Deep-Learning based Classification of Executed and Imagined Motor Movement EEG Signals

(Pre) Final Project Presentation of the courcse Advanced Topics in Machine Learning (ATML)

-Prof. Favaro-

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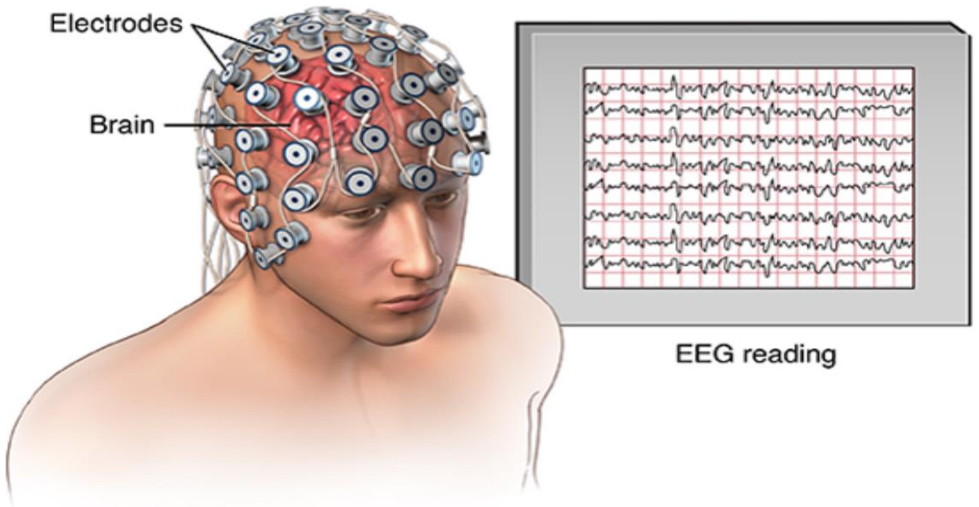
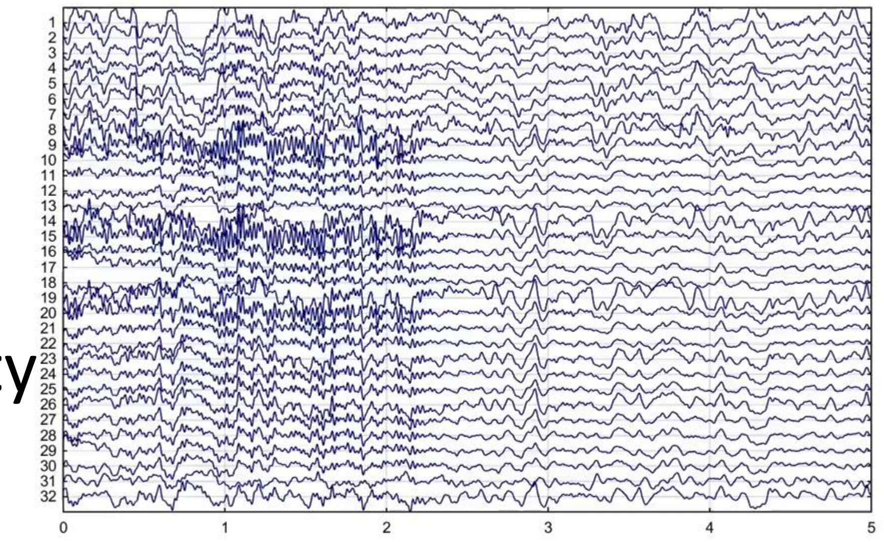


[http://sipl.eelabs.technion.ac.il/projects/examination-of-tms-effect-using-eeg-signal/]

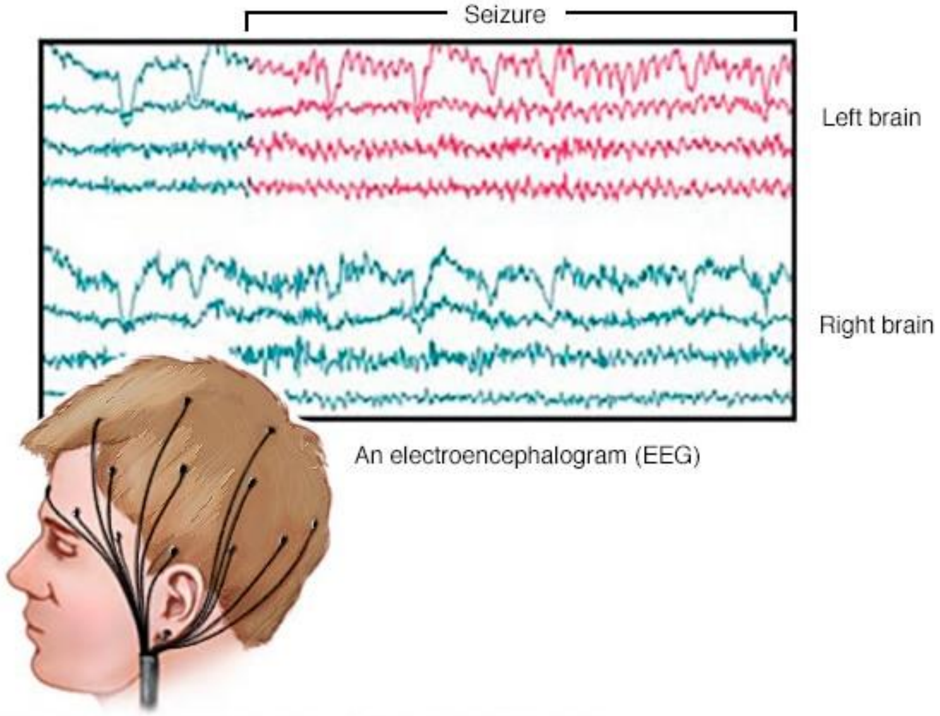
What is an EEG?

