

## GROUP ANALYSIS

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Sandra Iglesias

*With many thanks for slides & images to Guillaume Flandin*



University of  
Zurich <sup>UZH</sup>

**ETH**

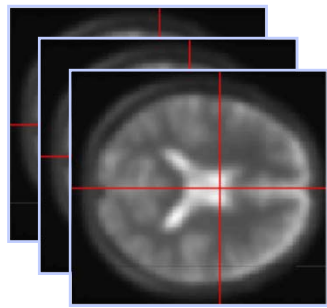
Eidgenössische Technische Hochschule Zürich  
Swiss Federal Institute of Technology Zurich



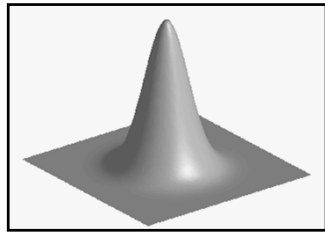
Translational Neuromodeling Unit

# Overview of SPM Steps

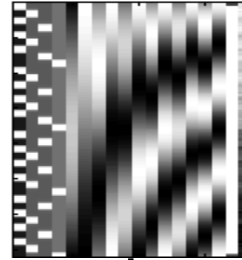
Image time-series



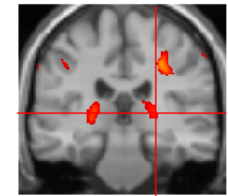
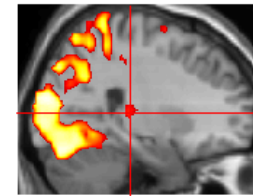
Spatial filter



Design matrix



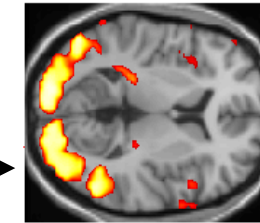
Statistical Parametric Map



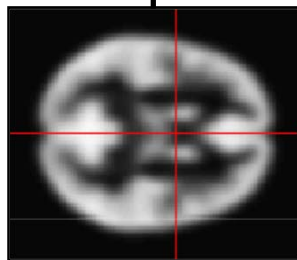
Realignment

Smoothing

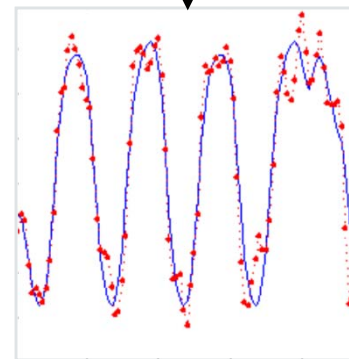
General Linear Model



Normalisation



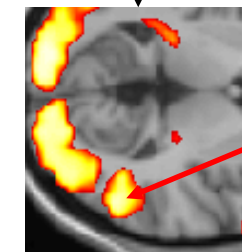
Anatomical reference



Parameter estimates

Statistical Inference

RFT

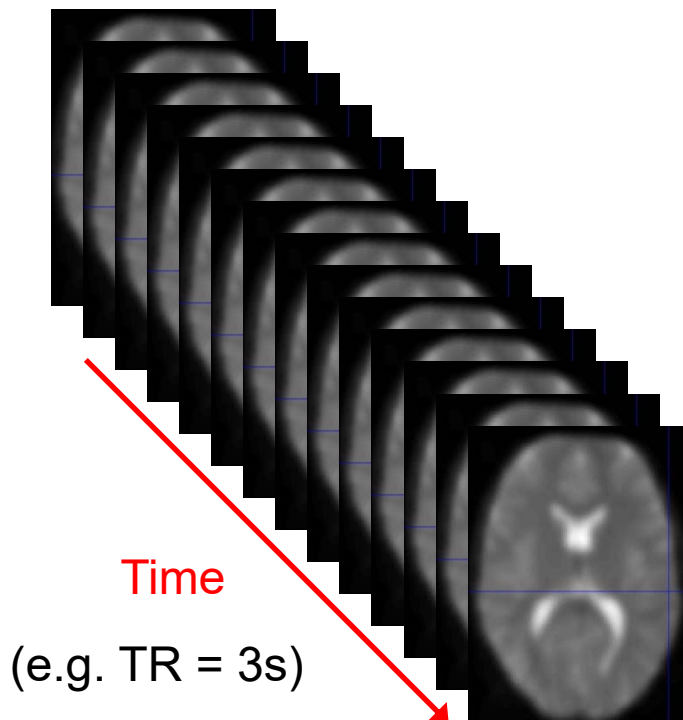


$p < 0.05$

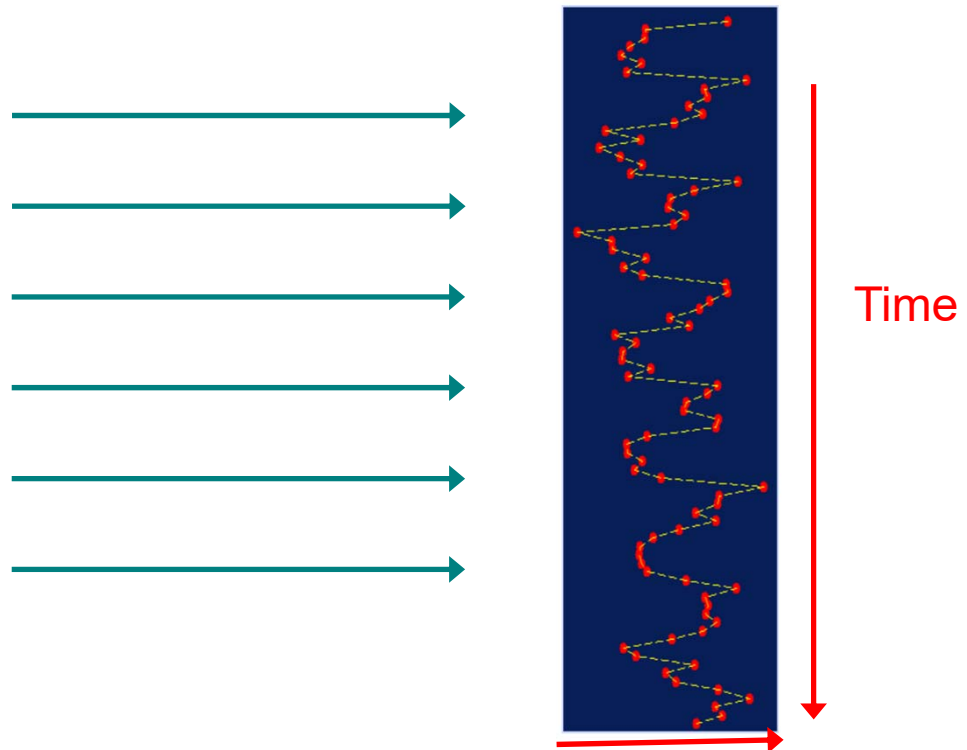
# 1<sup>st</sup> Level Analysis is within subject

