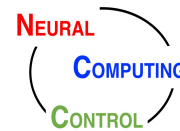




南方科技大学
SOUTHERN UNIVERSITY OF SCIENCE AND TECHNOLOGY



生物医学工程系
Department of Biomedical Engineering



神经计算与控制实验室
NCC lab

Spatial Temporal-pyramid Graph Convolutional Networks for Interpretable fMRI-based Brain Decoding

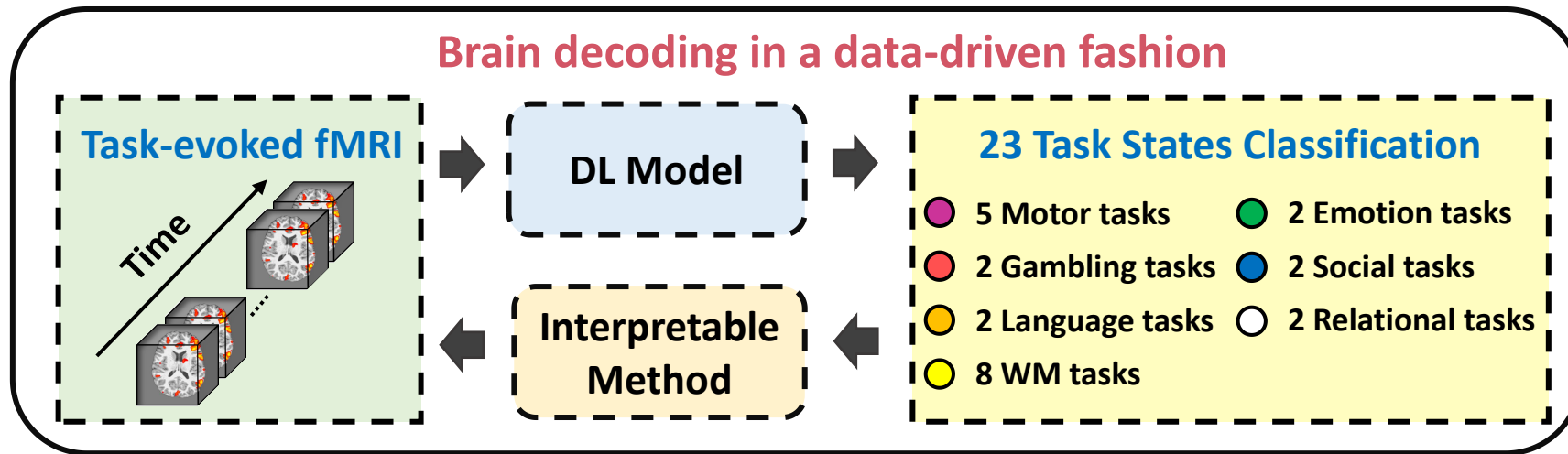
Presenter: Ziyuan Ye (叶梓元)

Thursday, May 26, 2022

Background

Motivation

- Interpretable brain decoding is a core aspect of **understanding our brain**.



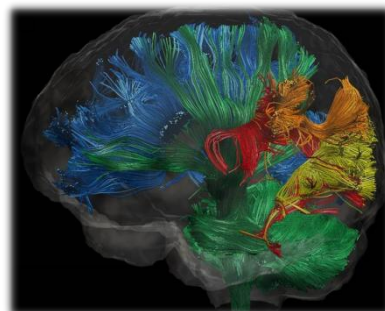
Current bottleneck

- **DL models** for brain decoding can achieve high decoding performance while **suffering very poor interpretability**.
- **Interpretation methods** for DL models are **limited in brain decoding task**.