- Representation of an electrical voltage curve in time.
  - Most important variables for describing an EEG curve: Amplitude and Frequency
- Non-invasive and cost-effective method for direct measurement of electrical brain activity
- Advantage: High temporal resolution
- Disadvantage: Relatively low spatial resolution



Why do we record an EEG?

- Diagnose of brain related diseases
- Identifaction of mal functioning areas
- Level of brain function (e.g. coma)
- BMI: Applications in prosthetics

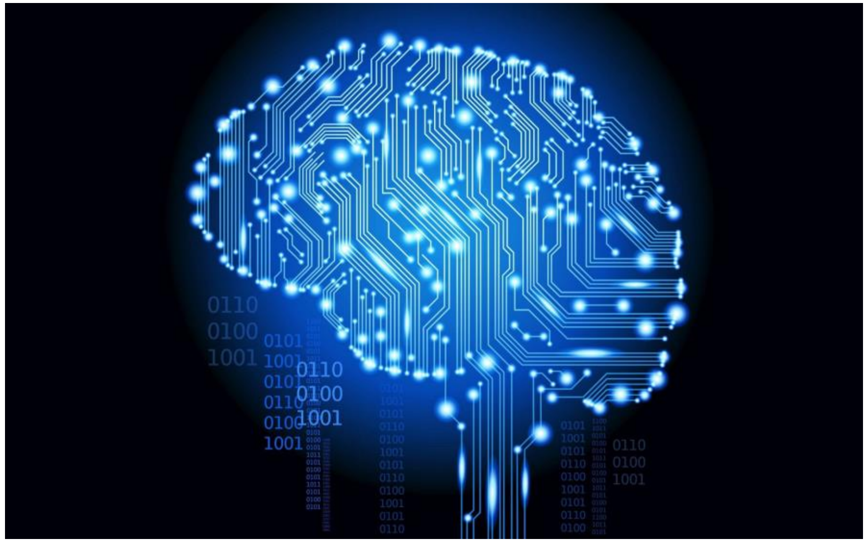


Why Deep Learning?

- Standard approaches are domain specific
  - Highly trained personal
  - Preprocessing
  - Inter subject variability

