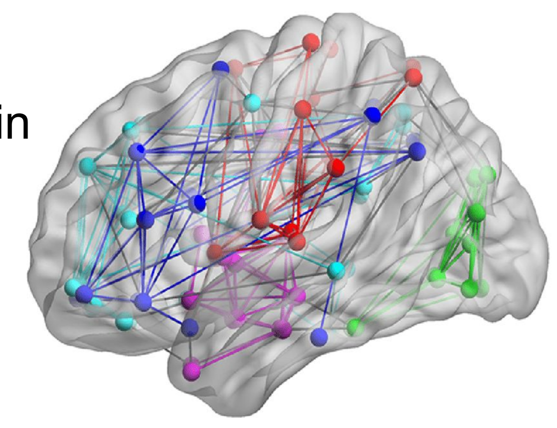
#14: Dynamic Brain Connectome Learning

Kim Junyup (20190169) Kyaw Ye Thu (20220929)

Motivation and Dynamic Graph

Connectome (Connection Matrix of the Human Brain)
- point-to-point spatial connectivity of neural pathways in the brain
- Commonly conducted using functional MRI (fMRI) images



Connectome changes over time => Need to consider **temporal dimension** of fluctuating activation

Limitations of current approaches
- Little research regarding **temporal dimension** — $G(V(t), E(t), X_V(t), X_E(t))$ (**Dynamic Graph Learning**)
- Much reliance on **resting-state fMRI images** — (**Task fMRI Images**)

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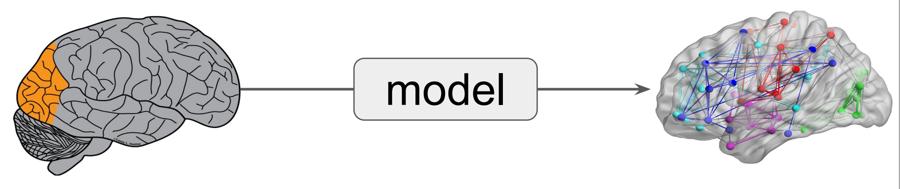
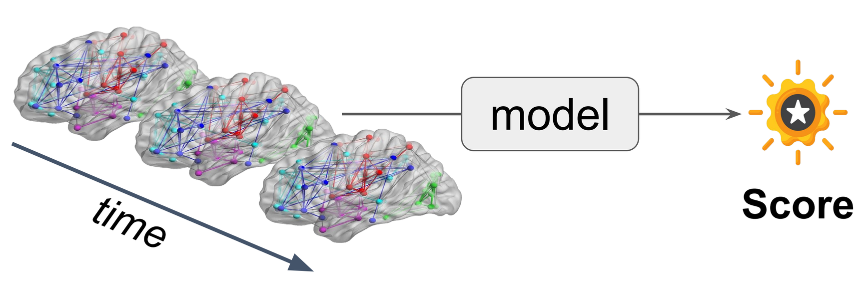
Problem Statement

Dataset: fMRI images of subjects performing a **language** task from *Human Connectome Project (HCP)*

Task 1: Link Prediction

Given **regions of interest (RoIs)** of a brain, predict if there are **connections** in between. (Predicting which parts of the brain are likely to be activated during a language task)





Task 2: Graph Regression

Given **connections between RoIs across time**, predict the language accuracy score. (Predicting how well a person is performing a language task based on their brain activations)

