

LEARNING DEEP TEMPORAL REPRESENTATIONS FOR BRAIN DECODING

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ABSTRACT

Functional magnetic resonance imaging produces high dimensional data, with a less than ideal number of labelled samples for brain decoding tasks (predicting brain states). In this study, we propose a new deep temporal convolutional neural network architecture with spatial pooling for brain decoding which aims to reduce dimensionality of feature space along with improved classification performance. Temporal representations (filters) for each layer of the convolutional model are learned by leveraging unlabelled fMRI data in an unsupervised fashion with regularized autoencoders. Learned temporal representations in multiple levels capture the regularities in the temporal domain and are observed to be a rich bank of activation patterns which also exhibit similarities to the actual hemodynamic responses. Further, spatial pooling layers in the convolutional architecture reduce the dimensionality without losing excessive information. By employing the proposed temporal convolutional architecture with spatial pooling, raw input fMRI data is mapped to a non-linear, highly-expressive and low-dimensional feature space where the final classification is conducted. In addition, we propose a simple heuristic approach for hyper-parameter tuning when no validation data is available. Proposed method is tested on a ten class recognition memory experiment with nine subjects. The results support the efficiency and potential of the proposed model, compared to the baseline multi-voxel pattern analysis techniques.

1 INTRODUCTION

Revealing the relation between brain activity and stimuli is one of the milestones to be reached in order to understand the neural code. Data driven approaches such as Multi-Voxel Pattern Analysis (MVPA) in systems neuroscience help to achieve this goal by formulating it as a machine learning task. When presented a stimulus and the simultaneous brain activity is recorded for a subject, the relation between the recorded signal and the category of the stimulus may provide percepts for the underlying cognitive process. And the classification problem of predicting the stimulus from the brain recording is called brain decoding. Brain decoding using functional magnetic resonance imaging (fMRI) is a challenging problem that has received much attention recently because of its non-invasive nature, see Haxby et al. (2014) for a review.

The major difficulty for the machine learning tasks using fMRI data is the scarcity of labelled samples compared to the high dimensional input spaces. In a typical task related fMRI experiment, the number of labelled samples over several time points reaches at most hundreds while dimension of the input space (number of voxels) easily exceeds thousands even if a small region of interest is considered. Therefore, in order to improve the classification accuracy and significance, there has been a

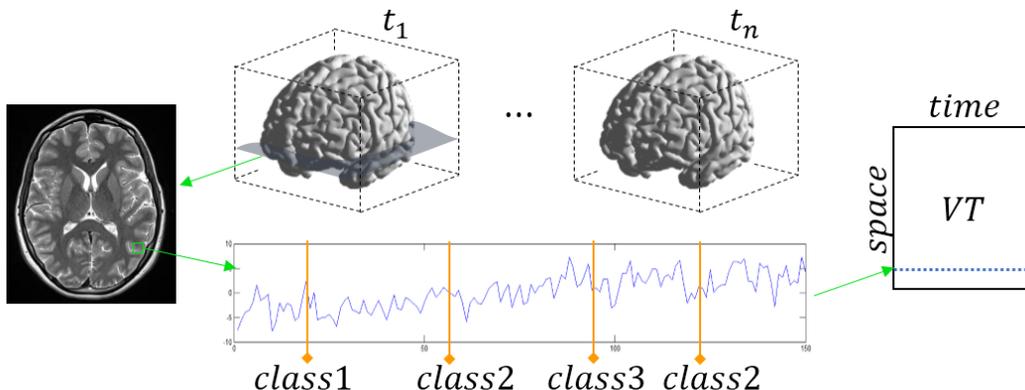


Figure 1: Example of a typical task fMRI experiment for brain decoding. 4-dimensional fMRI data consists of several volumes across time, some of which are assigned to a class label according to the semantic type and timing of the stimulus. The classification problem is to predict the class of a labelled sample given rest of the samples. Unlabelled volumes, majority of the samples, are usually consist of interstimulus side-tasks or resting periods, and usually discarded during the classification in classical MVPA methods. The whole experimental data can be used to form a data matrix, rows correspond to voxel time-series (time-axis) and columns correspond to voxels in a 3-dimensional volume (space/spatial-axis).

