# Learning Dynamic Graph Representation of Brain Connectome with Spatio-Temporal Attention

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# Background

➢ Functional Connectivity (FC); correlation of different brain regions over time

{ fMRI + BOLD } →

non-invasive

→ {FC} →

**HOW THE BRAIN WORKS!**

# Previous Work | Limitations

A. Models missing dynamic component; provided by temporal data
B. Dynamic Features of FC
    a. Lower accuracy level (example: gender misclassification)
    b. Lacking temporal explainability; FC brain changes over time

# Paper's Contribution

Uncover functional basis of the brain

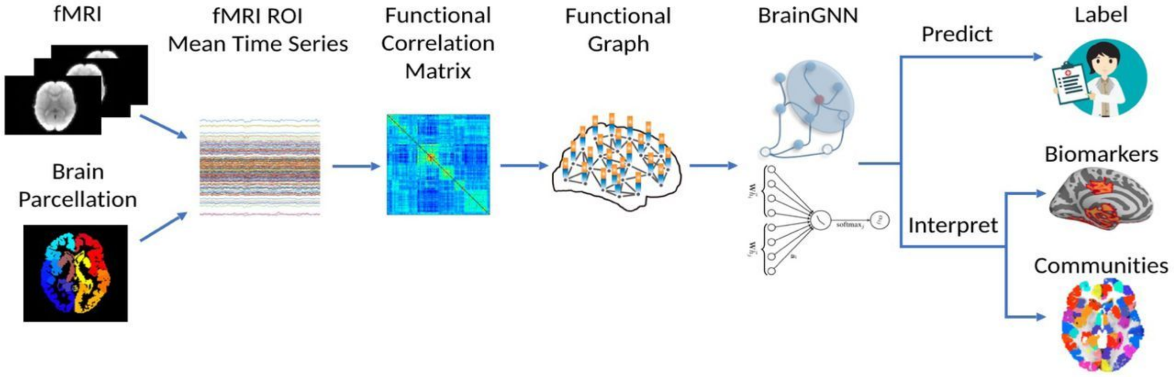
1. Attention-based readout functions
2. Transformer encoder

K-means clustering
+
Linear model for statistical mapping

→ **State-of-the-art**

# Related Work & Challenges

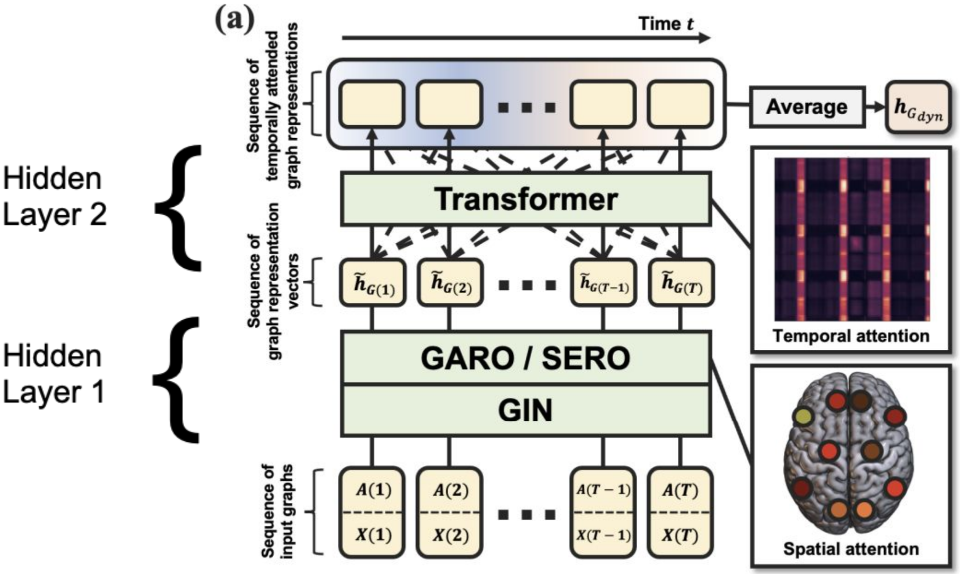
- ➢ The dynamic brain graphs do not include any addition or deletion of nodes and are sampled uniformly over time
- ➢ Pooling function | Graph Neural Networks (GNN)
  - ○ data aggregation can be tricky
  - ○ randomly initialized parameters or local graph structures, suboptimal for graph classification tasks that require the graph as a whole.