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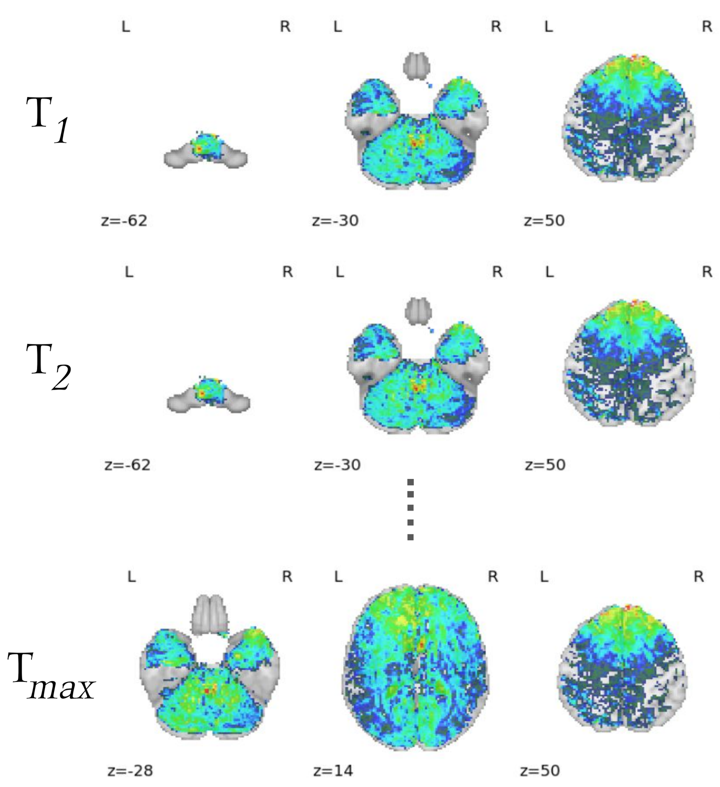
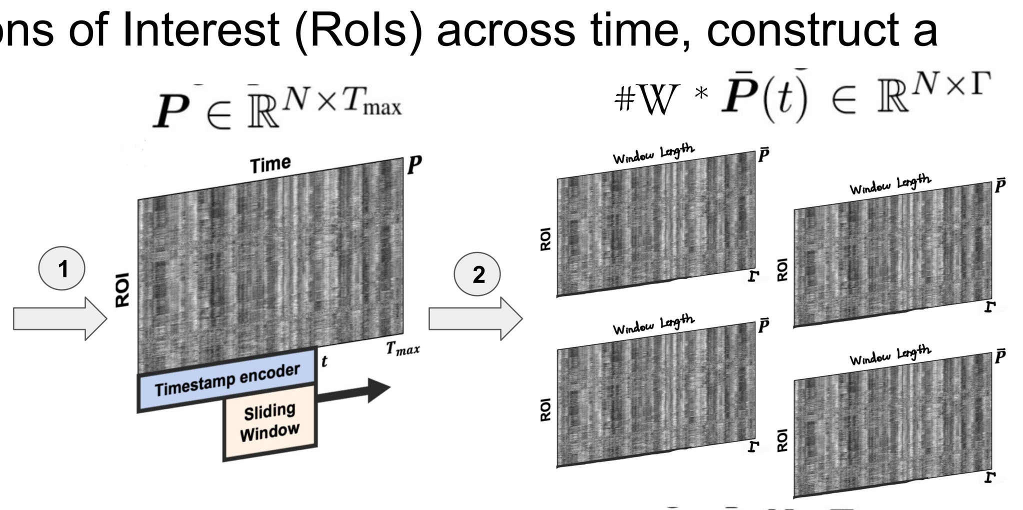
4D fMRI image -> Functional Connectivity Matrix (FC)

From brain activations at Regions of Interest (RoIs) across time, construct a dynamic graph.





1. The **ROI-timeseries matrix** $P \in \mathbb{R}^{N \times T_{\max}}$ is extracted by taking the mean values of brain activity signal within a predefined 3D atlas which consists of *N* ROIs at each timepoint.
2. Using sliding-window of window of length Γ, obtain #W numbers of **windowed matrices** $\bar{P}(t) \in \mathbb{R}^{N \times \Gamma}$

#W = number of windows

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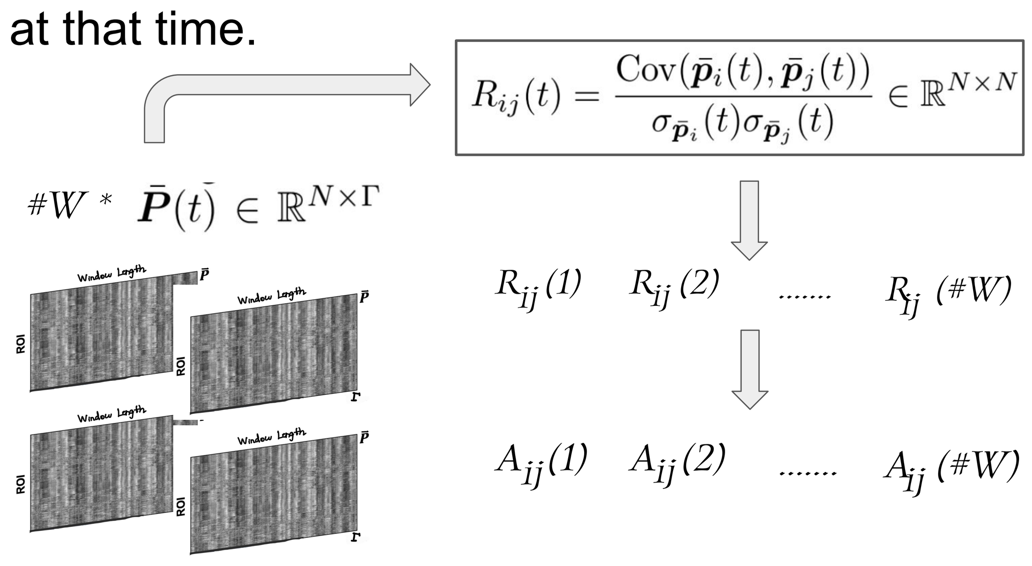
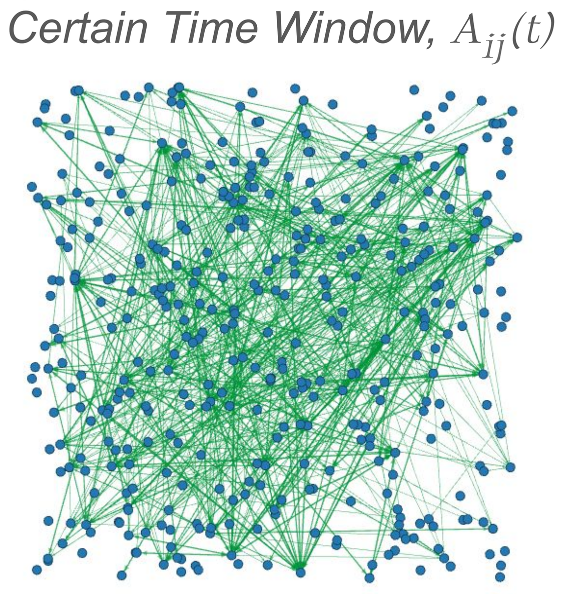
FC Matrix -> Adjacency Matrix

