



**WPI**

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# Collective Discovery of Brain Network with Unknown Groups

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# Network Representation of Brain

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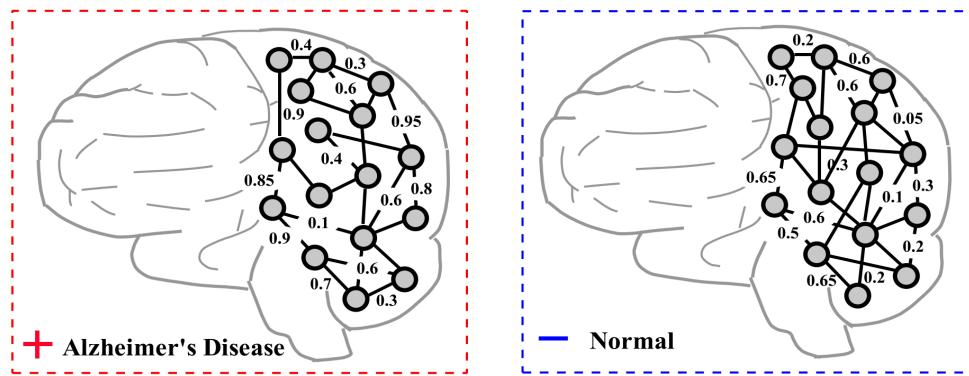


