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Toward a Psychometric Analysis of Violations of the Independence Assumption in Process Dissociation

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The authors outline a psychometric analysis of effects of violating the independence assumption underlying the process-dissociation procedure. That analysis distinguishes between *process dependence* and *aggregation bias*. Process dependence results when subjects rely on a strategy that makes recollection dependent on automatic influences of memory and is reflected by a correlation that can only be imagined, not observed. Aggregation bias results when parameters from a subject–item specific psychometric model are estimated by aggregating across observed subject and item data. Quantifying the magnitude of aggregation bias also requires speculation about a correlation that is not directly observed. Easily observed correlations calculated from aggregated estimates of automatic and recollective processes over subjects or items cannot be used to diagnose process dependence and are of limited utility for diagnosing aggregation bias. A postscript responds to T. Curran and D. L. Hintzman's (1997) reply.

In the article preceding this one, Curran and Hintzman (1997) provided a critique of the arguments we presented in Jacoby, Begg, and Toth (1997). They claimed that "properly conceived" (Curran & Hintzman, 1997, p. 499), even modest correlations are capable of producing large underestimations of *A*. They went on to object to conditions we set for our process-dissociation procedure and our characterization of their results in Jacoby et al.'s (1997) Table 1.

In this article, we further describe a conception of correlations between automatic and recollective memory processes that is indeed proper from the perspective of classical psychometrics (see Lord & Novick, 1968, pp. 173–197).[1] Curran and Hintzman's (1997) critique suggests a misunderstanding of our psychometric analysis of effects of correlations and leads us to begin by clarifying the description of our psychometric model. This model allows us to distinguish several very different kinds of correlations and to argue that evidence about one kind is not informative about the others, contrary to arguments of Curran and Hintzman (1997). We maintain that Curran and Hintzman (1995, 1997) provide neither statistical nor empirical evidence that our assumption of independence of cognitive processes was violated. Although we develop our arguments in technical psychometric detail, we build on the more intuitive discussion of Jacoby et al.'s (1997) Table 2 and the coin example used.

Psychometric Model and Notation

To make our arguments precise, it is necessary to introduce mathematical notation to describe the automatic and recollective memory processes of a given subject (subject *s*) who is exposed to a specific item (item *i*) on a specified trial (trial *t*). We build on the notation of Curran and Hintzman (1997), who asked the reader to consider Bernoulli variables to represent success–failure of automatic and recollective memory processes when a subject encounters an item on a given trial. We let A_{sit} and R_{sit} represent these variables; they take the value 1 for success and 0 for failure. The subscripts *s, i,* and *t* allow us to specify precisely a given subject, item, and trial. The inclusion of the subscript for *t* is a refinement of the notation used by Curran and Hintzman. Their notation represents trials only implicitly.

Independence Across Trials

It is important to make trials explicit to understand the independence assumption we make in the development of the process-dissociation estimation equations. When we assume that automatic and recollective memory processes are independent, we mean that A_{sit} and R_{sit} are independent over trials for a given subject and a given item. Stated another way, for a fixed subject and item, the outcome of the automatic memory process is assumed to be uninformative about the outcome of the recollective memory process. This assumption implies that the expected correlation of A_{sit} and R_{sit} over trials is zero, and we write this implication as $\rho_{si} = 0$. In principle, ρ_{si} should be considered for each subject–item combination.

As we discussed in our previous article (Jacoby et al., 1997), our independence assumption is analogous to the assumption that two flips of specific coins are independent. We explained that two coins can be flipped independently, even if both coins are biased (e.g., their probabilities of heads are not .50). If it is possible to conduct many trials (pairs of flips), one can estimate the correlation between flips

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[1] The psychometric analysis portion of this article was largely written by Patrick E. Shrout, whose area of expertise is psychometrics.

empirically. For independent flips, this estimate will converge to zero as the number of trials becomes large.

In the case of automatic and recollective memory outcomes, A_{sit} and R_{sit}, the assumption of independence cannot be tested directly because it is not possible to repeat multiple independent trials with the same item and a given subject. The fact that ρ_{si} cannot be estimated directly does not diminish its importance. As we illustrate later, when a generate–recognize model holds, ρ_{si} is larger than zero, and our independence assumption is violated.