Idea: If two RoIs (nodes) are highly activated together during a window, they are connected at that time.



Visualization of ROI Connections (FC) during "Language" Task at a Certain Time Window, $A_{ij}(t)$



The final binary adjacency matrix $A(t) \in \{0,1\}^{N \times N}$ is obtained from the FC matrix, $R(t)$, by thresholding top 15-percentile values of the correlation matrix as connected, and otherwise unconnected.

For animation across time ->

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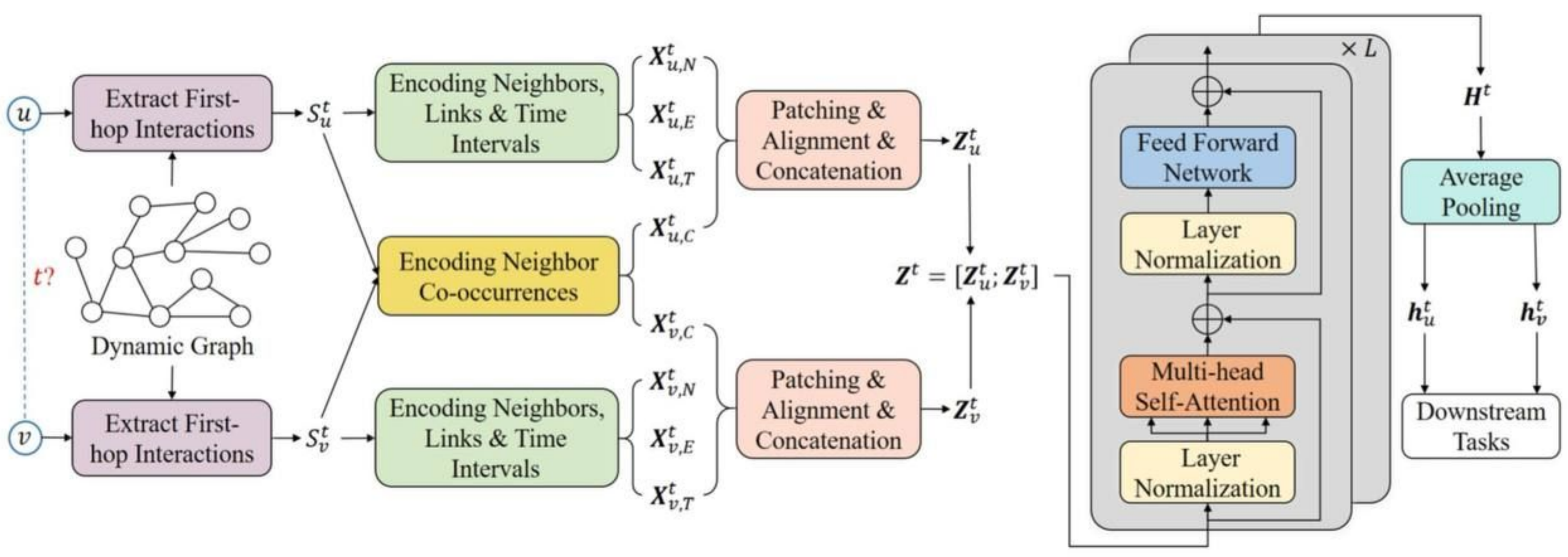
DyGFormer



