



Neural Imaging and Signal Systems

(BT 640)

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Ack: This is an Aggregated Lecture from lot of resources especially SPM12.



Feedback for Tutorial (Next week)



How did Tutorial 4 go?

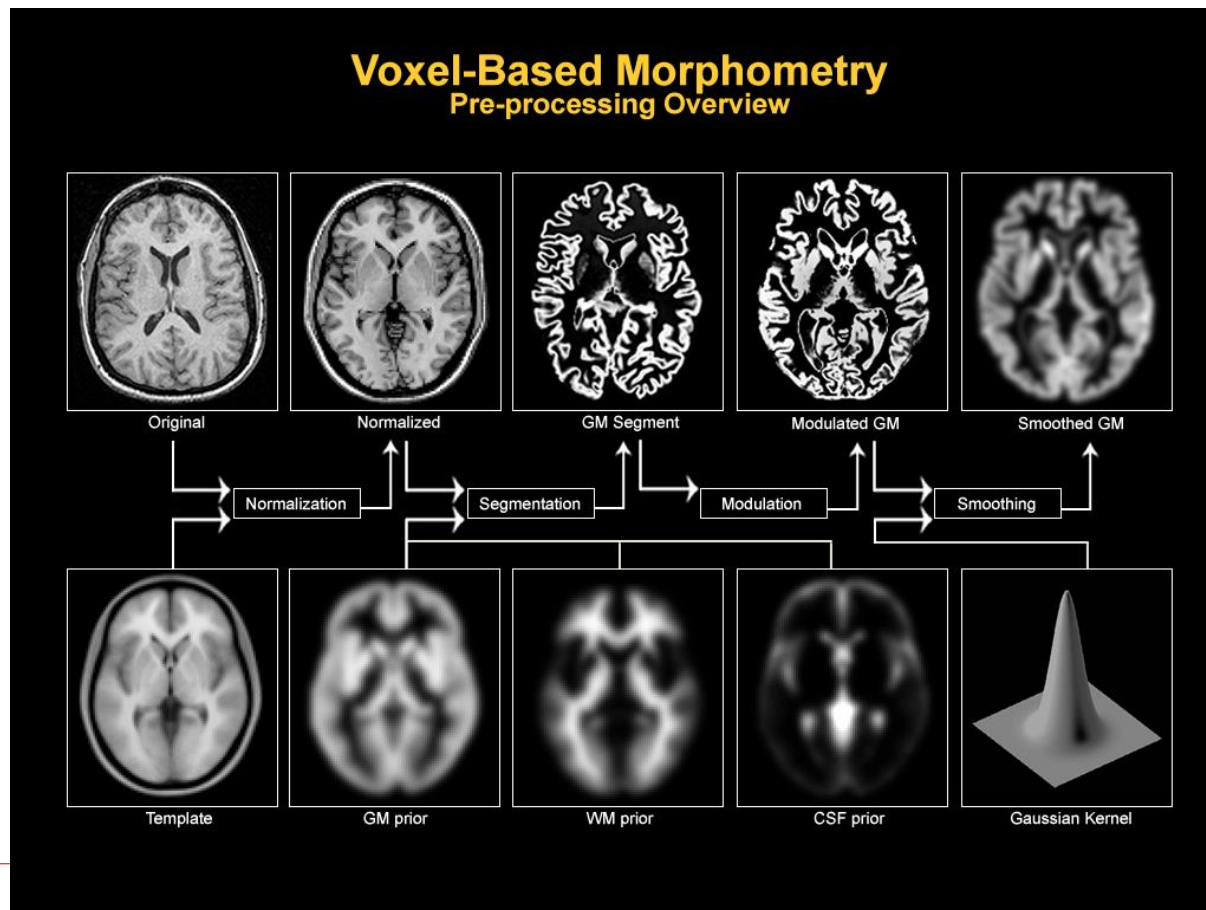


Quick Recap

Voxel Based Morphometry Blocks

Quick Recap

Voxel Based Morphometry Blocks





Quick Recap

**How will you find faulty MRI scans given
10,000 Scans**



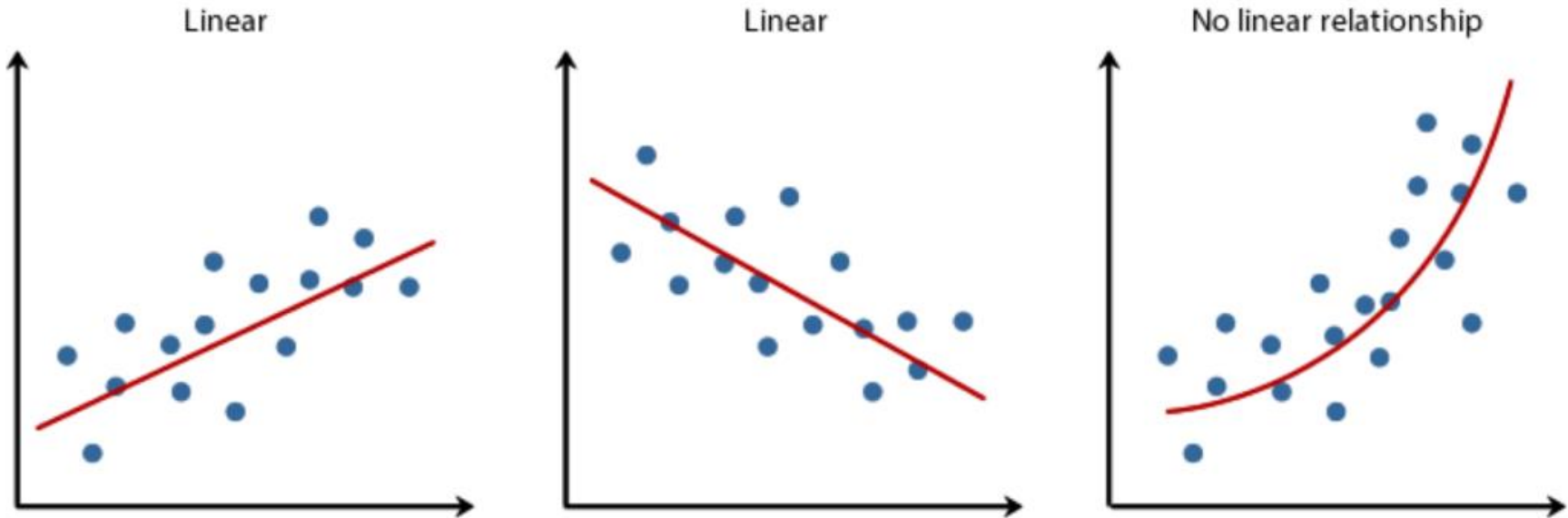
Today's Lectures