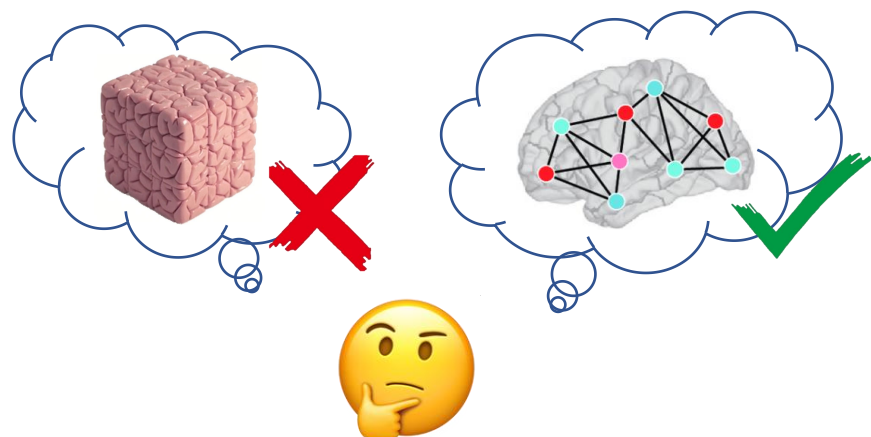
Breaking the bottleneck

Why the high decoding performance and high interpretability cannot be achieved at the same time by previous methods?

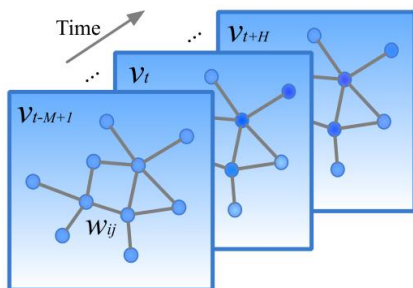
- From the perspective of the representation of data



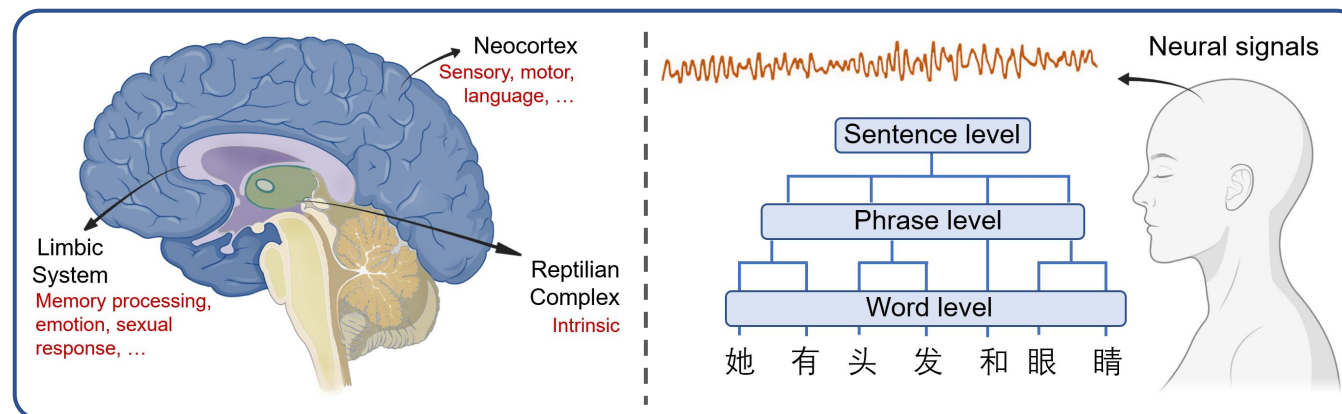
Diffusion Tensor Imaging (DTI) of the Brain



- From the perspective of model architecture



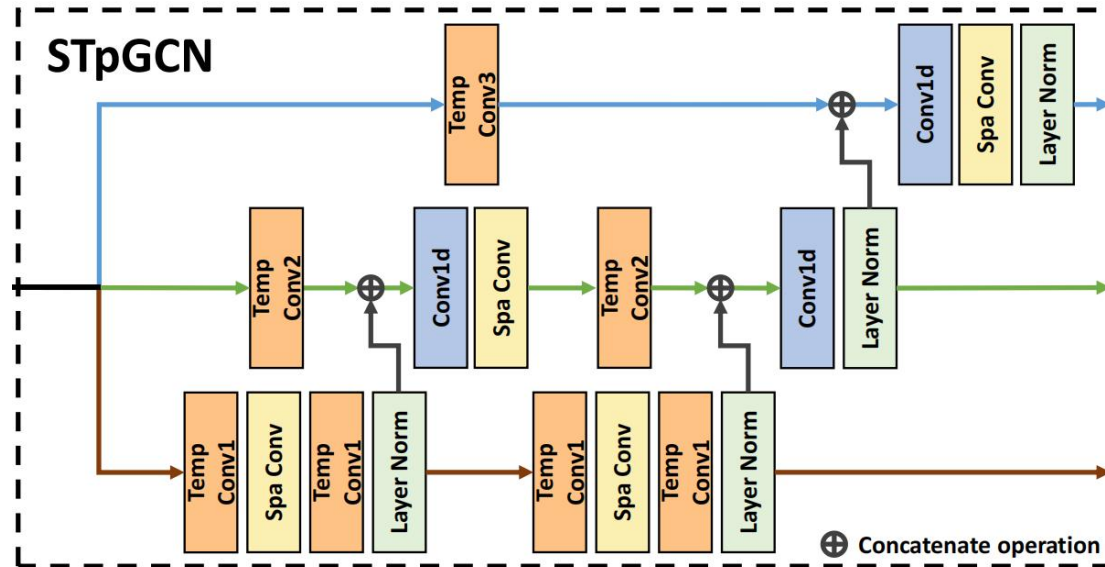
Common GNNs' architecture with temporal processing module



