Modeling the Serial Position Effect

Using the Emergent Neural Network Simulation System

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Abstract: The Serial Position Effect (SPE) is a well-studied phenomenon in experimental psychology. SPE captures the idea that, when subjects are asked to recall list items, they are more likely to remember the first items and the last items, whether those items are numbers, non-words or elements of a story. Until recently, SPE has been generally considered to rely upon a two-store memory model, i.e., primacy (remembering initial items) and recency (remembering latter items) were thought to be the work of long term memory and short term memory, respectively. This paper reports the results of a basic hippocampus simulation study using the Leabra algorithm within the Emergent Neural Network Simulation System to model the SPE. Simulation results demonstrate that both primacy and recency of the SPE in a serial recall task can be replicated using only the hippocampus, suggesting that a one-store model of memory for this recall task is sufficient. It remains to be seen if this simulation mirrors the actual biological mechanism utilized.

1 INTRODUCTION

In the process of investigating memory and learning, neuroscientists and their predecessors have discovered a number of memory biases that offer clues as to the biological functioning of our brains during memory and learning tasks. One such memory bias is the Serial Position Effect (SPE), first documented by Hermann Ebbinghaus in his seminal work, *Memory* (1885/1913). SPE is a memory bias for remembering early and late items in a list, and a bias against recall of items from the middle. The SPE is well-documented, with behavioural data relating to remembering non-words (Gupta, 2005), number sequences (Golob and Starr, 2004), and even stories (Brodsky et al., 2003). The SPE has been well-studied among healthy adults, and has also been used to better understand child development (Lehmann & Hasselhorn, 2010), aphasia (Brodsky et al., 2003) and Alzheimer's Disease (Bayley et al., 2000).

The classic graph of serial position data has the U-shape shown in Figure 1. The early and late effects are usually handled separately as *primacy* and *recency*, as depicted in Figure 1. Some researchers, dating back to at least Murdock (1962), assign separate biological mechanisms for primacy and recency, rather than one overall mechanism for the SPE.

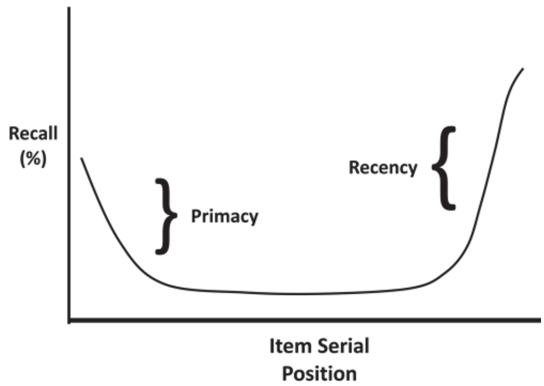

Figure 1: The Serial Position Effect Classic U Shape.

The two-store memory model has different variations, but generally assigns primacy to a long-term memory mechanism and recency to a short-term memory mechanism. Gradually, short-term memory has been replaced by the more complete term *working memory*, referring to both the short-term memory (storage) of information and the manipulation of that information, which is required by tasks such as serial recall, used to test SPE (Baddeley & Hitch, 2010).

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Differences in how well human subjects recall items under various conditions, e.g., lag time between training and testing, appear to support the two-store models, since the variable conditions affected primacy and recency to varying degrees. A common argument for long-term memory being the mechanism for primacy is the idea of rehearsal. As subjects learn each item in the list, there may be the opportunity to mentally repeat, or rehearse, the early items in the list, making them more likely to be committed to long term memory. (In fact, some studies have required subjects to rehearse items aloud.) Rehearsal is believed to transfer the items into long term memory.

Recency, in terms of the SPE, is often argued to be a result of the quick recall possible from working memory, but this does not account for long-term recency – that is, better recall of ending items in a list after hours or even days (Howard & Kahana, 1999), or the various effects involving the ratio rule, which "relates the recency effect in free recall to the ratio of the duration of the inter-item presentation interval (IPI) and the retention interval (RI)" (Nairne, et al., 1997).

