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t-BNE: Tensor-based Brain Network Embedding

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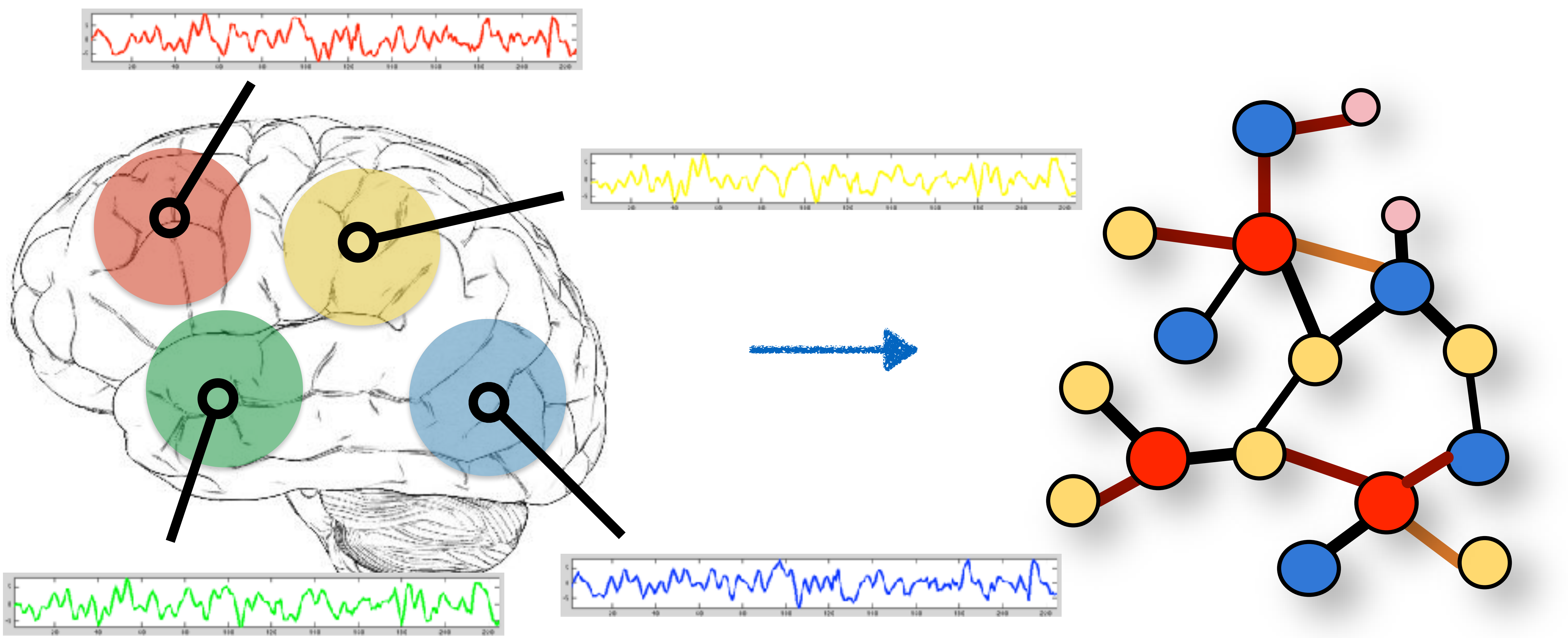
Brain Network