- 64 Channels -> Huge amount of data

- DL very successfull on image text and audio signals

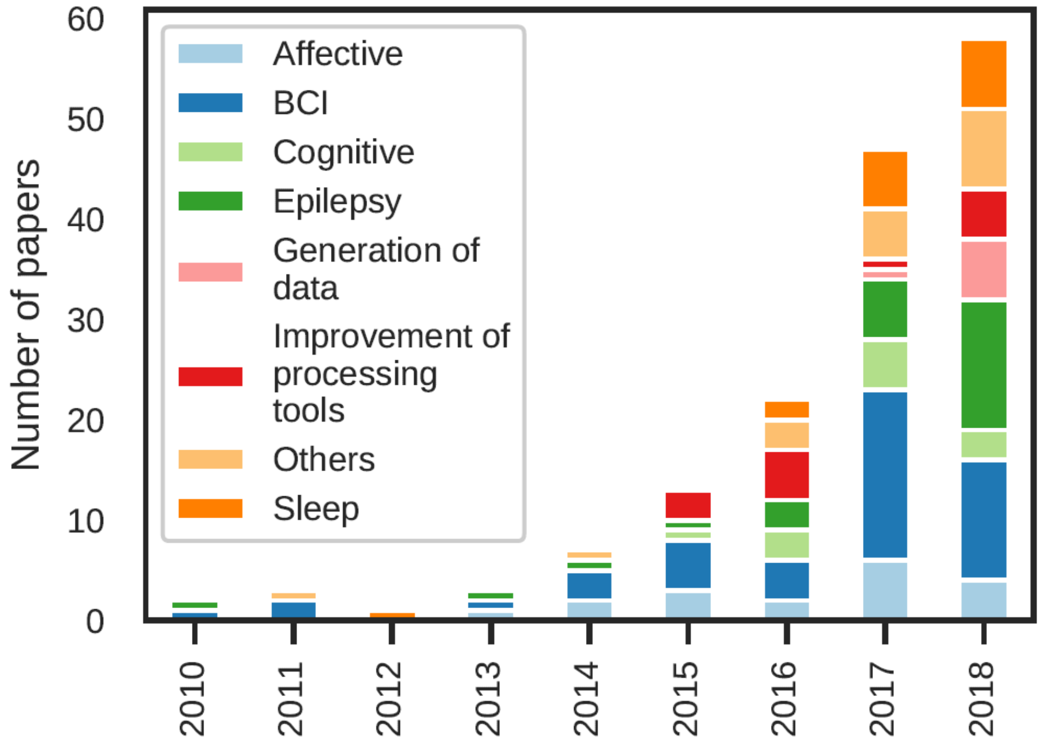


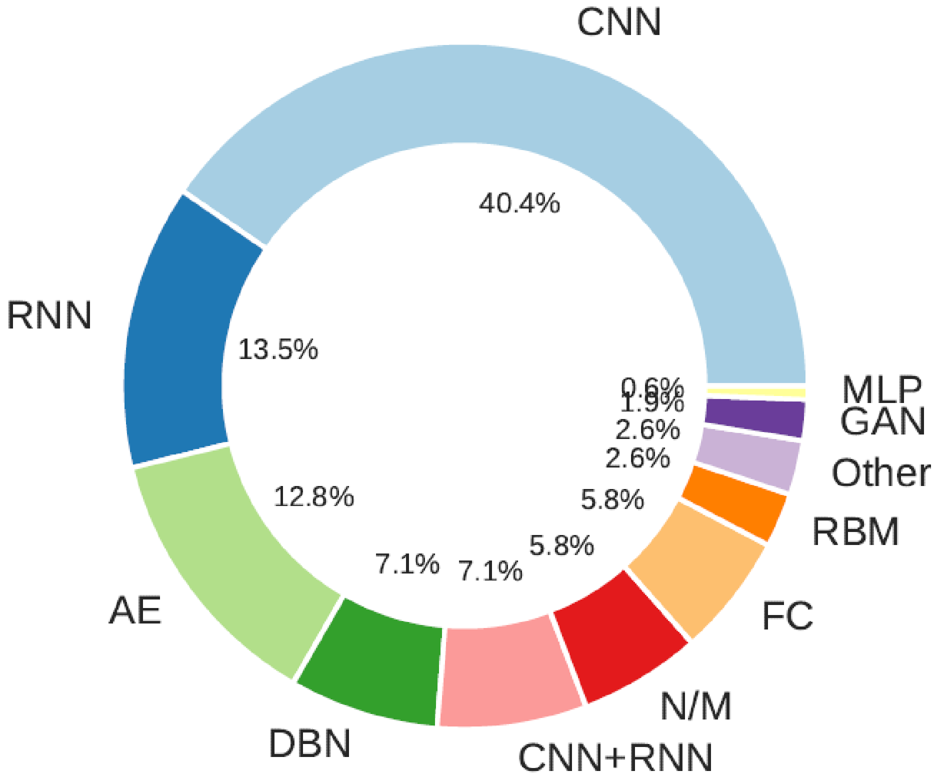
Difficulties

- Characteristics of the EEG Signal
  - Low SNR
  - Limited Data available + Collection is difficult
    - Not as many competitions and contributors as in CV
  - Inter subject variability (+ quality of measurements)
  - Images vs Time Series from 3D scalp surface

=> Hot Research Topic!

Literature





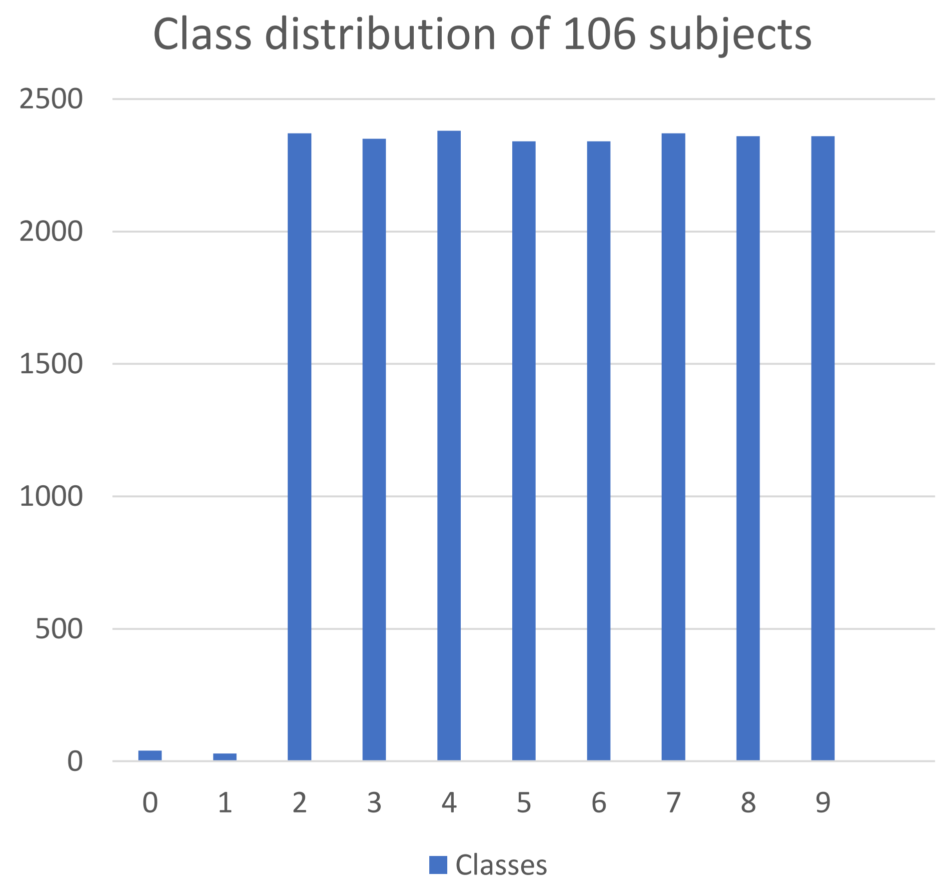
[Roy, Yannick et al. 2019. "Deep Learning-Based Electroencephalography Analysis: A Systematic Review."]

