Description of the Potential Research Project

Application for the Position of Assistant

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Over the last decades, our understand of the human brain have evolved thanks to the use of Functional Magnetic Resonance Imaging (fMRI) and Electroencephalography (EEG). fMRI allows one to capture brain activities by detecting changes associated with blood flow while EEG measures the electrical activity of the brain at extremely short time spans. This new wealth of data have extensively use to develop various machine learning models used in applications from anomaly detection using EEG data to static reconstruction or data augmentation when it comes to fMRI imaging data.

Despite the abundance of both fMRI and EEG data, their joint use remains limited. In epilepsy or other pathologies, rapid detection of abnormal brain states in both time and space could enable earlier warnings and more precise interventions. EEG captures neural dynamics at millisecond resolution but with poor spatial specificity whereas fMRI offers millimeter-scale spatial maps of brain activity but at a sluggish temporal pace. Bridging these modalities can yield a richer picture of how the brain functions. A joint representation would let us exploit EEG's fine temporal detail to "fill in" fast-changing patterns across the whole brain, while using fMRI's spatial precision to localize EEG-derived signals.

A potential PhD would try to address these limitations by identifying models that could be in order to allow for the joint use of fMRI and EEG. In fact, potential directions for such a proposal could be the use of contrastive learning on latent reprensentation of EEG and fMRI learned both through Vector Quantized Variational AutoEncoder (VQ-VAE) to understand how the brain react to video games stimuli. The two methods have been proposed in various settings. VQ-VAE for generating sequence and in discrete data analysis. Contrastive Learning has been used to learn cross-modal embeddings by aligning latent representations from disparate data sources such as image–text pairs by maximizing agreement between matching views. VQ-VAE and contrastive learning joint use remains limited and could eventually be used to first learn discrete representation of both fMRI and EEG across time using VQ-VAE and use these representation in constrative learning framework to align simultaneous EEG and fMRI.

This project would have the potential to harvests millisecond EEG detail to enrich whole-brain fMRI maps and vice versa. The unsupervised flexibility of constrative learning requires no labels beyond temporal alignment, making it scalable to large clinical and research datasets. Finally, it has real-time potential so that once trained, the model can run online—enabling near-instant spatial brain forecasts from EEG or fast temporal reconstructions from fMRI.

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