Deep Learning With Convolutional Neural Networks for EEG Decoding and Visualization

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Mehak Bindra 2015B5A70685P
Mriganskshi Kapoor 2015B3A70616P
Srishti Banzal 2015B3A70456P

Objective:

Classification of electroencephalographic (EEG) recordings of brain activity.

Using CNN instead of the state-of -the-art methods.

Scope:

Central component of many EEG-based brain-computer interface (BCI) systems. These systems:

1. Help people with severe paralysis to communicate
2. Control telepresence robots
3. Facilitate stroke rehabilitation
4. Can treat epilepsy

Introduction

EEG and CNNs

CNNs have two major pieces:

1. *Feature engineering / preprocessing* – turn our images into something that the algorithm can more efficiently interpret
2. *Classification* – train the algorithm to map our images to the given classes and understand the underlying relationship.

ConvNets can learn local non-linear features (through convolutions and nonlinearities) and represent higher-level features as compositions of lower level features (through multiple layers of processing).

In addition, many ConvNets use pooling layers which create a coarser intermediate feature representation and can make the ConvNet more translation invariant.

EEG and CNNs

The EEG signal has characteristics that make it different from inputs that ConvNets have been most successful on(images).

1. The EEG signal is a dynamic time series from electrode measurements obtained on the three-dimensional scalp surface.
2. The EEG signal has a comparatively low signal-to-noise ratio, that is, sources that have no task relevant information often affect the EEG signal more strongly than the task-relevant sources.

These properties could make learning features more difficult for EEG signals than for images. Thus, the existing ConvNets architectures from the field of computer vision need to be adapted for EEG input.

DATASETS

Data set 2a of the BCI Competition IV.

INPUT DATA

- There are 9 subjects
- Each subject undergoes 288 trials *2
- In each trial there are 22 channels(electrodes) being used
- Each channel records observations for 7 seconds at 250 Hz

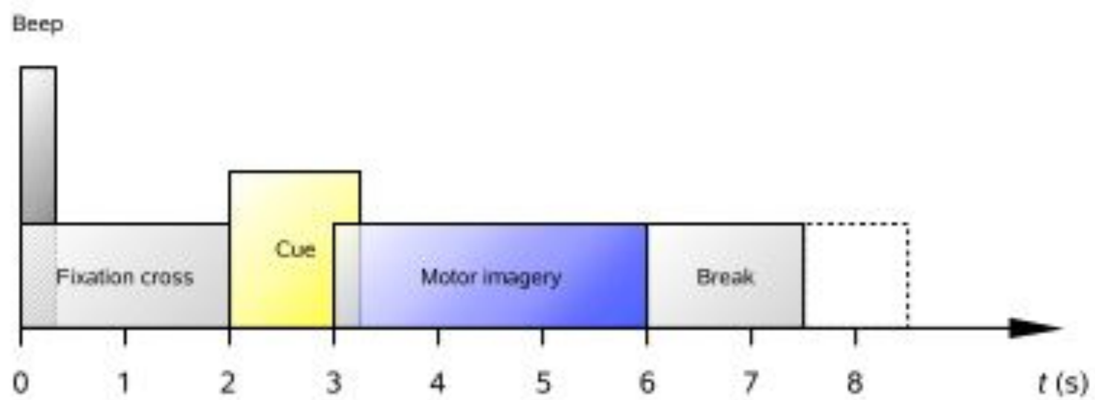


Figure 2: Timing scheme of the paradigm.