General Linear Model (GLM)

GLM for Voxel Based Morphometry

Simple regression

- One predictor and one outcome.

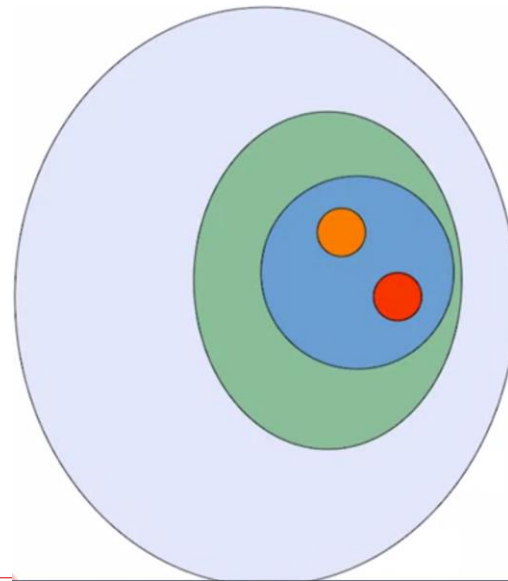




“Essentially, all models are wrong, but some are useful.”
George Box, 1987.

General Linear Model (GLM)

- GLM treats data as a linear combination of model functions (predictors) plus noise (error).
- The model functions are assumed to have known shapes (line or curve) but their amplitudes (slopes) are unknown and have to be estimated.



