DyslexNet - a neural network for classifying dyslexia from cortical activity

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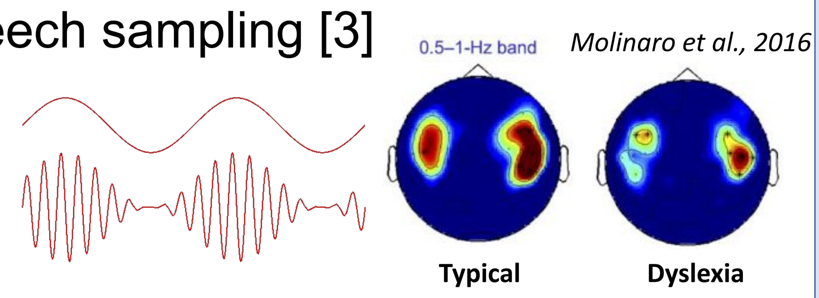
Aims

- ***Dyslexia*** → a phonological deficit that precedes formal reading tuition
- Linked to worse cortical ***entrainment to the speech envelope***, detectable early in life [1,2] -worse speech sampling [3]

Biomarkers for dyslexia from cortical activity?



- Can we detect presence of dyslexic symptoms from brain activity alone?
- A large ***attention-based Neural Network (NN)*** can find neural activity patterns linked to dyslexia and assist classification

Challenges and Advantages of the NN method:

- Atypical cortical development in dyslexia hard to identify and classify from structural images, with some progress achieved [4]
- Activity patterns encode rich information, can be used for classification
- Currently no advanced NN tools [but see 5] for classification form spatiotemporal pattern on the subject.
- ***Attention-based NN approaches*** offer a solution [6]
- Can ***transformer-based*** NN models surpass CNN-based ones [5]?
- Effective integration of the behavioral and neural features.
- Visualization of attention allows mapping model predictions to brain activity.

