# SECOND-LEVEL ANALYSIS OF PET AND MRI DATA

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# Basic problems associated with scientific measurement

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

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

TARGET (e.g. specific neuroreceptor)

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



PREDICTION OF BEHAVIOR (e.g. anxietylike behaviour)

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







### ARE THESE BRAINS STATISTICALLY DIFFERENT?





### 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
	- 4D image —> 3D image
	- Voxel intensities reflect outcome measure (receptor density, metabolism....)
- **Similarly, EPI data needs to be modelled** before population level inference
	- 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







• Pros: Anatomically accurate if ROIs well definied, data can be analyzed with simple univariate

• Cons: Laborious, using many ROIs not feasible, averaging within ROI not always appropriate

- statistical tests
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#### Univariate data regularly shaped can use univariate stats







## **MASS UNIVARIATE TESTING FOR ALL VOXELS**





## SUBJECT 1



## SUBJECT 2



## SUBJECT 3



#### STATISTICAL PARAMETRIC MAP TEMPLATE





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



# THE BASIC RECIPE

### THRESHOLD TO HIGHLIGHT

## SMOOTH **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



### NATIVE



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

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





# Smoothing





### FWHM = spatial extent of the filter





# Example on smoothing brain-PET images UNSMOOTHED 12mm FWHM







#### 16mm FWHM 32mm FWHM



# Why smooth?

- Smoothing neuroimaging data: reduces noise and anatomical discrepancies
- voxel size
- Enables hypothesis testing and dealing with multiple comparison problem in functional imaging
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• Assumption: error terms are roughly Gaussian; FWHM greater than

• However introduces problem of how to correct for multiple comparisons

### Raw data: 16384 independent numbers

### **Problem with kernel-based smoothing: How many numbers are independent?**

**8 by 8** 

**square** 

#### How many independent numbers? Image 1 - smoothed with Gaussian kernel of FWHM 8 by 8 pixels 20 40 Pixel position in Y 60 80 100 120 20 80 100 120 60 40

Kernel-based smoothing



https://matthew-brett.github.io/teaching/random\_fields.html

Pixel position in X





# Random Field Theory in nutshell

- Estimate the number of resels in the image
	- Resel= block of pixels / voxels of the same size as the FWHM of the smoothness of the image. Depends on both image size and FWHM
- Work out the Euler characteristic (EC) of the image
	- Property of the image after it has been thresholded. Roughly number of blobs in image after thresdholfing
- Resels and EC are linked: when Z thresholds increases and EC drops the expected EC approximates the probability of observing one or more blobs at that threshold.



# What sort of voxelwise model to fit?



### ANOVA, ANCOVA, linear regression…



# Masking the data





Applying explicit / threshold mask is necessary to avoid fitting model to noise



# Between-groups design



#### Group 1







Karlsson et al (2015 J Neurosci)

## 1) Mean images for each group



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



### 3) Region-of-interest data





# Challenge / longitudinal design



Voxelwise comparison with mass univariate repeated measures tests



Lag hours or days

**Challenge:**  Task, drug, etc.

#### Fast vs. Non-palatable

Fast vs. Palatable







$$
X=4
$$

$$
Y = -1
$$

#### $\square$  Non-palatable meal Palatable meal



Tuulari et al (2018 J Neurosci)



 $\blacksquare$  Fast

# Correlational design





### Baseline scan







#### **Lowered mu-opioid receptor levels in subclinical depression**

Nummenmaa et al (2020 Neuropsychopharmacology)

## SUBJECT 1



## SUBJECT 2



## SUBJECT 3



#### STATISTICAL PARAMETRIC MAP TEMPLATE



(BPND, contrast estimate, tissue probability) PND, contrast estimate, tissue probability) **Voxel intensity** = outcome measure outcome measure **Voxel intensity**  $\overline{\mathsf{B}}$ 







# THE BASIC RECIPE