



#### Analysis of Functional Magnetic Resonance Imaging (fMRI) **Brain Decoding -**Multivariate Pattern Analysis (MVPA)

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### **Teaching Materials**

- http://www.ym.edu.tw/~cflu/CFLu course fMRIana.html
- Week 15: Brain Decoding Multivariate Pattern Analysis (MVPA)
- <Handout >Lesson15\_slides.pdf

<Materials >fMRIana15 materials.zip

Original Dataset (Haxby dataset) from http://www.mlnl.cs.ucl.ac.uk/pronto/prtdata.html

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**Employed Software** 



- MRIcro
  - https://people.cas.sc.edu/rorden/mricro/mricro.html#Installation
- Statistical Parametric Mapping (SPM 12)
  - http://www.fil.ion.ucl.ac.uk/spm/
- PRoNTo Software
  - http://www.mlnl.cs.ucl.ac.uk/pronto/



[Caution] File name\path contains Chinese character or space may cause error!

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## **fMRI** Analysis





R<sup>2</sup>=0.493

2



**Brain Activation** 





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# Multivariate Pattern Analysis (MVPA)

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#### **Decoding Activity Pattern of Brain**



Illustration by Pim Mostert http://blog.donders.ru.nl/?p=4361&lang=en

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### Brain Activation → Brain Decoding



7

5

#### • Mass-univariate model-based analysis

- Analyze every voxel (~50,000) one at a time
- General Linear Model, GLM (since 1995)

• Multivoxel Pattern Analysis, MVPA

#### Multivariate Pattern Analysis, MVPA

- Original version: correlation analysis
- Machine learning: Support Vector Machine, SVM

#### Why we need multivariate analysis?







### Major limitations of GLM



#### • The basic assumption that the covariance across neighboring voxels is not informative about the cognitive function under examination.

- Such covariance is considered as uncorrelated noise and normally reduced using spatial filters that smooth BOLD signals across neighboring voxels.
- Additionally, the GLM approach is inevitably limited by the model used for statistical inference.

→ Fail to capture "distributed" neural codes.

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#### **Origin of MVPA**



9

#### **Object form topography**

- The ventral temporal cortex has a topographically organized representation of attributes of form that underlie face and object recognition.
  - Can produce unique representations for a virtually unlimited number of categories.



#### Science, 293(5539), 2425-2430, 2001. 11

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#### **Origin of MVPA**

Three hypothesis made by James V. Haxby, 2001.

- Each object category would evoke a distinct pattern of response in ventral temporal cortex.
- These distinctive patterns would not be restricted to category-selective regions, such as the FFA (face) and PPA (other objects).
- Neural activity patterns within categoryselective regions would carry information that discriminates between categories.

Science, 293(5539), 2425-2430, 2001.



Parahippocamp Place Area (PPA)

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#### **Origin of MVPA**

Science, 293(5539), 2425-2430, 2001

Split-sample crosscorrelation (odd vs. even runs)

• The response to that category should be more similar to each other than to responses to different categories.



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#### **MVPA: A Classification Problem**



- Classification consists in determining a decision function f that takes the values of various "features" in a data "example" x and predicts the class of that "example."
- An "example" may represent a given trial in the experimental run.
- The "features" may represent the corresponding fMRI signals in a cluster of voxels.
- The experimental conditions may represent the different "classes".

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## Support Vector Machine (SVM)





#### Searchlight Approach

- Kriegeskorte, N., Goebel, R. and Bandettini, P., 2006. Informationbased functional brain mapping. Proceedings of the National Academy of Sciences, 103(10), pp.3863-3868.
- Where in the brain does the activity pattern contain information about the experimental condition?
  - Rather than asking where in the brain does the average activity changes across experimental condition.



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### Searchlight Approach



### **Searchlight Approach**



- An optimal radius of 4mm contains 33 2mm-isotropic voxels.
- The resulting map shows how well the multivariate signal in the local spherical neighborhood differentiates the experimental conditions.
  - Average absolute t value
  - Mahalanobis distance

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Local-pattern-effect map

B Smoothed data -mm-radius sph



activation-based (map B) information-based intersection of maps B and C

### **Pattern Similarity Analysis**



Compared between regions, species, mental states, and diseases.