$$y = X\beta + e$$

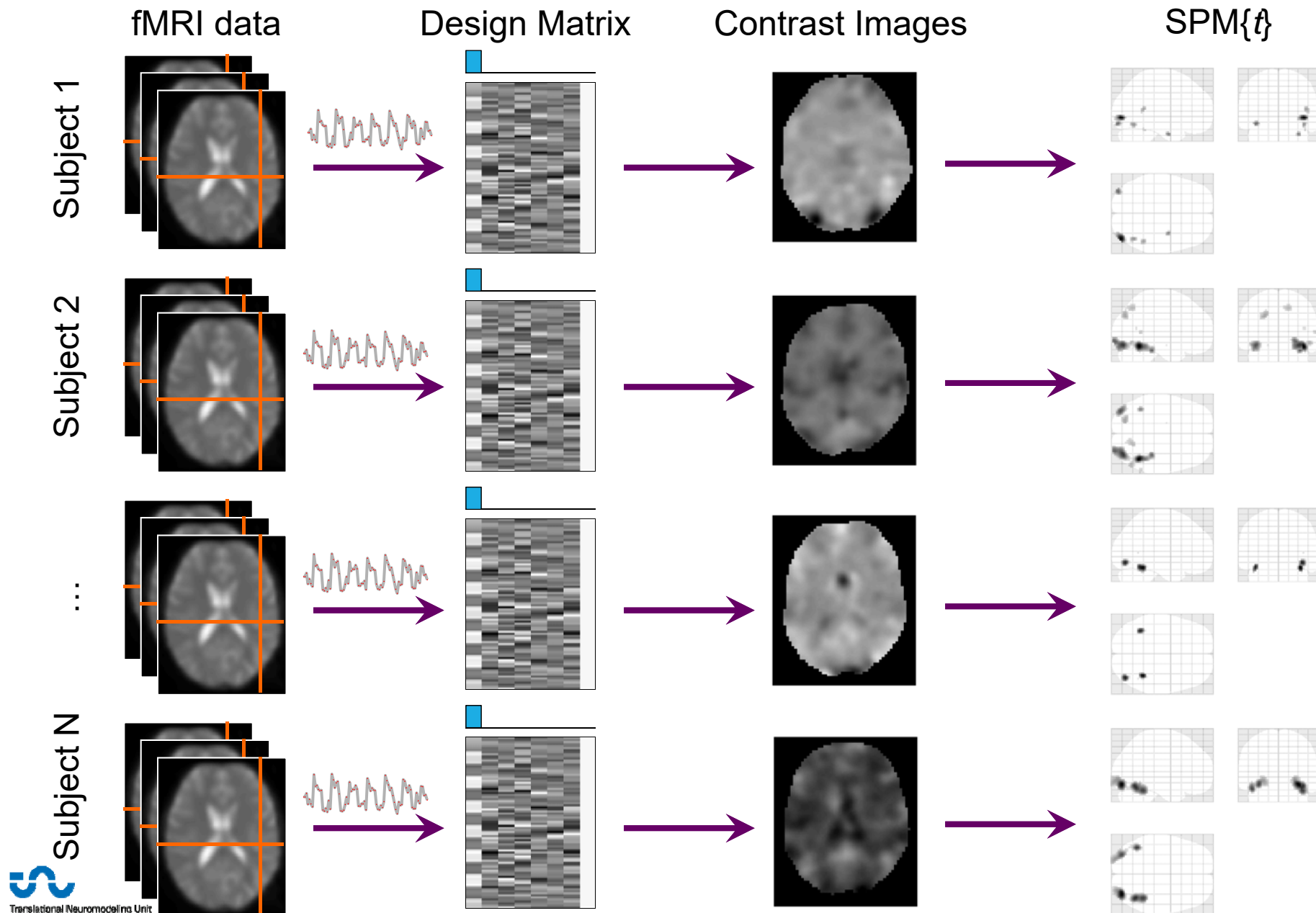
fMRI scans



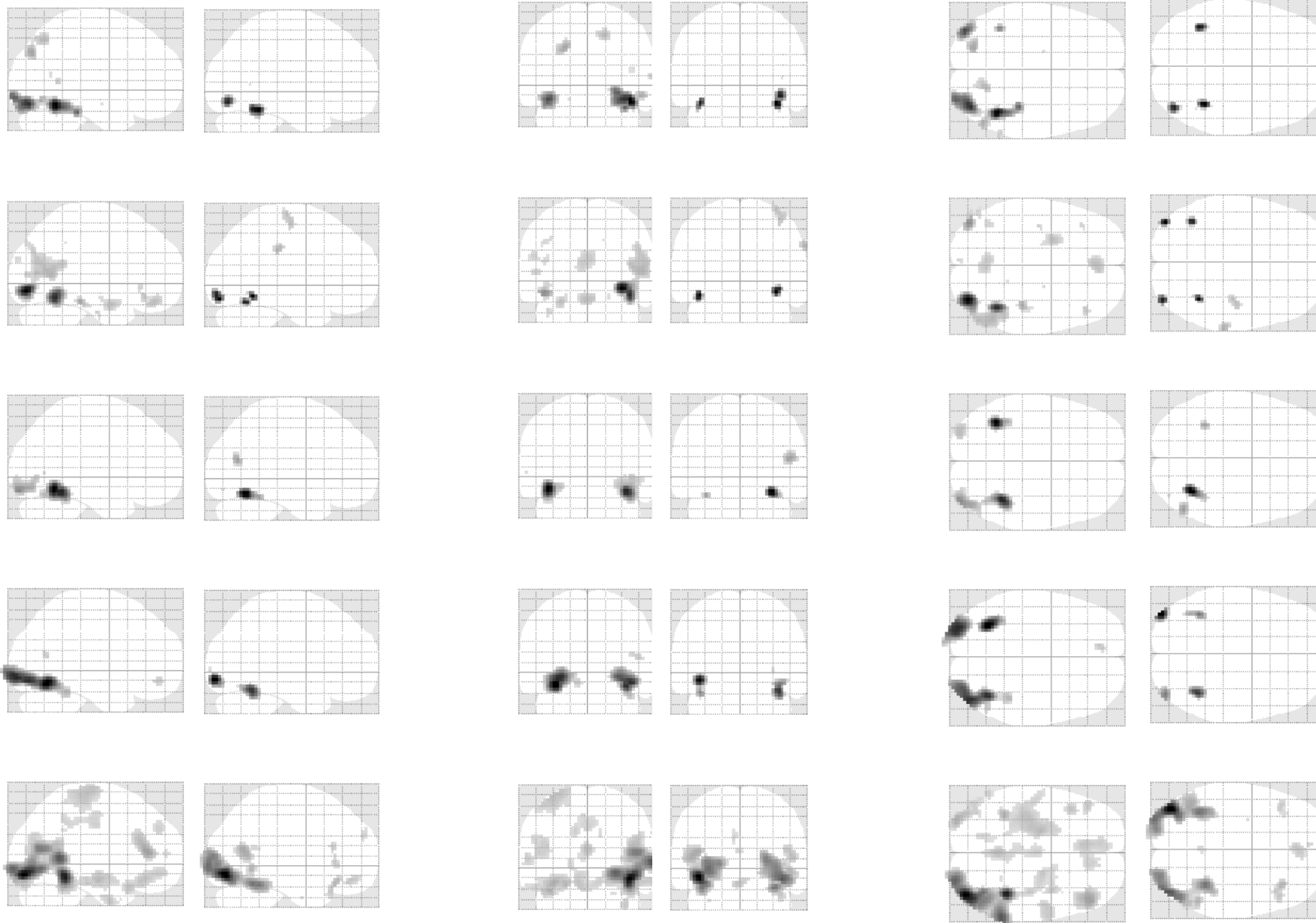
Voxel time course



# GLM: repeat over subjects



# First level analyses ( $p < 0.05$ FWE):



## 2<sup>nd</sup> level analysis – across subjects

- It isn't enough to look just at individuals.
- So, we need to look at which voxels are showing a significant activation difference between levels of X consistently within a group.
  1. Average contrast effect across sample
  2. Variation of this contrast effect
  3. T-tests

# Group Analysis: Fixed vs Random

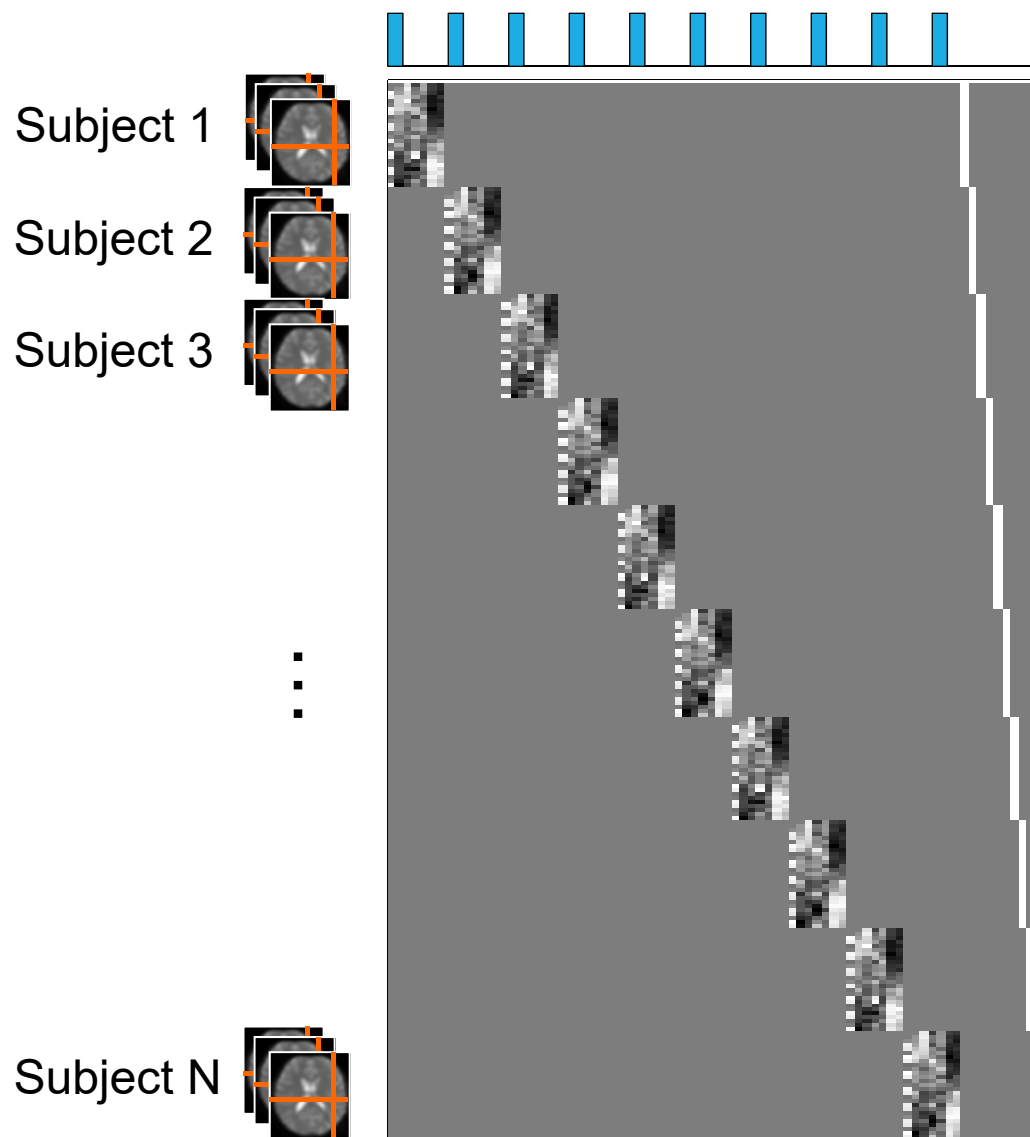
Does the group activate on average?



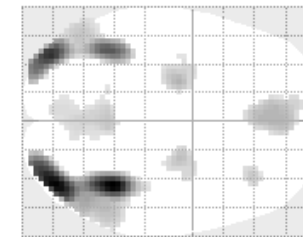
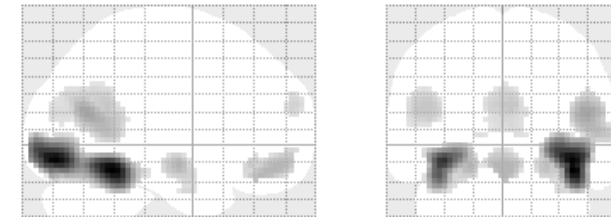
What group mean are we after?

- The group mean for those exact 7 subjects?  
→ **Fixed effects analysis (FFX)**
- The group mean for the population from which these 7 subjects were drawn?  
→ **Random effects analysis (RFX)**

# Fixed effects analysis (FFX)



Modelling all subjects at once



variance over subjects at each voxel



# Fixed effects analysis (FFX)

$$y = X^{(1)}\beta^{(1)} + \varepsilon^{(1)}$$

The diagram illustrates the matrix structure of the fixed effects model equation  $y = X^{(1)}\beta^{(1)} + \varepsilon^{(1)}$ . It shows a large black matrix  $X^{(1)}$  on the left, which is partitioned into three white rectangular blocks labeled  $X_1^{(1)}$ ,  $X_2^{(1)}$ , and  $X_3^{(1)}$ . To the right of the matrix is a plus sign followed by a gray vertical bar representing the vector  $\beta^{(1)}$ . Further to the right is another plus sign followed by another gray vertical bar representing the vector  $\varepsilon^{(1)}$ . The entire expression is preceded by the variable  $y$  and an equals sign.