Newer understanding of the role of contextual cues in memory tasks has strengthened support for a one-store memory model, which can account for both primacy and recency in the SPE (Polyn & Kahana, 2008). Researchers are refining computational models to explore these possible mechanisms. For example, Sederberg et al. (2011) explore the memory phenomenon of reconsolidation using a "Temporal Context Model," including predictions regarding the SPE (p. 466). However, as recently as 2008, there was still debate as to what, exactly, these computational models represent. For example, Usher, Davelaar, Haarmann, and Goshen-Gottstein (2008) disputed Polyn and Kahana's results, to which Kahana, Sederberg, & Howard (2008) replied, reasserting the validity of these results.

To test these ideas, we developed a basic hippocampus simulation study using the Emergent Neural Network Simulation System to model the SPE. The remainder of this paper describes this experiment and its results. We observed that both primacy and recency of the SPE in a serial recall task can be replicated using only the hippocampus, suggesting that a one-store model of memory for this recall task is sufficient.

2 METHODOLOGY

2.1 General Approach

We tested the one-memory vs. two-memory SPE theory using the Emergent neural modeling system. Emergent is "a powerful tool for the simulation of biologically plausible, complex neural systems" (Aisa, Mingus, & O'Reilly, 2008, p. 1146), making it a good tool for exploring the biological mechanisms conjectured for various phenomena, including SPE.

Biologically, working memory is associated with active maintenance in the Prefrontal Cortex (PFC), while encoding long term memories is more closely associated with the hippocampus (O'Reilly et al., 2012). We used the basic hippocampus simulation in Emergent, and looked for differences in primacy and recency effects that might suggest a difference in underlying memory mechanisms. If primacy and recency have similar biological mechanisms (such as a one-store memory model would suggest), we predicted that using only the hippocampus would show both effects, while finding only one effect (likely primacy) would tend to support the two-store model.

2.1.1 Using Emergent

The Emergent Neural Network Simulation System (Emergent) is "a powerful tool for the simulation of biologically plausible, complex neural systems" (Aisa, Mingus, & O'Reilly, 2008, p. 1146), making it a useful tool for exploring the biological mechanisms conjectured for various phenomena, including SPE.

Emergent is a computational tool for modeling the human brain and cognitive processes, intended for use in both research and teaching. It is based in part on its predecessors PDP and PDP++ (Parallel Distributed Processing).

Using neural networks, Emergent allows users to develop complex, layered system models, such as those that might represent the human cognitive processes, in order to test different theories about how the brain functions. This process generally involves training the network on sets of data, and then testing the network on that data. The Emergent graphical interface allows users to see each layer of the model, in which "units" (colored squares representing neurons or groups of neurons) are activated, as well as projections between layers.

In Emergent, biologically-based models can be built relatively quickly and tested against data from experimental psychology. For example, O'Reilly et al. (2013) developed an object recognition model within Emergent with layers and projections based upon the relevant visual pathways in the brain. This model, using biologically plausible learning mechanisms, consistently recognizes 100 different object categories, each with around 9 exemplars, even with variations in lighting, location in the field of vision, size, and rotation. This particular model was also able to recognize partially occluded objects.

For the purposes of teaching, the Emergent website features a wikibook called *Computational Cognitive Neuroscience*, that includes sample simulations for each chapter (O'Reilly et al., 2012), in the form of project files (*.proj). The research reported here utilizes the available hippocampus model, hipp.proj.

2.1.2 Leabra

The default algorithm in Emergent is called Leabra, or local error-driven and biologically realistic algorithm, initially developed by O'Reilly (1997). This algorithm balances Hebbian and error-driven learning. Leabra uses a variant of Hebbian learning called self-organized learning, which is sometimes characterized as 'what fires together, wires together,' referring to the ability to learn generalities. Error-driven learning in Leabra is based upon the eXtended Contrastive Attractor Learning (XCAL) rule that communicates error signals through the network bidirectionally (O'Reilly et al., 2012).

These two types of learning are layered over "a biologically-based point-neuron activation function with inhibitory competition dynamics" (O'Reilly et al., 2012). These competition dynamics can be implemented with kWTA (k-Winners-Take-All) approximations or through inhibitory interneurons. We utilized the kWTA approximations in this project.

