Précis of Resource Depletion and Recovery in Human Memory

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Overview

Why can we only process and maintain a limited amount of information at any given time? Multiple explanations exist, but as of yet there is no consensus – proposals include a decay of information over time[1,2], interference among concurrently active representations[3,4], and a limited cognitive resource shared among various cognitive operations[5,6]. The idea that processing information depends on a limited pool of cognitive resources has multiple, varying formulations. The limited resource could be considered as either continuous[7] or discrete[8]; as reflecting limits on activation[5,9], attentional control[10], the number of slots in memory[8], or an unspecified abstract quantity[7,11,12].

Despite these differences, most resource-based theories share several assumptions. The resource is a psychological/physiological quantity used to perform cognitive operations. Since this quantity is limited, using it for one process comes at the cost of performing other processes, and the amount of resources consumed determines the success/efficiency of the process. Furthermore, most resource-based theories assume that once a cognitive process is complete, the resources previously dedicated to it become immediately available for further operations. For example, in slot-based models of working memory, when information is no longer relevant, the slots occupied by it become immediately available for storing new representations. This assumption is shared by most current memory models, but it has gone largely unexamined.

In this dissertation I argue otherwise: rather than becoming immediately available for use, the resource used for memory storage/formation recovers gradually over time[11,12]. I comprehensively tested this proposal using behavioral experiments and computational modeling with an updated version of the Source of Activation Confusion (SAC) model of memory. The model makes specific predictions concerning how the difficulty of processing at one point in time affects the processing of subsequent information.

The combination of computational modeling and novel behavioral experiments helped unify previously disparate findings from many subfields of cognitive psychology – episodic long-term memory, working memory, visual perception, child development and healthy aging. The computational modeling allowed us to move beyond a circular concept of resources and performance by providing a falsifiable mathematical description of resource depletion and recovery.

Chapters 2 and 3: The Source of Activation Confusion (SAC) memory model and existing empirical challenges for a theory of frequency effects

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Normative word frequency has played a key role in empirical research and theoretical development on human memory[13–17]. This is because word frequency can either facilitate or impair memory performance depending on the nature of the study task, the test, and the details of the study sequence.

These disparate effects provide a challenge for memory models. For example, item recognition for high-frequency (HF) words is worse than for low-frequency (LF) words[18,19]. Despite the LF recognition advantage, memory for HF words is better in free recall[20], serial recall[15] and associative recognition[13]. In cued recall the frequency of the target affects memory more than the frequency of the cue[21,22]. These effects appear in pure lists that contain either only HF or LF words, but they disappear in mixed lists of both HF and LF words[23]. The frequency effect also depends on the relative proportion of HF and LF words in a list[24], it grows with serial position during study[25], and it depends on the order of HF and LF words in mixed lists[26]. Frequency effects also interact with the study presentation rate – presenting words faster tends to reduce[27] or even reverse the LF advantage in item recognition[28], and it increases the HF advantage in free recall[29]. Finally, the effects of word frequency increase when the working memory load increases[30,31].

Verbal theories[15,32] and computational models[12,27,28] exist for various subsets of these findings; however, there has been no systematic integration within a single model framework. The current work builds on and revises earlier SAC models that accounted for a subset of these effects[12,18]. I used computational modeling to investigate whether these interactions between word-frequency, list-composition, presentation rate, type of task and working memory load can be explained by the following assumptions:

- memory formation depletes a limited memory resource that recovers gradually over time
- the amount of resources required to encode a memory item is an inverse function of the item's current strength in long-term memory
- memory traces are less likely to be formed or are weaker when resources are insufficient
- HF words have stronger representations in memory compared to LF words
- HF words have more associations in memory compared to LF words, and are less effective in retrieving any specific one of them

Two key insights of the model allowed me to fit most of word-frequency puzzles. First, there is a trade-off between a HF encoding advantage and a LF retrieval advantage. Since HF words require less resource for their encoding, more resources are available to bind them to an experimental context. This leads to stronger episodic bindings for HF relative to LF words. Conversely, LF words have been experienced in fewer previous contexts. Since previously bound contexts compete for retrieval, when memory is cued by a LF word, the correct episodic context is retrieved more easily. As a result, in item recognition tasks, the retrieval advantage of LF cues overcomes their weaker item-context bindings. In recall tasks, however, memory is cued by the context instead, and the lack of context retrieval competition reveals the HF encoding benefit. This trade-off was supported by fits of the model to both recall and recognition data.

The second insight is that any experimental variable that increases resource consumption or reduces resource recovery would 1) increase the positive effects of word-frequency in recall tasks or 2) reduce the negative effects of word-frequency in recognition tasks. Simulations revealed that this occurs because binding strength/probability is proportional to the amount of remaining resources – fewer overall resources lead to a greater difference in binding strength between HF and LF words. This principle applies to the following variables:

- As the presentation rate increases, resources recover to a lesser degree between stimuli presentations. As a result, speeding up presentation rate reverses the LF recognition advantage (Figure 1) and it increases the HF recall advantage (Figure 2)
- Dividing attention during encoding reduces the amount of available resources which eliminates the LF recognition advantage
- Aging, associated with a decline in cognitive resources, also reduces/eliminates the LF hit rate advantage
- The presence of LF words in a list decreases memory for other items on the list by leaving fewer resources for them (Figure 3)
- In cued recall the frequency of the cue has a smaller effect relative to the frequency of the target – cues suffer from contextual competition, while targets do not (Figure 4)

