Distributional Analysis and De Jong, Liang, and Lauber's (1994) Dual-Process Model of the Simon Effect

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R. De Jong, C.-C. Liang, and E. Lauber (1994) proposed a dual-process model to account for the Simon effect and its reversal. Their proposal included a distributional analysis whose results, they claimed, support the time-course assumptions they make for the 2 processes of the model. It is shown that the 2 functional components of the dual-process model, the unconditional and conditional automaticity, are equivalent to earlier accounts of the Simon effect and its reversal, namely automatic response activation of the dimensional overlap model (S. Kornblum, T. Hasbroucq, & A. Osman, 1990) and logical recoding (A. Hedge & N. W. A. Marsh, 1975), respectively. It is also shown that the distributional analysis is a simple computational procedure that reflects fundamental statistical properties of the underlying reaction time distributions and their interrelationships and that De Jong et al.'s time-course assumptions precluded at least half of these interrelationships. Indeed, experimental results from tasks in which the Simon effect is obtained often violate these assumptions, as is demonstrated in this article. Finally, it is also shown that De Jong et al.'s data are consistent with the hypothesis that the Simon effect and its reversal, irrespective of the task type in which it is obtained, can be accounted for by a common mechanism with 2 independent functional components.

During the past 5 years there has been a significant increase in the number of articles published on stimulus–response compatibility (SRC). This is due in part to the fact that SRC is beginning to be seen as encompassing a broad spectrum of performance complexity, ranging from the relatively simple perceptual–motor tasks first studied by Fitts (Fitts & Deininger, 1954; Fitts & Seeger, 1953) to the cognitively more complex Stroop tasks that have defied explanation from the day the original one was first described (Stroop, 1935). Among the SRC phenomena that have recently attracted a great deal of attention is the Simon effect (e.g., De Jong, Liang, & Lauber, 1994; Hommel, 1993; Lu & Proctor, 1995; Umilta, 1994).

The Simon effect, narrowly defined, refers to the finding that in two-choice reaction time (RT) tasks in which the spatial position of the stimuli is irrelevant and the responses are made at the same relative spatial positions as the stimuli, the RT on trials on which the stimulus and response locations correspond is usually faster than on trials in which they do not correspond (see Simon, 1990, for a summary). Under some conditions, however, this effect is reversed.

That is, the RT on trials in which the stimulus and response locations correspond, instead of being faster, is slower than on trials in which they do not correspond. This has been a puzzle and has challenged a number of models in the literature that have attempted to account for the Simon effect (see Lu & Proctor, 1995, for a summary). Hedge and Marsh (1975), who first reported this reversal, accounted for it in terms of the logical recoding hypothesis. In their task, the stimuli consisted of the colors red and green, presented to the left and right of a central fixation point; the responses consisted of left and right keypresses, and the keys themselves were colored red and green. The stimuli and the responses thus had two attributes each: color and position. Hedge and Marsh argued that

> the logical character of the recoding which would relate either of these (stimulus) attributes to the attributes of the response might be either "identity" (same colour or same position) or "reversal" (alternate colour or alternate position).... For a given logical recoding (identity or reversal) of the relevant attribute (color) responding was faster for trials in which the recoding of the irrelevant attribute (position) was of the same logical type as that of the relevant attribute, than for trials in which the logical recoding of the irrelevant attribute was opposite in type. (Hedge & Marsh, 1975, p. 435)

In one of the recent articles to address this issue, De Jong et al. (1994) proposed a dual-process model in which they postulated two functional components together with specific assumptions concerning the relative time course of these components. They also presented results of a distributional analysis of their data in support of these assumptions. The model is presented as an all inclusive account of the Simon effect and its reversal. The purpose of the present article is to examine De Jong et al.'s model and distributional analysis

technique in detail. We shall argue the following points. (a) The dual-process model does not explain or clarify the reversal of the Simon effect beyond the logical recoding hypothesis account originally proposed by Hedge and Marsh (1975); the core of De Jong et al.'s new proposal lies in the time-course assumptions of these two functional processes. (b) Whereas the distributional analysis proposed by De Jong et al. uncovers interesting patterns in their data, we show that these patterns are mathematically derivable from the statistical properties of the RT distributions and are not necessarily related to the time-course assumptions of the dual-process model. (c) We present the results of experiments in which robust Simon effects were obtained and for which the results of the distributional analysis violate De Jong et al.'s time-course assumptions. (d) We show that De Jong et al.'s data strongly suggest that a common mechanism is generating the Simon effect across different types of tasks. This mechanism is most likely made up of two independent components; however, the details of how it produces the observed properties of the RT distribution remain to be identified. We take up these points in the order in which they are listed.

The Dual-Process Model

According to De Jong et al. (1994), the mechanism underlying the effects of an irrelevant stimulus position on performance has two components: (a) the unconditional priming component, "abrupt stimulus onset results in the strictly automatic priming of the spatially corresponding response" (p. 732); and (b) the conditional component, "when the task-defined S–R transformation (identity or reversal) is applied to the relevant stimulus attribute, it will tend to generalize to the spatial stimulus code resulting in the priming of the spatially corresponding or noncorresponding response, respectively" (p. 732). These two components are assumed to have different time courses. The first, the unconditional component, is assumed to become effective soon after stimulus onset, and to dissipate rapidly. The second, the conditional component, is assumed "not to be time-locked to stimulus onset, but to arise at the point in time when the transformation rule (identity or reversal) is applied to the relevant stimulus attribute and also, unintentionally, to the spatial stimulus code" (De Jong et al., 1994, pp. 732–733).