great deal of effort spent to either reduce the dimensionality Viviani et al. (2005); Sidhu et al. (2012); Mwangi et al. (2014) or employ spatial/temporal structures Battle et al. (2006); Pereira & Botvinick (2011); Firat et al. (2013) for a better representation. As a result, many brain decoding systems rely on cleverly hand-crafted features Norman et al. (2006); Haynes & Rees (2006); Shirer et al. (2012); Hausfeld et al. (2014) to represent cognitive processes. Another issue related to the low number of labelled samples is the labelling procedure which is strongly coupled with the experimental design. Within the time points acquired during an experiment, only few are assigned to corresponding class labels by considering timing of the stimulus. For example in a block design, a predetermined number of time points within a block are averaged to obtain a smoothed intensity value Mitchell et al. (2008) and assigned to a single class label. Similarly, in an event related design, class labels are assigned to time points according to the prior knowledge of the peaks of hemo-dynamic response function (e.g. 2-3 time points after the stimulus) Norman et al. (2006); Oztekin & Badre (2011). The rest of the unlabelled samples are generally thrown away and not used further in the decoding tasks. A typical fMRI experiment for brain decoding is depicted in Figure 1.

Recent improvements in unsupervised feature learning and transfer learning points out the importance of employing unlabelled data for a better classification Raina et al. (2007); Erhan et al. (2010), especially for the cases that we do not have enough labelled data. It is hypothesised that learning the data generating distribution $p(x)$ by leveraging unlabelled data improves further discriminative tasks $p(y|x)$, when $p(x)$ and $p(y|x)$ share some structure Bengio et al. (2013). We experimented this hypothesis by proposing that the discarded unlabelled samples of fMRI data still contain information and can be exploited in brain decoding tasks. Learning of $p(x)$ is reformulated as learning a set of basis functions that can be used to represent temporal behaviour of brain activity. Likewise, and learning of $p(y|x)$ is formulated as a mapping between learned representations and class labels.

In this paper, we attack the brain decoding problem from perspectives of dimensionality reduction and leveraging the unlabelled data. In order to represent noisy and redundant fMRI data, we employ an unsupervised feature learning algorithm that can automatically extract multiple levels of temporal features using unlabelled data. Such approaches are common in computer vision Le et al. (2011) but have not been adapted for neuroimaging data, especially for brain decoding. By incorporating unlabelled data and very little prior knowledge, we learn two levels of temporal filters for fMRI data representation without hand-crafting them. Further, we integrate learned temporal representations into a deep temporal convolutional neural network (CNN) which have demonstrated many successes recently Krizhevsky et al. (2012). We employ the temporal representations to capture the temporal information by convolution following spatial pooling within CNN layers to reduce dimensionality.

By leveraging unlabelled data and the representational power of CNNs, we are able to train robust classifiers. The constructed feature spaces are automatically formed by temporal representations and have a reduced dimensionality thanks to spatial pooling. The proposed method substantially improves classical and enhanced multi-voxel pattern analysis (MVPA) methods for brain decoding on a recognition memory experiment with nine participants. Although there exist few studies that employ and analyse deep learning methods for neuroimaging data Cadieu et al. (2014); Hjelm et al. (2014); Plis et al. (2014), we believe that the potential of deep learning should be further studied thoroughly for brain decoding tasks as well.