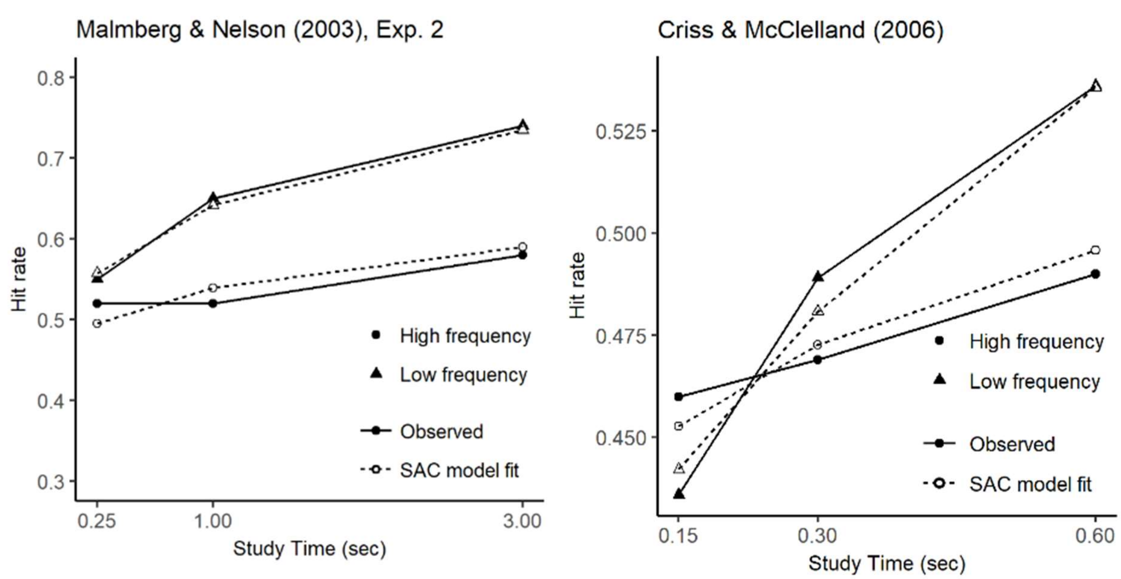

Figure 1. Hit rate for item recognition of low and high frequency words depending on the trial duration during study. Solid lines show the empirical data. Dashed lines show the fits of the SAC model

- Very rare words are difficult to process and show worse recognition memory than HF words
- In serial-recall tasks the HF recall advantage increases with serial position because fewer resources are left after each subsequent serial position (Figure 5)

In summary, the resource demands principle suggests that as the demands of the task increase, due to manipulations of the stimuli (e.g., number of items, frequency of other items), the procedure (e.g., dividing attention, faster presentation rate, increasing working memory load, increasing serial position), or due to individual differences (e.g. aging), the mnemonic benefit moves towards the direction of HF items.

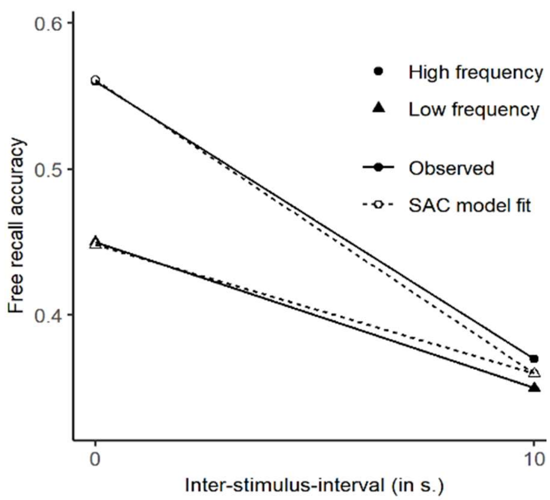

Figure 2. Free recall probability as a function of word frequency and the inter-stimulus interval. Solid lines show the empirical data. Dashed lines show the fits of the SAC model

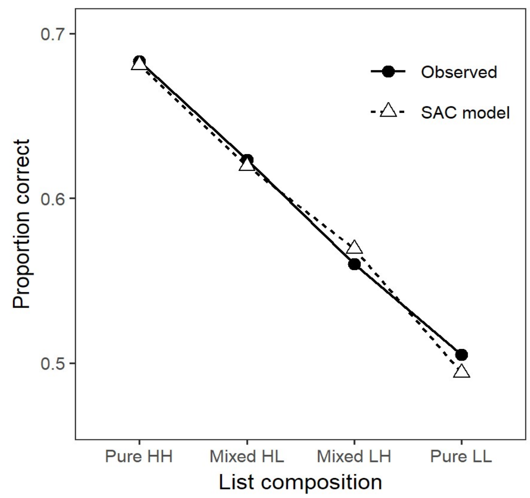

Figure 3. WF effects in pure and mixed lists in immediate serial recall, depending on which half of the mixed lists contained LF. Data from Miller & Roodenrys (2012)

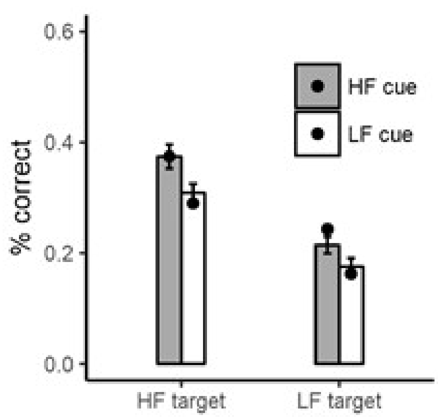

Figure 4. Cued recall accuracy as a function of word frequency of the cue and the target. Dots represent the fit of the SAC model

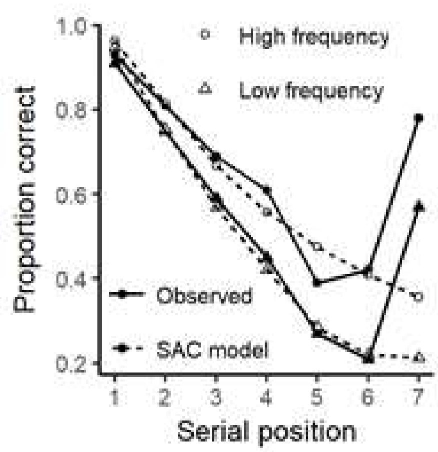

Figure 5. Word-frequency effects interact with serial position in immediate serial recall. Data from Hulme et al (1997)

Chapter 4: Sequential Study Effects – word and exposure frequency

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A model should be judged not only by its ability to fit existing data, but also by its ability to make novel predictions. According to SAC, memory for one item will depend on the frequency of the immediately preceding items during study. Since LF items deplete more resources, and the resources recover gradually over time, memory should be worse for items that are preceded by LF items during study. In fact, any manipulation that causes the processing of some items to deplete more resources should lead to sequential study effects. Chapters 4-6 test these predictions using three different paradigms.

