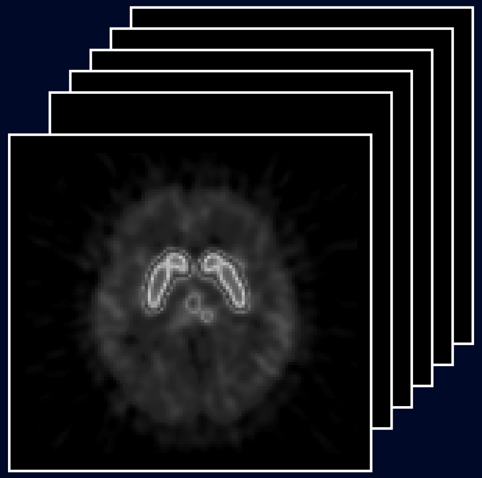
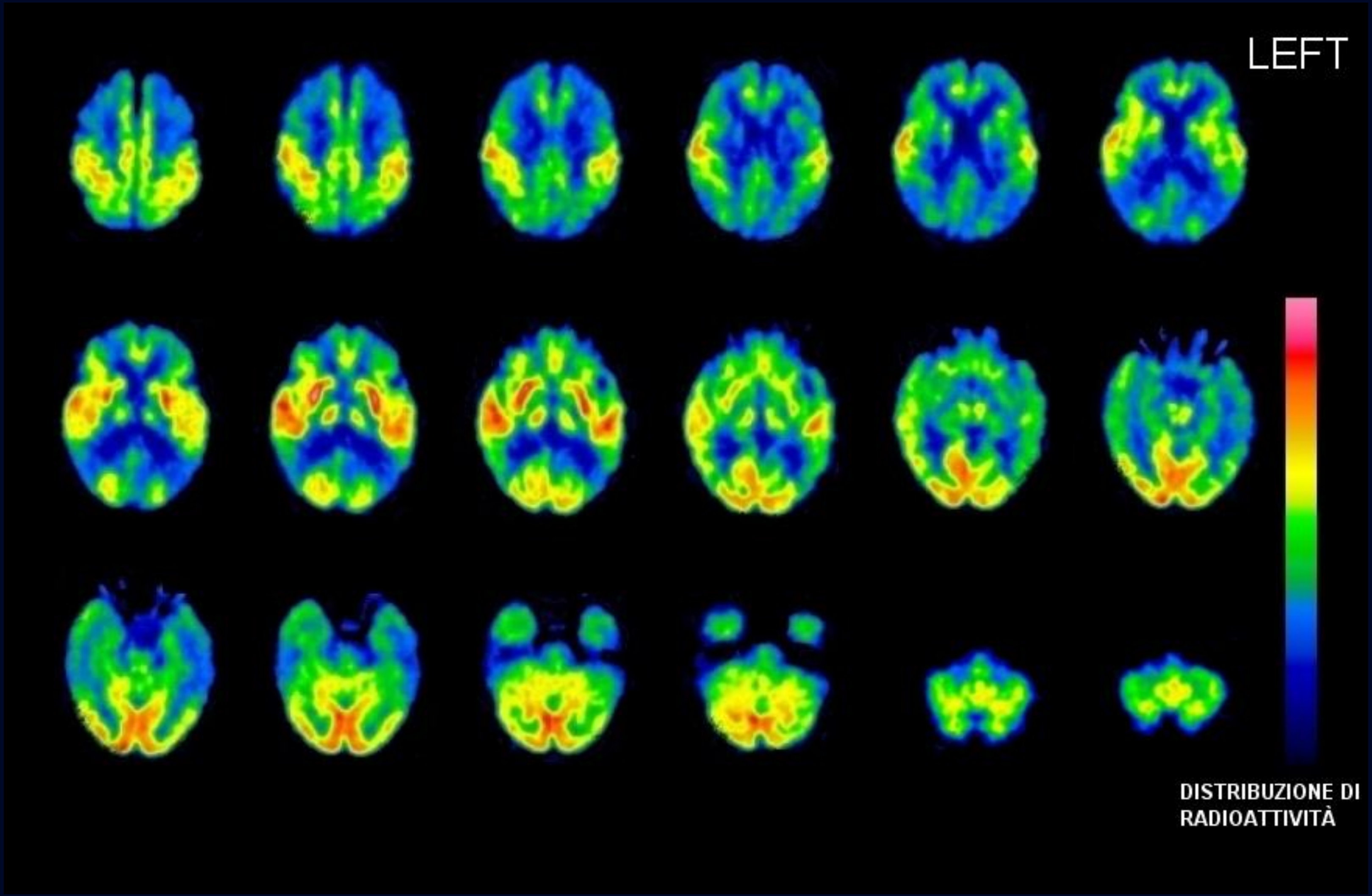
Analisi semi-quantitativa di immagini cerebrali



Medical Imaging & Big Data | Data Science
Università degli studi di Milano-Bicocca

2019



Studio ^{8}F-FDG PET. Paziente con AD in fase avanzata. Oltre alla tipica riduzione di metabolismo temporo-parietale si osserva una estensione dell'ipometabolismo anche alle regioni frontali.

Refertazione convenzionale: analisi qualitativa immagini di flusso

F18-FDG

L' analisi qualitativa delle immagini non evidenzia anomalie della distribuzione del tracciante nelle regioni corticali, sottocorticali e cerebellari. Studio metabolico nei limiti della norma.

L' analisi qualitativa delle immagini evidenzia riduzione dell' accumulo di tracciante in corrispondenza del lobo parietale inferiore, bilateralmente, maggiore a destra. Ipometabolismo nelle regioni sovradescritte

Tc99-ECD

L' analisi qualitativa delle immagini non evidenzia anomalie della distribuzione del tracciante nelle regioni corticali, sottocorticali e cerebellari. Studio di flusso nei limiti della norma.

L' analisi qualitativa delle immagini evidenzia riduzione dell' accumulo di tracciante in corrispondenza del lobo parietale inferiore, bilateralmente, maggiore a destra. ipoperfusione parietale analisi semi-quantitativa mediante confronto statistico di immagini di flusso con gruppo di controllo (soggetti normali)

Statistical Parameter Mapping (SPM)

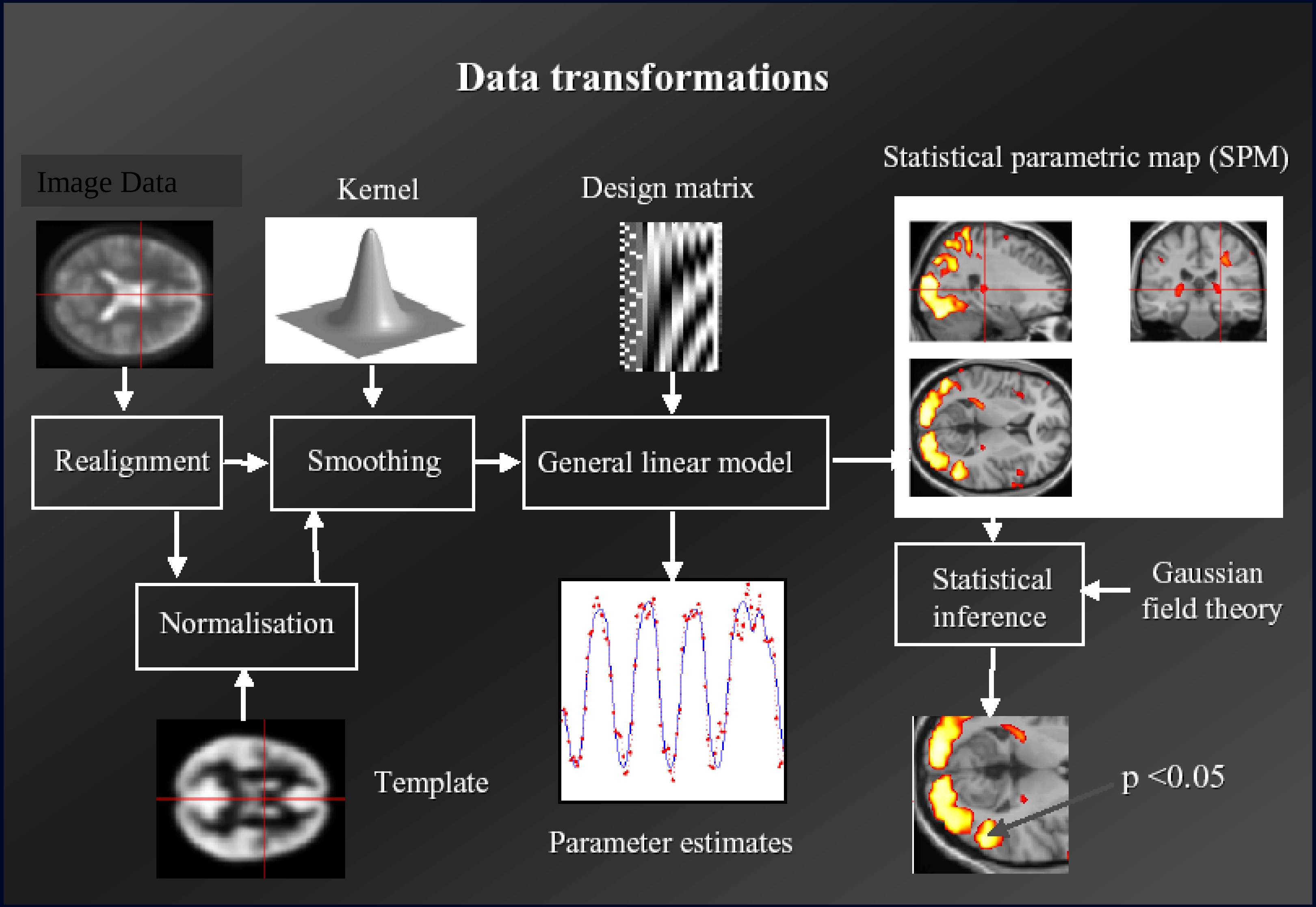
Software Statistical Parameter Mapping (SPM)