Simple regression

ANOVA

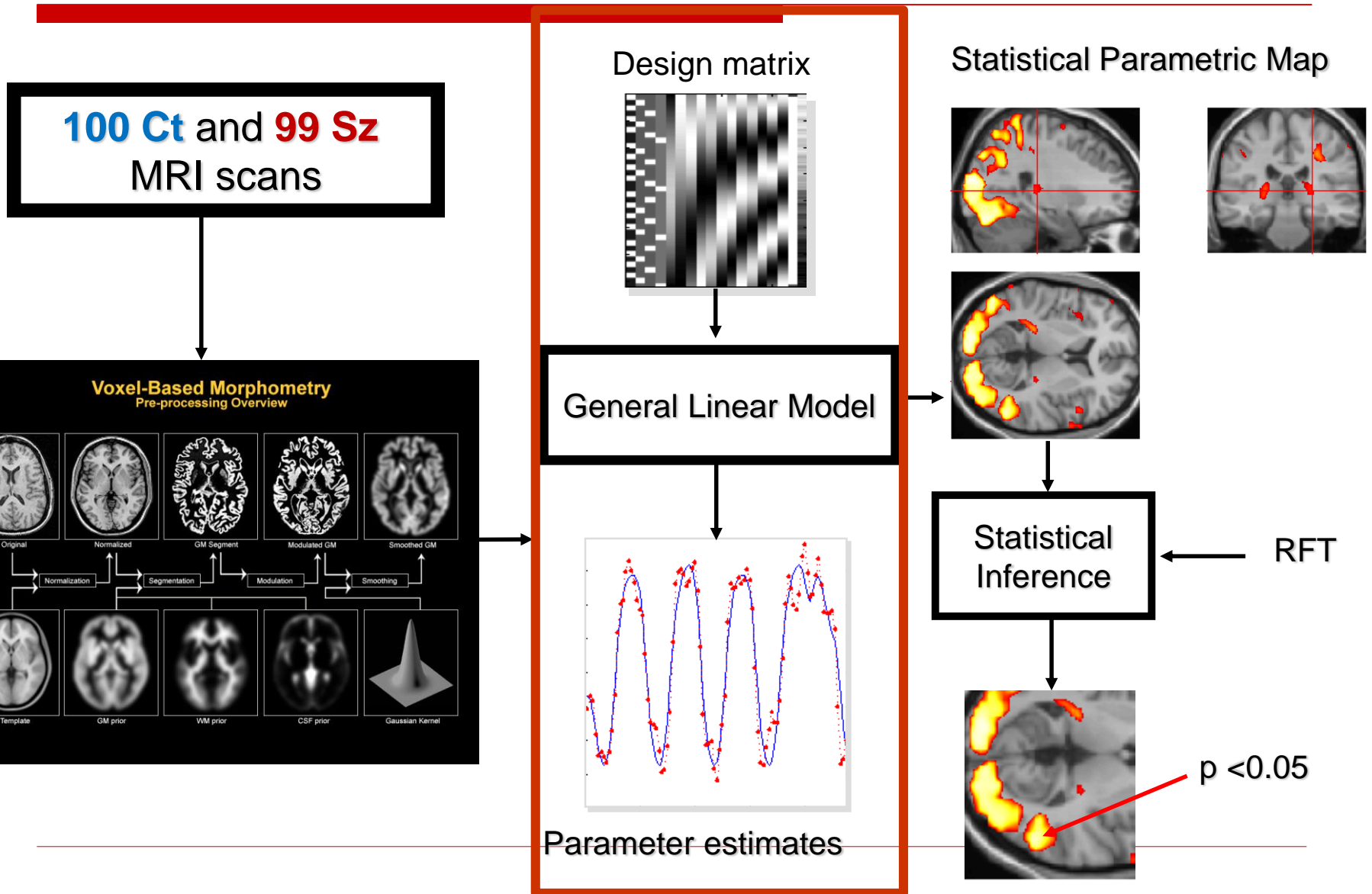
Multiple regression

General linear model

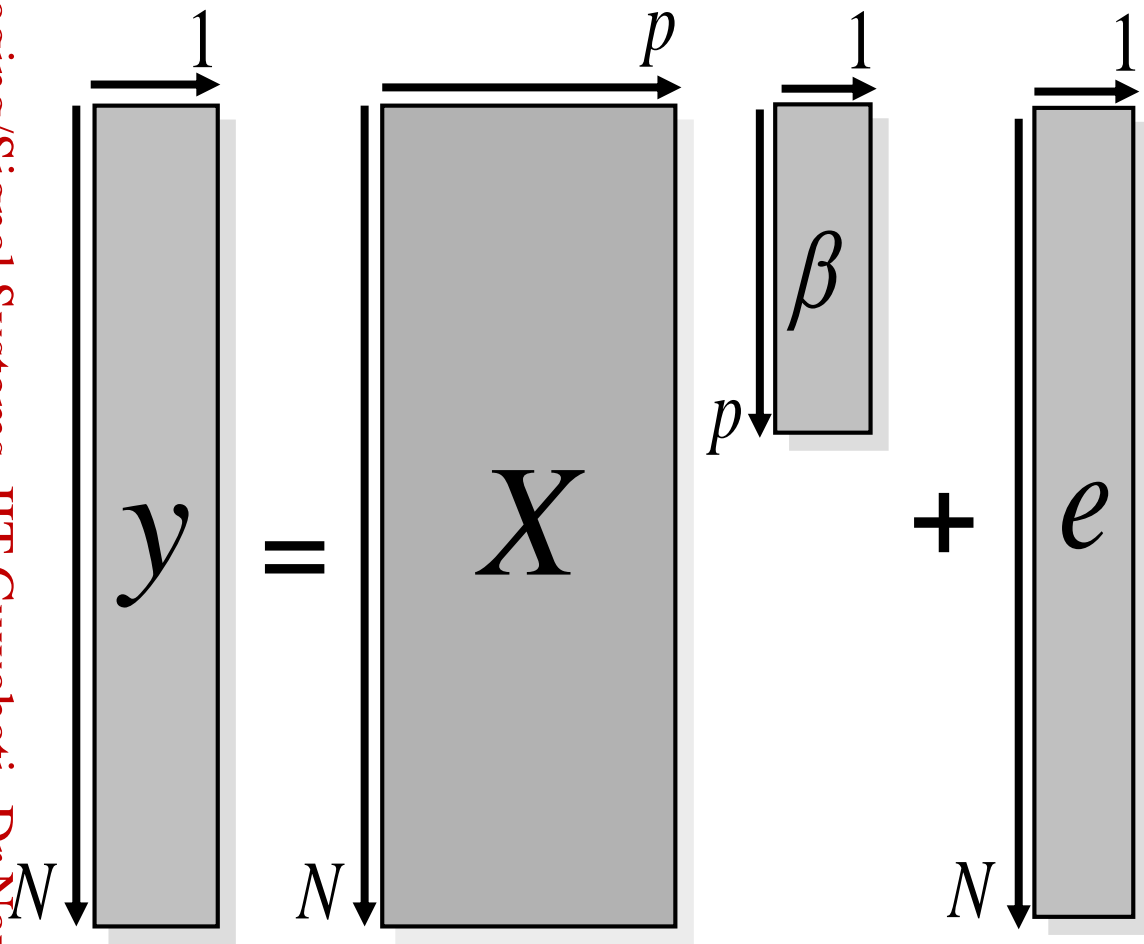
- Mixed effects/hierarchical
- Timeseries models (e.g., autoregressive)
- Robust, penalized regression (LASSO, Ridge)



General Linear Model (VBM Context)



