

**Edinburgh course – Avril 2010**

**Linear Models – Contrasts – Variance components**

*Jean-Baptiste Poline*

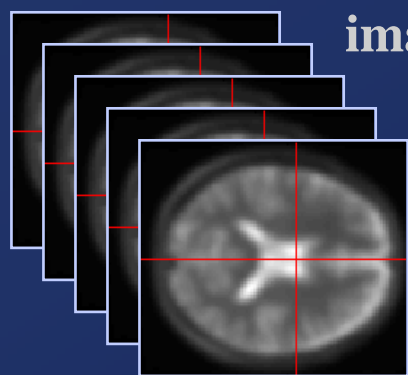
*Neurospin, I2BM, CEA Saclay, France*

Credits: Will Penny, G. Flandin, SPM course authors

# Outline

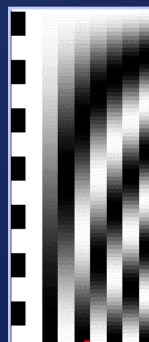
- **Part I: Linear model and contrast: going through it again and going further**
- **Part II: Variance component and group analyses\***

**\* (shamelessly stolen from Will Penny SPM course)**

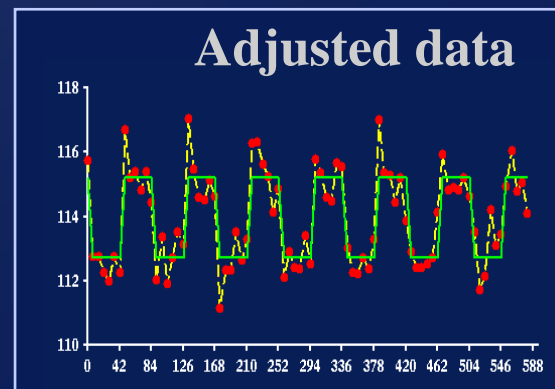
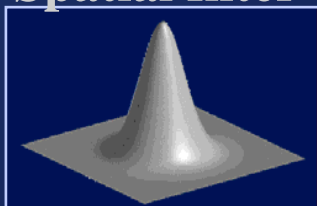


images

Design matrix



Spatial filter



Your question:  
a contrast



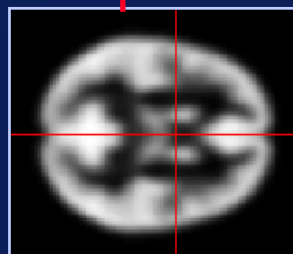
realignment &  
coregistration

smoothing

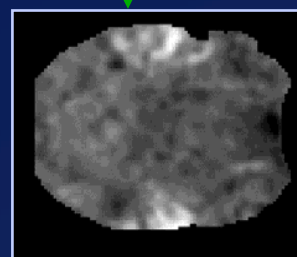
General Linear Model  
Linear fit  
→ statistical image

Random Field  
Theory

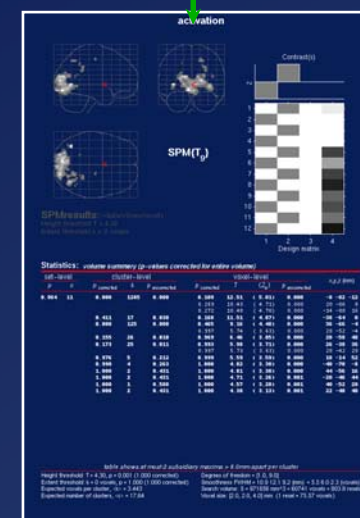
normalisation



Anatomical  
Reference



Statistical Map  
Uncorrected  $p$ -values

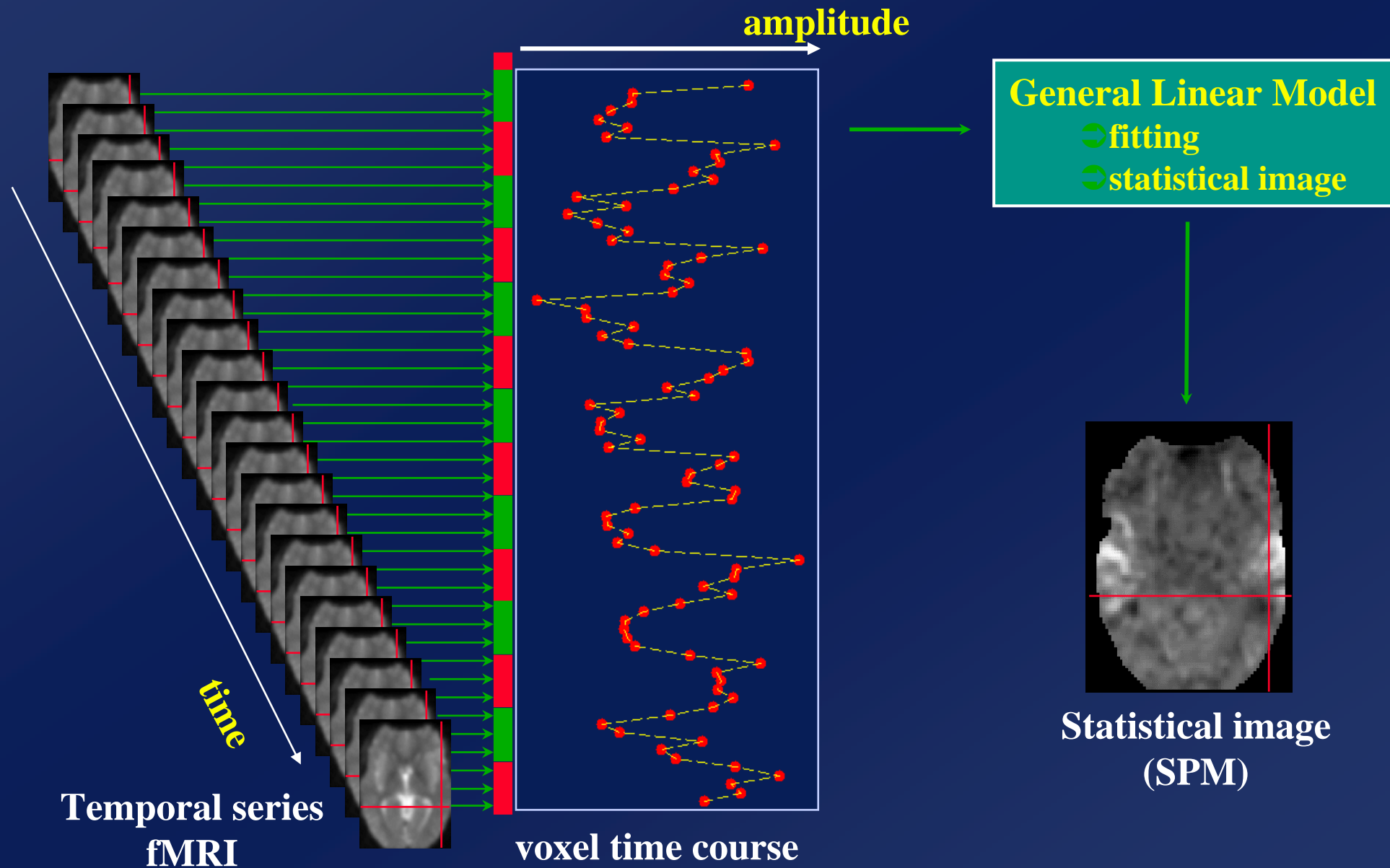


Corrected  $p$ -values

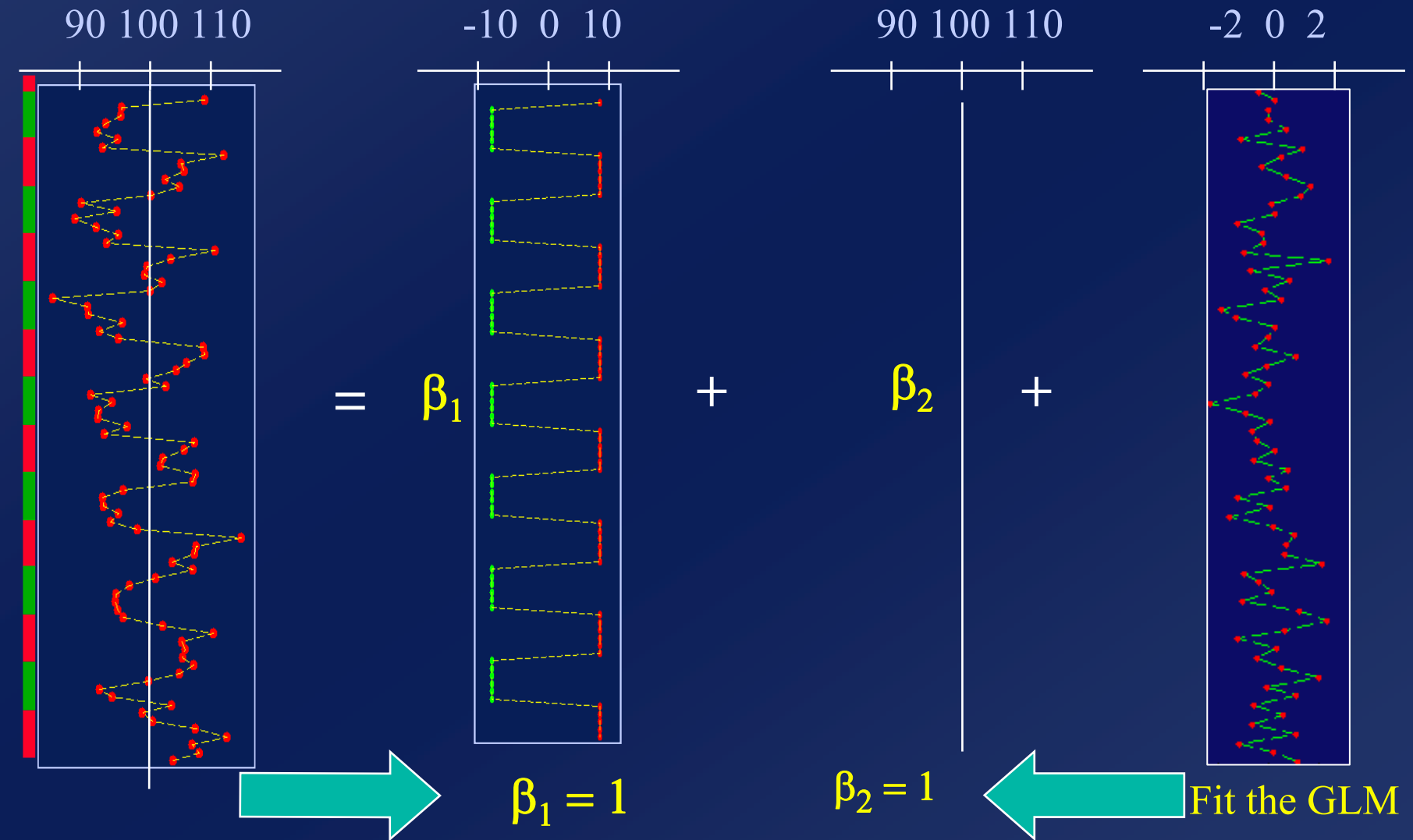
# Plan

- ♦ *REPEAT: model and fitting the data with a Linear Model*
- ♦ *Make sure we understand the testing procedures :  $t$ - and  $F$ -tests*
- ♦ *But what do we test exactly ?*
- ♦ *Examples – almost real*