2 UNSUPERVISED LEARNING OF TEMPORAL REPRESENTATIONS AND CONVOLUTIONAL ARCHITECTURE

In this section, we describe proposed unsupervised learning architecture for deep temporal representations. fMRI data is composed of 3-dimensional brain volumes across time $\{t_i\}_{i=1}^n$, where each 3D volume is formed by stacking several 2D slices (scans) and n is the total length of the experiment across runs (see Figure 1). Each pixel in these 2D images actually represents the intensity of a small volume of brain tissue (voxel) at a time instant t_i . The intensity value of a voxel at location j at a time instant i can be denoted as v_i^j , where $j = 1, \dots, m$ and m is the total number of voxels in the experiment. A typical fMRI experiment consists of several runs in which the subjects are presented task specific stimuli at predetermined time points. Each of these stimulus corresponds to a class (semantic class label) and the data acquired at that instant is assigned to corresponding class label (orange vertical lines in Figure 1). The entire experimental data can be represented by a voxel \times time matrix VT , where columns are representing the brain volumes in terms of voxels (space), the rows stand for voxel time series (time). Further in the classification, the labelled samples are separated into two sets, where the first set is employed in training the classifier and the second set is used for generalization test. Conventional MVPA methods discard columns of the data matrix VT that do not have class labels and represent the cognitive states by using raw voxel intensity values as features. Although the discarded data do not carry label information, it carries the temporal structure (activation pattern) of each voxel across time. In order to improve representation power of features, it is promising to capture and employ the temporal activation pattern as a substitute for raw intensity values.

In this study we use the entire VT matrix (except the columns separated for test) to learn temporal filters in two layers. Our aim is to learn a number of activation patterns delimited by short time-window and able to reflect temporal regularities in the data without hand-crafting them. For the aim of learning temporal filters in an unsupervised fashion, we employ sparse autoencoders Kavukcuoglu et al. (2009). An autoencoder is a neural network trained by back-propagation which attempts to reconstruct its input by setting the target values to be equal to the inputs, $x \approx \tilde{x}$. Let x be the dataset of time windows of length τ_1 that are randomly sampled from the rows of the VT matrix. Autoencoder consists of two consecutive functions. First, an encoder function $f_{\theta_1}(x)$ is applied on x with parameters θ_1 which maps x to a hidden representation h . Second, a decoder function $g_{\theta_2}(f_{\theta_1}(x))$ mapping the hidden representations to the reconstruction \tilde{x} with parameters θ_2 . By enforcing a sparsity constraint (activation around zero) to hidden layer neurons via the cost function, autoencoder learns a compact, non-linear and possibly over-complete representation of its input x . The number of hidden neurons is equal to the number of filters (bases) to be learned and will be referred as k_1 for the first layer temporal representations. The sparse autoencoder having k_1 hidden neurons is trained to minimize reconstruction error using back-propagation by minimizing the following cost function,

$$J_{\text{sparse}}(\Theta) = J_{NN}(\Theta) + \beta J_{\hat{\rho}} + \lambda \|\Theta\|_2^2, \quad (1)$$

where $J_{NN} = \frac{1}{2} \sum_i \|\tilde{x}^{(i)} - x^{(i)}\|_2^2$ is the neural network reconstruction term and $\lambda \|\Theta\|_2^2$ is the L2 regularization term on parameters and β is the hyper-parameter controlling importance of sparsity in the model. Sparsity term $J_{\hat{\rho}}$ is the crucial term in our autoencoder. Let $a(\cdot)$ be an element-wise non-linear activation function and $\hat{\rho}_j = \mathbb{E}[a_j(x)]$ be the expected activation of hidden unit j over the dataset. By enforcing the constraint $\hat{\rho}_j = \rho$ where ρ is the sparsity hyper-parameter, hidden layer activations can be adjusted to be sparse. In order to measure the sparsity cost, Kullback-Leibler divergence between average activation of a unit $\hat{\rho}$ and sparsity parameter ρ is calculated

