Title

Multi-voxel pattern classification differentiates personally experienced event memories from secondhand event knowledge

Authors

Chow, Tiffany E
Westphal, Andrew J
Rissman, Jesse

Publication Date

2018-08-01

DOI

10.1016/j.neuroimage.2018.04.024

Peer reviewed

NeuroImage 176 (2018) 110–123

Contents lists available at ScienceDirect

NeuroImage

journal homepage: www.elsevier.com/locate/neuroimage

Multi-voxel pattern classification differentiates personally experienced event memories from secondhand event knowledge

Tiffany E. Chow [a,*], Andrew J. Westphal [a], Jesse Rissman [a,b,c,d,**]

[a] Department of Psychology, University of California Los Angeles, Los Angeles, CA, 90095, USA
[b] Department of Psychiatry & Biobehavioral Sciences, University of California Los Angeles, Los Angeles, CA, 90095, USA
[c] Brain Research Institute, University of California Los Angeles, Los Angeles, CA, 90095, USA
[d] Integrative Center for Learning and Memory, University of California Los Angeles, Los Angeles, CA, 90095, USA

ARTICLE INFO

Keywords:
Autobiographical memory
Episodic retrieval
fMRI
MVPA
Decoding
Wearable cameras

ABSTRACT

Studies of autobiographical memory retrieval often use photographs to probe participants' memories for past events. Recent neuroimaging work has shown that viewing photographs depicting events from one's own life evokes a characteristic pattern of brain activity across a network of frontal, parietal, and medial temporal lobe regions that can be readily distinguished from brain activity associated with viewing photographs from someone else's life (Rissman, Chow, Reggente, and Wagner, 2016). However, it is unclear whether the neural signatures associated with remembering a personally experienced event are distinct from those associated with recognizing previously encountered photographs of an event. The present experiment used a novel functional magnetic resonance imaging (fMRI) paradigm to investigate putative differences in brain activity patterns associated with these distinct expressions of memory retrieval. Eighteen participants wore necklace-mounted digital cameras to capture events from their everyday lives over the course of three weeks. One week later, participants underwent fMRI scanning, where on each trial they viewed a sequence of photographs depicting either an event from their own life or from another participant's life and judged their memory for this event. Importantly, half of the trials featured photographic sequences that had been shown to participants during a laboratory session administered the previous day. Multi-voxel pattern analyses assessed the sensitivity of two brain networks of interest—as identified by a meta-analysis of prior autobiographical and laboratory-based memory retrieval studies—to the original source of the photographs (own life or other's life) and their experiential history as stimuli (previewed or non-previewed). The classification analyses revealed a striking dissociation: activity patterns within the autobiographical memory network were significantly more diagnostic than those within the laboratory-based network as to whether photographs depicted one's own personal experience (regardless of whether they had been previously seen), whereas activity patterns within the laboratory-based memory network were significantly more diagnostic than those within the autobiographical memory network as to whether photographs had been previewed (regardless of whether they were from the participant's own life). These results, also apparent in whole-brain searchlight classifications, provide evidence for dissociable patterns of activation across two putative memory networks as a function of whether real-world photographs trigger the retrieval of firsthand experiences or secondhand event knowledge.

Introduction

Photography has become a ubiquitous means for documenting the events of our lives, and the images captured by cameras provide potent cues for later triggering recollection of event details. Many cognitive neuroscientific studies of autobiographical memory have capitalized upon this by incorporating photographs as memory probes to assess the retrieval of personally experienced events (for review, see Chow and Rissman, 2017; St. Jacques and De Brigard, 2015). However, the mnemonic processes evoked during the viewing of photographs can be multifaceted, and it is important for researchers to appreciate the distinction between memories for the originally experienced event and

* Corresponding author. 1285 Franz Hall, Box 951563, Los Angeles, CA, 90095-1563, USA.
** Corresponding author. 1285 Franz Hall, Box 951563, Los Angeles, CA, 90095-1563, USA.
E-mail addresses: tiffanychow@ucla.edu (T.E. Chow), rissman@psych.ucla.edu (J. Rissman).

https://doi.org/10.1016/j.neuroimage.2018.04.024
Received 11 July 2017; Received in revised form 25 March 2018; Accepted 10 April 2018
Available online 11 April 2018

memories for having previously viewed photographs of the event. These memories may often go hand in hand, but they are theoretically dissociable. For example, a novel photograph can trigger the recollection of the depicted event or a previously viewed photograph depicting someone else's life experience can be recognized as a visual image that has been encountered in one's past. Although neuroimaging investigations of autobiographical memory have provided valuable insights into the contributions of cortical and medial temporal lobe (MTL) regions in various aspects of retrieval (Cabeza and St Jacques, 2007; Svoboda et al., 2006), it remains unclear to what degree the act of remembering an experience depicted in a photograph can be neurobiologically dissociated from the recognition of the photograph itself.

This distinction has important implications not only for our understanding of the neural correlates of episodic retrieval, but also for potential forensic applications of fMRI as a tool for memory detection (Meegan, 2008; Peth et al., 2015; Rissman et al., 2010). For instance, if fMRI were to have any practical utility as a means to assess the presence or absence of specific memories in a judicial context (Brown and Murphy, 2010; Lacy and Stark, 2013; Meixner, 2015; Schacter and Loftus, 2013), it would be critical to know whether a crime-relevant probe stimulus was recognized because it depicted a specific episode from the subject's past, or whether recognition was elicited simply by virtue of the fact that the subject had previously heard about or seen a photograph of the stimulus in question. This distinction between recognition per se and the source of that recognition is pivotal, and yet underexplored.

The vast majority of extant fMRI studies examining episodic memory have utilized laboratory-based experiences, rather than those derived from the real world. Studies of autobiographical and laboratory-based memories typically differ with regards to the temporal remoteness of the probed memories and the vividness of retrieval (Gilboa, 2004; McDermott et al., 2009; Svoboda et al., 2006). Laboratory-based memory studies generally involve encoding and retrieving a set of homogenous stimuli with limited personal relevance and context. Furthermore, the memories used in laboratory-based paradigms are often formed over a short period of time, with memory performance typically assessed shortly after encoding. In contrast, autobiographical memory studies often utilize memory probes that are more personally relevant to participants, such as words or phrases that refer to a specific life event or photographs of an event. These stimuli may be more likely to trigger the retrieval of memories entailing the re-experience of various sensory and emotional qualities (Gilboa, 2004; McDermott et al., 2009). Autobiographical memory studies often involve the retrieval of remote events: the memories probed in these paradigms are typically older, with their initial encoding ranging from weeks to years prior, and the age of the tested memories may also be less homogenous than laboratory-based studies (Cabeza and St Jacques, 2007; McDermott et al., 2009). These differences between autobiographical and laboratory-based tasks may lead to qualitative differences in participants' retrieval experiences, potentially associated with distinct neural correlates.

Several previous fMRI studies have reported notable differences in the brain regions engaged during the retrieval of autobiographical and laboratory-encoded memories (e.g., Burianova and Grady, 2007; Cabeza et al., 2004), and an Activation Likelihood Estimate (ALE) meta-analysis confirmed that studies of autobiographical memories tend to evoke brain activation in a different set of regions than studies of laboratory memories, with only a few small regions exhibiting overlapping effects (McDermott et al., 2009). Whereas retrieval of autobiographical memories was consistently associated with the recruitment of areas such as the bilateral MTL and medial prefrontal cortex (PFC), retrieval of laboratory memories was more consistently associated with recruitment of areas such as the bilateral middle frontal gyrus, inferior parietal cortex, and left inferior frontal gyrus. In support of these meta-analytic observations, recent behavioral findings suggest that performance on standard laboratory-based memory tasks can be largely uncorrelated with one's performance on assessments of autobiographical recall, as demonstrated by recent reports of exceptional individuals exhibiting a phenomenon known as “highly superior autobiographical memory,” (LePort et al., 2012, 2017; Patihis et al., 2013) as well as those exhibiting the converse phenomenon known as “severely deficient autobiographical memory” (Palombo et al., 2015). Dissociations like these have led some to propose that retrieving autobiographical event knowledge is fundamentally different from other forms of episodic retrieval (Roediger and McDermott, 2013).

One relatively new experimental approach that attempts to increase the ecological validity of autobiographical memory retrieval studies involves the use of naturalistic stimuli derived from wearable digital cameras, which unobtrusively capture photographs of participants' lives (for review, see Chow and Rissman, 2017). Over the past few years, several studies have used wearable camera technology to investigate various aspects of memory for everyday occurrences and events (e.g., Milton et al., 2011a; Milton et al., 2011b; Nielson et al., 2015; Rissman et al., 2016; St. Jacques et al., 2011; St. Jacques et al., 2013). However, of these experiments, few have utilized multivariate techniques such as multi-voxel pattern analysis (MVPA) (Norman et al., 2006; Tong and Pratte, 2012) to characterize the neural signatures of retrieval. MVPA can be used to provide information regarding both the process of autobiographical memory retrieval as well as the content of the retrieved memories (e.g., Chadwick et al., 2010; Polyn et al., 2005; Rissman et al., 2016; Rissman et al., 2010; Uncapher et al., 2015) and has proven to be a particularly useful technique in fMRI experiments using naturalistic stimuli (Spiers and Maguire, 2007).

Only two extant fMRI experiments have combined MVPA methods with camera-based experimental paradigms to examine naturalistic autobiographical memory retrieval. Nielson et al. (2015) assessed hippocampal representations of temporal and spatial information during real-world autobiographical memory retrieval through the use of customized smartphones that collected both photographs and GPS data. Participants wore a smartphone over the course of a month, and the resulting photographs were later presented during fMRI scanning as cues to recall specific events. Both the spatial distance and temporal distance between events could be predicted based on the similarity structure of neural activity patterns within the left anterior hippocampus during retrieval. A recent study by Rissman et al. (2016) utilized wearable digital cameras to assess the whole-brain patterns of neural activation accompanying the retrieval of real-world event memories. Participants wore a digital camera device for a period of three weeks, and were scanned a week later while making mnemonic judgments concerning brief photographic sequences portraying their own life events or events from other individuals' lives. Not only could MVPA-based classifiers be trained to reliably differentiate the neural signatures of novel events that were correctly rejected from personally experienced events that were correctly recognized, but classifiers could also distinguish between the activity patterns associated with varying degrees of perceived novelty, familiarity, and recollection.

The present fMRI experiment sought to extend the findings of Rissman et al. (2016) by developing an experimental protocol that would allow us to disentangle the neural signatures of event retrieval and photograph recognition. We adopted a similar wearable camera approach for collecting photographs of participants' experiences across a three-week time frame, but we added a critical experimental manipulation in the form of a laboratory session that took place one week after the camera-wearing period. During this session, participants were exposed, for the very first time, to a subset of their own photographs as well as to photographs from another participant's life. The next day, they were scanned while judging whether each depicted event was from their own life or someone else's life. Of particular interest was assessing whether MVPA methods could reliably decode brain activity patterns associated with the photographic source of an event (whether the photographs depicted an event from one's own life or someone else' life) and its pre-exposure status (whether photographs of the event had been previously encountered). More importantly, we sought to determine the degree to which the decoding of these mnemonic attributes was driven by

unique neural signatures. To this end, our analyses focused on querying the sensitivity of the autobiographical retrieval and laboratory-based retrieval networks identified by McDermott et al. (2009). Our study is only the third fMRI study to combine MVPA methodology with wearable camera technology, and the first to assess differences in the autobiographical retrieval and laboratory-based retrieval networks with such approaches. We hypothesized that activity patterns within the autobiographical network might be better able to decode photographic source than those within the laboratory-based network, whereas activity patterns within the laboratory-based network would be better able to decode photographic pre-exposure than those within the autobiographical network.

