Is EEG Really Better Left Alone with Developmental Datasets?

Will Decker and Julie M. Schneider
Louisiana State University

Acknowledgments

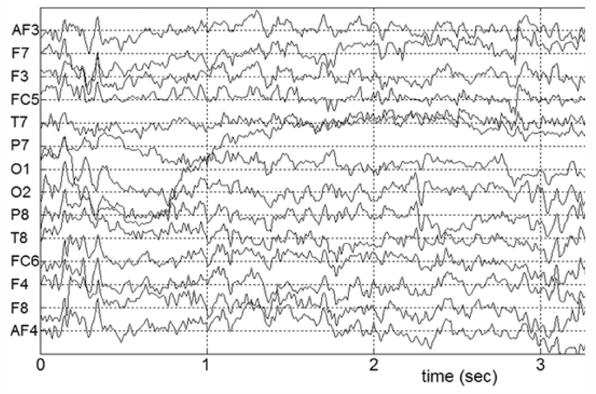
This research was funded by an Undergraduate Research Grant from the Discover Undergraduate Research Program at Louisiana State University.

Background

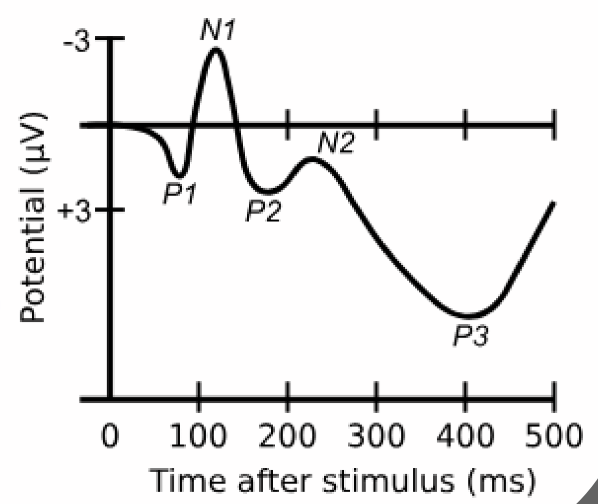
- Electroencephalography (EEG) is a common modality used to understand the neurobiological processes underpinning cognitive functioning.
- Event-related potentials (ERPs) are spikes in EEG data temporally bound to a stimulus.
  - Modulations in ERP voltage can tell us how our brain responds to different stimuli.
- Within EEG/ERP data exists noise brought on by salient and generally immutable factors within the environment, like electrical noise from a phone or the sound from an air conditioner.
- There are other biological forms of noise brought on by a participants, like pulse artifacts, motor movements, and eye blinks.
- To reduce and remove noise from EEG/ERP data, we can employ a variety of signal processing techniques.
  - Some of these techniques, like filtering and interpolation, rely on mathematical computations.
  - Other techniques, like artifact rejection, rely on machine learning algorithms.
- With such a variety of techniques and many parameters existing within a technique, there is a lack of standardization.
- Recent efforts have identified the most optimal techniques for preprocessing adult EEG/ERP data: Delorme (2023) in his paper "EEG is better left alone"[1] demonstrated this concept on publicly available data across a range of cognitive tasks.
- It is unclear whether the same optimal standards apply to child EEG/ERP data as there are greater factors affecting EEG data quality from children than adults [5].
- Therefore, we set out to determine the most optimal preprocessing choices for child EEG data.