Functionally, the unconditional component is indistinguishable from the automatic response activation process of the dimensional overlap (DO) model (Kornblum et al., 1990; Kornblum & Lee, 1995)—including its underlying priming mechanism. As for the conditional component, De Jong et al. (1994) took as a given that the task-defined transformations consist of applications of the identity–reversal rule—which Hedge and Marsh (1975) had postulated (logical recoding hypothesis) in their original proposal. De Jong et al.'s idea of conditional automaticity suggesting the automatic application of the identity (or reversal) rule from the relevant to the irrelevant dimension is embodied in Hedge and Marsh's

hypothesis that the logical recoding of the same type is faster than if the recoding is of the opposite type.[1]

De Jong et al.'s (1994) dual-process model thus appears to be a hybrid consisting in one part of the DO model's automatic response activation process, and in the other part Hedge and Marsh's (1975) logical recoding hypothesis. The core of De Jong et al.'s new proposal lies in their time-course assumptions and their novel distributional analyses. We turn to these next.

The Distributional Analysis

Background

The distributional analysis of RT data is a computational procedure that De Jong et al. (1994) proposed for getting at the temporal dynamics of their two hypothesized processing components. First they calculated the RT distributions for spatially consistent (corresponding, in their term) and spatially inconsistent (noncorresponding) trials for each subject. The cumulative probability distributions are denoted as $P_c(t)$ and $P_i(t)$, respectively. Then, they divided each of these distributions into N quantiles or proportional bins, such that each bin contained the same proportion $(1/N)$ of trials (depending on the experiments, N was either 5 or 10).[2] An individual bin is identified by j, its quantile ID. The mean RT of those trials contributing to a particular bin (j) in the consistent distribution $[P_c(t)]$ is denoted as $t_c^{(j)}$, and in the inconsistent distribution $[P_i(t)]$, $t_i^{(j)}$. The difference between these corresponding mean RTs, $t_i^{(j)} - t_c^{(j)}$, is a bin-by-bin measure of the Simon effect, and when plotted as a function of the averages of these means, $(t_i^{(j)} + t_c^{(j)})/2$, it provides a measure of the changes over time in the magnitude of the Simon effect—we call this the distributional plot (see Figure 1). De Jong et al. (1994) found that for their data this function was roughly linear, with a negative slope that had roughly the same value across different S–R mapping conditions and experiments. That is, the magnitude of the Simon effect appeared to be greatest at fast responses and to decrease as responses slowed. S–R mapping instructions, on the other hand, appeared to change the intercept of this function (i.e., its vertical position in the distributional plot) without affecting the slope. De Jong et al. interpreted the slope of the distributional function as a measure of the time course for the unconditional component and the intercept as a measure of the conditional component and concluded that these effects were additive. The conclusion about the data showing additivity of factor effects is probably correct and, if so, important. However, whether these results necessarily

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[1] Until now, the DO model has not specified any mechanism for generalizing such rules to the outcome of the automatic process (but see Zhang, 1994). However, it does not seem that De Jong et al.'s (1994) dual-process model has articulated such a mechanism either. The sketch of a connectionist model in De Jong et al.'s Figure 11 does little to make this process explicit.

[2] In fact, the cumulative probability distributions had been horizontally averaged (Vincentized curve; see Ratcliff, 1979) across subjects before the quantization procedure to represent group data.

a)

Reaction Time
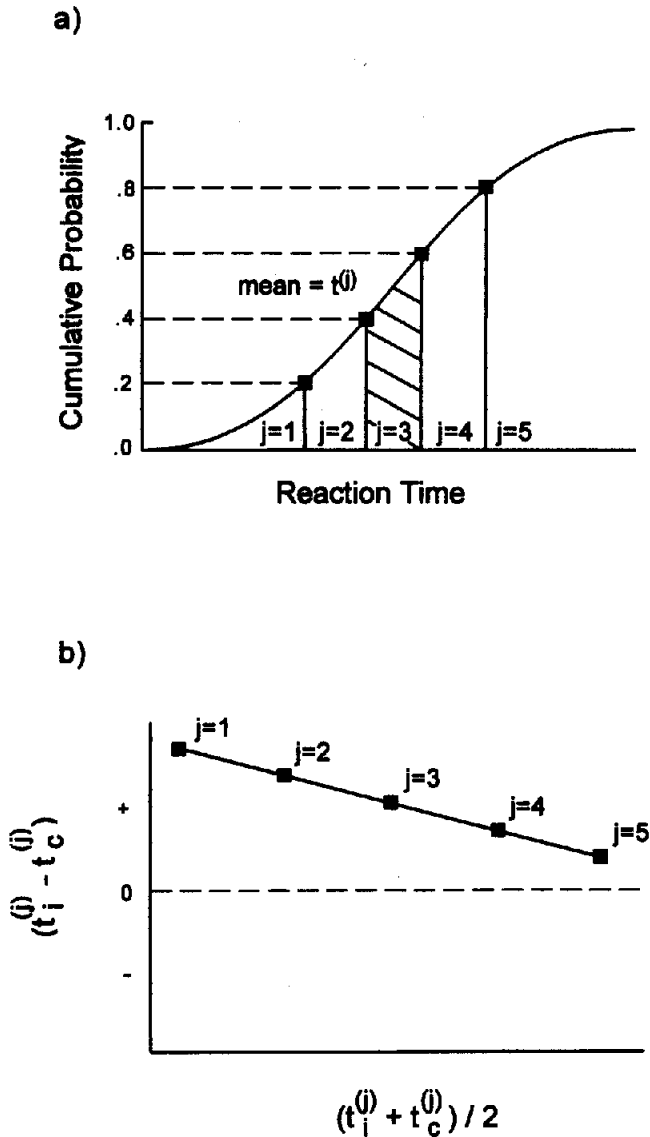
b)

