How old is your brain?

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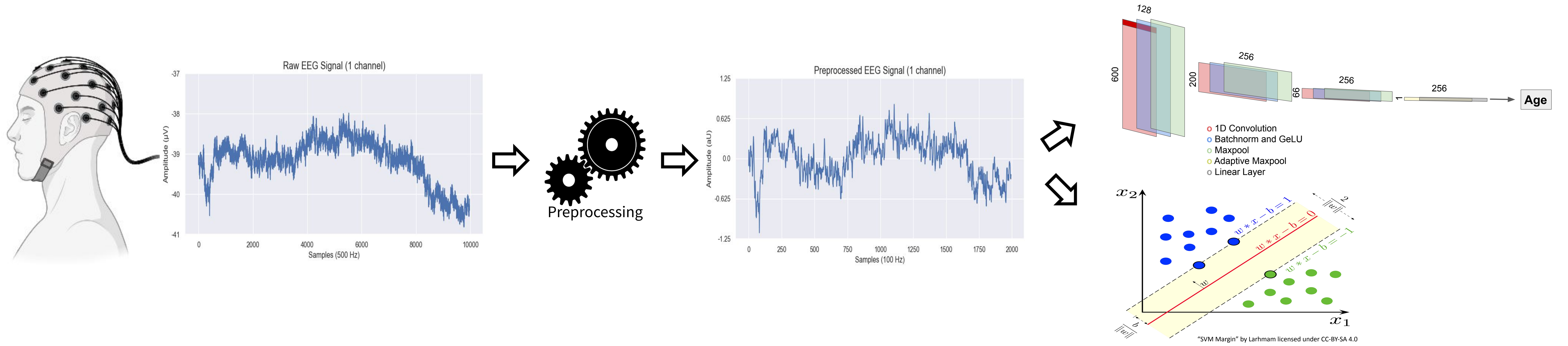
In a nutshell



Abstract

How old is your brain? What may sound confusing at first is actually a relevant parameter towards more quantitative diagnostic approaches in neuropsychiatry. Researchers use magnetic resonance imaging (MRI) and electroencephalography (EEG) to study the structure and activity of the brain. From these measurements, a so-called brain-age can be predicted. The deviation of the predicted to the actual age may then be used to detect aberrant developmental processes posing relevant diagnostic indications. Key to this approach is machine learning. Therefore, NeuroTechX initiated the brain age prediction challenge. Here, we will present our approach to that challenge.

Main Research Question

What is the state-of-the art in predicting brain age from EEG signals?

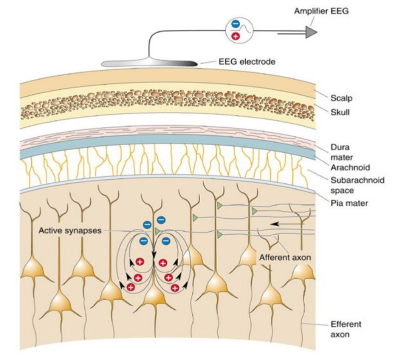
Highlights

- we present place 1 and 3 of the brain age prediction challenge
- age can be predicted from EEG recordings with a mean average error of 1.16 years
- the deep learning approach outperforms a standard machine learning approach
- brain age prediction benefits from large number of participants (~ 3500)

Background

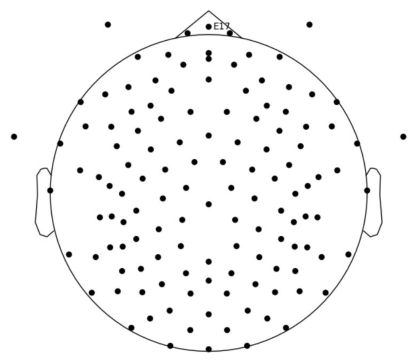
EEG

- Electroencephalogram (EEG) is a **non-invasive** method to measure signals from the brain
- EEG has **high temporal** and low spatial resolution
- Measures summation of postsynaptic potentials of neurons with parallel geometric orientation
- EEG is prone to artifacts (hence, preprocessing)



Bear, Connors & Paradiso, 2015

Electrical Geodesics, Inc.



