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Designing graphs and graph-kernels to characterize cortical representations measured with functional MRI

MLNI workshop, November 9 2011

http://mlni2011.sciencesconf.org/

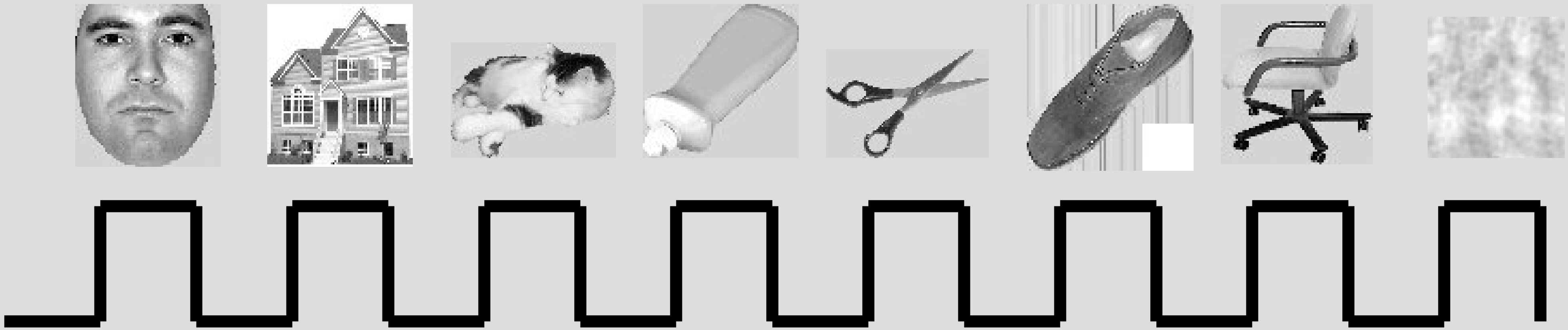
Outline

1. Introduction: the “fMRI decoding” framework
2. Graphs and graph-kernels for “fMRI decoding”
3. Graph kernel on the image grid
4. Graph kernel on parcels-based graphs
5. Perspectives

The fMRI “decoding” framework

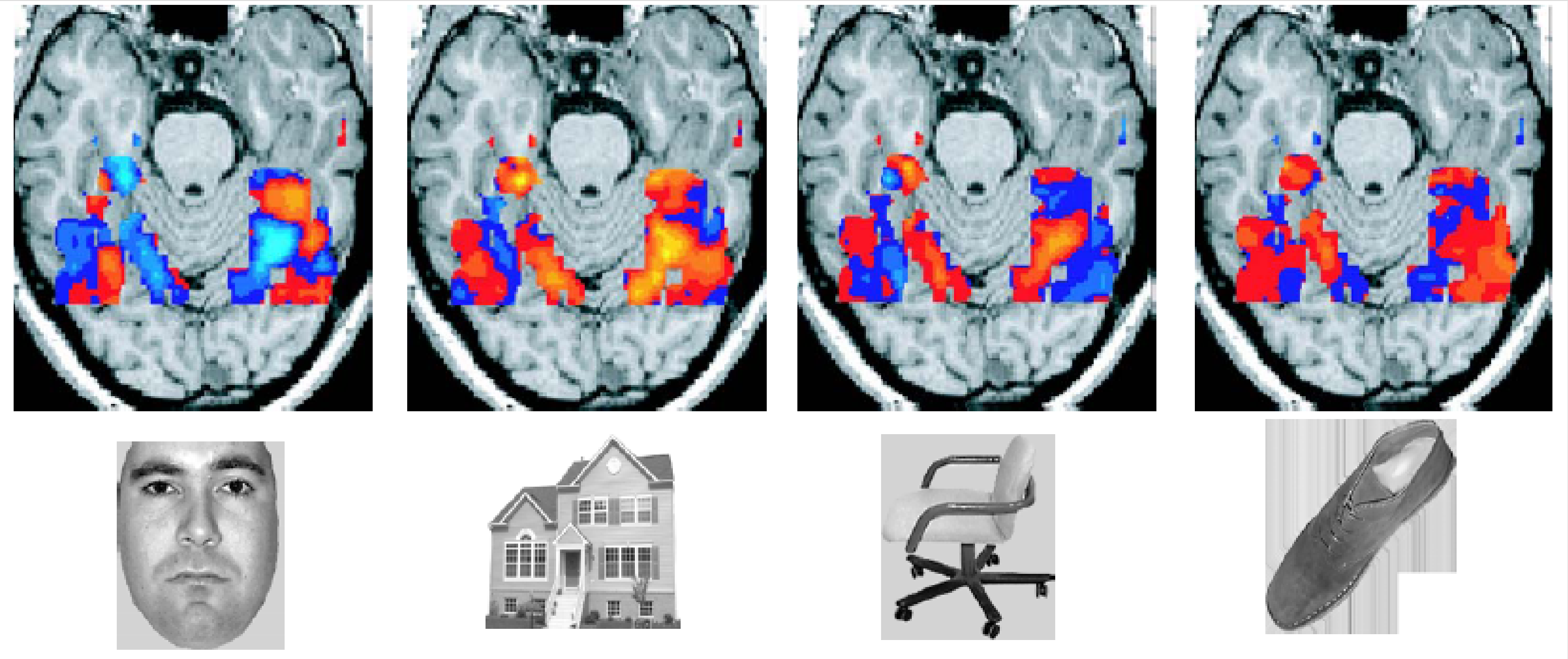
An example...

Haxby, J. V., Gobbini, M. I., Furey, M. L., Ishai, A., Schouten, J. L., & Pietrini, P. (2001). Distributed and overlapping representations of faces and objects in ventral temporal cortex. Science, 293(5539).

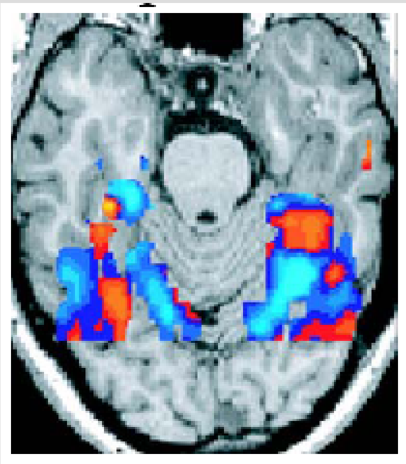


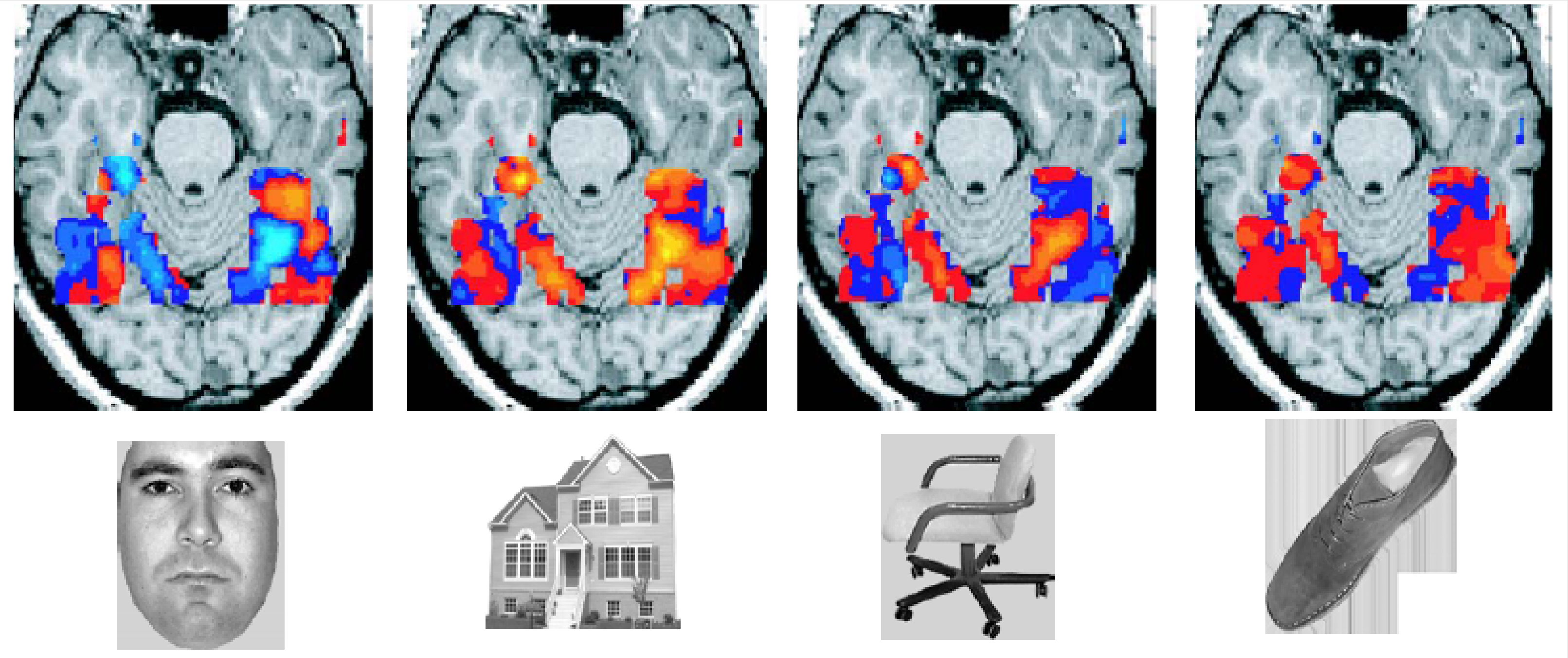
task: 1-back repetition detection task within each block

