# **Supplementary Materials**

## Image Guessability Analysis

Without study, subjects were able to name object and scene image patches on 26.1% and 29.9% of trials respectively (Fig. S2). To investigate if image differences might be contributing to the estimated neural recall effect we computed a "guessability" score for each image. Guessability was operationalized as the proportion of times (across subjects) that an image was correctly named despite not being studied. Post-test data from the present study (n=20) was combined with post-test data from a pilot study (n=19) giving a mean of 9.75 unstudied trials for each of the 120 objects and 120 scenes. In line with the subject analysis (Fig. S3), which suggested that false recall (i.e., responding 'Recall Image' at test to an unstudied image) was not associated with improved naming, image guessability did not correlate with the probability that an image would be falsely recalled during the scanned test phase (Objects, r=.046, p=.617; Scenes, r=.048, p=.603). However, image guessability was correlated with correct recall (i.e., responding 'Recall Image' at test to a studied image-patch; Objects, r=.612, p<.001; Scenes, r=.370, p<.001), suggesting that guessability may have interacted with memory to increase recall rates for items that were studied. Note that this is simply an item effect and since items were counterbalanced across subjects it does not provide an alternative explanation for any of our key findings. Together, these findings suggest that although guessability may influence subjects' ability to encode and later recall an image, it does not influence the likelihood of incorrect 'recall' for unstudied items. That is, guessability may interact with study (i.e., memory) to boost recall, but there is no evidence that guessability interacts with the perception of unstudied items to spuriously enhance recall via some purely 'perceptual' pattern completion process.

#### Post-Hoc DCM

Our DCM model space (Fig. S5) is simply a subset of a larger possible model space. For example, because there is strong anatomical evidence that HC receives much of its input via PHG we chose to exclude models with a direct driving input into HC. We also chose to consider only fully connected models since our primary interest was to investigate the modulation of connectivity by recall, rather than to investigate connectivity per se (see Staresina et al., 2013 for a similar approach). However, to ensure that these assumptions did not unintentionally bias the findings we conducted a post-hoc selection procedure to identify the best model family out of all possible connection architectures and driving input locations. Briefly, post-hoc Bayesian model selection allows the estimation of a large space of nested models by fitting (optimizing) only the most complex model (Friston and Penny 2011; Rosa et al. 2012). Under the assumption that the full model is characterized by the same likelihood as the set of nested models, evidence for a given nested model is thereafter obtained analytically from the full model, using a generalization of the Savage-Dickey density ratio. This is achieved by fixing a subset of the full model's parameters to have a mean and precision of zero (effectively removing those parameters), and evaluating the evidence for the model under those conditions.

The post-hoc analyses were implemented in SPM 12 using the function spm\_dcm\_post\_hoc.m. First, we specified a fully interconnected 3-ROI DCM (LO, PHG, HC) with driving input (studied cue trials) into all three ROIs and modulation (recall trials) of all connections. As with the other DCM analyses the model was separately fitted to each subject's data in each hemisphere, for both objects and scenes. Next, to evaluate the evidence for different connection architectures we specified 64 connectivity families. Connectivity families differed from each other by the particular combination of the six extrinsic (i.e., between-ROI) connections, which could be either be present or absent (i.e. 2<sup>6</sup> possible families), with each family containing all possible variations of modulation and driving input. We also specified a set of 7 model families that differed from each other in terms of the location of the driving input, i.e., input into any one of the three ROIs, or into all possible combinations of two ROIs, or into all three ROIs.

(having no driving input is not possible with deterministic DCMs). The evidence for each model family is shown in Fig. S6, separately for objects and scenes in the left and right hemispheres. In terms of driving input location, the model probabilities indicate that in all cases there is almost no evidence for the model family that includes a driving input into HC, or for a model family in which PHG alone receives driving input; these results confirm that the two options for driving input location that we assumed in our DCM analyses – that is, LO alone or LO and PHG together – were reasonable choices. In terms of connectivity, although the post-hoc family comparison did not provide clear evidence (>0.95) in favor of any particular connectivity family, in all cases the most probable family by a large margin was the family in which the models were fully interconnected, providing some support for the assumption of full intrinsic connectivity that was made in our DCM simulations.