BA	Toolbox of MVPA	<b>NBA</b>
1	<ul> <li>Hanke, M., Halchenko, Y.O., Sederberg, P.B., Hanson, S.J., Haxby, J Pollman, S., 2009. PyMVPA: a Python toolbox for multivariate pat analysis of fMRI data. <i>Neuroinformatics</i> 7, 37–53.</li> </ul>	.V., tern
	<ul> <li>An MVPA toolbox using Matlab (the Princeton MVPA toolbox) (http://code.google.com/p/princeton-mvpa-toolbox/).</li> </ul>	
	<ul> <li>Schrouff J, Rosa MJ, Rondina JM, Marquand AF, Chu C, Ashburner C, Richiardi J, Mourão-Miranda J. PRONTo: pattern recognition for neuroimaging toolbox. Neuroinformatics. 2013 Jul 1;11(3):319-37</li> </ul>	J, Phillips 7.
	<ul> <li>Oosterhof, N.N., Connolly, A.C. and Haxby, J.V., 2016. CoSMoMVP, modal multivariate pattern analysis of neuroimaging data in Mathe Octave. Frontiers in neuroinformatics, 10, p.27.</li> </ul>	<mark>A</mark> : multi- ab/GNU
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### **PRoNTo Software**

#### **Relevant Publications**



#### **PRoNTo Software:**

• Schrouff J, Rosa MJ, Rondina JM, Marquand AF, Chu C, Ashburner J, Phillips C, Richiardi J, Mourão-Miranda J. **PRoNTo**: pattern recognition for neuroimaging toolbox. **Neuroinformatics**. 2013 Jul 1;11(3):319-37.

#### Dataset:

• **Haxby JV**, Gobbini MI, Furey ML, Ishai A, Schouten JL, Pietrini P. Distributed and overlapping representations of faces and objects in ventral temporal cortex. **Science**. 2001 Sep 28;293(5539):2425-30.

Chia-Feng Lu http://v	/www.ym.edu.tw/~cflu	21	Chia-Feng Lu http://www.ym.edu.tw/~cflu 22
<ul> <li>PRONTO Software Include PRONTO_v2.1.1 path and key in pronto</li> <li>PRONTO (Pattern Recognition for Neuroimaging Toolbox)</li> <li>Brain scans are treated as spatial patterns and statistical learning models are used to identify statistical properties of the data that can be used to discriminate batween experimental conditions</li> </ul>	in MATLAB command window	or Neuroimaging bbox Review options Review kernel & CV Display results	• Haxby_dataset •       •       Specified SPM.mat for imaging parameters and block/condition onset setup.         • Haxby_dataset •       •       Specified SPM.mat for imaging parameters and block/condition onset setup.         • Haxby_dataset •       •       Preprocessed fMRI data without spatial smoothing.         • Mak images to identify the region of interests (ROIs).       Preprocessed fMRI.         • Mak images to identify the region of interests (ROIs).       Preprocessed fMRI.         • Image: *:       •       •         • Image: *:       •       •         • Maxima image: *:       •       •         • Image: *:       •       •         • Image: *:       •       •       •         • Image: *:       •       •       •         • Image: *:       •       •       •       •         • Image: *:       •
or groups of subjects (classification models) or to predict a continuous measure (regression models).	Run model Compute weights	Display weights Batch Credits	<ul> <li>c. Cats: 35 142 248 412 576 683 818 925 1003 1110 1216 1423</li> <li>d. Shoes: 49 156 320 369 562 654 775 896 1046 1181 1273 1409</li> <li>e. Bottles: 92 199 305 455 519 697 832 910 1060 1195 1259 1337</li> <li>f. Chairs: 106 170 291 398 547 668 747 939 989 1167 1245 1366</li> <li>g. Scissors: 6 184 277 469 505 711 761 882 1074 1152 1316 1437</li> </ul>
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25

#### Step 2-1: Data & Design



#### **Step 2-2: HRF Corrections**





26

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The HRF delay: time it takes for the hemodynamic response to peak after the stimulus, which will shift the onsets in time. The HRF overlap: the dispersion of the HRF.

### Step 3: Prepare feature set

Build kernel / data ma			Done		
Build kernel / data ma		Atlas definir	g regions of interest (ROIs)		1
One kernel per modality (for MKL)		Build one kerne	el per region		
	*	vy_dataset\Haxby_d	lataset/masksi/usiform_gyrus.	ing, f	Mask of
		Features			
Selected modalities MRI	•	Scaling	No scaling	•	
Number of modalities to concatenate/combine	1	Order		1	
Modalities		Detrend	Polynomial		for fMRI
FS		Parameters	Detromial	_	
		Conditions	All conditions	•	
H:\Haxby_dataset\Haxby_dataset\Results	PRT.mat	Modality	MRI	•	





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31

#### **Step 4: Review results**



#### **Step 4: Review results**



Total accuracy:	91.67 %
Balanced accuracy (BA):	91.67 %
BA p-value:	0.0099
Class accuracy (CA):	100.00 % 83.33 %
CA p-value:	0.0099 0.0198
Class predictive value:	85.71 % 100.00 %

#### **Step 5: Compute weights**

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#### **Step 6: Review weights**



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30





## THE END

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33