The fMRI “decoding” framework



The fMRI “decoding” framework





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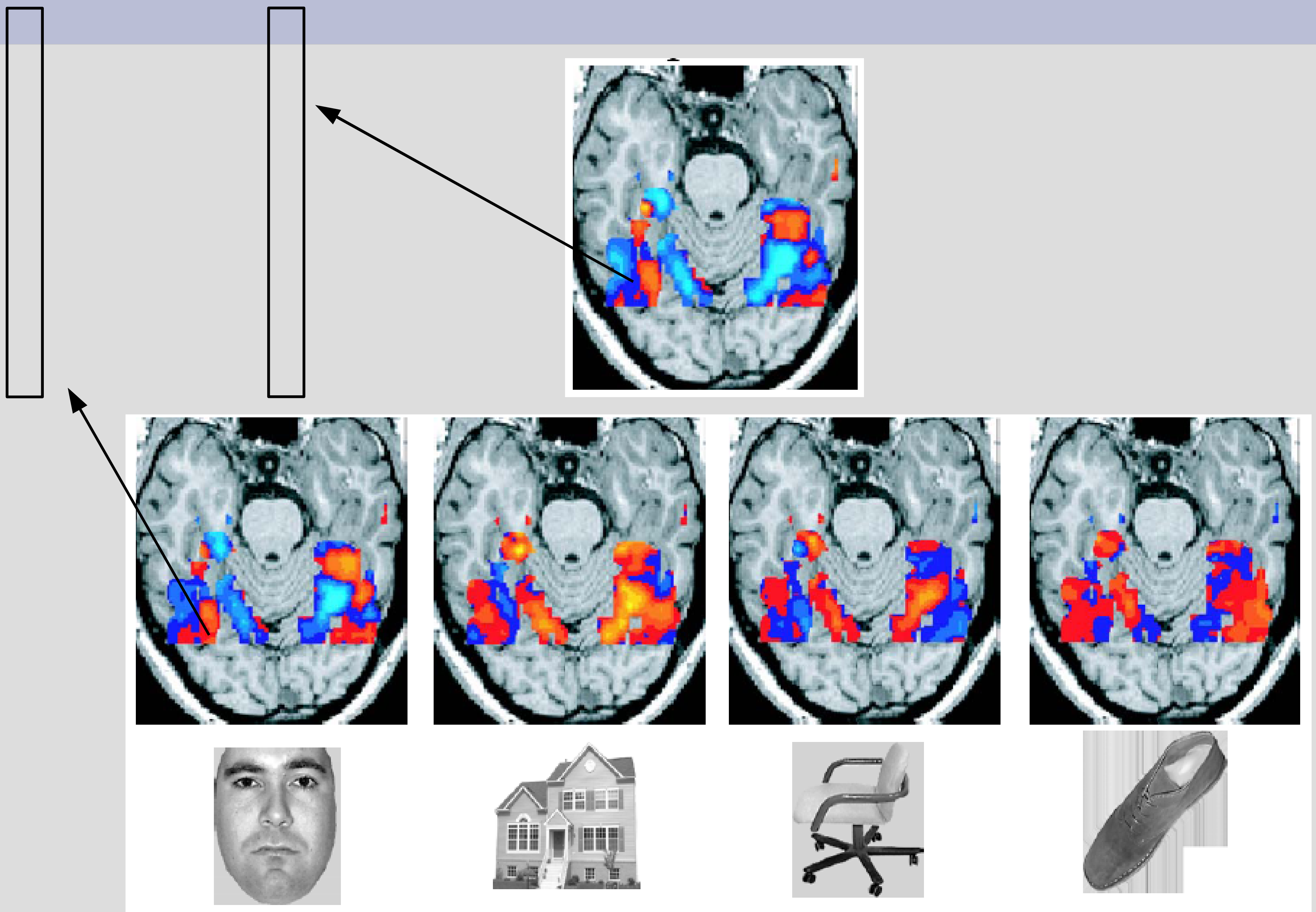

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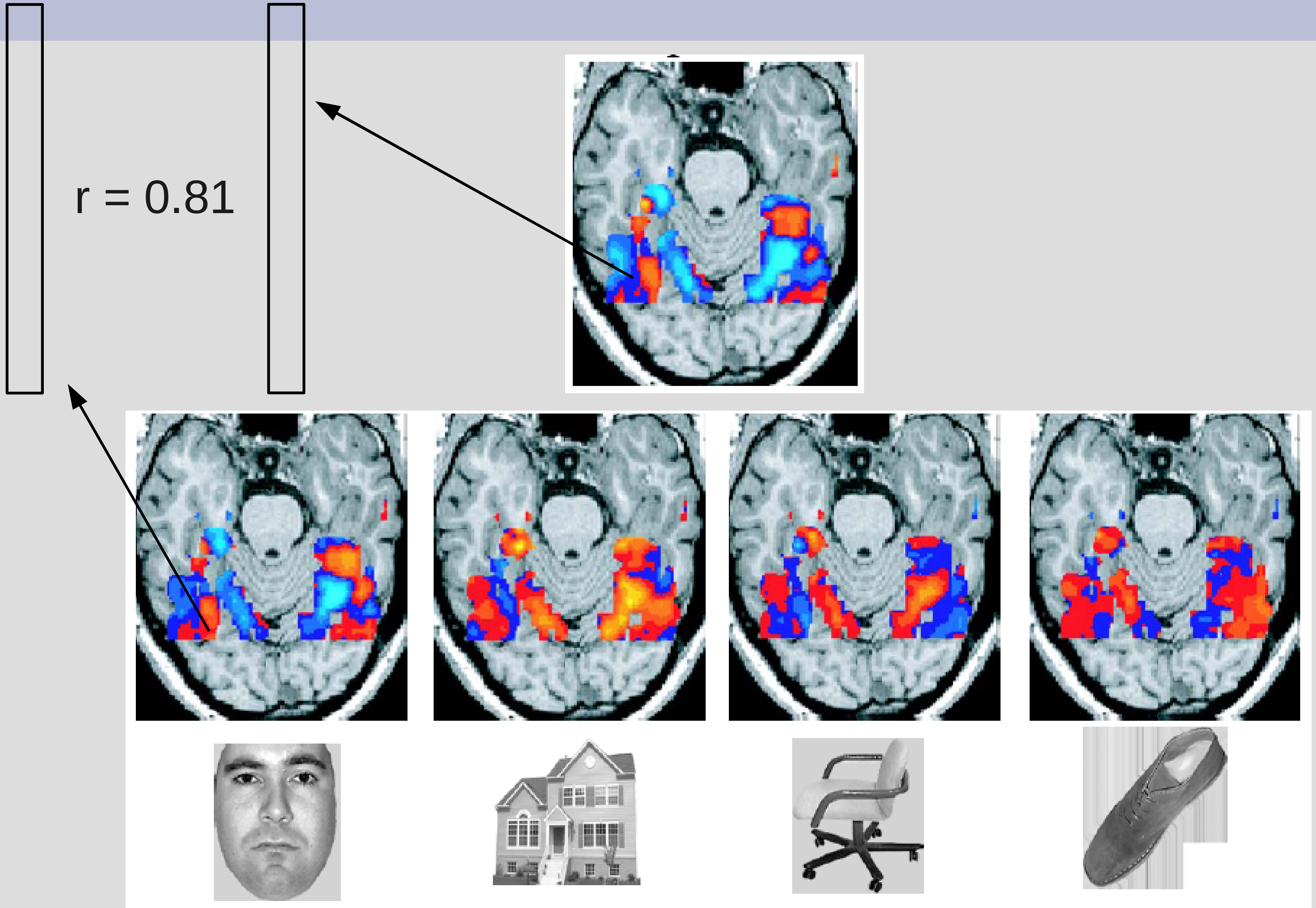

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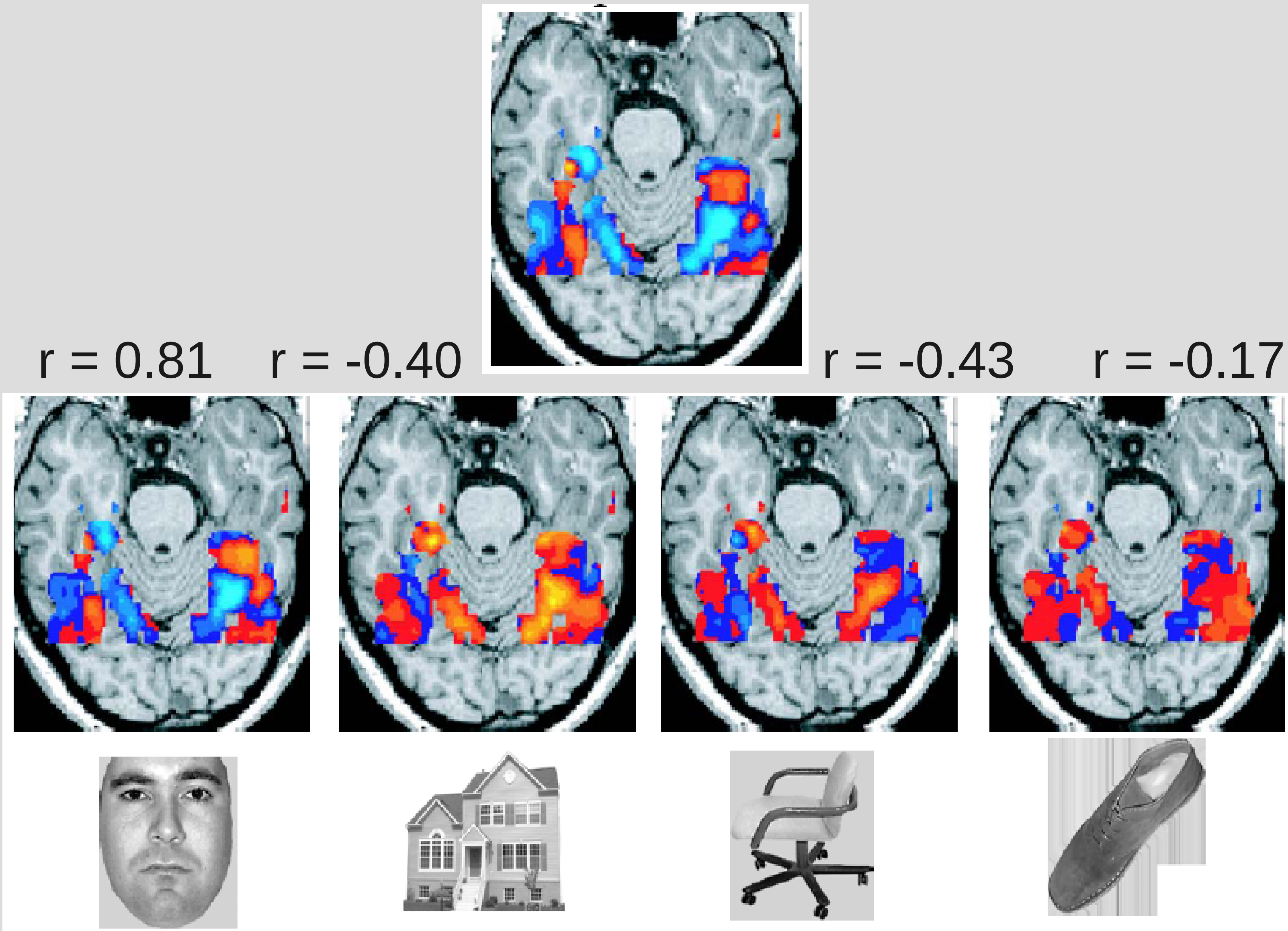


The fMRI “decoding” framework

in the neuroimaging litterature, it's called...