Methods

Participants

Eighteen participants (9 females; 18–22 years old) with no prior history of neurological or psychiatric issues completed the experiment. Two other individuals initially took part in the experiment, but their participation was discontinued prior to the fMRI scan session (one due to loss of interest and one due to non-compliance). All participants were right-handed native English speakers with normal or corrected-to-normal vision. Additionally, participants were screened for MRI compatibility and contraindications. Participants gave written informed consent in accordance with the Institutional Review Board procedures at the University of California, Los Angeles (UCLA). Participant enrollment was limited to UCLA undergraduate students in an effort to limit the variance in the types of life experiences and environmental settings captured by their wearable digital cameras. Participants consented for their camera's photographs to be viewed by the experimenters and by other participants in the experiment. Participants were remunerated with $215 for their time and effort.

Procedure

Wearable cameras

All participants were provided with a necklace-mounted Autographer device (OMG Life, Oxford, UK); this small 5-megapixel digital camera contains electronic sensors that detect variations in the external environment, including changes in ambient light and movement. When the Autographer's sensors are triggered, it automatically takes color still-photographs (2592×1936 pixels) using its forward-facing, wide-angle lens with a 136° field of view. The Autographer does not include a display screen, so participants were unable to review any of their photographs. Participants retained complete discretion over when and where their cameras were actively taking photographs; participants were able to turn off their Autographer cameras whenever they desired.

Stimuli

Experimental stimuli consisted of image sequences created from the photographs captured by participants' Autographer cameras. After the completion of the three-week camera-wearing interval, 40 unique events per week were identified for each participant. For each unique event, eight photographs were selected based on their ability to best depict the temporal progression of that experience. These eight photographs formed one "event sequence." The amount of time elapsing between the first and last photograph of each event sequence was constrained to be no more than 15 min. A total of 120 event sequences were created from photographs of each participant's life. All event sequences were manually selected by the same experimenters throughout the study. Event sequences were chosen according to a set of predetermined criteria, delineated prior to the start of the experiment, such that there was an emphasis on selecting more unique events over generic ones (since all participants were UCLA students, an effort was made to ensure that the photographs within each event sequence contained sufficient details so that the camera wearer would have a reasonable chance of determining that the event was from his/her own life). We also attempted to sample a wide variety of experiences and avoid overrepresentation of specific activities, individuals, and locations that tended to recur day after day. When selecting event sequences within a given day, our protocol enforced a rule that no more than two event sequences could be drawn from a single activity (e.g., if a participant attended a football game, we might create two event sequences depicting different aspects of that experience).

Participants' event sequences were constructed from experiences throughout each day and contained both indoor and outdoor events. Due to the limited number of Autographer cameras in our possession and the time-consuming nature of our stimulus selection procedures, participants were recruited in a rolling fashion. Although this could raise potential concerns that participants would be able to differentiate their photographs from those of another participant based on superficial characteristics like weather conditions and people's clothing choices, we were fortunate that the year-round temperate climate of Los Angeles and minimal rainfall led all participants' photographs to appear highly similar in terms of lighting, weather, and clothing. Minor edits were performed on some images to ensure that the photographs did not contain visual cues that could immediately enable self-identification, such as cropping to remove participants' visible body parts. All stimuli were standardized to the same dimensions (460×345 pixels) and presented against a gray background (1440×900 pixels) during both the photograph pre-exposure session and the fMRI scan session.

Experimental phases

This study consisted of three phases: a camera-wearing phase, a photograph pre-exposure phase, and a fMRI scan phase.

Phase 1: camera wearing. In the first phase of the experiment, participants wore Autographer cameras daily over the course of three weeks. Participants were instructed to wear their camera devices, at their discretion, for at least 8 h a day to ensure that a sufficient number of photographs were captured and that these photographs depicted a reasonably diverse set of life events. Participants made weekly visits to the laboratory where the experimenters downloaded their photographs. The cameras were returned to the experimenters after 21 days. The number of viable photographs per week ranged between 1620 and 10,594 images (median = 4332), depending on participants' camera-wearing habits. Participants were unaware of the goals of our research study and had no knowledge of how the photographs captured by the camera would be used in the upcoming experimental task.

Phase 2: photograph pre-exposure. The second phase of the experiment consisted of the photograph pre-exposure session, which was conducted in the laboratory one week after the conclusion of the camera-wearing phase. The purpose of this session was to expose participants to a subset of their own event sequences as well as a subset of another randomly selected participant's event sequences in order to subsequently measure the behavioral and neural consequences of this pre-exposure. Participants were presented with 120 event sequences (60 from their own life and 60 from another participant's life; evenly sampled from the three weeks of camera-wearing) in random order, with the constraint that no more than three sequences in a row were from their own life or another participant's life. The eight photographs within each event sequence were shown in the original temporal order in which they had been captured. For each event sequence, participants were asked to rate the distinctiveness of the depicted event on a 4-point scale. This task was used to ensure attentive processing and incidental encoding of the stimuli. Participants were not explicitly informed as to which event sequences were derived from their own cameras and which were derived from other individuals' cameras. Event sequences that appeared during the pre-exposure phase will be referred to as "Previewed" sequences, whereas event sequences that did not appear during this phase will be referred to as "Non-Previewed" sequences.

The trial structure of the pre-exposure session was equated with that

of the subsequent fMRI scan session as closely as possible. The timing of each trial was identical. All trials began with the presentation of an 8-photograph event sequence, where each individual photograph within a sequence was shown for 0.8 s, with a 0.2-s fixation interval between successive images. Presentation of the event sequence was followed by a 4-s response period for participants to indicate their distinctiveness rating and then a 6-s inter-trial interval (ITI) with fixation.

Phase 3: fMRI scanning. The last phase of the experiment occurred one day after the pre-exposure session was administered. Participants underwent fMRI scanning while viewing and making judgments about 240 event sequences (120 from their own life and 120 from another participant's life, with 50% of the sequences from each condition previously encountered during the pre-exposure session). During each trial, an 8-photograph sequence was presented with the same timing used during the pre-exposure session (Fig. 1). Participants were required to make two judgments about each event sequence: (1) a judgment about the source of the photographs indicating whether the depicted event was captured by one's own camera ("Self") or whether it was from another person's life ("Other"), and (2) a judgment about whether the photographs were presented in their originally acquired temporal order ("Intact") or whether some of the photographs were presented in a temporally scrambled order ("Scrambled"). The inclusion of temporally scrambled sequences in this experiment—which comprised 50% of all trials (evenly distributed across conditions) and involved the rearrangement of the final four photographs of a sequence—was intended to facilitate an analysis of temporal order memory and schema-based prediction error, but this is beyond the scope of the present investigation and will be featured in a separate report. Thus, for the purposes of the present report, we have elected to collapse across Intact and Scrambled trials and focus our analyses on the neural signatures of the two other critical experimental factors of photographic source (Self vs. Other) and pre-exposure (Previewed vs. Non-Previewed).

Participants were instructed to indicate their judgments by pressing one of four keys on an MRI compatible button-box using the fingers of their right hand. The two judgments required on each trial (photographic source and temporal order) were combined into a single response with the following options: "Self and Intact," "Self and Scrambled," "Other and Intact," and "Other and Scrambled." Although participants were informed that some trials would feature event sequences that they had encountered in the laboratory on the previous day (in their original temporally intact order), they were not asked to make judgments indicating whether or not each trial's event sequence had been pre-exposed. Over the course of a scanning session, participants viewed all 120 of the event sequences selected from their own life and all 120 of those selected from another participant's life; thus, the Self/Other conditions were matched in terms of the number of event sequences that were selected from each of the three weeks of the respective wearers' lives. Additionally, an equal number of event sequences per week were randomly assigned to be Previewed/Non-Previewed. This ensures that both the temporal remoteness of events and the variability of life experiences across time were not confounded with our four experimental conditions of interest.

fMRI data acquisition

All neuroimaging data were acquired on a Siemens 3.0 T Tim Trio MRI scanner at the UCLA Staglin IMHRO Center for Cognitive Neuroscience. Functional volumes were obtained with T2*-weighted whole-brain echo-planar imaging (EPI) sensitive to blood-oxygen-level-dependent (BOLD) contrast. Each EPI volume consisted of 35 axial slices acquired in an interleaved manner (TR = 2000 ms, TE = 27 ms, flip angle = 75°, FoV = 192 mm, voxel size = 3.0 × 3.0 × 3.5 mm). The experiment included 10 functional runs, each with 221 vol, where the first 3 vol of each run were discarded to account for T1 stabilization. A whole-brain high-resolution anatomical scan (T1-weighted structural MPRAGE) and a T2-weighted in-plane anatomical scan were also collected for each participant to aid in spatial registration and normalization. Additionally, a field map image was acquired for each participant to assist in unwarping procedures for areas susceptible to distortion.

fMRI preprocessing and univariate analysis

Prior to analysis, EPI timeseries data were preprocessed using conventional procedures from SPM8 (http://www.fil.ion.ucl.ac.uk/spm/software/spm8/) including slice time correction, motion correction with a six-parameter rigid-body realignment procedure, unwarping, co-registration, segmentation, and normalization to MNI stereotactic space. Co-registration involved a two-part procedure where the in-plane anatomical image was registered to the mean functional image and the MPRAGE was registered to the in-plane anatomical. The MPRAGE was then segmented into cerebrospinal fluid, white matter, and gray matter. Nonlinear warping parameters were computed to normalize each participant's grey matter image to a grey matter template in MNI space, and these warping parameters were applied to all functional images, which were resampled into 3-mm isotropic voxels. Finally, potential artifacts in the EPI data were mitigated using the GLMdenoise procedure (https://www.nitrc.org/projects/glmdenoise/); Kay et al., 2013). This denoising procedure begins by identifying task-unrelated brain voxels from a univariate general linear model (GLM), and then uses the timeseries of these "noise pool" voxels to develop a set of nuisance regressors, which we then regressed out of the timeseries of all voxels to generate a denoised timeseries. To ensure independence of data across runs, a 5-fold cross-validation procedure was performed where the 10 runs of the study were split into 5 pairs and the GLMdenoise cross-validation procedure

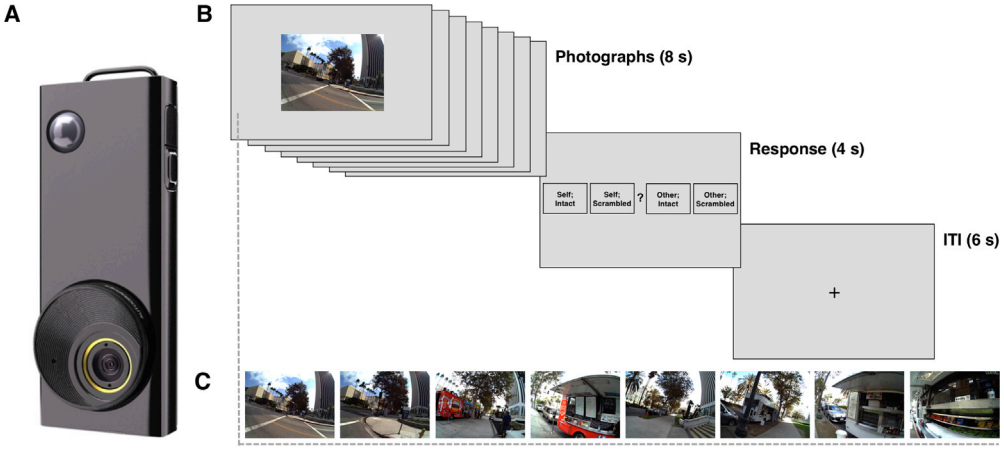

Fig. 1. (A) An Autographer digital camera was worn by participants for 3 weeks to automically capture photographs of their life events. (B) Schematic of an experimental trial from the fMRI session. In each trial, the 8 photographs of an event sequence were presented for 0.8 s each, separated by 0.2-s fixation intervals. Presentation of the event sequence was followed by a 4-s response period. A 6-s inter-trial interval (ITI) of resting fixation separated trials from one another. (C) An example of an event sequence that might be presented during one trial.

was implemented within each of the pairs.