PREPROCESSING

- EEG data in .gdf files (General Data Format)
- Convert to .mat
- Convert to Data Vectors as explained:

For each subject i

For each trial j

$X^j \in R^{E.T}$

E -> recorded electrodes

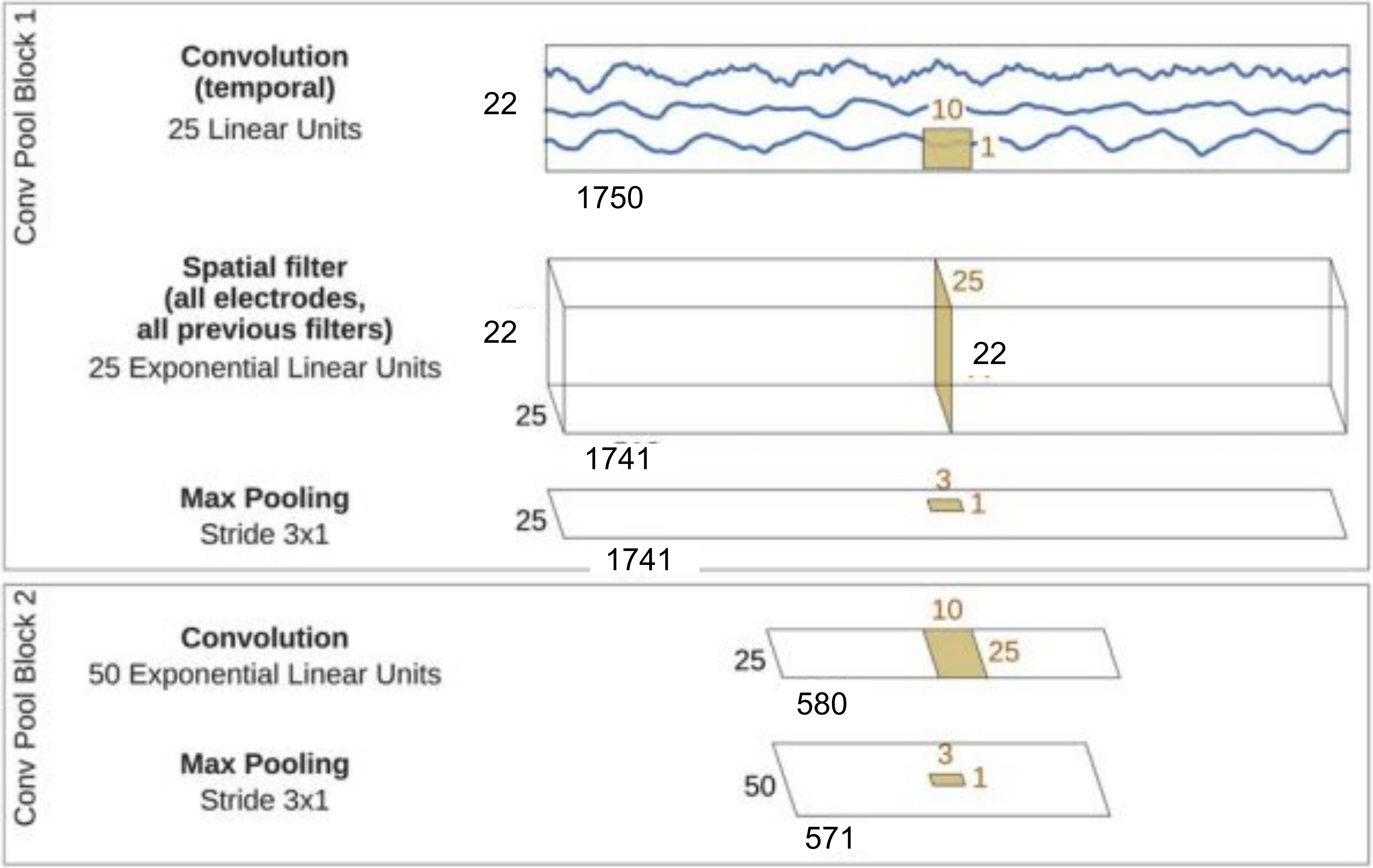
T -> discretized time steps

Corresponding class label of trial j

