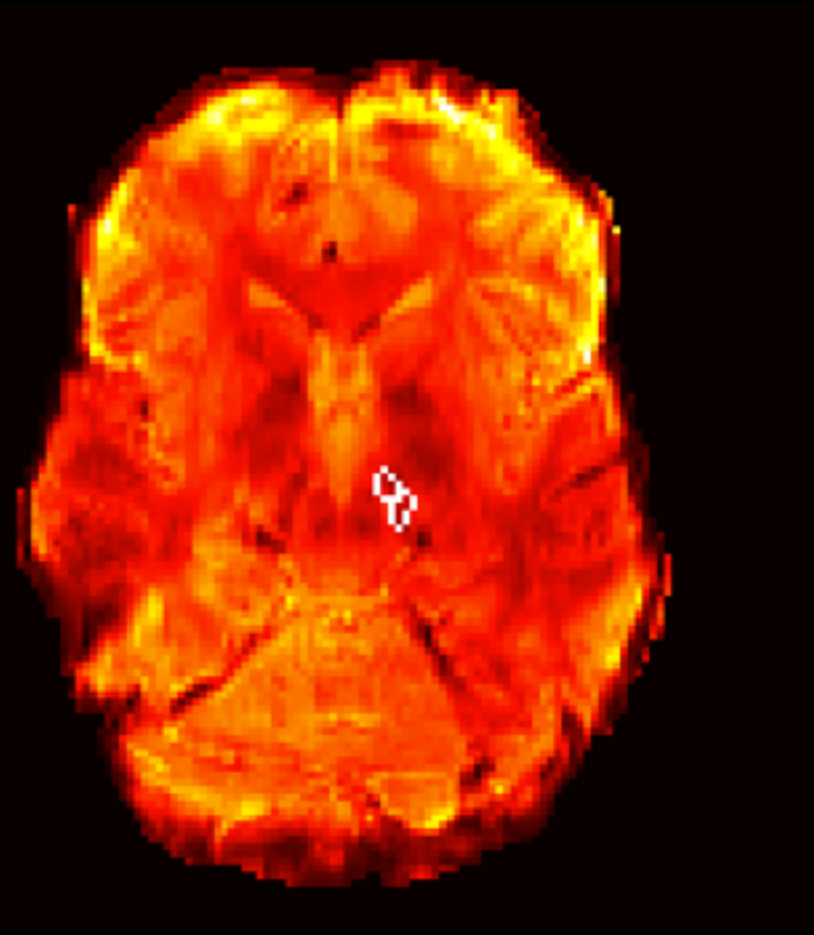


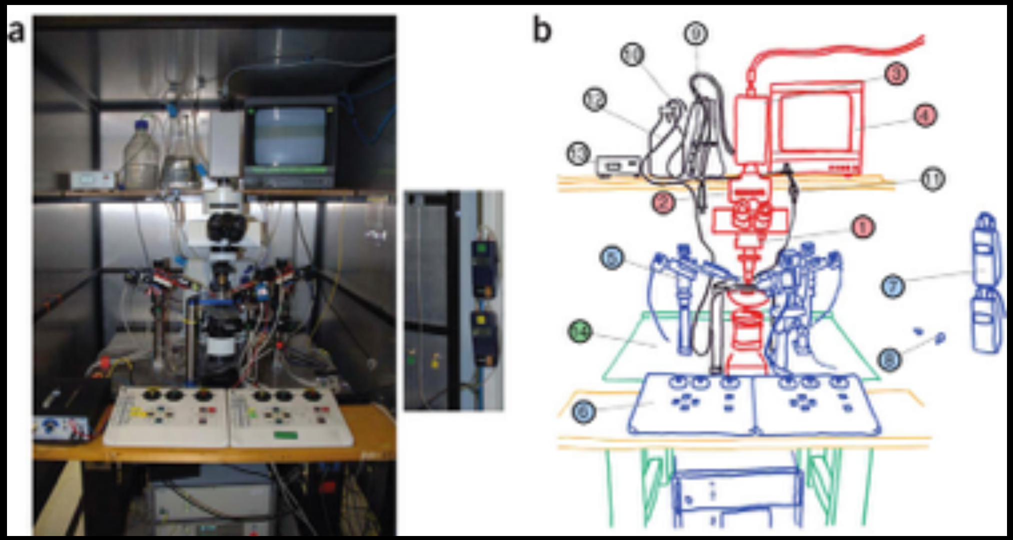
Functional Magnetic Resonance Imaging

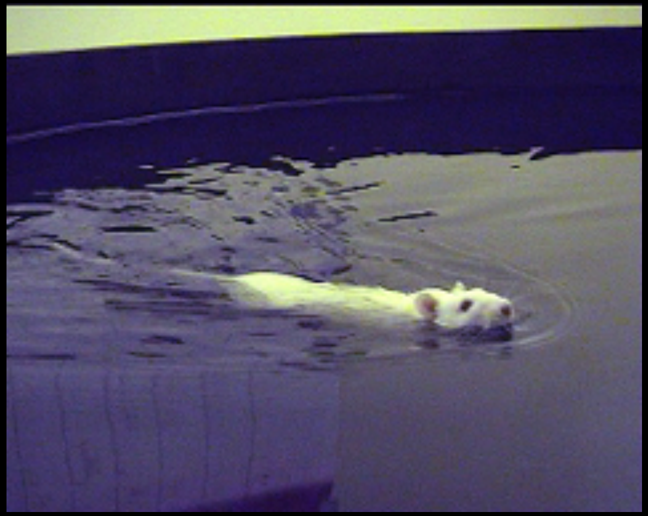
Gilles de Hollander
Model-based Neuroscience Summer School
Amsterdam, 2 june 2015

What can be learned from fMRI?

What can be learned from fMRI?

- You don't even know what you're measuring





What can be learned from fMRI?

- “We” actually know it pretty well.

What can be learned from fMRI?

- “We” actually know it pretty well.
- This is also besides the point: we don’t claim to make a complete model of brain functioning

What do we claim

What do we claim

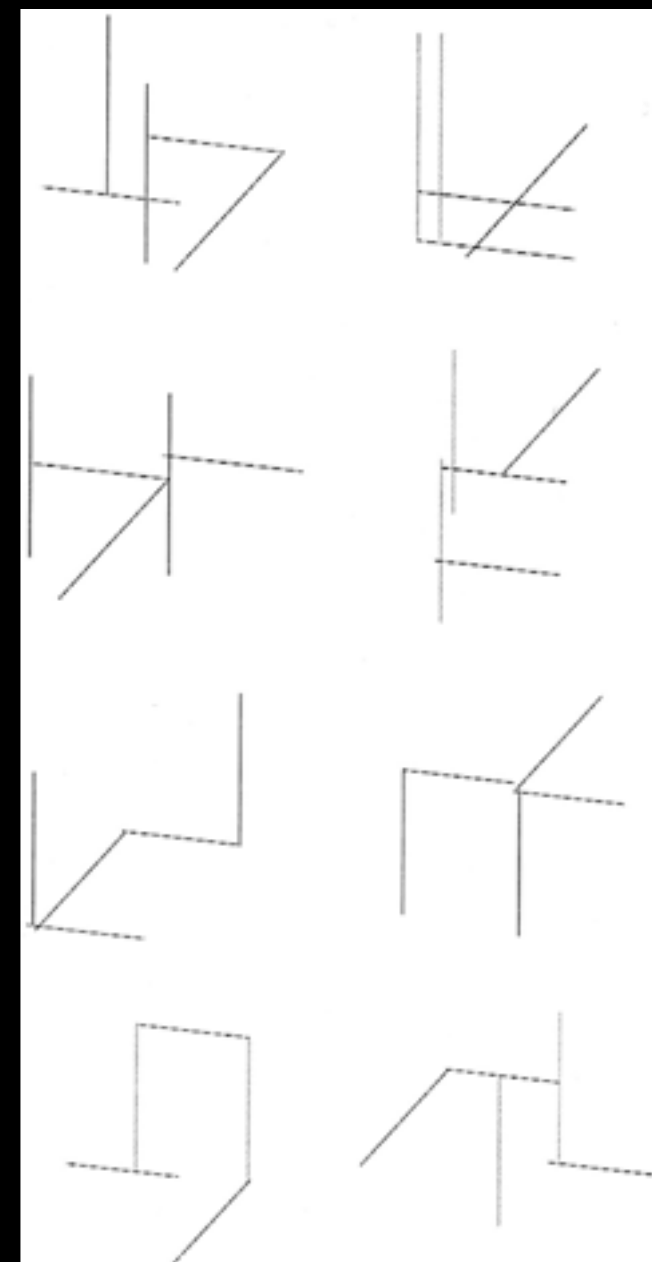
- “Sluggish indirect measure of neural activity, with a temporal resolution of 1-3 s and a spatial resolution of 25-30mm3.”

What do we claim

- “Sluggish indirect measure of neural activity, with a temporal resolution of 1-3 s and a spatial resolution of 25-30mm3.”

- “Because of its limited temporal and spatial resolution, fMRI is most appropriate for answering questions about gross neural architecture, rather than about neural process.”

What do we claim (1)



Waldschmidt & Ashby (2011)

What do we claim (1)

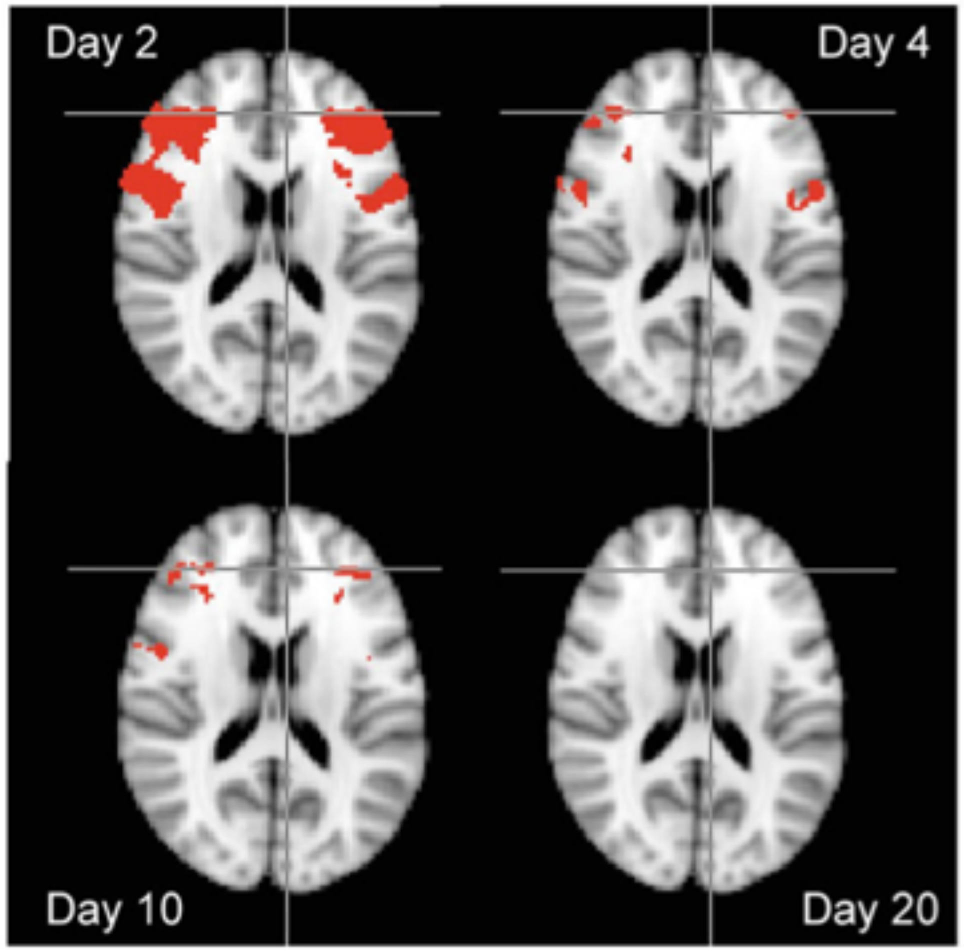
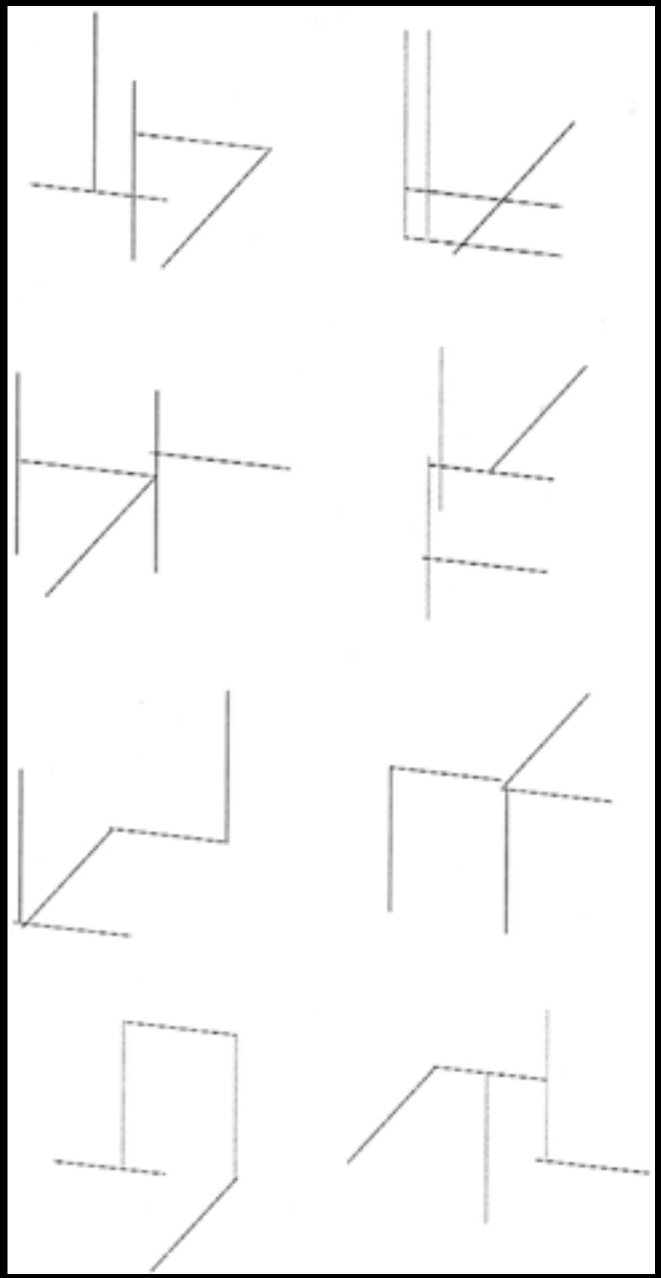
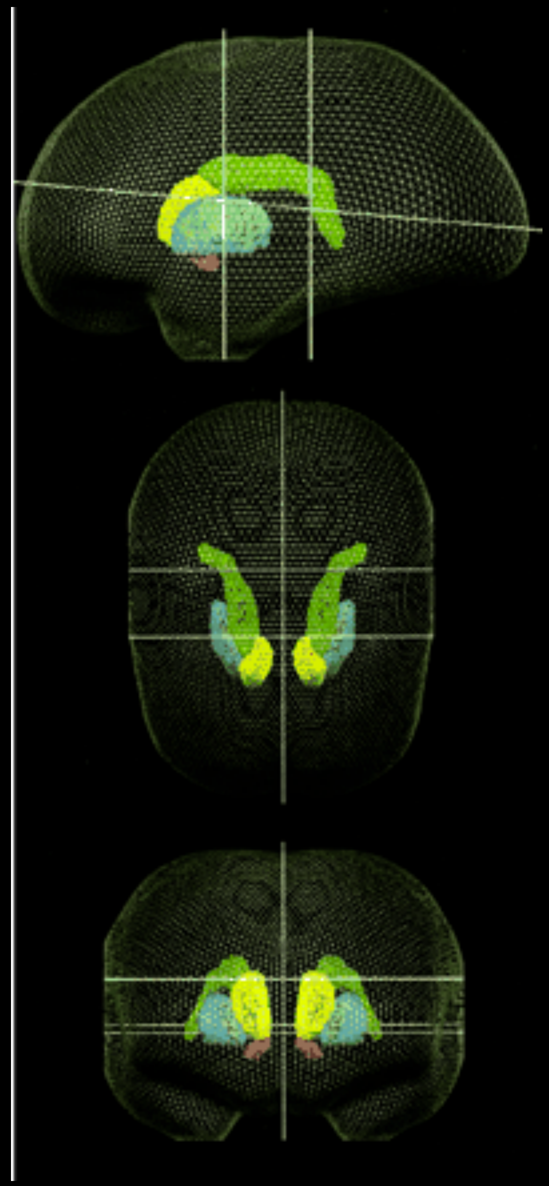


Fig. 5.1 Significant BOLD activation in prefrontal cortex on four different days of training on the same categorization task [8]

Waldschmidt & Ashby (2011)

What do we claim (2)





Lopez-Paniagua & Seger (2011)

What can fMRI tell us

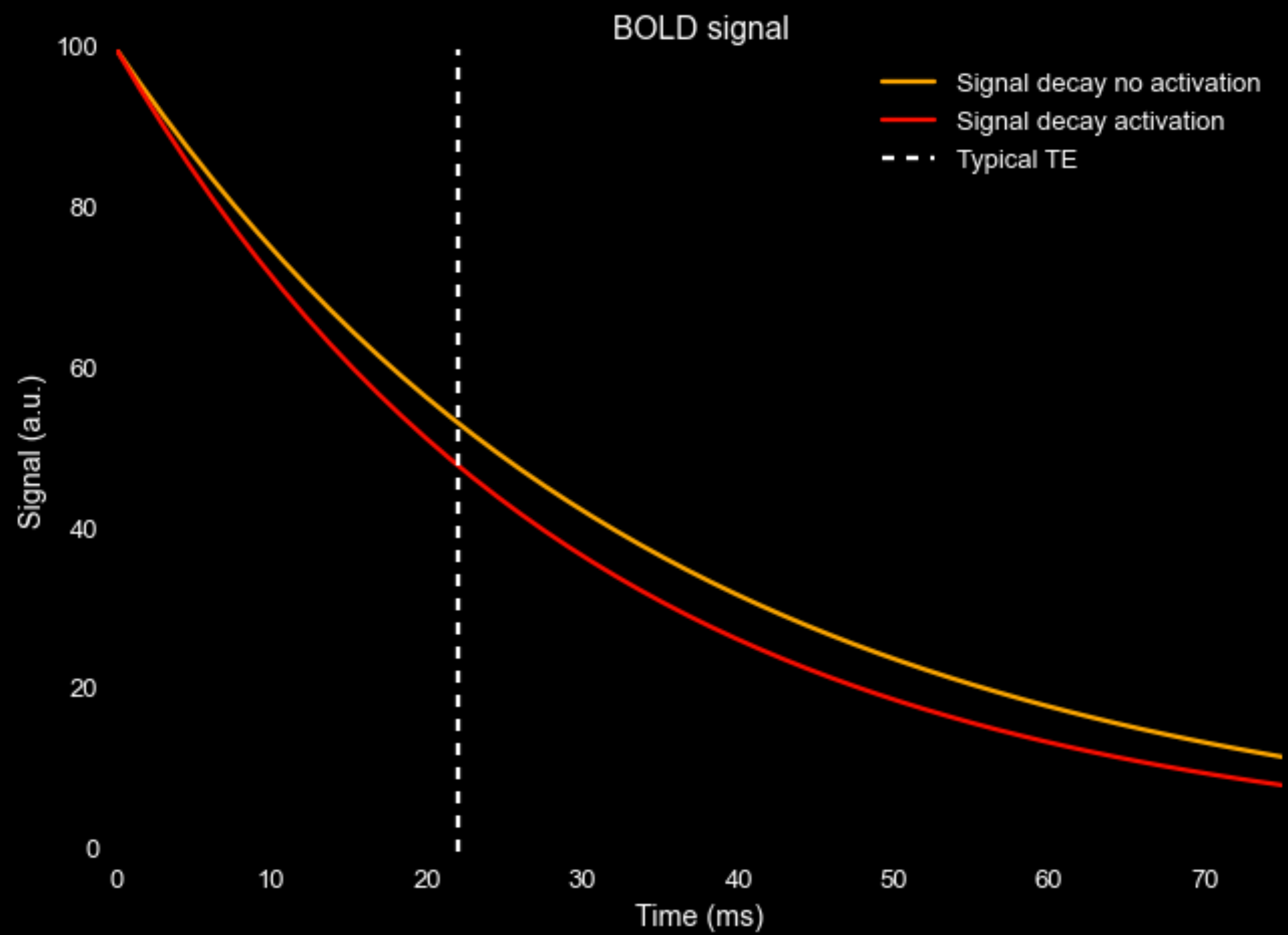
- In sum
  - Good measure to understand neural and cognitive architecture
  - Less powerful to understand exact computational processes