Data

Physionet Dataset: EEG Motor Movement/Imaginery Dataset (bci2000.org)

[Goldberger et al. 2000 PhysioBank, PhysioToolkit, and PhysioNet: Components of a New Research Resource for Complex Physiologic Signals. *Circulation* **101**(23):e215-e220 2000 (June 13)]

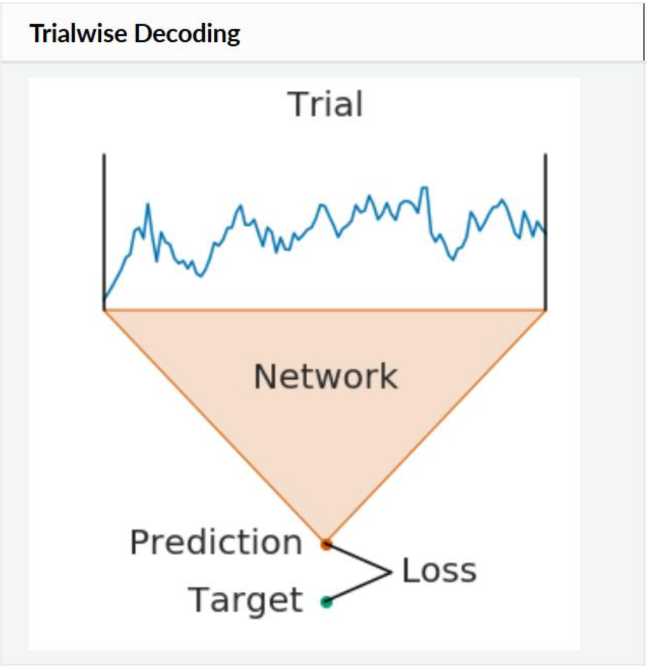
Label	Description
0	Baseline, eyes open
1	Baseline, eyes closed
2	Motor execution: Left Hand
3	Motor execution: Right Hand
4	Motor imagery: Left Hand
5	Motor imagery: Right Hand
6	Motor execution: Both Hands
7	Motor execution: Both Feet
8	Motor Im: Both Hands
9	Motor imagery: Both Feet

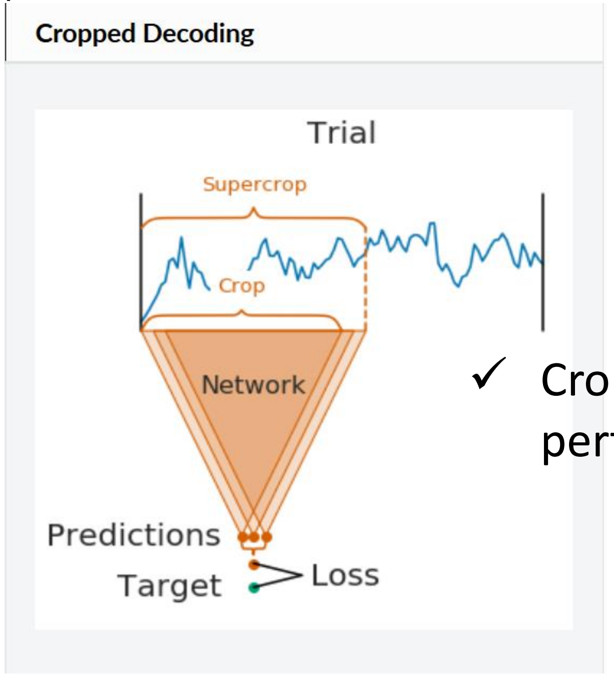


Input Data

- Raw EEG Data (normalized -1 to 1), split into trials
  - Epoch begins 1s before trial and ends 4s after the trial (Experimental)

[Roy, Yannick et al. 2019. "Deep Learning-Based Electroencephalography Analysis: A Systematic Review."]