# One voxel = One test (t, F, ...)

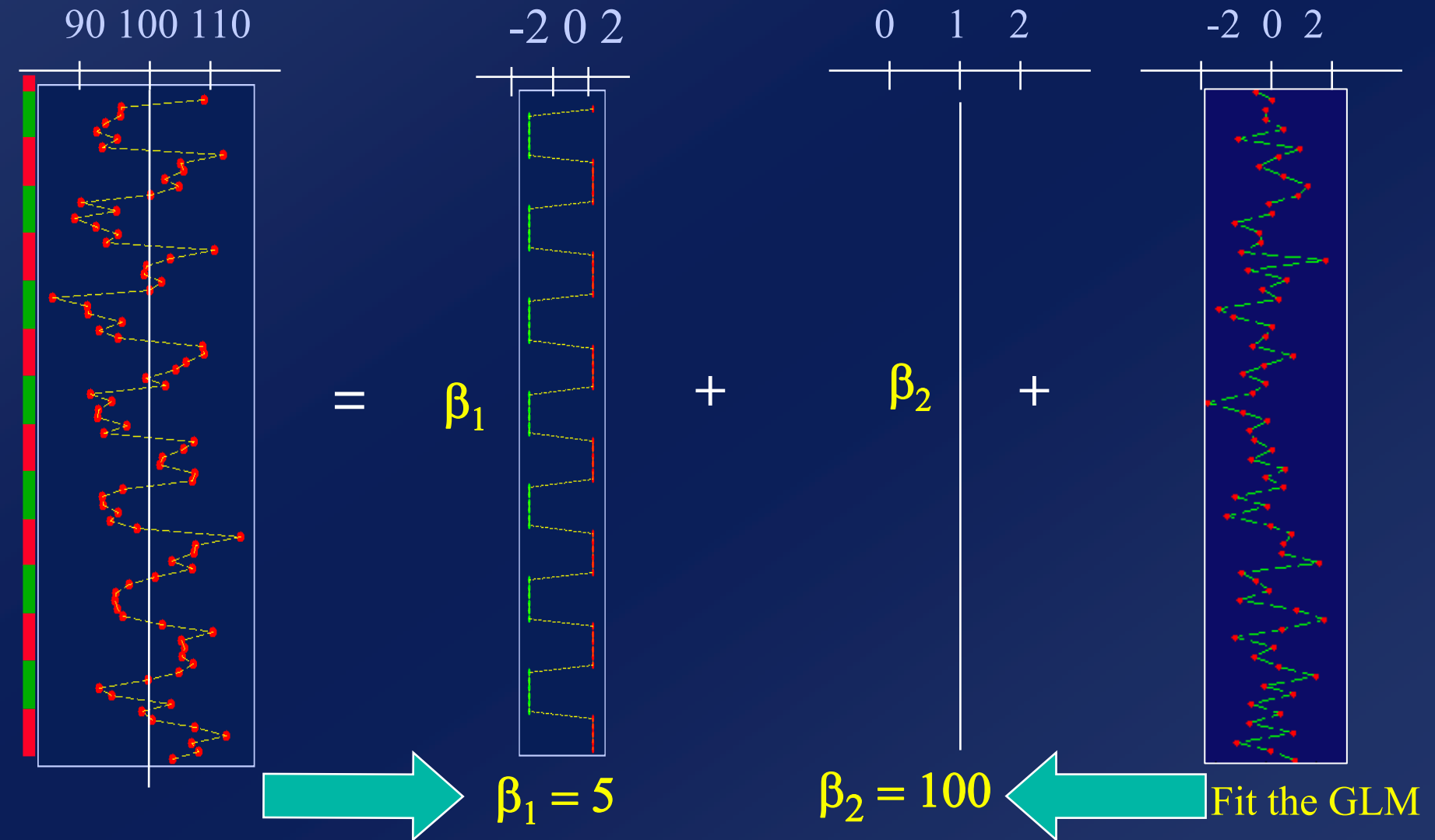


# Regression example...



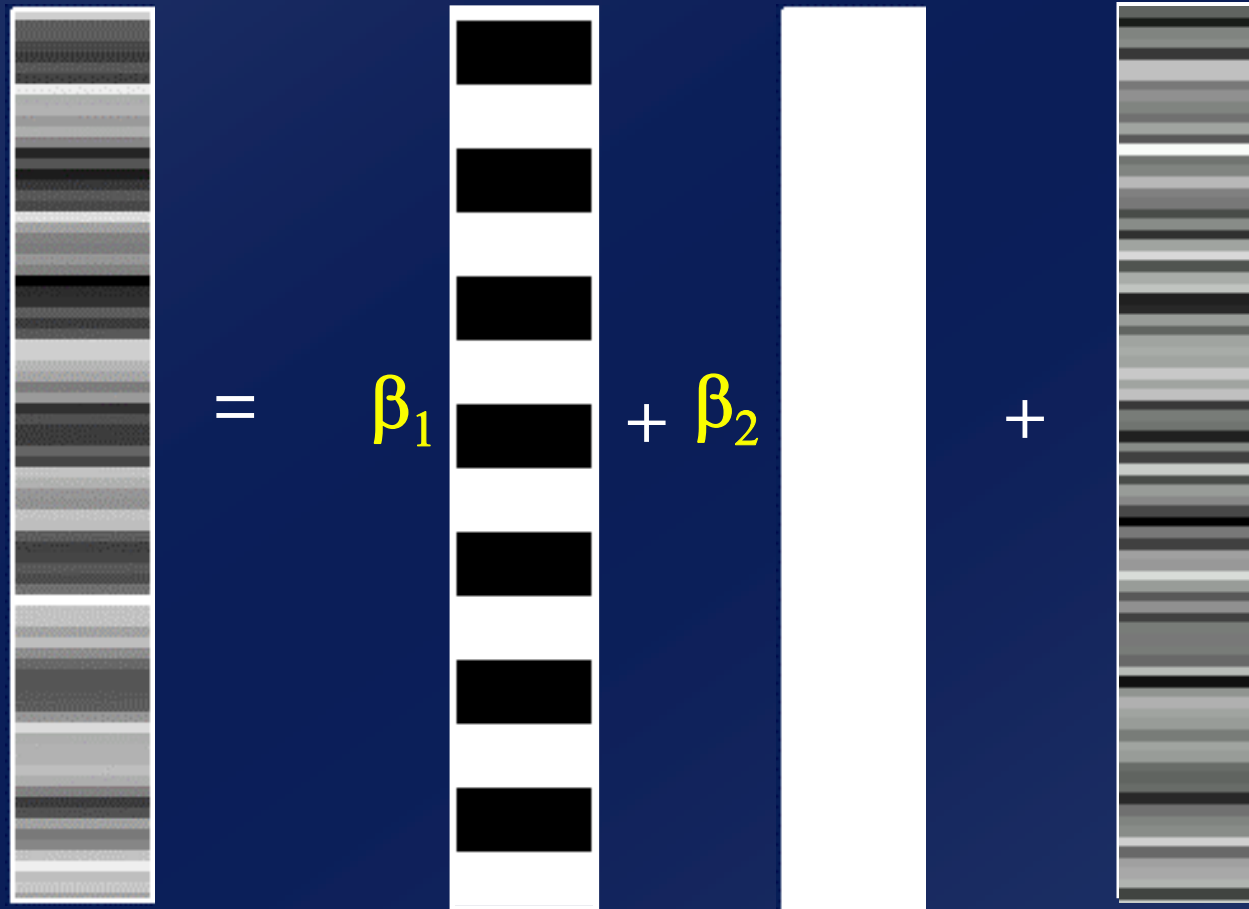
voxel time series   **box-car reference function**   Mean value

# Regression example...



voxel time series    box-car reference function    Mean value

## ...revisited : matrix form



The diagram illustrates the matrix form of a linear regression model. It shows a vertical vector of grayscale images (Y) on the left, followed by an equals sign. To the right of the equals sign is a yellow coefficient  $\beta_1$  multiplied by a vertical vector of feature images (f(t)). This is followed by a plus sign, a yellow coefficient  $\beta_2$  multiplied by a vertical vector of ones (1), another plus sign, and finally a vertical vector of residuals (epsilon).

$$Y = \beta_1 \times f(t) + \beta_2 \times 1 + \varepsilon$$



# Box car regression: design matrix...

The diagram illustrates the box car regression model equation. It features four vertical vectors and two matrices, each enclosed in large white brackets. The first vector, labeled  $\underline{Y}$  at the bottom, is a grayscale image of a brain slice and is labeled "data vector (voxel time series)" in red text above it. The second matrix, labeled  $\underline{X}$  at the bottom, is a green matrix with alternating black and white horizontal bars, labeled "design matrix" in green text above it. The third vector, labeled  $\underline{\beta}$  at the bottom, is a yellow vector with two entries,  $\beta_1$  and  $\beta_2$ , labeled "parameters" in yellow text above it. The fourth vector, labeled  $\underline{\varepsilon}$  at the bottom, is a grayscale image of a brain slice and is labeled "error vector" in white text above it. The equation is represented by the symbols  $=$ ,  $\times$ , and  $+$  between the components. The entire diagram is set against a dark blue background.

$$\underline{Y} = \underline{X} \times \underline{\beta} + \underline{\varepsilon}$$

data vector (voxel time series)

design matrix

parameters

error vector

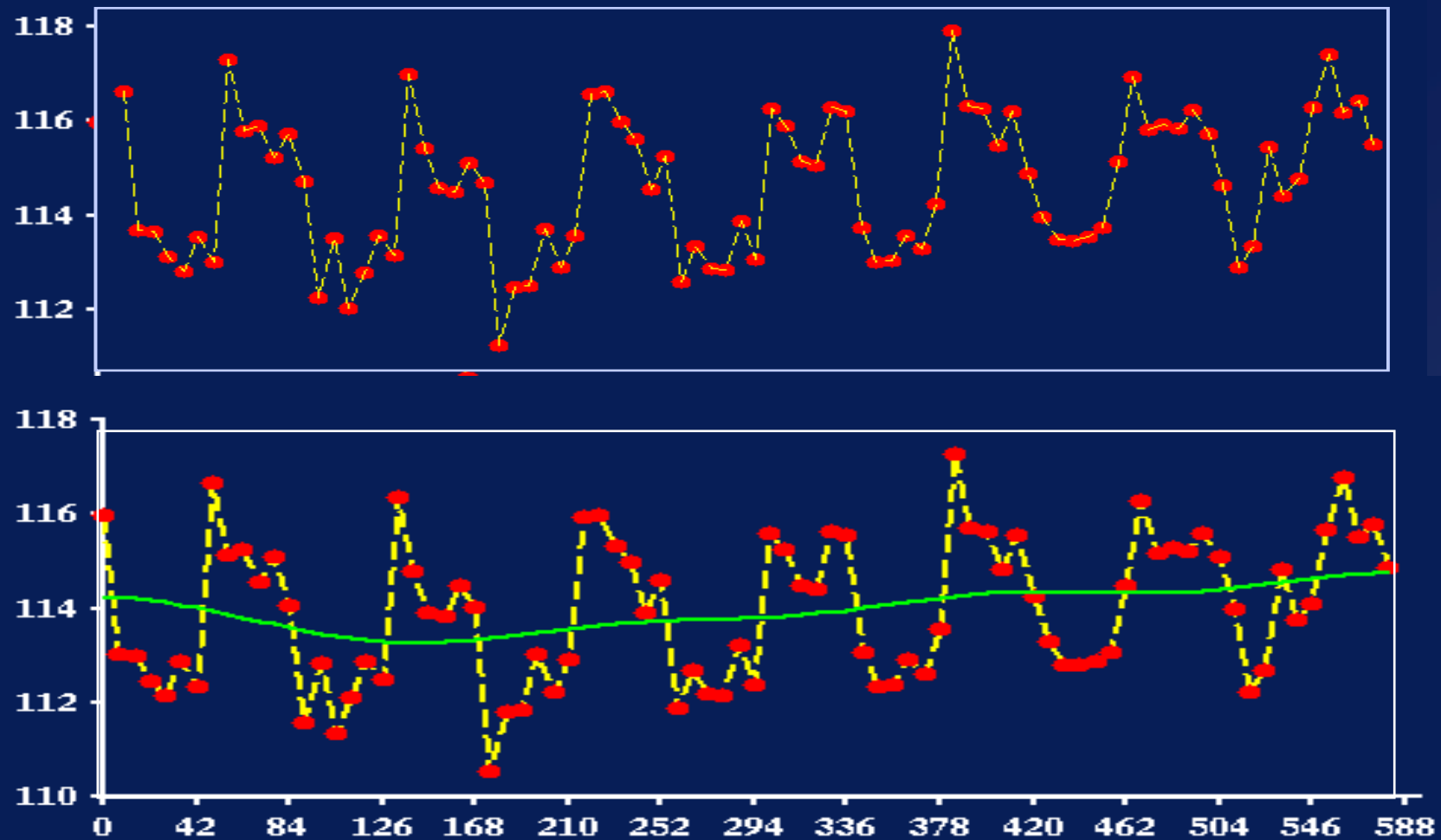
*Fact: model parameters depend on regressors scaling*

**Q: When do I care ?**

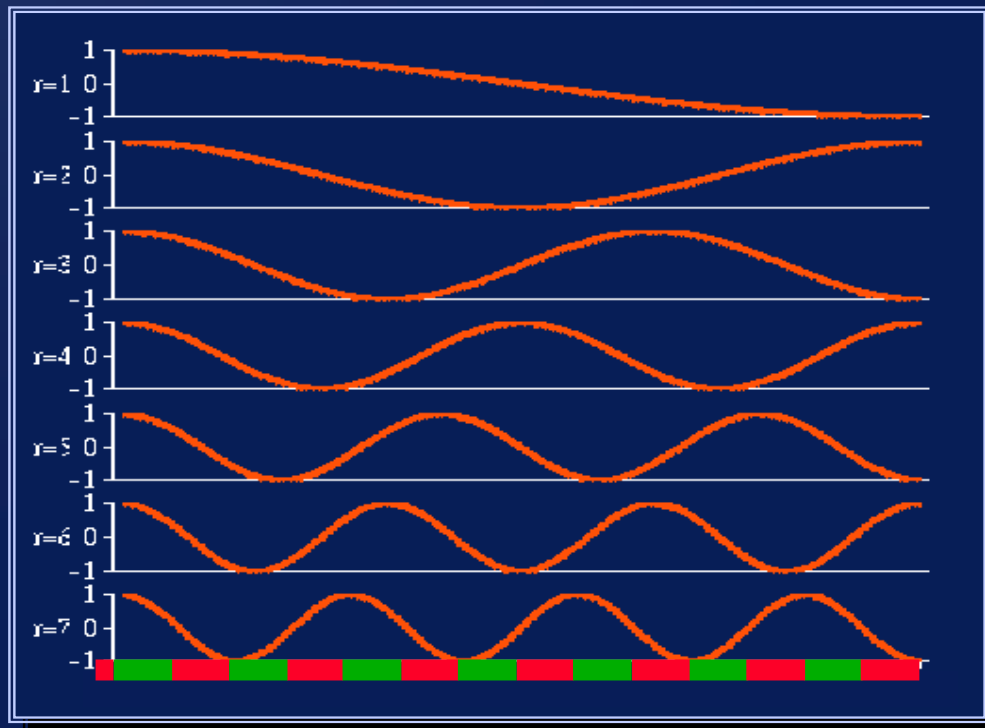
*A: ONLY when comparing manually entered regressors (say you would like to compare two scores)*

*What if two conditions A and B are not of the same duration before convolution HRF?*

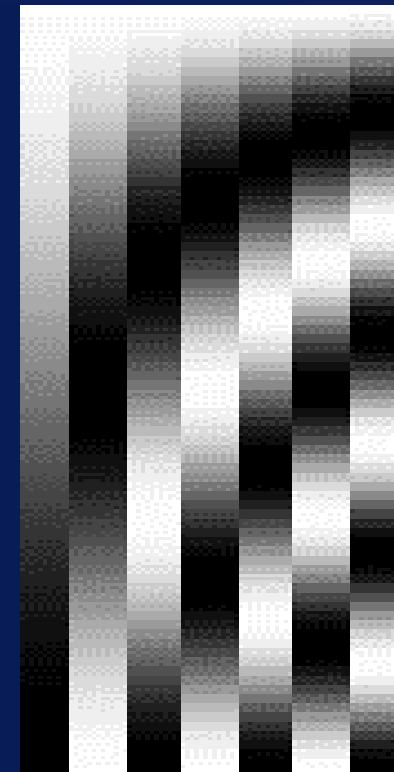
# What if we believe that there are drifts?