Each node = a brain region

Each edge = a functional connection

# Use of Brain Network

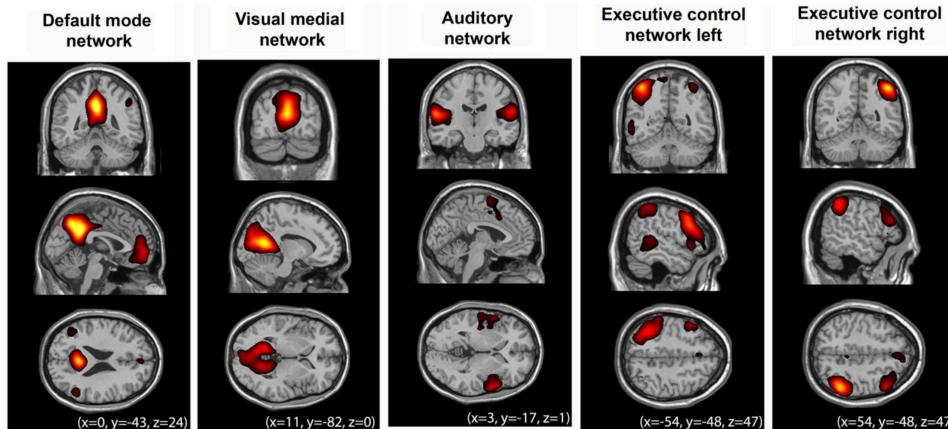
## Disease Diagnosis



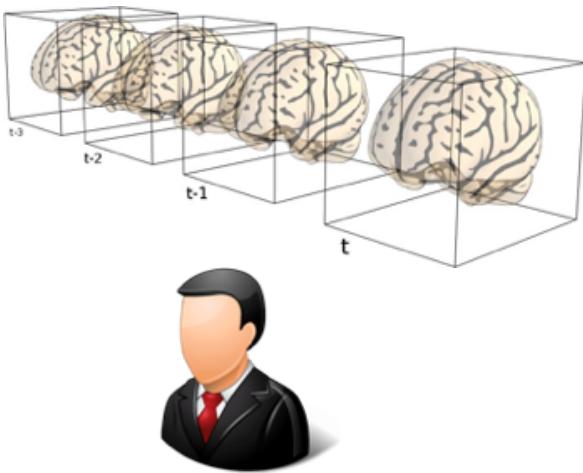
**Not Given!**

Should be derived from  
neuroimaging data

## Functional Study



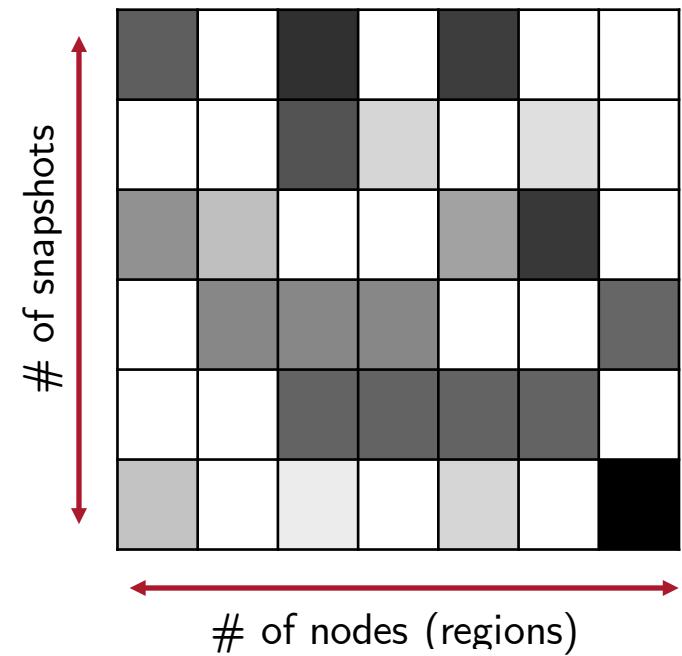
# The fMRI Data



The Data Matrix  
 $X \in R^{m \times n}$



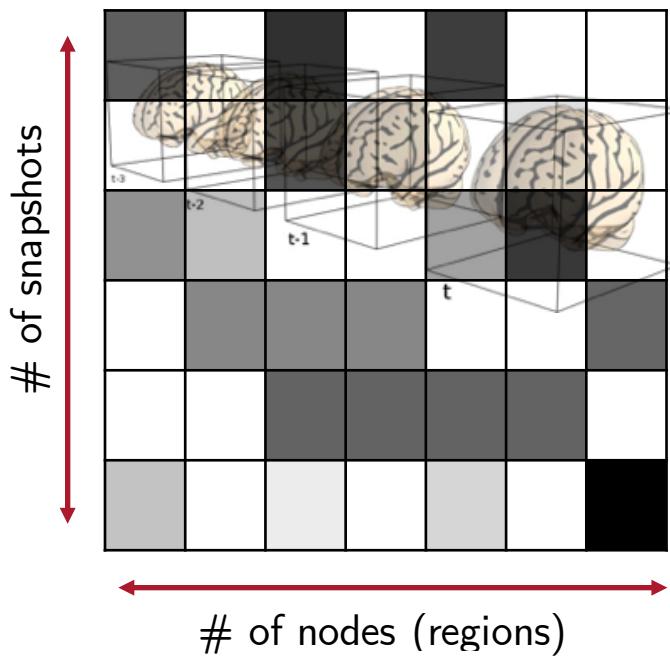
Each column refers to a voxel of the brain  
Each row refers to a snapshot of the brain