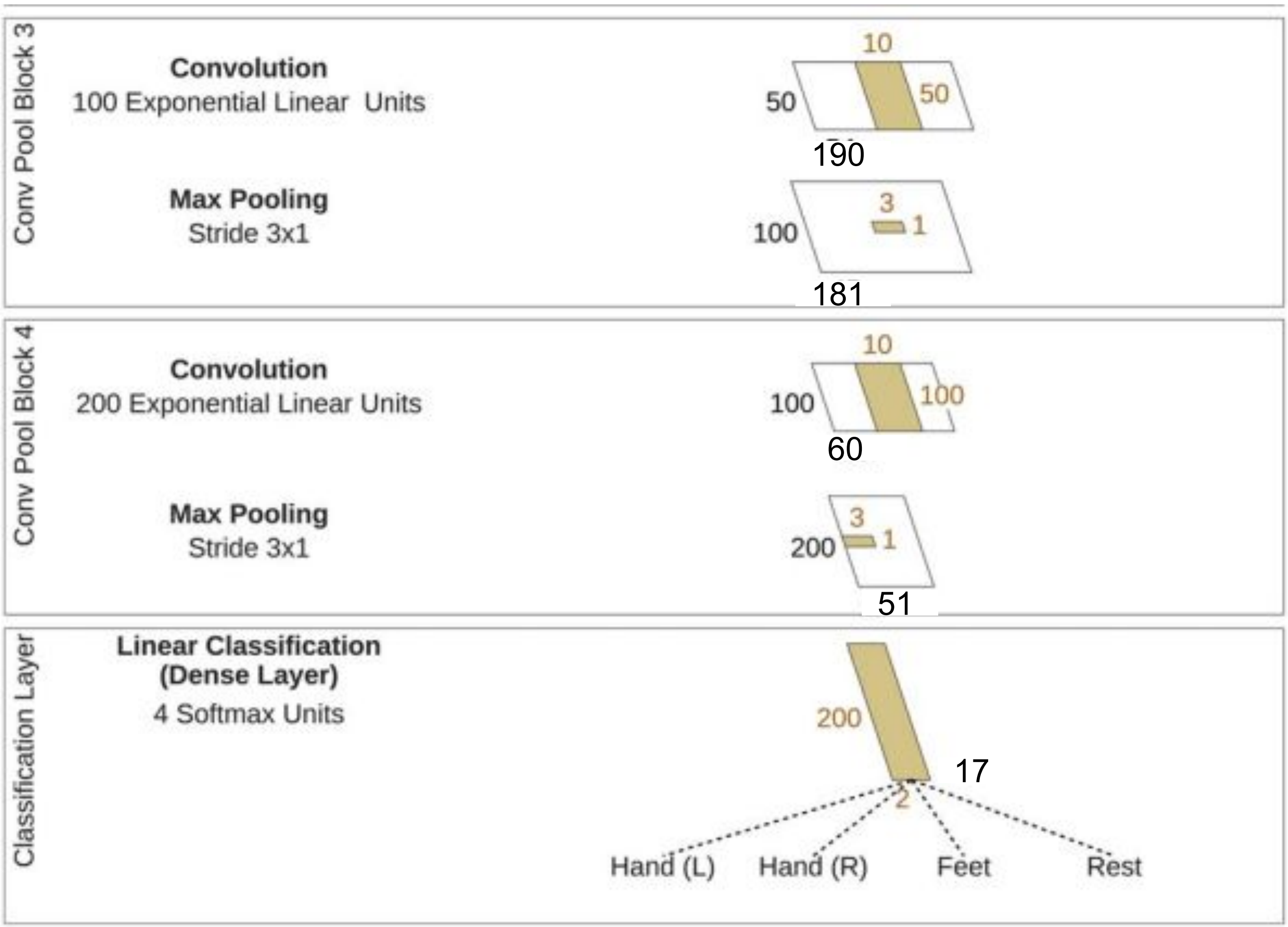
$y^j \in L = \{l_1, l_2, l_3, l_4\}$

ARCHITECHTURE

DEEP CONVNET ARCHITECTURE



DEEP CONVNET ARCHITECTURE



Four convolution-max-pooling blocks

First block designed to handle EEG input , followed by three standard convolution-max-pooling blocks and a dense softmax classification layer