Vantaggi

- free download
- Compatibilità con sistemi Windows e Linux

Constraints

- Protocolli di acquisizione rigidi
- Software: matlab


Data transformations
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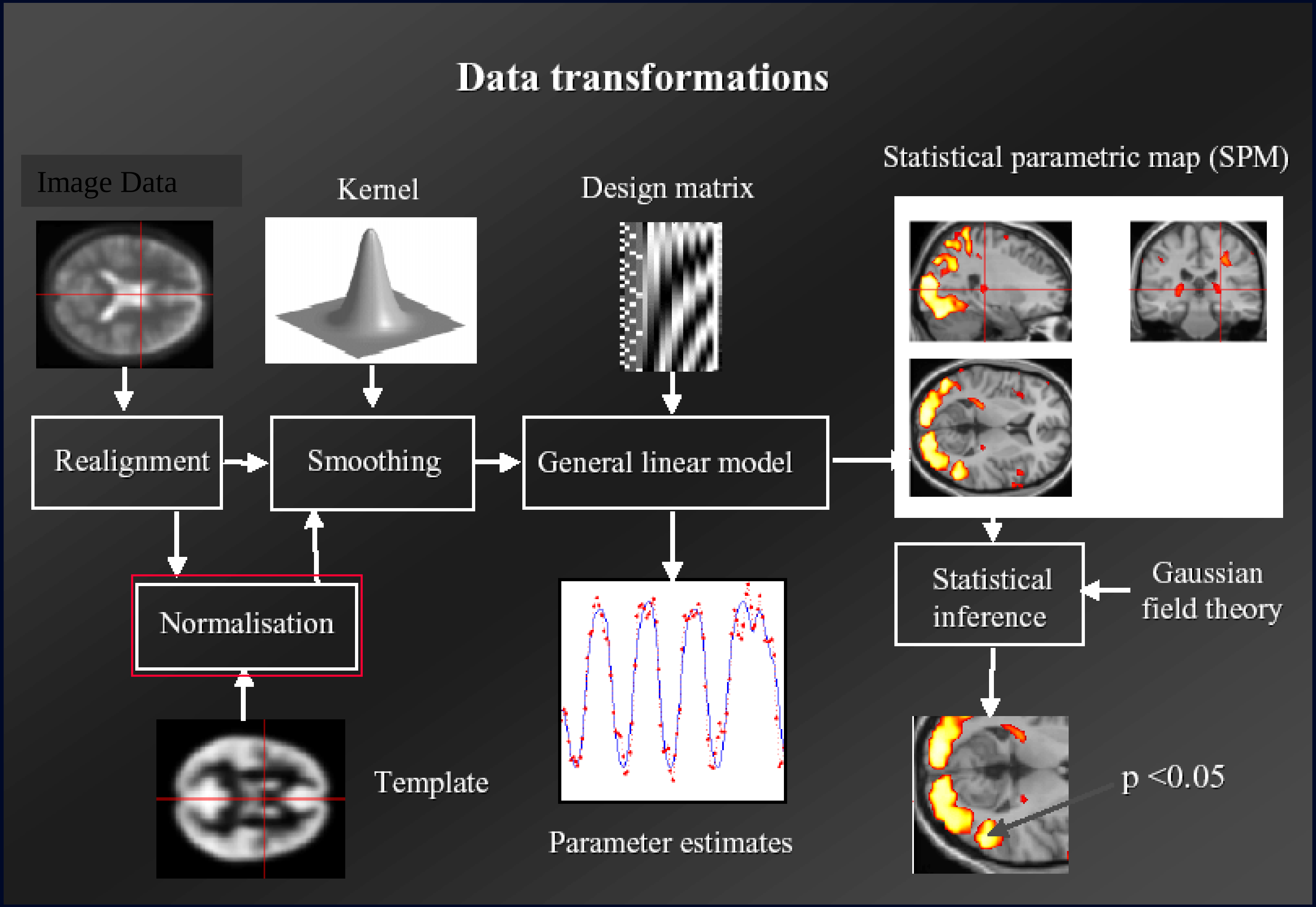
Design matrix
Statistical parametric map (SPM)
Realignment
Smoothing
General linear model
Normalisation
Template
Parameter estimates
Statistical inference
Gaussian field theory
p <0.05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Spatial normalisation

- Inter-subject averaging
  - extrapolate findings to the population as a whole
  - increase activation signal above that obtained from single subject
  - increase number of possible degrees of freedom allowed in statistical model
- Enable reporting of activations as co-ordinates within a known standard space
  - e.g. the space described by Talairach & Tournoux

- Warp the images such that functionally homologous regions from the different subjects are as close together as possible
  - Problems:
    - no exact match between structure and function
    - different brains are organised differently
    - computational problems (local minima, not enough information in the images, computationally expensive)
- Compromise by correcting for gross differences followed by smoothing of normalised images

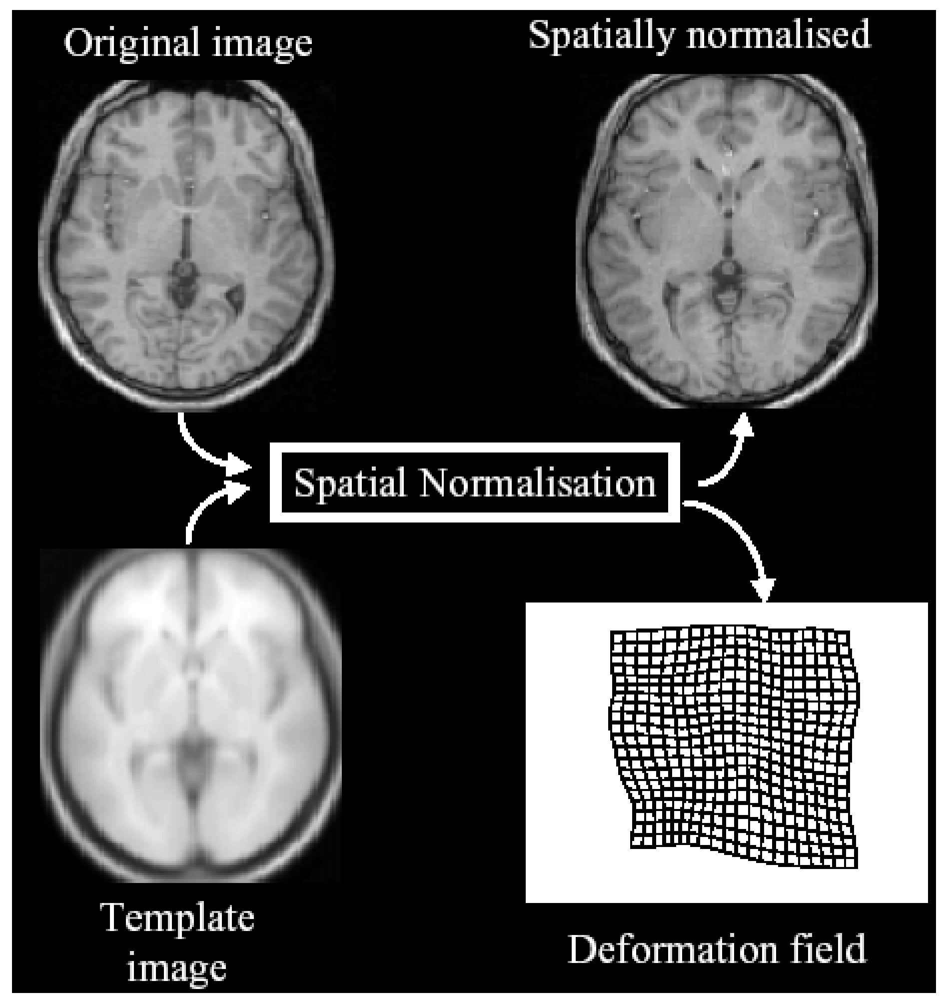
Spatial Normalisation

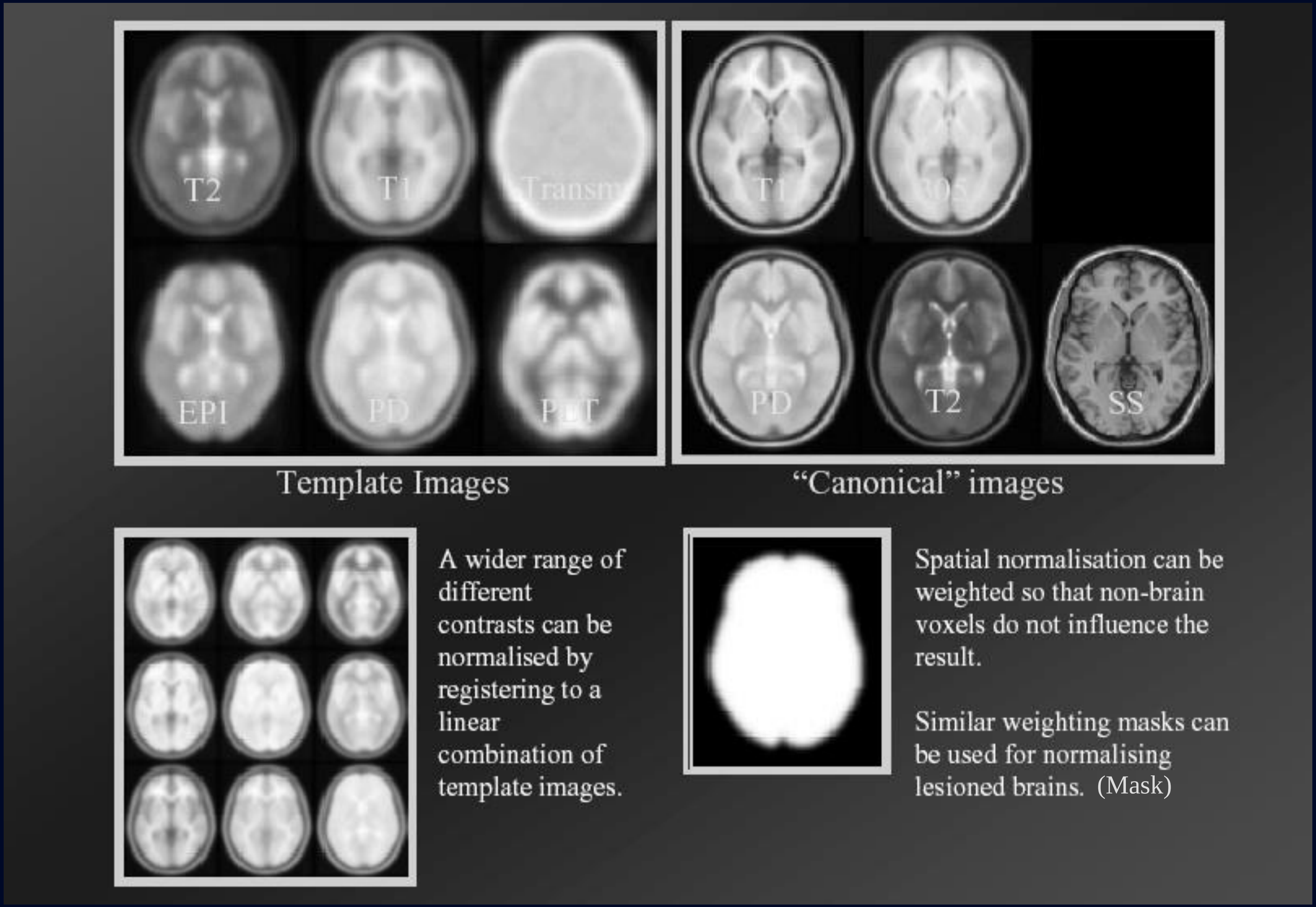
Determine the spatial transformation that minimises the sum of squared difference between an image and a linear combination of one or more templates.

Begins with an affine registration to match the size and position of the image.

