task. Non-decision times ($\tau$) were faster in the match task than the search and stop task, which likely reflects the smaller perceptual encoding effort required for the match task (average of two stimuli to encode on each trial, compared with four for the search and stop tasks).

Table 2
Mean (and SD) of the estimated marginal posterior distributions for the LBA mean parameters from the three tasks in the experiment; see text for details. For ease of interpretation, these parameters are transformed back to the positive real line.

|          | Match     | Search    | Stop      |
|----------|-----------|-----------|-----------|
| $b^{(1)}$| 2.15 (.069)| 1.71 (.049)| 2.74 (.171)|
| $b^{(2)}$| 2.34 (.073)| 1.79 (.050)| 2.87 (.177)|
| $b^{(3)}$| 2.42 (.075)| 1.95 (.055)| 3.04 (.180)|
| $v^{(c)}$| 0.86 (.043)| 1.19 (.056)| 0.77 (.084)|
| $v^{(1)}$| 2.94 (.049)| 3.82 (.048)| 4.04 (.086)|
| $v^{(2)}$| 3.19 (.050)| 3.62 (.046)| 3.96 (.094)|
| $v^{(3)}$| 2.79 (.044)| 3.42 (.053)| 3.80 (.094)|
| $\tau$  | 0.17 (.008)| 0.22 (.008)| 0.23 (.008)|

Figure 5 uses the same plotting format as used for Forstmann et al.’s (2008) data, in
Figure 5. Posterior means for the correlation matrix between parameters estimated for the three tasks (Match, Search, and Stop) in our experiment. Correlations near zero are shown as white squares. Positive and negative correlations are shown by green and red shades, respectively. Cells enclosed by black borders are strongly reliable correlations, as indicated by having a posterior mean \( \pm 3 \) or more standard deviations away from zero.
Figure 2, so that red and green shades indicate negative and positive parameter correlations, respectively, with darker shades corresponding to stronger correlations. The positioning of the panels is the same in Figure 5 as for the lower triangle of Figure 4. Appendix B gives the correlation values corresponding to Figure 5.

The dark green patches on the left-hand sides of the two left panels indicate that the threshold estimates for the match task correlate positively with threshold estimates from both other tasks, and also with correct-accumulator drift rates for the stop task. The light-shaded horizontal and vertical sections for parameter \( v^{(e)} \) suggest that the drift rates for the incorrect accumulator have low or no correlations with any other estimates. This result is consistent with the idea that error drift rates are noisy to estimate, especially when accuracy is high. The non-decision time parameter (\( \tau \)) from the search task does not correlate strongly with any other parameters except for the non-decision time parameter for the stop task. The two non-decision time parameters for those two tasks correlated strongly (bottom right element in the lower right panel), which makes sense given that the stop task and search task used identical response rules – participants responded to the side of the target stimulus which showed a small gap. The non-decision time parameter for the match task does not correlate with those from the other tasks, which also makes sense because the match task required a different response rule (match to memory, which presumably requires different encoding than the gap identification, and also a different mapping to the response key).

**Implications for test batteries.** The second application demonstrates that our correlation-estimation approach can identify relationships between the latent cognitive processes involved in different tasks; in our case, this was finding a target among distractors, decisions in the context of response inhibition, and matching stimuli to previously-remembered referents. In this application one might suggest our approach is not necessary, and it may be reasonable to use the standard two-step approach. That is, given we had a considerable number of decisions per task, we could have independently estimated the parameters of the cognitive model for each task, and then conducted pairwise correlations between the parameter estimates. Even in this many-trials context, we believe our method has important uses. For example, it provides a new method for assessing test-retest reliability of model parameters across testing occasions.

