



# Statistical analysis of PET data

Lauri Nummenmaa

Turku PET Centre / TYKS

Twitter: [@TurkuPETcentre](https://twitter.com/TurkuPETcentre)

WWW: <http://pet.utu.fi>

# Basic problems associated with scientific measurement

ERRORS PRESENT AT ALL LEVELS; THEY ALSO ACCUMULATE FROM LEVEL TO LEVEL

**TARGET**  
(e.g. specific neuro-receptor)

**TRUE SCORE (T)**  
How target is defined  
(e.g. number of receptors)

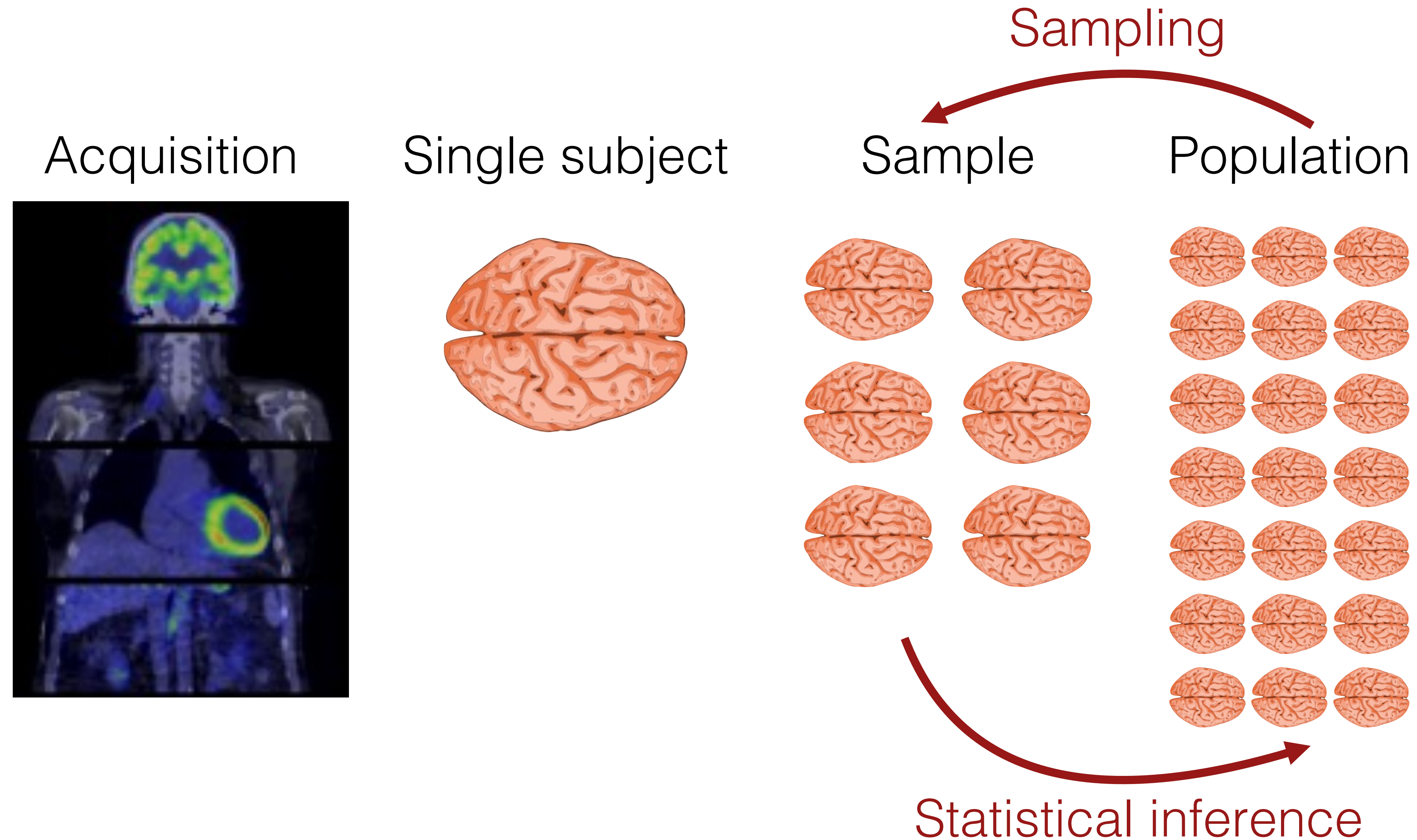


**OBSERVED SCORE**  
(Outcome measure such as BPND)

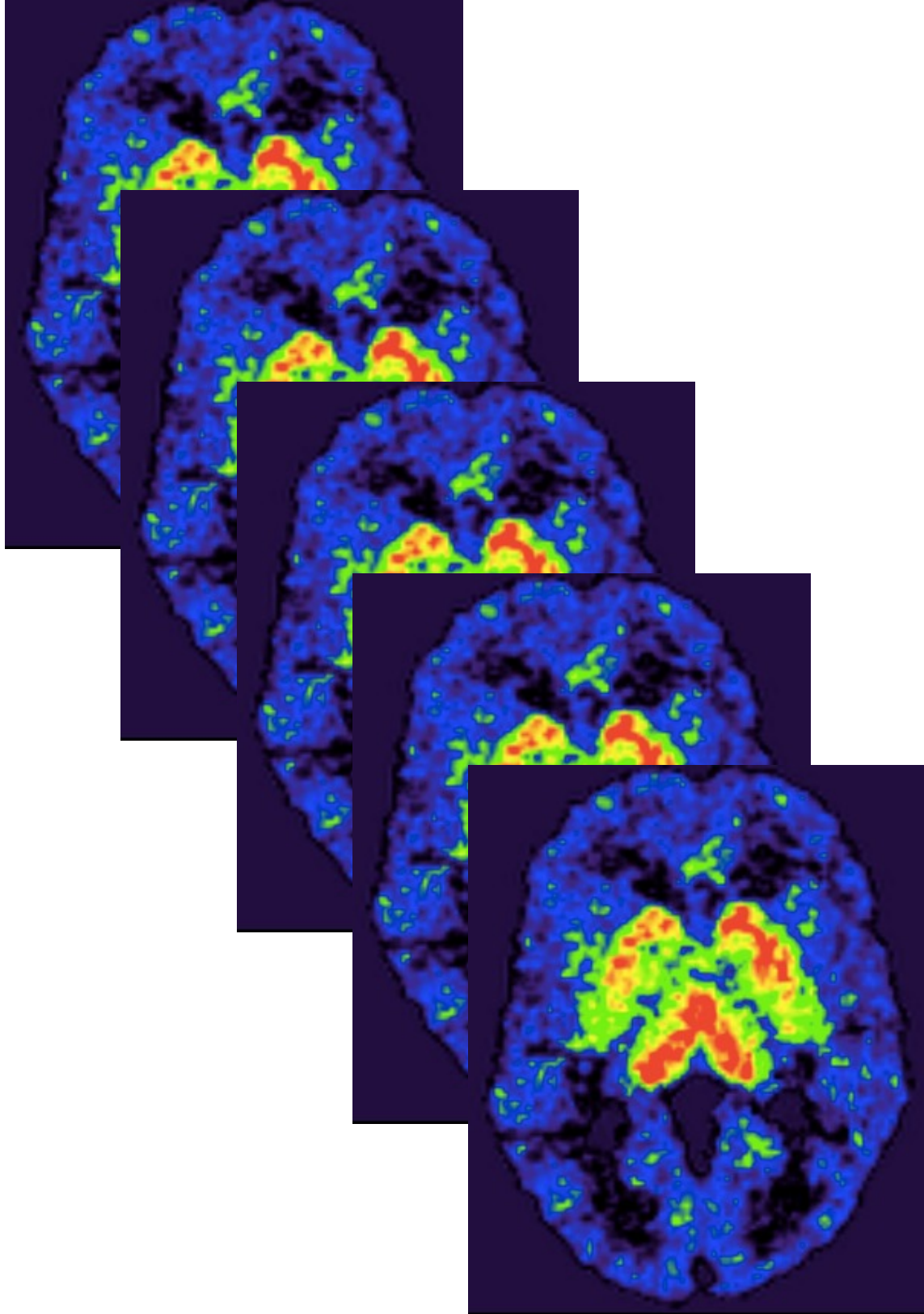
**PREDICTION OF BEHAVIOR**  
(e.g. anxiety-like behaviour)

- How well is target variable reflected in true score (construct validity)
- How well true score is reflected in observed score? (reliability)
- How well does observed score predict behaviour? (criterion-based validity)

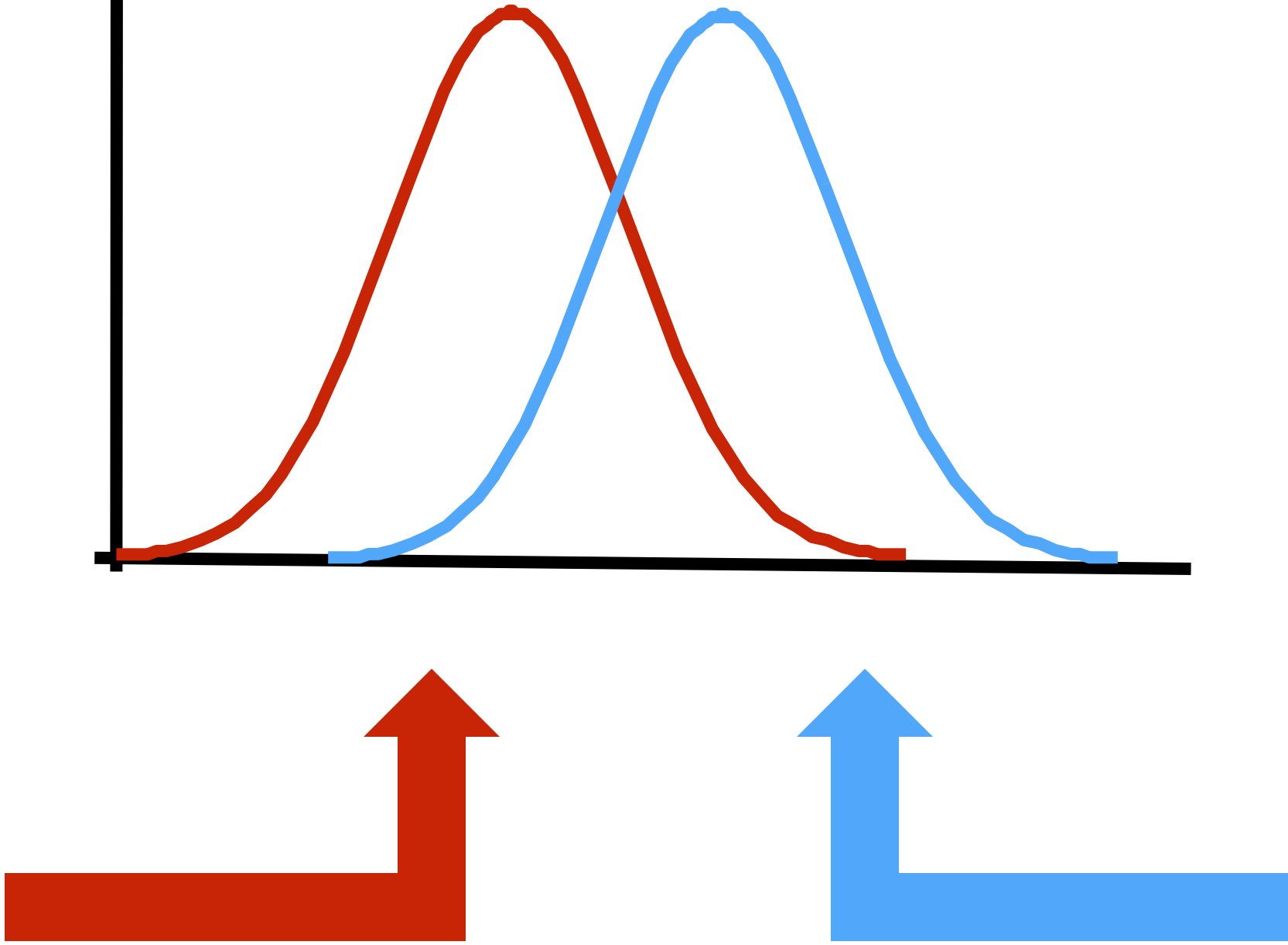
# Making inferences about the population



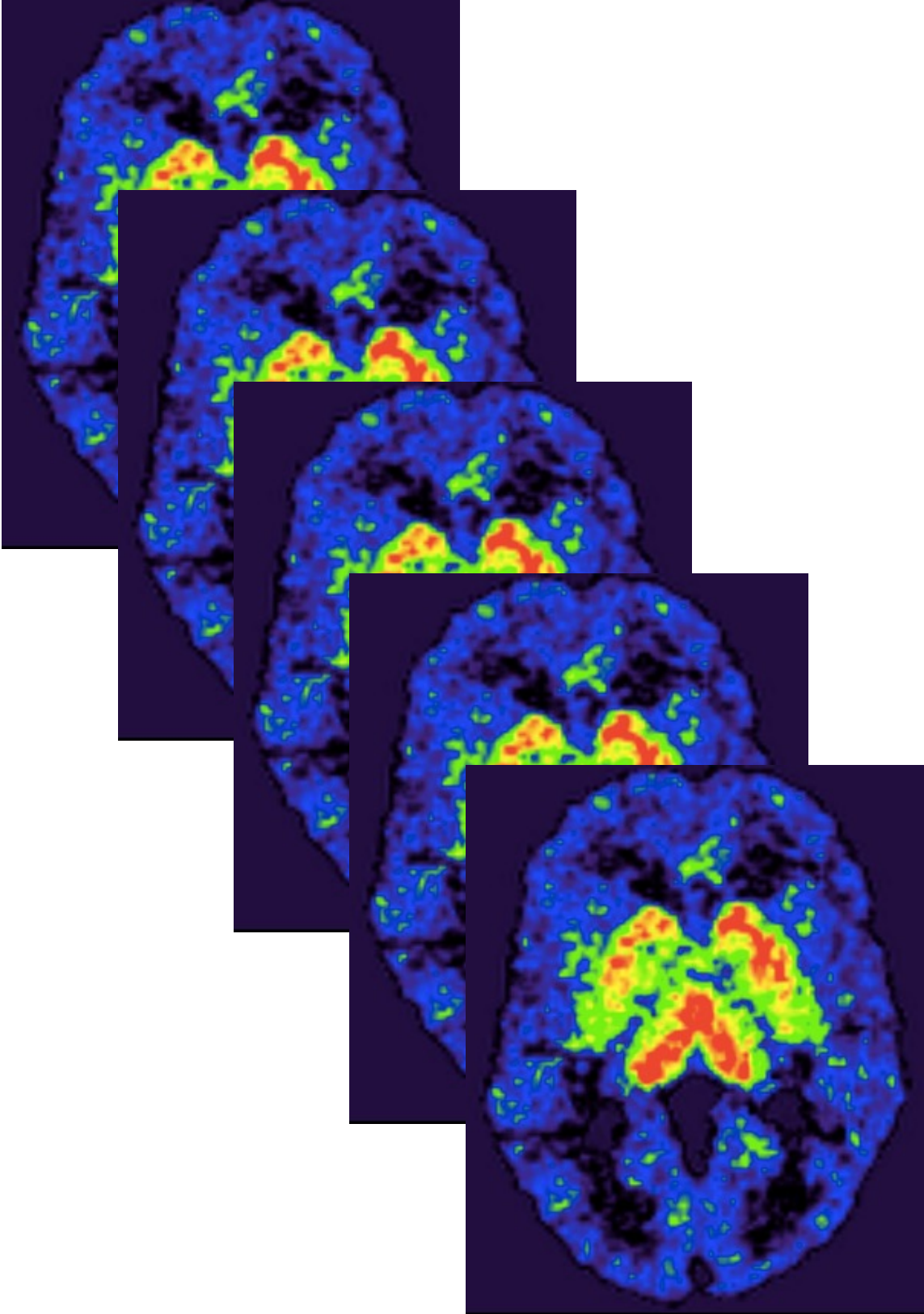
CONTROLS



ARE THESE BRAINS  
STATISTICALLY  
DIFFERENT?



PATIENTS

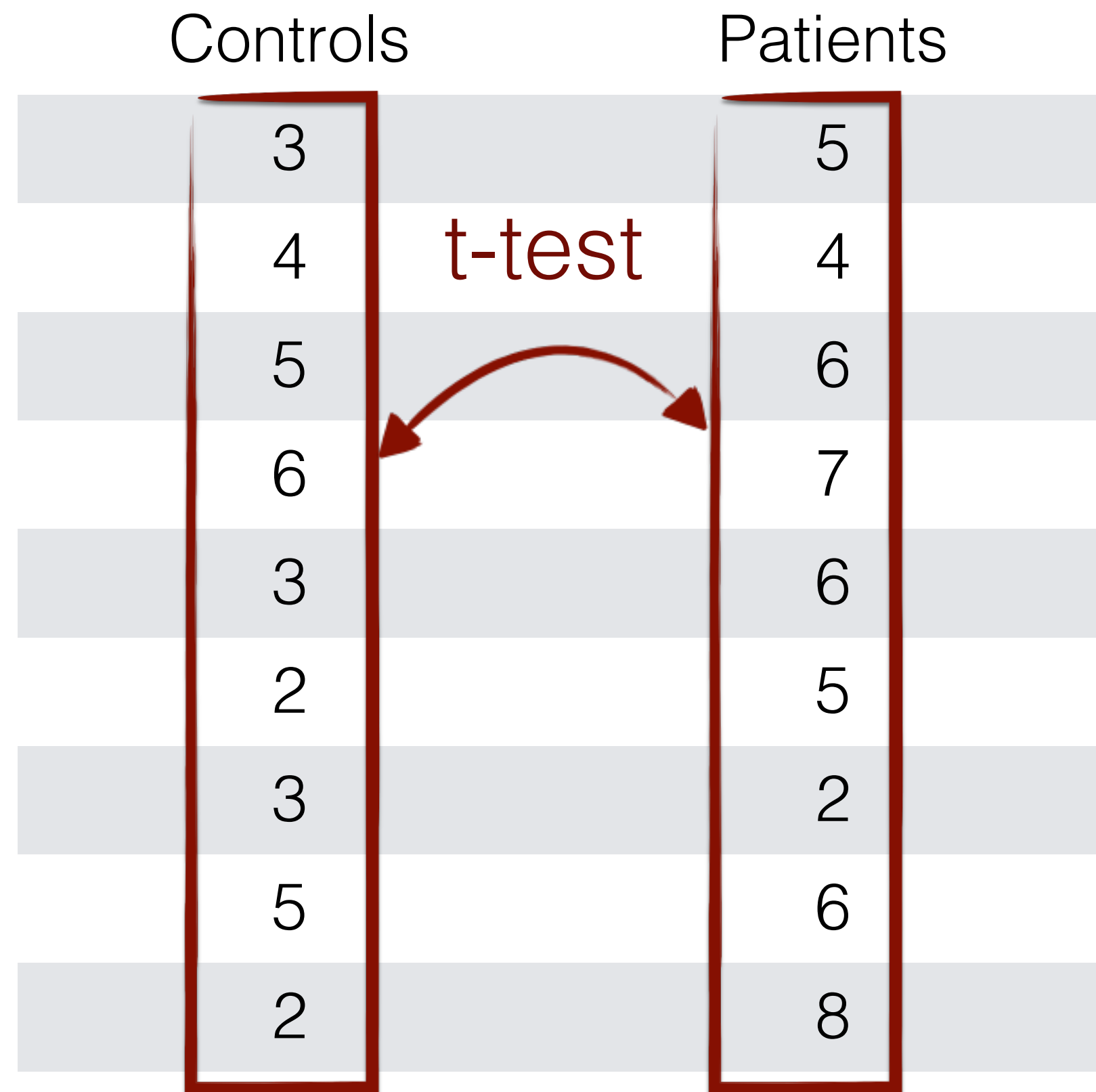


Starting point: Images where voxel intensities reflect the outcome measure

# Sneak peek: Analysis of PET vs. fMRI data

- **PET data needs to be modelled** before population level inference
  - Dynamic 4D image or static 3D image → 3D image
  - Voxel intensities reflect outcome measure (receptor density, metabolism....)
- **Similarly, EPI data needs to be modelled** before population level inference
  - Dynamic 4D image → 3D image
  - Voxel intensities reflect the fit of the stimulation model to the BOLD time series

