Memory Processes in Perceptual Decision Making

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Abstract

In a decision making task repeated encounters of a visual stimulus attribute to improved performance in identification and classification of that stimulus. This process is termed as repetition priming. Recent studies have proposed that response learning (RL), where previous decision gets associated with that item, accounts for a significant portion of performance gains observed in repetition priming. However, RL is unable to explain intact priming in amnesic patient population and residual priming in healthy population after the decision cue was switched. Furthermore, it is still unclear whether RL is dependent on the well structured knowledge and object representations. In this paper two-fold approach is taken to fully address the aforementioned issues. First, to test the boundaries of RL and its dependence on knowledge structures, a new repetition priming experiment using 2-D novel objects is presented in healthy population. Experimental results indicated that novel objects result in short-term priming, and presenting the object multiple times did not further facilitate reduction in response time. This pattern does not fit prevailing theories of repetition priming, including RL. A new perceptual memory-based association mechanism is thereby required. Second, to formalize and test such a mechanism, a computational model is developed. The model was further extended to formulate priming using known objects, thereby providing explanation for residual priming in case of cue-inversion in healthy population and intact priming in amnesic patient population. Altogether this paper presents the missing link, perceptual memory-based association mechanism, to fully capture all the memory processes involved in decision making.

Keywords: Repetition priming, response learning, fMRI, computational modeling, convergence zones.

Introduction

The phenomenon, in which previous experiences aid in the performance of a task without conscious awareness of these previous experiences, has been associated with *implicit memory* (Schacter et al. 1987). Widely used paradigm for characterizing it is *repetition priming*. That is, when an item is presented multiple times, the subject becomes better in identifying, or classifying that item. In order to understand the underlying mechanisms of priming, Wiggs & Martin (1998) proposed that the subject *tunes* object identification and knowledge systems, i.e., neurons that are not essential for recognizing the object, show decreased responding. Thus the neural feature representation becomes selective, and this neural "tuning" is linked with faster and more efficient processing. However, in a recent series of studies, Schnyer et al. (2006) and Dobbins et al. (2004), have argued that if facilitation associated with *repetition priming* is only due to efficient *tuning* of object identification and knowledge

representation systems then changes in decision cues should have little effect on priming. In Dobbins et al. (2004), participants were asked to make size judgments about visually presented objects (like "is it bigger than a shoebox?"). After they were exposed to items either once or three times, the decision cue was inverted ("is it smaller than a shoebox?"), a manipulation that should not significantly alter the processes associated with item identification or access to item-related size knowledge. However, they found that changes in the decision cue disrupted a significant portion of response time facilitation even at the level of single repetition. Moreover, the neural-priming signature across cortical areas, where repetition related reductions in neural activity were evident with same cue, was completely eliminated during cue-inversion. Hence, it was concluded that participants appeared to be learning their responses to items. Subsequently, Schnyer et al. (2006) tested the effect of cue-inversion on amnesic patients with damage to the medial temporal lobe (MTL). Although significant reduction in response time was found between items that were exposed once and more, no disruption effect on priming due to cue inversion was found. Additionally, multiple repetitions did not facilitate reduction in response time. Thus it was concluded that response learning is dependent on an MTL based learning mechanism whereby a particular response or decision is associated with that item. However, the mechanism for behavioral priming, which was preserved in amnesic patients, still remains ill defined.

Altogether these findings suggest that priming, even within a single task, may reflect multiple mechanisms. In order to understand these mechanisms two key issues needs to be resolved. First, to test boundaries for response learning, i.e., whether a direct association between visual representation of an item and previous decision can be made, thereby bypassing more processing layers (Figure1). To address this issue, a new repetition priming experiment using novel objects is presented. Second, well defined explanation is required for residual priming in healthy participants after cue-inversion and intact priming in amnesic patient population. This issue was addressed using computational modeling.