Nevertheless, in many contexts it is not possible to independently estimate cognitive models for each task. For example, in clinical contexts it is common for participants to complete many different tasks – up to 10 in a session – with very few trials per task. Performance in such “test batteries” including the BACS (Kaneda et al., 2007), CANTAB (Robbins et al., 1996) and MiniMental (Folstein, Folstein, & McHugh, 1975) are used to inform important clinical decisions about cognitive functioning in patients, and are often used in research to assess whether an intervention is effective at improving cognition (Demant, Vinberg, Kessing, & Miskowiak, 2015; John, Yeak, Ayres, & Dragovic, 2017). It is therefore of practical and theoretical importance that the inferences drawn from test batteries are based on precise measurement. However, these inferences are typically based on composite scores derived from summary statistics such as the mean RT or number of lapses, calculated from small data samples. There are likely to be substantial person-wise correlations across the multiple tasks, though current treatments assume independence, which is wrong. Our method allows us to explicitly model the dependence across tasks, which provides more
precise parameter estimates, and the benefits of shrinkage. This brings with it an additional theoretical advantage: the possibility to test cognitive models of performance in the constituent tests in the battery. This has been inaccessible to cognitive modelling, at least in applied domains, owing to the issue of few data per task.

Conclusions

Our article develops a statistically principled approach to estimate the degree of association between the latent cognitive processes that drive performance across tasks, contexts, and time. Our method is a significant step forward for the field. Previous research assessing parameter correlations across testing occasions has been restricted to estimating the parameters of cognitive models independently for each test session, and then correlating the pointwise estimates of those parameters in a second-step analysis. This approach has conceptual and statistical shortcomings.

Conceptually, existing approaches start with the assumption that cognitive processes are independent over tasks, contexts and time. This is surely not true, and is inconsistent with an assumption underlying all psychological research that there is some non-zero degree of stability in psychological processing across contexts and over time. It is this consistency we aim to uncover and use as a basis for generalisation. Our method allows us to identify the similarity in cognitive processing between different testing occasions, without making the (implicit) assumption that the latent drivers of observed performance are independent across testing occasions.

Statistically, existing approaches are over-confident: they use point estimates of the parameters from independent model fits to each task. This assumes the parameters of participants are known with certainty within a task, which is never true when analysing data; providing the machinery to deal with this uncertainty has been one of the primary advantages of Bayesian estimation methods. Furthermore, with existing approaches we have just two ways to assess relatedness in parameters across testing occasions: assuming independence or equivalence (i.e., tying parameters across conditions or tasks). Where it is a priori unclear which parameters can be assumed to be constant across conditions or tasks, we can get stuck with independent fits, or even without being able to progress. Estimating a dependent pair of parameter vectors allows for a “soft” version of tying parameters across conditions. Parameters which are related will then show up as correlated, and statistical borrowing of strength will take place via the covariance matrix.
Open Practices Statement

The two applications cover a previously published data set (Forstmann et al., 2008) and a new experiment that was not preregistered. Data and code for both applications are available at osf.io/rf8nd.
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Appendix A
The New Experiment

Method

Design. The experiment used a 3 (task) × 3 (set size) within-subjects design: all
three tasks had a three-level manipulation of the number of items in the stimulus array (set
size). In the search task participants were required to look for a target (always present)
amongst one, three or seven distractors (implying search set sizes of 2, 4, and 8). The
stop-signal task was identical to the search task except that on 25% of trials a stop-signal
was presented after the onset of the search array. The time between the onset of the search
array and the stop-signal (called the stop-signal delay) was dynamically adjusted for each
participant and each set size, using a staircase algorithm. In the match task participants
were required to identify if the currently presented stimulus set was a match (the same
shapes and colours) or not a match (at least one difference) to the stimulus set presented
on the previous trial. The number of stimuli present on screen in each trial was either one,
two, or three, and this was manipulated between blocks of trials. Response time and the
response itself were recorded for all trials.

Participants. Participants were students from first and second year psychology
courses at the University of Newcastle who received course credit for their participation.
Informed consent was obtained for all participants. Participants had the opportunity to
complete the task online (N = 106) or in a lab (N = 81).

Although 187 students participated in the study, only 148 participants are included
in the combined analysis. Participants were excluded if they had greater than 0.05% of
non-responses due to “too fast” or “too slow” feedback cut offs, as defined in the procedure
(n = 8 match, n = 10 search, n = 13 stop) or had accuracy lower than 75%, 85% or
90% for the match, search and stop-signal tasks respectively (n = 17 match, n = 8 search,
n = 27 stop). The exclusion criteria were set by investigating the data and removing outliers
indicating the participant was performing considerably worse at the task than the bulk of
the other participants. This resulted in n = 145 complete data sets for the match task,
n = 157 for the search and n = 133 for the stop-signal. There were n = 110 participants
who had valid data for all three tasks. These were the participants used in all analyses.