Modelling all subjects at once

- ✓ Simple model
- ✓ Lots of degrees of freedom
- ✗ Large amount of data
- ✗ Assumes common variance over subjects at each voxel

# Fixed effects

$$y = X^{(1)}\beta^{(1)} + \varepsilon^{(1)}$$



- Only one source of random variation (over sessions):

→ measurement error

Within-subject Variance

- True response magnitude is *fixed*.

# Whole Group – FFX calculation

- N subjects = 12 with each 50 scans = 600 scans

$c = [4, 3, 2, 1, 1, 2, 3, 3, 3, 2, 4, 4]$

Within subject variability:

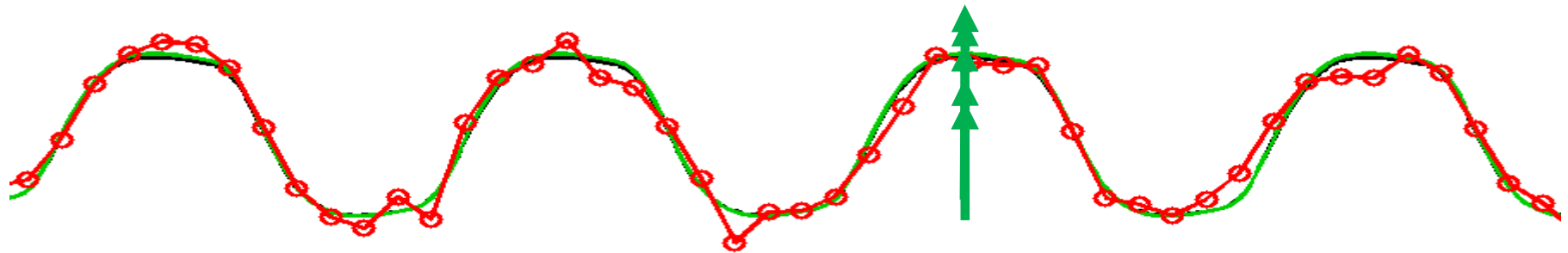
$\sigma_w^2 = [0.9, 1.2, 1.5, 0.5, 0.4, 0.7, 0.8, 2.1, 1.8, 0.8, 0.7, 1.1]$

- Mean group effect = 2.67
- Mean  $\sigma_w^2 = 1.04$
- Standard Error Mean (SEM) =  $\sigma_w^2 / (\text{sqrt}(N)) = 0.04$

$t = M / \text{SEM} = 62.7, p = 10^{-51}$

# Random effects

$$y = X^{(1)} \beta^{(1)} + \varepsilon^{(1)}$$
$$\beta^{(1)} = X^{(2)} \beta^{(2)} + \varepsilon^{(2)}$$



- Two sources of random variation:

→ measurement errors

→ response magnitude (over subjects)

Within-subject Variance

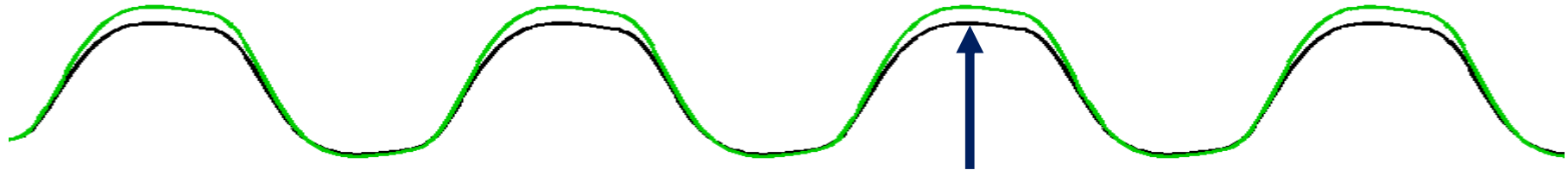
Between-subject Variance

- Response magnitude is *random*

→ each subject/session has random magnitude

# Random effects

$$y = X^{(1)} \beta^{(1)} + \varepsilon^{(1)}$$
$$\beta^{(1)} = X^{(2)} \beta^{(2)} + \varepsilon^{(2)}$$



- Two sources of random variation:

→ measurement errors

→ response magnitude (over subjects)

Within-subject Variance

Between-subject Variance

- Response magnitude is *random*

→ each subject/session has random magnitude

→ but population mean magnitude is *fixed*.

# Whole Group – RFX calculation

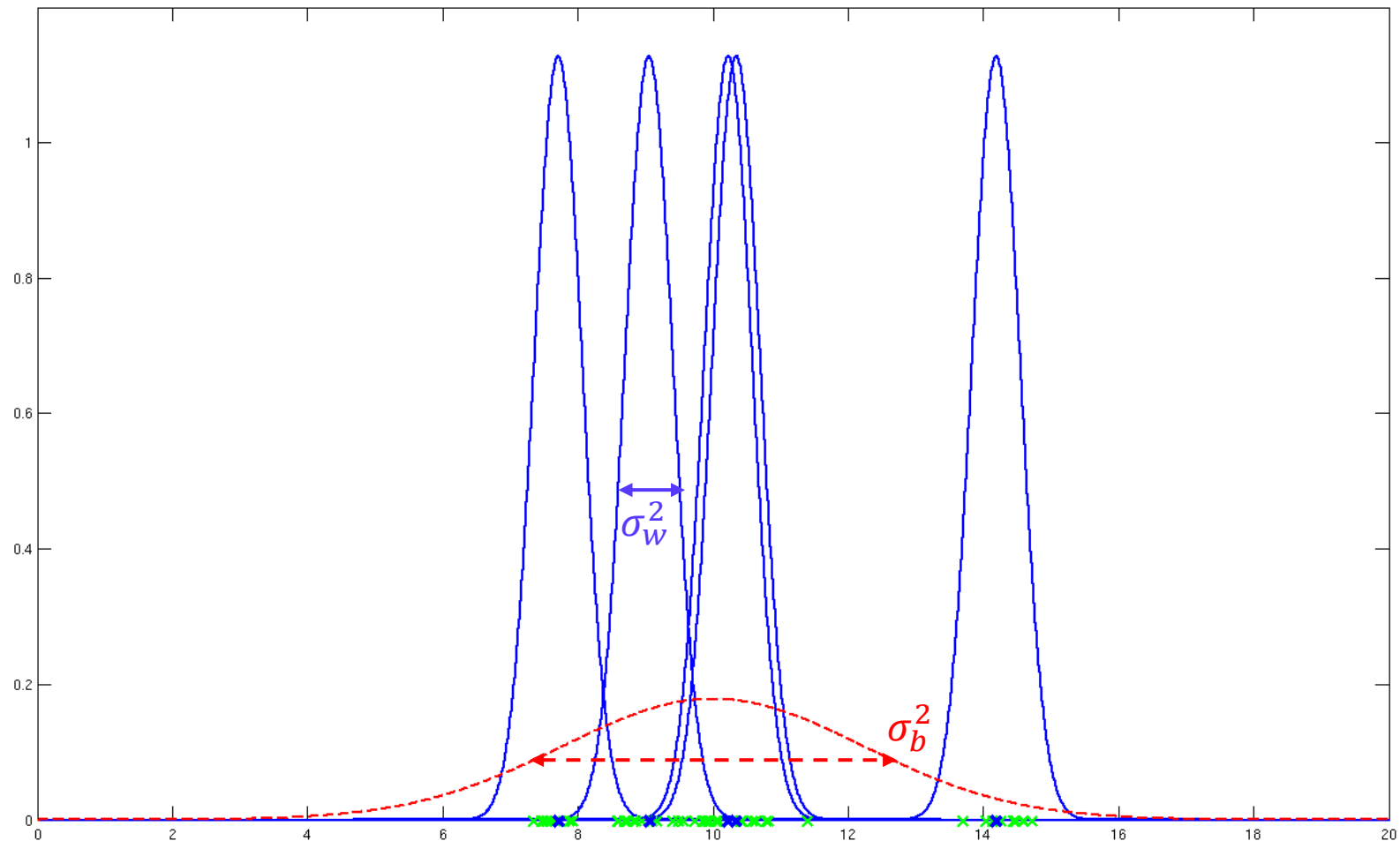
- N subjects = 12

$c = [4, 3, 2, 1, 1, 2, 3, 3, 3, 2, 4, 4]$

- Mean group effect = 2.67
- Mean  $\sigma_b^2$  (SD) = 1.07
- Standard Error Mean (SEM) =  $\sigma_b^2 / (\text{sqrt}(N)) = 0.31$