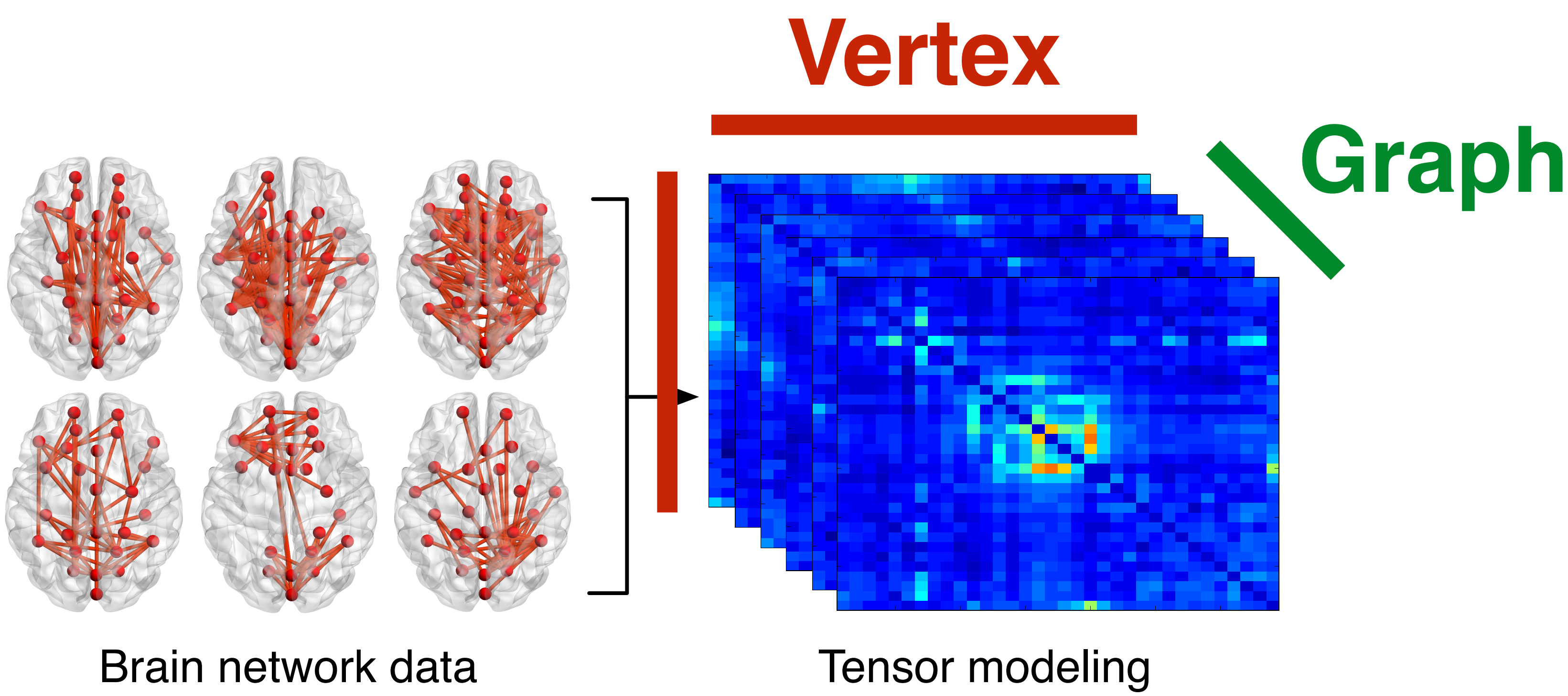
Neuroimaging **Brain network**

Graph Classification

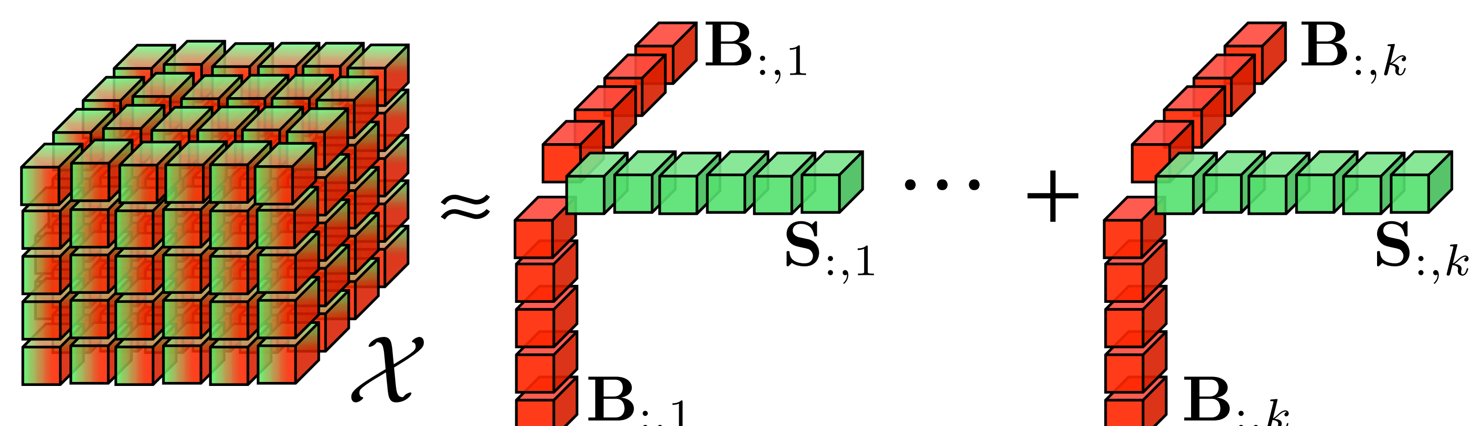
- Existing work
  - Computing graph-theoretical measures.
  - Extracting subgraph patterns.
- This work
  - Learning latent representations via tensor factorization.
  - Embedding the graph in addition to embedding nodes.

Problems & Solutions

- (P1) How can we preserve the graph property in the tensor factorization process?