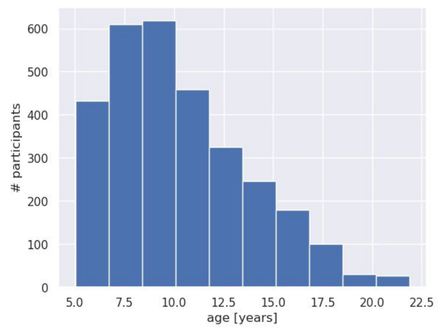
Brain Age Prediction

- Psychiatry is the only medical field without quantitative diagnostic criteria
- Brain Age is a promising physiological parameter to detect discrepancies between normal and pathological developments
- EEG approach is superior to MRI regarding **cost and availability**

Dataset

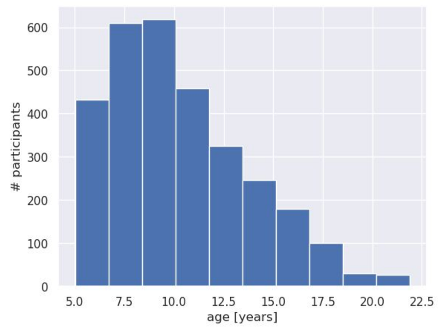
Codalab Challenge Dataset

- resting-state EEG, 129 channels, 500Hz
- 1 EC & 1 EO per subject
- Training: 1200 subjects, age 5-21
- Testing (Phase 1): 400 subjects
- Testing (phase 2): 400 subjects

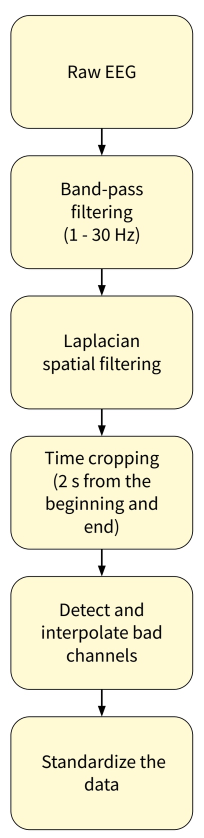


Healthy Brain Network (HBN)

- resting-state EEG, 129 channels, 500Hz
- eyes-closed (EC) & eyes-open (EO)
- >3500 subjects, age 5-21
- up to 5 EC/EO recordings per subject
- age information for every subject



Preprocessing



Bandpass:
- Remove line noise
- Remove drift

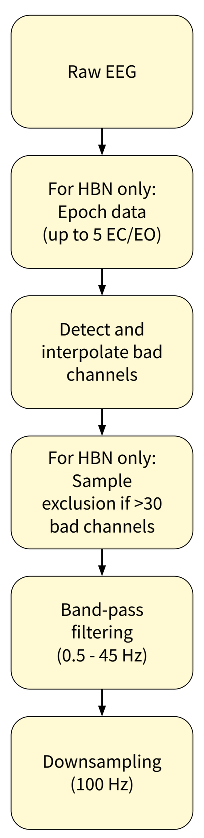
Detect and interpolate bad channels:
- Bad data is not healthy for the pipeline
- Bad channel: electrode detach, malfunction, etc.
- Detection: extremely large noise, flat signal

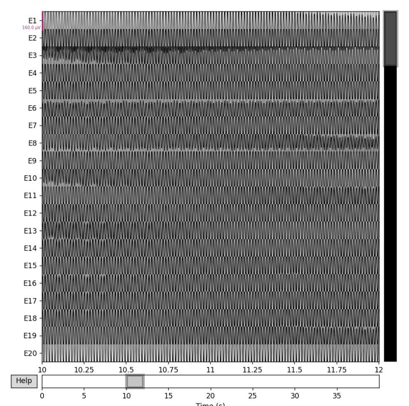
Laplacian filter:
- Enhance signal-to-noise ratio
- Reference to neighboring channels

Time Crop:
- Remove noise at start and end of recording

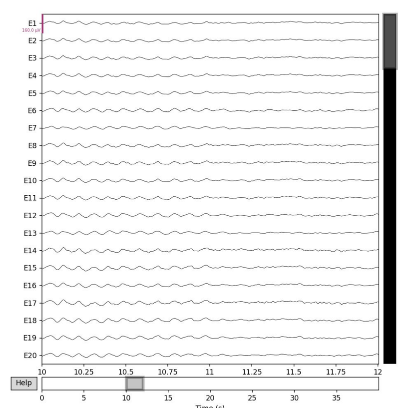
Standardizing data:
- More suitable for Machine learning

Downsampling:
- Reduce input size for pipeline





RAW DATA:
- Noisy
- Line signal interference (60Hz)
- High DC biases
- Contains channels without signals