## Psychophysiological Interaction Analyses

Our primary motivation for conducting DCM analyses was to investigate changes in the strength and direction of connectivity between our ROIs during recall. In order to validate the results of the DCM with a second, complementary method, we conducted an additional psychophysiological interaction (PPI) connectivity analysis on the same ROI timecourse data. PPI can be used in event-related designs to measure the changes in connectivity associated with a particular condition (e.g. recall) by partialling out the connectivity associated with the baseline condition (e.g. familiar). Unlike DCM, PPI does not provide directional information in its estimates of connectivity, but the pattern of connection magnitudes estimated by PPI can nevertheless be compared to DCM results to increase or decrease confidence in the findings from DCM. We conducted the PPI analyses using the SPM 12 implementation. First, for each ROI used in the DCM analysis (LO, PHG, HC) we extracted a signal timecourse (first eigenvariate). As is standard in SPM, the timecourse in each ROI was then deconvolved (using a canonical HRF) and multiplied by a vector of zeros and ones specifying the psychological factor of interest across trials (e.g.,

recall trials, familiar trials, other trials). We then computed the correlation (Pearson's r) between PPI vectors (calculated within SPM) for pairs of ROIs – for example, correlating the LO x familiar vector with the HC x familiar vector. Finally, for each subject we calculated the difference in the correlations for the recall and familiar condition for each ROI-pair and transformed the values using the fisher z-transform (Fig. S7).

# **Supplementary References**

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From:	То:	Objects		Scenes	
		Left	Right	Left	Right
LO	LO	-0.98	-0.65	-	-
	PHG	0.40	ns.	-	-
	HC	0.53	0.52	-	-
PHG	LO	-	-	0.61	0.45
	PHG	-	-	-0.87	-0.72
	HC	-	-	0.46	0.44
НС	LO	-	-	-	-
	PHG	-	-	-	-
	HC	-	-	-	-

**Connectivity Modulation (B Matrix)** 

**Table S1.** DCM parameter estimates for Objects and Scenes obtained by Bayesian model-averaging (BMA) across the winning model family. Numbers correspond to the modulation of connectivity by recall (B matrix) and are shown separately for the left and right hemispheres. Parahippocampal Gyrus (PHG label) refers to perirhinal cortex (PRC) for analyses of Object data and parahippocampal cortex (PHC) for analyses of Scene data. For objects, there was an increase in the flow of information from LO to HC in both hemispheres and from LO to PHG in the left hemisphere. There was also disinhibition of LO, indicated by the negative modulation of the inhibitory self-connection parameter (Friston et al. 2003; Gu et al. 2015). This is consistent with recall being associated with increased excitability of the neuronal population within LO. For scenes, there was an increase in the flow of information from PHG to HC and PHG to LO in both hemispheres. There was also disinhibition of PHG, consistent with recall being associated with increased excitability of the connections that could be modulated in the winning model family, other parameters are marked by the - symbol.

# **Supplementary Figure Captions**

#### Figure S1.

Examples of object and scene stimuli used in the experiment. During the study phase, subjects first saw 90 whole-object and 90 whole-scene stimuli (Left) and then saw half of the stimuli for a second time with the patch-cue removed to create an aperture stimulus (Center). In the test and post-test phases, subjects were shown patch-cues (Right) taken from both studied (i.e., studied once or studied twice) and unstudied stimuli. The purpose of including the Studied-Twice condition was to increase patch-cued recall (i.e., remembering the whole) without increasing the familiarity of the patch (see Fig. S2).

#### Figure S2.

Behavioral performance on patch-cued test phase for objects and scenes. **(A)** Mean proportion of Studied Twice (45 trials), Studied Once (45 trials), and Unstudied (30 trials) patch-cue trials on which subjects responded Recall Image, Patch Familiar, or New. **(B)** Corresponding response times. There was a significant main effect of study (twice, once, unstudied), F(2,38)=81.5, p<.001, and stimulus (object, scene), F(1,19)=9.5, p=.006, on the proportion of 'Recall Image' responses but no interaction between study and stimulus (p=.12). The study-twice manipulation was included to provide objective verification that 'Recall Image' responses reflected memory for the whole image and not just the familiarity of the patch. Because the second study presentation did not include the patch we reasoned that any increase in the proportion of 'Recall Image' responses must reflect increased memory for the image whole, not the patch alone. In line with this, there were more 'Recall Image' responses to images that were studied once, t(19) = 5.83, p<.001, but there was no increase 'Patch Familiar' responses, t(19) = .739, p=.469, after controlling for the number of 'Recall Image' responses to images

that were studied once than to images that were unstudied (recall,  $t_{19}$ =8.59,p<.001; familiar,  $t_{19}$ =2.64,p=.016). None of the corresponding comparisons were significant in the reaction time data. Error bars show 95% CIs around the means.