**Add more reference functions / covariates ...**



**Discrete cosine transform basis functions**



...design matrix

data vector

$\beta_1$   $\beta_2$   $\beta_3$   $\beta_4$  ...

error vector

$Y = X\beta + \epsilon$

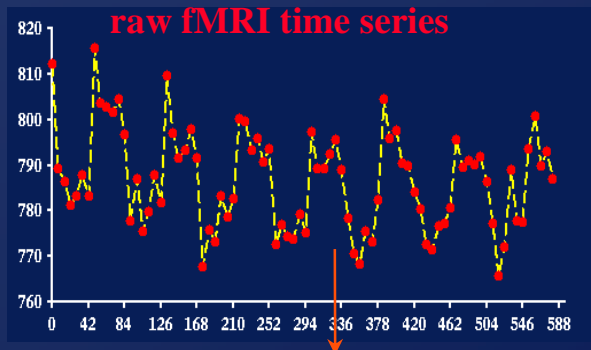
## ...design matrix

The diagram illustrates the linear regression equation  $Y = X\beta + \epsilon$  with visual representations of each term:

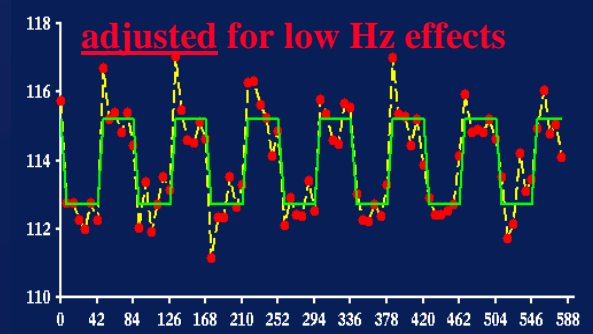
- $Y$ : data vector (represented by a vertical vector of grayscale patterns)
- $X$ : design matrix (represented by a matrix of grayscale patterns)
- $\beta$ : parameters (represented by a vertical vector of  $\beta_1, \beta_2, \beta_3, \beta_4, \beta_5, \beta_6, \beta_7, \beta_8, \beta_9$ )
- $\epsilon$ : error vector (represented by a vertical vector of grayscale patterns)

The equation is shown as  $Y = X \times \beta + \epsilon$ . A yellow diagonal label  $= \text{the betas (here : 1 to 9)}$  points to the  $\beta$  vector, and another yellow label  $\text{parameters}$  also points to the  $\beta$  vector.

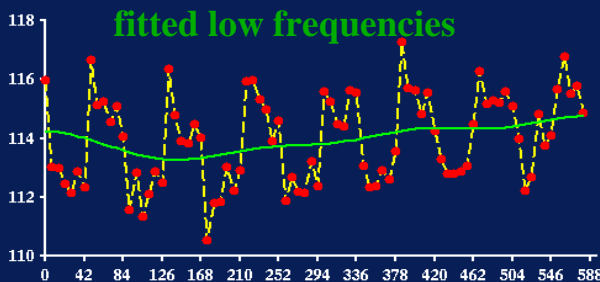
Fitting the model = finding some **estimate** of the betas



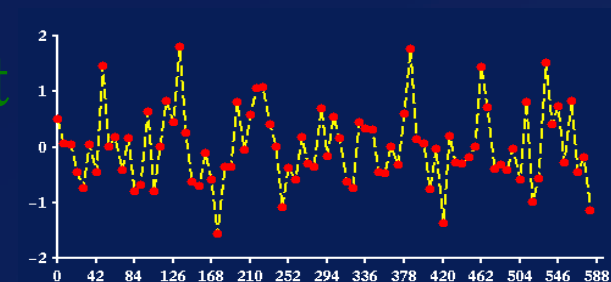
Raw data



fitted signal



fitted drift



residuals

How do we find the betas estimates? By minimizing the residual variance

Fitting the model = finding some **estimate** of the betas

$$Y = X \beta + \varepsilon$$

$$Y = X \beta + \varepsilon$$

finding the betas = **minimising the sum of square of the residuals**

$\| Y - X \hat{\beta} \|^2 = \sum_i [y_i - \hat{\beta} X_i]^2$   
 when  $\hat{\beta}$  are estimated: let's call them  $\hat{\beta}$   
 when  $\varepsilon$  is estimated : let's call it  $\hat{\varepsilon}$   
 estimated SD of  $\varepsilon$  : let's call it  $s$



## Take home ...

- ♦ *We put in our model regressors (or covariates) that represent how we think the signal is varying (of interest and of no interest alike)*
  - ♦ ***WHICH ONE TO INCLUDE ?***
  - ♦ ***What if we have too many?***
- ♦ *Coefficients (= parameters) are estimated by minimizing the fluctuations, - variability – variance – of estimated noise – the residuals.*
- ♦ *Because the parameters depend on the scaling of the regressors included in the model, one should be careful in comparing manually entered regressors, or conditions of different durations*

# Plan

- ♦ *Make sure we all know about the estimation (fitting) part ....*

- ♦ *Make sure we understand  $t$  and  $F$  tests*

- ♦ *But what do we test exactly ?*

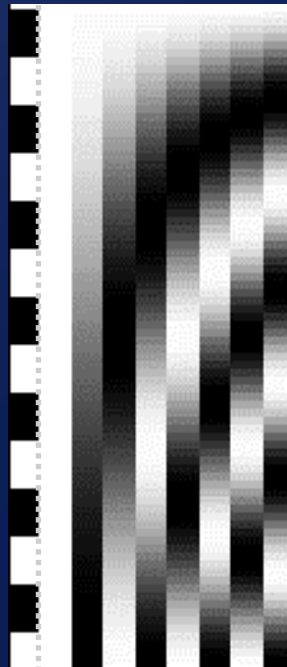
- ♦ *An example – almost real*

# T test - one dimensional contrasts - SPM{t}

$$c' = 1 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0$$



$b_1 \ b_2 \ b_3 \ b_4 \ b_5 \dots$



A contrast = a weighted sum of **parameters**:  $c' \times b$

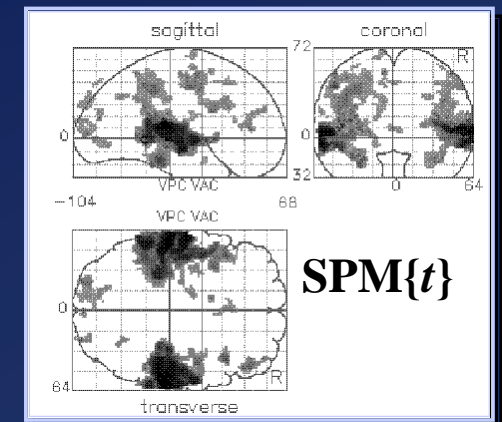
$$b_1 > 0 ?$$

Compute  $1 \times b_1 + 0 \times b_2 + 0 \times b_3 + 0 \times b_4 + 0 \times b_5 + \dots$

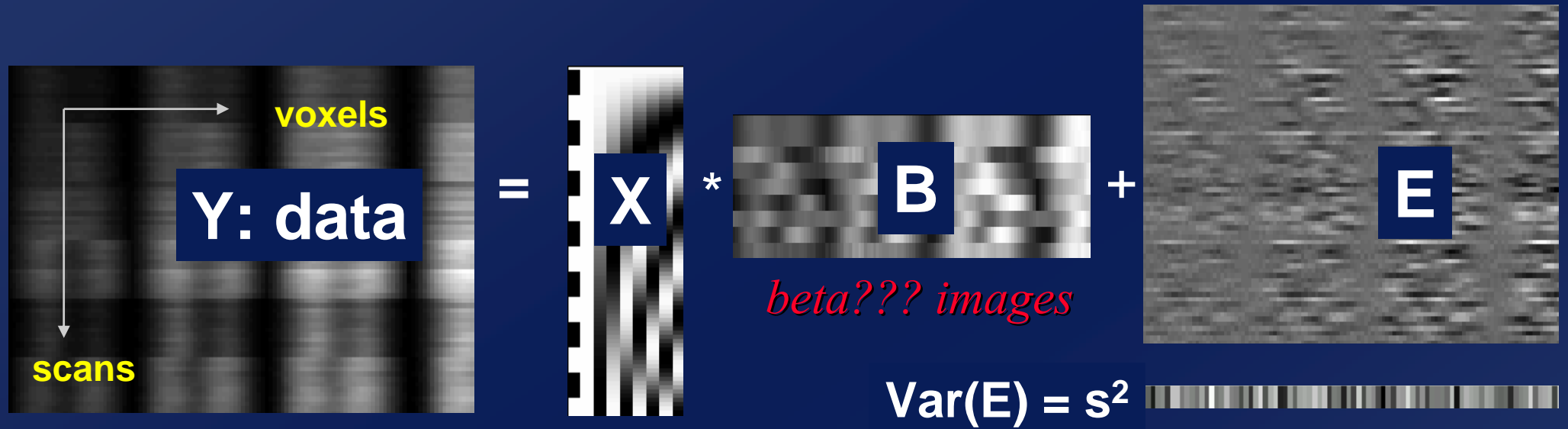
divide by estimated standard deviation of  $b_1$

$$T = \frac{\text{contrast of estimated parameters}}{\sqrt{\text{variance estimate}}}$$

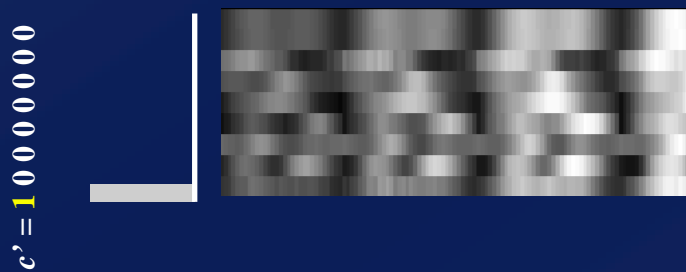
$$T = \frac{c'b}{\sqrt{s^2 c' (X'X)^{-1} c}}$$



# From one time series to an image

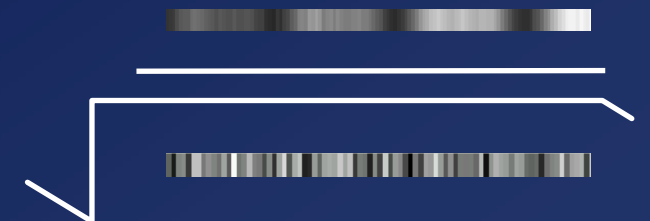


*spm\_ResMS*



*spm\_con??? images*

$$T = \frac{c'b}{\sqrt{s^2 c' (X'X)^{-1} c}} =$$

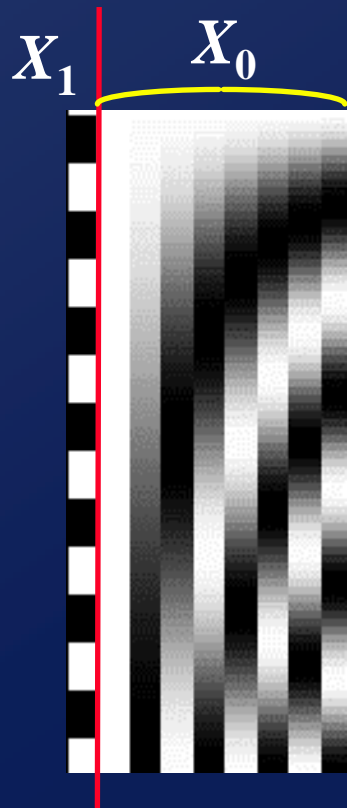


*spm\_t??? images*

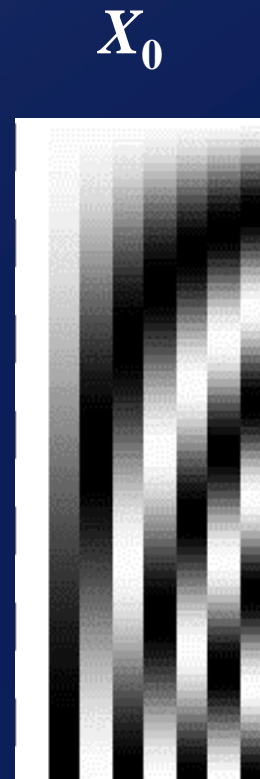
# F-test : a reduced model

$H_0$ : True model is  $X_0$

$H_0: \beta_1 = 0$

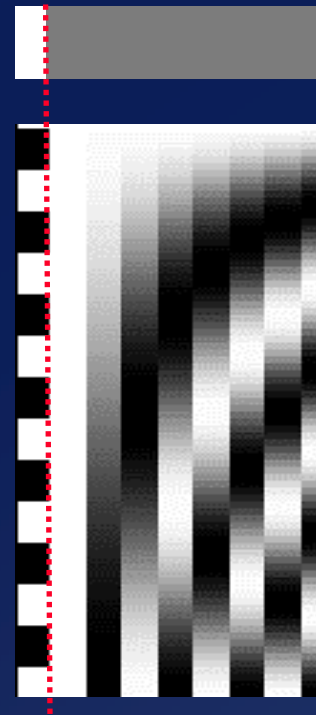


$\rightarrow S^2$



$\rightarrow S_0^2$

$c' = 10000000$



$$F \sim (S_0^2 - S^2) / S^2$$

T values become  
F values.  $F = T^2$

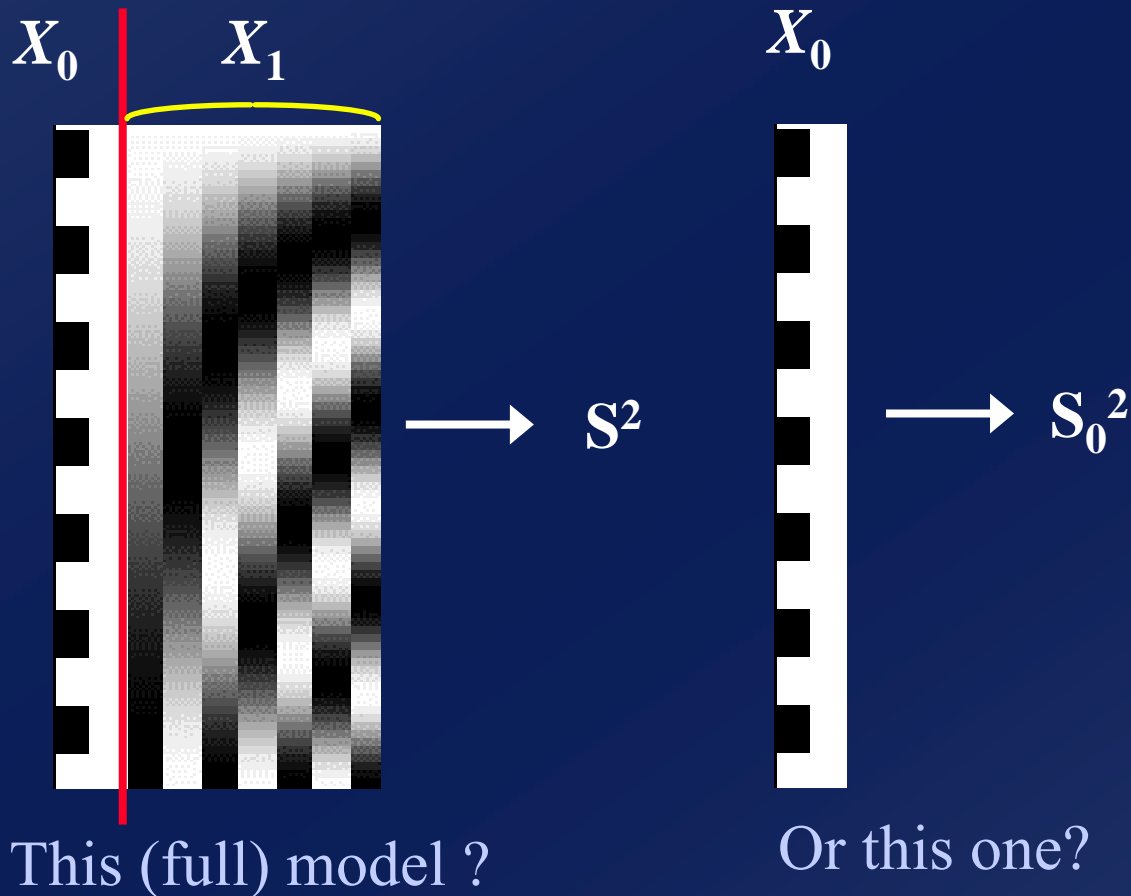
Both “activation”  
and  
“deactivations”  
are tested. Voxel  
wise p-values are  
halved.