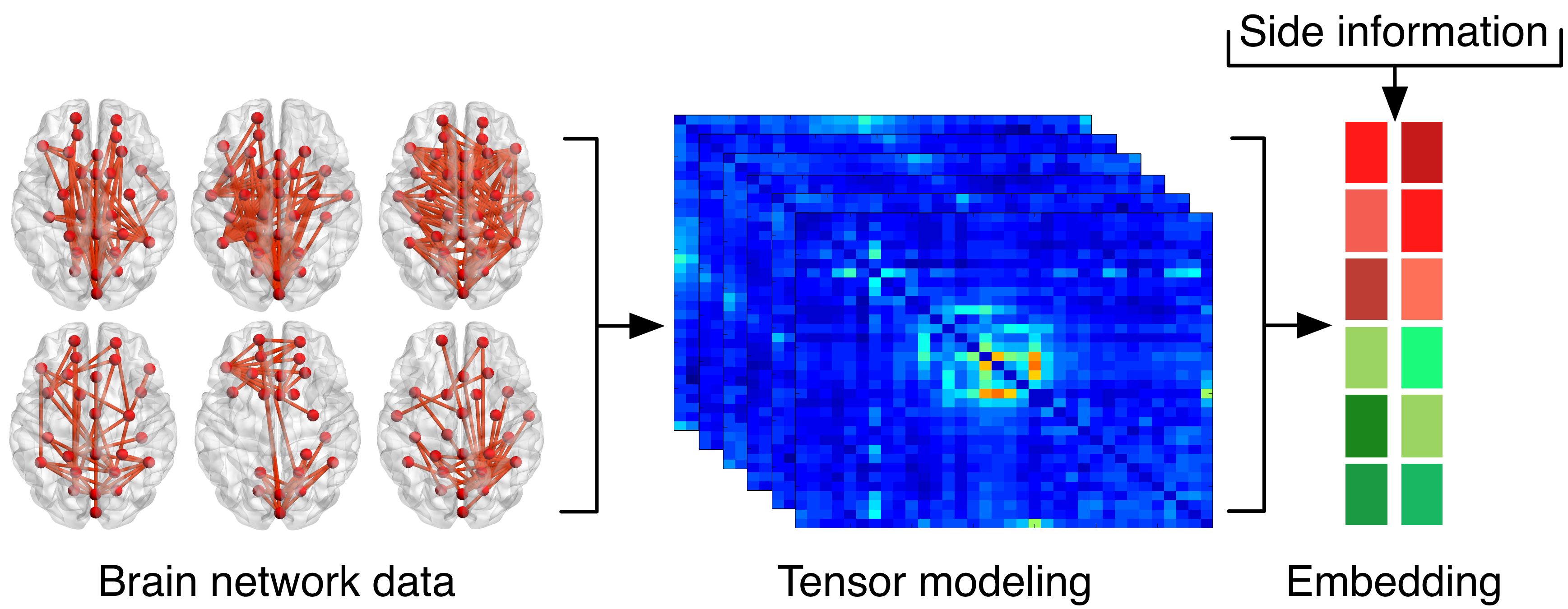


Partially symmetric tensor factorization



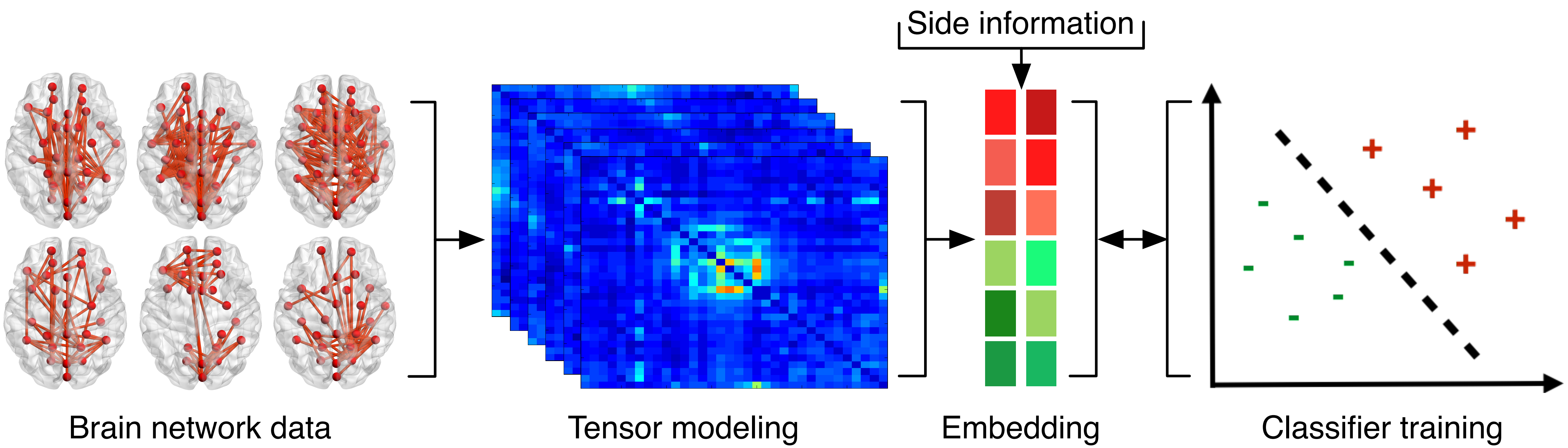
Problems & Solutions

- (P2) How can we leverage the side information associated with brain networks?