MR Physics

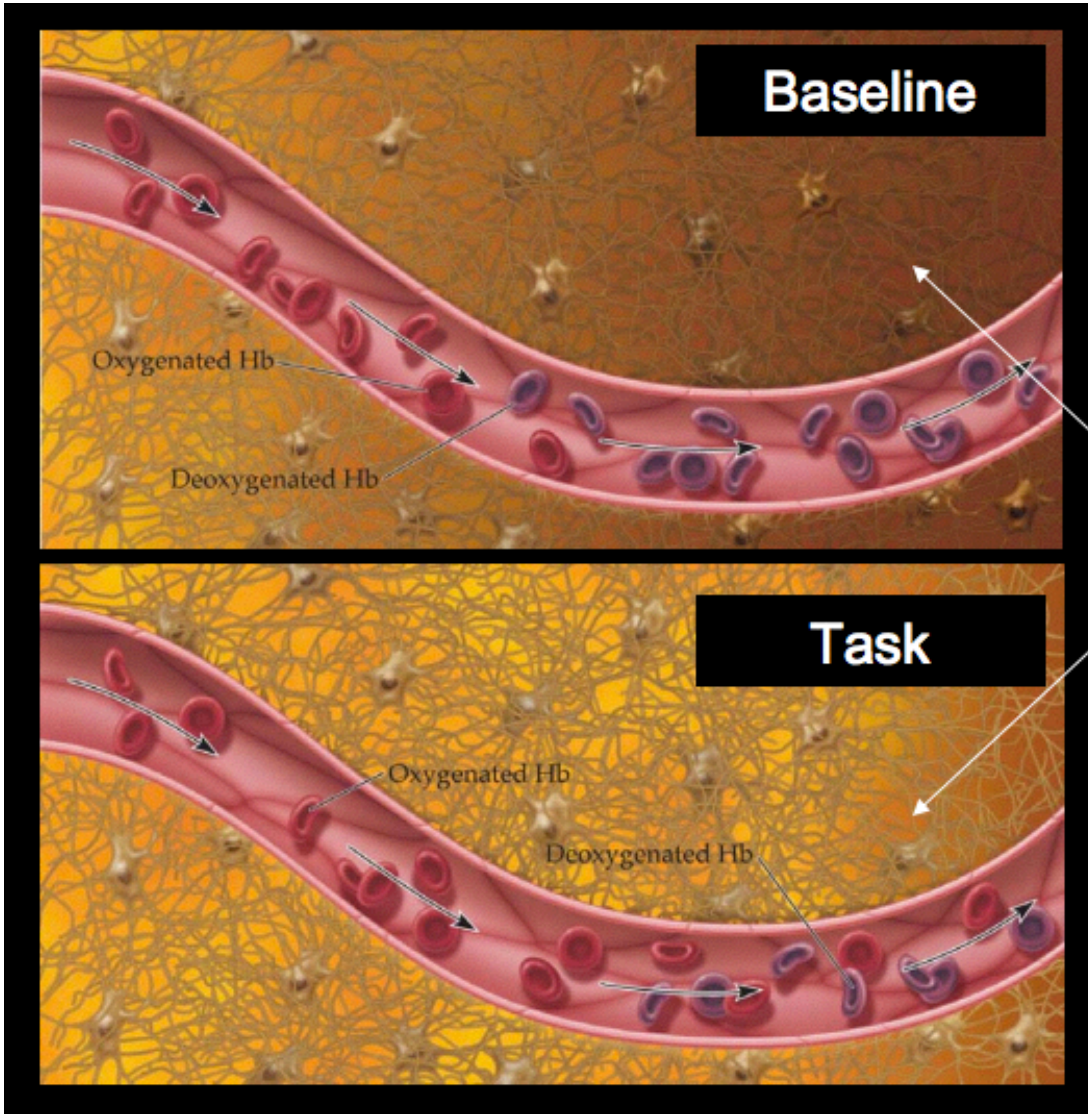
MR Physics

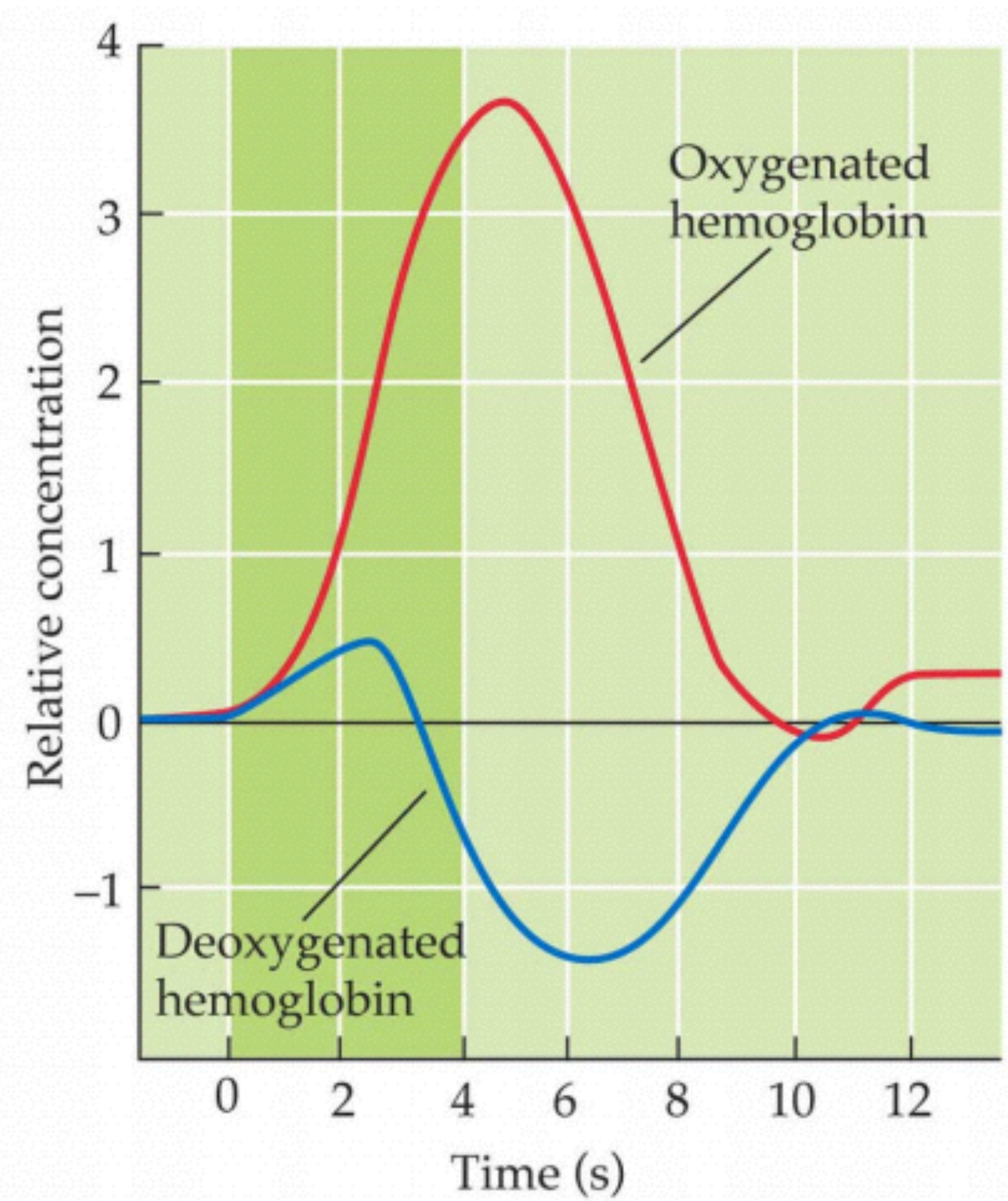
- Comes down to measuring magnetic properties in the brain
- Hydrogen protons align with strong magnetic field (B0)
- Brought in higher energy state by transmit coils
- Amount of returned energy measured using receive coils
- Spatial location is encoded using gradient coils

MR Physics



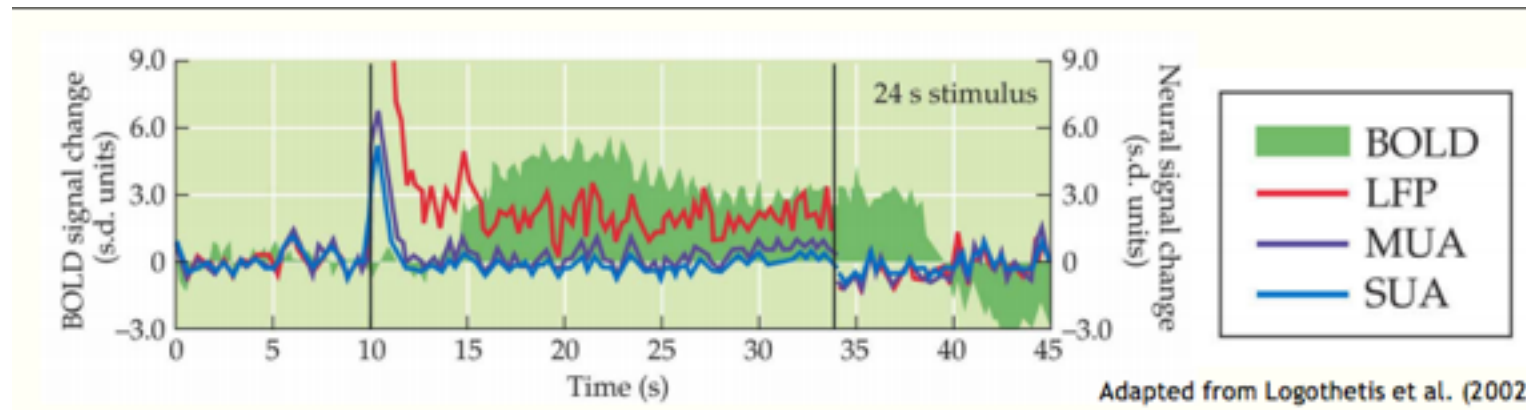
BOLD signal
Signal decay no activation
Signal decay activation
Typical TE
Signal (a.u.)
0
20
40
60
80
100
0
10
20
30
40
50
60
70
Time (ms)


Baseline
Oxygenated Hb
Deoxygenated Hb
Task
Oxygenated Hb
Deoxygenated Hb

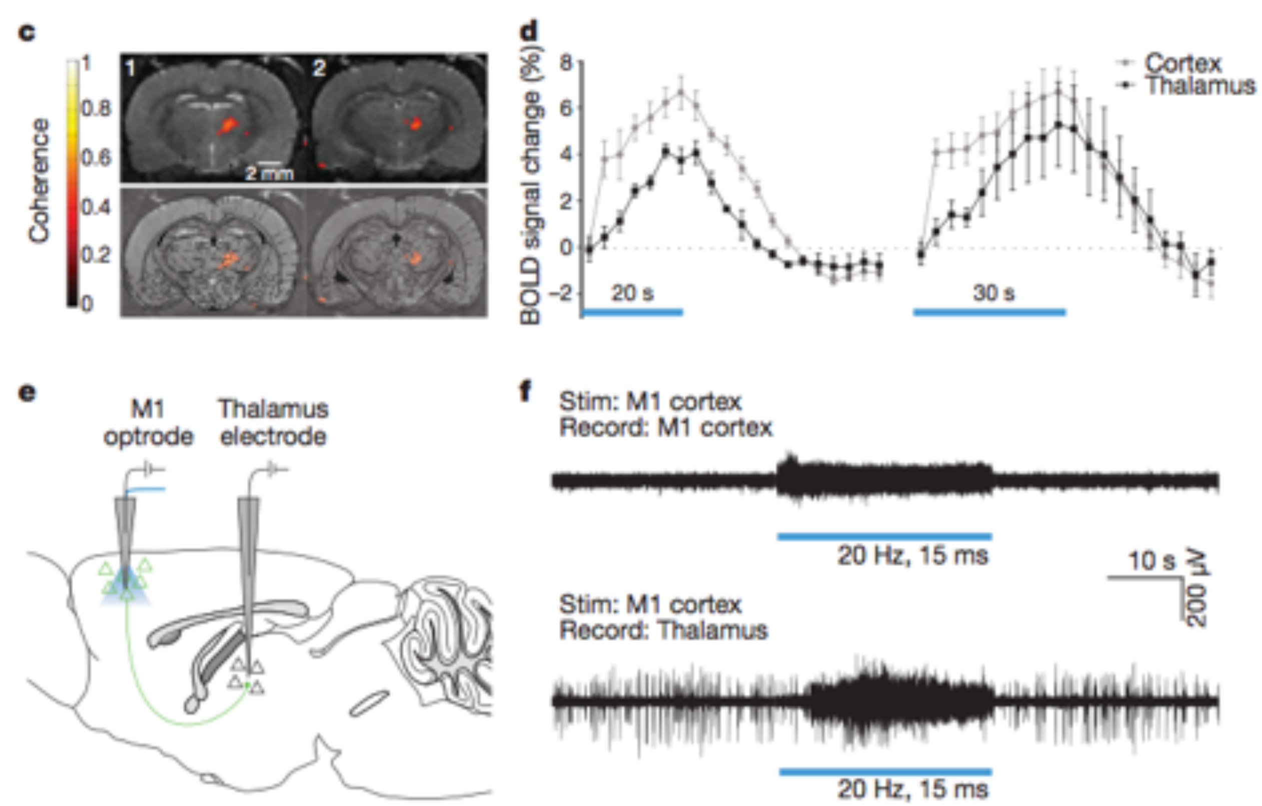

4
3
2
1
0
−1
Relative concentration
Oxygenated hemoglobin
Deoxygenated hemoglobin
0
2
4
6
8
10
12
Time (s)

BOLD = neural activity?

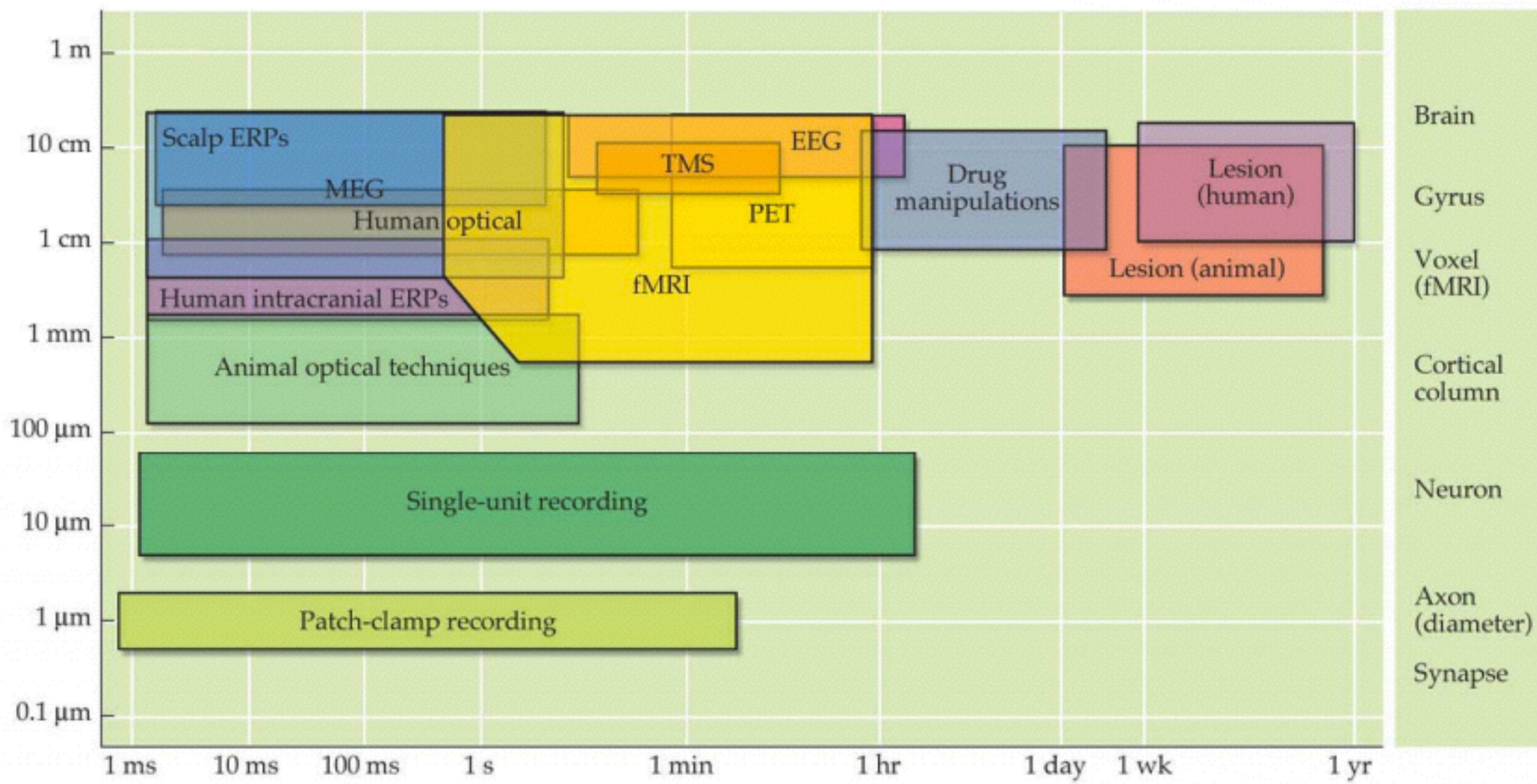
- Logothesis (2002) used electrical recordings



- Lee et al. (2010) used optogenetics

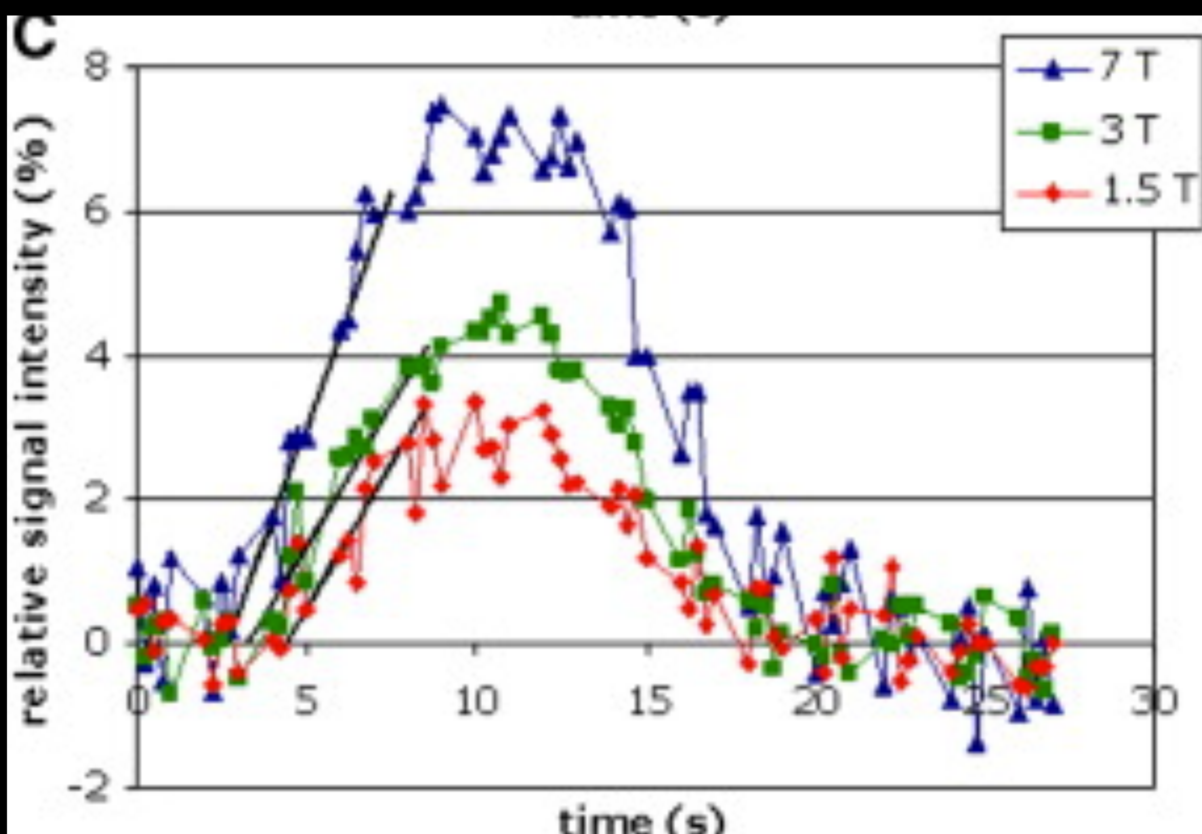


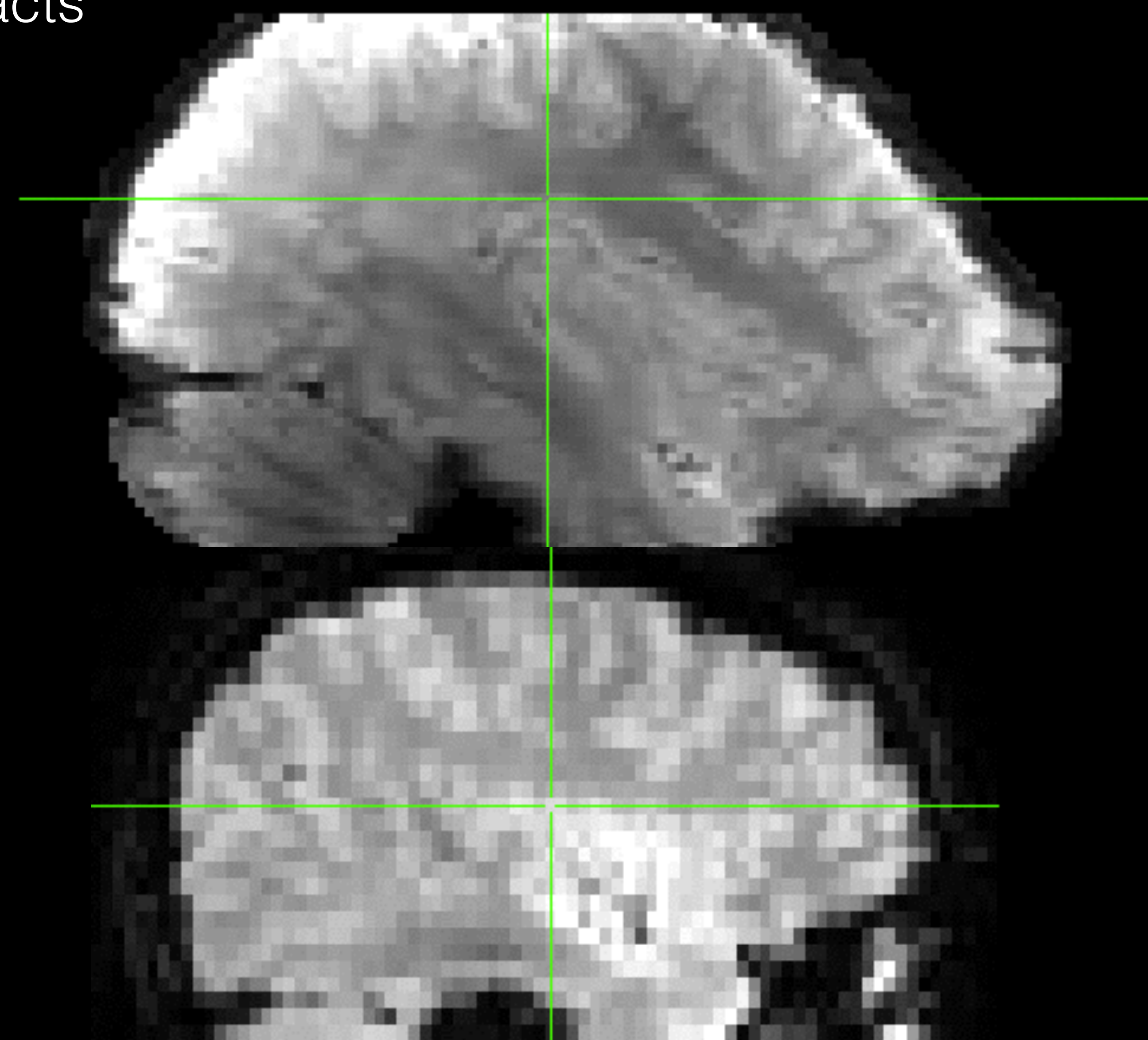
Resolution of fMRI compared to other methods