Neighbor Co-occurrence Encoding Scheme to compute representations of node u and v while modeling their correlations

Patching Technique to capture long-term temporal dependencies

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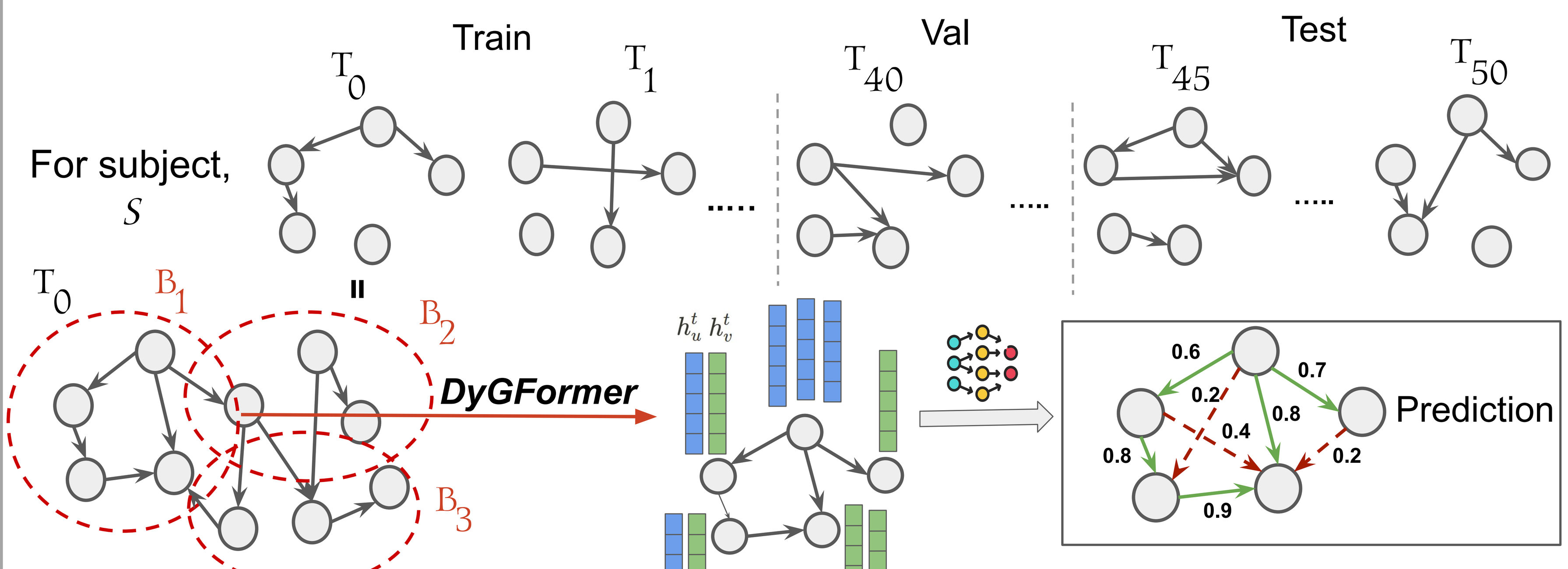
Task 1: Link Prediction



One batch of each epoch includes a subset of nodes and their interactions at a particular time window depending on the batch size.

Using DyGFormer, embeddings of source and destination nodes are computed.

Given node embeddings, predict the probability of the link between pairs of nodes by forwarding through some fully connected layers.