2.2 Methodology

We employed Emergent Version 6.1.0 and the basic version of the hippocampus simulation that accompanied the software (O'Reilly et al., 2012). Figure 2 shows the layout of this simulation with inputs from the Entorhinal Cortex (EC) going to the Dentate Gyrus (DG) and to the different layers of the cornu ammonis or CA, with outputs going to the EC Output layer. A full list of the connections is provided in Table 1.

Table 1: Connections Between the Layers in the Hippocampus Simulation.

Layer	Sends To	Receives From
Input	EC_in	(none)
EC_in	DG,CA1, CA3	Input, EC_out
DG	CA3	EC_in
CA3	CA1, DG	EC_in, DG
CA1	EC_out	EC_in, CA3
EC_out	EC_in	CA1, EC_in

2.3 Design of the Baseline Simulation

Our experiments began with the hippocampus simulation (hipp.proj). This basic simulation is designed to train the network on the classic AB-AC paired associate list learning task. This task is particularly useful because it has been well-studied in human experimentation (e.g. Barnes & Underwood, 1959), and it caused difficulties for early neural network models. As McCloskey and Cohen showed, neural networks relying on back-propagation experience catastrophic interference on the AB-AC learning task (1989).

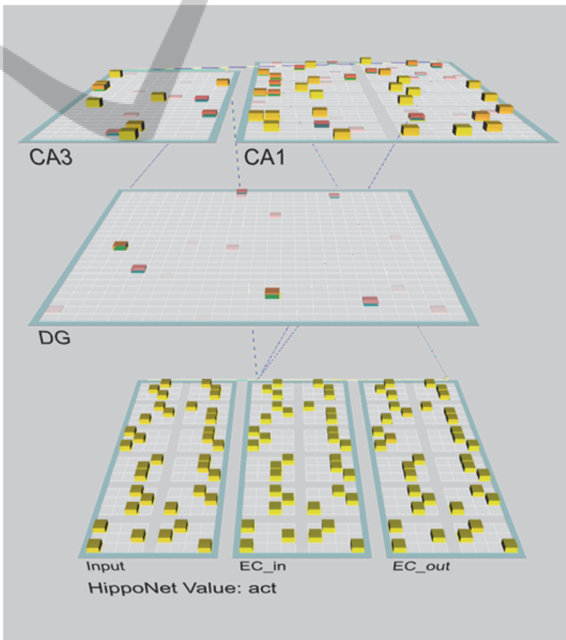

Figure 2: The basic hippocampus simulation within Emergent. The Input Layer feeds directly into the Entorhinal input layer (EC_in), which is encoded by the Dentate Gryus (DG), the cornu ammonis area 3 (CA3), and CA1. Memory retrieval is driven by connections from CA1 back to the EC_out.

As initially designed, the simulation is trained on a list of ten AB pairs (labeled ab_0 through ab_9) in three sets of trials, then tested on those pairs by removing the B units and allowing the network to attempt to fill them in (see Figure 3).

That test is followed by the AC list and set of novel lure items, to verify that the network is still reacting as expected to new inputs. This full cycle (three sets of training trials, one set of tests each for AB, AC, and lure) is considered an epoch. For the purposes of our experiments, time tested on the AC list and lure items represented a time lag between training on the AB list and recall of that list.

Because of that time lag and because the A items are always presented in the original order, these experiments mimic the serial delayed recall task, in contrast to free recall and immediate recall. Weights were initialized before starting each experiment. The simulation was run for ten epochs.

Data sets for subsequent experiments were manipulated by exporting the original dataset into a spreadsheet, manually editing the AB context sets, and importing the changed file into the model.

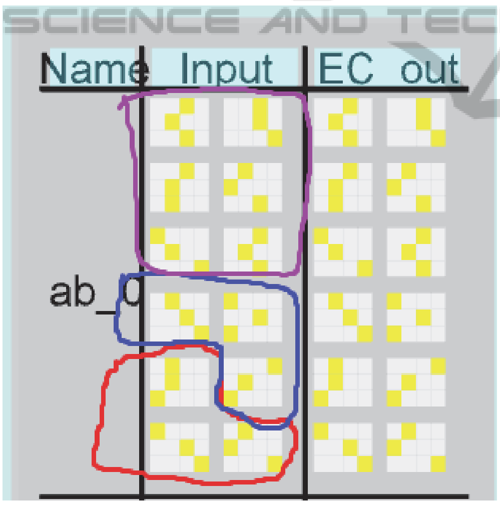

Figure 3: A single input AB pair within Emergent. A items are circled in red; B items are circled in blue. During memory retrieval, B items will be blank, and recalled (if possible) from CA1 via EC_out . The top six groups of units (circled in purple) are context. During baseline trials, these were unique for each AB pair. Experiment 1 made the context identical for all pairs except ab_0 and ab_9. Experiment 2 made the context identical for sets of pairs, while context for ab_0 and ab_9 remained unique.

