The Existence of Two Variant Processes in Human Declarative Memory: Evidence Using Machine Learning Classification Techniques in Retrieval Tasks

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Abstract. This work use supervised machine learning methods on fMRI brain scans, taken/measured during a memory-*retrieval* task, to support establishing the existence of two distinct systems for human declarative memory ("Explicit Encoding" (EE) and "Fast Mapping" (FM)). The importance of using retrieval is that it allows a direct comparison between exemplars designed to use EE and those designed to use FM. This is not directly available under *acquisition* tasks because of the nature of the purported memory systems since the tasks are necessarily somewhat distinct between the two systems under acquisition. This means that there could be a confounding of the distinction in the *task* with the difference in the representation and mechanism of the internal memory system during analysis. *Retrieval* tasks, on the other hand allow for identity of task. Thus this work fills a lacuna in earlier work which used memory acquisition tasks. In addition, since the data used in this work was gathered over a two day period, the classification methods is also able to identify a distinction in the *consolidation* of the memories in the two systems. The results presented here clearly support the existence of the two distinct memory systems.

Keywords: Machine learning · Classification · Functional Magnetic Resonance Imaging (fMRI) · Feature selection · Support vector machines · Decision trees · Radial basis function kernel · Declarative memory · Consolidation · Semantic memory · Informational biomarkers

1 Introduction

Human declarative memory is defined as the conscious recollection of facts and events [1]. Under the theory of declarative memory systems, novel information is encoded into the memory using, amongst other brain parts, the hippocampus [2]. In this study,

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standard, hippocampal dependent memory is represented by "Explicit Encoding (EE)" procedure. According to memory transformation theories of declarative memory, the encoded information is slowly transferred from the hippocampus to the neo-cortex where it becomes permanently stored [3, 4]. Over time, the initially hippocampal dependent memories become independent of the hippocampus. It has been suggested that this re-organization process is done during sleep [5].

Amongst toddlers, the process of rapid language acquisition occurs prior to the full development of the hippocampus [6, 7]. Moreover, some evidence from hippocampal injured subjects demonstrated an ability to acquire information which seems to have declarative-like characteristics, despite severe damages in the hippocampus [8, 9] and so, must involve a different brain network than the one which engages the hippocampus This alternative learning mechanism can be acquired via "Fast Mapping (FM)". It is unclear if the memory representations following FM undergo consolidation processes overtime, as do memories gained through EE. However, since it was shown that patients with hippocampal damages as well as healthy controls could learn and store information acquired via FM [8, 9], the scheme used to explain memory consolidation of declarative memories cannot be applied for FM in a straightforward manner.

In this work we aim to demonstrate the distinctiveness of brain systems, which support EE and FM memory process, by extracting activity patterns directly from brain data, using Functional Magnetic Resonance Imaging (fMRI) method. fMRI captures information from thousands of different localities (voxels) of the brain, simultaneously. Then multivariate pattern analysis approach (MVPA) [10] utilizes these activities by looking for changes in Blood Oxygen Level-Dependent (BOLD) signal across different voxels. Different methods can be used for analysis on such complex data depending on the question of study (retrieval or decoding stimuli, mental states, behavior and other variables of interest). A growing number of studies [11–14] shows some of the capability in using machine learning methods for analysis of neuroimaging data. Moreover, the feasibility to achieve successful results using machine learning on fMRI multivariate data is not trivial and relies on the sensitive choice of features to be considered in the analysis.

In this work we focused on classification techniques, in particular using SVM and decision trees. The overriding motif was that if machine learning can distinguish between tasks from the fMRI data, then they are performed differently.

2 Related Work

The mechanism of FM was examined among healthy individuals [14, 15]. It was shown that two learning mechanisms, EE and FM, can be discriminated from fMRI data during memory acquisition, using machine learning based classifiers. In addition, scans taken while memory acquisition were tested for success in a consecutive retrieval task, outside the fMRI machine. Successful accuracy results were achieved when identifying scans corresponding to correct and incorrect retrieval, within the EE group and within the FM group, for each participant separately and cross-participant.

However, the different nature of the procedures used for acquisition of information (EE and FM), did not allow for complete control over the task with regard to the

behavioral experience. Therefore, the possibility remained that the successful classification obtained in the experiment was a result of differences in the acquisition procedures and not in the learning mechanisms.

