EEG-GRAPH: A Factor-Graph-Based Model for Capturing Spatial, Temporal, and Observational Relationships in Electroencephalograms

MAYO CLINIC HEALTH SYSTEM

MAYO CLINIC & ILLINOIS ALLIANCE For Technology-Based Healthcare

Mayo Systems Electrophysiology Laboratory

ECE ILLINOIS

CSL: COORDINATED SCIENCE LAB

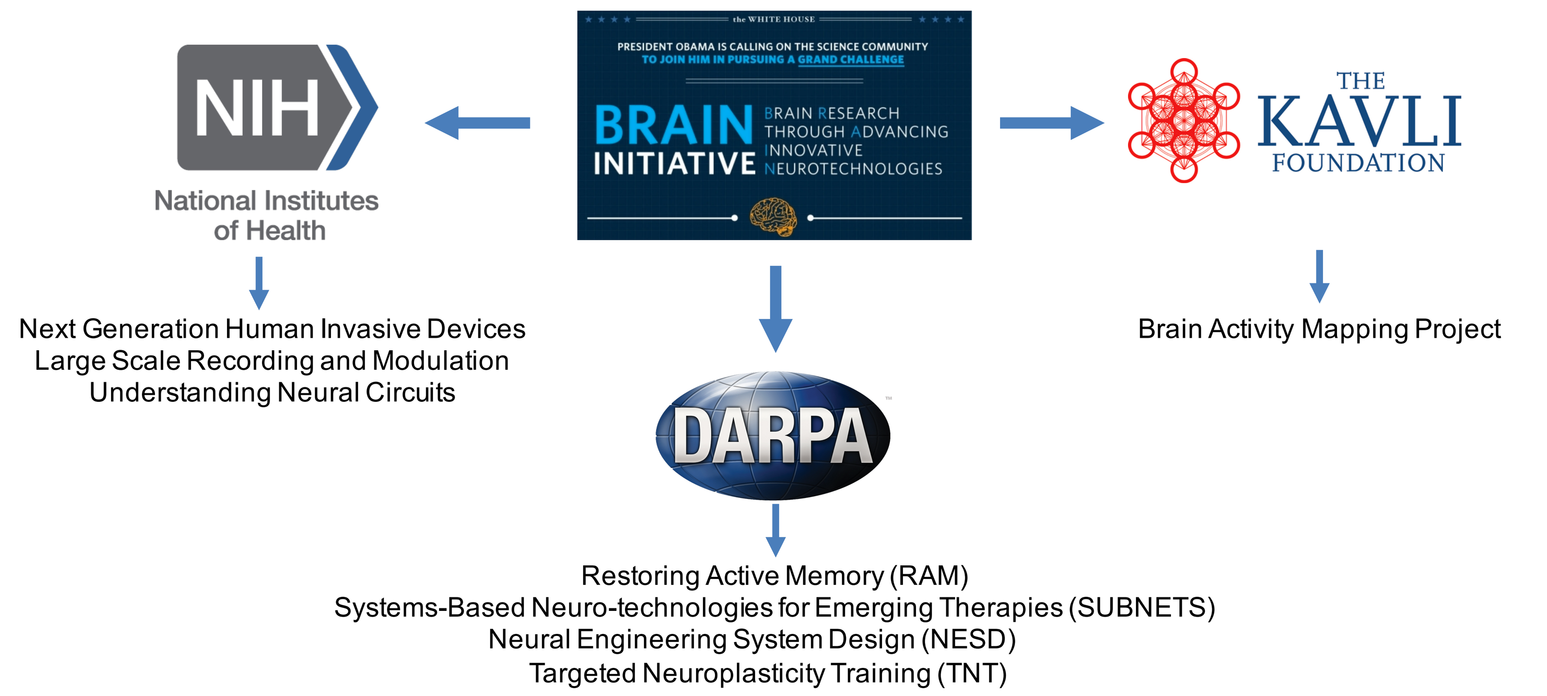
DEPEND Research Group

Yogatheesan Varatharajah[1], Min Jin Chong[1], Krishnakant Saboo[1], Brent Berry[2], Benjamin Brinkmann[2], Gregory Worrell[2], and Ravishankar Iyer[1]

[1]Dept. of Electrical and Computer Engineering, University of Illinois at Urbana-Champaign, Urbana, IL 61801, USA.