Networks of interest

Networks of interest were obtained from the McDermott et al. (2009) ALE meta-analysis. Their meta-analysis identified one set of brain regions consistently associated with autobiographical memory, derived from peak coordinates reported in 14 prior fMRI studies in which activation associated with the retrieval of personal events (typically cued with words, sentences, or pictures) was compared to that of a control task. They also identified another largely non-overlapping set of regions associated with the retrieval of laboratory-based memories, derived from peak coordinates reported in 18 prior fMRI studies in which participants made recognition judgments on either word, picture, object, or face stimuli that had been studied in a laboratory setting (the activation maps in these studies were typically derived from contrasts of hits > correct rejections). The "Autobiographical Network" included areas such as the medial PFC, posterior cingulate/retrosplenial cortex, angular gyrus, and bilateral MTL (hippocampus/parahippocampal gyri). The "Laboratory-based Network" included areas such as the left inferior frontal gyrus, bilateral middle frontal gyri, bilateral frontal operculum, precuneus, bilateral inferior parietal cortex, posterior cingulate cortex, and left MTL (posterior parahippocampal gyrus). Overlap between the Autobiographical Network and the Laboratory-based Network was very limited—indeed, the only shared regions were a few small clusters in the lateral inferior frontal gyrus, posterior cingulate cortex, and thalamus.

The FDR-corrected ALE maps were obtained from McDermott et al. (2009) and resampled to 3-mm^3 voxel resolution to create two networks of interest for use as masks in the following analyses (Fig. 2). The Autobiographical Network (originally 1526 voxels) and the Laboratory-based Network (originally 2580 voxels) were then modified to ensure coverage in all of our participants, to exclude all overlapping voxels (94 voxels), and to equate their total size. The latter was done to ensure that any differences in classification performance between the two networks could not be attributable to a greater number of features (i.e., voxels) in one network. Given the smaller size of the resulting Autobiographical Network mask (1432 voxels), the most significant 1432 voxels in the Laboratory-based Network were retained, and the ALE values of the voxels within each network were binarized to create masks. These masks, along with other additional results, have been made publically available (https://neurovault.org/collections/3412/) on Neurovault (Gorgolewski et al., 2015).

Multi-voxel pattern analysis (MVPA)

MVPA was applied within each network of interest to evaluate the sensitivity of the BOLD activation patterns to photographic source (Self vs. Other) and pre-exposure status (Previewed vs. Non-Previewed). MVPA was conducted in MATLAB with the Princeton MVPA Toolbox (http://code.google.com/p/princeton-mvpa-toolbox) and custom code. The unsmoothed timeseries data of each voxel within each run was first detrended to eliminate both linear and quadratic trends, high-pass filtered (128-s period), and then z-scored. No feature selection was implemented (i.e., all voxels with a given network-of-interest mask were used as features). For each trial, BOLD signal was averaged across the 4th, 5th, 6th, and 7th post-onset volumes (TRs), which correspond to 6–14 s after event sequence onset and thus capture the window of peak activation associated with stimulus processing and evaluation. In order to diminish the likelihood that the classifier's predictions could be influenced by activity fluctuations that scale with subtle, yet consistent, response time (RT) differences between conditions, we removed the effects of RT from each voxel's activity on a trial-by-trial basis with linear regression and retained the residuals for our analyses (Todd et al., 2013). The resulting single trial activity patterns were then z-scored once more (across trials) and used to train a regularized logistic regression (RLR) algorithm to classify between trials of two different conditions. We have found this classification algorithm to perform well in similar experimental paradigms (Rissman et al., 2010, 2016; Uncapher et al., 2015). This algorithm included a ridge penalty term as a Gaussian prior on the feature weights; following Rissman et al. (2016), this penalty parameter was set to a fixed value of 100 for all classifications.

Within-subjects pattern classification was run using a 5-fold cross-validation procedure, with each fold comprised of the data from two runs (corresponding to the same two-run subsets used for the GLMdenoise procedure). Within each fold, if the number of trials from each condition were unequal, the trial counts were balanced by randomly discarding trials from the more plentiful condition. Trials from four of the five folds (eight of the original 10 runs) were used to train the classifier, and its performance was then assessed by having the classifier predict the condition labels of each trial from the held-out fold (the remaining pair of runs). These probabilistic predictions were tabulated across all testing trials and ranked to allow the calculation of receiver operating characteristic (ROC) curves, reflecting the relationship between the classifier's true positive and false positive rate across a range of potential decision boundaries. Our primary classification performance metric was the area under the curve (AUC). This measure, widely used in the machine learning literature and considered more informative than overall accuracy (Bradley, 1997), can be interpreted as the probability that a randomly chosen member of one class has a smaller estimated probability of belonging to the other class than has a randomly chosen member of the other class. In other words, AUC indexes the mean accuracy with which a randomly chosen pair of Class A and Class B trials could be assigned to their correct class (0.5 is chance performance; 1.0 is perfect performance). The ROC curves reflecting classifier performance within the Autobiographical and Laboratory-based Networks, from which the AUCs are derived, can be seen in Supplementary Fig. 1. Because our trial count balancing procedure involved discarding random subsets of trials, we repeated the entire 5-fold cross validation procedure 20 times for each participant and saved the mean AUC. Group-level analyses were implemented as one-sample, two-tailed *t*-tests comparing the AUC results from a given classification against a theoretical null hypothesis value of 0.5. We adopted a significance threshold of $t_{(17)} = 2.458$ ($p < 0.025$,

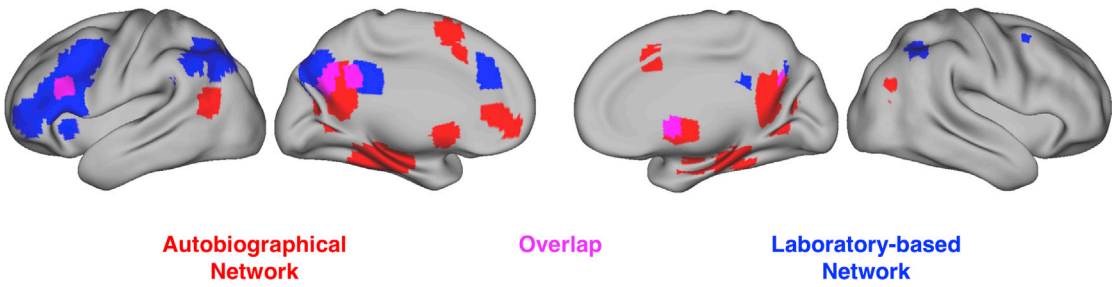

Fig. 2. Networks of interest used for our multi-voxel pattern analyses. These networks were derived from the McDermott et al. (2009) meta-analysis of fMRI studies of autobiographical memory (red regions) and laboratory-based memory (blue regions). Prior to analyses, areas of overlap (magenta regions) were excluded, and networks were equated for voxel size, with only the top 1432 voxels included in each network of interest.

two-tailed) for these results in order to apply Bonferroni correction accounting for two tests (i.e., the fact that we ran classifications on two different networks). An additional set of analyses using shuffled class labels confirmed that the empirical chance-level indeed converged on AUC = 0.5, indicating that no insidious biases were present in our classification workflow. For each classification, a paired-samples, two-tailed *t*-test was then run to compare the decoding performance resulting from application of MVPA within the two networks of interest.

Although our primary analyses focused on the comparison of classification performance for our two meta-analytically defined networks-of-interest, we also conducted exploratory whole-brain searchlight mapping analyses (Kriegeskorte et al., 2006) to provide a more complete portrait of the anatomical distribution of regions sensitive to photographic source and pre-exposure. The searchlight analyses were implemented by training and testing a series of RLR classifiers, each using the voxels within a small spherical mask (radius = 3 voxels; maximum volume = 123 voxels). This process was repeated with spheres centered at all brain voxels within an 80,126-voxel whole-brain mask. Each classification was performed using the same 5-fold cross-validation procedures described above (including linearly regressing out the response times); the only difference was that instead of re-running each classification 20 times with different balanced trial selections, each classification was run once (due to the computationally-intensive nature of this analysis). Group-level *t*-maps were created by comparing the mean AUC across subjects to the null hypothesis of 0.5 for each voxel. The resulting maps were corrected for multiple comparisons using AFNI's 3dClustSim (Cox, 1996), which employs Monte Carlo simulations to calculate the cluster size required to achieve a whole-brain corrected threshold of $p < 0.05$. Specifically, our correction procedure utilized one of the more recent 3dClustSim approaches.[1] This procedure requires an estimate of the empirical smoothness of the data under null hypothesis conditions, which we derived by re-running the searchlight classifications 20 times using shuffled class labels and averaging the resulting maps; smoothness was computed using AFNI's 3dFWHMx, resulting in an estimated effective smoothness of FWHM = 16.15 mm. Using this method, we determined that the combination of a voxel height threshold of $p < 0.005$ (one-tailed) and a minimum cluster size of 89 voxels yielded appropriate correction at $p < 0.05$.

Results

Behavioral results

On average, participants were 89.0% correct in indicating the photographic source (Self vs. Other) of the depicted event sequences, which was well above chance ($t_{(17)} = 24.506$, $p < 10^{-13}$). Although the experimental task did not prompt subjects to indicate the pre-exposure status of events, participants' performance can be assessed based on whether the photographs of an event had been previously encountered during Phase 2 (Previewed) or whether they were being encountered for the first time (Non-Previewed); Fig. 3A. A repeated measures ANOVA conducted on photographic source judgment accuracy revealed no main effect of photographic source (Self events: 89.8%, Other events: 88.1%; $F_{(1,17)} = 0.744$, $p = 0.401$), but there was a main effect of pre-exposure (Previewed events: 90.9%, Non-Previewed events: 87.0%; $F_{(1,17)} = 19.348$, $p < 10^{-3}$). There was also a significant interaction between photographic source and pre-exposure ($F_{(1,17)} = 22.624$, $p < 10^{-3}$) such that Self events were more successfully labeled as "Self" when they had been Previewed (93.7%) than when they were Non-Previewed (85.9%) ($p < 10^{-4}$), whereas Other events were equally likely to be successfully labeled as "Other" when they had been Previewed (88.1%) as when they were Non-Previewed (88.1%) ($p = 0.934$).