$t = M / \text{SEM} = 8.61, p = 10^{-6}$

# Random effects



Probability model underlying random effects analysis

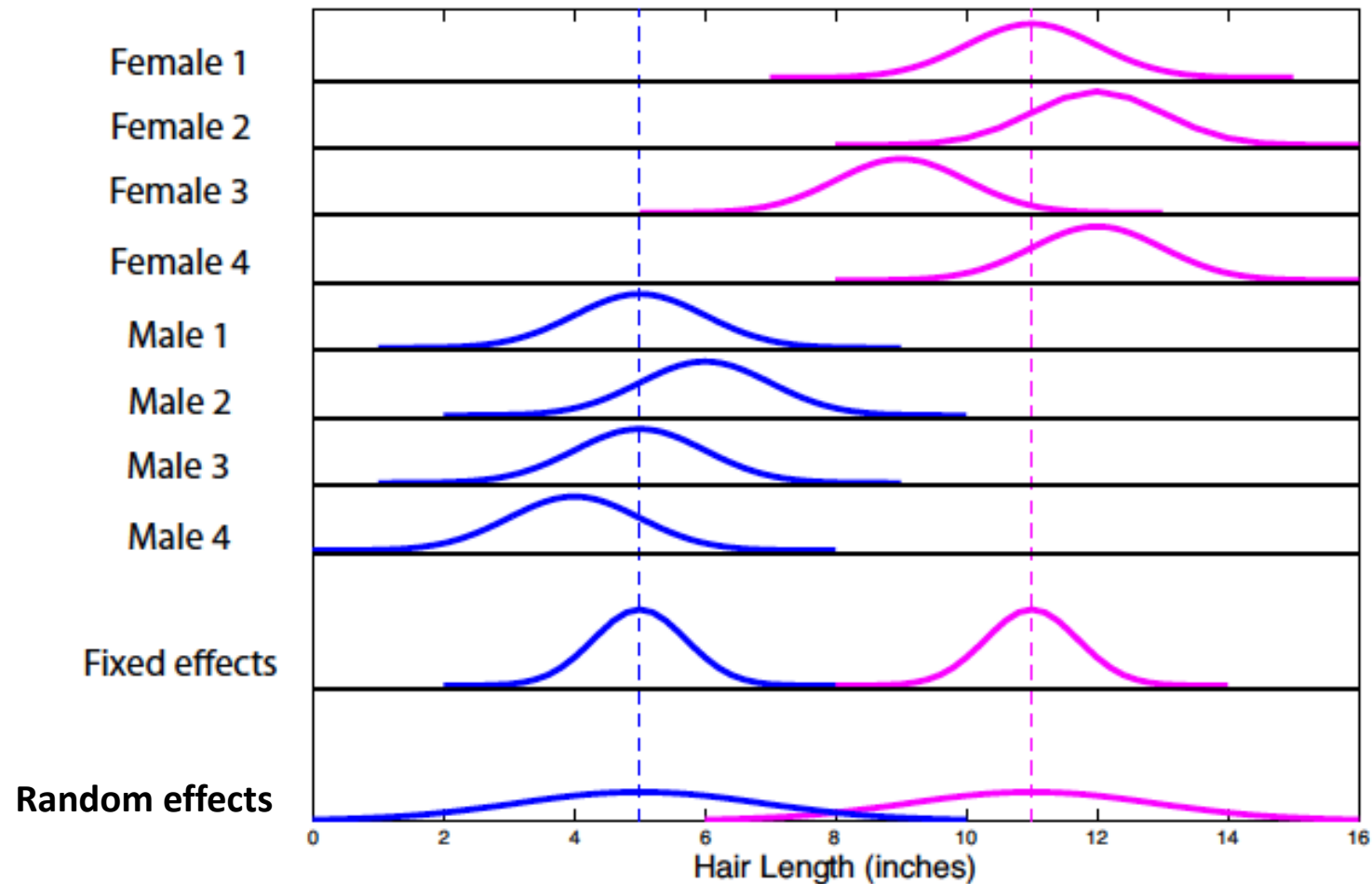
# Fixed vs random effects

With **Fixed Effects Analysis (FFX)** we compare the group effect to the *within-subject variability*. It is not an inference about the population from which the subjects were drawn.

With **Random Effects Analysis (RFX)** we compare the group effect to the *between-subject variability*. It is an inference about the population from which the subjects were drawn. If you had a new subject from that population, you could be confident they would also show the effect.



# Fixed vs random effects

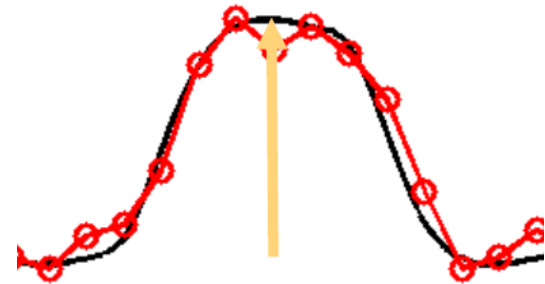


*Handbook of functional MRI data analysis.* Poldrack, R. A., Mumford, J. A., & Nichols, T. E. Cambridge University Press, 2011

# Fixed vs random effects

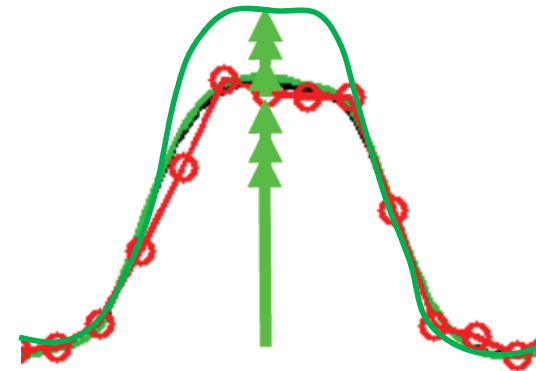
## Fixed-effects

- Is not of interest across a population
- Used for a case study
- Only source of variation is measurement error (Response magnitude is **fixed**)



## Random-effects

- If I have to take another sample from the population, I would get the same result
- Two sources of variation
  - Measurement error
  - Response magnitude is **random** (population mean magnitude is fixed)



# Fixed vs random effects

- Fixed isn't "wrong", just usually isn't of interest.
- Summary:
  - **Fixed effects inference:**  
*"I can see this effect in this cohort"*
  - **Random effects inference:**  
*"If I were to sample a new cohort from the same population I would get the same result"*

# Terminology

## **Hierarchical linear models:**

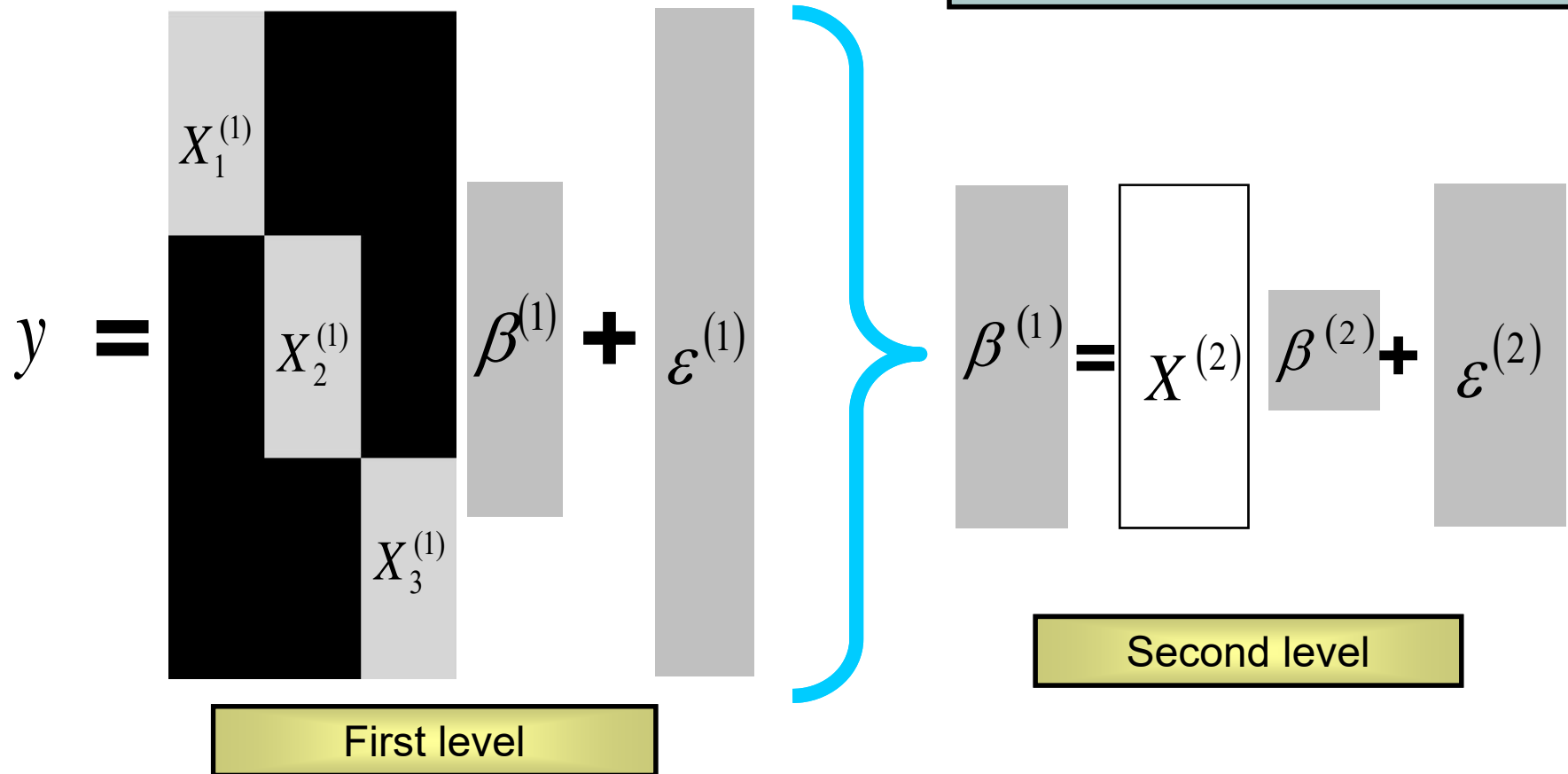
- Random effects models
- Mixed effects models
- Nested models
- Variance components models

... all the same

... all alluding to multiple sources of variation  
(in contrast to fixed effects)

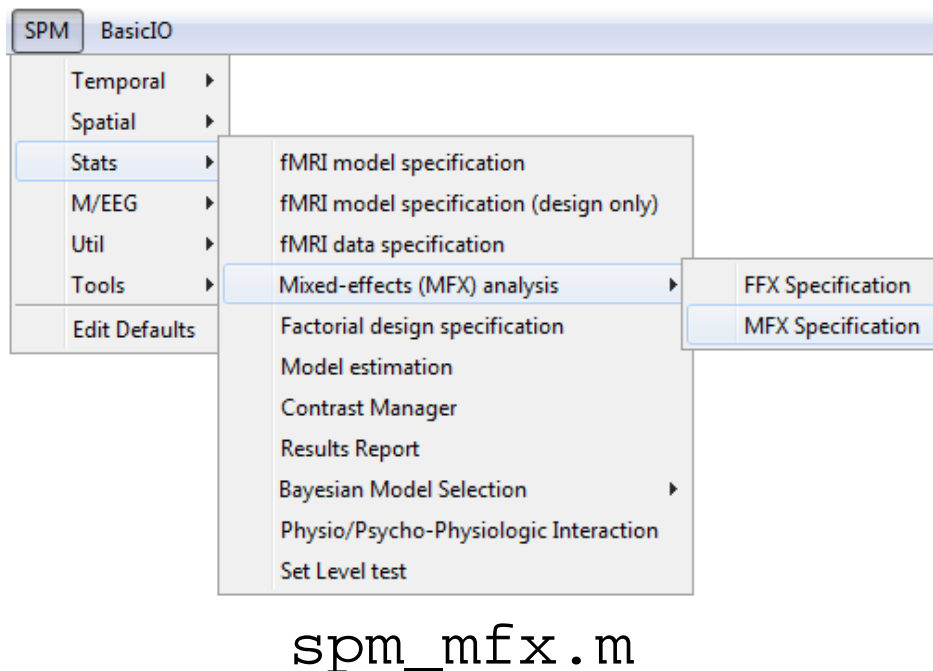
# Hierarchical models

Example: Two level model



# Hierarchical models

- Restricted Maximum Likelihood (ReML)
- Parametric Empirical Bayes
- Expectation-Maximisation Algorithm