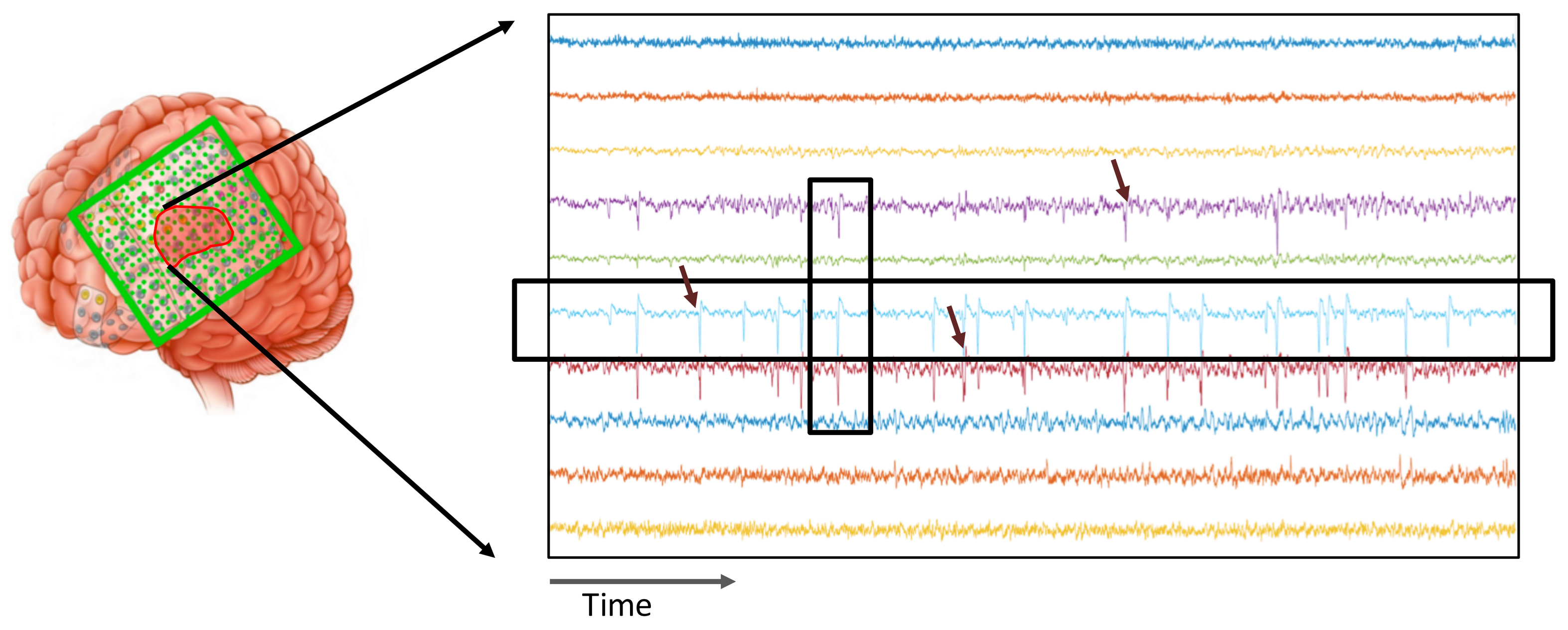
[2]Mayo Clinic, Dept. of Neurology, Rochester MN 55904, USA.

Introduction



1. Study of neurophysiological processes is important for understanding the brain.
2. Electroencephalography (EEG) is an exceptional tool for this type of studies.
3. EEG contains rhythms and discrete neurophysiological events.
4. Neural activities in different brain regions have spatial and temporal associations.