SAC makes several distinct predictions concerning the effect of the preceding study items. Memory for an item X_k will depend on how much of the resource was spent in memorizing the immediately preceding items X_{k-1},X_{k-2},X_{k-i} etc (k denotes the study position of the current item; *i* denotes the lag or the temporal distance to the preceding items). Memory for item X_k (denoted by $P(X_k)$) will be worse when the preceding item is weaker (e.g., LF vs. HF). This effect is also not discrete: $P(X_k)$ should be proportional to the strength of item X_{k-1}. These effects should also be cumulative such that $P(X_k)$ should be monotonically worse the more of the preceding items that are weak. The effect of the preceding items X_{k-i} should increase when the current item X_k requires more resources. Finally, the effect of X_{k-1} should be stronger than the effect of X_{k-2}, etc, because more time and intervening items would have passed.

I evaluated these predictions by reanalyzing eight existing datasets and one new experiment and by fitting the SAC model to each. Five studies used word frequency as a factor[33–37], two studies manipulated presentation frequency of each item in the experiment[38,39] and two directed-forgetting studies manipulated whether each item should be remembered or forgotten[40,41]. The predictions and results are summarized in Table 1.

In each of the eight existing datasets I reanalyzed, participants studied either individual words[18,34,35] or word pairs/word-image pairs[33,36,38–40] presented sequentially in multiple study lists. After seeing all stimuli in a given list, participants had to perform a free recall[34,35,40], cued recall[36,39], item recognition[33,36,37], or associative recognition[36,38] task.

Most predictions were supported by most the studies (23 out of 31, Table 1). An individual Participant Data (IPD) meta-analysis confirmed that all five predictions had overall support. In summary, these analyses provided a key novel set of results in human memory – memory performance for one item depends on how difficult the preceding items during study were to process. These results provided strong support for the claim that memory formation depletes a limited pool of resources as a function of the current strength of items, and that these resources recover gradually over time.

Table 1.

Predictions About the Effects of Prior Item Strength

#	Predictions	Studies									Overall
		Diana	Ward	Buchler	Aue	Reder	Marevic	Popov	Cox	PEERS	
1	Discrete effect of prior item strength. *Example:* $P(X_k)$ is worse when X_{k-1} is LF.	0	+	+	+	0	+	+	NA	NA	+
2	Continuous effect of prior item strength. *Example:* $P(X_k)$ is proportional to $freq(X_{k-1})$.	NA	NA	+	NA	NA	NA	NA	+	+	+
3	Cumulative effect of prior item strength. *Example:* $P(X_k)$ is worse when more of the preceding items are LF.	+	0	+	0	+	+	+	NA	NA	+
4	Interaction between prior and current item strength. *Example:* The effect of $freq(X_{k-1})$ should be stronger when X_k is LF.	+	+	+	+	0	0	NA	NA	NA	+
5	Interaction between prior item strength and lag. *Example:* The effect of $freq(X_{k-i})$ should decrease as the lag *i* increases.	+	0	+	0	0	+	+	+	+	+

Note. + = effect found in study; 0 = null effect; − = effect found in opposite of predicted direction; NA = prediction could not be tested; Diana = Diana and Reder (2006); Ward = Ward et al. (2003); Buchler = Buchler et al. (2008); Aue = Aue et al. (2017); Reder = Reder et al. (2002); Marevic = Marevic, Arnold, and Rummel (2018); Popov = Popov et al. (in press); Cox = Cox et al. (2018); PEERS = Penn Electrophysiology of Encoding and Retrieval Study (Healey & Kahana, 2016); Overall = estimate from a meta-analytic mixed-effects regression.

Chapter 5: Sequential Study Effects – directed forgetting

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The word-frequency sequential study effects should occur with other variables that affect how much resources are spent. In Chapter 5, we tested whether similar effects occur in an item-method directed forgetting (DF) paradigm in which each item is followed by either a to-be-forgotten (TBF) or a to-be-remembered (TBR) instruction[42,43]. Previous studies with this paradigm have showed worse TBF than TBR recall (i.e., a DF effect), but it was unknown whether memory differs for items that *follow* a TBR or a TBF item (i.e., a DF after-effect).

Based on the SAC model, we proposed that before the remember/forget instructions appear, participants process each item similarly, spending a proportion of their existing resources. After instruction presentation, participants only continue resource-demanding processing of TBR but not TBF items. As a result, a new prediction of the model was that fewer resources remain to process items that follow one or more TBR items.

We tested this prediction in two experiments – Experiment 5.1 was a novel reanalysis of a published dataset by Marevic et al. (2018); Experiment 5.2 was a new experiment designed to test alternative explanations. Participants studied word pairs and half of the word pairs were followed by TBR instructions, while the other half was followed by TBF instructions. Consistent with the predictions of the model, we found that recall for a word pair was worse, if the preceding word pair was TBR rather than TBF. This effect was cumulative – the recall impairment increased when the number of preceding TBR pairs during study increased. Finally, instructions for the immediately preceding study item had a greater impact on recall than instructions for the item two positions prior, etc. The SAC model provided excellent fits to the data (see Figure 6).

Experiment 5.2 tested alternative explanations. People may rehearse or reactivate the memory traces of preceding items *while processing the current item*[2]. Such rehearsal or attentional borrowing is more likely when the preceding item had to be remembered, resulting in diminished processing for the current item. We used a double-task paradigm to test whether suppressing rehearsal or dividing attention during study would eliminate the DF after-effect. A stable DF after-effect under suppressed rehearsal or divided attention would support the resource depletion explanation.

Participants performed the directed-forgetting task under four dual-task conditions: a *control* condition; a *rehearsal suppression* condition in which participants repeated out-loud two-digit numbers presented auditorily at regular intervals; a *divided attention* condition in which participants pressed a key to indicate whether the two-digit numbers were odd or even; a combined *suppressed rehearsal and divided attention* condition in which the odd/even judgements were made vocally.