$$(t_i^{(j)} + t_c^{(j)})/2$$

Figure 1. Distributional analysis of reaction time (RT) data. (a) A cumulative RT distribution $P(t)$, over many trials of a certain condition, is divided into N quantiles, that is, bins of equal proportion (here $N = 5$, indicating that each bin contains 20% of the total number of trials). The mean RT for the j-th quantile (bin) is calculated and denoted as $t^{(j)}$. (b) The above procedure is applied separately to the RT distribution for spatially consistent (i.e., corresponding) trials, $P_c(t)$, and to the RT distribution for spatially inconsistent (i.e., noncorresponding) trials, $P_i(t)$, so as to calculate the bin-averaged mean RTs, $t_c^{(j)}$ and $t_i^{(j)}$, respectively. The difference, $t_i^{(j)} - t_c^{(j)}$, and the average, $(t_i^{(j)} + t_c^{(j)})/2$, of the two means are plotted against each other to form the distributional plot (which appears linear from the data of De Jong et al., 1994).

reflect the effects of a differential time course for the two functional components is questionable, for there is an alternative interpretation. We shall prove that the distributional analysis procedure per se reflects statistical properties of the underlying RT distributions, rather than being based on De Jong et al.'s time-course assumptions.

Mathematical Foundation

We note that when $N \rightarrow \infty$, bins becomes increasingly smaller, so that the mean RT of a bin is closer to the boundary RT values defining the bin. The above procedure for determining the mean RT (averaged within each bin) then becomes finding corresponding t_c and t_i in the pair of RT distributions such that the cumulative probabilities (P) up to that bin, as indexed by t_c and t_i, respectively (we drop the bin ID j for simplicity), are equal (see Figure 1):

$$P_c(t_c) = P_i(t_i). \tag{1}$$

Now, given that the difference $(t_i - t_c)$ and the average $(t_i + t_c)/2$ of all corresponding bins obey a linear relationship with slope κ and ordinate intercept δ,

$$t_i - t_c = \kappa \cdot \left(\frac{t_c + t_i}{2}\right) + \delta, \tag{2}$$

and a linear relationship between t_c and t_i is inferred:

$$t_i = \lambda t_c + \tau, \quad t_c = \frac{t_i - \tau}{\lambda}, \tag{3}$$

with

$$\lambda = \frac{1 + \kappa/2}{1 - \kappa/2}, \qquad \tau = \frac{\delta}{1 - \kappa/2}. \tag{4}$$

Substituting Equation 3 into Equation 1, we have (because these equations hold for all corresponding pairs of t_c and t_i, we simply use t to denote this running variable)

$$P_c(t) = P_i(\lambda t + \tau), \qquad P_i(t) = P_c\left(\frac{t - \tau}{\lambda}\right). \tag{5}$$

This is to say, the two distributions are related to each other through an affine transformation on the time variable, that is, a shift τ plus a scaling λ. The forms of the two RT distributions are identical apart from an affine mapping A: $t \rightarrow \lambda t + \tau$. The grand means (mean RT) of the original distributions and their variances are, respectively,

$$\mu_c = \int_{-\infty}^{\infty} t dP_c(t), \quad \sigma_c^2 = \int_{-\infty}^{\infty} (t - \mu_c)^2 dP_c(t),$$

and

$$\mu_i = \int_{-\infty}^{\infty} t dP_i(t), \quad \sigma_i^2 = \int_{-\infty}^{\infty} (t - \mu_i)^2 dP_i(t).$$

We can easily derive, on the basis of Equation 4,

$$\mu_i = \lambda \mu_c + \tau, \qquad \sigma_i = \lambda \sigma_c. \tag{6}$$

Thus, the grand means and variances of the pair of RT distributions are related to each other through λ and τ or,

because of Equation 3, through κ and δ, the slope and intercept in the distributional plot. To work out the exact relationship, denote

$$\Delta\mu = \mu_i - \mu_c, \qquad \Delta\sigma = \sigma_i - \sigma_c$$

as the difference and

$$\hat{\mu} = \frac{\mu_c + \mu_i}{2}, \qquad \hat{\sigma} = \frac{\sigma_c + \sigma_i}{2}$$

as the average, respectively, of the grand mean and the variance for the pair of RT distributions $P_c(t)$ and $P_i(t)$. Equation 6 can be recast as

$$\Delta\mu = \kappa\hat{\mu} + \delta, \qquad \Delta\sigma = \kappa\hat{\sigma}. \tag{7}$$

Because $\delta' = \kappa\hat{\mu} + \delta$ is simply the vertical intercept calculated at the RT mean (this is actually how De Jong et al., 1994, defined intercept; see their footnote 2), we have the following conclusions: (a) The difference in mean for the pair of RT distributions, $\Delta\mu$, is only related to the vertical intercept at the mean δ' (and not to the slope κ), and (b) the difference in variance for the pair of RT distributions, $\Delta\sigma$, is related only to the slope κ (and not the vertical intercept δ'); its magnitude is proportional to κ as well as to the average variance (of the two distributions) $\hat{\sigma}$.

