Running head: CONDITIONAL RECENCY

Dissociating conditional recency in immediate and delayed free recall: A challenge for unitary models of recency

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Word count: 14904 excluding references (approximate count due to use of LaTeX)

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Abstract

Temporal distinctiveness models of recency in free recall predict that increasing the delay between the end of sequence and attempting recall of items from that sequence will reduce recency. An empirical dissociation is reported here that violates this prediction when the delay is introduced by the act of recall itself. Analysis of data from a number of previously published free recall studies shows that when the assumed availability of final list items is taken into account, recency increases across the first few output positions in immediate recall despite the delay introduced by recalling items; no such change, with a trend to decreasing recency, is observed in delayed recall. Simulations are presented, showing that two models accounting for recency in free recall, the Temporal Context Model (M. W. Howard & M. J. Kahana, 2002) and the SIMPLE model (G. D. A. Brown, I. Neath & N. Chater, 2007), are unable to account for this novel pattern of data. Further simulations show that the results are consistent with a short-term buffer contributing to recency in immediate free recall, and that ordered probing of items may also contribute to this effect; both of these are consistent with the formulation of a short-term buffer akin to models of serial recall.

Dissociating conditional recency in immediate and delayed free recall: A challenge for unitary models of recency

A prominent characteristic of episodic memory is the enhanced recall of events that have happened in the recent past. This *recency effect* is particularly apparent in the free recall task, and has been instrumental in guiding theorizing on episodic memory (e.g., Atkinson & Shiffrin, 1968; Davelaar, Goshen-Gottstein, Ashkenazi, Haarmann, & Usher, 2005; Glenberg & Swanson, 1986; Howard & Kahana, 2002). Recency is most apparent when the unconstrained nature of output in the free recall task is capitalized upon by examining the probability that each list item is recalled in the first output position (Hogan, 1975; Howard & Kahana, 1999; Laming, 1999); this is commonly referred to as the first recall probability function (FRP; e.g., Howard & Kahana, 1999). The FRP function generally shows a large extent of recency, accompanied by a small amount of primacy depending on the task (Howard & Kahana, 1999; Laming, 1999).

A popular class of theory attributes the recency effect in overall recall accuracy and the FRP function to the relatively greater temporal distinctiveness of list-final items (the last few items at the end of the list). These theories assume that items are represented along some temporal continuum (e.g., Brown, Neath, & Chater, 2007; Glenberg & Swanson, 1986) or associated with a temporal context that changes across the list (e.g., Glenberg et al., 1980; Howard & Kahana, 2002; Mensink & Raaijmakers, 1988), and can therefore be used to discriminate events in terms of their time of occurrence. The free recall recency effect in these models is produced by assuming some compression that increases the relative distinctiveness of recent items (Brown, Neath, & Chater, 2007; Neath & Crowder, 1990), or follows from the overlap between the context of list-final items and the context that is used to recall items (Howard & Kahana, 2002).[1] This distinctiveness is captured in an atheoretical manner in the ratio rule: the "law" that the extent of recency is determined solely by the logarithm of the ratio of the time separating list items and the time intervening between the final list item and recall (see, e.g., Bjork & Whitten, 1974; Neath & Crowder, 1990). Via the ratio rule, these models also explain the reduced recency in delayed recall, as any delaying activity will compress the recency items along with the rest of the list, and thus reduce the recency effect. These models also predict the surprising finding that placing a distractor after every item, in addition to the last, is sufficient to bring recency up to levels witnessed when recall is immediately cued (e.g., Bjork & Whitten, 1974; Howard & Kahana, 1999). The distractor activity increases the temporal separation of items and therefore acts to offset the compression due to the distracting activity, increasing the relative distinctiveness of list-final items. These models reject the short-term/long-term distinction assumed in "buffer" models of recency (e.g., Atkinson & Shiffrin, 1968), and instead constitute a strong claim for a unitary model of episodic memory, with the single principle of scale-invariant temporal discrimination (Brown, Neath, & Chater, 2007; Howard & Kahana, 2002).

Davelaar et al. (2005) have recently challenged these unitary models by claiming that there are two types of recency in the free recall task. Specifically, Davelaar et al. (2005) suggested that although the recency observed in continuous distractor conditions visually resembles that in immediate free recall, two types of recency can be distinguished on certain properties. For example, Davelaar et al. (2005) highlighted the finding that recency in immediate recall is reduced by instructing participants to initiate recall with early list items, whilst recency in delayed recall is not significantly affected by these instructions (Dalezman, 1976). Neuropsychological evidence also supports a distinction between short- and long-term recency: compared to controls, amnesic patients have unimpaired recall of list-final items in immediate free recall, but are impaired on these items in delayed free recall (Carlesimo, Marfia, Loasses, & Caltagirone, 1996). Davelaar et al. (2005) concluded that such evidence is consistent with the notion that immediate recency follows from an activation-based short-term memory mechanism that supports recall of the last few items in a list, while long-term recency (recency in delayed recall) follows from contextual overlap between list-final items and recall.

Although these dissociations present some convincing evidence for a dual-store model of memory, Neath and Brown (2006) have shown that a unitary temporal distinctiveness theory, in the form of the Scale-Invariant Memory, Perception and Learning model (SIMPLE; Brown, Neath, & Chater, 2007), is able to account for such dissociations. For example, Neath and Brown (2006) showed that although recall order (forward vs. backward) affected immediate recall performance, delayed recall was not affected because the temporal compression introduced by the act of recall was minimal compared to that introduced by the delay task. In examining overt rehearsal protocols, Brown, Della Salla, Foster, and Vousden (2007) showed that apparent dissociations in free recall performance of amnesic patients could be explained by the tendency of those patients to rehearse only the last few presented items, rather than adopt a cumulative rehearsal strategy, due to general impairments in memory ability (which in turn have knock-on effects on rehearsal). When this was taken into account by plotting recall as a function of the last rehearsal, SIMPLE was able to account for the apparent dissociation in memory performance. Thus, differences between immediate and delayed recall that are confounded with recall delay may explain apparent dissociations in recency (see Neath & Brown, 2006, for further discussion).

In the following, analyses of free recall data from a number of experiments are presented, which show a further dissociation in recency between immediate and delayed recall: In immediate recall, recency *increases* across output positions, whilst in delayed recall recency is relatively constant with a trend to drop across output positions. This pattern of results is inconsistent with models following the ratio rule, as any delay intervening between list presentation and a recall attempt should reduce the recency effect. In confirmation, fits of two such models of recency in free recall are presented, showing that neither model is able to account for this new dissociation.

Effects of delay during recall on conditional recency

As mentioned, the FRP function is a useful method for examining recency because it estimates the accessibility of list-final items at the time of initiating recall. The analyses presented here carry the FRP analysis further into recall by calculating the probability that the item presented at each serial position is recalled at a particular output position. The only existing analysis of this type was conducted by Howard and Kahana (1999), who plotted the probability of recalling the item from each serial position at each of the first several output positions for data of Murdock (1962). However, this analysis does not take into account the dependence between output positions introduced by participants' unwillingness to repeat items in recall. If not accounted for, this produces an artifactual decrease in recency across output positions; since the last list item is quite often recalled first (see FRPs in Laming, 1999 and Howard & Kahana, 1999), this will leave that item unavailable for recall at following output positions. Accordingly, in the analyses presented here the probability of recall is conditionalized on the assumed availability of items; that is, the probability of recalling the item from a particular serial position is only considered at a particular output position if that item has not already been recalled previously on the trial. As an example, consider the particular sequence of recall "8 10 2" from a participant, where the numbers indicate the serial positions of items recalled from a list of 10 items. At the first output position, the FRP would be calculated as per usual (Hogan, 1975; Howard & Kahana, 1999): the numerator for the 8th item would be incremented, and the denominator for all positions would be incremented. Then, at the second output position the numerator for the 10th (and, in this case, final) input position would be incremented, and the denominator would be incremented for all input positions except the 8th. Finally, at the third output position, the numerator for the 2nd item would be incremented, and the denominator for all items except items 8 and 10 would be incremented. Of interest here is the change in the resulting conditional recall probabilities across output positions. One constraint imposed in these analyses (and the identical analyses of model predictions below) is that recall is only examined up to the first error (intrusion, omission, or response repetition), as the nature of the recall processes following an intrusion are uncertain, and one of the models examined below is not currently constructed to account for errors or the responses following errors.[2]

Figure 1 (squares) shows the results of an analysis across 15 conditions in 6 experiments (Howard & Kahana, 1999; Howard, Venkatadass, Norman, & Kahana, 2007; Murdock, 1962; Murdock & Okada, 1970); these are the same data analyzed by Farrell and Lewandowsky (2008) in their critique of the temporal context model.[3] For each experiment, the change in conditional recency across early output positions (output positions 1–4) was examined for each participant. Specifically, at each output position the conditional probability of recalling the final list item next given it hadn't yet been recalled on that trial was calculated; this is referred to as the recency recall probability (RRP). A simple linear regression was then fit to each participant's data, relating output position to the RRP. A linear regression was used simply to pick up any general trends in the change in RRP across output positions; as is discussed shortly, these functions are not necessarily linearly increasing or decreasing. Participants were required to produce RRPs for at least two output positions; the actual number of points entering into the regression varied across participants (because, for example, a participant who always recalled the final list item at one of the first three output positions would have no legitimate responses entering the fourth output position, given that the recall probabilities were conditional on the final list item not having yet been recalled).

The squares in Figure 1 show the mean regression slope for each condition, with the conditions grouped by whether recall was immediate (left) or delayed (right), with some of the conditions on the right also involving continuous distraction (Howard & Kahana, 1999). Figure 1 shows a strong tendency for recency to increase across initial output positions in immediate recall, whereas in delayed recall recency changes little across output position, with a trend to decrease across recall. The mean slopes (averaged across experiments separately for immediate and delayed recall) are given in Table 1. One immediate concern is that any increase is artefactual, following from the conditionalization: even if the recall probability is held constant across list items, there is a necessary increase in the conditional probability of recalling the last list item next simply because of the diminishing size of the pool of potential responses. To address this potential issue, Figure 1 also plots mean control slopes predicted from a chance model in which participants are assumed to sample the next item for recall randomly from the remaining list items with equal probability for all items (dashed lines). These mean slopes, which were calculated on a trial-by-trial basis and analyzed in exactly the same fashion as the data, are always close to 0 (means shown in Table 1) and do not constitute a major contributor to the positive conditional recency slopes in immediate free recall.

To statistically confirm the overall difference between immediate and delayed conditions apparent in Figure 1, a multilevel linear regression taking the difference between slopes for individual participants and the control slopes as the dependent variable, immediate vs delayed recall as predictor, and a random effect on the intercept for experiments was conducted. This multilevel regression confirmed a significant effect of immediate vs delayed recall on the conditional recency slopes [$\beta = .13$; $t(20.58) = 5.68, p < .001$].[4] One objection to this analysis is that it makes comparisons across experiments that vary substantially in their methodology, such that the obvious difference between the immediate and delayed recall conditions in Figure 1 is confounded with some other uncontrolled variable. We can address this issue by determining whether the difference between immediate and delayed recall holds up in a controlled comparison.

One such comparison is possible in the data shown in Figure 1, between the immediate and delayed recall conditions in Experiment 1 of Howard and Kahana (1999). Indeed, this experiment employed a repeated measures design and thus allows for a controlled examination with sufficient power. A paired-samples t-test[5] revealed the mean slope difference (the difference between the observed slope and that predicted from chance) to differ significantly between the immediate and delayed recall conditions [mean difference = .135, $t(55) = 3.96$, $p < .001$]. Though lacking the validity of the full analysis, this reinforces the dissociation between immediate and delayed recall in conditional recency.

This previously unreported empirical pattern constitutes a clear challenge to models which accord with the ratio rule in free recall. According to the ratio rule, the delay introduced by recalling items will increase the denominator in the ratio while the numerator stays constant, which universally predicts a decrease in recency across output position. In the framework of temporal distinctiveness models, delays introduced by output should lead to further temporal compression of the representations of list items, resulting in a reduced recency effect (e.g., Brown, Neath, & Chater, 2007). Similarly, models in which recency follows from overlap in the temporal context between the time of recall and that of list items (e.g., Glenberg et al., 1980; Howard & Kahana, 2002; Mensink & Raaijmakers, 1988) predict a decrease in recency, as recall of items will render the current context less similar to that corresponding to the last few items on the list. Although this common prediction of a decrease in recency is consistent with the pattern in conditional recency across output in delayed recall, this clearly does not accord with the increase in recency across early output positions in immediate recall demonstrated here.

Before moving on to present some simulations of this effect, one further question is first considered: What happens at later output positions? Does the initial increase in conditional recency in immediate free recall continue throughout recall? Figure 2 plots conditional recall of the final list item across up to eight output positions from several of the conditions in Figure 1. In each panel participants have been grouped together on the basis of the range of output positions to which they contributed legitimate data; some participants, for example, will not contribute any data beyond the 5th output position because they either a) always recalled the final list item by that point, and/or b) recalls at the next output position were always illegitimate responses (e.g., repetitions, intrusions, omissions). The range of output positions for each group can be determined from the point at which their line terminates, and the number of participants in each group is written above the corresponding termination points. As data from groups containing minimal numbers of participants will be overly determined by individual participants, only groups containing at least three participants are plotted. The groups are plotted separately in this fashion to avoid averaging artifacts.

There are two general identifiable patterns in the output position functions from this set of data. The top row of Figure 2 plots the results from two conditions that are representative of the many of the conditions examined. In these conditions, the conditional probability of recall of the final item initially increases across output positions up to output position 4 or 5, at which point the function flattens or becomes negative. The second pattern, shown in the bottom row of Figure 2, is for the output position function to increase monotonically, though not always in a linear fashion. The most striking of these patterns is shown in the bottom-right panel of Figure 2, whereby the RRP changes little across output position, before kicking up at the terminating position within each group of participants. Both of these patterns is at least partially inconsistent with the ratio rule behavior predicted by TCM and SIMPLE. The inverse U-Shaped function in the top half of Figure 2 suggests that participants shift from one method of accessing memory to another as recall progresses; we consider the exact nature of the change below. Although the flat or decreasing functions typifying the early period of recall in the bottom half of Figure 2 is consistent with the ratio rule, the increase in the RRP at later output positions is not.

Some caution must be adopted in inferring from these results to more detailed computational models, as in some cases the behavior of models may not strictly adhere to the ratio rule. For example, Howard (2004) has shown that TCM predicts transient increases in recency with increasing delay for certain parameter values, a violation of the ratio rule. Similar concerns are presented by Brown, Neath, and Chater (2007), who showed that SIMPLE could account for apparent departures from the ratio rule (Cowan, Saults, & Nugent, 1997) when possible proactive interference effects considered negligible by previous researchers were taken into account. To demonstrate that the dissociation in recency between immediate and delayed recall demonstrated here cannot be explained by these models of free recall, two models accounting for recency in free recall were applied to the data. The two models, TCM (Howard & Kahana, 2002) and SIMPLE (Brown, Neath, & Chater, 2007) were chosen given their popularity in the field of episodic memory, their convincing account of recency effects in free recall (the objections of Davelaar et al., 2005; Usher, Davelaar, Haarmann, & Goshen-Gottstein, 2008, notwithstanding), and their differing mechanisms for driving changes in context or distinctiveness.

Conditional recency in the Temporal Context Model

TCM (Howard & Kahana, 2002) assumes that the temporal context that distinguishes between episodic memories is driven by retrieval of contexts associated with prior episodes. In free recall, a distributed representation of context at position i, $\mathbf{t}_i$, is obtained from that at position $i-1$ according to:

$$\mathbf{t}_i = \rho\mathbf{t}_{i-1} + \beta\mathbf{t}_i^{IN}, \tag{1}$$

where $\mathbf{t}_{i-1}$ is the context from the previous time step, $\mathbf{t}_i^{IN}$ is the temporal context retrieved by the item presented at position $i-1$, and ρ and β are parameters controlling the rate of temporal evolution (see Howard & Kahana, 2002, for a full description). Items are retrieved by using the current state of temporal context to cue for items associated with that context; as a result of the gradual contextual evolution at list presentation, a temporal cue for a list item will also serve as a partial cue for nearby items. TCM explains recency as the overlap between the context at the end of the list (which is then used to initiate recall), and that associated with the last few list items (see also Brown, Preece, & Hulme, 2000). A recent version of TCM—called TCM-A—has been supplemented with a leaky accumulator model that constitutes a full retrieval mechanism. We consider the more basic version of TCM here; because it is a stochastic model lacking an analytic solution, application of TCM-A to the data at the level of individual trials and participants could not realistically be expected (Sederberg, Howard, & Kahana, 2008).