Univariate data  
Regularly shaped

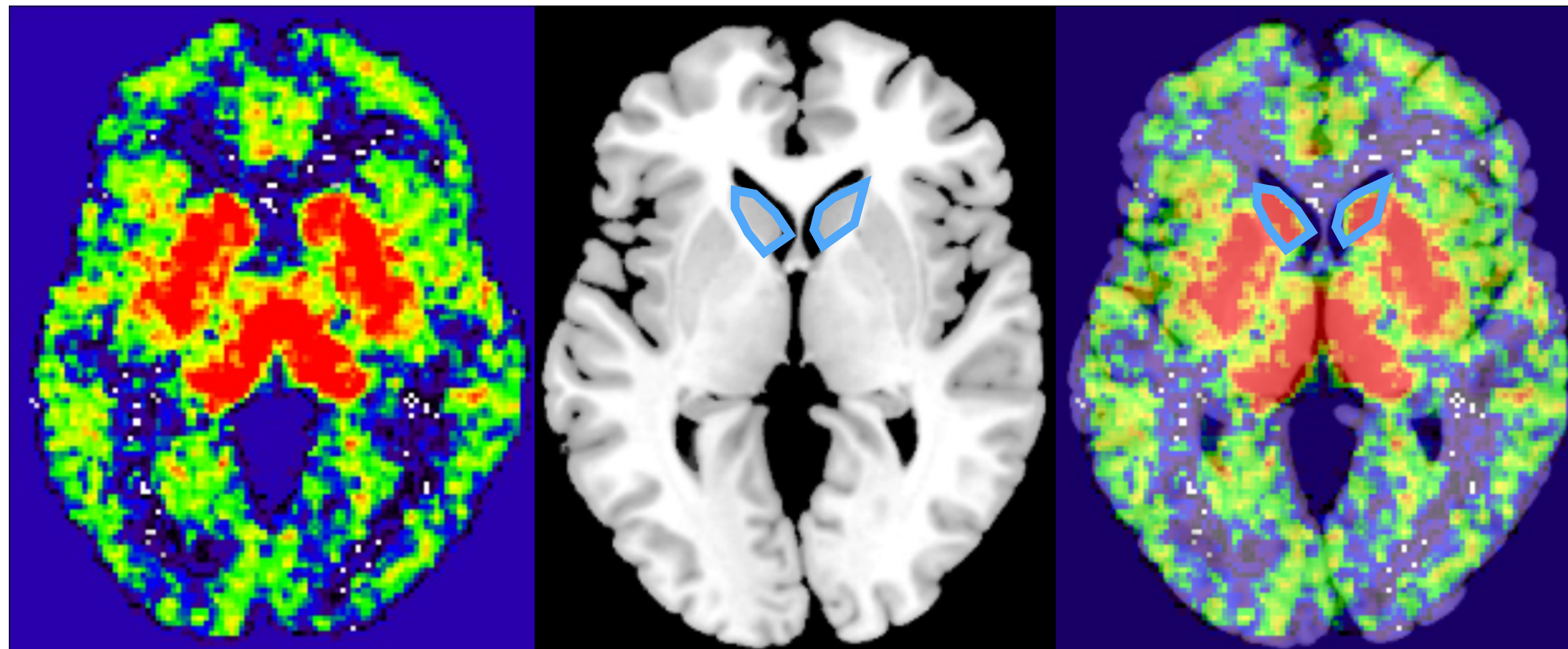


3D neuroimaging data  
Irregularly shaped



# ROI-based analyses

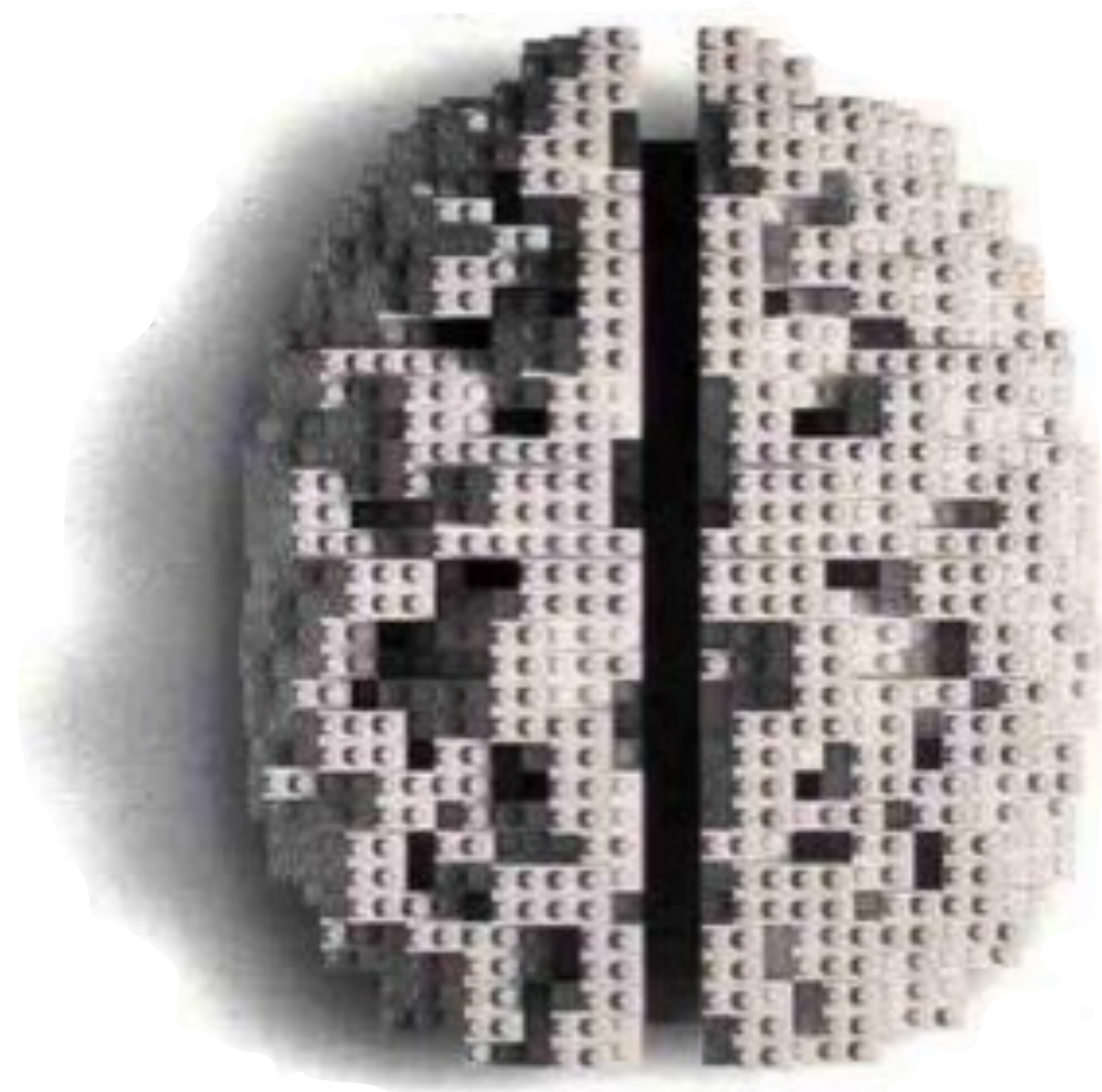
Univariate data  
regularly shaped  
can use univariate stats



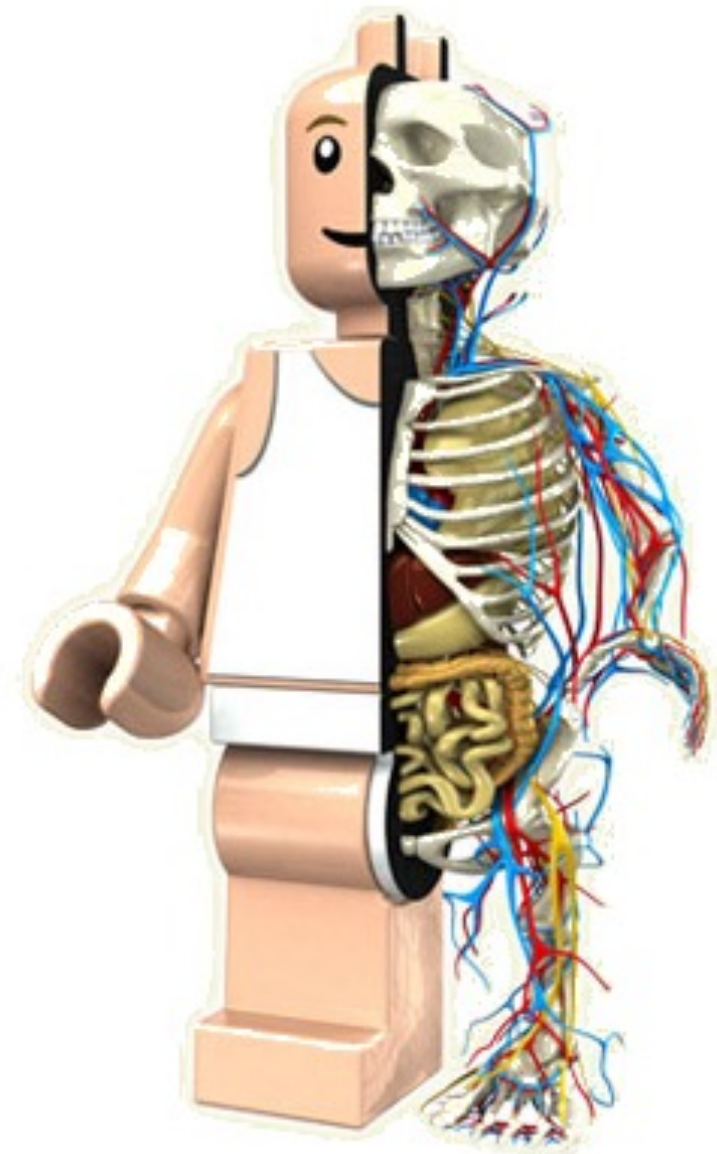
Extract  
outcome  
measure  
in ROI

Controls	Patients
3	5
4	4
5	6
6	7
3	6
2	5
3	2
5	6
2	8

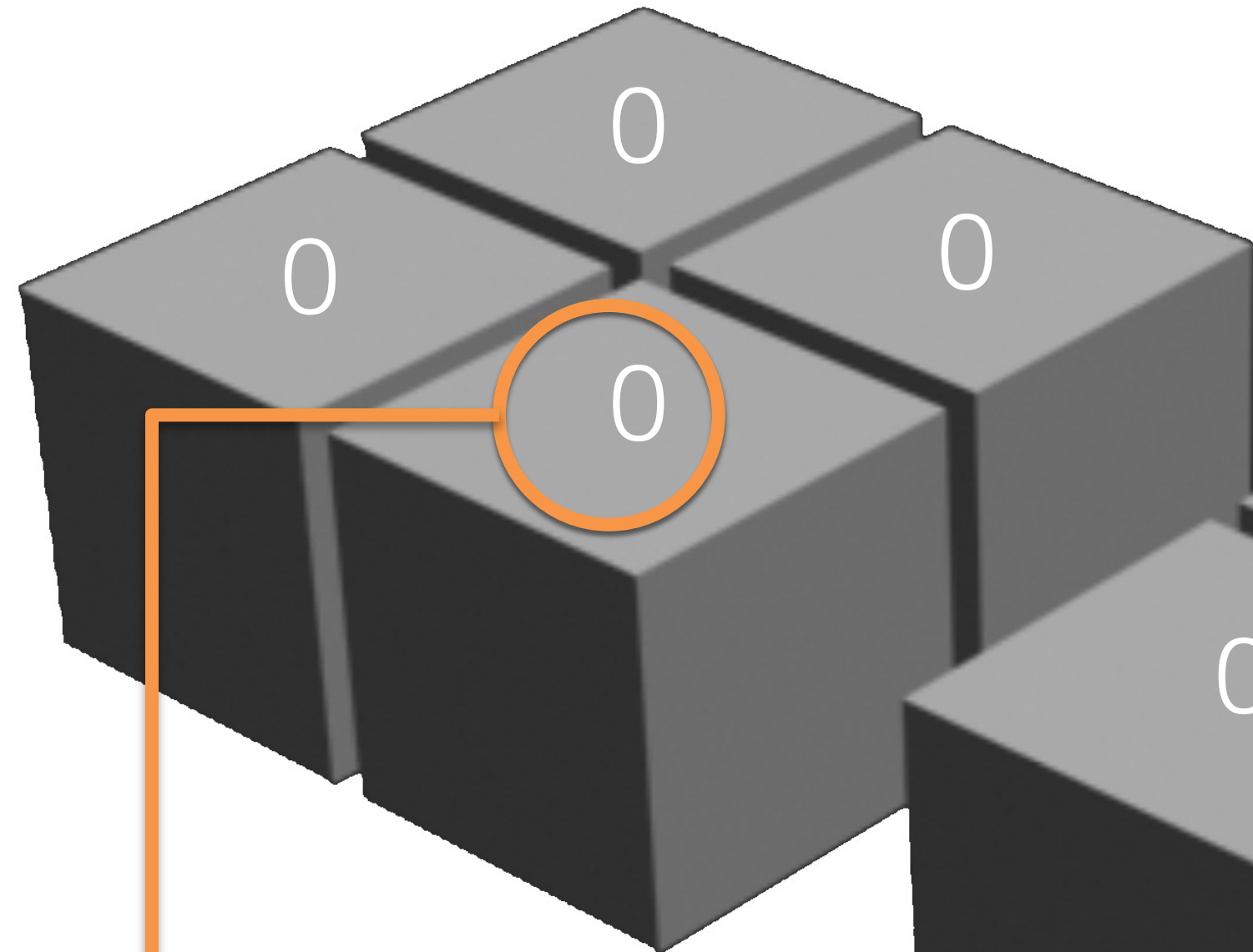
- **Pros:** Anatomically accurate if ROIs well defined, data can be analyzed with simple univariate statistical tests
- **Cons:** Laborious, using many ROIs not feasible, averaging within ROI not always appropriate