2.4 Baseline – Unique Contexts

The simulation was run using the input data "Train_AB" available within the simulation. After opening the project file within Emergent, the network weights were initialized. We used the Step:Epoch function so that we could note results after each epoch. On the third epoch, the network had learned the AB list. We ran a total of ten epochs to have a fair basis of comparison across experiments.

2.5 Experiment 1 – Full Overlap of Middle Contexts

The Train_AB input data file was copied from the project file. Leaving the A and B inputs untouched, the groups of context units were altered such that ab_1 through ab_8 had the same context. Items ab_0 and ab_9 were unaltered. After uploading the new data table into the project, the weights were initialized, and we used the Step: Epoch function as before for ten epochs.

2.6 Experiment 2 – Partial Overlap of Middle Contexts

The Train_AB input data file was copied from the project file. Leaving the A and B inputs untouched, the context units were altered such that pairs of trials now had the same context. For example, ab_1 and ab_2 had the same context, ab_3 and ab_4 had the same context, and so on. Items ab_0 and ab_9 were unaltered. After uploading the new data table into the project, the weights were initialized, and we used the Step: Epoch function as before for ten epochs.

2.7 Experiment 3 – Full Overlap of First Eight Contexts

At this point, we wanted to see if the order of the items during testing was having any effect on the results, or if results were from the uniqueness of the contexts alone. In order to test whether being first and last was truly having an effect in the network, we took the data from Experiment 1, and simply moved ab_0 to the end of the data set, relabeling the items to match their new position. Thus, ab_0 through ab_7 now had identical contexts, ab_8 and ab_9 were unique. As before, we initialized the activation weights in the network and used the Step:Epoch function to run ten epochs.

2.8 Experiment 4 – Permuted Full Overlap

Finally, for comparison, we ran the same data as in Experiment 1, with the data loop order parameter changed from sequential to permuted. That is, during testing trials, the items would be presented in a different order from that of the training trials, thus

Table 2: For each experiment, the first column represents how well the network learned the AB list overall. Subsequent columns show how often the network remembered the B portion of the AB pair out of 10 epochs (trials). Shaded cells represent items with unique context. In Experiment 2, dark outlines group the items with duplicate context.

	Best Epoch Score	ab_0	ab_1	ab_2	ab_3	ab_4	ab_5	ab_6	ab_7	ab_8	ab_9
Baseline	100%	9	10	10	9	9	9	10	10	10	8
Exp. 1	50%	9	3	0	5	10	0	0	0	0	10
Exp. 2	70%	9	8	2	10	0	9	1	7	6	8
Exp. 3	70%	9	8	2	6	3	4	0	0	0	10
Exp. 4	50%	9	3	2	3	10	0	0	0	0	10

simulating a free recall task. As before, we initialized the activation weights in the network and used the Step:Epoch function to run ten epochs.

3 RESULTS

Results are summarized in Table 2. The baseline version of the simulation was able to perfectly remember the AB list by the third epoch. The last list item (ab_9) was the last item learned. The graph is almost the inverse of the classic SPE U-shape (see Figure 4).

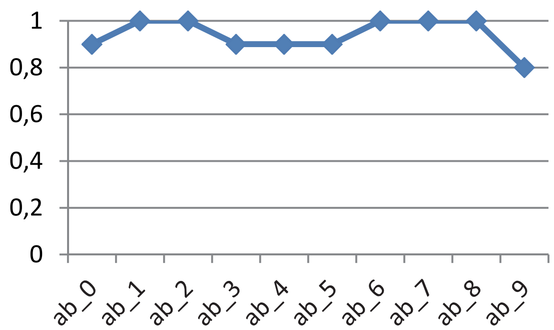

Figure 4: Results by list item pair for baseline simulation, percent recalled. Each ab had unique context. Note that ab_9 was the last item learned.