To overcome this limitation, in this work we examine data obtained in another study [16]. There, the neural correlates of FM and EE were explored during a retrieval procedure, designed to be identical for both mechanisms. In addition, the study focused on overnight re-organization of memory representations, following both EE and FM, by comparing recent memories to remote ones (obtained in the previous day). Findings suggested that, despite the identical retrieval tasks, memories that were gained through FM induced distinct neural substrates from those involved EE [16]. While retrieval of data learned through EE engaged the expected hippocampal and vmPFC related network, retrieval of information acquired through FM immediately engaged an ATL related network, typically supporting well-established semantic knowledge. In addition, analysis of neuroimaging data associated with EE showed the expected overnight changes in network connectivity where for FM minimal overnight changes were presented. The analysis was performed by a multivariate technique of Spatiotemporal Partial Least Squares (PLS), helping to identify assemblies of brain regions that co-vary together.

3 Current Study

In this study, fMRI brain data were captured during the retrieval of memories, acquired through either EE or FM. The goal is to provide a biomarker directly from these fMRI scans using machine learning methods. Such classification ability based on the neural activity data gives strong evidence for the existence of distinct neural processes associated with EE and FM.

Multivariate classification is performed on fMRI features obtained during memory retrieval where tasks performed by the participants are identical for EE and FM. We also perform classification to explore the overnight re-organization processes following both learning mechanisms. Classification was performed over brain scans which were acquired either 30 min before scanning (recent memory) or a day before scanning (remote memory).

Regarding the distinction between the two memory processes during retrieval, we address two questions:

- Is it possible to distinguish between the two learning modes (i.e. EE and FM) based on neural activity information, collected during the retrieval of memories?
- Is it possible to distinguish between items learned recently and remotely?

4 Experiment Procedure

4.1 Participants

The experiment, full details of which can be seen in Merhav et al. [16], was conducted in Rotman Research Institute at Baycrest, Canada. Here, we mention the salient points.

22 participants were recruited and randomly assigned to one of the two groups (EE or FM). All participants were English native speakers, right-handed and had no history of neurological or psychiatric disorders and no learning disabilities. A written informed consent was obtained according to Baycrest's Research Ethics Board's guidelines. Gender and age distributions (10 females in each group) were similar in the FM and in the EE groups, respectively. The two groups also did not differ on the number of years of education, I.Q. estimates and WMS-III Verbal Paired Associates retention.

4.2 Experiment Paradigm and Procedure

22 healthy adult participants were randomly assigned of one to two groups (EE or FM). On day 1 the participants learned 50 new unfamiliar picture-word associations. On day

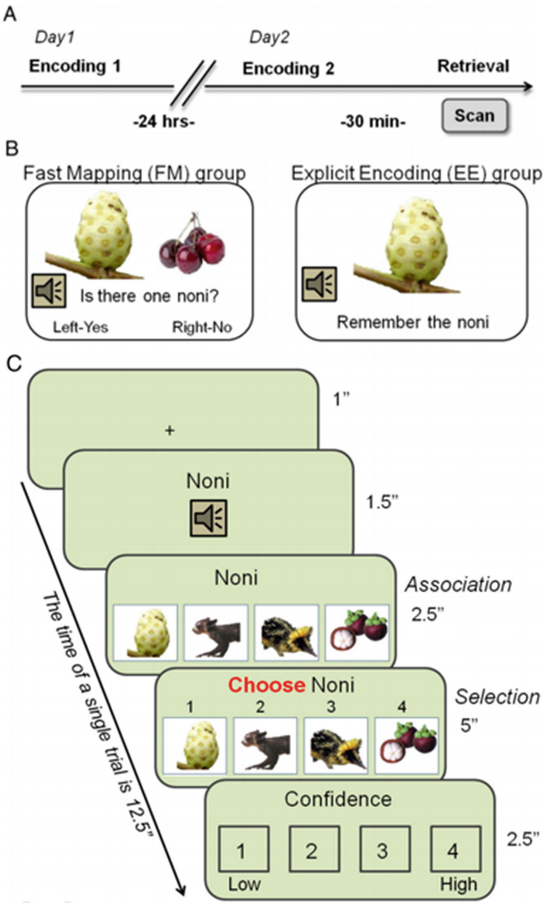

Fig. 1. (A) The experiment structure. (B) Examples of acquisition through FM (left) and through EE (right). (C) Retrieval test design which took place inside the fMRI scanner.