Different scanners

- 1.5, 3, or 7 Tesla
- Increased SNR, but also increased artefacts



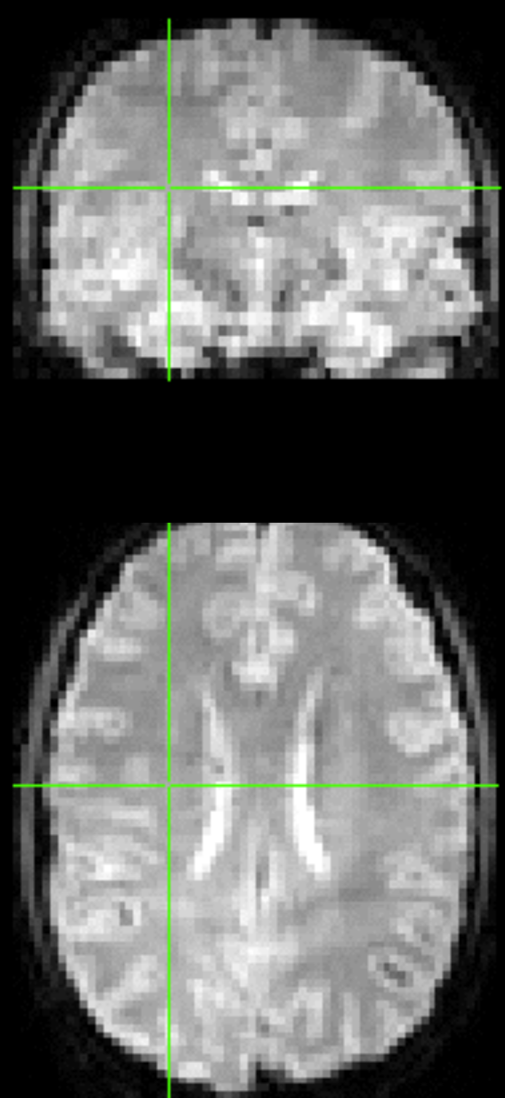


Typical scanning session

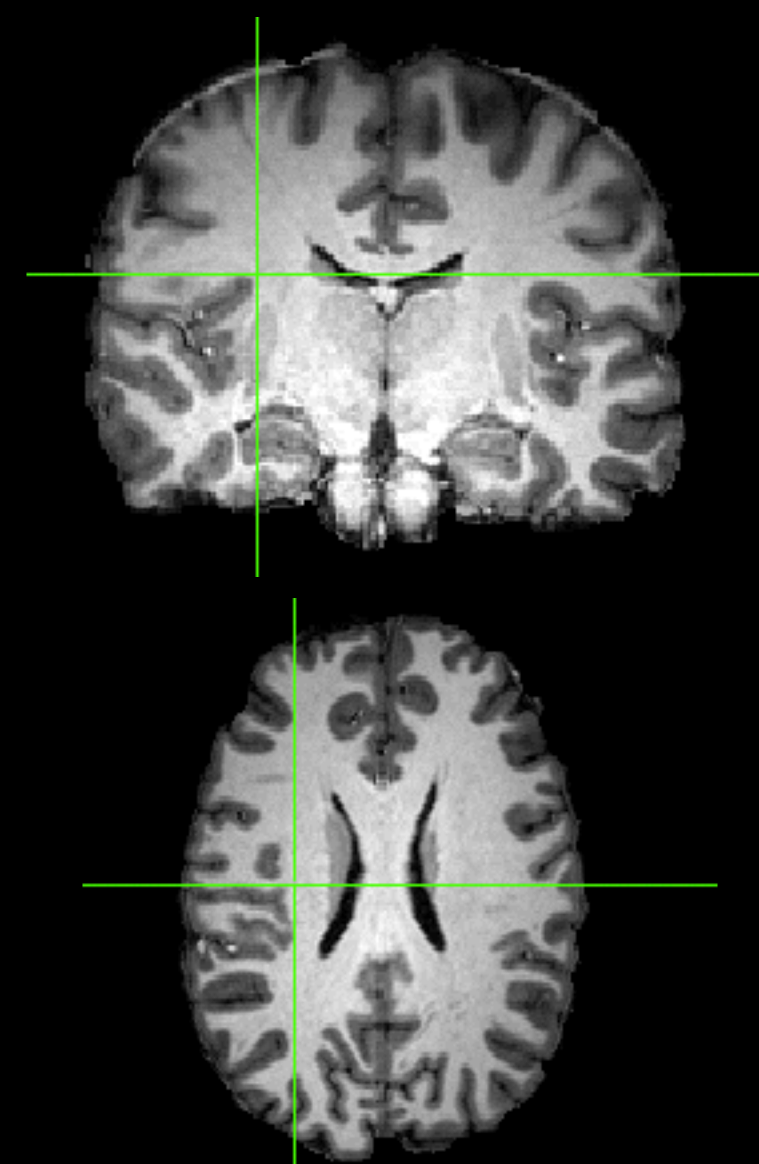
- Localizer (2min)
- Structural scan (8-10 min)
- Functional scan (30-60 min)
- Fieldmap (5 min)

“Two” scans

Functional
(approx 3mm isotropic)

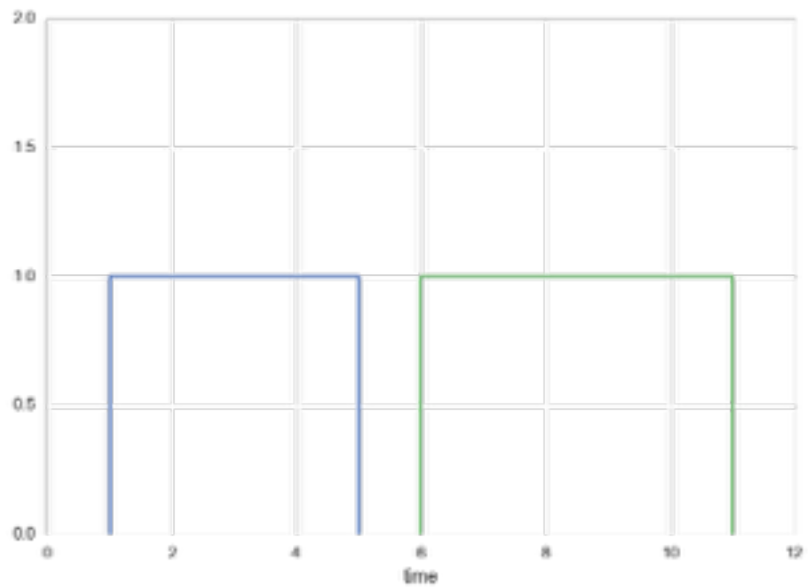


Structural
(approx 1mm isotropic)

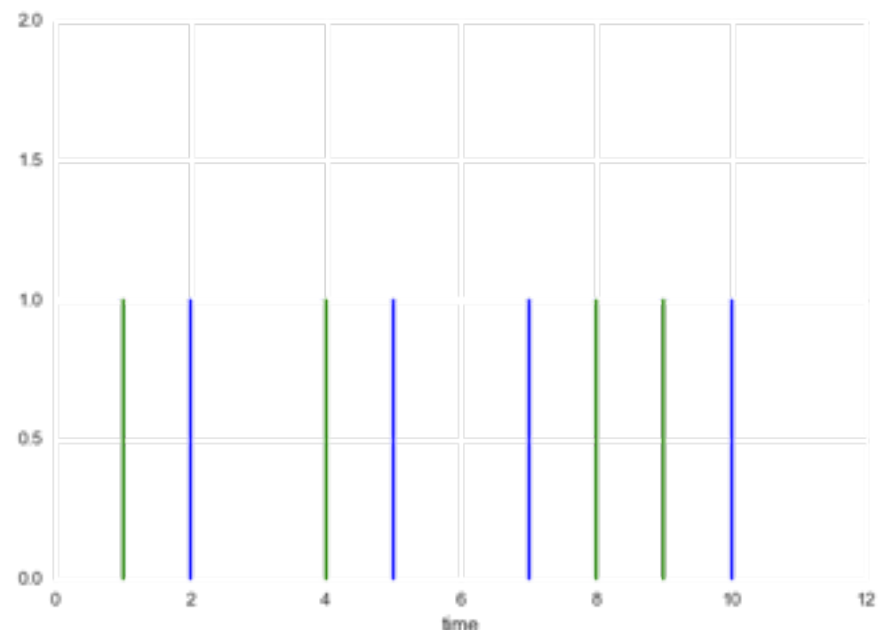


Experimental design:

Block



Event-related



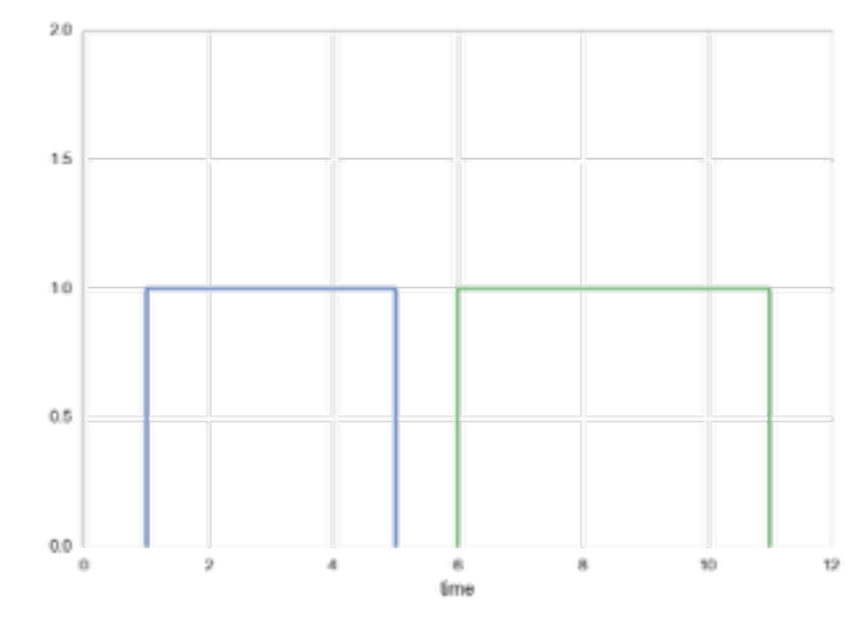
Free-running

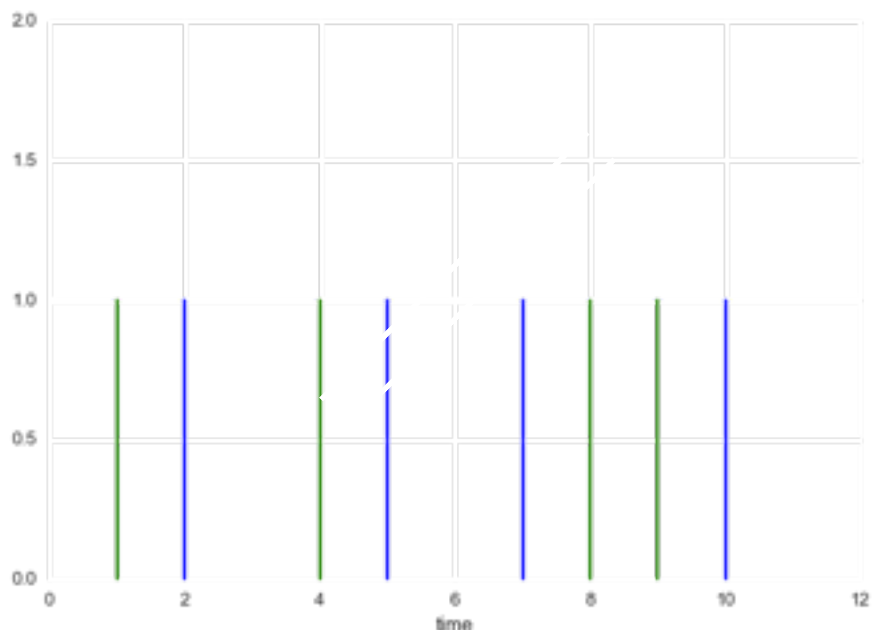
Experimental design:

Block

Event-related

Free-running





inter-trial-interval

Goals

- Find differences in neural activation between conditions (contrast)
- Find correlations between fMRI and behavioural measures (parametric design)

Data Analysis

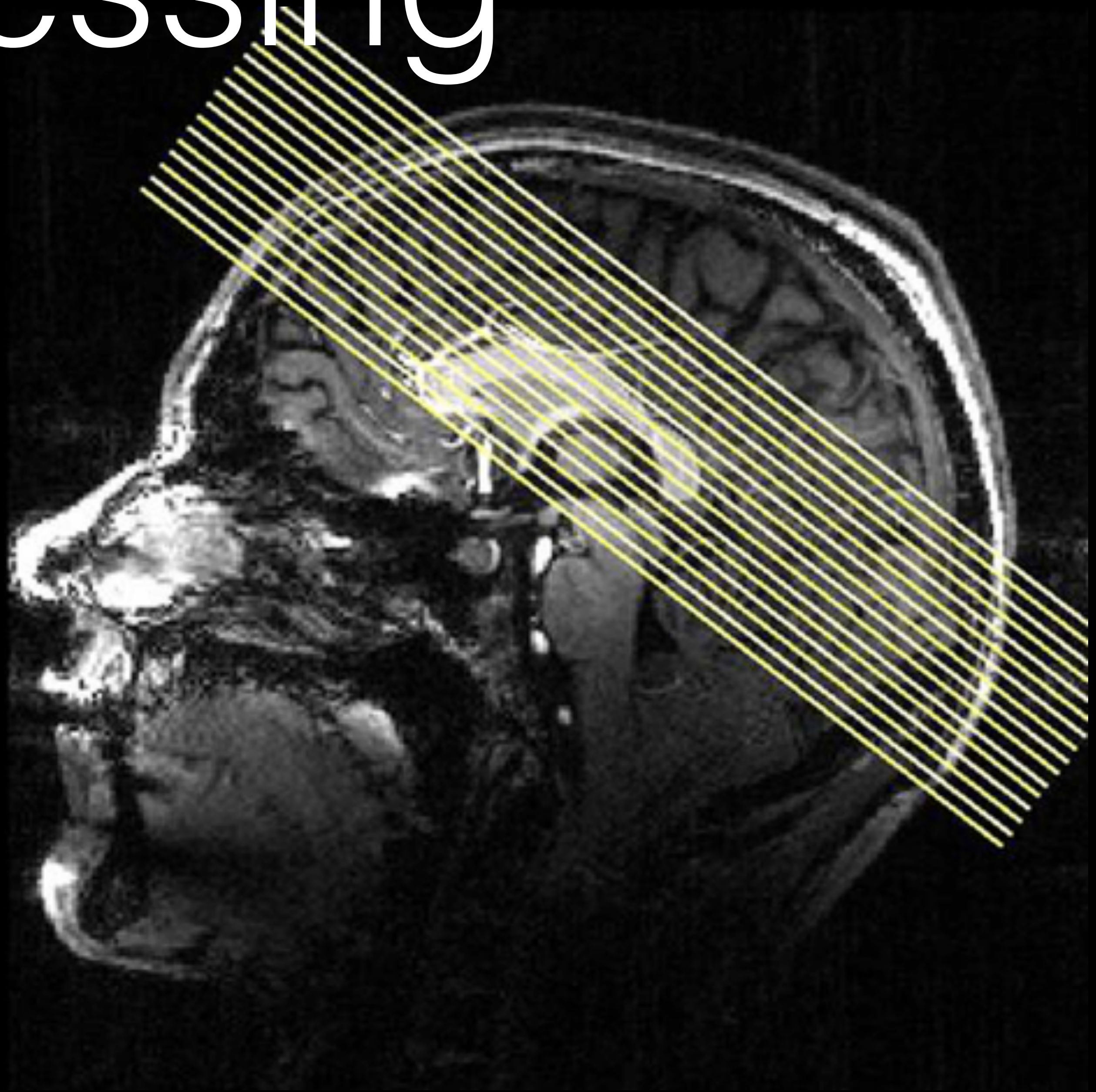
- Very challenging
  - Large amounts of data
  - Spatial and temporal correlation
  - Large amounts of noise