# STAGIN Model [1/2]

A. Achieve high classification of human activity
    a. Resting state
    b. Active state

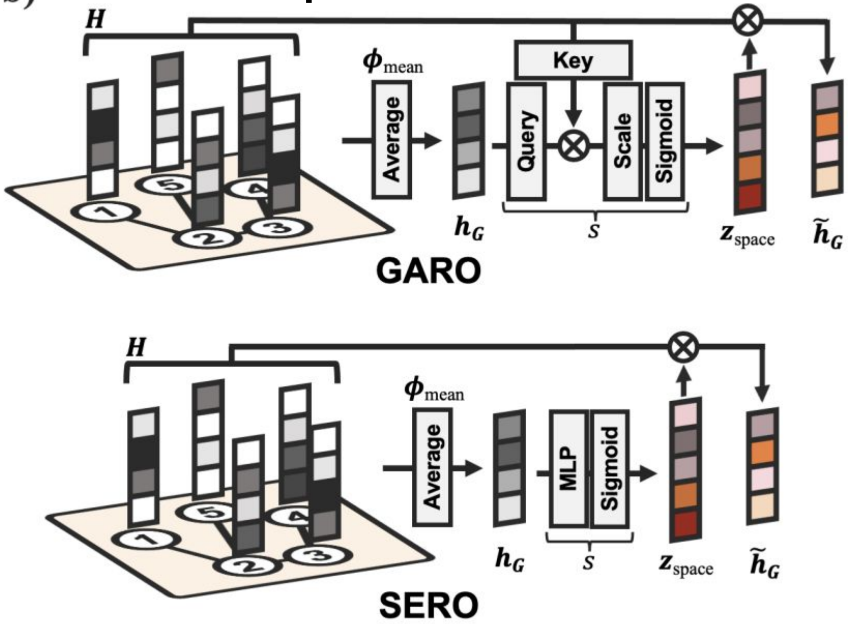
**Overall Framework**



# STAGIN Model [2/2]

A. Spatial Attention
   a. Graph-Attention READOUT (GARO)
   b. Squeeze-Excitation READOUT (SERO)
B. Prior Knowledge
   a. $h_g$ global average-pooled graph feature