To date, TCM has only been tasked with accounting for recency in FRPs only (Howard, 2004; Howard & Kahana, 2002; Howard, Kahana, & Wingfield, 2006). For mathematical convenience, the temporal context used for recall at later output positions has been assumed to depend only on the context retrieved during output (Howard & Kahana, 2002). When this version of the model was implemented in some preliminary simulations, it was found that the conditional recency functions predicted by the model were much flatter than those witnessed in the data. As an alternative, a version of TCM developed by Farrell and Lewandowsky (2008) was applied. In this alternative version which directly implements the core assumptions of TCM, context is assumed to be gradually and continually updated (via Equation 1) across list presentation and recall. As items are recalled during the recall period, Equation 1 will on average rotate the temporal context away from that overlapping with list-final items. Equations for the model are given in Appendix A.

To determine whether TCM captures the increasing conditional recency across initial output positions, and the trend in the opposite direction for delayed recall, maximum likelihood (ML) parameter estimates were obtained for TCM for each participant in the experiments analyzed in Figure 1. The modeling procedure followed that applied in Farrell and Lewandowsky (2008), who provided a solution for TCM when Equation 1 applies across list presentation and recall. The procedure for calculating log-likehood ($\ln\ell$) for the model on a response-by-response basis are given in Appendix A. Two parameters were estimated in the fitting: β, which controls the rate of contextual evolution, and τ, which varies the "noisiness" of responding in the choice rule used in the model.

Goodness-of-fit values are given in Table 2 and Table 3 in the form of Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) differences. The AIC and BIC both correct the maximum log-likelihood ($\ln\ell$, the minimized deviation between the model and the data) for the bias introduced by using the same data are used both to estimate parameters, and to determine goodness of fit from those parameters. Formally, the AIC is given by $-2\ln\ell + 2k$, where k is the number of free parameters; the BIC is given by $-2\ln\ell + \ln(N)k$, where N is the number of observations being fit. Both the AIC and the BIC have their uses in model selection: Model selection by BIC approximates full Bayesian model selection, but is easier to compute and interpret (Wagenmakers & Farrell, 2004), whilst the AIC approximates the average expected Kullback-Leibler distance, a measure in the overlap of information between a particular model and the process generating the data (e.g., Burnham & Anderson, 2002). Both AIC and BIC statistics are presented here. Specifically, since only the difference in AIC or BIC between models is indicative of their relative fit, information criterion *differences* are presented. Accordingly, the best-fitting model will have an AIC or BIC of 0, and worse fitting models will have positive AIC/BIC differences. In Table 2, AIC values have been summed across participants for each experiment, and then AIC differences calculated to express fit relative to the best-fitting model; the AIC differences for TCM appear in the left column labeled 'standard'. Similarly, Table 3 gives differences in summed BIC; the corresponding mean parameter estimates are given in Appendix B.[6]

The predictions of TCM under best-fitting parameter estimates are summarized in Figure 1 by circles, with the average slope presented in Table 1. The figures show that TCM fails to give a satisfactory account of the data. Although the model somewhat approximates the data in the delayed recall conditions, in immediate recall the model generally predicts a negative relationship between output position and conditional recency. This is what would be expected from the strict ratio rule, but is inconsistent with the clearly positive slopes seen in the data in Figure 1. This failure of TCM is shown in greater detail in Figure 3, which plots RRPs across output position as in Figure 2. TCM predicts a monotonic decline across output position. Although there is a slight upturn in the bottom-right panel of the plot in line with the data in Figure 2, this is simply mirrors the increasing probabilities predicted by the chance model and does not capture the increase seen in the data. Overall, TCM fails to produce the dissociation between immediate and delayed recall displayed in the data. The implications of the failure of TCM, and some possible modifications to the model to account for this dissociation, are discussed after presentation of the fits of another model of recency in free recall.

Conditional recency in SIMPLE

SIMPLE is a distinctiveness model that explains memory, perception and learning in a common set of fundamental principles. The most basic of these is that phenomena in these domains (such as serial position effects and patterns of confusability) are attributed to the discrimination of items in multidimensional space. One additional assumption, made in explaining phenomena of episodic memory (where information must be temporally discriminated), is that events are expressed with respect to the current recall perspective and that these temporal distances are logarithmically compressed. Formally, if two events i and j occur at times T_i and T_j, then their psychological distance from the present (at time T_r) is given by $M_i = \log(T_r - T_i)$ and $M_j = \log(T_r - T_j)$, respectively. The similarity of memory for the two events is then given by

$$s_{ij} = \exp(-c|M_i - M_j|^{\alpha}), \tag{2}$$

where c is a scaling parameter (a free parameter) and α determines the form of the similarity relationship (here, following Brown, Neath, & Chater, 2007, α was set to 1.0, making the inner part of Equation 2 the city block metric). Full details of the model are given in Appendix A. SIMPLE is noteworthy in having been applied to a large range of episodic memory phenomena, and in extending to perceptual tasks such as absolute identification (Brown, Neath, & Chater, 2007; Neath & Brown, 2006).

SIMPLE was applied exactly as described in the published version of the model (Brown, Neath, & Chater, 2007), with a few additional assumptions to allow application to these specific experiments. One additional assumption was in regards to the output order that participants attempted, as SIMPLE does not currently account for response-by-response output. The assumption adopted here involved repeated probing of the last list position, with the understanding that this would give a graded match to all items (according to Equation 2). This is equivalent to assuming that participants use the last remembered context from the list to cue for items on the list in a non-specific fashion. As for TCM, a mechanism was also required to prevent repeated recalls of the same item. Accordingly, it was assumed that once an item was recalled, it was not considered a candidate for further recalls and was removed from the set of list exemplars to which the probe was matched. As for the TCM fits, only responses up to (and excluding) the first repetition, omission, or intrusion were considered; since omissions were not modeled, this allowed the exclusion of two model parameters that were introduced by Brown, Neath, and Chater (2007) to account for omissions.

The procedure for fitting SIMPLE was identical to that for fitting TCM (see

Appendix A). The exponent c determining the noisiness of responding was left as a free parameter. Additionally, the time (in seconds) taken to recall and produce a response at each output position was assumed to be constant, and was left as a second free parameter (t_{out}) given that this information was generally not available in the data sets. The time intervening between list items was approximated from presentation times given in the method section describing the experiments, with an additional 0.5 s delay assumed between the final list item and recall (Brown, Neath, & Chater, 2007).

AIC and BIC differences for each condition are given in Tables 4 and 5 respectively (left column in both tables). Note that the AIC and BIC differences are calculated with respect to the best-fitting model across all implementations of TCM and SIMPLE considered here. The corresponding mean parameter estimates are given in Appendix C. As shown by the mean predicted slopes in Table 1, SIMPLE predicts a downwards trend in recency across output position in immediate free recall. Figure 4 further confirms the monotonic decrease in conditional recency across output positions, reinforcing SIMPLE's failure to capture the specific increase in RRP across output positions in immediate free recall. Tables 4 and 5 also show that the SIMPLE model provides a consistently worse fit to the data than TCM.

One objection might be that the conception of "response suppression" here was inappropriate when considered in the framework of sampling models of memory (e.g., Raaijmakers & Shiffrin, 1981). In the one-step models here, sampling without replacement was assumed. However, in models such as SAM (Raaijmakers & Shiffrin, 1981), sampling is performed with replacement, with the prevention of repetitions occurring in some later recovery stage. In terms of probability of recall, the locus of the prevention of repetitions is not identifiable: all the cases in which an item is sampled but not recovered will be indistinguishable from the case where an item is not sampled in the first place; both result in no response being given. However, this distinction *is* visible in response latencies; the cumulative distribution of response frequency in free recall as a function of the time since the cue to recall is exponential, as would be expected from a sampling with replacement + recovery model with prevention of repetitions occurring in the recovery stage (e.g., Rohrer & Wixted, 1994; Wixted & Rohrer, 1994). One possibility is that although the models considered here do not make any predictions about latency, the slowing of responses across the recall period may modulate the effects shown here. Although this does not impact on the conclusions from TCM (which is not sensitive to time per se), it is possible that the slowing of the rate of recall may modify the conditional recency slopes observed in SIMPLE. To address this issue, several experiments were re-examined where the latencies of participants' responses were recorded and provided in the data files (Howard & Kahana, 1999; Murdock & Okada, 1970). Rather than leaving output time as a free parameter in SIMPLE, the model was fit to these data with participants' output times fed in to the model to determine the passing of time across output. These results are not reported here as this modification made little difference to the fit of the model; the timing of output appears not to be involved in the increase in conditional recency in immediate recall.

Before moving on, it should be noted that these fits of TCM and SIMPLE also reinforce the conclusion that the increase in RRP across output positions is not due to some unconsidered statistical artifact. The predictions of the chance model shown in Figure 1 strongly suggest that statistical artifacts are not driving the increase in RRP in immediate recall seen in the data. The predictions of TCM and SIMPLE were obtained in exactly the same manner as for the data (including determining which participants contributed data to which range of output positions), such that their failure to account for the increase in RRP reinforces the non-arbitrary nature of the core effect.

Accounting for increases in conditional recency

Neither TCM nor SIMPLE can account for the differences between immediate and delayed recall in their patterns of conditional recency across output position. Both models follow the ratio rule in predicting that the delay introduced by recalling and producing items at test will reduce the accessibility of the last item when correcting for its lack of availability if it has already been recalled. What, then, are the implications of the positive relationship between conditional recency and output position at the start of recall, and what mechanism or set of mechanisms could produce the pattern of results seen in Figure 2? Below, several possible explanations for the change in conditional recency across output positions in the context of TCM and SIMPLE are examined.

Constraints on recall set

One explanation for the increase in conditional recency is the selection of items from a limited pool or search set. As items are recalled, they are removed from a pool of potentially recallable items and no longer offer competition for recall (as assumed in TCM and SIMPLE above). If it is assumed that more recent items offer more competition than less recent items, this will translate into an increasing likelihood of recalling the last item, as the last item will become more and more competitive as other competitors for recall are successively removed. This parallels primacy gradient models of serial recall (e.g., Farrell & Lewandowsky, 2002; Page & Norris, 1998), in which items are recalled from memory on the basis of their strength of activation or encoding (Farrell & Lewandowsky, 2002; Page & Norris, 1998). One phenomenon seen empirically in serial recall, and which is a hallmark of these models, is known as "fill-in". If an item is not recalled in the correct position (and has not yet been recalled), then that item will have been replaced in the recall sequence by some other item; this recalled item will then be removed from the pool of recallable items using a process called response suppression, akin to the removal of items from the pool of competitors here (e.g., Henson, 1998; Lewandowsky, 1999). Since the intruding item will tend to be a strong competitor for the item that should have been recalled, this effectively increases the competitiveness of the displaced item, as its strength is maintained with respect to other items not yet recalled, but it has now had its closest competitor removed. The consequence in serial recall is that an anticipatory recall (recalling an item ahead of its correct position) is often followed by recall of the displaced item (e.g., Surprenant, Kelley, Farley, & Neath, 2005). It is possible that a similar mechanism here may account for the increase in conditional recency across output positions. One necessary condition will be something like a decrease in accessibility across positions from the end of the list (i.e., a recency gradient), and that this gradient is constant across output positions (response suppression notwithstanding). Although these assumptions sound feasible, the second assumption regarding the stationarity of the recency gradient is in conflict with the ratio rule, which requires that list items become less discriminable with delay. In TCM and SIMPLE, the act of output moves the context vector (TCM) or recall perspective (SIMPLE) away from the most recent item, thereby effectively reducing its distinctiveness. In the next set of simulations, the behavior of TCM and SIMPLE was explored when the effective recency gradient was held static across successive recall attempts.

Clamping the recency gradient in TCM and SIMPLE required similar but separate changes to the operation of the two models. In the case of TCM, it was assumed that temporal context was not updated during recall, and thus that the context carried over from the last item of the list was always used to cue for the next recall (that is, Equation A1 was always used to calculate recall probabilities). For SIMPLE, all recall attempts were presumed to occur instantaneously after presentation of the recall cue, such that no temporal compression occurred during recall. As seen in Table 1, this assumption did produce an increase in RRPs across initial output positions in immediate free recall in comparison to the standard versions of the models (left columns of Table 1; rows labelled 'no delay'). However, this increase is only slight, and the result is that the models predict little or no difference between immediate and delayed recall in the mean RRP slope (left vs right columns in Table 1).

A more principled problem with this assumption is that it sits in direct opposition to the core assumptions of TCM and SIMPLE. In the case of TCM, the assumption that the list-final context is always used to cue for recall prevents the model from capturing transitional probabilities between items as represented by the lag-recency effect (e.g., Howard & Kahana, 2002; Kahana, 1996), a phenomenon that is uniquely associated with TCM (Farrell & Lewandowsky, 2008; Howard & Kahana, 2002). The second column of Tables 2 and 3 confirms the universally larger (i.e., worsened) IC differences for these fits (see Appendix B for maximum likelihood parameter estimates). In the case of SIMPLE, the assumption that time does not pass during recall violates the assumption in the model that representations are constantly compressed by time. Although there are mechanisms in SIMPLE to modify the attention given to the temporal dimension, this weighting is non-specific and cannot distinguish between different time periods along that dimension. Violating this assumption by preventing the passing of time during retrieval generally worsened the fit (Tables 4 and 5), except for some delayed recall conditions under the BIC. The occasional enhanced fit under the BIC in SIMPLE is not surprising given that the assumption of no delay during recall removed one parameter from the model (that estimating the time taken for each recall); given the BIC greatly favors simpler the model, the worse fit under this assumption was canceled out by the removal of a free parameter.

Random buffer

The principle of a restricted search set heavily based on recency items is fully consistent with dual-store models of memory such as those of Atkinson and Shiffrin (1968) and Davelaar et al. (2005). For example, in the model of Atkinson and Shiffrin (1968) it is assumed that items are placed in a short-term buffer, and are transferred from there into long-term memory. At the end of presentation of a sequence, an item will reside in long-term memory with an encoding strength determined by the time it spent in the buffer previously, and may also reside in buffer itself. If an item still dwells in the buffer, it is assumed to be output with perfect accuracy; otherwise, retrieval relies on error-prone retrieval from long-term memory. On the assumption that an item is removed from the buffer once recalled, this framework can naturally account for the increase in conditional recency across initial output positions in immediate recall. With the additional assumption that distractor activity between presentation and test in delayed recall removes list items from the buffer, this also offers an explanation for the relative lack of effect of recall-imposed delay in delayed recall.

To maintain consistency with the models examined thus far, and to keep the models as simple as possible, a buffer component was added to TCM and SIMPLE. Although this "bolt-on" may be considered inelegant, and is antithetical to the core principles of TCM and SIMPLE, the intention was to examine the specific contribution of a short-term buffer by holding all other assumptions constant from previous simulations. That is, the intention is not to offer a specific model of free recall, but rather explore the consequences of the assumption of a buffer for conditional recency. Having said that, TCM or SIMPLE are successful models of long-term free recall, and something similar to their core mechanisms is likely to underlie longer-term episodic memory, such that it seems reasonable to incorporate these models in place of the classic long-term store (Atkinson & Shiffrin, 1968).