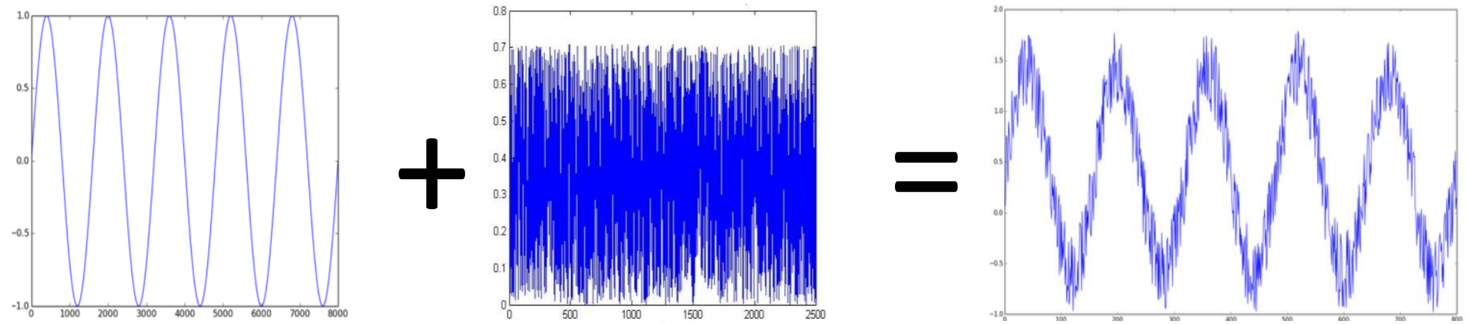


✓ Cropping increased the performance on the testset

[Schirrmeister et al. 2017. "Deep Learning with Convolutional Neural Networks for EEG Decoding and Visualization"]

Input Data

- Adding white noise to augment the training data*
  - Generalization



[Wang, Fang et al. 2018. “Data Augmentation for EEG-Based Emotion Recognition with Deep Convolutional Neural Networks.” In , 82–93.]

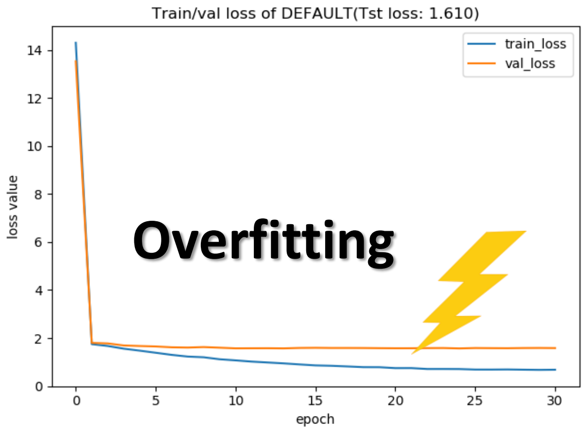
✓ Adding White Noise increased the performance on the testset

* 5x increasement of the training data size

Models … we tried and tried…

- Simple FC Models
  - Deeper and wider FC Models ….
    - ➔ Very low results on the test set + shallow traning curves

- Simple, deep and wide combinations of CNNs 1D and 2D



➔Regularization: Dropout … batch normalization …. Weight decay …

Literature and EEG Models

- EEGNet, Deep4Net, EEGNetv4 …..

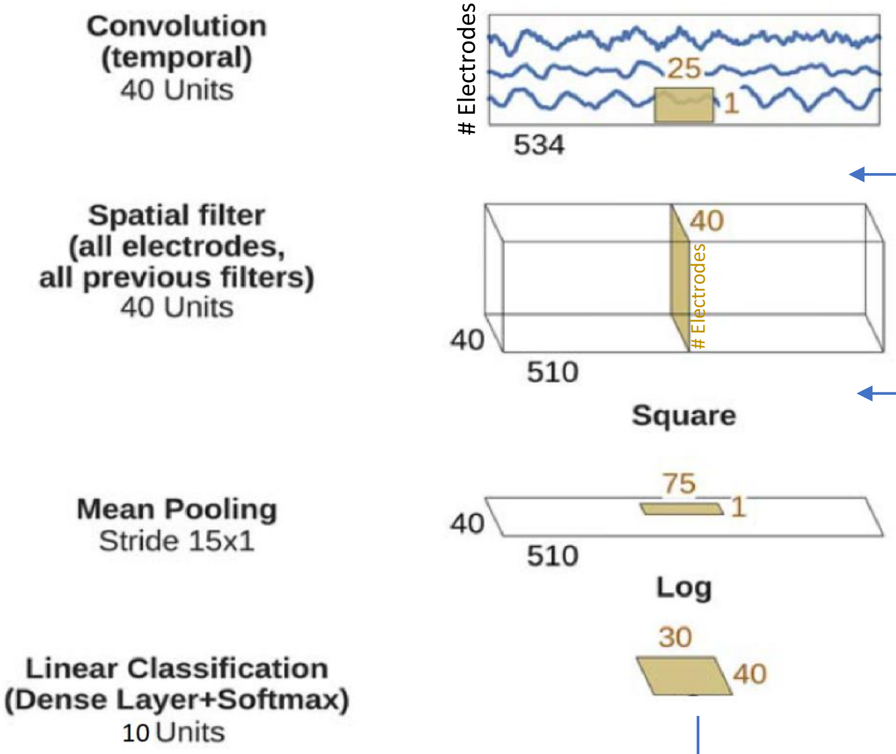
➔ Already way better results than „our“ models!