Materials and Stimuli. All three tasks were written in JavaScript and HTML5.
Although it was impossible to keep screen size and resolution identical across subjects
who completed the task online, the relative size and positioning of stimuli was constant.
Instructions at the beginning of the experiment required participants to alter the zoom
settings to ensure maximum consistency in the displays across participants. On a 1920x1080
resolution and 13.3 inch screen, with the participants 60cm away from the screen, each shape
subtended approximately 1° of visual angle, and was approximately 5° of visual angle away
from the center of the screen. The fixation point was a small cross subtending much less
than 1° of visual angle. Stimuli only ever appeared in eight different locations, representing
equally-spaced points around a circle 5° in radius. For stimulus displays with fewer than
eight stimuli, locations were sampled randomly without replacement from the eight possible
positions.

The search arrays for all three tasks used just four stimuli: a red circle, green circle,
red square, and green square (see Figure A1). A small gap in the shape, on either the left
or right side, was used as the decision stimulus in the search and stop-signal tasks. There
was no gap in any stimulus during the match task. The three colours used (red and green for the stimuli, and blue for the stop-signal) were presented at the maximum intensity of their respective hue in the computer’s RGB colour model.

Figure A1. Screenshots from: (left) the search task, set size eight, with the green circle as the target; (middle) the stop-signal task, set size eight, target red square, with the stop-signal present; and (right) the match task, set size two.

Procedure. Participants completed all three tasks in one sitting with opportunities for self-timed breaks within and between tasks. Participants were randomly allocated to one of the six possible task orders. Each task contained on-screen instructions with examples, followed by a series of practice trials and then three experimental blocks with a fixed number of trials each.

For the search task, participants were first presented with instructions that identified which of the four stimuli would constitute their target stimulus (e.g., “search for a red square”). The target was randomly allocated to participants at the start of the task and remained consistent for the duration of that task. This process also occurred in the stop-signal task and thus the target could change across tasks but not within a task. Participants were informed that all shapes have a gap in the left or the right side and that once participants had located the target they should indicate via the “z” and “/” keys if the gap was on the left or right side of the target respectively. Participants were told to respond as quickly as possible.

There were three blocks of 200 trials each, with 10 practice trials at the start. At the beginning of each trial a fixation cross was presented for 700ms. This was then replaced by the search array. The location of the target and the target gap side were randomly chosen at the beginning of each trial. The number of distractors, their shape, colour, location and gap side were also randomly chosen at the start of each trial. A trial concluded after a response. If a response was faster than 250ms or slower than 2,000ms then feedback of “TOO FAST” or “TOO SLOW” was provided, displayed for 1,500ms or 5,000ms respectively. Participants also received accuracy feedback for the first 10 experimental trials. This feedback was presented for 1,000ms and 2,500ms for correct and error responses respectively.

Stop-signal tasks typically have a very simple, almost automatic task for most trials in which participants rapidly press a key to respond on each trial (these are called the “go” trials). A stop-signal appears during the other trials (the “stop” trials), after some delay from the onset of the trial, and participants must withhold their response. In our stop-signal task, the go trials were identical to the search task. All details of the search task were identical except that in the instructions participants were shown a large blue square (see Figure A1) and told “when you see this symbol DO NOT RESPOND”. They were reminded to respond as quickly as possible when the symbol is not presented to ensure the
easy, automatic response style.

Each trial had an independent and identical 25% probability of being a stop-signal trial. At the beginning of the experiment the stop-signal delay (SSD; the time between the presentation of the stimuli and the presentation of the stop-signal) was set to zero across all set sizes, and then adjusted by a staircase procedure independently for each set size. After each correct inhibition, SSD was increased by 50ms (thus making it harder to inhibit) and after each failed inhibition, SSD was decreased by 50ms, with a minimum of zero. These staircases converge to the SSDs corresponding to 50% successful inhibition in each set size. Figure A1 shows the stop-signal task, consisting of a blue square in the center of the screen, inside the eight pointed star of shapes (subtending approximately 5° x 5° of visual angle), and a larger outline of a square outside the eight pointed star (approximately 15° x 15° visual angle in size, width of outline approximately 1.75° visual angle. To reduce so-called “trigger failure” (see Matzke, Hughes, et al., 2017) the stop-signal was maintained on screen until the end of the trial. To also prevent participants ignoring the stop-signal they were provided with feedback after every stop trial. Successful inhibitions produced “Good stopping!” while failed inhibitions resulted in “You should have stopped”.

