Modeling and Classification of EEG using Recurrent Neural Networks

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Practical Applications for EEG Classification

The long term goal of this project is to develop reliable brain-computer interfaces (BCI).

BCI can enable those with locked-in syndrome caused by ALS or other severe disabilities to operate brain actuated devices such as wheelchairs, keyboards and environmental controls.

Effective EEG classifiers may also prove to be useful for various forms of neurological study and medical diagnosis of diseases like epilepsy and sleep disorders.

Why Recurrent Artificial Neural Networks?

Electroencephalogram (EEG) is highly temporal in nature.

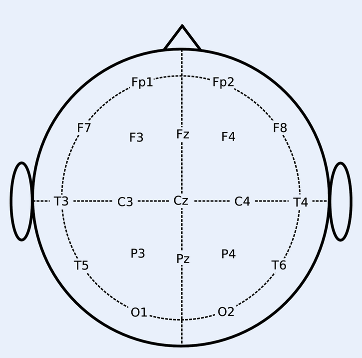
Most current approaches account for this by passing a small window of inputs to the classifier. This is limited by window size, computational performance and a higher dimensional input space.

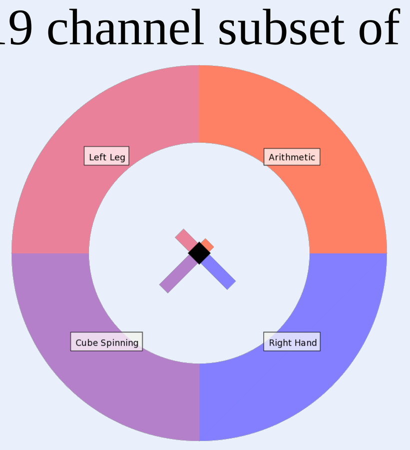
In our approach, Artificial Recurrent Neural Networks (RNN) are first used to build a model for each type of EEG. Since RNN's have feedback connections, they possess an intrinsic state that allows them to learn complex nonlinear temporal dependencies.

Classification is then performed by applying each RNN and selecting the class associated with the model that performs best.

Data Acquisition

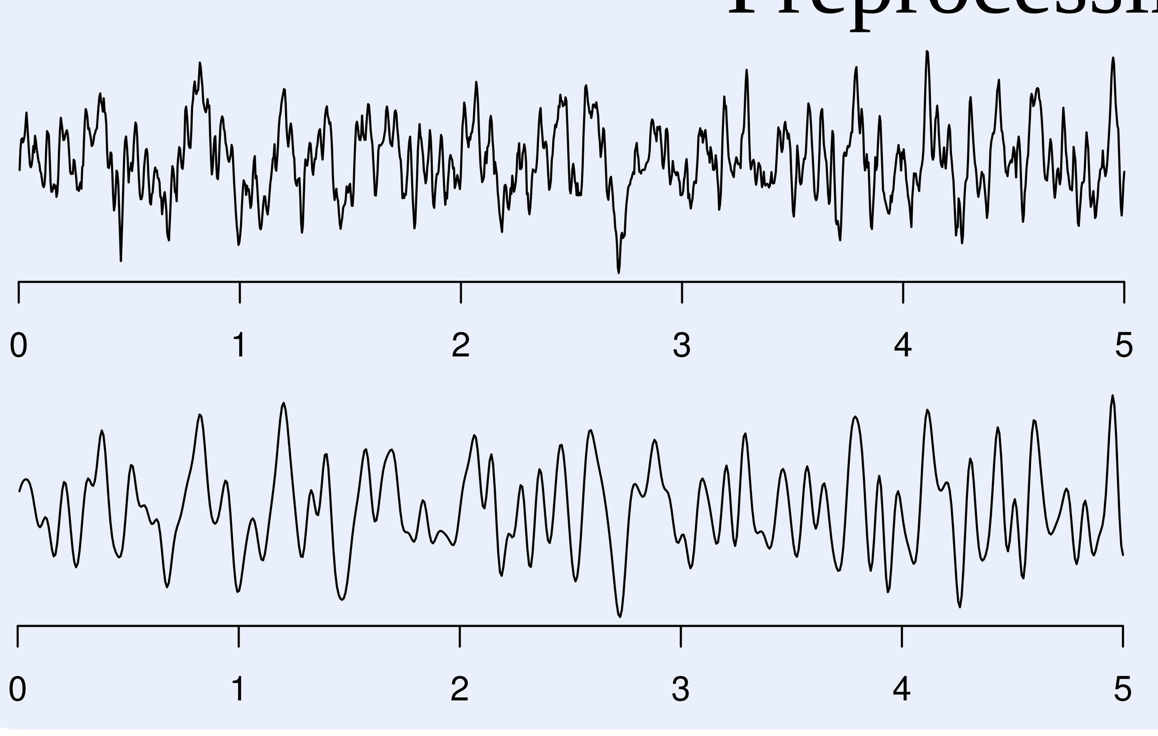
Electroencephalogram is sampled at 256Hz using a Mindset-24 digital amplifier. A 19 channel subset of the 10-20 system is used with earlobe references.