For the simulations, the buffer was arbitrarily assumed to hold three items, and incoming items were assumed to replace an item already in the buffer with probability α. Under the assumption that items were perfectly recalled from the buffer (e.g., Atkinson & Shiffrin, 1968), the probability of recall of an item for the first three positions was then the probability the item was in the buffer (given it hadn't already been recalled), with items being sampled randomly from the buffer (see Appendix A for technical details). At output positions exceeding the buffer size (three) it was assumed that recall switched to use of TCM or SIMPLE; a similar switch from a short-term buffer to a more involved long-term memory recall process is assumed in classic dual-store models (Atkinson & Shiffrin, 1968; Waugh & Norman, 1965). It was also assumed that while items were directly recalled from the buffer for the first few positions, the temporal context in TCM was nonetheless updated by recall of these items; equivalently, in SIMPLE time was assumed to pass while recalling items from the buffer.

The information criterion differences in Tables 2, 3, 4 and 5 (mean parameters in Appendices B and C) show that the addition of the buffer improved the fit of the models for 7 out of the 9 immediate recall conditions in both models, even when taking into account the additional parameter introduced in the random buffer model (via the penalty term in the AIC and BIC). For both models, no improvement in fit was obtained for the data of Howard and Kahana (1999) and Howard et al. (2007). The mean slopes in Table 1 reveal a positive conditional recency slope for both models across all immediate recall conditions, though quantitatively this differs somewhat from that found in the data. For delayed recall, it is assumed that the buffer will not contain any list items (at least, this is a reasonable assumption for the conditions examined here), such that the fit and predictions of the models are assumed to be identical to those of the standard mechanisms of TCM and SIMPLE. Nevertheless, the random buffer model was fit to the delayed recall data to confirm that something like a buffer was not in use in delayed recall. In no case was the fit superior to that of the standard versions of TCM and SIMPLE (see Tables 2 to 5).

One consequence of the use of the buffer only in the initial portion of immediate recall (i.e., until the buffer is exhausted) is shown in Figure 5. The top two rows in the figure show that the shift between a reliance on the short-term buffer and on a long-term mechanism—in the case of Figure 5, TCM—produces the inverse U-shaped functions witnessed in many of the immediate free recall conditions. Unsurprisingly, the model fails to account for the large increases in RRP at later output positions seen in some of the data sets (particularly the experiment of Howard et al., 2007 in Figure 5), as by that time the standard TCM mechanisms are driving recall. The predictions of the buffer-supplemented version of SIMPLE are not shown given their similarity to the predictions of the TCM version.

Ordered buffer model

Is there any other feature of the buffer model that might offer an even better account of immediate free recall data, in particular the size of the slope relating conditional recency to output position? One possibility explored here is that the buffer is similar in nature to models of serial recall (e.g., Brown et al., 2000; Burgess & Hitch, 1999; Farrell & Lewandowsky, 2002; Lewandowsky & Farrell, 2008), such that items are output in forward order from the buffer. Some motivation for this suggestion is found in previous examinations of free recall. In their footnote 2, Howard and Kahana (1999) noted that some of the FRP functions in immediate free recall are non-monotonic, with participants systematically beginning recall with an item several positions preceding the end of the list. A tendency for recall to proceed in a forward direction in free recall has been observed by a number of other researchers (e.g., Bhatarah, Ward, & Tan, 2006, 2008; Laming, 1999; Nilsson, Wright, & Murdock, 1975). In two experiments in which participants were required to recall lists following free recall or serial recall instructions, Bhatarah et al. (2008) noted the similarity between serial and free recall, in particular a preference for forward recall order in free recall. This is consistent with Laming's (2006, 2008) statistical modelling work linking together rehearsal and recall. Laming noted the strong tendency for recall sequences to be composed of ordered recall of sequences produced as rehearsals during list presentation in overt rehearsal experiments. If recall is initially driven by forward serial recall, this should increase the conditional recency slope, as conditions will become more ideal for recalling the final item as the end of the buffer (i.e., the third output position for buffer size of three) is approached.[7]

The exact model implemented was an empirical generalization of the behavior of extant models of short-term memory (see Lewandowsky & Farrell, 2008, for a recent summary). Specifically, it was assumed that the last three positions were cued in order, but that there was some uncertainty about the position of items (for possible mechanisms, see Brown et al., 2000; Estes, 1972; Page & Norris, 1998; Farrell & Lewandowsky, 2002; Henson, 1998; Burgess & Hitch, 1999). When position i was probed, each item j was assumed to be activated with strength a_{ij} according to

$$a_{ij} = \exp(-\theta|i-j|), \tag{3}$$

where θ is a free parameter (see, e.g., Farrell & Lewandowsky, 2004). Equation 3 captures one prominent characteristic of serial recall data, known as the locality constraint (e.g., Henson, 1996): When people recall an item in the incorrect position, they tend to recall it in a position near the correct position. These values were then rescaled to sum to 1, to give the probability $p_{pos}(j)$ of recalling item j in response to the probe for position i. These probabilities were then multiplied with the corresponding probability that item j was in the buffer ($p_{buff}(j)$; see Appendix A) to give a probability of probing for an item that is also in the buffer.

The forward buffer model generally improves the fit of both TCM and SIMPLE over the standard version of these models when applied to immediate recall conditions, and also improves over models with an added random buffer (Tables 3 and 5). Specifically, the forward buffer model shows an improvement over the standard models for all conditions except those of Howard and Kahana (1999) and Howard et al. (2007), and improves the fit in all conditions in comparison to the random buffer model, for both models under both information criteria. Table 1 shows that the forward buffer models produce positive slopes of a size more commensurate with that found in the data. Figure 6 shows qualitatively similar results to those from the unordered short-term buffer in Figure 5, in particular the shift from an increase to a flattening or decreasing RRP across output positions. One quantitative difference, in line with the larger slopes in Table 1, is a steeper increase in RRP across the first few output positions in Figure 5.

The results of the simulations using a short-term buffer show the utility of that mechanism in explaining patterns of conditional recency across output, and also provide support for the serial nature of this buffer. A further possibility is that an increase in conditional recency might be explained by order of cueing of items without necessarily relying on a short-term buffer, or buffer-like mechanism. On the basis of their comparison of forward serial recall and free recall, Bhatarah et al. (2008) argued that both free and serial recall are supported by a single memory mechanism, a characteristic of which is a tendency to forward recall, rather than a specific short-term buffer given to forward recall. Additionally, Laming (2006, 2008) assumed that ordered recall of rehearsal subsequences was accomplished by sampling presentation and rehearsal sequences from the entire episodic record in a manner reminiscent of the SIMPLE model. Accordingly, a "forward probing" version of SIMPLE was implemented, in which it is assumed that individuals attempt forward recall of last 3 items, and then continue probing for the last item (i.e., the most recent temporal context from the list), analogous to the short-term buffer implementation of this model. This modification was not applied to TCM as there was no clear manner in which to combine an enforced cueing order with the natural evolution of temporal context that is a core feature of the model. Although the lack of specification of a mechanism for generating cues in SIMPLE can generally be considered a weakness of the theory, it is useful here in allowing the provision of arbitrary orderings of probes to the model.

This version of SIMPLE performed fairly well in accounting for the overall results for immediate recall, under the best-fitting parameter values (see Appendix C). The mean slope for this model is close to that observed in the data (Table 1), and the model outperforms the standard version of SIMPLE for 5 out of 9 immediate recall conditions (Tables 4 and 5). Nonetheless, the improvement in fit is not comparable to that seen in the versions of SIMPLE complemented with a buffer, forward or random. Additionally, the model fails to produce the required dissociation between immediate and delayed recall. Although the positive recency change across output position is reduced in delayed recall, the model still predicts increases in conditional recency across output position (see bottom section of Table 1); this is reflected in the comparatively poor quantitative fits of this version of SIMPLE for delayed recall (Tables 4 and 5).

Together, these results show that a distinction between short- and long-term memory is not strictly needed to produce a qualitative increase in conditional recency across output positions in immediate free recall. However, universally assuming forward probing also leads the model to predict an increase in recency across delayed recall, where the trend is for a decrease in conditional recency. We discuss the possibility of participants strategically switching between ordered and unordered cueing in the General Discussion.

Determining buffer size empirically

One remaining puzzle is the relatively poor fit of the buffer models, particularly the ordered buffer model, to the immediate free recall data of Howard and Kahana (1999) and Howard et al. (2007), despite their more realistic predictions of changes in conditional recency across output position (Table 1). One clue to this discrepancy comes from examining what happens at the very first output position. Figure 8 shows first recall probability (FRP) functions for two conditions for which the forward buffer model provides a superior fit to the data (top row), and two cases where the standard version of TCM provided the best account of the data (bottom row). The functions plotted in the top row show a clear non-monotonicity in the data, with a peak at the third to last serial position (as observed by Laming, 1999 and discussed by Howard & Kahana, 1999). This peak can be interpreted as the tendency for participants to begin recall near the end of the list and recall in a forward order to the end of the list, exactly as assumed in the forward buffer version of the models implemented here. Figure 9 plots the FRP functions predicted by the forward buffer model under the ML parameter estimates for those conditions, and indeed it confirms that this peak follows from the forward buffer mechanism. In contrast, a comparison of the bottom row of Figures 8 and 9 reveals a discrepancy: while the FRPs in the data describe fairly smooth, monotonic curves, the predicted FRPs are irregular in shape; though not showing the peaking apparent in the top row, there is some plateauing in the predicted FRP. The extent of non-monotonicity in existing free recall is of some debate (Kahana, Sederberg, & Howard, 2008; Usher et al., 2008); it is clear though, that in at least some cases the FRP function for immediate free recall is smoother than that predicted by the forward-buffer-supplemented TCM.

One explanation for the monotonic function shown in the bottom row of Figure 8 is simply that it follows from the standard version of TCM, and that model is a sufficient model of the data. However, it might also be that this apparently uncomplicated function hides a mixture of different buffer sizes across trials and participants. To address this possibility, another version of the TCM + forward buffer model was fit to the data from Howard and Kahana (1999) and Howard et al. (2007), but with the size of the buffer determined by the data. Specifically, if the first item output by a participant on a particular trial was from one of the last four serial positions, the participant were assumed to use a forward buffer to serially recall the remaining list items. Because the buffer size was determined with probability 1.0 on each trial, only position distinctiveness was used to determine the probability of recall from the buffer for each item; that is, Equation 3 was directly used to determine recall probabilities. If the first output item was from earlier in the list, it was assumed that a forward buffer was not in use, and recall was assumed to depend wholly on the standard TCM mechanism. The probability of first recall was assumed to follow from a distribution across possible starting points (with starting points within 4 positions of the end of the list indicating recall from the buffer) at the beginning of recall (e.g., Kahana, 1996; Laming, 2006, 2008). For convenience, the standard TCM mechanism was used to predict recall probabilities at the first output position.

The mean ML parameter estimates were $\beta = .57$, $\tau = .37$, and $\phi = 13.24$ for the data of Howard and Kahana (1999), and $\beta = .56$, $\tau = .28$, and $\phi = 6.44$ for the data of Howard et al. (2007). Figure 10 shows the RRP across output position predicted by the model for the data of Howard and Kahana (1999) and Howard et al. (2007). The model produces functions that are a visually closer match to the data than either the standard TCM or the TCM with a fixed-size forward buffer, with no initial increase across positions (or even a slight decrease) followed by an increase at later output positions. This predicted pattern can be understood in light of the ML parameter estimates. The large value for ϕ means that successive positional cues are highly distinctive; as a consequence, there are few positional errors (with errors being introduced via the Luce selection rule), and the probability of recall of the last item is increased on arriving at the end of the buffer when the highly specific cue for the last list item is presented. The general trend was for this TCM + forward model to fit the data of Howard and Kahana (1999) and Howard et al. (2007) better than the standard TCM model (and by implication the TCM supplemented by a fixed-size ordered buffer). For Howard and Kahana's (1999) experiment, both AIC [AIC difference (standard model − buffer model) = 195.01] and BIC (BIC difference = 89.38) revealed an improvement over the standard TCM. For the data of Howard et al. (2007), an improvement over the standard TCM was revealed by the AIC difference (480.31); the BIC difference still favoured the standard version of TCM, but was much reduced (BIC difference = -258.47).

One consequence of the assumption of a variable ordered buffer for these data is an explanation for one other noted feature of free recall data. It has been demonstrated that there is some dependency in responses in free recall: recall of an item will tend to be followed by recall of a nearby item, often the following item (e.g., Farrell & Lewandowsky, 2008; Howard & Kahana, 1999; Kahana, 1996; Laming, 1999). This is often plotted in a lag conditional response probability function (lag-CRP) function which plots the probability that recall of item n will be followed by item $n+1$, $n+2$ ... and $n-1$, $n-2$ .... This tends to show a forward asymmetry (forward transitions are more likely than backward transitions; Kahana, 1996), and a decrease in probabilities with increasing absolute lag, except for extreme lags, which show an upturn in probabilities (Farrell & Lewandowsky, 2008). Of interest here is that for the data of Howard and Kahana (1999) and Howard et al. (2007), amongst others, it has been noted that this function changes across early output positions: as recall progress, the lag-CRP function becomes flatter (Howard & Kahana, 1999; Howard et al., 2007; Kahana, Howard, Zaromb, & Wingfield, 2002). This can be see in the left-most column of Figure 11, which plots the lag-CRP functions for output positions 1, 2, 3, and the average for output positions 4–6 (for details of construction of such plots, see Howard & Kahana, 1999 or Farrell & Lewandowsky, 2008). Notably, this is not the case for otherwise identical delayed or continuous distractor recall conditions (Howard & Kahana, 1999).

This aspect of the data appears to be problematic for the standard version of TCM (e.g., Howard & Kahana, 2002), as the model's operation is homogeneous throughout recall. In confirmation, the middle column of Figure 11 shows the predictions of TCM under its ML parameter estimates. The model does not produce a systematic change in the lag-CRP function across output positions: output positions 1 and 2 produce very similar lag-CRP functions, and only a small difference emerges across later output positions.

In contrast, TCM supplemented by a variable size ordered buffer should be able to produce this change across output position. Indeed, it has been noted on several occasions that the change in lag-CRP with output position could be accounted for by serial recall from a short-term buffer (Davelaar et al., 2005; Howard & Kahana, 1999). Kahana (1996) demonstrated that a version of the SAM model (e.g., Raaijmakers & Shiffrin, 1981) produced this interaction with some assumptions about variable buffer size and displacement from the buffer (Phillips, Shiffrin, & Atkinson, 1967). The simple serial recall model forming the buffer component of the models here will predict localized transitions in a similar manner to TCM. This short-term mechanism is expected to produce more localized transitions than those from a model like TCM. For example, Bhatarah et al. (2008) presented lag-CRP functions suggesting greater locality in serial recall than in free recall, suggesting the ordered serial recall buffer produces more localized transitions. In a similar vein, Laming (2008) noted that constructing lag-CRPs on the basis of rehearsal lag (the lag of the items given their likely origin in the rehearsal record) rather than lag in the original list order gave much more localized transition probabilities. This is also reflected in the low estimates of positional confusability in the fits of the data-determined forward buffer presented above. Accordingly, it is expected that when recall transits from use of the ordered buffer (very localized transitions) to that of the standard TCM mechanism (less localized transitions) later in recall, the lag-CRP will flatten out. Furthermore, because the buffer is of variable size (consistent with Kahana's 1996 simulation of the lag-CRP–output position interaction), this is expected to happen in a continuous fashion across early output positions: moving from the first to the second output position, buffers of size 2 and above will contribute to the lag-CRP function. Moving from the second to the third output position, only a buffer of size 3 or above will contribute to the lag-CRP, with the contribution of the size 2 buffer being replaced by the standard TCM mechanism. The right column of Figure 11, which presents lag-CRP functions calculated from the fits presented in Figure 10, confirms that the TCM with a variable size ordered buffer does indeed produce a realistic change in the lag-CRP function across output positions.

General discussion

Conditional recency—the probability of recalling the final list item given it has not yet been recalled, as measured by the RRP—initially increases across output position in immediate free recall; in contrast, delayed recall produces no change in recency across output position, or a trend to decrease across output positions. This pattern of results has not been reported in the literature, and constitutes a hitherto unreported empirical regularity in episodic memory.