Next section is devoted to the fMRI experiment, followed by a section on computational modeling and conclusion in the end.

fMRI Experiment

Response learning is defined as associating an item with its previous response, which in turn helps bypass intermediate stages of information retrieval and comparison, thereby

producing faster responses (Figure 1a). However, it is unclear whether additional layers, like item identification itself, could be bypassed to attain even faster responses with repetition. Thus the boundaries for response learning are not well defined. In order to see whether it is possible to associate visual representation with previous decision, a new fMRI based repetition priming experiment is developed using novel objects (Slotnick & Schacter, 2004). This experiment will also help in answering the dependence of response learning on well structured object and knowledge representations.
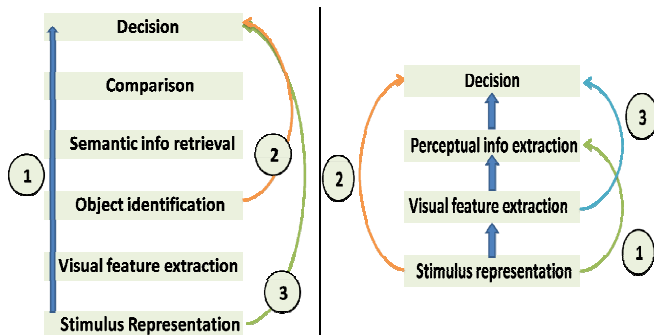

Figure 1(a) Series of cognitive processes that a brain goes through during a decision making task using known objects (Path 1). Path 2 and 3 depicts response learning based association between previous response and object identification and stimulus visual representation respectively. Schnyer et al. (2006) provided conclusive evidence for Path 2 being used after repeated encounters of the same item. However, it is unclear whether more processing stages could be bypassed as well, e.g., Path 3, during repeated encounters. **(b)** Series of cognitive steps during decision making task using novel objects. Path 1 shows, possible lower level perceptual memory based linkage, to bypass visual feature extraction stage, given a novel stimulus as input. Path 2 and 3 depicts, possible response learning based associations, associating response with various other lower level stages. Thus if response learning based signatures are observed, Path 2 or 3 are accountable. However, if responses learning based signatures are not found, then Path 1 would be responsible for observed priming.

Given a novel object and a perceptual size-judgment task, the series of cognitive processes that the brain would go through to make such a decision are depicted in Figure 1b. Given an input stimulus for the first time, representing a novel object on the display, the first step is to extract visual features from the input (like color, shape, texture), then next is to extract cue-based perceptual information (size or aspect ratio of the input stimulus on the display), to make a final decision in the end. However on second encounter with the same stimulus one of three associative pathways could be chosen, (1) associating stimulus representation to perceptual information extraction, thereby bypassing visual feature extraction, and then decision making, or (2) associating stimulus representation directly to previous decision, bypassing both visual feature extraction and perceptual information extraction, or (3) starting from stimulus representation followed by associating visual feature extraction to previous response and bypassing perceptual

information extraction. Note that pathways 2 and 3 corresponds to response learning, since previous response is being associated with other layers of processing, where as pathway 1 corresponds to lower level perceptual memory-based association.

The hypothesis for this experiment was that any priming gains found would be based on the above mentioned association pathways. Thus if typical signatures of response learning are found in this experiment then we can conclude that its due to either pathway 2 or 3 and further experiments would be required to figure out which of these pathways was chosen. Furthermore, we can conclude that response learning is not dependent on well structured knowledge and object representations. However, if typical signatures of response learning are not found, but priming gains are still there then it can be concluded that pathway 1 is in fact the chosen pathway. Hence a new and previously hidden perceptual memory based association system could be discovered. Furthermore, the results of this experiment would shed light on its characteristics. Finally, it can be concluded the RL is dependent on previously formed well structured knowledge and object representations.

Methods

In order to compare the findings with previous response learning studies, the paradigm and procedures were similar to those of described in Schnyer et al. (2006).

Subjects. Twenty-two young (age range from 18 to 28) native speakers of English, with normal or corrected to normal vision, took part in the experiment. Written informed consent was obtained from each subject prior to experimental session. The Institutional Review Board (IRB) of University of Texas at Austin approved all procedures.

Materials. Two hundred and fifty novel object images were used (Slotnick & Schacter, 2004).