The match task commenced with on-screen instructions that informed the participant green and red circles and squares would be shown on a trial and they needed to remember what they saw for the next trial. At first, they would only be shown one shape to remember, then two and then three shapes. If the stimulus array on any trial consisted of the same stimuli as the previous trial (i.e., with the same shapes and colours), then participants were to press a key indicating match (“/” key). If any shape or colour differed, participants were to indicate a non-match (“z” key, as seen in Figure A2). Participants were explicitly instructed that the position of the stimuli on screen was irrelevant.

![Figure A2. Example trial sequence from set size two in the match task. The correct response for the second screen would be “non-match”, and the correct response for the third screen would be “match”. Both colours and shapes must be the same, but location does not matter.](image)

Unlike the other two tasks, set size was not randomised from trial-to-trial for the match task, because match vs. non-match is not well defined for arrays of unequal size. Instead, set sizes occurred in blocks in a fixed order from one to three, with 100 trials per block. Half of the trials were randomly selected to be matching trials, and the other half were non-matching trials. During the experiment, if the upcoming trial was a match trial, the stimuli were kept fixed from the previous trial, however their locations were randomly re-sampled. If the upcoming trial was not a match then both the stimuli and location were both randomly sampled, subject to the constraint that a match did not occur by
chance. The feedback was the same as for the search task; however, the timeout for “too long” responses was 3,000ms and the accuracy feedback continued for the duration of the experiment in the match task. These changes in feedback were implemented after pilot testing, to allow for the greater difficulty of the match task.

Results

Figure A3 shows the mean response time (RT) and accuracy for different conditions, and for each of the three tasks.

Figure A3. Accuracy (top row) and response time (RT; bottom row) for the three tasks (columns) in the experiment. Accuracy and median RT were calculated for each participant and each condition. Lines show the averages of these across conditions for data, and symbols show the same but for posterior predictive data generated by the LBA model described in the main text. Red and green colours indicate trials in which the features of the target stimulus appeared in the distractor items (“conjunction”) and when they did not (“feature”), respectively. Error bars show ±1 standard error of the mean for differences between participants in the model fits.

Bayesian repeated measures ANOVAs (Morey & Rouder, 2013) were conducted on the mean RT and accuracy data for each set size, separately for the three tasks. Figure A3 shows that there is a strong effect of set size on RT for all three tasks, reflected in the RT Bayes factors in Table A1. This is not true of accuracy. Although the match task shows an effect of set size on accuracy, for both the search task and the stop task accuracy did not change reliably across set size (see Table A1). This may be due to ceiling effects, as in both of those tasks average accuracy is around 95% or above for all conditions. Even in the match task, accuracy does not decrease monotonically over set size as expected. Instead, there is a small increase from the smallest set size (one) to the medium set size (two) and then a decrease to the largest set size (three). This is most likely due to practice effects, as the conditions were administered in blocks with increasing set size.
Table A1
Bayes factors in favour of a model including an effect of set size vs. a null model, for the three tasks, for mean RT and accuracy.

| Task  | Variable | Set Size BF<sub>10</sub> |
|-------|----------|--------------------------|
| Search| RT       | $> 10^6$                 |
|       | Accuracy | 5.8                      |
| Stop  | RT       | $> 10^6$                 |
|       | SSRT     | $> 10^6$                 |
|       | Accuracy | 0.060 *                  |
| Match | RT       | $> 10^6$                 |
|       | Accuracy | $> 10^5$                 |

The RT data are simpler to interpret. The only noteworthy point is that RT was substantially faster for the search task than both the stop and match tasks. As the RTs presented in the table and figure for the stop task are the RTs from the go trials (which were identical to trials in the search task), this increase in RT from the search to the stop task suggests that participants slow their responses when a stop is introduced to the task.
Appendix B
Estimated Correlation Matrices

Tables B1 and B2 show the full correlation matrices for the two applications of the new method reported above.