General Linear Model



$$y = X\beta + e$$

$$e \sim N(0, \sigma^2 I)$$

- Model is specified by
1. Design matrix X
 2. Assumptions about e

N : number of scans
 p : number of regressors

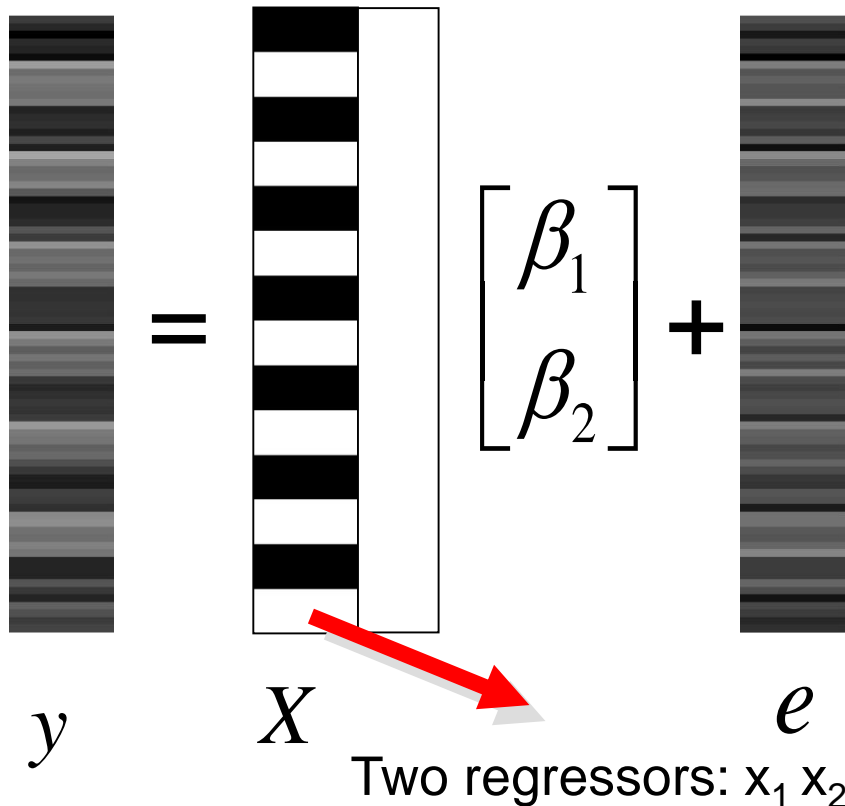
The design matrix embodies all available knowledge about experimentally controlled factors and potential confounds.

GLM: a flexible framework for parametric analyses

- one sample t -test
- two sample t -test
- paired t -test
- Analysis of Variance (ANOVA)
- Analysis of Covariance (ANCOVA)
- correlation
- linear regression
- multiple regression

ALL CLASSICAL TESTS possible based on DESIGN MATRIX

Parameter estimation



$$y = X\beta + e$$

Objective:
estimate parameters
to minimize

$$\sum_{t=1}^N e_t^2$$

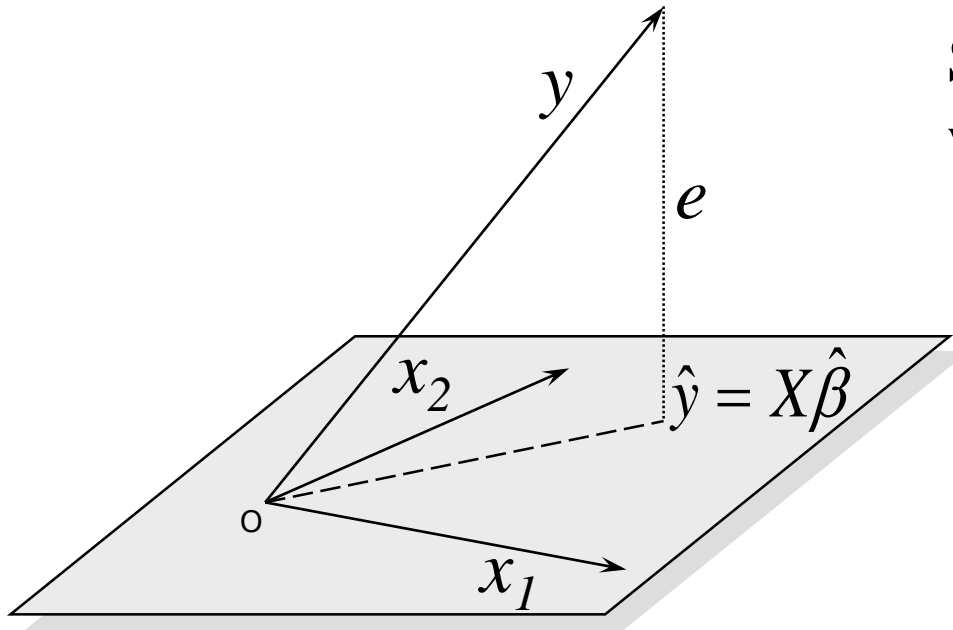
Ordinary least squares
estimation (OLS) (assuming
i.i.d. error):

$$\hat{\beta} = (X^T X)^{-1} X^T y$$

$$\hat{\beta} \sim N(\beta, \sigma^2 (X^T X)^{-1})$$

GLM- Geometric Perspective

Consider x_1 and x_2 as two regressors



Smallest errors (shortest error) when e is orthogonal to X

$$X^T e = 0$$

$$X^T (y - X\hat{\beta}) = 0$$

$$X^T y = X^T X\hat{\beta}$$

$$\hat{\beta} = (X^T X)^{-1} X^T y$$

Design space defined by X

Objective:
estimate parameters
to minimize

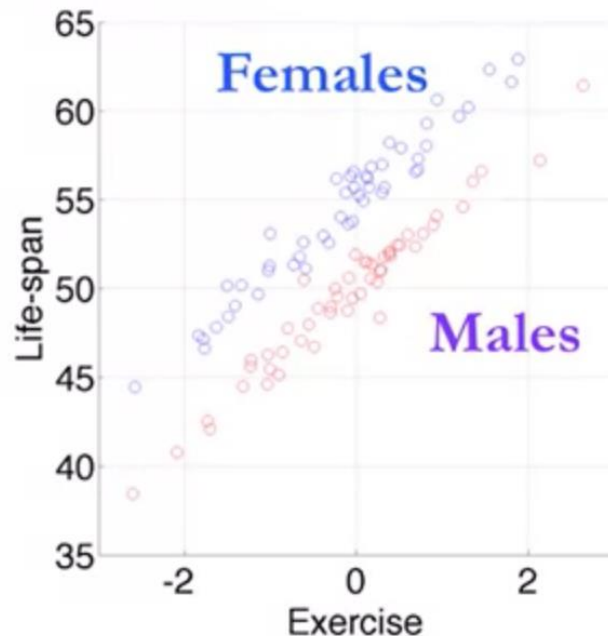
$$\sum_{t=1}^N e_t^2$$

Ordinary Least Squares (OLS)