EEG CAP

Raw EEG



ERP



Results

Optimized Pipeline

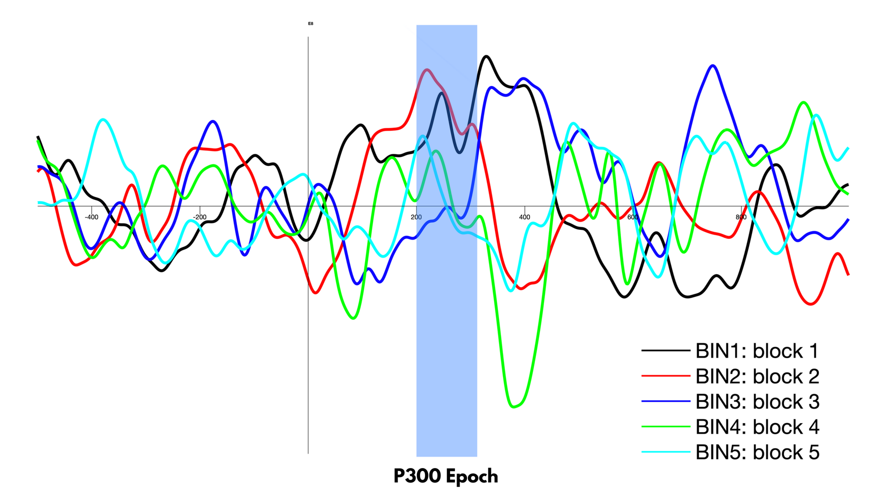
- **Filter:** 0.1Hz
- **Line-noise correction:** Notch linear filter
- **Reference:** Cz*
- **Channel rejection:** [0.15 - 0.975]
- **ASR:** 20
- **ICA:** runica
- **Eye & Muscle:** 0.5 - 1

What did we find?

Developmental datasets require...

- A more conservative filter.
- Line-noise correction using notch linear filter.
- Re-reference*
- Channel rejection with a correlation threshold range of 0.15 to 0.975.
- ASR with a standard deviation threshold of 20.
- ICA
- Eye and muscle artifact removal with a probability threshold of 0.5 to 1.0