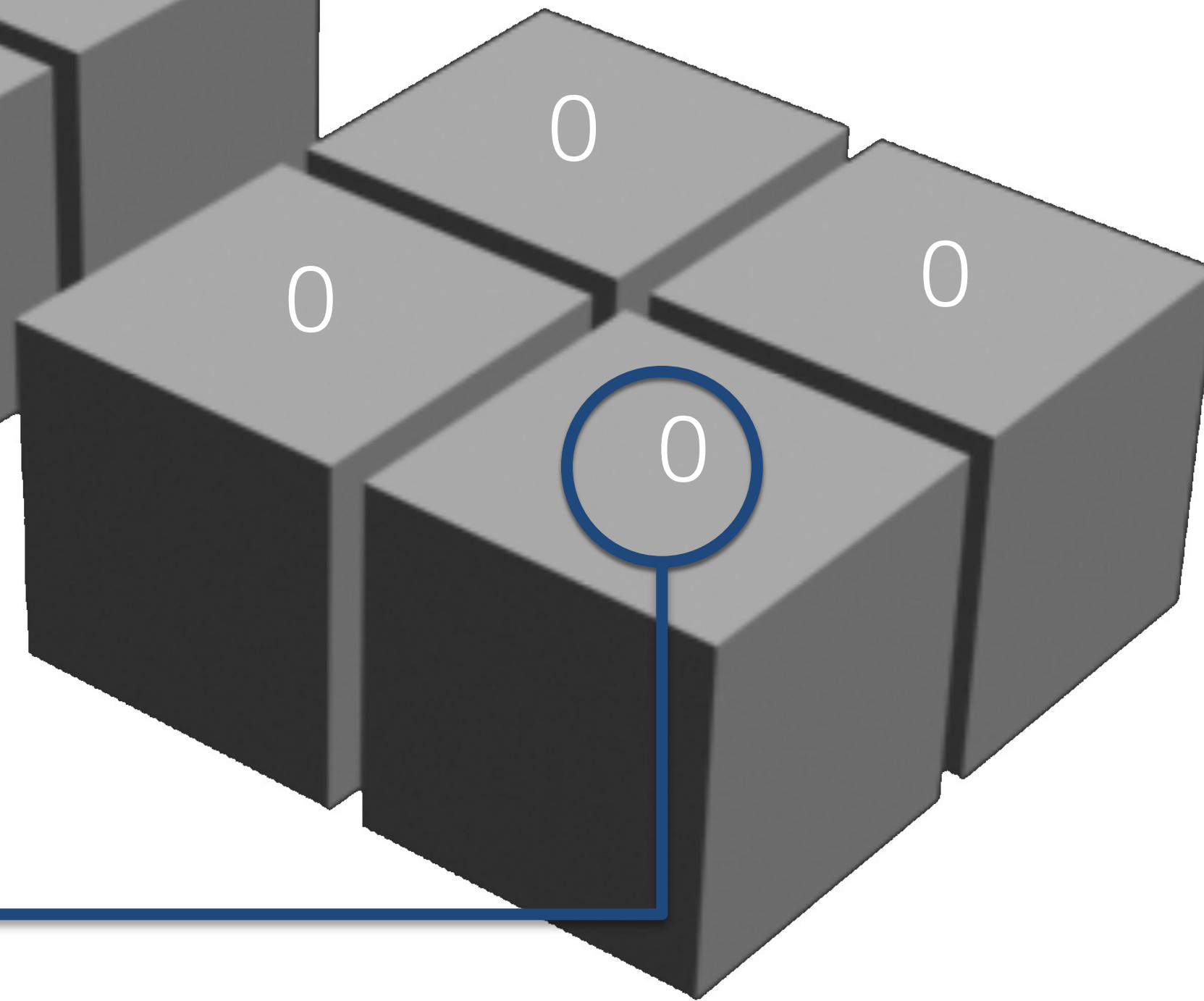


Controls

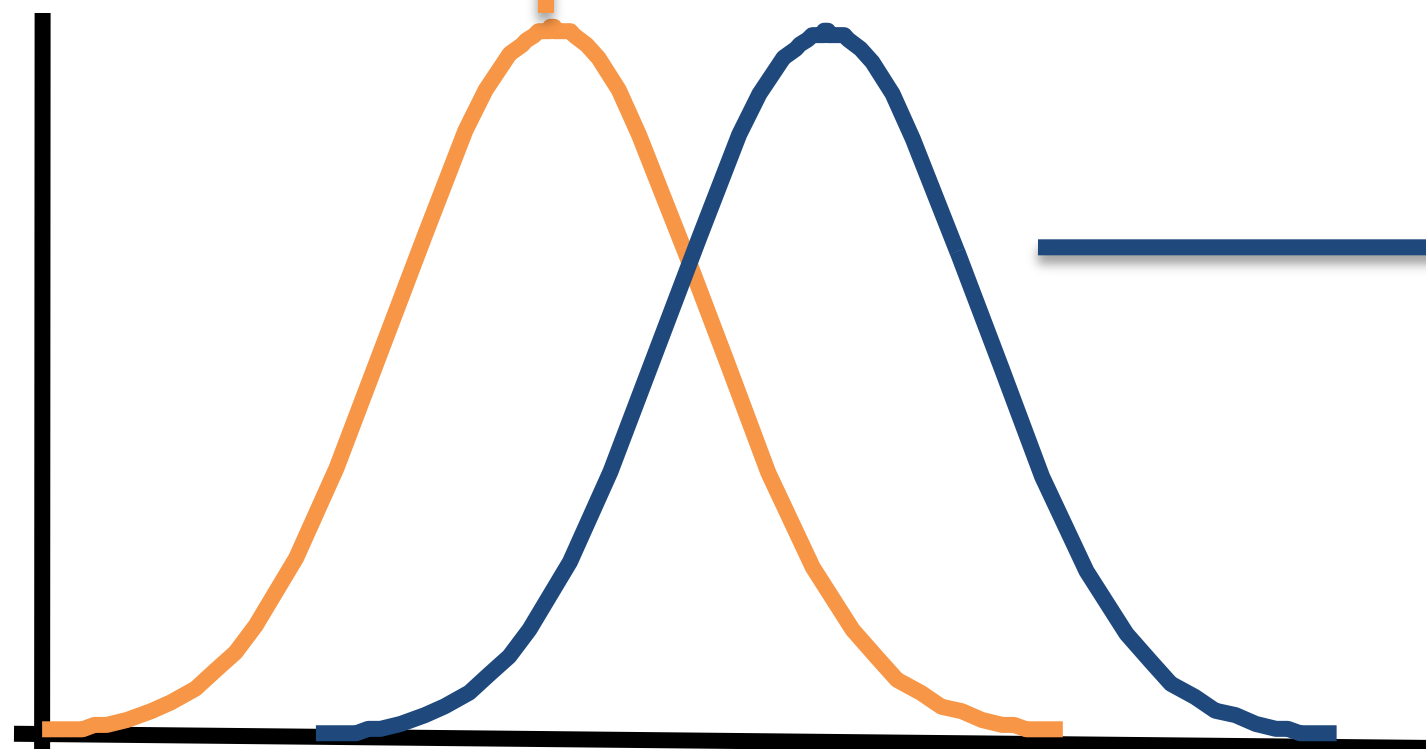


Voxelwise  
outcome  
measures

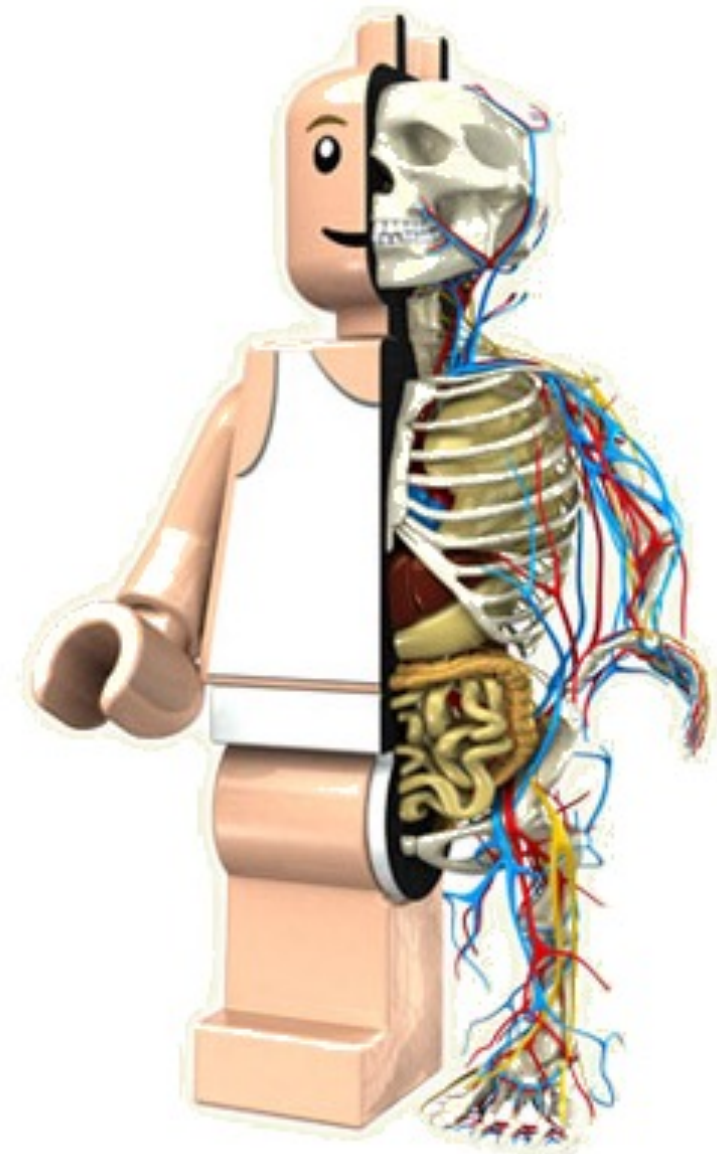
Patients



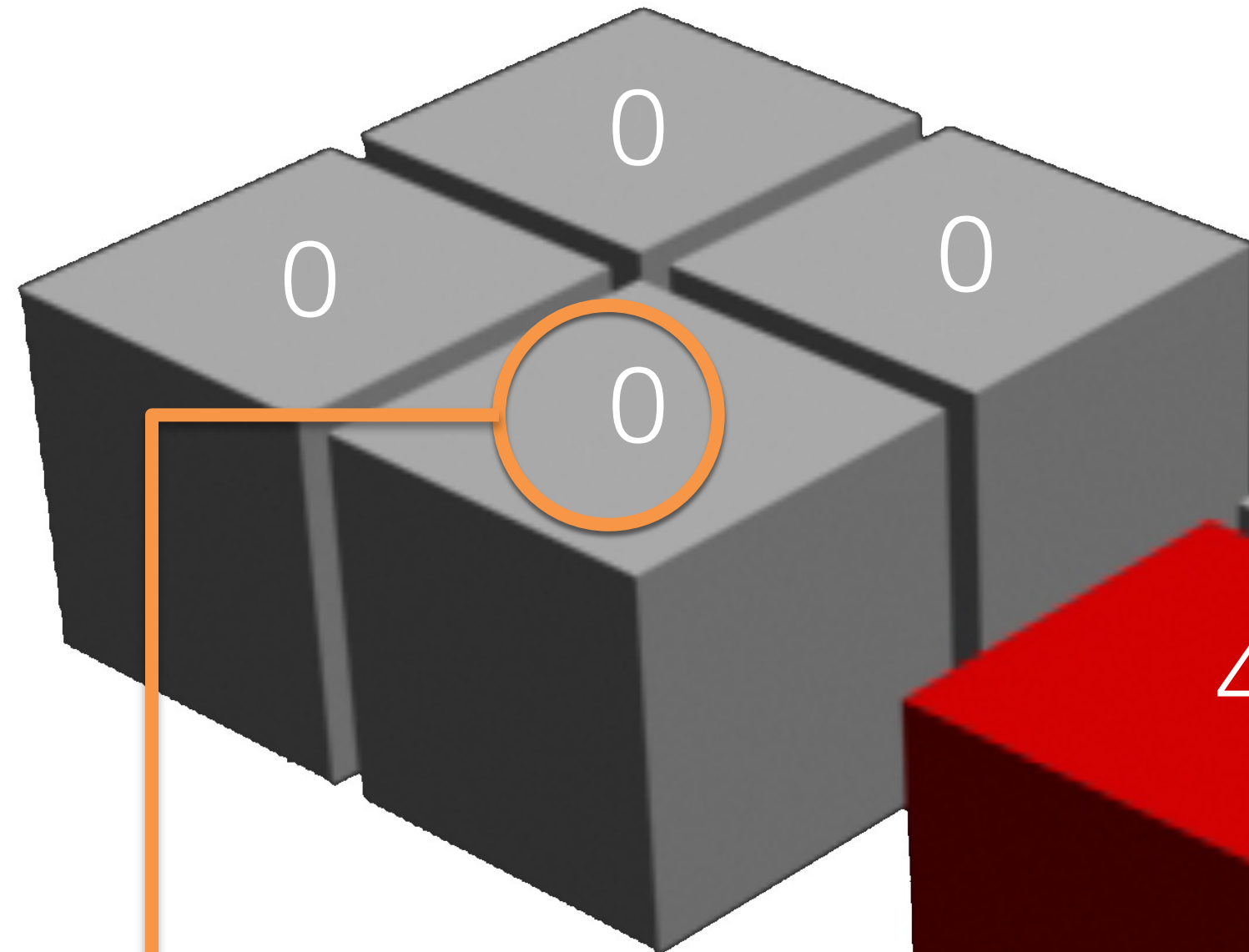
Univariate voxelwise data  
regularly shaped  
can use mass  
univariate stats



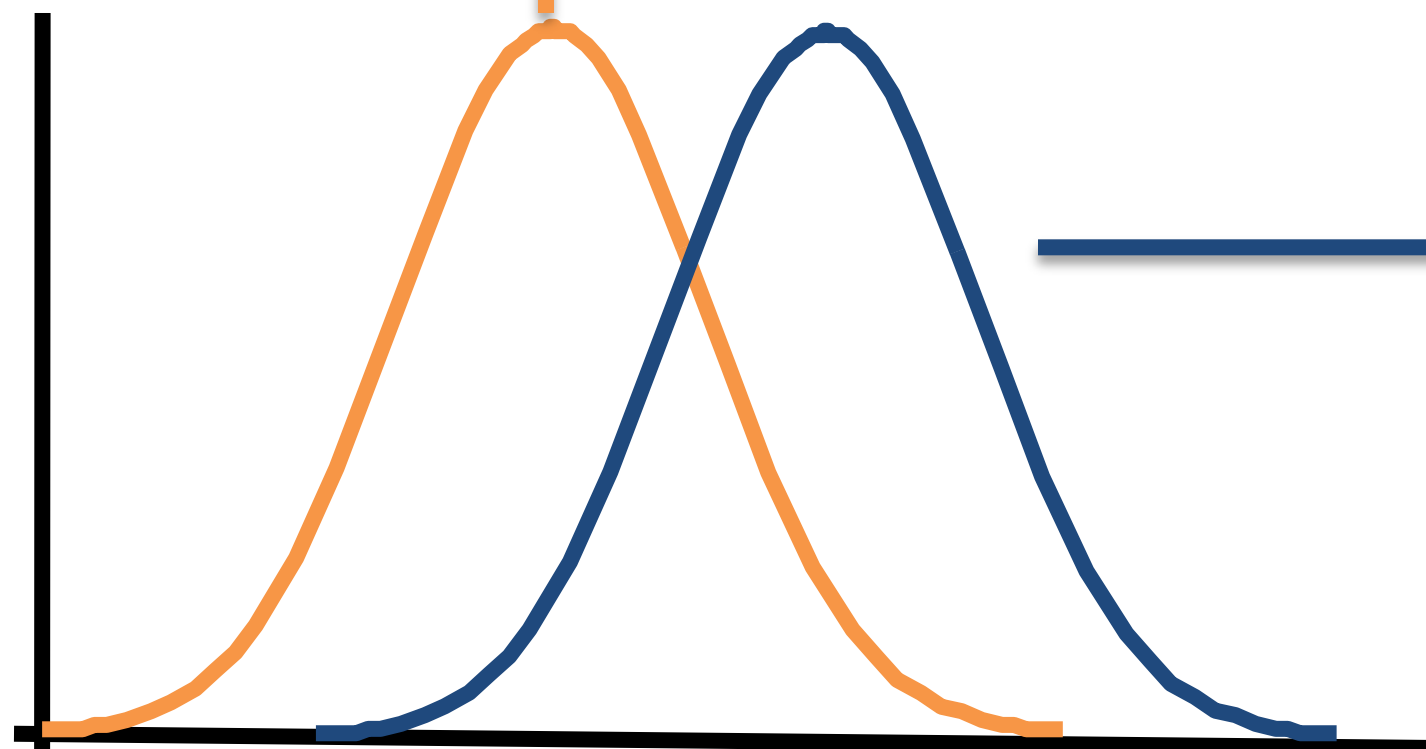
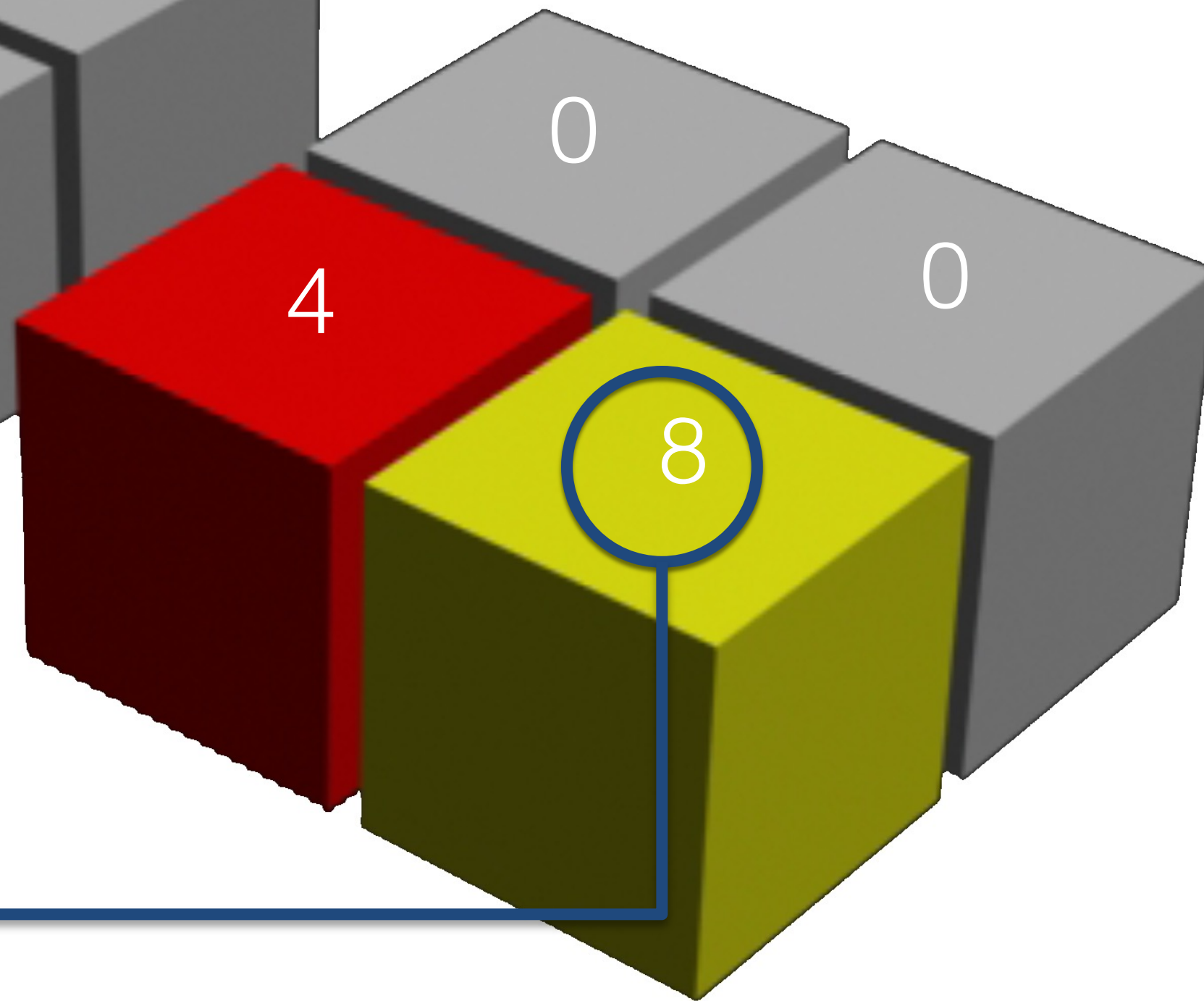
**MASS UNIVARIATE TESTING FOR ALL VOXELS**



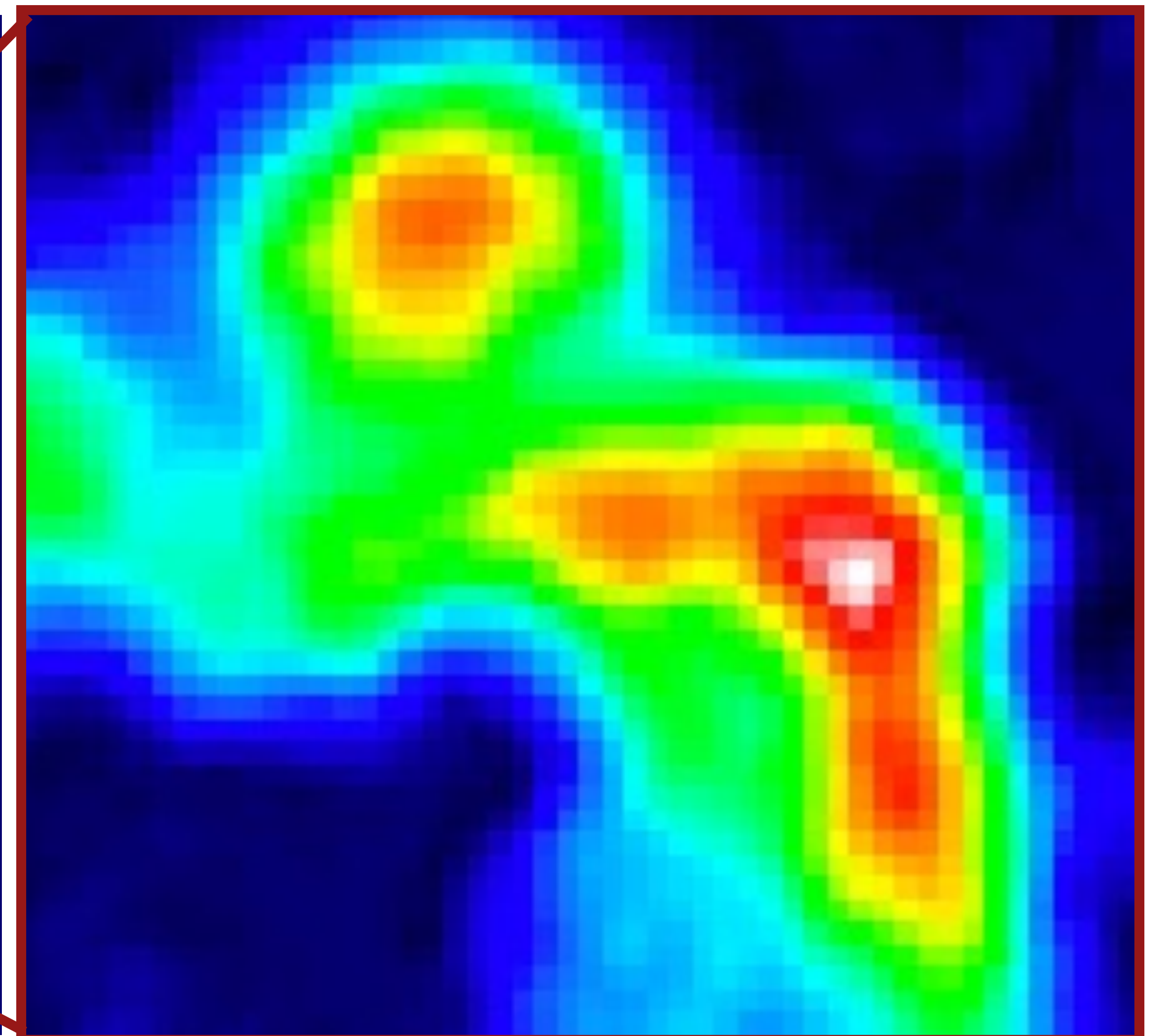
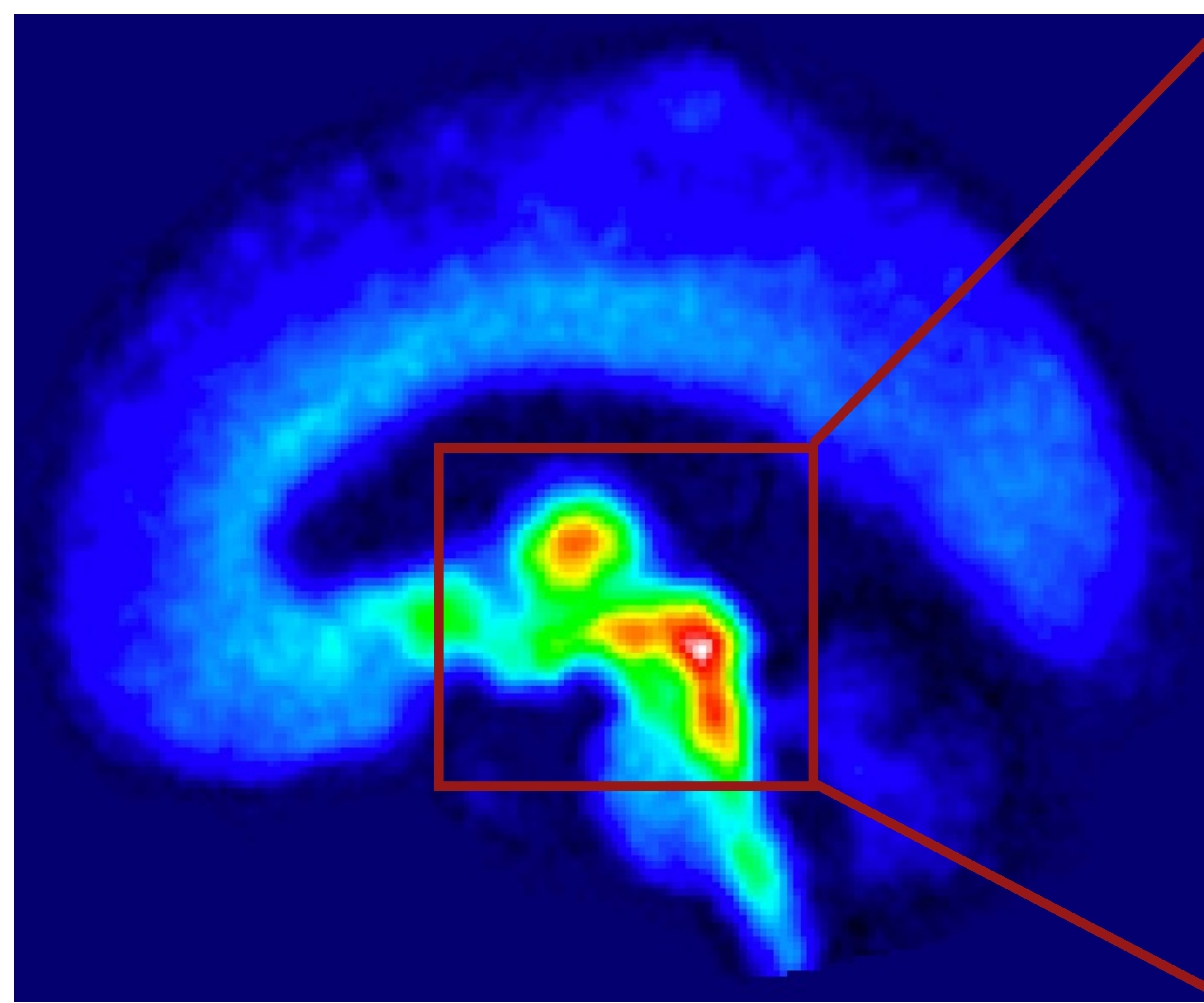
Controls