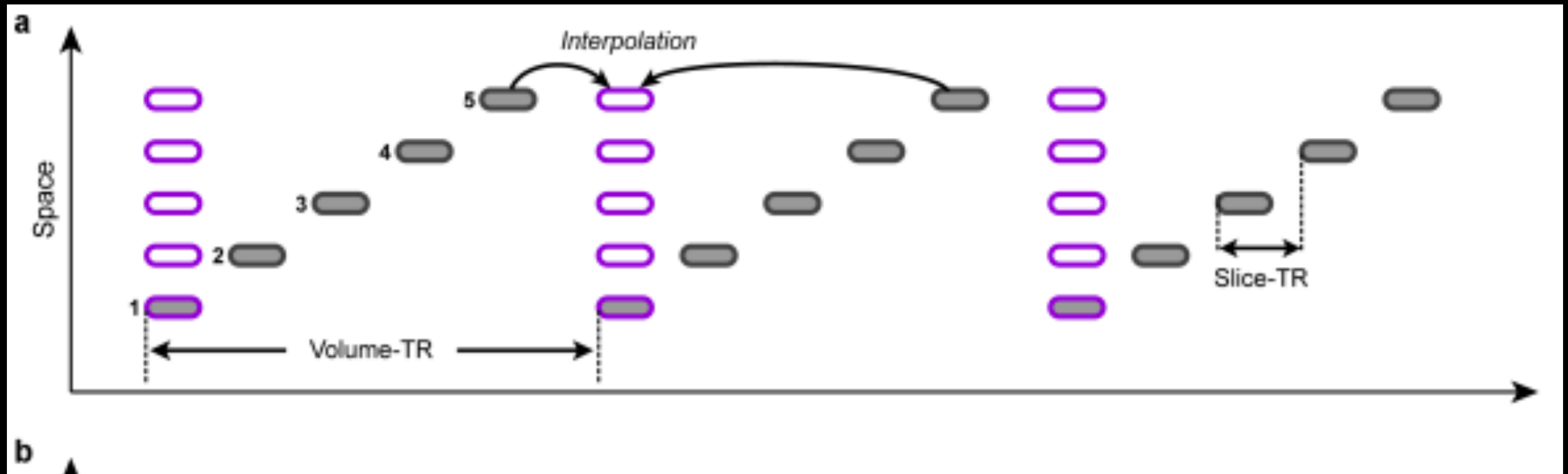
Data Analysis

- Two stages
  - Preprocessing
  - Task-related analysis

Preprocessing

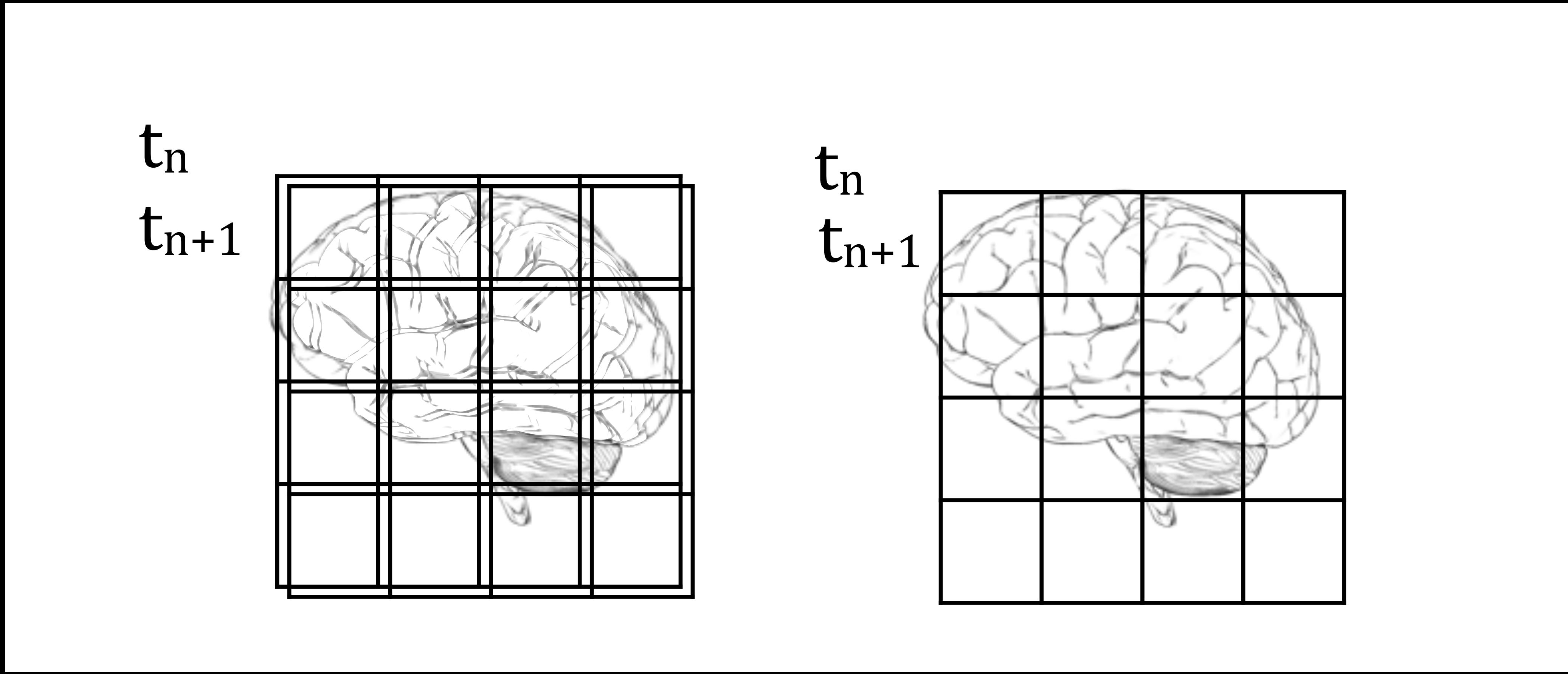
- 1. Slice-time correction





Preprocessing

- 2. Motion correction

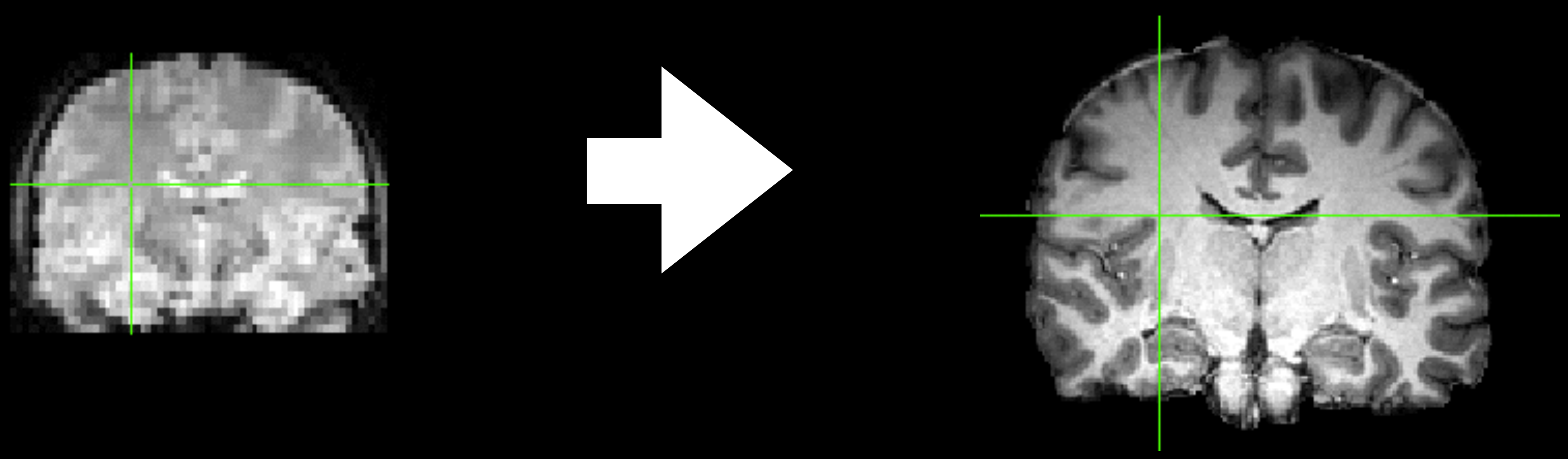


Preprocessing

- 3. Coregistration

Functional
(approx 3mm isotropic)

Structural
(approx 1mm isotropic)

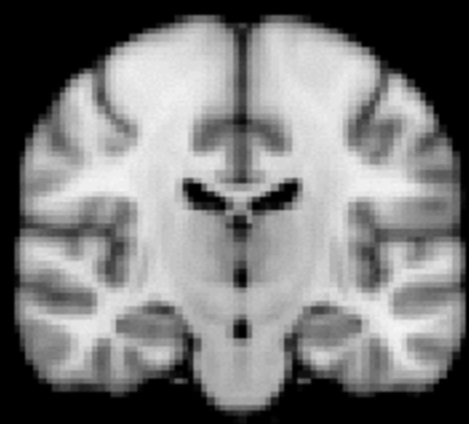


Preprocessing

- 4. Normalization

Structural
(approx 1mm isotropic)

MNI152
(0.4/1/2 mm isotropic)

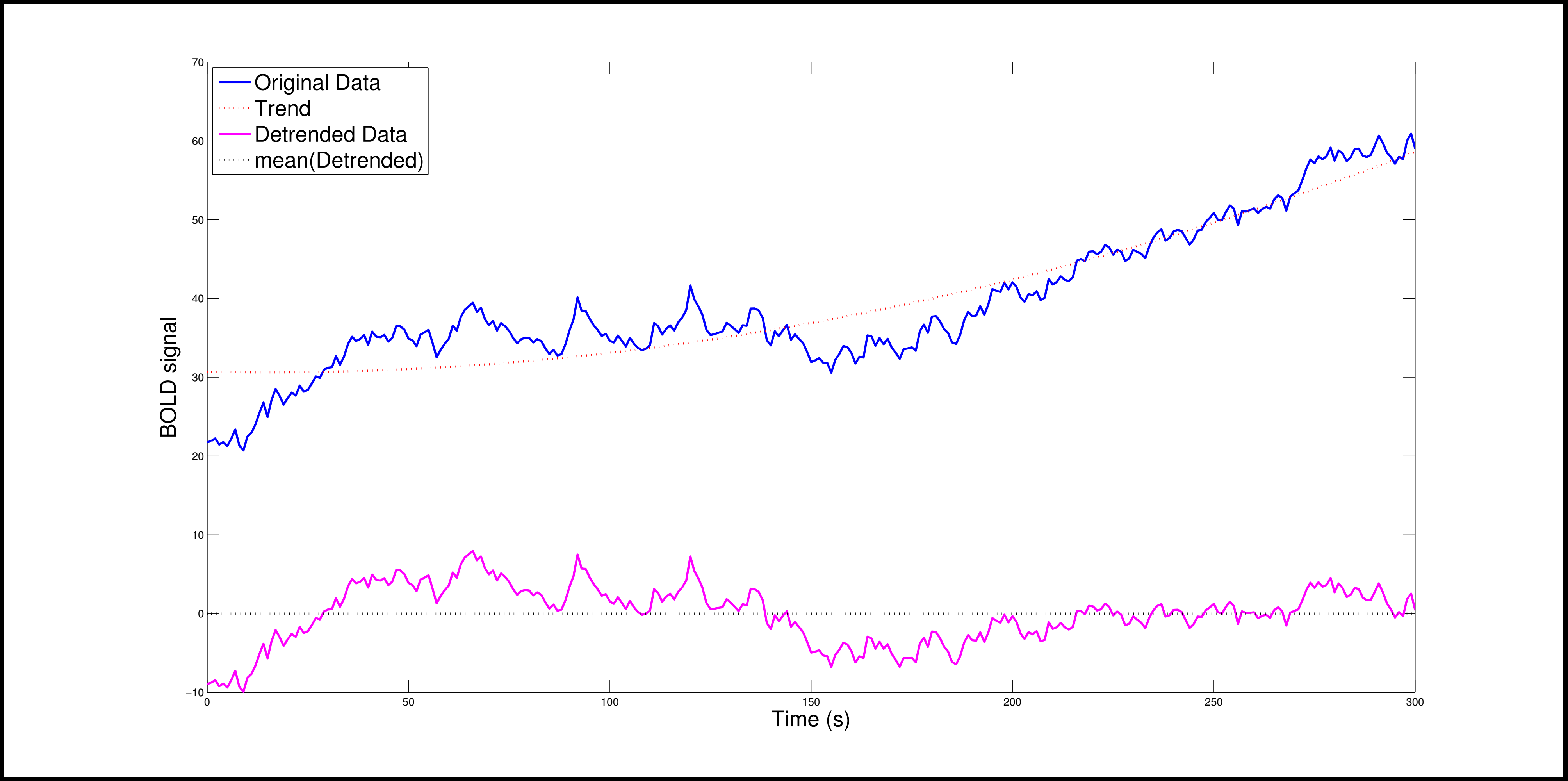


Preprocessing

- 5. Smoothing

Preprocessing

- 6. Temporal filtering

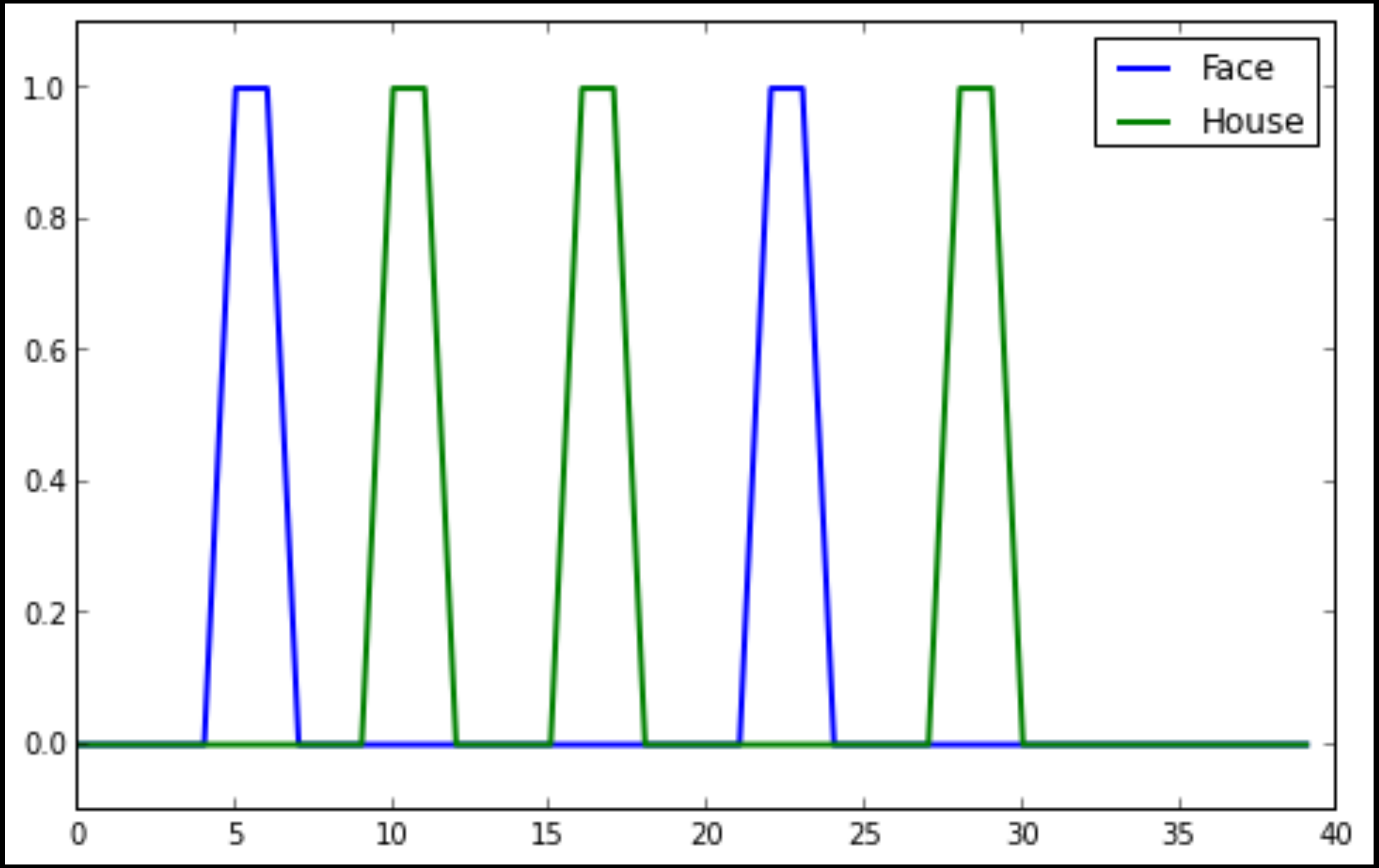


Task-related data analysis

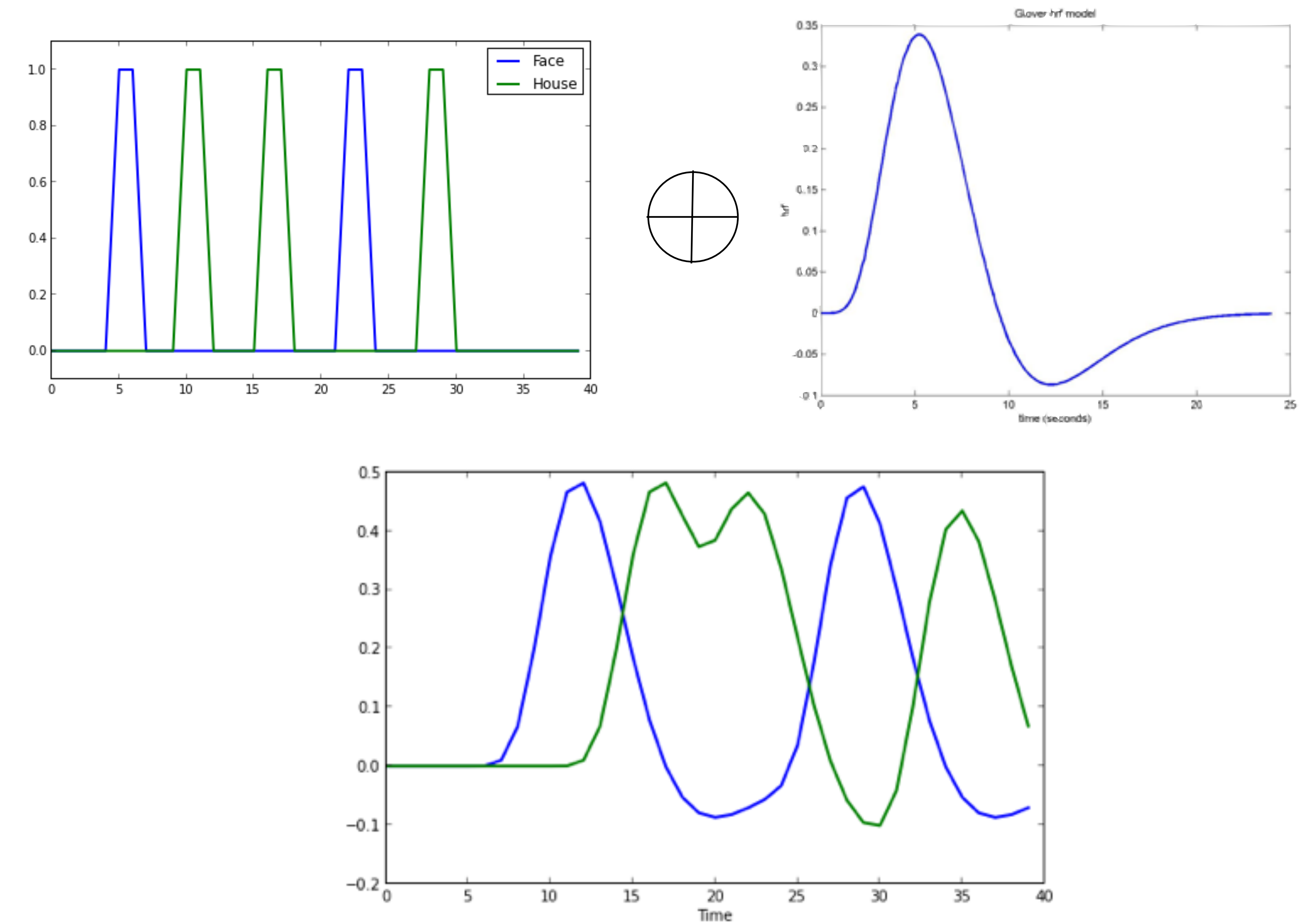
Task-related data analysis

- General idea:
  - “What would a task-related BOLD signal look like?”
  - Correlate this hypothetical signal to all voxels in the brain

