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Analysis of Response Time Distributions in the Study of Cognitive Processes

William E. Hockley
University of Toronto, Ontario, Canada

The convolution analysis of response time (RT) distributions (Ratcliff & Murdock, 1976) was examined in three experiments employing four different cognitive tasks. In Experiment 1, a visual search task was contrasted with a short-term memory (Sternberg, 1966) search task. In Experiments 2 and 3, a relative judgment of recency task was contrasted with a two-alternative, forced-choice recognition task. Taken together, the experiments demonstrate that the convolution analysis provides a good description of RT distributions in a variety of tasks, and more important, that the parameters of the convolution analysis can behave differentially in different tasks. It is argued that the parameters of the convolution analysis can play an important role in discriminating between models and in critically evaluating models that may be otherwise acceptable.

Mean response time (RT) has often been used to study cognitive processes, but other properties of RT distributions have received far less attention. Nevertheless, other properties of RT distributions provide more information than can be obtained from mean RT alone, and these have been shown to be important in discriminating between models (Sternberg, 1973) and in critically evaluating otherwise acceptable models (Ratcliff & Murdock, 1976).

Two methods have been used to characterize the properties of RT distributions. Sternberg (1964, 1969) used moments and cumulants to describe distributional properties. However, Ratcliff (1979) identified three major problems with this method. First, the variance associated with the estimates of the higher moments and cumulants is extremely large. Thus, to obtain stable estimates of higher moments, a large number of observations per subject condition are required. Second, estimates of moments are extremely sensitive to outlier RTs. Finally, the third and fourth moments provide information about a part of the frequency curve that may be of little theoretical interest.

An alternative method for analyzing RT distributions was advocated by Ratcliff and Murdock (1976) and Ratcliff (1979). Ratcliff and Murdock argued that the convolution of normal and exponential distributions (Hohle, 1965) provides a good description of observed RT distributions and yields parameters that are important in the evaluation of specific models of cognitive processing. The convolution is the distribution of the sum of a normally distributed and an exponentially distributed variable.

The purpose of the present article is twofold. First, the present study extends the work of Ratcliff and Murdock (1976) by applying the convolution analysis to a variety of cognitive tasks to examine the usefulness of this method of analysis. Second, and more important, the present study was designed to compare and to contrast the behavior of the parameters of the convolution analysis of RT distributions in several different cognitive tasks in order to draw inferences concerning processing in these tasks.

The expression for the convolution of normal and exponential distributions is given by the following:

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Requests for reprints should be sent to William E. Hockley, Department of Psychology, University of Toronto, Toronto, Ontario, Canada M5S 1A1.

$$f(t) = \frac{e^{-[(t-\mu)/\tau]+\sigma^2/2\tau^2}}{\tau(2\pi)^{1/2}} \int_{-\infty}^{[(t-\mu)/\sigma]-\sigma/\tau} e^{-y^2/2}dy,$$

where μ (mu) and σ (sigma) are the mean and standard deviation, respectively, of the normal distribution and τ (tau) is the parameter (and mean) of the exponential distribution. Roughly, mu and sigma reflect the leading edge of the distribution (the minimum RTs), and tau reflects the tail of the positive skew of the distribution. Although the convolution analysis represents RT distributions in an explicit form, it does not identify stages of processing with the component mathematical stages.

Ratcliff and Murdock (1976) used the convolution analysis to evaluate critically the conveyor-belt model (Murdock, 1974; Murdock & Anderson, 1975; Murdock, Hockley, & Muter, 1977) of item recognition. The conveyor-belt model postulates a backward, self-terminating comparison process in order to account for the linear lag-latency functions observed in the study-test paradigm. A serial processing model that assumes that the comparison rate is constant or does not vary too greatly predicts that the entire RT distribution should shift as the number of items involved in the comparison process increases (Hockley & Corballis, 1982; Ratcliff & Murdock, 1976). In terms of the parameters of the convolution analysis, the increase in mean RT is predicted to be reflected largely in the parameter mu. In the study-test paradigm, the linear increase in mean RT was found principally to be a result of an increase in the convolution parameter tau (Ratcliff & Murdock, 1976). Hockley and Corballis (1982) also found that the linear increase in mean RT as a function of memory set size in the prememorized-list recognition paradigm is largely a result of an increase in tau and similarly argued against serial processing.

The finding that a linear increase in mean RT is largely a result of an increase in tau (an increase in the positive skewness of the RT distribution) rather than an increase in mu (an increase in the leading edge of the RT distribution) seems to be problematic for serial processing models. However, for this argument to be entirely convincing, it is necessary to show that under all reasonable circumstances changes in mean RT are largely reflected in mu rather than in tau. In other words, it is important to examine the behavior of the convolution parameters in different situations. (It should be noted that mu and tau are not mathematically independent. If different random samples are taken from a particular distribution and the convolution analysis is performed, then one would find that the fitted parameters vary but in such a way that mu and tau are negatively correlated; R. Ratcliff, personal communication, November 23, 1983.)

The convolution analysis has been applied to a variety of recognition paradigms (Hockley, 1982; Hockley & Corballis, 1982; Ratcliff, 1978; Ratcliff & Murdock, 1976). The general pattern that has emerged from these studies is that the increase in mean RT as a function of test lag or memory set size is, in large part, reflected in the parameter tau. In contrast, Hacker (1980) found in a study of choice reaction time for relative judgments of recency that the change in mean RT as a function of the study position of the later probe was largely reflected in the parameter mu. This suggests that mu and tau behave differentially in recognition and judgment of recency. However, a more direct test of the differentiation of mu and tau would involve demonstrating a different pattern of results in a within-subjects comparison. Experiments 1 and 2 were designed to offer such comparisons.

Experiment 1

In Experiment 1, subjects received alternate blocks of trials on two different tasks within each session. The first task was a visual search task based on the visual search experiments of Neisser (1963). Subjects were presented with a target item followed by a vertically presented search set of 3, 4, 5, or 6 items. Subjects were required to determine whether the target item was contained in the search set. The search set was displayed until the subject responded. On the basis of the studies on visual search by Atkinson, Holmgren, and Juola (1969), Burrows and Murdock (1969), and Neisser (1963), it was expected that the visual search process would be serial in nature, and thus, mean RT for both positive and negative responses would be a linear function of the size of the search set. In addition, the search process was expected to be self-terminating for positive tests, so that the slope of the positive function would be approximately half of the slope of the negative function because, on the average, a target would be found in the middle of the search set.

The second task was a memory search task based on the Sternberg (1966) varied-set paradigm, in which subjects are presented with a to-be-remembered set of 3, 4, 5, or 6 items followed by a single recognition probe. The typical finding in this paradigm is that mean RT for both positive and negative responses is a linear function of memory set size with the slopes of the positive and negative functions being comparable. On the basis of these results, Sternberg (1966) proposed a serial, exhaustive-search model of item recognition.

For both the visual search task and the memory search task, if the rate of each serial comparison process is assumed to be relatively constant, then the increase in mean RT should be largely the result of an increase in the leading edge of the RT distribution because each additional comparison would take additional time. If such is the case, then the increase in mean RT would be principally reflected in an increase in the distribution parameter mu because mu characterizes changes in the leading edge of the RT distribution. (The degree to which successive comparisons must be "constant" for this prediction to hold will be explored later.)

Method

Subjects. Six right-handed University of Toronto students each completed 11 1-h sessions. Subjects were tested individually and were paid for their participation.

Apparatus. In all experiments, list generation, display, and response recording were controlled by a PDP12A laboratory computer. Stimuli were presented on a cathode-ray (CRT) screen, which was approximately 75 cm from the subject. Subjects responded on the two outer keys of a six-key response panel connected to the computer via the sense lines. For each response, the key pressed and the latency of the response (measured from the onset of the test stimuli to the key press) were recorded on magnetic tape. Response latency was measured in units of 5 ms.

Stimuli. The stimulus set consisted of the letters of the alphabet excluding vowels. All letters were presented in uppercase.