This (full) model ? Or this one?

## F-test : a reduced model or ...

*Tests multiple linear hypotheses : Does  $X_1$  model anything ?*

**$H_0$** : True (reduced) model is  $X_0$



**additional  
variance  
accounted for  
by **tested** effects**

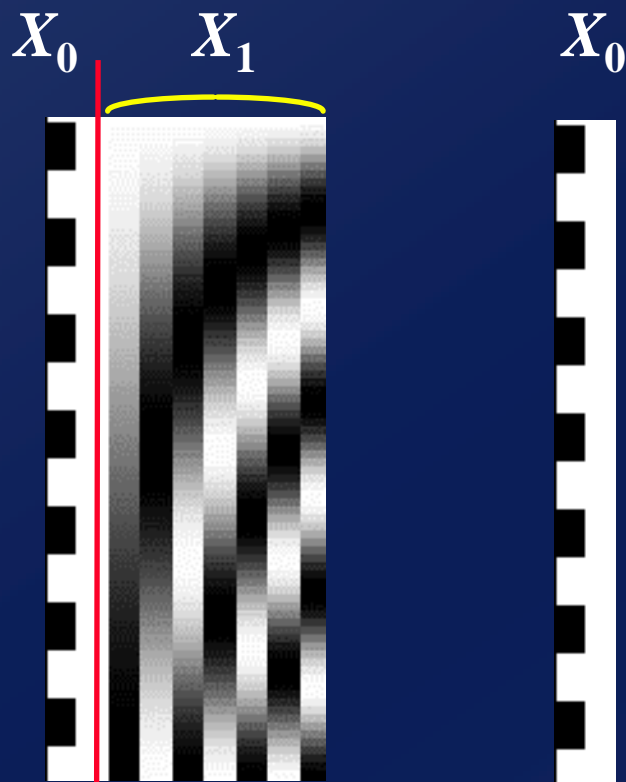
$$F = \frac{\text{additional variance accounted for by tested effects}}{\text{error variance estimate}}$$

$$F \sim (S_0^2 - S^2) / S^2$$

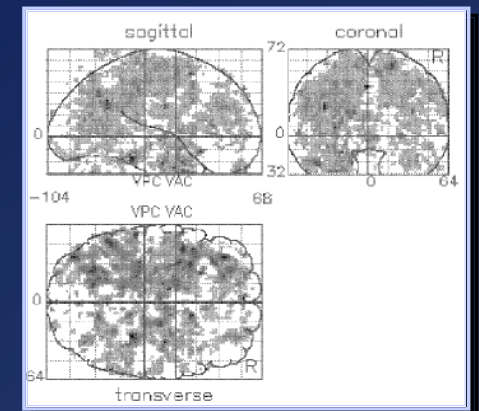
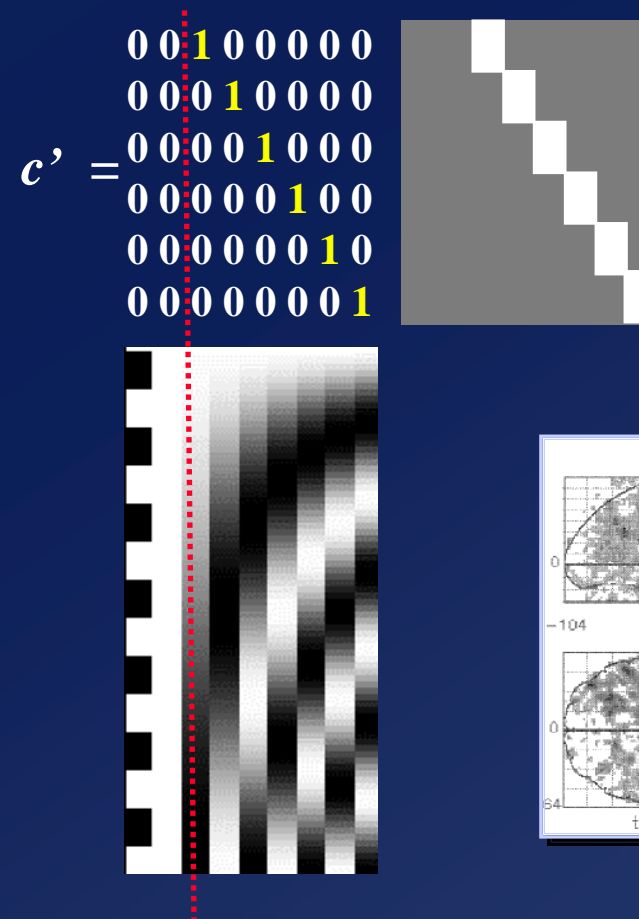
# F-test : a reduced model or ... multi-dimensional contrasts ?

*tests multiple linear hypotheses. Ex : does drift functions model anything?*

**H<sub>0</sub>**: True **model** is  $X_0$

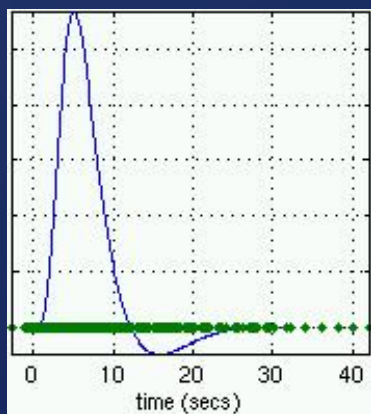


**H<sub>0</sub>**:  $\beta_{3-9} = (0 \ 0 \ 0 \ 0 \ \dots)$

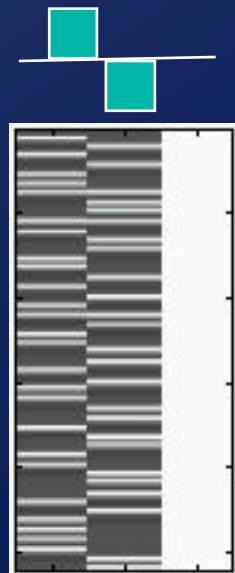


This (full) model ? Or this one?

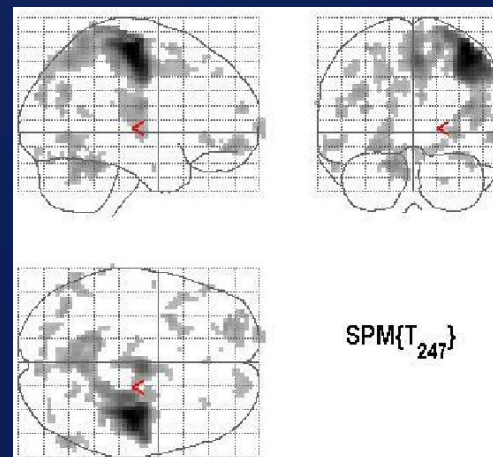
## Convolution model



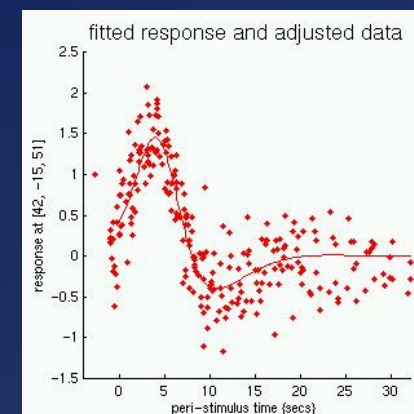
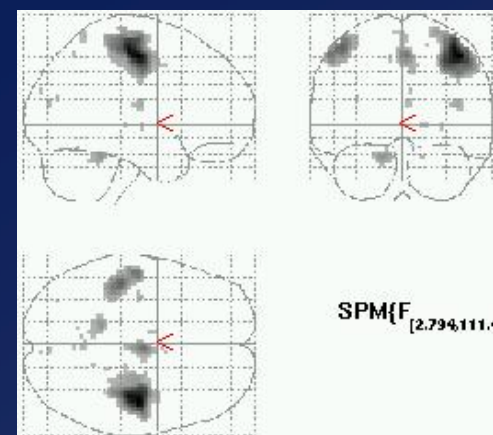
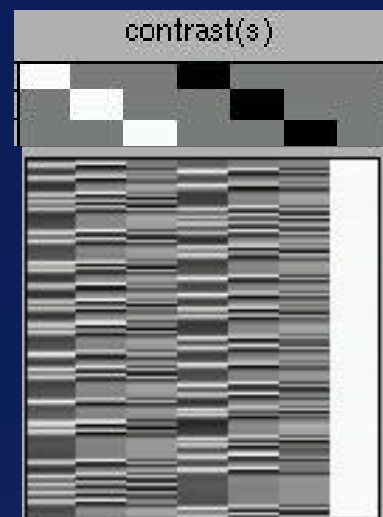
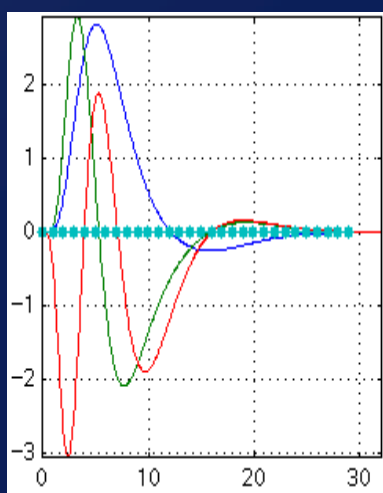
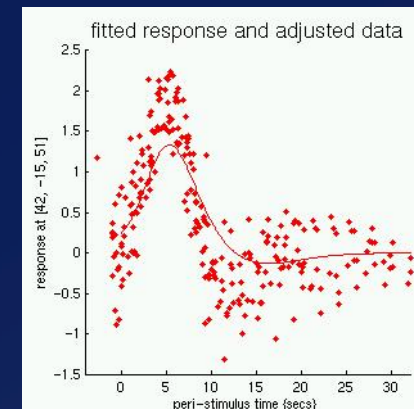
## Design and contrast



## SPM(t) or SPM(F)



## Fitted and adjusted data





## T and F test: take home ...

- ♦ *T tests are simple combinations of the betas; they are either positive or negative ( $b_1 - b_2$  is different from  $b_2 - b_1$ )*
- ♦ *F tests can be viewed as testing for the additional variance explained by a larger model wrt a simpler model, or*
- ♦ *F tests the sum of the squares of one or several combinations of the betas*
- ♦ *in testing “single contrast” with an F test, for ex.  $b_1 - b_2$ , the result will be the same as testing  $b_2 - b_1$ . It will be exactly the square of the t-test, testing for both positive and negative effects.*

# Plan

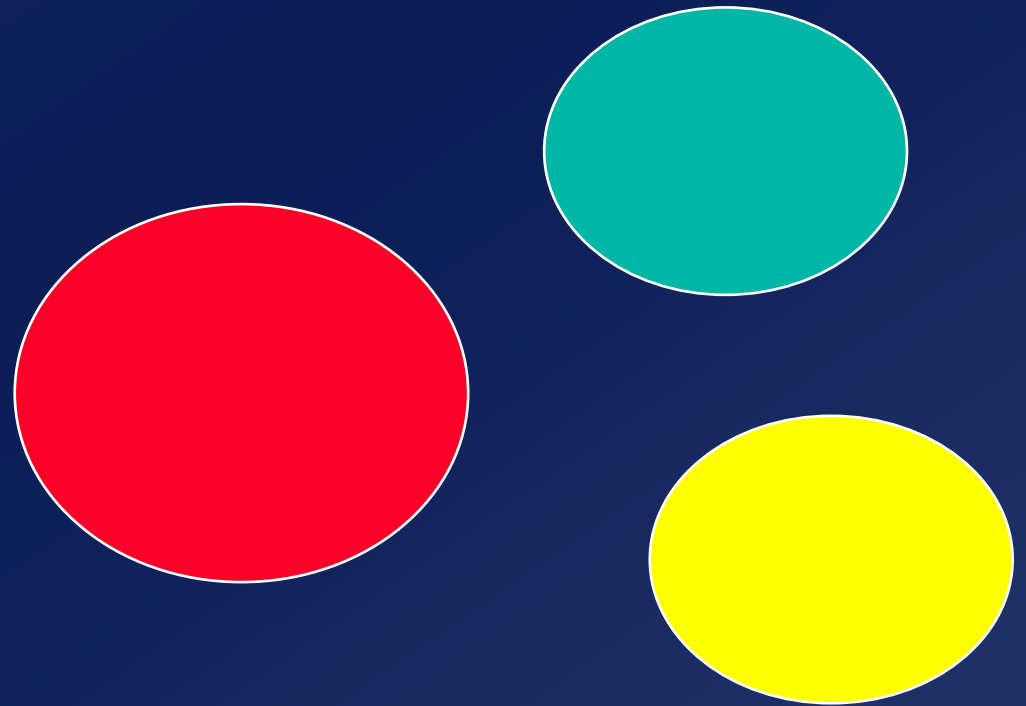
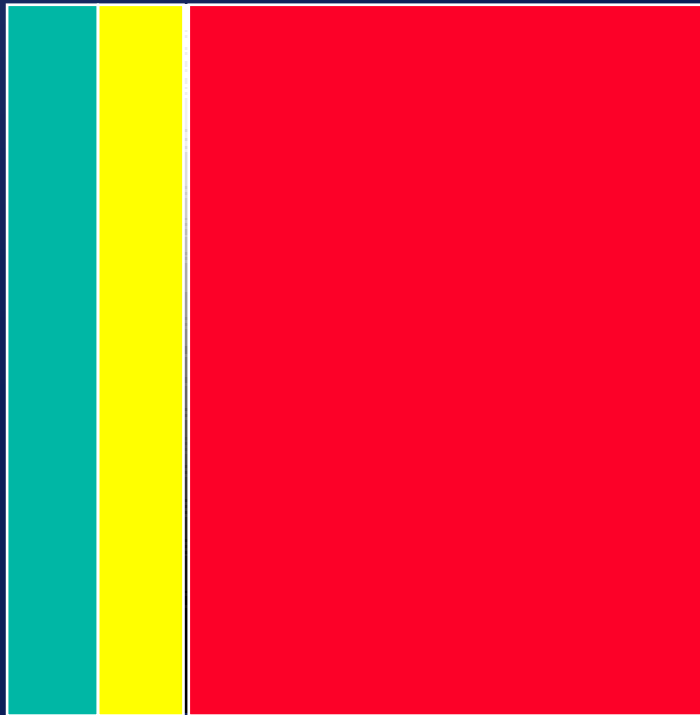
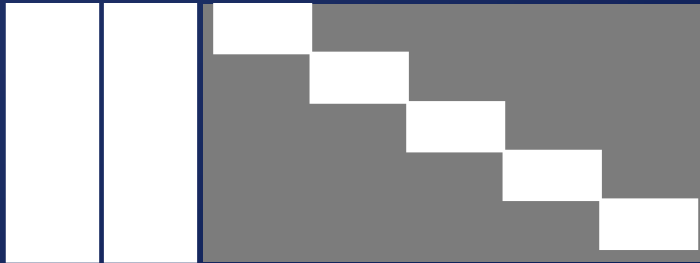
- ♦ *Make sure we all know about the estimation (fitting) part ....*