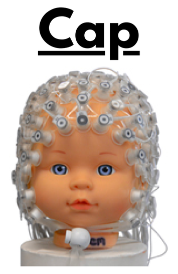
ERP



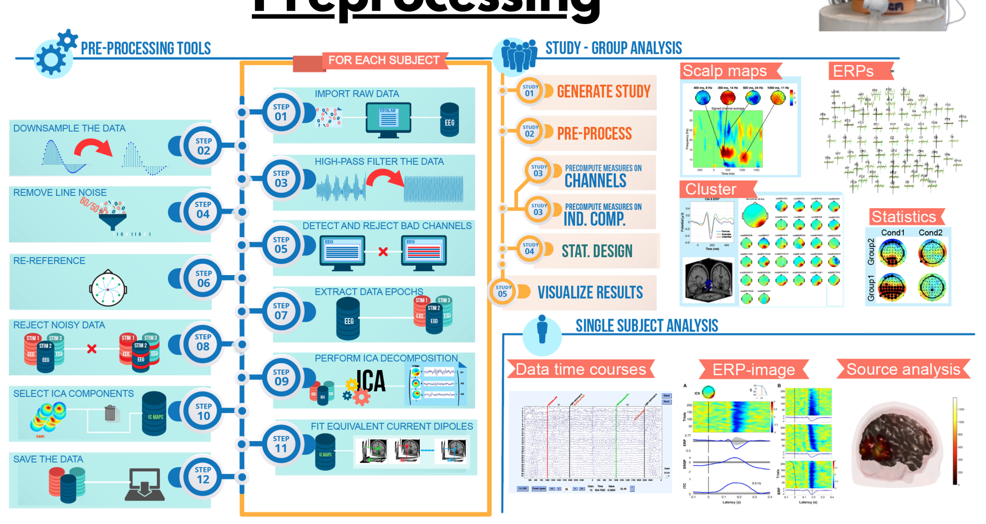
Methods

Task

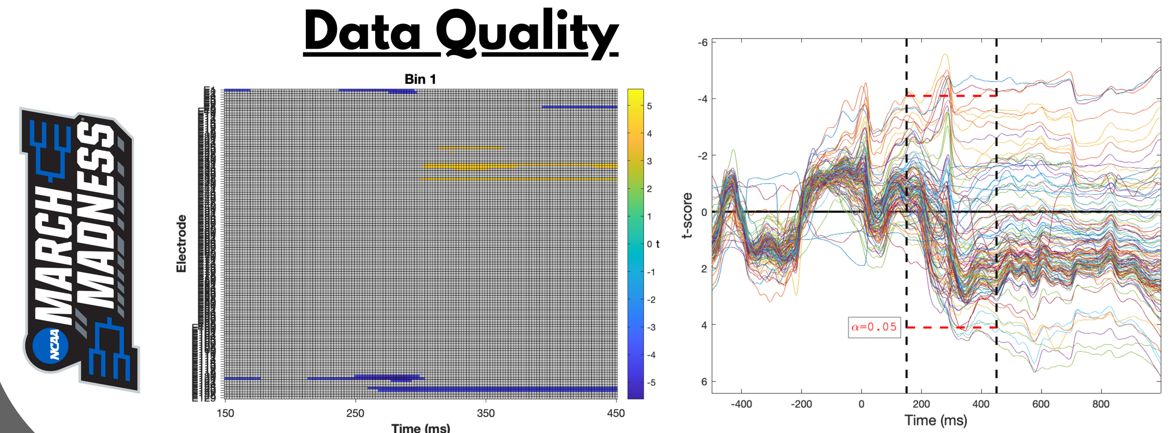
Cap



Preprocessing



Data Quality



Data and Task

- EEG data was taken from an open source (publicly available) dataset [3].
- Participants were between ages 6 and 9 years and completed a sequence learning task.
- Based on the original publication, we examined changes in the the P300 [3][6].
- EEG data was collected on a 128-channel EEG Geodesic Hydrocel system.

Signal Processing Operations

- highpass filter: 0.01Hz, 0.1Hz, 0.25Hz, 0.5Hz, 0.75Hz, 1.0Hz
- line-noise correction: notch linear filter, IIR filter, CleanLine plugin
- re-reference: average, Cz electrode
- channel rejection: correlation range of 0.15 - 0.975 with step of 20
- artifact subspace rejection (ASR): standard deviation thresholds 5 to 100 in steps of 20.
- independent component analysis (ICA)
- eye and muscle artifact rejection: probabilities 0.5-0.9 with step of 0.2

Data Quality Metrics

- A tmax statistical test [2] to test the null hypothesis that channels are not significantly different from μ (mu; 0).
  - Parameters with largest number of significant channels moved on. Think March Madness.
- The standard measurement error (SME)[4] was calculated to quantify the amount of variance in the ERP signal.

Discussion

- A careful approach must be taken when preprocessing developmental data and the P300 component.
- There are standard preprocessing methods that are common across all populations, like re-referencing and ICA.
- There are optimal parameters for filtering, channel rejection and ASR for developmental datasets.
  - Past research using standard parameters may over or understate results.
- Future evaluations should attempt to investigate this phenomenon across different tasks and ERP components.

References

1. Delorme, A. (2022). EEG is better left alone (p. 2022.12.03.518987). bioRxiv. https://doi.org/10.1101/2022.12.03.518987
2. Groppe, D. M., Urbach, T. P., & Kutas, M. (2011). Mass univariate analysis of event-related brain potentials/fields I: A critical tutorial review. Psychophysiology, 48(12), 1711–1725. https://doi.org/10.1111/j.1469-8986.2011.01273.x
3. Langer, N., Ho, E. J., Alexander, L. M., Xu, H. Y., Jozanovic, R. K., Henin, S., Petroni, A., Cohen, S., Marcelle, E. T., Parra, L. C., Milham, M. P., & Kelly, S. P. (2017). A resource for assessing information processing in the developing brain using EEG and eye tracking. Scientific Data, 4(1), Article 1. https://doi.org/10.1038/sdata.2017.40
4. Luck, S. J., Stewart, A. X., Simmons, A. M., & Rhemtulla, M. (2021). Standardized measurement error: A universal metric of data quality for averaged event-related potentials. Psychophysiology, 58(6), e13793. https://doi.org/10.1111/psyp.13793
5. Meyer, M., Lamers, D., Kayhan, E., Hunnius, S., & Oostenveld, R. (2021). Enhancing reproducibility in developmental EEG research: BIDS, cluster-based permutation tests, and effect sizes. Developmental Cognitive Neuroscience, 52, 101036. https://doi.org/10.1016/j.dcn.2021.101036
6. Picton, T. W. (1992). The P300 wave of the human event-related potential. Journal of Clinical Neurophysiology : Official Publication of the American Electroencephalographic Society, 9(4), 456–479. https://doi.org/10.1097/00004691-199210000-00002

Open Science

Analysis

Check out the in-progress, open source, pipeline on GitHub!

Pipeline

Check out the analysis on GitHub!