Procedure. Each session was divided into eight blocks of trials. The two tasks alternated between blocks. The order of the tasks was counterbalanced across sessions and subjects. A cue was presented at the beginning of a block, indicating the nature of the task for the following trials.

Each block consisted of 40 trials. The memory search sets and the visual search sets consisted of 3, 4, 5, or 6 letters. For each trial, the letters were selected randomly from the stimulus set. The order of set sizes was random within a block with the restriction that each set size was presented 10 times. The order of positive and negative trials was also random with the constraint that positive and negative trials occurred equally often within a block. For positive trials, the serial position of the target item was selected randomly without constraint.

Each trial was preceded by a ready signal that was displayed until the subject pressed any key. For a visual search trial, the sequence of events was as follows: presentation of the target letter for 1,250 ms, a blank interval of 500 ms, a warning signal (three asterisks) for 250 ms, a blank interval of 500 ms, and the presentation of the search set. The letters of the search set were displayed vertically with the top-most letter of the set occupying the same position on the screen as the target letter and warning signal. The search set was displayed until the subject made a response. Subjects were then given feedback on the accuracy of their responses.

The sequence of events for a memory search trial was as follows: presentation of the memory set at a rate of 1,200 ms/item, with a blank interval of 50 ms after each item; a 2,750-ms blank delay; the presentation of the warning signal for 250 ms; a blank interval of 500 ms; and the presentation of the probe. The probe was displayed until a response was made. Subjects then received feedback on the accuracy of their responses.

Half of the subjects were instructed to press Key 1 on the left of the response panel for a negative response and to press Key 6 on the right of the response panel for a positive response, and half of the subjects were given the reverse instructions. Subjects used the index finger of each hand in responding. Subjects were instructed to make their responses both as accurately and as quickly as possible, but the emphasis was placed on accuracy. In addition to feedback after each response, subjects also received feedback on the total number of correct and incorrect responses for each task in the form of a summary table printed at the end of each session.

Results and Discussion

Of the total number of observations collected (21, 120), there were 9 responses recorded with a latency of 0 and 36 responses, with a latency greater than 4 s. These responses were omitted from the data analyses.

Visual search. Mean RT averaged over subjects for both correct positive and negative responses as a function of set size and for correct positive responses as a function of serial position are given in Figure 1. The mean latency–set-size functions were well fit by linear functions. The best-fitting linear

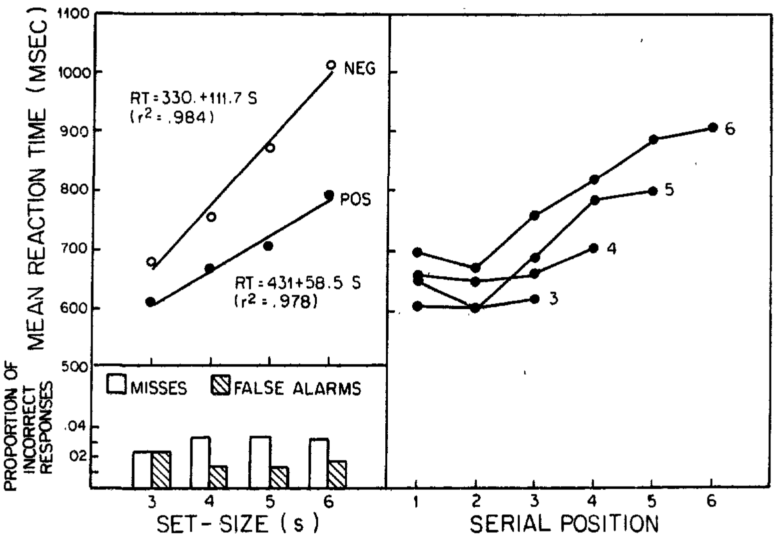

Figure 1. Mean response time (RT) for correct positive and negative responses as a function of set size, the proportion of misses (open bars) and false alarms (crossed bars) for each set size (left panel), and mean RT for correct positive responses for each set size as a function of serial position (right panel) for the visual search task of Experiment 1.

functions derived from a least squares fit of mean RT are included in Figure 1. The proportions of misses and false alarms for each set size are also included in Figure 1. The overall miss rate was .031 and the overall false-alarm rate was .017.

An analysis of variance (ANOVA) of correct RTs based on subject means showed that the main effect of set size was significant, $F(3, 15) = 21.15$, $p < .0001$; the difference between positive and negative RTs was significant, $F(1, 5) = 10.69$, $p < .05$; and the Set Size × Response (positive or negative) interaction was significant, $F(3, 15) = 17.65$, $p < .0001$. For correct positive RTs, the effect of serial position was analyzed separately for each set size. Serial position was not significant for Set Size 3, $F(2, 10) < 1$, or for Set Size 4, $F(3, 15) = 1.34$. However, the effect of serial position was significant for Set Size 5, $F(4, 20) = 10.62$, $p < .001$), and for Set Size 6, $F(5, 25) = 19.13$, $p < .001$.

The pattern of results depicted in Figure 1 is consistent with a serial search process that is exhaustive for negative responses and self-terminating for positive responses. First, the latency–set-size functions for both negative and positive responses are linear. Second, the slope of the positive function is approximately half of the slope of the negative function. Finally, there are pronounced serial position effects for positive responses for Set Sizes 5 and 6.

If the visual search process is a serial, self-terminating process for positive responses and the order of the visual search proceeds from top to bottom, then mean RT for the bottom serial position as a function of set size should be comparable to the mean RT function for correct negatives as a function of set size. The best-fitting linear function for correct positive mean RT for the bottom serial position of each set-size is as follows: $RT = 324.1 + 96.2\,s$ (with $r^2 = .998$), where s denotes set size. This function is very similar to the function for mean RT of correct negative responses given in Figure 1.

The obtained RT distributions for correct negative responses for each set size for each individual subject were fit by the convolution of normal and exponential distributions by SIMPLEX, a method of function minimization (Nelder & Mead, 1965). The goodness of fit of the convolution analysis was determined by a chi-square goodness of fit statistic in the same manner as was done by Ratcliff and Murdock (1976, p. 198). Of the 24 fits, only 1 fit was significantly different by the chi-

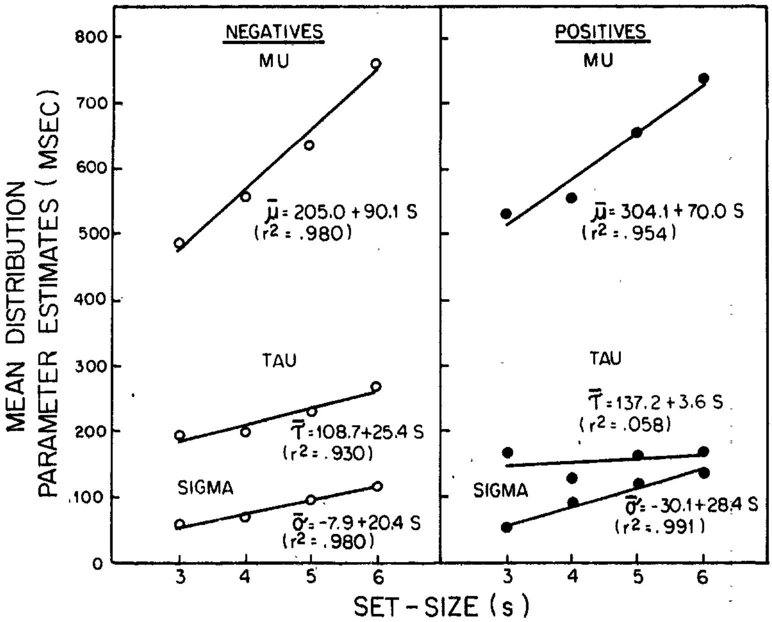

Figure 2. Mean distribution parameter estimates for correct negative responses as a function of set size (left panel) and for correct positive responses for the bottom serial position of each set size (right panel) for the visual search task of Experiment 1.

square test ($p < .05$). The obtained parameter estimates of mu, sigma, and tau for each set size, averaged over subjects, are presented in Figure 2.