This dissociation presents a challenge to existing unitary accounts of free recall, including the general principle of the ratio rule, that do not specify separate mechanisms, processes or representations giving rise to recency in immediate and delayed free recall (e.g., Brown, Neath, & Chater, 2007; Howard & Kahana, 2002; Nairne, Neath, Serra, & Byun, 1997). This challenge was confirmed in fits of two models of recency in free recall. TCM (Howard & Kahana, 2002), which assumes that the recall of items updates the temporal context to be used for future recall attempts, predicted a slight but consistent negative change in recency across output positions in both immediate and delayed free recall. A similar failure to capture the dissociation was displayed by a version of SIMPLE (Brown, Neath, & Chater, 2007) in which participants were assumed to repeatedly probe for the last list item. In both cases, the models failed to capture the qualitative difference between immediate and delayed recall in the change in recency across output.

Several modifications to the models demonstrated several principles that could give rise to an increase in conditional recency across the first several output positions in immediate recall. One initial modification was to assume that time does not pass during recall. Although this assumption could in principle produce the required increase in conditional recency, it also produced a similar qualitative and quantitative increase in conditional recency across early output in delayed recall. Along with other principled objections to holding context or time constant across output (see earlier discussion), this inability to account for the data argues for the dismissal of this possible modification.

Two further modifications examined here could account for both the increase in conditional recency in immediate recall, and the dissociation between immediate and delayed recall. One of these was to incorporate a short-term buffer of the classic type as assumed in models such as those of Atkinson and Shiffrin (1968)—and akin to the activation-based short-term memory mechanism in the model of (Davelaar et al., 2005)—into TCM and SIMPLE. This modification is similar in principle to the assumption of no delay during recall. In both cases, the fundamental feature producing an increase in conditional recency is a restricted set of items favoring recall of the last item. Since stronger competitors of the last item are more likely to be recalled in place of that item, these stronger competitors are also more likely to be removed from further competition early in recall, which effectively increases the competitiveness of the last item. In the buffer model, there is a temporal limit on this effect; if the last item is not in the buffer, this restricted set explanation will not aid in its recall, such that once the buffer is emptied and recall switches to use of a longer-term memory component, a non-monotonicity in recency is predicted (Figure 5). Finally, this effect is not produced in delayed recall, under the assumption that the buffer has been emptied by activities intervening between list presentation and recall, leading to a reliance on the standard mechanisms in TCM and SIMPLE, and thus to a flat or decreasing relationship between conditional recency and output position in delayed recall.

A second modification, instantiated in two separate simulations, was to assume some form of forward cueing of the last several list items in immediate free recall. In one case, supplementing the random buffer with the assumption that recall proceeds in a forward order improves the fit of this model further: the increase in conditional recency across output is more pronounced (Table 1) and the deviation between the model and data is substantially reduced (Tables 2 to 5). This model inherits the notion of a restricted set, but supplements this with a forward recall mechanism, based on a simplification of models of serial recall (e.g., Brown et al., 2000; Burgess & Hitch, 1999; Lewandowsky & Farrell, 2008). By doing so, the increasing accessibility of the last item is enhanced as the cue for recall approaches that which is most conducive to recall of the last item. To account for the data of Howard and Kahana (1999) and Howard et al. (2007), it was found necessary to assume variability in buffer size across trials, and to estimate the buffer size on a trial-by-trial basis, which also accounted for changes in lag-CRP across output position. In a second account developed in a similar spirit, it was assumed in SIMPLE that the last few list items are probed in a forward order, without the assumption of a short-term buffer. Although this model produced the required change in conditional recency across initial output positions in immediate free recall, it produced a similar increase across delayed recall, in conflict with the data.

Together, these results suggest that both a short-term buffer and forward probing are important for producing the increase in conditional recency seen in immediate free recall data. Of all the models considered here, the one generally giving the best and most parsimonious fit to the data is the version of TCM incorporating a forward buffer (see Table 2 and Table 3); when looking only at SIMPLE, this variant of the model also gives the best fit for the majority of conditions (Tables 4 and 5). This version of the model also gives noticeably greater and more realistic mean slopes relating conditional recency to output position when compared to the random buffer version (Table 1), reinforcing a specific role for forward output order in producing the effect.

In comparing the forward buffer version of SIMPLE and TCM to the forward probing version of SIMPLE, all of which provide realistic average conditional recency slopes in immediate free recall, it can be noted that the latter model provides worse fits overall, and fails to dissociate between immediate and delayed recall. One solution for the forward probing version of SIMPLE would be to assume that in immediate free recall people tend to probe their memory in a forward order across the last few list items, while in delayed recall a static recency-based probing strategy is used. However, such a suggestion introduces a critical explanatory gap between the core principles of the model (that memory phenomena can be explained as confusability in multidimensional space) and arbitrary supplemental assumptions needed to account for specific effects in the data. There is no independent evidence to suggest that forward probing will be more beneficial in immediate recall in SIMPLE, while recency probing (or some similar strategy such as backward recall) will be more optimal in delayed recall. In the absence of such evidence, there is little empirical motivation for assuming a dissociation of ordered recall according to recall delay. Since the model does not currently provide any specification of output processes (Brown, Neath, & Chater, 2007; Lewandowsky, Nimmo, & Brown, 2008; Neath & Brown, 2006), there is also the additional question of how participants know which items to probe, in which order, without relying on some other memory mechanism such as a short-term buffer. This challenge is in the spirit of a comment by Dalezman (1976) that the mechanisms responsible for the storage or maintenance of information in episodic memory, as well as control processes for input, should be complemented by processes for output control, such as retrieval strategies. Nonetheless, the simulations of the forward probing version of SIMPLE serve the valuable purpose of cautioning that the dissociation in conditional recency between immediate and delayed recall need not imply a separation of stores or representations, and that this may possibly reflect a dissociation in the strategic use of memory to solve the task required of participants. More generally, they serve as a caution that assumptions about retrieval order (and rehearsal order, not considered here; see Laming, 2006; Tan & Ward, 2000) may modulate the predicted change in recency.

Dissociating different mechanisms for recency

One possible objection to the conclusions presented here is that the difference in slopes observed overall between immediate and delayed free recall is confounded with specific differences between the immediate and delayed recall conditions. Some evidence against this comes from the single controlled comparison within Experiment 1 of Howard and Kahana (1999) showing a significant difference in RRP slope between immediate and delayed recall. The only plausible alternative to the difference between immediate and delayed recall given the results in Figure 1 is that immediate and delayed free recall do not differ, and that the conditional recency slope is positive for both immediate and delayed free recall [as implied by an overall significantly positive slope in Figure 1 revealed by mixed-effects modelling: $\beta = .054, t(12.67) = 2.73, p < .05$]. This would actually present a stronger challenge to models like TCM and SIMPLE, as we would then have evidence of a pattern of results in conflict with these models across both the immediate and delayed recall conditions. However, given the significance of the controlled repeated measures comparison within Howard and Kahana (1999)'s Experiment 1, and given the overall difference between the immediate recall conditions (which are quite heterogeneous) and the delayed recall conditions, the most obvious conclusion is that immediate and delayed recall differ in their pattern of conditional recency.

One important caveat relating to the dissociation between immediate and delayed recall is that a buffer may not always contribute to recency in free recall, even in immediate recall. Under the models presented here, recency in immediate recall may be supported by either of a short-term buffer or a unitary mechanism such as TCM or SIMPLE, which also naturally produce a large recency effect in immediate recall. Although having two mechanisms that produce recency in immediate free recall may seem overly complicated, these two sources can be distinguished experimentally. For the models considered here, any manipulation which interferes with the short-term buffer (or modifies the likelihood that people will use it for recall; see below) should decrease the conditional recency slope without necessarily affecting recency in the accuracy serial position function. Such a suggestion urges qualification of claims by, for example, Bhatarah et al. (2006) that the lack of disruptive effects of continuous distractor serial recall on recency in free recall argues against the role of a limited-capacity short-term buffer in free recall; if the short-term buffer is sufficient but not necessary for recency in free recall, under such conditions participants may rely on mechanisms (e.g., TCM or SIMPLE) other than the short-term buffer for recall of recent items. A further empirical distinction is offered by the work of Howard et al. (2007), who showed that when an item is presented both in the middle and near the end of a list, early recall of that item increased the probability of next recall the list neighbor of the first presentation of that item. This phenomenon is consistent with a contribution of associative processes, such as those assumed in TCM, to recency in immediate recall. The smaller conditional recency increase observed in that experiment here is consistent with a greater reliance being placed on a long-term memory mechanism suggested in TCM, perhaps in strategic response to the repeated items. The results of Howard et al. (2007) and the conditional recency analysis examined here can be reconciled by assuming a mixture (across participants or individual trials) of the use of a short-term buffer or TCM to accomplish initial recall of items in immediate free recall.

One variable that might determine use of a short-term buffer, and thus the increase in RRP, is the modality of presentation of items. The classic modality effect refers to the finding that auditorily presented items are more likely to be recalled than those present visually, but only for items in the recency portion of the curve (e.g. Beaman & Morton, 2000; Murdock & Walker, 1969). It is also possible that the different modalities give rise to different orders of output in free recall, which in turn may give rise to modality effects on accuracy according to differential effects of output interference. The results on this are unclear. On the one hand, Nilsson et al. (1975) used an analysis of distribution of input-output lags in the data of Murdock and Walker (1969) to argue that auditory presentation tends to encourage forward recall of the last few list items, while visual presentation encourages backward recall of those items (for a consideration with respect to output interference, see Nilsson, Wright, & Murdock, 1979). On the other hand, Beaman and Morton (2000) found no effect of presentation modality on the preference for a forward recall order of the last few items in their immediate free recall experiment.

The immediate free recall conditions examined here used a mixture of auditory and visual presentation, but there are other differences between the conditions that prevent an unconfounded comparison based only on modality. The one possible comparison is between the results for Murdock and Okada (1970) and the 20-1 and 20-2 conditions of Murdock (1962), which use equal list length and similar experimental design, but vary in the modality of presentation. The experiment of Murdock (1962) involving auditory presentation appears to produce a greater increase in conditional recency across input position. This would follow naturally from the assumption, based on the observations of Nilsson et al. (1975) and Nilsson et al. (1979), that auditory presentation encourages use of a forward probed buffer, while visual presentation encourages use of a random buffer (which will tend to encourage a backward recall order in the same way that a primacy gradient generates forward recall in models such as those of Farrell & Lewandowsky, 2002, and Page & Norris, 1998). This is consistent with the findings of Li and Lewandowsky (1993, 1995) that forward and backward recall are differentially affected by tasks that either interfere with inter-item associations (intra-list distractor task such as mental rotation) or modify visuo-spatial properties of items (such as placement on the screen). On the basis of their results, Li and Lewandowsky argued that presentation in the auditory modality encourages temporal coding while backward (or here, random) recall relies more on visual representations. Given the uncertainty about modality effects on retrieval order in free recall, and their concomitant effects on output interference (compare Nilsson et al., 1979, and Beaman & Morton, 2000), further experiments are warranted.

Together, these considerations may explain why some conditions examined here show a greater conditional recency slope than others. Although the average slope for immediate recall as given in Table 1 is high, one or two of the estimates in Figure 1 are somewhat closer to zero, in particular that of Howard et al. (2007). The non-significant random effect for experiments suggests that this variance is due to sampling error, and that the variability at the level of experiments is negligible. Nonetheless, the experiment of Howard et al. (2007) and, to a lesser extent, that of Howard and Kahana (1999) are worth mentioning given the small slope in the experiment of Howard et al. (2007), and the different form of their RRP functions by output position (Figure 2). These studies differ from the others examined in a number of ways, including that items were presented visually, recall was spoken (rather than written), the repetition of items in Howard et al. (2007) discussed above, and a semantic orienting procedure was used during presentation to prevent rehearsal, any of which may have encouraged participants to rely less on a short-term buffer and introduced variability in the number of items initially lined up for serial recall. This is generally consistent with the observation by Davelaar et al. (2005) that the lack of primacy in the continuous distractor tasks of Howard and Kahana (1999) was likely to be due to Howard and Kahana's use of the semantic orienting task, which may have changed participants deployment of attention during the task. More generally, it is also consistent with Atkinson and Shiffrin's (1968) emphasis on the role of control processes in memory. Atkinson and Shiffrin's statement that "In situations [...] where coding, long-term search, hypothesis testing, and other mechanisms appreciably improve performance, it is likely that a trade-off will occur in which the buffer size will be reduced and rehearsal may even become somewhat random while coding and other strategies increase" (p. 113) offers to explain smaller conditional recency slopes as a consequence of de-emphasizing or varying the size of the short-term buffer in response to other forms of coding, as would be expected by use of a semantic orientation task.

Towards a model of free recall

As stressed earlier, the models such as the TCM model supplemented by an ordered buffer presented here do not constitute full models of free recall. The buffer size is unlikely to be static across participants, and some theoretically motivated specification of buffer size across trials and participants has not been presented. Additionally, it is quite possible for recall on some trials to be dependent entirely on long-term memory, depending on the strategy adopted by the participant. Another aspect of the data not accounted for by the models is the primacy observed in first recall probabilities, a feature that is also beyond the purview of the basic TCM model (Howard & Kahana, 2002). Additionally, and as noted above, the distinction between immediate and delayed recall may rely not on some short-term buffer, but on different methods for cueing unitary memory. Davelaar et al. (2005) have also pointed out that the behavior of strict slot-based short-term buffer can be produced by an activation-based gradient across all list items. The simulations here instead point to some ingredients for a successful and comprehensive model of free recall, and highlight the insufficiency of unitary models such as TCM and SIMPLE.

In discussing the conclusions from the fits of the models, one finding to highlight is the relatively poor fit of SIMPLE in comparison to TCM. The AIC and BIC values in Tables 2, 3, 4, and 5 show that, for equivalent versions of the models, TCM always gives a better fit to the data than SIMPLE. Although a number of implementation issues may give rise to this, one important difference between SIMPLE and TCM is that TCM accounts for another type of conditional probability observed in free recall, and present in the data here, in which recall of item is often followed by recall of an item nearby in the list (as illustrated in Figure 11). In its present form, SIMPLE has difficulties in accounting for localized transitions in free recall (though see Brown, Chater, & Neath, 2008). The contribution of such localized transitions can also be seen when comparing the standard version of TCM to that in which no delay occurs during output. One major difference between these two versions of TCM is that the "no delay" model does not capture localized transitions because the same cue is used for recall at all output positions. The relative poverty of the "no delay" version of TCM in accounting for the data can, to a great extent, be attributed to this difference in scope.

Overall, the results of the data analysis and model simulations encourage a re-examination of the unitary, temporal distinctiveness framework for explaining recency effects, and are consistent with the notion that some form of short-term memory buffer can support recency in immediate free recall (e.g., Atkinson & Shiffrin, 1968; Davelaar et al., 2005). In particular, the data are particularly consistent with the notion that recency in immediate recall is often supported by an ordered recall buffer akin to popular models of serial recall (e.g., Brown et al., 2000; Burgess & Hitch, 1999; Lewandowsky & Farrell, 2008; Page & Norris, 1998). Support for the assumption that recall shifts to use of a long-term memory mechanism once the short-term buffer has been exhausted is provided by the observed shift, in immediate recall, from an increase in conditional recency across the first few output positions to a flattening or decrease across later output positions (Figure 2). The models developed here were constructed to test specific hypotheses about the source of increases in conditional recency, and do not provide a complete computational model of free recall. Given the complexity of some current free recall models (Davelaar et al., 2005; Sederberg et al., 2008), and the possibility that the relevant behavior of the model might depend on specific assumptions and factors as rehearsal strategy (Laming, 2006; Tan & Ward, 2000), we leave exploration of the phenomena reported here in such models to future modeling efforts.

