Hierarchical Mixture of Classification Experts Uncovers Interactions between Brain Regions

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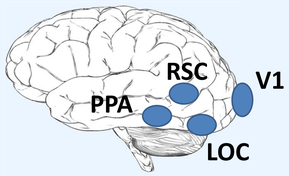
Motivation

Regions of interest (ROI) that encode information for scene perception

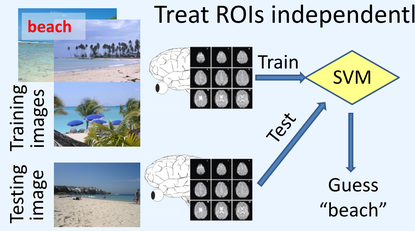


6 categories of natural scenes

Multi-Voxel Pattern Analysis (MVPA) using fMRI data

- Our previous work [Walther et al, JoN 2009]

Treat ROIs independently

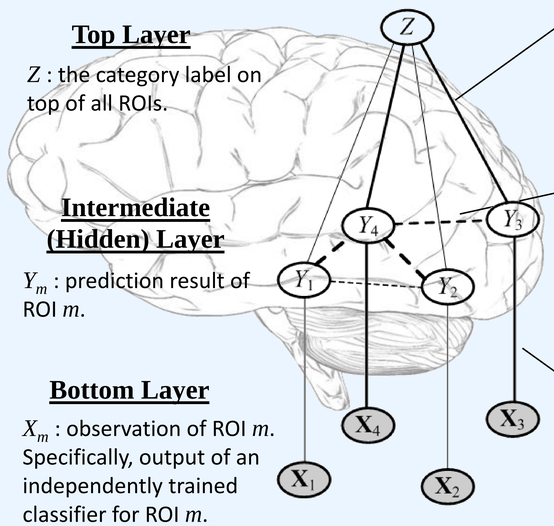


- Other MVPA methods
  - Also treat ROIs independently;
  - Model temporal dependencies instead of structural connections;
  - Did not associate the connections with categories.

Our Work

- **Objective:** Using multi-voxel patterns to learn the connections between ROIs associated with natural scene categories.
- **Method:** Modeling interactions of brain regions as a hidden conditional random field; Using structural learning to uncover the interactions.

Modeling Interactions of Brain Regions: a Hidden Conditional Random Field (HCRF) Representation



Top Layer

Z : the category label on top of all ROIs.

Intermediate (Hidden) Layer

Y_m : prediction result of ROI m.

Bottom Layer

X_m : observation of ROI m. Specifically, output of an independently trained classifier for ROI m.

Type-III Potential: distribution over the category label and the prediction result of each ROI.

$$f_{yz}(Y_m, Z) = \begin{cases} \beta, & Y_m = Z \\ 0, & Y_m \neq Z \end{cases}$$

Type-II Potential: dependencies between ROIs, connectivity determined by structural learning.

$$f_{yy}(Y_m, Y_l) = \begin{cases} \alpha, & Y_m = Y_l \\ 0, & Y_m \neq Y_l \end{cases}$$

Type-I Potential: distribution of class labels of different ROIs conditioned on the observations.

$$f_{yx}(Y_m, \mathbf{X}_m) = x_{m,Y_m}$$

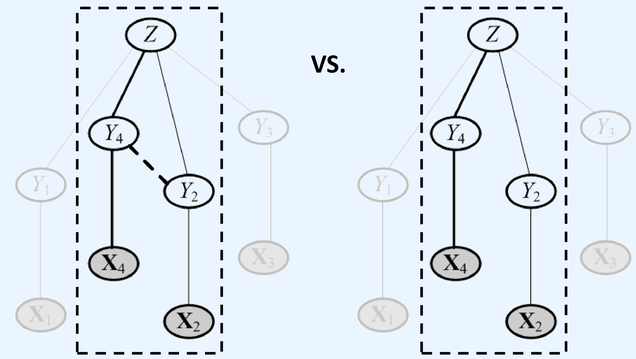
$$p(Z^i|\mathcal{X}^i;\boldsymbol{\theta}) = \sum_{\mathcal{Y}} p(Z^i, \mathcal{Y}|\mathcal{X}^i;\boldsymbol{\theta}) = \frac{\sum_{\mathcal{Y}} \exp(\Psi(Z^i, \mathcal{Y}, \mathcal{X}^i;\boldsymbol{\theta}))}{\sum_Z \sum_{\mathcal{Y}} \exp(\Psi(Z, \mathcal{Y}, \mathcal{X}^i;\boldsymbol{\theta}))}$$

Learning Procedure

Training data → Structural learning → Gradient descent parameter estimation → Output