Breaking the bottleneck

STpGCN

- captures **multi-scale temporal features** and fuses the **multi-level semantic information**.



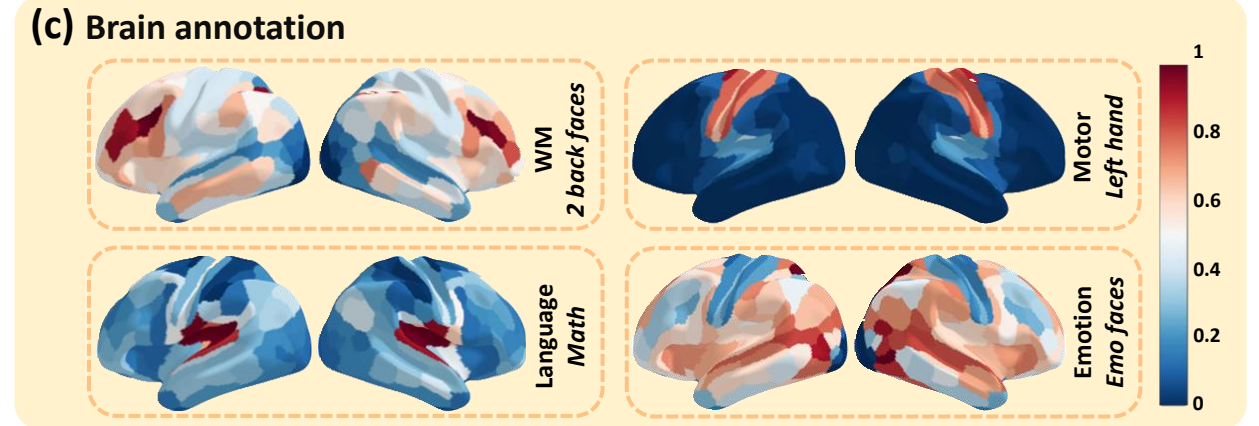
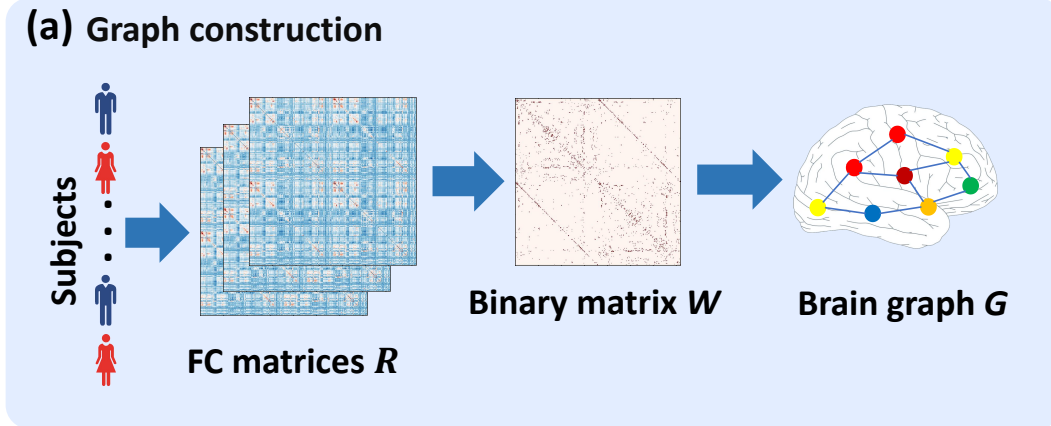
NeurocircuitX