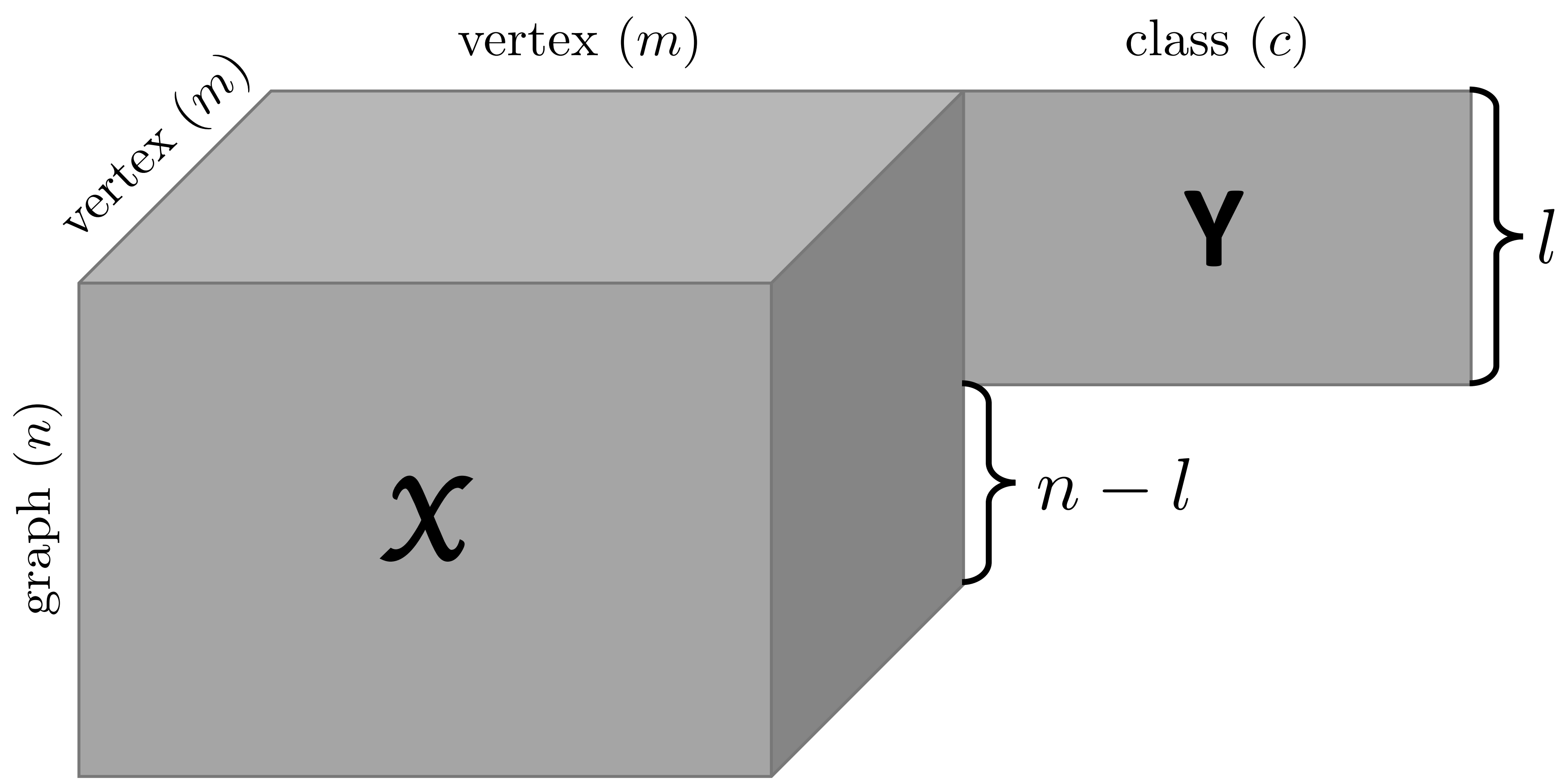


Problems & Solutions

- (P3) How can we fuse the classifier training and the representation learning procedures?