**X**

# Brain Network Discovery Problem

Input

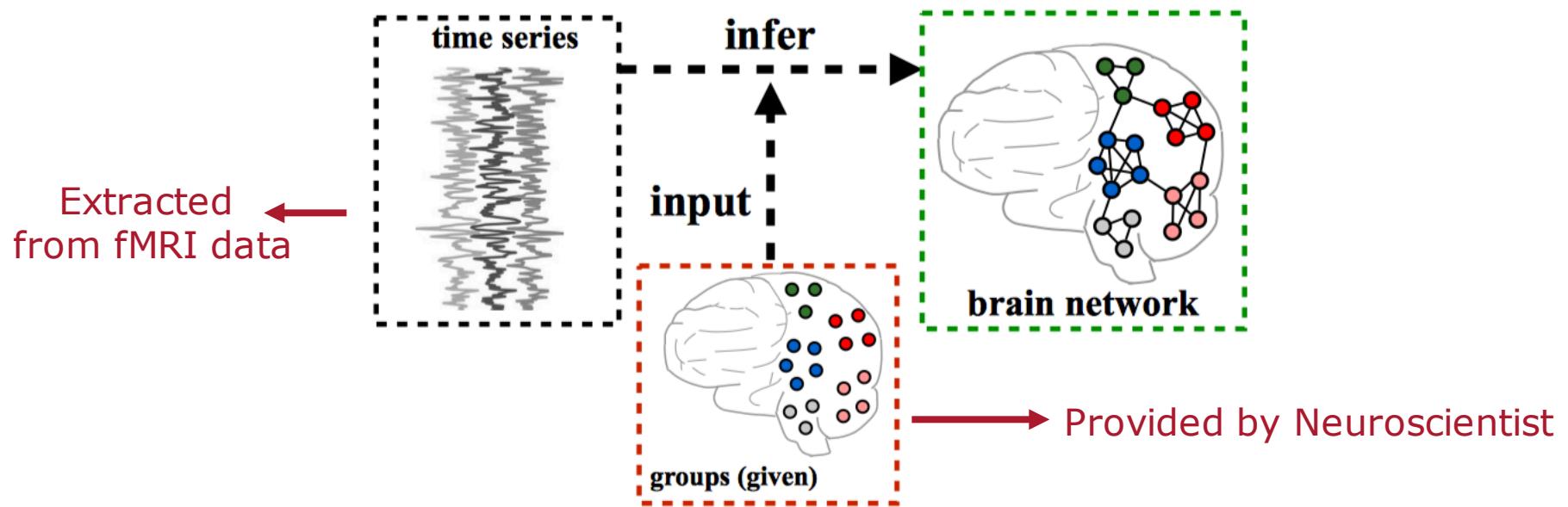


**X**

Output

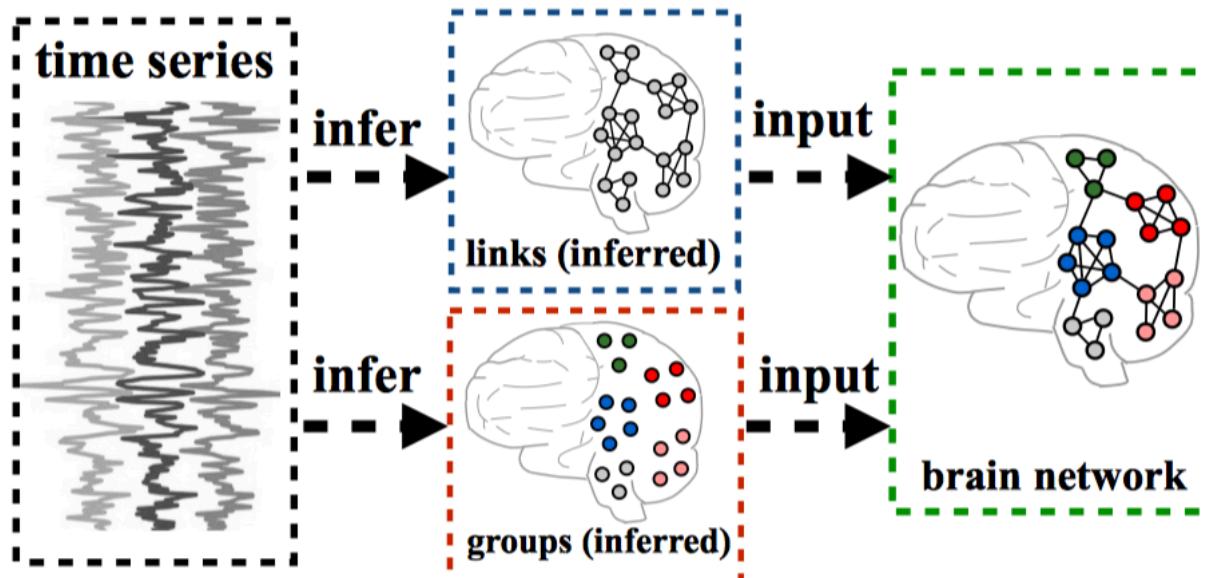


# Brain Network Discovery



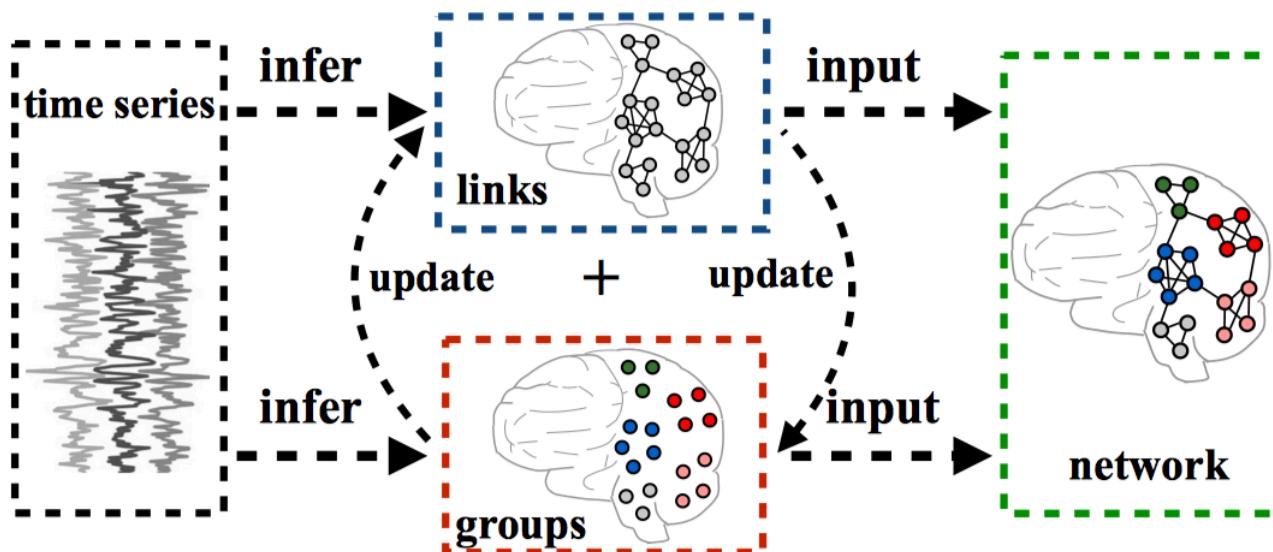
(a) Edge Inference with Known Groups

# Brain Network Discovery Cont.



(b) Independent Inference

# Collective Brain Network Discovery



(c) Collective Inference (Proposed)

# Why Collective?

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- [Edge/Link]: The predefined groups may be inferred anatomically and contain sub-regions that are each characterized by **different functional connectivity patterns**.
- [Node/Group]: In most brain network inference model, once the groups (nodes) are derived, it is **difficult or impossible to improve it based on edges/links discovered in latter stages**.