- provides a **whole-brain** and **neural-circuit level explanation** for each task state

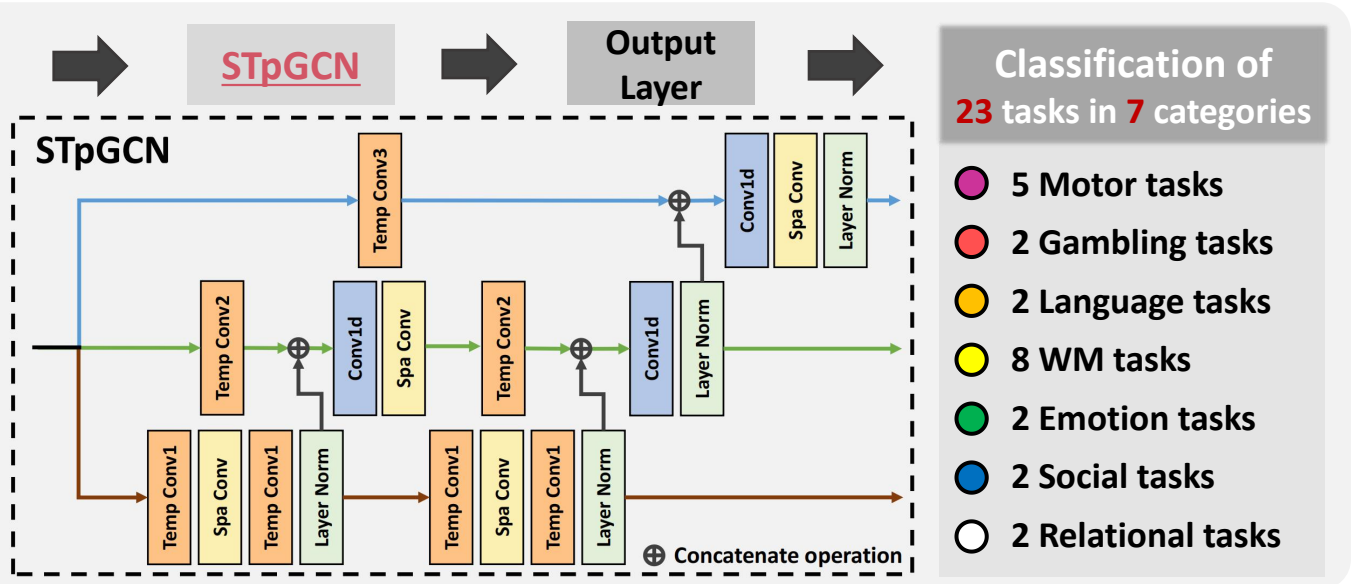
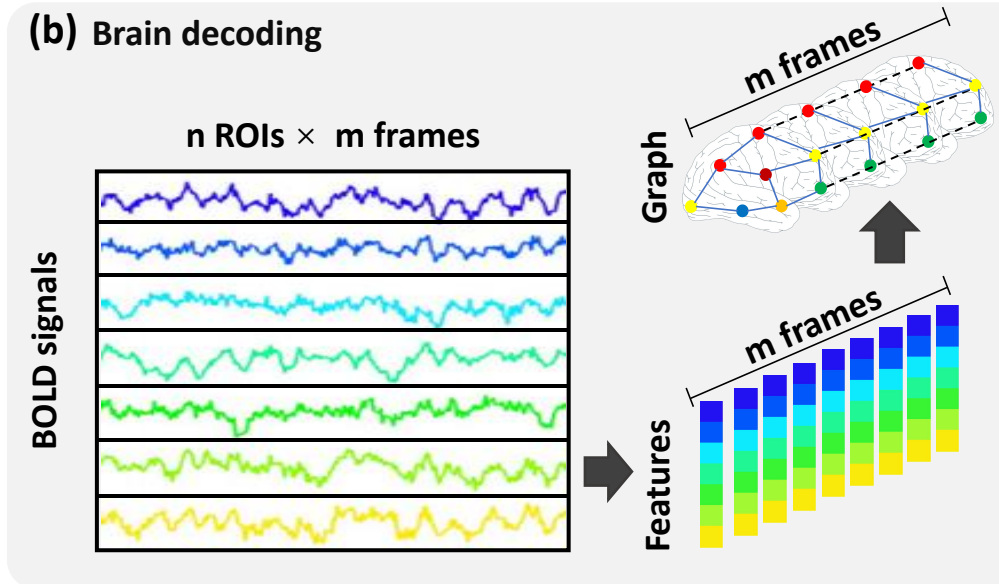
$$\Omega(p_i) = (1 - \alpha)f(p_i) + \alpha[f(P) - f(P \setminus \{p_i\})]$$