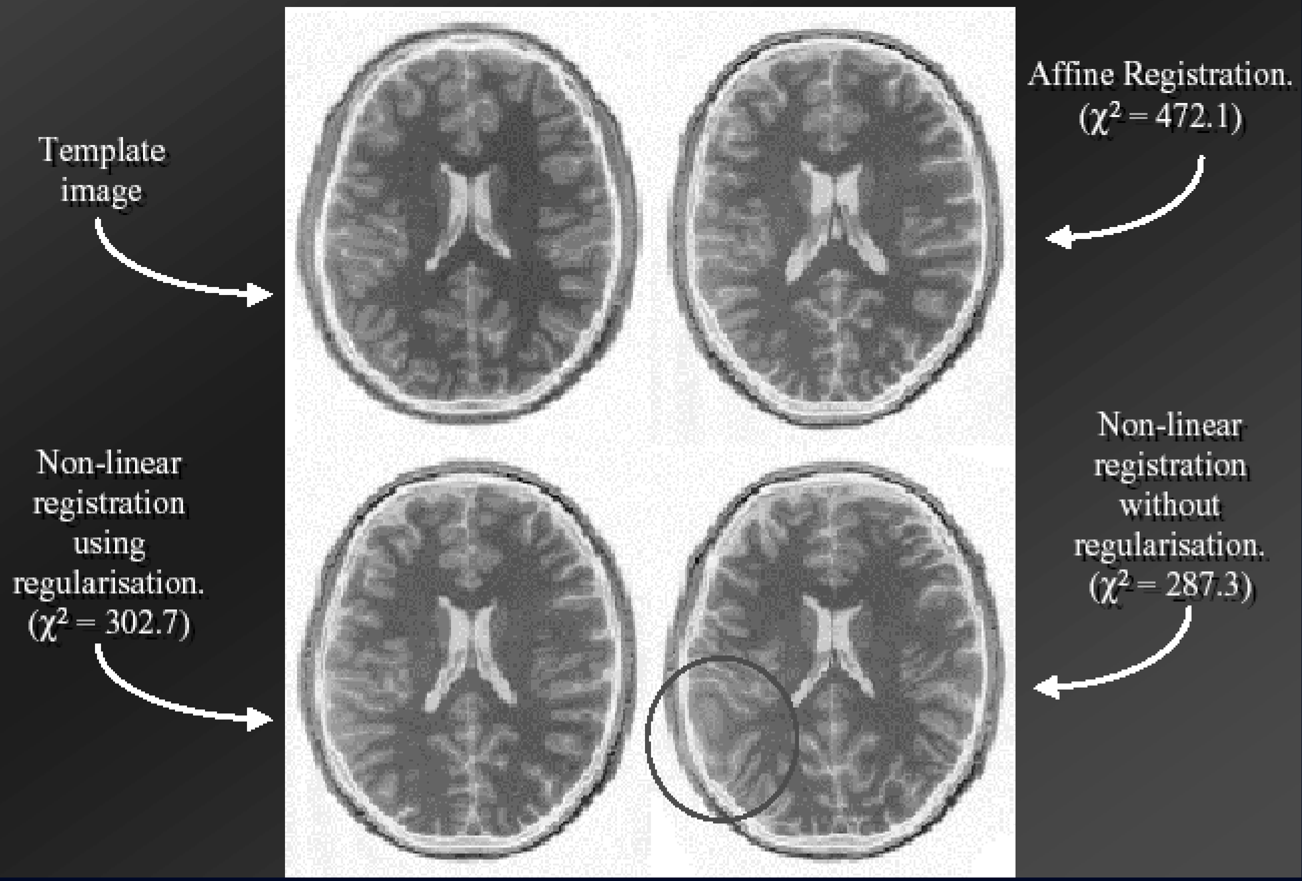
Followed by a global non-linear warping to match the overall brain shape.

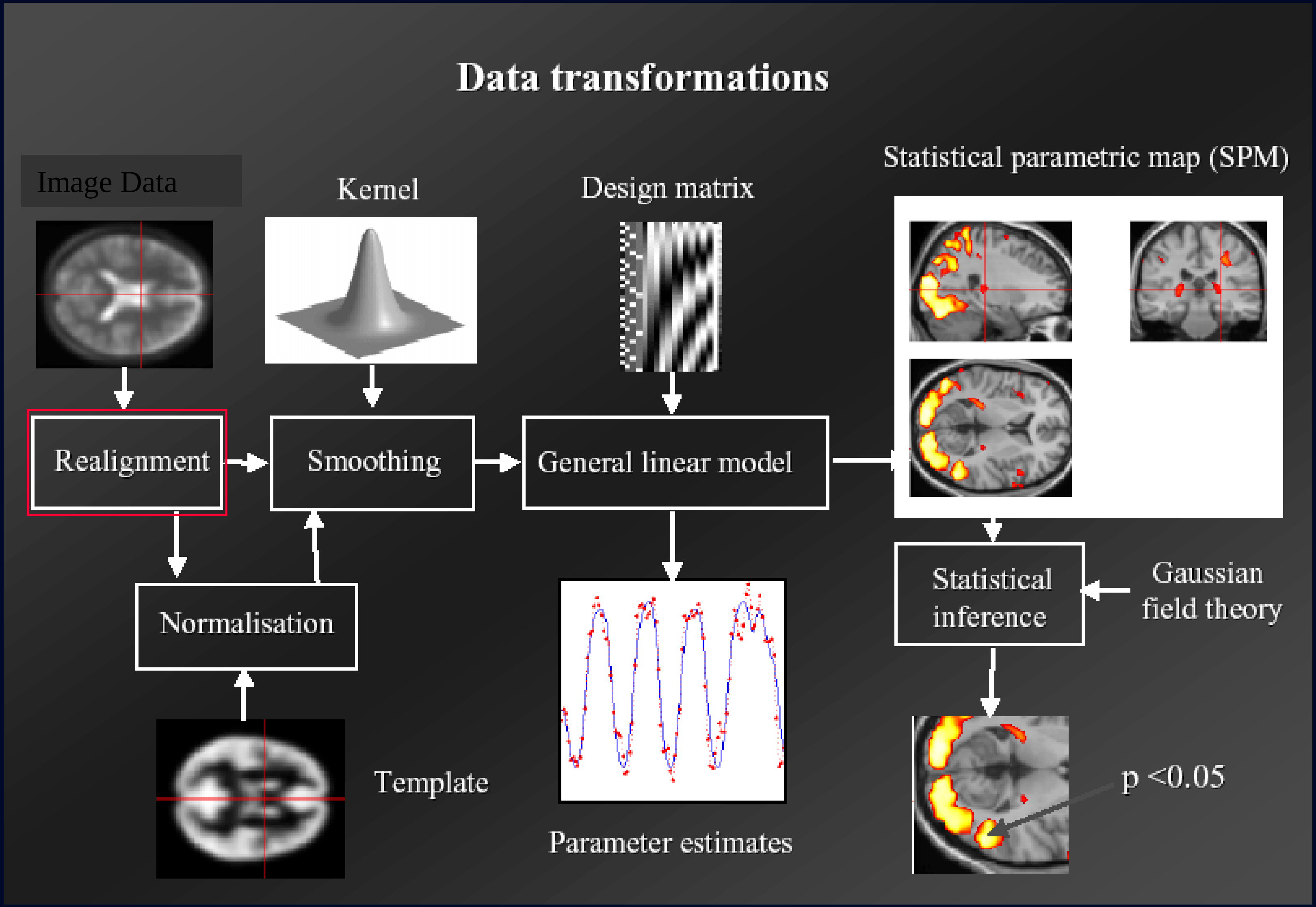
Uses a Bayesian framework to simultaneously maximise the smoothness of the warps.




T2
T1
EPI
PD
T1
PD
T2
SS
Template Images
“Canonical” images
A wider range of different contrasts can be normalised by registering to a linear combination of template images.
Spatial normalisation can be weighted so that non-brain voxels do not influence the result.
Similar weighting masks can be used for normalising lesioned brains. (Mask)

Without the Bayesian formulation, the non-linear spatial normalisation can introduce unnecessary warping into the spatially normalised images.

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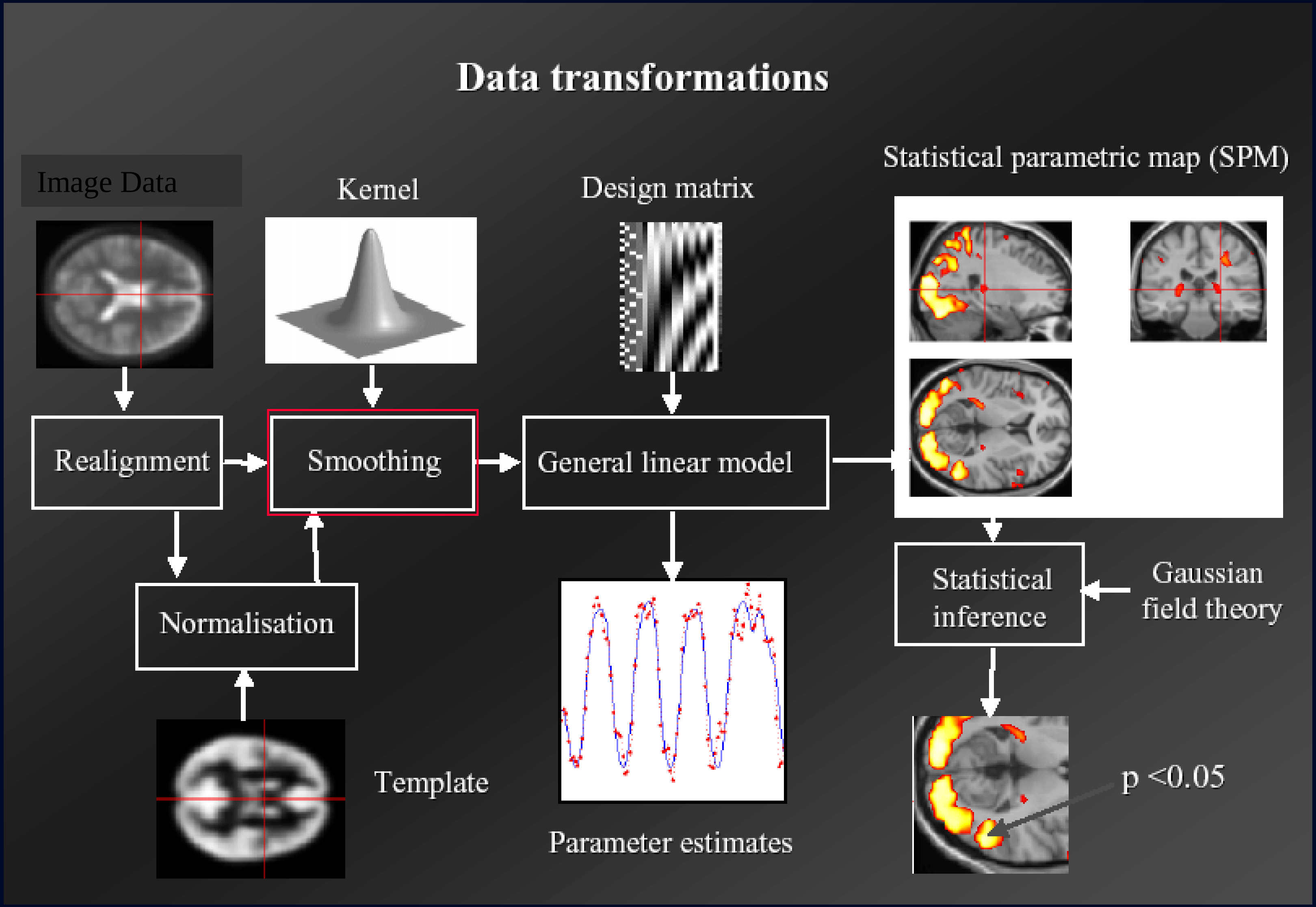
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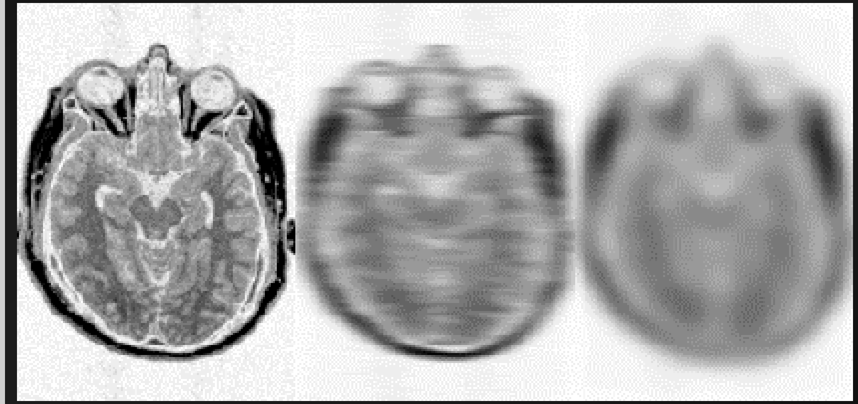
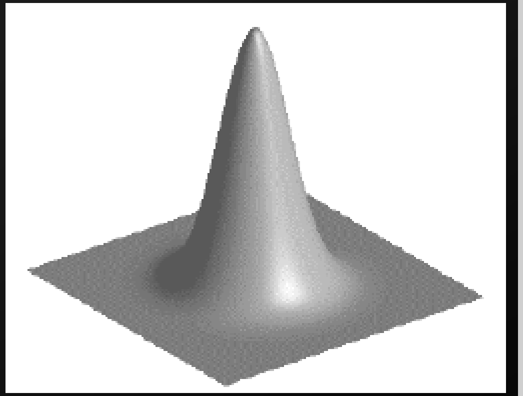
Smoothing