We also analyzed the response times of trials with correct photographic source judgments; Fig. 3B. A repeated measures ANOVA revealed no main effect of photographic source (Self events: 2.112 s, Other events: 2.094 s; $F_{(1,17)} = 0.231$, $p = 0.637$). However, there was a main effect of pre-exposure (Previewed events: 2.065 s, Non-Previewed events: 2.141 s; $F_{(1,17)} = 11.235$, $p = 0.004$). There was also a significant interaction ($F_{(1,17)} = 14.026$, $p = 0.002$), such that Self events more rapidly labeled as "Self" when they had been Previewed (2.040 s) than when they were Non-Previewed (2.183 s) ($p < 10^{-3}$), whereas Other events had comparable RTs whether they had been Previewed (2.091 s) or Non-Previewed (2.098 s) ($p = 0.784$).

MVPA results

We assessed the performance of separate classifier models trained and tested using the voxel activity patterns within either the Autobiographical Network or within the Laboratory-based Network. Only trials for which participants indicated the correct photographic source (Self/Other status) of the event were used in the classification analyses. While analyses of the incorrectly performed trials (e.g., false memories and forgotten experiences) could potentially be of interest, participants' generally high accuracy levels resulted in low trial counts for these conditions, rendering classification too underpowered. Our MVPA analyses first examined the ability of each network to decode the photographic source of individual events (i.e., to discriminate Self events from Other events); Fig. 4A. This classification was highly accurate for both the Autobiographical Network (mean AUC = 0.843; $t_{(17)} = 22.201$, $p < 10^{-13}$) and the Laboratory-based Network (mean AUC = 0.793; $t_{(17)} = 13.435$, $p < 10^{-9}$); for group-averaged classification importance maps (Johnson et al., 2009) depicting which regions within each network provided maximally diagnostic signals for discriminating Self vs. Other events, see Supplementary Figs. 2A–B. A direct comparison between the classification performance of each network revealed that the Autobiographical Network outperformed the Laboratory-based Network ($t_{(17)} = 6.594$, $p < 10^{-5}$). This robust decoding of photographic source held up when we separately analyzed trials of only Previewed events or only Non-Previewed events, despite an approximately 50% reduction in the dataset for each case. When the analysis was restricted to Previewed events, classification of Self/Other status remained well above chance in both the Autobiographical Network (mean AUC = 0.798; $t_{(17)} = 16.683$, $p < 10^{-11}$) and the Laboratory-based Network (mean AUC = 0.746; $t_{(17)} = 9.828$, $p < 10^{-7}$), with the Autobiographical Network showing significantly better performance ($t_{(17)} = 4.174$, $p < 10^{-3}$). When the analysis was restricted to Non-Previewed events, classification of Self/-Other status remained well above chance in both the Autobiographical Network (mean AUC = 0.821; $t_{(17)} = 16.882$, $p < 10^{-11}$) and the Laboratory-based Network (mean AUC = 0.788; $t_{(17)} = 11.174$, $p < 10^{-8}$), with the Autobiographical Network again showing significantly better performance ($t_{(17)} = 2.124$, $p = 0.049$). Finally, we examined whether the Self/Other status of events could be decoded even when never-before-seen photographs of one's own life events (i.e., Self, Non-Previewed) were compared to previously seen photographs of someone else's life events (i.e., Other, Previewed). This analysis pits memories for firsthand experiences of an event against secondhand knowledge of someone else's experiences, allowing a critical test of whether a brain-based classifier is capable of distinguishing between these two forms of event recognition. As with the prior analyses, this classification was found to be highly accurate in both the Autobiographical Network (mean AUC = 0.817; $t_{(17)} = 14.525$, $p < 10^{-10}$) and the Laboratory-based Network (mean AUC = 0.773; $t_{(17)} = 9.577$, $p < 10^{-7}$), with the former network outperforming the latter ($t_{(17)} = 4.299$, $p < 10^{-3}$).

We next examined the ability of brain activity patterns within each network to decode the pre-exposure status of individual events (Fig. 4B).

[1] This 3dClustSim method involved deriving the ACF parameters from a mixed-model calculation such that "a*exp(-r*r/(2*b*b))+(1-a)*exp(-r/c)" where a, b, and c indicate three shape variables (Cox, 1996). Our ACF parameters were 0.33, 7.12, and 11.2.

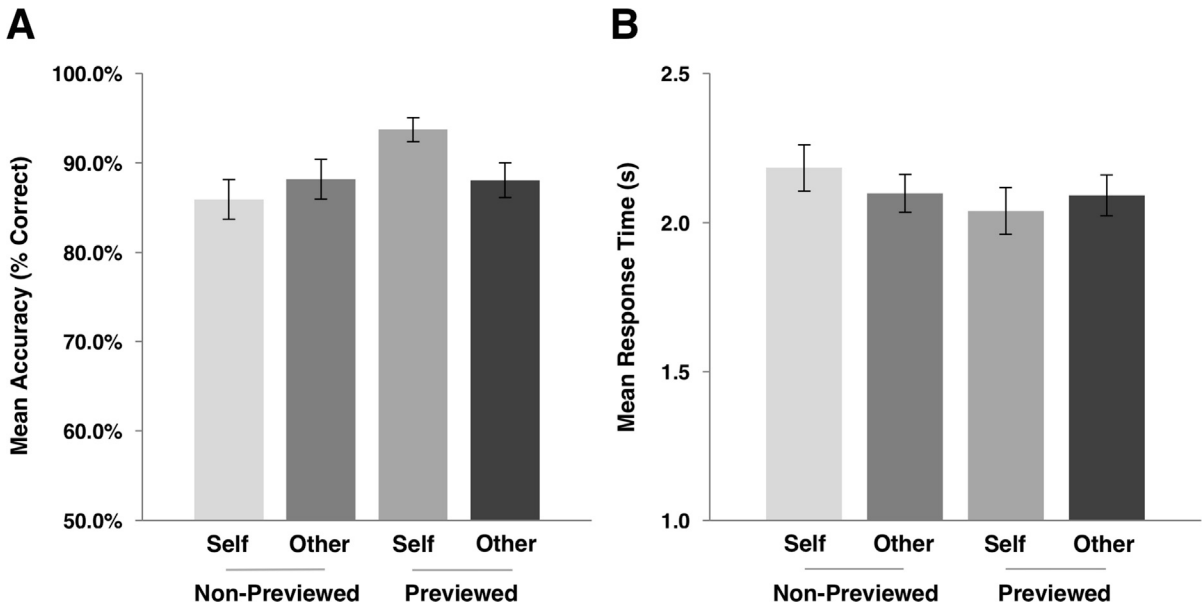

Fig. 3. Behavioral results. (A) Mean accuracy of photographic source judgments and (B) mean response times to correctly performed trials are shown for the individual photographic source and pre-exposure conditions. Error bars represent standard error.

We anticipated that this distinction might be harder to decode, given that photograph pre-exposure was not a task-relevant variable (i.e., participants were not explicitly asked to judge whether photographs were Previewed or Non-Previewed). This was indeed the case for the Autobiographical Network, where classification of Previewed vs. Non-Previewed trials was no better than chance (mean AUC = 0.518; $t_{(17)} = 1.524$, $p = 0.146$). However, activity patterns within the Laboratory-based Network showed pre-exposure decoding performance that was reliably above-chance (mean AUC = 0.585; $t_{(17)} = 6.379$, $p < 10^{-5}$). Direct comparison of classification performance in the two networks showed a significant advantage for the Laboratory-based Network ($t_{(17)} = 5.417$, $p < 10^{-4}$). A group-averaged classification importance map depicting which regions within the Laboratory-based Network tended to be most diagnostic for discriminating Previewed vs. Non-Previewed events is provided in Supplementary Fig. 2C.

We next repeated the Previewed vs. Non-Previewed classifications separately for Self events and for Other events. When restricting the analysis to Self events, classification performance within the Autobiographical Network improved slightly but did not achieve Bonferroni-corrected significance relative to chance (mean AUC = 0.543; $t_{(17)} = 2.189$, $p = 0.043$). Classification within the Laboratory-based Network remained above chance (mean AUC = 0.599; $t_{(17)} = 6.644$, $p < 10^{-5}$) and was significantly better than that of the Autobiographical Network ($t_{(17)} = 2.813, p = 0.012$). When restricting the analysis to Other events, classification within the Autobiographical Network was at chance (mean AUC = 0.510; $t_{(17)} = 0.680$, $p = 0.506$). Classification within the Laboratory-based Network (mean AUC = 0.559) was significantly better than that of the Autobiographical Network ($t_{(17)} = 2.242, p = 0.039$) and was also significantly better than chance ($t_{(17)} = 2.481, p = 0.024$).

These findings suggest that the Autobiographical and Laboratory-based Networks are preferentially sensitive to different mnemonic characteristics, with the Autobiographical Network being better than the Laboratory-based Network at decoding whether a depicted event is from one's own life and the Laboratory-based Network being better than the Autobiographical Network at decoding whether the photographs of an event have been previously encountered. A repeated measures ANOVA confirmed this interaction ($F_{(1,17)} = 81.685$, $p < 10^{-7}$; Fig. 5). Importantly, this interaction remained significant when the classification analyses were re-run using only the data from the temporally intact event sequences ($F_{(1,17)} = 19.346$, $p < 10^{-3}$). Moreover, paired-sample, two-tailed *t*-tests revealed that Self vs. Other decoding accuracy was not significantly influenced by photograph pre-exposure, nor was Previewed vs. Non-Previewed decoding accuracy influenced by personal relevance (when Bonferroni correction was applied for two comparisons within each network; critical alpha level: $p < 0.025$, two-tailed). Within the Autobiographical Network, the difference between Self, Previewed vs. Self, Non-Previewed and Other, Previewed vs. Other, Non-Previewed trials was not significant ($t_{(17)} = 1.210$, $p = 0.243$), nor was the difference between Self, Non-Previewed vs. Other, Non-Previewed and Self, Previewed vs. Other, Previewed ($t_{(17)} = 2.086$, $p = 0.052$). Similarly, within the Laboratory-based Network, the difference between Self, Previewed vs. Self, Non-Previewed and Other, Previewed vs. Other, Non-Previewed was not significant ($t_{(17)} = 1.536$, $p = 0.143$), nor was the difference between Self, Non-Previewed vs. Other, Non-Previewed and Self, Previewed vs. Other, Previewed ($t_{(17)} = 2.043$, $p = 0.057$).

Even though our two networks of interest do not contain many regions typically associated with motor responses, we sought to assuage potential concerns that our results could be influenced by a confound between our memory conditions and the associated button-mappings (note that this is only an issue for the Self/Other distinction; since the Previewed/Non-Previewed distinction was not task-relevant, the decoding of pre-exposure status cannot be influenced by response demands). To this end, we explicitly excluded any portions of our two network masks that overlapped with any motor-related anatomical regions (precentral gyrus, postcentral gyrus, supplementary motor area, and cerebellum) as defined by the Automated Anatomical Labeling atlas (Tzourio-Mazoyer et al., 2002), and we then reran the classifications of photographic source and pre-exposure status. For the Self vs. Other classification, the Autobiographical Network (mean AUC = 0.848; $t_{(17)} = 24.001$, $p < 10^{-13}$) continued to show significantly greater decoding performance ($t_{(17)} = 5.713$, $p < 10^{-4}$) than the Laboratory-based Network (mean AUC = 0.798; $t_{(17)} = 13.937$, $p < 10^{-10}$). Likewise, for the Previewed vs. Non-Previewed classification, the Laboratory-based Network (mean AUC = 0.580; $t_{(17)} = 6.584$, $p < 10^{-5}$) continued to demonstrate significantly greater decoding performance ($t_{(17)} = 4.762$, $p < 10^{-3}$) than the Autobiographical Network (mean AUC = 0.520; $t_{(17)} = 1.869$, $p = 0.079$). Thus, our core MVPA effects remained significant regardless of whether voxels from motor regions were included in our networks of interest, indicating that these findings are not likely dependent upon motor contributions.