The top panels of Figure 6 show that even though all three dual-task conditions lead to poorer overall memory, they did not attenuate the DF after-effect. If the DF after-effect was due to selective rehearsal or attentional refreshing of prior TBR items, then the effect should have disappeared when rehearsal/refreshing was prevented. These findings are inconsistent with prior proposals that forgetting is an active, resource demanding process[44]. Instead, the two experiments combined with the SAC model fits provide support for the idea that TBR items deplete more resources during encoding, and that these resources recover gradually over time.

Chapter 6: Sequential Study Effects – inter-stimulus interval

In Chapter 6, I tested another prediction of the resource-recovery assumption, namely, that items preceded by longer inter-stimulus-intervals (pre-ISIs) would be remembered better. The model predicts that if more "free" time passes between the encoding of the previous and the current stimulus, resources would recover to a greater degree leading to better memory for the current stimulus. Furthermore, the pre-ISI effect should interact with the word frequency sequential effects – as the pre-ISI increases, the sequential frequency effect should decrease (see Figure 7 for an illustration of the experimental procedure and a summary of the prediction from 4 alternative accounts). This is because greater resource recovery between stimuli would partially negate the differential resource depletion of the preceding LF or HF stimulus.

I reanalyzed data from the Penn Electrophysiology of Encoding and Retrieval Study (PEERS), a large-scale multi-session experiment on free recall[35,45]. As Figure 8 shows, the results supported the model's predictions. Additional analyses disconfirmed three alternative explanations – that items surrounded by longer ISIs become more temporally distinct; that participants selectively rehearse preceding low-frequency words; that memory consolidation is more likely to complete successfully with longer ISIs. None of these alternative explanations can account for the full pattern of results (Figure

7b/c). The findings presented in Chapter 6 are theoretically important, as the three alternative explanations discussed above are the dominant candidates in the literature to explain why longer ISIs improve memory. The resource-depletion-and-recovery assumption can account for the data naturally, without any extensions to the SAC model.

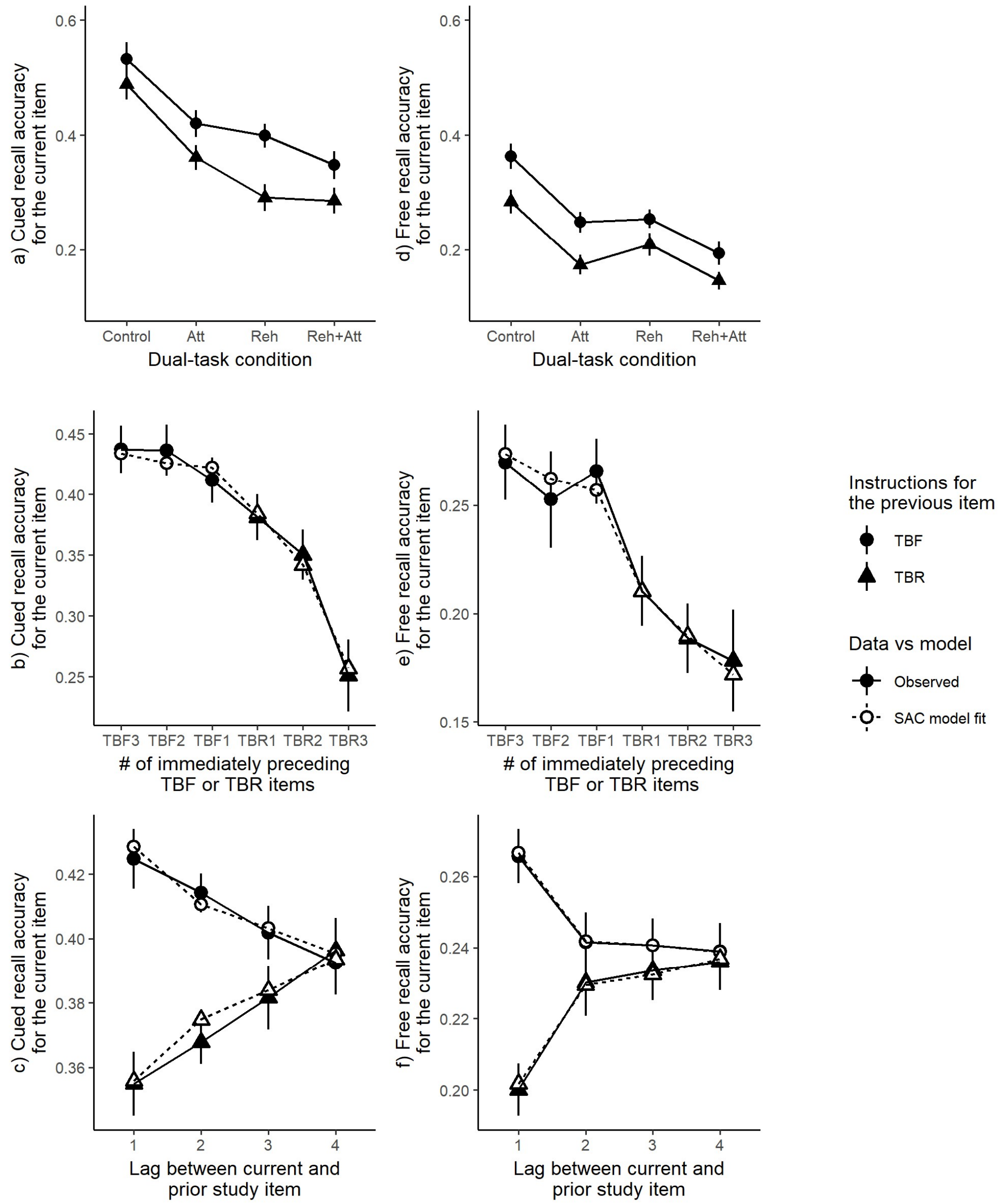

Figure 6. Results of Experiment 5.2 and SAC model fits – cued recall (a,b,c) and free recall (d,e,f) for the current item depending on (a, d) whether it was preceded during study by a TBR or a TBF item and the dual task condition (Control = No dual task, Att = Divided attention, Reh = suppressed rehearsal, Reh+Att = simultaneous divided attention and suppressed rehearsal; (b, e) how many of the immediately preceding items during study were TBR or TBF; (c, f) what was the study position lag between the current and the prior item (e.g., how many trials ago did the previous item occur). Error bars represent ±1 SE.