- fMRI decoding

- brain-reading

- multi-voxel pattern analysis (MVPA)

The fMRI “decoding” framework

some pitfalls:

The fMRI “decoding” framework

some pitfalls:

- no use of the spatial structure
(lost in the vectorization)

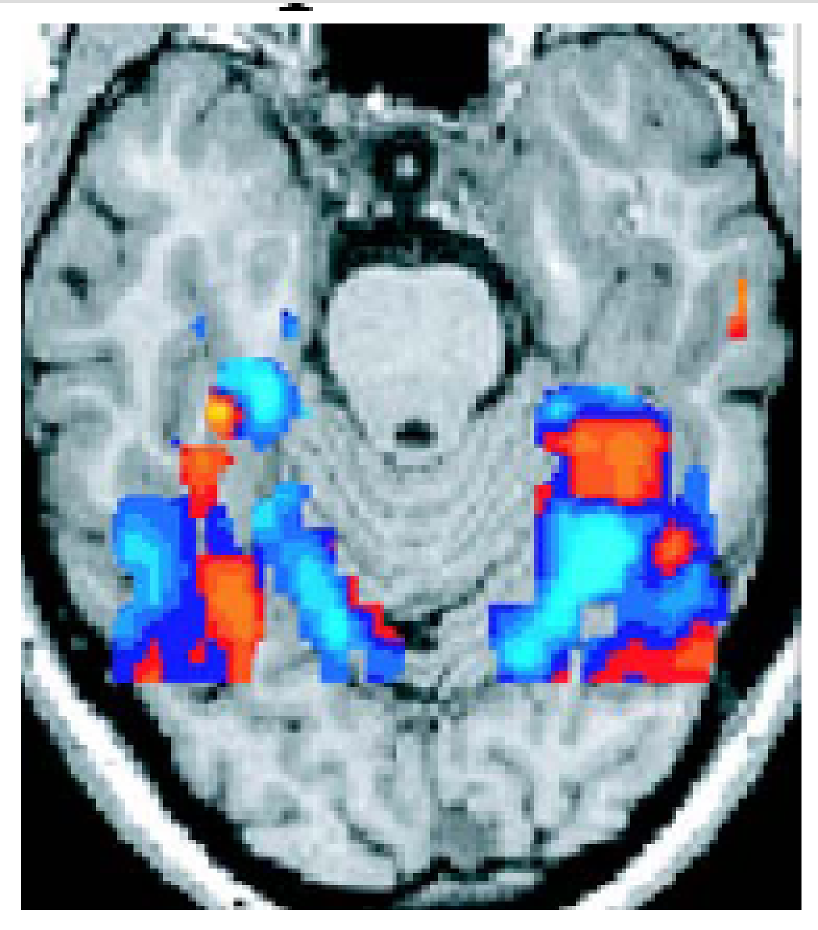
The fMRI “decoding” framework

some pitfalls:

- no use of the spatial structure
(lost in the vectorization)

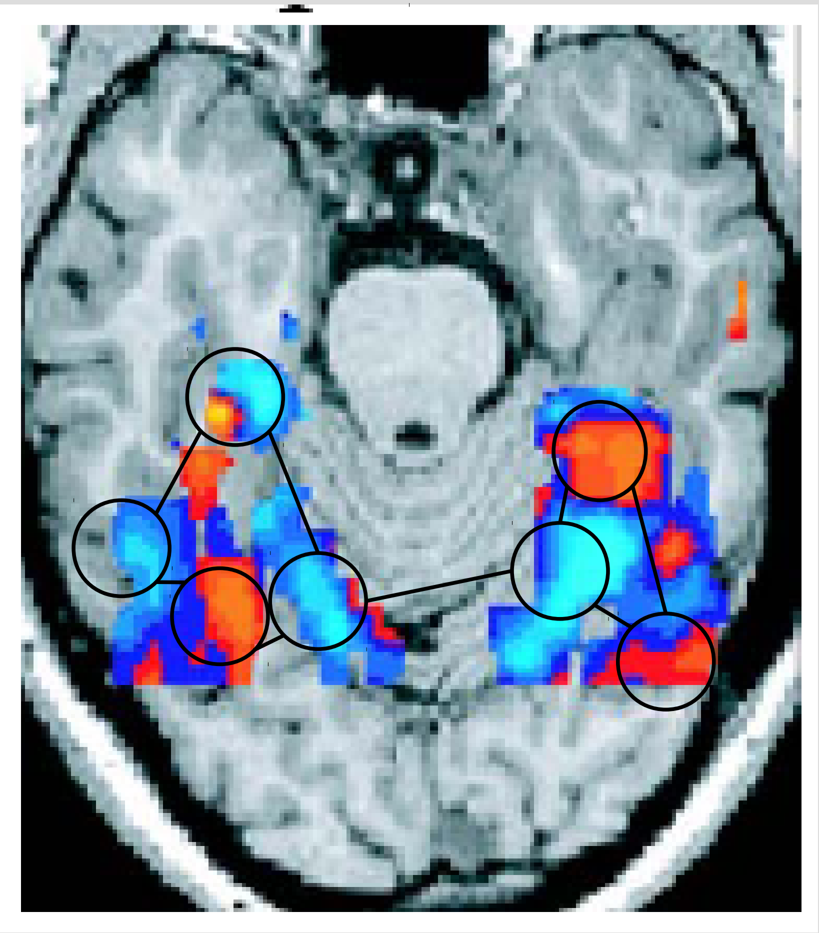
- difficult to use to understand brain functions...

Using the spatial structure...



Using the spatial structure...

spatial graphical model:



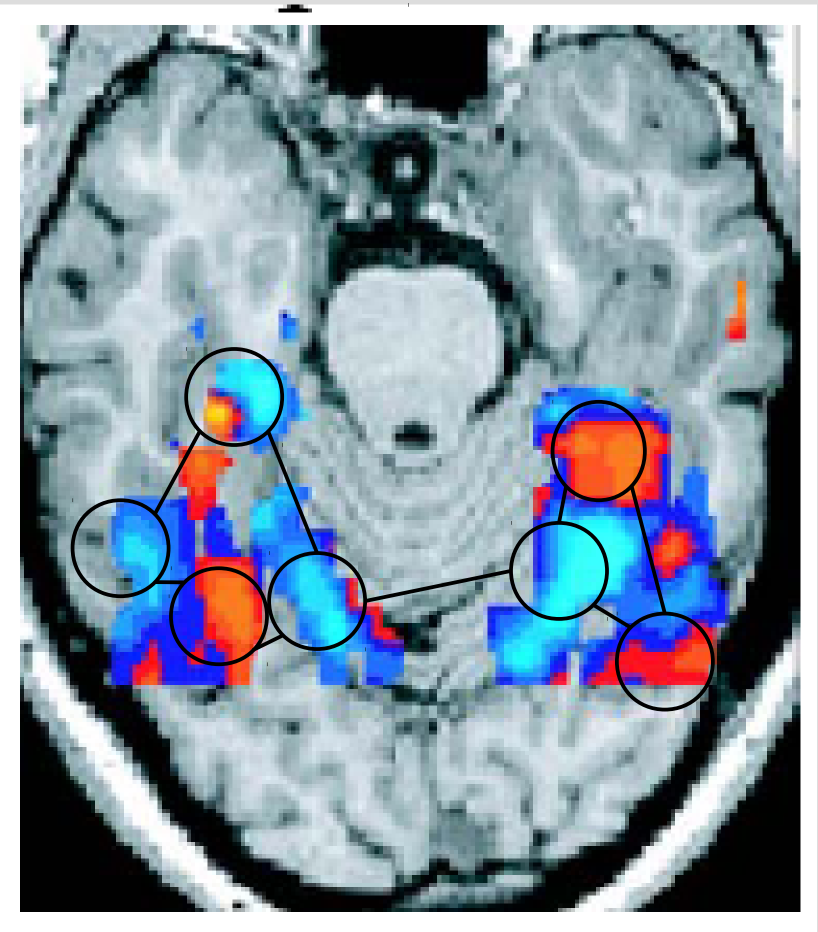
Using the spatial structure...

spatial graphical model:

- a list of nodes

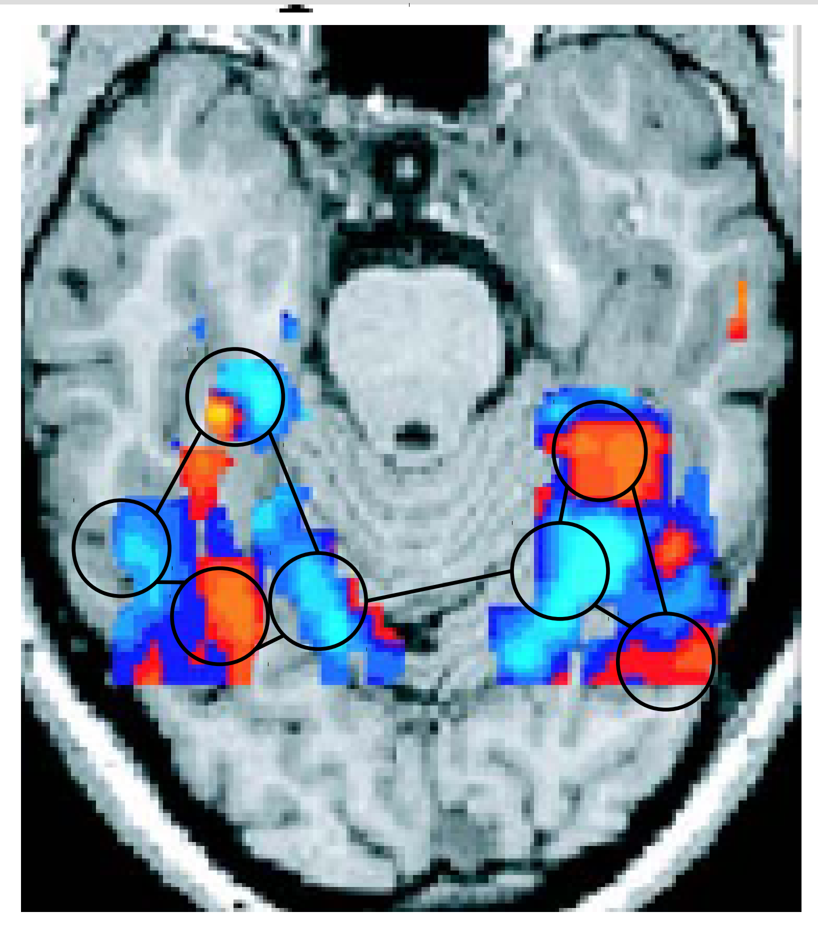
- $A = (a_{ij})$, adjacency matrix

- $V = (v_i)$, attribute(s) of the nodes



Using the spatial structure...