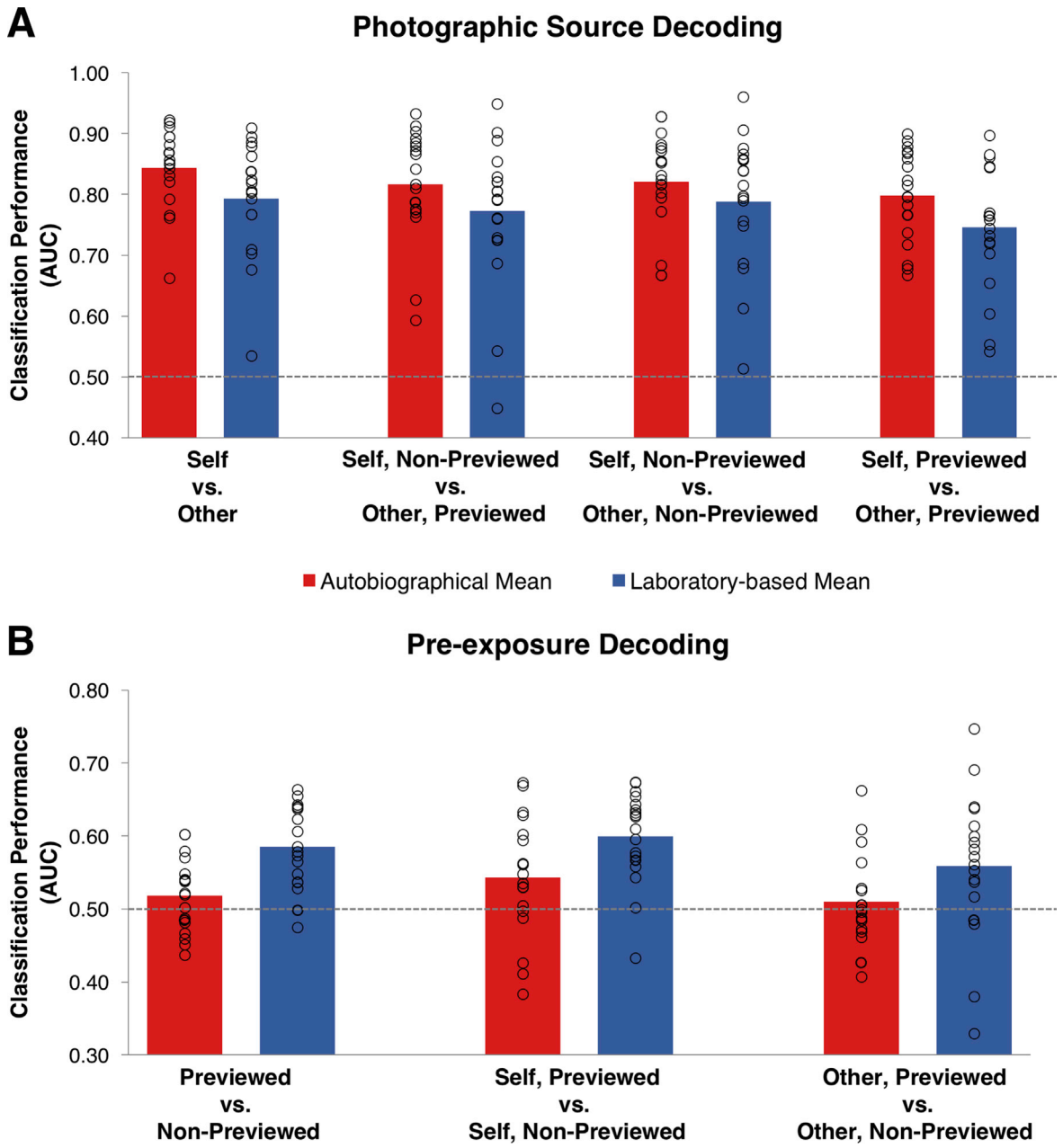

Fig. 4. Classification performance within the Autobiographical Network (red bars) and the Laboratory-based Network (blue bars). (A) Decoding of photographic source (Self vs. Other) across all trials and for analyses restricted to subsets of trials based on their pre-exposure status. (B) Decoding of pre-exposure status (Previewed vs. Non-Previewed) across all trials and for analyses restricted to subsets of trials based on their photographic source. The bars depict mean AUC across subjects, and the markers depict the AUC values of individual subjects. The dashed line indicates chance-level performance.

As a further indication that our findings are not likely driven by motor contributions, we ran a separate set of analyses in which we trained and tested classifiers using the data from individual post-onset time points. We found that decoding of Self vs. Other status (the task-relevant dimension) achieved significance in both networks as early as the 3rd TR. This represents BOLD data acquired 4–6 s into the trial, which reflects neural activity evoked during the first few seconds of stimulus viewing and likely well before participants had prepared a response; Supplementary Fig. 3. Decoding performance levels across the two networks did not diverge until later in the timecourse (i.e., the 6th and 7th TRs) when classification within the Autobiographical Network began to show a significant advantage. This is likely because autobiographical retrieval processes (e.g., memory search, mental time travel, contextual reinstatement, etc.) supported by the Autobiographical Network take several seconds to emerge and are aided by the additional context cues provided by each successively presented image in a sequence. Although BOLD data from these later time points could potentially be influenced by response demands, it is notable that the Autobiographical Network demonstrated better classification than the Laboratory-based Network, despite the fact that the latter network contains more brain regions that have been associated with decision and response-related processes.

Many MVPA studies incorporating comparisons of classifier performance utilize parametric statistical tests such as *t*-tests. However, there have been suggestions that nonparametric statistical tests are more appropriate for classification-based analyses (e.g., Pereira et al., 2009), in part as such tests require fewer statistical assumptions. To ensure that our set of MVPA results were robust and did not depend on potentially problematic statistical assumptions, comparisons of classification

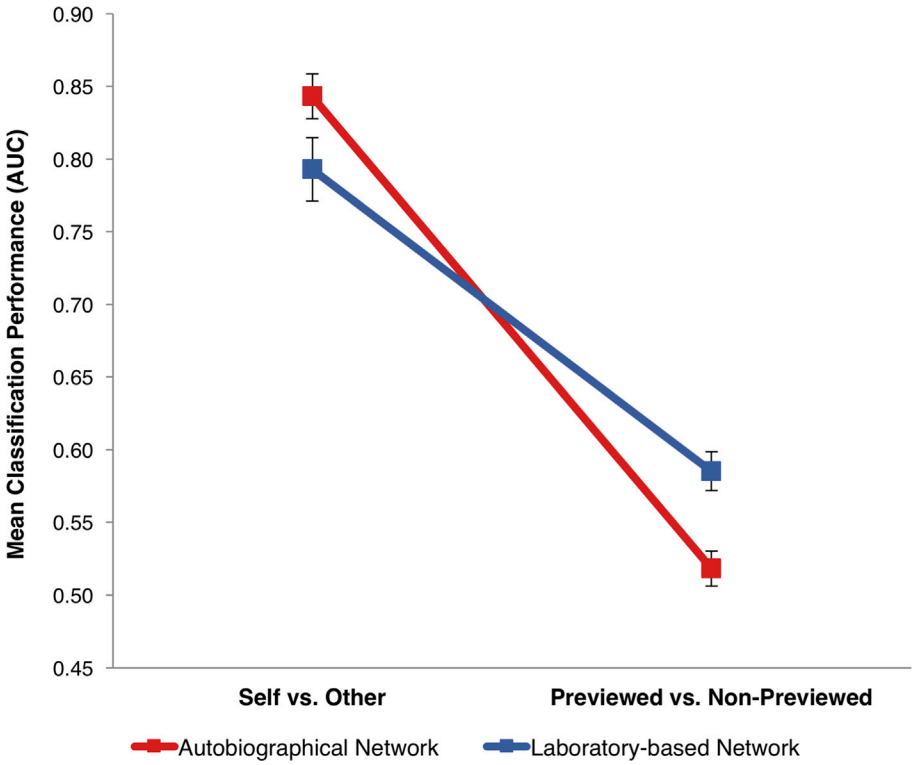

Fig. 5. The interaction between the Autobiographical Network and the Laboratory-based Network's ability to classify photographic source and pre-exposure status. Relative to the Laboratory-based Network, the Autobiographical Network demonstrated better decoding of photographic source (Self vs. Other), but poorer decoding of pre-exposure status (Previewed vs. Non-Previewed).

performance across photographic source and pre-exposure status were assessed again using two-tailed, nonparametric paired Wilcoxon signed ranks exact tests conducted with SPSS. When assessing decoding performance regarding the photographic source of events, classification within the Autobiographical Network continued to be significantly better than the Laboratory-based Network for: Self vs. Other events ($p < 10^{-5}$); Self, Non-Previewed vs. Other, Previewed events ($p < 10^{-3}$); and Self, Previewed vs. Other, Previewed events ($p<10^{-3}$). In comparison, classification within the Laboratory-based Network continued to be significantly better than the Autobiographical Network for: Previewed vs. Non-Previewed events ($p < 10^{-4}$); Self, Previewed vs. Self, Non-Previewed events ($p = 0.003$); and Other, Previewed vs. Other, Non-Previewed events ($p = 0.038$). As such, all of our core classification results remained unchanged, with the exception of decoding performance for Self, Non-Previewed events vs. Other, Non-Previewed events ($p = 0.054$), which although strongly trending with the Autobiographical Network outperforming the Laboratory-based Network, narrowly failed to achieve significance.

While our network-based classification analyses demonstrated a clear dissociation, presumably reflecting the differential contributions of these two networks to memory retrieval, we next used whole-brain searchlight analyses to evaluate whether the anatomical distribution of decoding effects would roughly adhere to these networks (Fig. 6). As with the network-based analyses, group-level searchlight maps revealed that decoding of photographic source (Self vs. Other) was much more robust than decoding of pre-exposure status (Previewed vs. Non-Previewed). This was true throughout much of the brain, and indeed no regions showed significantly greater decoding performance for pre-exposure than photographic source. That Self/Other status was more readily decodable is not surprising, given that this distinction was task-relevant to participants and highly salient. The more interesting question pertains to the relative anatomical distribution of peak decoding performance. The strongest effects for the Self vs. Other classification were observed in regions that overlapped heavily with the Autobiographical Network, including the ventral and posterior aspect of lateral parietal cortex (bilaterally, but with preferential effects in the left hemisphere), medial parietal cortex (including posterior cingulate and retrosplenial cortex), anterior ventromedial PFC, and regions of the MTL (including parahippocampal cortex). We note that the robust classification performance observed in left dorsal motor cortex is likely linked to participants' use of their right hand to make different finger presses for Self and Other trials. In contrast, regions exhibiting significant decoding of Previewed/Non-Previewed status showed notable overlap with the regions of the Laboratory-based Network, including prominent involvement of the left lateral PFC and bilateral posterior parietal cortex (including regions concentrated along the lateral bank of the intraparietal sulcus). Peak searchlight effects within regions of the two networks are listed in Table 1, and the maps are publically accessible on Neurovault (https://neurovault.org/collections/3412/). Interestingly, several of the regions that the McDermott et al. (2009) meta-analysis had identified as being associated with both autobiographical and laboratory-based retrieval (i.e., the regions depicted in magenta in Fig. 2B, which were excluded from our networks-of-interest analyses) showed significant decoding of both photographic source and pre-exposure status in our searchlight analyses.

