Structured Probabilistic Machine Learning for Neuroimaging

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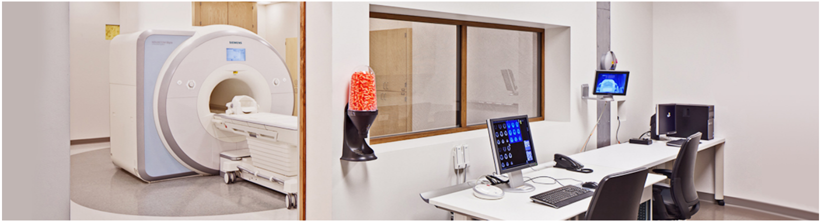
Exploratory and Predictive Models for Neuroimaging Data

- Functional Magnetic Resonance Imaging (fMRI) measures blood flow correlated with neuronal activity
- Main technique for non-invasive measurements of human brain structure and function.



Key Challenge

With millions of simultaneous measurements from relatively few (10's to 1000's) participants, how do we learn interpretable models that can generalize from limited samples?

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Towards a solution

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Towards a solution

Structured Probabilistic Machine Learning

Incorporate domain knowledge to enable learning from limited samples.

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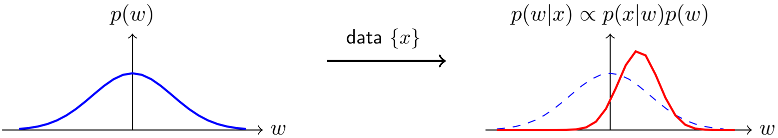
Towards a solution

Structured Probabilistic Machine Learning

Capture uncertainty in model parameters

Probabilistic Models

Bayesian Models

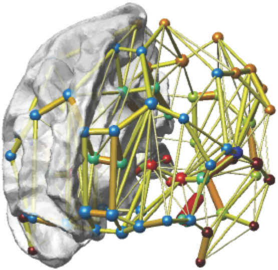


$p(x|w)$ **likelihood:** model for brain images given model parameters

$p(w)$ **prior:** incorporating expert knowledge

$p(w|x)$ **posterior:** estimated model parameters

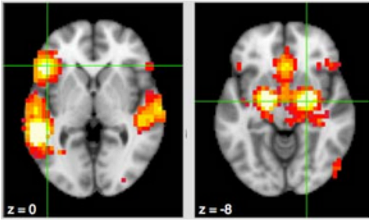
Structure in Large Scale Neuroimaging Data



- **hypothesis:** fMRI signal is spatially smooth, due to anatomy, preprocessing ...

- "soft" constraints e.g. *shrinkage, smoothness* easily incorporated using priors

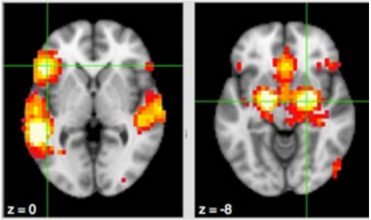
Structure in Large Scale Neuroimaging Data - II



- **hypothesis:** mental processes are spatially localized (Cohen and Bookheimer, 1994)

- "hard" constraints i.e. *structure* are much more challenging

Structure in Large Scale Neuroimaging Data - II

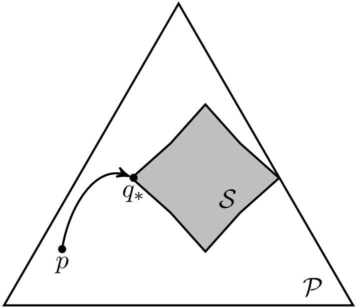


- **hypothesis:** mental processes are spatially localized (Cohen and Bookheimer, 1994)

- "hard" constraints i.e. *structure* are much more challenging
- Construct models that jointly incorporate *spatial sparsity* and *spatially smoothness*

Structured Distributions via Information Projection

Key Idea: Information projection of the model $p(x, w)$ to the structured set $\mathcal{S}$



$$q^* = \arg\min_{q \in \mathcal{S}} \mathrm{KL}(q \| p(x, w))$$

Koyejo and Ghosh (2013); Koyejo et al. (2014)