In Experiment 1, the simulation ran for ten epochs. The highest percentage remembered correctly for any given epoch was 50%, so at no time did it achieve perfect recall, which the baseline simulation did in three epochs. However, far more important in understanding the SPE, were the results by list item (see Figure 5). Here we see that the first and last items (which had unique context) are more often remembered than any item, with exception of ab_4. Both primacy and recency effects were replicated by this experiment.

In Experiment 2, the simulation ran for ten epochs. The highest percentage remembered correctly for any given epoch was 70%, an improvement over Experiment 1, perhaps due to the lower overlap in contexts. In terms of understanding the SPE, the pairs sharing context exhibited an interesting pattern (see Figure 6). Again, ab_0 and ab_9 were recalled significantly more than the overall average, 9/10 and 8/10 respectively, in contrast to 5.4/10. Also, the initial trial in each pair of identical-context trials outperformed the second in every case. In the most extreme case, ab_3 was recalled correctly in all 10 epochs, whereas ab_4 was never recalled. Again, primacy and recency effects were replicated here, albeit complicated by the strong results from each initial item in the same-context paired trials.

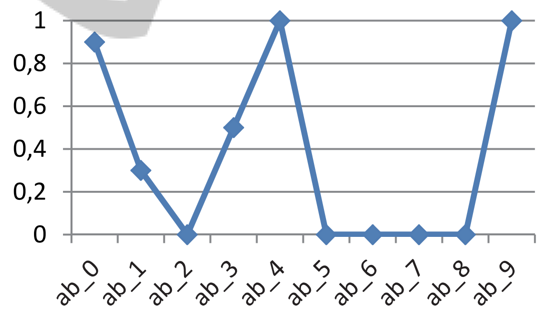

Figure 5: Percent recalled by list item pair for Experiment 1, with all middle items having identical context.

In Experiment 3, the highest percentage remembered correctly for any of the ten epochs was 70%, the same result as Experiment 2. Once again ab_0 and ab_9 were recalled better than other items, 9/10 and 10/10, in contrast to the overall average of 4.2/10 (See Figure 7.) As the first of the group of context-overlapping items, recall of ab_0 appeared to correspond with the results of Experiment 2, where the first of each pair was recalled more often than the second. What was unexpected was the network's complete failure to recall item ab_8 (which had a unique context). Again, primacy and recency effects were replicated, but the effect of unique context was contradicted by the failure to recall uniquely-contexted item ab_8.

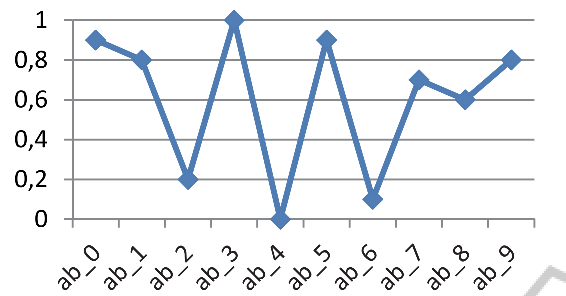

Figure 6: Percentage of times recalled, by item for Experiment 2, with context identical for pairs of trials. Notice that the first of each pair is remembered more easily than the second. For instance, ab_3 and ab_4 have identical contexts; ab_3 was recalled in every epoch; ab_4 was never recalled.

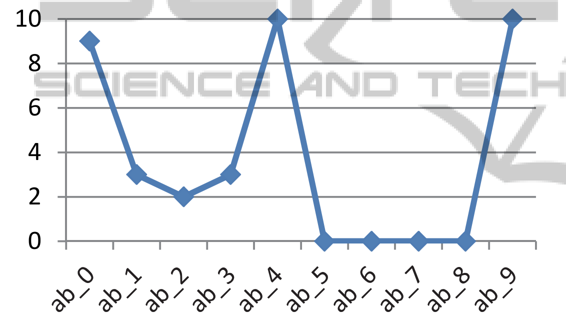

Figure 7: Percent recalled in Experiment 3. Items ab_0 – ab_7 had identical context. Notice that ab_8, with unique context, is never recalled.