2 (24 h later) they learned another set of 50 new picture-word associations. A retrieval memory test for all the 100 new picture-word associations took place 30 min after the acquisition of the second set of associations. During the retrieval, brain activity was scanned (Fig. 1A). Therefore, the participants were tested on both recently and remotely encoded information. The two learning tasks (EE / FM) were designed differently due to different nature of both learning procedures (Fig. 1B).

The retrieval task was designed as an event related fMRI experiment in which memory for all 100 items was assessed via an associative four-alternative forced choice recognition task. The retrieval procedure was identical for EE and FM as it was performed inside the scanner (Fig. 1C). Retrieval trial of each item was 12.5 s long and contained the following intervals: blank screen (1 s), target label as text and auditory input (1.5 s), 4 choice pictures appeared on screen, below the target label (2.5 s), the word "choose" appeared onscreen and participants had to respond by selecting the appropriate key (5 s), confidence rating (2.5 s).

The experiment was intentionally designed to have participants perform either EE or FM, rather than perform both EE and FM tasks. It was important that learning through FM will be implicit and unintentional, so participants should not know that the task involves memory. However, in EE, participants are explicitly asked to remember the name of the item.

4.3 Data Acquisition and Pre-processing

The participants were scanned using the Siemens Trio 3T scanner, at Baycrest Institute. They acquired T2*-weighted images, covering the whole brain using an echo-planar imaging (EPI) sequence of 50 slices, with repetition time (TR) of 2500 ms, echo time

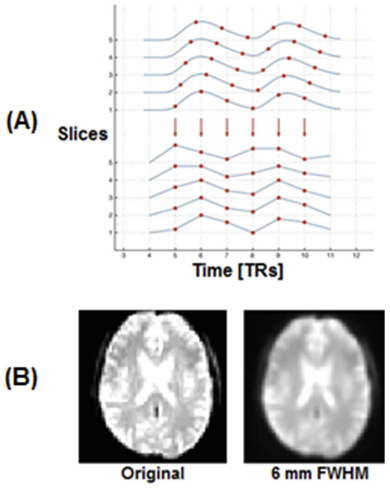

Fig. 2. Examples for pre-processing steps on fMRI data. (A) Correction of individual's hemodynamic responses slices acquired aligned to the exact same time [18]. (B) Performance of spatial smoothing on fMRI volume taken from single participant.

(TE) of 27 ms, 64 × 64 matrix, slice thickness of 3.5 mm and a field of view (FOV) of 200 mm. The procedure was designed as an event related fMRI study.

The pre-processing steps included conversion to 4-dimensional AFNI format [25], followed by slice timing correction using the first slice as a reference (Fig. 2A), latter movement correction for unintended head motions and spatial smoothing with 6 mm FWHM Gaussian kernel to increase signal-to-noise ratio was applied (Fig. 2B). Finally, the individual participant's data was converted to a standard coordinate system (Talairach [26]) to allow data analysis across individuals.

The scanning of each participant was done during four runs, creating a joint dataset out of four time-series datasets, with approximately 150 data volumes each of size 109 × 91 × 91, resulted as a dataset with approximately 600 data volumes. Therefore, each data volume (data point) contained 1490580 different voxels. We demonstrate the structure of the collected data in Fig. 3.

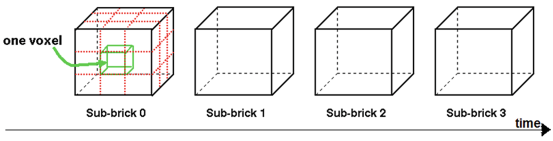

Fig. 3. 4-dimensional structure of AFNI format BRIK (Cox, 1996) file including 3-dimensional dataset over time sequence.

5 Methods

The data points used for analysis were constructed using scan data obtained for TR=2. This temporal cut was selected after performing pre-test classification as suggested in Atir-Sharon et al. work [14], taking into consideration the accordance to the expected HRF response.

We performed further pre-processing over the time-series data. At first, all non-brain voxels were removed using a mask. This was done by selecting voxels from the fMRI dataset that correspond to non-zero elements in the mask (creating data points of approximately 200,000 voxels). Afterwards, linear de-trending was performed on each participant's data set and for each run separately in order to remove low frequency signal intensity drifts.