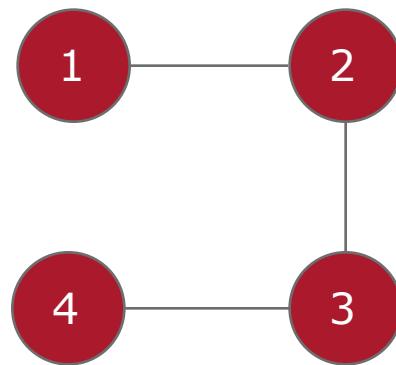
# Preliminary: Inverse Covariance

Given time series signal  
of neurons

Covariance Matrix

Light Gray	Dark Gray	Light Gray	Light Gray
Dark Gray	Light Gray	Dark Gray	Light Gray
Light Gray	Dark Gray	Light Gray	Dark Gray
Light Gray	Light Gray	Dark Gray	Light Gray

Indirect Connections



One can infer the  
connections between  
pairs of neurons using  
Pearson correlation

Inverse Covariance Matrix

Light Gray	Dark Gray	White	White
Dark Gray	Light Gray	Dark Gray	White
White	Dark Gray	Light Gray	Dark Gray
White	White	Dark Gray	Light Gray

Direct Connections

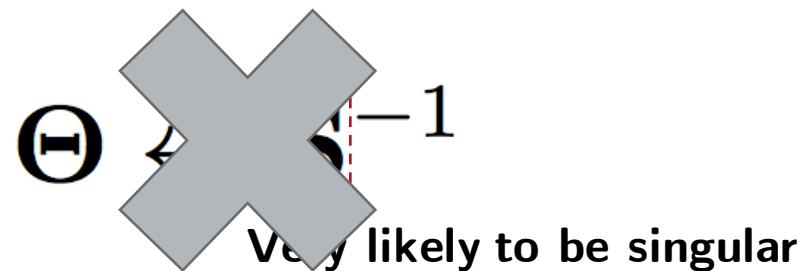
# Preliminary: Compute the Inverse

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$$\mathbf{S} = \frac{1}{n} \mathbf{X}^T \mathbf{X}$$

empirical covariance matrix

Find the precision (inverse covariance) matrix



# Preliminary: Graphical Lasso

$$\underset{\Theta \succ 0}{\text{minimize}} \quad -\log \det \Theta + \text{tr}(\mathbf{S}\Theta) + \lambda \|\Theta\|_1$$

positive definite constraint

Negative Log Likelihood

L1-norm Regularization

Find a sparse positive definite matrix  $\Theta$  which has high likelihood to be the precision matrix of  $\mathbf{S}$

# SGGL Model: Step 1 (Group Constrained Graphical Lasso)

$$\arg \min_{\Theta \succ 0} -\log \det \Theta + \text{tr}(\mathbf{S}\Theta) + \sum_{i,j} \lambda_{ij} \|\{\Theta_{G_i, G_j}\}\|_F$$

positive definite constraint

Negative Log Likelihood

Group-wise Sparseness Regularizer

The diagram illustrates the SGGL objective function. It features a red bracket grouping the first two terms, labeled "Negative Log Likelihood". A blue bracket groups the third term, labeled "Group-wise Sparseness Regularizer". A dashed box encloses the constraint  $\Theta \succ 0$ , with an arrow pointing down to the text "positive definite constraint".

Solved by Spectral Projected  
Gradient Descent

# SGGL Model: Step 2 (Spectral Clustering)

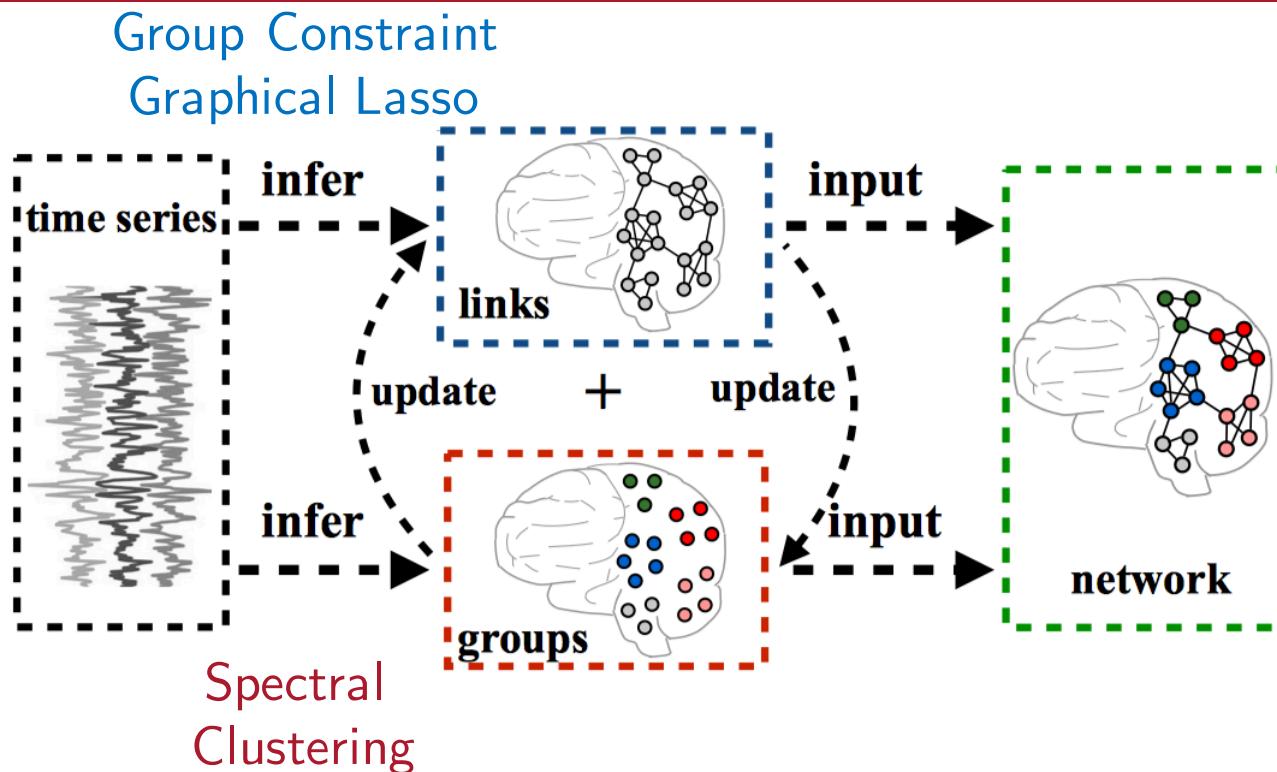
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use  $\Omega(\hat{\Theta}) = \text{abs}(\hat{\Theta})$