Drop out the inputs to all convolutional layers after the first with a probability of 0.5

Loss used = Cross Entropy

Activation function = ELU

Batch normalization applied to the output of convolutional layers before the nonlinearity

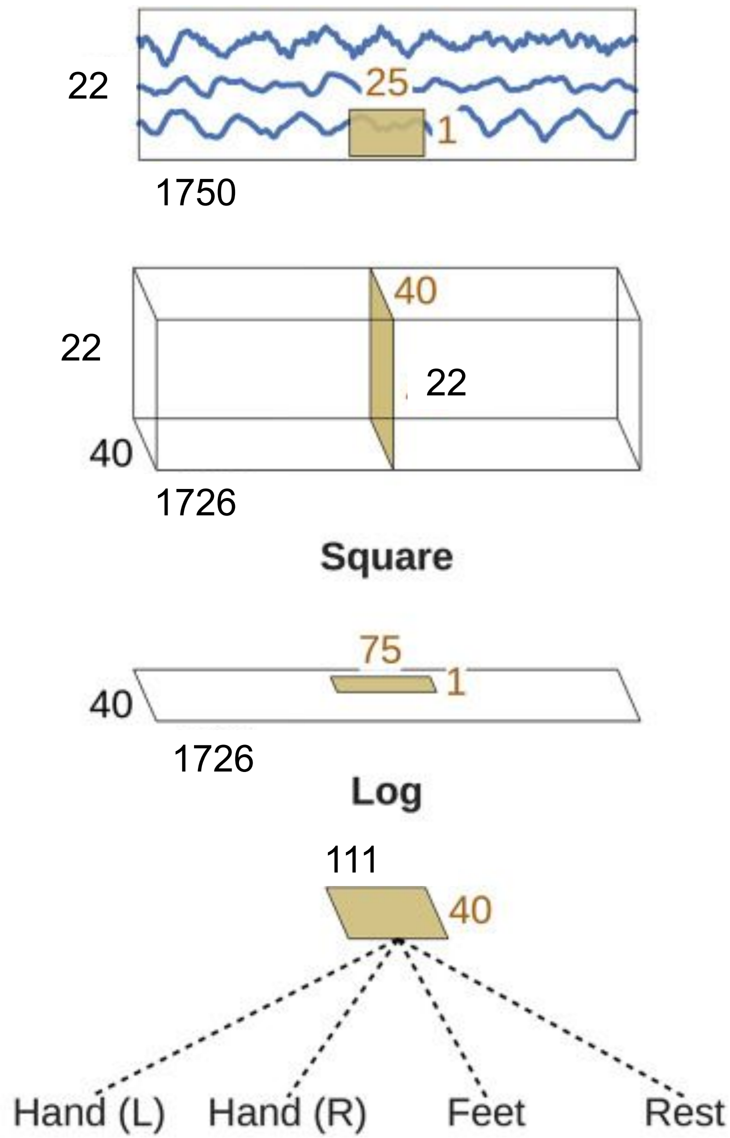
SHALLOW CONVNET ARCHITECTURE

Convolution (temporal)
40 Units

Spatial filter (all electrodes, all previous filters)
40 Units

Mean Pooling
Stride 15x1

Linear Classification (Dense Layer+Softmax)
4 Units



RESULTS

LIMITATIONS

Owing to limited memory and processing capabilities, we couldn't train and evaluate our model on the actual dataset which is huge, settling for random subsets of it.

However Taking 9 Training files for training and 1 Evaluation file for testing, we were able to reach accuracies as good as 50% for the models

The Authors of the paper were able to achieve accuracies around 82-84 % using all the data and probably more epochs

CONCLUSION

EEG signals were decoded successfully with the CNNS.

As given by the authors we can also use CNNs for visualization