Because of the large serial position effects for positive responses, serial position is the appropriate independent variable for the distribution analysis of positive responses. Accordingly, the RT distributions of correct positive responses for the bottom serial position of each set size for each subject were fit by the convolution analysis. The estimates of the convolution parameters for each set size, averaged over subjects, are also given in Figure 2.

In order to characterize the relative increases of the distribution parameter estimates, the parameter estimates presented in Figure 2 were also fit by linear functions. It is shown in Figure 2 that the increase in mean RT is largely reflected by an increase in the parameter mu. It will be demonstrated later that this pattern of results is consistent with a serial processing account of visual search that assumes that the component comparison processes are not too extremely skewed.

Memory search. Mean RT for correct positive and negative responses as a function of set size and for correct positive responses as a function of serial position are presented in Figure 3. The mean positive and negative latency–set-size functions were well fit by linear functions. The best-fitting linear functions are included in Figure 3. The proportion of misses and false alarms for each set size are also included in Figure 3. The overall miss rate was .043, and the overall false-alarm rate was .042.

An ANOVA for correct RT based on subject means showed that the main effects of set size, $F(3, 15) = 19.87$, $p < .0001$, and the difference between positive and negative responses, $F(1, 5) = 14.34$, $p < .02$, were significant. The Set Size × Response Type interaction was not significant, $F(3, 15) < 1$. Separate ANOVAs for positive RTs revealed that the effect of serial position was not significant for Set Size 3, $F(2, 10) = 1.38$; Set Size 4, $F(3, 15) = 2.16$; Set Size 5, $F(4, 20) < 1$; or Set Size 6, $F(5, 25) = 1.44$; all $ps > .05$.

The pattern of results given in Figure 3 represents a reasonable replication of Stern-

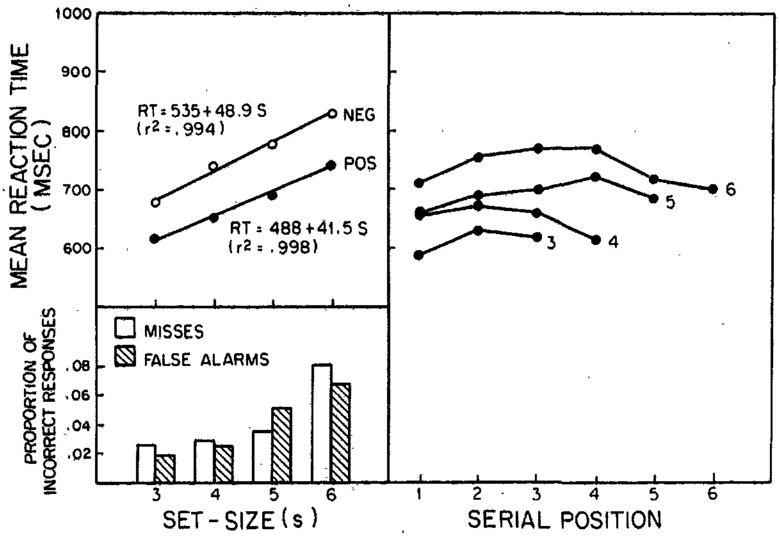

Figure 3. Mean response time (RT) for correct positive and negative responses as a function of set size, the proportion of misses (open bars) and false alarms (crossed bars) for each set size (left panel), and mean RT for correct positive responses for each set size as a function of serial position (right panel) for the memory search task of Experiment 1.

berg's (1966) classic findings: The functions for both positive and negative responses are linear with comparable slopes, and the serial position effects for positive responses are not significant.

The RT distributions for both correct negative and positive responses for each set size for each subject were fit by the convolution analysis. Of the 48 total fits, only 2 were significant ($p < .05$) by a chi-square test. The obtained estimates of mu, sigma, and tau, averaged over subjects, are given in Figure 4. The mean estimates were fit by linear functions that are also included in Figure 4. The

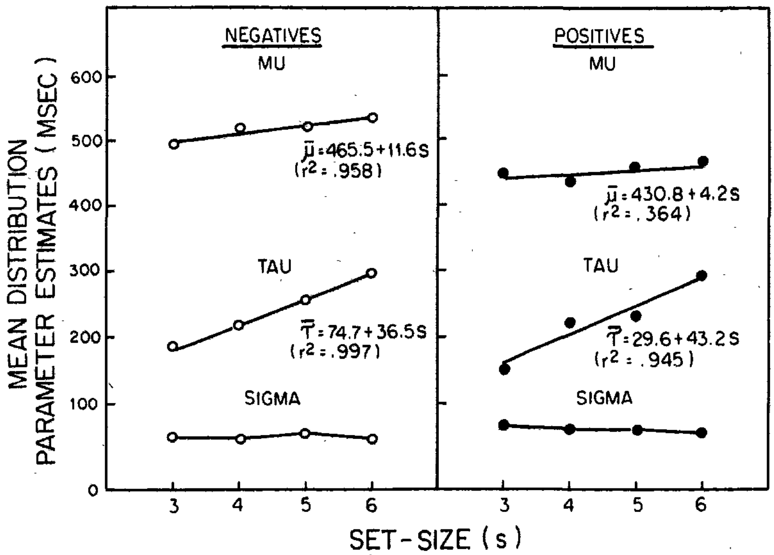

Figure 4. Mean distribution parameter estimates as a function of set size for correct negative responses (left panel) and correct positive responses (right panel) for the memory search task of Experiment 1.

parameter sigma did not vary greatly over set size. Both mu and tau increased as a function of set size. However, the increase in tau was much greater than the increase in mu.

The results of the RT distribution analysis of the memory search task stand in contrast to the pattern of results observed for the visual search task. In the memory search task, much of the increase in mean RT as a function of set size was a result of an increase in the parameter tau, whereas in the visual search task, much of the increase in mean RT was a result of an increase in the parameter mu. Thus, the results of Experiment 1 offer a clear demonstration of the differential patterns of mu and tau between the two tasks. This difference in the pattern of change between the RT distributions in the two tasks is also illustrated in Figure 5. In Figure 5, the obtained RT distributions of Subject 2 for correct negative responses for each set size for each of the two tasks are presented. It is clear in Figure 5 that the leading edge of the distribution increases with set size for the visual search task. However, for the memory search task, the leading edge stays relatively constant while the distribution becomes more positively skewed as a function of set size.

It was previously noted that if a serial search process underlies performance in the visual search task and in the memory search task, and if the rate of each serial comparison process is assumed to be relatively constant, then the increase in mean RT should be largely reflected in the distribution parameter mu. The distribution analysis results of the visual search task are consistent with a serial search process as the increase in mean RT is largely a result of an increase in the parameter mu, or an increase in the leading edge of the RT distribution. However, the results of the distribution analysis for the memory search task showed that much of the increase in