Procedure. The participants were shown stimulus on the display and were asked to decide whether the shown stimulus is fat? (or slim? during cue-inversion). The experiment was divided into four runs; each run was further divided into two phases, study and test phase. Every study phase had 20 trials per condition and a total of four conditions – no-prime (shown once), low-prime (shown twice), high-prime (shown thrice) and no-prime never repeated. The test phase consisted of 20 high-prime trials from study phase 20 novel trials that were never shown before. Each trial was shown for three seconds, except the null trials. In a null trial, blank screen was shown. The duration and positioning of null trials were based on the optimal sequence, derived using optseq2 program.

Data Acquisition. Scanning was performed on a 3T GE scanner using an 8-channel phased array head coil. Multi-echo GRAPPA parallel imaging EPI sequence developed at Stanford was used. Functional images were collected utilizing whole head coverage with slice orientation to reduce frontal artifact (approx 20 degrees off the AC-PC plane, TR = 2 sec., 3 shot, TE = 30 msec., 35 axial slices oriented for best whole head coverage, acquisition voxel

size = 3.125 x 3.125 x 3 mm with a .3 mm inter-slice gap). In addition, two high-resolution T1 SPGR scans were acquired in the sagital plane using a 1.3mm slice thickness with 1 cubic mm in plane resolution.

fMRI data analysis. Data were processed using FSL. For fMRI analysis, images were motion corrected, smoothed with a 8mm Gaussian filter, high pass filtered and "prewhitened" before event-related responses were estimated using event-related convolution with an ideal hemodynamic response represented by a gamma function and its temporal derivative. Explanatory variables were modeled for each of the 3 conditions (novel, low-prime and high-prime) in study phase and 2 conditions (novel, and very-high prime) in test phase. A second-level analysis was conducted on each individual subject by registering each subject to the standard MNI152 template and combining the critical contrasts from the 4 runs. The following contrasts were calculated in study phase: (1) Novel > all prime, (2) high prime, and (3) low-prime and in test phase: (1) Novel > very high prime.
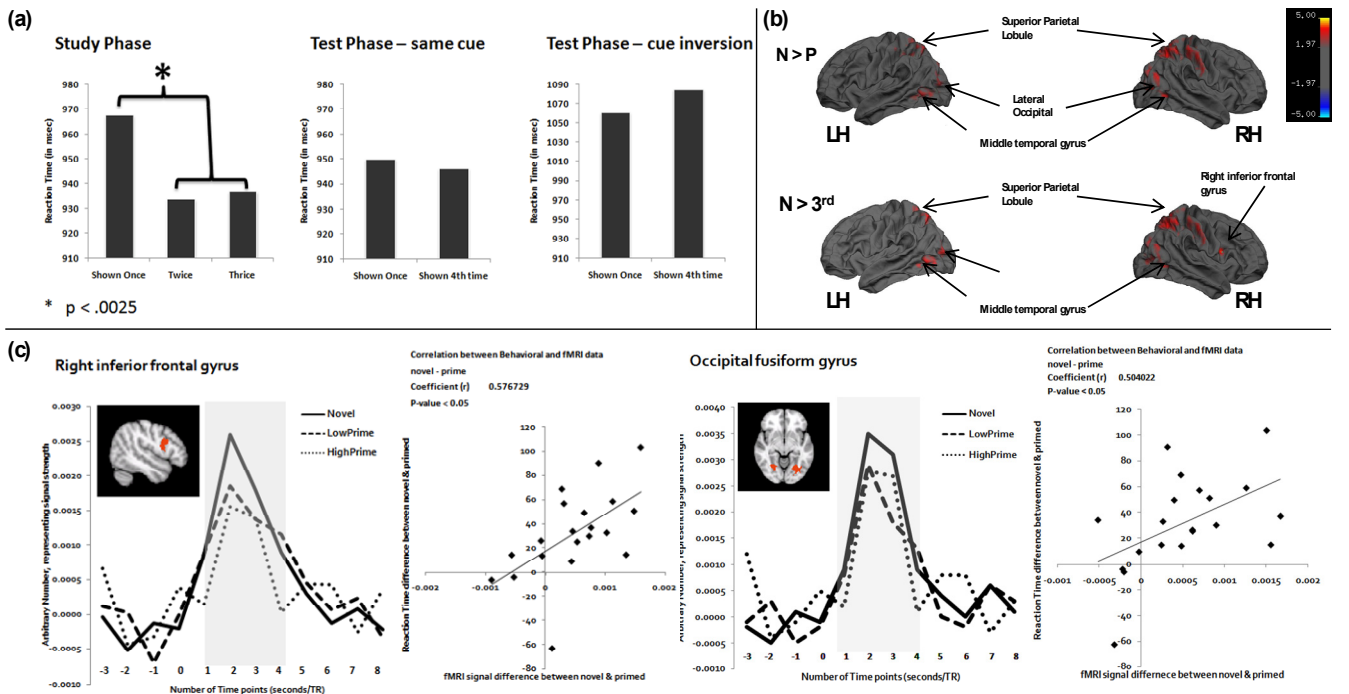

