Ph.D. thesis in signal processing & machine learning (2023–2026)
CRAN (UL – France) / MLSP Lab (UMBC – USA)

Tensor methods for multi-subject fMRI data fusion

Context: Given the recent explosion in the amount of data from multiple modalities, data fusion has been growing in importance for multiple applications [1]. A fundamental problem is fusing heterogeneous datasets containing dataset-specific information [4], such as in multi-task functional magnetic resonance imaging (fMRI) data [2] or multimodal image fusion [3]. In multi-subject fMRI data, this can have significant societal impact through personalized medicine by finding subject-specific features that are predictive of mental disorders [2,5]. Of particular interest are longitudinal studies such as the ABCD [6], which collect fMRI and non-neuroimaging data (e.g., cognitive scores, substance use) of the same subjects over time. This requires methods that jointly leverage multi-subject, longitudinal fMRI and non-neuroimaging data to extract features that can reveal the evolution of cognitive processes and characterize subtypes of diseases and risk groups for addictive behavior early in the study, being an important step towards personalized medicine.

Challenges: Neuroimaging data presents multiple challenges. With the growing emphasis of data-driven methods approaches based on matrix and tensor decompositions, which are directly interpretable, the field is transforming. However, the theoretical study of more flexible factorizations is still in its infancy. The uniqueness of coupled tensor decompositions was only investigated recently [7]. More flexible decompositions have been proposed [8], but existing uniqueness results are still incipient [3].

Research program: The Ph.D. candidate will focus on developing new flexible matrix/tensor decomposition methods with application to neuroimaging. The objectives include: 1) develop new coupled low-rank tensor decomposition methods applicable to multi-subject fMRI data and investigate their uniqueness; 2) develop physically interpretable decompositions that account for longitudinal data and multiple (e.g., non-neuroimaging) modalities; 3) validate the developed methods for analyzing longitudinal multi-subject fMRI data for personalized medicine.

Supervision and environment: The candidate will be jointly supervised by Prof. David Brie, Dr. Ricardo Borsoi, members of the Multidimensional Signal Processing (SiMul) team (`https://cran-simul.github.io/`), CRAN Laboratory, University of Lorraine, France, and by Prof. Tülay Adali, director of the Machine Learning for Signal Processing (MLSP) Laboratory (`https://mlsp.umbc.edu/`), University of Maryland Baltimore County (UMBC), USA. He/She will be primarily based in the CRAN Laboratory, University of Lorraine, in Vandoeuvre-lès-Nancy, France, with the possibility for research visits to the MLSP lab in Baltimore, USA. The thesis has a duration of 36 months, starting after October 2023.

Expected profile: Master's degree or equivalent, with experience in one or more of the following topics: data analysis, signal processing, machine learning, applied mathematics. Good communication skills in English (written and oral). Candidates should send their application to david.brie@univ-lorraine.fr, ricardo.borsoi@univ-lorraine.fr, adali@umbc.edu, including an academic CV and a motivation letter (1 page max.) explaining their research interests and their motivation for this position.

References

[1] D. Lahat et al., "Multimodal data fusion: an overview of methods, challenges, and prospects," Proceedings of the IEEE, vol. 103, no. 9, pp. 1449–1477, 2015.

[2] M. Akhonda et al., "Disjoint subspaces for common and distinct component analysis: Application to the fusion of multi-task FMRI data," Journal of Neuroscience Methods, vol. 358, p. 109214, 2021.

[3] R. A. Borsoi et al., "Coupled tensor decomposition for hyperspectral and multispectral image fusion with inter-image variability," IEEE Journal of Selected Topics in Signal Processing, vol. 15, no. 3, pp. 702-717, 2021.

[4] A. K. Smilde et al., “Common and distinct components in data fusion,” Journal of Chemometrics, vol. 31, no. 7, p. e2900, 2017.

[5] E. S. Finn et al., “Functional connectome fingerprinting: identifying individuals using pat- terns of brain connectivity,” Nature Neuroscience, vol. 18, no. 11, pp. 1664-1671, 2015.

[6] B. J. Casey et al., “The adolescent brain cognitive development (ABCD) study: imaging acquisition across 21 sites,” Developmental Cognitive Neuroscience, vol. 32, pp. 43-54, 2018.

[7] M. Sørensen and L. D. De Lathauwer, “Coupled canonical polyadic decompositions and (coupled) decompositions in multilinear rank-$(L_{r,n}, L_{r,n}, 1)$ terms-part I: Uniqueness,” SIAM Journal on Matrix Analysis and Applications, vol. 36, no. 2, pp. 496-522, 2015.

[8] E. Acar et al., “Structure-revealing data fusion,” BMC Bioinformatics, vol. 15, no. 1, pp. 1-17, 2014.