Of special interest are the expected means of A_{sit} and R_{sit} over trials ($\overline{A}_{si}$ and $\overline{R}_{si}$). They are interpretable as the probabilities of success for the automatic and recollective memory processes.[2] They are also the appropriate marginal values of the 2×2 tables that cross-classify A_{sit} with R_{sit}, such as the tables shown in Curran and Hintzman's (1997) Table 1.

Although we did not label them as such, the values in Jacoby et al.'s (1997) Table 2 can be interpreted as examples of $\overline{A}_{si}$ and $\overline{R}_{si}$ (shown in the R and A columns above the line). The table shows how $\overline{A}_{si}$ and $\overline{R}_{si}$ might vary across items for a fixed subject. The table illustrates that even though processes may be independent at the level of individual trials (A_{sit} and R_{sit}), this does not guarantee that the means ($\overline{A}_{si}$ and $\overline{R}_{si}$) are uncorrelated. A subject might have high values of both $\overline{A}_{si}$ and $\overline{R}_{si}$ for one item and low values of both $\overline{A}_{si}$ and $\overline{R}_{si}$ for another item.

Correlation might also be evident in the pattern of higher order means over items or over subjects. Let ($\overline{A}_s$, $\overline{R}_s$) be the means over items for each subject and ($\overline{A}_i$, $\overline{R}_i$) be the means over subjects for each item. Just as correlation across $\overline{A}_{si}$ and $\overline{R}_{si}$ is uninformative about ρ_{si}, so are the correlations of ($\overline{A}_s$, $\overline{R}_s$) or of ($\overline{A}_i$, $\overline{R}_i$).

Aggregation Bias Versus Process Dependence

Although they are not informative about the assumption that $\rho_{si} = 0$, the correlation among the subject or item means is relevant to bias due to aggregation. Jacoby et al.'s (1997) Table 2 shows an example of bias in the estimate of A when aggregate information is used in the process-dissociation estimation equations. If we could simply average the $\overline{A}_{si}$ and $\overline{R}_{si}$ values, we would get an unbiased average, but these values are not known in practice. Even though aggregating across items and subjects introduces bias, Jacoby et al.'s (1997) Equation 1 and Table 2 show that the aggregation bias can be trivial and not differential across conditions—even when there is a near perfect correlation between $\overline{A}_{si}$ and $\overline{R}_{si}$.

The reader should distinguish our claim that high correlation among the item means, ($\overline{A}_i$, $\overline{R}_i$), is likely to be inconsequential with regard to aggregation bias from any assertions regarding the consequences of nonzero correlations at the level of ρ_{si}. The impact of a violation of our assumption about ρ_{si} would be much more substantial and would be expected to disrupt the regularity of the findings from the process-dissociation paradigm. The bias described by Jacoby et al.'s (1997) Equation 1 is more modest and is the only bias that can be inferred from correlations among item means.

Figure 1 gives a concrete example of the fact that observable correlations among the item means are uninformative about ρ_{si}. This figure contrasts our direct-retrieval model to the generate–recognize model that is plausible but is not believed to apply to data gained with the experimental procedures we have outlined. Figure 1A shows hypothetical associations between A_{sit} and R_{sit} under the direct-retrieval model. For two subjects and two items, we show the expected frequency of responses in the (1, 1), (1, 0), (0, 1) and (0, 0) cells for each subject–item combination within each of the smaller tables. Under the independence assumption, the probability of a successful recollection on a given trial (R_{sit}) is the same regardless of the outcome of automatic processes on that same trial (A_{sit}), just as the probability of a head on a second coin is the same regardless of whether a first coin returns a head or a tail. As shown in Figure 1A, if outcomes are independent, the probabilities of different combinations of outcomes (e.g., $A_{sit} = 0$; $R_{sit} = 1$) are equal to the product of the relevant marginal probabilities. The independence is reflected in the phi correlations for each table that provides estimates of ρ_{si}. The tables have been constructed so that the phi correlations are zero for all four tables.

