**Overview**

- (P1) How can we preserve the graph property in the tensor factorization process?
- (P2) How can we leverage the side information associated with brain networks?
- (P3) How can we fuse the classifier training and the representation learning procedures?

**Dataset**

- Emotion Regulation Tasks: Neutral, Maintain, and Reappraise
- Positive samples: 37 patients with anxiety disorder
- Negative samples: 32 healthy participants
- n = 69 samples
- m = 34 scalp channels

**Method**

- Vertices: sensors or electrodes.
- Edges: functional correlation between regions of interest.

**Experiments**

- Classification Performance
  - Methods
    - t-BNE
    - CMTF
    - ALR
    - gMSV
    - C:
  - Datasets
    - Neutral
    - Maintain
    - Reappraise

- Parameter Sensitivity

- Factor Analysis

**Algorithm 1 t-BNE**

\[
\begin{align*}
\min_{B, S, W} & \left\| X - C \right\|_F^2 + \alpha \left( \text{tr}(S^T S) + \beta \left\| D_S W - Y \right\|_F^2 + \gamma \left\| W \right\|_F^2 \right) \quad \text{reg.} \\
\text{s.t.} & \quad S^T S = I \quad \text{orthogonality} \\
& \quad \text{(S2) Partially coupled matrix and tensor factorization} \\
& \quad \text{(S3) Partially symmetric tensor factorization} \\
& \quad \text{(S1) The brain network embedding problem is modeled as partially symmetric tensor factorization which is suitable for inherently undirected graphs.} \\
& \quad \text{(S2) The self-report data is incorporated as guidance in the tensor factorization procedure to learn latent factors that are consistent with the side information.} \\
& \quad \text{(S3) The representation learning and classifier training are blended into a unified optimization problem, which is equivalent to partially coupled matrix and tensor factorization.} \\
\end{align*}
\]