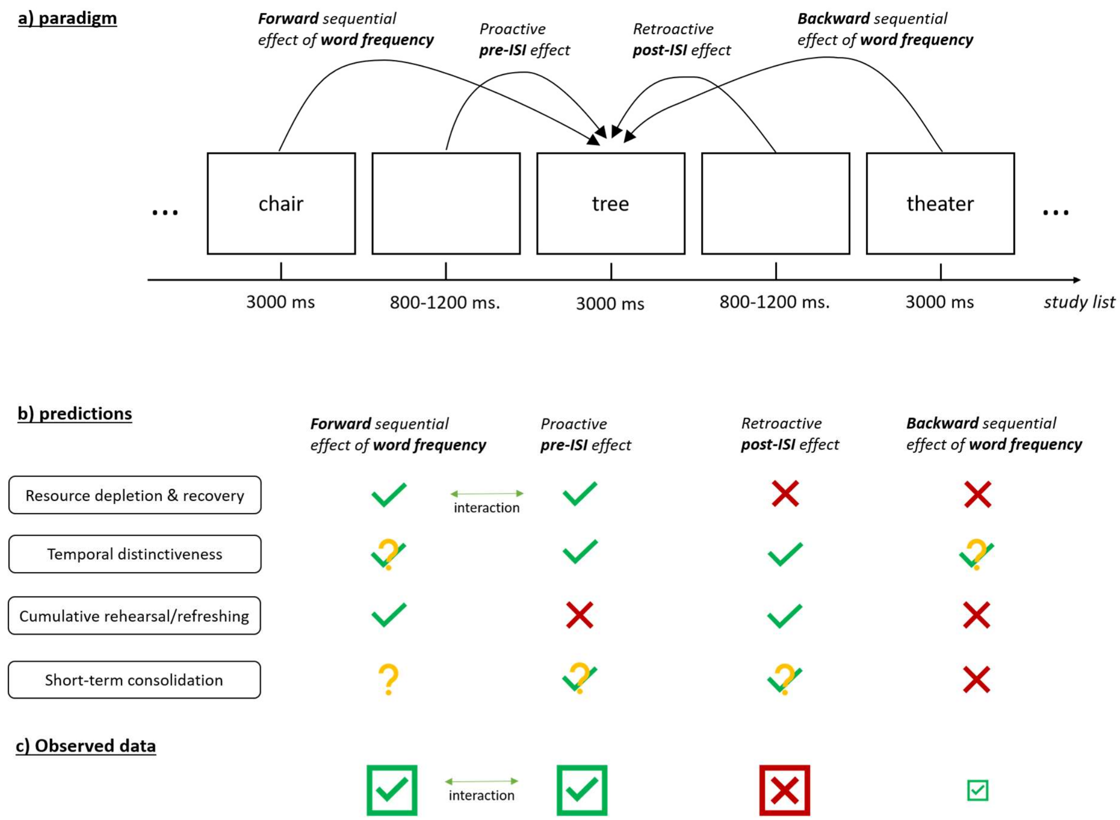

Figure 7. a) An illustration of the study procedure in the PEERS dataset. Words were presented for 3000ms and the ISI was uniformly distributed between 800ms and 1200ms; free recall for the word "tree" could depend on the frequency of the preceding study word (forward sequential effect of word frequency), on the frequency of the subsequent word (backward sequential effect of word frequency), on the duration of the preceding interval (proactive pre-ISI effect), or on the duration of the subsequent interval (retroactive post-ISI effect). b) Predictions about the four different sequential effects for the for candidate theories. Green checkmarks mean that the effects is predicted by the theory, red X marks mean that the theory predicts no effect, and the yellow question marks mean that the prediction from the theory is unclear because it depends on additional assumptions. c) Observed data pattern (a smaller checkmark reflects a smaller effect).

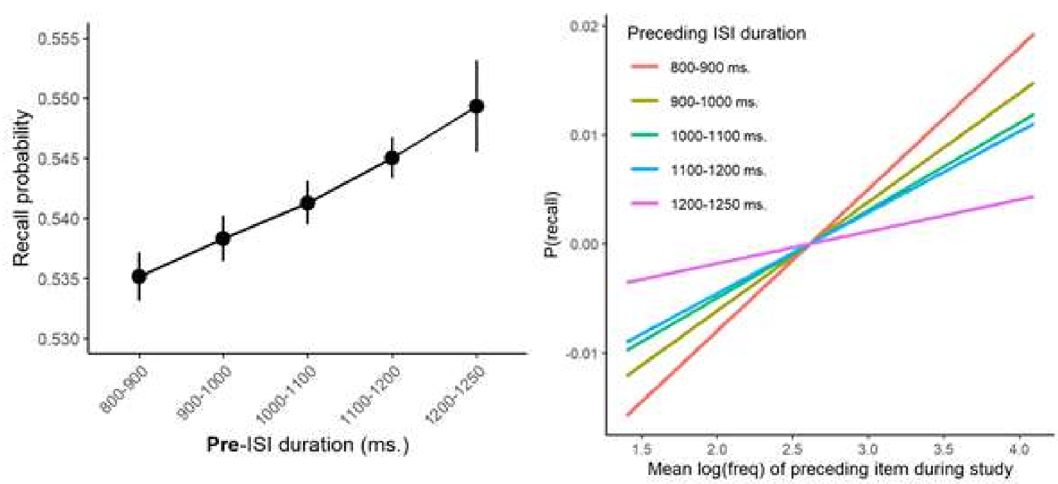

Figure 8. Recall probability in the PEERS dataset depending on the pre-ISI duration (left panel), and the interaction between pre-ISI and word frequency of the preceding study word (right panel, lines show the best fitting regression slope for each condition).

Chapter 7: Word frequency affects binding errors, not memory precision

What happens when there are insufficient resources to store a new item in memory? We envisioned two possibilities. First, people might fail to bind the item to the study context and no memory trace is created. A second possibility is that a memory trace is created with lower precision, proportional to the amount of resources remaining.