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Appendix A

Procedure for maximum likelihood estimation

TCM

The activation of item i at the first output position is given by

$$a_i = \rho^{((L-i)(d_i+1)+d_r)}, \tag{A1}$$

where L is the list length, d_i is the effective duration of the distractor activity, if any, following each list item (assumed to be constant across the list), and d_r is the effective duration of distractor activity intervening between presentation of the last list item and the cue to recall (cf. Equation 12 in Howard, 2004). At later positions, the activations of items are calculated by updating Equation A1 based on the items output thus far:

$$\begin{aligned} a_j &= \mathbf{t}_{T+1} \bullet \mathbf{t}_j \\ &= (\rho_T \mathbf{t}_T + \beta \mathbf{t}_r^{IN}) \bullet \mathbf{t}_j \\ &= \rho_T \mathbf{t}_T \bullet \mathbf{t}_j + A\beta \mathbf{t}_i^{IN} \bullet \mathbf{t}_j + B\beta \mathbf{t}_i \bullet \mathbf{t}_j. \end{aligned} \tag{A2}$$

The repetition of items (i.e., recall of items presented earlier, which effectively constitutes re-presentation of the item) requires a departure requires departure from the standard version of TCM since ρ in Equation 1 will need to be recomputed at each time step during recall:

$$\rho_i = \sqrt{1 + \beta^2[(\mathbf{t}_{i-1} \bullet \mathbf{t}_i^{IN})^2 - 1]} - \beta(\mathbf{t}_{i-1} \bullet \mathbf{t}_i^{IN}). \tag{A3}$$

This in turn involves calculating a value for $\mathbf{t}_i^{IN} \bullet \mathbf{t}_{T-1}$. This dot product is given by:

$$\mathbf{t}_R^{IN} \bullet \mathbf{t}_{T-1} = A_i \mathbf{t}_i^{IN} \bullet \mathbf{t}_{T-1} + B_i \mathbf{t}_i \bullet \mathbf{t}_{T-1}, \tag{A4}$$

where the term $\mathbf{t}_i \bullet \mathbf{t}_{T-1}$ is given by a_i from the previous retrieval step, and $\mathbf{t}_i^{IN} \bullet \mathbf{t}_{T-1}$ is given by re-expressing Equation 1:

$$\mathbf{t}_i^{IN} \bullet \mathbf{t}_{T-1} = \frac{1}{\beta}\left(\mathbf{t}_i \bullet \mathbf{t}_{T-1} - \rho_l \mathbf{t}_{i-1} \bullet \mathbf{t}_{T-1}\right), \tag{A5}$$

where ρ_l is the constant value of ρ applying throughout list presentation and $\mathbf{t}_i \bullet \mathbf{t}_{T-1}$ is given by a_i from the previous retrieval time step. In the simulations, to obtain $\mathbf{t}_{i-1} \bullet \mathbf{t}_{T-1}$ we calculated a_{i-1} at the first retrieval attempt. These values are already given by the above equations for all items except the first.

The activations can then be converted into probabilities using the Luce-Shepard choice rule (Luce, 1963; Shepard, 1957). Following a derivation in Howard and Kahana (2002), the probability of recalling list item j given the activations is given by

$$p(j) = \frac{\exp\left(\frac{2a_j}{\tau}\right)}{\sum_k \exp\left(\frac{2a_k}{\tau}\right)}, \tag{A6}$$

where j and k only index items that have not yet been recalled.

SIMPLE

The likelihood of a response in SIMPLE is given by application of the Luce-Shepard choice rule to temporal distances of items from the present. Formally, the probability of recall of item j given the temporal probe i is given by

$$p(j) = \frac{s_{ij}}{\sum_k s_{ik}} \tag{A7}$$

where s_{ij} and all s_{ik} are given by Equation 2. As for TCM, items that have already been recalled are excluded from the numerator and denominator of Equation A7.

Random buffer

Calculation of the probability that an item is in the buffer at the end of list presentation in immediate recall involves enumeration of cases where it is in the buffer for exactly e presentation events, and working out the probability that it is still in the buffer at the end of list presentation by implication. The probability that the item stays in the buffer for exactly e events is given by

$$\beta_e = \begin{cases} 1-\alpha, & e = 0, \\ (1-\beta_0)(1-\alpha/r)^{e-1}\alpha/r, & e > 0, \end{cases} \tag{A8}$$

(Murdock, 1974), where r is the buffer size, and α is the probability of an item entering the buffer. Based on this, the probability of the item presented at serial position i being in the buffer at the end of recall is given by

$$p_{buff}(i) = 1 - \sum_{k=0}^{i} \beta_k. \tag{A9}$$

Equation A9 gives the probability that item i occupies any of the slots in the buffer (for output positions $\leq r$). In order to obtain the probability of recall of item i at a particular output position, these probabilities were rescaled to sum to 1; as for the preceding models, the probability that a recalled item was in the buffer was set to 0 and ignored in the rescaling.

Forward buffer

After applying Equation 3, the probability of cueing for an item j given the probe for position i was obtained by rescaling the values from Equation 3 to sum to 1:

$$p_{pos}(j) = \frac{a_{ij}}{\sum_k a_{ik}}. \tag{A10}$$

These values were then combined with the probability of an item being in the buffer (p_{buff}) to give the joint probability of an item being cued for by the positional probe and being available in the buffer:

$$p(j) = p_{pos}(j)p_{buff}(j). \tag{A11}$$

These probabilities were rescaled to sum to 1 to give probabilities of recall (i.e., cases where an item was cued for, but not available in the buffer, were discounted); as for the preceding models, the probability that a recalled item was in the buffer was set to 0 and ignored in the rescaling. For output positions exceeding the buffer size, probability of recall switched to use of Equation A6 or A7.

Likelihood estimation

A log-likelihood value was obtained for each response in all models by determining the predicted probability of making that response given all previous recalls on that trial by the participant. For example, if a participant recalled the item at serial position 18 at the first output position, a log-likelihood value would be obtained in TCM by taking the log of $p(18)$ given by feeding the activations from Equation A1 into Equation A6; in SIMPLE, the log of $p(18)$ from Equation A7 would be used. At later steps in recall the calculation changes slightly as the contextual evolution in TCM depends on moment to moment events at encoding and retrieval (i.e., Equation A2 is used to calculate activations), and in both models the recall of items is conditional on them not yet having been recalled. Log-likelihood values were accumulated across output positions in a trial up to the first non-legitimate response (a recall repetition; recall of a non-list item; or an omission). A $\ln \ell$ value was obtained for each participant by summing the $\ln \ell$ values from all trials for that person.

To examine the predictions of the models, probability distributions were scored.

That is, whereas in the data each response added an increment of one to the numerator for that response (where the numerator is a vector tracking the number of recalls of each list item at each output position), in the models the predicted probability distribution (which necessarily summed to one) was added to the numerator. In both cases (i.e., data and model), an identical denominator tracked which recalls would have been possible given the recalls already made.

Appendix B

Maximum likelihood parameter estimates for TCM

See Table B1.

Appendix C

Maximum likelihood parameter estimates for SIMPLE

See Table C1.

Author Note

I am grateful to Mike Kahana and Marc Howard for making a number of the data sets analyzed here publicly available, and to the original authors for initially releasing their data for analysis. Correspondence should be addressed to Simon Farrell, Department of Experimental Psychology, University of Bristol, 12a Priory Road, Clifton, Bristol BS8 1TU, UK; e-mail: Simon.Farrell@bristol.ac.uk.

Footnotes

[1] A recency effect is also predicted by some of these models because items at the end of a list will have fewer interfering neighbors (i.e., local distinctiveness; Brown, Neath, & Chater, 2007).

[2] This analysis should be distinguished from the analysis of lag-recency used by Kahana (1996), Howard and Kahana (1999), and others. Analyses of lag-recency also involve examination of conditional probabilities; however, those analyses examine responses as a function of the lag (separation in input positions) between successive recalls. Here, scoring is conditional only on the event that an item has not been recalled, and does not otherwise take into account conditional relationships involving the identity of previously recalled items. Analyses of lag-recency are presented later in the paper.

[3]The data were retrieved from the web site of Michael Kahana's Computational Memory Lab, at http://memory.psych.upenn.edu/, and Marc Howard's lab at http://memory.syr.edu/.

[4]Note that the two conditions of Experiment 1 of Howard and Kahana (1999) are from a within-participants design. For ease of application, the multilevel modeling employed assumed this was a between-participants manipulation as for all other conditions. This assumption is likely to have worked against the difference between immediate and delayed recall

[5]Only participants contributing conditional probabilities for at least two output positions in both immediate and delayed recall were included in the analysis, so as to permit a repeated measures analysis

[6]Note that AIC and BIC differences are equal when the number of parameters is equivalent for two models; this is the case, for example, for some of the differences in the first two columns of Tables 2 and 3.

[7]Given the slope analysis conducted here was applied to the first four output

positions, there is some motivation for examining a recall buffer of size four (e.g., Raaijmakers & Shiffrin, 1981). Some unreported simulations examined a buffer of size four and found similar results (particularly an increase in conditional recency slopes and corrected quality of fit).

Table 1

Mean slopes across immediate (left) and delayed (right) conditions, with standard deviations across experiments.

		Immediate		Delayed	
		Mean	SD	Mean	SD
Data		0.11	0.03	-0.03	0.03
Chance		0.01	0.01	0.01	0.00
	Standard	-0.05	0.02	0.00	0.01
TCM	No delay	0.04	0.01	0.02	0.00
	Random buffer	0.04	0.02		
	Forward buffer	0.09	0.03		
	Standard	-0.02	0.02	-0.01	0.01
	No delay	0.03	0.01	0.02	0.00
SIMPLE	Forward probe	0.14	0.04	0.04	0.02
	Random buffer	0.03	0.04		
	Forward buffer	0.08	0.05		

Table 2

AIC differences for the fit of TCM to each experiment/condition. A small value indicates a better relative fit. Condition names correspond to those in Figure 1.

		TCM	No delay	Rand buffer	Fwd buffer
	H&K-1	0	98.01	642.60	532.71
	M&O	760.20	2682.95	295.35	0
	10-2	609.49	1216.47	340.26	0
	15-2	1336.68	3176.67	463.73	0
Immediate	20-1	1454.59	2407.69	599.56	0
	20-2	2087.25	4245.45	437.08	0
	30-1	1040.43	3445.76	487.29	0
	40-1	446.03	2923.09	333.06	0
	HVNK	0	790.07	7839.60	5981.91
	H&K-1	0	345.90	370.99	469.95
	ISI=0	0	10.65	37.41	69.22
Delayed	ISI=2.5	34.35	0	72.80	107.26
	ISI=8	0	135.00	267.93	293.25
	ISI=16	0	135.48	232.26	268.60

Table 3

BIC differences for the fit of TCM to each experiment/condition. A small value indicates a better relative fit. Condition names correspond to those in Figure 1.

		TCM	No delay	Rand buffer	Fwd buffer
Immediate	H&K-1	0	98.01	748.23	743.96
	M&O	377.31	2300.05	103.91	0
	10-2	486.21	1093.19	278.62	0
	15-2	1207.79	3047.77	399.28	0
	20-1	1331.71	2284.81	538.11	0
	20-2	1958.32	4116.53	372.62	0
	30-1	913.04	3318.36	423.59	0
	40-1	319.81	2796.87	269.95	0
	HVNK	0	790.07	8578.37	7454.58
Delayed	H&K-1	0	345.90	445.26	618.48
	ISI=0	0	10.65	87.76	169.93
	ISI=2.5	34.35	0	116.53	194.71
	ISI=8	0	135.00	317.87	393.15
	ISI=16	0	135.48	275.40	354.89

Table 4

AIC differences for the fit of SIMPLE to each experiment/condition. A smaller value indicates a better fit. Condition names correspond to those in Figure 1.

		SIMPLE	No delay	Fwd probe	Rand buffer	Fwd buffer
Immediate	H&K-1	320.65	2263.34	2414.48	768.62	658.47
	M&O	3180.44	1349789	3139.07	1907.64	1609.54
	10-2	1536.22	1657.81	2405.15	872.30	538.44
	15-2	3689.93	3878.84	4528.39	2308.98	1871.02
	20-1	3216.30	3248.45	2328.51	1706.77	1107.22
	20-2	5053.42	5090.14	4222.09	3047.84	2611.84
	30-1	4596.36	4784.85	4338.92	3045.27	2557.98
	40-1	4186.20	4447.69	4179.38	2749.86	2416.79
	HVNK	3372.13	3418.64	31303.07	7965.36	6214.68
Delayed	H&K-1	399.99	302.78	486.70	492.71	585.51
	ISI=0	54.09	68.84	146.44	102.54	134.52
	ISI=2.5	34.33	58.52	235.20	97.86	129.86
	ISI=8	186.42	203.44	471.08	285.00	317.03
	ISI=16	148.60	163.98	723.43	295.88	327.92

Table 5

BIC differences for the fit of SIMPLE to each experiment/condition. A smaller value indicates a better fit. Condition names correspond to those in Figure 1.

		SIMPLE	No delay	Fwd probe	Rand buff	Fwd buff
Immediate	H&K-1	320.65	2157.71	2414.48	874.25	869.73
	M&O	2797.55	12923.55	2756.18	1716.19	1609.54
	10-2	1412.93	1472.89	2281.87	810.66	538.44
	15-2	3561.03	3685.49	4399.49	2244.53	1871.02
	20-1	3093.42	3064.12	2205.63	1645.33	1107.22
	20-2	4924.50	4896.76	4093.17	2983.37	2611.84
	30-1	4468.96	4593.75	4211.52	2981.57	2557.98
	40-1	4059.97	4258.35	4053.16	2686.74	2416.79
	HVNK	3372.13	2687.19	31303.07	8696.80	7677.58
Delayed	H&K-1	399.99	228.51	486.70	566.98	734.04
	ISI=0	54.09	18.48	146.44	152.90	235.24
	ISI=2.5	34.33	14.79	235.20	141.58	217.31
	ISI=8	186.42	153.49	471.08	334.94	416.93
	ISI=16	148.60	120.84	723.43	339.03	414.21

Table B1

		Standard		No delay		Random buffer			Forward buffer			
		β	τ	β	τ	β	τ	α	β	τ	α	ϕ
Immediate	H&K-1	0.57	0.33	0.65	0.46	0.53	0.27	0.87	0.59	0.30	0.79	0.22
	M&O	0.61	0.48	0.60	0.72	0.81	0.25	0.69	0.85	0.24	0.32	0.19
	10-2	0.52	0.44	0.55	0.74	0.76	0.25	0.69	0.76	0.28	0.38	0.23
	15-2	0.59	0.39	0.68	1.13	0.81	0.24	0.88	0.87	0.22	0.48	0.30
	20-1	0.52	0.39	0.60	0.66	0.80	0.25	0.76	0.80	0.25	0.21	0.32
	20-2	0.56	0.41	0.58	0.63	0.84	0.21	0.77	0.84	0.21	0.20	0.30
	30-1	0.59	0.38	0.61	0.53	0.81	0.22	0.79	0.81	0.22	0.35	0.25
	40-1	0.57	0.35	0.60	0.47	0.78	0.22	0.77	0.78	0.22	0.34	0.23
	HVNK	0.57	0.27	0.65	0.39	0.52	0.24	0.97	0.55	0.25	0.93	0.23
Delayed	H&K-1	0.79	0.25	0.63	0.20	0.58	0.18	0.35	0.66	0.25	0.27	0.06
	ISI=0	0.79	0.49	0.75	0.13	0.57	0.29	0.25	0.91	0.40	0.25	0.00
	ISI=2.5	0.73	0.27	0.70	0.39	0.76	0.34	0.33	0.77	0.44	0.33	0.00
	ISI=8	0.58	0.48	0.54	0.62	0.89	0.27	0.31	0.72	0.46	0.31	0.00
	ISI=16	0.43	0.35	0.39	0.47	0.62	0.29	0.53	0.63	0.36	0.53	0.00

Table C1

		Standard		No delay	Forward probe		Random buffer			Forward buffer			
		c	t_{out}	c	c	t_{out}	c	t_{out}	α	c	t_{out}	α	ϕ
	H&K-1	1.87	0.79	1.36	1.22	0.32	1.80	2.23	0.87	1.84	2.12	0.79	0.22
	M&O	0.94	0.63	0.76	1.66	1.95	0.56	1.53	0.69	0.58	1.52	0.32	0.19
	10-2	0.70	0.85	0.57	0.83	0.80	0.92	0.90	0.69	1.00	1.17	0.38	0.23
	15-2	0.87	0.74	0.74	1.45	1.65	0.83	1.73	0.88	0.93	2.06	0.48	0.30
Immediate	20-1	0.98	0.11	0.91	1.86	0.90	1.16	0.67	0.76	1.16	0.67	0.21	0.32
	20-2	0.74	0.18	0.68	1.68	2.39	0.78	0.68	0.77	0.88	1.00	0.20	0.30
	30-1	1.14	0.40	0.97	2.01	1.64	1.02	1.35	0.79	1.02	1.35	0.35	0.25
	40-1	1.22	0.54	1.03	2.00	1.70	0.82	0.67	0.77	0.82	0.67	0.34	0.23
	HVNK	1.70	0.48	1.46	0.88	0.39	2.45	2.19	0.97	2.47	2.18	0.93	0.23
	H&K-1	2.30	2.54	1.97	2.48	2.37	6.79	2.78	0.35	5.08	3.32	0.27	0.06
	ISI=0	1.89	3.54	1.34	1.61	3.46	0.96	1.88	0.25	0.96	1.74	0.25	0.00
Delayed	ISI=2.5	1.13	4.66	0.84	0.81	4.34	0.45	3.79	0.33	0.44	4.02	0.33	0.00
	ISI=8	0.67	4.43	0.54	0.40	4.20	0.21	2.92	0.31	0.21	3.60	0.31	0.00
	ISI=16	0.89	4.55	0.79	0.53	3.58	0.55	2.30	0.53	0.54	2.44	0.53	0.00

Figure Captions

Figure 1. Mean slopes predicting the conditional next recall probability of the last list item from output position, for output positions 1-4. Immediate free recall conditions are grouped on the left, and delayed free recall conditions are grouped on the right. For each condition, results are displayed for the data (squares), TCM (circles), and SIMPLE (crosses). The conditions are, from left to right: Immediate recall condition of Experiment 1 of Howard & Kahana (1999); Murdock & Okada (1970); the 6 conditions of Murdock (1962), where the first number gives the list length, and the second number gives the presentation time per item; Howard et al. (2007); delayed recall condition of Experiment 1 of Howard & Kahana (1999); and the four conditions of Experiment 2 of Howard & Kahana (1999), with the labels indicating the duration of continuous distraction between items at presentation. Error bars show single-sample confidence intervals.