The Slope (κ) and De Jong et al.'s (1994) Time-Course Assumptions

Clearly, if the slope of the distributional plot is negative, that is, if $\kappa < 0$, then the variance of the inconsistent distribution must be smaller than that of the consistent distribution $(\sigma_i < \sigma_c)$, which is exactly what De Jong et al. (1994, Figure 4) found in their data. However, if the slope of the distributional plot is positive, then the variance ordering is reversed, that is, the variance of the inconsistent distribution is larger than that of the consistent distribution $(\sigma_i > \sigma_c)$. This is summarized in Figure 2. If such a function were to be obtained for a set of data that also displayed the Simon effect, it would constitute a direct violation of De Jong et al.'s time-course assumption. We illustrate such a case in Figure 3, which is a distributional plot calculated for previously published data (Kornblum, 1994).

In Kornblum's experiment, the relevant stimuli consisted of the colors green and blue, presented in the left, right upper, or lower half of a rectangle (3.2 × 1.2 cm) and viewed on a CRT screen from a distance of 75 cm. The spatial position of the color patches was irrelevant, as was a letter string presented in the center of the rectangle. The responses consisted of left–right keypresses. Each trial began with a warning signal consisting of the four corners of the stimulus rectangle. The stimulus was presented following a randomly selected interval of between 400 and 600 ms and was terminated by the subject's response. At a randomly selected interval of between 600 and 1,200 ms after the end of the posttrial feedback, the warning signal for the next trial was presented. In one third of the trials of a "pure" block,
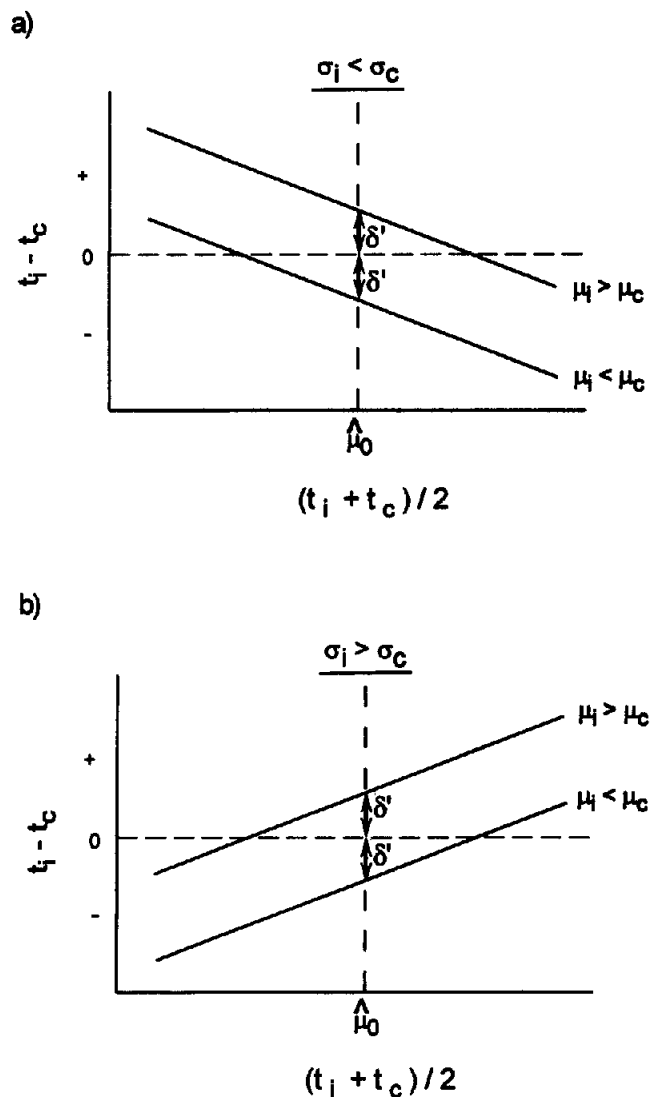
a)

$(t_i + t_c)/2$

b)

$(t_i + t_c)/2$

Figure 2. Possible relationships between the respective means μ_c, μ_i and variances σ_c, σ_i of the two reaction time distributions for spatially consistent (corresponding) and spatially inconsistent (noncorresponding) trials. (a) When the slope is negative ($\kappa < 0$), $\sigma_i < \sigma_c$ is inferred. The line at the top (with a positive vertical intercept δ') implies $\mu_i > \mu_c$, whereas the line at the bottom (with a negative δ') implies $\mu_i < \mu_c$. (b) When the slope is positive ($\kappa > 0$), $\sigma_i > \sigma_c$ is inferred. The line at the top (with a positive δ') implies $\mu_i > \mu_c$, whereas the line at the bottom (with a negative δ') implies $\mu_i < \mu_c$.

the colors appeared in either the upper or lower half of the rectangle (neutral condition), in another third of the trials they appeared in either the left or right half of the rectangle that corresponded to the spatial position of the response (S–R-consistent condition), and in another third they appeared in either the left or right half of the rectangle that corresponded to the opposite spatial position of the response (S–R-inconsistent condition). In the "mixed" blocks, half of the trials were identical to those we have just described, and in the same proportion, and the other half were slightly

different (see Kornblum, 1994, for details—there was no significant interaction between conditions in the mixed blocks).