Patients



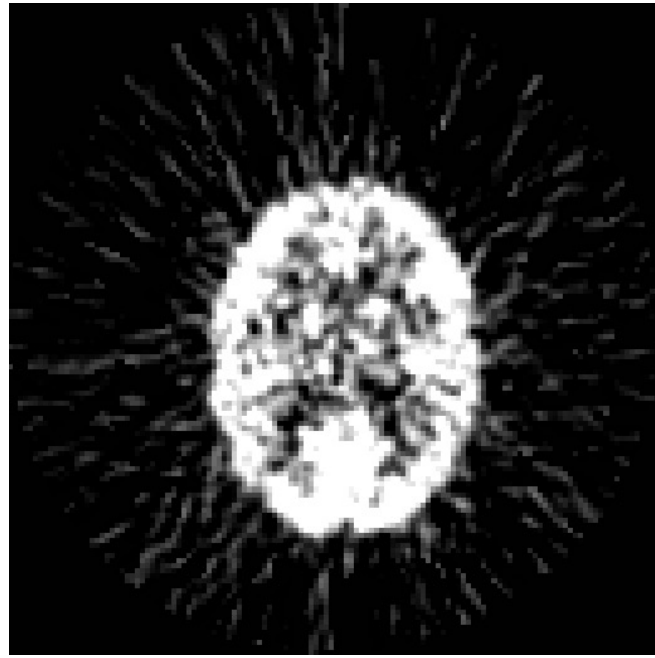
**MASS UNIVARIATE TESTING FOR ALL VOXELS**



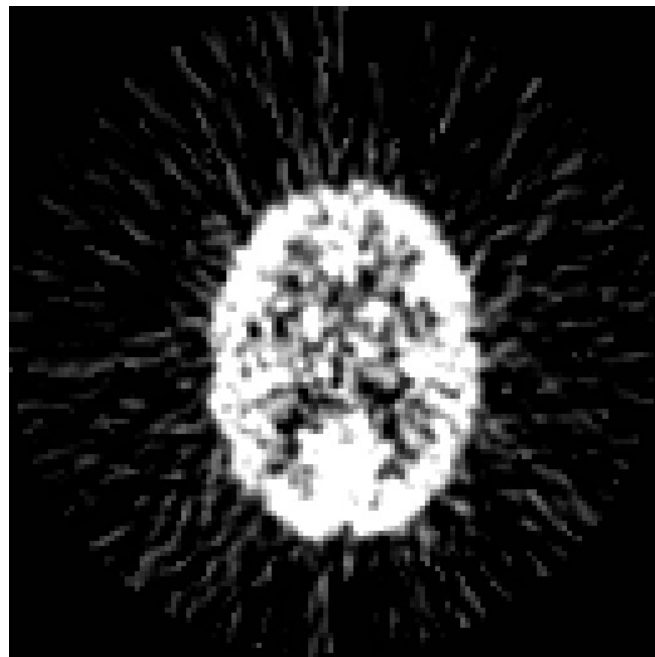
**Voxel intensity** = outcome measure  
(BPND, contrast estimate, tissue probability)

# THE BASIC RECIPE

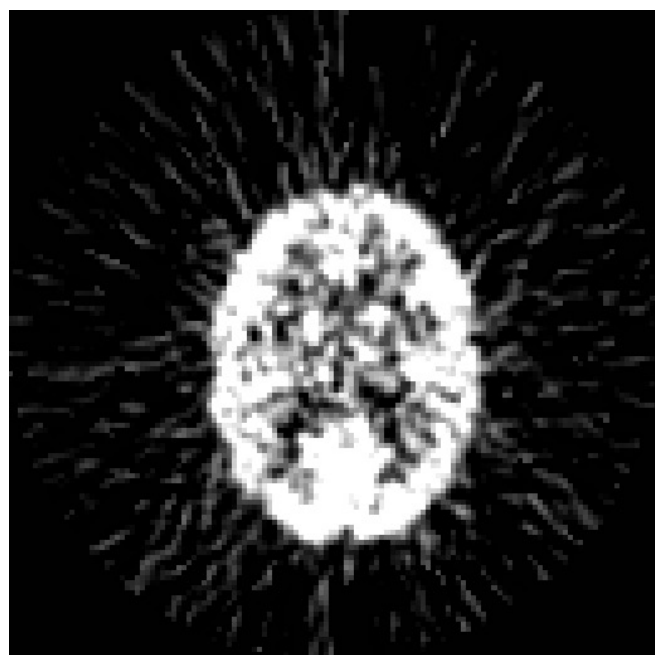
SUBJECT 1



SUBJECT 2

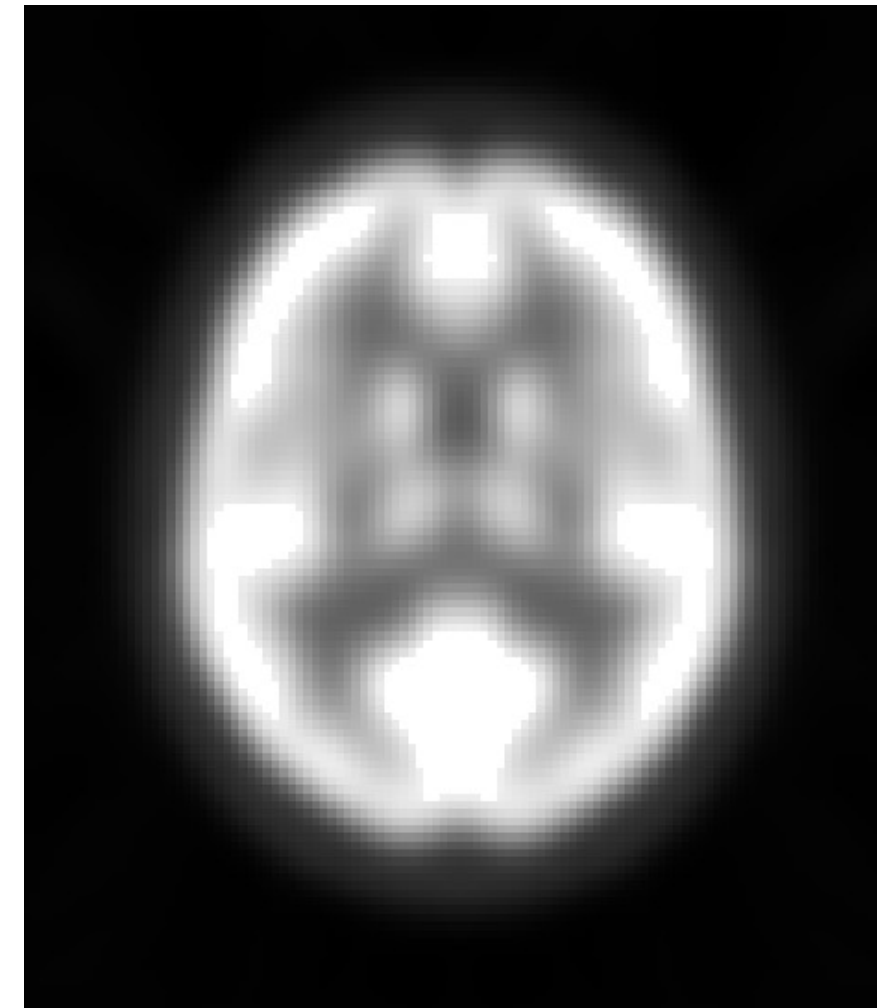


SUBJECT 3



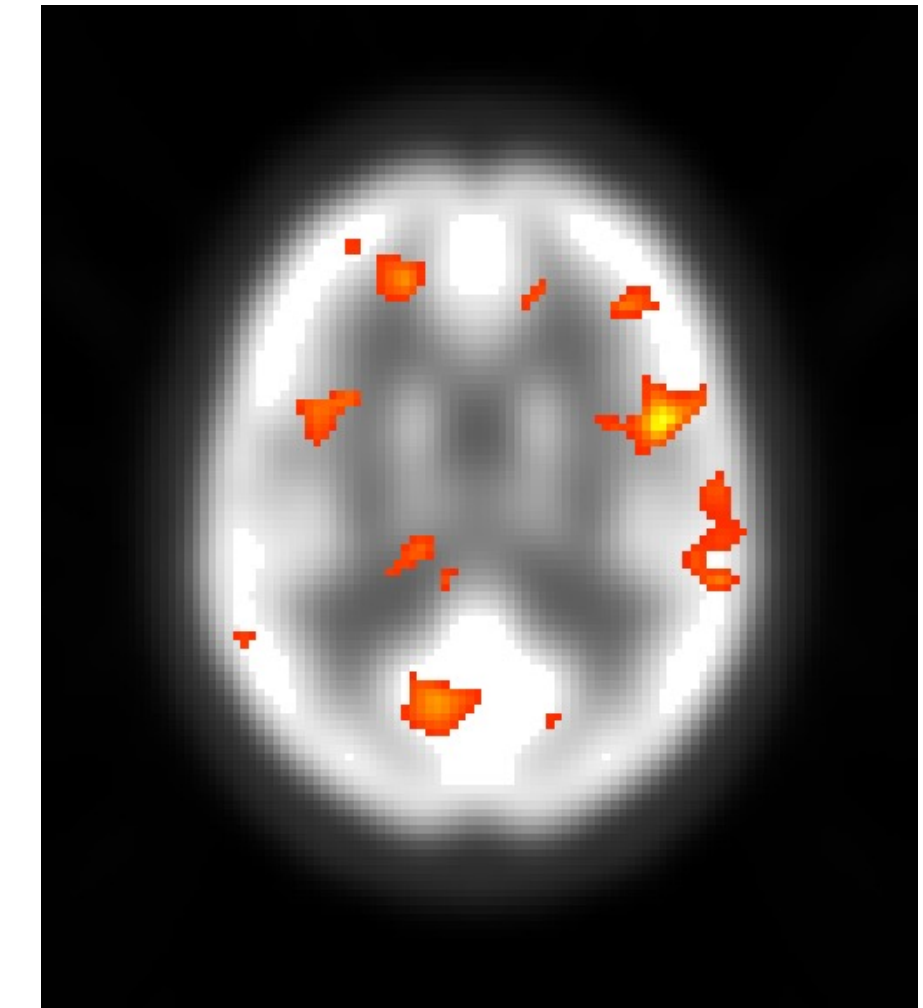
NORMALI-  
ZATION

TEMPLATE



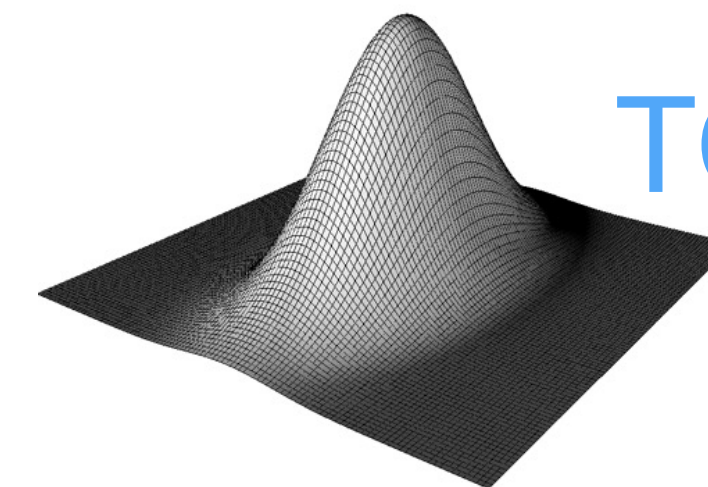
GLM

STATISTICAL  
PARAMETRIC MAP



THRESHOLD  
TO HIGHLIGHT

SMOOTH

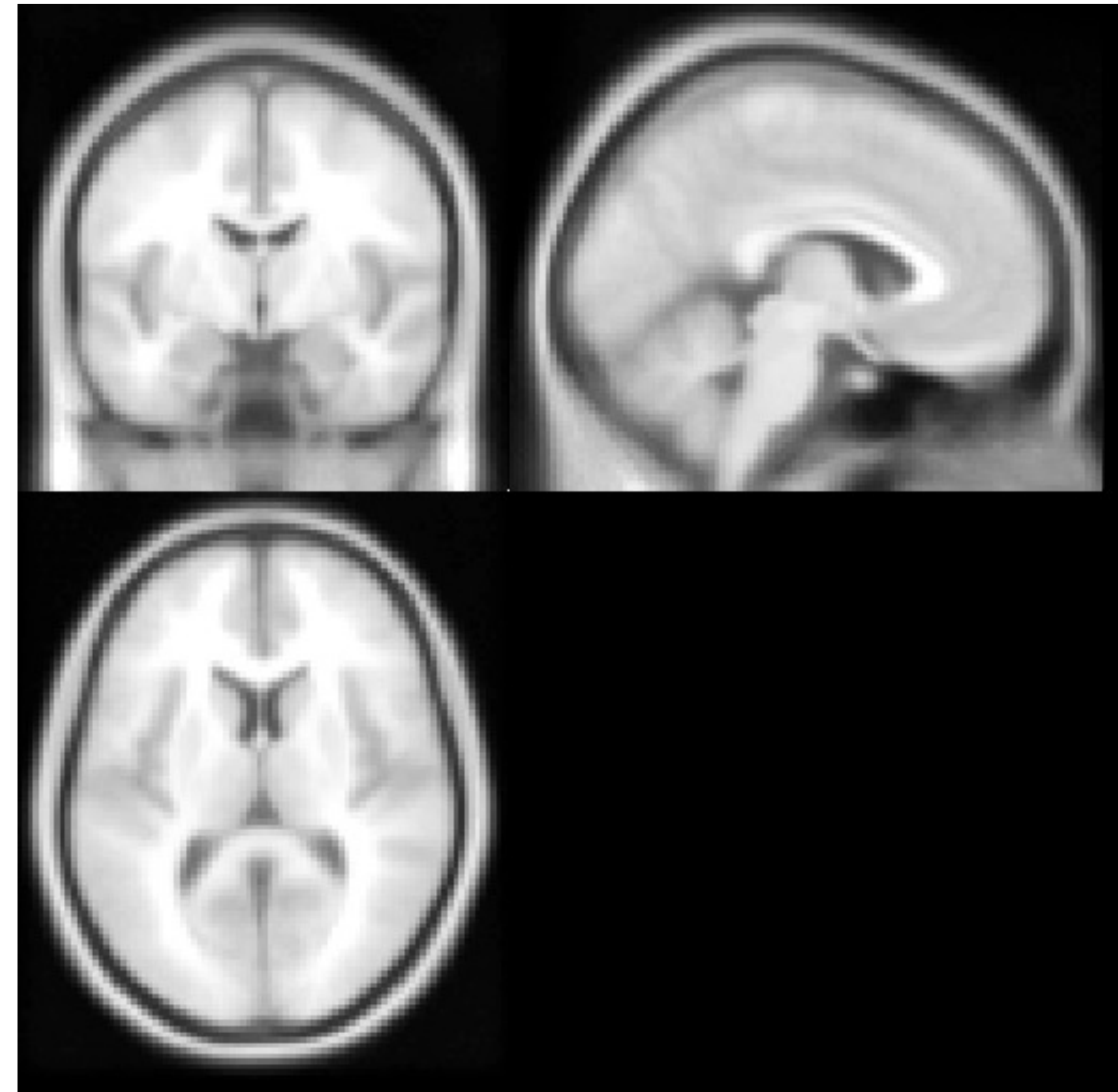


# Full-volume analyses with real brains

- Basic problem: Individual brains differ in size and shape
- Solution to the problem: Make brains similar by warping them
- Problems with the solution
  - Warps distort anatomy
  - Anatomical information is not the precise anyway
  - How should we warp the brains?

# The MNI space as the target

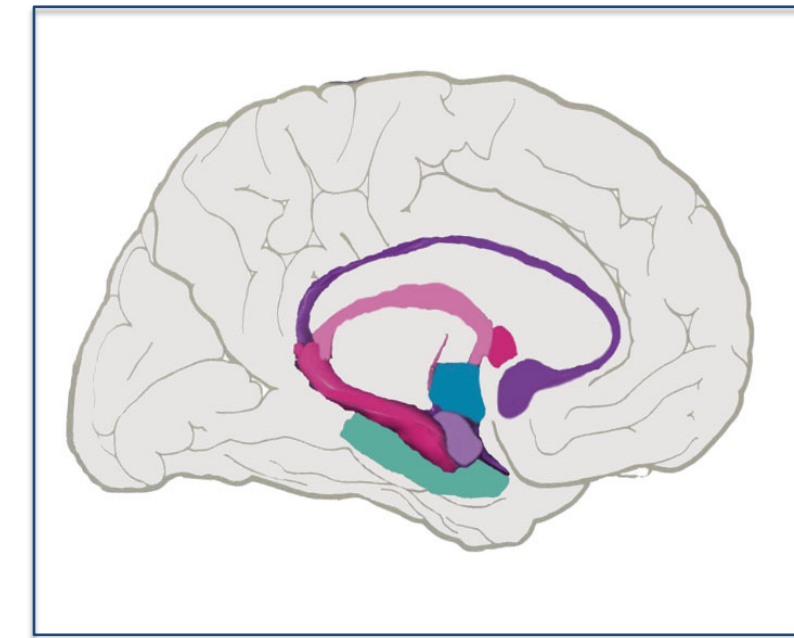
- **ICBM 152 template**
- Based on average of 152 brains that have been spatially normalized
- Statistical average of the typical western adult brain
- Problem: not necessarily representative of study sample
- In fMRI can also use e.g. spherical models



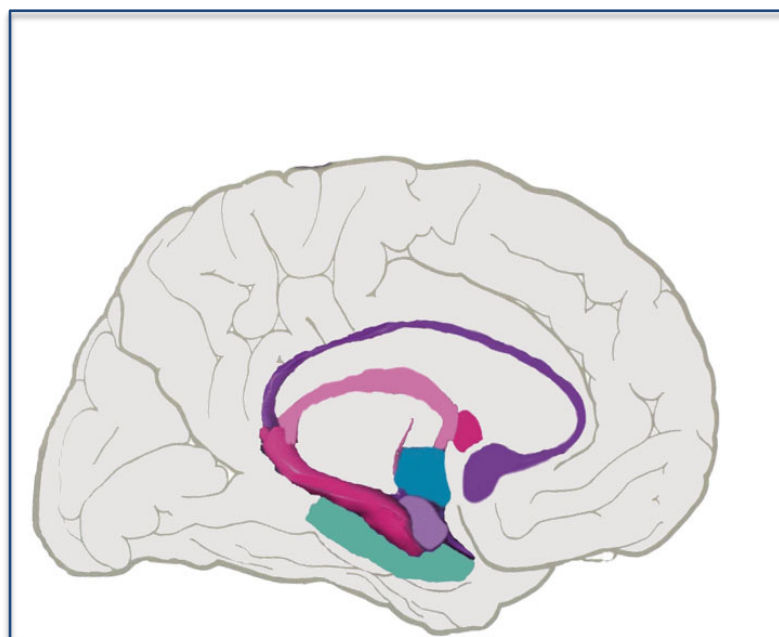
# Spatial normalization in practice

1. Linear (12-parameter affine) normalization
  - Match size and position
2. Nonlinear normalization
  - Linear combinations of smooth discrete cosine basis functions