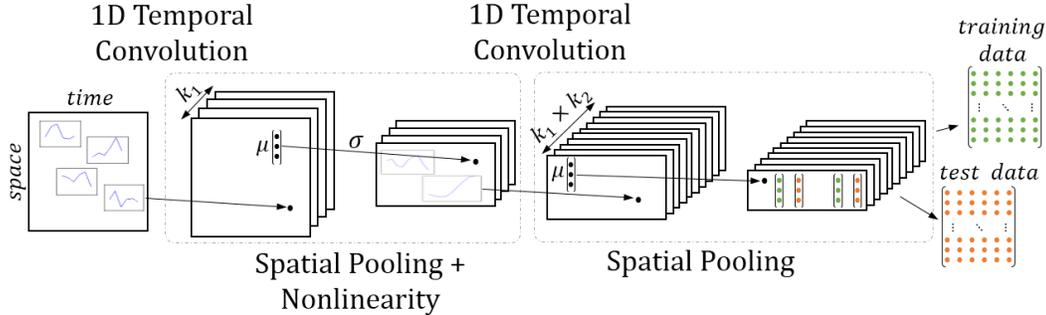


Figure 2: Temporal Convolutional Neural Network with spatial pooling units used for brain decoding.

as $J_{\hat{\rho}} = \sum_j^{k_1} KL(\rho || \hat{\rho}_j)$. The optimization of the cost function (1) yields the model parameters $\Theta = \{\theta_1, \theta_2\}$, and columns of the transition weights θ_1 of encoder function $f_{\theta_1}(x)$, constitutes the temporal filters. After learning k_1 number of filters in the first layer, VT matrix is convolved along the time axis (1D full temporal convolution) with the learned filters and k_1 number of response matrices are extracted. Note that resulting response matrices are the same size as VT with a full convolution.

In a convolutional neural network, a general processing block is constructed by three consecutive operations; convolution, pooling and applying an element-wise non-linearity Krizhevsky et al. (2012). Further, these blocks can be repeated consecutively by feeding output of one block to the next one Le et al. (2011). We construct our temporal convolutional model with two processing blocks as shown in Figure 2 with dashed boxes. To complete our first processing block, we determine a spatial pooling function μ , a pooling range in a vicinity δ_1 and point-wise non-linearity function σ . Considering the capillary structure of the brain and point spread function of fMRI medium, it is expected that nearby voxels exhibit correlated activations Pereira & Botvinick (2011). Therefore for the choice of μ we employ max pooling function on the columns of response matrices. Note that the columns of the response matrices correspond to spatial domain of fMRI data. As we increase the pooling range without any overlaps between pooling functions, the final dimensionality decreases. As an example, a spatial pooling with range $\delta_1 = 2$ on a response matrix with m rows (voxels) and n columns (time points) response matrix results in an $m/2$ rows and n columned pooled response matrix where the maximum of each of 2 closest voxel responses are taken¹. We finalize the first processing block by applying σ , which is set to hyperbolic tangent, to all elements of the pooled response matrices.

The second level of our deep temporal convolutional net takes the pooled response matrices as input and repeats the same pipeline conducted in the first block. The only difference for the second block is the number of input matrices, which is k_1 number of m/δ_1 rowed and n columned pooled response matrices. For each of these matrices, a separate k_2 number of temporal filters are learned again by employing sparse autoencoders for each. Same procedure is followed k_1 times: first collecting τ_2 length time windows from the rows of an input response matrix then training a sparse autoencoder having k_2 number of hidden units. Each k_2 filters are then convolved with the corresponding first level pooled response matrix. Repeating this process for all inputs of the second block then applying pooling and non-linearity similarly, we obtain $k_1 \times k_2$ number of second level pooled response matrices. Note that second level pooled response matrices have $m/(\delta_1 \times \delta_2)$ rows and n columns, where δ_2 is the pooling range for second processing block. As mentioned above, the class labels are carried along the columns of the initial VT matrix. After processing raw input data with the proposed temporal convolutional model, the resulting second level pooled response matrices have the same number of columns n , hence still carries the class label information. Finally at this point, all the second level pooled response matrices are concatenated along their time axis resulting our final representation matrix which has $(m \times k_2)/(\delta_1 \times \delta_2)$ rows and n columns. We then separate the training and test data by extracting corresponding columns of VT matrix, according to the experiment design class labels positions.

¹Pooling functions are applied to closest voxel pairs in the 3D-brain volume, not in the consecutive elements of VT matrix columns. Pooling regions in Figure 2 are drawn for the ease of understanding.