Figure 2. Conditional probability of recalling the final list item across output positions for four immediate recall conditions. In each panel, each line corresponds to a group of participants providing legitimate data up to a given output position. The cut-off for each group of participants can be read off from the terminating output position for that line. The numbers above each termination point give the number of participants in the group terminating at that point. The dashed line shows the conditional recall probability predicted by the chance model (discussed in text). The four panels correspond to different conditions. M&O: Murdock & Okada (1970); 40-1: 40-1 condition from Murdock (1962); H&K-1: Experiment 1 of Howard & Kahana (1999); HVNK: Howard et al. (2007).

Figure 3. Conditional probability of recalling the final list item across output positions for four immediate recall conditions predicted by TCM. Details as in Figure 2. The four panels correspond to different conditions. M&O: Murdock & Okada (1970); 40-1: from Murdock (1962); H&K-1: Experiment 1 of Howard & Kahana (1999); HVNK: Howard et

al. (2007).

Figure 4. Conditional probability of recalling the final list item across output positions for four immediate recall conditions predicted by SIMPLE. Details as in Figure 2. The four panels correspond to different conditions. M&O: Murdock & Okada (1970); 40-1: 40-1 condition from Murdock (1962); H&K-1: Experiment 1 of Howard & Kahana (1999); HVNK: Howard et al. (2007).

Figure 5. Predicted conditional probability of recalling the final list item across output positions for four immediate recall conditions. Predictions come from TCM supplemented by a random short-term buffer. Details as in Figure 2. The four panels correspond to different conditions. M&O: Murdock & Okada (1970); 40-1: 40-1 condition from Murdock (1962); H&K-1: Experiment 1 of Howard & Kahana (1999); HVNK: Howard et al. (2007).

Figure 6. Predicted conditional probability of recalling the final list item across output positions for four immediate recall conditions. Predictions come from TCM supplemented by an ordered short-term buffer. Details as in Figure 2. The four panels correspond to different conditions. M&O: Murdock & Okada (1970); 40-1: 40-1 condition from Murdock (1962); H&K-1: Experiment 1 of Howard & Kahana (1999); HVNK: Howard et al. (2007).

Figure 7. Predicted conditional probability of recalling the final list item across output positions for four immediate recall conditions. Predictions come from SIMPLE assuming forward-ordered probing of the last three list items. Details as in Figure 2. The four panels correspond to different conditions. M&O: Murdock & Okada (1970); 40-1: 40-1 condition from Murdock (1962); H&K-1: Experiment 1 of Howard & Kahana (1999); HVNK: Howard et al. (2007).

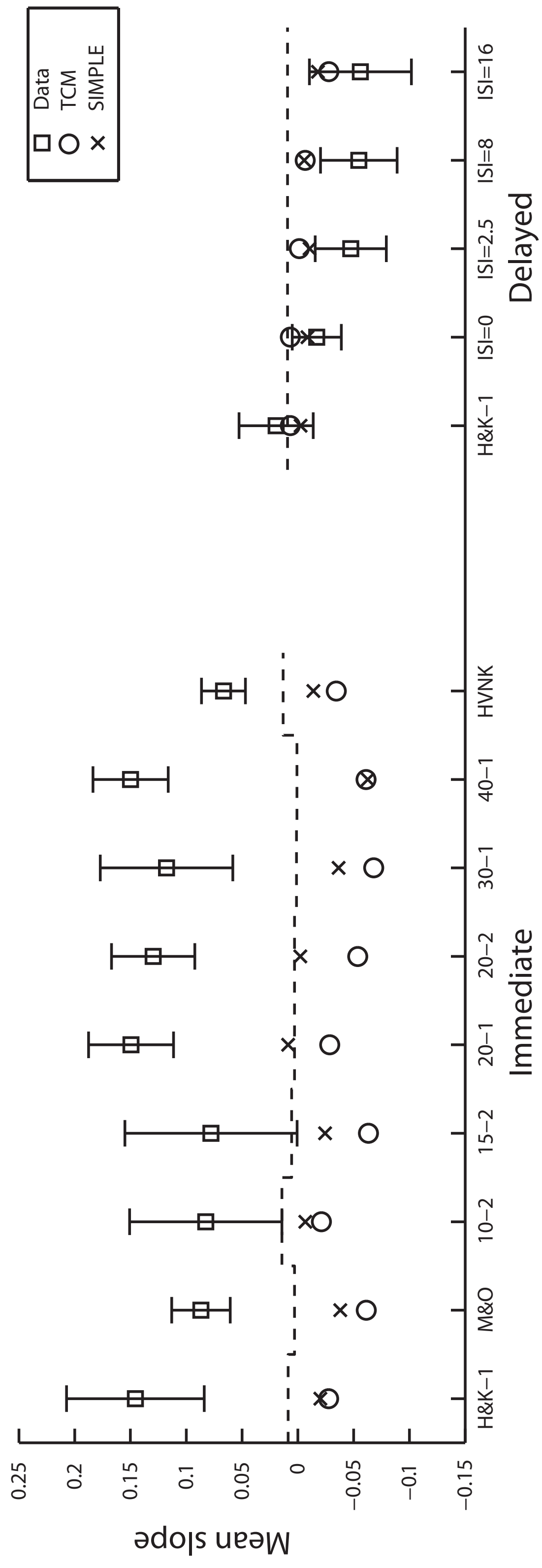
Figure 8. Probability of first recall by serial positions for four immediate recall conditions.

The four panels correspond to different conditions. M&O: Murdock & Okada (1970); 40-1: 40-1 condition from Murdock (1962); H&K-1: Experiment 1 of Howard & Kahana (1999); HVNK: Howard et al. (2007).

Figure 9. Probability of first recall by serial positions for four immediate recall conditions. The four panels correspond to different conditions. M&O: Murdock & Okada (1970); 40-1: 40-1 condition from Murdock (1962); H&K-1: Experiment 1 of Howard & Kahana (1999); HVNK: Howard et al. (2007).

Figure 10. Predicted conditional probability of recalling the final list item across output positions for four immediate recall conditions. Predictions come from TCM + forward buffer model, with the size of the buffer determined from the first response on each trial. M&O: Murdock & Okada (1970); 40-1: 40-1 condition from Murdock (1962); H&K-1: Experiment 1 of Howard & Kahana (1999); HVNK: Howard et al. (2007).

Figure 11. Lag conditional response probability curves for the data of Howard & Kahana (1999) (top row) and Howard et al. (2007) (bottom row). The left column plots the functions for the data; the middle column plots predictions of the standard version of TCM, and the right column plots the predictions of the TCM supplemented by a forward buffer whose size is determined from the first response in each trial.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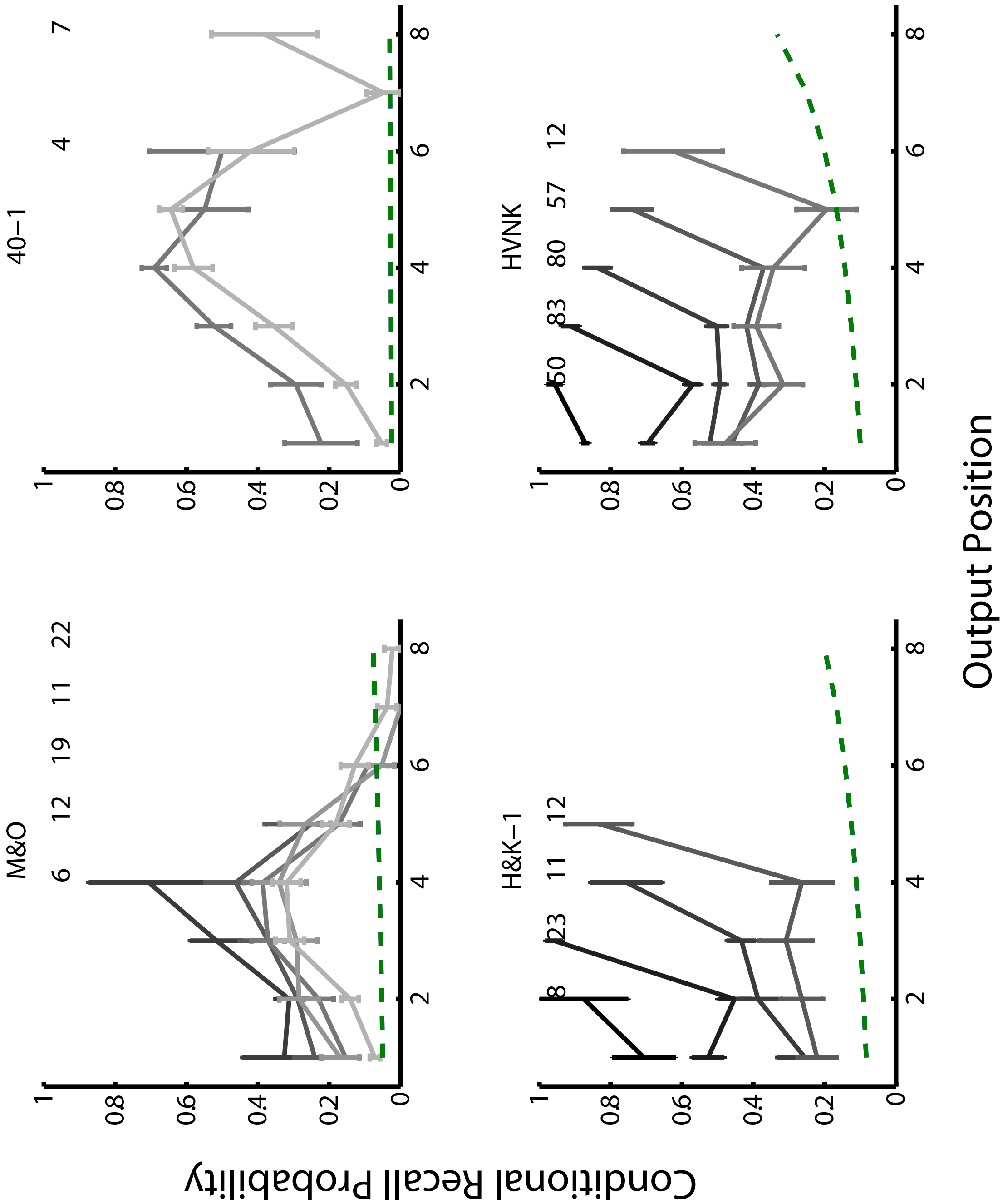
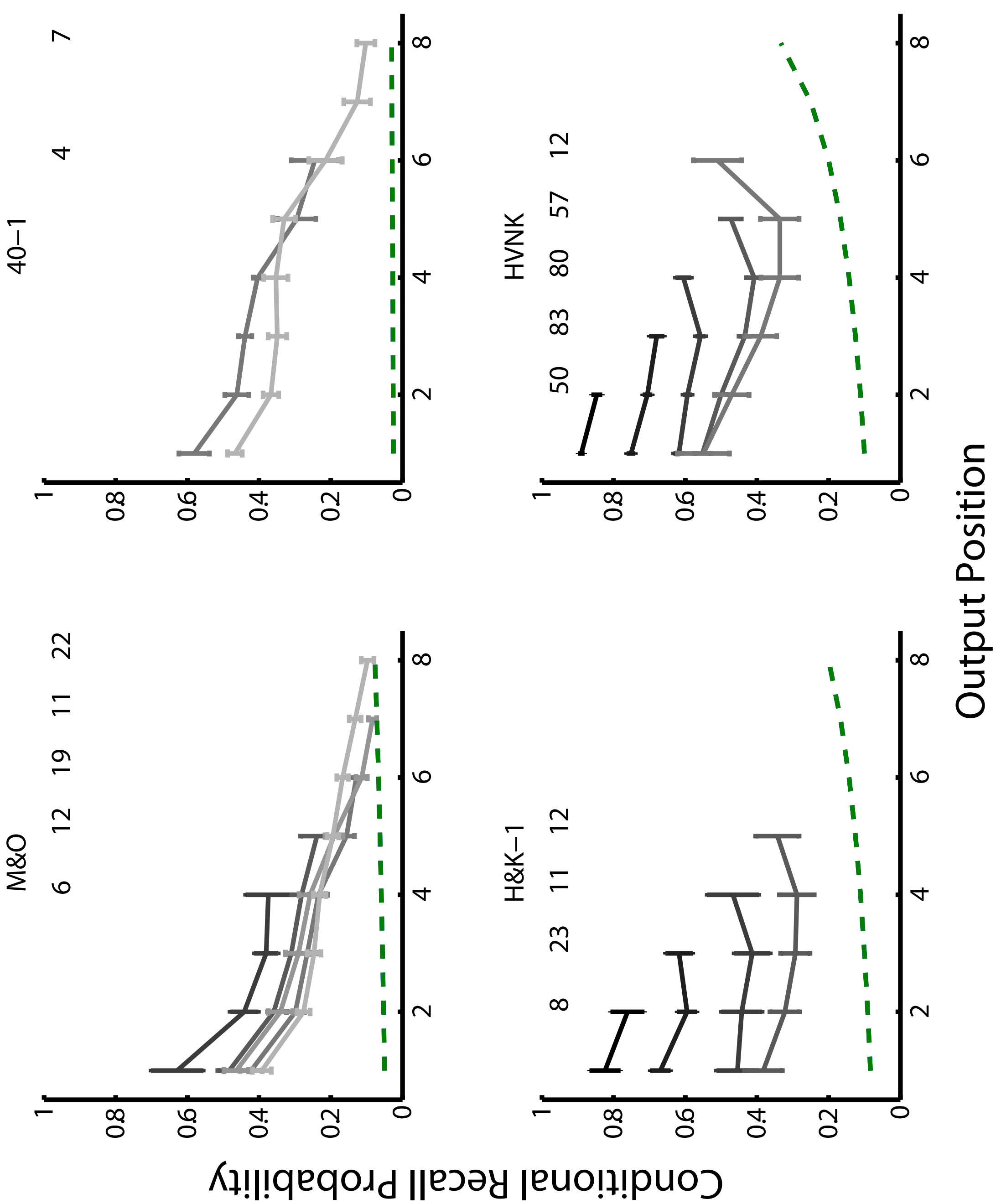
TCM
SIMPLE
Mean slope
0.25
0.2
0.15
0.1
0.05
0
−0.05
−0.1
−0.15
H&K−1
M&O
10−2
15−2
20−1
20−2
30−1
40−1
HVNK
ISI=0
ISI=2.5
ISI=8
ISI=16
Immediate
Delayed