To better quantify the differences in classification performance, the number of significant voxels with accuracy values corresponding to $p < 0.05$ were calculated for each participant's searchlight results (based on comparison of each searchlight's observed classification accuracy relative to the binomial distribution null-hypothesis) and compared across the two networks. The difference in voxel numbers was evaluated with a paired-samples, two-tailed *t*-test that was Bonferroni corrected for two comparisons (critical alpha level: $p < 0.025$). For decoding of Self vs. Other trials, the Autobiographical Network (mean number of voxels = 1008.3; 70.4% of the network) contained a larger number of significant voxels ($t_{(17)} = 3.543$, $p = 0.003$) in comparison with the Laboratory-based Network (mean number of voxels = 878.1; 61.3% of the network). In contrast, for the decoding of Previewed vs. Non-

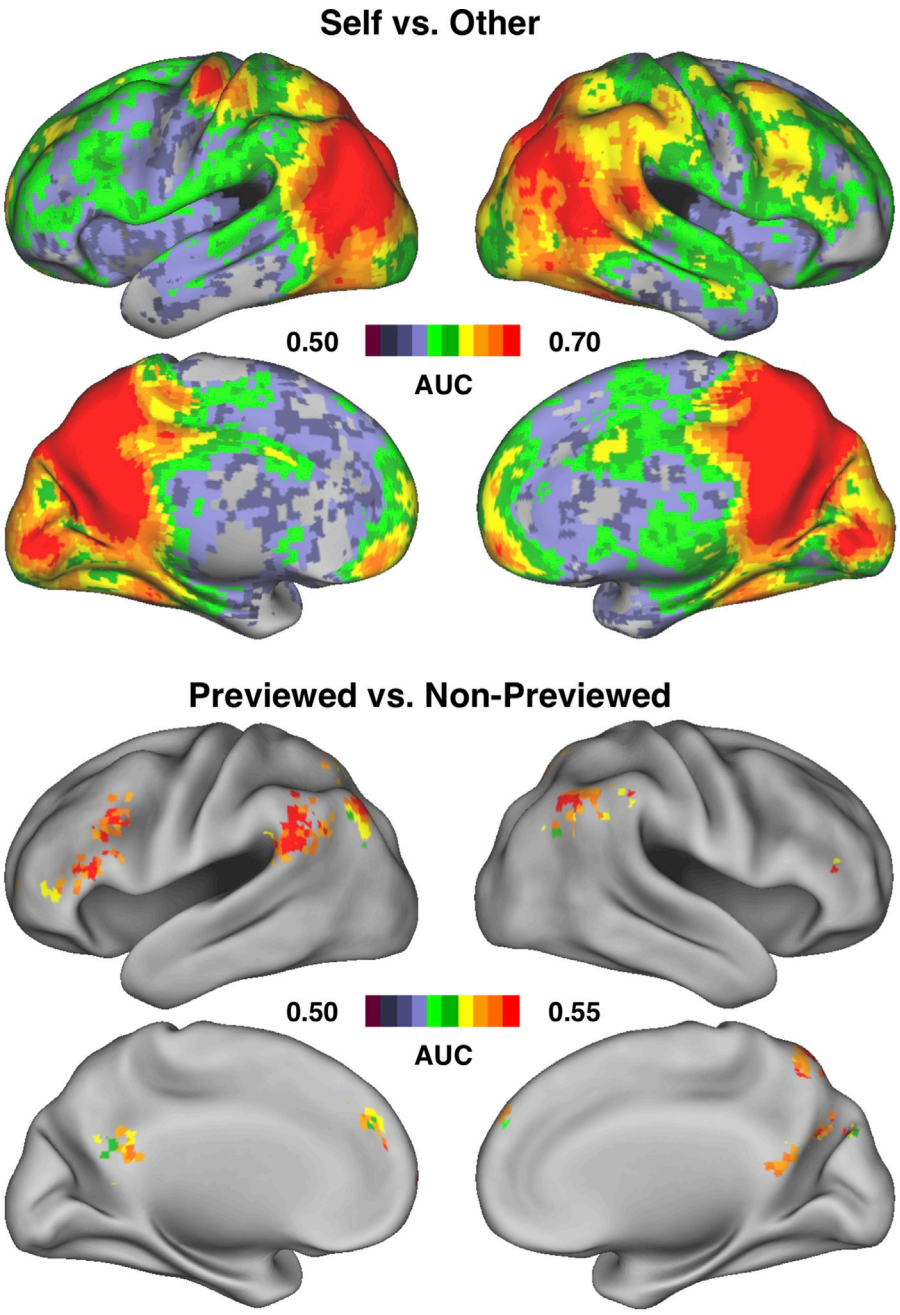

Fig. 6. Group-averaged searchlight maps for decoding of photographic source (top) and pre-exposure status (bottom). Only regions achieving whole-brain corrected significance at $p < 0.05$ are shown. The color intensity of a given voxel indicates the mean decoding performance (AUC) of a classifier trained and tested using activity patterns localized to a 3-voxel radius sphere centered around that voxel. For visualization purposes, the AUC values associated with the upper-bound of the color scale differs between the two classification maps in order to showcase the dynamic range as well as the peak magnitudes of the respective effects.

Previewed trials, the Laboratory-based Network (mean number of voxels = 266.7; 18.6% of the network) contained a larger number of significant voxels ($t_{(17)} = 2.912$, $p = 0.010$) than the Autobiographical Network (mean number of voxels = 173.7; 12.1% of the network). These findings were significant even when accounting for the total number of significant searchlight voxels in each participant's whole brain map. The Autobiographical Network still contained a greater proportion of significant voxels than the Laboratory-based Network for the photographic source classification ($t_{(17)} = 3.042$, $p = 0.007$) and the Laboratory-based Network still contained a greater proportion of significant voxels than the Autobiographical Network for the pre-exposure status classification ($t_{(17)} = 3.294$, $p = 0.004$). Moreover, a repeated measures ANOVA revealed an interaction between the number of significant voxels in each network for the photographic source and pre-exposure status searchlight classifications ($F_{(1,17)} = 26.216$, $p < 10^{-4}$). These results corroborate our findings that the Autobiographical and Laboratory-based Networks are differentially sensitive to photographic source and pre-exposure status.

This difference between classification performance was also apparent when examining the mean AUC of voxels within the Autobiographical Network and the Laboratory-based Network for each participant's individual searchlight results with regards to the decoding of photographic source and pre-exposure status. The decoding performance of the two networks was assessed with a paired-samples, two-tailed *t*-test with the critical alpha level Bonferroni corrected for two comparisons. Across the photographic source decoding performance for all participants, the mean AUC of the searchlight voxels in the Autobiographical Network (mean AUC = 0.650) was greater than that of the Laboratory-based Network (mean AUC = 0.622), and this difference was significant ($t_{(17)} = 4.622$, $p < 10^{-3}$). For the pre-exposure status decoding performance, the mean AUC of the searchlight voxels in the Laboratory Network (mean AUC = 0.525) was significantly greater ($t_{(17)} = 4.133$, $p < 10^{-3}$) than that of the Autobiographical Network (mean AUC = 0.508). These results

Table 1
Regions of peak decoding performance within the Autobiographical Network (Auto) and the Laboratory-based Network (Lab) for the group-level searchlight classifications of photographic source (Self vs. Other) and pre-exposure status (Previewed vs. Non-Previewed). MNI coordinates and Brodmann Area (BA) are listed for each peak, along with the corresponding AUC and *t*-value. Negative X coordinates indicate left hemisphere regions.

Classification	Region	BA	Peak					Network
			X	Y	Z	AUC	*t*-value	
Self vs. Other	Cingulate Gyrus	31	−3	−60	27	0.790	17.268	Auto
	Middle Temporal Gyrus	39	−48	−63	18	0.741	11.445	Auto
	Cingulate Gyrus	24	0	9	36	0.647	10.632	Auto
	Middle Temporal Gyrus	39	48	−66	18	0.728	9.406	Auto
	Medial Orbitofrontal Cortex	10	−3	48	−6	0.666	9.067	Auto
	Fusiform Gyrus	37	−33	−42	−18	0.689	7.436	Auto
	Fusiform Gyrus	37	27	−39	−18	0.668	7.186	Auto
	Thalamus	–	3	−12	3	0.610	6.858	Auto
	Superior Frontal Gyrus	10	−15	54	21	0.585	4.159	Auto
	Middle Frontal Gyrus	9	−48	15	30	0.618	7.026	Lab
	Cingulate Gyrus	32	−3	24	33	0.593	6.734	Lab
	Inferior Parietal Lobule	40	39	−54	45	0.655	5.483	Lab
Previewed vs. Non-Previewed	Calcarine Fissure	31	0	−69	18	0.555	4.148	Auto
	Inferior Parietal Lobule	19	−33	−75	39	0.557	5.782	Lab
	Supramarginal Gyrus	40	−54	−48	30	0.556	5.266	Lab
	Inferior Parietal Lobule	40	45	−51	39	0.548	4.663	Lab
	Middle Frontal Gyrus	9	−45	9	30	0.560	4.290	Lab
	Inferior Frontal Gyrus	45	−51	21	15	0.550	3.435	Lab

remained significant even when analyses were restricted to only searchlight voxels with AUC values in the top 50% of each participant's whole-brain searchlight map. The Autobiographical Network (mean AUC = 0.725) demonstrated better mean classification performance of photographic source ($t_{(17)} = 5.324$, $p < 10^{-4}$) than the Laboratory-based Network (mean AUC = 0.692). In comparison, the Laboratory-based Network (mean AUC = 0.569) showed significantly better mean decoding of pre-exposure status ($t_{(17)} = 3.769$, $p = 0.002$) than the Autobiographical Network (mean AUC = 0.552). A repeated measures ANOVA demonstrated an interaction between the two networks when decoding photographic source and pre-exposure status ($F_{(1,17)} = 36.345$, $p < 10^{-4}$). Thus, our searchlight findings—whether summarized by counting significant voxels or averaging classification performance across voxels—indicate that the Autobiographical and Laboratory-based Networks differ in terms of their sensitivity to whether events are from an individual's own life or whether photographs have been previously encountered.

Overall, even though the searchlight mapping procedure was not confined to the regions that comprised the networks used in our core MVPA analyses, we found that decoding of the photographic source and pre-exposure status of events was predominately associated with regions of the Autobiographical Network and the Laboratory-based Network respectively. Despite the strong convergence across analytic approaches, we acknowledge that the peak searchlight effects did not map perfectly onto the boundaries of the two networks, nor was the dissociation absolute. Nonetheless, these findings suggest that the brain regions whose activity patterns most strongly code for retrieval of self-relevant life experiences are largely distinct from those that code for one's experiential history with visual stimuli such as photographs.