Figure 2. Behavioral and functional results (a) RT data for study and test phase (with and without cue inversion). Significant reduction in response time during study phase only. Further, reduction was not facilitated with repetitions. Significant (*p<0.05*) cortical activity reduction was found (b) in primed conditions as opposed to shown once trials, during study phase. Further, when second repetition was compared with shown once trials, during study phase, cortical activity reduction was observed in right inferior frontal gyrus. (c) ROI and correlation analysis between behavioral and functional data, during study phase. Lack of facilitation in response time reduction with multiple repetitions and lack of cortical activity reduction in left-prefrontal area, provides conclusive evidence that the priming gains observed in this experiment are not due to response learning. Hence from hypothesis, it is due to perceptual memory-based association.

Results

Behavioral data: Reaction times (RT) were examined separately for the study phase and the test phase (with same and inverted cue). In study phase pair-wise t-tests indicated significant priming (p<0.003) between the stimulus shown once and its repetition (once and twice). Priming did not interact with the number of repetitions. Thus a threshold type reduction in reaction times with repetition was found (Figure 2a). On the other hand, in the test phase while there was an overall slowing with cue inversion (2-way ANOVA, F=9.12 and p<0.0035), no significant repetition-induced reduction in response time was found. Thus no significant difference of RT was found between stimuli that was shown once and the fourth time in either same cue or switched cue condition (pair-wise t-tests, p = 0.79 and 0.17 respectively) (Figure 2b).

Typical behavioral signatures of response learning including, response time facilitation with repetitions, robust priming effects, and significant disruption of priming during cue-inversion were not observed. Rather, threshold type reduction, no facilitation of response time with repetitions, short term priming effects that did not transfer to the test phase and no significant disruption of priming during cue-inversion, were found.

Functional data: Reduced cortical activity was found, during study phase only, in occipital-fusiform gyrus, superior parietal lobule, temporal-occipital-fusiform cortex, and lateral occipital cortex regions for primed (shown twice or thrice) relative to items that were shown once (Z, Gaussianized T/F > 2.3 and a corrected cluster significance threshold of p = 0.05). Additionally, significant reduction in cortical activity was found in right inferior frontal gyrus for

high prime (shown thrice) condition relative to items that were shown once (Figure 2b). Following pattern from behavioral data, there were no significant differences in cortical activity between items that were shown for the first time and very high prime (shown fourth time) condition in the test phase (with or without cue inversion).

Typical neural signatures of response learning were absent, i.e. lack of reduced BOLD signal in left pre-frontal cortex, and lack of disruption of cortical activity reductions during cue-inversion. Although reduced activity in right inferior pre-frontal cortex was found, in high-prime condition as compared to condition where stimulus was presented for the first time, in study phase.

To determine whether regional activity paralleled response time reduction in the study phase, the MR signal from specific regions of interest (ROIs) was extracted. The regions were those implicated in previous priming studies (Dobbins, et al, 2004) demonstrating cortical activity reductions in regard to response learning, namely the pre-frontal cortex and ventral-temporal cortex, particularly in the fusiform gyrus. As shown in Figure 2c, significant reduction in cortical activity in case of primed items relative to items shown for the first time was found for both right inferior frontal and occipital-fusiform gyrus. Further, correlation analysis was performed between MR signal from ROIs and behavioral response time data. As shown in Figure 2c both right inferior frontal and occipital fusiform gyrus revealed significant positive correlation values.