Methods

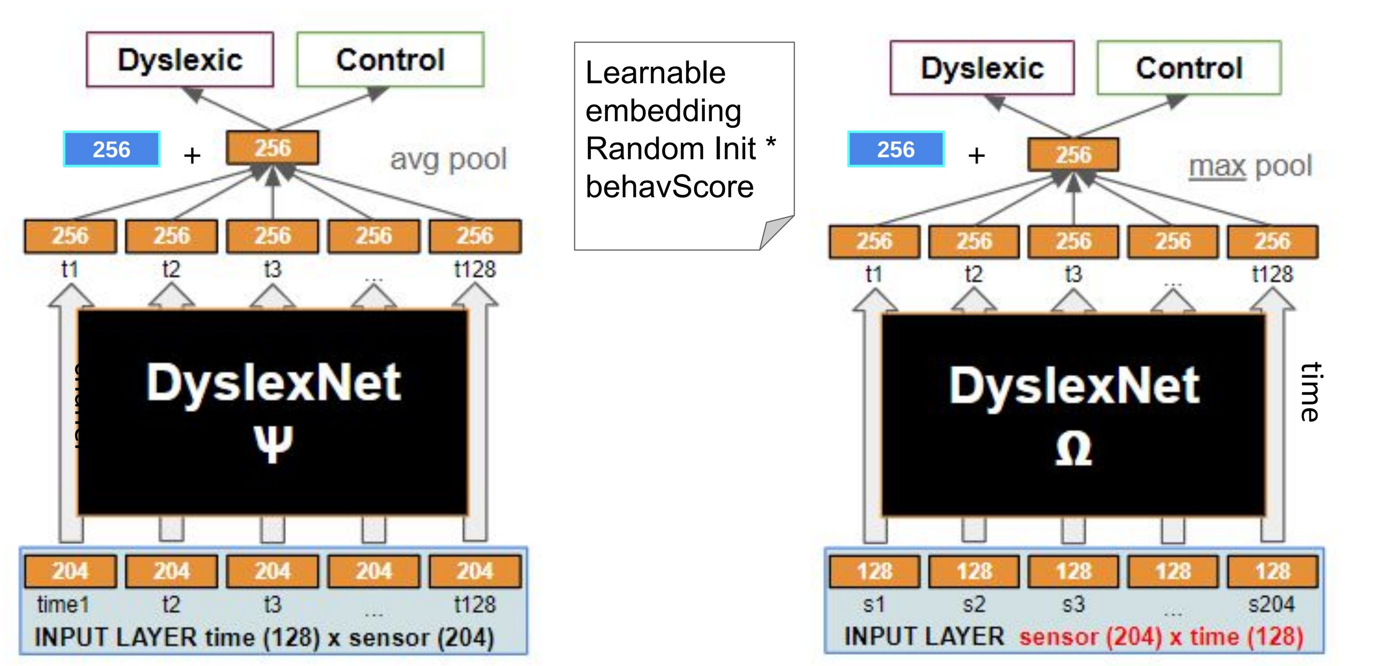
MEG data collection

Experiment **design**: natural ***sentence listening*** (total time: 300 sec) during MEG + behavioural ***tests of phonological and reading skills*** (PROLEC: words and pseudoword reading, phonological deletion)
Participants: 46 right-handed monolingual Spanish native speakers, 22 control and 24 participants with prior formal dyslexia diagnosis, age M=32.4; Data from Molinaro et al., 2016 & Lizarazu et al., 2015
Neural Data processing: per participant → Maxfilter, 0.05-45Hz bandpass filter, ICA blink removal, epoching into 1 sec slices, aligned to the sentence onset. 128 Hz downscaling.

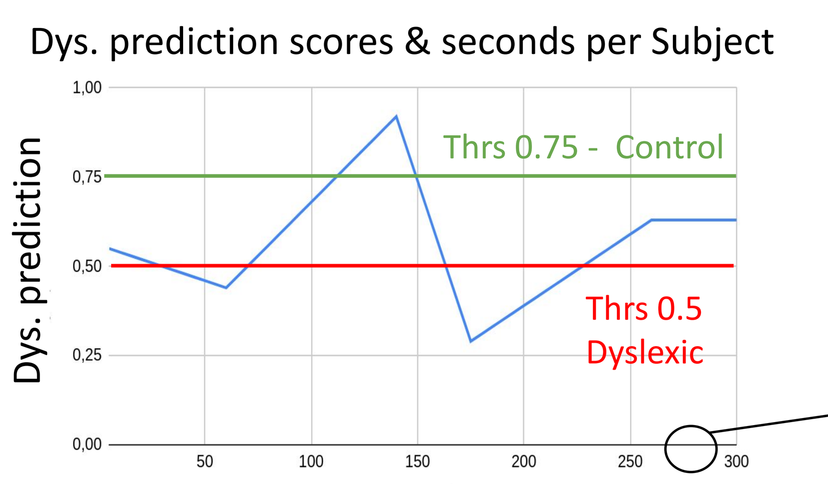
Neural Network design and analysis

Key goal: classify 1 sec neural data slices as either Control/Dyslexia, aggregate across slices and classify the participant.
Neural Network & training properties: *Transformers & self-attention,* average of leave one out cross-validation, local and global optimizations.