Problems & Solutions



Partially coupled matrix and tensor factorization

Tensor-based Framework

(S1) Partially symmetric tensor factorization

(S3) Partially coupled matrix and tensor factorization

$$\min_{\mathbf{B},\mathbf{S},\mathbf{W}} \underbrace{\|\mathcal{X} - \mathcal{C} \times_1 \mathbf{B} \times_2 \mathbf{B} \times_3 \mathbf{S}\|_F^2}_{\text{factorization error}}$$

$$+ \alpha \underbrace{\mathrm{tr}(\mathbf{S}^{\mathrm{T}}\mathbf{L}_{\mathbf{Z}}\mathbf{S})}_{\text{guidance}} + \beta \underbrace{\|\mathbf{DSW} - \mathbf{Y}\|_F^2}_{\text{classification loss}} + \gamma \underbrace{\|\mathbf{W}\|_F^2}_{\text{reg.}}$$

(3.7)

$$\text{s.t.} \quad \underbrace{\mathbf{S}^{\mathrm{T}}\mathbf{S} = \mathbf{I}}_{\text{orthogonality}}$$

(S2) Side information guidance

Optimization: ADMM

Algorithm 1 t-BNE

Input: $\mathcal{X}, \mathbf{Z}, \mathbf{Y}, \alpha, \beta, \gamma$

Output: $\mathbf{B}, \mathbf{S}, \mathbf{W}$

1: Set $\mu_{max} = 10^6, \rho = 1.15$
2: Initialize $\mathbf{B}, \mathbf{S}, \mathbf{W} \sim \mathcal{N}(0, 1), \mathbf{U} = \mathbf{0}, \mu = 10^{-6}$
3: **repeat**
4: Update $\mathbf{B}$ and $\mathbf{P}$ by Eq. (3.11) and Eq. (3.13)
5: Update $\mathbf{U}$ by Eq. (3.14)
6: Update μ by $\mu \leftarrow \min(\rho\mu, \mu_{max})$
7: Update $\mathbf{S}$ by Eq. (3.16) with the curvilinear search
8: Update $\mathbf{W}$ by Eq. (3.18)
9: **until** convergence

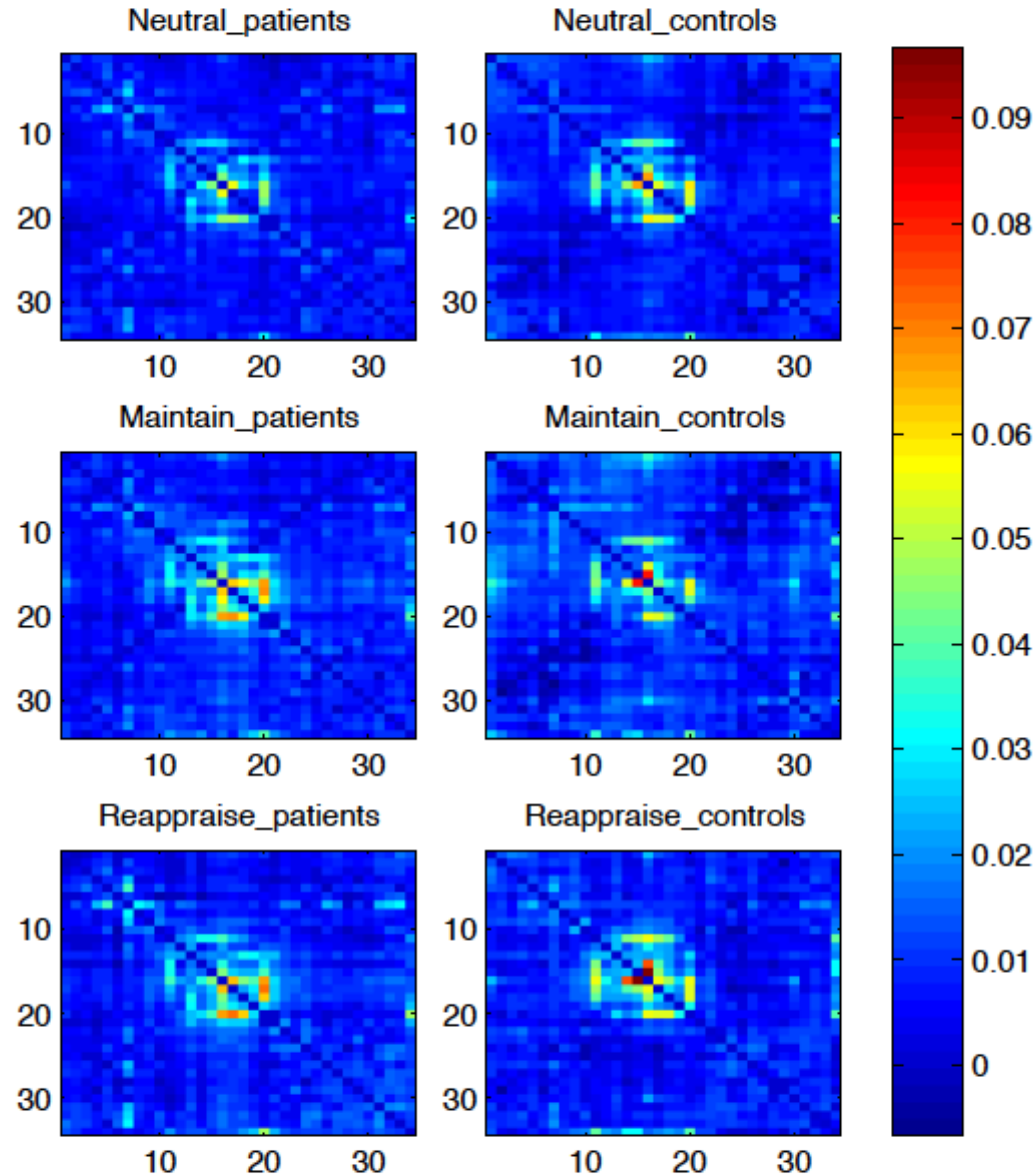
code available at: https://www.cs.uic.edu/~bcao1/code/t-BNE.zip