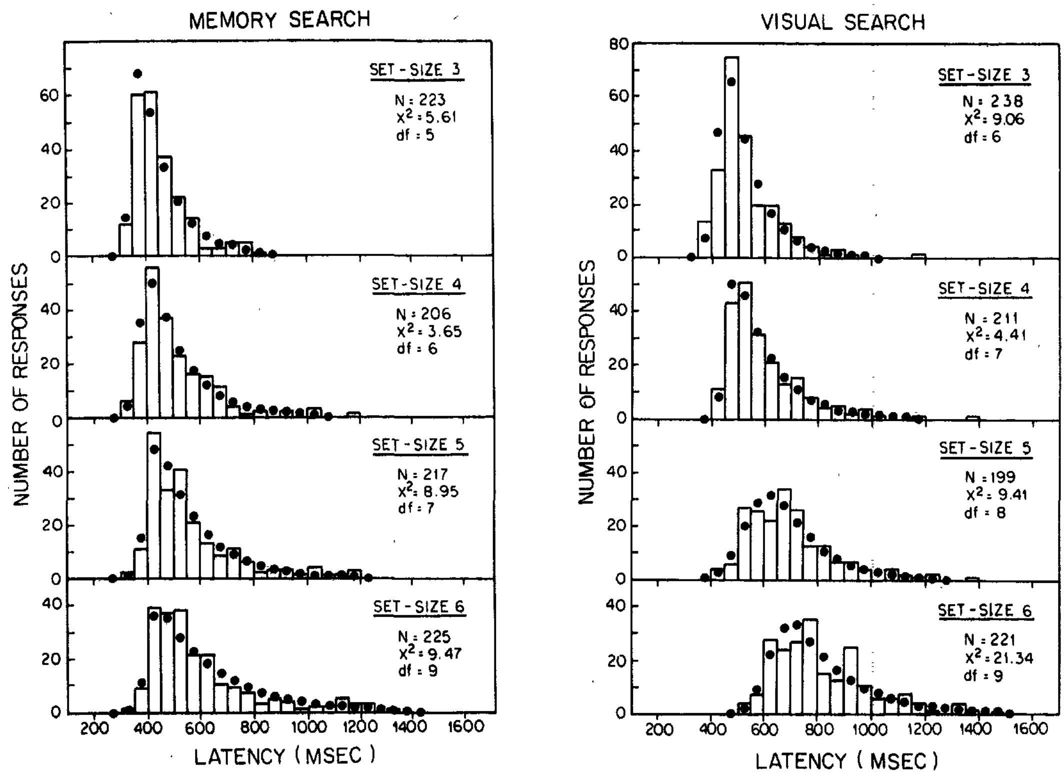

Figure 5. Obtained negative response time distributions (bar graphs) and theoretical fits of the convolution model (dots) for Subject 2 for the memory search task (left panel) and the visual search task (right panel) of Experiment 1.

Table 1
Mean Response Times (RT), Standard Deviations (SD), Distribution Parameter Estimates (in Milliseconds), and Chi-Square Values From the Simulations of an Exponentially Variable Serial Comparison Process

n	*M* RT	*SD*	Mu	Sigma	Tau	χ^2	*dfs*
			Normal distribution (500, 100) + exponential distribution (40)[a]				
1	540.3	105.1	498.6	96.5	41.2	1.967	7
2	578.5	113.7	521.2	97.9	57.2	5.658	7
3	617.4	119.5	566.3	108.2	50.3	2.390	7
4	658.0	129.5	598.0	114.7	59.9	11.305	8
5	696.3	129.8	629.3	111.2	67.0	5.471	8
6	737.5	133.9	662.8	111.1	74.6	7.147	8
			Normal distribution (500, 100) + exponential distribution (100)[b]				
1	600.5	139.8	504.4	97.8	96.2	6.455	8
2	696.0	169.2	568.1	111.3	126.6	10.178	10
3	793.4	195.2	658.4	142.6	135.1	6.801	12
4	894.9	226.7	736.9	164.3	157.9	11.845	13
5	990.5	232.7	821.2	166.5	168.4	8.344	13
6	1,093.5	249.9	927.4	188.4	166.2	11.433	14

Note. The parameter *n* refers to the number of comparisons. *dfs* = degrees of freedom. The linear functions for *M* RT, mu, and tau were derived from a least squares fit of the mean estimates.
[a] *M* RT = 500.0 + 39.4*n*, with r^2 = .999. *M* mu = 461.7 + 33.6*n*, with r^2 = .996. *M* tau = 37.8 + 5.9*n*, with r^2 = .864. [b] *M* RT = 499.8 + 98.6*n*, with r^2 = .999. *M* mu = 407.5 + 84.4*n*, with r^2 = .996. *M* tau = 91.9 + 14.2*n*, with r^2 = .905.

mean RT as a function of set size was a result of the increasing positive skewness of the RT distributions. This result rules out a memory serial search process that assumes a constant comparison rate.

It is, however, more reasonable to assume that the serial comparison rate is variable. In order to test whether a serial search process with a variable comparison rate is compatible with the present results, two simulations were done. Following Ratcliff and Murdock (1976, p. 205), it was assumed that the distribution for comparison time and switching time is exponential. The time for other stages (encoding, decision, and response execution) was assumed to be normally distributed. The mean and standard deviation of the normal distribution in each simulation were 500 ms and 100 ms, respectively. The mean and standard deviation of the exponential distribution in each simulation were 40 and 100 ms, respectively. To simulate the search task for Set Sizes 1–6, successive samples from the exponential distribution were added to samples from the normal distribution. Thus, for Set Size *n*, the probability distribution function for the *n* comparisons is the sum of *n* exponential distributions. This results in a gamma distribution with parameter *n*. The sample size in each simulation was 250. The obtained mean RT and standard deviation of each generated distribution are given in Table 1. Mean RT increased linearly with the number of "comparisons." The best-fitting linear functions for mean RT as a function of the number of comparisons are given in Table 1.

The generated distributions were fit by the convolution analysis in the same manner as was done for the results of Experiment 1. The distribution parameter estimates of mu, sigma, and tau, and the chi-square values for each fit are also presented in Table 1. Mu, sigma, and tau increased with the number of comparisons. To determine the relative increases of mu and tau, these parameters were fit by linear functions. The best-fitting linear functions are also presented in Table 1. The increase in mu as a function of the number of comparisons was far greater than the increase in tau. Thus, when the rate of the serial comparison process is assumed to vary exponentially, the increase in mean RT as a function of the number of comparisons should be largely reflected in the parameter mu. The

Table 2
Mean Response Times (RT), Standard Deviations (SD), Distribution Parameter Estimates (in Milliseconds), and Chi-Square Values From the Simulations of a Serial Comparison Process With Extreme Variability

n	*M* RT	*SD*	Mu	Sigma	Tau	χ^2	*dfs*
			Normal distribution (500, 100) + Distribution A[a]				
1	540.1	135.1	438.6	80.3	100.6	4.522	8
2	580.1	159.1	450.7	81.8	128.7	12.390	8
3	620.1	171.4	461.1	66.1	159.0	10.963	9
4	660.1	191.5	483.8	80.3	176.7	7.595	10
5	700.1	200.2	515.3	91.4	183.8	4.948	10
6	740.1	214.5	535.3	92.3	204.6	7.589	11
			Normal distribution (500, 150) + Distribution B[b]				
1	540.7	200.5	396.9	88.3	158.0	11.154	10
2	581.3	243.0	390.3	80.1	207.2	14.794	10
3	621.9	258.0	403.7	80.5	228.4	7.235	11
4	662.5	293.2	403.6	82.9	271.8	12.783	12
5	703.1	303.2	416.7	99.3	294.3	12.756	13
6	743.7	330.2	417.5	109.0	328.0	22.877	14

Note. The parameter *n* refers to the number of comparisons. *dfs* = degrees of freedom. The linear functions for *M* RT, mu, and tau were derived from a least squares fit of the mean estimates.
[a] Distribution A had 250 observations and a variance greater than the mean squared; it had a mean of 40.0 ms, a variance of 7,249 ms^2, and a range of 10 ms to 610 ms. *M* RT = 500.1 + 40.0n, with r^2 = 1.00. *M* mu = 410.8 + 20.0n, with r^2 = .966. *M* tau = 88.6 + 20.1n, with r^2 = .962. [b] Distribution B had 250 observations and a variance greater than the mean squared; it had a mean of 40.6 ms, a variance of 16,982 ms^2, and a range of 10 ms to 860 ms. *M* RT = 500.1 + 40.6n, with r^2 = 1.00. *M* mu = 386.6 + 5.2n, with r^2 = .819. *M* tau = 132.5 + 33.0n, with r^2 = .989.

results of the visual search task are consistent with the pattern of results obtained in the simulation (cf. Table 1 with Figure 2).

Schneider and Shiffrin (1977) and Sternberg (1964) used more extreme distributions to characterize the comparison-time distribution, f(t). Schneider and Shiffrin used a gamma distribution, and Sternberg used a beta distribution. Both of these distributions are similar: The densities of the distributions descend sharply and monotonically from an infinite peak when t is very small, and both have long tails extending toward large values of t. Schneider and Shiffrin found it necessary to use such a distribution because their variance estimates were larger than the estimates of the mean squared.