[Lawhern, Vernon J. et al. 2016. “EEGNet: A Compact Convolutional Network for EEG-Based Brain-Computer Interfaces.”]

[Schirrmeister et al. 2017. “Deep Learning with Convolutional Neural Networks for EEG Decoding and Visualization”]

- *Train accuracies = Test accuracies* ➔ UNDERFITTING
  - Make it **deeper** and wider -> No improvement

ConvNetFBCSP



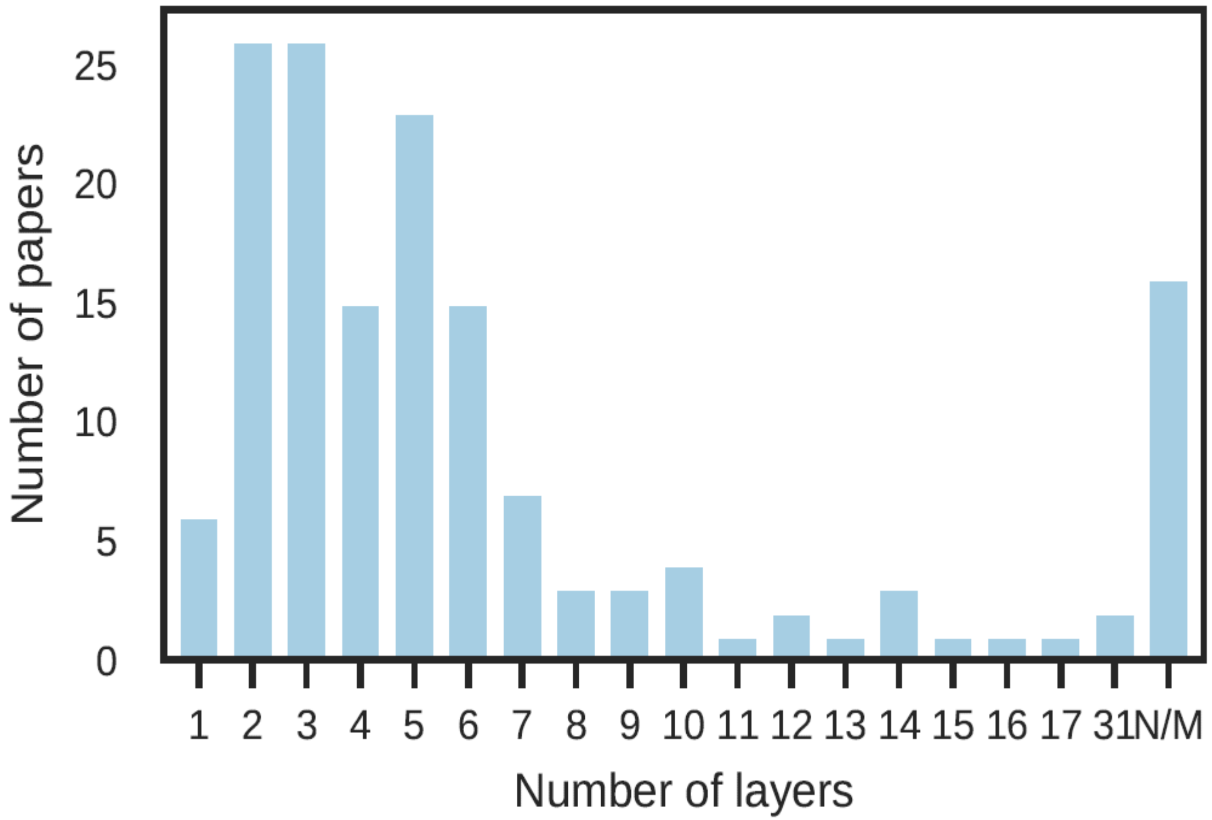
Dropout + ReLu + Batch Normalization

Dropout + ReLu + Batch Normalization

Class 0 - 9 probabilities

[Schirrmeister et al. 2017. “Deep Learning with Convolutional Neural Networks for EEG Decoding and Visualization”]

ConvNetFBCSP – Why so shallow?