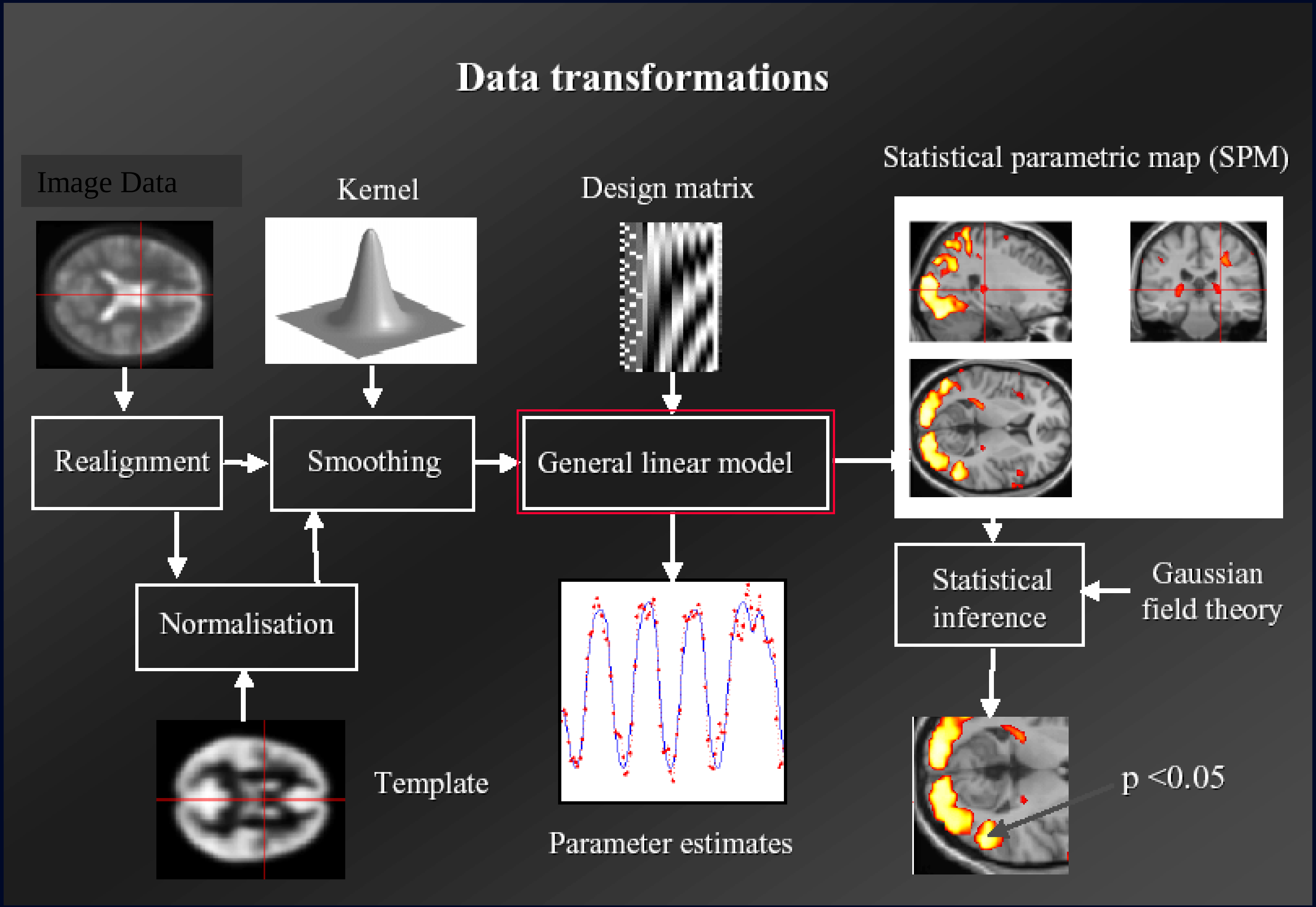
- Why Smooth?
  - Potentially increase signal to noise.
  - Inter-subject averaging.
  - Increase validity of SPM.
- In SPM, smoothing is a convolution with a Gaussian kernel.
- Kernel defined in terms of FWHM (full width at half maximum). (e.g. 8, 8, 8 mm)

Gaussian convolution is separable



Gaussian smoothing kernel

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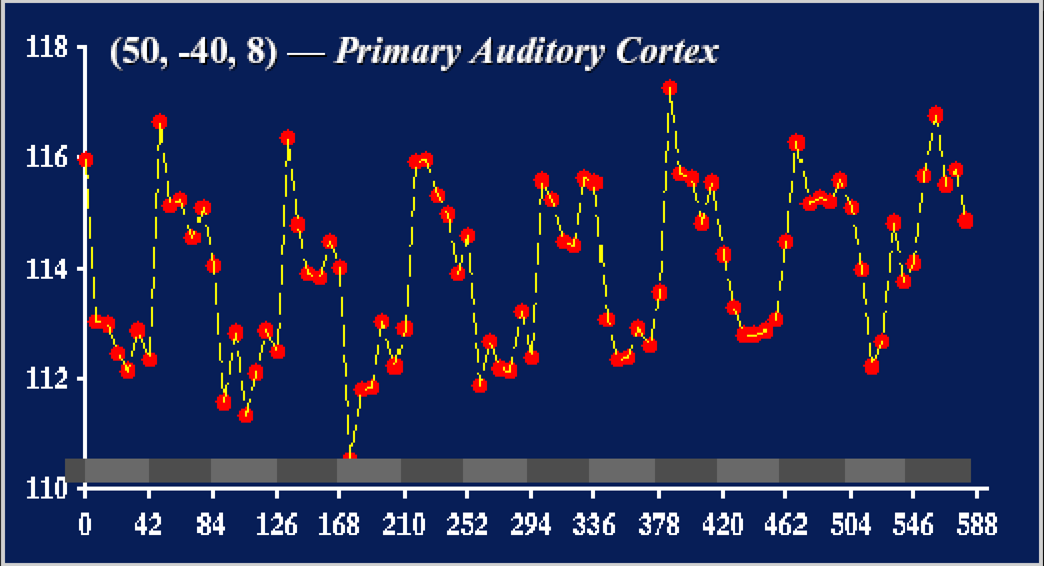
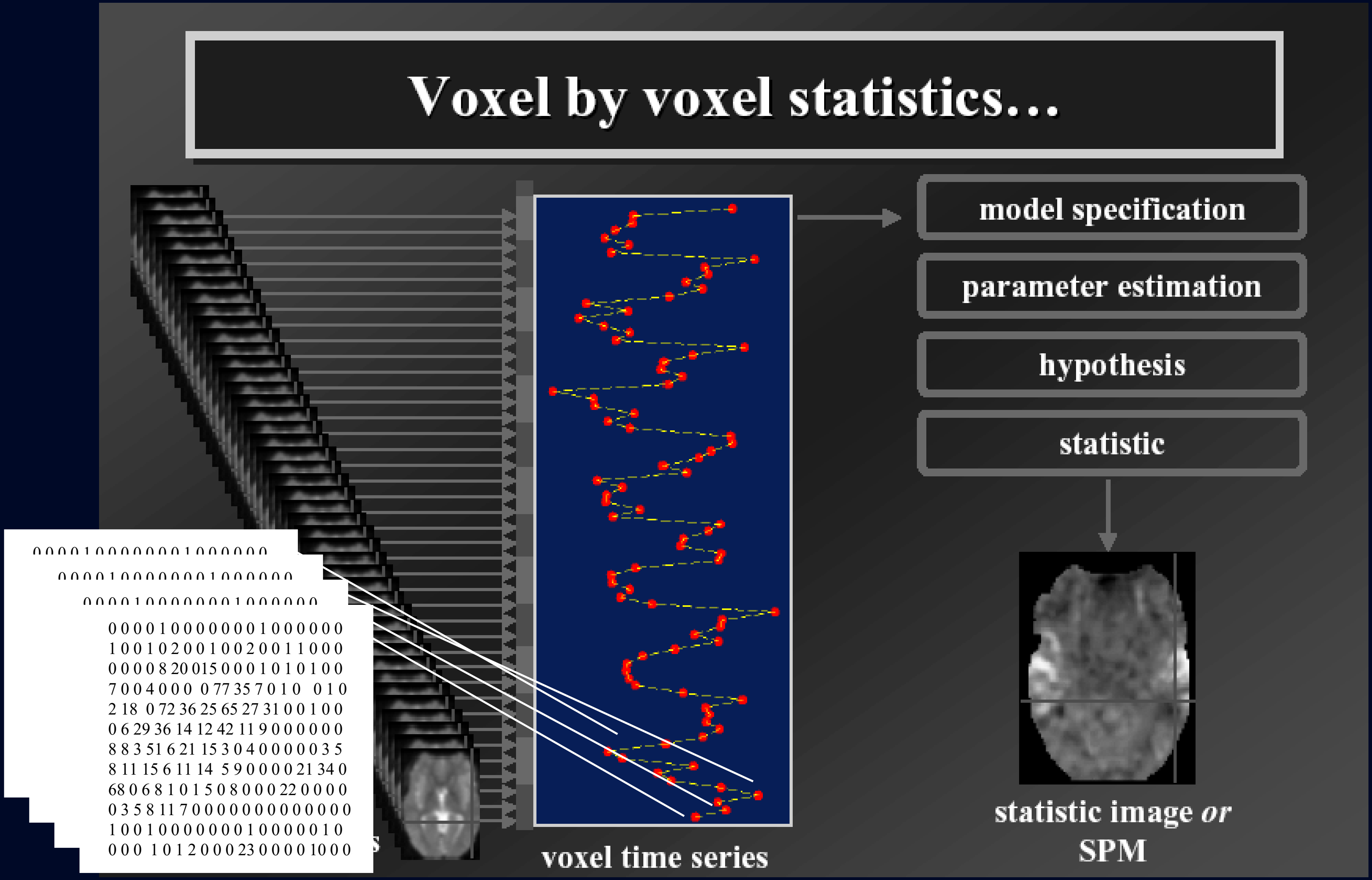
Example epoch *f*MRI activation dataset: Auditory stimulation

