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A Report on Applying EEGnet to Discriminate Human State Effects on Task Performance

**by Ashton Gauff, Humberto Muñoz-Barona,
Addison Bohannon, and Jean Vettel**

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A Report on Applying EEGnet to Discriminate Human State Effects on Task Performance

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14. ABSTRACT In this project, we utilized optimization to discriminate brain data. Participants completed 2 cognitive tasks while ongoing brain activity was recorded from electrodes on their scalp. Our analysis examined whether we could identify what task the participant was performing from differences in the recorded brain time series. We modeled the relationship between input data (brain time series) and output labels (task A and task B) as an unknown function, and we found an optimal approximation of that function from among a family of functions. We employed stochastic gradient descent to minimize the estimation error known as the loss function. The optimal function from among our family of approximate functions, EEGNet, successfully discriminated brain data from a single participant with approximately 90% accuracy. Future research will apply EEGNet on data from more participants as well as develop approaches to adapt its architecture for the non-Euclidean domains.					
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1. Introduction

As the amount of battlefield technology continues to increase, Soldiers are faced with a daunting task of trying to integrate diverse information across numerous devices. The growing information burden across devices has spawned a strong interest in “smart technology,” where algorithms strive to become a digital assistant to streamline information processing for the end user. Unfortunately, users typically have as many examples of the technology making pervasive errors as examples where the technology provides helpful assistance, such as the numerous auto-correct fail memes, comical questions incorrectly deduced by voice recognition software, or lane-keeping sensors on cars that alert for highway medians or chain link fences. These failures often originate from a rigid application of an algorithm. We posit that the technology would become smarter if there was real-time feedback from the user that could modify the algorithm. Thus, research at the US Army Research Laboratory (ARL) targets the development of adaptive technology based on the real-time detection of human state (*e.g.*, engagement or fatigue) to improve the integrated performance of humans and systems.

While the concept of human state is inherently nebulous, the intuition is that the configuration of our physiology underlying our behavior is predictive of upcoming performance. Take the example of driving while fatigued. When we are tired, we may swerve out of a lane unexpectedly. If sensors could use real-time physiology to detect a human state that is predictive of decreased vigilance, smart technology could intelligently assist with lane-keeping technology. In contrast, on days where the driver does not have physiological markers of decreased vigilance, the smart technology would not interfere with human driving as the swerving in and out of lanes may be necessary in a construction zone. This is just one example about how knowledge of the human state could enable technology to adapt more intelligently to the user’s real-time needs.

These adaptive technologies depend on a fundamental scientific achievement to reliably detect physiological states that are indicative of performance. Ongoing work at ARL examines physiological signals across the brain and body, including how well brain activity can predict upcoming task performance. In this research, brain activity is often measured from the scalp using electroencephalogram (EEG) sensors that record ongoing electrical activity generated when different brain regions

are communicating information in support of behavioral performance. Fluctuations in the functional activity are then linked to variability in task performance, attempting to capture the physiological features of human state needed to predict real-time human task needs. Based on the success of convolutional neural networks (CNN) in extracting meaningful representations of data in image and speech processing, we would like to be able to apply these methods to EEG.¹ Currently, the need for lots of training data poses the most significant obstacle to implementing these powerful algorithms on EEG.

In my summer internship, I learned about ongoing work at ARL to overcome this data challenge of EEG by using CNNs with minimal parameters. I used my background in mathematics to understand the algorithms involved in implementing EEGNet, an ARL-developed CNN for EEG data, and apply EEGNet to a new problem.² This report summarizes that work. CNNs are powerful function approximators, and in the first section of the technical approach, I review the functions that make up the EEGNet convolutional neural network. To understand EEGNet, I had to learn about maximum likelihood estimators that allow us to pose learning problems as optimization problems. I derive the EEGNet objective function from a maximum likelihood estimate in the second section. In the third section of the technical approach, I describe stochastic gradient descent, the learning algorithm used with CNNs. Then, I describe the implementation of EEGNet and its application to an ARL data set that examines how human state changes following naturalistic sleep loss. The preliminary results effectively discriminate between human states, and this leads to a discussion of future directions in which I propose using EEGNet to ask further questions about physiological state changes and how they impact task performance.