Then, normalization over all scans was conducted. The normalization was done voxel-wise using z-score for each participant separately. In our case, the combined dataset involved scans from different groups and participants taken from different distributions. Therefore, transformation of features from different scales to a single scale, with consideration to the original distributions, was needed. The z-score method considers the different distribution characteristics of every group [17], hence, it was chosen as the normalization procedure. The z-score formula is presented in (1), where z-val is the new z-scored value, f-val is the original feature value and (μ, σ) are the mean and standard deviation values:

$$\text{z-val} = (\text{f-val} - \mu)/\sigma \quad (1)$$

For the mean and standard deviation computation in the z-score equation, several assignments were tested: (i) from all scans in the dataset; (ii) from individual participants' scans and (iii) from the distribution of scans marked as control (baseline) in the training set. Best classification results were achieved by using the mean and standard deviation normalization as computed from the distribution of baseline scans (option (iii)).

Each volume was represented as an individual data point in the dataset (i.e. each voxel was considered as a feature). Since the amount of scans from EE and FM groups was not equal, counter-balancing of the dataset was performed. This was done by randomly sampling data points from the smaller group. This method was applied only on the training set. (Otherwise, more weight would have been given to prediction accuracies of duplicated data points against weight of accuracies for data points that were not duplicated.) Therefore, the testing set was left untouched.

Machine learning classification techniques were used for data analysis. Considering the high dimensionality of data used in the current study, feature selection procedures were performed. The purpose of these procedures is to reduce the number of feature-voxels used for multivariate classification analysis. Such reduction is meant to remove irrelevant voxels and to improve training time.

There are several generic methods for selecting informative features. We aimed to select the features that best discriminate between conditions based on their activation values. It was achieved by ranking the importance of each feature according to the ANOVA F-score value obtained for the corresponding contrast (e.g., Correct vs. Incorrect Retrieval in FM condition) comparisons.

To find the optimal subset of features for analysis, we examined different sizes of features sets starting from 10 features to full brain scans. Eventually, based on the obtained accuracy values, the top 1000 voxels with highest F-scores were selected. This relatively large number of features was chosen to include some weakly informative voxels which can contribute to an increase in classification rates [19].

In Fig. 4, we illustrate the extracted features in the form of a brain map. In this example, we display selected subset of features for retrieval (Correct vs. Incorrect) classification. This brain map is an example showing the voxels selected on a specific individual's fMRI data that belongs to the FM group. Although not reproduced here, a detailed list of the top ANOVA chosen features for FM task shows the ATL area well represented and this accords with current ideas of the location of the FM activity.

In the first stage, a cross-validation classification scheme using Support Vector Machine classifier [20] with RBF (Radial Basis Function) kernel [21] was applied to the selected features. Parameters that are not learnt directly within estimators can be set by searching a parameter space for the best cross-validation score. Grid search for C and gamma parameters was performed in the ranges of 2^{-5} to 2^{15} and 2^{-15} to 2^{3} respectively. Grid search was executed before training on a training portion of the dataset to achieve increase in accuracy rates. A pseudo-code for the performed grid search is presented in Fig. 5. In all runs parameters C and gamma were set to 1 and 2^{-3} respectively.