M&O
40−1
H&K−1
HVNK
Conditional Recall Probability
Output Position


M&O
6 12 19 11 22
40−1
4 7
H&K−1
8 23 11 12
HVNK
50 83 80 57 12
Conditional Recall Probability
Output Position
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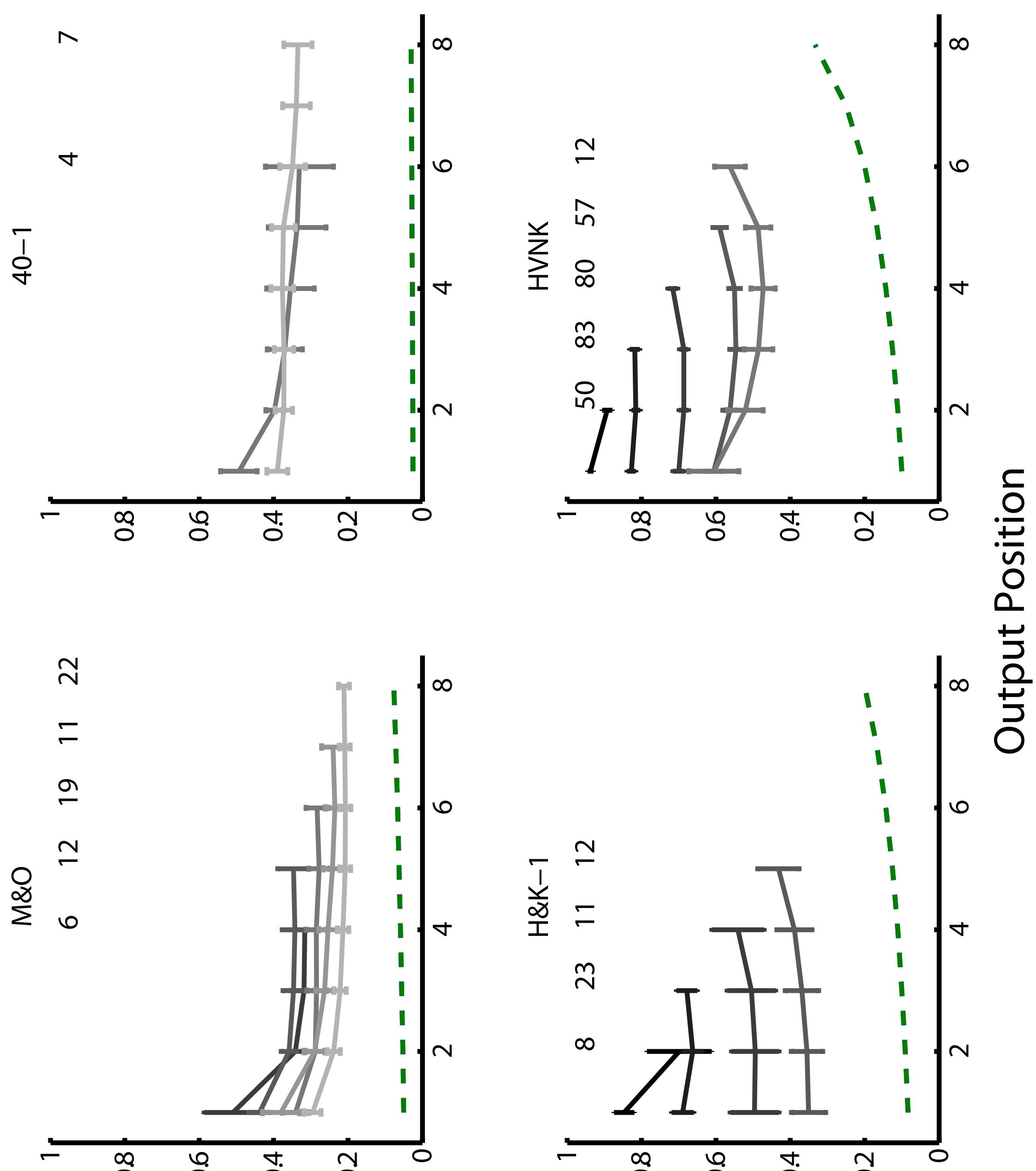
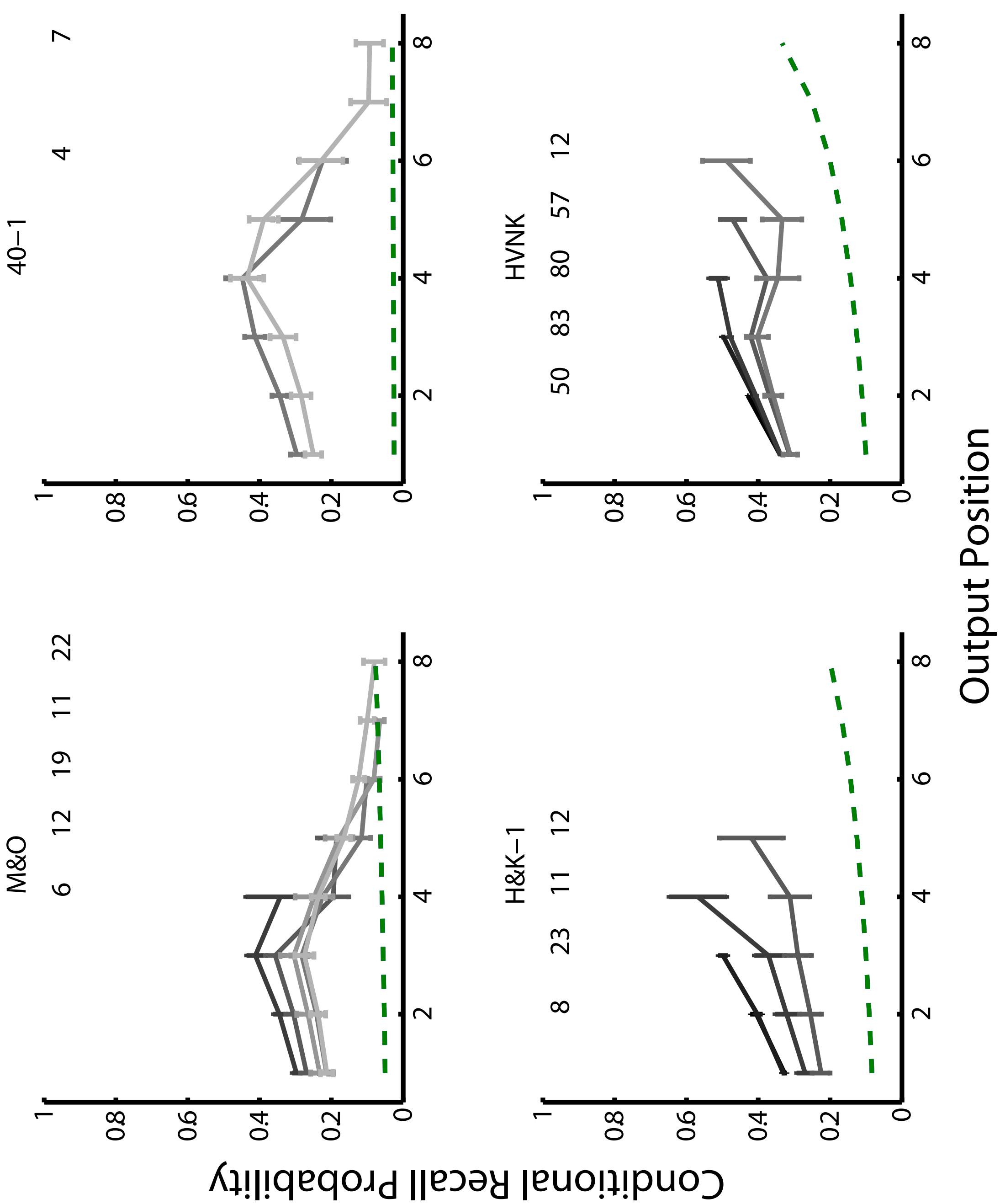
0.4
0.6
0.8
1
2
4
6
8