as the **affinity/similarity matrix** for spectral clustering

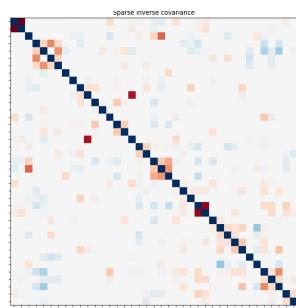
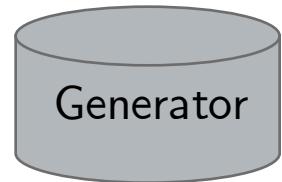
to update the group/node  $(G_1, \dots, G_N)$

# SGGL Model: Iterative Inference



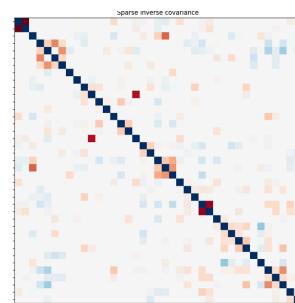
(c) Collective Inference (Proposed)

# Synthetic Data

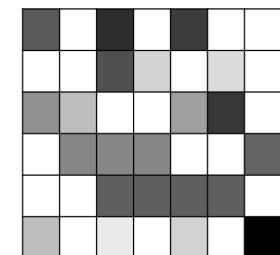


Ground Truth  
Precision Matrix

Add Noises

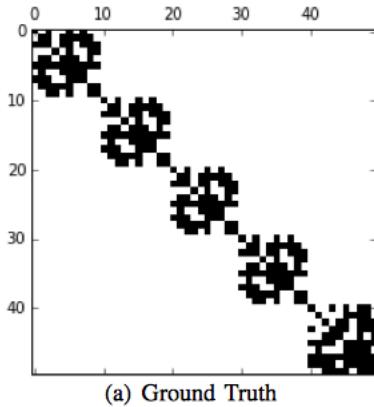
A gray right-pointing arrow indicating the flow from the ground truth matrix to the noisy matrix.

Draw from  
Multi-variate  
Gaussian Dist.

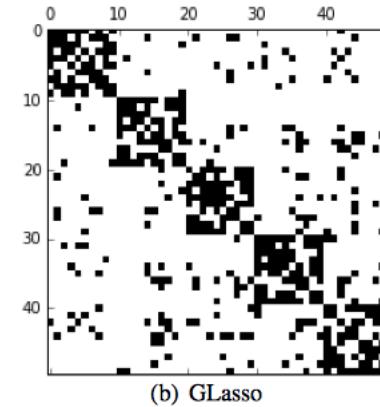
A large gray right-pointing arrow indicating the final step of generating synthetic data.