**Spatial Attention**



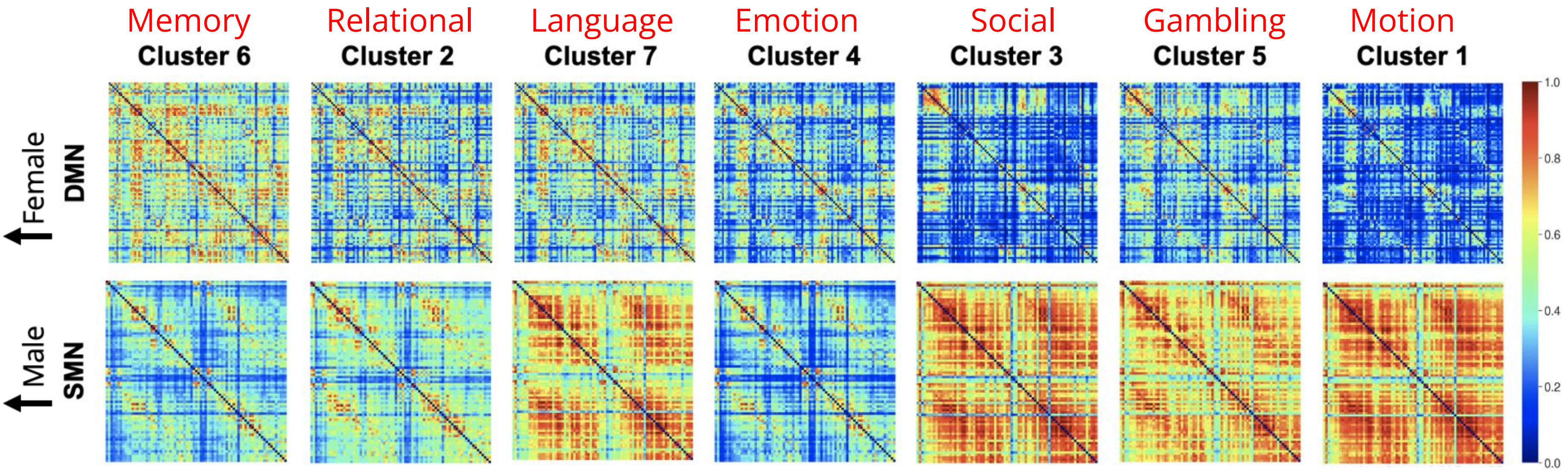
# Experimental settings

A. Supervised manner with the loss function $\mathcal{L} = \mathcal{L}_{xent} + \lambda \cdot \mathcal{L}_{ortho}$
B. Dynamic learning rate α
C. Region of Interest (ROI)-timeseries matrix P (n = 400)
D. The time dimension of P was randomly sliced with a fixed length

Table 1: Comparative study on HCP-Rest and HCP-Task dataset.

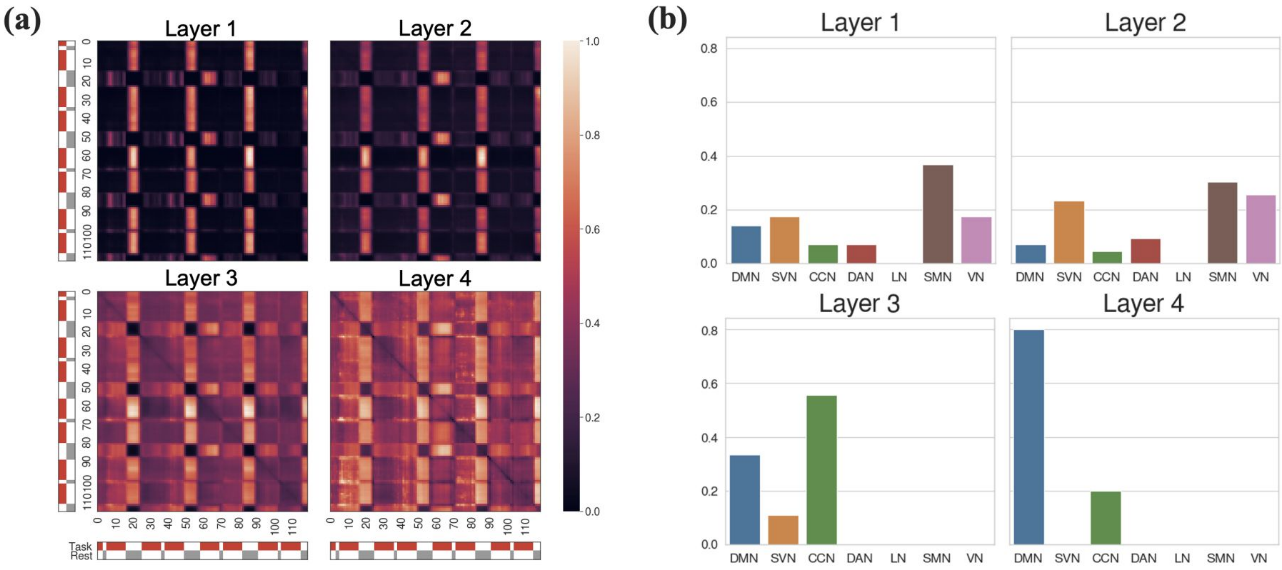
| Model | HCP-Rest | | HCP-Task | Type of FC | # Params |
|---|---|---|---|---|---|
| | Accuracy (%) | AUROC | Accuracy (%) | | |
| STAGIN-SERO | **88.20** ± 1.33 | **0.9296** ± 0.0187 | **99.19** ± 0.20 | Dynamic | 1,209k |
| STAGIN-GARO | 87.01 ± 3.00 | 0.9151 ± 0.0258 | **99.02** ± 0.17 | Dynamic | 1,068k |
| ST-GCN [15] | 76.95 ± 3.00 | 0.8545 ± 0.0316 | 98.92 ± 0.27 | Dynamic | 355k |
| MS-G3D [10] | 79.16 ± 2.53 | 0.8912 ± 0.0329 | - | Dynamic | 3,045k |
| BAnD++ [36] | - | - | 97.20 ± 0.57 | None | 2,010k |
| BAnD [36] | - | - | 95.10 ± 0.62 | None | 2,010k |
| r-BAnD | - | - | 98.90 ± 0.27 | Dynamic | 664k |
| GIN [23] | 81.34 ± 2.40 | 0.8955 ± 0.0237 | 93.87 ± 0.66 | Static | 169k |
| GCN [24] | 80.79 ± 2.00 | 0.8741 ± 0.0174 | 45.07 ± 1.63 | Static | 101k |
| GraphSAGE [31] | 75.48 ± 1.97 | 0.8237 ± 0.0228 | 54.52 ± 0.97 | Static | 202k |
| ChebGCN [2] | 77.76 ± 2.09 | 0.8582 ± 0.0233 | 73.06 ± 0.68 | Static | 704k |