To adjudicate between these possibilities, we adapted a continuous reproduction task, which is often used in visual working memory research[7,8]. On each trial, participants studied five words presented sequentially at different locations on an invisible circle. Immediately after, one studied word was presented in the center and participants indicated its studied location on the circle. Across three experiments, we varied word frequency, presentation rate, and list composition (pure vs mixed frequency lists). We used the three-parameter mixture model[7] to analyze the error distributions and to determine whether word frequency affects binding probability, guessing rates or memory precision.

Results (raw error): In pure lists, HF cues lead to better location recall; the opposite was true in mixed lists (Figure 10). Additionally, we see that the benefit of HF cues is reduced when the presentation rate is slowed down. The trade-off between the HF encoding advantage, the LF retrieval advantage, and the resource demands on the task condition predicted by SAC can be seen in the interaction between word-frequency, list-composition, and presentation rate. As we slow down the presentation rate, resources recover more, which minimizes the differences between HF and LF words in pure lists. In mixed lists, the presence of LF words hurts memory for HF words, while the presence of HF words helps memory for LF words.

Results (mixture-model parameters): The higher angle error for LF words in pure lists was entirely due to a higher probability of misbinding errors – recalling a location associated with a different studied word. There was no difference in precision for HF and LF words. Slowing down the presentation rate also decreased misbinding errors, while having no effect on memory precision. The mixture modelling results tentatively suggest that when resources are depleted, the word-location binding fails altogether, resulting in misbinding errors. This conclusion relies on the assumption that if a memory trace exists, the correct location will be recalled and that its precision will be proportional to the strength of the memory trace. It is possible that the retrieval process is probabilistic and that weaker traces have a lower probability of being retrieved, leading to more misbinding errors.

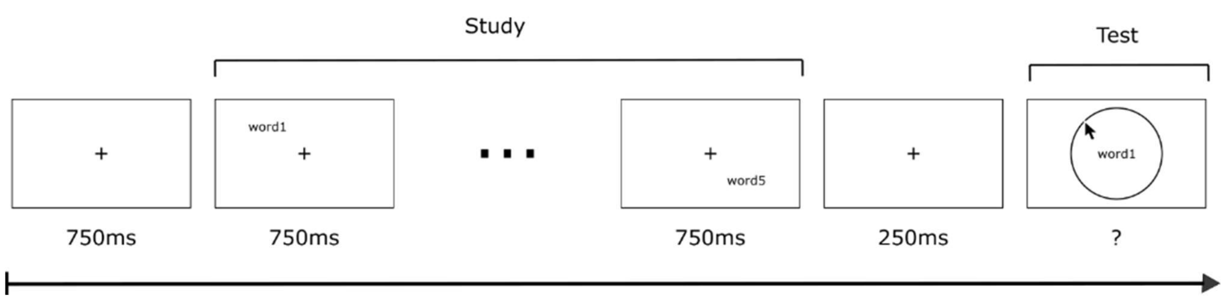

Figure 9. An illustration of a single tria in Experiment 7.1. Each participant completed 300 such trials. Experiments 7.2 & 7.3 also varied the presentation rate during study (500/750/1000 ms).

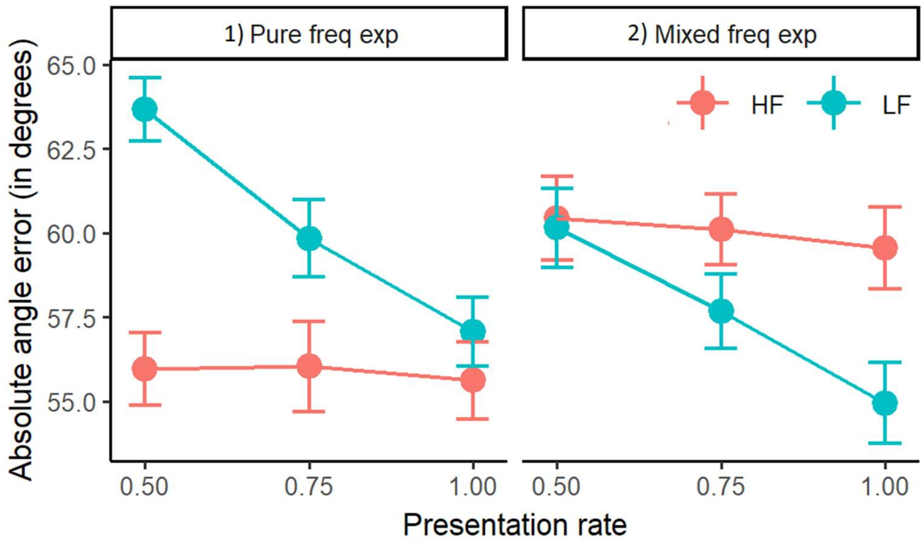

Figure 10. The effect of word frequency, presentation rate and list-composition on raw recall error. 1) Experiment 7.2, pure lists of 100% HF or 100% LF; 2) Experiment 7.3, mixed lists.

Chapter 8: The benefit of greater discrimination difficulty during learning

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Intuitively, the greater the similarity between two different objects, the more difficult it should be to distinguish them. Research using the visual search task has repeatedly confirmed this intuition - when a target is more similar to distractors in the search array, accuracy decreases, response times increase, and more errant saccades are made to the highly similar distractors[46–48]. The apparent robustness of this negative target-to-distractor (TD) similarity effect has played a pivotal role in the development of many visual search theories[47,49,50].

In this study, we explored how the TD similarity effect changes as people gain visual expertise with novel stimuli over an extended period. US undergraduates with no previous knowledge of Chinese performed a visual search task with 64 novel Chinese characters for 12 hour-long visual search sessions over 4 weeks. We found a striking pattern - the search time and accuracy advantages for a target among dissimilar distractors were short-lived and *reversed* after only a single session of training, such that *greater* TD similarity lead to better performance over time.

Why would the TD similarity effects reverse with learning over time? We suggest that when it is more difficult to discriminate a target from distractors during learning, participants are forced to develop richer and more detailed representations of the novel characters to be able perform the task better in the future. Additionally, we found that the effect was driven by post-error feedback, which caused participants to pay more attention to the target the next time it appeared.