Subjects are presented with a visual queue that selects one of several imagined mental tasks to perform in a random order. Examples include imagined motor movement, visualization, arithmetic or language tasks.

Preprocessing



An approximated bandpass filter is used to attenuate noise from ocular, muscular and external electrical sources.

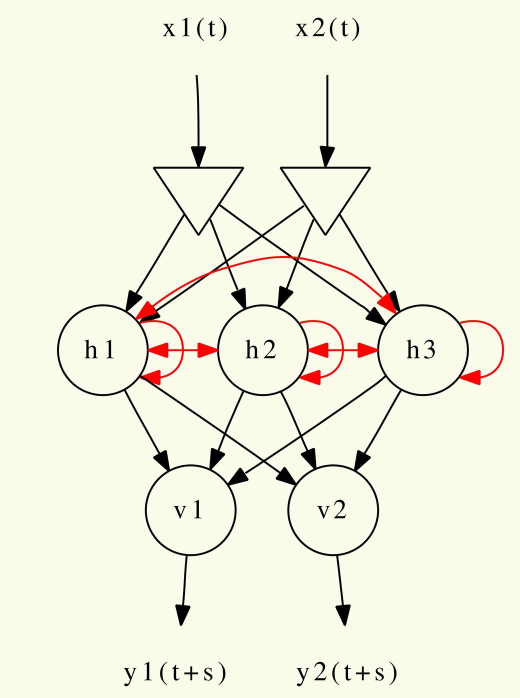
The data is then downsampled and normalized to zero-mean and unit standard deviation in order to improve training speed.

Elman Recurrent Networks

Elman Recurrent Networks contain a single hidden layer using a hyperbolic tangent transfer function and a visible layer with a linear transfer function.

The hidden layer is fully connected, including recurrent connections. These connections allow the network to maintain a state and utilize previous input values.

Backpropagation through time (BPTT) is used to approximate the error gradient and a scaled conjugate gradient algorithm is used to adjust connection weights, minimizing training error.