# Gender Classification | Results




| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Female | 1.299 | 1.208 | 1.228 | 0.807 | 0.690 | 0.642 | 0.576 |
| Male | 0.927 | 0.950 | 0.967 | 1.036 | 1.079 | 1.041 | 1.128 |
| **F/M** | **1.401** | **1.272** | **1.269** | **0.778** | **0.640** | **0.617** | **0.510** |

# Task decoding | Results




SMN, visual network (VN), and salience/ventral attention network (SVN) dominance

DMN and cognitive control network (CCN) dominance


# The Code

In the context of spatial-temporal context in smart homes…

- K-means clustering
- Elbow Method to choose optimal k

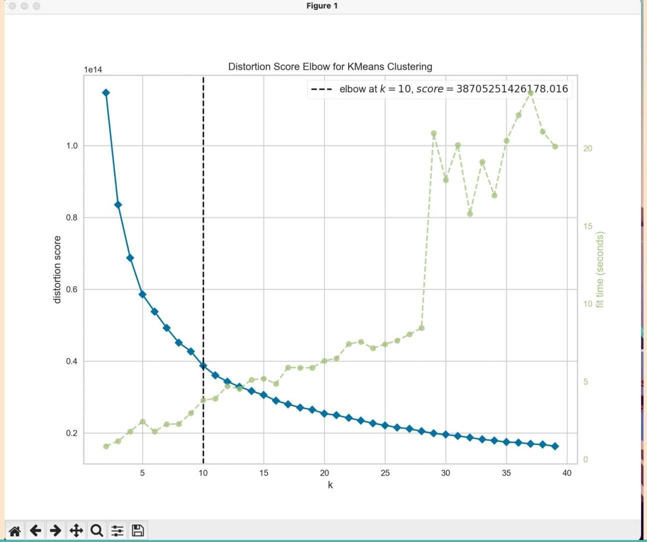


Figure 1
Distortion Score Elbow for KMeans Clustering
1e14
elbow at $k = 10$, $score = 38705251426178.016$
distortion score
fit time (seconds)
k
1.0
0.8
0.6
0.4
0.2
20
15
10
5
0
5
10
15
20
25
30
35
40

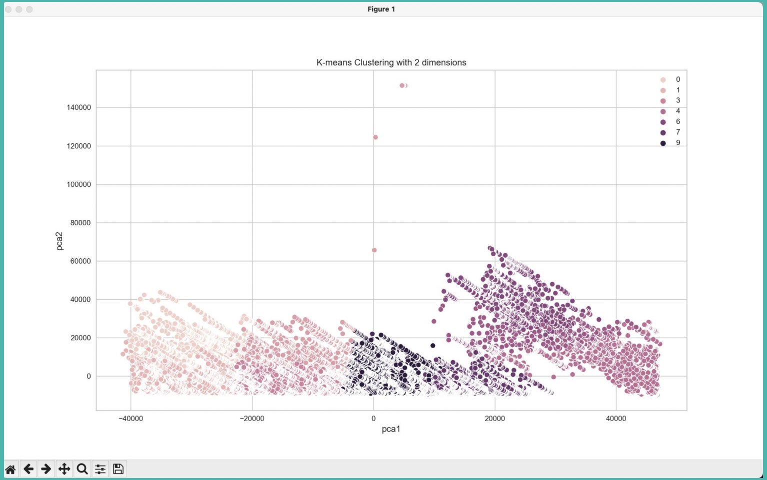


Figure 1
K-means Clustering with 2 dimensions
0
1
3
4
6
7
9
pca2
pca1
140000
120000
100000
80000
60000
40000
20000
0
−40000
−20000
0
20000
40000

# Thank you!