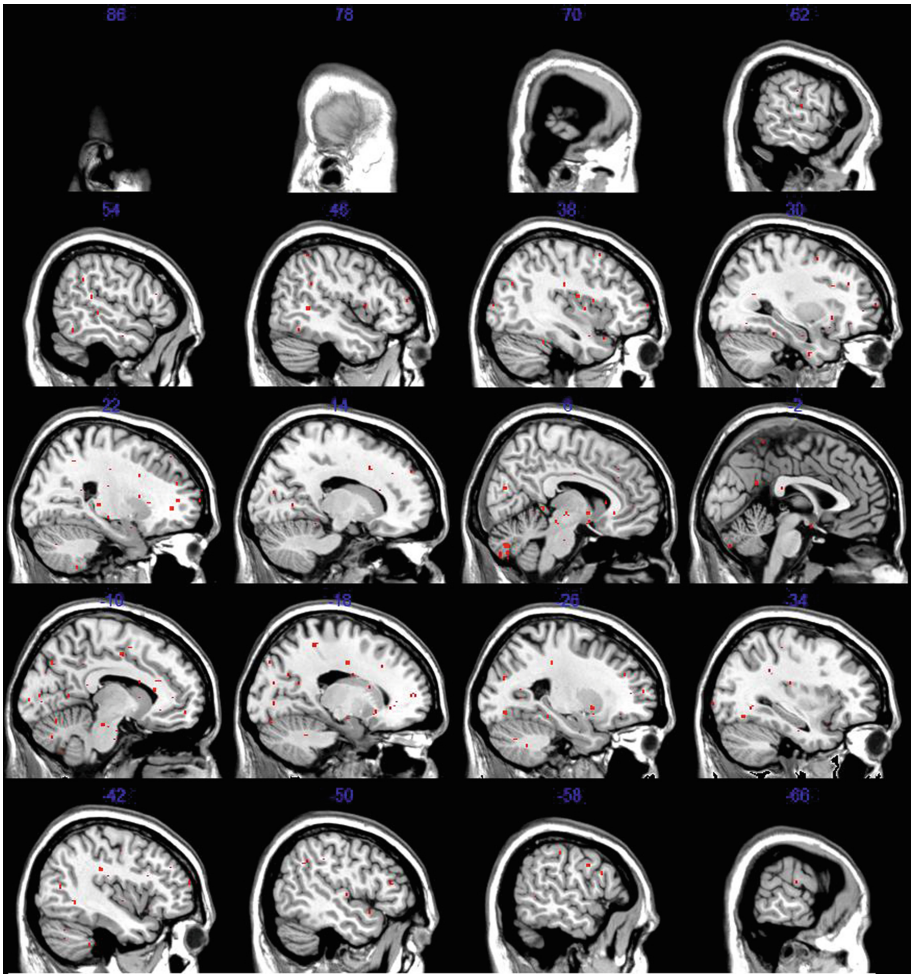

Fig. 4. Brain map displaying features selected for classification analysis

```
for c in [2^-5, 2^-3,...,2^15]:
 for g in [2^-15, 2^-13, ..., 2^5]:
  for train, test in partition:
    model = svm_train(train, c, g)
    score = svm_predict(test, model)
    cv_list.insert (score)
  scores_list.insert(mean(cv_list),c,g)
print max(scores_list)
```

Fig. 5. Pseudo-code for the grid search procedure.

In cases where the testing set consisted of scans that were taken from one group only (i.e. all scans were EE or all scans were FM), a decision making function was applied. We used majority voting method as a decision making function, defined as follows: if the majority of the scans were rated correctly per participant, the accuracy was set to 1, otherwise, the accuracy was set to 0.

The software used for the classification was developed using Python programming language and based on LibSVM [22] and PyMVPA software packages [23]. In Fig. 6 we present a complete analysis flow diagram including all the relevant pre-processing and processing stages.

Later we saw that this approach has several disadvantages in the context of this problem: (i) a best kernel for the specific problem needs to be found, (ii) an exhaustive parameter search need to be applied in order to optimize the parameters of the kernel for a specific problem, and (iii) the initial dimension of the data is already high (1000 features after the feature selection process), so projection of this data into a much higher space results in sparsity (due to the relatively small set of the data points) and hence a poorer generalization during the margins maximization process (which in turn results in a relatively high standard deviation). (In addition, as a practical matter, the computational resources for SVM are rather high which limits the freedom of experimentation of variants. In our work, the SVM methodology including the grid search for the parameters "C" and "Gamma" as well as the cross-validation means the time was of the order of several hours for each experiment. Further, it is important to notice