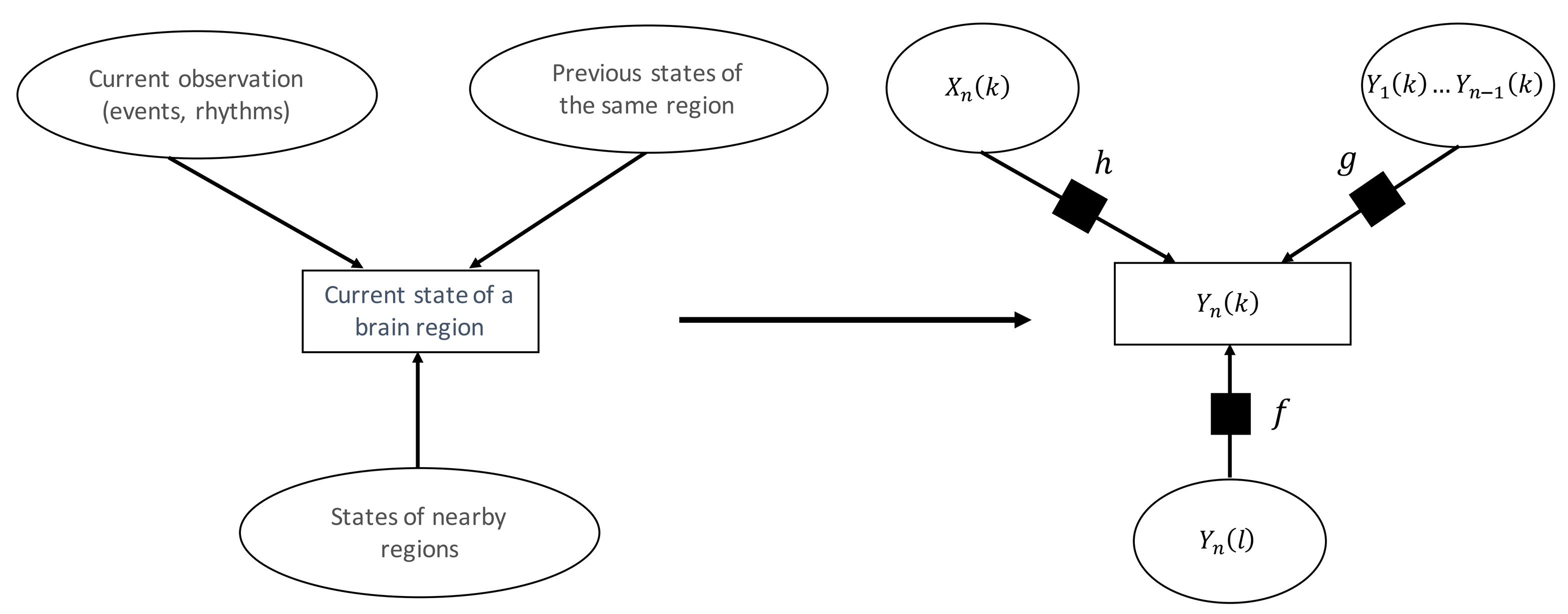
Motivation and Goals of the Project



Our goals

1. To develop a probabilistic model to infer characteristics of neural activity.
2. To model observational, spatial, and temporal dependencies.
3. Utilize domain knowledge to finesse model specification.
4. Evaluate the feasibility in an important clinical problem.