- ♦ *Make sure we understand  $t$  and  $F$  tests*

- ♦ *But what do we test exactly ? Correlation between regressors*

- ♦ *An example – almost real*

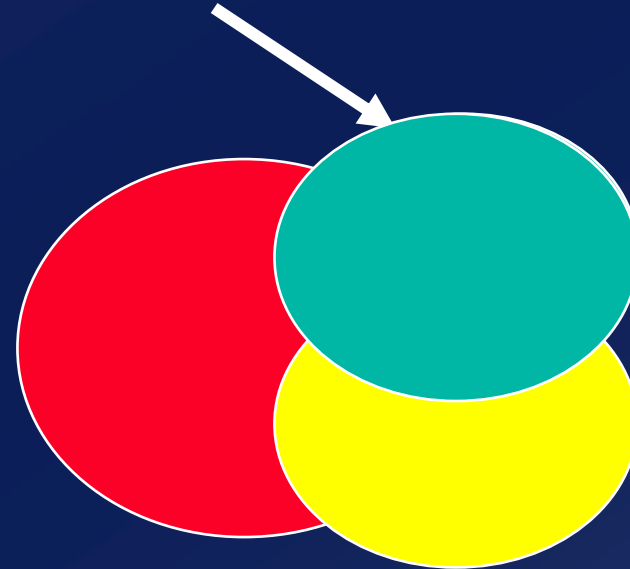
## « Additional variance » : Again



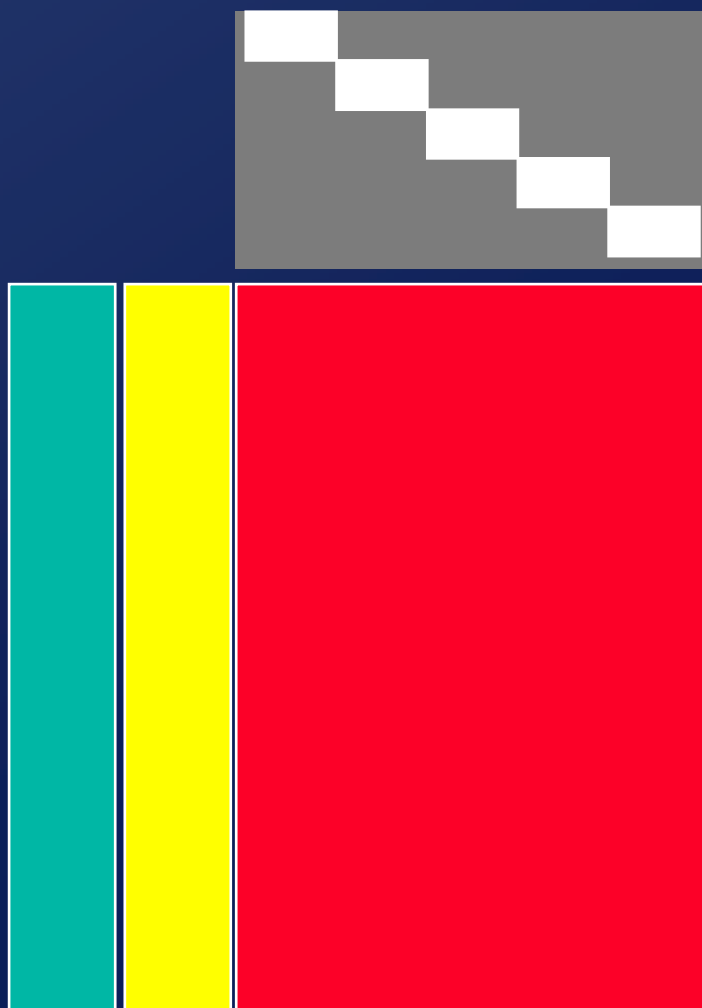
No correlation between green  
red and yellow



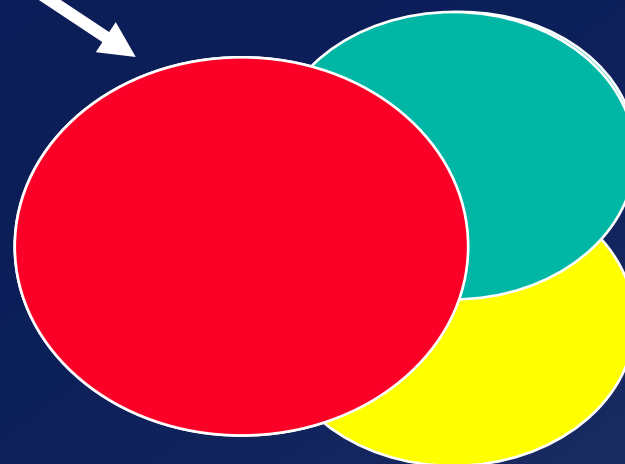
Testing for the green



correlated regressors, for example  
green: subject age  
yellow: subject score



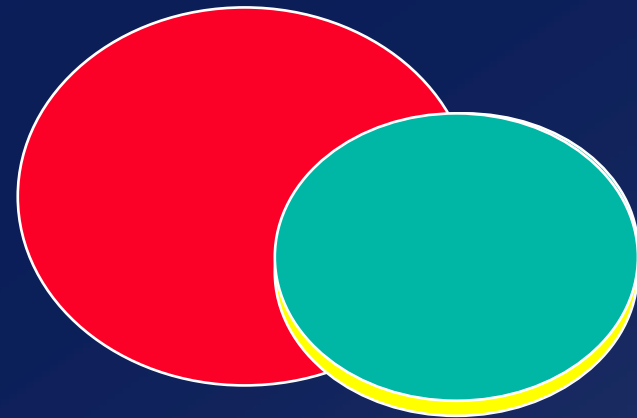
Testing for the red



correlated contrasts



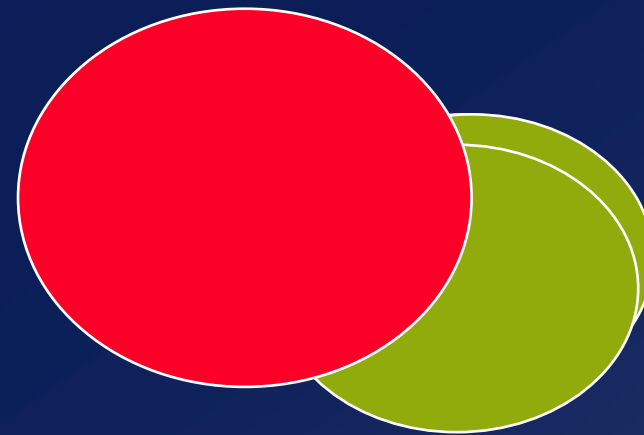
Testing for the green



Very correlated regressors ?

Dangerous !

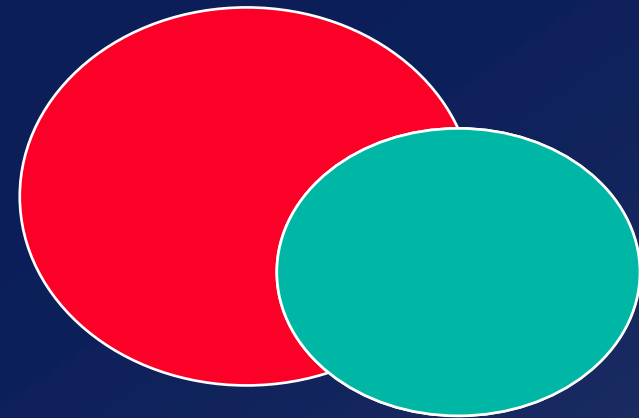
Testing for the green and yellow



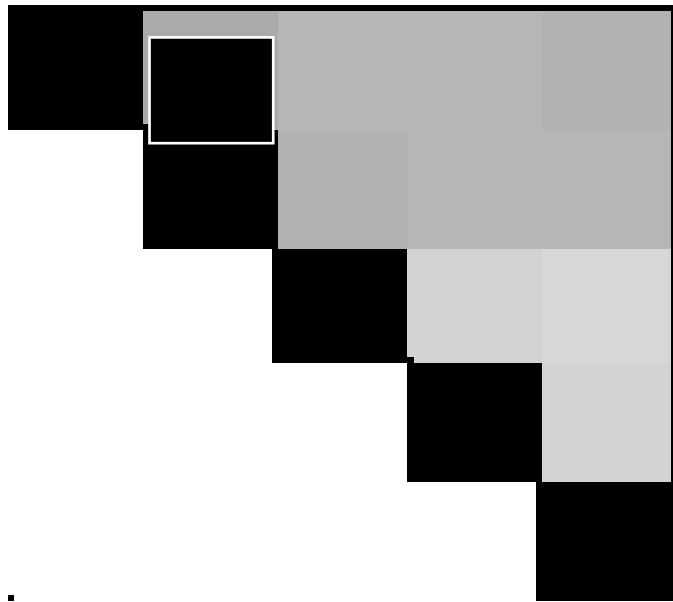
If significant ? Could be G or Y !



Testing for the green



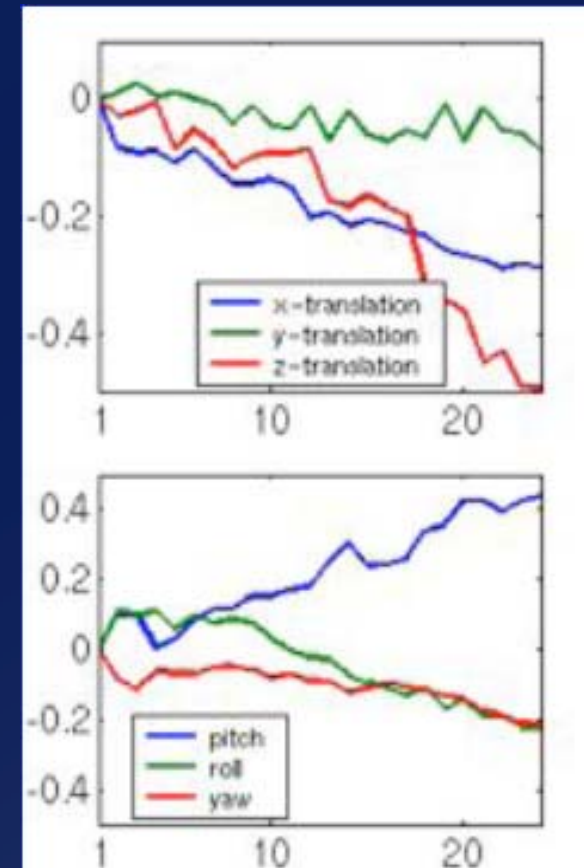
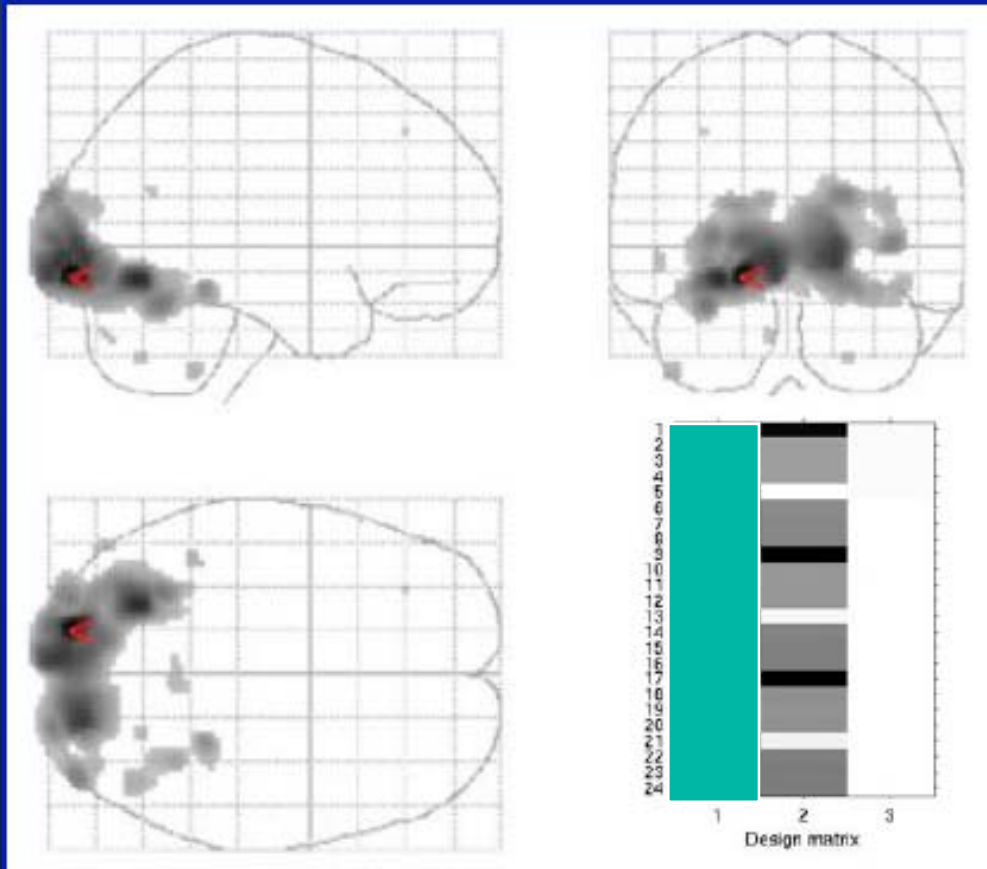
design orthogonality