General Linear Model (Exercise affect life span)

□ Non Neural Imaging Example

- Does exercise predict life-span?
- Made-up (not real data)
- Control for other variables that might be important, i.e., gender (M/F)



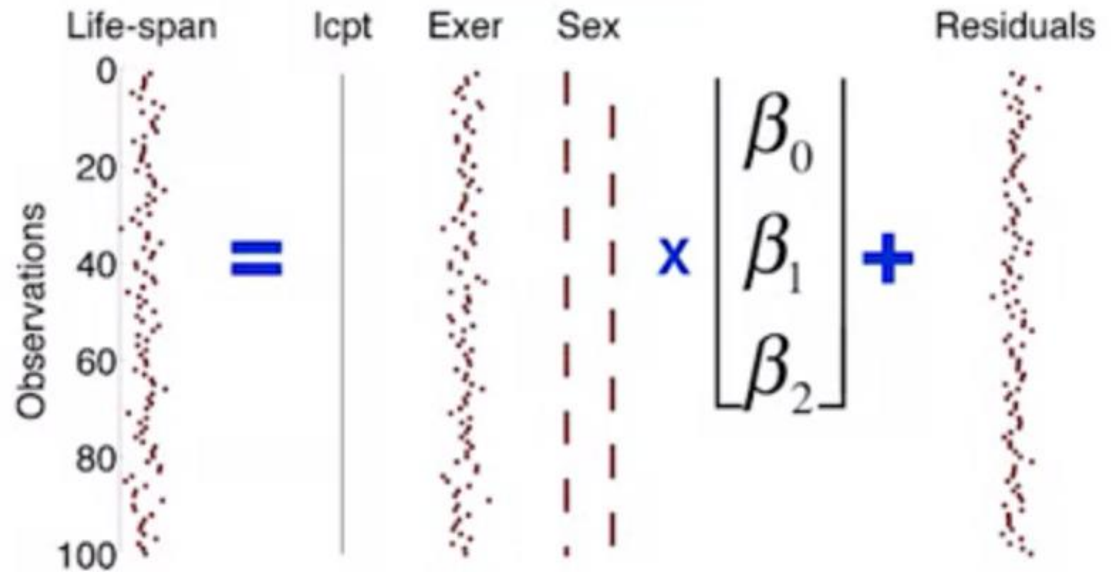
General Linear Model

□ Non Neural Imaging Example

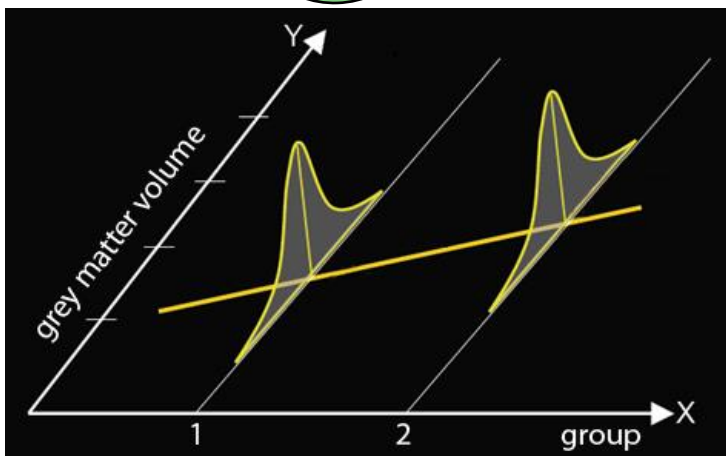
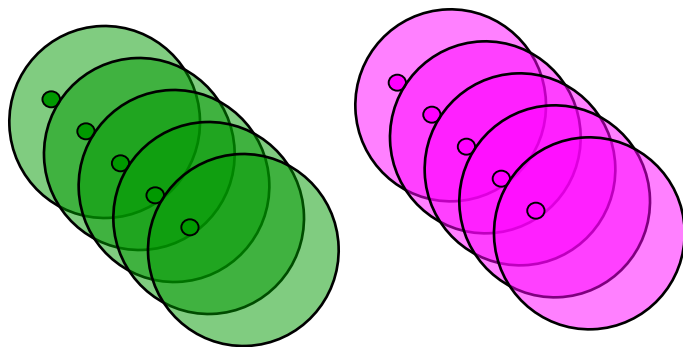
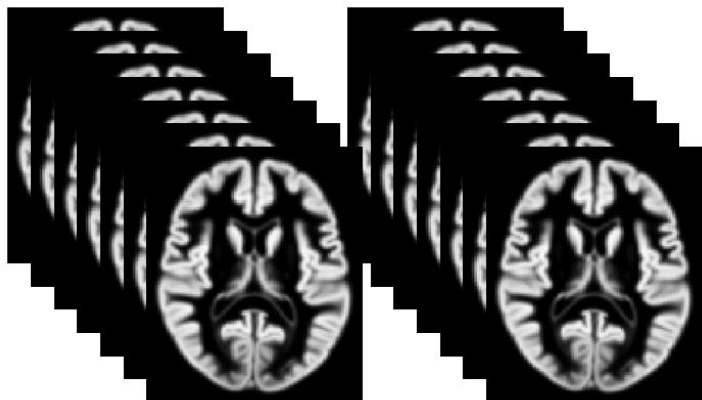
$$Y = X\beta + \epsilon$$