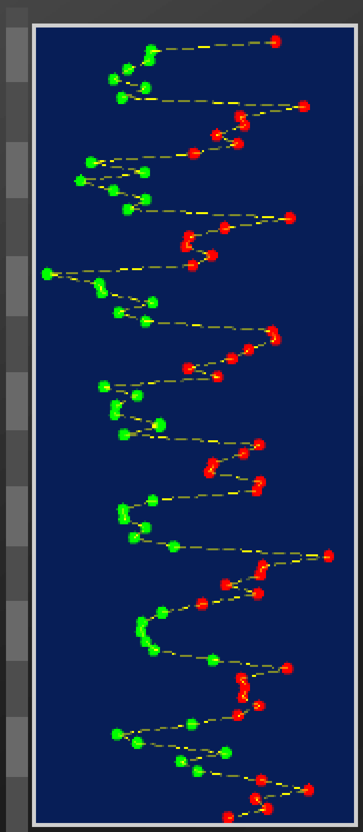
- Single subject
  - RH male
- Conditions
  - Passive word listening
  - Bisyllabic nouns
  - 60wpm
  - against rest

- Epoch *f*MRI
  - rest & words
  - epochs of 6 scans
  - ⇒42 second epochs
  - 7 BA cycles
    experiment was 8 cycles: first pair of blocks dropped
  - →BABABABABABABA
  - ⇒last 84 scans of experiment
    images 16–99
  - →~10 minutes scanning time

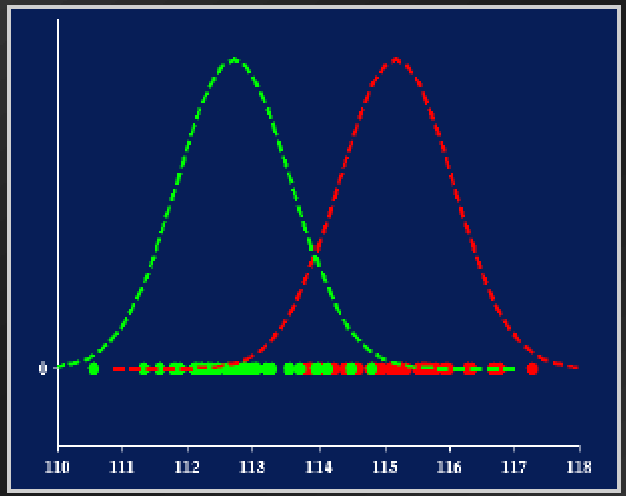



Voxel by voxel statistics…
model specification
parameter estimation
hypothesis
statistic
voxel time series
statistic image *or* SPM

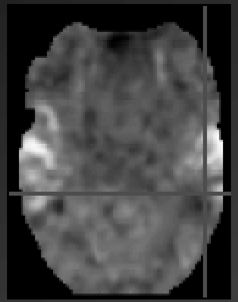
…e.g. two-sample *t*-test?



voxel time series



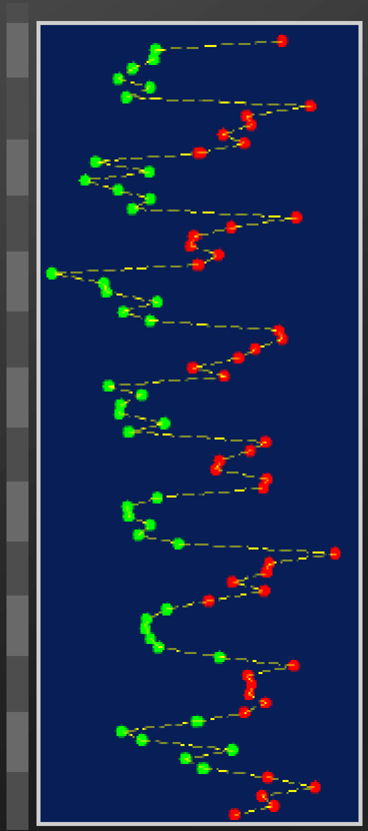
$$t = \frac{\overline{Y_{1\bullet}} - \overline{Y_{0\bullet}}}{\sqrt{\hat{\sigma}^2\left(\frac{1}{n_1} + \frac{1}{n_0}\right)}}$$



t-statistic image
SPM{*t*}
compares size of effect to error variance

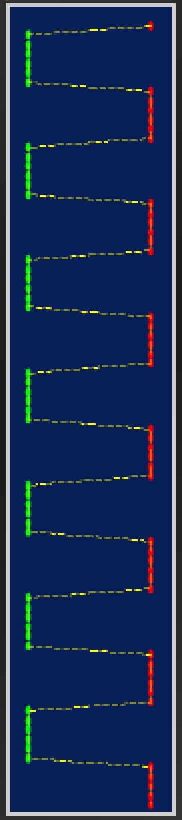
❢ *standard t-test assumes independence*
⇒ *ignores temporal autocorrelation!*

