Research Program

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Artificial Intelligence in Neuroscience

Generative Modelling to Increase Classification Performance of EEG Signals

With over a decade of experience, my research program improves the methodological practices of electroencephalography (EEG) science by leveraging artificial intelligence. For instance, my research has validated the augmentation of EEG datasets through generative modelling and provides an open-source python toolbox - EEG-GAN - so that researchers can easily apply these techniques to their own research. Specifically, I use Generative Adversarial Networks (GANs) to create trial-level synthetic EEG samples, which can be used as extra training data in classification analyses. GANs are machine learning frameworks that consist of two adversarial neural network agents, namely the generator and the discriminator. The generator is trained to create novel samples that are indiscernible from real samples. In the current context, the generator produces realistic continuous EEG activity, conditioned on a set of experimental variables, which contain underlying neural features representative of the outcomes being classified. For example, depression manifests as increased alpha oscillatory activity in the EEG signal, and thus, an ideal generator would produce continuous EEG that includes these alpha signatures. In contrast to the generator, the discriminator determines whether a given sample is real or synthetically produced by the generator. The core insight of GANs is that the generator can effectively learn from the discriminator. Specifically, the generator will consecutively produce more realistic synthetic samples with the goal of "fooling" the discriminator into believing them as real. Once it has achieved realistic samples that the discriminator cannot discern, it can be used to generate synthetic data—or in this context, synthetic EEG data. This generated data enhances classification performance, with the largest enhancements in smaller sample sizes (as low as 5 participants), opening the potential for small sample studies to reach reliable classification outcomes.

Symbolic Regression to Discover Computational Models of Cognition

As a statistician and data scientist, I have experienced the rapid growth of complex datasets within the field of psychology first hand. 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. I have confirmed the effectiveness of symbolic regression in recovering computational models of cognition and information processing, and have contributed to an open-source python suite - Autora - that contains symbolic regression algorithms. One such symbolic regression approach is the Bayesian Machine Scientist (BMS), which employs Bayesian inference to derive mathematical equations linking input variables to an output variable. My research has demonstrated BMS to outperform benchmark computational models across a range of realistically noisy data. As such, BMS has potential for discovering psychological models of human information processing. My research also seeks to improve these regression techniques by, for example, providing them with domain-specific priors of operations of functions. Although these findings are preliminary, I have found that priors can enhance BMS performance. Thus, my research demonstrates the effectiveness of symbolic regression in recovering computational models of human cognition and information processing with improved insights when integrating expert knowledge into the BMS framework.

Reasoning in the Brain

My secondary research program investigates neural systems that underlie human reasoning, with particular interest in determining the complexity of cognitive mechanisms involved. Specifically, my research program partners electroencephalography (EEG) with computational modelling to determine the cognitive mechanisms involved in reasoning, and to expand existing computational models of reasoning. Intuitive reasoning is fast and effortless but can lead to mistakes, while analytical reasoning is slow and accurate but takes considerable effort. We rely on intuitive reasoning for the majority of our decisions as it most often leads to an acceptable outcome, yet it can fail us when decisions require more thought and consideration. In these instances, we turn to analytical reasoning. As such, there is an intimate balance between intuitive and analytical reasoning where we operate to conserve energy until we must exert effort when faced with a difficult decision. But how do we decide whether to reason intuitively or analytically?

One model of reasoning, the Expected Value of Control (EVC) model (Kool et al., 2017), posits that the recruitment of reasoning systems (intuitive versus analytical) is determined by an assessment of costs and benefits. If the benefits outweigh the costs, effort is exerted to reason analytically, but if the costs outweigh the benefits, effort is withheld to reason intuitively. In line with the EVC model, my research has posited that the crossroads between intuitive and analytical reasoning is cognitive control wherein there is an increased need for control as one reasons more analytically. Cognitive control, however, is not the whole story. Rather, I have found that mechanisms of attention, working memory, and long-term memory interact with cognitive control during reasoning, as evidenced by the complexity of involved neural signals. As such, when investigating reasoning, it is imperative to adopt a network science approach rather than focusing on individual mechanisms in isolation. Correspondingly, my research program investigates the interactive complexity of cognitive mechanisms involved in reasoning as informed by EEG-derived neural signals.

Research Practices

The success of my research programs demands my adoption of rigorous research practices – namely, my commitment to inclusivity, open-science, and collaborative initiatives. First, the consideration of equity, diversity, and inclusion in my research is of primary focus. By recruiting diverse participants, I will ensure my findings are sensitive to individual differences (e.g., gender, ethnicity), and thus generalizable to a large population of people. Similarly, I find it important to build a laboratory with a diverse team of researchers as I value how different perspectives and experiences will improve the laboratory environment, interpretations of findings, and applicability of research to society. Next, I believe that open and transparent science is necessary to achieve proper scientific rigour. All of my research follows open-science protocols, providing data and scripts freely available. Moreover, I have built and collaborated on multiple open-source python packages to allow researchers to easily use my research techniques in their own work. See the development section of my website for more information. Finally, science is quickly moving away from isolated research groups and into vast collaborative networks as the combination of diverse expertise propagates creativity in research beyond what could be accomplished by an expert alone. I have a rich network of both academic and industrial collaborators and have worked on projects ranging from deciphering brain states to using brain-computer interfaces to control technology.