2. Technical Approach

We wanted to discriminate between human states from individuals performing different cognitive tasks versus observing their EEG activity alone. For this particular project, we used EEG recordings from individuals during either rest or while performing an attentional bias task. Our goal was to discriminate between the 2 tasks. We used machine learning to discriminate between the states. We modeled the cognitive task as a Bernoulli trial from which we observed the EEG recording. This made the state discrimination problem one of state detection. Then, we posed our learning problem as one of posterior inference, in which we used EEGNet² for the

inference model. Finally, we used stochastic gradient descent as our learning algorithm to fit EEGNet to the observed data.

In this section, we will briefly review CNNs, introduce EEGNet, derive the posterior inference problem, and review stochastic gradient descent.

2.1 Convolutional Neural Networks

CNNs are powerful machine learning algorithms that have been successfully applied to image processing, automatic speech recognition, speech translation, and natural language processing.¹ More recently, they have even been applied to the analysis of EEG data.² CNNs are a subset of algorithms known as deep learning. Deep learning essentially implies the composition of multiple nonlinear functions.

$$f(x) = (f_n \circ \cdots \circ f_0)(x). \quad (1)$$

CNNs comprise particular functions: 2-dimensional convolutions, pooling, and batch normalization.

2.1.1 2-Dimensional Convolution

Convolutions are a common tool in signal processing. These are linear transformations that filter a signal to accentuate or attenuate particular features. In CNNs, we use the 2-dimensional generalization of the convolution $*$: $\mathbb{R}^n \times \mathbb{R}^m \rightarrow \mathbb{R}^{n \times m}$:

$$(f * g)(x, y) = \sum_{i=1}^n \sum_{j=1}^m f(i, j)g(x - i, y - j). \quad (2)$$

Here, f is the signal and g is the filter. During the learning process, we are selecting the filters that capture the most important features of the signal. In images, these features are often edges and blobs. A visualization of 2-dimensional convolution is shown in Fig. 1.

2.1.2 Pooling

Pooling, or downsampling, reduces the dimensionality of the signal and decreases the sensitivity of the algorithm to noise in the signal. Pooling is a dimensionality reduction technique:

$$P: \mathbb{R}^n \rightarrow \mathbb{R}^{\frac{n}{p}}. \quad (3)$$

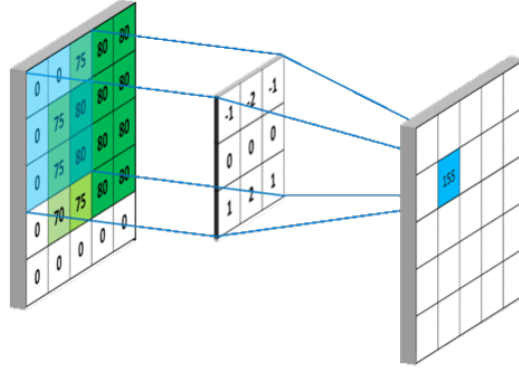


Fig. 1 2-dimensional discrete convolution

Figure reprinted from <https://mlnotebook.github.io/post/CNN1/>.³

Normally, this operation is either the average or maximum of adjacent elements of the signal. A visualization of pooling is shown in Fig. 2.

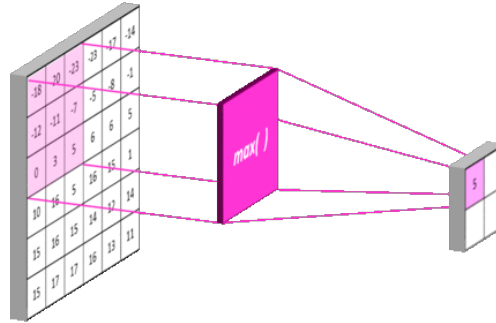


Fig. 2 2-dimensional max pooling operator

Figure reprinted from <https://mlnotebook.github.io/post/CNN1/>.³

2.1.3 Batch Normalization

Batch normalization is a technique for improving the learning process. It normalizes the features of signals in subsequent functions within the CNN, enforcing a multivariate Gaussian distribution of features. Figure 3 shows the distribution of observations before and after batch normalization.

