



TG-DGM: Clustering Brain Activity using a Temporal Graph Deep Generative Model

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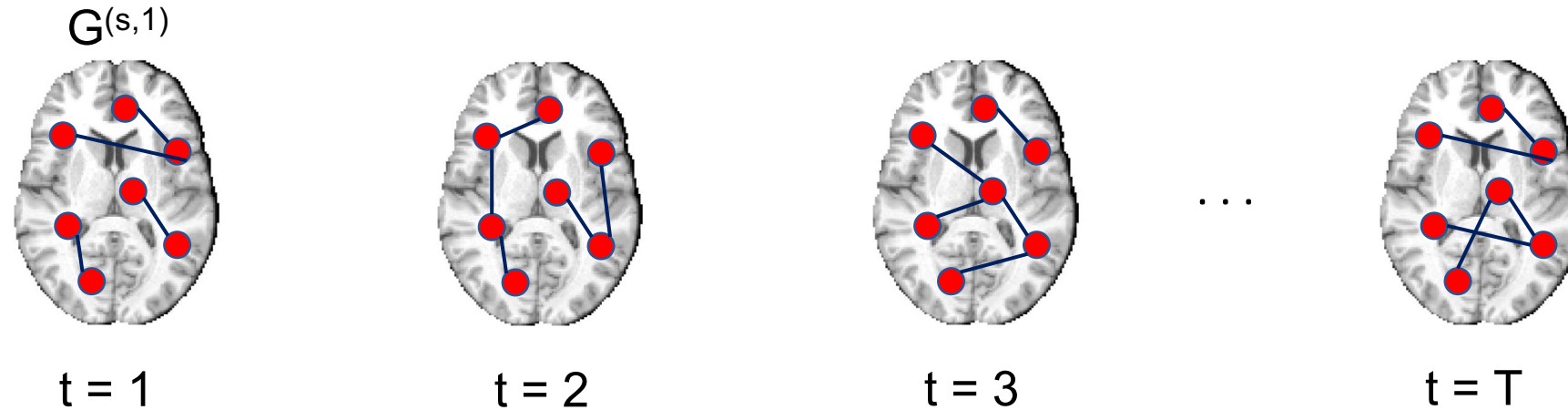
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Introduction



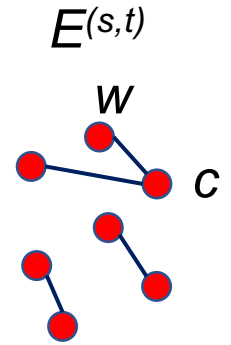
- The brain can be seen as a **temporally evolving graph** where nodes are spatially distributed ROIs
- Edges can be determined as ROI **correlations** of BOLD signals from fMRI data
- Temporal dynamics of ROI **clusters** are useful for understanding brain function

We propose an **unsupervised** deep generative model which can:

1. Learn subject embeddings as well as evolving node and community embeddings
2. Can be used for downstream tasks (e.g. subject stratification or other predictive tasks)
3. Parameterized by neural networks and fast to train

Notation

- Data is a set of dynamic graphs for S subjects $\mathcal{D} = \{G^{(s,t)} \text{ for } s = 1, \dots, S; t = 1, \dots, T\}$
- The vertex set is fixed and represents the Roles $V = \{1, \dots, N\}$
- Each $G^{(s,t)}$ has an associated edge set $E^{(s,t)} = \{(w, c) : w, c \in N\}$



The Generative Model

Initialize a subject embedding matrix alpha $\alpha \in \mathcal{R}^{S \times D}$

For each subject s in $1, \dots, S$:

Initialize community $\beta^{(s,0)}$ and node $\phi^{(s,0)}$ embeddings as NNs of α

For time t in $1 \dots T$:

Evolve $\beta^{(s,t)} = \text{GRU}(\beta^{(s,0:t-1)})$ and $\phi^{(s,t)} = \text{GRU}(\phi^{(s,0:t-1)})$

For each edge (w, c) in $G^{(s,t)}$:

Sample prior community assignment z for source node w

Sample neighbour c

} Node and community
distributions are neural network
transformations of ϕ and β

Results

- Data taken from UK Biobank. fMRI from $S = 560$ gender and age matched subjects.
- $N = 360$ RoI time series of length 490 (using Glasser parcellation [2]).
- We use time window W of varying lengths to calculate correlations. This gives different temporal resolution T .
- We apply logistic regression on the learnt embeddings to predict biological sex.

Table 1: AUC ROC results on biological sex classification using TG-DGM embeddings

W	T	α	β	$\alpha \beta$
490	1	0.70 ± 0.03	0.73 ± 0.04	0.75 ± 0.03
245	2	0.74 ± 0.07	0.72 ± 0.04	0.74 ± 0.06
98	5	0.78 ± 0.03	0.78 ± 0.04	0.80 ± 0.06
49	10	0.79 ± 0.04	0.78 ± 0.05	0.80 ± 0.04
35	14	0.70 ± 0.06	0.79 ± 0.05	0.77 ± 0.04
14	35	0.80 ± 0.02	0.79 ± 0.05	0.81 ± 0.03
7	70	0.69 ± 0.06	0.73 ± 0.07	0.70 ± 0.06

Key points

1. Our **unsupervised** model gives ROC AUC of up to 0.81
2. Temporal dynamics improve performance (up to a point)
3. Both subject and community embeddings are predictive of biological sex.