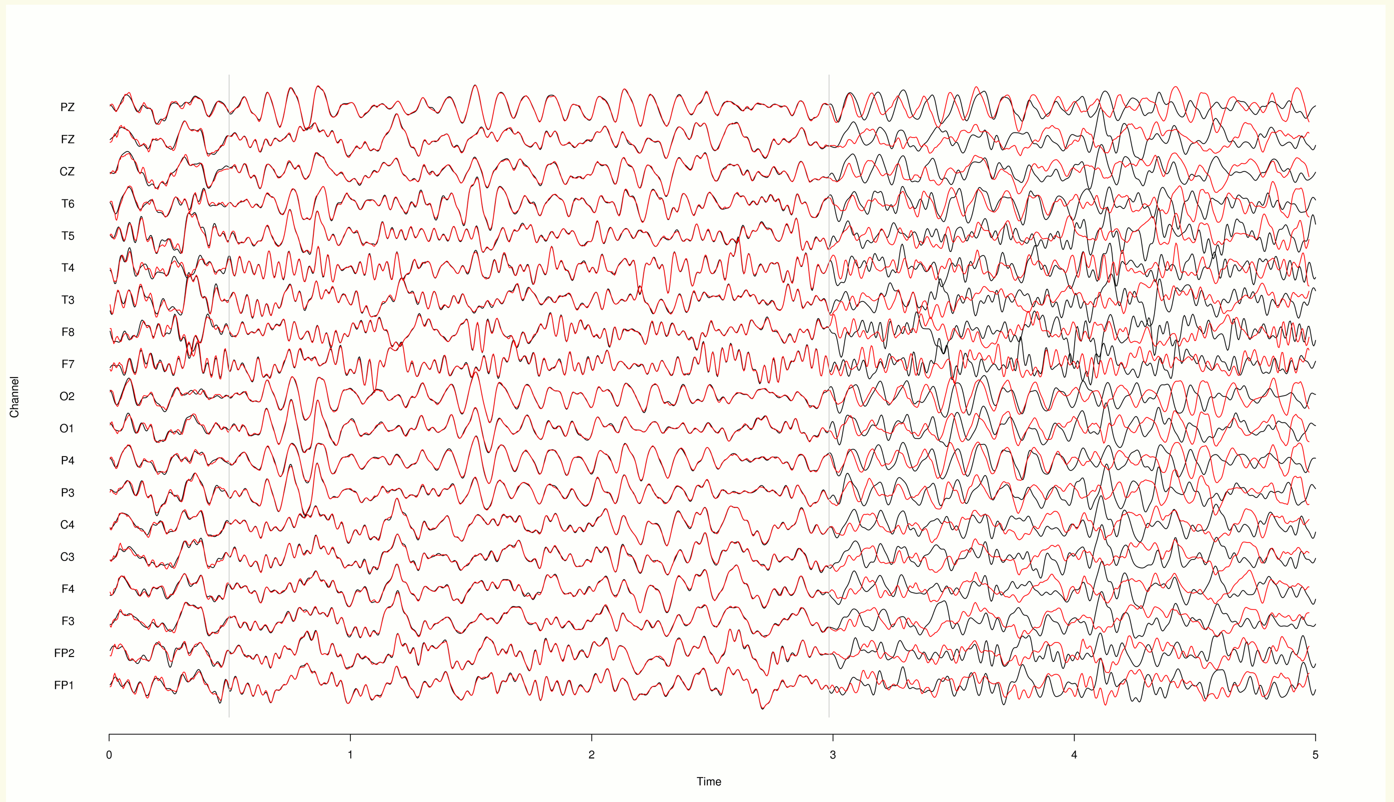


Modeling EEG

An EEG sequence can be modeled by training an RNN to predict the sequence several steps ahead in time.

To the right we see an EEG sequence (black) and a model trained over the sequence (red). After 3 seconds, the model is allowed to operate over its own predictions, instead of the EEG, forming a dynamical system. This system continues to produce very "EEG like" rhythms.

Combined with low training errors, this suggests that Elman Networks can model EEG well.



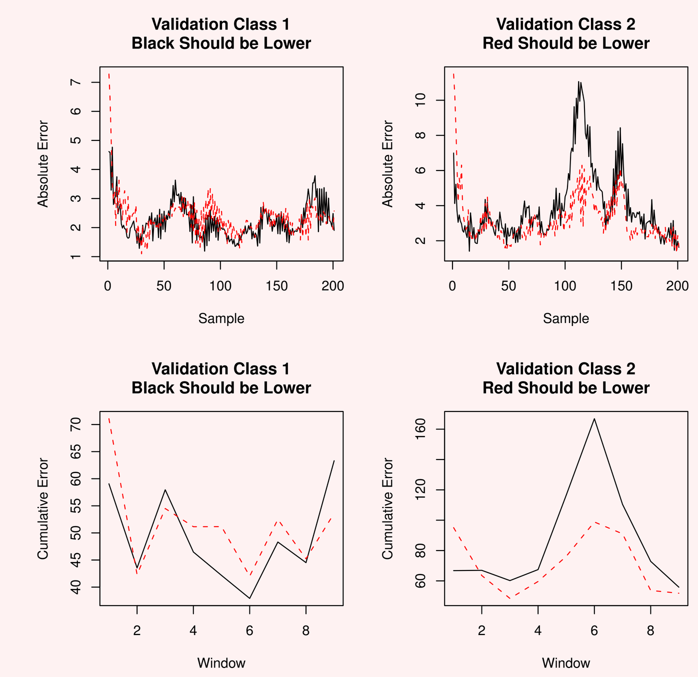
Classification of EEG

A separate RNN is trained over several sample sequences recorded during each mental task. This results in an "expert" at predicting EEG each type of EEG.

Classification of previously unseen sequences proceeds by applying each RNN and assigning the class associated with the model that produced the lowest error.

Results are improved by accumulating errors over half second windows.

Preliminary results achieve 75% correct on a two task problem and 46% correct on a four task problem.



Predicted

Actual	Motor Right	Motor Left	Visualization	Arithmetic
Motor Right	40%	43%	7%	10%
Motor Left	20%	57%	23%	0%
Visualization	13%	23%	60%	4%
Arithmetic	23%	33%	17%	27%

Predicted

Actual	Motor	Visualization
Motor	83%	17%
Visualization	33%	67%