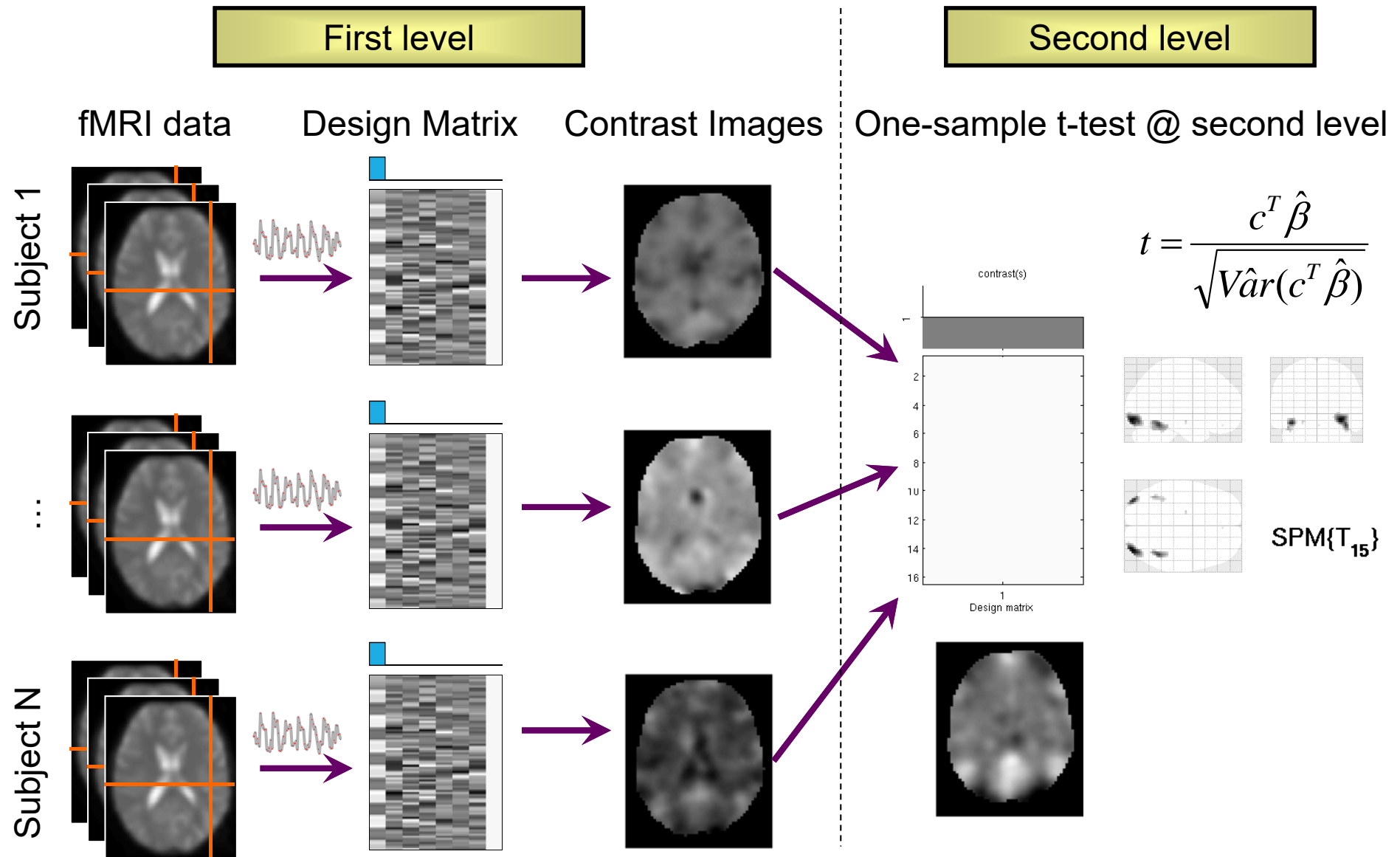


## But:

- Many two level models are just too big to compute.
- And even if, it takes a long time!
- Any approximation?

*Mixed-effects and fMRI studies.* Friston et al., NeuroImage, 2005.

# Summary Statistics RFX Approach



$$t = \frac{c^T \hat{\beta}}{\sqrt{\text{Var}(c^T \hat{\beta})}}$$

# Summary Statistics RFX Approach

## Assumptions

- The summary statistics approach is exact if for each session/subject:
  - Within-subjects variances the same
  - First level design the same (e.g. number of trials)
- Other cases: summary statistics approach is robust against typical violations.

*Mixed-effects and fMRI studies.* Friston et al., NeuroImage, 2005.

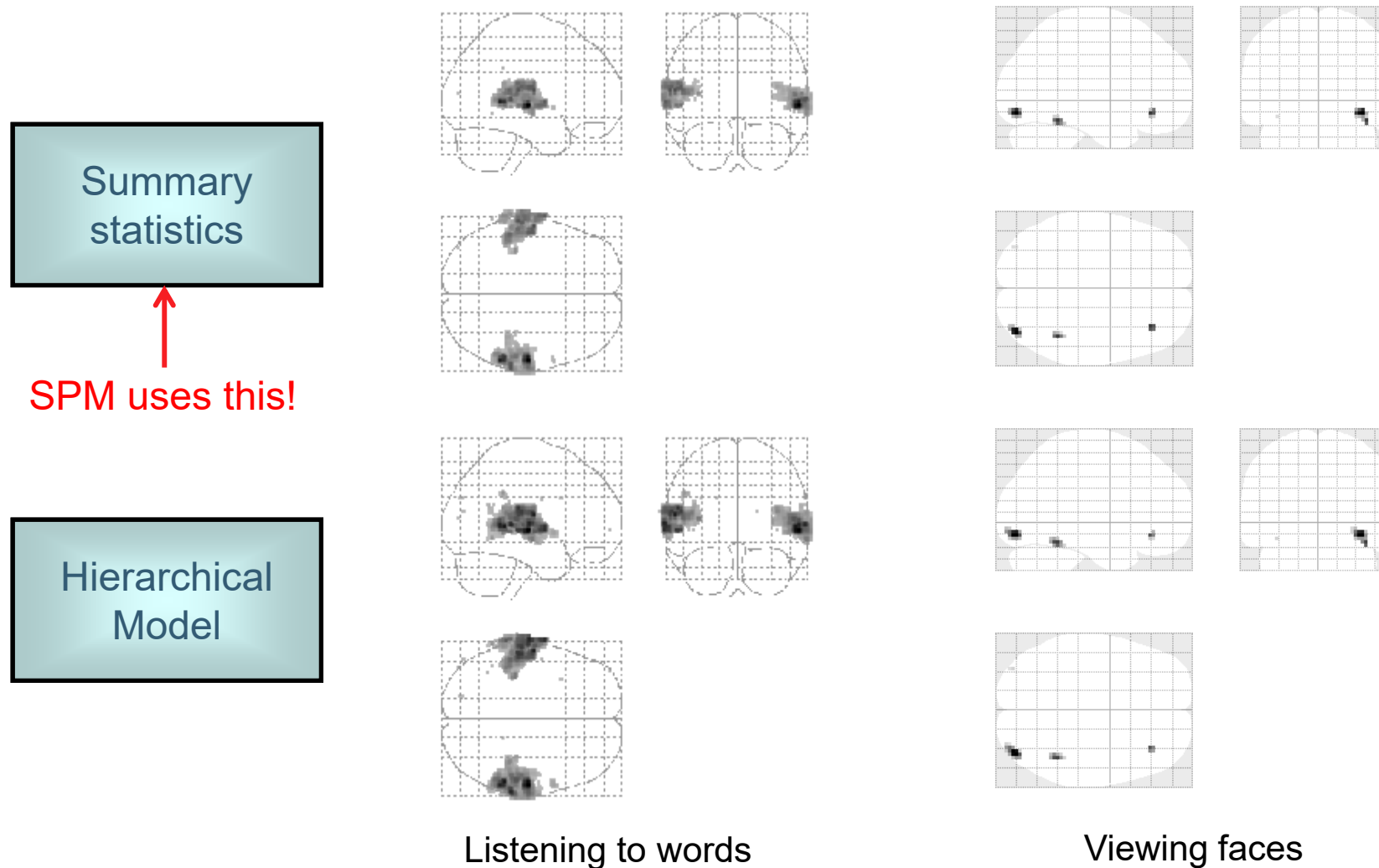
*Statistical Parametric Mapping: The Analysis of Functional Brain Images.* Elsevier, 2007.

*Simple group fMRI modeling and inference.* Mumford & Nichols. NeuroImage, 2009.