# Synthetic Study (Illustration)

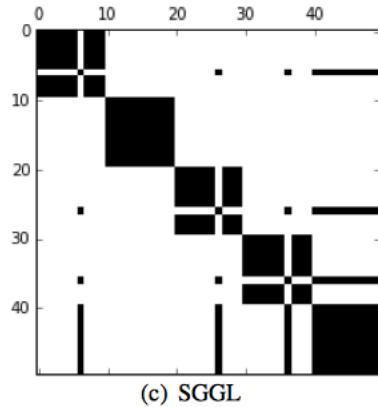
Data set 1



(a) Ground Truth

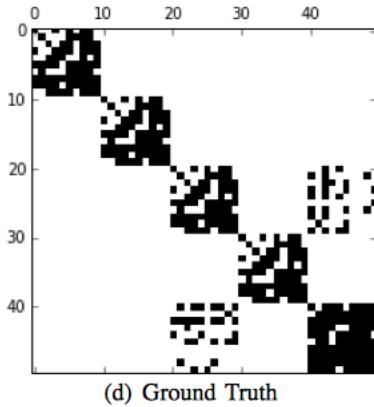


(b) GLasso

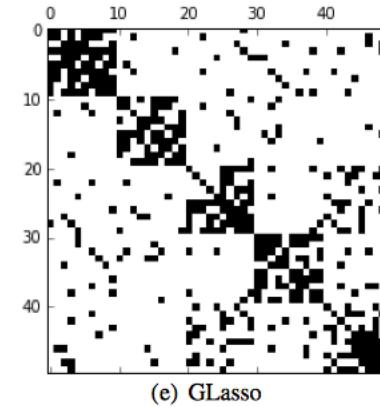


(c) SGGL

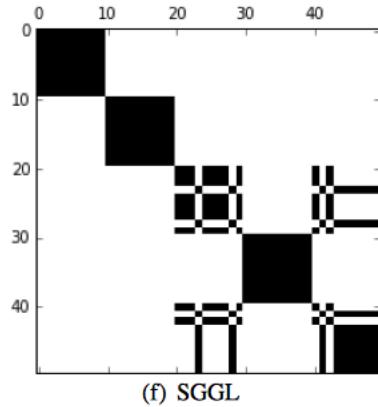
Data set 2



(d) Ground Truth

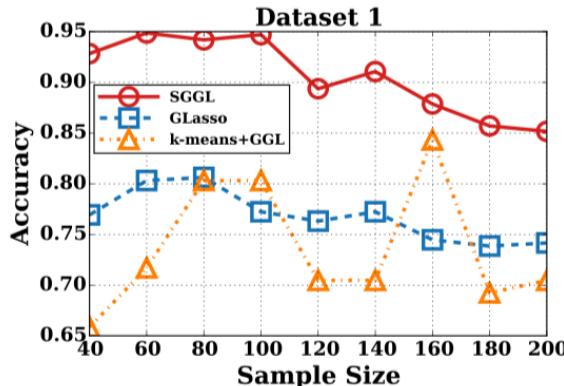


(e) GLasso

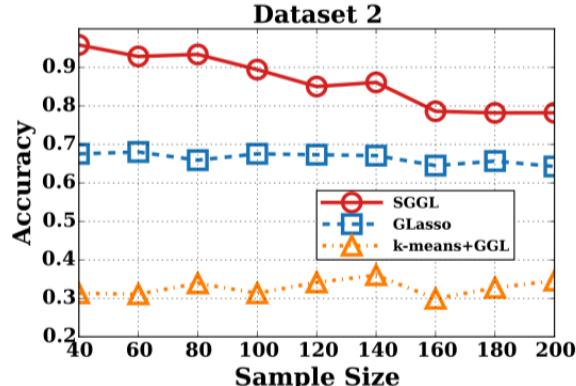


(f) SGGL

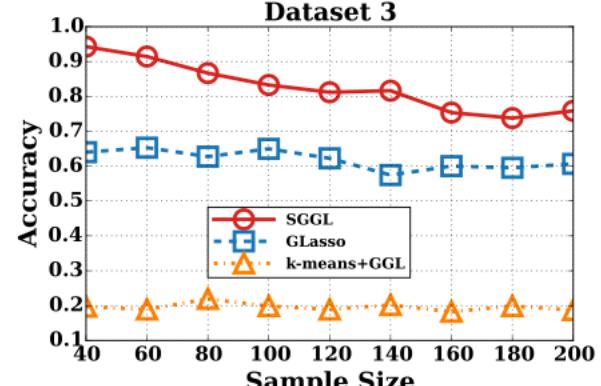
# Synthetic Study (Edge Inference)