Table B1
The lower triangle of the estimated posterior mean of the correlation matrix for Forstmann et al.'s (2008) experiment; the main text gives further details. The lower-left square shows between-session correlations; these are also shown in the main text as a heat map. The triangles on the diagonal blocks show within-session correlations.

|       | $b^{(a)}$ | $b^{(n)}$ | $b^{(s)}$ | A   | $v^{(e)}$ | $v^{(c)}$ | $\tau$ |
|-------|-----------|-----------|-----------|-----|-----------|-----------|--------|
| Out of Scanner |          |           |           |     |           |           |        |
| $b^{(a)}$ | .97       |           |           |     |           |           |        |
| $b^{(n)}$ | .94       | .9        |           |     |           |           |        |
| A       | .75       | .74       | .67       |     |           |           |        |
| $v^{(e)}$ | .74       | .71       | .74       | .32 |           |           |        |
| $v^{(c)}$ | .64       | .66       | .59       | .2  | .66       |           |        |
| $\tau$  |-.67       | -.65      | -.66      | -.48| -.51      | -.41      |        |
| In Scanner |          |           |           |     |           |           |        |
| $b^{(a)}$ | .38       | .33       | .36       | .59 | .2        | -.22      | -.32   |
| $b^{(n)}$ | .29       | .28       | .26       | .59 | .08       | -.31      | -.23   |
| $b^{(s)}$ | .35       | .29       | .38       | .57 | .17       | -.28      | -.32   |
| A       | .39       | .35       | .37       | .62 | .17       | -.22      | -.34   |
| $v^{(e)}$ | .56       | .53       | .54       | .47 | .57       | .15       | -.41   |
| $v^{(c)}$ | .59       | .57       | .54       | .39 | .55       | .41       | -.43   |
| $\tau$  | .24       | .29       | .16       | -.03| .21       | .61       | -.12   |
Table B2

The lower triangle of the estimated posterior mean of the correlation matrix for our experiment; the main text gives further details. The three lower-left squares show between-task correlations; these are also shown in the main text as heat maps. The three triangles on the diagonal blocks show within-task correlations.

|       | Match Task | Search Task | Stop Task |
|-------|------------|-------------|----------|
|       | b(2)       | b(3)        | A        |
|       | v(1)       | v(2)        | v(3)     |
|       | v(e)       | v(f)        | v(4)     |
|       | v(5)       | v(6)        | v(8)     |
|       | τ          |             |          |
| b(2)  | .95        | .90         | .90      |
| b(3)  | .9         | .93         | .93      |
| A     | .90        | .87         | .87      |
| v(e)  | -.03       | -.09        | -.2      |
| v(1)  | .16        | .21         | .06      |
| v(2)  | .08        | .22         | .05      |
| v(3)  | .13        | .22         | .3       |
| τ     | -.39       | -.32        | -.16     |
| b(4)  | .48        | .46         | .47      |
| b(5)  | .53        | .51         | .47      |
| A     | .47        | .4          | .42      |
| v(e)  | -.01       | -.05        | -.06     |
| v(1)  | .13        | .16         | .19      |
| v(2)  | .31        | .34         | .35      |
| v(3)  | .27        | .32         | .32      |
| τ     | -.2        | -.17        | -.12     |
| b(8)  | .50        | .53         | .48      |
| b(9)  | .53        | .54         | .31      |
| A     | .47        | .4          | .33      |
| v(e)  | -.06       | -.09        | -.05     |
| v(1)  | .13        | .16         | .19      |
| v(2)  | .31        | .34         | .33      |
| v(3)  | .27        | .32         | .32      |
| τ     | -.2        | -.17        | -.12     |
| b(8)  | .50        | .53         | .48      |
| b(9)  | .53        | .54         | .31      |
| A     | .47        | .4          | .33      |
| v(e)  | -.06       | -.09        | -.05     |
| v(1)  | .13        | .16         | .19      |
| v(2)  | .31        | .34         | .33      |
| v(3)  | .27        | .32         | .32      |
| τ     | -.2        | -.17        | -.12     |

The data above show the estimated correlations between different tasks. Each entry represents the correlation between two tasks. The main text provides further details on the interpretation of these correlations.