The results, which have been reported previously (Kornblum, 1994), are quite straightforward: There was a statistically significant Simon effect in both pure (44 ms) and mixed (36 ms) blocks. Of particular interest, however, are the variances: For pure blocks, S–R-consistent trials had a standard deviation of 57 ms, as against 78 ms for the S–R-inconsistent trials; for mixed blocks, S–R-consistent trials had a standard deviation of 58 ms, as against 77 ms for the S–R inconsistent trials. According to our analysis, this particular ordering of the variances should produce distributional plots with a positive slope which, according to De Jong et al.'s (1994) time-course assumption, would preclude the occurrence of a Simon effect. The distributional plots for these data are shown in Figure 3. As can be seen, the slopes are positive. The fact that they were obtained from a set of data that also display the Simon effect constitutes a clear violation of De Jong et al.'s time-course assumption.

Additional evidence is presented in Table 1 (which should not be considered exhaustive[3]), where we show that for a number of studies in the literature that reported robust Simon effects, the order of the variances (or standard errors) for the S–R-consistent and S–R-inconsistent conditions in some cases conforms, and in other cases is opposite, to the order called for by De Jong et al. (1994). A smaller standard deviation or standard error for the S–R-consistent than for the S–R-inconsistent condition would imply a positive slope, κ, which of course would be a violation of De Jong et al.'s time-course assumptions. From Table 1, it is clear that there is not a consistent trend of the ordering of standard errors and, hence, the sign of the slope, as required by De Jong et al.'s time-course assumption.
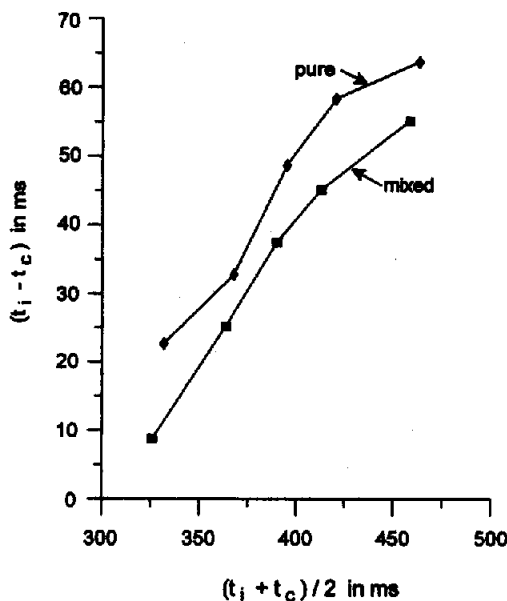
Table 1
Simon Effect: Stimulus–Response Consistent and Inconsistent Mean RTs and Variances

		Consistent		Inconsistent	
Article	Condition	M	SE	M	SE
Simon, Hinrich, &	Left	385	13.6	445	13.2
Craft (1970)	Right	386	12.0	457	13.7
Craft & Simon (1970)	Left	438	10.0	479	9.9
	Right	439	9.6	493	10.4
Simon & Craft (1970)	Left	530	12.7	511	10.3
	Right	485	11.3	577	11.2
Simon, Sly, & Vilapak-	Compatible	633	103	746	113
kam[a] (1981)	Incompatible	868	204	804	174
Kornblum & Lee[b]	Experiment 2	596	72.8	646	66.4
(1995)	Experiment 3	553	148.2	608	153.4

[a]In this experiment stimulus location, instead of being irrelevant (i.e., random with respect to the response), is redundant with the relevant stimulus, which is color. Standard deviations are reported here instead of standard errors. [b]Both experiments used Type 3 ensembles (see taxonomy in the section The Simon Effect). However, the irrelevant stimulus dimensions and the responses were spatial as well as nonspatial. Standard deviations are reported here instead of standard errors.

De Jong et al.'s (1994) Numerical Simulation

The appendix of De Jong et al.'s (1994) article contains a numerical simulation that is intended to rule out an alternative interpretation of linear distribution plots, one that attributes the observed negative slope to random trial-to-trial variability in the size of the Simon effect, that is, the statistical properties of RT distribution, as we propose here. By performing the simulation (which is described below), De Jong et al. claimed to have established conditions under which a negative (or a positive) slope will occur—the conditions have to do with the ratio of standard deviation and mean of the Simon effect. This conclusion is false. In this section, we show that all simulation results in Table A1 (p. 749) of De Jong et al. can be parsimoniously explained by the difference in variance between the relevant RT distributions, and may have nothing to do with the conditions under which a distributional plot reveals actual temporal dynamics, as claimed by De Jong et al.

The simulation used two RT distributions (both skewed Gaussians), one as a standard, reference distribution, called X, with $M = 400$ ms and $SD = 100$ ms; the other, a distribution representing the Simon effect, called Y ($M = 20$ ms, $SD = 10, 20$, and 50 ms for the low, medium, and high variance conditions, respectively). Random samples of $x \in$ X and $y \in$ Y were generated and were combined to generate RT of a simulated trial. Three different hypotheses or rules for generating RT distributions of corresponding–noncorresponding locations (denoted here as RT_c and RT_i) are simulated: for the "advantage only" rule, RT_c is generated by $x - y$, and RT_i by x; for the "disadvantage only" rule, RT_c is generated by x, and RT_i by $x + y$; for the "both" rule, RT_c

Figure 3. Distributional plots for some of the data of Kornblum (1994), in which the slopes are positive.