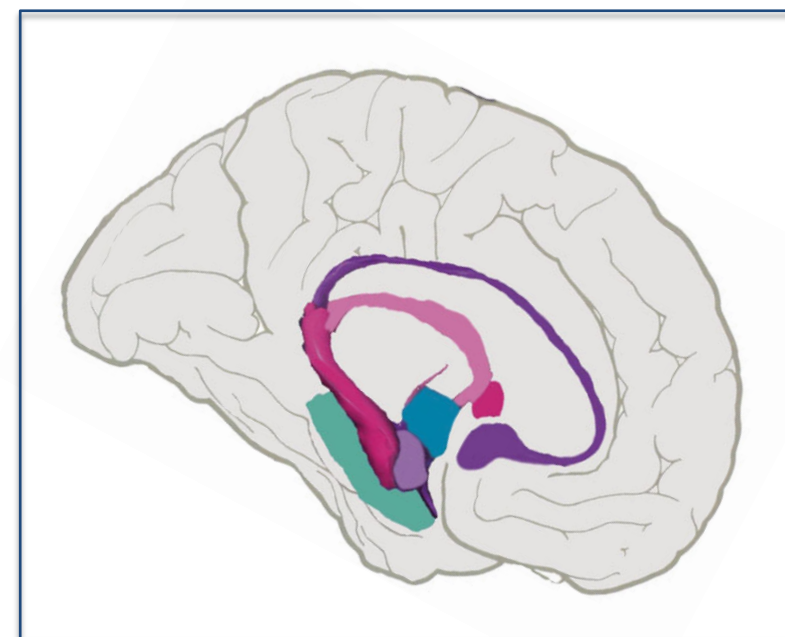
NATIVE



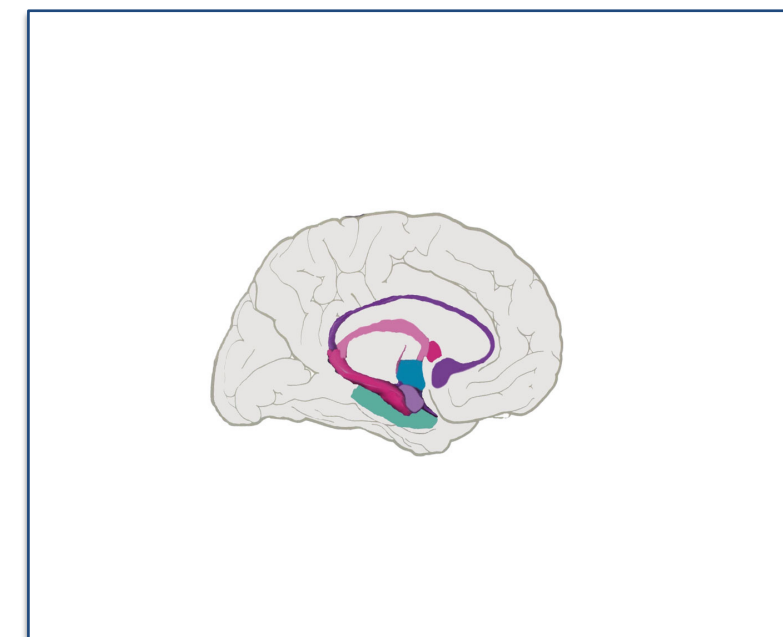
TRANSLATION



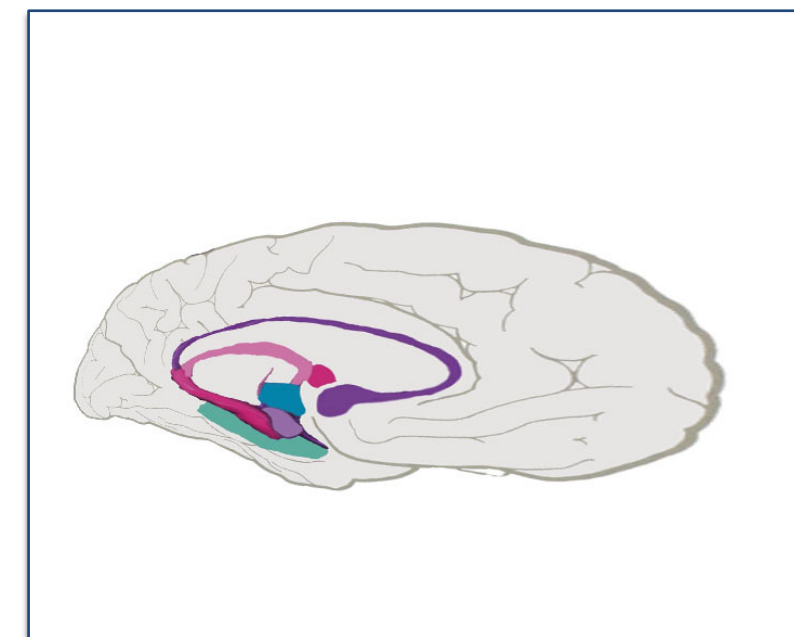
ROTATION



ZOOM

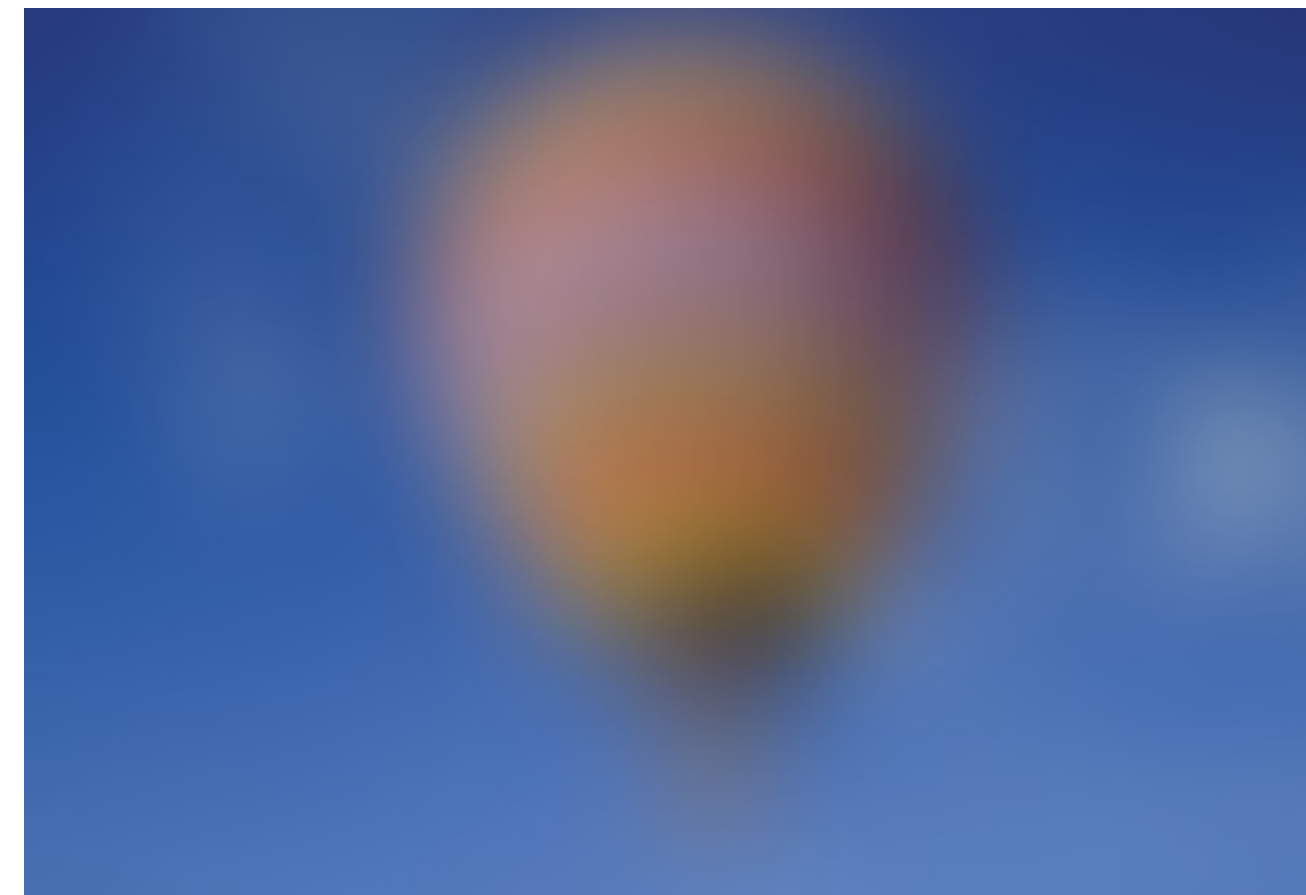
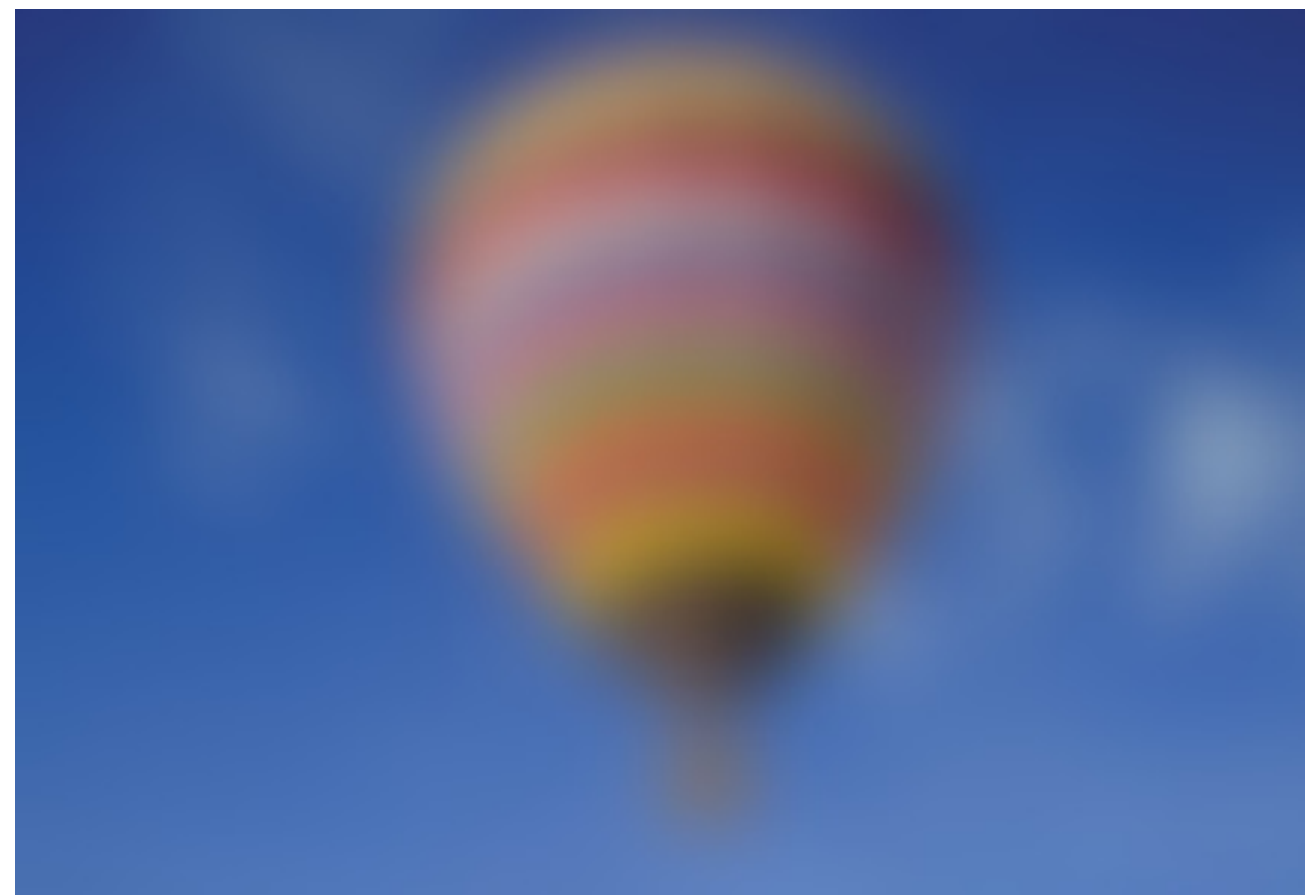


SHEAR



**AFFINE NORMALIZATION: 4\*3 PARAMETERS**

# Smoothing



FWHM = spatial extent of the filter



# Example on smoothing brain-PET images

UNSMOOTHED



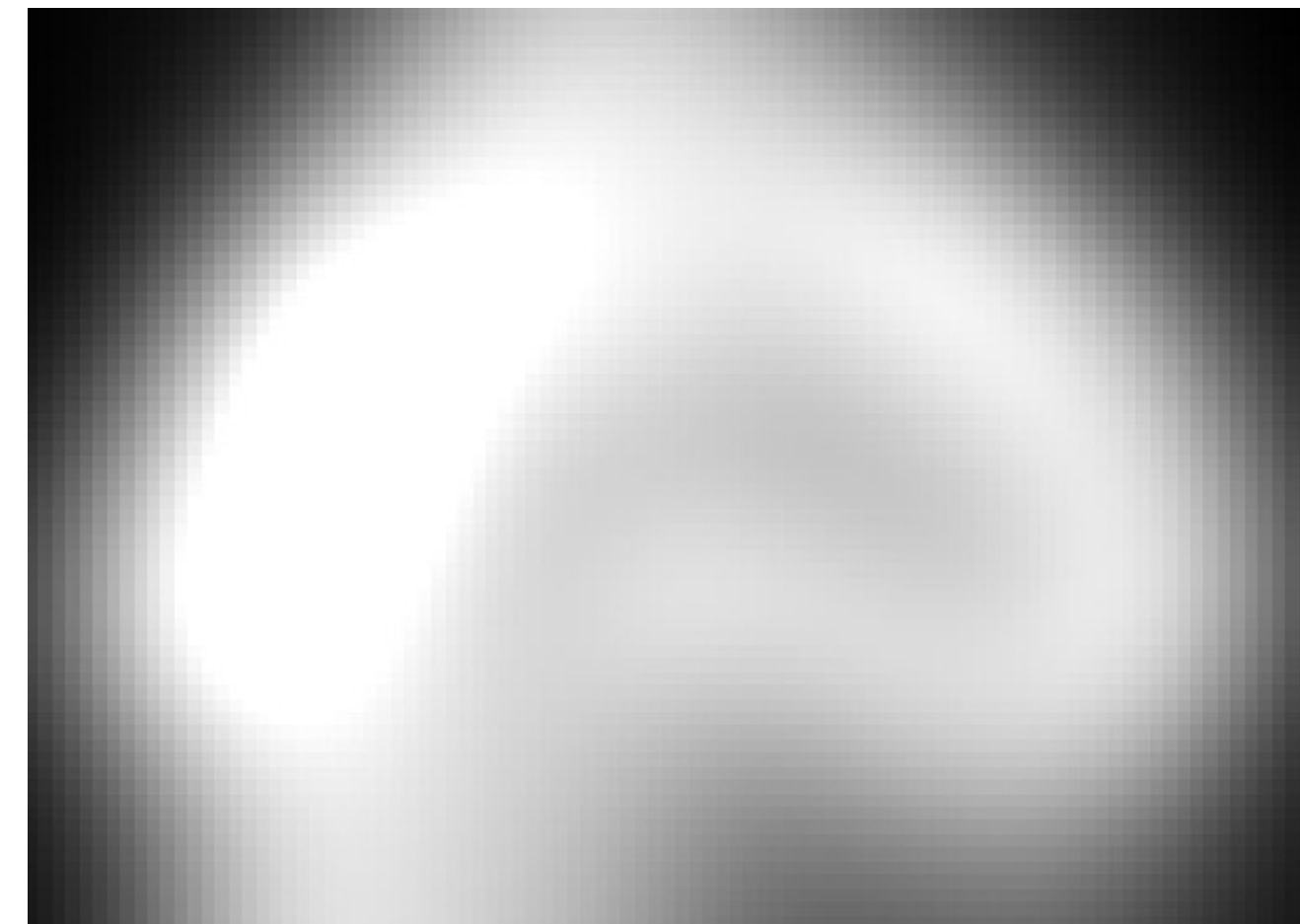
12mm FWHM



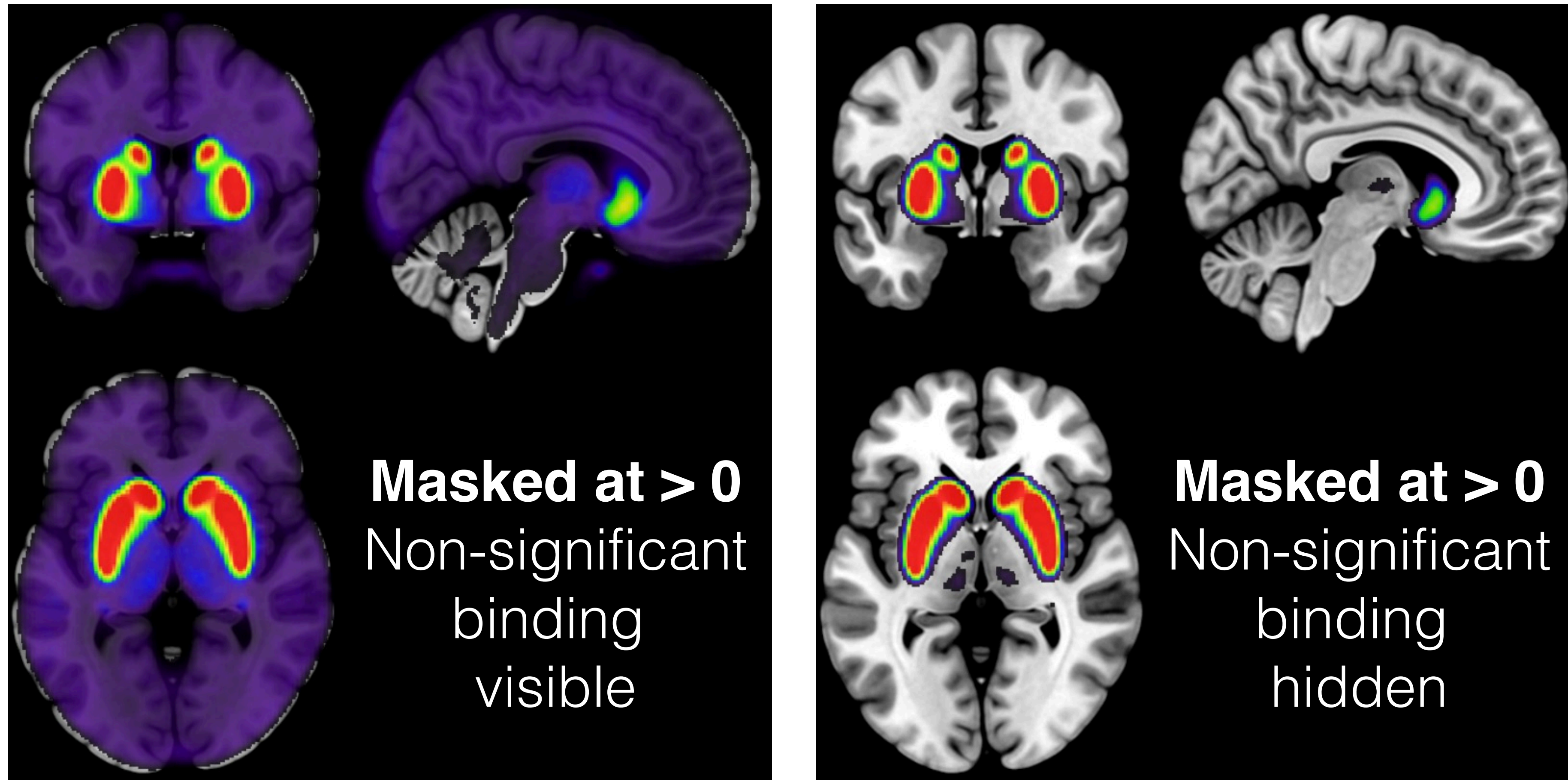
16mm FWHM



32mm FWHM



# Masking the data



Applying explicit / threshold mask is necessary to avoid modelling noise

# What sort of voxelwise model to fit?

# GLM

ANOVA, ANCOVA, linear regression...