In contrast to the above, reliance on a generate–recognize strategy would produce dependence at the level of outcomes on a particular trial. For a generate–recognize strategy, recollection is possible only if automatic processes are successful—an item cannot be recognized as old if it is not generated as a completion. That is, the combination $A_{sit} = 0$; $R_{sit} = 1$ is an impossible one. Figure 1B shows the expected distribution of A_{sit} and R_{sit} under this model. The presence of the empty cell is reflected by correlation between outcomes. We refer to correlation at this outcome level as *process dependence.* When a generate–recognize model is correct, as it sometimes is, the independence assumption is wrong and ρ_{si} is greater than zero.

In addition to illustrating the difference between the direct retrieval and generate–recognize models, Figure 1 shows that correlations over the marginal means for each table ($\overline{A}_{si}$ and $\overline{R}_{si}$) or over the item means ($\overline{A}_i$ and $\overline{R}_i$) do not distinguish between the two models. For both parts of the figure, the item means for the two processes ($\overline{A}_i$ and $\overline{R}_i$) are systematically higher for Item 2 than for Item 1. This amounts to a perfect correlation of A and R at the item-mean level for both the independence model and the generate–recognize model, even though the phi values are zero in one case and large in the other. Although the marginal values can constrain the size of the largest or smallest correlation, they do not determine whether the correlation is zero.

Proper Versus Improper Analysis of Independence

In their critique, Curran and Hintzman (1997) claimed that our arguments regarding the effects of correlation at the item-mean level were not properly conceived. Without

[2] Curran and Hintzman (1997) used the notation (P^A_{si}, P^R_{si}) to refer to ($\overline{A}_{si}$ and $\overline{R}_{si}$). We prefer our notation because it makes it clear that these probabilities are simply the expected means of A_{sit} and R_{sit} over trials.

A

Subject 1

	Item 1: $R_{11t}=1$	$R_{11t}=0$				Item 2: $R_{12t}=1$	$R_{12t}=0$		
$A_{11t}=1$	.053	.298	$\bar{A}_{11}=.35$	$\phi_{11}=.00$	$A_{12t}=1$	.158	.293	$\bar{A}_{12}=.45$	$\phi_{12}=.00$
$A_{11t}=0$	.098	.553	.65		$A_{12t}=0$	.193	.358	.55	
	$\bar{R}_{11}=.15$	.85	1			$\bar{R}_{12}=.35$	.65	1	

Subject 2

	$R_{21t}=1$	$R_{21t}=0$				$R_{22t}=1$	$R_{22t}=0$		
$A_{21t}=1$	.248	.303	$\bar{A}_{21}=.55$	$\phi_{21}=.00$	$A_{22t}=1$	.270	.330	$\bar{A}_{22}=.60$	$\phi_{22}=.00$
$A_{21t}=0$	.203	.248	.45		$A_{22t}=0$	.180	.220	.40	
	$\bar{R}_{21}=.45$	.55	1			$\bar{R}_{22}=.45$	.55	1	

item-mean values (calculated over subjects)

$\bar{R}_{.1}=.30$ $\bar{A}_{.1}=.45$ $\bar{R}_{.2}=.40$ $\bar{A}_{.2}=.525$

B

Subject 1

	Item 1: $R_{11t}=1$	$R_{11t}=0$				Item 2: $R_{12t}=1$	$R_{12t}=0$		
$A_{11t}=1$	.15	.20	$\bar{A}_{11}=.35$	$\phi_{11}=.57$	$A_{12t}=1$	.35	.10	$\bar{A}_{12}=.45$	$\phi_{12}=.81$
$A_{11t}=0$	0	.65	.65		$A_{12t}=0$	0	.55	.55	
	$\bar{R}_{11}=.15$	.85	1			$\bar{R}_{12}=.35$	.65	1	