Task-related data analysis



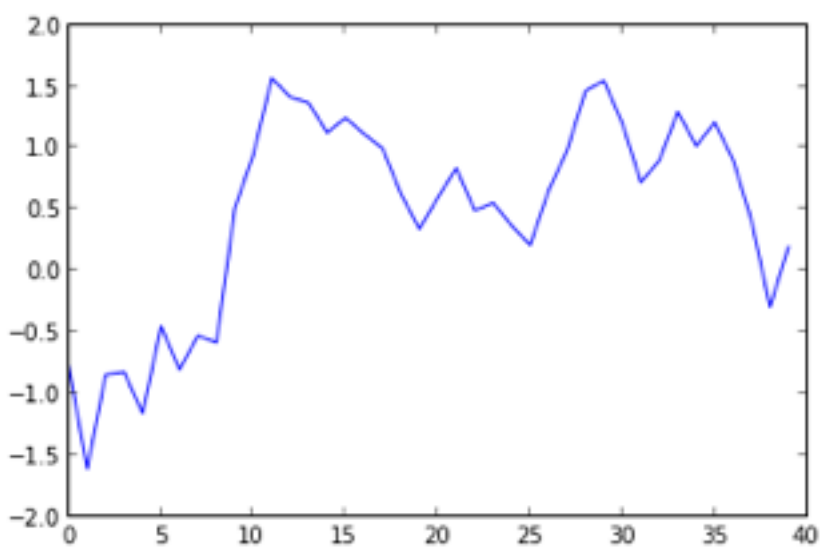
Task-related data analysis



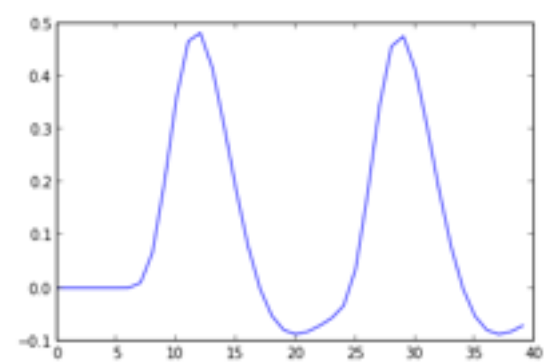
GLM

$$Y_i = \beta X + \varepsilon$$

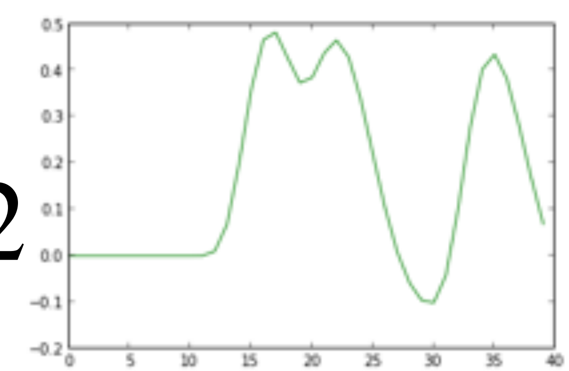
$$Y_i = \beta_0 + \beta_1 X_1 + \beta_2 X_2 \ldots \beta_n X_n + \varepsilon_i$$



$$= \beta_0 + \beta_1$$



$$+ \beta_2$$

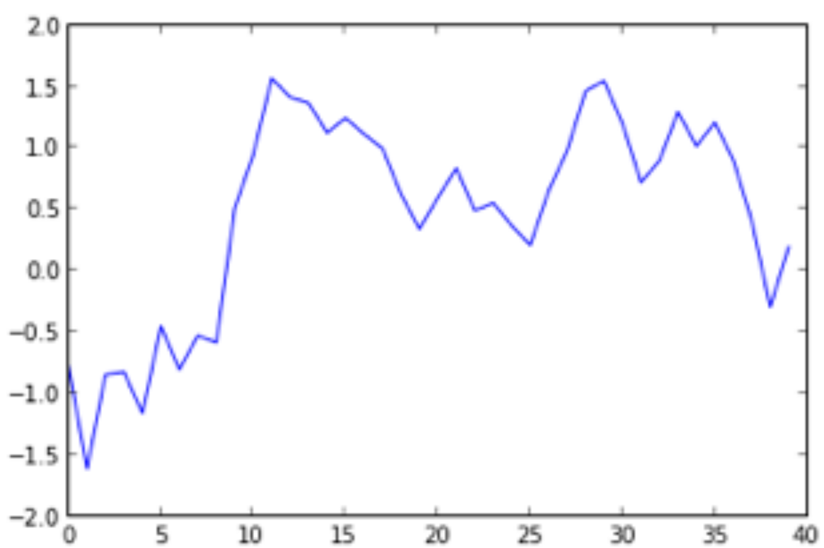


GLM

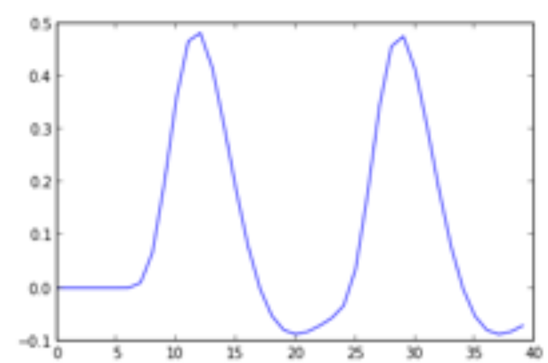
$$\beta_0 = 0$$

$$\beta_1 = 4$$

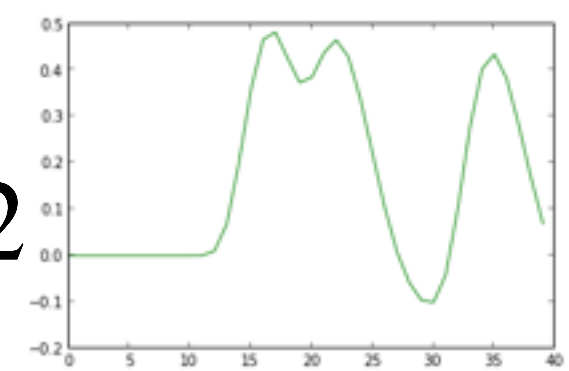
$$\beta_2 = 3$$



$= \beta_0 + \beta_1$



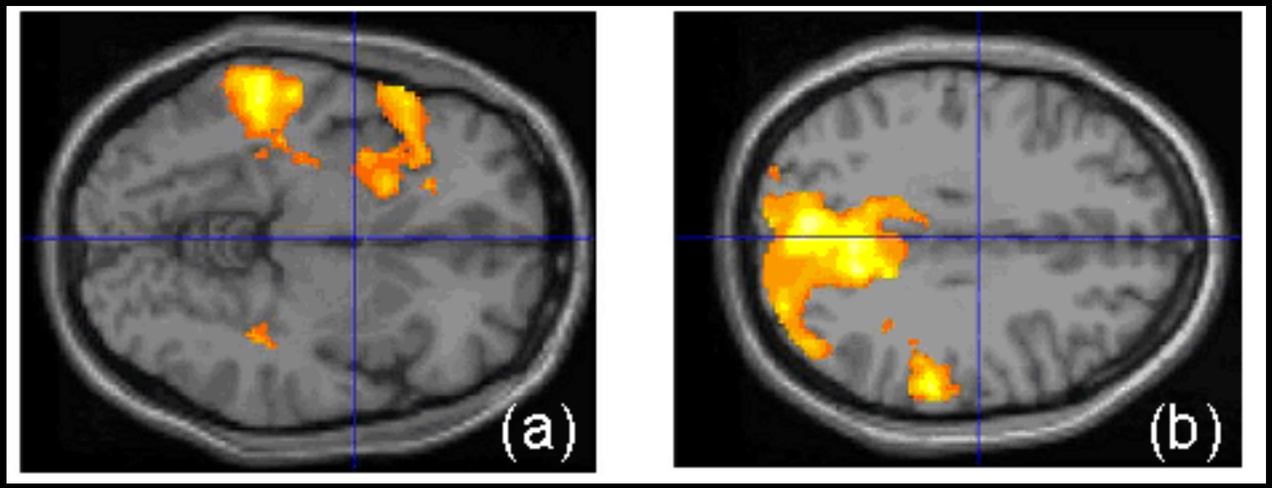
$+ \beta_2$

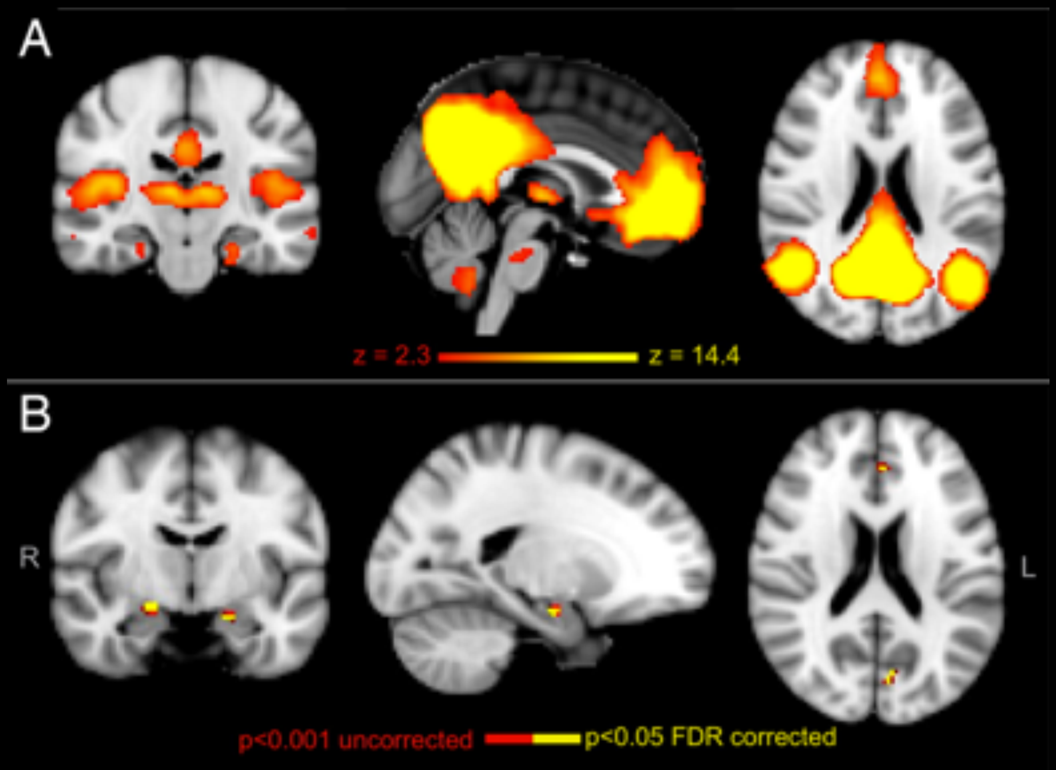


Result

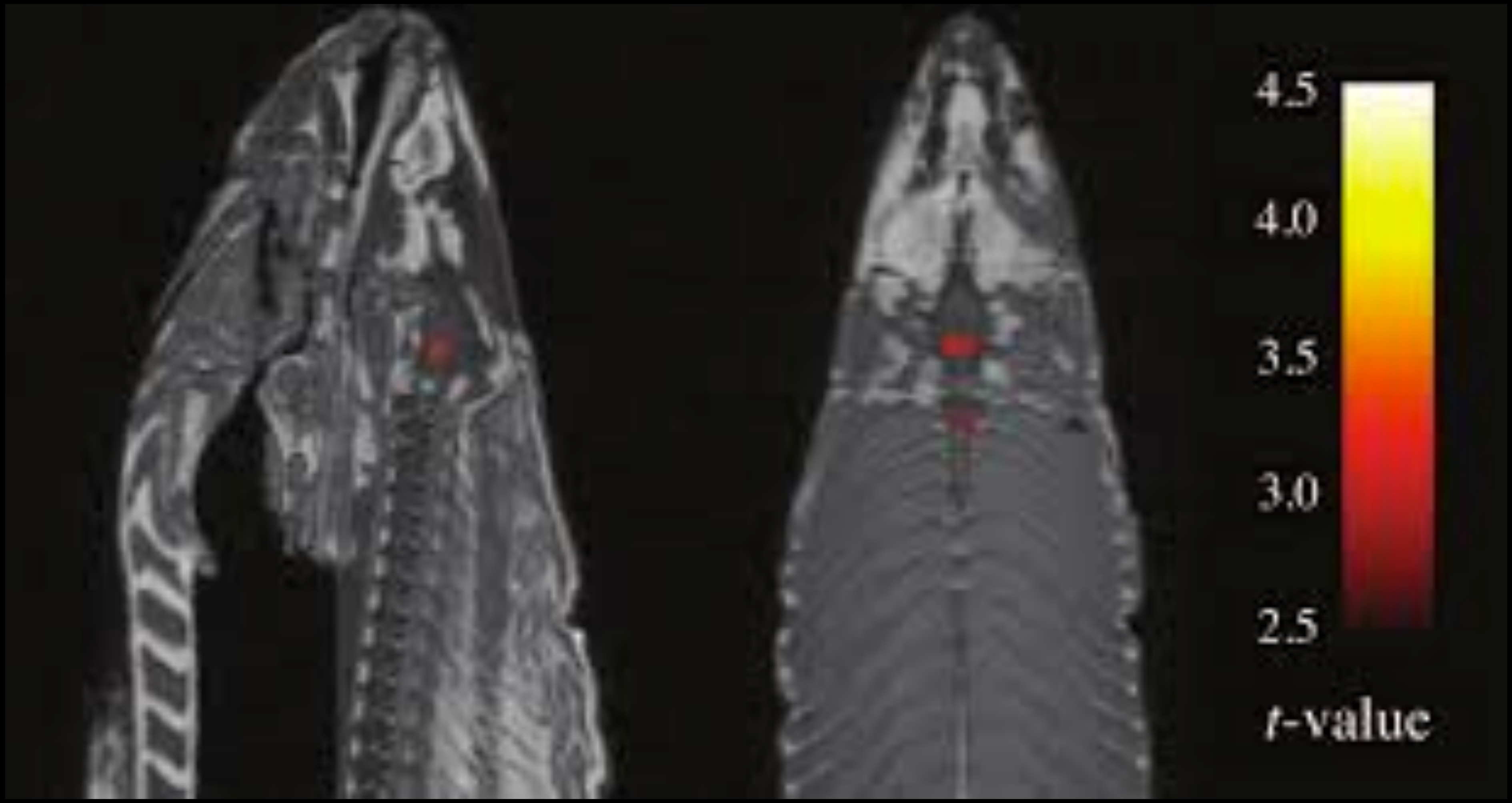
- For every subject a brain map with
  - For every voxel
    - Beta-value for every regressor
    - Variance for every regressor
  - (contrasts)

Statistical Parametric Mapping





Multiple comparisons



Multiple comparisons

- False Discovery Rate
- Gaussian Random Field Theory

Model-based fMRI

- Us mathematical models of cognition to increase sensitivity/interpretability of both behavioural and neural data

Model-based fMRI

- **Individual differences-approach**
  - Fit computational model to behaviour
    - Yields parameter fits
  - Relate these parameter fits to neural signal

Striatum and pre-SMA facilitate decision-making under time pressure

Birte U. Forstmann[a,1], Gilles Dutilh[b], Scott Brown[c], Jane Neumann[d], D. Yves von Cramon[d], K. Richard Ridderinkhof[a], and Eric-Jan Wagenmakers[b]

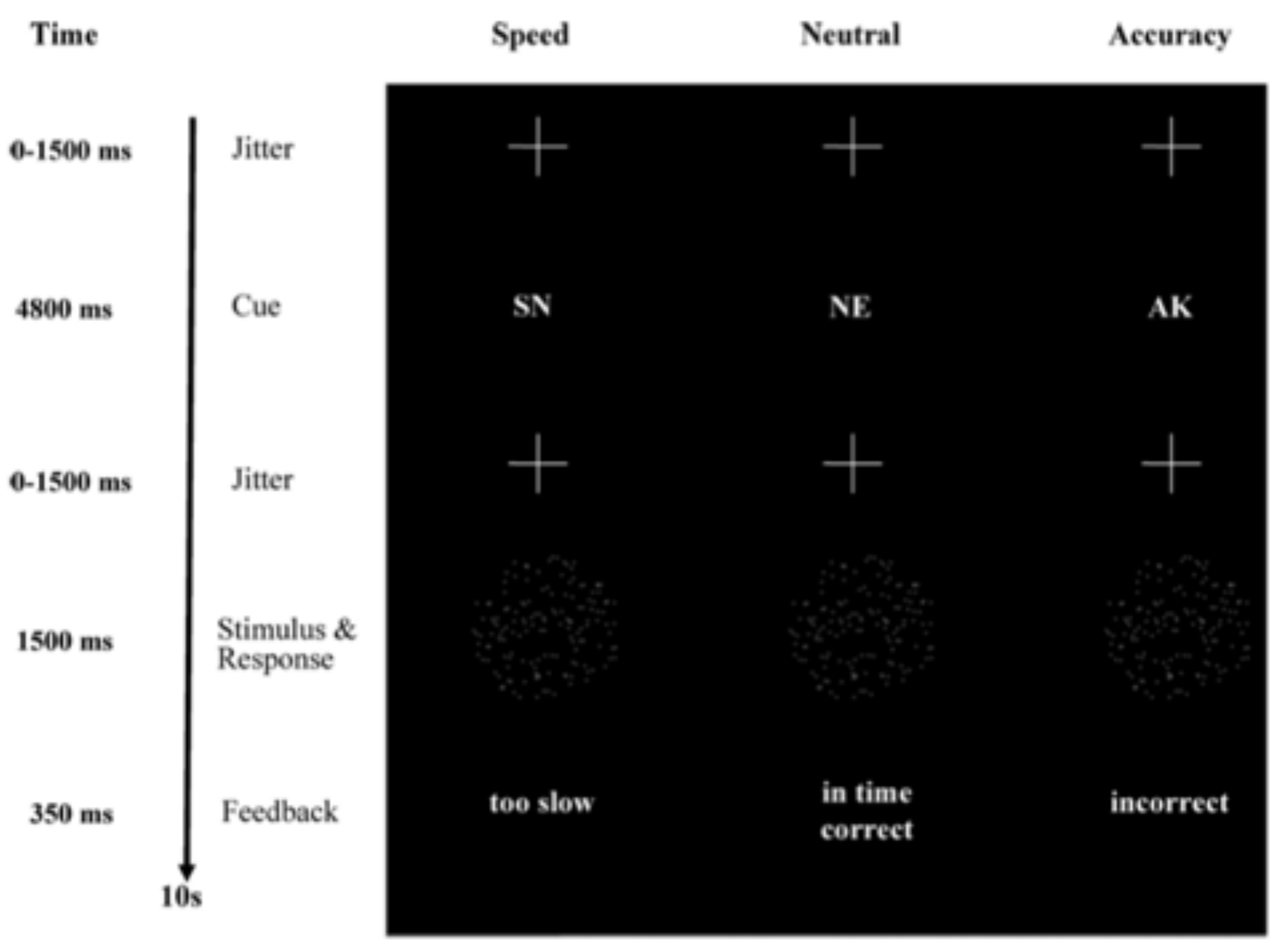
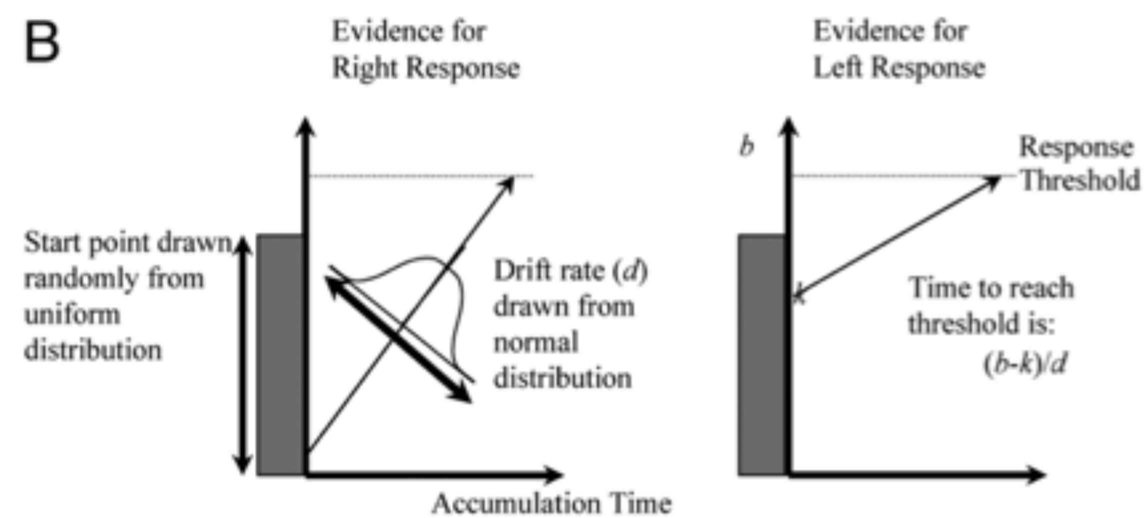


Fig. 1. Paradigm outline. Moving dots paradigm with cues emphasizing speed (SN for schnell), both speed and accuracy, that is, neutral (NE) and accuracy (AK for akkurat).