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ConvNetFBCSP*

- Filtering **in the frequency domain** is equivalent to **convolution in the time domain**.
- Whats the characteristics?
  - Mimiques Bandpasses and CSP filter steps for each bandpass
    - Select discriminative pairs of frequency bands and corresponding CSP features
  - Several Pooling Regions within one trial
    - Learns temporal structure of the band power changes

[Sakhavi S, Guan C, Yan S. (2015): Parallel convolutional-linearneural network for motor imagery classification. In *2015 23rd European Signal Processing Conference (EUSIPCO)*, IEEE, 2736–40]

*FBCSP = Filter Bank Common Spatial Pattern => Selects the best CSP Features.
CSP = CSP **Common spatial pattern** (**CSP**) is a procedure for separating a signal into additive subcomponents which have maximum differences in variance

[Kai Keng et al. 2008. “Filter Bank Common Spatial Pattern (FBCSP) in Brain-Computer Interface.” In *2008 IEEE International Joint Conference on Neural Networks*, IEEE, 2390–97.]

Overview + (Pre) Final Results

- Intensive literature research

  +
- Applying data augmentation

  +
- Applying regularization

  +
- Trying + tweaking our own models

  +
- Implementing models from papers

  +
- Tweaking models from papers

Testset overall Accuracy: 51.2144%

```
Accuracy of class 0 : 25 % of 4 labels
Accuracy of class 1 :  0 % of 3 labels
Accuracy of class 2 : 60 % of 237 labels
Accuracy of class 3 : 54 % of 235 labels
Accuracy of class 4 : 50 % of 238 labels
Accuracy of class 5 : 52 % of 234 labels
Accuracy of class 6 : 48 % of 234 labels
Accuracy of class 7 : 56 % of 237 labels
Accuracy of class 8 : 37 % of 236 labels
Accuracy of class 9 : 50 % of 236 labels
```

(Train/Val) Test Split: (90/10) /10
Loss: Cross-Entropy Loss
Optimizer : AdamW
Learning Rate Adaption: Cosine Annealing Curve
[Loshchilov, Ilya, and Frank Hutter. 2016. "SGDR: Stochastic Gradient Descent with Warm Restarts."]

Discussion

- Regarding results in Computer Vision, poor.
  - But our problem is more difficult (see „Difficulties“ slide)
- No Paper used all subjects (cherry picking) **nor** all 10 classes (max. 5).

Low SNR

Limited Data available + Collection is difficult
Not as many competitions and contributors as in CV

Inter subject variability (+ quality of measurements)

Images vs Time Series from 3D scalp surface

Future Work

- Further Methodologies:
  - Try light preprocessing of obvious artifacts
  - Try more data augmentation (changing electrodes for symmetric tasks)

    [Deiss,et al. 2018. "HAMLET: Interpretable Human And Machine Co-Learning Technique."]
  - Try convert EEG to video and use optical flow
    - Apply transferlearning on established classifiers

      [Tan, Chuanqi, Fuchun Sun, and Wenchang Zhang. 2018. "Deep Transfer Learning for EEG-Based Brain Computer Interface."]
  - Make a combination with RNN (or LSTM) network to extract temporal patterns in the frame sequences

    [Bashivan et al. 2015. "Learning Representations from EEG with Deep Recurrent-Convolutional Neural Networks."]

    [Zhang, Dalin et al. 2018. "Fuzzy Integral Optimization with Deep Q-Network for EEG-Based Intention Recognition." In Springer, Cham, 156–68.]

Thank you very much for your attention!

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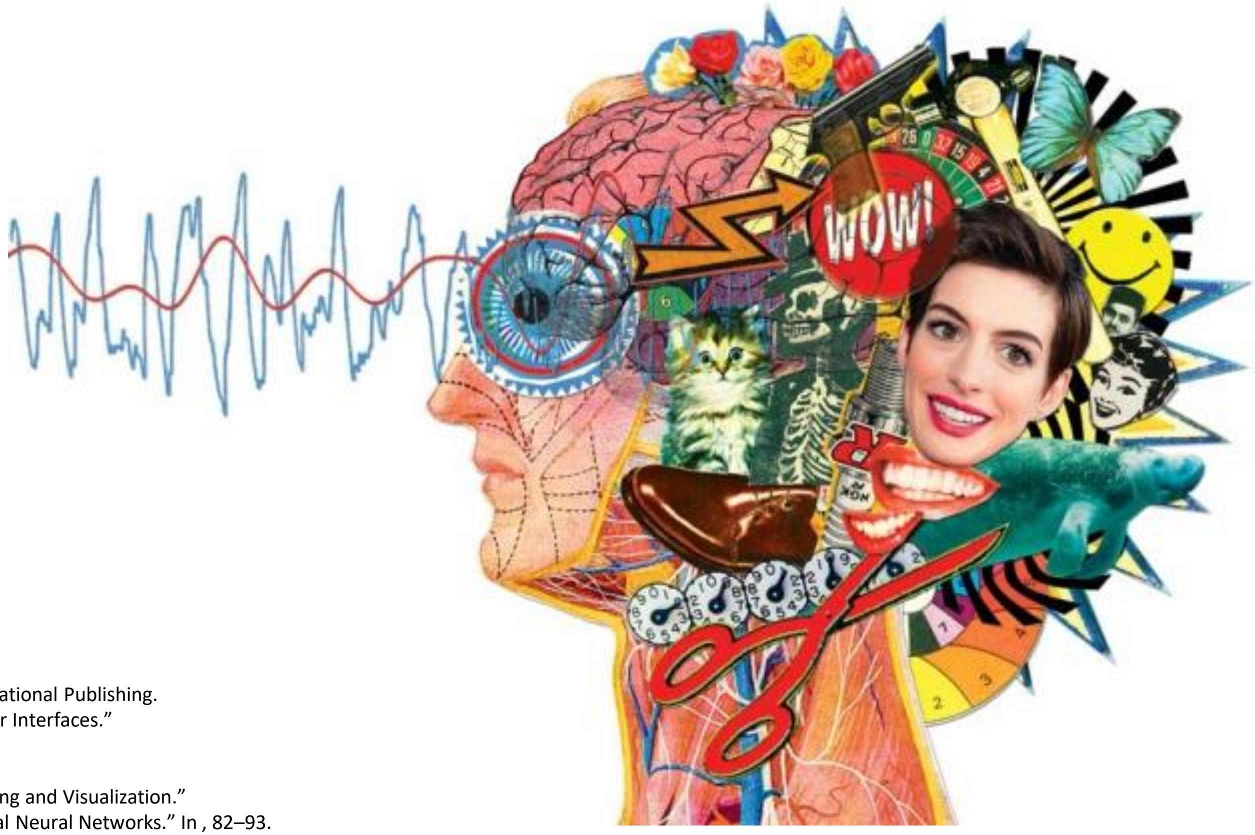