Subject 2

	$R_{21t}=1$	$R_{21t}=0$				$R_{22t}=1$	$R_{22t}=0$		
$A_{21t}=1$	.45	.10	$\bar{A}_{21}=.55$	$\phi_{21}=.82$	$A_{22t}=1$	.45	.15	$\bar{A}_{22}=.60$	$\phi_{22}=.74$
$A_{21t}=0$	0	.45	.45		$A_{22t}=0$	0	.40	.40	
	$\bar{R}_{21}=.45$	.55	1			$\bar{R}_{22}=.45$	.55	1	

item-mean values (calculated over subjects)

$\bar{R}_{.1}=.30$ $\bar{A}_{.1}=.45$ $\bar{R}_{.2}=.40$ $\bar{A}_{.2}=.525$

Figure 1. A: Examples of automatic (A) and recollective (R) process associations under the direct-retrieval model (A and R assumed to be independent). B: Examples of automatic and recollective process associations under the generate–recognize model (A and R assumed to be related). In both A and B, tables show what proportions of trials would be expected to result in combinations of automatic memory (A_{sit} = 1 for success; A_{sit} = 0 for failure) and of recollective memory (R_{sit} = 1 for success; R_{sit} = 0 for failure). Each table is specific for a given subject and item. Because A_{sit} and R_{sit} are > (0, 1) Bernoulli variables, their means over trials are simply equal to the sums of the relevant joint probabilities in the 2 × 2 table. s = subject; i = item; t = trial; ϕ = phi correlation.

showing weaknesses in our arguments regarding the minimal effects of correlation at the item-mean level on the process-dissociation estimates, they shifted their focus to the item–subject level of analysis. Their Figure 1 lays out a 2 × 2 table that could be used to estimate ρ_{si} by using a phi coefficient if the latent Bernoulli trial results (what they call A_{si} and R_{si} and what we call A_{sit} and R_{sit}) could be observed. The cells of the 2 × 2 table would be filled with trial × trial events, as is evident from Curran and Hintzman's (1997) comment (p. 499) regarding the relation of our model to their Figure 1.

However, the clarity they achieved with the format of their Figure 1 was lost in their discussion and in the development of their formulas. Instead of restricting their attention to the stochastic independence of A_{sit} and R_{sit} across trials, they apparently considered the covariation of A_{sit} and R_{sit} across subjects and items as well as trials. They imply that their consideration of this new level of analysis is informative about the arguments made in Curran and Hintzman's (1995) article about the effects of correlation across $\overline{A}_i$ and $\overline{R}_i$. As we show in Figure 1, correlations at the levels of ρ_{si} and of $\mathrm{Corr}(\overline{A}_i, \overline{R}_i)$ are not the same.[3]

Interpretation of $\mathrm{Corr}(\hat{\overline{A}}_i, \hat{\overline{R}}_i)$

Curran and Hintzman (1997, p. 501) called for an interpretation of the item- and subject-level correlations. We have already pointed out that the correlations based on mean values cannot be interpreted in terms of the correlation of the basic processes. What accounts for the substantial correlations observed by Curran and Hintzman and ourselves for estimates of A and R computed at the aggregate item or subject level? One source of correlation is an artifact of the mathematics involved in the estimation of $\overline{A}_i$ and $\overline{R}_i$. In practice, these are not observed averages but are rather estimated from the results of the include and exclude conditions of the process-dissociation paradigm. Call these estimates $\hat{\overline{A}}_i$ and $\hat{\overline{R}}_i$. Even if the $\overline{A}_i$ and $\overline{R}_i$ were truly uncorrelated as unknown random variables, when $\hat{\overline{A}}_i$ and $\hat{\overline{R}}_i$ are calculated from exclusion and inclusion experiments, the estimates will be correlated. Recall that the estimates make use of two empirical results from the process-dissociation procedure, the probabilities of reporting an *old* word in the inclusion test and in the exclusion test conditions. The nonlinear dependence of both $\hat{\overline{A}}_i$ and $\hat{\overline{R}}_i$ on the same two empirical facts induces correlation between the two estimates. A mathematical analysis of this correlation reveals that it can be either positive or negative, depending on the underlying parameters for the automatic and recollective memory processes. When parameter values similar to those shown in Jacoby et al.'s (1997) Table 1 are used, the expected correlation is modest and negative in sign.