Ψ model - Which ***Times?*** **Ω model** - Which ***Sensors?***

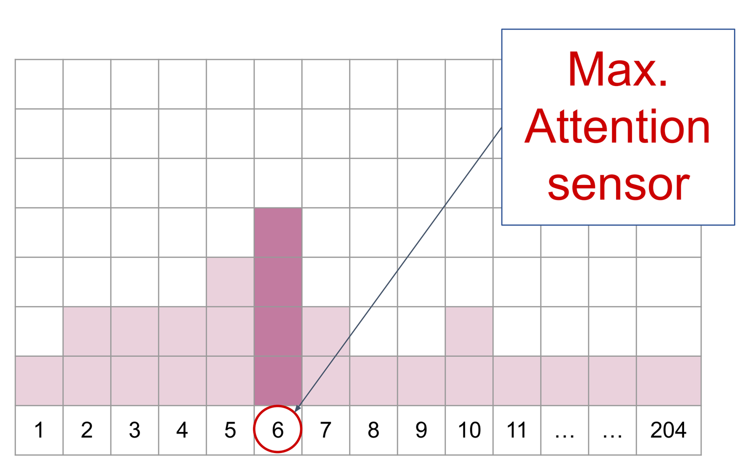


Global Optimization based on thresholds



Local score threshold 0.5 (default)
Global score optimized threshold

Self-Attention based approach

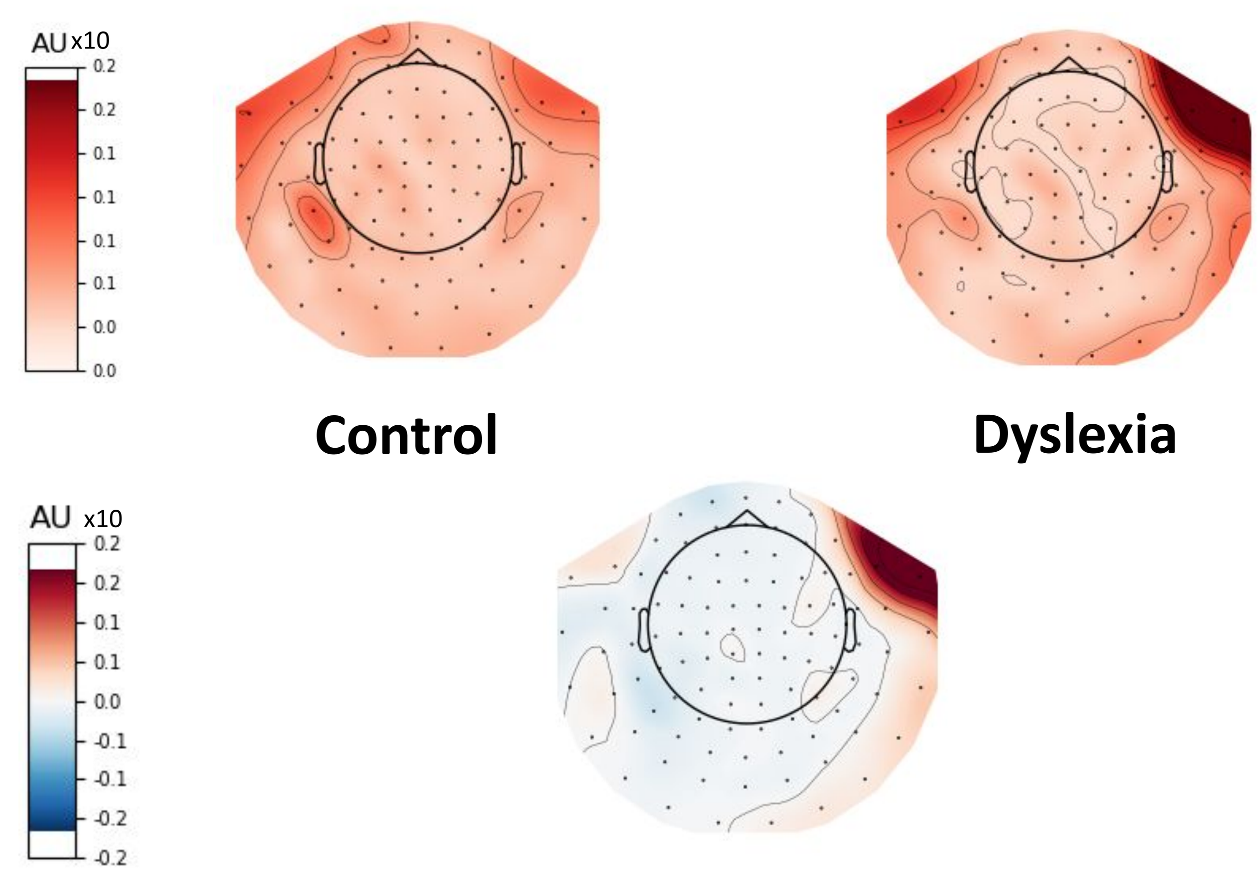


Self-attention plot = Average of 300 max. attention over sensors per subject

Results

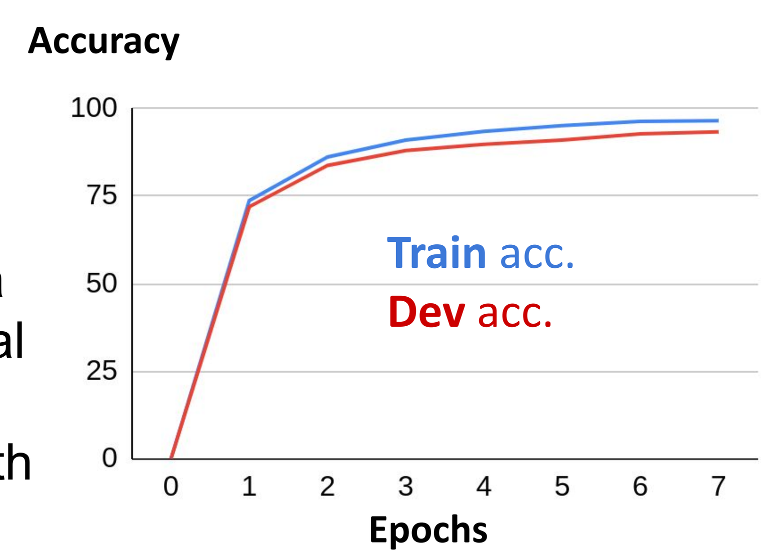
Model	Local Accuracy	Global Accuracy
Behavioural Scores	82.83%	82.83%
CNN Scores [5]	48.57%	–
MEG **Ψ**	51.43%	54.29%
MEG **Ψ** + **Behav**.	74.29%	77.14%
MEG **Ω**	51.43%	**85.71%**
MEG **Ω** + **Behav**.	77.14%	**88.57%**

Attention over sensors for Ω Model



Key Outcomes:

- Transformers win over CNN
- **Ω** model wins over **Ψ** model
- **Ω** model wins over Behavioural data
- ***Dyslexia-specific RH frontal*** spatial activation when listening to speech
- Best results when **Ω** is combined with behavioural scores



Conclusions

- It is possible to detect dyslexia from the spatio-temporal cortical activity using ***Attention-based Transformer NN***
- Best classification when ***cortical*** and ***behavioural*** (phonological skills) data are ***combined***
- Dyslexia → ***atypical processing of speech*** & ***Right Frontal*** sensors are key for classifying dyslexia in language tasks - consistent with previous findings [1]