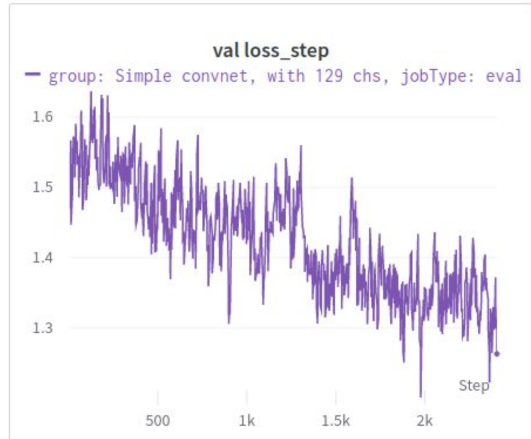
PRE-PROCESSED DATA:
- Mostly clean
- No more line interference
- No DC bias
- Downsample for lighter processing

Modeling

Deep Learning Approach

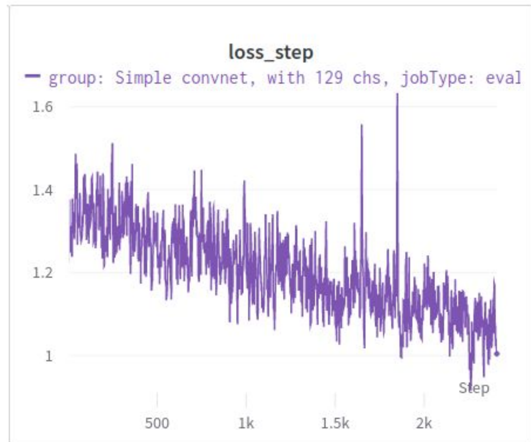
<u>**Data insights:**</u>

- **Per channel normalization** > global normalization
- **Random crop** for variable-length samples
- **Interpolating** channels > dropping them



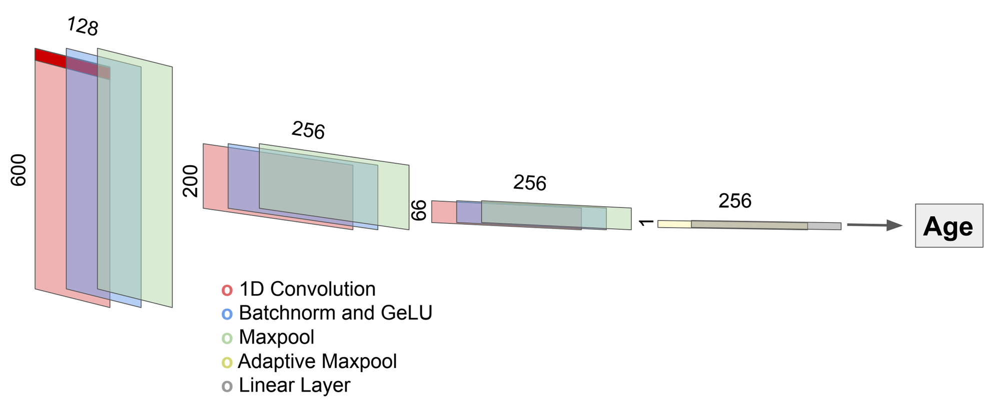
<u>**Architectural insights:**</u>

- **GELU** better than ReLU
- **Constant dilation** to regularize without changing the receptive field
- 4 layers < **3 layers,** possibly because hyperparameter tuning is slower



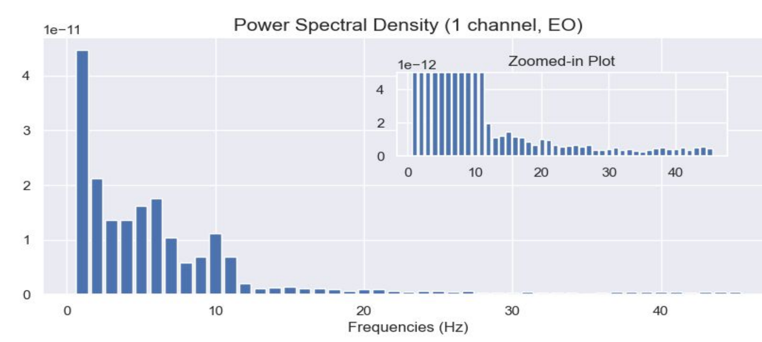
<u>**Training process:**</u>

- **Staging** is helpful:
  - **overfit on part** of the data - choose transforms
  - buy resources to **train on the full dataset to regularize**
- **Half-precision** is a must! Reduces iteration time by 3-5 times