Regression example…



voxel time series

$= \mu + \alpha$



box-car reference function

$+$ error

$$Y_s = \mu + \alpha f(t_s) + \varepsilon_s$$

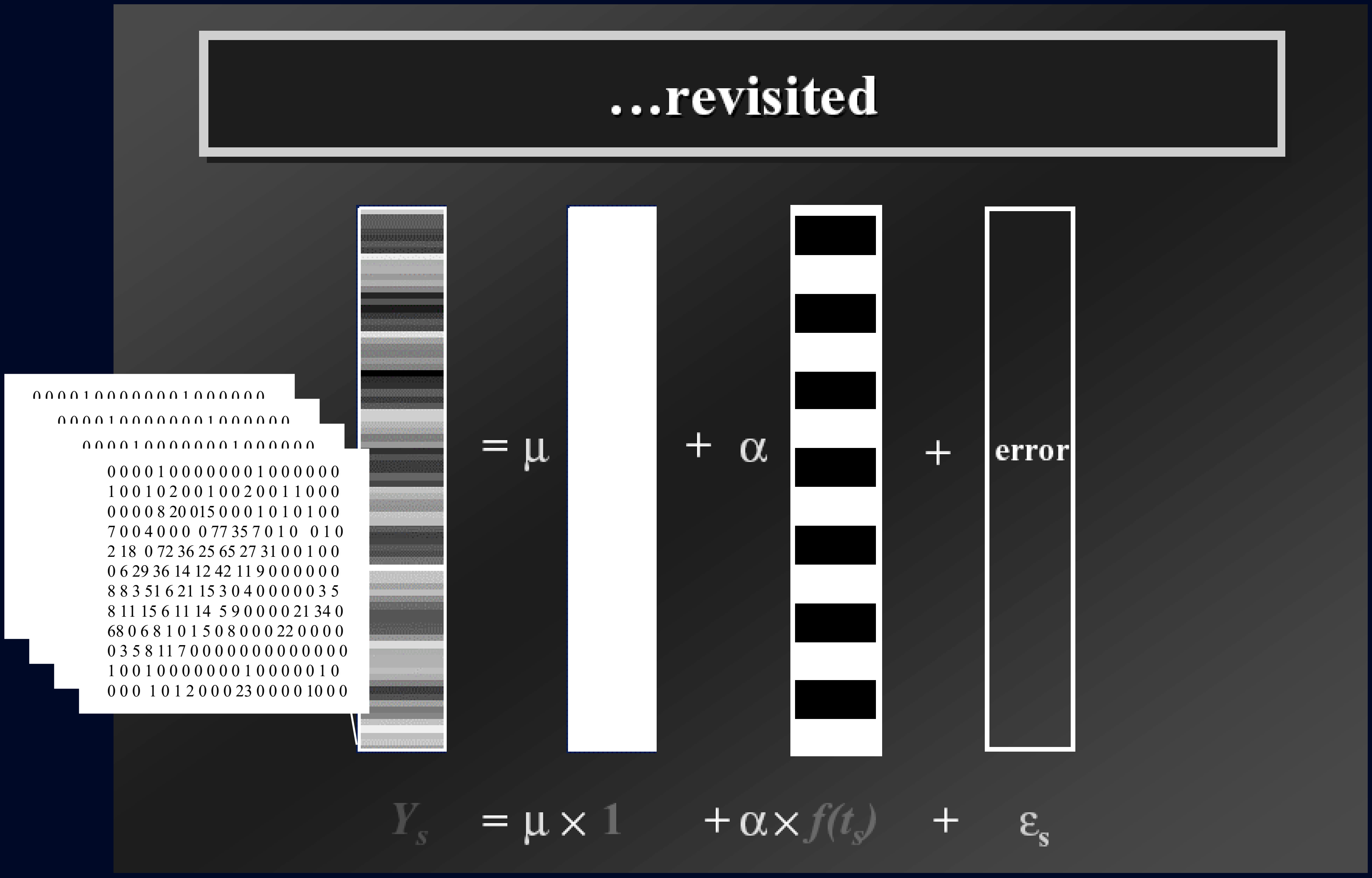
$$f(t_s) = 0 \text{ or } 1$$

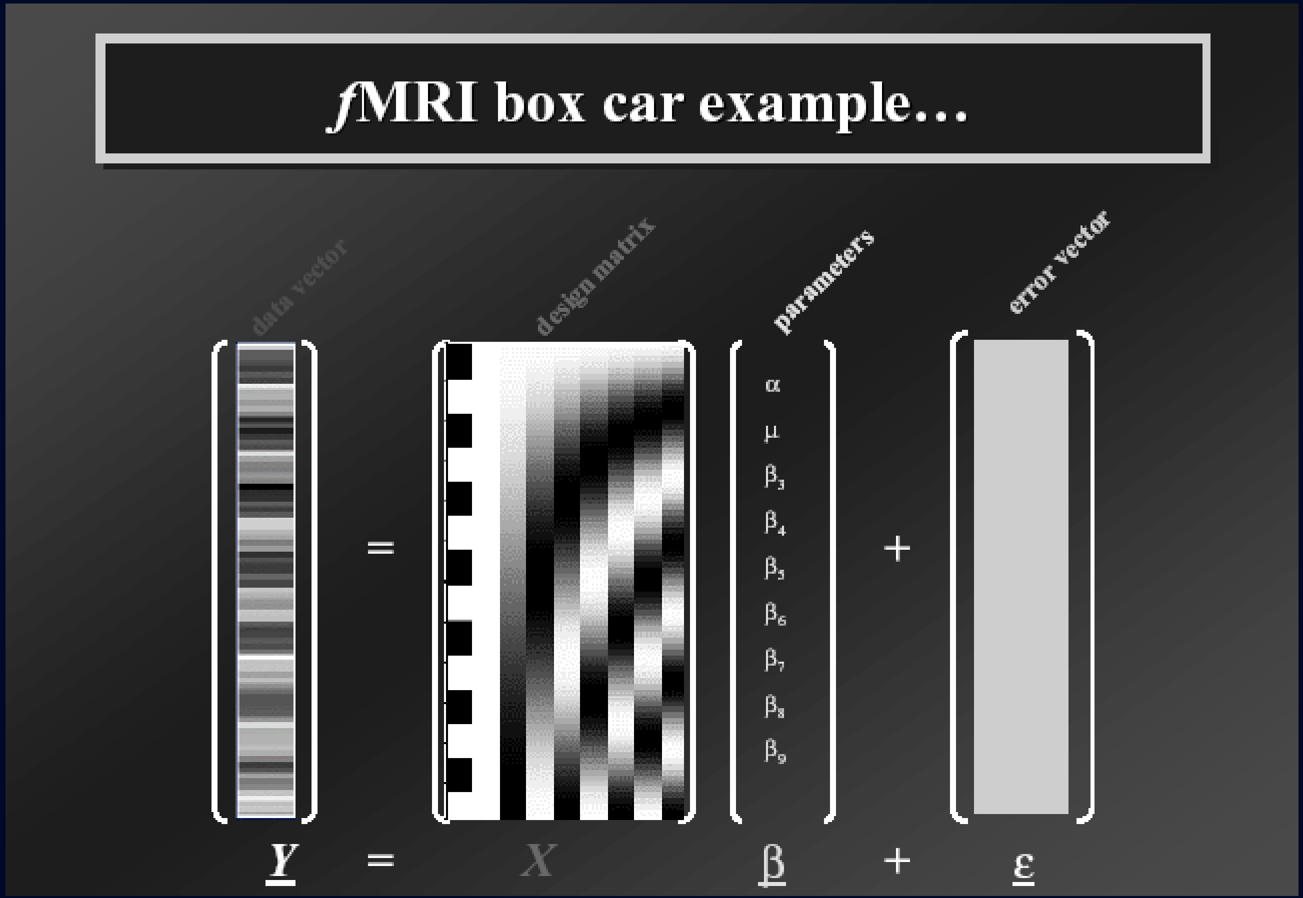
$$\varepsilon_s \sim N(0,\sigma^2)$$

→ t-statistic for H_0: $\alpha > 0$

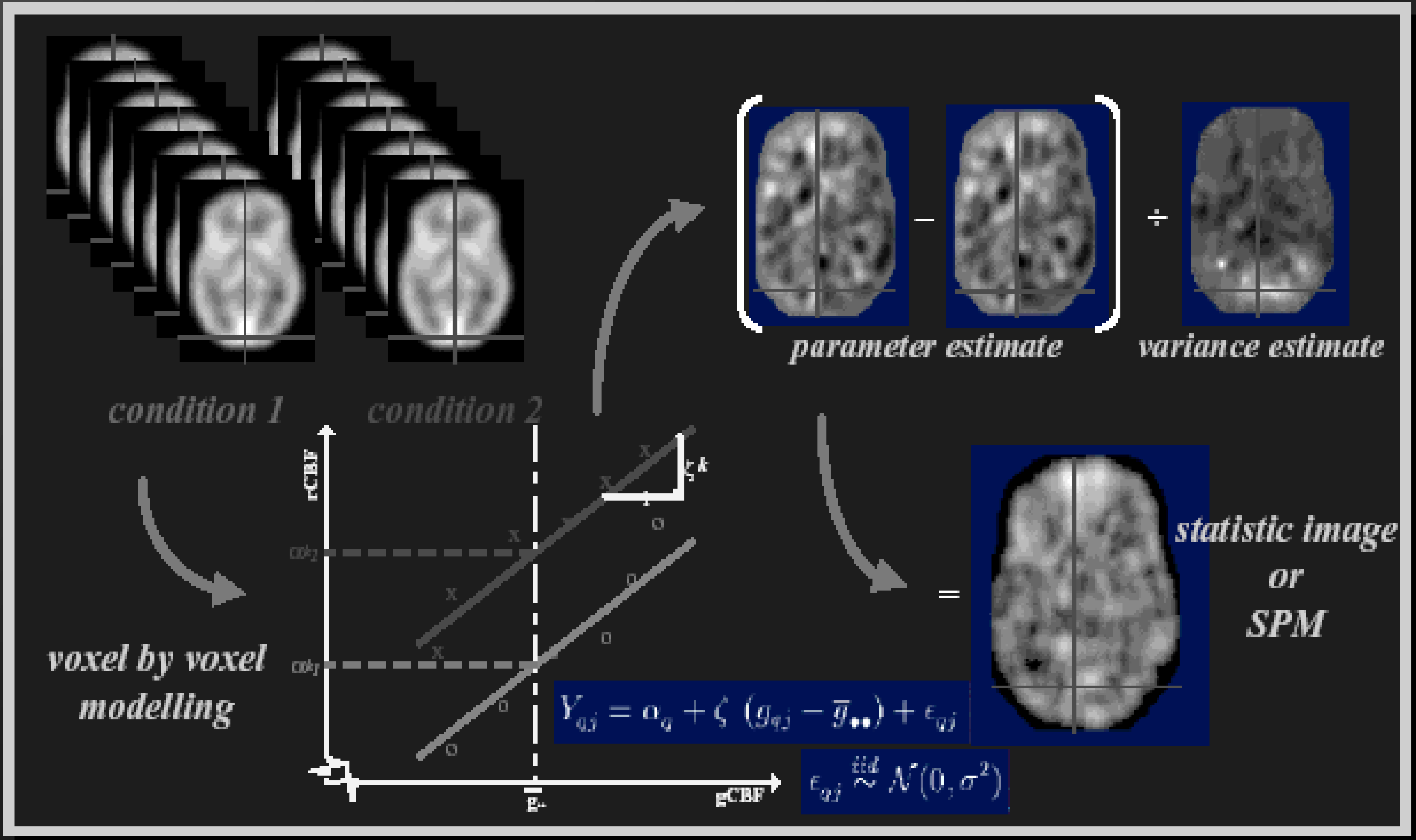
- **correlation:**
  test H_0: $\rho = 0$ equivalent to
  test H_0: $\alpha = 0$
- **two-sample t-test:**
  test H_0: $\mu_0 = \mu_1$ equivalent to
  test H_0: $\alpha = 0$

✔ *can extend to account for temporal autocorrelation!*


…revisited
0 0 0 0 1 0 0 0 0 0 0 0 1 0 0 0 0 0 0
1 0 0 1 0 2 0 0 1 0 0 2 0 0 1 1 0 0 0
0 0 0 0 8 20 015 0 0 0 1 0 1 0 1 0 0
7 0 0 4 0 0 0 0 77 35 7 0 1 0 0 1 0
2 18 0 72 36 25 65 27 31 0 0 1 0 0
0 6 29 36 14 12 42 11 9 0 0 0 0 0 0
8 8 3 51 6 21 15 3 0 4 0 0 0 0 0 3 5
8 11 15 6 11 14 5 9 0 0 0 0 21 34 0
68 0 6 8 1 0 1 5 0 8 0 0 0 22 0 0 0 0
0 3 5 8 11 7 0 0 0 0 0 0 0 0 0 0 0 0 0
1 0 0 1 0 0 0 0 0 0 1 0 0 0 0 0 1 0
0 0 0 1 0 1 2 0 0 0 23 0 0 0 0 10 0 0
= μ
+ α
+
error
$Y_s = \mu \times 1 + \alpha \times f(t_s) + \varepsilon_s$


fMRI box car example…
data vector
design matrix
parameters
error vector
α
μ
β3
β4
β5
β6
β7
β8
β9
=
+
Y = X β + ε

Statistical Parametric Mapping…



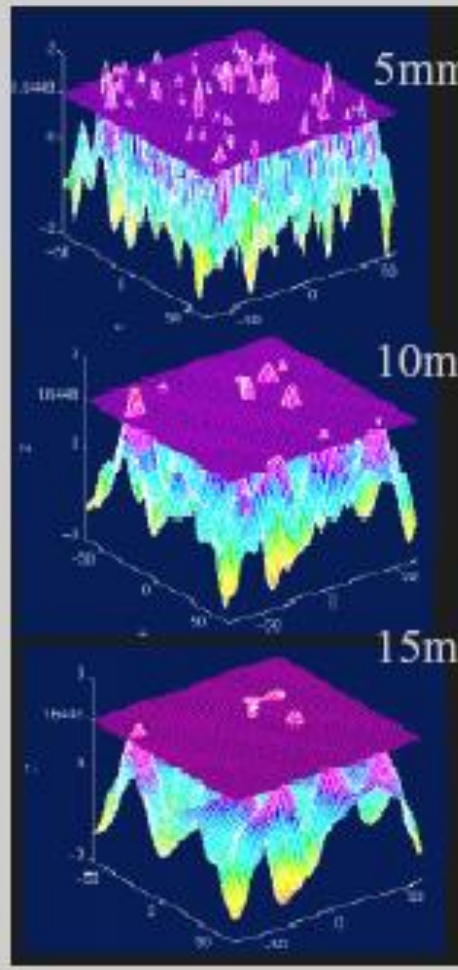
SPM approach: Random fields…

- Consider statistic image as lattice representation of a continuous random field
- Use results from continuous random field theory