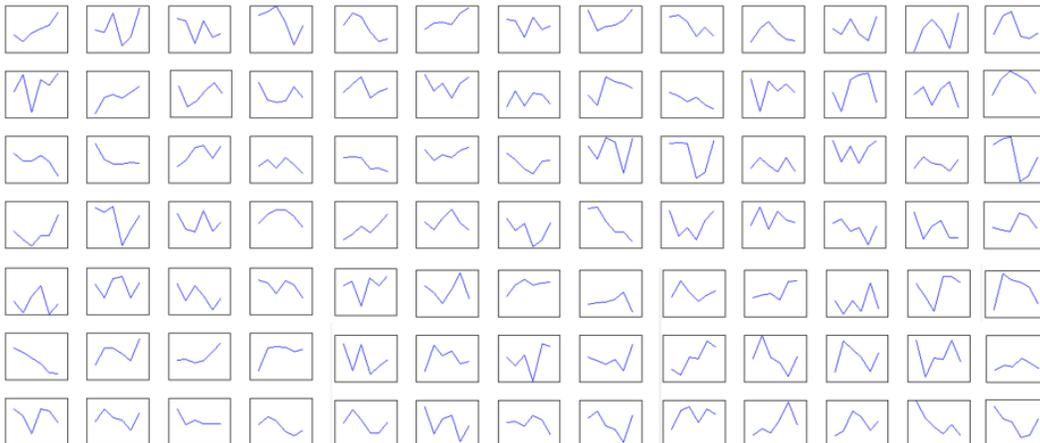


Figure 3: A collection of the first level temporal filters learned from unlabelled data across different subjects. Each small box represents a temporal filter. Filters are randomly chosen across all subjects.

3 EXPERIMENTS ON fMRI DATA

fMRI recording was conducted during a recognition memory task on nine participants. Each participant is shown a list of words belonging to a specified semantic category in the working memory encoding phase within ten categories, namely fruits, vegetables, furniture, animals, herbs, clothes, body parts, chemical elements, colors and tools. Following a delay period where the participant solves mathematical problems, a test probe is presented and the participant executes a yes/no response indicating whether the word belongs to the current study list (e.g., see Oztekin & Badre (2011)). For the decoding task, we focused on anterior lateral temporal cortex region having 1024 voxels (m). fMRI data consists of 2400 time points (n) in 8 runs, with 240 class labels for the memory encoding phase and 240 class labels for the memory retrieval phase (for each of ten classes, 24 samples for both memory encoding and memory retrieval). The classification task we seek to accomplish is to predict class labels of the samples in the memory retrieval phase by using samples in the memory encoding phase. Measurements recorded in the memory encoding phase are used as labelled training samples and measurements in the memory retrieval phase are used as test samples. The recording was conducted using a 3T Siemens scanner with a 2 seconds TR (repetition time), meaning that we obtained a separate brain volume each 2 seconds (0.5 Hz sampling rate). Apart from slice-scan time correction, 3D motion correction and registration, no additional pre-processing was employed.

3.1 MODEL DETAILS

The proposed model is tested using fMRI experiment data with various architectural choices. Our main consideration was to reduce the final representation dimensions with varying pooling ranges. For this purpose, we adjusted the pooling ranges δ_1 and δ_2 to retract number of dimensions comparable with the standard MVPA method (which is equal to number of voxels m) and even lower. It is well known that, hemo-dynamic response function (HRF) peaks around 4-6 seconds after a stimulus and returns to baseline after 10-12 seconds Huettel et al. (2004). Considering the experimental protocol TR as 2sec, a full HRF could be captured with a temporal window size of 6 samples. Therefore the sampling window length for the first convolutional block τ_1 (resp. input unit size for the first autoencoder, filter length), is set to 6. It is also common for CNNs that the higher level receptive fields get wider to capture more abstract regularities Krizhevsky et al. (2012), so we increased the second block temporal sampling window length τ_2 , to 9 samples (7-10 range give similar results). Note that the collected windows that overlap with the test samples are discarded for fairness. The necessity to explicitly increasing the window length of the second layer compared to standard CNNs is that we do not conduct convolution and pooling in the same domain, namely we conduct pooling on spatial domain not in time domain. Another important difference compared to common CNNs is the summation of the response maps for each filter. The pattern we seek for brain decoding is the