questions:



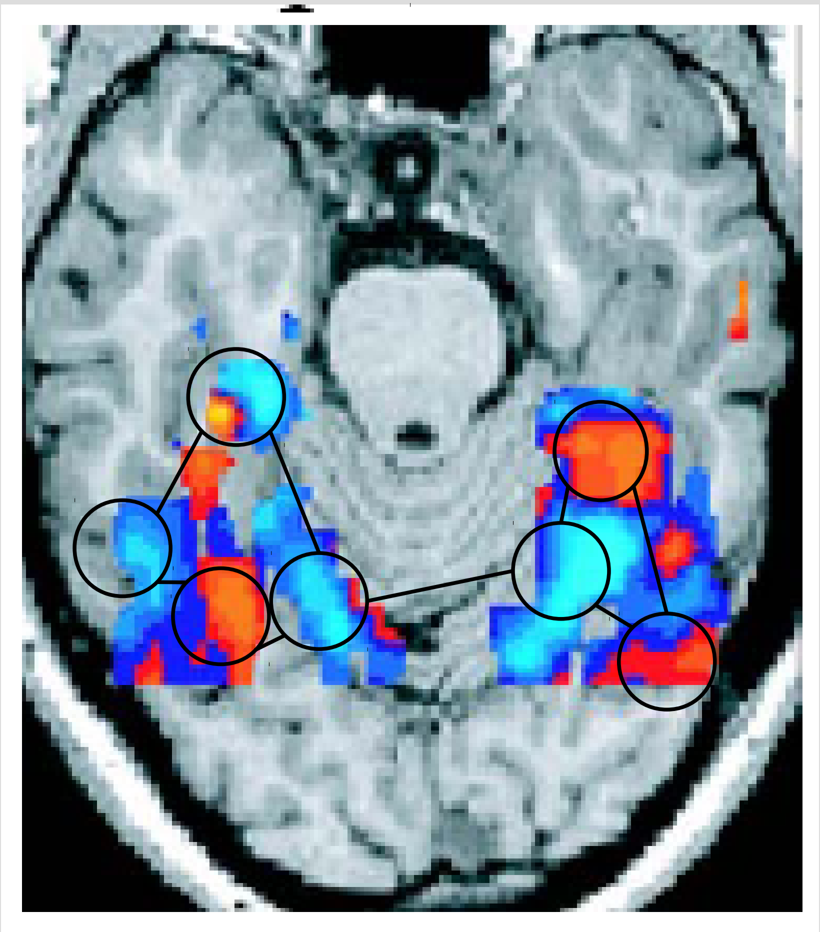
Using the spatial structure...

questions:

- which graphical model?

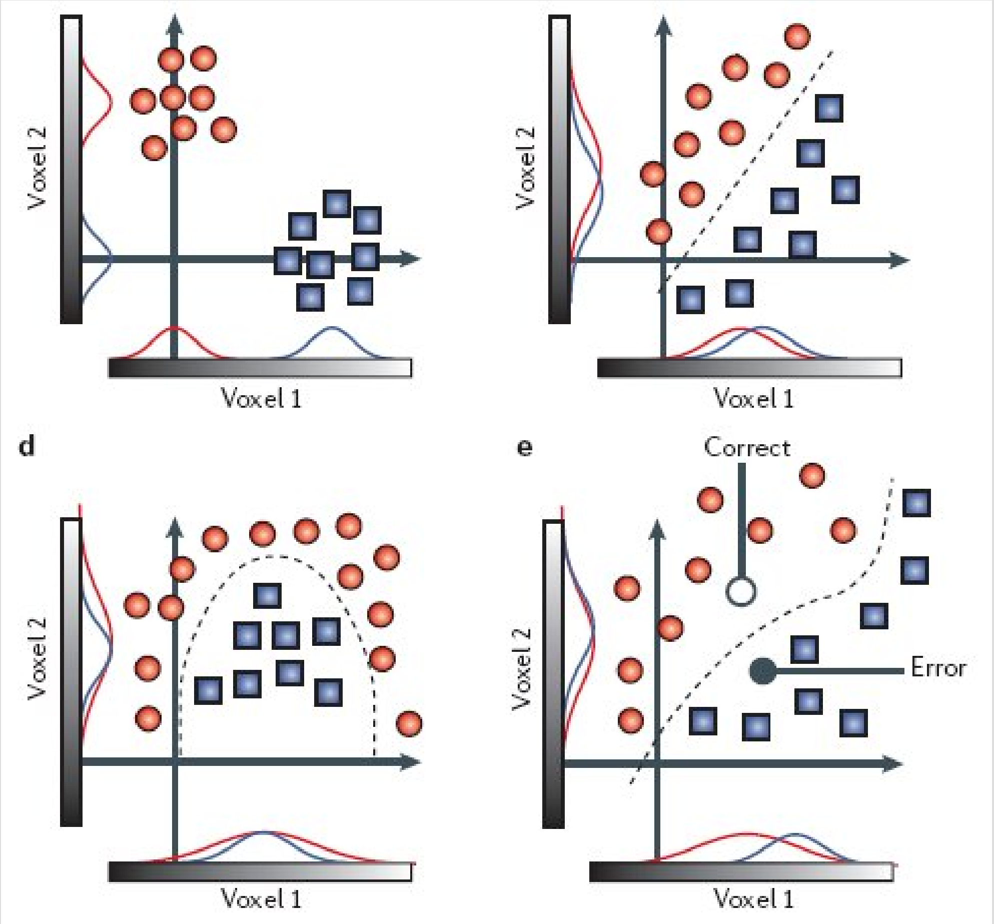
- which similarity measure between graphs?

- which analysis tools?



Using the spatial structure...

Support Vector Machines (SVM)

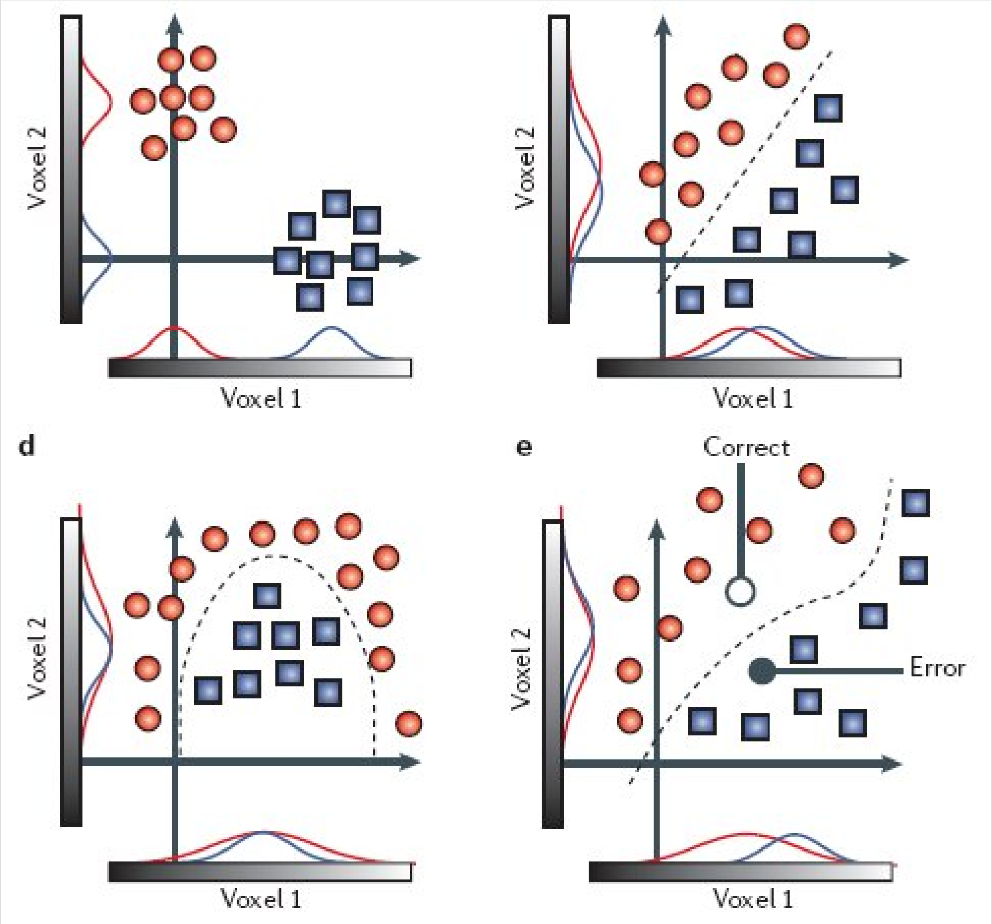


Using the spatial structure...

Support Vector Machines (SVM)

The kernel trick

$$K(X_1,X_2) = <\phi(X_1),\phi(X_2)>$$



Using the spatial structure...

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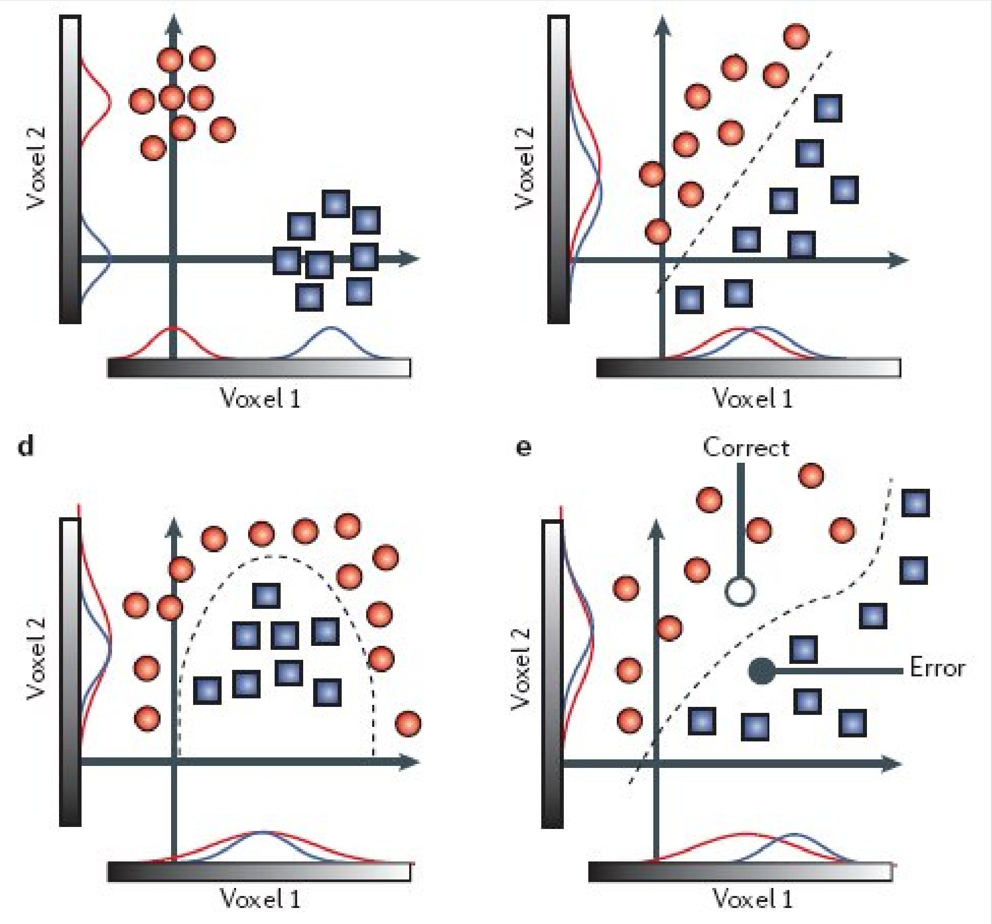
Graph kernels