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[3] Unfortunately, very few studies on the Simon effect have reported standard deviations or standard errors.

is generated by $x - y/2$, and RT_i by $x + y/2$. (The plus or minus signs imply addition or subtraction of RTs drawn from the respective distributions, as in additive stage models.) Distributional analysis performed on the pair of distributions RT_i and RT_c reveal the following pattern of simulation results presented in their Table A1: (a) For the "advantage only" rule, the slope is negative; (b) for the "disadvantage only" rule, the slope is positive; (c) for both of the above rules, the absolute magnitude of the slope (regardless of sign) increases as the variance of Y increases; and (d) for the "both" condition, the slope is essentially zero (flat).

This pattern of data is easily understood in terms of the simple relationship derived in Equation 7: The slope κ is directly proportional to the difference of variance between RT_i and RT_c. A basic background observation is that the distribution of the addition $(x + y)$ or subtraction $(x - y)$ of two independent, random variables $x \in X$ and $y \in Y$ is simply the convolution of X with Y or with $-Y$. Because their variances are additive and because var$(-Y)$ = var(Y), the variance (of both the additive and subtractive combination) equals the variance of X *plus* the variance of Y. Therefore, for the "advantage-only" condition, a negative slope is predicted:

$$\text{var}(RT_i) - \text{var}(RT_c) = \text{var}(X)$$

$$- [\text{var}(X) + \text{var}(Y)] = -\text{var}(Y).$$

For the "disadvantage only" condition, a positive slope is predicted:

$$\text{var}(RT_i) - \text{var}(RT_c) = [\text{var}(X) + \text{var}(Y)/4]$$

$$- \text{var}(X) = \text{var}(Y).$$

For the "both" condition, an overall zero slope is predicted:

$$\text{var}(RT_i) - \text{var}(RT_c) = [\text{var}(X) + \text{var}(Y)4]$$

$$- [\text{var}(X) + \text{var}(Y)/4] = 0.$$

This is exactly the pattern of results in their Table A1! Another way of looking at this is that for the "advantage only" rule, RT_c is generated from a compound distribution (X convolving with $-Y$) and RT_i from a simple distribution (X), whereas for the "disadvantage only" rule, RT_c is generated from a simple distribution (X) and RT_i from a compound one (X convolving with Y). Because the variance of the compound distribution exceeds that of either simple distribution, the ordering of variances between RT_i and RT_c is just reversed for these two rules. This causes an apparent difference in the sign of the slope. The variance-based analysis above also explains why the magnitude of the slope (for both the "advantage only" condition and the "disadvantage only" condition) increases with an increase of the variance of Y, as is observed when one moves from low to medium to high in that table. To conclude, the simulation results in the appendix of De Jong et al.'s (1994) article in fact support the variance interpretation (our position) of the

slope of the distributional plot rather than the time-course interpretation (De Jong et al.'s position).

Discussion

The distributional analysis proposed by De Jong et al. (1994), when separated from their constraining and unwarranted time-course assumptions, has advantages as well as limitations. We have shown that the slope and intercept of a distributional plot are generated by the differences between the means and variances of the two underlying RT distributions and that these slopes can be positive or negative in principle as well as in fact. When the differences between the means and the variances are small and theoretically interesting, distributional analyses are especially valuable because they magnify such differences. However, we have also shown that if the distributional plots depart from linearity, as is evident from some of De Jong et al.'s data, it implies that the two underlying RT distributions differ in functional form. Such differences may be small, as, for example, when the two distributions differ in skewness, or large. In case of the latter, such differences may give rise to nonmonotonicity in the distributional plots, so that piecewise linear approximations might be adopted. Strictly speaking, when the two underlying distributions are not affine-related, Equation 7 is meaningless. Nevertheless, in practice, when N is small (as in the case of De Jong et al.), linear regression may be used to derive an equivalent slope and intercept so that Equation 7 holds approximately. In fact, it can be further shown that the distributional plot is intimately related to the so-called Q–Q plot that has been used extensively to study a family of probability distribution functions (see Appendix).

The Simon Effect

Thus far, we have shown that De Jong et al.'s (1994) time-course assumptions are theoretically unwarranted as well as unsupported by data in the literature. This brings into question De Jong et al.'s version of the dual-process account of the Simon effect. However, we have also shown that the distributional analysis per se is a potentially useful analytical tool. In this section, we show that De Jong et al.'s orderly data may also be a source of useful empirical information concerning the Simon effect. In particular, the strong similarities that emerge between characteristics of the Simon effect when obtained under different experimental paradigms strongly suggests that a common mechanism may be operating across all these paradigms that, as classified by the DO (dimensional overlap) taxonomy, all contain overlaps between an irrelevant stimulus and the response dimensions.

