DyslexNet - neural network for dyslexia classification from cortical activity.

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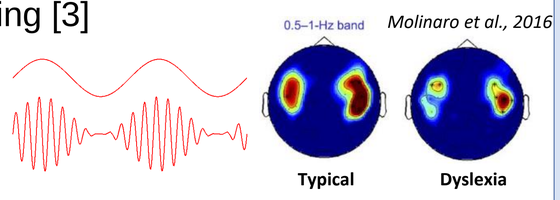
Aims

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

Early Biomarker for dyslexia from cortical activity?



A large ***transformer-based Neural Network (NN)*** can find dyslexia-linked neural activity patterns in spatiotemporal activity.

Challenges and Advantages of the transformer NN method:

- **Progress** in machine learning classification of dyslexia: 90% classification accuracy in children from cortical *entrainment to synthesised sounds* [4]
- **Issues**: not naturalistic, bias to acoustic (non-linguistic) features.
- Activity patterns encode rich information about acoustic and linguistic analysis, ***attention transformer NNs*** [5] can be used with naturalistic paradigms ***without bias*** to specific features, allow ***pattern visualisation***.

Questions:

- Can ***transformer NNs*** classify better than classical ML approaches [4]?
- Added value in neural-based classification ***over behavioural scores***?
- Classification ***differences in children and adults***? Is visualization of attention weights (dyslexia neural patterns) across sensors informative?

Methods

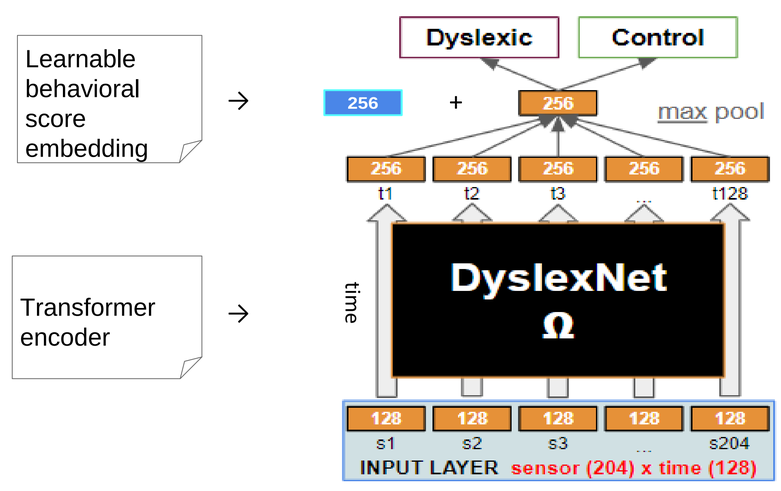
MEG data collection

Experiment **design**: natural ***sentence listening*** (total time: 300 sec) during MEG + behavioural ***tests of phonological and reading skills***
Behavioural scores: *Words & Pseudoword* reading *Accuracy* and *Time*
Participants: 46 right-handed monolingual Spanish native speakers, 23 adult (M Age=31.65, 10 with dyslexia) and 23 children (M Age=12, 13 with dyslexia). Data from Molinaro et al., 2016 & Lizarazu et al., 2015
Neural Data processing: per participant → Maxfilter, 0.05-45 Hz bandpass filter, ICA blink removal, epoching into 1 sec slices, aligned to the sentence onset. 128 Hz downscaling.

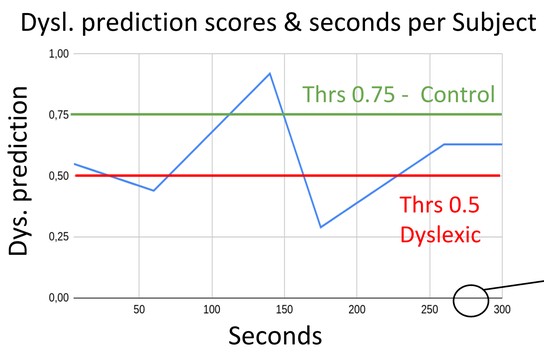
Neural Network design and analysis

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.