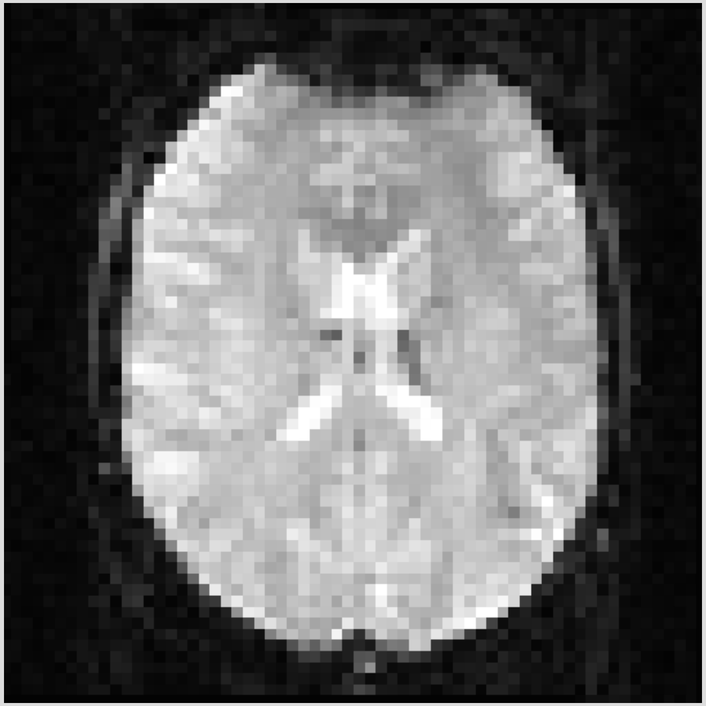


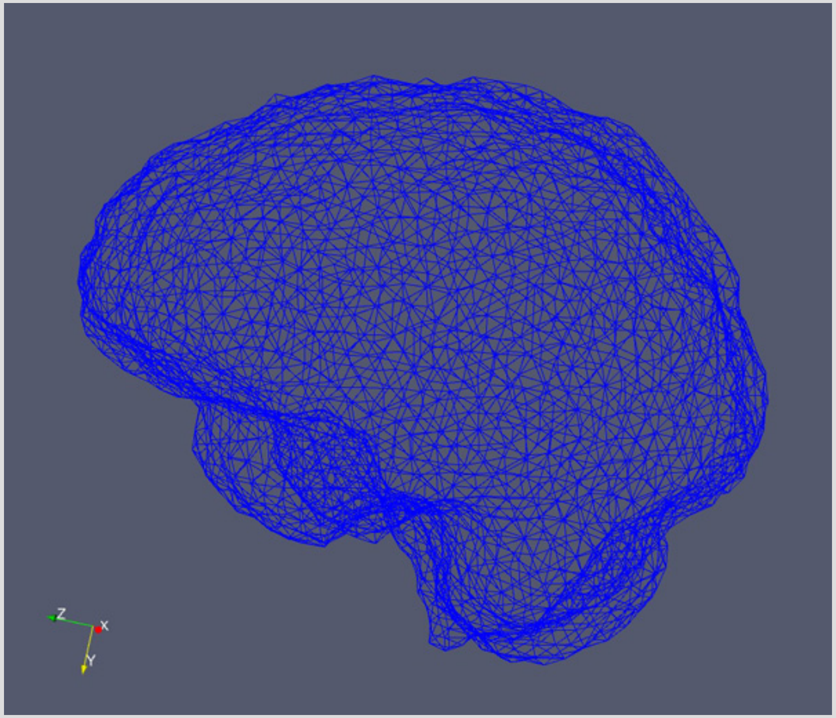
Using the spatial structure #1

Using the spatial structure #1

fMRI data lives on an intrinsically structured space:

the 3D image grid or the 2D cortical mesh





Using the spatial structure #1

Graph *G* construction:

- nodes = the voxels / the vertices of the mesh

- A = (a_{ij})= 1 if nodes *i* and *j* are neighbors

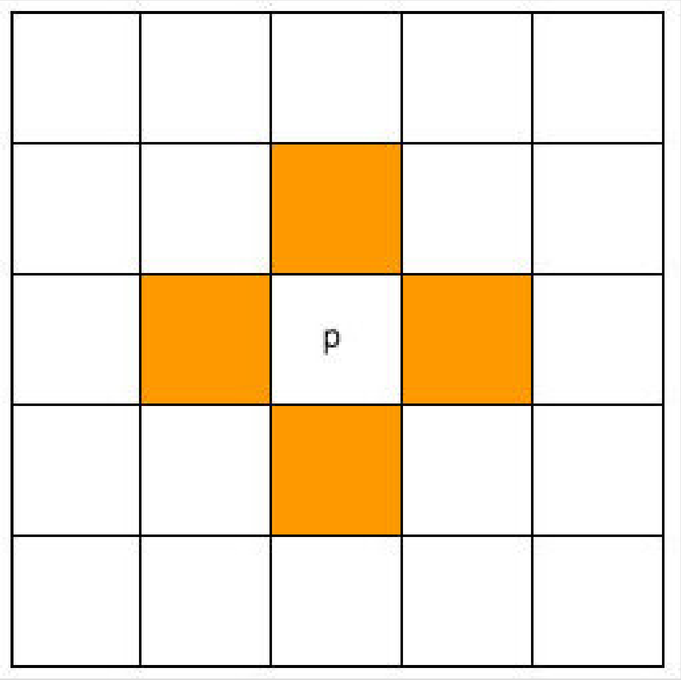
- V = (v_i) = fMRI “activation” value

(within a ROI: fixed A)

Using the spatial structure #1

Graph - kernel:

$$K(G_1,G_2) = V_1^T \,.\, (I + \lambda\, V_1 \,.A\, .V_2^T).\, V_2$$



Using the spatial structure #1

Results of within subject classification (leave-one-session-out cross-validation) for different experiments, within a ROI

Using the spatial structure #1

Experiment	Subject	ROI	Classes	Linear	RBF	Polynomial	Graph kernel
#1	#1	#1	3	0.644	0.644	0.65	**0.661**
#1	#1	#2	3	0.8	0.778	0.8	**0.805**
#1	#1	#3	3	0.65	0.65	0.65	**0.678**
#2	#1	#1	8	0.617	0.61	0.626	**0.629**
#3	#1	#1	4	**0.778**	0.764	**0.778**	0.75
#3	#2	#1	4	0.597	0.597	0.611	**0.653**
#3	#3	#1	4	**0.847**	0.833	**0.847**	0.819
#3	#4	#1	4	**0.889**	0.875	**0.889**	0.833
#3	#5	#1	4	**0.681**	0.653	**0.681**	0.569
#3	#6	#1	4	0.889	**0.931**	0.917	0.917
#3	#7	#1	4	0.667	**0.681**	0.667	0.625
#3	#8	#1	4	0.806	**0.833**	0.806	0.819
#3	#9	#1	4	**0.528**	0.514	**0.528**	**0.528**
#3	#10	#1	4	**0.972**	0.958	**0.972**	0.944

Table 1: Maximum performance of each kernel (across all values of the kernel parameters and the SVM regularization constant)

$C \in \{10^{-2}, 10^{-1}, 1, 10^{1}, 10^{2}\}$

$n \in \{2,3,4,5\}$

$\sigma \in \{10^{-2}, 10^{-1}, 1, 10^{1}, 10^{2}\}$

$\lambda \in \{0.01, 0.1, 0.25, 0.75, 1\}$

Using the spatial structure #1

conclusions:

- we designed a new kernel that uses the intrinsic structure of (neuro)imaging data

- we demonstrated good performances

- but...?

Using the spatial structure #2

Using the spatial structure #2

- do we have any knowledge about the spatial structure of the activation pattern?