Dependencies - Graphical Representation



Observational factor function: $f\big(Y_n(k), X_n(k)\big)$

Spatial factor function: $g\big(Y_n(k), Y_n(l)\big)$

Temporal factor function: $h\big(Y_n(k), \Omega_{n-1}(k)\big)$

Definitions of Factor Functions

Notation

$X_n(k) \in \{0,1\}$ - abnormal event at the n^{th} epoch of channel k

$Y_n(k) \in \{0,1\}$ - the SOZ likely state of the n^{th} epoch of channel k

Abnormal events

$$f\big(Y_n(k), X_n(k)\big) = e^{-(Y_n(k)-\phi(X_n(k)))^2}$$

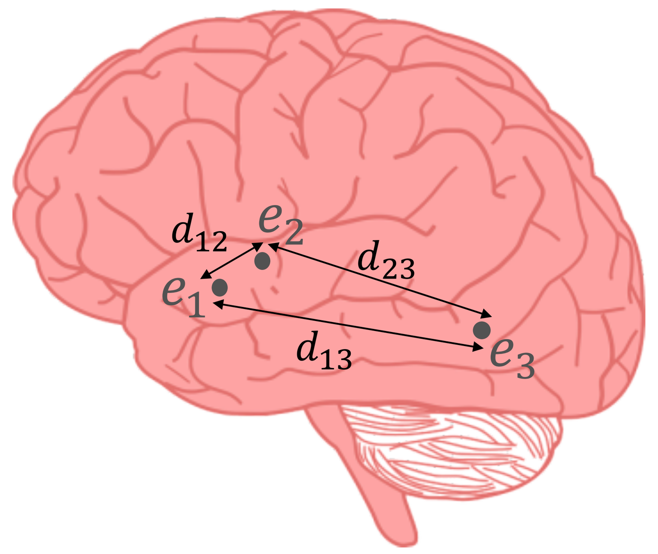
Spatial correlation

$$g\big(Y_n(k), Y_n(l)\big) = e^{-\frac{1}{d_{kl}^2}(Y_n(k)-Y_n(l))^2}$$

Temporal correlation

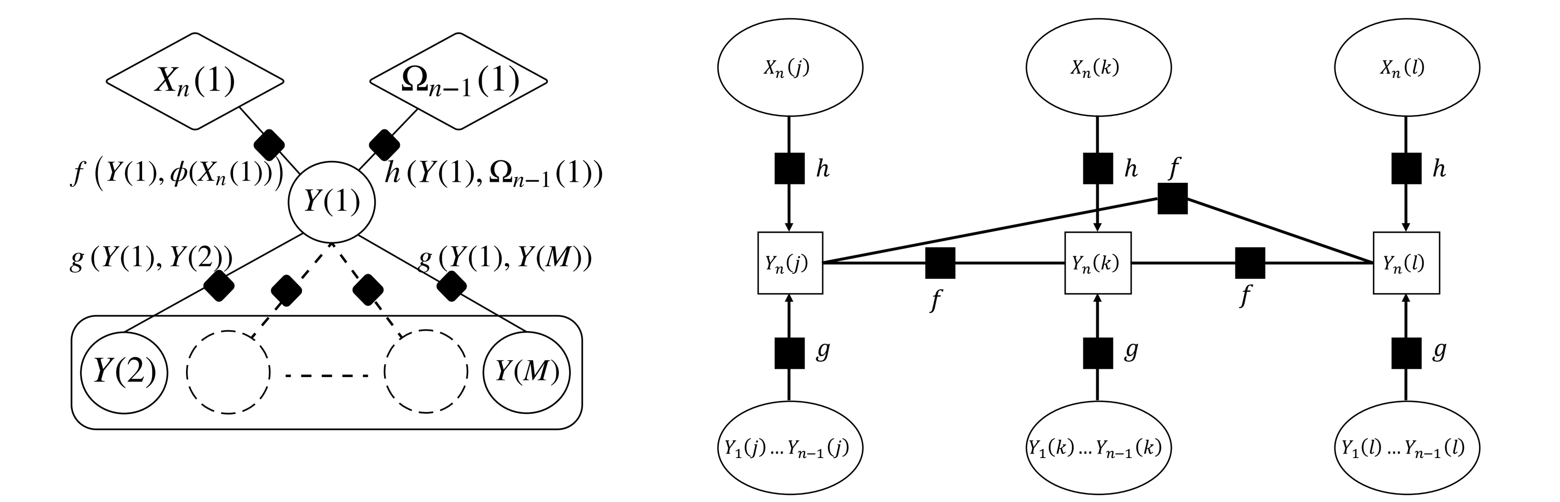
$$h\big(Y_n(k), \Omega_{n-1}(k)\big) = e^{-(Y_n(k)-\Omega_{n-1}(k))^2}$$

where $\Omega_{n-1}(k) = \frac{\sum Y_i(k)}{n-1}$



Graph Inference

Graph structure of an EEG with M channels **Graph structure for an EEG with 3 channels**