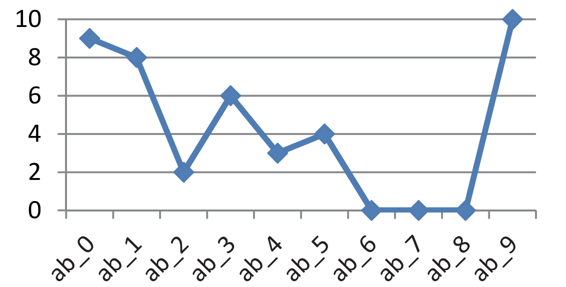

Figure 8: Percent recalled in the permuted order – Experiment 4, simulating free recall. Only ab_0 and ab_9 had unique context.

In Experiment 4, the simulation ran for ten epochs. Similar to Experiment 1, ab_0 and ab_9 had unique contexts while ab-1 though ab_8 had identical contexts. In contrast to the other experiments, Experiment 4 had permuted testing order to simulate free recall (see Figure 8). The highest percentage remembered correctly for any given epoch was 50%, making it similar to Experiment 1. The three best recalled items were ab_0 (9/10), ab_4 (10/10) and ab_9 (10/10), with the overall average as 3.7/10. This suggests that uniqueness of contexts did improve recall, in contrast to the results of Experiment 3.

4 DISCUSSION

These results demonstrate that both primacy and recency of the SPE in a serial recall task can be replicated using only the hippocampus simulation, a result suggesting that a one-store model of memory for this recall task is sufficient. It remains to be seen if this simulated model mirrors the actual biological mechanisms utilized.

The results also suggest that both unique context and order have impacts on recall in the network. Certainly in Experiments 1 and 2, both primacy and recency occurred, but the odd results in Experiment 3, where a unique-context item was never corrected recalled (ab_8), and strong recall of a non-unique item (ab_4) deserve closer examination.

At first we conjectured that the particular pattern in ab_4 of Experiment 3 was distinctive in some way not immediately apparent, similar to a human subject finding pre-existing meaning in a random string of numbers (such as a date), making it more memorable. However, a comparison of the patterns of each individual item against each of the others did not reveal any outliers. In fact, if this sort of "distinctiveness" of the A and B portions of the item could have predicted the more "memorable" items, ab_5 in Experiment 3 should have been successfully recalled, as it has the least similarities with other items.

We also compared each A portion of the item against its own B portion. If a high similarity between the two portions of each item were a predictor of successful recall, then ab_6 and ab_7 should have been the most recalled items in Experiment 3.

It could be argued that uniqueness (or distinctiveness) and position are related. In trials with human subjects, the first and last items in a list have the distinction of being the "book ends"; their context is unique by virtue of their positions. Distinctive items are more easily remembered. That is, in some sense, what the context represents in these experiments. In the simulations, we sought to recreate that distinctiveness by altering the groups of context units for each list pair. However, recreating context analogous to the human perception of context within the model is the big challenge. In behavioural studies of context, the strongest cues are often emotional ones such as fear (e.g. Rudy, Barrientos & O'Reilly, 2002), and how to replicate that neurobiological effect in the computational models is not clear.

5 CONCLUSIONS

The Serial Position Effect has historically been explained using a two-store memory model. Primacy and recency were thought to be the work of long term memory and working (short term) memory, respectively. This paper has used simulation to explore the theory that a one-store model of memory can account fully for SPE. Simulation results demonstrate that both primacy and recency of the SPE in a serial recall task can be replicated using only the hippocampus simulation, a result suggesting that a one-store model of memory for this recall task is sufficient.

While we deliberately restricted this work to the hippocampus-only simulation in order to test the one-store memory model of the SPE, future computational simulations for the SPE should be expanded to use the prefrontal cortex/hippocampus combined simulation. As outlined in Atallah, Frank, and O'Reilly (2004), memory encoding is distributed, and memories are not "located" in either the hippocampus or the cortex, but in both. A connected PFC-hippocampus simulation would allow this distributed model of memory to be more thoroughly tested. The fact that the Serial Position Effect is so thoroughly studied in experimental psychology suggests that further investigation along these lines will improve our understanding of the biological mechanisms of memory.

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