Learning Structural Connectivity among ROIs

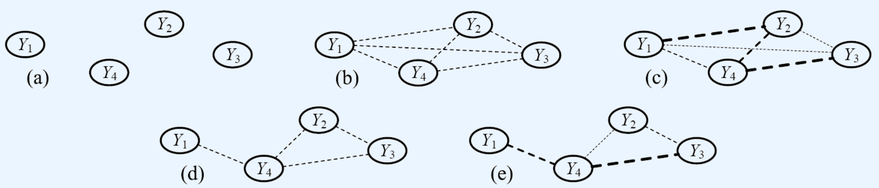
Evaluate each connection respectively:



Training accuracy: P_c Training accuracy: P_n

- Connect Y_2 and Y_4 if and only if $P_c > P_n$.
- The method can evaluate all connections very fast.
- **Complementary connections** will be discovered.

Experiment 1 – Scene Classification



Recognition accuracy for predicting natural scene categories (chance 1/6, *p<0.01, **p<0.005):

Method		SVM	Fig(a)	Fig(b)	Fig(c)	Fig(d)	Fig(e)
Overall classification		N/A	31%*	29%*	33%**	34%**	**36%****
ROI	V1	21%	22%	25%	24%	27%	**28%***
	left LOC	22%	23%	27%	29%*	31%*	**32%****
	right LOC	25%	24%	27%	30%*	29%*	**33%****
	left PPA	27%	27%	26%	28%*	**31%***	**31%***
	right PPA	26%	28%*	28%*	31%*	31%*	**32%****
	left RSC	30%	30%*	30%*	32%*	33%**	**35%****
	right RSC	26%*	27%	29%*	30%*	30%*	**32%****

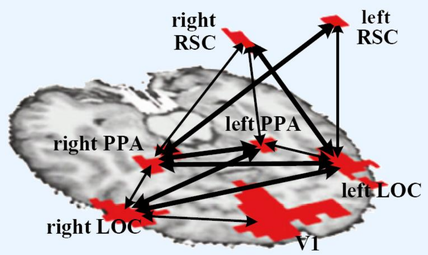
Observations:

(b)(c)(d)(e) outperform (a) – Considering dependency among ROIs helps.

(d) outperforms (b), (e) outperforms (c) – Structural learning helps.

(c) outperforms (b), (e) outperforms (d) – Assigning weights to connections helps.

Experiment 2 – Structural Learning Results



Observations:

- Strong interactions between contralateral counterparts or across hemispheres are observed.
- Such connections link two **complementary ROIs**.

Strength of different connections on different subjects:

Connection	Sbj.1	Sbj.2	Sbj.3	Connection	Sbj.1	Sbj.2	Sbj.3
V1-leftLOC	0.67	0.25	0.33	**rightLOC-leftPPA**	**0.58**	**0.58**	**0.66**
V1-rightLOC	0.50	0.29	0.54	rightLOC-rightPPA	0.36	0.58	0.89
V1-leftPPA	0.44	0.29	0.36	rightLOC-leftRSC	0.63	0.38	0.31
V1-rightPPA	0.38	0.33	0.69	rightLOC-rightRSC	0.36	0.30	0.87
V1-leftRSC	0.29	0.30	0.23	**leftPPA-rightPPA**	**0.99**	**0.56**	**0.78**
V1-rightRSC	0.36	0.29	0.59	leftPPA-leftRSC	0.97	0.34	0.46
leftLOC-rightLOC	**0.66**	**0.88**	**0.71**	leftPPA-rightRSC	0.61	0.53	0.40
leftLOC-leftPPA	0.46	0.64	0.76	**rightPPA-leftRSC**	**0.67**	**0.74**	**0.51**
leftLOC-rightPPA	**0.75**	**0.96**	**0.65**	rightPPA-rightRSC	0.93	0.74	0.41
leftLOC-leftRSC	0.41	0.78	0.61	leftRSC-rightRSC	0.65	0.20	0.45
leftLOC-rightRSC	**0.75**	**0.83**	**0.76**				

Larger font size denotes the connections that are strong on more subjects.

Conclusion

Our Contribution:

- A HCRF to model the interactions among brain regions associated with scene categories.
- Structural learning for automatically discovering the connectivity among brain regions.

Future Work:

- More effective, global structural learning method to uncover connections between ROIs.

Reference

Bangpeng Yao, Dirk B. Walther, Diane M. Beck*, and Li Fei-Fei*. "**Hierarchical Mixture of Classification Experts Uncovers Interactions between Brain Regions**." In *Proceedings of Advances in Neural Information Processing Systems (NIPS)*, pages 2178-2186, 2009. (* indicates equal contribution)

Project Page:

http://vision.stanford.edu/projects/sceneclassification/index.html