# Summary Statistics RFX Approach

## Robustness

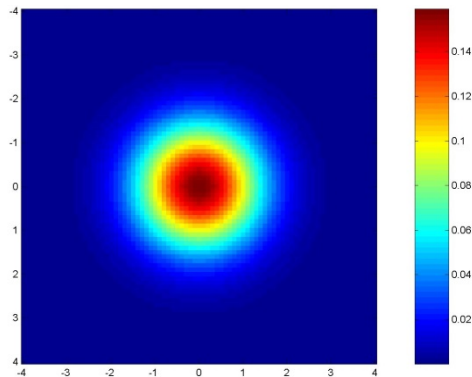


# ANOVA & non-sphericity

- **One effect per subject:**
  - Summary statistics approach
  - One-sample t-test at the second level
- **More than one effect per subject or multiple groups:**
  - Non-sphericity modelling
  - Covariance components and ReML

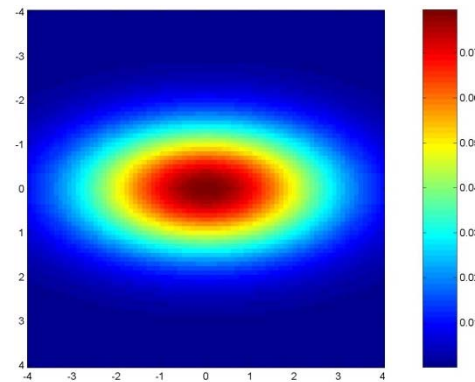
# GLM assumes Gaussian “spherical” (i.i.d.) errors

**sphericity = iid:**  
error covariance is  
scalar multiple of  
identity matrix:  
 $\text{Cov}(e) = \sigma^2 \mathbf{I}$



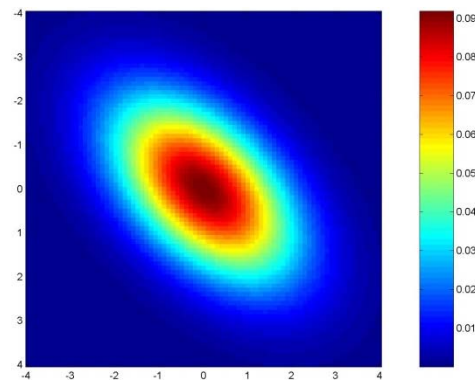
$$\text{Cov}(e) = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

Examples for non-sphericity:



$$\text{Cov}(e) = \begin{bmatrix} 4 & 0 \\ 0 & 1 \end{bmatrix}$$

non-identically  
distributed



$$\text{Cov}(e) = \begin{bmatrix} 2 & 1 \\ 1 & 2 \end{bmatrix}$$

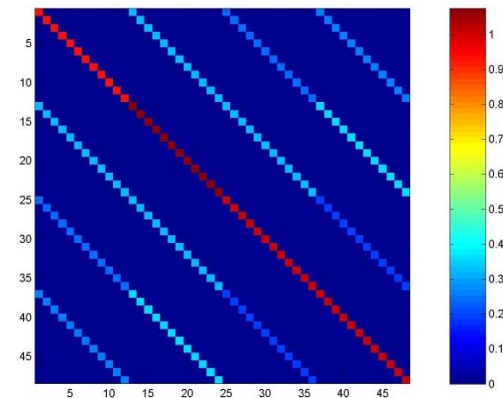
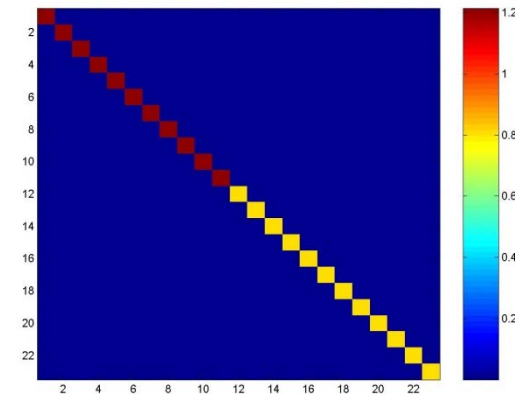
non-independent

## 2nd level: Non-sphericity

Errors are independent  
but not identical  
(e.g. different groups (patients, controls))

Errors are not independent  
and not identical  
(e.g. repeated measures for each subject  
(multiple basis functions, multiple  
conditions, etc.))

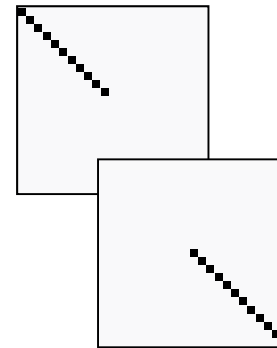
Error covariance matrix



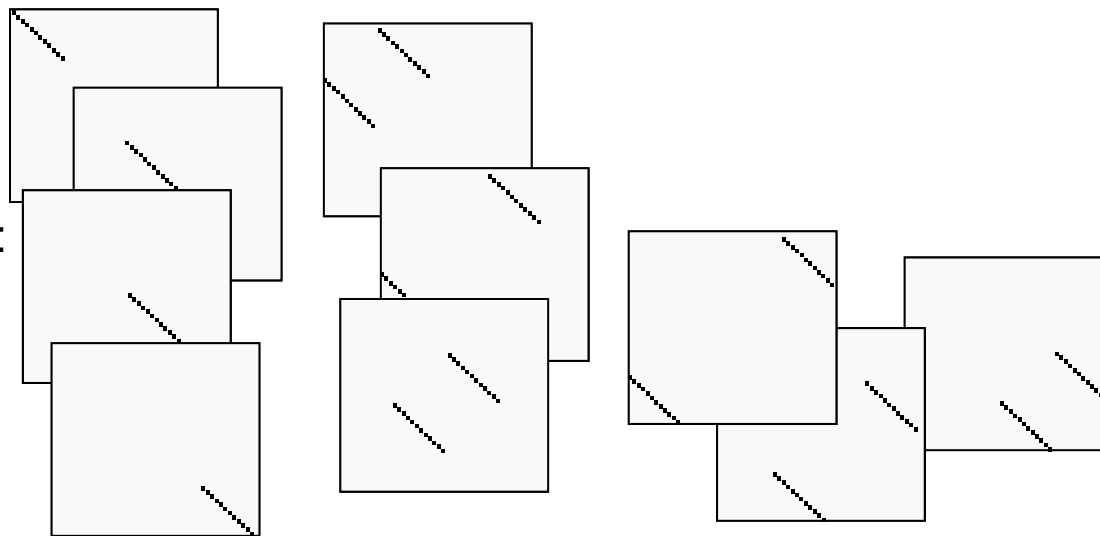
## 2nd level: Variance components

$$\text{Cov}(\varepsilon) = \sum_k \lambda_k Q_k$$

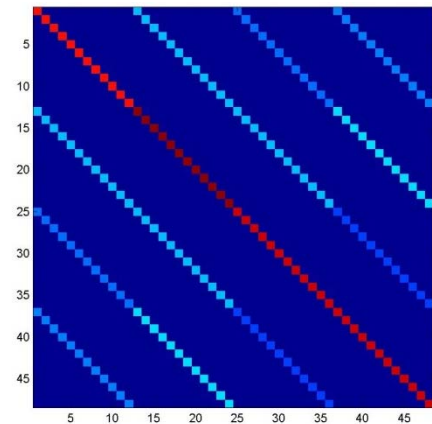
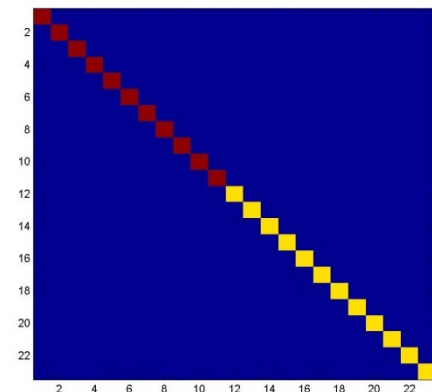
$Q_k$ 's:



$Q_k$ 's:



Error covariance matrix

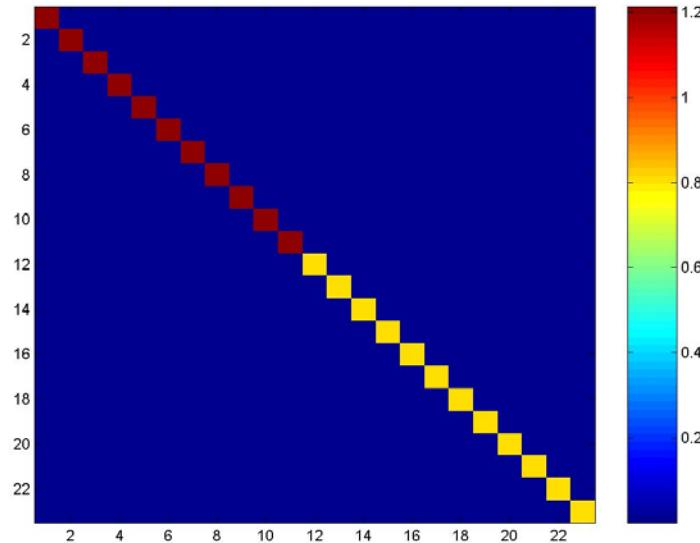
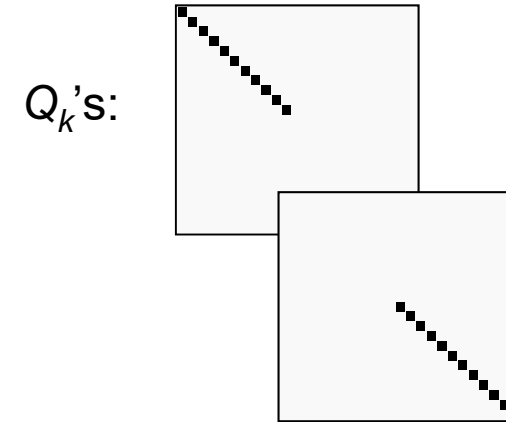


# Example 1: between-subjects ANOVA

- Stimuli:
  - Auditory presentation (SOA = 4 sec)
  - 250 scans per subject, block design
  - 2 conditions
    - Words, e.g. “book”
    - Words spoken backwards, e.g. “koob”
- Subjects:
  - 12 controls
  - 11 blind people