Let $X_1^{(k)}, \dots, X_N^{(k)}$ be a subset of the observations where k corresponds to the batch.

More generally, these could be the input to any function f_i in the CNN. We would like to model these observations to be nearly independent and identically distributed (IID) Gaussian samples $X_i^{(k)} \sim \mathcal{N}(x; \mu = 0, \sigma^2 = 1)$. In practice, we can estimate

the mean and variance of each batch with the sample mean $\bar{x}^{(k)}$ and sample variance $(s^2)^{(k)}$ and normalize the observations accordingly as in a z-score.

$$z_i^{(k)} = (s^2)^{(k)} x_i^{(k)} + \bar{x}^{(k)}. \quad (4)$$

Learning parameters for the sample mean $\beta \approx s^2$ and sample variance $\gamma \approx \bar{x}$ make this procedure more computationally efficient and the learning more smooth.⁴

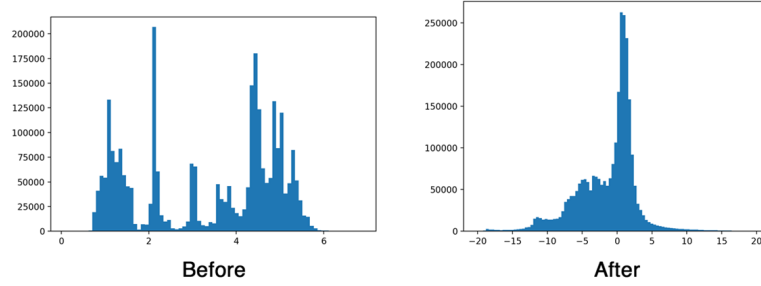


Fig. 3 Batch normalization

2.2 EEGNet

EEGNet is a particular instance of a CNN with a set of functions optimized for EEG observations. The functions that compose EEGNet are shown in Fig. 4. It is divided into 4 layers, in which most have a 2-dimensional convolution, pooling operation, and batch normalization. The first layer can be interpreted as a nonlinear spatial filter. The second layer can be interpreted as a nonlinear temporal filter. Then, the third layer aggregates the global features of the signal.

Layer	Input ($C \times T$)	Operation	Output	Number of Parameters
1	$C \times T$	$16 \times \text{Conv1D} (C \times 1)$	$16 \times 1 \times T$	$16C + 16$
	$16 \times 1 \times T$	BatchNorm	$16 \times 1 \times T$	32
	$16 \times 1 \times T$	Transpose	$1 \times 16 \times T$	
	$1 \times 16 \times T$	Dropout (.25)	$1 \times 16 \times T$	
2	$1 \times 16 \times T$	$4 \times \text{Conv2D} (2 \times 32)$	$4 \times 16 \times T$	$4 \times 2 \times 32 + 4 = 260$
	$4 \times 16 \times T$	BatchNorm	$4 \times 16 \times T$	8
	$4 \times 16 \times T$	Maxpool2D (2,4)	$4 \times 8 \times T/4$	
	$4 \times 8 \times T/4$	Dropout (.25)	$4 \times 8 \times T/4$	
3	$4 \times 8 \times T/4$	$4 \times \text{Conv2D} (8 \times 4)$	$4 \times 8 \times T/4$	$4 \times 4 \times 8 \times 4 + 4 = 516$
	$4 \times 8 \times T/4$	BatchNorm	$4 \times 8 \times T/4$	8
	$4 \times 8 \times T/4$	Maxpool2D (2,4)	$4 \times 4 \times T/16$	
	$4 \times 4 \times T/16$	Dropout (.25)	$4 \times 4 \times T/16$	
4	$4 \times 4 \times T/16$	Softmax Regression	N	$TN + N$
Total				$16C + N(T+1) + 840$