Experiments

Datasets: neutral, maintain, reappraise

37 patients with anxiety disorder (positive samples), and 32 healthy participants (negative samples)

n = 69 samples
m = 34 scalp channels

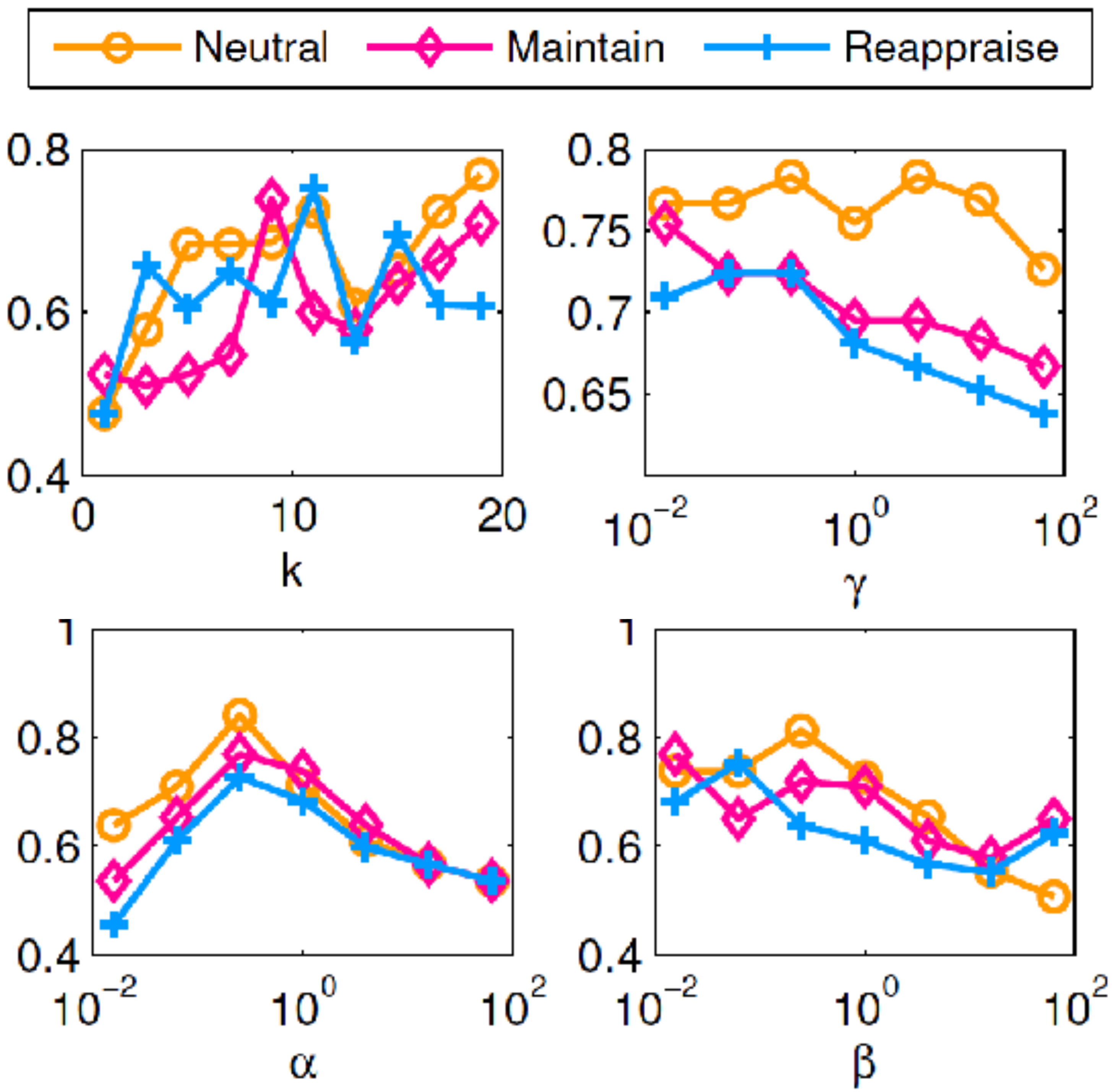


Classification Performance

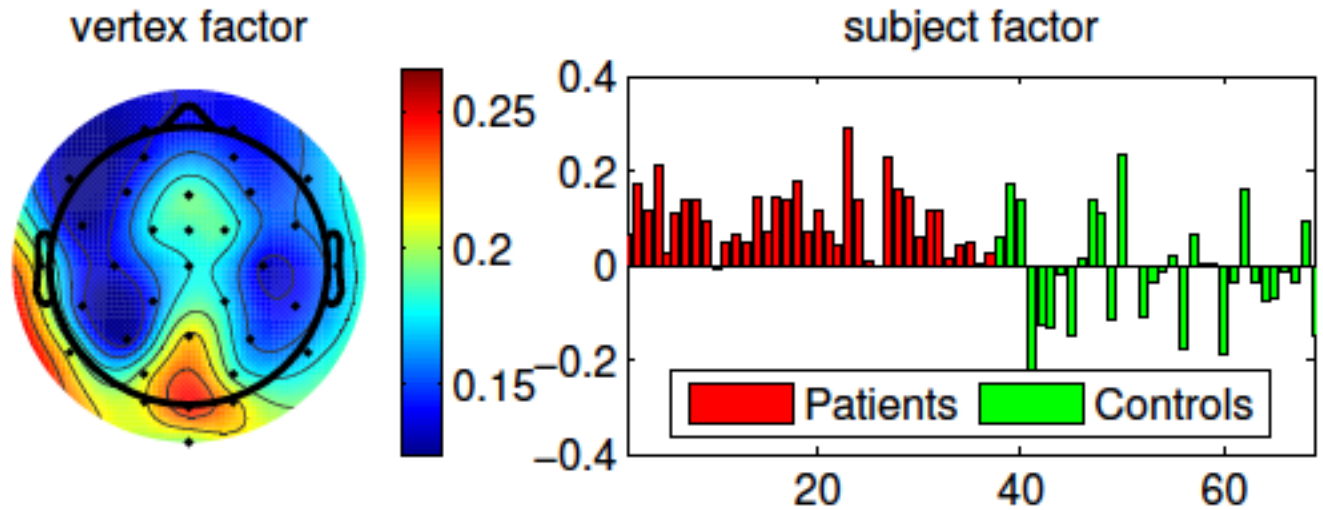
Methods	Datasets		
	Neutral	Maintain	Reappraise
t-BNE	0.7833	0.7548	0.7524
CMTF	0.5810	0.7095	0.6381
Rubik	0.6405	0.6833	0.6667
ALS	0.6119	0.6667	0.6524
gMSV	0.6500	0.6548	0.5952
CC	0.5357	0.6667	0.5357

- t-BNE: The proposed tensor factorization model for brain network embedding.
- CMTF: Coupled matrix and tensor factorization where brain networks and side information are coupled in the subject mode.
- Rubik: Tensor factorization with orthogonality and sparsity constraints.
- ALS: Tensor factorization using alternating least squares without any constraint.
- gMSV: A discriminative subgraph selection approach using side information.
- CC: Extracting local clustering coefficients as features.