activity peaks corresponding to the cognitive task which is very sensitive to noise and comparably small signal in magnitude. We observed that summation of the response maps for each filter results very smoothed activity peaks in the response map, which makes it difficult for decoding task to distinguish between class specific activations. Therefore, we avoided such summations for all of the learned filters. Lastly, we observed a rapid overfitting as we fine-tune the whole model with labelled data, which is expected with such high capacity models, hence we did not finetune our pre-trained model.

3.2 SELECTION OF HYPER-PARAMETERS WITHOUT A VALIDATION SET

A major strait of CNNs and many other deep learning methods is the large number of hyper-parameters to be tuned Bengio et al. (2013). Without a proper cross-validation set, as in our case, these hyper parameters are left to be tuned with trial and error fashion which we avoided in this study. As a heuristic, for the hyper-parameters of the autoencoders in both levels $k_1, k_2, \beta, \rho, \lambda$, we propose following numerical quality assurance. It is obvious that the hidden representations of an autoencoder are expected to learn different regularities from the input, hence, the representation power will be increased and diversified as the learned filters are decorrelated. We searched in a parameter search space for these hyper-parameter combinations. For k_1 , the interval 9-25 and for k_2 the interval 4-9, for sparsity parameter ρ 0.01-0.3 with multiples of 3 and 1,3,5 for β . For each learned filter bank with an hyper-parameter combination, we calculated the correlation matrix of learned filters. In fully decorrelated filters case, the diagonalized correlation matrix should be close to the identity matrix (all eigenvalues should be equal to one). Therefore, we calculated the L1 distance between the eigenvalues of the correlation matrix of the learned filters to a vector of ones. For example, the hyper-parameters k_1, β and ρ for the first layer autoencoder are calculated as follows,

$$\arg \min_{k_1, \beta, \rho} \|diag(I) - eigs(R_{\theta_1})\|_1 \quad (2)$$

where I is identity matrix and R_{θ_1} is the correlation matrix for filters θ_1 (columns of the encoder parameter matrix). We determine the hyper-parameter combination having the lowest distance, as $k_1 = 16, k_2 = 4, \rho = 0.03$ and $\beta = 1$. The first layer temporal representations are illustrated in Figure 3, where we observe several HRF alike filters. Moreover, the filters learned directly from unlabelled data are capable of representing several other activation patterns such as linear trends, boxcar, rapid dips and peaks, even some baseline trends. Note that the proposed model takes raw fMRI intensity values as input without any normalization or pre-processing such as whitening or z-scores.

3.3 TESTING PROCEDURES AND COMPARISON

For the validity of the proposed model, we map the raw input fMRI data into the learned representation space with our pre-trained temporal CNN. Further, in the representation space, training and test samples are extracted and final design matrix is formed for classification. In order to compare proposed method with other MVPA methods, we employ a k-nearest neighbor classifier for all methods. For the proposed model, we also evaluate a single level temporal convolutional network to monitor the impact of the depth. Three different MVPA approaches are taken into consideration. The baseline is Raw MVPA method where raw intensity values are directly fed to classifier. To make a fair comparison, we further employ temporal information in classical MVPA method in two different ways. First, to account for temporal activation pattern in a hand-crafted fashion, we convolved the raw intensity values with a double gamma HRF function spanning 6 samples, which we called as HRF MVPA. After convolving with the HRF, resulting response matrix is used in a similar way with Raw MVPA. Second, we considered a 6 sample time window from onset of the stimulus and concatenated all of the intensity values acquired during that period, which we called as Temporal MVPA (T-MVPA). This process yields a single feature vector for each sample which is 6 times larger than MVPA and HRF MVPA.