B



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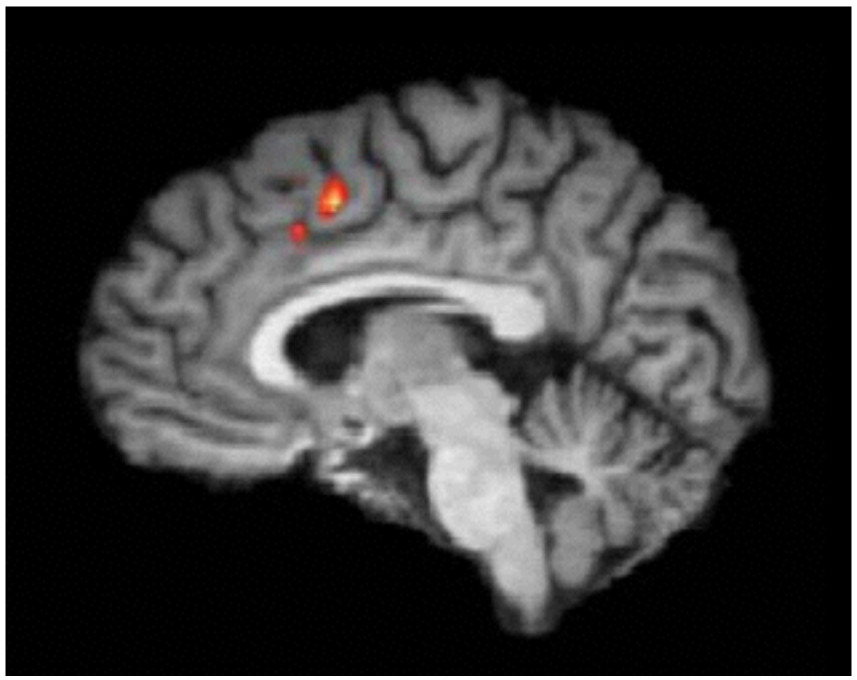

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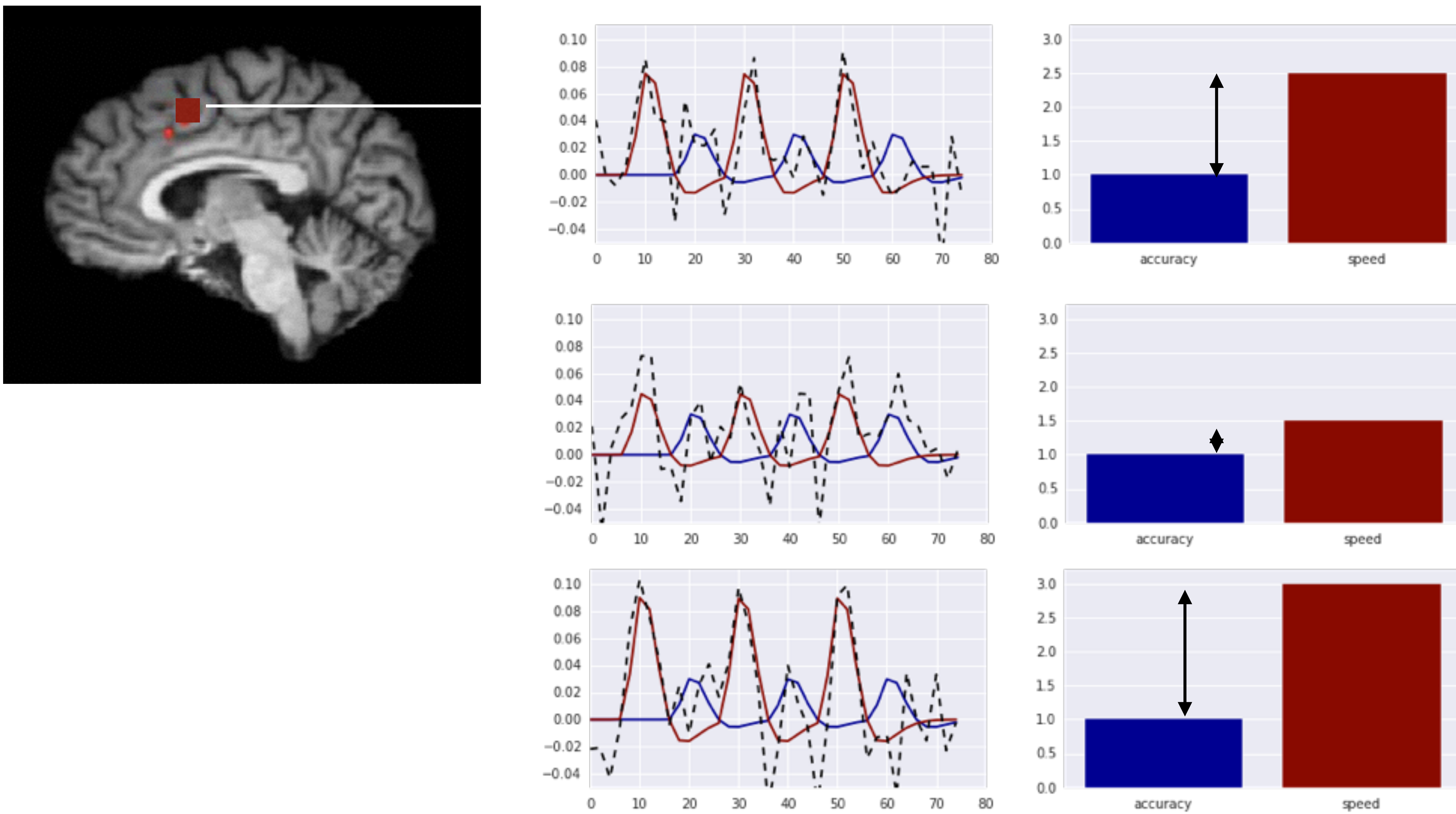

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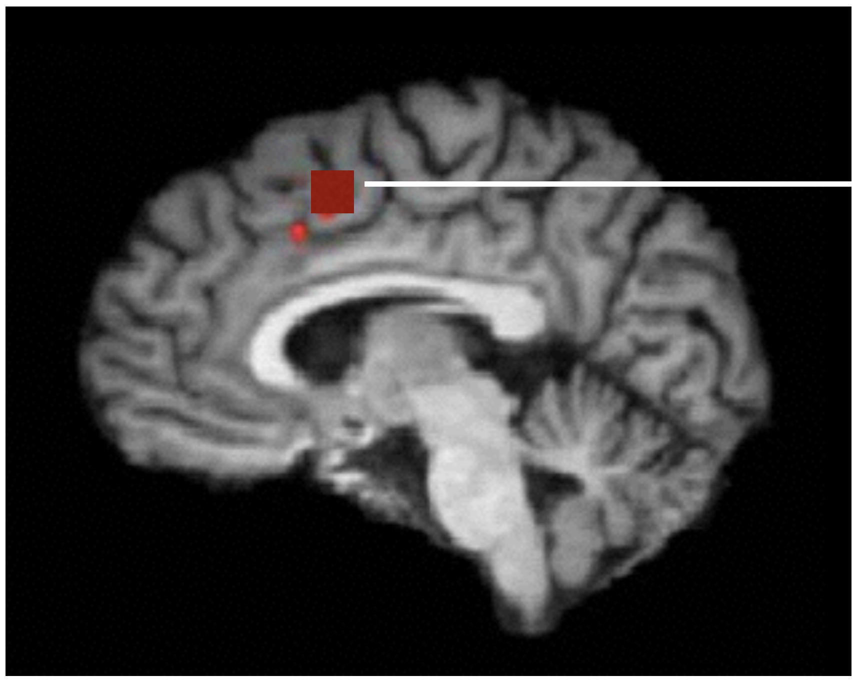
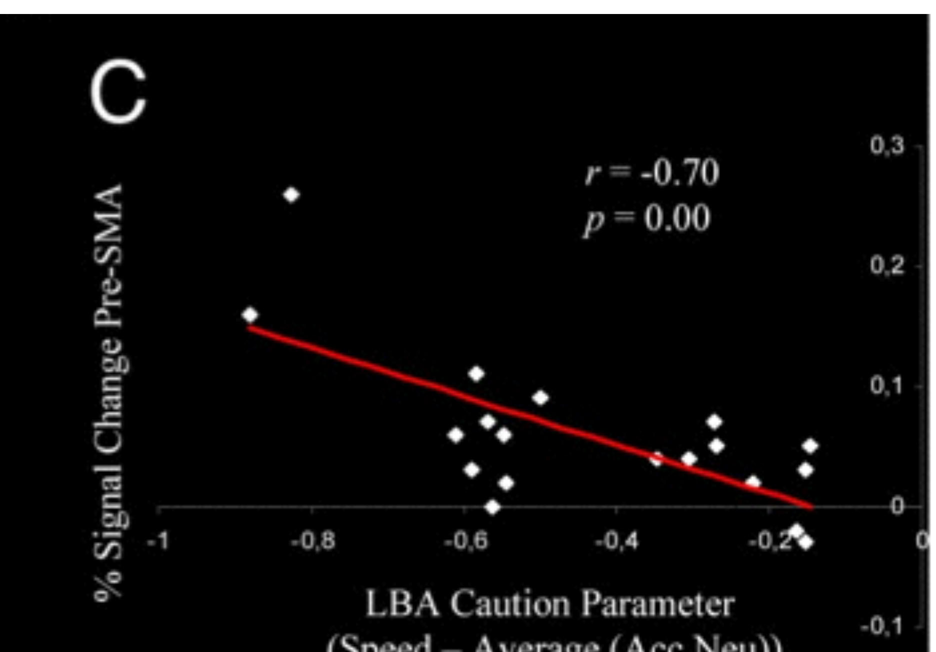
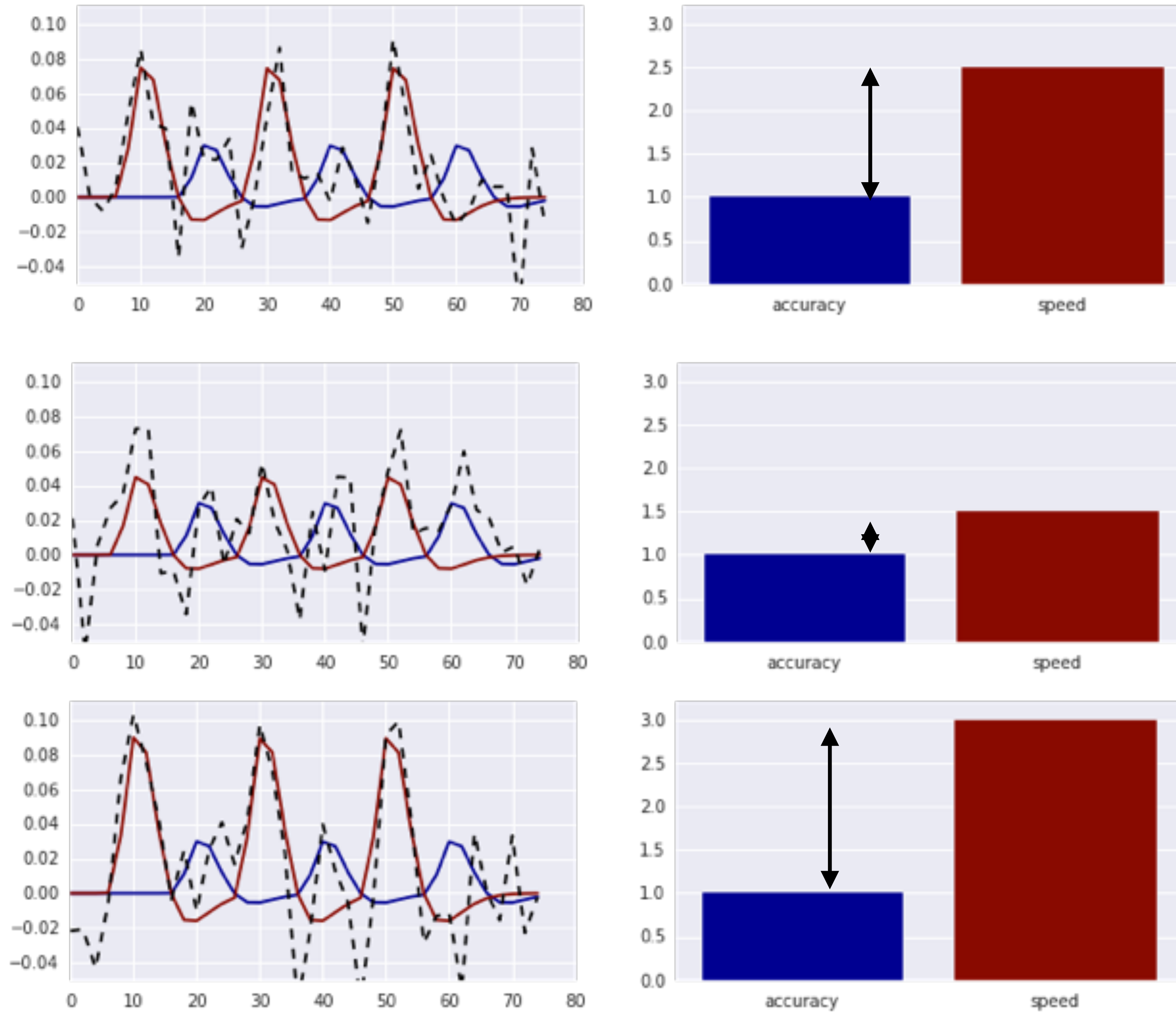






Model-based fMRI

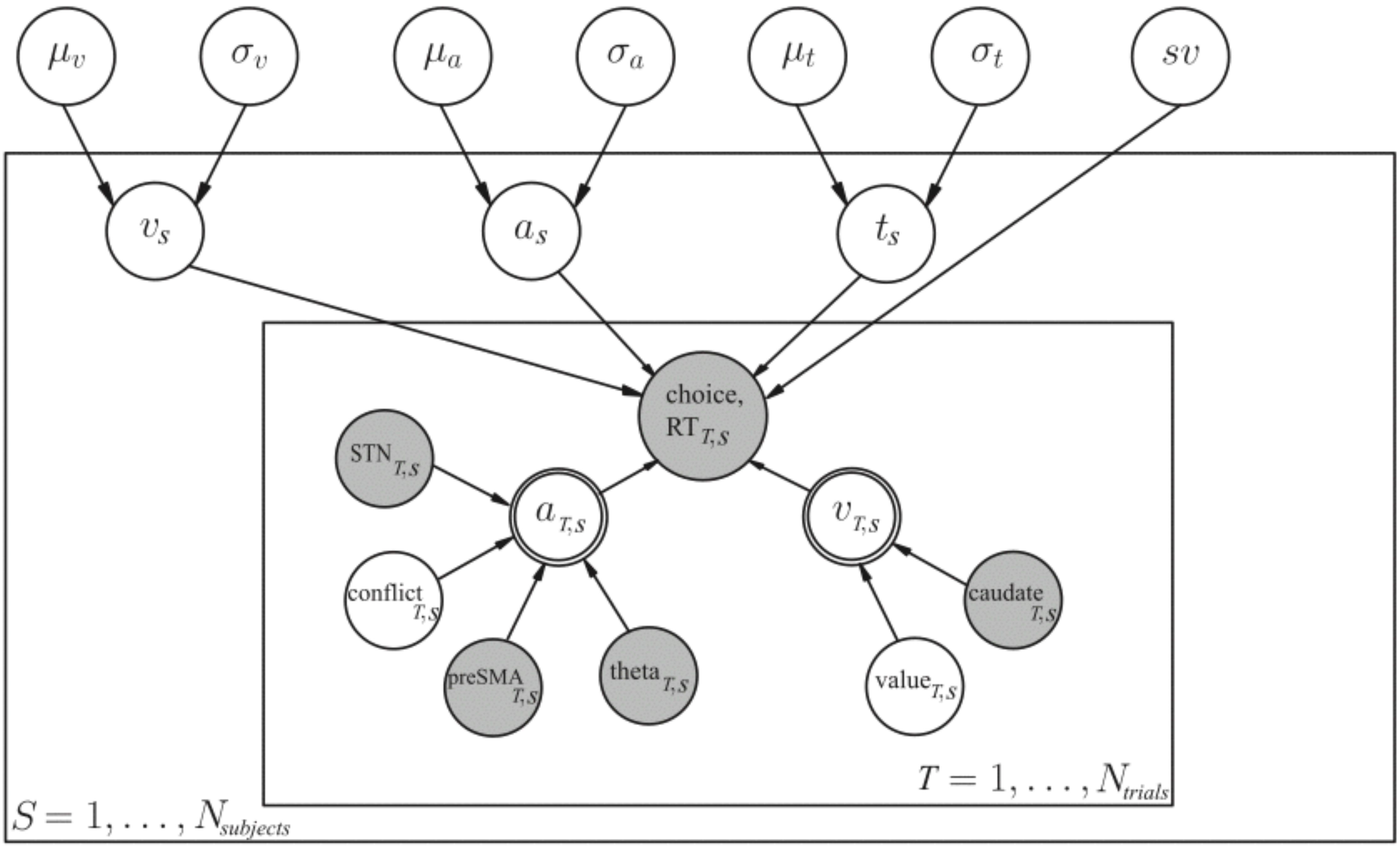
- **Inter-trial variability/regression-approach**
    - Extract summary statistic from fMRI-data
    - Use this as input for computational model.
        - e.g. v ~ v_intercept + BOLD * v_beta1

The Journal of Neuroscience, January 14, 2015 • 35(2):485– 494 • **485**

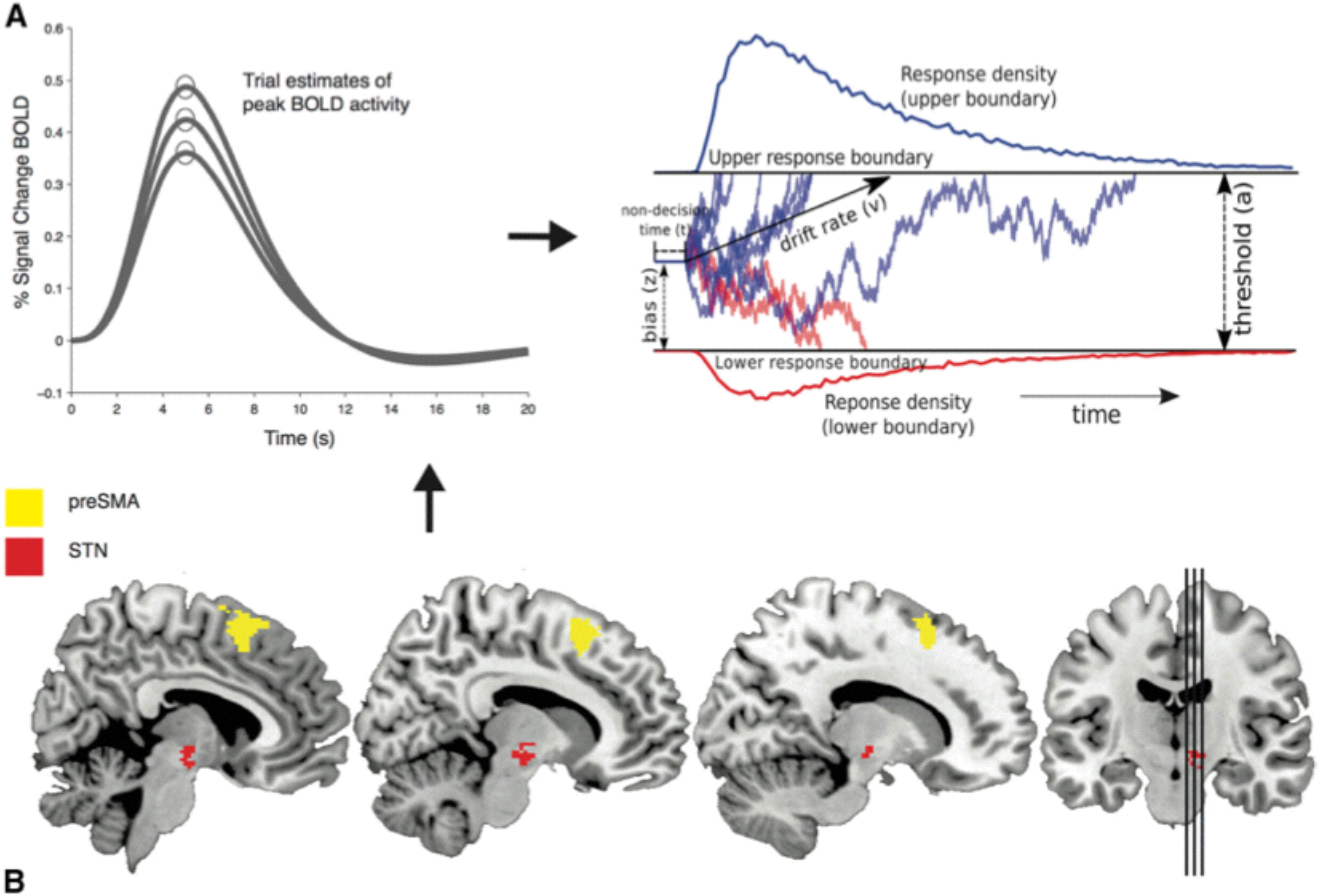
Behavioral/Cognitive

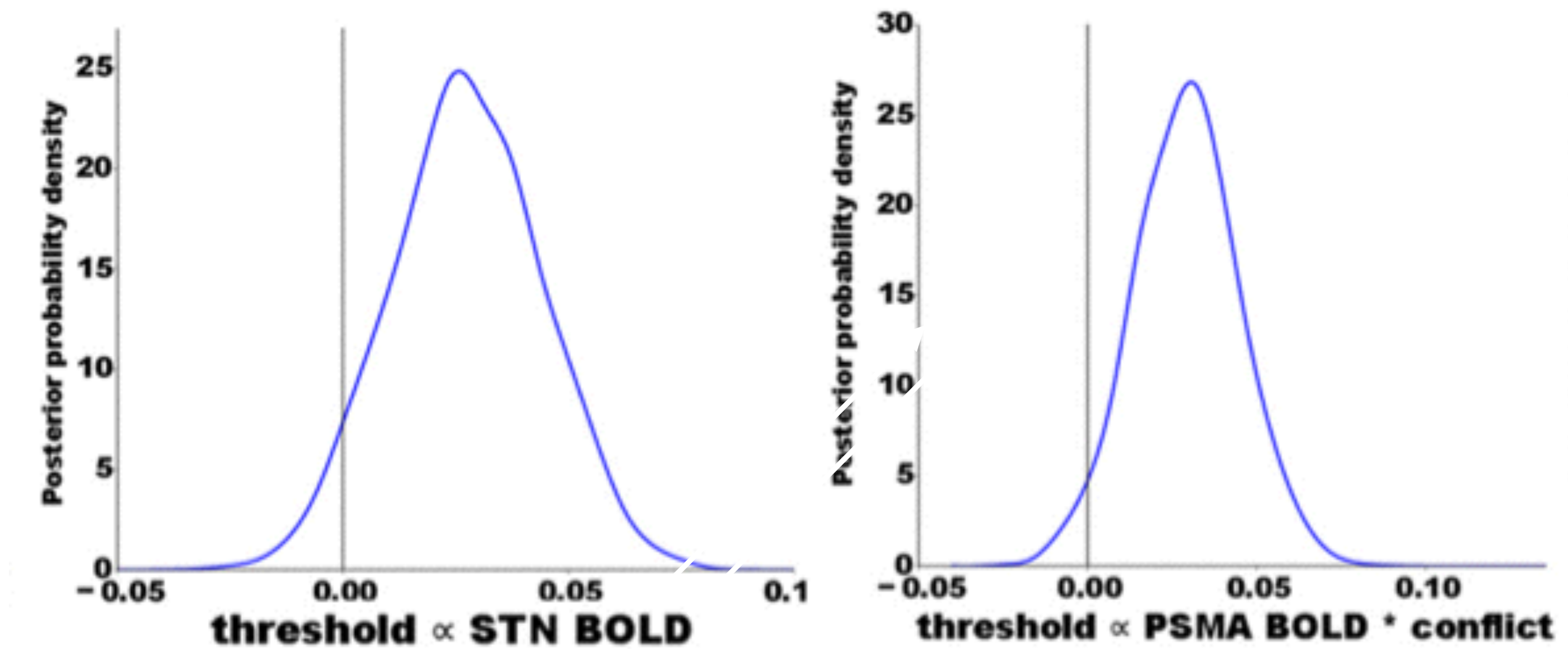
fMRI and EEG Predictors of Dynamic Decision Parameters during Human Reinforcement Learning