Fig. 4 Layers of EEGNet model

Table reproduced from Lawhern, et al.²

2.3 Learning Objective

Following the maximum likelihood formulation of Duda et al. in Pattern Classification,⁵ we modeled the cognitive task to be distributed according to a Bernoulli distribution conditioned on the associated realization of EEG recording. Our goal was then to infer the cognitive task given the EEG realization, a statistical inference task. We used EEGNet to estimate the Bernoulli parameter for each EEG realization so that we could pose the inference problem as a parameter estimation problem. This allowed us to use a maximum likelihood estimate to formulate the learning problem as an optimization problem.

Let $X_1, \dots, X_N$, be IID observations of EEG recordings and $Y_1, \dots, Y_N$ to be the associated cognitive task. As mentioned above, let $Y_i|X_i \sim \text{Bern}(p(X_i))$:

$$f_{y|x}(y_i|x_i) = p(x_i)^{y_i} (1 - p(x_i))^{1-y_i}. \quad (5)$$

We will consider the log likelihood of all EEG observations:

$$\ln \prod_{i=1}^N f_{y|x}(y_i|x_i) = \ln \prod_{i=1}^N \left[p(x_i)^{y_i} (1 - p(x_i))^{1-y_i} \right] \quad (6)$$

$$= \sum_{i=1}^N \ln \left[p(x_i)^{y_i} (1 - p(x_i))^{1-y_i} \right] \quad (7)$$

$$= \sum_{i=1}^N y_i \ln p(x_i) + (1 - y_i) \ln (1 - p(x_i)). \quad (8)$$

Now, we want to maximize the log likelihood. We can consider the joint probability distribution $f(x, y)$ for the random variables X, Y and maximize the expected value $\mathbb{E}_{x,y}$:

$$\max_p \mathbb{E}_{X,Y \sim f} [y \ln p(x) + (1 - y) \ln (1 - p(x))]. \quad (9)$$

If $p = p(X; \omega)$ is a function of both the EEG observation and parameters $\omega \in \Omega$, then we have the more commonly known binary cross-entropy loss:

$$\mathcal{L}(\omega) = \min_{\omega \in \Omega} \mathbb{E} [-y \ln p(x; \omega) - (1 - y) \ln (1 - p(x; \omega))]. \quad (10)$$

2.4 Stochastic Gradient Descent

Since we were able to pose our state detection problem as an optimization problem, we selected the commonly used stochastic gradient descent algorithm for our learning algorithm.⁶ This is a first-order method, which scales well to large data sets and complex models.

The gradient descent algorithm is a powerful unconstrained optimization method with convergence guarantees for strongly convex functions. It is an iterative technique that uses only knowledge of the gradient of the function. Let f be a function of ω and $0 < \eta < 1$ be the learning rate. The algorithm is as follows:

$$\omega_{k+1} \leftarrow \omega_k - \eta_k \nabla_{\omega} f(\omega). \quad (11)$$

For objectives that have the form $\mathcal{L}(\omega) = \mathbb{E}_X f(X; \omega)$, gradient descent can be computationally expensive. An alternative approach is stochastic gradient descent, which uses Monte Carlo sampling to estimate the gradient:

$$\mathbb{E}_X f(X; \omega) \approx \sum_{i=1}^N f(x_i; \omega), \quad (12)$$

where $x_i \sim f_X$. Therefore, we can estimate the gradient of our maximum likelihood objective as follows:

$$\begin{aligned} & \nabla_{\omega} \mathbb{E}_{X,Y \sim f} [y \ln p(x; \omega) + (1 - y) \ln (1 - p(x; \omega))] \\ & \approx \nabla_{\omega} \frac{1}{m} \sum_{i=1}^m y_i \ln p(x_i; \omega) + (1 - y_i) \ln (1 - p(x_i; \omega)), \end{aligned} \quad (13)$$

which yields the following iterative algorithm:

$$\omega_t \leftarrow \omega_{t-1} + \eta_t \nabla_{\omega} \frac{1}{m} \sum_{i=1}^m y_i \ln p(x_i; \omega) + (1 - y_i) \ln (1 - p(x_i; \omega)). \quad (14)$$

3. Implementation and Analysis Using EEGNet

Using Python, we implemented EEGNet in Keras⁷ with Tensorflow⁸ back-end according to Fig. 4. We used the default parameters for the Adam⁹ optimizer (a variant of stochastic gradient descent). We trained the algorithm for 10 epochs.