$$\begin{bmatrix} Y_1 \\ Y_2 \\ \vdots \\ Y_n \end{bmatrix} = \begin{bmatrix} 1 & X_{11} & \dots & X_{1p} \\ 1 & X_{21} & \dots & X_{2p} \\ \vdots & \vdots & & \vdots \\ 1 & X_{np} & \dots & X_{np} \end{bmatrix} \times \begin{bmatrix} \beta_0 \\ \beta_1 \\ \vdots \\ \beta_p \end{bmatrix} + \begin{bmatrix} \epsilon_1 \\ \epsilon_2 \\ \vdots \\ \epsilon_n \end{bmatrix}$$

Outcome Data Design matrix Model parameters Residuals



Using GLM for VBM (sMRI Images)



Compare the GM/ WM differences between 2 groups

$$\begin{array}{c} \text{grey matter} \\ Y_1 \\ Y_1 \\ Y_1 \\ Y_1 \\ Y_1 \\ Y_2 \\ Y_2 \\ Y_2 \\ Y_2 \\ Y_2 \end{array} = \begin{array}{cc} \text{Control} \\ \begin{pmatrix} 1 & 0 \\ 1 & 0 \\ 1 & 0 \\ 1 & 0 \\ 1 & 0 \\ 0 & 1 \\ 0 & 1 \\ 0 & 1 \\ 0 & 1 \\ 0 & 1 \end{pmatrix} \begin{pmatrix} \beta_1 \\ \beta_2 \end{pmatrix} + \epsilon
 \end{array}$$

β_1 ← mean group 1
 β_2 ← mean group 2

H_0 : There is no difference between these groups

β : Other covariates, not just the mean

GLM for VBM

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

Slide from SPM 12

□ **Intensity** for each voxel (V) is a function that models the different things that account for differences between scans:

□ $V = \beta_1(\text{AD}) + \beta_2(\text{control}) + \beta_3(\text{covariates}) + \beta_4(\text{global volume}) + \mu + \varepsilon$



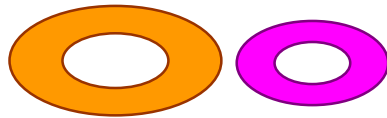
- $V = \beta_1(\text{AD}) + \beta_2(\text{control}) + \beta_3(\text{age}) + \beta_4(\text{gender}) + \beta_5(\text{global volume}) + \mu + \varepsilon$
- which covariate (β) best explains the values in GM/ WM
- In practice, the contrast of interest is usually t-test between β_1 and β_2 , ***

*** Eg, "is there significantly more GM (higher v) in the controls than in the AD scans and does this explains the value in v much better than any other covariate?"

In your VBM Model: TIV as covariate

□ Global or local differences

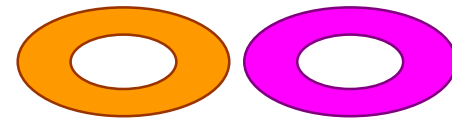
- *Uniformly* bigger brains may have *uniformly* more GM/WM
- considering the effects of overall size (total intracranial volume) may make a difference at a local level



Brain A Brain B

Differences without accounting for TIV

(TIV = global measure)



Brain A Brain B

Differences after TIV has been “covaried out”
(differences caused by bigger size are uniformly distributed with hardly any impact at local level)

In your VBM Model: Scanner Site as covariate



- Include site of the scan as co-variate
(if Different scanners)



VBM Model in SPM 12 Toolbox

VBM Model Setup

File Edit View Insert Tools Desktop Window Help Color Clear SPM-I Result TASS

PM Jobs

- Stats
- Factorial design specification
- Design
 - Full factorial
 - Factors
 - Factor
 - Name
 - Levels
 - Independence
 - Variance
 - Grand mean
 - ANCOV
- Specify cells
 - Cell
 - Levels
 - Scans
 - Cell
 - Levels
 - Scans
- +Covariates

Specify Files

Input to "Factorial design specification"

riateCobre/CobreCt/sM8

riateCobre/CobreCt/sM8

riateCobre/CobreCt/sM8

riateCobre/CobreCt/sM8

riateCobre/CobreCt/sM8

riateCobre/CobreCt/sM8

riateCobre/CobreCt/sM8

riateCobre/CobreCt/sM8

Save Load Run

Scans

- Covariates
 - Covariate
 - Vector
 - Name
 - Interactions
 - Centering
 - Covariate
 - Vector
 - Name
 - Interactions
 - Centering
 - Covariate
 - Vector
 - Name
 - Interactions
 - Centering
- +Masking
- +Global calculation
- +Global normalisation
- Directory