Sources:
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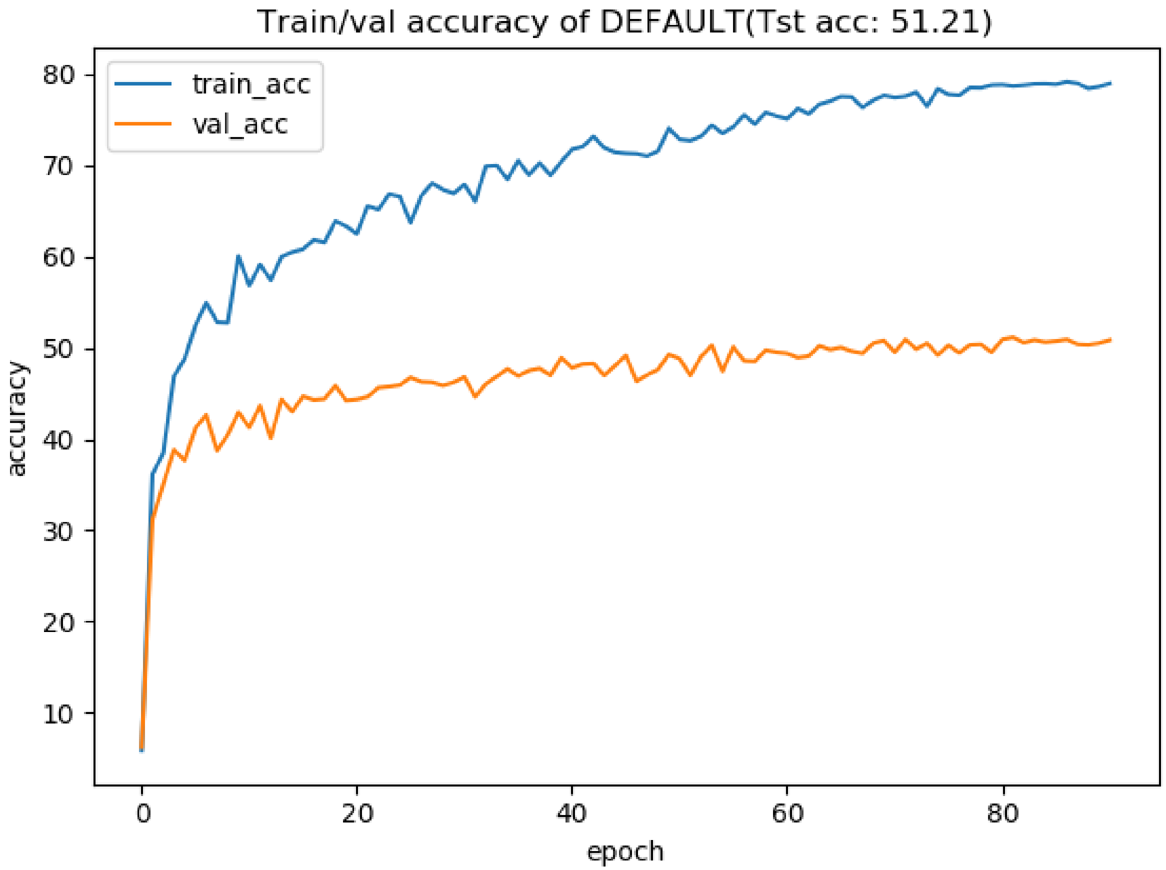
Train/val accuracy of DEFAULT(Tst acc: 51.21)
train_acc
val_acc
accuracy
epoch
80
70
60
50
40
30
20
10
0
20
40
60
80