Completely correlated  
regressors ?  
Impossible to test ! (not  
estimable)

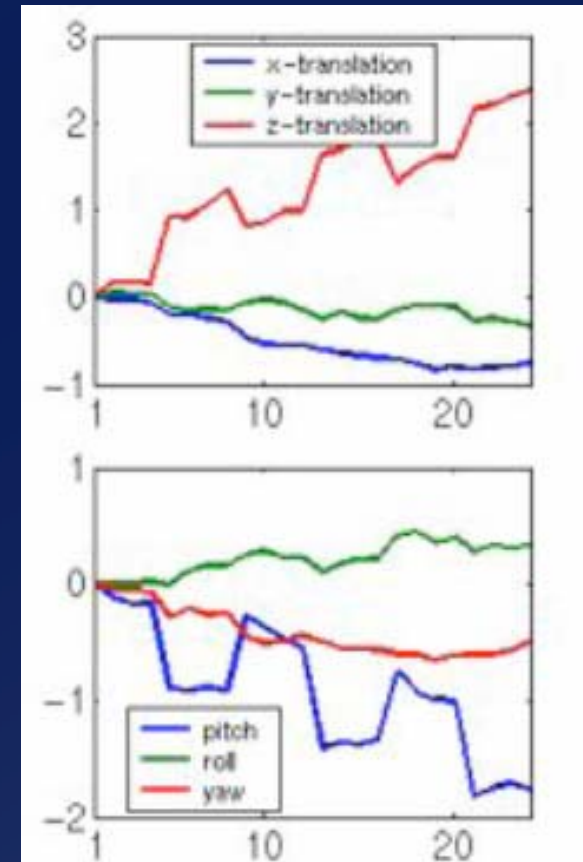
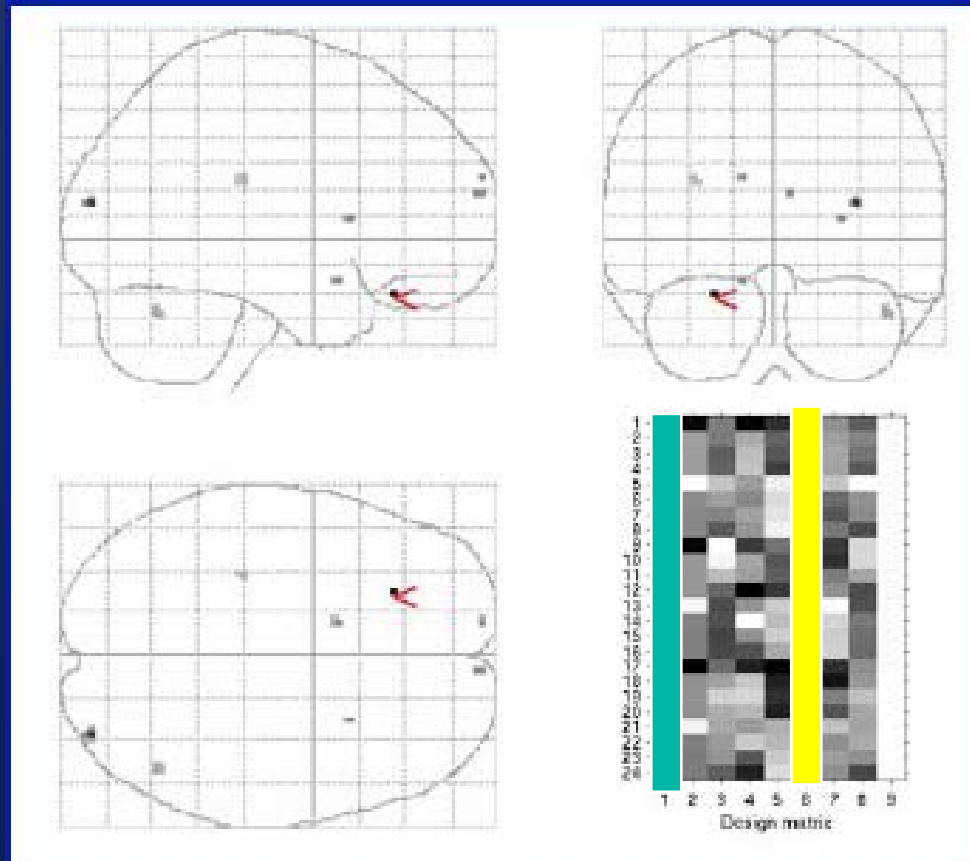


# An example: real



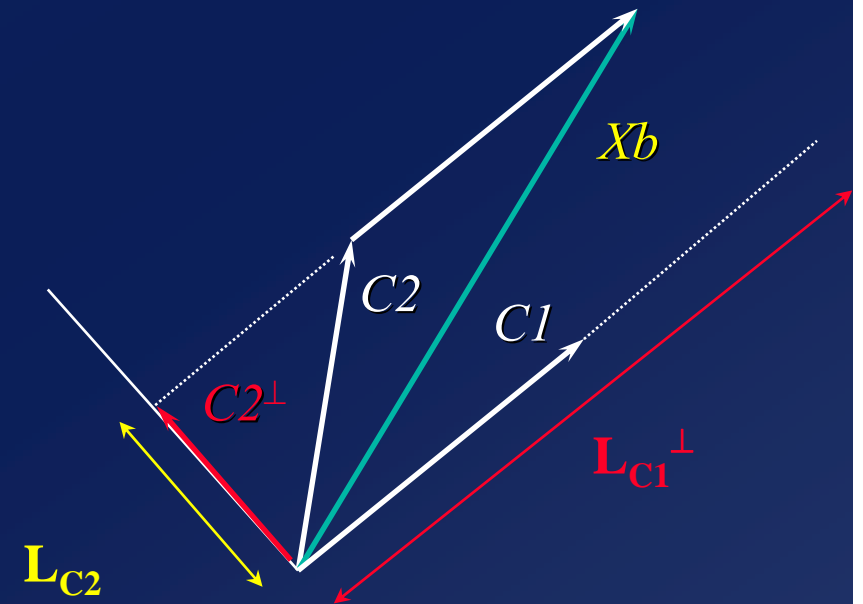
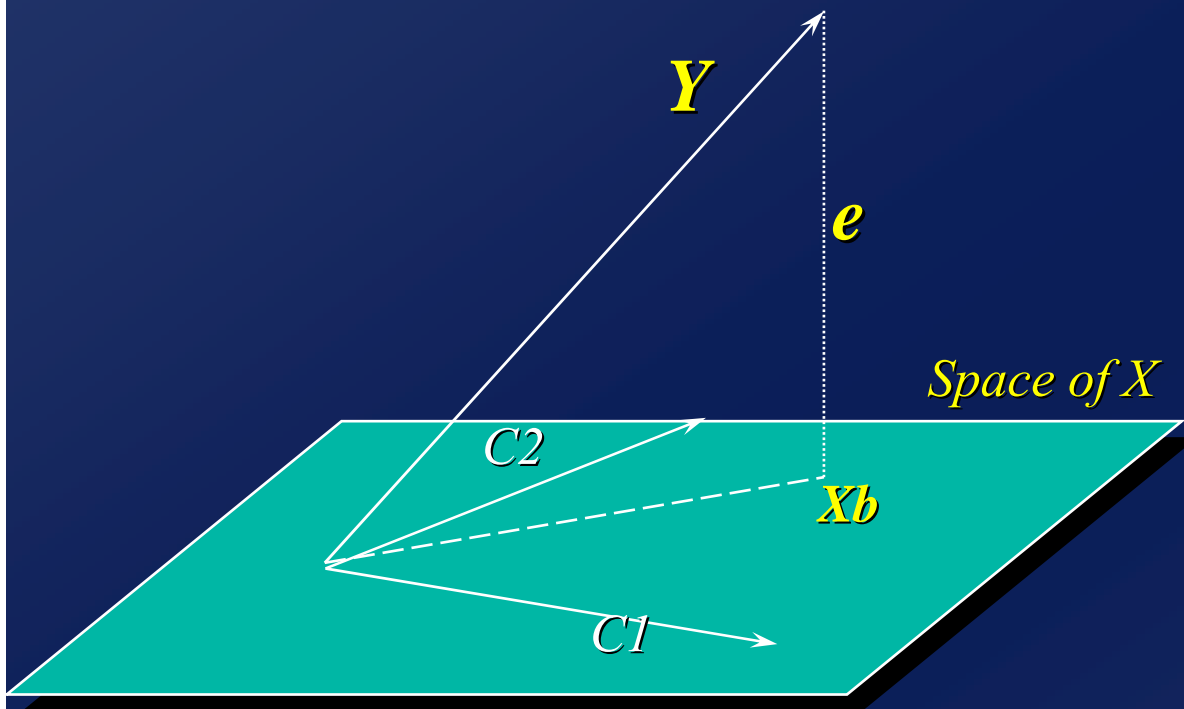
Testing for first regressor:  $T_{\max} = 9.8$

# Including the movement parameters in the model



Testing for first regressor: activation is gone !

# Implicit or explicit ( $\perp$ ) decorrelation (or orthogonalisation)



This generalises when testing  
several regressors (F tests)

*cf Andrade et al., NeuroImage, 1999*

$L_{C2}$  : test of  $C2$  in the  
implicit  $\perp$  model

$L_{C1}^\perp$  : test of  $C1$  in the  
explicit  $\perp$  model

## Correlation between regressors: take home ...

- ♦ *Do we care about correlation in the design ?  
Yes, always*
- ♦ *Start with the experimental design : conditions should be as uncorrelated as possible*
- ♦ *use  $F$  tests to test for the overall variance explained by several (correlated) regressors*

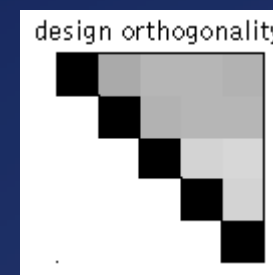
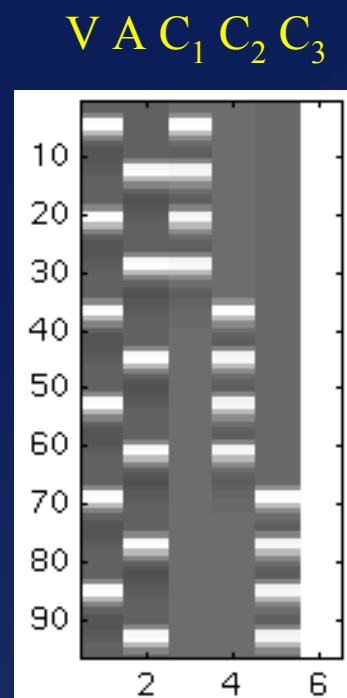
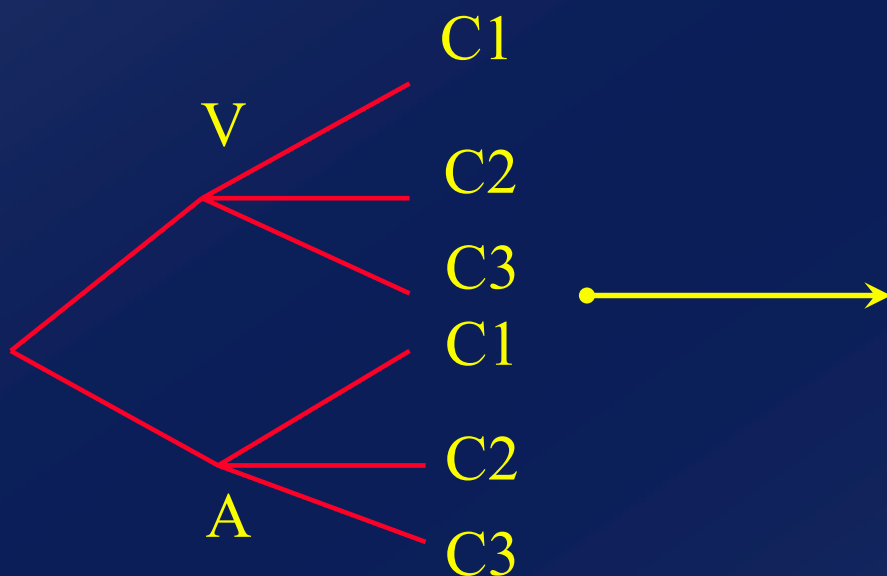
# Plan

- ♦ *Make sure we all know about the estimation (fitting) part ....*
- ♦ *Make sure we understand  $t$  and  $F$  tests*
- ♦ *But what do we test exactly ? Correlation between regressors*
- ♦ *An example – almost real*

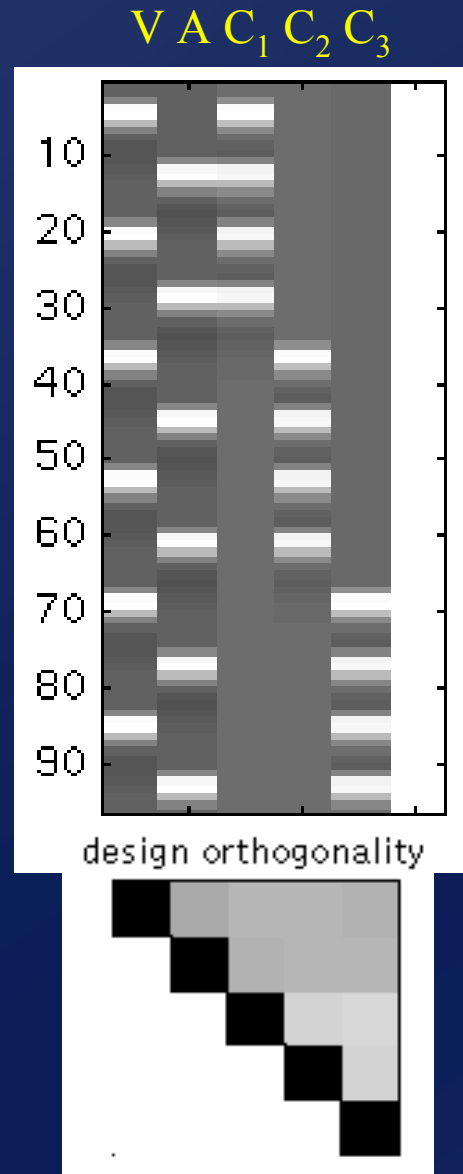
# A real example (almost !)