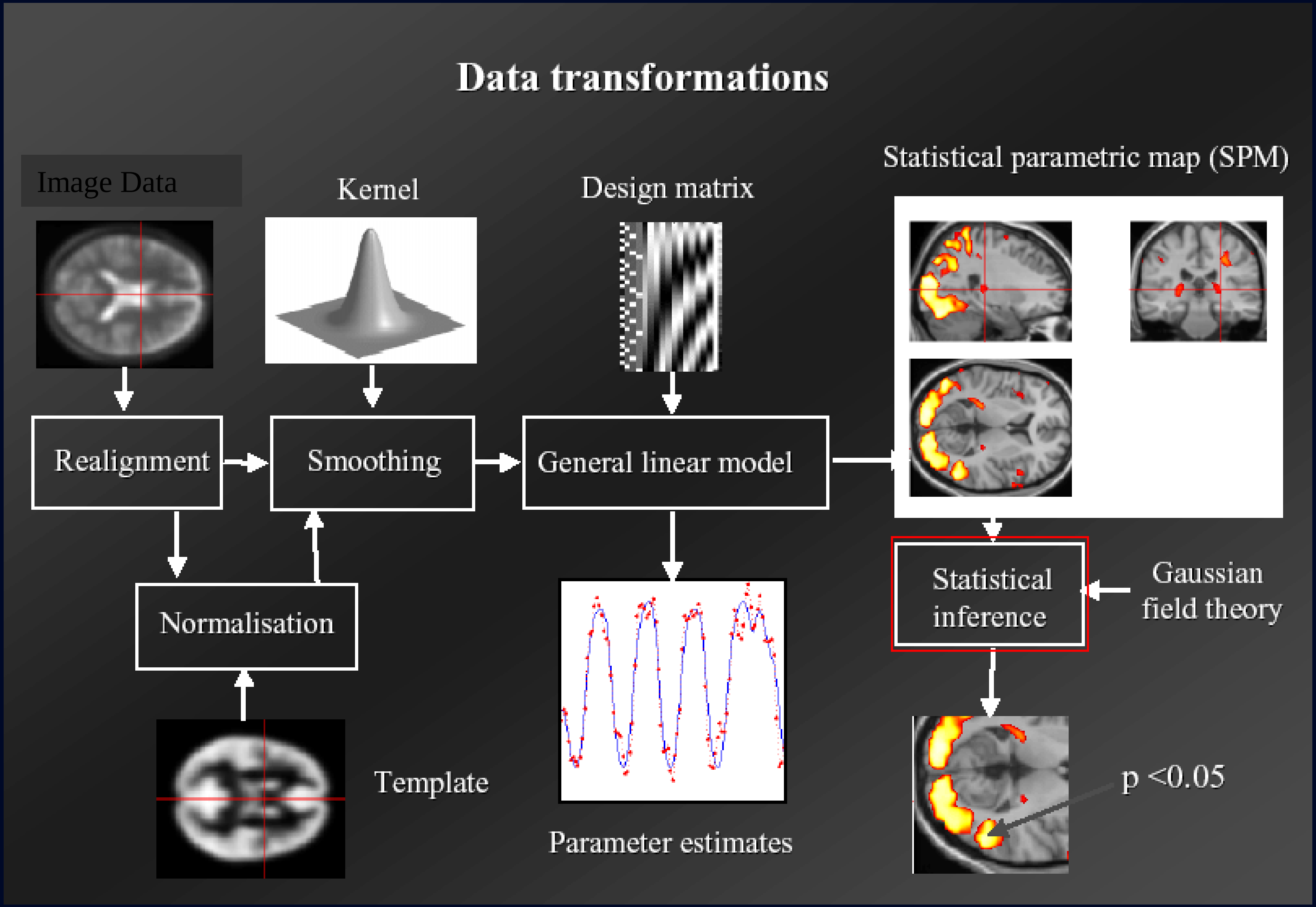
Suprathreshold cluster tests…

- **Primary threshold *u***
  - examine connected components of excursion set
  - *Suprathreshold clusters*
  - Reject H^W for clusters of voxels W of size $S > s_\alpha$
- **Localisation (Strong control)**
  - at cluster level
  - increased power
  - esp. high resolutions (*f* MRI)
- **Thresholds, *p* –values**
  - $\Pr(S^\Omega_{max} > s_\alpha \mid H^\Omega) \leq \alpha$

    Nosko, Friston, (Worsley)
  - Poisson occurrence *(Adler)*
  - Assumme form for $\Pr(S=s \mid S>0)$



(2mm² pixels)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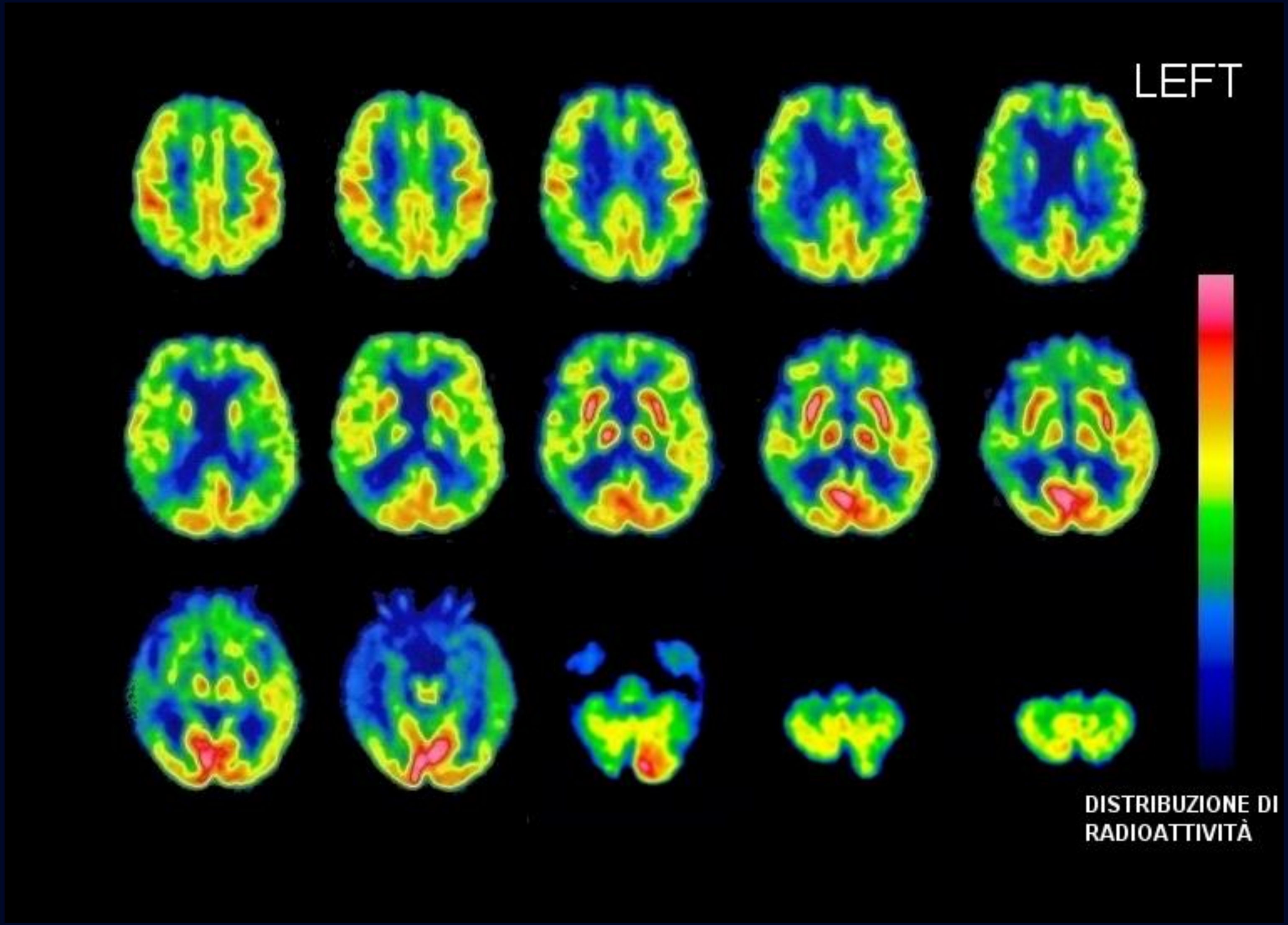
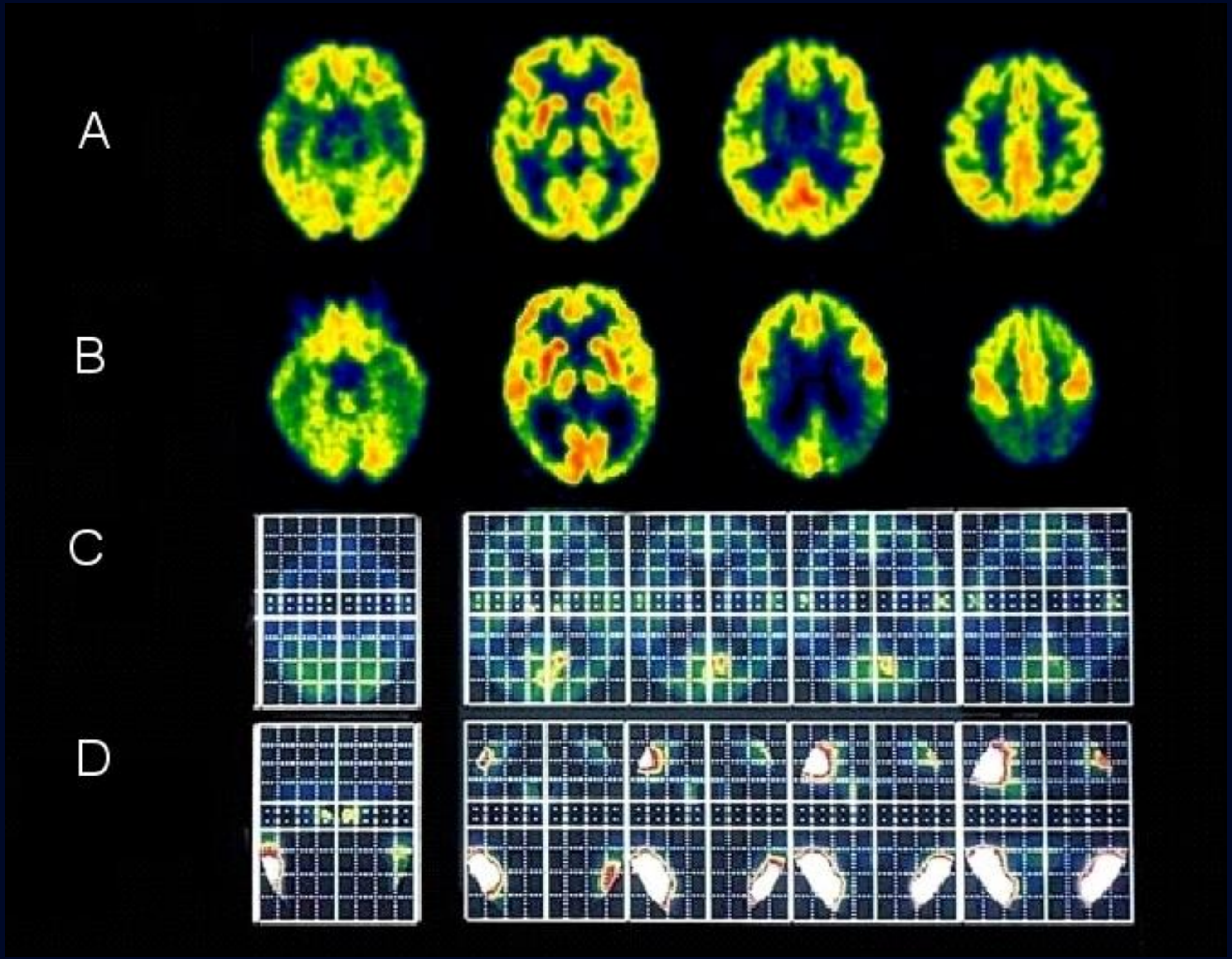
Principali applicazioni cliniche di SPM in Neurologia PET