The Simon effect, as the term is used in the literature, requires that a consistency–inconsistency relationship exist between the irrelevant, spatial aspect of a stimulus and the spatial aspect of a response. This relationship may occur in a number of different experimental paradigms in which the responses are spatially defined or have a spatial attribute. These have been classified in the DO taxonomy (e.g., Kornblum, 1992) on the basis of whether there is DO between three different aspects of the task: the response, the

relevant stimulus, and the irrelevant stimulus. The resulting eight-class taxonomy is as follows. (1) Cases in which the relevant stimuli are neutral (i.e., have no DO) with respect to both the irrelevant stimuli and the responses. For example, tasks in which the relevant stimuli are, say, colors presented to the left or right of a central fixation point (with spatial position irrelevant, of course), and the responses consist of left–right keypresses. These are called Type 3 ensembles in the taxonomy. (2) Cases in which the stimuli and the responses are both two-dimensional (i.e., with two attributes), but the two dimensions are dissimilar. For example, tasks in which the relevant stimuli are colors, presented to the left or right of a central fixation point (with spatial position irrelevant, of course, as before), and the responses are left–right keypresses. Thus far, these conditions are identical to those in Type 3 above. However, in these new tasks the keys themselves are also colored. Thus, the two dimensions of the stimuli (color and position) overlap with the two dimensions of the responses (color and position) but not with each other. Either of the stimulus dimensions may be mapped onto either of the response dimensions, making the dimensions not included in the mapping irrelevant. These are called Type 5 ensembles in the taxonomy. (3) Cases in which the stimulus is three-dimensional and there is overlap between the relevant and one of the irrelevant stimulus dimensions, as well as between the other irrelevant stimulus dimension and the response. These are called Type 7 ensembles in the taxonomy (examples may be found in Kornblum, 1994). (4) Cases with two-dimensional stimuli and one-dimensional responses, in which the relevant stimulus dimensions overlap with the response and with each other. These, of course, are Stroop or Stroop-like tasks where, for example, the relevant stimuli are the words *left* or *right*, presented left or right of a central fixation point (with spatial position irrelevant), and the responses consist of left–right keypresses. These are called Type 8 ensembles in the taxonomy. Hedge and Marsh (1975) used Type 5 ensembles in their study. De Jong et al. (1994) used Type 5 ensembles in Experiments 1 and 4 of their study; Type 3 ensembles in Experiment 2, as well as in the control condition of Experiment 3; and a Type 7 ensemble in Experiment 3 (even though De Jong et al. called it a Stroop task—presumably because they thought it was a Type 8 ensemble).[4]

Regardless of the details, all theories of the Simon effect assume, implicitly or explicitly, that when two stimulus attributes, or a stimulus and a response attribute, have DO, some sort of automatic associative, attentional, or activation process occurs that may interfere with, or facilitate, performance. In Type 3 ensembles (which produce the pure Simon effect), the only viable candidate relationship is that between the irrelevant spatial aspect of the stimulus and the response.[5] The occurrence and origin of the Simon effect (as previously defined) in those ensembles is, therefore, clear and unambiguous. In Type 5 ensembles with incongruent S–R mapping instructions, there are, in principle, at least two potential sources of conflict—one for each of the S–R overlapping dimensions. The origin of the Simon effect in these ensembles is, therefore, less clear. Because these

dimensions are themselves dissimilar, Type 5 may in fact be a dual task in which the same effector is used to execute the two responses—thus complicating matters considerably (e.g., see Structural Interference in Kahneman, 1973, p. 196). Type 7 ensembles, which combine Type 3 with Type 4 ensembles (Type 4 ensembles are those in which the relevant and irrelevant stimulus dimensions overlap with each other, but neither overlaps with the response—these are sometimes called Stroop-like stimuli) have been studied by Kornblum (1994), who has shown that the effects of these two ensemble types seem to be additive. The occurrence of the Simon effect in these ensembles is, therefore, clearly identifiable and similar to those in Type 3. In Type 8 ensembles, because of the overlap (i.e., similarity) between the stimulus and the response dimensions, and between the stimulus dimensions themselves, the situation is much less clear than in Type 3. Here, there are three potential sources of conflict: two between the response and each of the two stimulus attributes (relevant and irrelevant), and one between the two stimulus attributes themselves. These attributes could all be having an effect, either simultaneously, selectively, additively, or interactively. The origin and identification of a Simon effect in Type 8 ensembles are, therefore, much more ambiguous than in Type 3. These taxonomic distinctions and their potential functional consequences raise the question of whether the Simon effect, when obtained in all these different experimental paradigms, can be accounted for by a common mechanism.

De Jong et al.'s (1994) data may help shed some light on this question. For, regardless of the ensemble type (3, 5, or 7), De Jong et al. obtained a Simon effect and their data had two consistent trends: (a) negative slopes with constant magnitude (κ between -0.09 and -0.12) and (b) vertical intercepts that vary systematically depending on the S–R mapping conditions (when applicable). The intercepts values were positive for identity, or congruent, mapping and negative for reverse, or incongruent, mapping. This pattern strongly suggests the influence of two independent factors on RT: (a) an automatic response activation process that is associated with the presence of DO between the irrelevant stimulus dimension and the response and affects the variances of the S–R-consistent and S–R-inconsistent RT distributions (this is equivalent to De Jong et al.'s unconditional automaticity) and (b) a controlled process associated with the S–R mapping of the relevant stimulus that affects the means of the RT distributions; note that this factor is different from De Jong et al.'s conditional automaticity. The

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[4] The tasks themselves all had a slight twist in trial blocking that made them different from the standard tasks ordinarily run with these ensembles. In particular, either the irrelevant dimension was made relevant on a certain proportion of the trials, that is, the required response was made contingent on it, or the required response changed on a certain proportion of trials (e.g., keypress to verbal); or variables that are usually blocked, like response labels, or S–R mapping, were randomized within blocks.