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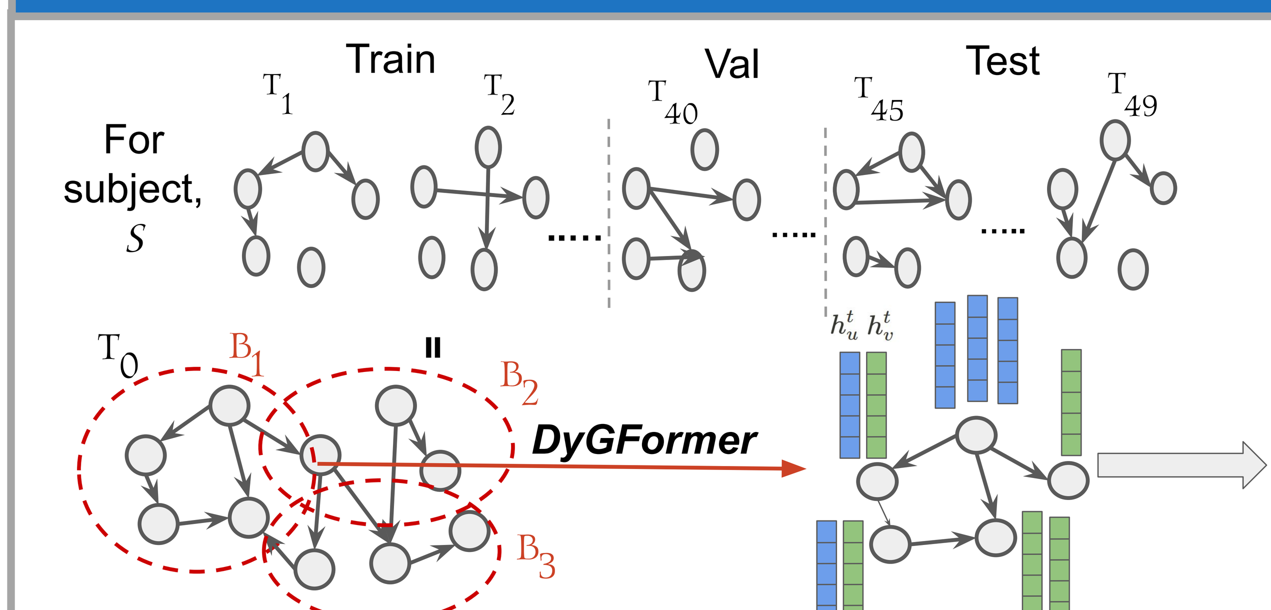
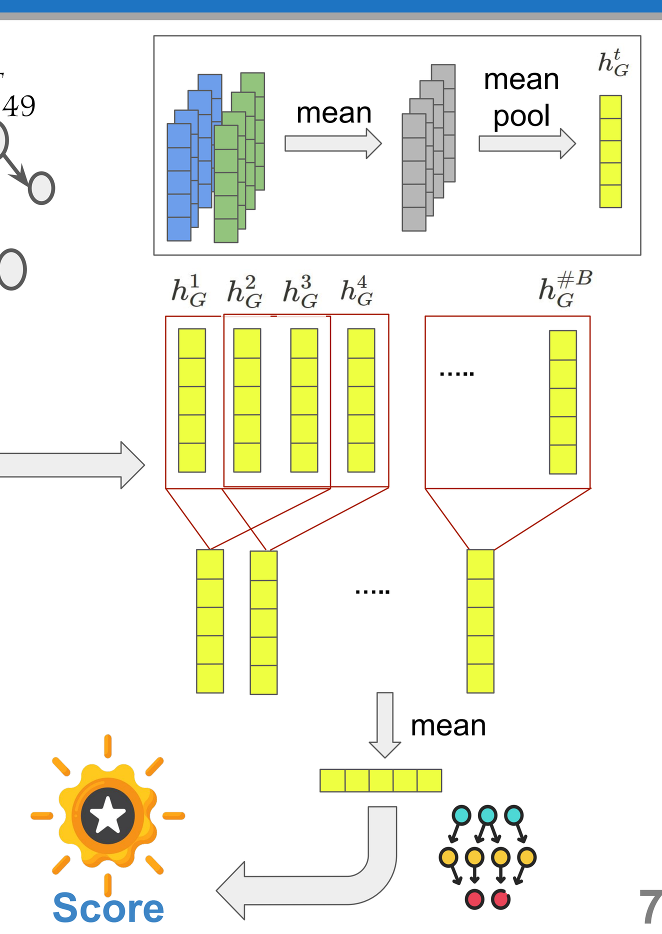
Task 2: Graph Regression





By mean pooling, obtain graph embedding, h_G^t, for each batch from node embeddings, h_u^t and h_v^t.

From graph embeddings across batches, obtain a **predicted language score** by forwarding through convolution layers followed by MLP.

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Experiments & Future Work

	Batch size	Threshold	Epochs Trained	Subjects	Performance
Link Prediction	1000	top 5%	10	1	**0.9220** (ROC AUC)
Graph Regression	1000	top 5%	1	50 (30/10/10)	**11±1** (MSE Loss)

For one subject,
- # nodes: 400
- # possible edges: 160,000 (400 * 400)
- # actual edges per window: 80,000 (5% threshold)
- # actual edges across time: **400,000** (8000 * 50)

Due to time/computation constraint, we could only train only with very few epochs, small batch size, and very high percentile.

Expectation: The **bigger the batch size**, the more temporal features can be captured. With the **more epochs**, the model can learn more. With a **lower threshold**, more edges can be considered.

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