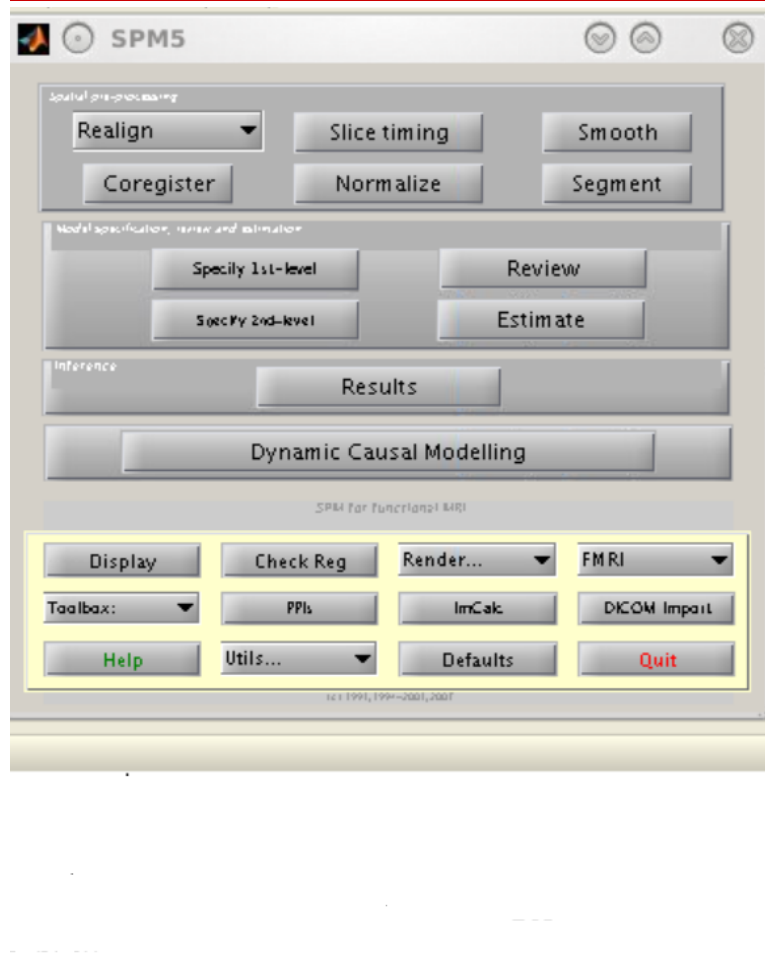
Remove Item "Covariate"

Replicate Item "Covariate"

branch holding 4 items.

Save Load Run

VBM Model Setup



Contrasts for T-test

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

$$b_1 > 0 ?$$

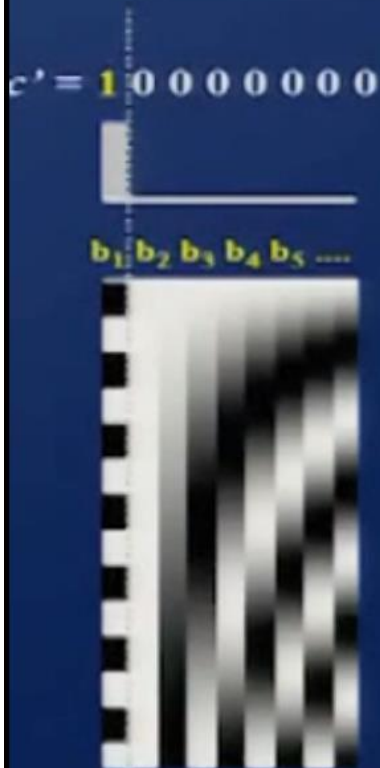
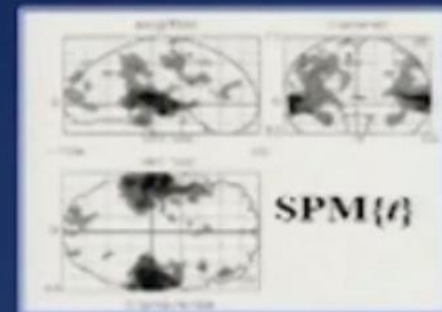
Compute $1 \times b_1 + 0 \times b_2 + 0 \times b_3 + 0 \times b_4 + 0 \times b_5 + \dots = c'b$

$$c' = [1 \ 0 \ 0 \ 0 \ 0 \ \dots]$$

divide by estimated standard deviation of b_1

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

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



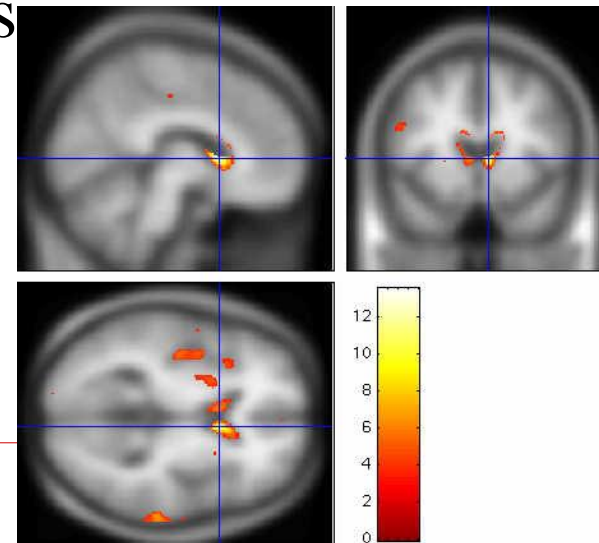
Multiple Comparison Problem

- Introducing false positives when you deal with more than one statistical comparison
 - detecting a difference/ an effect when in fact it does not exist.

- Bonferroni-Correction (controls false positives at individual voxel level):
 - divide desired p value by number of comparisons
 - $.05/1000000 = p < 0.00000005$ at every single voxel

VBM Output in SPM12 on T₁ Template

- ❑ Voxelwise (mass-univariate: independent statistical tests for every single voxel)
- ❑ Employs GLM, providing the residuals are normally distributed, GLM: $Y = X\beta + \varepsilon$
- ❑ Outcome: statistical parametric maps, showing areas of significant difference/ correlations
 - Look like blobs
 - Uses same software as fMRI.



