UNIST-UTA Joint Research Assistantship (RA) in Neuroimaging

Description:

Dr. Younggeun Kim (Department of Mathematical Sciences, UNIST) and Dr. Xi Zhu (Department of Bioengineering, University of Texas at Arlington (UTA)) are seeking up to **TWO** highly motivated students. The students will apply deep representation learning methods to ENIGMA project data (https://enigma.ini.usc.edu/) to investigate and identify complex patterns in multi-modal neuroimaging associated with psychiatric disorders.

Program Highlights:

International Visit: Includes an opportunity to visit UTA for up to 6 months. (In the event of administrative conflicts with regular semester schedules, we may alternatively consider shorter stays during the summer or winter breaks.)

Funding: Students will be hired as Research Assistants at UTA during their visiting period (earning approx. $1,500 per 4 weeks), supported by a grant from the NIH in the US.

Long-Term Mentorship: A 1-year joint research program featuring regular, direct mentoring from Drs. Kim and Zhu, with the goal of publishing papers with students as lead authors.

Eligibility and Minimum Qualifications:

Open to students who are available to participate in the visiting period at UTA (for non-US citizens, a J-1 visa may be required). The minimum required qualifications include:

a) The ability to implement autoencoders for image data in GPU environments.
b) A basic understanding of functional and structural neuroimaging.

We may conduct interviews to assess these technical skills and English proficiency.

Required Documents:

Please send your academic transcripts to Dr. Kim (younggeun91@unist.ac.kr) by **May 1st, 2026**. After the initial screening, we may contact you to request your CV and research statement (although you are welcome to submit these documents at the initial screening stage if you prefer). All documents must be written entirely in **English**.

Program Narrative:

This program is designed to train students to become independent researchers in neuroimaging using deep learning. Students will begin by mastering single-modality data analysis before advancing to develop conditional generative models for multi-modal data under the joint guidance of Drs. Kim and Zhu. Using pre-processed datasets provided by Dr. Zhu's lab, students will analyze complex cluster structures in functional and structural neuroimaging.

Scientifically, the occurrence of posttraumatic stress disorder (PTSD) or major depressive disorder (MDD) significantly affects psychiatric development, and understanding the distinct association patterns between neurobiological measurements and behavioral outcomes under these conditions has become increasingly important. The large-scale ENIGMA-PTSD study provides a unique opportunity to investigate these relationships by offering diverse structural and functional brain data modalities accompanied by clinical scores (such as CAPS or HAM-D). However, despite the richness of this dataset, the frequent occurrence of missing modalities and the inherently high-dimensional structure of the data pose significant analytical challenges.

Traditional linear methods for multi-modal data in the presence of missingness, such as joint and individual variation explained (JIVE) and multi-block partial least squares (MB-PLS), can learn lower-dimensional factors (often referred to as *representations*) that generate the original high-dimensional data. Crucially, they decompose these factors into a joint component, capturing shared information across modalities, and individual components, capturing modality-specific information. However, their strict linear assumptions hinder their ability to capture the highly nonlinear patterns inherent in neuroimaging data, resulting in less effective representations.

Several recent works have introduced deep learning approaches, but they typically restrict their focus to a single modality or prioritize downstream tasks (e.g., classification) over learning lower-dimensional representations to interpret underlying patterns. Notably, some recent studies have employed variational autoencoders (VAEs) to extract explainable representations from multi-modal ENIGMA data. However, their representations are not explicitly disentangled into joint and individual components as they are in JIVE or MB-PLS. Furthermore, these deep learning pipelines either rely solely on subjects with completely observed modalities or employ traditional imputation methods followed by VAE application in a disjointed, two-step procedure.

To address these limitations, this program aims to leverage deep learning-based multi-modal representation learning tailored to missing data situations. With a particular focus on advanced VAE methodologies for multi-modal data, our goal is to learn representations that are explicitly disentangled into a shared component across all modalities and modality-specific components for structural and functional MRI.