3.4 SIGNIFICANCE TESTS AND OVERFITTING ANALYSIS

The fewer number of samples (as in our case) may result in greater variability of the estimation. We conducted simple, yet diagnostic tests to determine how precise the proposed method performs. Sta-

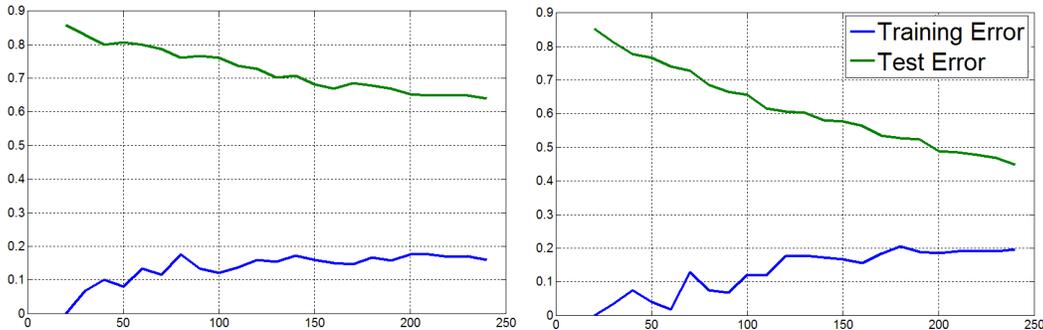


Figure 4: Learning curves of Raw MVPA (1024 dimension) on left and our method (256 dimension) with 16 pooling range in both layers on right. The horizontal-axis corresponding to number of training samples while the vertical-axis is presenting error of the model.

tistical significance measures the improbability of the observed classification accuracy given the null hypothesis is true. Pereira et al. (2009) proposes Binomial test (see Alpaydin (2010)) to estimate the significance of a classifier provided that the samples are drawn independently. In our experiment, the trials were clearly separated by irrelevant tasks between memory encoding and memory decoding phases, which makes it plausible to assume that precondition holds. The null hypothesis was regarded as randomness, i.e., the classifier performs at chance level (10% for general, 50% for one-vs-all fashion). The largest p-value the tests yielded was 0.0004, and the null hypothesis was rejected for all methods proposed.

Learning curve is a modest diagnosis tool, telling how fast a model learns with respect to training data size and whether it suffers more from variance or bias error (see Ng notes). For an ideal setting, both test and training error curves need to be converging to each other. A large gap between them is an indication of high-variance problem. With very few number of samples in relatively high dimensional feature space of fMRI data, a model can easily over fit. In terms of data, getting more training examples or using smaller set of features are possible solutions likely to help the high-variance problem. However, for fMRI case, it is usually hard to increase number of samples due to the physical limitations of MRI, forcing us to learn fewer number of representative features. To be able to observe effect of different feature sets, learning curves of two methods are presented in Figure 4. We mixed samples of different runs to get a larger pool of samples. At each step, 20 new samples (uniformly distributed) are inserted into the training set, and test and training errors are plotted. The gap between test and training errors of MVPA remains much larger as amount of training data increases. However, by using the temporal representations learned by our model, we are able to get a method suffering much less from high-variance problem. However, the end point of the plots (training with all samples) is indicating that both methods still requires more data before convergence.

4 RESULTS

In this section, we present and analyse performance results of the proposed approach. Experimental results are analysed by considering final feature space dimensions (last column of Table I) in classifiers by comparing classification accuracies. Overall results are also illustrated in Table 1. For the classical and temporal MVPA approaches (first three rows of Table 1), Raw MVPA approach is taken as baseline method. HRF convolved MVPA model performed poorly compared to Raw MVPA results only for two subjects (indicated by Sub) and improved performance up to 8% for the rest of the participants. This is expected as we employ temporal information. However, without adjusting HRF to the regularities in the data, it remains rather hand-crafted. Similarly T-MVPA method use temporal information without any HRF assumption and improves performance compared to other MVPA methods.