Discussion

This fMRI experiment utilized wearable digital cameras to assess real-world autobiographical memory retrieval with MVPA methods. Importantly, this approach increased ecological validity by allowing the incorporation of participants' daily life events as retrieval cues without the need for explicit encoding of these autobiographical experiences. The experimental paradigm consisted of participants wearing a camera device for three weeks to automatically photograph a wide variety of their life events. Participants then returned to the laboratory a week later where they were exposed to a subset of photographic event sequences from their lives and the lives of other individuals. Participants were scanned the following day while making mnemonic judgments about event sequences drawn from their own lives and from the lives of other participants, half of which had been pre-exposed. The critical question was whether distributed fMRI activity patterns within two putatively distinct brain networks—identified via meta-analysis as preferentially associated with the retrieval of autobiographical and laboratory-based memories—would show differential sensitivity to the source of the event photographs (i.e., whether or not they were from one's life) and their pre-exposure status (i.e., whether or not the photographs themselves had been previewed the day before the scan). To this end, we ran a series of MVPA classifications on fMRI data from the so-called Autobiographical Network and Laboratory-based Network (McDermott et al., 2009), after matching these networks in size and removing all overlapping regions. Our analyses revealed a striking dissociation in the degree to which each network was sensitive to these orthogonal dimensions of retrieval: the Autobiographical Network, which included regions such as the bilateral MTL and medial PFC, was better at decoding the photographic source of a given event than the Laboratory-based Network, whereas the Laboratory-based Network, which consisted of regions such as the left lateral prefrontal and posterior parietal cortex, was more accurate than the Autobiographical Network at decoding whether photographs of an event had been previously encountered. These effects were also apparent in unconstrained whole-brain searchlight analyses, which found that the peak decoding effects for photographic source and pre-exposure status were located in regions roughly approximating the two networks.

Remarkably, the activation patterns associated with photograph pre-exposure could be reliably decoded even though participants were not explicitly instructed to evaluate whether photographs of events were recognized or novel. The ability to classify between Previewed and Non-Previewed events was found exclusively within the Laboratory-based Network; activity patterns within the Autobiographical Network were not sensitive to this distinction. The Laboratory-based Network's advantage over the Autobiographical Network for pre-exposure decoding could be found even when the analysis was re-run using only trials depicting events from the participant's own life, or when it was run using only events from someone else's life. As such, this shows that the neural signatures associated with the recognition of event photographs (whether explicitly noticed by participants or implicitly processed) are dissociable from those associated with the determination of whether the photographs depict an event from one's own life. This is broadly consistent with the observation by McDermott et al. (2009) that the

majority of the laboratory-based memory studies included in their meta-analysis featured activation foci derived from old/new recognition effects. Likewise, our finding that activity patterns within the Autobiographical Network were preferentially associated with photographic source is consistent with previous studies linking several areas within this network—such as the medial PFC and hippocampus—to the retrieval of contextual source details and self-referential processing (Addis et al., 2004; Cabeza and St Jacques, 2007; Gilboa, 2004; Maguire and Mummery, 1999; Rissman et al., 2016; Svoboda et al., 2006). Critically, our results demonstrate that personally experienced event memories are capable of being distinguished from previously encountered depictions of events, which can be considered a form of secondhand event knowledge.

These findings comport nicely with those from a recent fMRI study by Chen et al. (2017), which examined univariate activity differences associated with the successful retrieval of visual memories that were either recently learned in a laboratory context (participants evaluated whether or not each scene image had been previously studied) or based upon their own life experiences (participants evaluated whether or not each scene image reminded them of a specific event from their own personal past). Successful retrieval of the laboratory-encoded events preferentially recruited regions of the frontoparietal control network, including lateral PFC regions, as well as areas of the so-called parietal memory network (Gilmore et al., 2015); these regions were highly overlapping with the Laboratory-based Network defined in the McDermott et al. (2009) meta-analysis. In contrast, successful retrieval of autobiographical events tended to be associated with activation within the default mode network, including prominent effects within the medial PFC, which was comparable to the Autobiographical Network in McDermott et al. (2009). Although this study did not present participants with photographs captured from their own life events, nor attempt MVPA-based decoding of the trial-specific activity patterns, their results add support to the notion that the brain processes mediating the retrieval of recently-encoded laboratory events can differ markedly from the retrieval of autobiographical ones.

Despite the dissociation we found between the event attributes that could be most strongly decoded within the Autobiographical and Laboratory-based Networks relative to one another, it is important to note that activity patterns within both networks were able to reliably decode the photographic source of events. Indeed, the whole-brain searchlight maps showed that the Self/Other distinction was particularly robust across large swaths of the posterior parietal cortex and posterior midline regions—effects that overlapped with several clusters present in both the Autobiographical and Laboratory-based Network masks. That the Laboratory-based Network, putatively associated with processing the perceived oldness (or familiarity) of environmental stimuli, was also highly sensitive to Self/Other status could be at least partly attributable to the fact that photographs of personally experienced events likely contained familiar faces, objects, and/or locations that could evoke a strong sense of recognition, regardless of whether or not the photographs themselves had been previewed. Accordingly, in this study, the processes involved in laboratory-based and autobiographical retrieval may not be mutually exclusive. Previous work provides evidence for some degree of similarity between these retrieval processes. Rissman et al. 2016 assessed whether a MVPA classifier that was trained to distinguish between mnemonic retrieval states for laboratory-based memories from a previous face memory experiment (Rissman et al., 2010) would be capable of differentiating between the same states (e.g., hits vs. correct rejections; recollection vs. familiarity) for real-world memories. Their results suggest that real-world autobiographical memories and laboratory-based ones are similar enough to generalize predictions from one dataset to another. That said, across-experiment memory classification accuracy was notably poorer than within-experiment accuracy, likely owing to differences in the underlying retrieval processes—and their neural signatures—associated with the recognition of laboratory-encoded stimuli and real-world events.

More work will be needed to fully characterize the nature of the similarities and differences between autobiographical and laboratory-based memories. In some ways, the term "laboratory-based" may be a misnomer, since there is nothing intrinsically special about encoding information while participating in a psychology experiment versus encoding information outside of the lab (i.e., in "real life"). Thus, the divergent patterns of brain activation observed during the retrieval of these kinds of memories may be driven to a large degree by differences in the mnemonic processes evoked (e.g., recognition as based on either contextual recollection or item familiarity), methodology (e.g., perceptual qualities of the stimuli used to probe memories), or even characteristics of the tested memories themselves (e.g., personal relevance or temporal remoteness). For instance, differences in the way photographic source and pre-exposure status were assessed in our study may have contributed to the dissociable neural activation patterns. Photographic source was always task-relevant during the scanning session, in that participants were explicitly instructed to evaluate whether each event was from their own life or someone else's life, and only correct trials were included in our classification analyses. In contrast, pre-exposure status was not task-relevant, in that participants were never explicitly queried as to whether they had previously seen the photographs of each event. Moreover, memories of events from participants' own lives were likely not only stronger and richer than memories of having recently-encoded photographs in the laboratory session, but these own-life events were also more temporally remote, occurring up to four weeks prior to the fMRI scan session. Photographs from one's own life (Self events) also tended to contain familiar elements (e.g., frequently encountered people and places) and may evoke brain responses related to stimulus recognition in addition to those related to autobiographical event recollection. Consequently, successful classification of Self vs. Other may be bolstered by neural activation patterns associated with recognition/familiarity. This may be one reason that Self vs. Other decoding accuracies were higher than Previewed vs. Non-Previewed decoding accuracies. However, it is noteworthy that photographic source decoding accuracy was not significantly influenced by pre-exposure status, nor was pre-exposure status decoding accuracy significantly influenced by photographic source.

Follow-up studies that aim to equate task-relevance, temporal remoteness, and retrieval strength across laboratory-encoded and autobiographical memories would help isolate the factors responsible for the apparent neural dissociation. Care should be undertaken when interpreting classification performance that does not differ significantly from chance: failure to decode between two task conditions (e.g., the fact that the Autobiographical Network could not differentiate Previewed vs. Non-Previewed trials) does not necessarily indicate the complete absence of information related to these conditions within the underlying neural tissue. Rather, this could suggest that these conditions could not be reliably discriminated given our specific classification parameters and the characteristics of our fMRI dataset; the possibility remains that different data acquisition and processing procedures or a different classification algorithm might yield above-chance performance in regions where we reported a null result. Future work may also benefit from larger sample sizes, as it is possible that the statistical power of our analyses was limited by our experiment's modest sample size of 18 participants, which was constrained by the month-long enrollment period for each participant and the substantial effort required to prepare each participant's photographs for the fMRI session. While our sample size is comparable to other contemporary neuroimaging studies of autobiographical memory retrieval—especially those involving real-world stimuli (e.g., Nielson et al., 2015; Rissman et al., 2016)—and all of our classification analyses were performed at the individual participant level with participant-specific results reported to provide a fuller portrait of the robustness of each effect, lower participant sample sizes can potentially affect statistical reliability and interpretation. Problems with low participant sample sizes have been documented in neuroimaging studies more generally (Poldrack et al., 2017), so additional work incorporating larger samples sizes aimed at replication of our study is critical.

With respect to applied contexts, the use of fMRI techniques may hold important societal implications due to the remarkable accuracy with which brain activity patterns can be used to distinguish recognized stimuli from novel stimuli (Meegan, 2008; Rissman and Wagner, 2012). The growing use of neuroscience evidence in the United States legal system (Farahany, 2015; Meixner, 2015) raises the possibility that brain-based memory detection approaches could someday find their way into the criminal justice system. However, before neurotechnologies can be utilized for applied purposes, such as in forensic settings, it is imperative to determine whether scientific evidence legitimately justifies and supports such applications. Rigorous empirical investigation is needed to evaluate both the capabilities and limitations of fMRI memory measurements in order to prevent potentially detrimental or unforeseen consequences. Prior fMRI experiments have demonstrated robust MVPA-based decoding of specific mnemonic states—including novelty or recognition—even on single trials (Rissman et al., 2010, 2016; Uncapher et al., 2015). The results of the present experiment demonstrated that a MVPA classifier could distinguish participants' own photographs from previously encountered photographs of other individuals' lives. This indicates the possibility that the distributed neural activity patterns evoked during the retrieval of a personally experienced event may be differentiated from those evoked by secondhand event knowledge. Furthermore, our MVPA classifier was capable of differentiating whether or not photographs of events were being encountered for the first time, irrespective of their original source, even in the absence of explicit memory judgments. Therefore, the findings of this study not only further current understanding of autobiographical memory retrieval in naturalistic settings, but also may inform the utilization of fMRI methodology in applied contexts as well.