In the current experiment, relatively weak and short lived repetition-related effects were revealed by reduced behavioral RT during the study phase but not in the test phase, accompanied by reductions in fMRI signal across right inferior frontal gyrus, lateral occipital, and temporal fusiform regions, again only in study phase. Also priming did not benefit from multiple repetitions, i.e. a threshold type reduction in response times. Lack of evidence for response learning and from the hypothesis, it could be concluded that association pathways 2 and 3 were not responsible for the weak priming gains. Thus path 1 could be held accountable for the observed priming.

Altogether these findings provide conclusive evidence in formulating and characterizing, a relatively new mechanism, perceptual memory-based association system (Figure1b). The reason for its novelty goes to the fact that previous research was focused on known objects, or objects of daily life. Thus the gains achieved from by-passing higher level cognitive processes overshadowed the gains achieved from lower level perceptual memory-based association. However, the experiment in this paper, using novel objects, was able to uncover this otherwise hidden phenomenon. Furthermore, this experiment suggests that well structured and stable object representations or episodes are required for response learning. Thus the underlying phenomenon for response learning could be termed as episodic memory-based association system.

The next question, then, is to find out how perceptual memory-based association is mechanistically different from episodic memory-based association and how do they interact with each other, if at all. Additionally, it would be interesting to know if perceptual memory based association was the missing link in explaining residual priming in healthy control population and intact priming in amnesic patient population. It is hard to study these questions using human experimentation, thus a well formulated computational modeling approach was taken.

Computational Model

Developed computational model addresses three key goals which could advance our understanding of repetition priming phenomenon. First goal was to model the newly proposed perceptual memory based association system based on neural and behavioral results from the present experiment. Predictions from the model than could be used for future research. Second goal was to formally understand the mechanistic differences between episodic memory-based association (or response learning) and perceptual memory-based association system. Third goal was to integrate the two systems computationally and see if addition of perceptual memory-based system could help in providing explanation for residual priming after cue-switching in healthy control participants and intact priming in amnesic patient population.

Repetition priming using novel objects
Model architecture is shown in Figure 3a. The sequential pathway was modeled using recurrent artificial neural networks. The network was trained before hand, using back propagation learning, to extract visual features given an input stimulus. Followed by, extracting cue-based perceptual information to make decision. Variability was incorporated in order to match experimental RT behavior into the model, by selecting responses based on a random walk (Link, 1975) and a diffusion process (Ratcliff, 1978).

By definition novel objects lack stable object representations. Thus given an input stimulus for the first time the elementary visual feature extraction process takes place, followed by cue-based perceptual information extraction from those features. The extracted information then leads to comparison and decision making. The response time taken by the model to produce a final decision is summed response time over all stages. This is the computationally intensive pathway and is engaged whenever an item is seen for the first time.