In order to determine if an extreme distribution of comparison time would result in a greater increase in tau than in mu, two additional simulations were performed. Two arbitrary distributions were generated by hand. Each distribution had 250 observations and a variance greater than the mean squared. Distribution A had a mean of 40.0 ms, a variance of 7,249 ms^2, and a range of 10 ms to 610 ms. Distribution B had a mean of 40.6 ms, a variance of 16,982 ms^2, and a range of 10 ms to 860 ms. The two simulations were done in the same way as the previous simulations. The results of these simulations are presented in Table 2.

In the first simulation presented in Table 2, both mu and tau increased as a function of the number of comparisons, and their relative rates of increase were comparable. In the second simulation, the increase in tau was much greater than the increase in mu. This result is consistent with the results obtained for the memory search task of Experiment 1.

The simulations just described demonstrate that if serial search processes are assumed to underly performance in both the visual and the memory search tasks, then it is clear that the two search processes are quite different. For the memory search task, unlike the visual search task, it must be assumed that the serial comparison rate is extremely variable. These simulations also serve to demonstrate the stringent constraints posed by the convolution analysis of RT distributions for any theoretical account of a given task.

It is important to note that serial models cannot be ruled out simply by observing, within the convolution analysis, a greater increase in tau relative to mu. This observation applies to the studies mentioned at the beginning of this article as well as to the present investigation. Of course, serial models that will exhibit a greater increase in tau than in mu must be based on extremely variable and skewed component distributions. It may be that in a given experimental setting such distributions can be ruled out on some other basis.

Of the other models that have been developed to account for performance in the Sternberg memory search paradigm, two are discussed briefly: Pike, Dalgleish, and Wright's (1977) multiple-observations model and Ratcliff's (1978) parallel processing model. The multiple-observations model predicts a decrease in skewness of the RT distribution as set size (and the parameter k) increases (Pike, 1973). This prediction is contrary to the present memory search findings. Ratcliff's parallel processing model predicts an increase in both mu and tau as a function of set size (assuming that probe–target "relatedness" decreases as set size increases), with the increase in tau being greater than the increase in mu (see Ratcliff, 1978, Figure 4). Thus, qualitatively, Ratcliff's model appears to be consistent with the present memory search findings.

Experiment 2

Experiment 2 was designed to contrast the pattern of RT distributions between a relative judgment of recency task and a forced-choice recognition task. The judgment of recency task was based on the recency discrimination studies reported by Muter (1979) and Hacker (1980). These investigators found that the serial position of the later probe was the principal determinant of performance. In addition, Muter (1980) and Hacker (1980) observed that the change in mean RT as a function of the serial position of the later probe was largely reflected as a change in the distribution parameter mu. Both Muter and Hacker proposed that relative judgments of recency are based on a backward, self-terminating serial search of the study list. The judgment of recency task of Experiment 2 was designed to replicate the findings of Muter and Hacker.

The forced-choice recognition task of Experiment 2 was based, in part, on the forced-choice recognition study reported by Murdock and Anderson (1975, Experiment 3). Murdock and Anderson used a 15-item study list and a multiple-test procedure. They also varied the number of test alternatives from two to six. They found that correct mean RT was a linear function of the study-test lag. The slope of the function increased in direct relation with the number of test alternatives. As discussed earlier, it is typical in recognition that the increase in mean RT is largely reflected as a change in the distribution parameter tau. A similar result was expected for the forced-choice recognition task of Experiment 2.

In both tasks, subjects were presented with a six-item study list followed by a two-item probe set. In the judgment of recency task, both probe items were from the study list, and subjects were required to indicate which item occurred more recently in the study list. In the recognition task, one probe item was from the study list and one item was a lure, and subjects were required to indicate which probe item had been in the study list. For both tasks, the study-list serial position of the target item was the principal independent variable.

Method

Subjects. Four right-handed University of Toronto students each completed 1 practice and 10 experimental sessions. Subjects were tested individually and were paid for their participation.

Stimuli. The stimulus set consisted of 512 common, two-syllable nouns not more than eight letters in length obtained from the word pool described by Friendly, Franklin, and Hoffman (1980). All words were presented in uppercase.

Procedure. Each session consisted of eight blocks of trials. The two tasks alternated between trial blocks. The order of the tasks alternated across sessions and was counterbalanced across subjects. At the beginning of each block, a cue was presented for 2 s, indicating the nature of the task for the block of trials to follow. Each trial was preceded by the task cue (OLD/NEW? or MOST RECENT?) and a ready signal (READY?). The task cue was presented above the ready signal. Subjects initiated a trial by pressing any key on the response panel.

For each task, the sequence of events for a trial was identical. After subjects pressed a key in response to the ready signal, there was a 500-ms blank interval followed by the presentation of the six-word study list. Each word was presented for 950 ms, with a 50-ms blank interval between presentations. A warning signal (***) was then presented for 500 ms, followed by a blank interval of 500 ms, and then the probe set was presented. The probe set remained on the screen until the subject responded. Subjects then received feedback on the accuracy of their response.

The probe set consisted of two words presented one above the other. The top test word appeared in the same vertical position as the ready signal, the study words, and the warning signal. The distance from the bottom of the top test word to the top of the bottom test word was approximately 10 cm. All words were centered on the screen with respect to the left–right dimension.

Each block consisted of 36 trials. Within each block, all words were selected randomly without replacement from the word pool. Thus, no word was presented in more than 1 trial within a block. For the recognition task, one test word was a study-list word, and one test word was a new word. The serial position of the study-list word was selected randomly with the constraint that all serial positions were tested equally often within a block. For the judgment of recency task, both test words were selected randomly from the study list with the constraint that the serial positions of each of the test words were tested equally often within a block. The order of the two test words (top vs. bottom) was determined randomly on each trial.

For the recognition task, subjects were instructed to press Key 1 on the left of the response panel if the top test word was the study-list item and to press Key 6 on the right of the response panel if the bottom test word was the study-list item. For the judgment of recency task, subjects were instructed to press Key 1 if the top word was the most recent and to press Key 6 if the bottom word was the most recent. Subjects used the index finger of each hand in responding. Subjects were instructed to respond as accurately and as quickly as possible in each task, but the emphasis was placed on accuracy. Subjects received feedback on the total number of correct and incorrect responses in the form of a summary table printed at the end of each session.

Results and Discussion

Of the total number of observations collected (11,520), there were 4 responses recorded with a latency of 0 and 288 responses, with a latency greater than 4 s. (Of the 288 responses greater than 4 s, 245 were in the judgment of recency task, and 43 were in the recognition task. One subject contributed 183 of the total number of responses greater than 4 s.) These responses were excluded from the following data analyses.

Judgment of recency. Mean RT, averaged over subjects, for correct recency judgments for each study position of the later probe as a function of the study position of the earlier probe is presented in Figure 6. It is clear from Figure 6 that the study position of the earlier probe had little effect on mean correct response latency, whereas the study position of the later probe had a large effect on response latency. Separate ANOVAs of RTs based on subject means showed that the study position of the earlier probe was not significant when the study position of the later probe was 3, $F(1, 3) = 2.58$; 4, $F(2, 6) < 1$; 5, $F(3, 9) = 2.41$; or 6, $F(4, 12) = 1.67$; all $ps > .05$. The proportion of correct responses for each study position of the later probe as a function of the study position of the earlier probe is also presented in Figure 6. The pattern of results for the proportions of correct responses is entirely consistent with the pat-

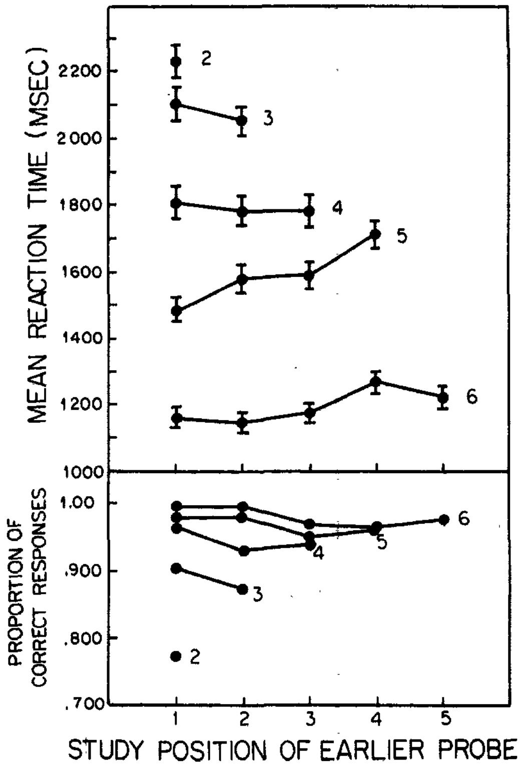

Figure 6. Mean correct response time (RT) and the proportion of correct responses as a function of the study position of the earlier probe for the judgment of recency task of Experiment 2. (The parameter is the study position of the later probe. The vertical bars represent the standard errors of the means.)