#### Figure S3.

Behavioral performance on post-test image-patch naming. Mean proportion of patches that were correctly named is shown separately for each combination of study condition (Studied Twice, Studied Once, or Not Studied) and test-phase memory response (Recall Image, Patch Familiar, New). Error bars show 95% CIs around the means

#### Figure S4.

Functional activity in the MTL during image-patch cued recall. Studied image-patch trials were binned by subject memory response (Recall Image, Patch Familiar, or New). Unstudied image-patch trials were binned together. Parameter estimates for object-patch trials (dark grey) and scene-patch trials (light grey) are show separately for the left **(A)** and right **(B)** hemispheres. A repeated measures ANOVA revealed a significant memory-response x stimulus-type x ROI interaction, F(4.04, 76.7) = 10.9, p <.01,  $\hat{\epsilon}$ =.673, with no significant interactions with hemisphere (all p>.05). Error bars show 95% CIs around the means.

#### Figure S5.

Schematic of the full DCM space. There were a total of 42 DCMs — six families (top to bottom) x seven variations (left to right). The six families were defined by input location (dashed arrows) – either LO alone (top three rows) or both LO and PHG (bottom three rows) — and by which ROI served as the source of recall-related modulation (bold circles) — either LO (rows 1 and 4), PHG (rows 2 and 5), or HC

(rows 3 and 6). Within each family there were seven model variations (left to right) that differed as to which of the connections emanating from the source ROI could be modulated by recall (solid bold arrows). All 42 models were fitted separately for each subject, hemisphere and stimulus type.

#### Figure S6.

DCM family probabilities from the post-hoc analysis (see Supplementary Methods) for object and scene conditions in left and right hemisphere ROIs. Each panel (A – D) shows the posterior probabilities for 64 DCM families grouped by intrinsic connectivity (top subpanel) and the posterior probabilities for 6 DCM families grouped by driving input location (bottom subpanel). Supporting the assumptions made in the DCM about underlying model architecture (see Dynamic Causal Modeling Data Analysis and Preprocessing), family 64 – corresponding to a fully connected model architecture – had the highest probability for all cases (probability values for the top two models are shown above the corresponding bars). Moreover, in line with the results of the full analysis there was strong evidence (a probability of almost 1) in favor of driving input entering at LO for objects in the left hemisphere (**A**) or LO and PHG for objects in the right hemisphere and scenes in both the left and right hemisphere (**B**, C & D). Note, model family 32, the second most probable model in all cases, included all connections except the forward connection from LO to PHG.

## Figure S7.

Psychophysiological Interaction (PPI) estimates of recall-related modulation of connectivity (i.e., the difference between the connectivity estimate in the recall condition minus the connectivity estimate in the familiar condition) and a comparison to the results of the DCM (see Supplementary Methods). PPI estimates have been averaged across left and right hemispheres. Note, PPI cannot be used to infer the direction of connectivity between two regions, so arrows for PPI are double-ended. **(A)** For Objects (dark

grey), PPI revealed increased connectivity between LO and PRC and between LO and HC during recall but no change in connectivity between PRC and HC. For Scenes (light grey), PPI revealed an increase in connectivity between PHC and HC during object recall but no change in connectivity between PHC and LO or HC and LO. **(B)** The PPI analysis (left) and DCM analysis (right) revealed similar, though not identical, patterns of connectivity. Note, some discrepancies between PPI and DCM would be expected given the more complex interactions that are captured by DCM. For example, DCM simultaneously accounts for the influence of all three ROIs rather than individually testing interactions between pairs of ROIs. Error bars show the 95% CIs around the means.