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WEARABLE BIOMETRICS | MACHINE LEARNING | SIGNAL PROCESSING

Artificial Intelligence in Neuroscience

Methodological Considerations of EEG Research in Learning and Reasoning

My career as a neuroscientist has centered on investigating the neural systems underlying human learning and reasoning, with particular interest in the complexity of cognitive mechanisms. My research integrates electroencephalography (EEG) with computational modelling to determine these mechanisms and enhance existing computational models of each. My work has revealed neural dissociations between uncertainty and prediction errors (Williams et al., 2017, 2018, 2020) and between intuitive and analytical reasoning (Williams et al., 2019, 2021a, 2023a). I proposed that learning and reasoning rely on shared prediction error mechanisms that involve a network of cognitive processes---including attention, working memory, and long-term memory---through cognitive control.

Through this research, I identified significant methodological inconsistencies in the literature, which led to variable findings across studies. This recognition motivated a shift in my focus towards improving EEG research methodologies. For instance, in a study published in *Psychophysiology* involving 500 participants, we investigated methodological approaches for ERP and frequency correlates of feedback processing and provided recommendations for standardization in future studies (Williams et al., 2021b). Furthermore, we emphasized the importance of open-science by publicly releasing the EEG data from all 500 participants along with the processing scripts. While refining standard practices was valuable, I recognized that more advanced solutions could offer more impact, prompting me to explore cutting-edge methodologies. This led me to explore artificial intelligence (AI) approaches for data processing and interpretation, ultimately refocusing my research program on uncovering their potential in EEG research.

EEG-GAN: A Generative Adversarial Network for Electroencephalography Data Augmentation and Classification

My research program enhances the methodological practices of EEG science with artificial intelligence. A focus of my research has been to validate the use of generative modeling for augmenting EEG datasets, while providing an open-source Python toolbox, EEG-GAN, to help researchers easily apply these techniques to their work. Specifically, EEG-GAN uses Generative Adversarial Networks (GANs) to generate trial-level synthetic EEG samples, which can serve as additional training data for neural decoding analyses. GANs are machine learning frameworks consisting of two adversarial neural network agents, trained to produce realistic continuous EEG activity. This activity is conditioned on experimental variables that capture neural features associated with the outcomes being classified. For example, depression manifests as increased alpha oscillatory activity in EEG signals, so an ideal generator would produce continuous EEG that incorporates these characteristic alpha signatures.

We validated EEG-GAN as a tool for enhancing classification performance across three classifiers and seven sample sizes, ranging from 5 to 100 participants (Williams et al., 2023b). In a reinforcement learning study, we observed up to a 12% increase in decoding accuracy with as few as 5 participants. Building on this validation, we released EEG-GAN v2.0 and demonstrated its efficacy in EEG data augmentation across a large range of experimental contexts (Williams, et al., *in prep*). Specifically, we evaluated the effects of GAN-augmentation across four datasets, five classifiers, seven sample sizes, three EEG systems, and three distinct processing pipelines. It achieved up to a 16% improvement in decoding accuracy, with consistent enhancements across datasets and their respective EEG processing pipelines. Augmentations were particularly effective for sample sizes ranging from 5 to 30, significantly improving 70% of classification analyses and only impairing 4%. Further, EEG-GAN outperformed six benchmark augmentation techniques for 69% of comparisons, while being outperformed in only 3% of cases.

Our findings highlight EEG-GAN's potential as a tool for enhancing EEG decodability across various research studies. Building on this foundation, future investigations will focus on validating EEG-GAN in studies on clinical populations, brain health assessments, and advancing neurotechnology applications. Additional future directions include exploring EEG-GAN's ability to recover lost EEG signals due to excessive noise and artifacts, increasing electrode density in sparse mobile EEG systems, and developing it as an AI-driven EEG processing pipeline.

Automated Research Assistant (AutoRA): A Framework for Automating the Empirical Research Process and its Application in Model Discovery of Information Processing

There has been a rapid growth of complex datasets within psychology and neuroscience. These complex datasets pose challenges for integrating observations into quantitative models of human information processing. Other fields of research, such as physics, have proposed symbolic regression techniques as a way of automating data-driven discovery of interpretable computational models. Symbolic regression is an artificial intelligence model discovery approach that, unlike traditional regression methods that assume a predefined form of the computational model, searches for both the structure and parameters of a mathematical model to link input variables to an output variable.