[5] Note that in the taxonomy of the DO model, this irrelevant dimension could be anything—color, number, letter, and so on. It is only when the Simon effect is narrowly defined that this dimension is spatial.

fact that this pattern of results was observed for a series of experiments that obtained the Simon effect with Ensemble 3, 5, and 7, all of which include an irrelevant stimulus dimension that overlaps with the response, strongly suggests that the mechanism underlying the Simon effect in these different tasks is probably the same. Of course, the precise operational details of this mechanism remain to be identified.

Conclusion

We have shown that De Jong et al.'s (1994) conditional and unconditional automatic processes are intimately related to the logical recoding hypothesis of Hedge and Marsh (1975) and to the automatic response activation process of Kornblum's (Kornblum et al., 1990) dimensional overlap model, respectively. We have also shown that De Jong et al.'s data and distributional analyses do not necessarily support their time-course assumptions and that these assumptions need not be satisfied in order to obtain the Simon effect. However, De Jong et al.'s data do seem to reflect independent influences of an automatic and a controlled process on the statistical characteristics of the underlying RT distributions. De Jong et al.'s empirical findings are intriguing, and our reanalysis of them redefines some of the questions in the area and, we hope, provides a new framework that may make them more tractable.

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Appendix

Distributional Plot and Q–Q Plot

The distributional plot proposed by De Jong et al. (1994) is intimately associated with the so-called Q–Q plot that has been used extensively to study a family of probability distribution functions (see, e.g., Thomas & Ross, 1980; Wilk & Gnanadesikan, 1968). The Q–Q plot, or quantile–quantile plot, is a means by which the running parameters generating corresponding quantiles of the two distributions are plotted against each other. In terms of our earlier notations, it is a plot of $t_c^{(j)}$ against $t_i^{(j)}$, as j varies for the two cumulative distributions $P_c(t)$ and $P_i(t)$. Thomas and Ross (1980) have shown that the necessary and sufficient condition for the two probability distributions to be related by an affine transform

A—this is when the commonly adopted Vincentizing procedure for across-subject averaging is valid—is that the Q–Q plot of these distributions is linear. The distributional analysis proposed by De Jong et al., on the other hand, plots $(t_i - t_c)$ against $(t_i + t_c)/2$. Obviously, the distributional plot is a 45°-rotated version of the Q–Q plot. Therefore, it is not surprising that a linear relationship in the distributional plot merely demonstrates that the two distributions, $P_c(t)$ and $P_i(t)$, are related through Equation 4 and have the same form (i.e., belong to the same "family"). Linearity in a distributional plot reflects the statistical properties of the pair of RT distributions and not necessarily functional hypotheses concerning processing mechanisms (see Figure A1).
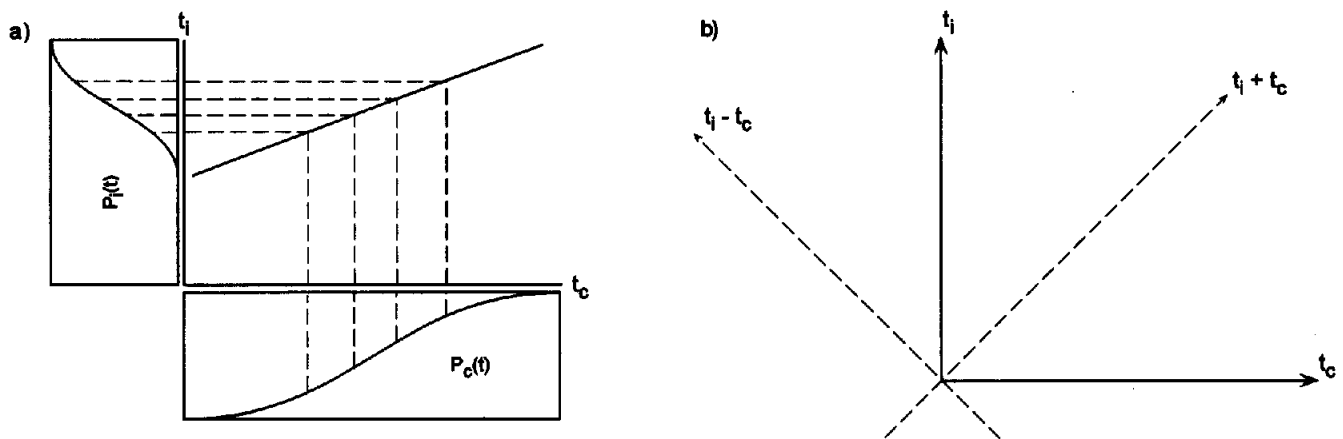

Figure A1. Relationship between distributional plot and Q–Q plot. (a) The Q–Q plot (quantile–quantile plot) is generated by directly plotting the bin-averaged mean reaction times for consistent and inconsistent trials, that is, $t_c^{(j)}$ and $t_i^{(j)}$, against each other (c.f. Figure 1). A linear function in the Q–Q plot implies that the two reaction time distributions are affine related, that is, they differ only by a scale and a shift factor (see Equation 4). (b) The distributional plot is merely a 45°-rotated Q–Q plot, so the linearity relationship is preserved. The slope and intercept in the Q–Q plot are λ and τ, as in Equation 3. In the distributional plot, they are κ and δ, as in Equation 2. The two sets of parameters are linked through Equation 4.