Let $f(\cdot)$ denotes a well-trained graph classification model. We can assign N ROIs into distinct cortical networks $P = \{p_1, \dots, p_{17}\}$. $\Omega(p_i)$ indicates the importance of the neural circuit p_i .

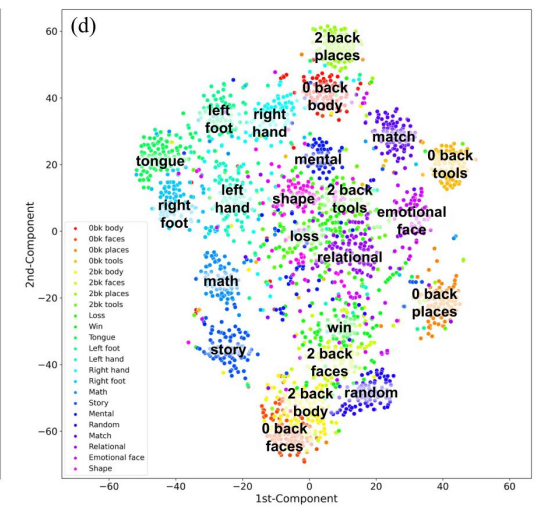
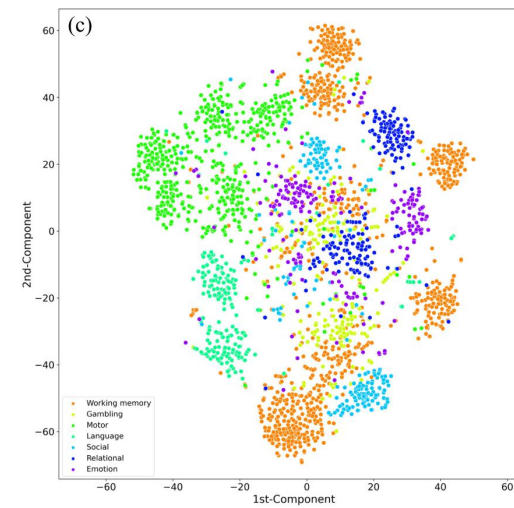
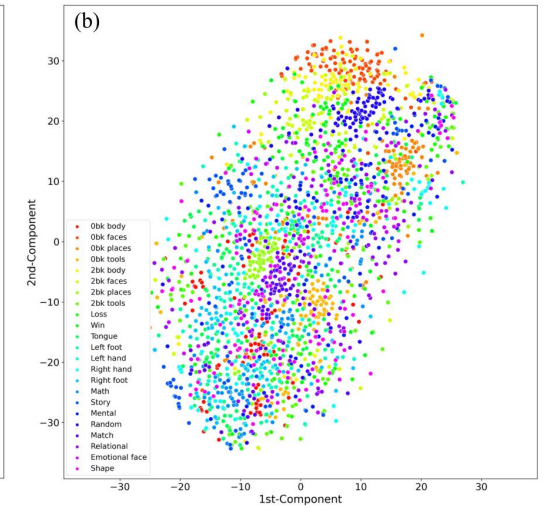
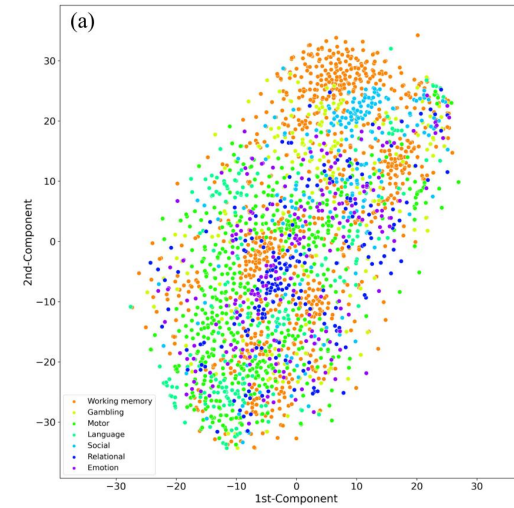
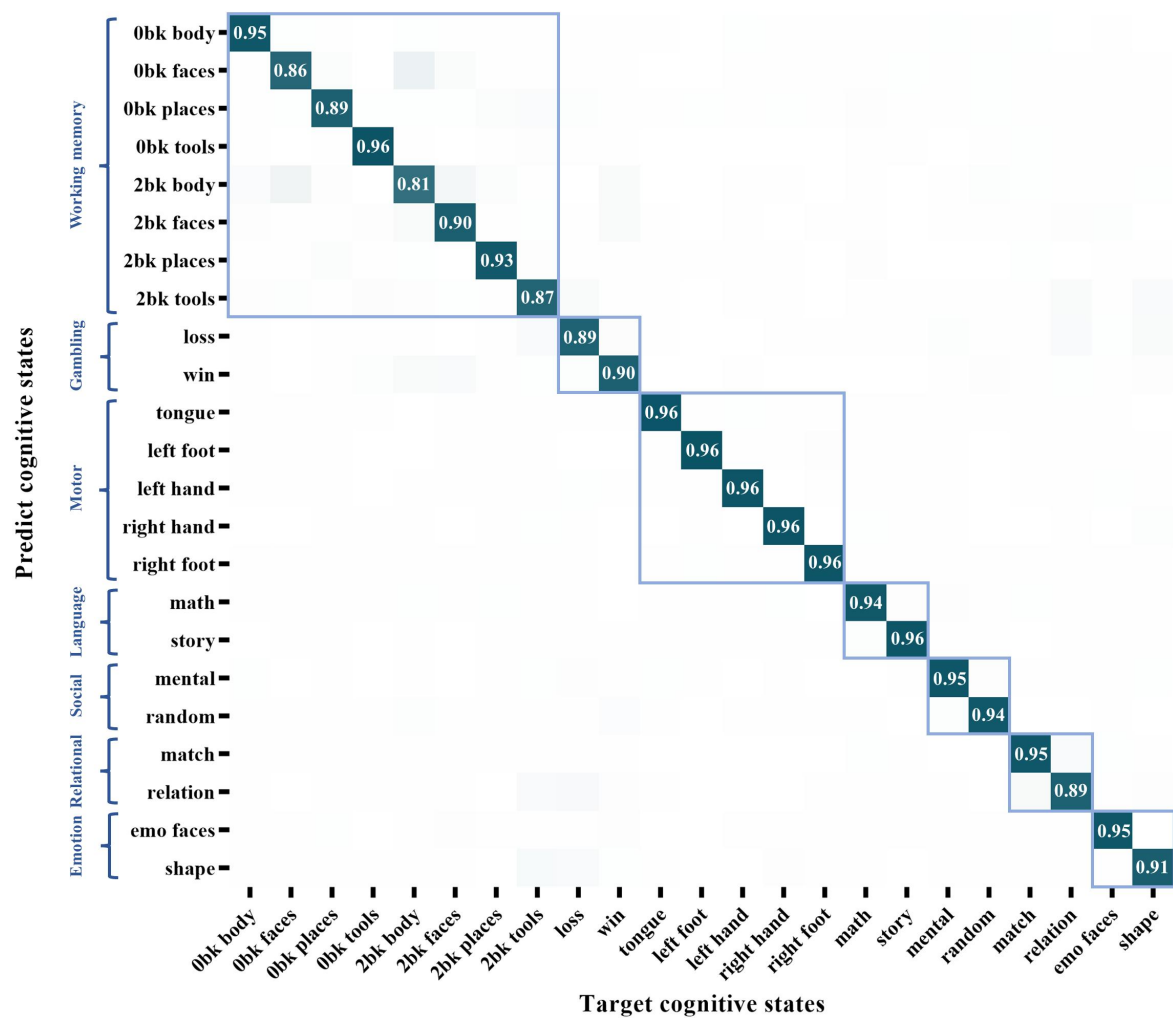
Interpretable decoding framework