Results from the fMRI experiment above provided characteristics for perceptual memory-based association system and thus formed the basis for modeling. Key characteristics include one-shot learning, i.e. significant
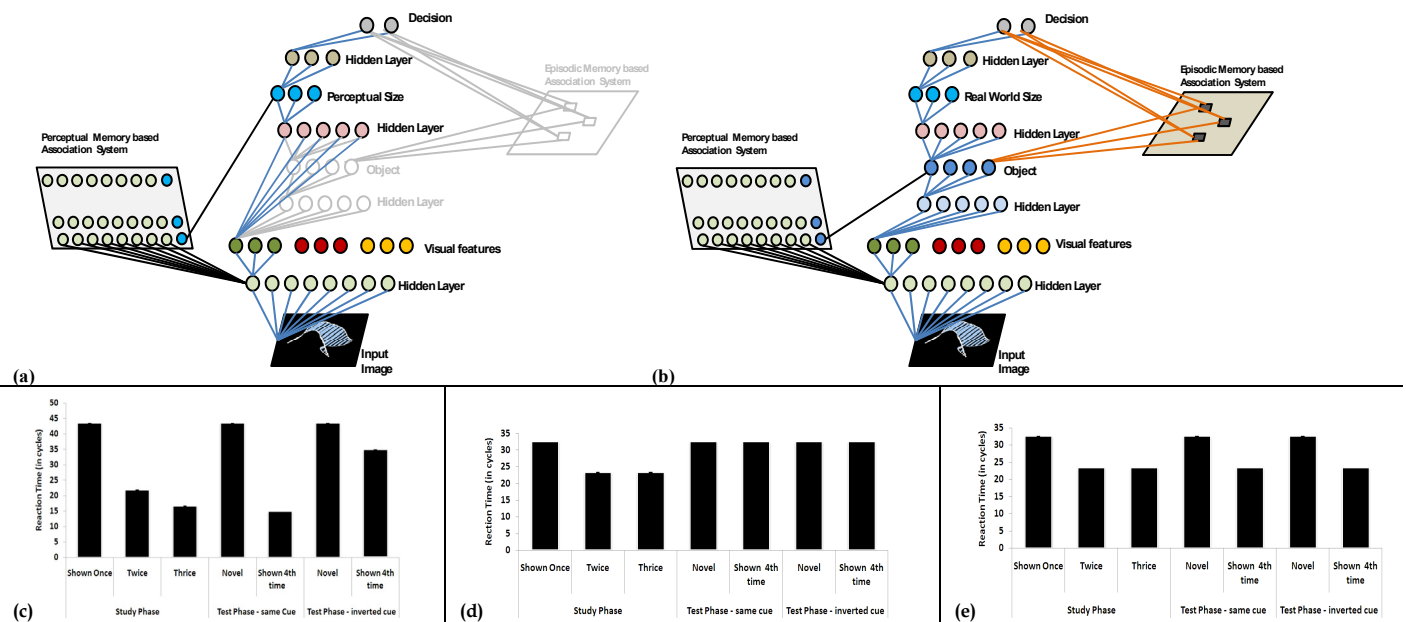
Figure 3a: Model architecture for novel objects. Once stimulus is presented, the visual feature extraction process is initiated, to extract color, shape, and texture information from the image. The extraction of visual features further leads to extraction of cue-based perceptual information, area occupied or aspect ratio in the current experiment to finally classify the image as slim or fat. The episodic memory linkage is not active as shown by shaded links. Parallel to this set of sequential processes, the perceptual memory-based caching layer stores association between visual representation of that item and corresponding extracted perceptual information. **(b)** Model architecture for known objects. The model makes a classification decision based on stored semantic information about the input stimulus, in four sequential stages. Parallel to this set of sequential processes, the perceptual memory-based caching layer stores association between visual representation of that item and corresponding unit in the object layer. Thus upon next encounter of the same item, visual feature extraction may be bypassed. Similarly, during first encounter with an item, the decision unit gets associated with the object representation unit utilizing the episodic memory-based association system. Thus, during second encounter with the same object, activation in the object representation layer retrieves the decision vector directly. The model was simulated in three different scenarios: **(c)** with known and **(d)** with novel objects in healthy participants and **(e)** with known objects in amnesic patients. In known-object priming simulation in healthy participants, significant priming took place both in study and test phase (p<0.05, using pair wise t-tests). Further, cue-inversion disrupted episodic memory-based associations but the perceptual-memory-based caching provided residual priming. In novel object priming in healthy participants, significant priming was observed only in the study phase. The simulation of repetition priming in amnesic patients using known objects, yielded threshold-type priming gains in both study and test phase. Further these gains were not affected by cue-inversion.

reduction in response time was found after single repetition of that item. Additionally, no further reduction in response time was found with two or more repetitions of the same item. Thus lack of facilitation with multiple repetitions was found. Both one-shot learning and lack of facilitation were captured in computational model by implementing simple activation based caching phenomenon. Thus the visual representation of an item and the perceptual information extracted, during first encounter with an item, are associated and cached in the perceptual memory based system. During second encounter with the same item, cached-association helps by-pass the visual feature extraction and lead directly to cue-based perceptual information required to make decision (Figure 1b-Path1). Lack of learning in this pathway produced one time reduction in response time (threshold type reduction), which accounts for similar behavioral results (Figure 3d), as found in fMRI experiment.

Due to the short-term nature (implemented using lack of storage capacity) of priming in novel objects, the effect of cue-inversion is hard to conclude from the experimental results. However, the proposed characteristics of perceptual memory-based system and the modeling results predicted no effect of inverting the cue on behavioral response times. This could be further bolstered by doing an experiment with lesser number of novel items. This work is left as part of future research.