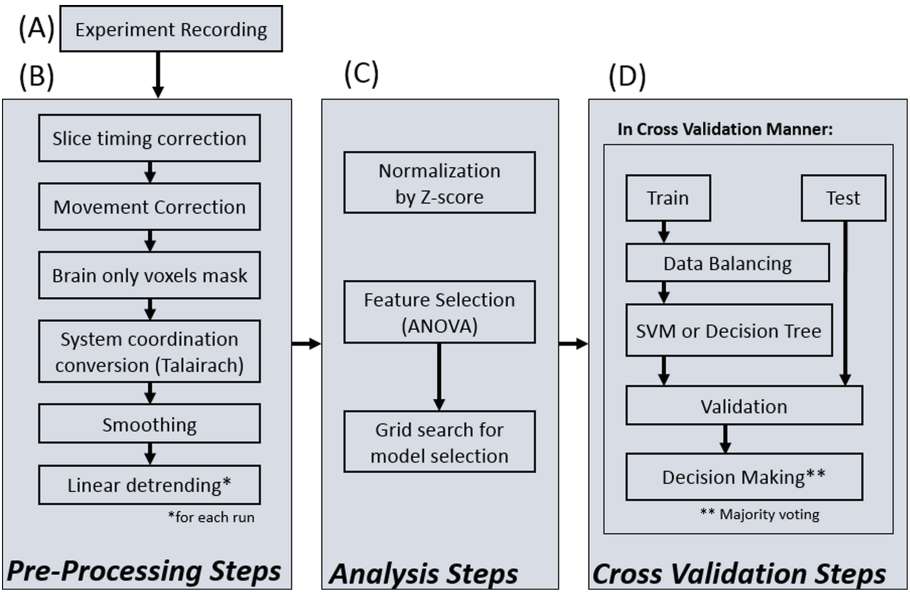

Fig. 6. Schematic diagram of the steps performed for whole brain analysis procedure. It consists of the following stages: (A) The initial stage representing the neuroimaging data delivery. (B) The pre-processing stage. (C) Data reduction stage: reducing data variability efficiently by feature selection. (D) Learning stage: performing multiple times by cross validation procedure.

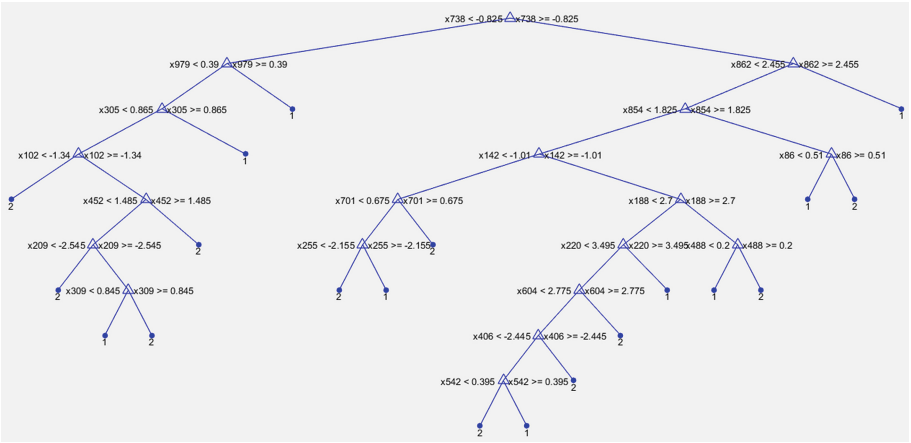

Fig. 7. An example of a Decision Tree trained on EE versus FM, on 70 % of the data and limited to minimum of 7 observations per tree leaf, the result for this tree on the test data is 70 %.

```
generateTree(scans)
Input: scans – fMRI scans (containing 1000 best voxels)
1.  Tree={}
2.  If scans is "pure" OR stopping criteria met then
3.    Terminate
4.  end if
5.  for all voxels ϵ scans do
6.    compute Gini's index criteria if we split on 'v'
7.  end for
8.  v_best = best voxel according to the computed criteria
9.  Tree = create decision node that tests v_best
10. Scans_sub = induced sub-datasets from scans based on
      v_best
11. for all scans_sub do
12.   Tree_sub = generateTree(scans_sub)
13.   Attach Tree_sub to the corresponding branch of Tree
14. end for
15. return Tree
```

Fig. 8. The Decision tree algorithm that used in this study for fMRI data classification

that for the current task (giving evidence for the existence of two declarative memory systems) it is not a priority to optimize the classification capability of the system. That is, it suffices to show that the systems can be separated in a significant manner.

Taking into account all of these issues we decided to also use a version of Decision trees [27] with a Gini index [28] as a splitting criteria, a competitive machine learning tool. That is, in our case, the splitting value for each node is calculated by choosing the

value for each potential feature that maximizes the homogeneity of the "Gini impurity function" over the split. (See [28] for a full description.) Note that machine learning generation of decision trees have a long history [27, 28]. Its advantages include (i) it is typically created in a "greedy" fashion and so needs much less computational resources, both time and memory (ii) it creates its tree in the original feature space and so this helps in later understanding of the classification. In addition, the use of alternative methods gives some additional insight into the results. The pseudo-code for tree creation is given below in Fig. 8. (While the time complexity of such a tree can be as the square of the number of features; in actual practice we found that the depth of the tree is quite small, and so it scales linearly as the number of features. See Fig. 7 for a typical tree. Including the cross validation calculations results in calculations that takes less than a minute. We mention that this speedup suggests the possibility of using a "wrapper approach" for the choice of features instead of the ANOVA and in future work, we will explore this possibility.)