Several methods of symbolic regression now exist, including the Bayesian Machine Scientist, Bayesian Symbolic Regression, and Differentiable Architecture Search. However, these algorithms have been difficult to incorporate into empirical research pipelines. The sparsity of such pipelines, particularly those incorporating symbolic regression methods, motivated the development of the open-source Python suite, Automated Research Assistant (AutoRA) (Musslick et al., 2024), which I helped create and continue to contribute as an active developer. AutoRA is a framework for automating the empirical research process including experimental design, data collection, model discovery, and documentation for open science.

Using AutoRA, we demonstrated the effectiveness of symbolic regression in recovering computational models of human information processing (Hewson et al., 2023). In this study, we validated the Bayesian Machine Scientist's (BMS) ability to recover four information processing models---Steven's Power Law, Weber-Fechner Law, Shepard-Luce Choice Rule, and Exponential Learning---using simulated data with varying noise levels. We found that BMS outperformed benchmark computational models 71% of the time, with no instances where it was outperformed. Performance converged between BMS and benchmark models only when excessive noise severely distorted the underlying signal of information processing. These results suggest that BMS holds significant potential for discovering psychological models of human information processing.

Symbolic regression could provide valuable insights into the neural mechanism underlying cognitive functioning by identifying interpretable models that link brain activity, derived by methods such as EEG, to behaviour. Future research will focus on applying symbolic regression for model discovery in EEG research, aiming to connect brain activity---such as ERP amplitudes, oscillatory power, and functional connectivity---to a broad spectrum of cognitive processes. For instance, future directions include exploring the relationship between EEG signals with the onset and severity of neurological and psychiatric disorders, as well as developing personalized treatment approaches by linking neural patterns to therapeutic outcomes, advancing precision medicine in neuroscience.

References

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Hewson, J. T. S., Strittmatter, Y., Marinescu, I., Williams†, C. C., & Musslick†, S. (2023). Bayesian Machine Scientist for Model Discovery in Psychology. In *NeurIPS 2023 AI for Science Workshop*.

Musslick, S., Andrew, B., Williams, C. C., Li, S., Marinescu, I., Dubova, M., ... & Holland, J. G. (2024). AutoRA: Automated Research Assistant for Closed-Loop Empirical Research. *Journal of Open Source Software*, *9*(104), 6839.

Williams, C. C., Ferguson, T. D., Hassall, C. D., Abimbola, W., & Krigolson, O. E. (2021b). The ERP, frequency, and time–frequency correlates of feedback processing: Insights from a large sample study. *Psychophysiology*, *58*(2), e13722.

Williams, C. C., Ferguson, T. D., Hassall, C. D., Wright, B., & Krigolson, O. E. (2021a). Dissociated neural signals of conflict and surprise in effortful decision Making: Theta activity reflects surprise while alpha and beta activity reflect conflict. *Neuropsychologia*, *155*, 107793.

Williams, C. C., Hassall, C. D., & Krigolson, O. E. (2023a). Stabilizing expectations when shifting from analytical to intuitive reasoning: The role of prediction errors in reasoning. *Cortex*, *161*, 145-153.

Williams, C. C., Hassall, C. D., Lindenbach, T., & Krigolson, O. E. (2020). Reward prediction errors reflect an underlying learning process that parallels behavioural adaptations: a trial-to-trial analysis. *Computational Brain & Behavior*, *3*, 189-199.

Williams, C. C., Hassall, C. D., Trska, R., Holroyd, C. B., & Krigolson, O. E. (2017). When theory and biology differ: The relationship between reward prediction errors and expectancy. *Biological psychology*, *129*, 265-272.

Williams, C. C., Hecker, K. G., Paget, M. K., Coderre, S. P., Burak, K. W., Wright, B., & Krigolson, O. E. (2018). The application of reward learning in the real world: Changes in the reward positivity amplitude reflect learning in a medical education context. *International Journal of Psychophysiology*, *132*, 236-242.

Williams, C. C., Kappen, M., Hassall, C. D., Wright, B., & Krigolson, O. E. (2019). Thinking theta and alpha: Mechanisms of intuitive and analytical reasoning. *NeuroImage*, *189*, 574-580.

Williams*, C. C., Weinhardt*, D., Hewson, J. T. S, Płomecka, M. B., Langer, N., & Musslick, S. (*in prep*). EEG-GAN: A generative adversarial network for electroencephalography data augmentation and classification.

Williams*, C. C., Weinhardt*, D., Wirzberger, M., & Musslick, S. (2023b). Augmenting EEG with generative adversarial networks enhances brain decoding across classifiers and sample sizes. In *Proceedings of the Annual Meeting of the Cognitive Science Society* (Vol. 45, No. 45).