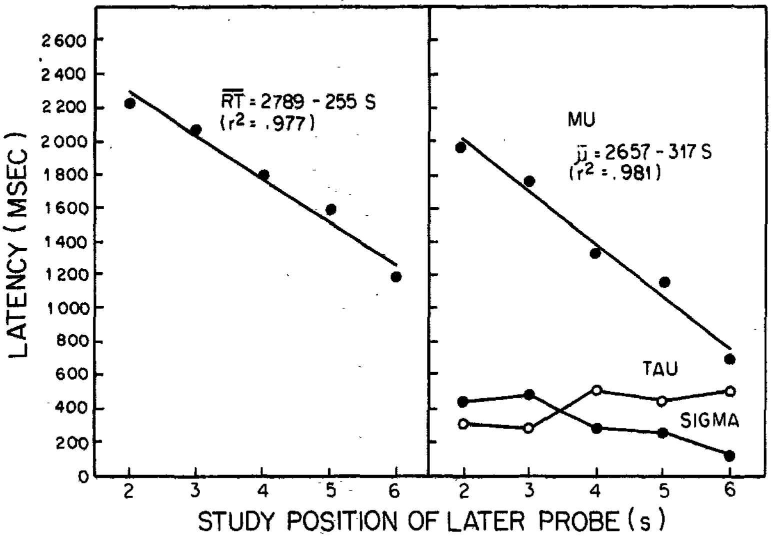

Figure 7. Mean correct response time (RT) (left panel) and the mean distribution parameter estimates (right panel) as a function of the study position of the later probe for the judgment of recency task of Experiment 2.

tern of results for mean RT. The results depicted in Figure 6 provide a good replication of the principal findings of Muter (1979) and Hacker (1980).

As the study position of the earlier probe had little effect on response latency, mean RT was analyzed as a function of the study position of the later probe collapsed over the study position of the earlier probe. An ANOVA of RT based on subject means showed that the main effect of the study position of the later probe was significant, $F(4, 12) = 11.68$, $p < .001$. The main effect of probe position (top vs. bottom) and the Probe Position $\times$ Study Position interaction were not significant, $F(1, 3) = 5.38$, and $F(4, 12) = 1.18$, respectively, both $ps > .05$. Mean RT for correct recency judgments, averaged over subjects, as a function of the study position of the later probe (collapsed over the study position of the earlier probe and probe position) is presented in the left panel of Figure 7.

The convolution analysis was performed on the RT distributions obtained for each subject for each study position of the later probe collapsed over the study position of the earlier probe and probe position. Of the 20 fits to the convolution model, 4 were significant by a chi-square test ($p < .05$). Of the 4 significant fits, 3 were for Study Position 2. This position had the fewest number of observations for each distribution. The parameter estimates of mu, sigma, and tau, averaged over subjects, are presented in the right panel of Figure 7. It is readily apparent that the large increase in mean RT as a function of the study position of the later probe shown in the left panel of Figure 7 is the result of an increase in the distribution parameter mu. This result is consistent with the backward, self-terminating serial model of recency judgments proposed by Hacker (1980); this model does not assume that the component processes are variable.

Forced-choice recognition. Mean RT for correct recognition decisions and the proportion of correct responses for both top and bottom probe positions as a function of the study position of the correct alternative are presented in Figure 8. Response latency was faster for the top probe item at all serial positions. The mean RT functions show a one-item primacy effect and a large and extensive recency effect. An ANOVA of correct RT based on subject means showed that the main effect of serial position was highly significant, $F(5, 15) = 35.05$, $p < .001$. The main effect of probe position and the Probe Position $\times$ Serial Position interaction were not

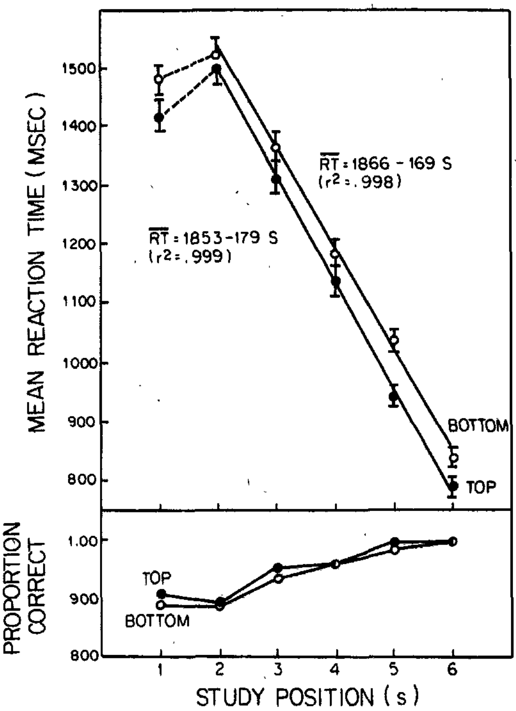

Figure 8. Mean correct response time (RT) and the proportion of correct responses as a function of study position for top and bottom probe positions for the forced-choice recognition task of Experiment 2. (The vertical bars represent the standard errors of the means.)

significant, $F(1, 5) = 5.09$, and $F(5, 15) < 1$, respectively. When the first study position is excluded, mean RT as a function of study position was well fit by linear functions. The best-fitting linear functions derived from a least squares fit of mean RT are included in Figure 8.

The convolution analysis was performed on the RT distributions of each subject for each study position for both probe positions. Of the 48 distributions fit, only 3 were significant by a chi-square test ($p < .05$). The convolution parameter estimates of mu, sigma, and tau, averaged over subjects, are presented in Figure 9. Linear functions were fit to the mean parameter estimates in the same manner as was done for mean RT, in order to compare their relative rates of change over study position. Both mu and tau increased as a function of study position. The difference in mean RT between top and bottom probe positions was almost entirely reflected in the parameter mu.

The forced-choice recognition results were surprising. In addition to the extremely large recency effect, the RT distribution analysis showed that the change in mean RT as a function of study position was reflected in changes of both mu and tau. This result stands in contrast to the typical pattern of results obtained in other recognition paradigms. Thus, the expected contrast for the distribution parameter mu between the two tasks of Experiment 2 was not obtained. However, the parameter tau did behave differently in the two tasks.