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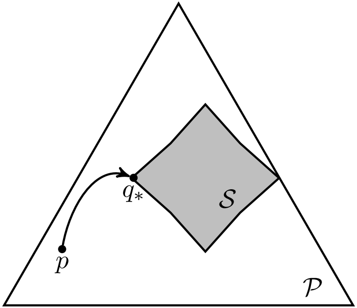

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- general purpose, easily applied to new structured sets

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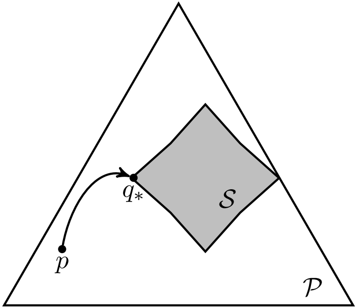

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- general purpose, easily applied to new structured sets
- state of the art performance in many cases

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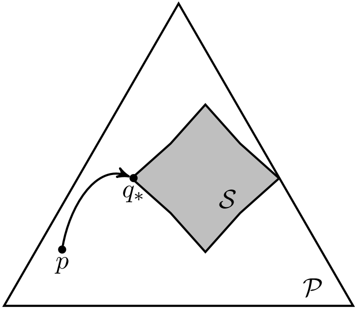


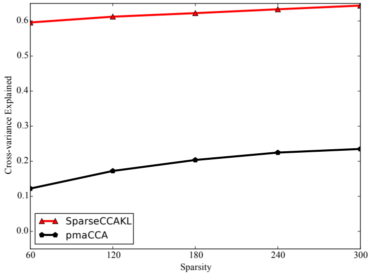
$$q^* = \arg\min_{q \in \mathcal{S}} \mathrm{KL}(q \| p(x, w))$$

- general purpose, easily applied to new structured sets
- state of the art performance in many cases
- often significantly more scalable than equiv. conventional model
- particularly effective in several cases where sampling inference fails

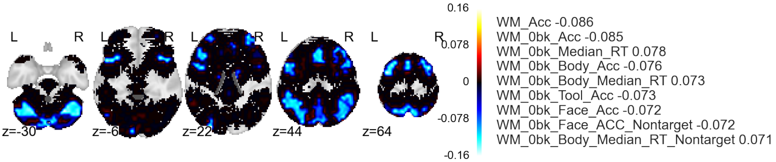
Koyejo and Ghosh (2013); Koyejo et al. (2014)

Human Connectome Project Data (Essen et al., 2013)

- Investigating association between human brain function and human behavior
- Joint exploratory analysis of task brain images and behavioral variables
- $n = 497$ adult subjects. Each subject has $d_1 = 380$ behavioral variables, $d_2 = 27000$ voxels



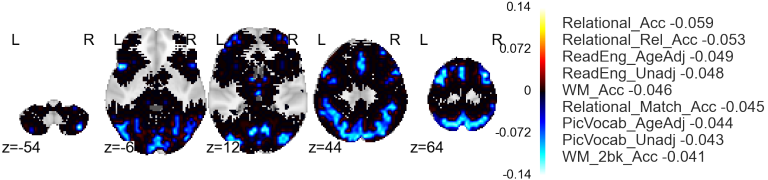
2 Back vs 0 Back contrast (measures working memory)



Neural support is seen in a number of frontal and parietal regions and cerebellum, consistent with cognitive control systems usually engaged by the task. Behavioral correlates including both reaction time and accuracy on the task, showing greater neural engagement associated with slower and less accurate performance.

(Khanna, Ghosh, Poldrack, and Koyejo, 2016)

REL vs MATCH contrast (measures relational processing)



Neural support is observed in frontal, parietal, and occipital cortex. Behavioral correlates captured both performance on this particular task, as well as independent measures related to higher cognitive functions including working memory capacity, vocabulary, and reading.

(Khanna, Ghosh, Poldrack, and Koyejo, 2016)

Summary

- Effective exploratory and predictive modeling of biological data requires incorporating domain knowledge.

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- Proposed structured probabilistic models via information projection as a promising framework.