DyslexNet model architecture

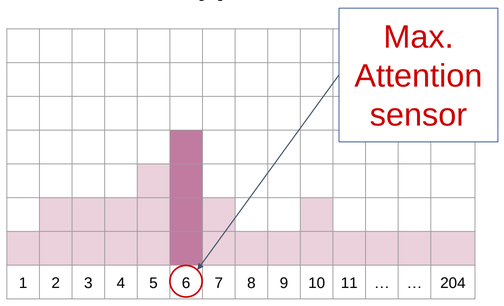


Global Optimization based on thresholds



Local score threshold 0.5 (default)
Global score optimized threshold

Self-Attention based approach

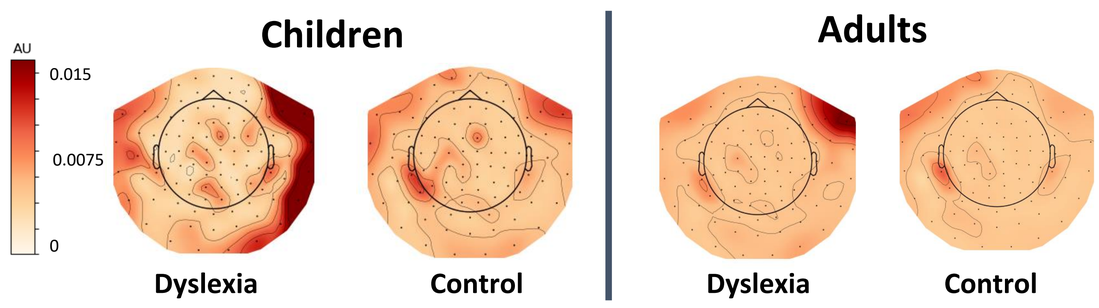


Self-attention plot = Average of 300 max. attention over sensors per subject

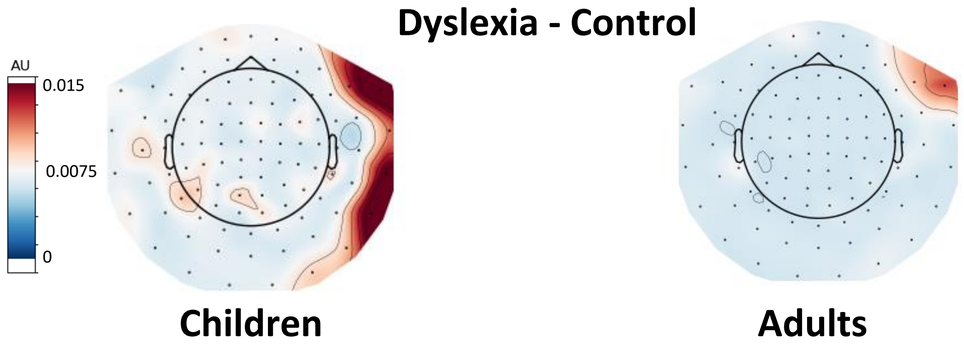
Results

Model	Accuracy Adults	Accuracy Children	Accuracy A+C
All behavioural Scores	80,7%	84,1%	82,7%
Logistic Regression	53%	50.4%	N/A
DyslexNet	13.9%	**82.6%**	**81.3%**
DyslexNet + Behav.	65.2%	**89.6%**	**79.1%**

Attention over sensors



Dyslexia - Control



Key Outcomes:

- DyslexNet outperforms simpler ML methods and is on par with behavioural scores in children (but not adults)
- Better classification for children than adults
- Best results for children when MEG combined with behavioural scores
- ***Dyslexia-specific RH frontal*** activation when listening to speech
- Frontal pattern in adults - frontotemporal in children

Conclusions

- We can reliably detect dyslexia from speech-induced spatiotemporal cortical activity with ***Attention Transformer NN.***
- **DyslexNet** classification with brain responses to speech is on par with reading and phonological score based classification in children → **prospect for pre-reading diagnostics.**
- Better classification in children - compensation in adults?
- Best classification when ***cortical*** + ***behavioural*** (reading and phonological) data are ***combined***
- Dyslexia → ***atypical processing of speech*** in ***RH Frontal and Temporal*** sensors are key for classifying dyslexia in language tasks - consistent with previous findings [1]

A step closer for designing ***NN-assisted biomarker approach*** for dyslexia detection

Advances for NN approaches of brain data analysis

- New architecture with ***self-attention*** and ***global threshold*** optimization gives ***best outcomes*** for developmental data
- Neural architectures allow to ***combine sparse neural features and behavioural scores*** in a very intuitive way.
- Ability to ***visualise model attention*** as a cortical ***biomarker***

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]** Gallego-Molina, Nicolás, et al. "A Survey on EEG Phase Amplitude Coupling to Speech Rhythm for the Prediction of Dyslexia." International Work-Conference on the Interplay Between Natural and Artificial Computation. Switzerland, 2024. **[5]** Vaswani et al. "Attention is All you Need." Advances in Neural Information Processing Systems 30 (NIPS 2017)