The pattern of results for the judgment of recency task, both at the level of analysis of mean RT and at the level of analysis of the properties of the RT distributions, is consistent with the backward, self-terminating search model of recency proposed by Hacker (1980). The pattern of results obtained in the forced-choice recognition task may be compatible with a backward, self-terminating

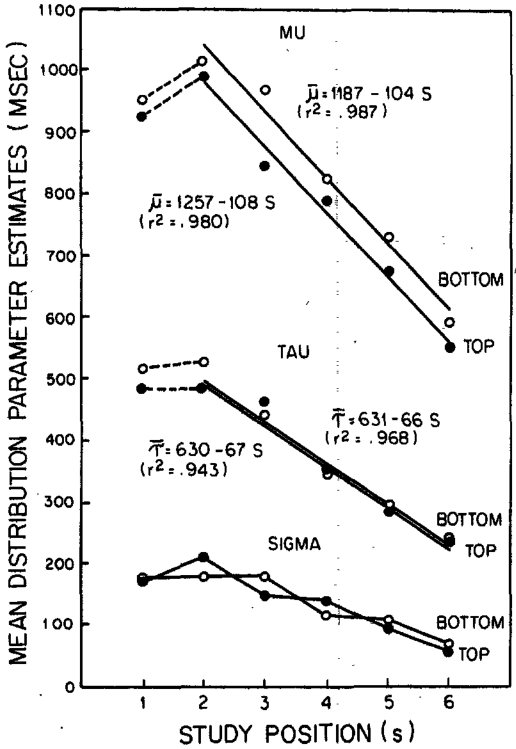

Figure 9. Mean distribution parameter estimates for top and bottom probe positions as a function of study position for the forced-choice recognition task of Experiment 2.

search process. However, such a serial search process would have to be based on extremely variable and skewed component processes in order to account for the relatively large increase in tau as a function of serial position. It is also possible that a parallel processing model (e.g., Murdock, 1971; or Ratcliff, 1978) or a familiarity model (e.g., Gillund & Shiffrin, 1984) could be extended to account for the forced-choice recognition results.

The forced-choice recognition results must be interpreted with some caution. It is possible that there was interference between the two tasks in Experiment 2. As the results of the recency task were largely in agreement with previous findings, it is reasonable to assume that the recognition task did not interfere with the judgment of recency task. However, the converse may not be true: The presence of the recency task might have influenced the recognition task. Subjects could have adopted a strategy appropriate for the recency task and could have employed this strategy on all or on a proportion of the recognition trials. As all subjects showed a similar pattern of results, any interference between the two tasks would not appear to reflect individual differences. Experiment 3 was designed to replicate the forced-choice recognition results of Experiment 2 in isolation. In order to increase the generality of the results, list length was also varied from three to six items.

Experiment 3

Method

Subjects. Four right-handed undergraduate students each completed 11 1-hr sessions. Subjects were paid for their participation.

Apparatus and stimuli. The apparatus and stimuli were the same as in Experiment 2.

Procedure. Each session consisted of four blocks of trials, and there were 72 trials per block. For each block of trials, all words were selected randomly without replacement from the word pool. Thus, no word was presented in more than 1 trial within each block. The length of the study list was varied from three to six items. The list lengths 3, 4, 5, and 6 were presented 12, 16, 20, and 24 times each, respectively, within each block of trials. The order of the list lengths within each block was random. The serial position of the target item and the order of the target and lure items in the probe set (top vs. bottom) were determined randomly for each trial. Each trial was preceded by a ready signal (READY?). Subjects initiated a trial by pressing any key in response to the ready signal. In all other respects, the procedure of Experiment 3 was identical to the procedure of the forced-choice recognition trials of Experiment 2.

Results and Discussion

There were 30 observations recorded with a response latency of 0 and 48 responses, with a latency greater than 4 s. These observations (0.62% of the total observations) were excluded from the data analyses.

Mean RT for correct responses (hits) for both top and bottom probe positions is presented as a function of study-list length in Figure 10. The latency–list-length functions were well described by linear functions. The best-fitting linear functions are included in Figure 10. An ANOVA based on subject means revealed that the main effect of the list length was highly significant, $F(3, 9) = 79.80$, $p < .0001$; the main effect of probe position (top vs. bottom) was significant, $F(1, 3) = 15.45$, $p < .029$; and the List Length $\times$ Probe Position interaction was not significant, $F(3, 9) < 1$.

The proportion of misses for both top and bottom probe positions for each list length is also presented in Figure 10. The overall miss rate was .039 for top probes and .056 for

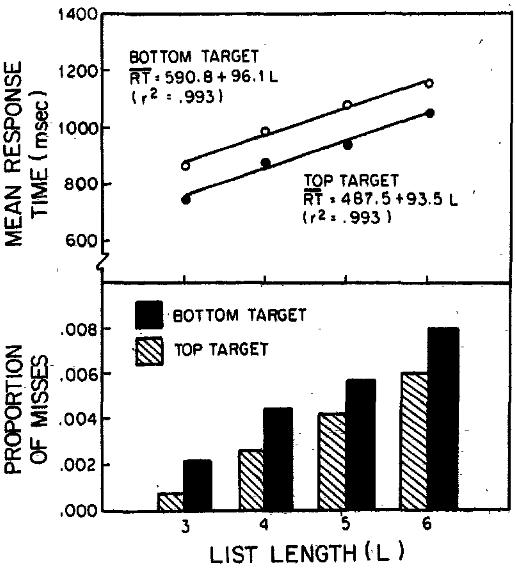

Figure 10. Mean correct response time (RT) and the proportion of misses for both top and bottom probe positions as a function of study list length for the forced-choice recognition task of Experiment 3.

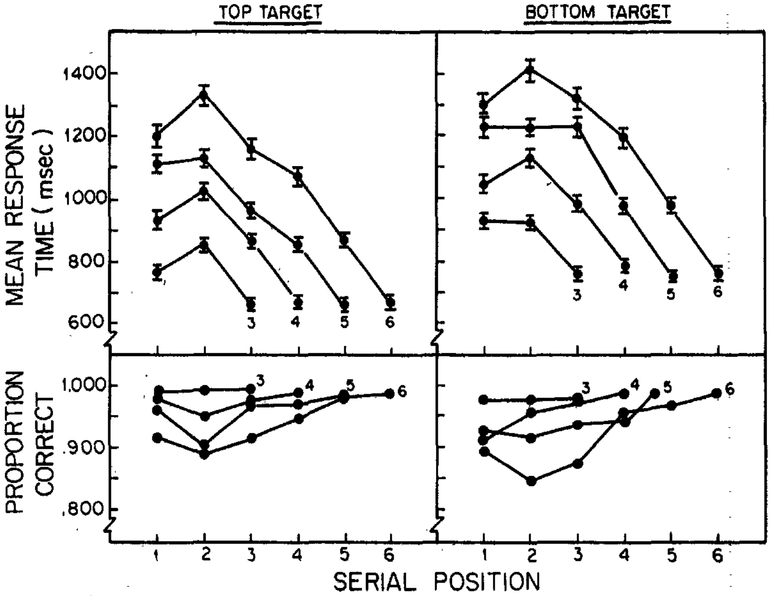

Figure 11. Mean correct response time (RT) and the proportion of correct responses for both top and bottom probe positions for each list length as a function of list serial position for the forced-choice recognition task of Experiment 3. (The vertical bars represent the standard errors of the RT means.)

bottom probes. The miss rate increased as list length increased.

Mean correct RT for each list length as a function of the serial position of the target item for both top and bottom probe positions is presented in Figure 11. The serial position functions show an extensive recency effect, and five of the eight functions show a one-item primacy effect. (The primacy effect is more prevalent for even list lengths than for odd list lengths.)

ANOVAS based on subject means were performed separately for each list length. The main effect of serial position was significant for List Lengths 3, 4, 5, and 6, $F(2, 6) = 10.35$, $p < .011$; $F(3, 9) = 13.91$, $p < .001$; $F(4, 12) = 26.09$, $p < .001$; and $F(5, 15) = 51.50$, $p < .001$; respectively. The main effect of probe position was significant for List Lengths 4, 5, and 6, $F(1, 3) = 11.26$, $p < .044$; $F(1, 3) = 13.92$, $p < .034$; $F(1, 3) = 10.70$, $p < .047$; respectively. The List Length × Probe Position interaction did not approach significance in any of the analyses.

The proportion of correct responses for each serial position of each list length for both probe positions is also included in Figure 11. The pattern of results for accuracy is consistent with the pattern of results for mean RT.