M&O
40–1
H&K–1
HVNK
Conditional Recall Probability
Output Position


M&O
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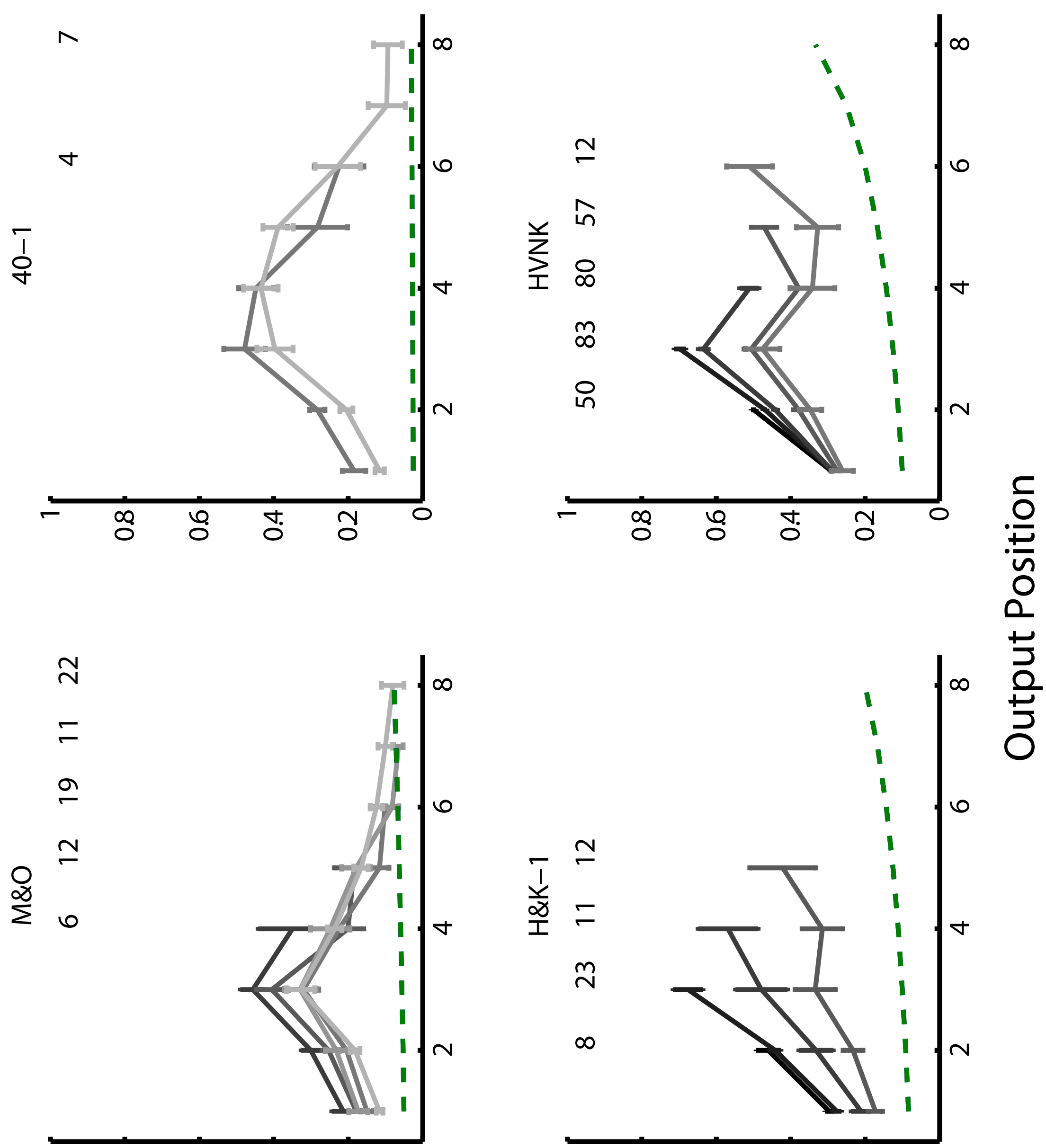
40−1
4 7
H&K−1
8 23 11 12
HVNK
50 83 80 57 12
0 0.2 0.4 0.6 0.8 1
2 4 6 8
Conditional Recall Probability
Output Position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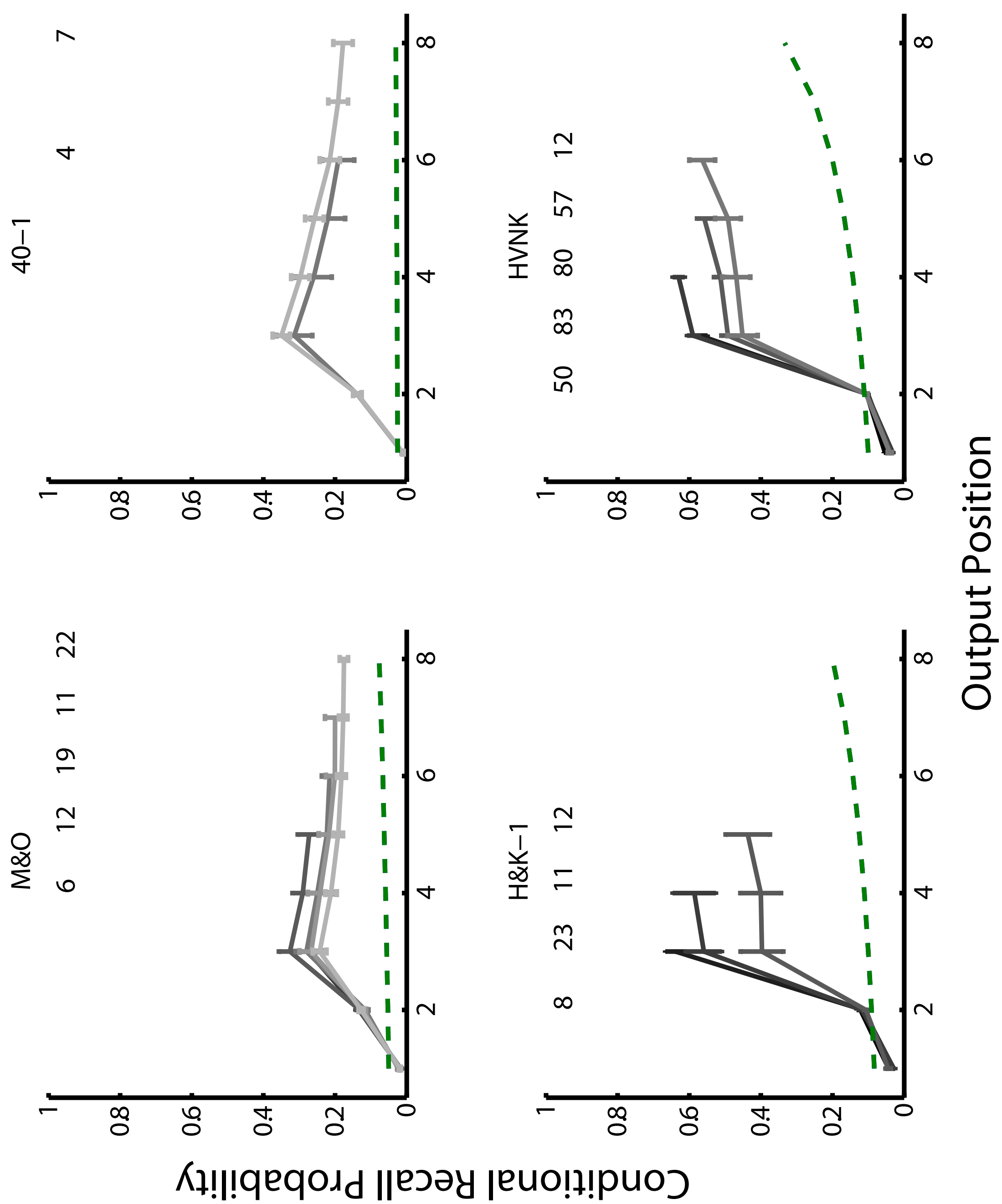
40−1
4 7
H&K−1
8 23 11 12
HVNK
50 83 80 57 12
Conditional Recall Probability
Output Position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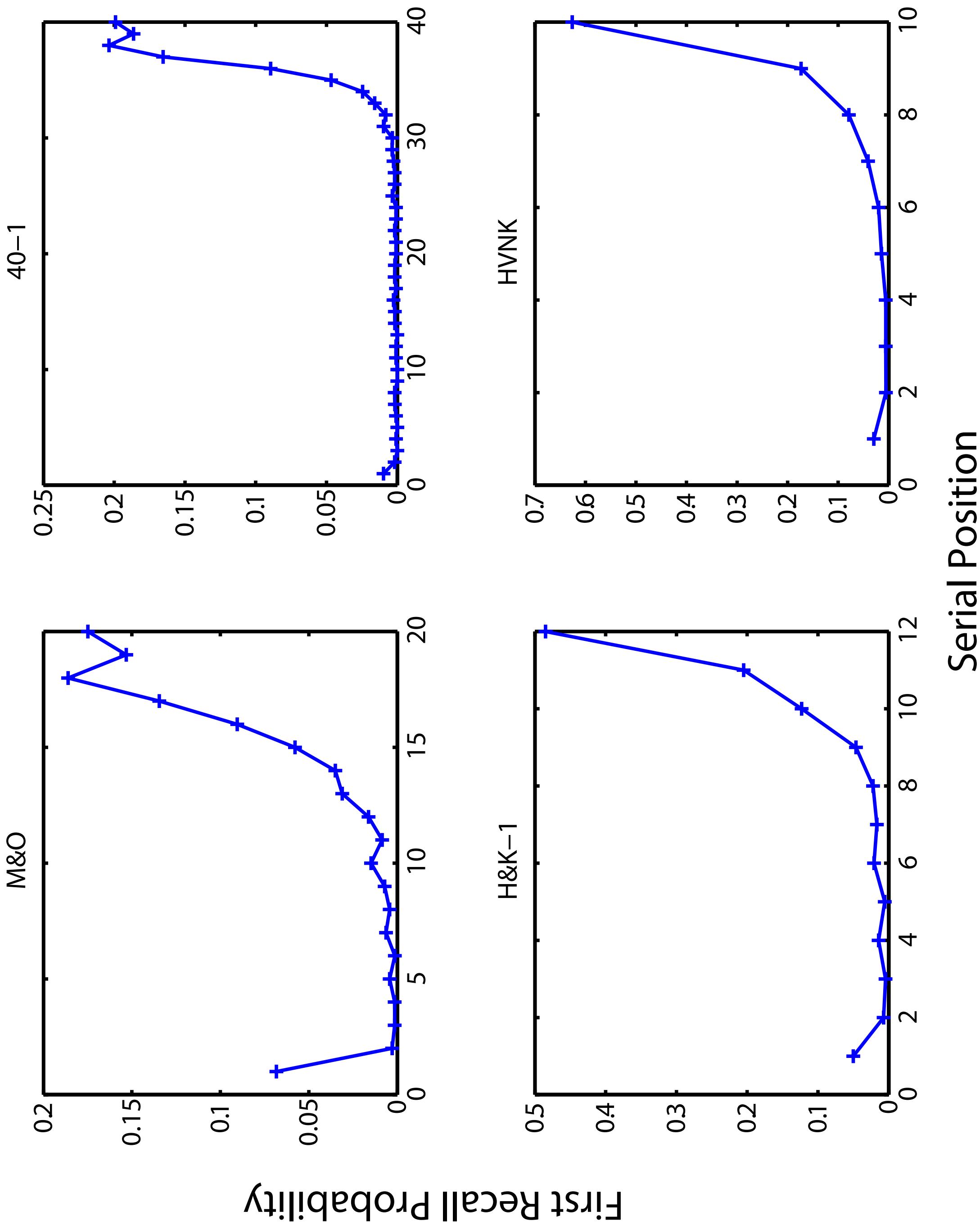
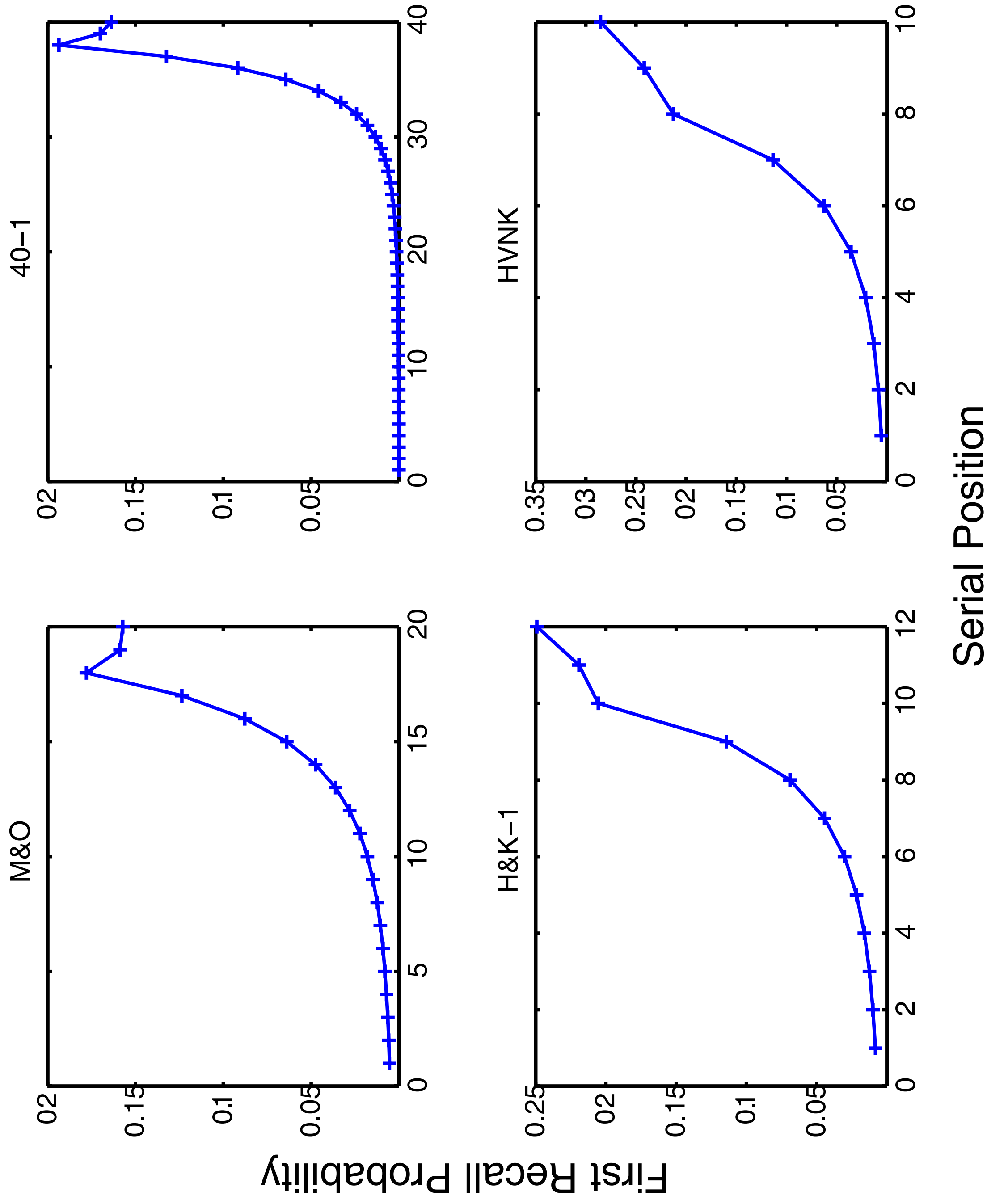
40−1
4 7
H&K−1
8 23 11 12
HVNK
50 83 80 57 12
Conditional Recall Probability
Output Position


M&O
40−1
H&K−1
HVNK
First Recall Probability
Serial Position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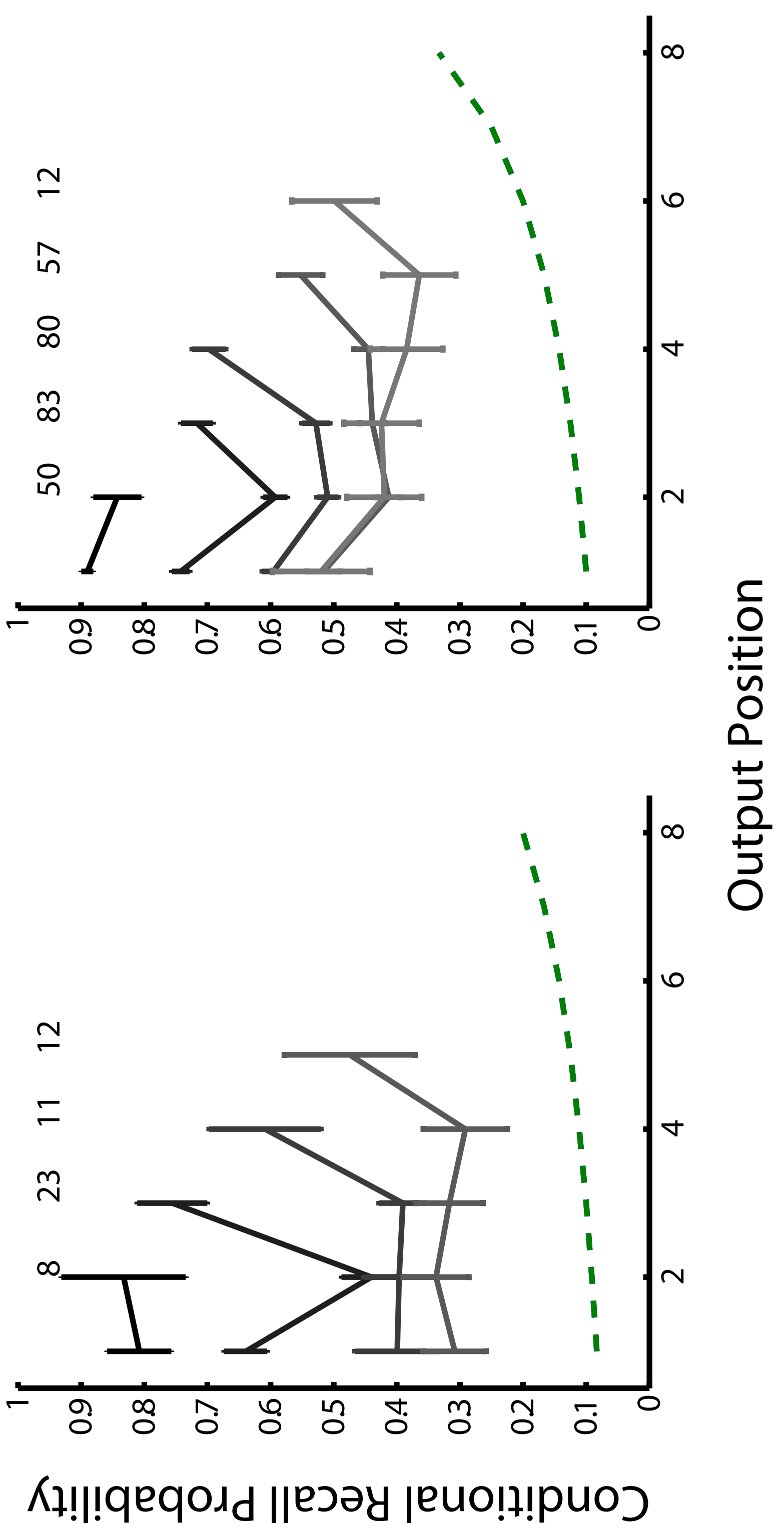
H&K−1
HVNK
First Recall Probability
Serial Position


Conditional Recall Probability
Output Position
H&K–1
8
23
11
12
HVNK
50
83
80
57
12
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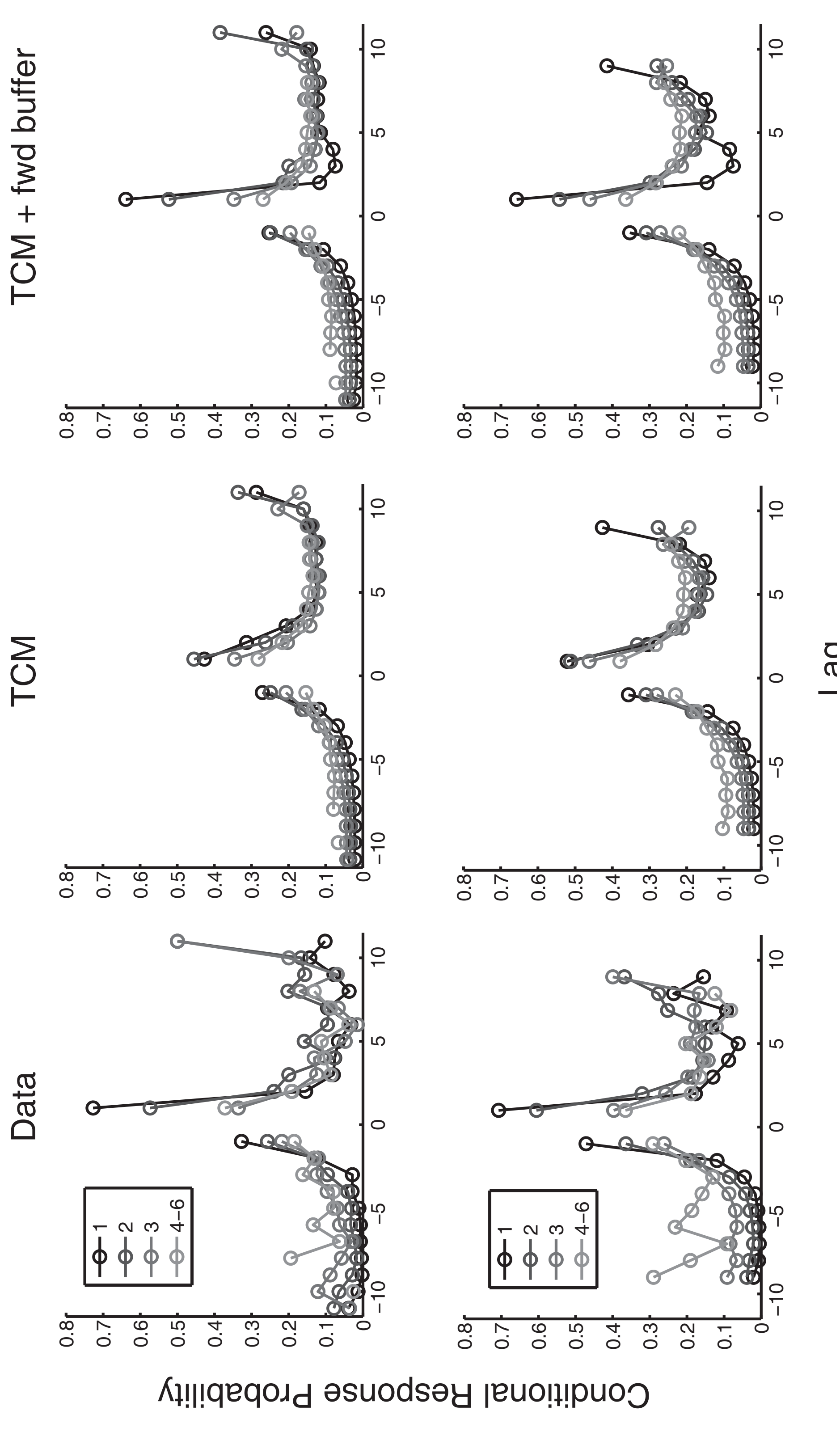
0.4
0.5
0.6
0.7
0.8
0.9
1
2
4
6
8


Data
TCM
TCM + fwd buffer
1
2
3
4–6
Conditional Response Probability
Lag