Using the spatial structure #2

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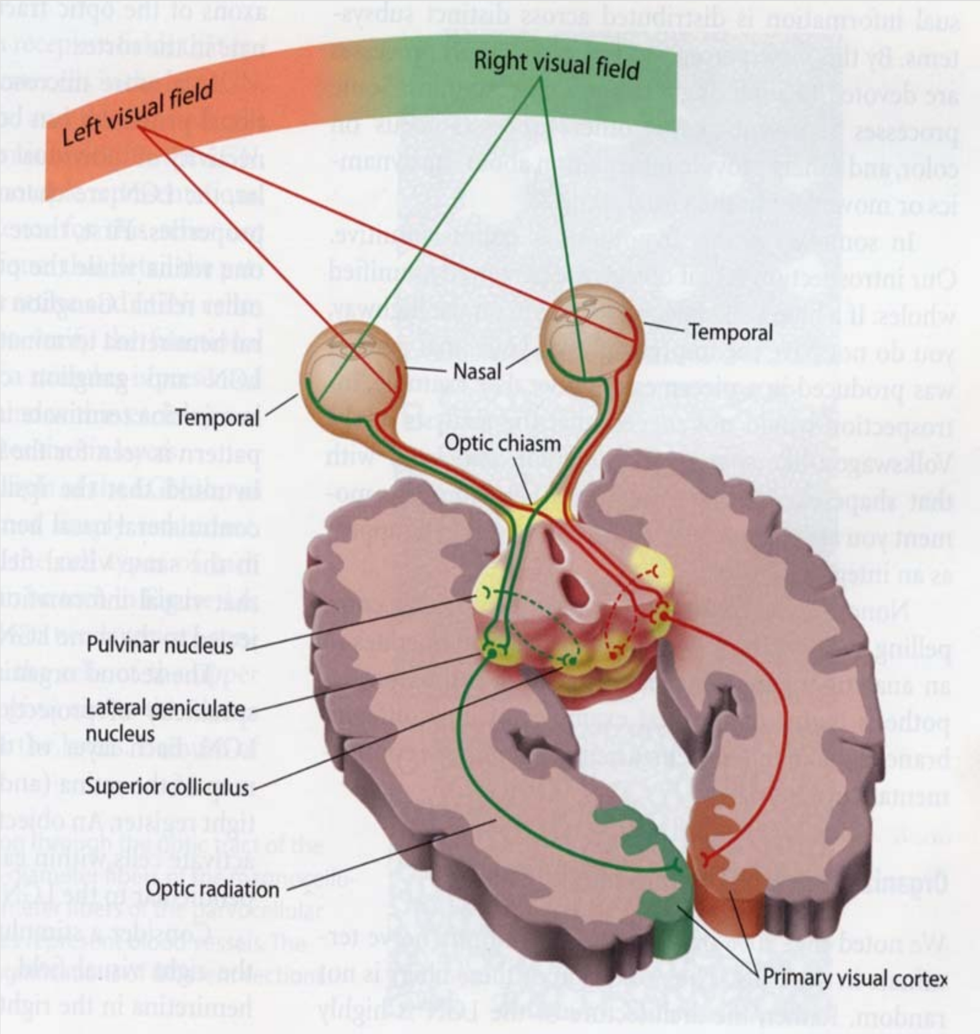
- in some cases: yes!

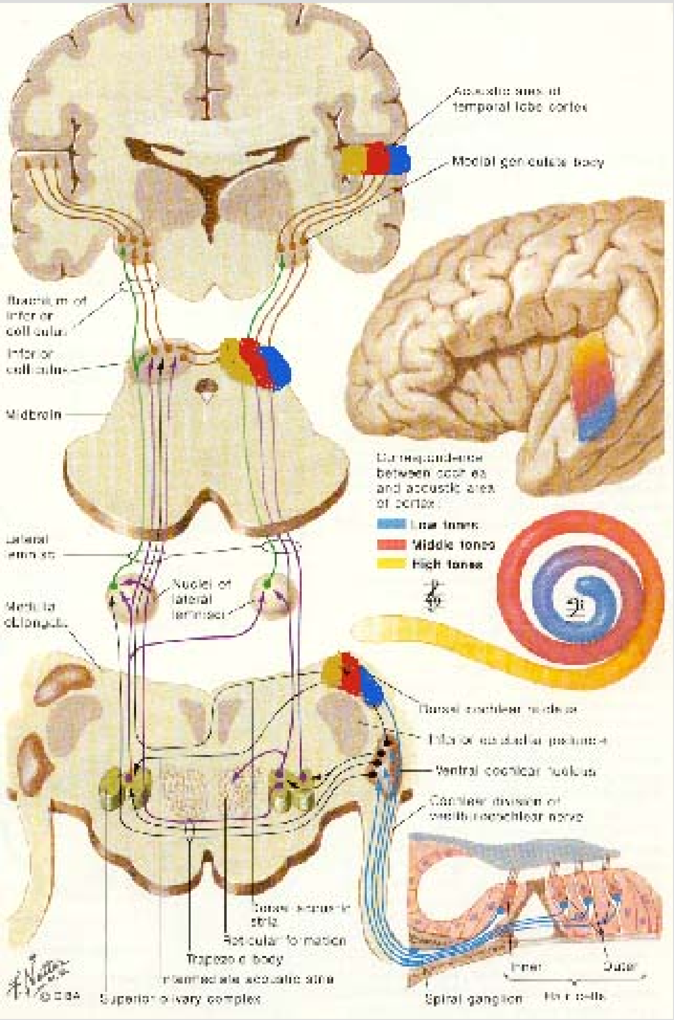
Using the spatial structure #2

retinotopy in the visual cortex



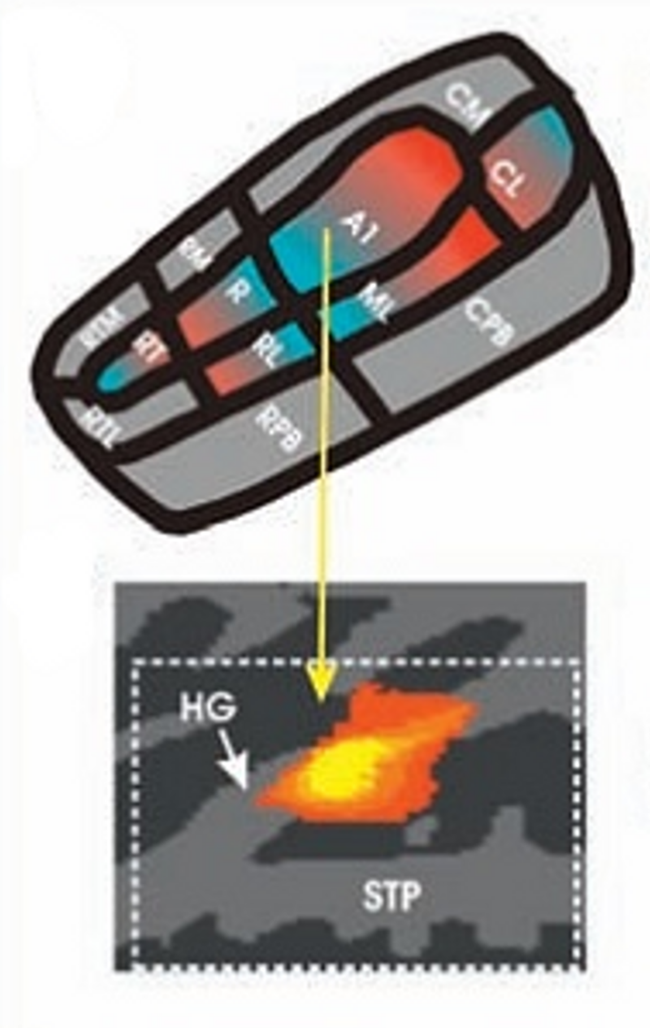
Using the spatial structure #2

tonotopy in the auditory cortex



Using the spatial structure #2

tonotopy in the auditory cortex



Using the spatial structure #2

topies...

the topological properties of the input are carried on in the cortical representations

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the topological properties of the input are carried on
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- a large contiguous input should result in a connected blob
  ...parcels

- the spatial adjacency should be informative
  ...graph

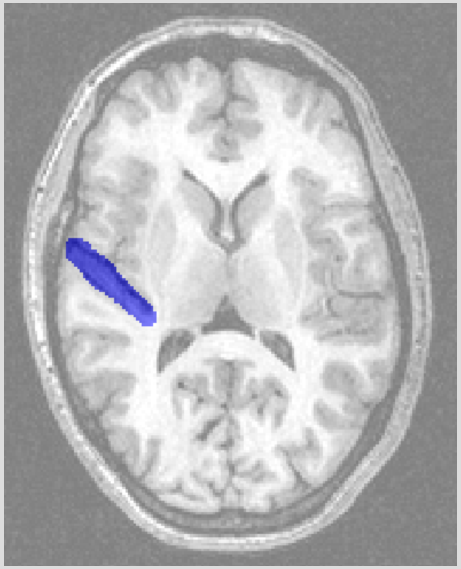
Using the spatial structure #2

Tonotopy fMRI experiment: mapping of the frequency response of auditory stimuli in the primary auditory cortex

Stimuli presented at five different frequencies: 300Hz, 500Hz, 1100Hz, 2200Hz, 4000Hz

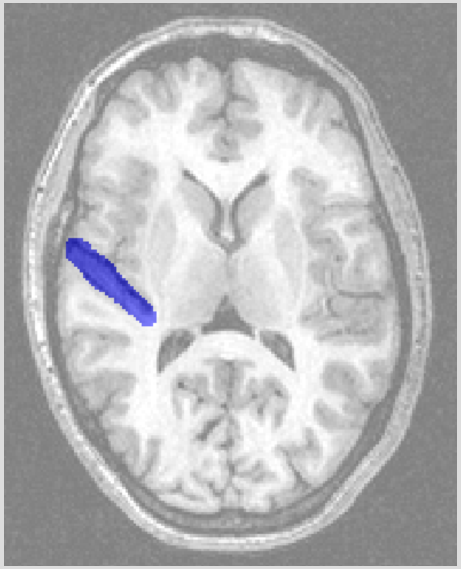
Using the spatial structure #2

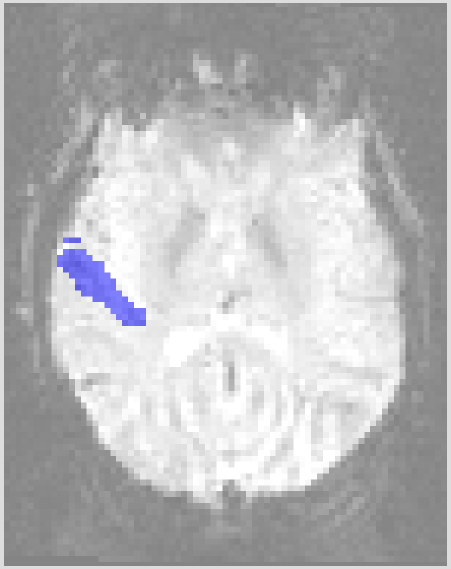
from an anatomical ROI to a parcellation