This reversal of the TD similarity effect suggests that people can flexibly and strategically allocate resources during visual learning depending on how difficult it is to discriminate a novel target object from distractors. People will invest more of their limited resources in encoding a rich representation of a novel object if they know that they will have difficulty recognizing it later.

Discussion - Rethinking resource models of memory

Even though SAC is specific computational memory model, one key theoretical contribution transcends this implementation of the theory. The idea that memory resource recover gradually over time is not tied to this model and it could be implemented by other memory models and tested separately. In fact, recent follow-up work from independent labs have considered whether this assumption can explain neural fatigue effects using intracranial EEG[51], the free-time benefit in working memory[52], and the semantic similarity effect in immediate recall[53].

The assumption that resources recover gradually over time may seem controversial at first – what is the nature of this resource that allows it to recover gradually rather than instantly after use, as in other resource-based models? It is difficult to image how this might work in models in which the resource is a number of discrete working memory slots[8] or time spent in the focus of attention[10]. Despite this, the resource recovery assumption can account for a surprising amount of otherwise puzzling empirical findings, and it led to the discovery of the sequential study effects described in Chapters 4-6. As such, this assumption has a lot of explanatory power, and it is exciting to think how it could be made compatible with other resource models, or, alternatively, to discover different ways to account for these effects without it.

The resource assumption could also provide a mechanistic reason behind primacy gradient parameters in models of memory that do not include the concept of resources. Models like the Temporal Context Model [54,55], for example, use a parameter to decrease activation of memory items as a function of serial position to explain primacy effects in free recall. This is a convenient way to fit the data, but is not a mechanistic explanation of primacy effects[55]. My thesis suggests that the primacy gradient arises due to the same mechanism discussed so far – that the encoding of items depletes a limited pool of resources, which recover over time.

References

1. Baddeley, A. D., Thomson, N. & Buchanan, M. Word length and the structure of short-term memory. *J. Verbal Learn. Verbal Behav.* **14**, 575–589 (1975).
2. Camos, V., Lagner, P. & Barrouillet, P. Two maintenance mechanisms of verbal information in working memory. *J. Mem. Lang.* **61**, 457–469 (2009).
3. Burgess, N. & Hitch, G. J. A revised model of short-term memory and long-term learning of verbal sequences. *J. Mem. Lang.* **55**, 627–652 (2006).
4. Oberauer, K. & Lin, H.-Y. An interference model of visual working memory. *Psychol. Rev.* **124**, 21–59 (2017).
5. Anderson, J. R., Reder, L. M. & Lebiere, C. Working memory: Activation limitations on retrieval. *Cognit. Psychol.* **30**, 221–256 (1996).
6. Ma, W. J., Husain, M. & Bays, P. M. Changing concepts of working memory. *Nat. Neurosci.* **17**, 347–356 (2014).
7. Bays, P. M., Catalao, R. F. G. & Husain, M. The precision of visual working memory is set by allocation of a shared resource. *J. Vis.* **9**, 7–7 (2009).
8. Zhang, W. & Luck, S. J. Discrete fixed-resolution representations in visual working memory. *Nature* **453**, 233–235 (2008).
9. Just, M. A. & Carpenter, P. A. A capacity theory of comprehension: individual differences in working memory. *Psychol. Rev.* **99**, 122 (1992).
10. Barrouillet, P., Bernardin, S. & Camos, V. Time constraints and resource sharing in adults' working memory spans. *J. Exp. Psychol. Gen.* **133**, 83 (2004).
11. Popov, V. & Reder, L. M. Frequency effects on memory: A resource-limited theory. *Psychol. Rev.* **127**, 1–46 (2020).
12. Reder, L. M., Paynter, C., Diana, R. A., Ngiam, J. & Dickison, D. Experience is a Double-Edged Sword: A Computational Model of The Encoding/Retrieval Trade-Off With Familiarity. *Psychol. Learn. Motiv.* **48**, 271–312 (2007).
13. Clark, S. E. Word frequency effects in associative and item recognition. *Mem. Cognit.* **20**, 231–243 (1992).
14. Glanzer, M. & Bowles, N. Analysis of the word-frequency effect in recognition memory. *J. Exp. Psychol. [Hum. Learn.]* **2**, 21–31 (1976).
15. Hulme, C., Stuart, G., Brown, G. D. A. & Morin, C. High- and low-frequency words are recalled equally well in alternating lists: Evidence for associative effects in serial recall. *J. Mem. Lang.* **49**, 500–518 (2003).
16. Mandler, G., Goodman, G. O. & Wilkes-Gibbs, D. L. The word-frequency paradox in recognition. *Mem. Cognit.* **10**, 33–42 (1982).

17. Popov, V. & Reder, L. M. Frequency effects on memory: A resource-limited theory. *Psychol. Rev.* Advanced Online Publication (2019) doi:10.1037/rev0000161.

18. Reder, L. M. *et al.* A mechanistic account of the mirror effect for word frequency: A computational model of remember–know judgments in a continuous recognition paradigm. *J. Exp. Psychol. Learn. Mem. Cogn.* **26**, 294 (2000).

19. Glanzer, M. & Adams, J. K. The mirror effect in recognition memory: data and theory. *J. Exp. Psychol. Learn. Mem. Cogn.* **16**, 5 (1990).

20. Deese, J. Frequency of usage and number of words in free recall: The role of association. *Psychol. Rep.* **7**, 337–344 (1960).

21. Madan, C. R., Glaholt, M. G. & Caplan, J. B. The influence of item properties on association-memory. *J. Mem. Lang.* **63**, 46–63 (2010).

22. Criss, A. H., Aue, W. R. & Smith, L. The effects of word frequency and context variability in cued recall. *J. Mem. Lang.* **64**, 119–132 (2011).

23. Ozubko, J. D. & Joordens, S. The mixed truth about frequency effects on free recall: Effects of study list composition. *Psychon. Bull. Rev.* **14**, 871–876 (2007).

24. DeLosh, E. & Mcdaniel, M. The role of order information in free recall: Application to the word-frequency effect. *J. Exp. Psychol. Learn. Mem. Cogn.* **22**, 1136–1146 (1996).