6 Results

6.1 Memory Performance

In the information retrieval test as fully presented in Merhav et al. [16], correct response rates for the recent and for the remote associations were significantly above chance (binomial tests, $p < 0.0001$, for both times-of-acquisition, in both learning groups). Overall, participants from the FM group were less successful in retrieval, compared to those from the EE group, in both the recent and the remote conditions ($F(1,30) = 12.2$, $p < 0.005$).

In both groups, recent items were better recognized than remotely presented items ($F(1) = 9.12$, $p = 0.005$) with no significant interaction between the time of acquisition and the learning mode ($F(1,15) = 0.334$, $p = 0.565$).

6.2 Classification

First, we addressed the question of classifying scans obtained during correct and incorrect retrieval. Using the proposed classification scheme, we performed 4-fold (leave one run out) cross-validation within participants. However, the mean values of classification accuracy were close to the chance level for both groups (EE and FM). We theorized that the reason could be the existence of two additional different sub-groups, recent and remote acquisition, within each of the initial groups.

Accordingly, we classified correct and incorrect scans within each possibility: EE recent, EE remote, FM recent, FM remote. For each possibility we chose 10 % of all data points randomly as a testing set. The rest of the data points were used for training. Then, 10-fold cross validation was performed. We report the values for mean and standard deviation of classification accuracy over 10 cross-validation folds for EE in Table 1 and for FM in Table 2.

These results show that a trained classifier was able to distinguish scans obtained during correct and incorrect word retrieval within each group. The accuracy is higher

for classification of scans for words learned recently, rather than for words learned remotely. Furthermore, the discriminating ability is better within EE group rather than within FM group. From Tables 1 and 2 we see that some significant change has taken place in the activation overnight for EE; and not much can be seen in FM.

This is in accordance with the current idea of how EE and FM are stored; i.e. FM is directly stored in cortex and EE initially involves the hippocampus and over some time undergoes consolidation into the cortex. It is possible that there is more variation in the specific activations in the prior to consolidation voxels than in the cortical ones; accordingly more of the ANOVA voxels are in the hippocampus. This would help account for the lowered accuracy in EE after time as seen in Table 1 and the continued lower accuracy in FM in Table 2. However, clarification of this point will require further experimentation.

Next, we classified whether the process used for information acquisition was EE or FM using only scans from the successful retrieval attempts in the behavioral experiment. We chose randomly 10 % from all these scans of all participants as a testing set. The rest of these scans were used as a training set. Under this protocol there is substantial training data from each participant. Table 3 shows that in this case EE and FM scans can be very well distinguished.

Table 1. Correct vs. Incorrect classification within Explicit Encoding (EE) using 10-fold cross validation.

	Mean accuracy	Standard deviation
Recent	0.708	0.09
Remote	0.584	0.067

Table 2. Correct vs. Incorrect classification within Fast Mapping (FM) using 10-fold cross validation.

	Mean Accuracy	Standard deviation
Recent	0.599	0.063
Remote	0.55	0.068

Table 3. EE vs. FM (using only scans with correct retrieval) random scan selection cross-validation.

Testing set selection method	Mean accuracy	Standard deviation
Random selection	0.937	0.069

These results raise the question of whether the representation of all the participants in the training set is crucial to the classification success. That is, can a machine learning classifier, trained over the collected data, successfully distinguish which label to assign to a new individual's scan, despite the fact that the classifier has never seen data from this participant. To answer this question, we performed a leave-one-participant-out classification. This was done across all 16 (one from EE and one from FM) participants in a cross-validation manner (leave one out). Note that per iteration, the scans in the testing set are all EE or all FM. Therefore, we were able to use the majority voting method for this analysis. The results averaged across all participants presented in Table 4.

Table 4. EE vs. FM (using only scans with correct retrieval scans) across participants using 16-fold cross-validation

Testing set selection method	Mean accuracy	Standard deviation
Leave one participant out	0.638	0.07