The obtained RT distributions of each subject for each serial position for each list length and each probe position were fit separately by the convolution of normal and exponential distributions. Of the 144 total fits, 43 were significant by a chi-square test ($p < .05$). (Of the 43 significant fits, 26 were obtained from 1 subject. It should also be noted that the number of observations per subject per condition was less in Experiment 3 than in the previous experiments.) The parameter estimates of mu, sigma, and tau, averaged over subjects, for each serial position for each list length and probe position are presented in Figure 12. Both the parameters mu and tau increased as a function of serial position at each list length.

In order to characterize the relative rates of increase of mu and tau, linear functions were fit to each of the functions presented in Figure 12 (excluding the first serial positions). The mean slopes (in milliseconds) of mu and tau, averaged over list lengths, were −97.2 and −72.6 for top targets and −83.8 and −83.3 for bottom targets, respectively. Linear functions were also fit to the mean parameter

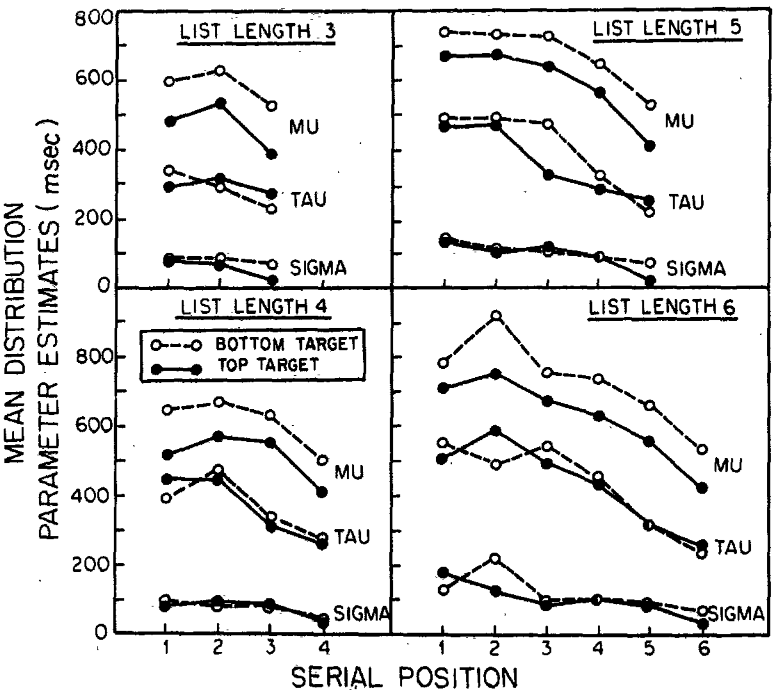

Figure 12. Mean distribution parameter estimates for top and bottom probe positions for each list length as a function of list serial position for the forced-choice recognition task of Experiment 3.

estimates, averaged over serial position, as a function of list length. The linear slopes (in milliseconds) of mu and tau as a function of list length were 54.3 and 40.3 for top targets and 50.6 and 46.4 for bottom targets, respectively. Thus, the relative increases of mu and tau were roughly comparable.

The results of Experiment 3 provide a reasonably good replication of the forced-choice recognition results of Experiment 2. In both experiments, mean RT was a function of the serial position of the target item. The serial position functions show an extensive (and reasonably linear) recency effect, and in most cases, a one-item primacy effect. In both experiments, the increase in mean RT was reflected in both the distribution parameters mu and tau.

In both Experiments 2 and 3, correct mean RT for the bottom probe was longer than correct mean RT for the top probe (although this difference was not statistically significant in Experiment 2). It is reasonable to assume that the difference in mean RT reflects a difference in the encoding time or a difference in the starting time of the memory comparison process for each probe item. Such a difference in encoding or starting time should result in a shift of the entire RT distribution for bottom probes, compared with top probes. Inspection of Figures 9 and 12 shows that the difference in mean RT between top and bottom probes is principally reflected in the distribution parameter mu, with little difference reflected in tau. As changes in mu reflect changes in the leading edge of the RT distribution, this result shows that the effect of probe position is reflected in a change in the leading edge of the RT distributions, with little effect on the positive skewness of the distributions. Thus, the distribution analysis shows that the difference in RTs between top and bottom probe positions could be due to a difference in encoding time and/or a difference in the time to initiate the memory comparison process for each probe.

The two-alternative, forced-choice recognition results of Experiments 2 and 3 suggest that the two probes are processed in parallel (but with different starting times). The memory comparison process would also appear to be self-terminating as RT is dependent on the serial position of the target item. The increase in mean RT as a function of serial position is a result of both an increase in the leading edge of the RT distributions and an increase in the positive skewness of the RT distributions. These results do not, at a qualitative level, distinguish between possible retrieval processes. The results do, however, pose stringent constraints for any model developed to account for performance in the forced-choice recognition task.

It is interesting to note, in passing, the differences between the yes–no recognition results of Experiment 1 and the forced-choice recognition results of Experiment 3. In both experiments, mean RT was a linear function of memory list length. However, the slope of the forced-choice recognition functions were almost twice as great as the slopes of the yes–no recognition functions. (Murdock & Anderson, 1975, Experiment 3, also found that the slope of the recognition latency function in the study-test paradigm increases in direct relation with the number of test alternatives.) The serial position effects were found to be relatively modest in yes–no recognition, whereas serial position effects were extremely pronounced in forced-choice recognition. Finally, changes in mean RT were largely reflected in a change in the distribution parameter tau in yes–no recognition, whereas changes in mean RT were reflected in both the distribution parameters mu and tau in forced-choice recognition.

Some of the differences just described may be the result of the difference in presentation time between the two experiments: Presentation time was slower, and there was a longer study-test interval in the yes–no recognition procedure. It would be interesting to compare these two recognition tasks under conditions that minimize such procedural differences in order to more fully establish the similarities and differences between these two recognition paradigms. Such a comparison may help to determine whether the results obtained in the two tasks can be accommodated within the same theoretical framework.

General Discussion

The present study attempted to apply Ratcliff and Murdock's (1976) convolution analysis of RT distributions to further our understanding of several memory paradigms. The convolution of normal and exponential distributions was shown to provide reasonably good fits to the observed RT distributions obtained from four different cognitive tasks.

The reported experiments were designed to determine if the parameters of the convolution analysis behave differentially in different tasks. Experiment 1 clearly showed that the convolution parameters mu, sigma, and tau can behave differently in a within-subjects comparison of two tasks. In the visual search task of Experiment 1, the linear increase in mean RT as a function of set size was principally reflected as an increase in the parameter mu. In the memory search task, the linear increase in mean RT was largely a result of an increase in the parameter tau. Although the parameter sigma varied with mu in the visual search task, sigma did not vary in the memory search task.

Experiments 2 and 3 also provided a contrast between the behavior of the distribution parameters. Although mu reflected the increase in mean RT as a function of the study position of the target item in both a judgment of recency task and a forced-choice recognition task, there was a differential effect of the parameter tau. In the recency task, tau did not increase with mu. However, tau did increase with mu in the forced-choice recognition task in both Experiments 2 and 3. On the basis of the results of all three experiments, it seems fair to say that an experimental separation of the distribution parameters mu and tau has been achieved.

The results of the present study also demonstrate that the parameters of the convolution analysis provide stringent constraints for any theoretical model of cognitive performance. The results of the distribution analyses were consistent with a serial process (with a comparison process that is not extremely variable and skewed) in the visual search task of Experiment 1 and in the recency discrimination task of Experiment 2. For the results of the distribution analyses to be consistent with a serial retrieval process in the memory search task of Experiment 1 and in the forced-choice recognition task of Experiments 2 and 3, however, it must be assumed that the rate of the serial comparison process is extremely variable. The constraints posed by the parameters of the convolution analysis can thus provide one way of discriminating between models and evaluating otherwise acceptable models.

Taken together, the results of the present study extend the work of Ratcliff and Murdock (1976) by demonstrating that the convolution of normal and exponential distributions provides a good description of RT distributions in a variety of cognitive tasks and that the convolution analysis yields parameters that may be important in the evaluation of specific models of cognitive processes.

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