Empirical Issues: The Importance of Dissociations

In contrast to arguments made by Curran and Hintzman (1997) about the importance of observed correlations, the standard way of gaining support for models such as ours is to show dissociations. This is done by showing that manipulations selectively influence parameters representing the two different processes. Manipulations meant to influence knowledge produce a change in the parameter representing knowledge (recollection) while leaving the parameter representing guessing (e.g., implicit memory) invariant and vice versa (e.g., Hay & Jacoby, 1996). Unless ρ_{si} is approximately equal to zero, such dissociations are not likely to be found.

Curran and Hintzman (1997, pp. 502–503) suggested that Jacoby et al.'s (1997) Table 1, which shows dissociations, is misleading, and they questioned the criteria used to select results for display in that table. The answer to their question is that we included results from experiments that we think are most comparable to their experiments. Of particular concern to them is our exclusion from that table of their experiments using their new "recollect-and-exclude method." We repeat the explanation that we offered in footnote 1 (Jacoby et al., 1997) for excluding that method (which should have kept readers from being misled): We believe their method is flawed. Regardless, results from many other experiments could have been included in Jacoby et al.'s (1997) Table 1 to make our point (e.g., results from Hay & Jacoby, 1996).

It is important to define boundary conditions to make the independence assumption plausible. It is only under those conditions that we predict relative invariance. Findings of paradoxical dissociations do not provide unambiguous evidence of violation of our independence assumption because they can as well arise from violation of other assumptions underlying our procedure, such as the assumption that R is equal for the inclusion and exclusion conditions. In their comments on the exclusion = 0 problem, Curran and Hintzman (1997) did not acknowledge our showing that a "paradoxical" dissociation can be removed by using a higher baseline so as to avoid exclusion = 0 (Jacoby, Toth, & Yonelinas, 1993). Also, significant baseline differences between inclusion and exclusion tests (Curran and Hintzman, 1995, Experiment 5) distort estimates of both R and A. Yonelinas and Jacoby (in press) discussed methods of taking baseline differences into account.

Curran and Hintzman (1997) complained that we have not provided evidence in the form of power analyses to show that we can convincingly accept the null hypothesis. However, if as they argue our independence assumption is implausible, large paradoxical dissociations should routinely be found. Results in Jacoby et al.'s (1997) Table 1 are not sufficient to accept the null hypothesis of absolute invariance, but they should discourage attempts to reject the null hypothesis within our boundary conditions against alternative hypotheses of wildly varying results. As far as we can see, Curran and Hintzman's (1997) only "out" for repeated failure to reject the null hypothesis is for them to explain away apparent findings of invariance (e.g., Curran

[3] For purposes of a formal psychometric analysis, it is important to note that variation over trials for fixed subjects and items is not necessarily the same as variation over subjects, for fixed items and randomly selected trials (Cronbach, Gleser, Nanda, & Rajaratnam, 1972; Shavelson & Webb, 1991). Covariation among variables can also be expected to differ across the subject, item, and trial domains. One problem with Curran and Hintzman's (1997) presentation is that they were unclear about which domains they were considering when they presented expressions for correlations, covariances, and variances. They used covariance operators with subject and item subscripts but without explicitly telling readers whether variation was defined over trials, items, subjects, or some combination of these.

and Hintzman, 1995, Experiment 4) as reflecting participants' failure to understand instructions in some mysterious way that routinely balances effects of violations of our "implausible" independence assumption.

Conclusions

The independence assumption we make is analogous to independence assumptions in signal-detection theory (Swets, Tanner, & Birdsall, 1961) and multinomial models of response bias (e.g., Buchner, Erdfelder, & Vaterrodt-Plünnecke, 1995; also see Yonelinas & Jacoby, in press, for a comparison of process-dissociation and multinomial models). If it were valid, Curran and Hintzman's (1997) strategy of using conveniently observed correlations to reject an underlying independence assumption would apply to those other models of response bias as well as to our model, and thus this strategy deserves wide and careful scrutiny.