# Example 1: Covariance components

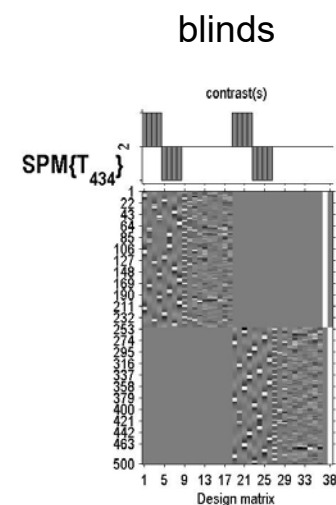
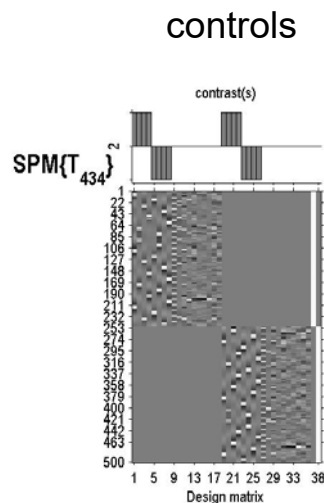
- Two-sample t-test:
  - Errors are independent but not identical.
  - 2 covariance components



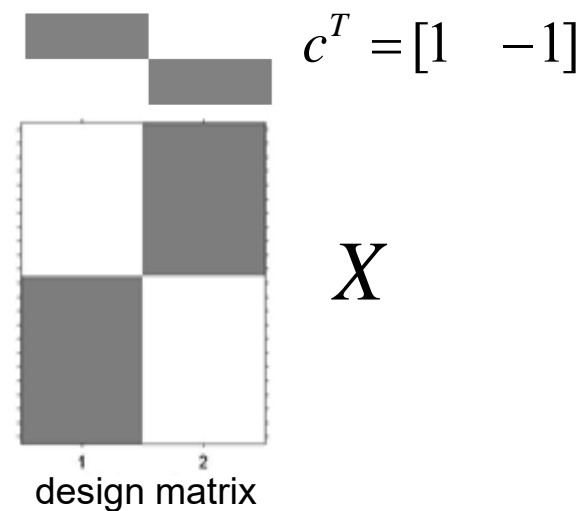
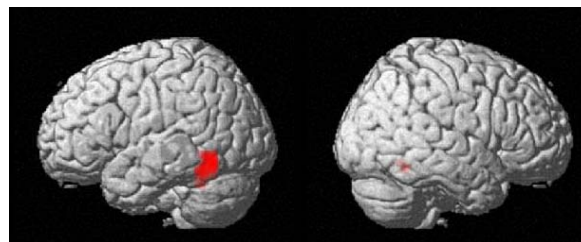
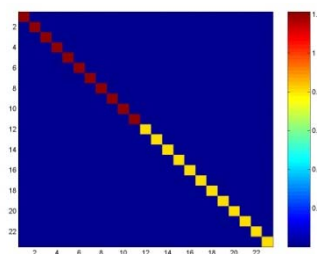
Error covariance matrix

# Example 1: Group differences

First  
Level



Second  
Level





## Example 2: within-subjects ANOVA

- Stimuli:

- Auditory presentation (SOA = 4 sec)
- 250 scans per subject, block design

- Words:

Motion	Sound	Visual	Action
“jump”	“click”	“pink”	“turn”

- Subjects:

- 12 controls

- Question:

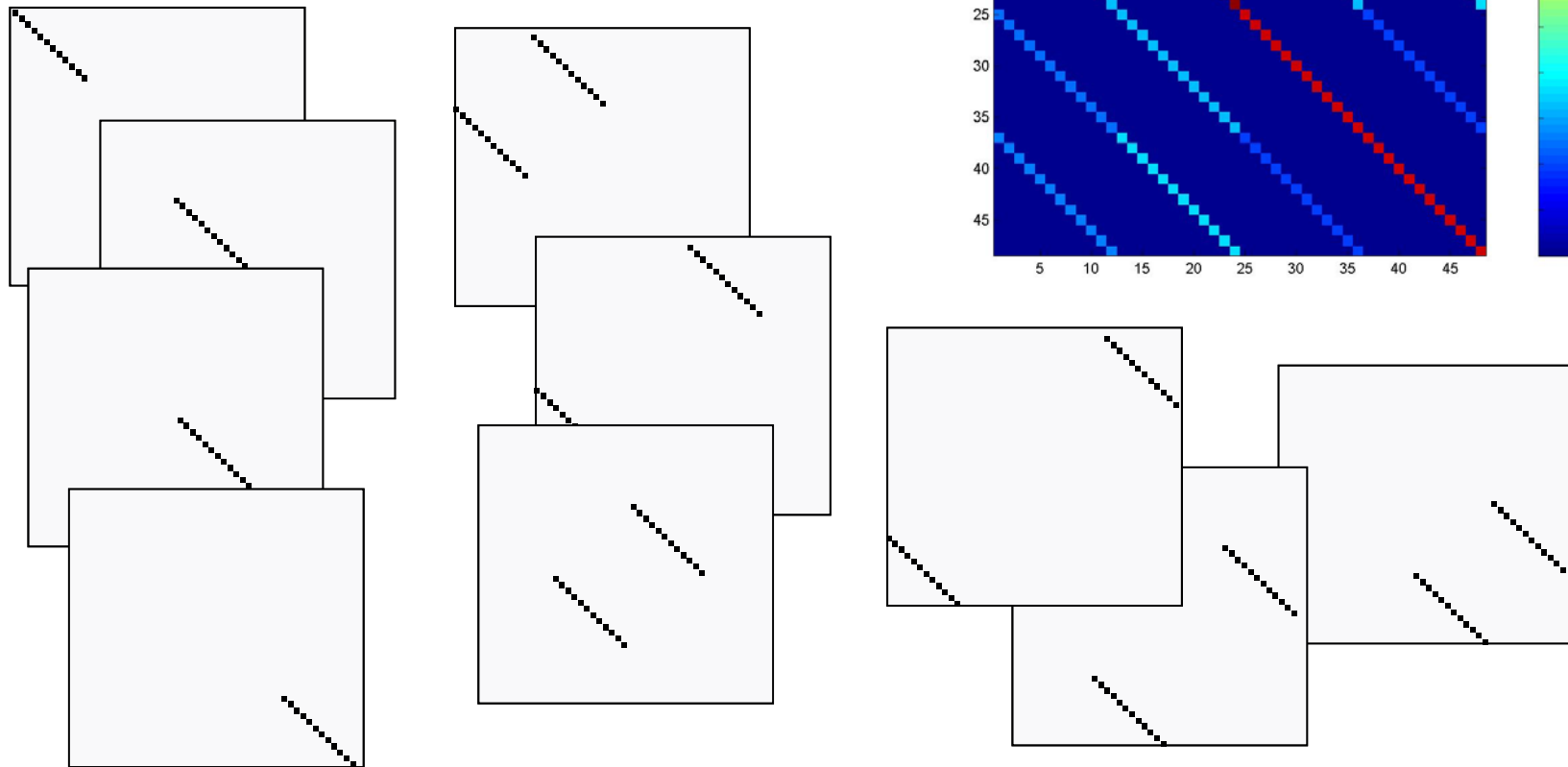
- What regions are generally affected by the semantic content of the words?

Noppeney et al., Brain, 2003.

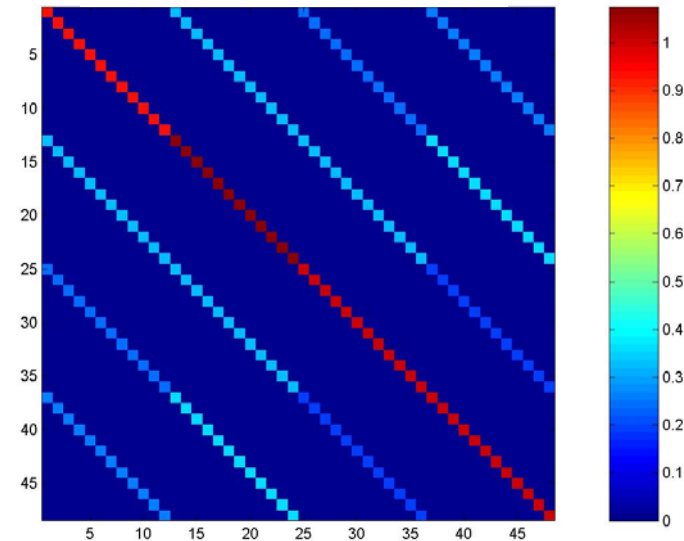
## Example 2: Covariance components

→ Errors are not independent and not identical

$Q_k$ 's:



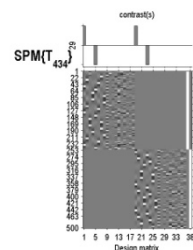
Error covariance matrix



# Example 2: Repeated measures ANOVA

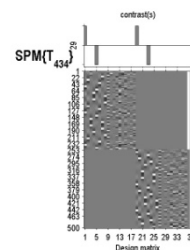
First Level

Motion



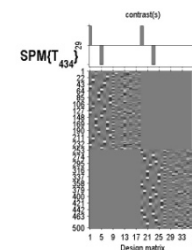
= ?

Sound



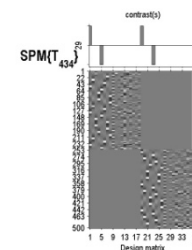
= ?

Visual

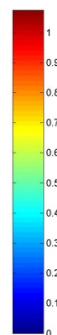
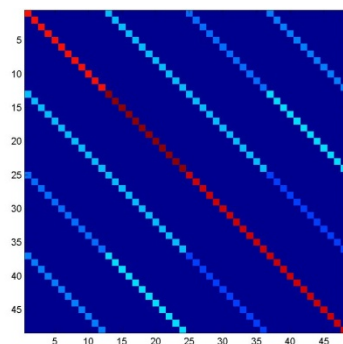


= ?