VBM Pros

- **Fully automated:** quick and not susceptible to human error and inconsistencies
- Unbiased and objective
- Not based on regions of interests; more exploratory
- Picks up on differences/ changes at a local scale
- In vivo, not invasive
- **Has highlighted structural differences and changes between groups of people as well as over time**
 - AD, schizophrenia, taxi drivers, quicker learners etc

VBM Cons

- Data collection constraints (exactly the same way)
- Statistical challenges:
 - Multiple comparisons, false positives and negatives
- Results may be flawed by preprocessing steps (poor registration, smoothing) or by motion artefacts (Huntingtons vs controls)- differences not directly caused by brain itself
 - Esp obvious in edge effects

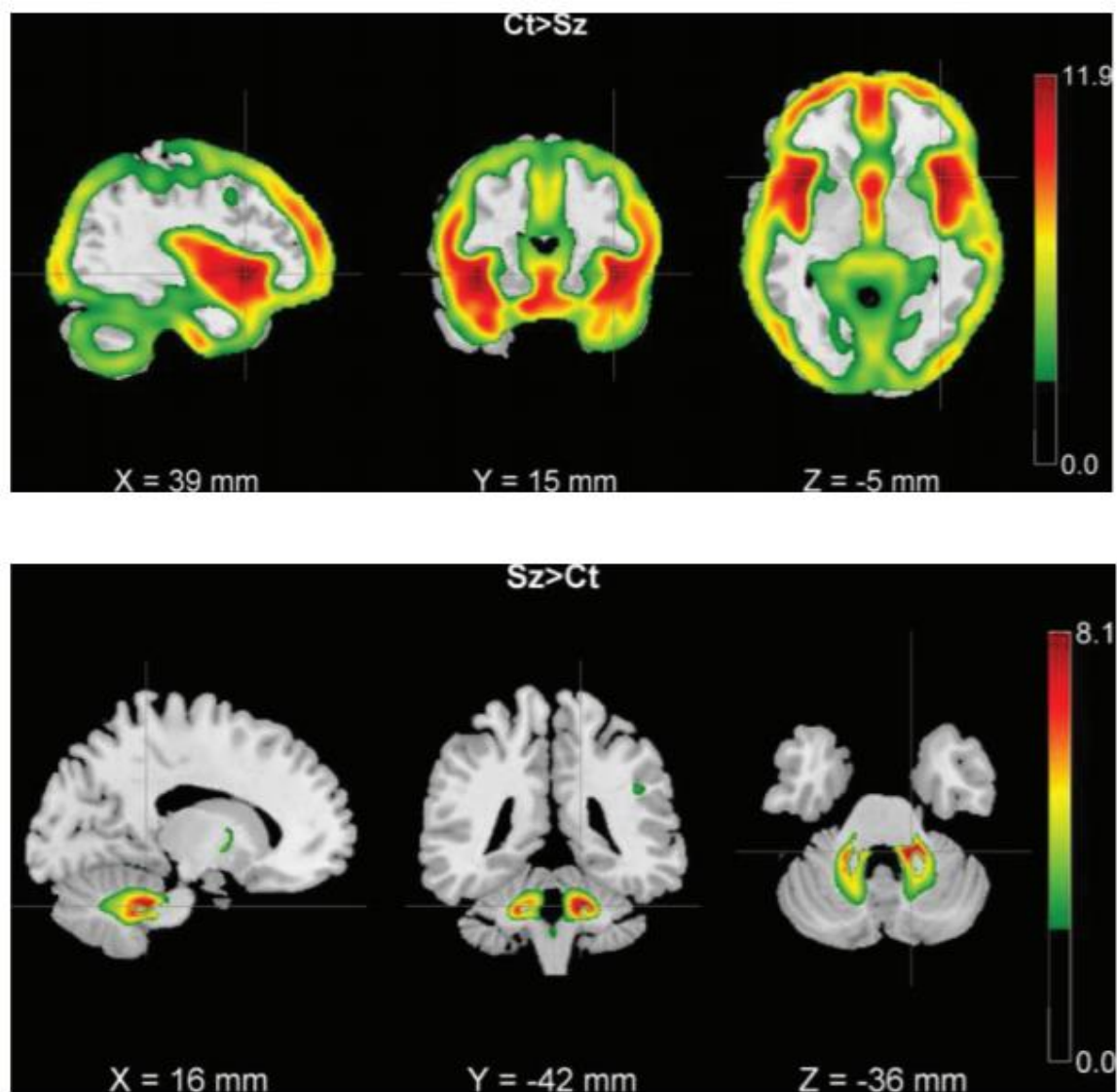


Fig. 2. Results of the VBM analysis; voxels above $|Z| > 2.5$ are shown. (a) Significant clusters where Ct > Sz. (b) Significant clusters where Sz > Ct. Ct, control; Sz, schizophrenia; VBM, voxel-based morphometry.

Thanks for Coming !

General Linear Model(Multiple regression)

- Multiple predictor and one outcome.

Variables

$$y_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \dots + \beta_k x_{ik} + \varepsilon_i$$

Parameters

intercept Slope 1 Slope 2 Slope k Error

- solve for beta vector

Matrix notation

$$y = X\beta + \varepsilon$$

- minimize sum of squared residuals

Slide from coursera