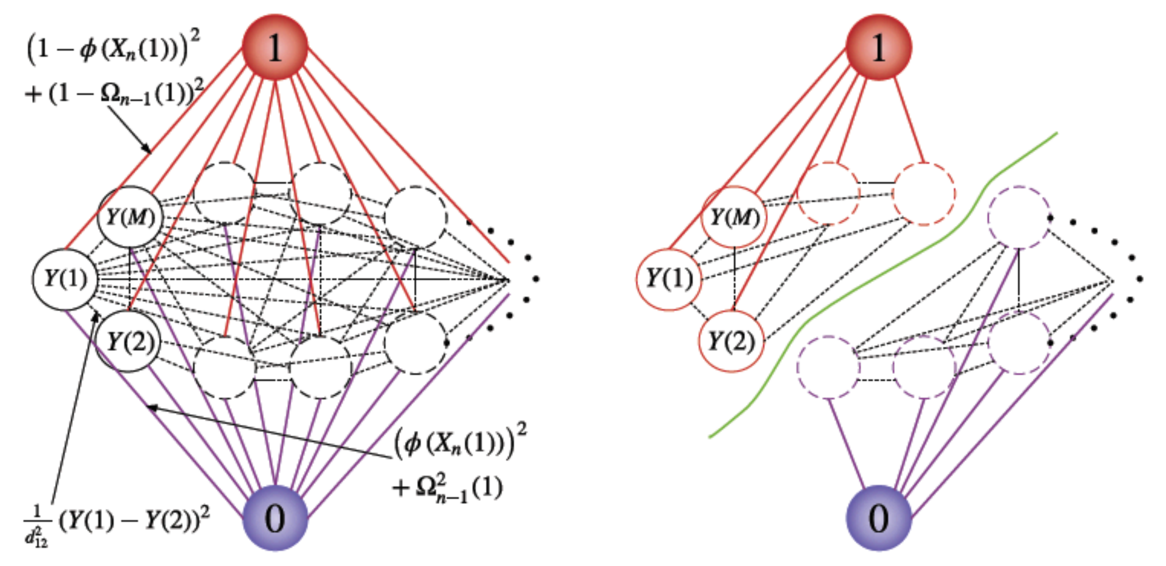


$$Y_n = \underset{Y\in\{0,1\}^M}{\arg\max} \prod_{k=1}^{M}\left[\prod_{i\neq k} g\big(Y(k),Y(i)\big)\times f\Big(Y(k),\phi\big(X_n(k)\big)\Big)\times h\big(Y_n(k),\Omega_{n-1}(k)\big)\right]$$

$$\Longrightarrow Y_n = \underset{Y\in\{0,1\}^M}{\arg\max} \prod_{k=1}^{M}\left[\prod_{i\neq k} e^{-\frac{1}{d_{kl}^2}(Y(k)-Y(l))^2} \times e^{-(Y(k)-\phi(X_n(k)))^2} \times e^{-(Y(k)-\Omega_{n-1}(k))^2}\right]$$