(a) Accuracy of Dataset 1



(b) Accuracy of Dataset 2

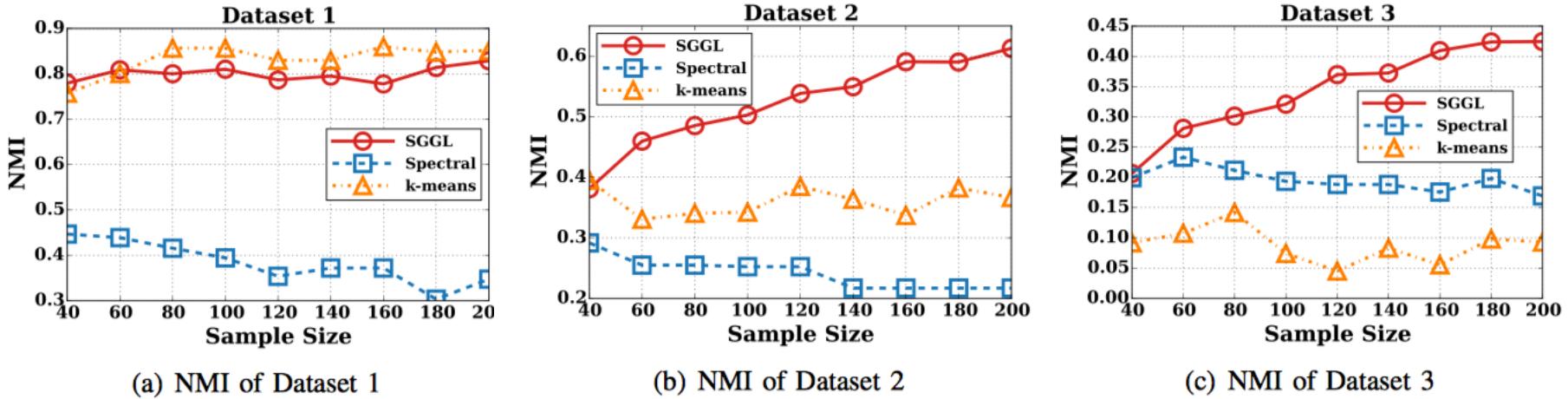


(c) Accuracy of Dataset 3

## Compared Method:

- SGGL (proposed)
- Graphical Lasso
- K-means + GGL

# Synthetic Study (Group Inference)



Compared Method:

- SGGL (proposed)
- Spectral Clustering
- K-means

# Real fMRI Data

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- ❑ ADHD-200
  - ❑ 20 healthy (TDC) subjects, 20 ADHD patients.
  - ❑ 3D brain images of size  $61 \times 73 \times 61 \sim 180$  time steps
- ❑ All parameters are tuning using DMN.

# Real fMRI data (DMN Recovery)

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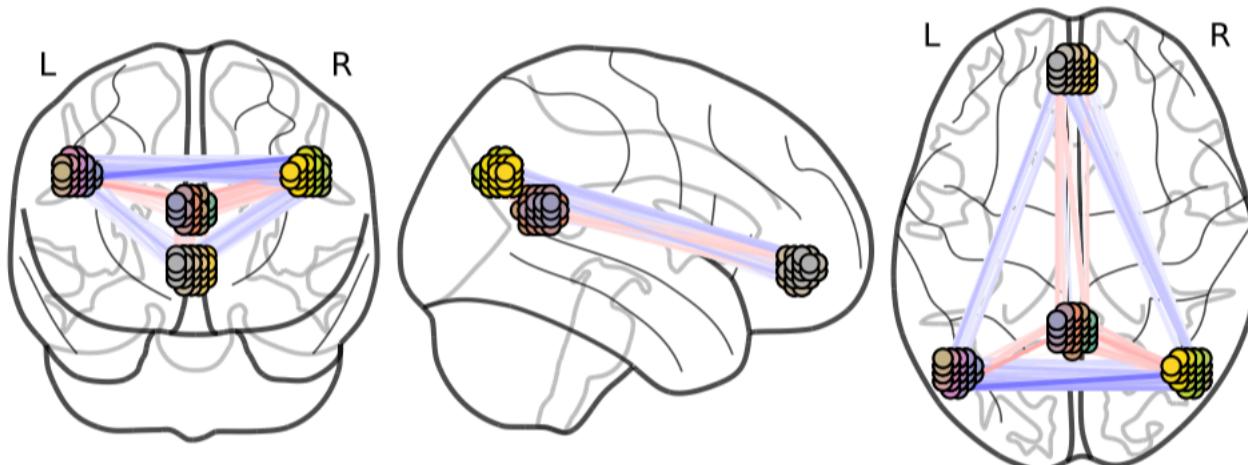


Fig. 7. The connectivity of DMN of ADHD group discovered by SGGL. All regions in the DMN are strongly connected to each other, which is consistent with the essence of DMN.

# Real fMRI data (DMN Recovery)

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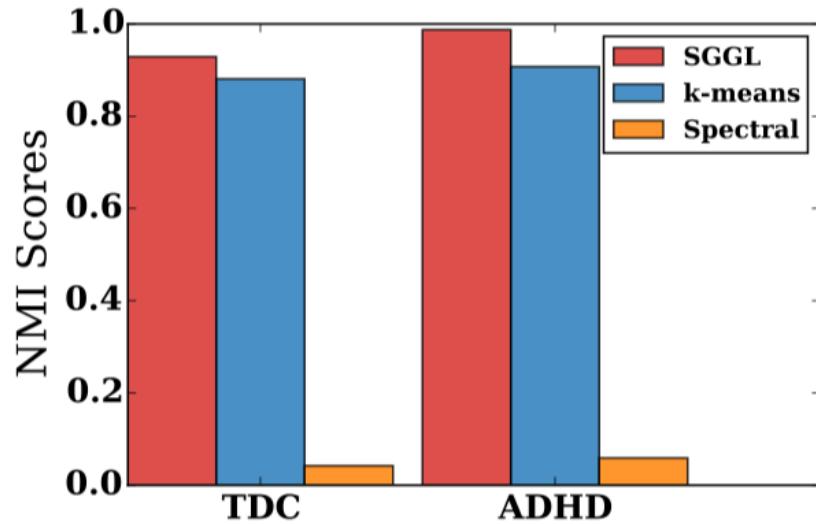
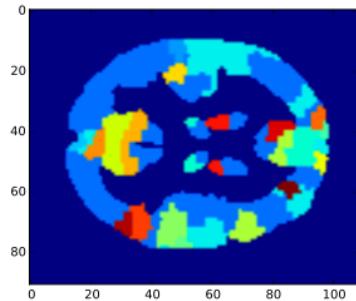


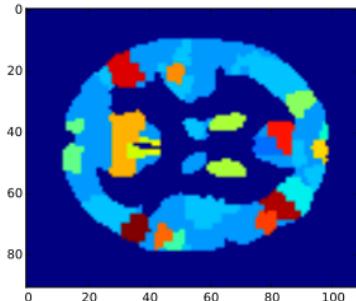
Fig. 6. Comparison of NMI scores on the DMN (Default Mode Network) of ADHD-200 Data.