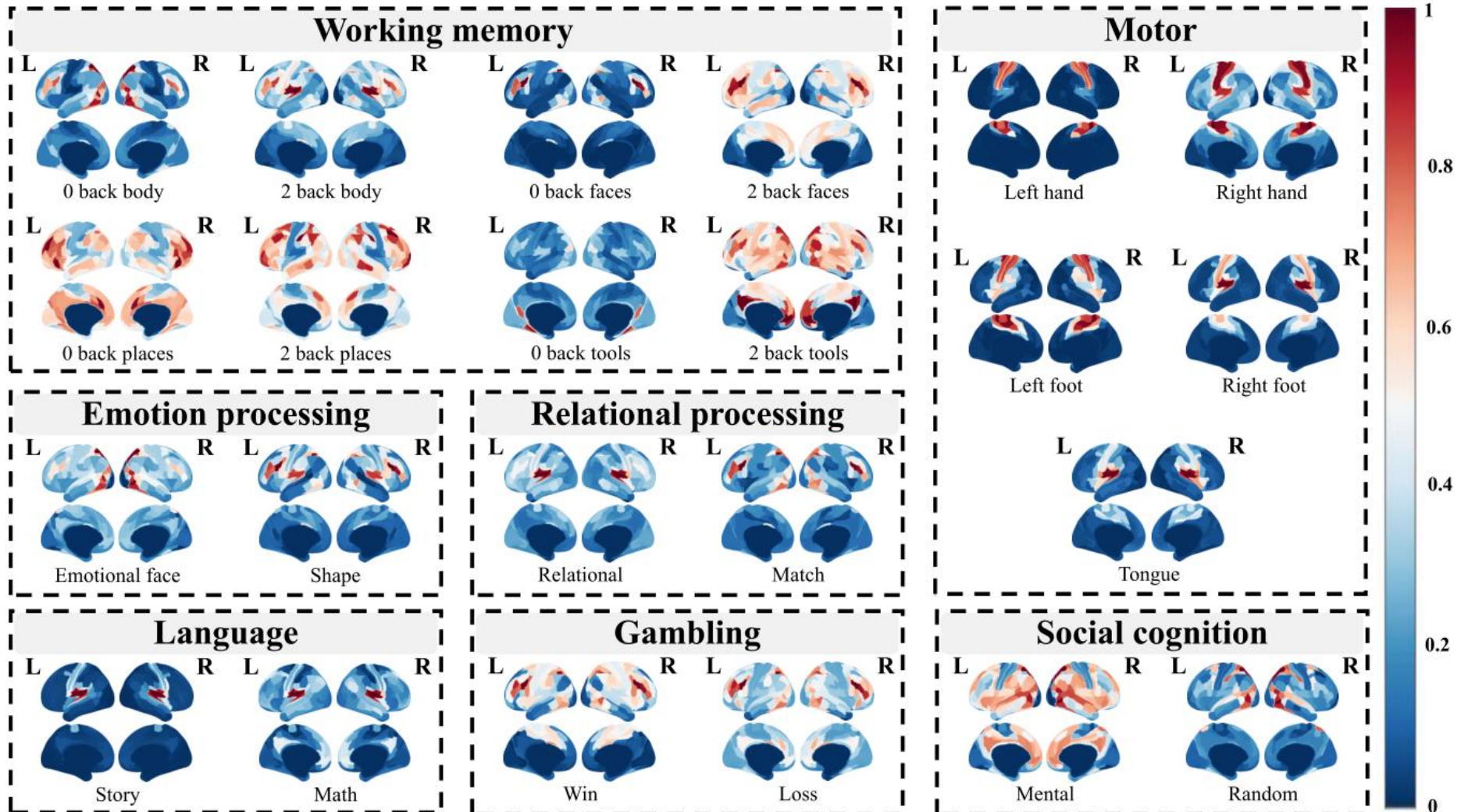
↑ **NeurocircuitX**



Decoding performance



Interpretability



Robustness and generalizability

Robustness

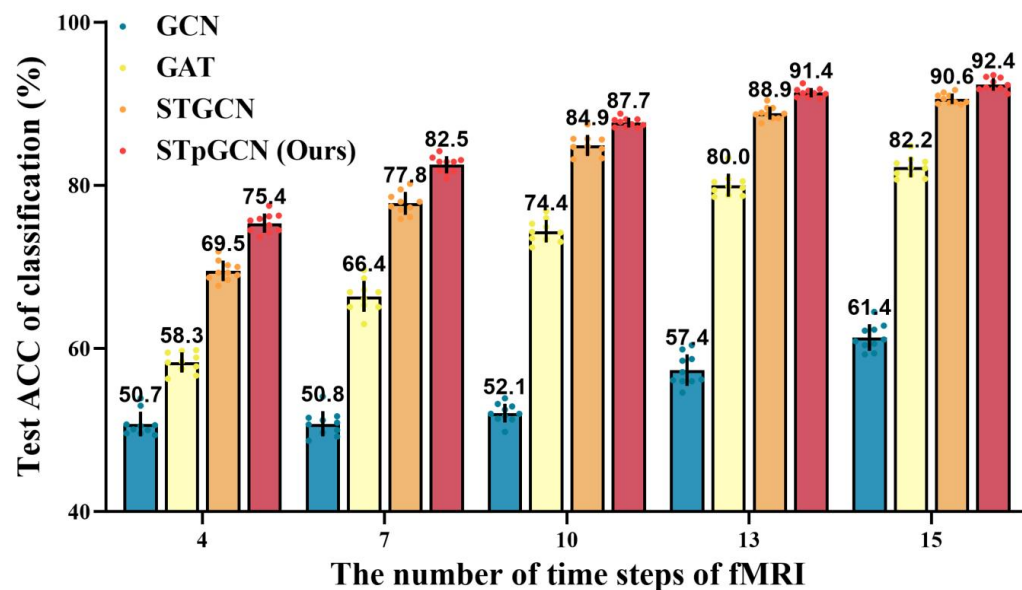
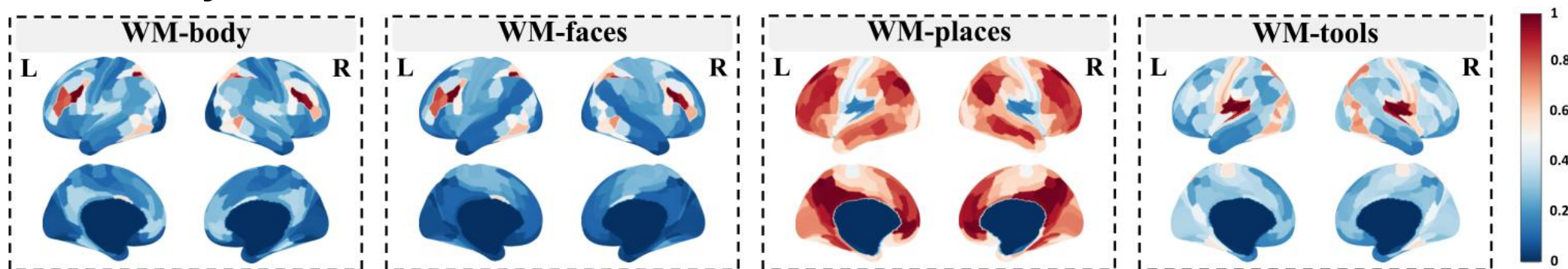


TABLE III
COMPARISON RESULTS OF 23 BRAIN STATES DECODING USING STpGCN ON 15 TIME STEPS OF fMRI WITH MMP ATLAS GIVEN DIFFERENT DATASET SPLIT RATIOS.

Training set ratios	ACC \uparrow	Macro Pre \uparrow	Macro R \uparrow	Macro F1 \uparrow
90%	92.4 \pm 0.8	92.5 \pm 0.7	92.4 \pm 0.8	92.4 \pm 0.7
70%	90.7 \pm 0.6	90.8 \pm 0.6	90.7 \pm 0.6	90.7 \pm 0.6
50%	88.8 \pm 0.5	88.8 \pm 0.5	88.8 \pm 0.5	88.8 \pm 0.5
30%	86.4 \pm 0.3	86.4 \pm 0.2	86.4 \pm 0.3	86.4 \pm 0.3
10%	79.2 \pm 0.5	79.3 \pm 0.4	79.2 \pm 0.4	79.2 \pm 0.5

Note: Mean \pm std (%) are from 10-fold cross validation.

Generalizability



Thanks for your attention!