Using the spatial structure #2

from an anatomical ROI to a parcellation





Using the spatial structure #2

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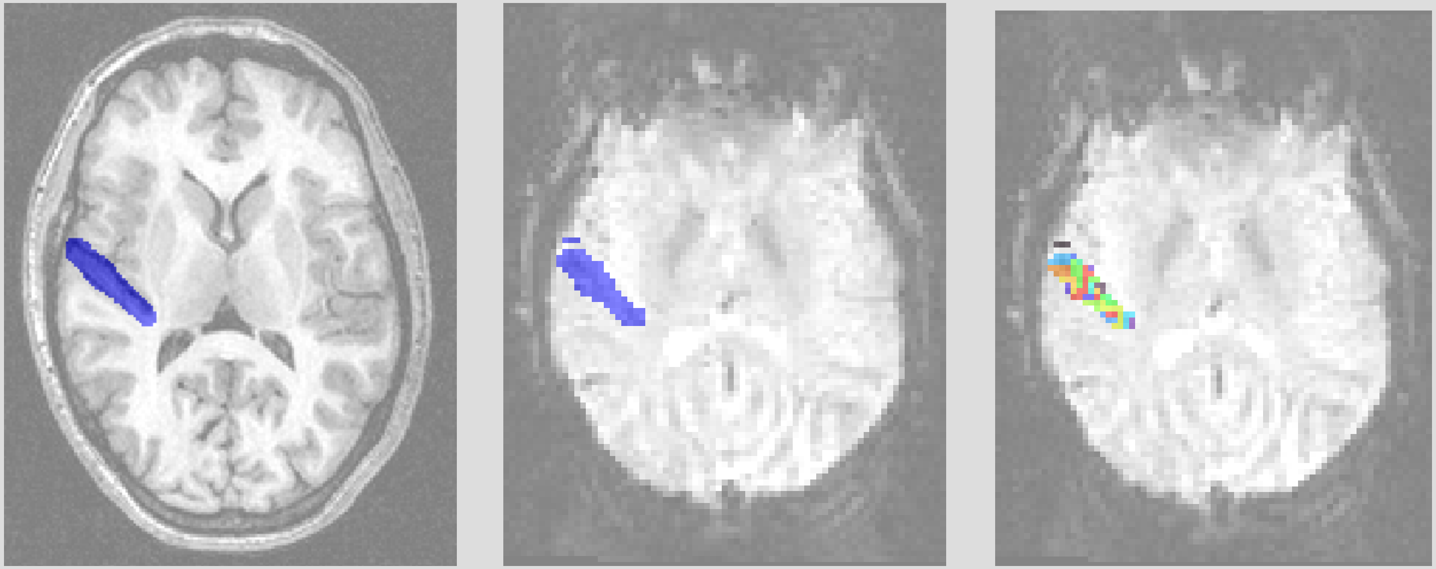
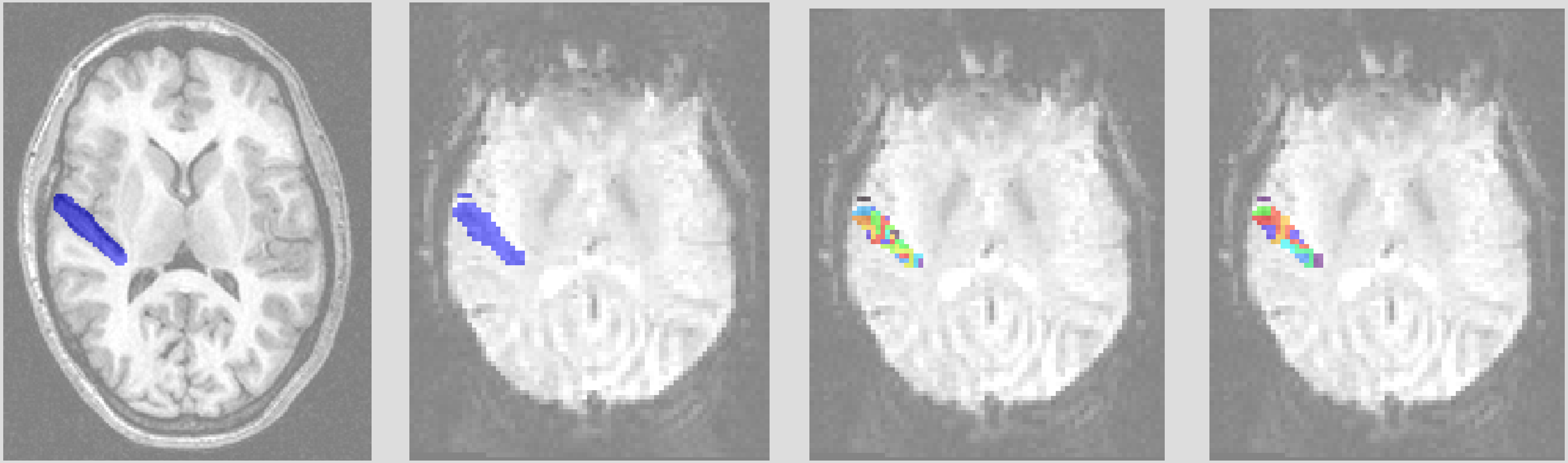


Ward's hierarchical clustering
(feature agglomeration with an added spatial constraint)

Using the spatial structure #2

from an anatomical ROI to a parcellation



Ward's hierarchical clustering
(feature agglomeration with an added spatial constraint)

Using the spatial structure #2

from parcels to a graph

Using the spatial structure #2

from parcels to a graph

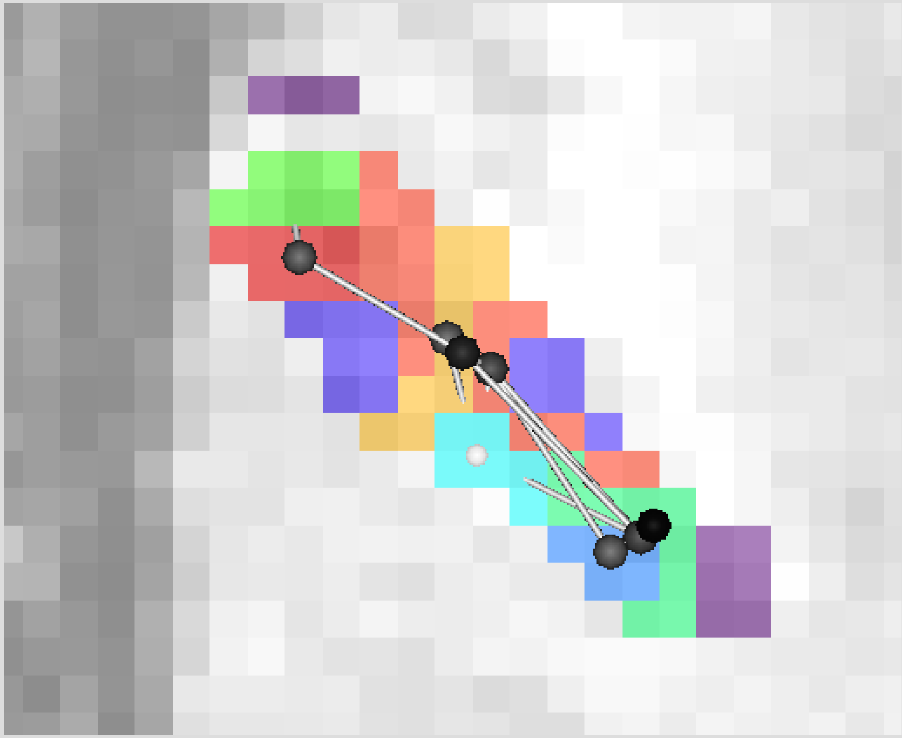
- nodes = parcels

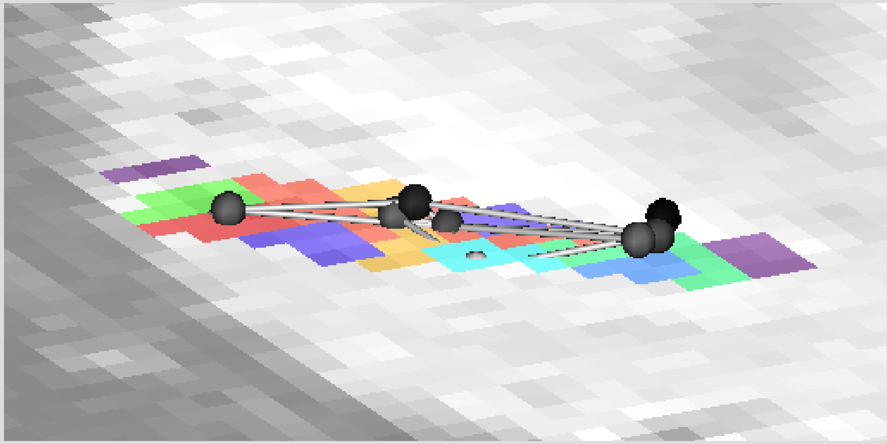
- A = adjacency matrix given by spatial adjacency of parcels (region adjacency graph: RAG)

- X = coordinates of the barycenter of the parcel

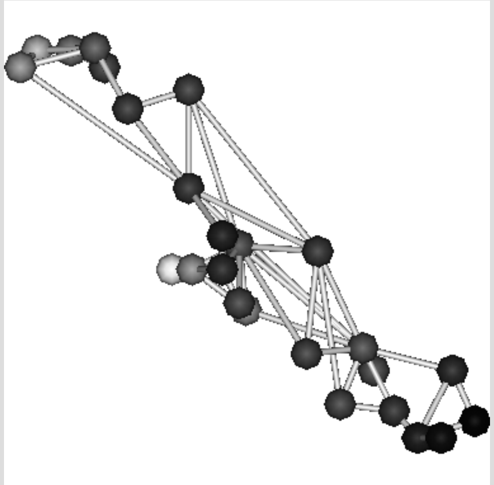
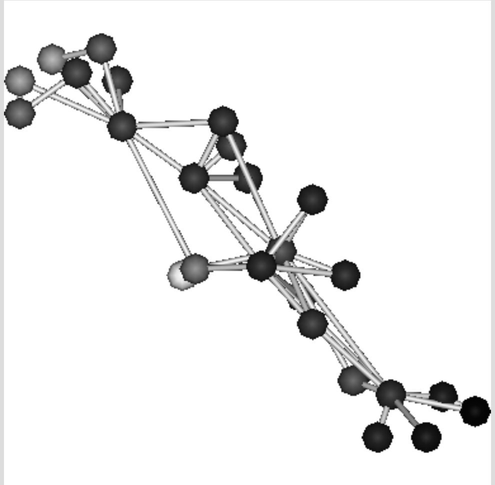
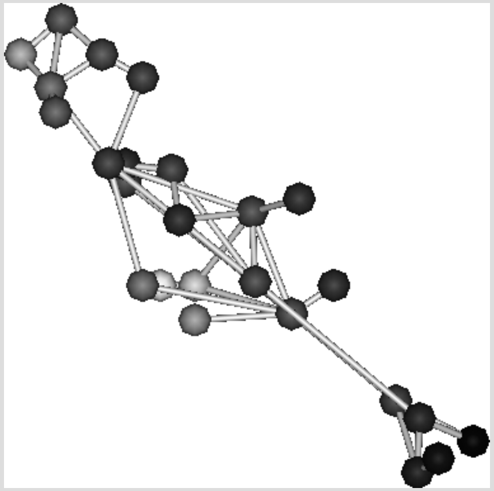
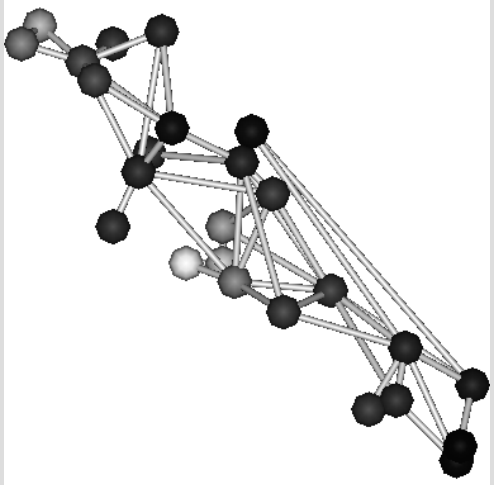
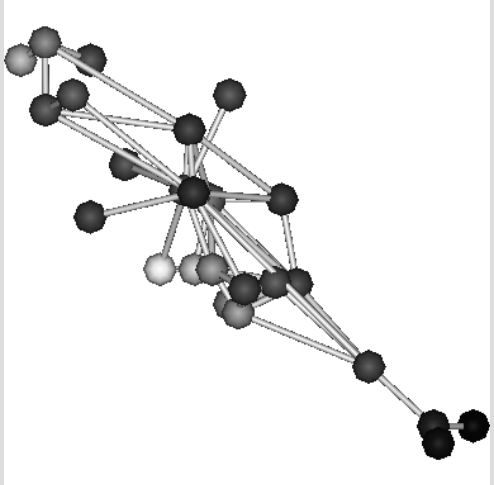
- V = mean “activation value” within the parcel