- A step closer for design ***NN-assisted biomarker approach*** to dyslexia detection

Advances for NN approaches of brain data analysis

- Transformer NNs are better than CNNs for spatio-temporal data analysis and classification
- New architecture with self-attention and global threshold optimization gives best outcomes
- Neural architectures allow to combine sparse neural features and behavioral scores in a very intuitive way.

References: [1] Molinaro, Nicola, et al. "Out-of-synchrony speech entrainment in developmental dyslexia." *Human brain mapping* 37.8 (2016): 2767-2783. **[2]** Kalashnikova, Marina, Usha Goswami, and Denis Burnham. "Sensitivity to amplitude envelope rise time in infancy and vocabulary development at 3 years: A significant relationship." *Developmental Science* 22.6 (2019): e12836. **[3]** Goswami, Usha. "A temporal sampling framework for developmental dyslexia." *Trends in cognitive sciences* 15.1 (2011): 3-10. **[4]** Tamboer, P., et al. "Machine learning and dyslexia: Classification of individual structural neuroimaging scans of students with and without dyslexia." *NeuroImage: Clinical* 11 (2016): 508-514. **[5]** Zubarev, Ivan, Gavriela Vranou, and Lauri Parkkonen. "MNEflow: Neural networks for EEG/MEG decoding and interpretation." *SoftwareX* 17 (2022): 100951. **[6]** Vaswani et al. "Attention is All you Need." Advances in Neural Information Processing Systems 30 (NIPS 2017)