Neuroimaging Data Analysis:

- Incorporate the domain knowledge of structured spatial sparsity.
- State of the art performance in exploratory and predictive analysis of neuroimaging data

Collaborators

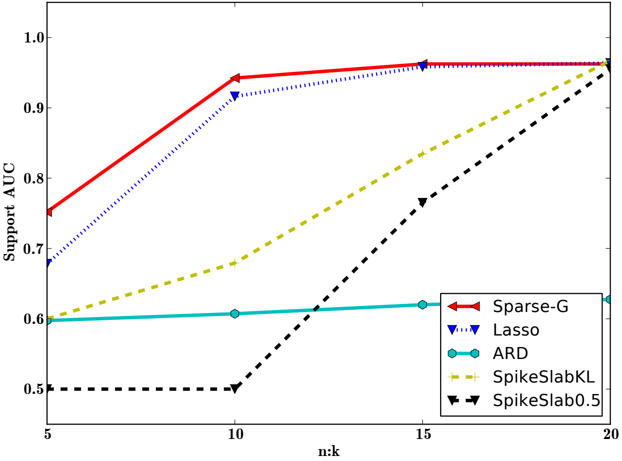
- Russell A. Poldrack (Stanford)
- Joydeep Ghosh (UT Austin)
- Rajiv Khanna (UT Austin)
- Michael Riis Andersen (TU Berlin)

Thank You

Backup Slides

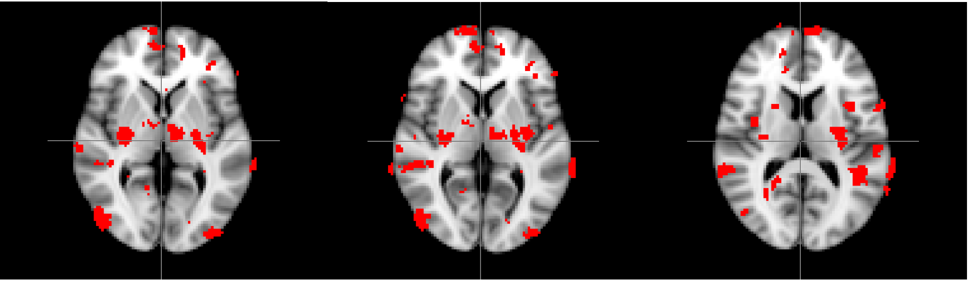
Simulated Data Results: Support Recovery

k=20, d=10,000, SNR $=20$dB , $n = 100, \ldots, 400$



FMRI stop signal task (White et al., 2014)

- **stop signal task:** designed to measure impulse control

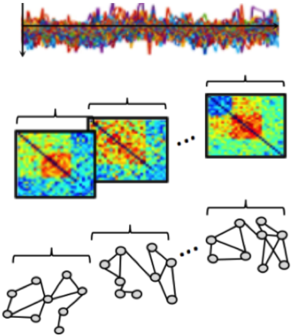


$z = 2$ $z = 5$ $z = 12$

- $n = 126, d = 10,000, k^* = 300$
- recovered regions correlated with stop signal reaction time e.g. include orbitofrontal cortex, dorsolateral prefrontal cortex, putamen, anterior cingulate, parietal cortex

(Koyejo et al., 2014)

Time varying brain networks from HCP



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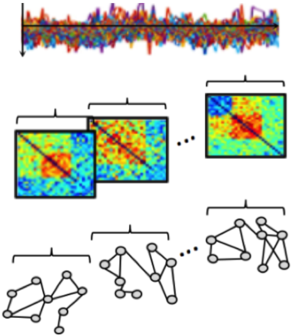

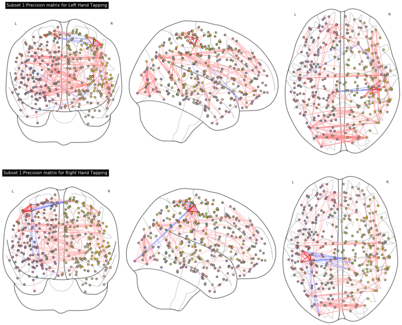

- Gordon atlas, Motor task

(Andersen, Koyejo, and Poldrack, 2016)

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