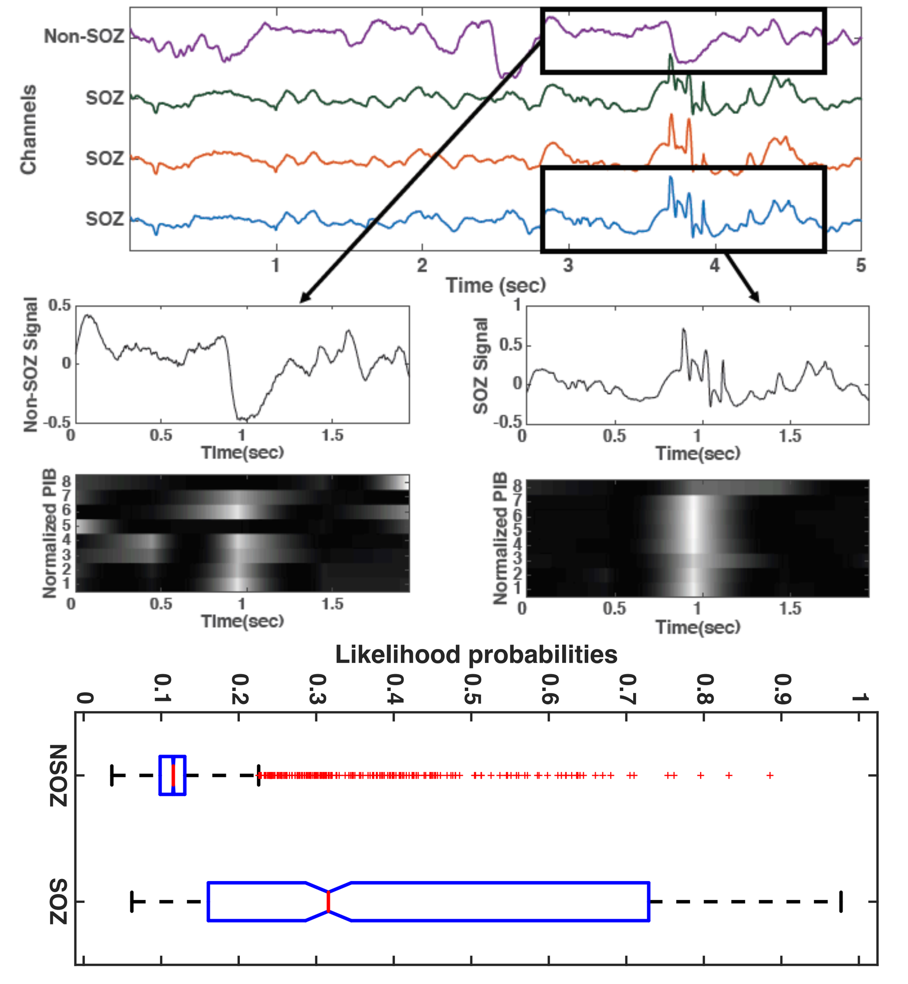
$$\Longrightarrow Y_n = \underset{Y\in\{0,1\}^M}{\arg\min} \sum_{k=1}^{M}\sum_{l\neq k}\frac{1}{d_{kl}^2}\big(Y(k)-Y(l)\big)^2 + \Big(Y(k)-\phi\big(X_n(k)\big)\Big)^2 + \big(Y(k)-\Omega_{n-1}(k)\big)^2$$