Table 5. EE versus FM Confusion Matrix, average accuracy is 73 %

	EE	FM
EE	67.88 ± 4.68	32.12 ± 4.68
FM	22.68 ± 3.65	77.32 ± 3.65

Table 6. Recent (EE versus FM) Confusion Matrix, average accuracy is 70 %

	EE	FM
EE	0.6425 ± 0.0738	0.3575 ± 0.0738
FM	0.2516 ± 0.0568	0.7484 ± 0.0568

Table 7. Remote (EE versus FM) Confusion Matrix, average accuracy is 68 %

	EE	FM
EE	62.56 ± 7.54	37.44 ± 7.54
FM	25.71 ± 5.15	74.29 ± 5.15

Table 8. Recent versus Remote Confusion Matrix, average accuracy is 61 %

	Recent	Remote
Recent	60.45 ± 4.29	39.55 ± 4.29
Remote	38.99 ± 4.97	61.01 ± 4.97

Table 9. EE (Recent versus Remote) Confusion Matrix, average accuracy is 63 %

	Recent	Remote
Recent	61.83 ± 6.28	38.17 ± 6.28
Remote	36.81 ± 6.22	63.19 ± 6.22

Table 10. FM (Recent versus Remote) Confusion Matrix, average accuracy is 50 %

	Recent	Remote
Recent	49.81 ± 6.90	50.19 ± 6.90
Remote	49.11 ± 6.64	50.89 ± 6.64

Tables 5, 6, 7, 8, 9 and 10 presents the classification results using 1000 best features selected by ANOVA F-score from the whole brain using the alternative Decision Tree methodology. To avoid over-fitting a minimum of 7 observations per tree leaf was required. All the results were generated using 80 cross-validation cycles with randomly chosen scans for testing and training. (The division was 30 % for testing and 70 % for training.)

Tables 5, 6 and 7 show how the decision trees succeed in separating EE from FM. In all cases (both all data and separated by time since acquisition) they can be separated in a significant fashion.

Tables 8, 9 and 10 relate to the issue of consolidation. The general conception ("standard model" [1] is that EE undergoes a transition between storage very dependent on the hippocampus to one based on the cortex; whereas under FM this process may be quite different. Comparing Tables 9 and 10, this is borne out.

In summary, we see that these results strongly affirm the distinction between EE and FM. In addition, we see that the retrievals between recent and remote are distinguishable only in EE. This indicates that re-organization takes place in the time frame of the experiment for EE examples; while we were unable to discern such a distinction for the FM mechanism. This corresponds to the theoretical expectation of the two system and further supports their existence.

7 Discussion and Conclusions

In this work, we showed that it is possible to identify correct and incorrect retrieval of memories acquired through two learning mechanisms: either Explicit Encoding (EE) or Fast Mapping (FM) directly from neuroimaging data, using machine learning techniques. The findings suggest (Tables 1 and 9) that it is easier to identify retrieval success and failure for information acquired recently rather than for information after a period of time through EE mechanism. At the same time, no significant change (Tables 2 and 10) between retrieval results of recent and remote acquisition was seen within the FM mechanism. This may indicate that FM does not engage reorganization processes during the 24 h since encoding.

It was also observed that one could directly classify which memory system was used regardless of when the memory was acquired (Tables 5, 6 and 7).

Accordingly, the current results provide additional evidence for the existence of two memory formation processes by successfully classifying scans of correct retrievals following EE and FM. Note that the classification results for scans taken from an individual's data, which were not used previously for training, were still significant. These findings suggest that associative learning through FM employs alternative neural pathways to acquire and maintain declarative knowledge. This also indicates that the FM process is eligible for therapeutic approach for people with hippocampal brain injuries.

8 Future Work

Future work should include mapping of the brain regions and extraction of functional networks associated with all four group combinations, EE recent, EE remote, FM recent and FM remote. A list of possible implementation approaches includes constructing brain maps using "searchlight" techniques [12].

Another novel approach is to consider the actual voxels used in the Decision Trees. Looking at a typical example (Fig. 7) shows many interesting aspects. Note that the decision is made by a very small number of voxels. Furthermore, the interaction between the voxels on each path through the tree is clearly indicated. This means that, taking into an account of the location of each voxel used, a careful analysis should indicate the interaction between areas of the brain for each memory system.

In addition, future work should include brain regions correlations tests during the retrieval of memory through EE and through FM in recent and in remote modes. Those correlations would provide information regarding the involvement of the hippocampus and vmPFC regions in the consolidation processes. To achieve that, one may use causality analysis techniques [24] to reveal the causality influences the brain regions, which are involved with each learning procedure, have on each other. This could help reveal new information regarding the mechanism involved in memory consolidation processes of FM.

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The research is based on data gathered by Rotman Research Institute at Baycrest, Toronto, Canada. The examining of this data was suggested by Dr. A. Gilboa and complements the work of Merhav, Karni and Gilboa [16]. The computational analysis of the data was performed at the Neuro-Computation Laboratory at the Caesarea Rothschild Institute at the University of Haifa, Israel under the supervision of Prof. Larry Manevitz. The authors are listed in alphabetical order.

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