Michael J. Frank,[1,2,3] Chris Gagne,[1] Erika Nyhus,[1,4] Sean Masters,[1,2] Thomas V. Wiecki,[1,2] James F. Cavanagh,[1,5] and David Badre[1,2]



μ_v
σ_v
μ_a
σ_a
μ_t
σ_t
sv
v_s
a_s
t_s
choice, $RT_{T,s}$
$STN_{T,s}$
$a_{T,s}$
$v_{T,s}$
conflict $_{T,s}$
preSMA $_{T,s}$
theta $_{T,s}$
value $_{T,s}$
caudate $_{T,s}$
$T = 1, \ldots, N_{trials}$
$S = 1, \ldots, N_{subjects}$


A
Trial estimates of
peak BOLD activity
% Signal Change BOLD
0.6
0.5
0.4
0.3
0.2
0.1
0
-0.1
0 2 4 6 8 10 12 14 16 18 20
Time (s)
Response density
(upper boundary)
Upper response boundary
non-decision
time (t)
drift rate (v)
bias (z)
threshold (a)
Lower response boundary
Reponse density
(lower boundary)
time
preSMA
STN
B



- threshold ~ threshold_intercept + BOLD * beta

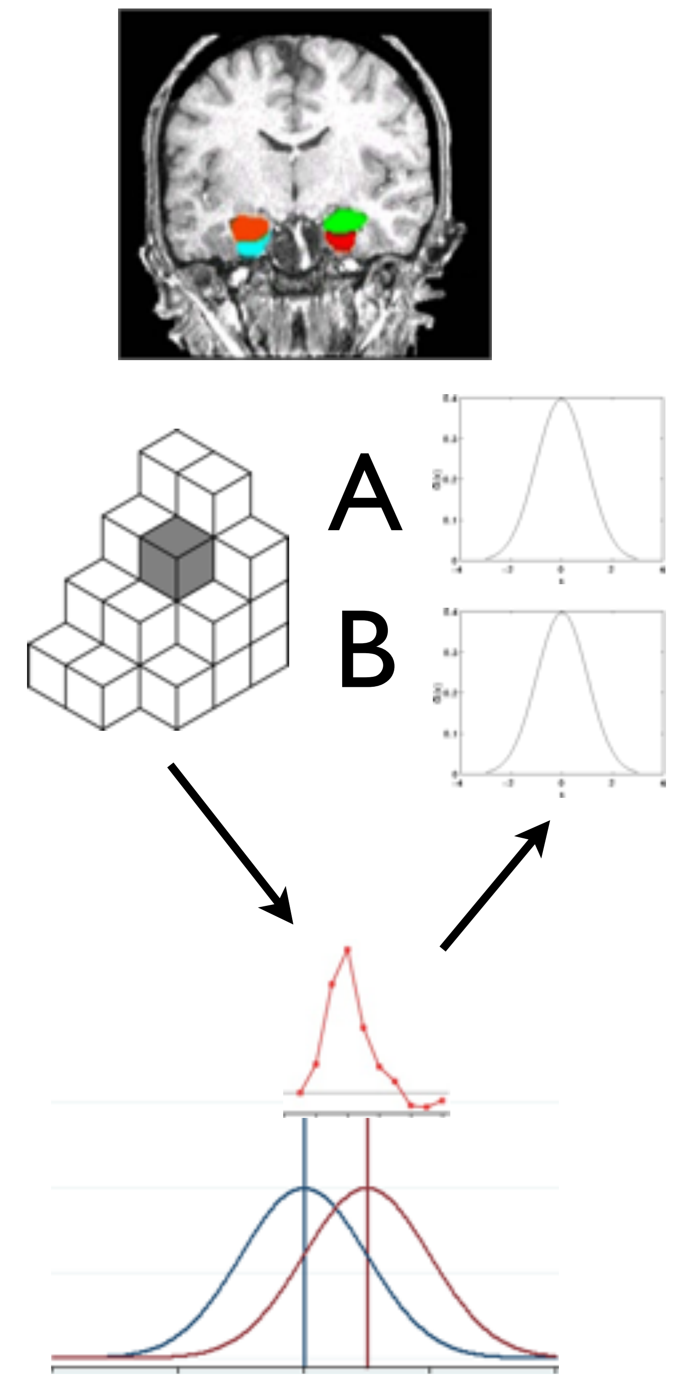
Multivariate fMRI

- **Exploit multivariate nature fMRI data**

Traditional ROI-fMRI study

1. For every voxel, *independently* estimate distribution of voxel activations across conditions
2. Is the mean activation of all voxels in area X different during condition A or B?

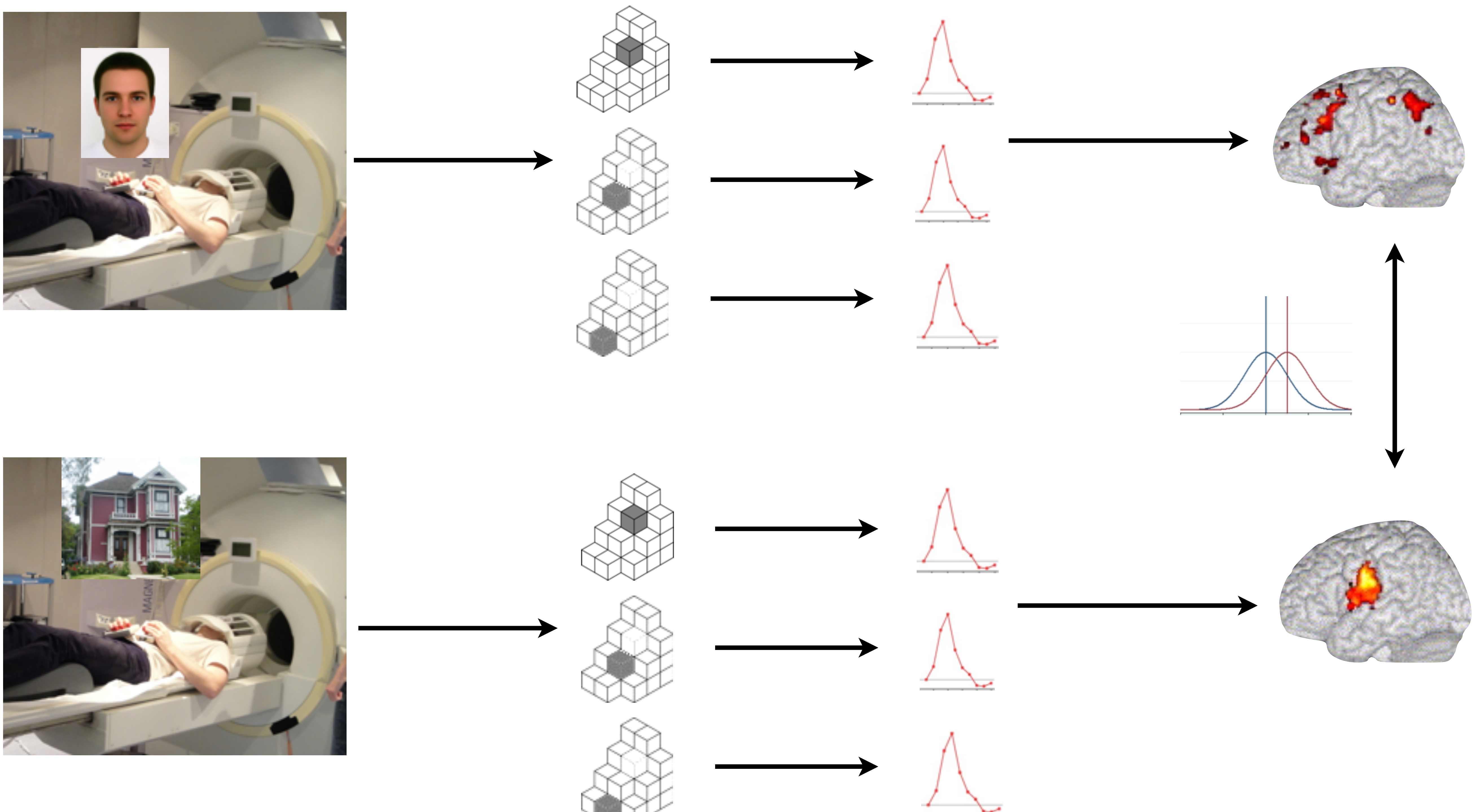
- *Massively Univariate*



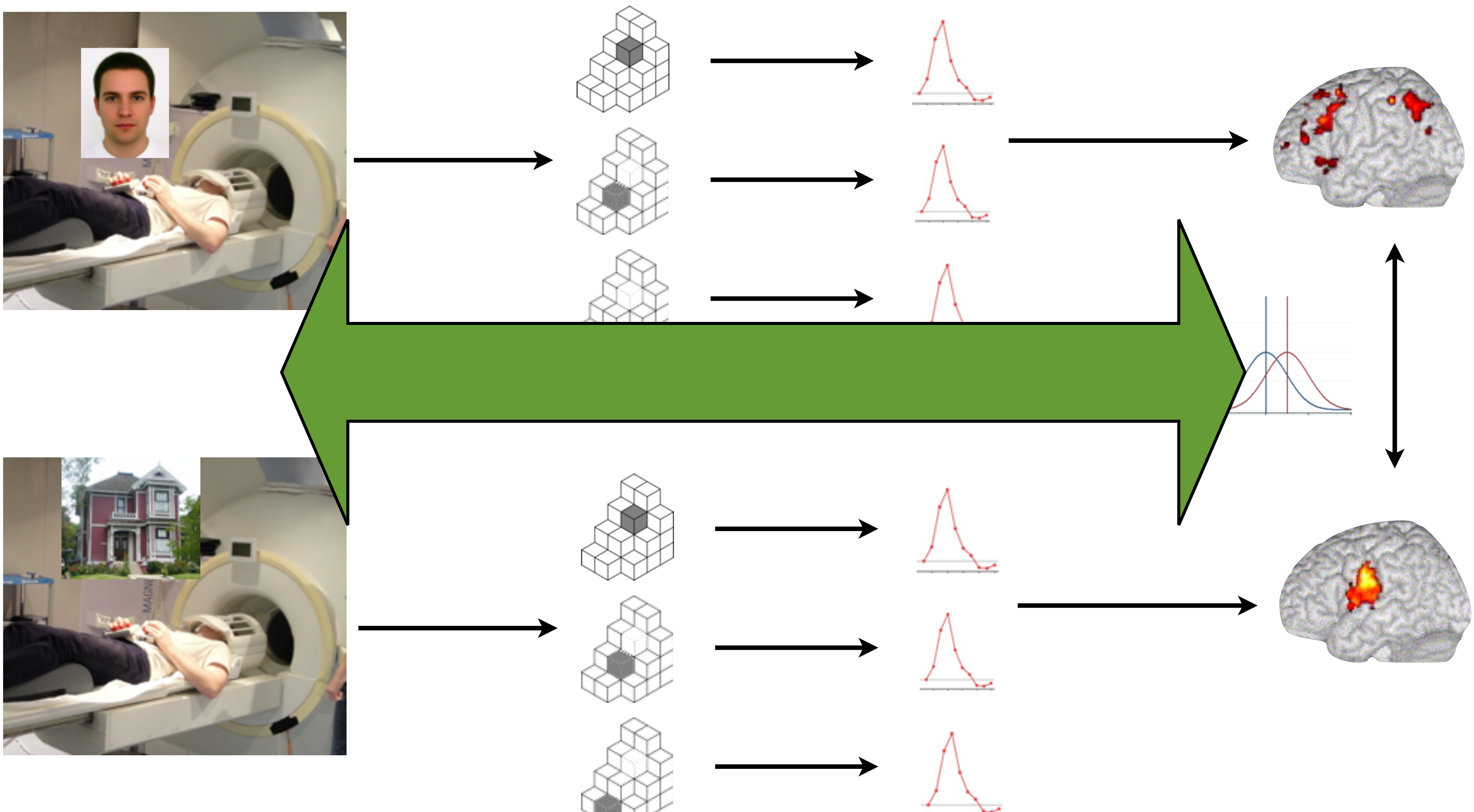
Traditional fMRI study

- Problem:
  - Data is highly <u>multivariate</u>
  - Great deal of information is thrown away!
    - Interaction between voxels
    - Need for smoothing
- Possible Solution:
  - Use *Big Data/Machine Learning* techniques from AI

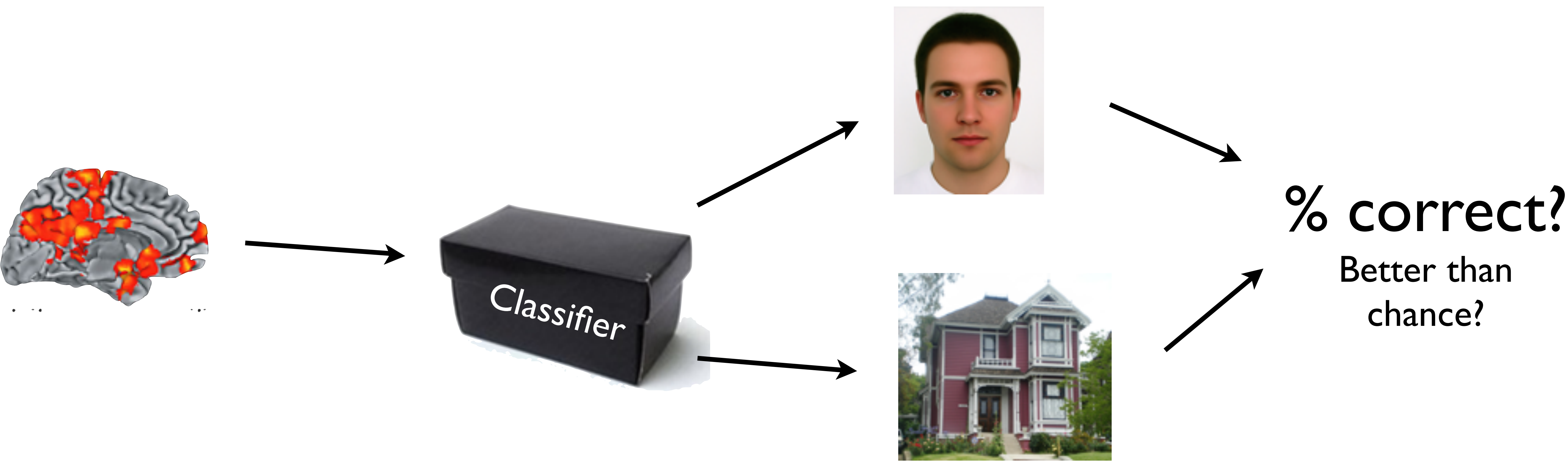
Univariate approach

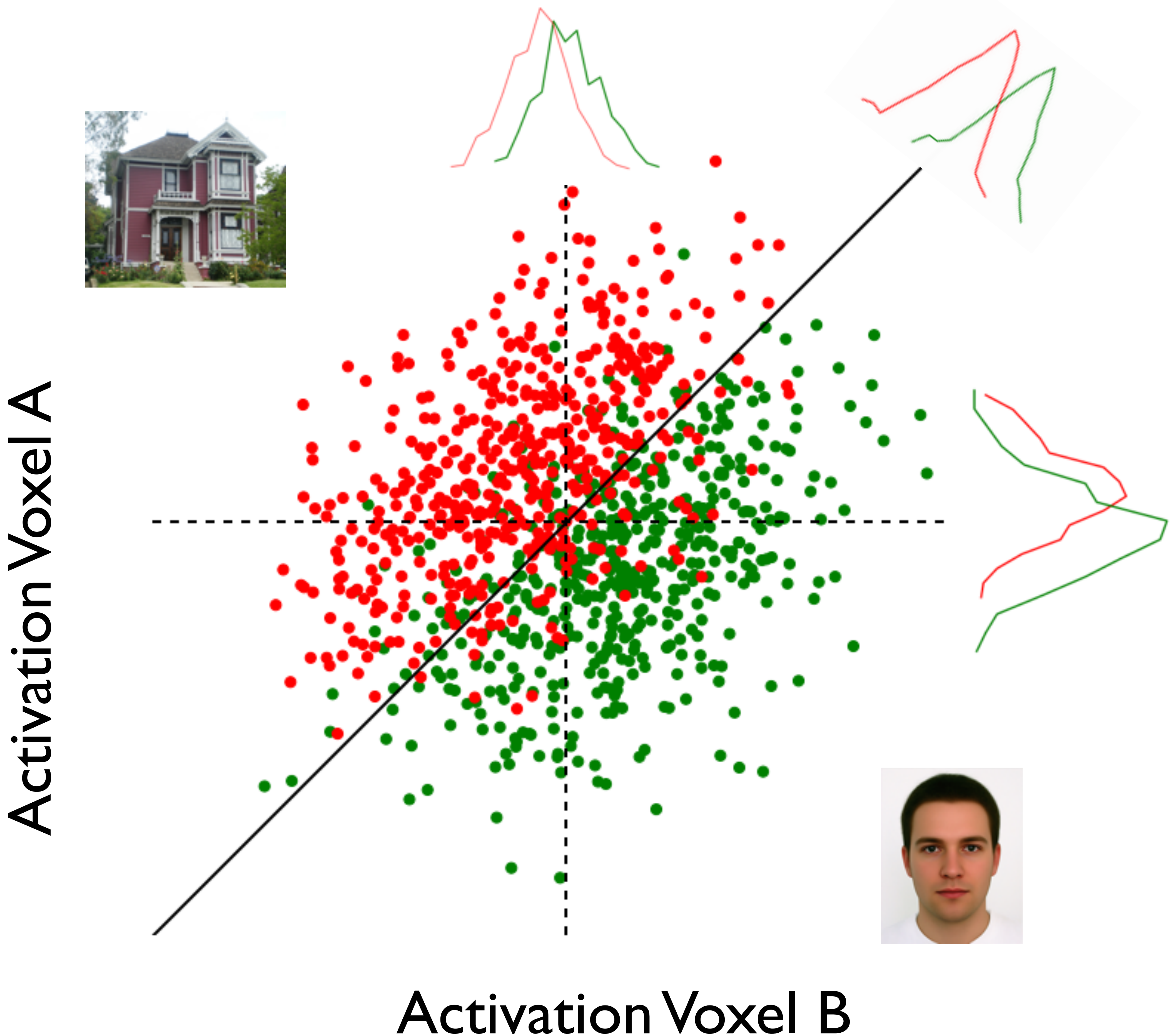


MVPA



MVPA




Activation Voxel A
Activation Voxel B

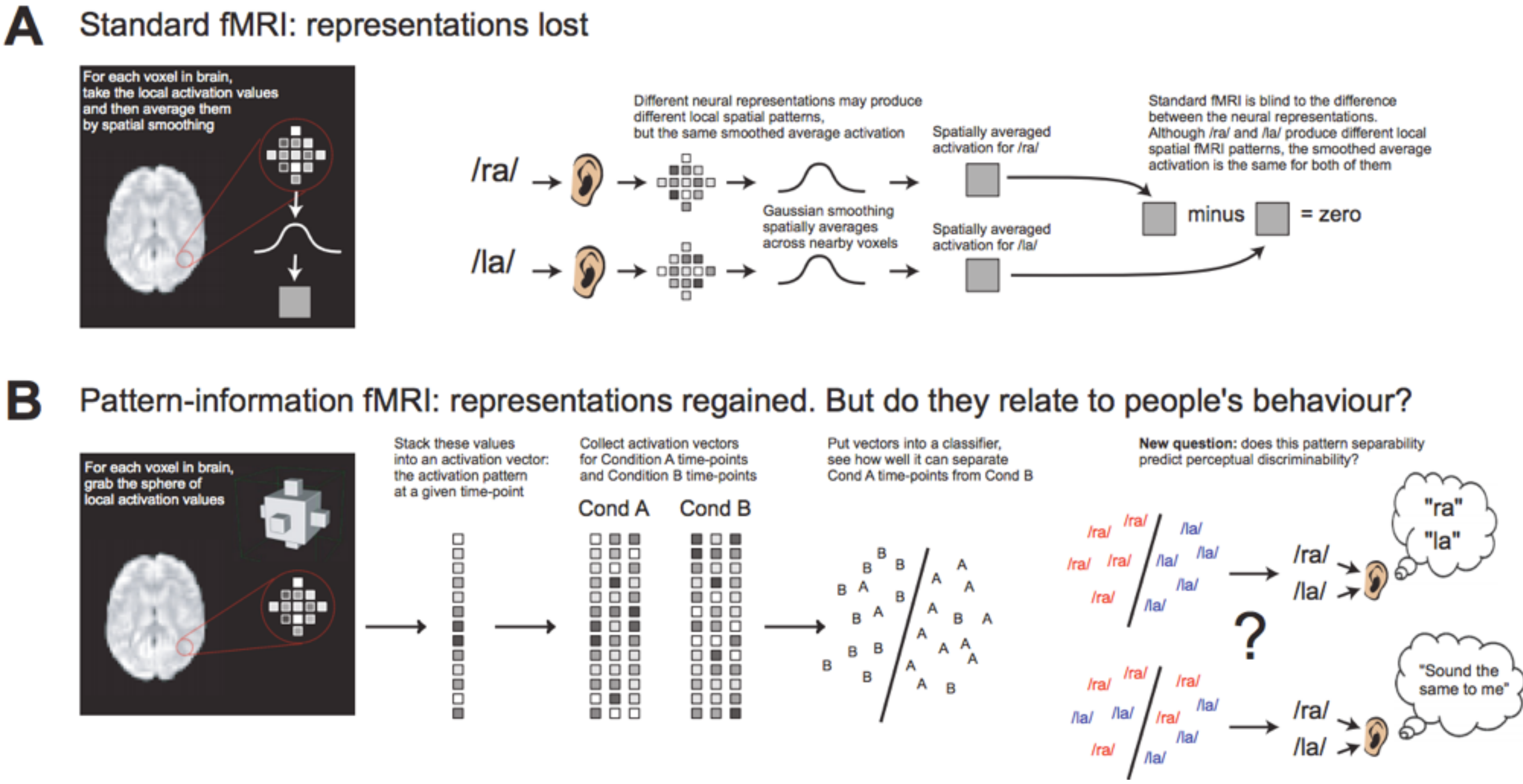
Why MVPA is more Sensitive

- Haynes (2006)