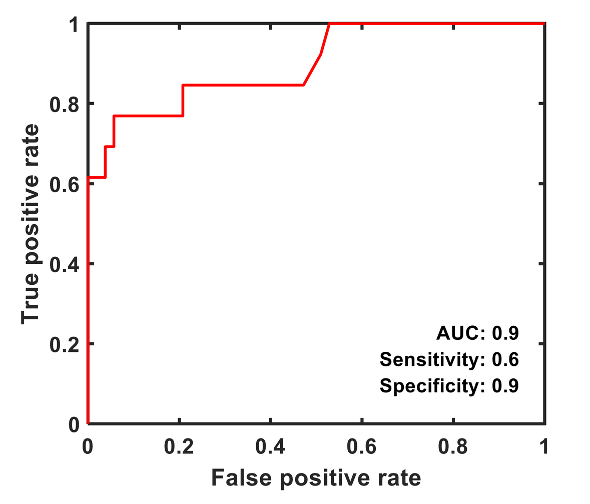
Exact Inference using Graph Cut

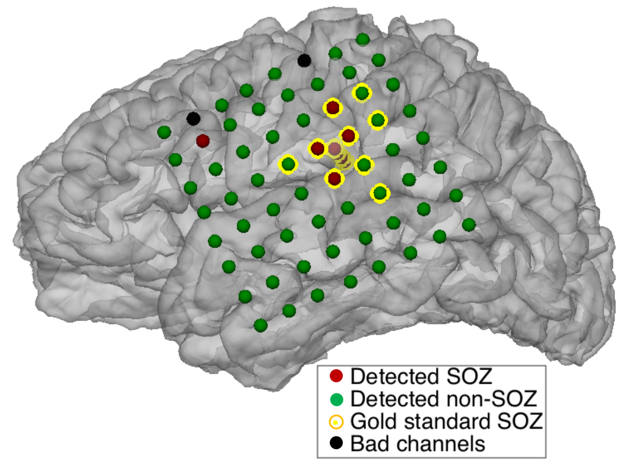


- Every channel is connected with every other channel, and the link between channels k and l is assigned a weight of $\frac{1}{d_{kl}^2}\big(Y(k)-Y(l)\big)^2$ based on the distance between them.
- Every channel is connected with the source node, and the link between channel k and the source is assigned a weight of $\big(1-\Omega_{n-1}(k)\big)^2 + \Big(1-\phi\big(X_n(k)\big)\Big)^2$.
- Every channel is also connected with the sink node, and the link between channel k and the sink is assigned a weight of $\Omega_{n-1}(k)^2 + \Big(\phi\big(X_n(k)\big)\Big)^2$.

Abnormal Brain Tissue Classification







Results

Method	AUC	Sensitivity	Specificity	Precision	Recall	F1-score
Evaluation: techniques for PIB to abnormal event mapping (ϕ)						
FG/**kmeans**/min-cut	**0.72±0.03**	**0.74±0.03**	0.61±0.02	0.39±0.05	**0.74±0.03**	**0.46±0.04**
FG/**spectral**/min-cut	0.68±0.03	0.60±0.07	0.48±0.05	0.31±0.05	0.60±0.07	0.36±0.05
FG/**hierarch**/min-cut	0.69±0.03	0.52±0.06	0.51±0.05	0.29±0.05	0.52±0.06	0.34±0.05
FG/**svm**/min-cut	0.71±0.03	0.68±0.06	0.54±0.05	0.36±0.05	0.68±0.06	0.43±0.05
FG/**glm**/min-cut	0.69±0.03	0.62±0.07	0.47±0.05	0.31±0.05	0.62±0.08	0.37±0.05
Evaluation: sampling vs. min-cut						
FG/kmeans/**Random**	0.62±0.03	0.51±0.08	0.40±0.07	0.35±0.06	0.51±0.08	0.32±0.05
FG/kmeans/**Prior**	0.69±0.03	0.65±0.04	0.66±0.04	0.40±0.04	0.65±0.04	**0.46±0.04**
Evaluation: comparison against conventional approaches						
Summation	0.67±0.04	0.59±0.05	0.67±0.03	0.38±0.05	0.59±0.05	0.43±0.05
Clustering	0.65±0.04	0.49±0.06	**0.72±0.04**	**0.42±0.06**	0.49±0.06	0.44±0.05

Acknowledgements

This research was partly supported by Mayo Clinic and Illinois Alliance Fellowships for Technology-based Healthcare Research, National Science Foundation grants CNS-1337732 and CNS-1624790, National Institute of Health grants NINDS-U01-NS073557, NINDS-R01-NS92882, NHLBI-HL105355, and NINDS-UH2-NS095495-01, IBM faculty award, Mayo Clinic Discovery Translation Grant, National Institutes of Health (R01-NS063039, R01-NS078136).