Experimental Design  $\longrightarrow$  Design Matrix

Factorial design with 2 factors : modality and category  
2 levels for modality (eg Visual/Auditory)  
3 levels for category (eg 3 categories of words)



# Asking ourselves some questions ...



Test  $C_1 > C_2$

$$: c = [0 \ 0 \ 1 \ -1 \ 0 \ 0]$$

Test  $V > A$

$$: c = [1 \ -1 \ 0 \ 0 \ 0 \ 0]$$

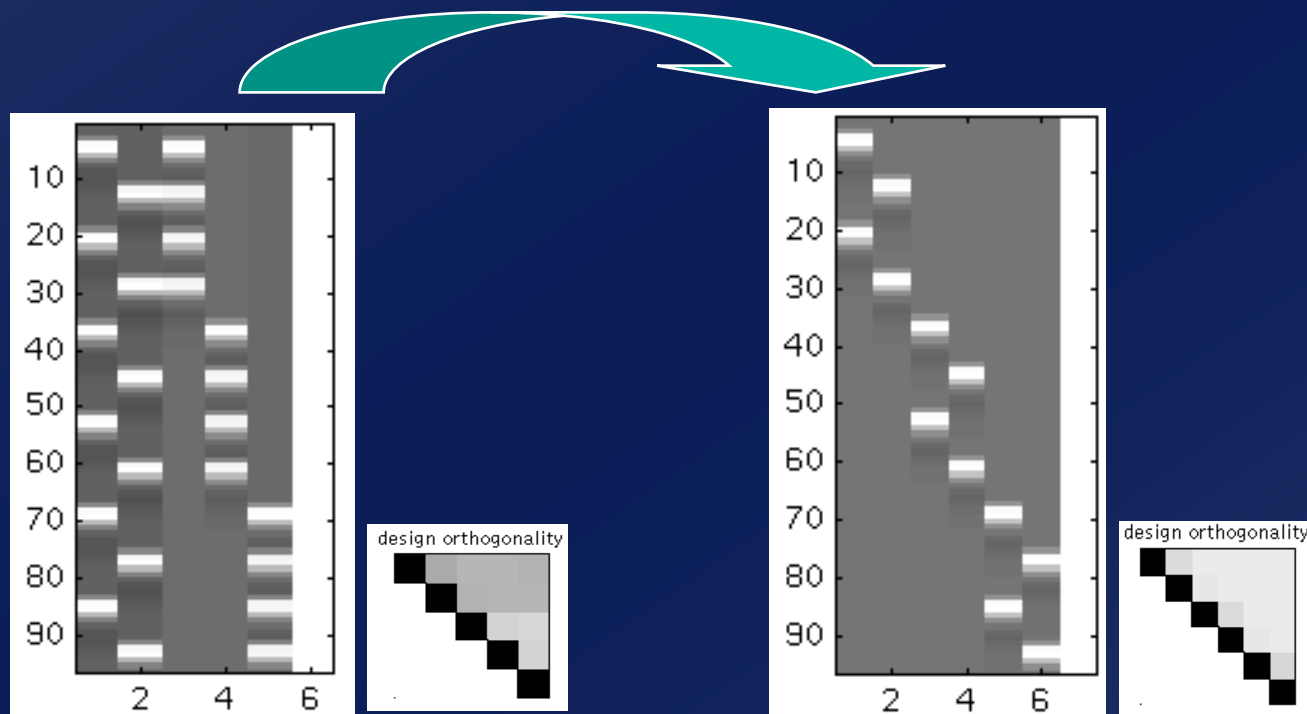
Test  $C_1, C_2, C_3 ?$  (F)

$$c = \begin{bmatrix} 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \end{bmatrix}$$

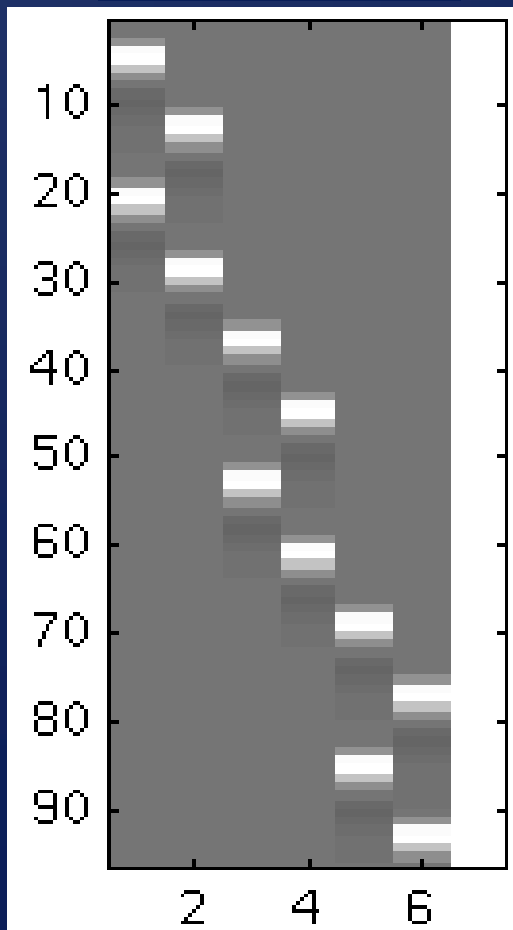
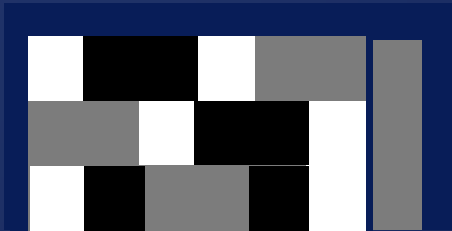
Test the interaction  $M \times C$  ?

- Design Matrix not orthogonal
- Many contrasts are non estimable
- Interactions  $M \times C$  are not modelled

# Modelling the interactions







Test  $C1 > C2$  :  $c = [1 \ 1 \ -1 \ -1 \ 0 \ 0 \ 0]$

Test  $V > A$  :  $c = [1 \ -1 \ 1 \ -1 \ 1 \ -1 \ 0]$

Test the category effect :

$$c = \begin{bmatrix} 1 & 1 & -1 & -1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 1 & -1 & -1 & 0 \\ 1 & 1 & 0 & 0 & -1 & -1 & 0 \end{bmatrix}$$

Test the interaction  $M \times C$  :

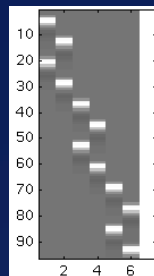
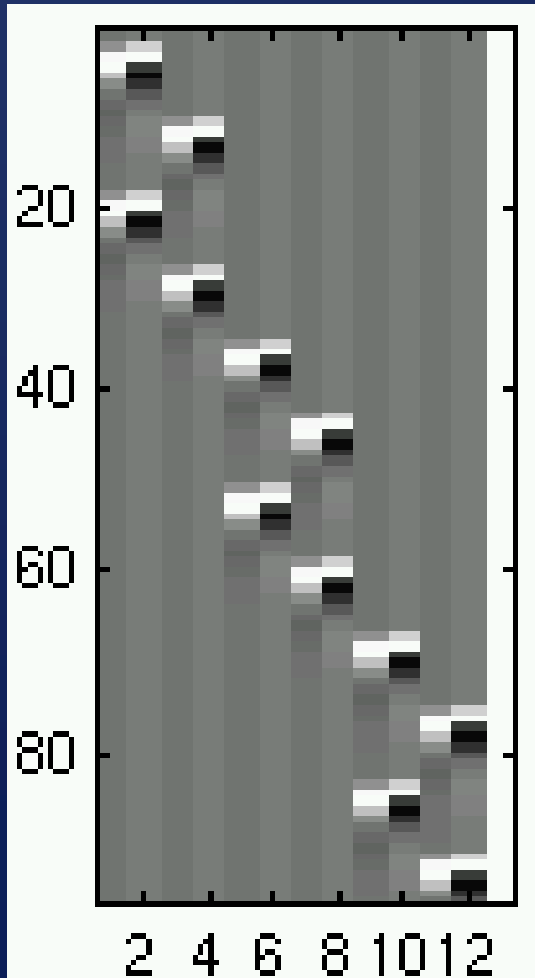
$$c = \begin{bmatrix} 1 & -1 & -1 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & -1 & -1 & 1 & 0 \\ 1 & -1 & 0 & 0 & -1 & 1 & 0 \end{bmatrix}$$

- Design Matrix orthogonal
- All contrasts are estimable
- Interactions  $M \times C$  modelled
- If no interaction ... ? Model is too “big” !



# With a more flexible model

$C_1$   $C_1$   $C_2$   $C_2$   $C_3$   $C_3$   
V A V A V A



Test  $C1 > C2$  ?

Test  $C1$  different from  $C2$  ?

from

$$c = [1 \quad 1 \quad -1 \quad -1 \quad 0 \quad 0 \quad 0]$$

to

$$c = \begin{bmatrix} 1 & 0 & 1 & 0 & -1 & 0 & -1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 1 & 0 & -1 & 0 & -1 & 0 & 0 & 0 & 0 \end{bmatrix}$$

becomes an F test!

What if we use only:

$$c = [1 \quad 0 \quad 1 \quad 0 \quad -1 \quad 0 \quad -1 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0]$$

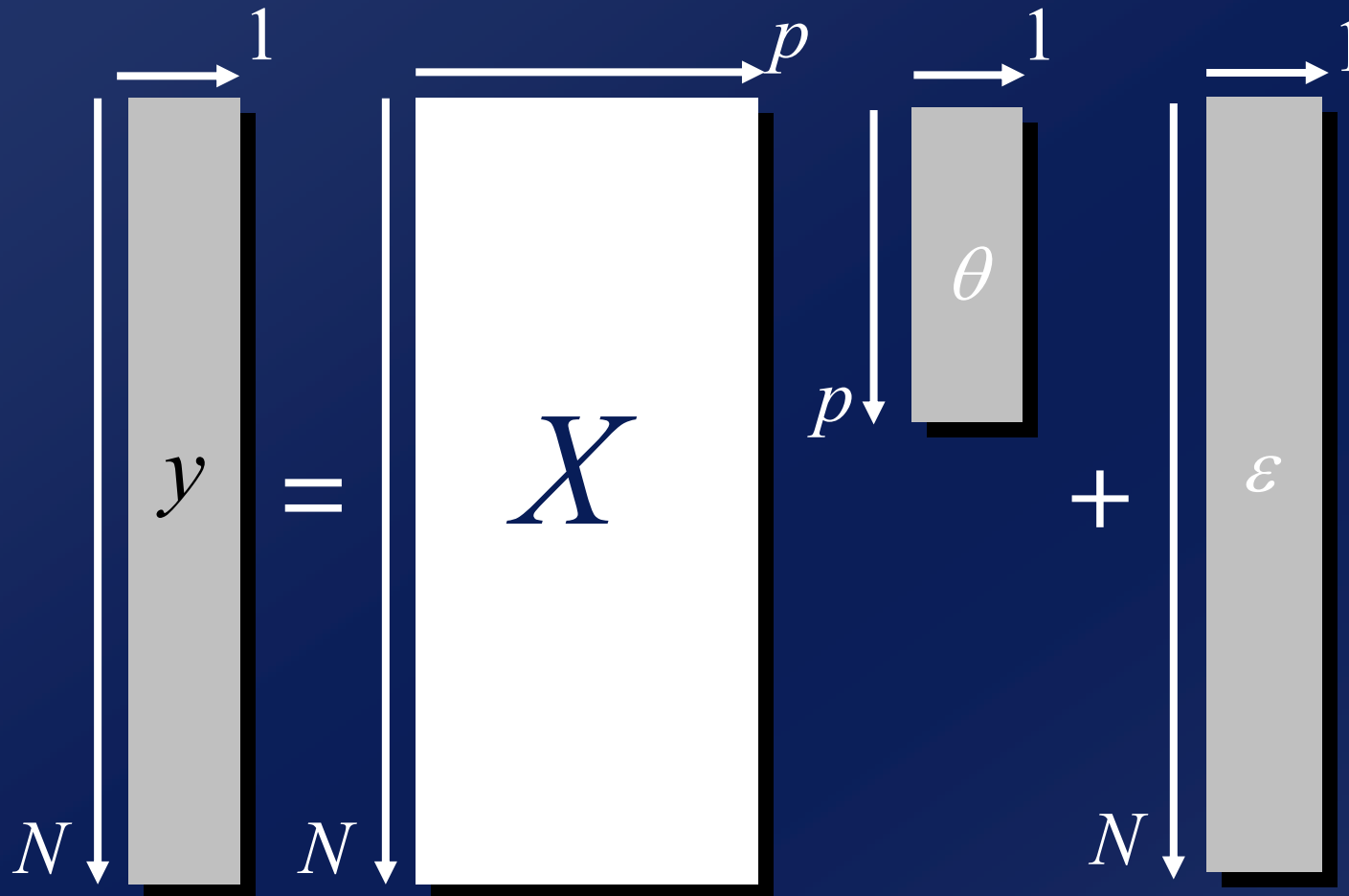
OK only if the regressors coding for the delay are all equal

## Toy example: take home ...

- ♦ *use  $F$  tests when*
  - *Test for  $>0$  and  $<0$  effects*
  - *Test for more than 2 levels in factorial designs*
  - *Conditions are modelled with more than one regressor*
- ♦ *Check post hoc*

# General Linear Model

$$y = X\theta + \varepsilon$$



$N$ : number of scans  
 $p$ : number of regressors

Error Covariance

$$C_{\varepsilon} = \sum_k \lambda_k Q_k$$

Model is specified by

1. Design matrix  $X$
2. Assumptions about  $\varepsilon$

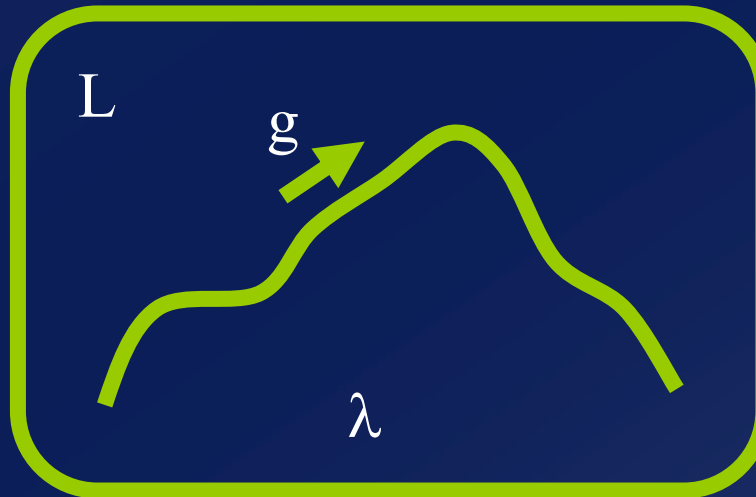
# Estimation

$$\begin{array}{ccccccc} y & = & X & \theta & + & \varepsilon \\ N \times 1 & & N \times p & p \times 1 & & N \times 1 \end{array}$$