Lawhern et al.² used EEGNet on data from standard brain-computer interface (BCI) paradigms (i.e., rapid serial visual presentation, motor imagery, and visually evoked potentials). In this project, we have examined whether EEGNet can be extended to detect more nebulous cognitive states that capture the influence of naturalistic sleep loss on task performance.

We tested the approach on data from a previously collected ARL study called Cognitive Resilience and Sleep History (CRASH). Participants (N=29) provided sleep history over an 18-week time period, including objective measurements of sleep duration and quality from actigraph wrist watches and subjective measurements from daily web-based questionnaires. They came into the laboratory every 2 weeks for a 4-h experimental session where brain data was collected while they performed 5 cognitive tasks and a resting state scan. In this novel data set, we have 8 brain-behavior sessions to assess the impact of naturalistic sleep loss on task performance over an 18-week timeframe.

To test the extension of EEGNet to state detection, we compared EEG data between the resting state, where the participant was able to mind wander as desired, and the attentional bias task, where the participant had to discriminate letters that followed emotional faces. We selected one subject from the CRASH data set and included observations from all 8 recording sessions. We separated the data into non-overlapping epochs of 500 ms. The data were previously processed using ARL's standard pipeline.¹⁰

We randomly partitioned our data into training (80%) and testing (20%) 10 times and reported the performance in Area Under the Receiver's Operating Characteristic Curve (AUC). The average AUC observed over the 10 iterations was 90% (see Fig. 5 for the results). This performance is significantly above chance and indicates that EEGNet shows promise for our extension of the method to discriminate cognitive states beyond those of standard BCI paradigms.

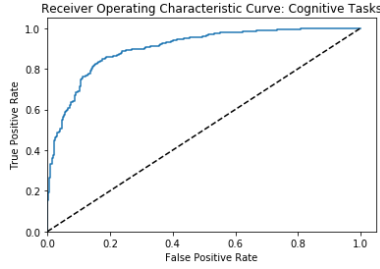


Fig. 5 Receiver’s operating characteristic curve for one random partition of the data

4. Conclusion and Future Directions

In my summer internship project, I learned how recent work at ARL has made it possible to apply CNNs to EEG data. Following the work of Lawhern et al.,² I implemented EEGNet, a CNN with relatively few parameters, and used it to classify human states from EEG recordings in a single subject from the CRASH data set. To complete this project, I learned how CNNs compose convolutions and pooling functions to build representations of data, how to use maximum likelihood estimators to pose learning problems as optimization problems, and how to use stochastic gradient descent to solve optimization problems. Our preliminary results indicate that EEGNet successfully discriminates between cognitive tasks.

In future work, I would like to use EEGNet to detect the presence of more complicated states. As described in the introduction, state detection will facilitate adaptive technologies that can respond to changes in the user’s state. In this preliminary work, we only discriminated the performance of one cognitive task from a rest state. However, the CRASH data set has recordings from several sessions for each subject. I would like to use EEGNet to discriminate between sessions for the same subject. Because the sessions differ by sleep history, the ability to discriminate by session would indicate that EEGNet could discriminate sleep history of a user. This could be used in future adaptive technologies to detect user fatigue and likely poor performance.

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List of Symbols, Abbreviations, and Acronyms

ARL	US Army Research Laboratory
AUC	area under the receiver's operating characteristic curve
BCI	brain-computer interface
CNN	convolutional neural network
CRASH	cognitive resilience and sleep history
EEG	electroencephalogram
EEGNet	ARL-developed CNN for EEG data
IID	independent and identically distributed

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