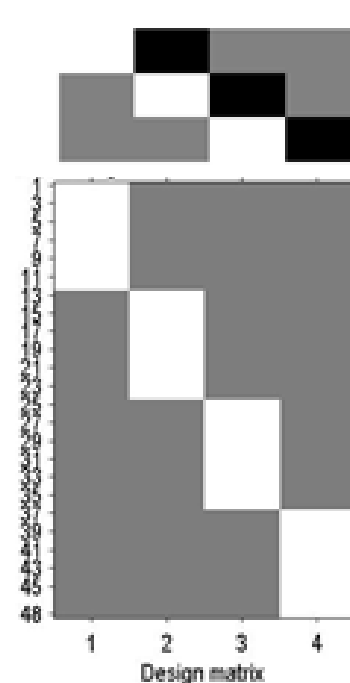
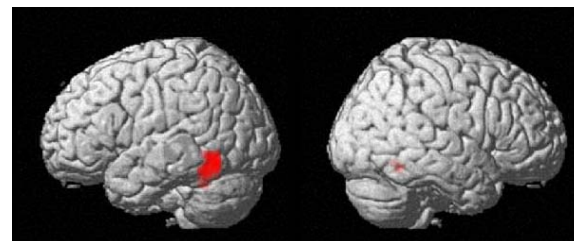
Action



Second Level



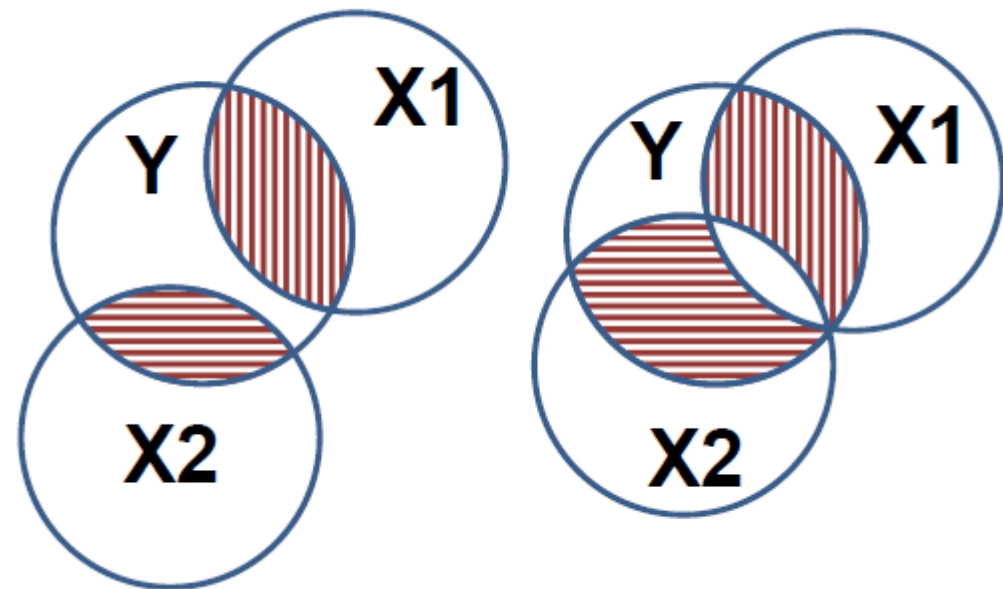
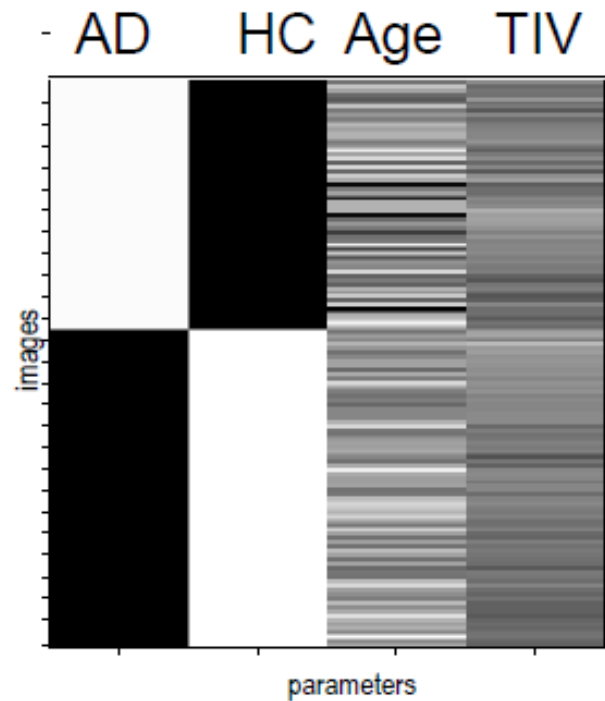
$Cov(\epsilon)$



$$c^T = \begin{pmatrix} 1 & -1 & 0 & 0 \\ 0 & 1 & -1 & 0 \\ 0 & 0 & 1 & -1 \end{pmatrix}$$

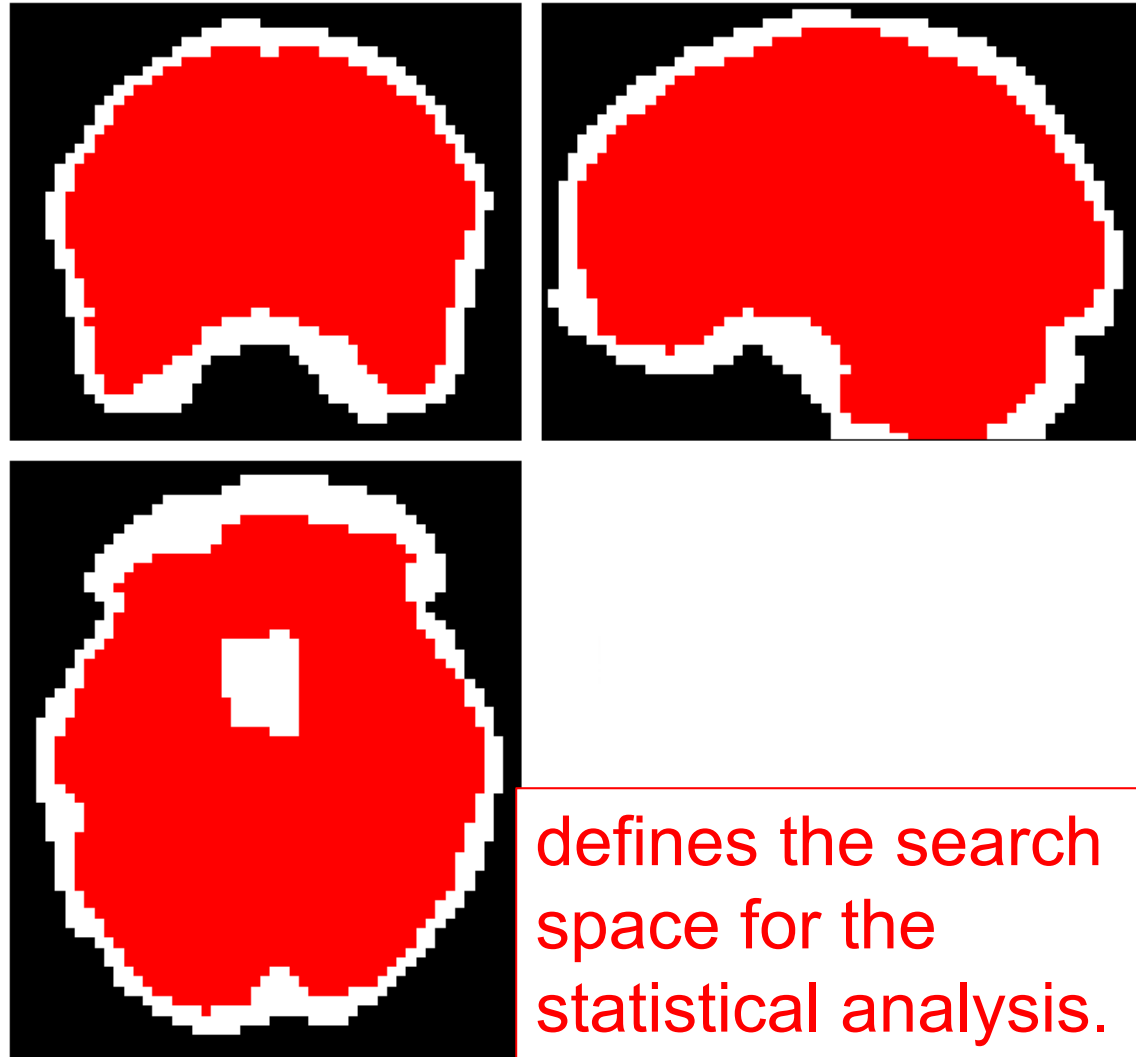
$X$

# ANCOVA model



Mean centering continuous covariates for a group fMRI analysis, by J. Mumford:  
[http://mumford.fmripower.org/mean\\_centering/](http://mumford.fmripower.org/mean_centering/)

# Analysis mask: logical AND



defines the search  
space for the  
statistical analysis.

# SPM interface: factorial design specification

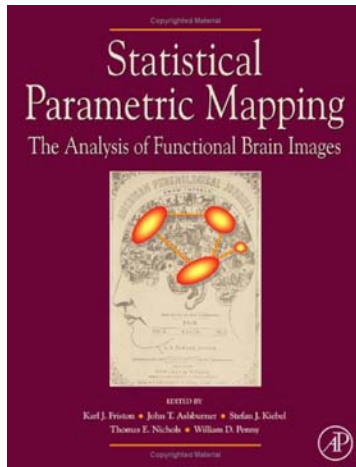
## Options:

- One-sample t-test
- Two-sample t-test
- Paired t-test
- Multiple regression
- One-way ANOVA
- One-way ANOVA – within subject
- Full factorial
- Flexible factorial

# Summary

- Group inference usually proceeds with **RFX analysis**, not FFX. Group effects are compared to between rather than within subject variability.
- **Hierarchical models** provide a gold-standard for RFX analysis but are computationally intensive.
- **Summary statistics** approach is a robust method for RFX group analysis.
- Can also use '**ANOVA**' or '**ANOVA within subject**' at second level for inference about multiple experimental conditions or multiple groups.

# Bibliography:



*Statistical Parametric Mapping:  
The Analysis of Functional Brain Images.*  
Elsevier, 2007.

- *Generalisability, Random Effects & Population Inference.* Holmes & Friston, NeuroImage, 1998.
- *Classical and Bayesian inference in neuroimaging: theory.* Friston et al., NeuroImage, 2002.
- *Classical and Bayesian inference in neuroimaging: variance component estimation in fMRI.* Friston et al., NeuroImage, 2002.
- *Mixed-effects and fMRI studies.* Friston et al., NeuroImage, 2005.
- *Simple group fMRI modeling and inference.* Mumford & Nichols, NeuroImage, 2009.