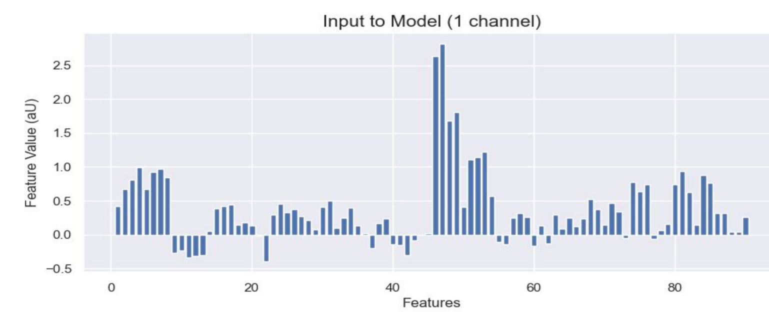


Machine Learning Approach

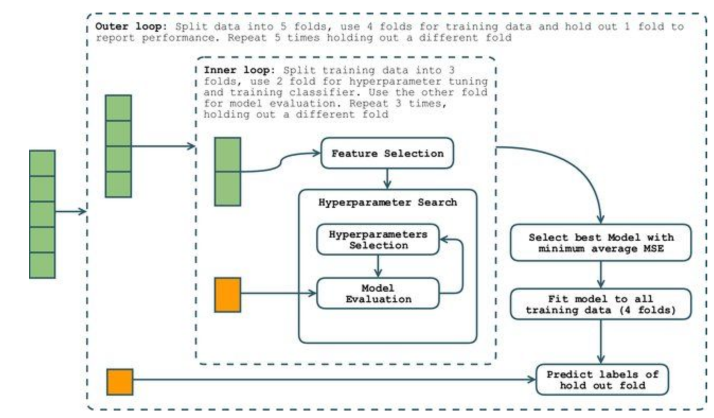
1. Sample Selection: select only samples that contain EO + EC
2. Welch's Method → PSDs (1-45Hz)



3. Standardization & Combination



4. Model Selection & Hyperparameter Tuning

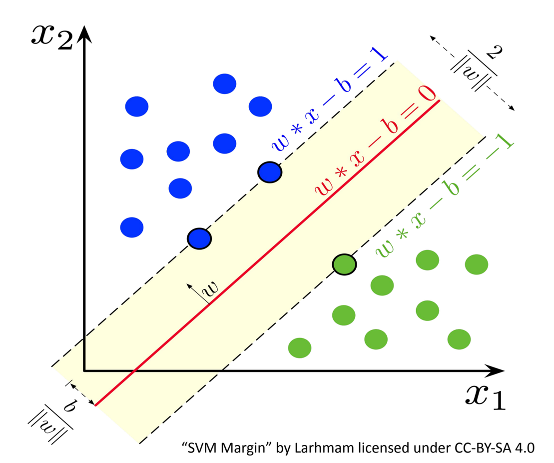


(Azevedo et al., 2019)

Search Space
Support Vector Machine
Kernel: Linear, Sigmoid, Poly, RBF
Gamma: logspace(-10:10)
C: logspace(-10:10)

Optimal Parameters
Support Vector Machine
Kernel: Linear
Gamma: 3.725e-9
C: 97e-5

5. Prediction



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Conclusion

Results					
#	User	Entries	Date of Last Entry	Team Name	Prediction score ▲
1	tsneurotech	1	11/21/22		1.156811 (1)
2	MethodA	1	11/24/22	State++	1.600948 (2)
3	thatsvenyouknow	7	11/20/22		1.603094 (3)
4	zeta	5	11/21/22		1.640561 (4)
5	Nitin_Singh	1	11/21/22	Gobias Industries	1.660653 (5)

Future Directions

- extend approach to other modalities (fMRI/MRI/fNIRS)
- further improve performance
- generalize to other age groups

References

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- Azevedo, T., Passamonti, L., Lió, P. & Toschi, N. (2019). A Machine Learning Tool for Interpreting Differences in Cognition Using Brain Features. In: MacIntyre, J., Maglogiannis, I., Iliadis, L., Pimenidis, E. (eds) Artificial Intelligence Applications and Innovations. AIAI 2019. IFIP Advances in Information and Communication Technology, vol 559. Springer, Cham. https://doi.org/10.1007/978-3-030-19823-7_40
- Bear, M.F., Connors, B.W. & Paradiso, M.A. (2016). Neuroscience: Exploring the Brain (4th ed.). Wolters Kluwer.