Repetition priming using known objects
Model architecture is shown in Figure 3b. The sequential algorithmic pathway was implemented, as in the case of novel objects, using recurrent artificial neural networks. Response learning was modeled based on its neural and behavioral signatures as found previously in the literature (Schnyer et al. 2006 and Dobbins et al. 2004). The key signatures include one shot learning and exponential or power law reduction in response time with multiple repetitions of an item. Thus it not only involves association between object representation and the previous decision, but also this association gets stronger with multiple repetitions, until it finally saturates. Further, as concluded from the fMRI experiment, response learning is dependent upon well structured object representations or an episode in order to associate the object with decision. To model all these key characteristics, episodic memory-based architecture was used, developed by Moll and Miikkulainen,

1997. This biologically motivated architecture of episodic memory exhibits capacity and behavior very similar to that of the hippocampus memory system. The idea was to include a randomly-sparse encoded binding layer, which acted as a convergence-zone between object representation and decision layer. Thus parallel to the sequential cognitive processing, when the object is encountered for the first time, the decision unit then gets associated with the object representation unit utilizing this binding layer. Further, the episodic memory-based architecture was modified to include continuous learning with repetitions. Thus, with each repetition, the synaptic strength between the binding layer, object unit, and decision unit grew stronger. Thus successive encounters with an item produced higher activation in the binding layer units and the associating decision unit. This high activation in decision units, in turn lead to faster response selection and hence the decrease in response time (processing cycles) with repetitions. This result mirrors the behavioral results of multiple-repetition priming in Dobbins, et al., (2004) and Buckner, et al. (1998)

Further, the perceptual and episodic memory-based association systems were integrated to see if the repetition priming results could be fully explained, especially the ones observed after cue-switching. Thus, also developing association between visual and object representation units, by-passing visual feature extraction process. After integrating the two systems, repetition priming results in known objects could now be fully explained. Episodic and perceptual memory-based systems work seamlessly to produce the priming gains. Now, during second encounter with an item, perceptual memory-based caching help by-pass the visual feature extraction step and episodic memory-based association learning help by-pass the higher order semantic information extraction and comparison steps to lead to decision. Thus repetition induced facilitation is characterized due to the learning involved in episodic memory-based system. However, upon inverting the cue, the item-decision associations of episodic memory are rendered useless and significant portion of priming gains are lost. Nonetheless, the preserved perceptual memory linkage between visual and object representation gives rise to the residual priming.

Repetition priming in amnesic patient population
The results presented in Schnyer et al. (2006) study, clearly showed intact priming gains in amnesic patient population. Response learning theory and knowledge-system tuning could not explain these preserved gains. The current model, however, proposes to formalize the underlying mechanism using perceptual memory-based association system. Due to lesioned MTL, the episodic memory-based association would not develop, in amnesic patients. Thus on second encounter with the same item, perceptual memory-based linkage would by-pass visual feature extraction process and thereby producing a relatively faster response. However, lack of learning in the perceptual memory-based system, would result in a threshold type reduction in response time with repetition rather than facilitation with multiple repetitions. Furthermore, there would be no effect of cue-

inversion on the priming gains, since there is no association with the decision outcome (Figure 3e).

Conclusion

This paper presented a two-fold approach to fully address the repetition priming. First, to test the dependence of RL on knowledge structures, a new repetition priming experiment using 2-D novel objects was presented. Experimental results indicated that novel objects result in short-term priming, and presenting the object multiple times did not further facilitate reduction in response time. This pattern does not fit previous explanations based on either RL or knowledge-system tuning. A new perceptual memory-based association mechanism is thereby required. Second, to formalize and test such a mechanism, a computational model is developed. The model was further extended to formulate priming using known objects, thereby providing explanation for residual priming in case of cue-inversion in healthy population and intact priming in amnesic patient population. The simulation results from modeling successfully mimics the behavioral priming results obtained in current and previous studies with known and novel objects. These results suggest that repetition priming is a complex result of multiple mechanisms, and a tight interaction between experiments and computational theory is necessary to understand it.

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