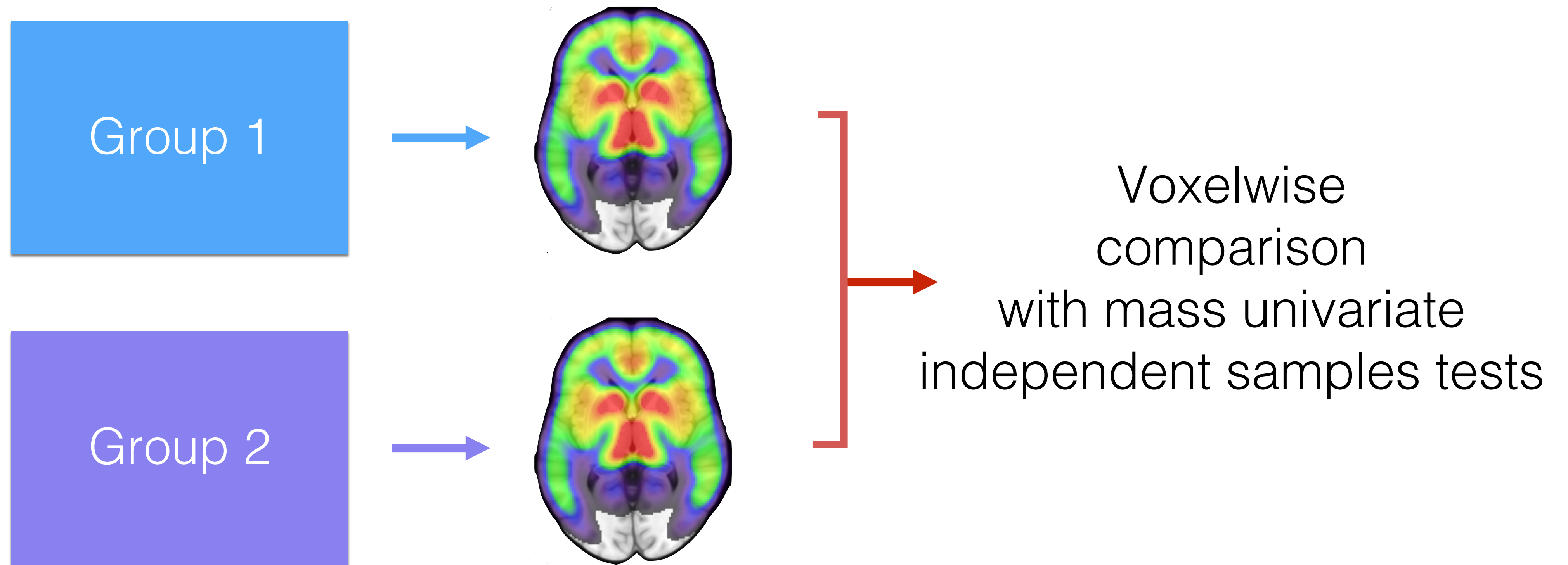
The diagram illustrates the linear regression equation  $Y_i = \beta_0 + \beta_1 X_i + \epsilon_i$  with the following labels and annotations:

- Dependent Variable:** Points to  $Y_i$ .
- Population Y intercept:** Points to  $\beta_0$ .
- Population Slope Coefficient:** Points to  $\beta_1$ .
- Independent Variable:** Points to  $X_i$ .
- Random Error term:** Points to  $\epsilon_i$ .

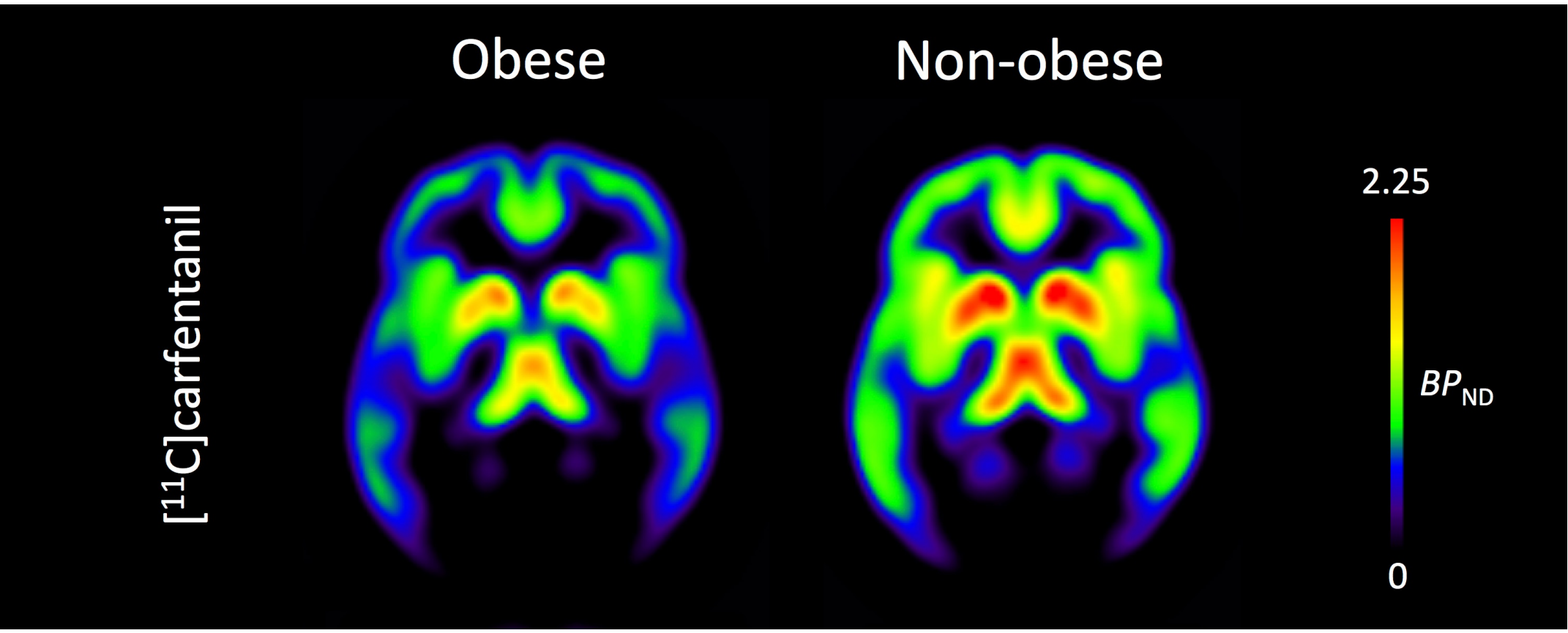
Blue brackets below the equation identify two components:

- Linear component:** A bracket under  $\beta_0 + \beta_1 X_i$ .
- Random Error component:** A bracket under  $\epsilon_i$ .

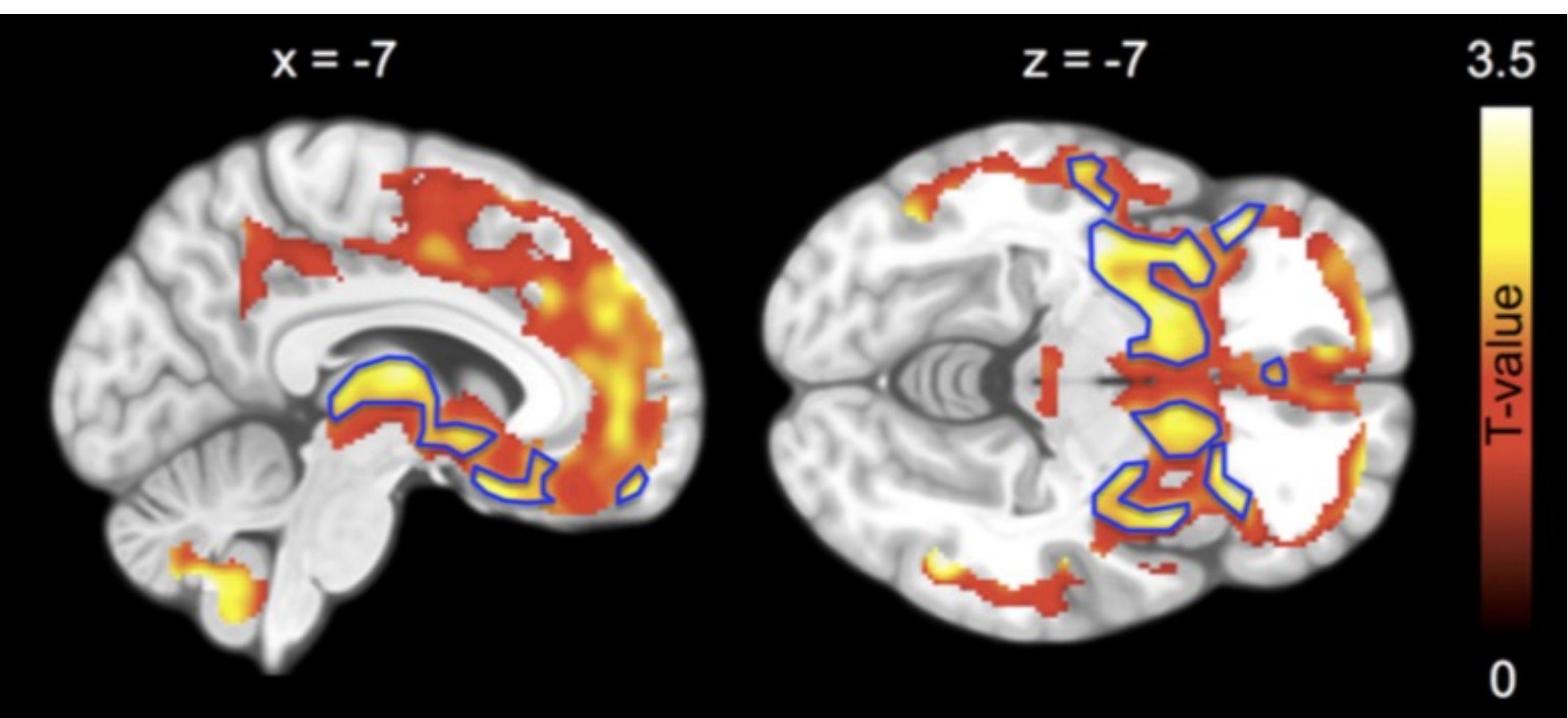
# Between-groups design



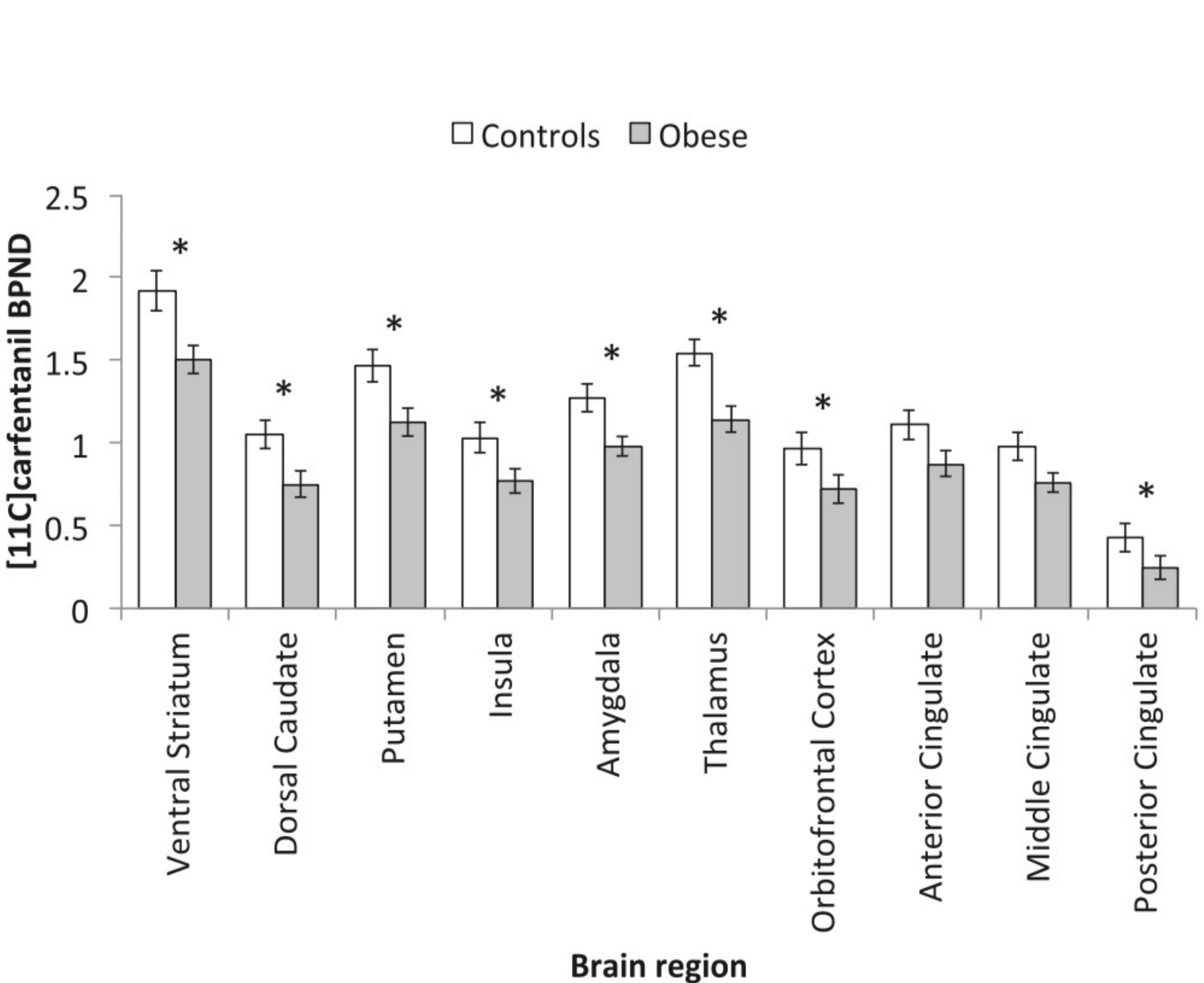
### 1) Mean images for each group



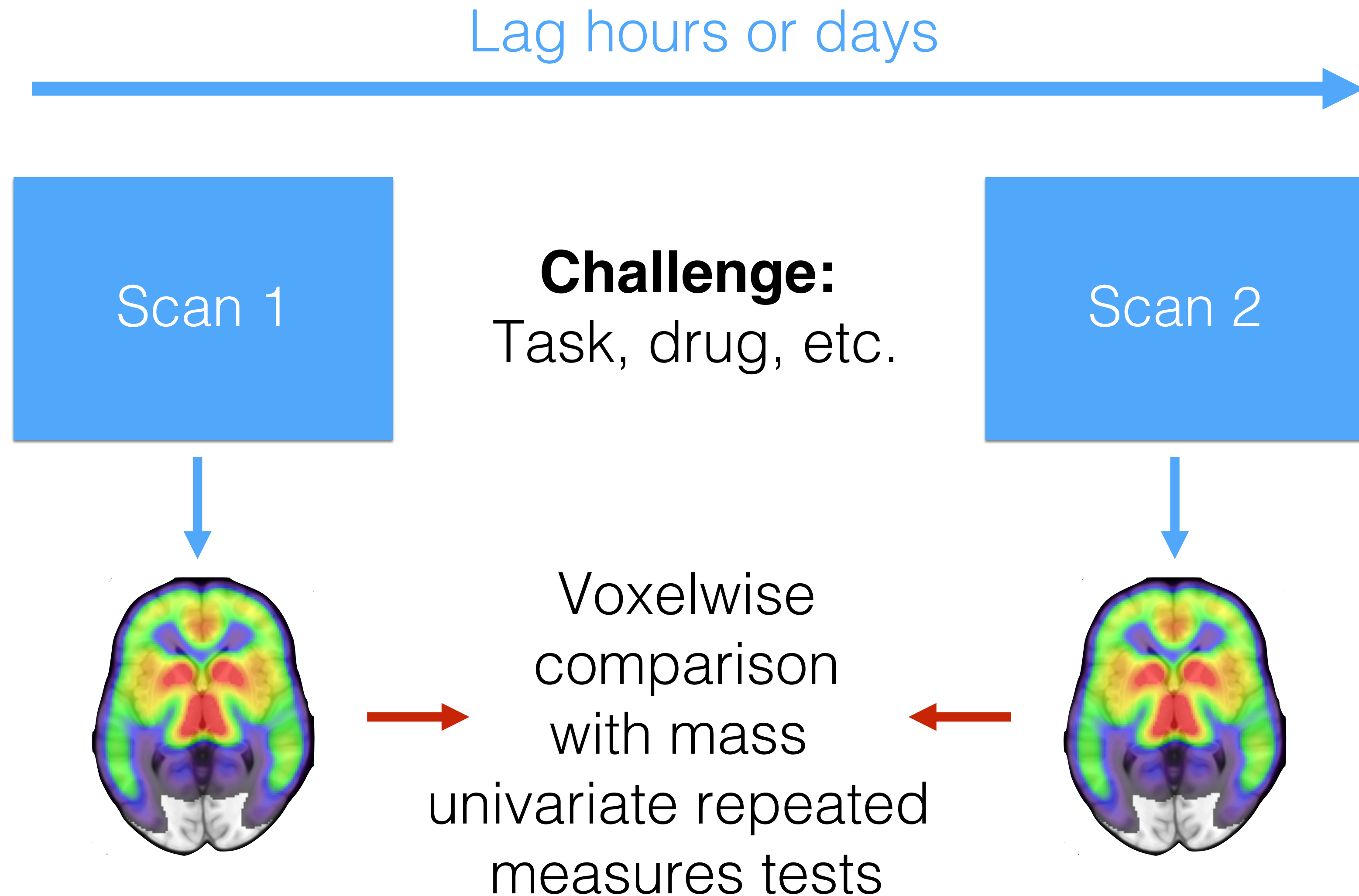
### 2) Statistical differences (t-map)



### 3) Region-of-interest data



# Challenge / longitudinal design

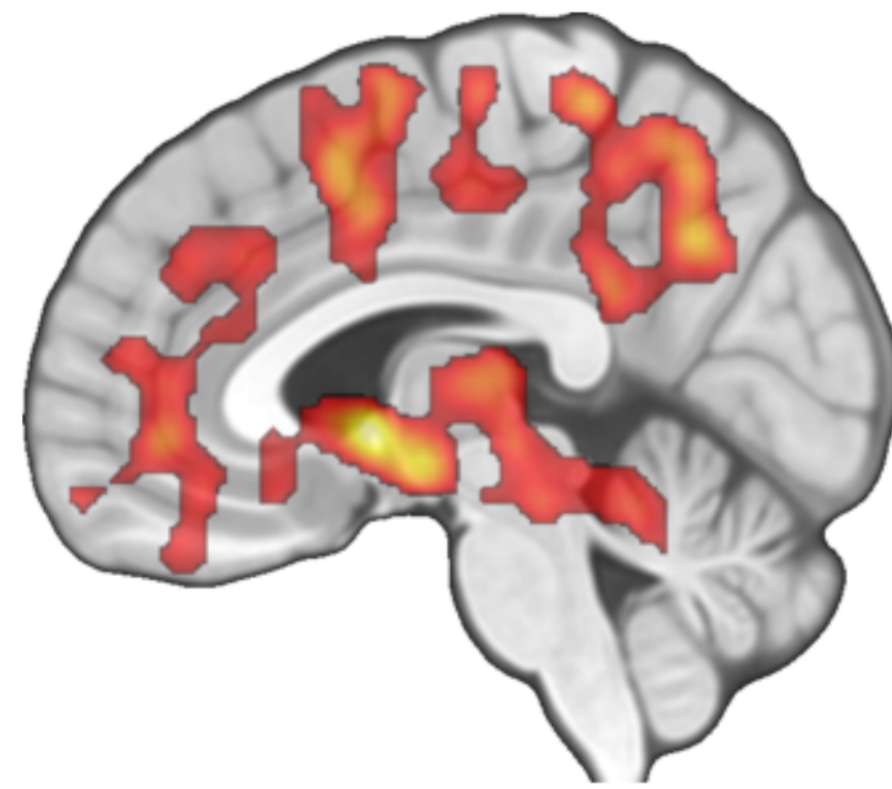
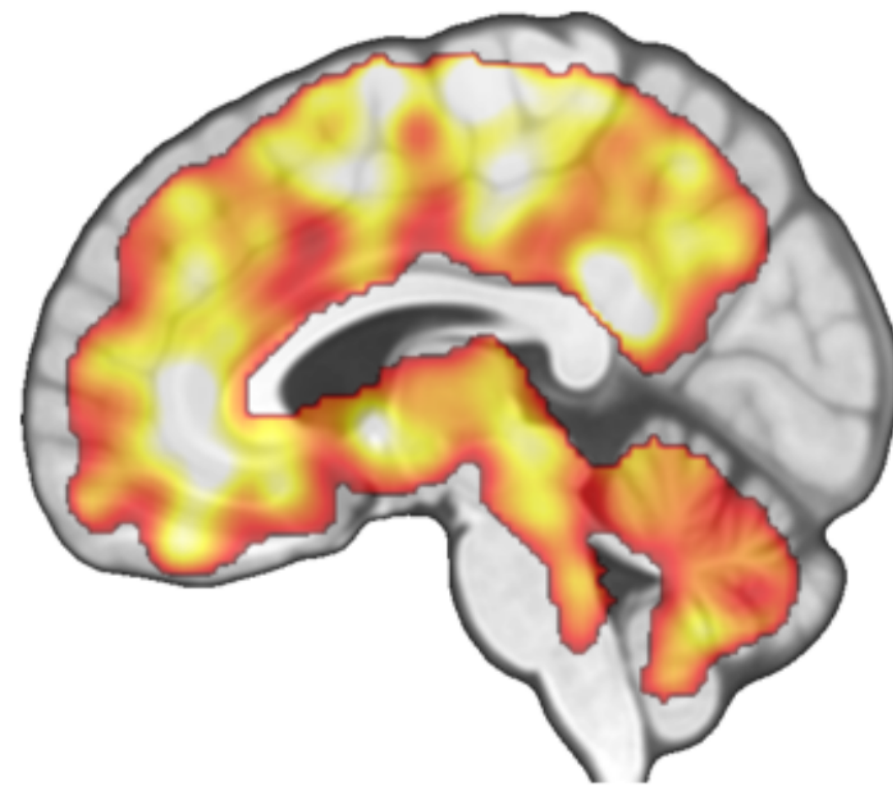