## 1. ReML-algorithm

$$C_{\varepsilon} = \sum_k \lambda_k Q_k$$

$$\text{Maximise } L = \ln p(y | \lambda) = \ln \int p(y | \theta, \lambda) d\theta$$



$$\begin{aligned} g &= \frac{dL}{d\lambda} \\ J &= \frac{d^2 L}{d\lambda^2} \\ \lambda &= \lambda + J^{-1}g \end{aligned}$$

## 2. Weighted Least Squares

$$\theta = (X^T C_e^{-1} X^T)^{-1} X^T C_e^{-1} y$$

*Friston et al. 2002,  
Neuroimage*

# Hierarchical model

---

## Hierarchical model

$$\begin{aligned}y &= X^{(1)}\theta^{(1)} + \varepsilon^{(1)} \\ \theta^{(1)} &= X^{(2)}\theta^{(2)} + \varepsilon^{(2)} \\ &\vdots \\ \theta^{(n-1)} &= X^{(n)}\theta^{(n)} + \varepsilon^{(n)}\end{aligned}$$

## Multiple variance components at each level

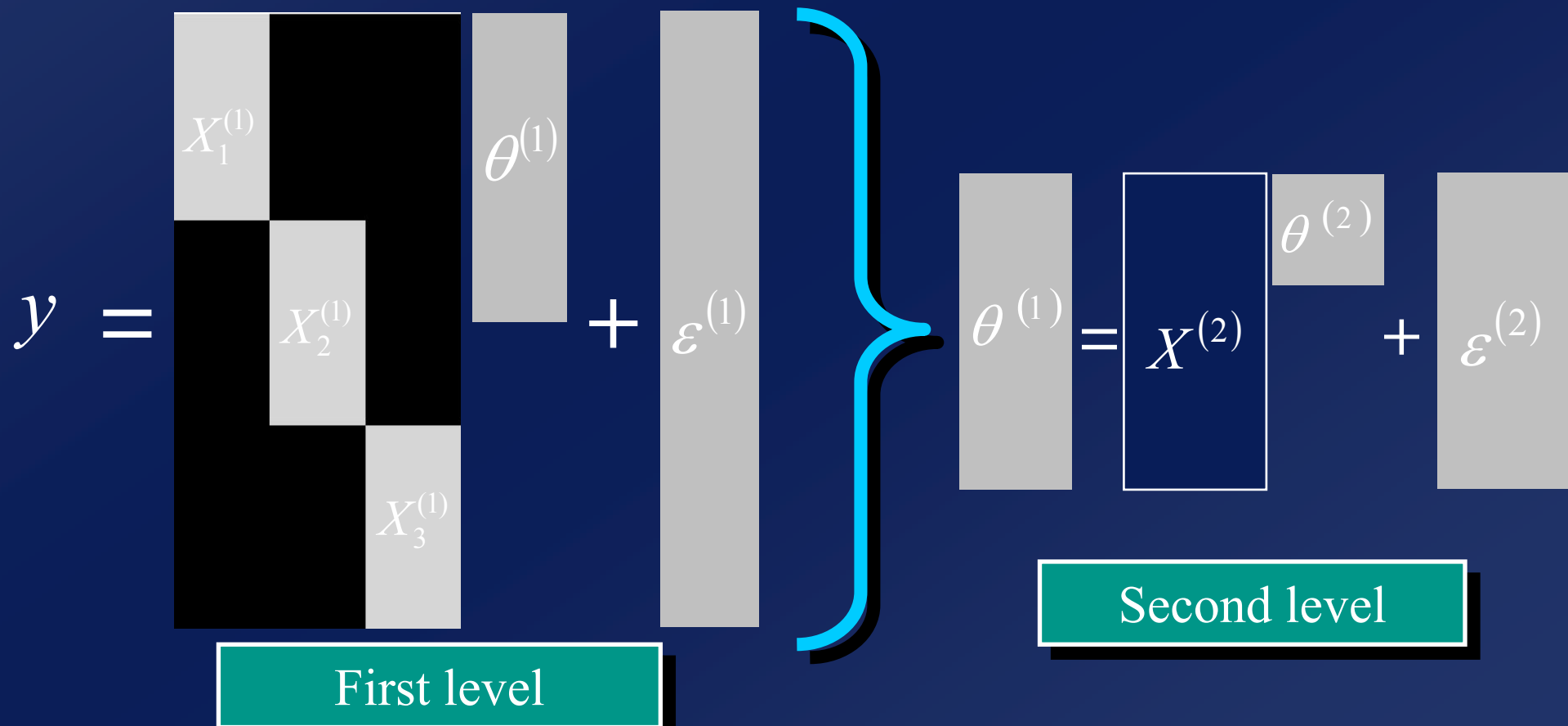
$$C_{\varepsilon}^{(i)} = \sum_k \lambda_k^{(i)} Q_k^{(i)}$$

At each level, distribution of parameters  
is given by level above.

What we don't know: distribution of  
parameters and variance parameters.

# Example: Two level model

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



# Estimation

---

Hierarchical  
model

$$\begin{aligned}y &= X^{(1)}\theta^{(1)} + \varepsilon^{(1)} \\ \theta^{(1)} &= X^{(2)}\theta^{(2)} + \varepsilon^{(2)} \\ &\vdots \\ \theta^{(n-1)} &= X^{(n)}\theta^{(n)} + \varepsilon^{(n)}\end{aligned}$$



Single-level  
model

$$\begin{aligned}y &= \varepsilon^{(1)} + X^{(1)}\varepsilon^{(2)} + \\ &\quad \dots + \\ &\quad X^{(1)} \dots X^{(n-1)}\varepsilon^{(n)} + \\ &\quad X^{(1)} \dots X^{(n)}\theta^{(n)} \\ &= X\theta + e\end{aligned}$$



# Group analysis in practice

---

Many 2-level models are just too big to compute.

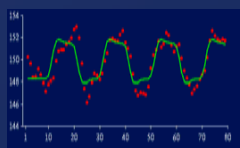
And even if, it takes a long time!

Is there a fast approximation?

# Summary Statistics approach

## First level

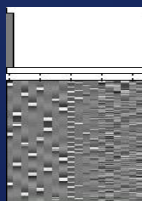
Data



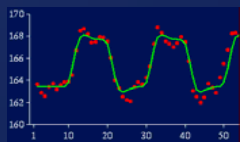
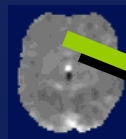
$$\hat{\alpha}_1$$

$$\hat{\sigma}_1^2$$

Design Matrix

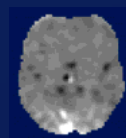
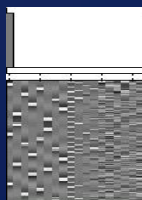


Contrast Images

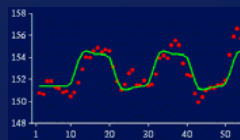


$$\hat{\alpha}_2$$

$$\hat{\sigma}_2^2$$

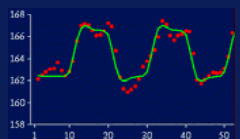
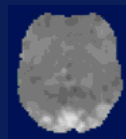
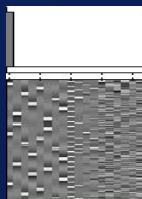


...



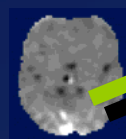
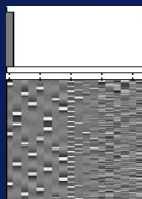
$$\hat{\alpha}_{11}$$

$$\hat{\sigma}_{11}^2$$



$$\hat{\alpha}_{12}$$

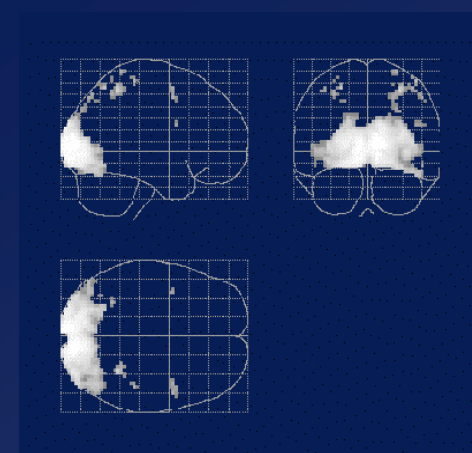
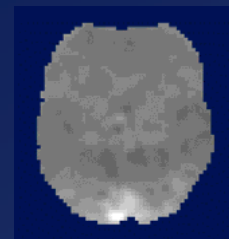
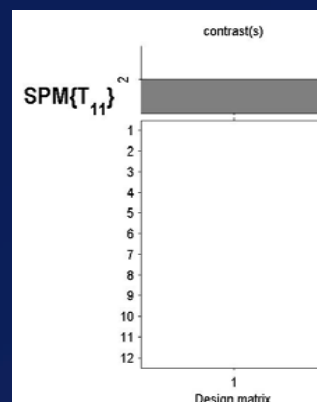
$$\hat{\sigma}_{12}^2$$



## Second level

$$t = \frac{c^T \hat{\alpha}}{\sqrt{V \hat{\alpha} (c^T \hat{\alpha})}}$$

SPM(t)



One-sample  
t-test @ 2<sup>nd</sup> level

# Validity of approach

---

The summary stats approach is exact if for each session/subject:

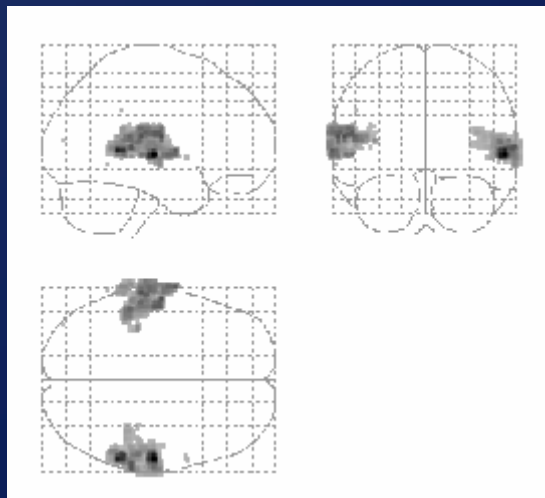
Within-session covariance the same

First-level design the same

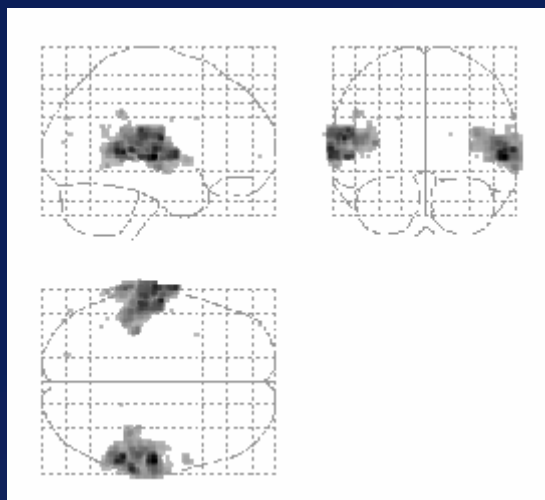
All other cases: Summary stats approach seems to be robust against typical violations.

# Auditory Data

Summary  
statistics



Hierarchical  
Model



*Friston et al. (2004) Mixed  
effects and fMRI studies,  
Neuroimage*

# Multiple contrasts per subject

**Stimuli:**

Auditory Presentation (SOA = 4 secs) of words

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

**Subjects:**

(i) 12 control subjects

**Scanning:**

fMRI, 250 scans per subject, block design

**Question:**

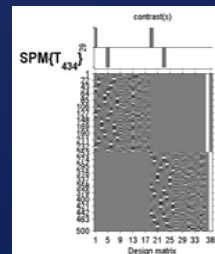
What regions are affected by the semantic content of the words?

*U. Noppeney et al.*

# ANOVA

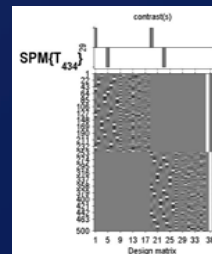
1<sup>st</sup> level:

1.Motion



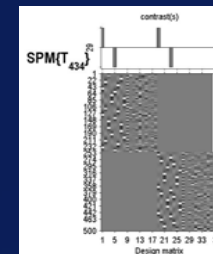
= ?

2.Sound



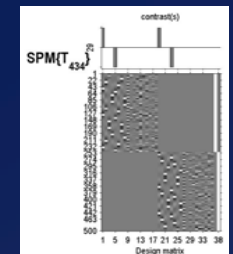
= ?

3.Visual

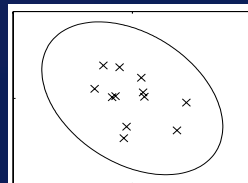


= ?

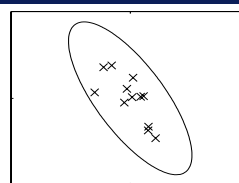
4.Action



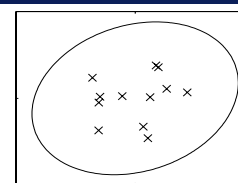
2<sup>nd</sup> level:



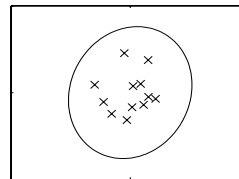
2,1



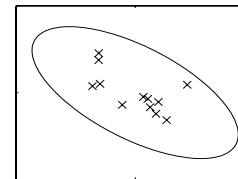
3,1



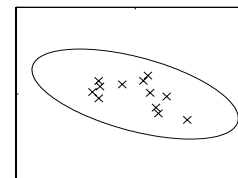
4,1



3,2



4,2

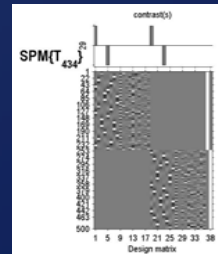


4,3

# ANOVA

1<sup>st</sup> level:

Motion



# Summary

---

Linear hierarchical models are general enough for typical multi-subject imaging data (PET, fMRI, EEG/MEG).

Summary statistics are robust approximation for group analysis.

Also accomodates multiple contrasts per subject.



**Thank you for your attention!**

**[jbpoline@cea.fr](mailto:jbpoline@cea.fr)**