That said, we strongly caution against the direct translation of our protocol for use as a forensic tool in detecting memories for past events. The primary goal of our investigation was to characterize the relative degree to which two large-scale brain networks that have been implicated in episodic retrieval carry information about individuals' experiential history with photographic stimuli and the life events depicted in those stimuli. While the performance of our neural classifier models achieved statistical significance when tested against chance at the group-level, accuracy levels were far from perfect, especially with respect to our ability to decode whether the photographic stimuli had been previously encountered prior to scanning. Also, all of our models were trained and tested within the brains of individual participants. While it is conceivable that within-participant classifier models could be used in forensic applications (e.g., if the classifier was first trained on a set of verifiable memories and then applied to classify crime-relevant memories), it would be more practical to have models that were pre-trained on a normative sample. We did not attempt across-subject classification in the present study, although previous results have shown that brain activity patterns associated with episodic retrieval states can be remarkably consistent across individuals (Rissman et al., 2010, 2016). Finally, participants in our study had no incentives to conceal their memories or be non-cooperative with the instructions of our explicit recognition task, but related work has shown that individuals motivated to "beat the system" can deploy simple cognitive strategies to mask their recognition of familiar stimuli or feign recognition of novel ones (Uncapher et al., 2015). Given all of these factors, along with the fact that first-person photographs captured by wearable cameras may be quite different in their ability to cue episodic retrieval than third-person photographs (e.g., security camera footage), we believe that much additional research will be needed before forensic applications are warranted.

Acknowledgements

The authors would like to thank Corey D. Ngoy, Laryssa A. Storozuk, and Brittney V. Medina for their hard work selecting and organizing participants' stimuli in addition to their assistance with data collection. Thanks also to Kathleen B. McDermott for providing the ALE meta-analysis maps resulting from McDermott et al. (2009). Funding for this work was provided in part by a National Science Foundation Graduate Research Fellowship Program award (DGE-1144087 and DGE-1650604) to T.E.C. as well as a Hellman Fellows Fund award and UCLA COR Faculty Research Grant to J.R.

Appendix A. Supplementary data

Supplementary data related to this article can be found at https://doi.org/10.1016/j.neuroimage.2018.04.024.

References

Addis, D.R., Moscovitch, M., Crawley, A.P., McAndrews, M.P., 2004. Recollective qualities modulate hippocampal activation during autobiographical memory retrieval. Hippocampus 14, 752–762.
Bradley, A.P., 1997. The use of the area under the roc curve in the evaluation of machine learning algorithms. Pattern Recognit. 30, 1145–1159.
Brown, T., Murphy, E., 2010. Through a scanner darkly: functional neuroimaging as evidence of a criminal defendant's past mental states. Stanford Law Rev. 62, 1119–1208.
Burianova, H., Grady, C.L., 2007. Common and unique neural activations in autobiographical, episodic, and semantic retrieval. J. Cognitive Neurosci. 19, 1520–1534.
Cabeza, R., Prince, S.E., Daselaar, S.M., Greenberg, D.L., Budde, M., Dolcos, F., LaBar, K.S., Rubin, D.C., 2004. Brain activity during episodic retrieval of autobiographical and laboratory events: an fMRI study using a novel photo paradigm. J. Cognitive Neurosci. 16, 1583–1594.
Cabeza, R., St Jacques, P., 2007. Functional neuroimaging of autobiographical memory. Trends Cognitive Sci. 11, 219–227.
Chadwick, M.J., Hassabis, D., Weiskopf, N., Maguire, E.A., 2010. Decoding individual episodic memory traces in the human hippocampus. Curr. Biol. 20, 544–547.
Chen, H.Y., Gilmore, A.W., Nelson, S.M., McDermott, K.B., 2017. Are there multiple kinds of episodic memory? An fMRI investigation comparing autobiographical and recognition memory tasks. J. Neurosci. 37, 2764–2775.
Chow, T.E., Rissman, J., 2017. Neurocognitive mechanisms of real-world autobiographical memory retrieval: insights from studies using wearable camera technology. Ann. N. Y. Acad. Sci. 1396, 202–221.
Cox, R.W., 1996. AFNI: software for analysis and visualization of functional magnetic resonance neuroimages. Comput. Biomed. Res. 29, 162–173.
Farahany, N.A., 2015. Neuroscience and behavioral genetics in US criminal law: an empirical analysis. J. Law Biosci. 2, 485–509.
Gilboa, A., 2004. Autobiographical and episodic memory—one and the same?: Evidence from prefrontal activation in neuroimaging studies. Neuropsychologia 42, 1336–1349.
Gilmore, A.W., Nelson, S.M., McDermott, K.B., 2015. A parietal memory network revealed by multiple MRI methods. Trends Cogn. Sci. 19, 534–543.
Gorgolewski, K.J., Varoquaux, G., Rivera, G., Schwarz, Y., Ghosh, S.S., Maumet, C., Sochat, V.V., Nichols, T.E., Poldrack, R.A., Poline, J.-B., 2015. NeuroVault. org: a web-based repository for collecting and sharing unthresholded statistical maps of the human brain. Front. Neuroinformatics 9, 8.
Johnson, J.D., McDuff, S.G., Rugg, M.D., Norman, K.A., 2009. Recollection, familiarity, and cortical reinstatement: a multivoxel pattern analysis. Neuron 63, 697–708.
Kay, K., Rokem, A., Winawer, J., Dougherty, R., Wandell, B., 2013. GLMdenoise: a fast, automated technique for denoising task-based fMRI data. Front. Neurosci. 7.
Kriegeskorte, N., Goebel, R., Bandettini, P., 2006. Information-based functional brain mapping. Proc. Natl. Acad. Sci. 103, 3863–3868.
Lacy, J.W., Stark, C.E., 2013. The neuroscience of memory: implications for the courtroom. Nat. Rev. Neurosci. 14, 649–658.
LePort, A.K., Mattfeld, A.T., Dickinson-Anson, H., Fallon, J.H., Stark, C.E., Kruggel, F., Cahill, L., McGaugh, J.L., 2012. Behavioral and neuroanatomical investigation of highly superior autobiographical memory (HSAM). Neurobiol. Learn. Mem. 98, 78–92.
LePort, A.K., Stark, S.M., McGaugh, J.L., Stark, C.E., 2017. A cognitive assessment of highly superior autobiographical memory. Memory 25, 276–288.
Maguire, E.A., Mummery, C.J., 1999. Differential modulation of a common memory retrieval network revealed by positron emission tomography. Hippocampus 9, 54–61.
McDermott, K.B., Szpunar, K.K., Christ, S.E., 2009. Laboratory-based and autobiographical retrieval tasks differ substantially in their neural substrates. Neuropsychologia 47, 2290–2298.
Meegan, D.V., 2008. Neuroimaging techniques for memory detection: scientific, ethical, and legal issues. Am. J. Bioeth. 8, 9–20.
Meixner Jr., J.B., 2015. Applications of neuroscience in criminal law: legal and methodological issues. Curr. Neurol. Neurosci. Rep. 15, 513.
Milton, F., Muhlert, N., Butler, C., Benattayallah, A., Zeman, A., 2011a. The neural correlates of everyday recognition memory. Brain Cognition 76, 369–381.
Milton, F., Muhlert, N., Butler, C., Smith, A., Benattayallah, A., Zeman, A., 2011b. An fMRI study of long-term everyday memory using SenseCam. Memory 19, 733–744.
Nielson, D.M., Smith, T.A., Sreekumar, V., Dennis, S., Sederberg, P.B., 2015. Human hippocampus represents space and time during retrieval of real-world memories. Proc. Natl. Acad. Sci. 112, 11078–11083.

Norman, K.A., Polyn, S.M., Detre, G.J., Haxby, J.V., 2006. Beyond mind-reading: multi-voxel pattern analysis of fMRI data. Trends Cognitive Sci. 10, 424–430.
Palombo, D.J., Alain, C., Söderlund, H., Khuu, W., Levine, B., 2015. Severely deficient autobiographical memory (SDAM) in healthy adults: a new mnemonic syndrome. Neuropsychologia 72, 105–118.
Patihis, L., Frenda, S.J., LePort, A.K., Petersen, N., Nichols, R.M., Stark, C.E., McGaugh, J.L., Loftus, E.F., 2013. False memories in highly superior autobiographical memory individuals. Proc. Natl. Acad. Sci. 110, 20947–20952.
Pereira, F., Mitchell, T., Botvinick, M., 2009. Machine learning classifiers and fMRI: a tutorial overview. Neuroimage 45, S199–S209.
Peth, J., Sommer, T., Hebart, M.N., Vossel, G., Buchel, C., Gamer, M., 2015. Memory detection using fMRI - does the encoding context matter? Neuroimage 113, 164–174.
Poldrack, R.A., Baker, C.I., Durnez, J., Gorgolewski, K.J., Matthews, P.M., Munafò, M.R., Nichols, T.E., Poline, J.-B., Vul, E., Yarkoni, T., 2017. Scanning the horizon: towards transparent and reproducible neuroimaging research. Nat. Rev. Neurosci. 18, 115–126.
Polyn, S.M., Natu, V.S., Cohen, J.D., Norman, K.A., 2005. Category-specific cortical activity precedes retrieval during memory search. Science 310, 1963–1966.
Rissman, J., Chow, T.E., Reggente, N., Wagner, A.D., 2016. Decoding fMRI signatures of real-world autobiographical memory retrieval. J. Cognitive Neurosci. 28, 604–620.
Rissman, J., Greely, H.T., Wagner, A.D., 2010. Detecting individual memories through the neural decoding of memory states and past experience. Proc. Natl. Acad. Sci. 107, 9849–9854.
Rissman, J., Wagner, A.D., 2012. Distributed representations in memory: insights from functional brain imaging. Annu. Rev. Psychol. 63, 101–128.
Roediger, H.L., McDermott, K.B., 2013. Two types of event memory. Proc. Natl. Acad. Sci. 110, 20856–20857.
Schacter, D.L., Loftus, E.F., 2013. Memory and law: what can cognitive neuroscience contribute? Nat. Neurosci. 16, 119–123.
Spiers, H.J., Maguire, E.A., 2007. Decoding human brain activity during real-world experiences. Trends Cogn. Sci. 11, 356–365.
St Jacques, P.L., Conway, M.A., Lowder, M.W., Cabeza, R., 2011. Watching my mind unfold versus yours: an fMRI study using a novel camera technology to examine neural differences in self-projection of self versus other perspectives. J. Cognitive Neurosci. 23, 1275–1284.
St Jacques, P.L., De Brigard, F., 2015. Neural correlates of autobiographical memory: methodological considerations. In: Addis, D.R., Barense, M., Duarte, A. (Eds.), The Wiley Handbook on the Cognitive Neuroscience of Memory. John Wiley & Sons.
St Jacques, P.L., Olm, C., Schacter, D.L., 2013. Neural mechanisms of reactivation-induced updating that enhance and distort memory. Proc. Natl. Acad. Sci. 110, 19671–19678.
Svoboda, E., McKinnon, M.C., Levine, B., 2006. The functional neuroanatomy of autobiographical memory: a meta-analysis. Neuropsychologia 44, 2189–2208.
Todd, M.T., Nystrom, L.E., Cohen, J.D., 2013. Confounds in multivariate pattern analysis: theory and rule representation case study. Neuroimage 77, 157–165.
Tong, F., Pratte, M.S., 2012. Decoding patterns of human brain activity. Annu. Rev. Psychol. 63, 483–509.
Tzourio-Mazoyer, N., Landeau, B., Papathanassiou, D., Crivello, F., Etard, O., Delcroix, N., Mazoyer, B., Joliot, M., 2002. Automated anatomical labeling of activations in SPM using a macroscopic anatomical parcellation of the MNI MRI single-subject brain. Neuroimage 15, 273–289.
Uncapher, M.R., Boyd-Meredith, J.T., Chow, T.E., Rissman, J., Wagner, A.D., 2015. Goal-directed modulation of neural memory patterns: implications for fMRI-based memory detection. J. Neurosci. 35, 8531–8545.