Fast vs.  
Non-palatable

Fast vs.  
Palatable

□ Non-palatable meal ■ Palatable meal ■ Fast

X = 4

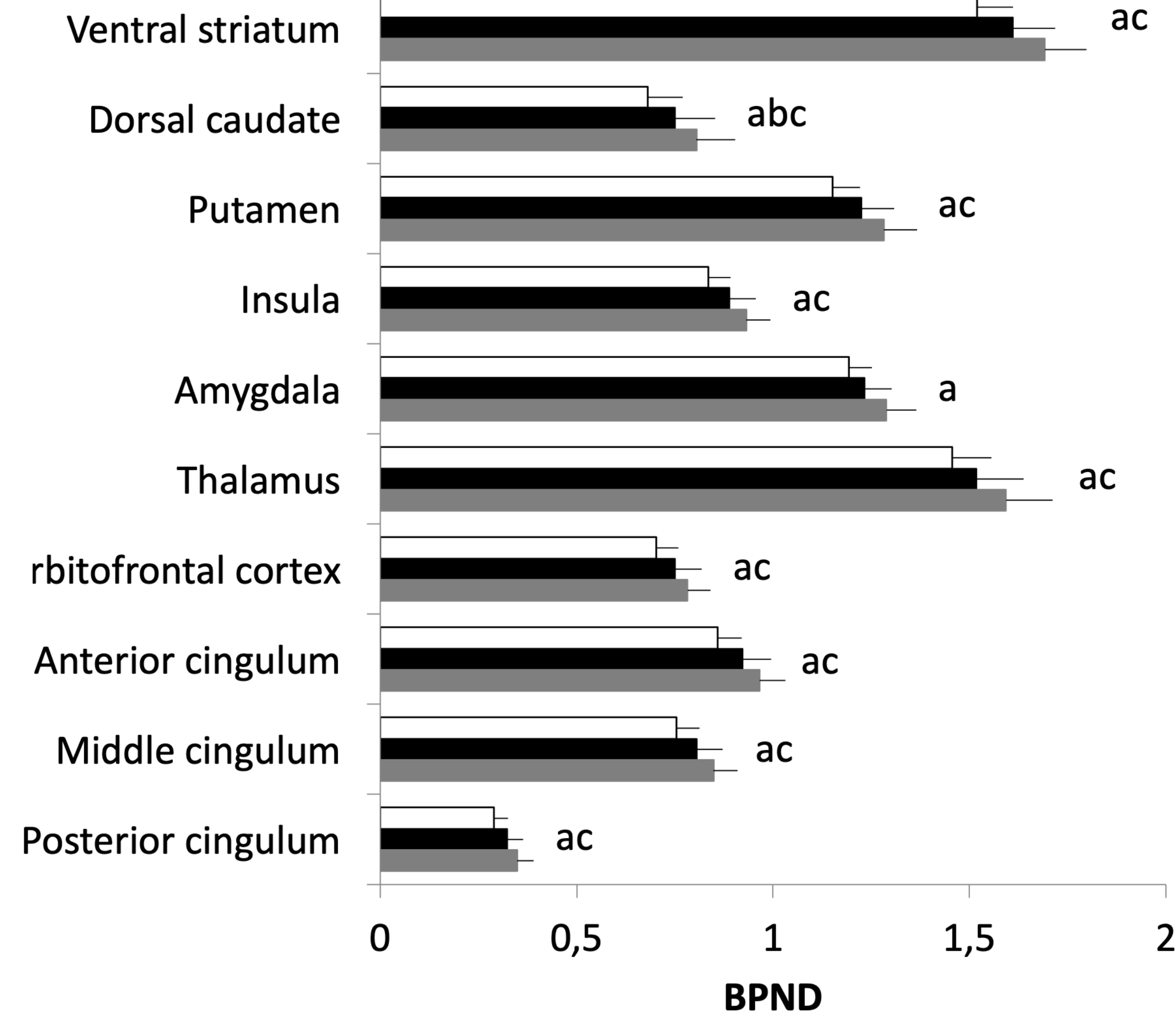
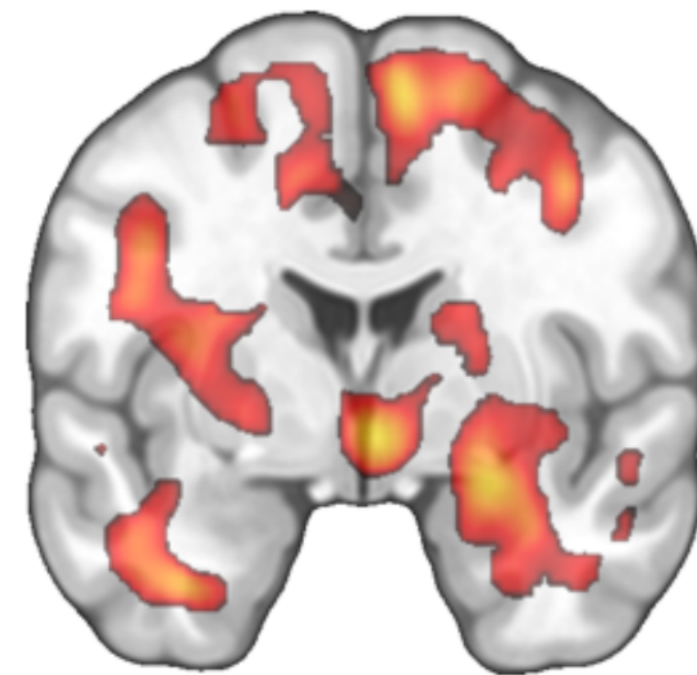
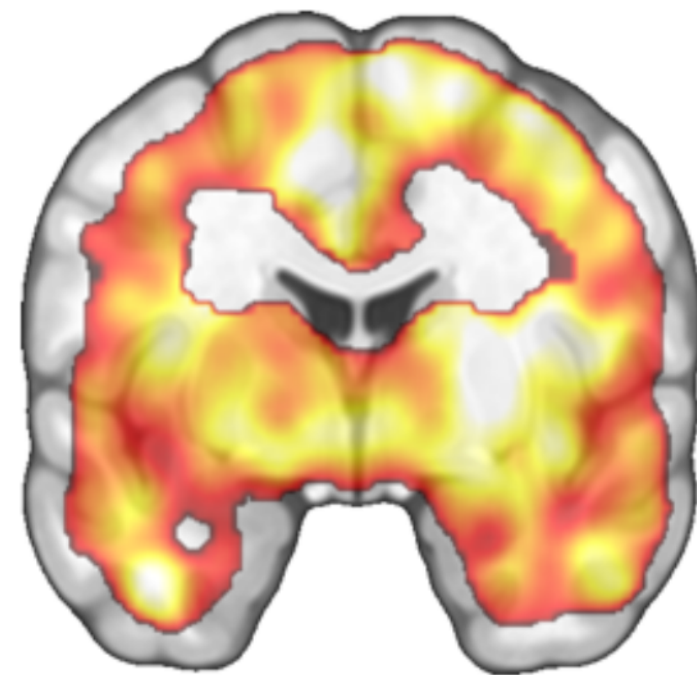


4

T-score

FDR

Y = -1

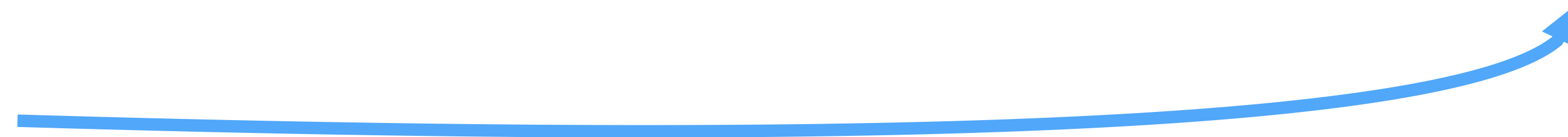
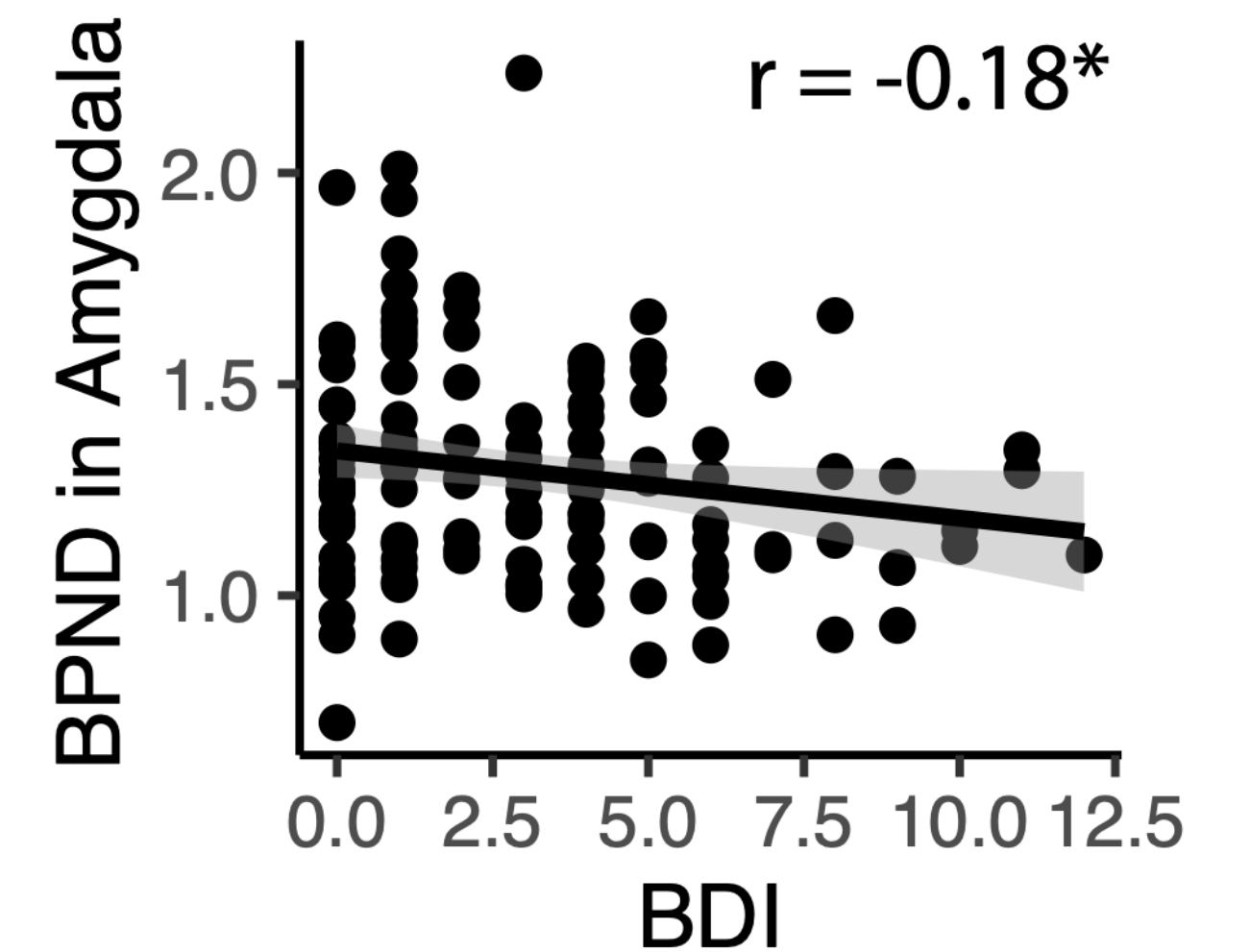
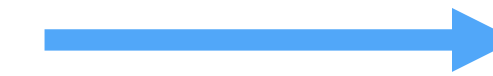
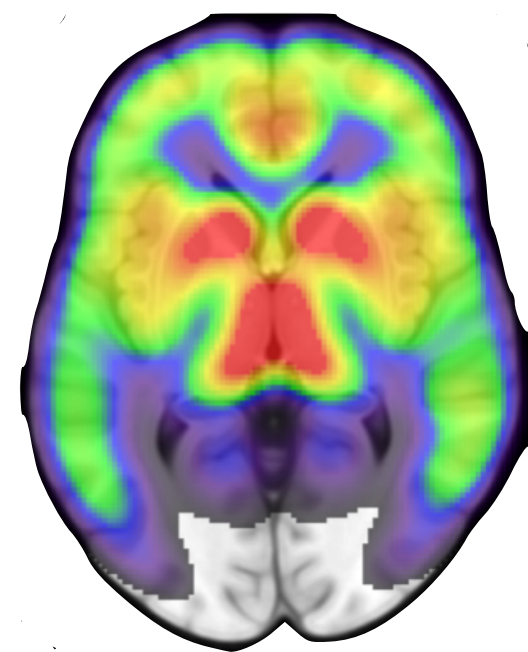


Tuulari et al (2018 J Neurosci)