Because of the ambiguity of their notation, we cannot be sure how to interpret all of Curran and Hintzman's (1997) arguments. However, we can be sure that they do not distinguish between aggregation bias and process dependence, a distinction that is crucial to our analysis. Also, we can be sure that the crucial level of correlation for our independence assumption is the correlation between outcomes on a particular trial—process independence. Observable correlations over items or subjects cannot provide evidence, direct or otherwise, concerning violation of independence at that crucial level of correlation. Rather, the correlations that Curran and Hintzman (1995, 1997) treat as "direct evidence" of violation of independence are *irrelevant* except for concerns about aggregation bias. Even then, observable correlations are useful only as a basis for guesses about the magnitude of the unobservable correlation, Corr($\overline{A}_{si}$ and $\overline{R}_{si}$), that is responsible for any aggregation bias that can come from use of our procedure. A guess about the magnitude of that unobservable correlation can be combined with a guess about unobservable variances to estimate the magnitude of aggregation bias. By our proper analysis, aggregation bias can be expected to be trivial and not differential across conditions.

A proper analysis will necessarily posit "hidden stochastic processes" (Curran & Hintzman, 1997, p. 499) to take into account correlation from sources such as the effects of momentary differences in attention as well as from any inherent differences among items. For that more sophisticated analysis, it is necessary to consider model-based "hypothetical probabilities" (Curran & Hintzman, 1997, p. 499) to determine through psychometric considerations the effects of aggregation, of nonlinear estimation, and of possible assumption violations such as would result from reliance on the generate–recognize strategy. However, preoccupation with hypothetical probabilities and with correlations that can only be imagined should not blind one to regularities in observed probabilities. Consistent finding of dissociations, such as those in Jacoby et al.'s (1997) Table 1, provides the strongest evidence for our independence assumption.

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(Postscript follows on next page.)

Postscript

Hintzman and Curran (1997) made it clear that their concern about correlation among item means, subject means, or even unobserved $\overline{A}_{si}$ and $\overline{R}_{si}$ means is due to the possibility of aggregation bias. They explicitly stated that their analysis assumes that $\rho_{si} = 0$. For several reasons, we believed that they had not made this independence assumption that is the basis of our estimation equations. Regardless, we all agree that correlations observed at the item or subject level cannot provide evidence of process dependence. Curran and Hintzman (1997) accepted our Equation 1 and extended it to describe aggregation over both subjects and items, which is an estimation procedure they prefer. While extending our equation, they cautioned the reader (Curran & Hintzman, 1997, p. 501) that the equations require information about correlations that cannot be directly observed. We agree with that cautionary statement.

What we continue to dispute is whether the examples of extreme aggregation bias that Hintzman and Curran (1997) described are relevant to the process-dissociation data that we or they have produced. We concur that if the standard deviations and the correlation in the numerator of our Equation 1 or their Equation 6 are large, then aggregation bias will tend to be large. So why are we not convinced by Curran and Hintzman's (1997) recasting of Jacoby et al.'s (1997) example that suggests that larger standard deviations are to be expected? The answer is that their change to the item–trial outcomes level influences more than the standard deviations. Although the standard deviations increase dramatically at that level, the correlation also goes down (Curran & Hintzman, 1997, p. 500) by an amount that leaves the estimate of aggregation bias about the same. Thus, the change in level of analysis does not matter in this case. Related to our basic dispute is our different speculation about how large the correlation in our various equations is likely to be. They argued that the correlation will be increased by subject–item interaction, and we argue that it is impossible to establish that these effects will lead to the extreme correlations they have considered. We also believe that one cannot make clear inferences about the unobservable correlation on the basis of correlations of *A* and *R* estimates. These observable correlations may be affected by the estimation process and ecological artifacts, as well as by the aggregation bias itself.

Although an important component of this article was developed to respond to a different understanding of Curran and Hintzman's (1997) article than we now have, we believe the general psychometric model of the process-dissociation procedure that we have outlined is useful. Not only has the exchange allowed us to clarify the nature of our fundamental independence assumption and the nature of aggregation bias, it has defined a framework for ongoing improvement of estimation methods and for refined specification of experimental procedures for dissociating automatic and recollective memory processes.