1. Information in separate voxels can be accumulated more efficient
2. Separate brain areas might interact
3. No need for Smoothing
4. Univariate analyses average over all timepoints

Representational Similarity Analysis

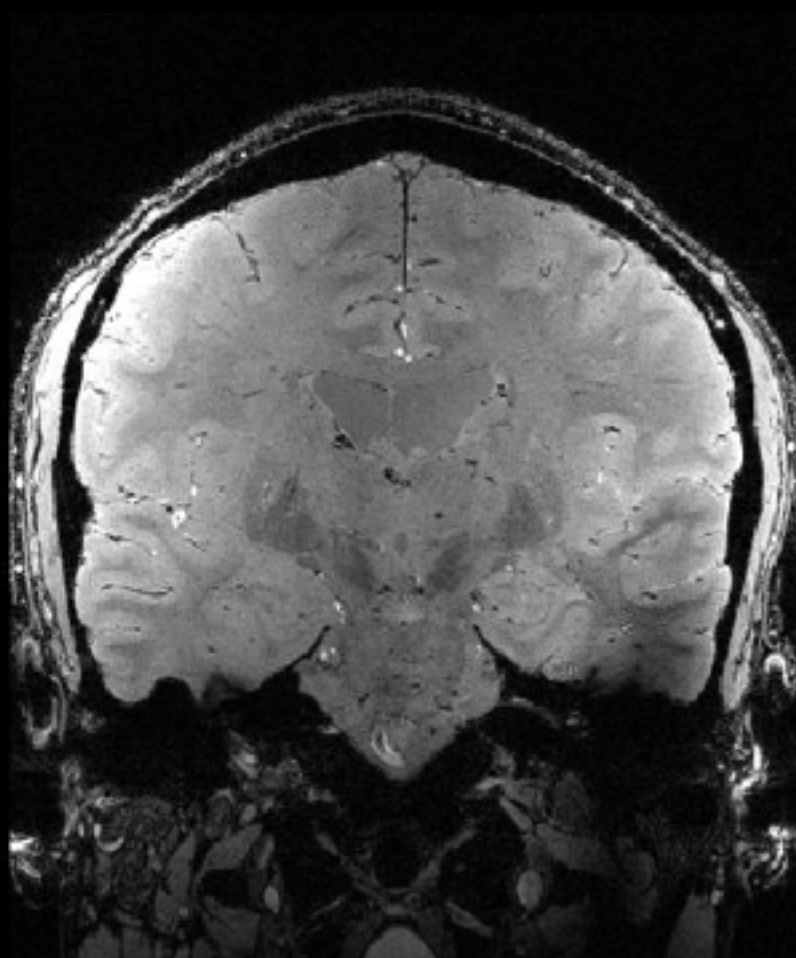
Multivariate Patterns



(Raizda, 2010)

MVPA

- Summary
  - Dependent variable and independent variable are turned around
  - Use data maximally by taking into account multivariate nature
  - Shift from
    - *Differences in activation in individual voxels*
    - *How do neural representations differ?*



Python and the Brain

python™

- Originated in late 80’s at CWI, Amsterdam
- Guido van Rossum
  - *Benevolent Dictator for Life (BDFL)*

The Zen of Python

```
In [1]: import this
The Zen of Python, by Tim Peters

Beautiful is better than ugly.
Explicit is better than implicit.
Simple is better than complex.
Complex is better than complicated.
Flat is better than nested.
Sparse is better than dense.
Readability counts.
Special cases aren't special enough to break the rules.
Although practicality beats purity.
Errors should never pass silently.
Unless explicitly silenced.
In the face of ambiguity, refuse the temptation to guess.
There should be one-- and preferably only one --obvious way to do it.
Although that way may not be obvious at first unless you're Dutch.
Now is better than never.
Although never is often better than *right* now.
If the implementation is hard to explain, it's a bad idea.
If the implementation is easy to explain, it may be a good idea.
Namespaces are one honking great idea -- let's do more of those!
```

- Interpreted Language
  - Tradeoff development productivity/runtime speed
  - Platform-independent
- Extensibility (*modules*)
  - Also with e.g. C-code (Cython)
  - Fits very well in open source model
  - APIs
  - `re-laptop-93-158:~ Gilles$ sudo pip install nipype`
- Easy to write/easy to <u>**read**</u>

Python in the Real World

Python in Science

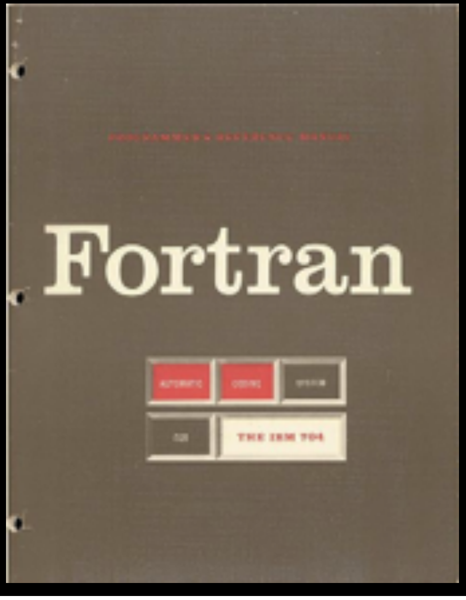
NumPy

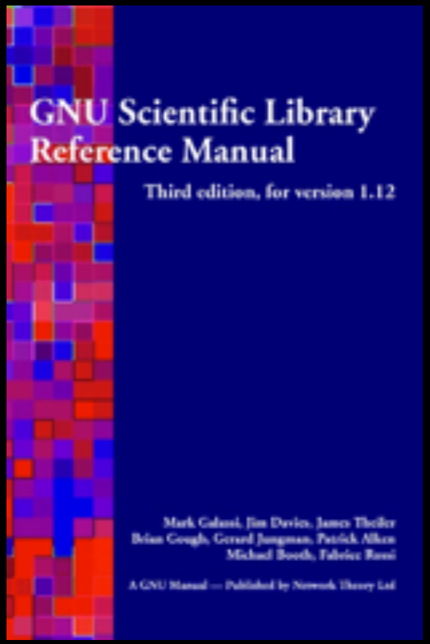
SciPy.org Sponsored By ENTHOUGHT

LAPACK — Linear Algebra PACKage

matplotlib

IP[y]: IPython Interactive Computing





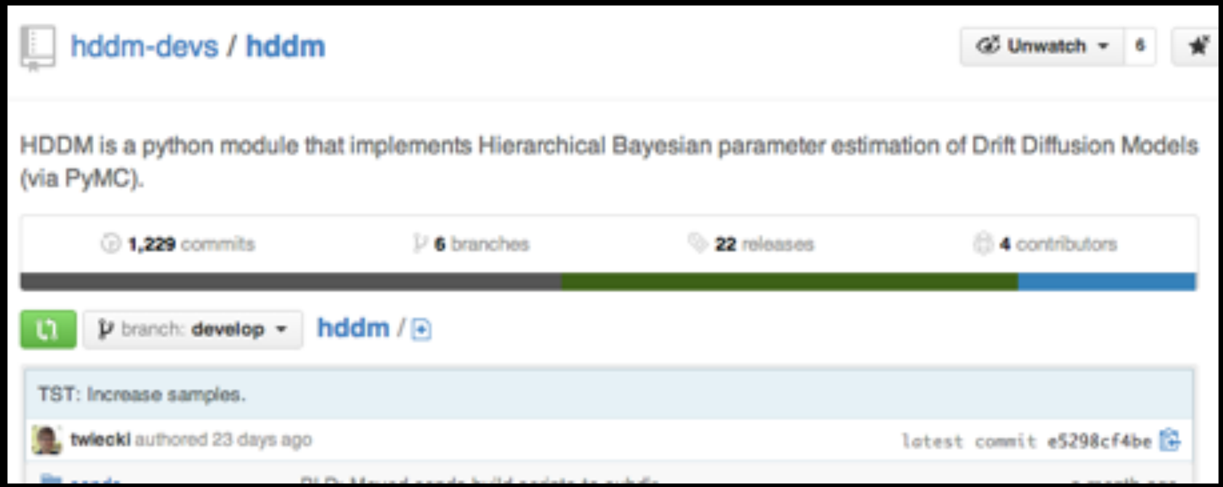
statsmodels

pandas $y_{it} = \beta' x_{it} + \mu_i + \epsilon_{it}$

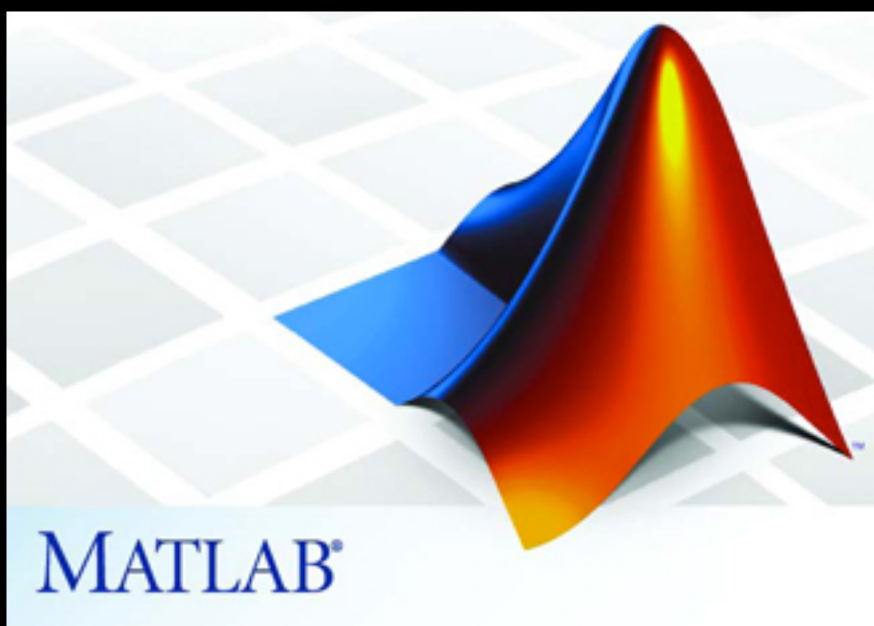
scikit-learn
Machine Learning in Python

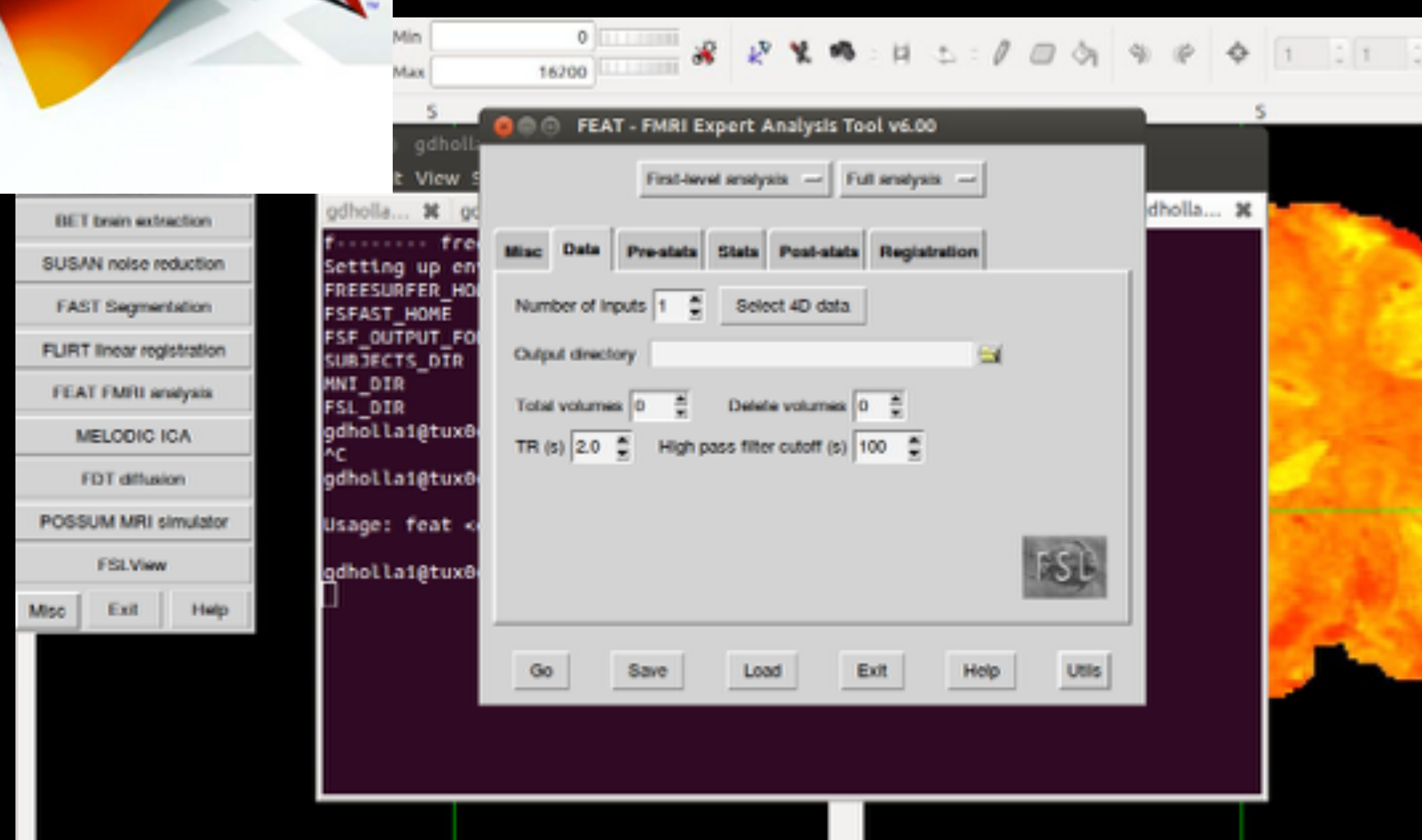
The Open Source/ github-model

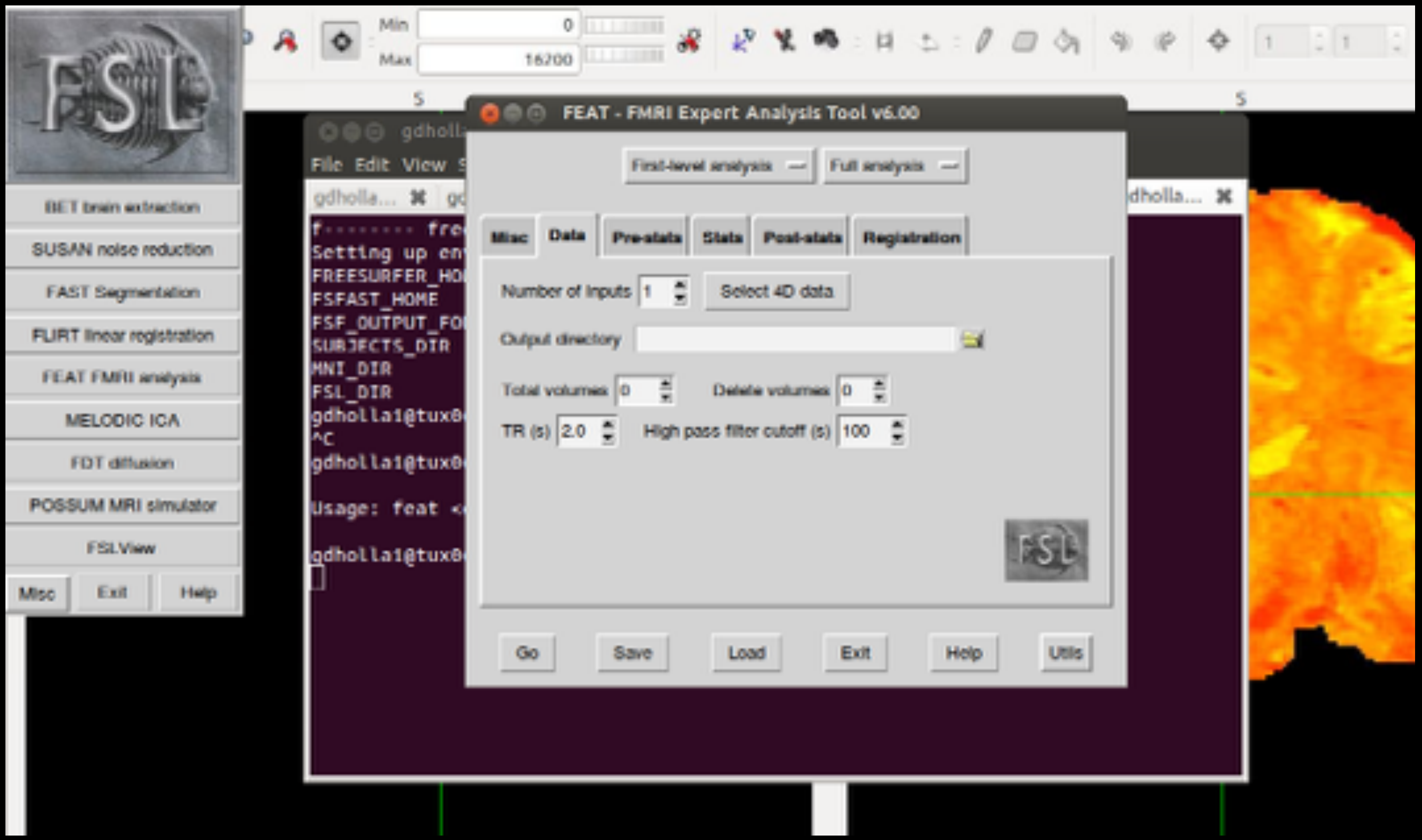
- Free
- Transparent
- Large group of collaborators
  - Closely linked to actual users
- Code review
- Unit tests
- Easy distributable
- Interaction with other packages



Python in Neuroscience?







- FSL
  - Does the UI really makes things easier?
  - Rather autistic: interaction with other software is pretty hard
  - No ‘easy acces’ to underlying code/data
  - Underlying algorithms are good!

- Expensive!
- Not open-source
- Really messy language
- Relatively hard to interact with other software
- People like the shell

- Really good open-source libraries in *statistics/ machine-learning*
- Not a general-purpose programming language
  - File handling
  - object-oriented
- Traditionally not well-suited for neuroimaging

Solution?

- Python as general-purpose scripting/ programming language, glueing data handling, C, R and FSL, SPM, ... together
- IPython (notebook) as interactive shell

frontiers in NEUROINFORMATICS

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Python in neuroscience

NIPY

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Diffusion Imaging In Python ¶

Nipype: Neuroimaging in Python Pipelines and Interfaces

nipy / pbrain

Python EEG and ECoG analysis software by John Hunter et al http://nipy.sourceforge.net/pbrain

PsychoPy

Psychology software in Python

Nitime: time-series analysis for neuroscience

NiBabel

Access a cacophony of neuro-imaging file formats

Today

- Do some preprocessing of fMRI-data with Nipype
- Plot and inspect data
- Fit hierachical drift diffusion model to behavioural data
- Link neural fMRI data to computational DDM model