# Correlational design

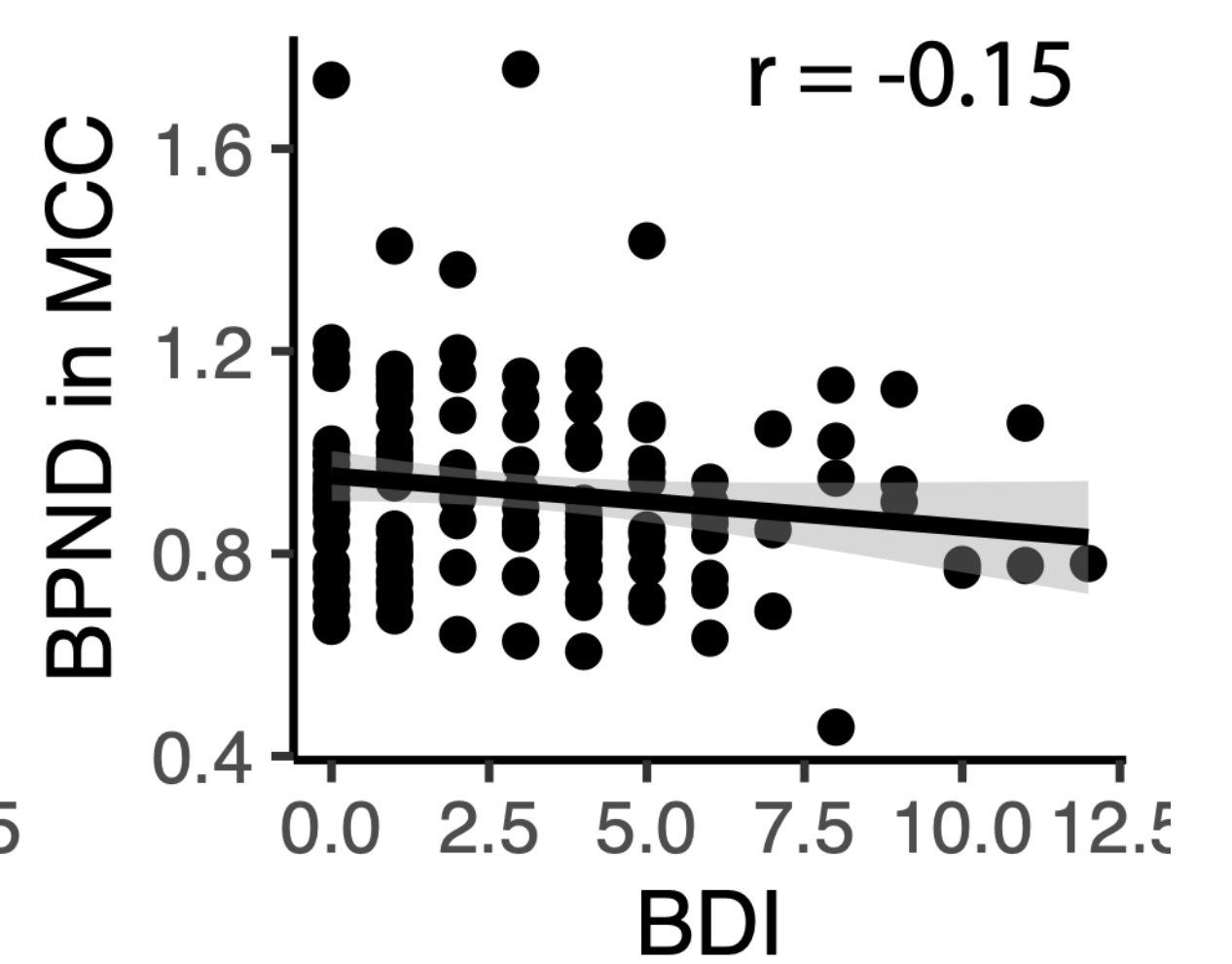
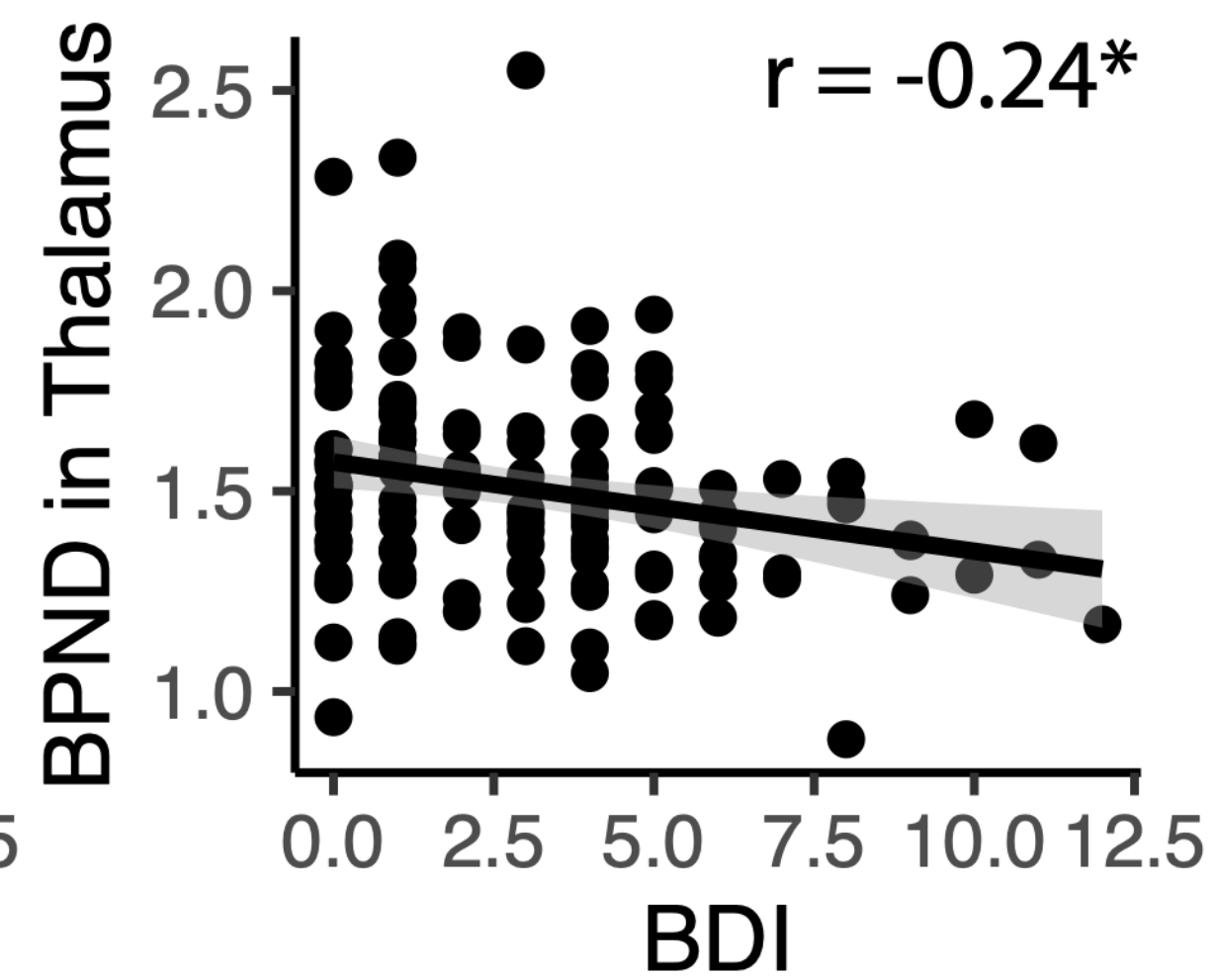
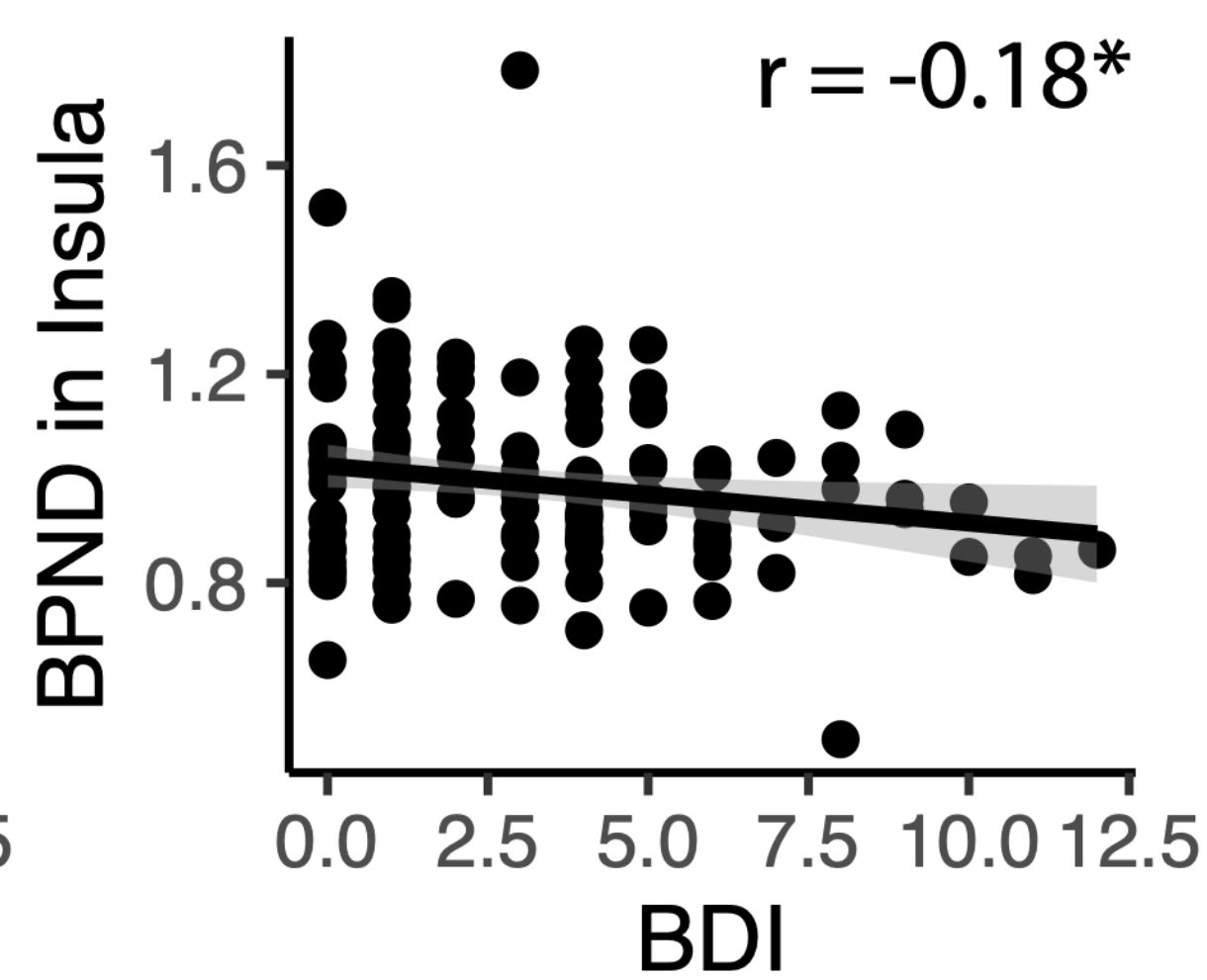
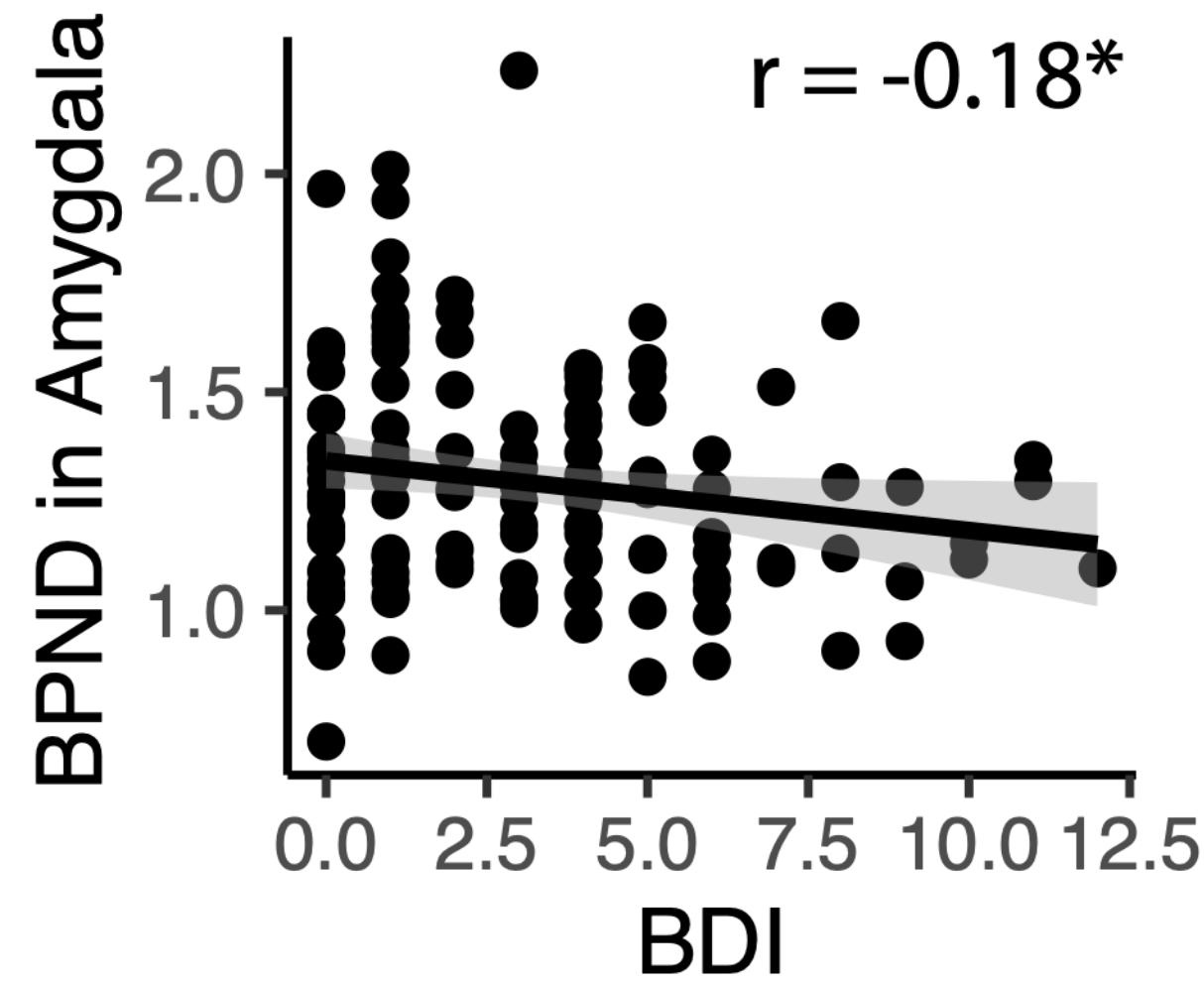
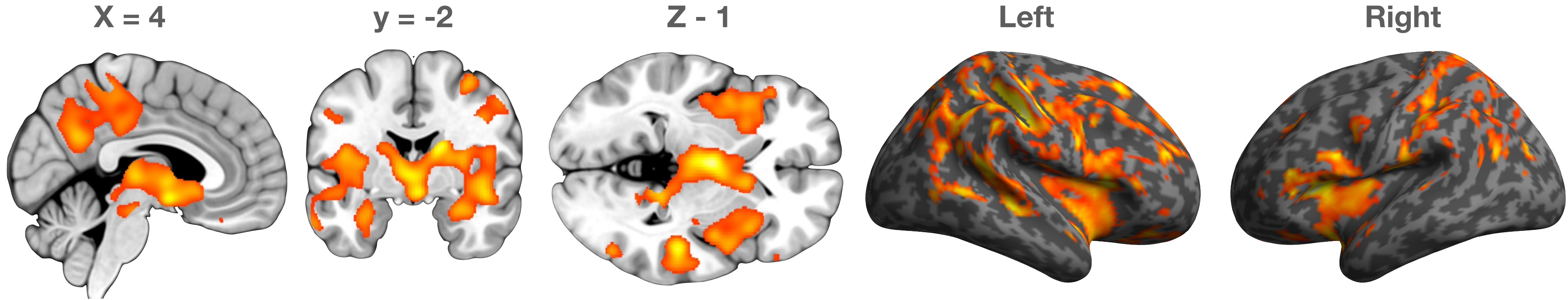
Baseline scan

Univariate biological variable



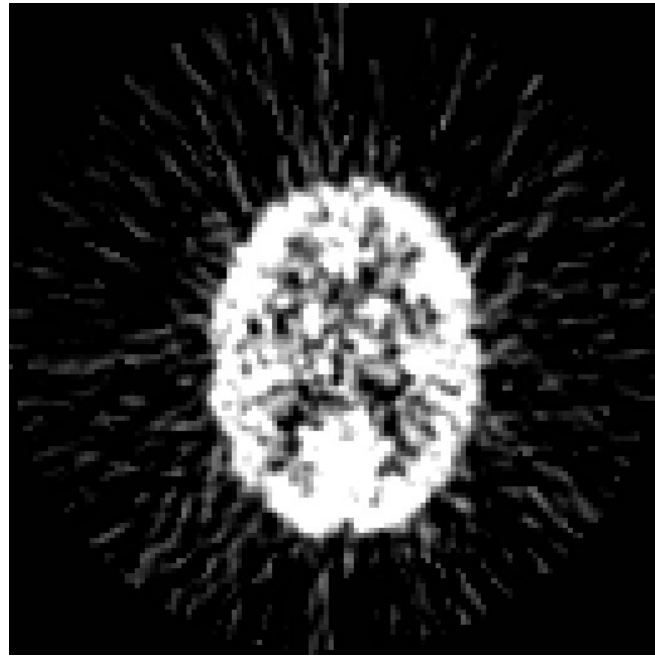


# Lowered mu-opioid receptor levels in subclinical depression

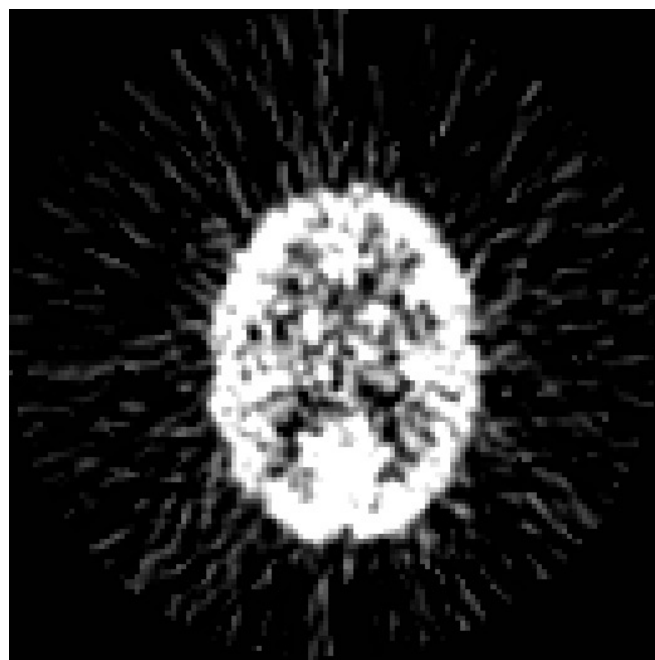


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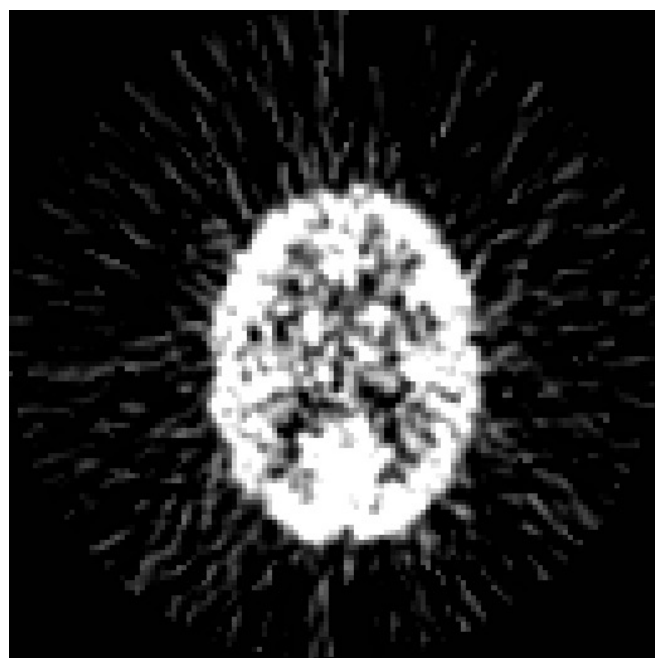
SUBJECT 1



SUBJECT 2



SUBJECT 3

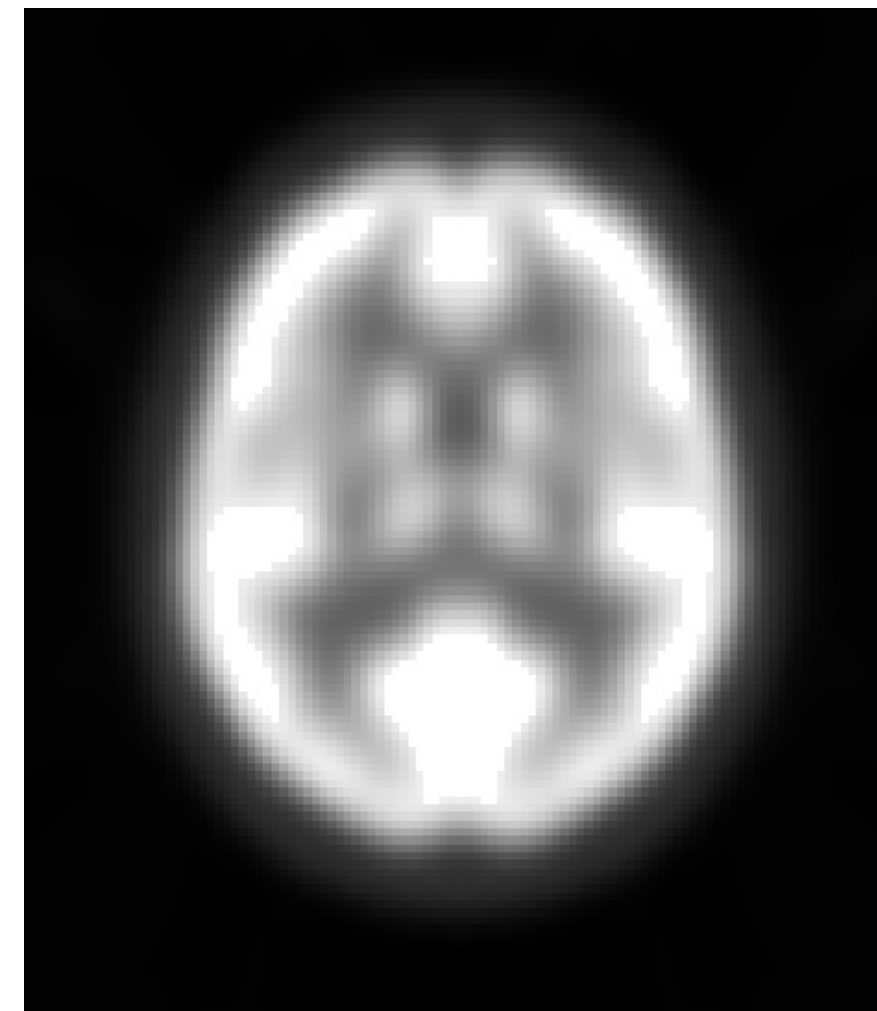


# THE BASIC RECIPE



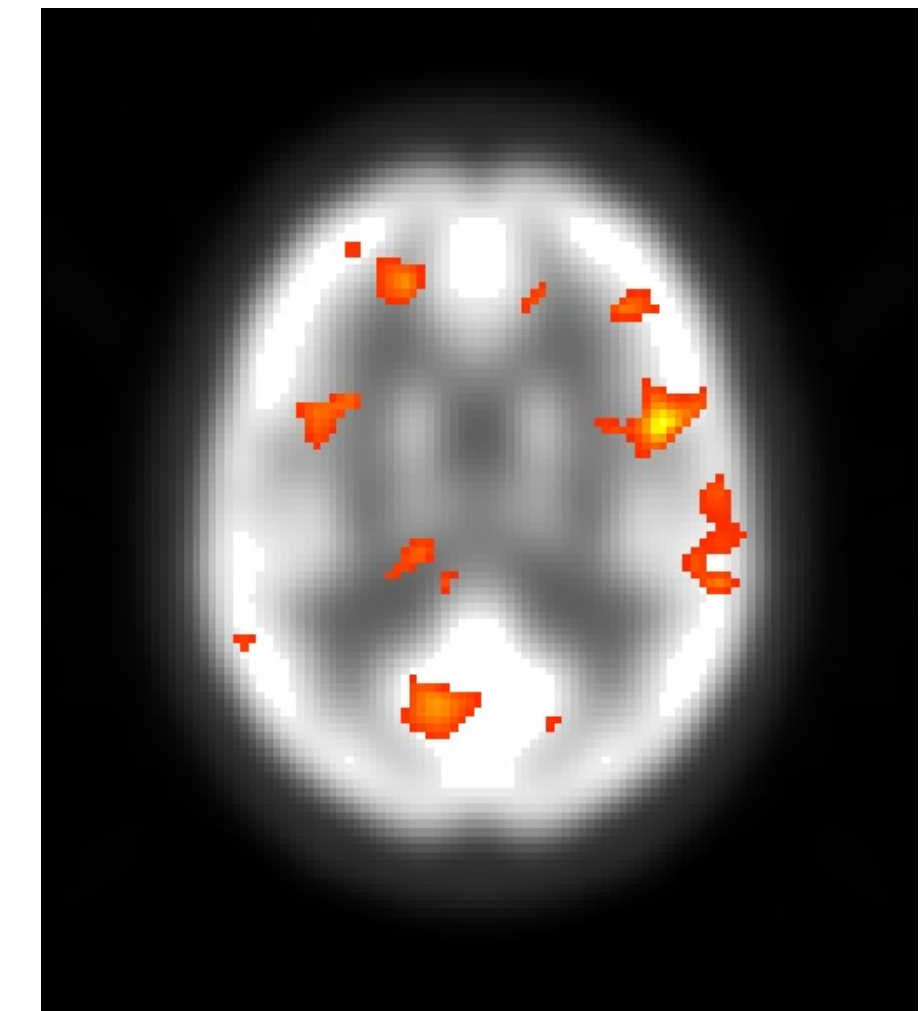
NORMALI-  
ZATION

TEMPLATE



GLM

STATISTICAL  
PARAMETRIC MAP



SMOOTH