Using the spatial structure #2





Using the spatial structure #2

Using the spatial structure #2

kernel design:

Using the spatial structure #2

kernel design: the convolution kernels...

$$K(G_1, G_2) = \sum_{g_1 \subset G_1, g_2 \subset G_2} \prod_d k_d(g_1, g_2)$$

D. Haussler. Convolution kernels on discrete structures. UCSC Technical Report, 1999.

T. Gärtner, J. W. Lloyd, P. A. Flach. Kernels and Distances for Structured Data. Machine Learning, 2004.

Using the spatial structure #2

“The advantage of convolution kernels is that they are very general and can be applied in many different situations. However,because of that generality, they require a significant amount of work to adapt them to a specific problem”

Using the spatial structure #2

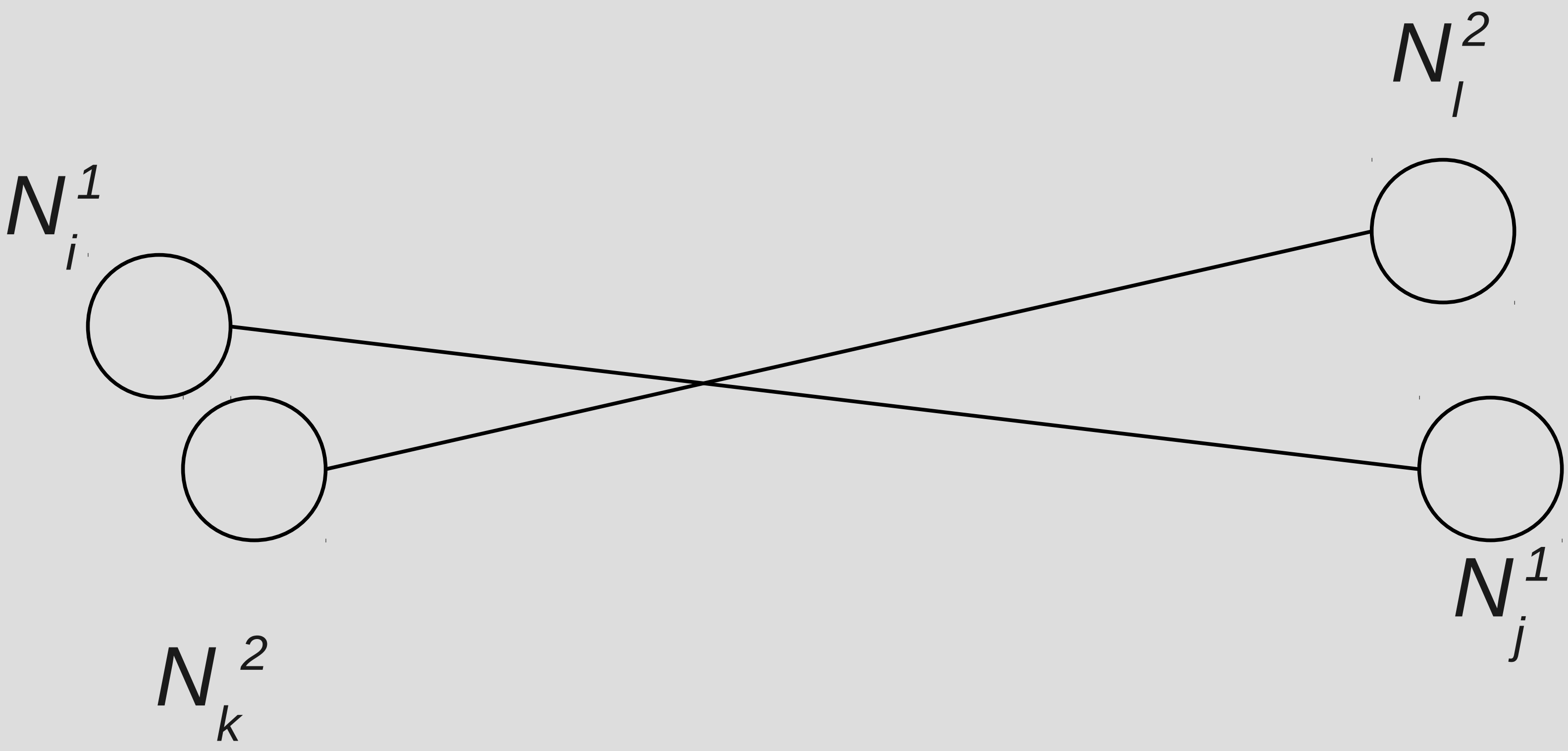
- should use the structure (spatial adjacency coded into the edges of the RAG: A)

- should take into account the anatomical information (locations of the parcels X)

- should take into account the functional information (“activation” value V)

Using the spatial structure #2

subgraphs: all pairs of nodes



Using the spatial structure #2

$$g_1 = \{N_i^1; N_j^1\} \qquad g_2 = \{N_k^2; N_l^2\}$$

$$k_A(g_1, g_2) = a_{ij}.a_{kl}$$

$$k_X(g_1, g_2) = e^{-\gamma_1 \|X_i - X_k\|^2}.e^{-\gamma_1 \|X_j - X_l\|^2}$$

$$k_V(g_1, g_2) = e^{-\gamma_2 \|V_i - V_k\|^2}.e^{-\gamma_2 \|V_j - V_l\|^2}$$

$$K(G_1, G_2) = \sum_{g_1, g_2} k_A(g_1, g_2).k_X(g_1, g_2).k_V(g_1, g_2)$$

Using the spatial structure #2

Results of within subject classification (leave-one-session-out cross-validation) for the tonotopy experiment

Using the spatial structure #2

Results of within subject classification (leave-one-session out cross-validation) for the tonotopy experiment

	A1L			A1R		
Subject	Linear	RBF	Graph kernel	Linear	RBF	Graph kernel
#1	**0.45**	0.44	0.39	**0.5**	**0.5**	0.4
#2	**0.63**	**0.63**	0.54	0.55	**0.61**	0.53
#3	0.48	0.48	**0.49**	0.48	0.49	**0.5**
#4	**0.34**	0.33	0.31	0.29	**0.31**	0.29
#5	**0.39**	**0.39**	0.34	**0.51**	**0.51**	0.46
#6	**0.55**	**0.55**	0.51	**0.38**	**0.38**	**0.38**
#7	0.35	0.35	**0.36**	0.35	**0.39**	0.35

$C \in \{10^{-2}, 10^{-1}, 1, 10^{1}, 10^{2}\}$

$(\sigma_V, \sigma_X) \in \{10^{-2}, 10^{-1}, 1, 10^{1}, 10^{2}\}^2$

#parcels $\in \{10,15,20,25,30,35,40\}$

Using the spatial structure #2

conclusions:

- we designed a graph kernel working on parcels-based graphs

- this opens several applications...

Using the spatial structure #2

- study cortical representations across subjects

Using the spatial structure #2

- study cortical representations across subjects

- study cortical representations across populations

Using the spatial structure #2

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- compare with data from other modalities

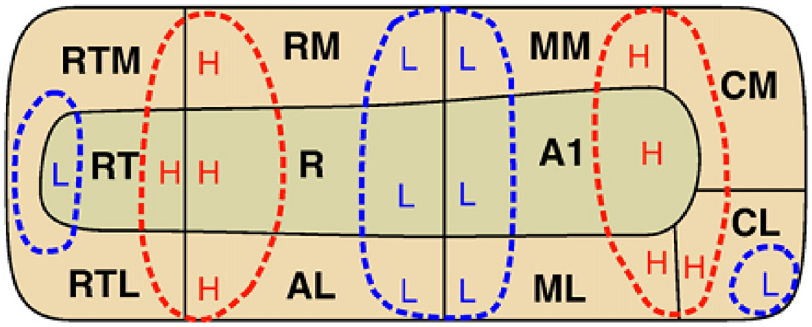


Fig. 1. Functional areas identified in previous studies of non-human primate auditory cortex. Tonotopic gradients are represented by high (H) and low (L) endpoints. Contiguous high areas are marked in red and contiguous low areas in blue.

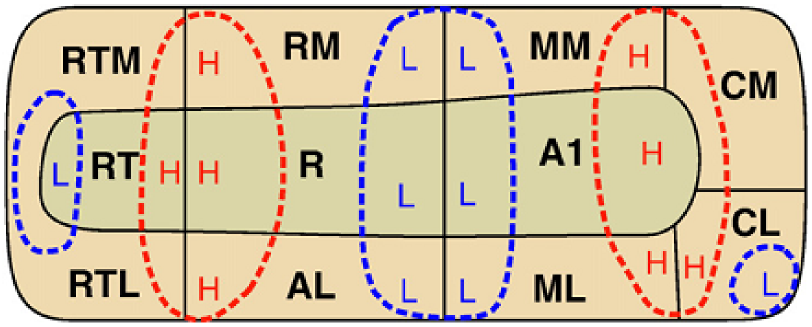
Using the spatial structure #2

- study cortical representations across subjects

- study cortical representations across populations

- compare with data from other modalities

- test generative models



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Thank you!

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Reference:

Graph-based inter-subject classification of local fMRI patterns.
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