Proposed temporal CNN architecture is tested with varying depth (single layer and two layer rows in Table 1) and pooling ranges (δ_1 and δ_2 columns). A single layer (shallow) temporal feature learning

Table 1: Comparison of Classification performance of the proposed method and Baseline methods.

Method	δ_1	δ_2	Sub1	Sub2	Sub3	Sub4	Sub5	Sub6	Sub7	Sub8	Sub9	Dim
Raw MVPA	-	-	28.9	41.5	43.1	45.5	42.3	31.9	34.0	40.6	41.4	1024
HRF MVPA	-	-	32.3	44.4	42.3	53.8	36.1	41.1	44.5	46.5	48.2	1024
T-MVPA	-	-	41.9	52.4	52.0	53.9	45.3	44.0	44.9	51.1	52.5	6144
Single Layer	2	-	54.0	65.7	65.3	67.8	66.7	64.1	66.1	65.7	69.5	8192
Single Layer	4	-	56.1	64.5	63.6	69.5	66.2	65.3	66.1	66.5	68.6	4096
Single Layer	8	-	55.7	65.3	62.8	69.5	64.0	64.9	66.1	67.4	70.0	2028
Single Layer	16	-	51.9	64.0	63.2	68.6	62.3	63.3	64.9	67.3	67.0	1024
Two Layers	4	2	69.0	71.6	72.9	72.4	72.8	71.2	72.3	70.3	71.2	8142
Two Layers	16	1	68.6	69.1	71.2	72.4	69.1	68.6	60.7	70.3	72.8	4096
Two Layers	16	2	69.5	68.6	71.6	73.2	70.0	69.9	66.1	70.3	72.8	2048
Two Layers	16	4	69.9	69.5	73.3	72.8	71.2	70.0	67.0	69.5	71.6	1024
Two Layers	16	8	68.6	67.4	72.0	70.8	71.1	68.7	67.0	70.3	70.8	512
Two Layers	16	16	63.6	66.5	69.9	70.7	68.3	66.6	64.4	68.2	66.5	256

and convolution architecture with varying pooling range between 2 to 16 yields a feature space with dimensions from 8192 to 1024. For all nine subjects, single layer architecture outperforms classical and temporal MVPA methods substantially and achieving performance up to 60%. By appropriate pooling, the feature dimensions of the single layer architecture retracted to 1024 where we still observe 20% improvement.

In order to analyse the impact of the depth and further reduce feature dimensionality, two layer architecture is tested with varying pooling ranges in the second level. The proposed model in two layers reduces feature dimensions down to 256 where we still observe better performance in 8 subjects compared to the single layer architecture with lowest dimensions. We did not observe any performance improvements by increasing depth more than two, as model gets more complex and starts to overfit rapidly. The results suggest that employing temporal structures with appropriate pooling for brain decoding gives rise to better classification accuracies. Hierarchical convolutional models pre-trained with a slightly larger amount of unlabelled data are appropriate candidates to employ temporal information in an efficient way. Furthermore, increasing depth of such temporal convolutional architectures up to some extent, makes it possible to reduce feature dimensionality, and the learned filters become more complex and non-linear, resulting a better classification performance.

5 CONCLUSION

In this study, we have considered a novel approach for brain decoding on fMRI data using unsupervised feature learning and convolutional neural networks. By leveraging unlabelled data and employing multi-layer temporal CNNs, we learn multiple layers of temporal filters which represent the activation patterns of voxels under experimental conditions. By making use of deep temporal representations, we train powerful and robust brain decoding models, which may initiate a slight departure from conventional MVPA approaches generally relying on voxel intensity values as features or carefully hand-crafting them. As evidence of the power of proposed model, we conducted a recognition memory experiment on 9 subjects and observed significant performance improvements. The proposed model has potential to further improvements by incorporating spatial structures with spatial convolution and pooling, or learning spatio-temporal filters all-together which is left as a future work. Also, hyper-parameter selection and preventing overfitting is partially and naively handled in this study, which should be further analysed in details.

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