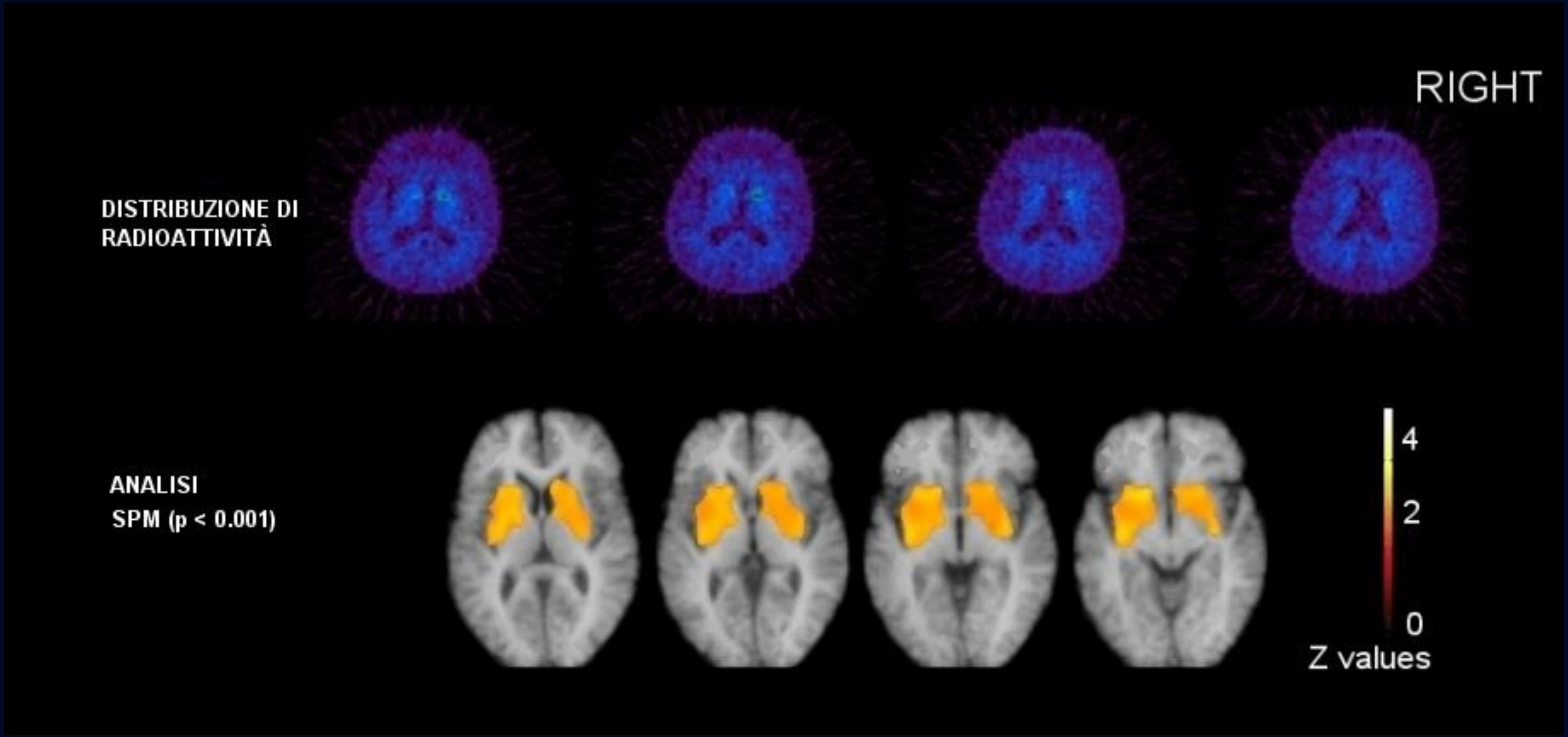
- Valutazione delle demenze e diagnosi precoce
- Valutazione e follow-up dei disordini del movimento
- Localizzazione del focolaio epilettogeno



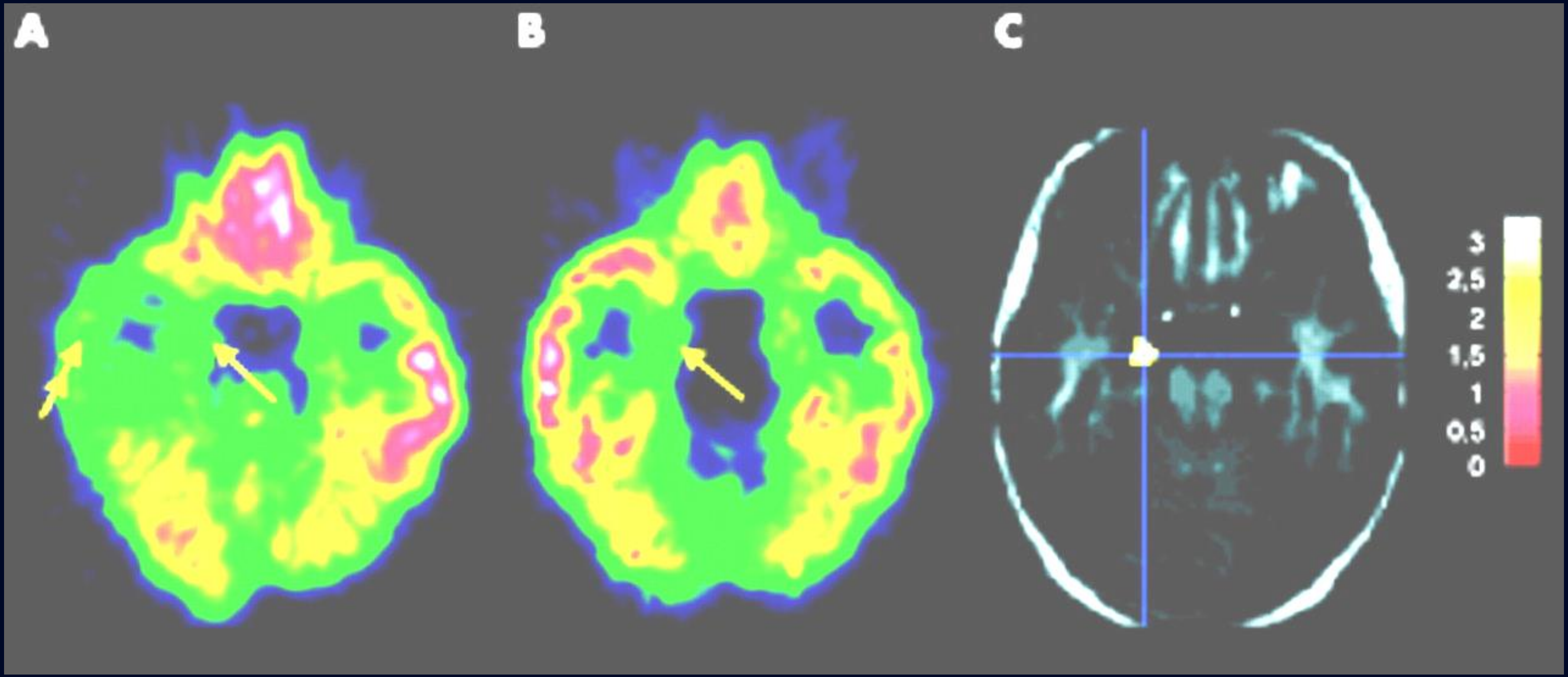
Studio ^{18}F-FDG PET in un caso di AD che presenta prevalenti disturbi visuospaziali. L' ipometabolismo è asimmetrico con prevalente compromissione emisferica destra.



SPM. I confronti statistici tra immagini normalizzate consentono di identificare le regioni in cui il metabolismo glucidico e’ inferiore in modo statisticamente significativo rispetto ai valori di un gruppo controllo. Tali pattern rappresentano biomarcatori per la diagnosi di AD.

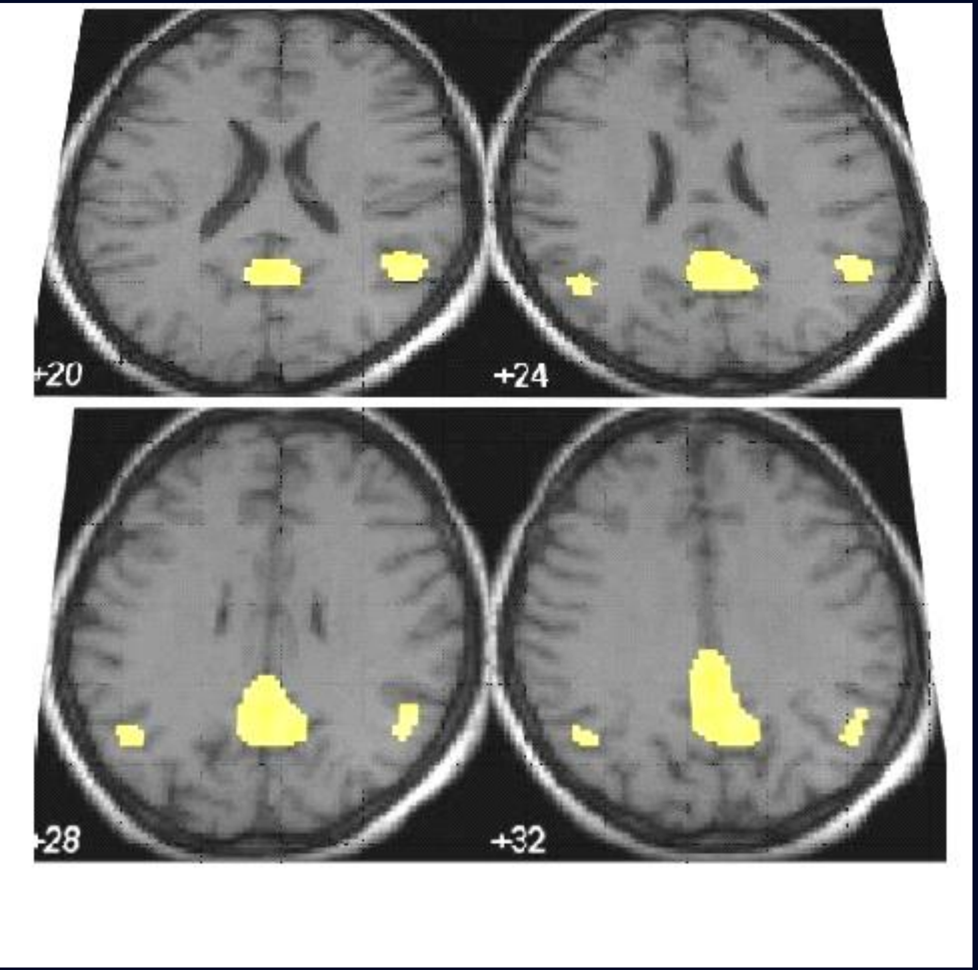


Studio PET con ^{11}C-beta-CIT-FE in un paziente con demenza a corpi di Lewy. L'analisi qualitativa e statistica delle immagini evidenzia riduzione bilaterale della captazione del radiotracciante a livello dei gangli della base, estesa a tutto lo striato. Tali pattern rappresentano biomarcatori per la diagnosi di AD.



28 year-old patient with complex partial seizure

A) ^{18}F-FDG-PET
B) ^{11}C-FMZ-PET
C) SPM : significant decrease of FMZ VD in the left anterior hippocampus compared with 21 controls. Statistical map is overlaid on the patient's own MRI.



Studio ^{18}F-FDG PET in soggetti con Mild Cognitive Impairment (MCI) che hanno successivamente dimostrato una progressione ad AD nel corso di un anno. In giallo aree ipometaboliche: corteccia retrospleniale e corteccia temporo-parietale bilaterale ($p < 0.001$). Tali pattern rappresentano biomarcatori per la diagnosi precoce di AD