25. Hulme, C. *et al.* Word-frequency effects on short-term memory tasks: Evidence for a redintegration process in immediate serial recall. *J. Exp. Psychol.-Learn. Mem. Cogn.* **23**, 1217–1232 (1997).

26. Miller, L. M. & Roodenrys, S. Serial recall, word frequency, and mixed lists: The influence of item arrangement. *J. Exp. Psychol. Learn. Mem. Cogn.* **38**, 1731–1740 (2012).

27. Malmberg, K. J. & Nelson, T. O. The word frequency effect for recognition memory and the elevated-attention hypothesis. *Mem. Cognit.* **31**, 35–43 (2003).

28. Criss, A. H. & McClelland, J. L. Differentiating the differentiation models: A comparison of the retrieving effectively from memory model (REM) and the subjective likelihood model (SLiM). *J. Mem. Lang.* **55**, 447–460 (2006).

29. Gregg, V., Montgomery, D. C. & Castano, D. Recall of common and uncommon words from pure and mixed lists. *J. Verbal Learn. Verbal Behav.* **19**, 240–245 (1980).

30. Reder, L. M., Liu, X. L., Keinath, A. & Popov, V. Building knowledge requires bricks, not sand: The critical role of familiar constituents in learning. *Psychon. Bull. Rev.* **23**, 271–277 (2016).

31. Shen, Z., Popov, V., Delahay, A. B. & Reder, L. M. Item strength affects working memory capacity. *Mem. Cognit.* (2017) doi:10.3758/s13421-017-0758-4.

32. Serra, M. & Nairne, J. S. Design controversies and the generation effect: Support for an item-order hypothesis. *Mem. Cognit.* **21**, 34–40 (1993).

33. Diana, R. A. & Reder, L. M. The low-frequency encoding disadvantage: Word frequency affects processing demands. *J. Exp. Psychol. Learn. Mem. Cogn.* **32**, 805–815 (2006).

34. Ward, G., Woodward, G., Stevens, A. & Stinson, C. Using overt rehearsals to explain word frequency effects in free recall. *J. Exp. Psychol. Learn. Mem. Cogn.* **29**, 186–210 (2003).

35. Karl, M. & Kahana, M. J. A Four-Component Model of Age-Related Memory Change. *Psychol. Rev.* No Pagination Specified (2015) doi:10.1037/rev0000015.

36. Cox, G. E., Hemmer, P., Aue, W. R. & Criss, A. H. Information and processes underlying semantic and episodic memory across tasks, items, and individuals. *J. Exp. Psychol. Gen.* **147**, 545–590 (2018).

37. Reder, L. M., Angstadt, P., Cary, M., Erickson, M. A. & Ayers, M. S. A reexamination of stimulus-frequency effects in recognition: Two mirrors for low- and high-frequency pseudowords. *J. Exp. Psychol. Learn. Mem. Cogn.* **28**, 138–152 (2002).

38. Buchler, N. G., Light, L. L. & Reder, L. M. Memory for items and associations: Distinct representations and processes in associative recognition. *J. Mem. Lang.* **59**, 183–199 (2008).

39. Aue, W. R., Criss, A. H. & Novak, M. D. Evaluating mechanisms of proactive facilitation in cued recall. *J. Mem. Lang.* **94**, 103–118 (2017).

40. Marevic, I., Arnold, N. R. & Rummel, J. Item-Method Directed Forgetting and Working Memory Capacity: A Hierarchical Multinomial Modeling Approach. *Q. J. Exp. Psychol.* **0**, 1–34 (2017).

41. Popov, V., Marevic, I., Rummel, J. & Reder, L. M. Forgetting Is a Feature, Not a Bug: Intentionally Forgetting Some Things Helps Us Remember Others by Freeing Up Working Memory Resources. *Psychol. Sci.* **30**, 1303–1317 (2019).

42. Bjork, R. A. Theoretical implications of directed forgetting. *Coding Process. Hum. Mem.* 217–235 (1972).

43. MacLeod, C. M. Directed forgetting. in *Intentional Forgetting: Interdisciplinary approaches* (eds. Golding, J. M. & MacLeod, C. M.) 993–995 (Lawrence Erlbaum Associates, 1998).

44. Fawcett, J. M. & Taylor, T. L. Forgetting is effortful: Evidence from reaction time probes in an item-method directed forgetting task. *Mem. Cognit.* **36**, 1168–1181 (2008).

45. Lohnas, L. J. & Kahana, M. J. Parametric effects of word frequency effect in memory for mixed frequency lists. *J. Exp. Psychol. Learn. Mem. Cogn.* **39**, 1943–1946 (2013).

46. Bichot, N. P. & Schall, J. D. Effects of similarity and history on neural mechanisms of visual selection. *Nat. Neurosci.* **2**, 549–554 (1999).

47. Duncan, J. & Humphreys, G. Beyond the search surface: visual search and attentional engagement. (1992).

48. Treisman, A. & Gormican, S. Feature analysis in early vision: Evidence from search asymmetries. *Psychol. Rev.* **95**, 15–48 (1988).

49. Treisman, A. & Gelade, G. A feature-integration theory of attention. *Cognit. Psychol.* **12**, 97–136 (1980).

50. Alexander, R. G. & Zelinsky, G. J. Effects of Part-based Similarity on Visual Search: The Frankenbear Experiment. *Vision Res.* **54**, 20–30 (2012).

51. Lohnas, L. J., Davachi, L. & Kahana, M. J. Neural fatigue influences memory encoding in the human hippocampus. *Neuropsychologia* **143**, 107471 (2020).

52. Mizrak, E. & Oberauer, K. What is time good for in working memory? *Psychological Science* (2021) doi:10.31234/osf.io/ahqwj.

53. Kowialiewski, B., Lemaire, B. & Portrat, S. How does semantic knowledge impact working memory maintenance? Computational and behavioral investigations. *J. Mem. Lang.* **117**, 104208 (2021).

54. Howard, M. W. & Kahana, M. J. A distributed representation of temporal context. *J. Math. Psychol.* **46**, 269–299 (2002).

55. Sederberg, P. B., Howard, M. W. & Kahana, M. J. A context-based theory of recency and contiguity in free recall. *Psychol. Rev.* **115**, 893–912 (2008).