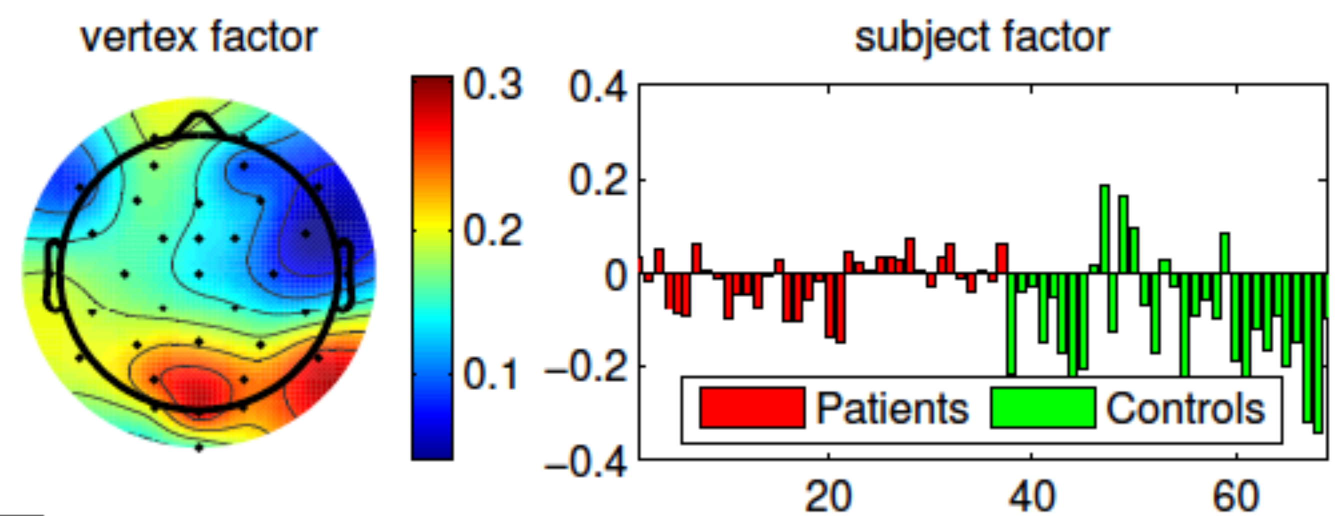
Parameter Sensitivity



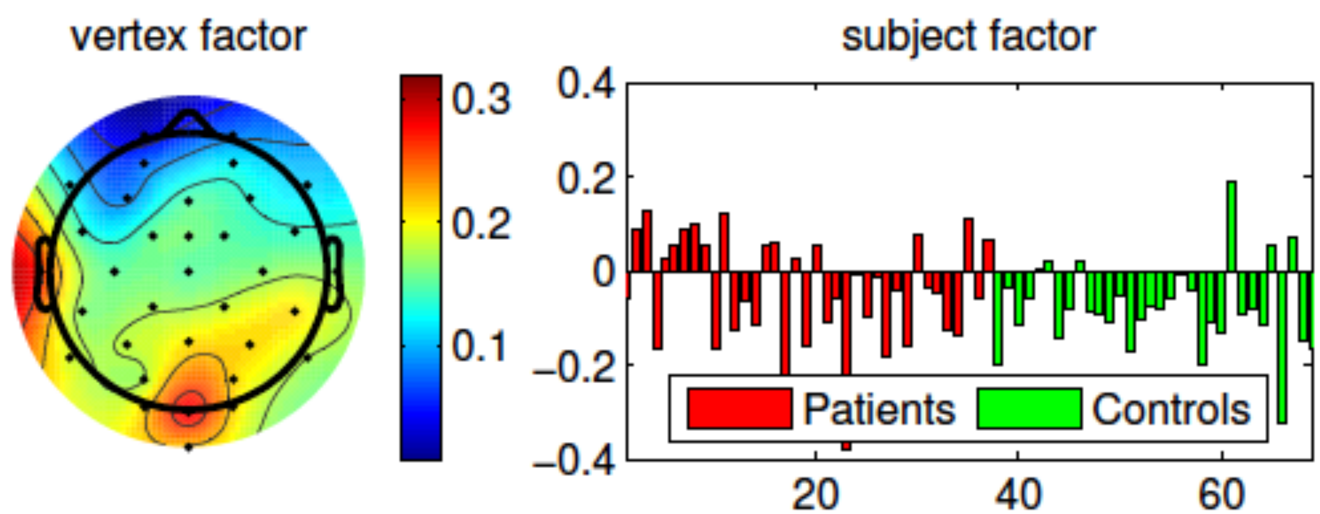
Factor Analysis



(a) Neutral.

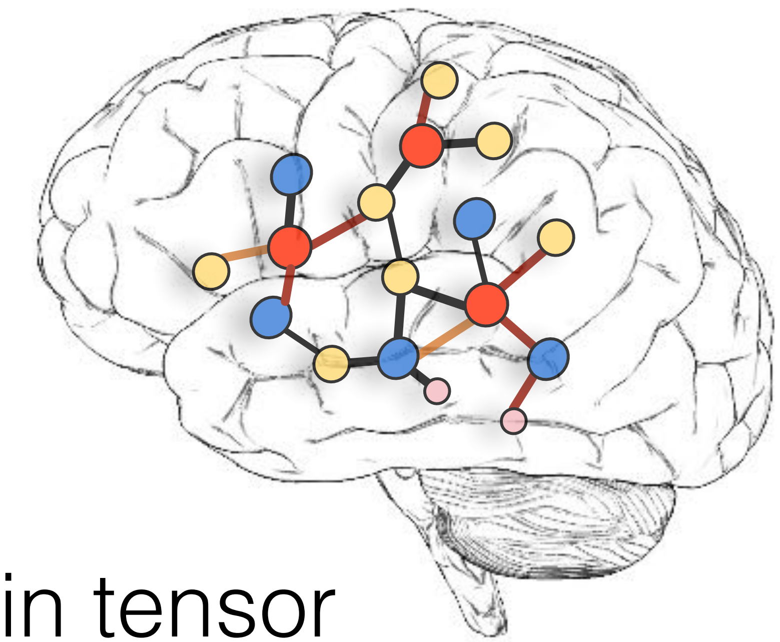


(b) Maintain.



(c) Reappraise.

Summary



- Preserved the symmetric graph property in tensor factorization
- Incorporated side information guidance and orthogonal constraint to obtain informative and distinct latent factors
- Fused the classifier learning procedure and tensor factorization
- Facilitated better understanding of brain mechanism with anxiety disorder under different emotion regulations

Extensions

- Guidance
  - Column-wise guidance from community information
- Supervision
  - Must-link, cannot-link, separability
- Multimodality
  - Joint tensor factorization to capture consensus information between fMRI and DTI

t-BNE: Tensor-based Brain Network Embedding

Q & A

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