# Real fMRI data (Entire Brain Group Inference)

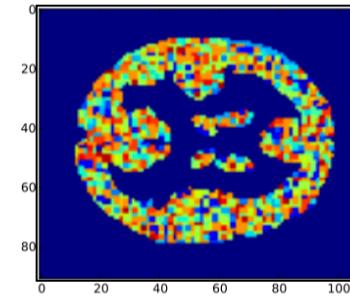


(a) Groups of TDC inferred by SGGL ( $k = 20$ )

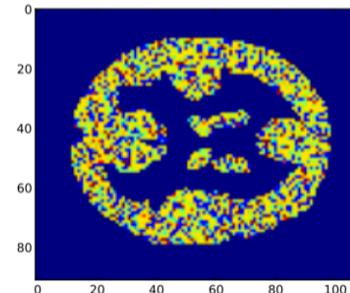
more  
Interpretable  
results



(b) Groups of ADHD inferred by SGGL ( $k = 20$ )



(c) Groups of TDC inferred by spectral clustering ( $k = 20$ )

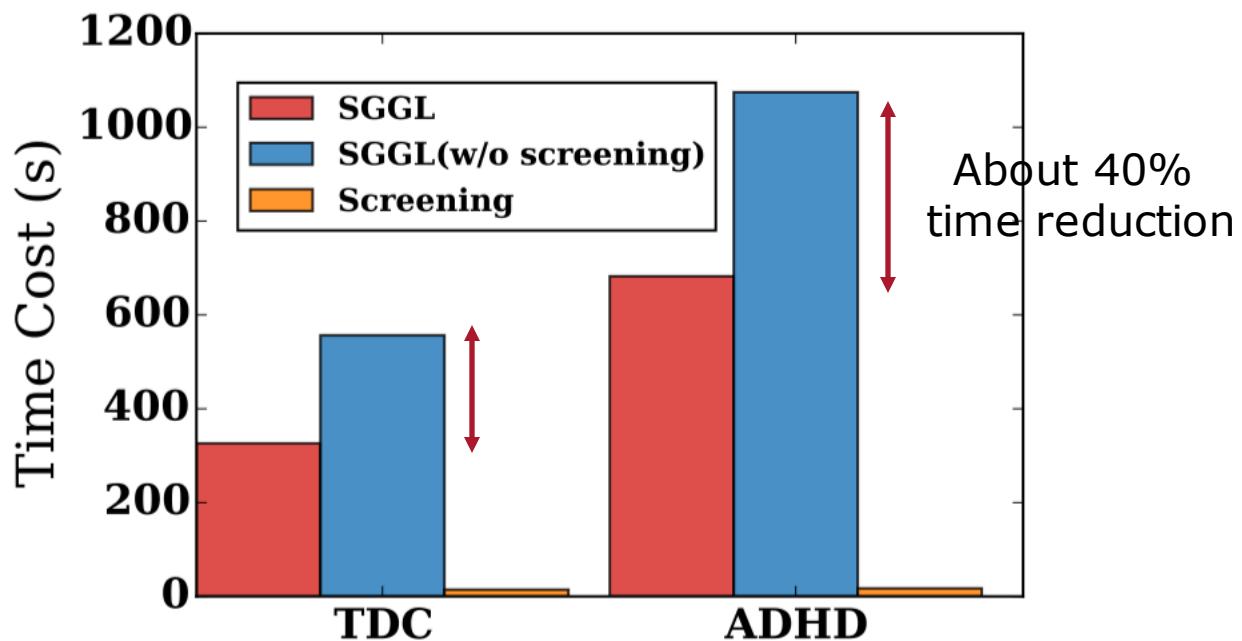


(d) Groups of ADHD inferred by spectral clustering ( $k = 20$ )

Scattered,  
hard to see  
difference

# Effect of Screening

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# Summary

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- Problem Studied
  - Collective brain network discovery (nodes + edges)
- Proposed solution
  - Use **Group Constrained Graphical Lasso** to infer the edges
  - Use **spectral clustering** with the masked precision matrix as the affinity matrix to update the group
  - Use the updated group to further update the edges and **to repeat** previous two steps until converge
  - A set of **screening rules** is proposed to speed up the edge inference
- Conclusion
  - Experiments on synthetic data and real-world fMRI demonstrated the superiority of the proposed SGGL method



# WPI

# Q&A

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