

MULTIVARIATE ANALYSES WITH fMRI DATA

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Motivation

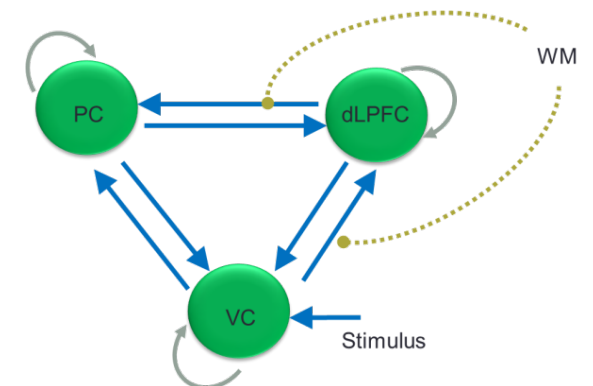
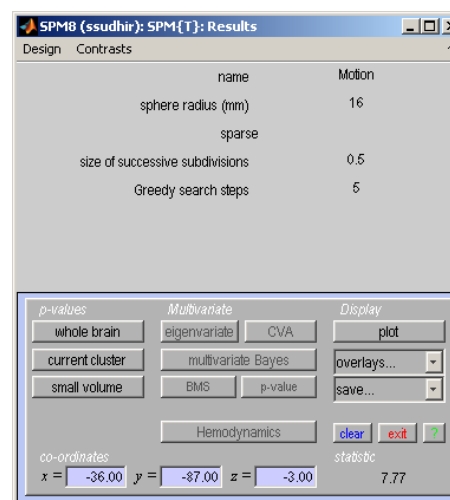
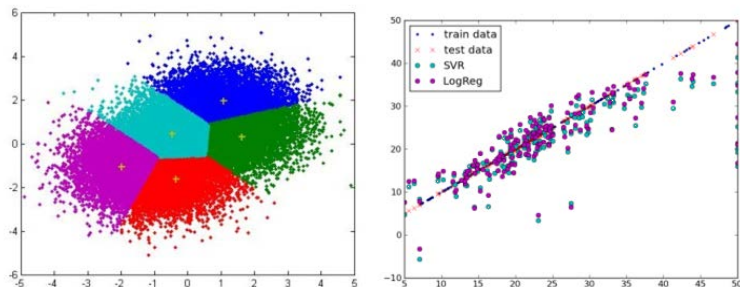


Modelling Concepts

Learning From Data

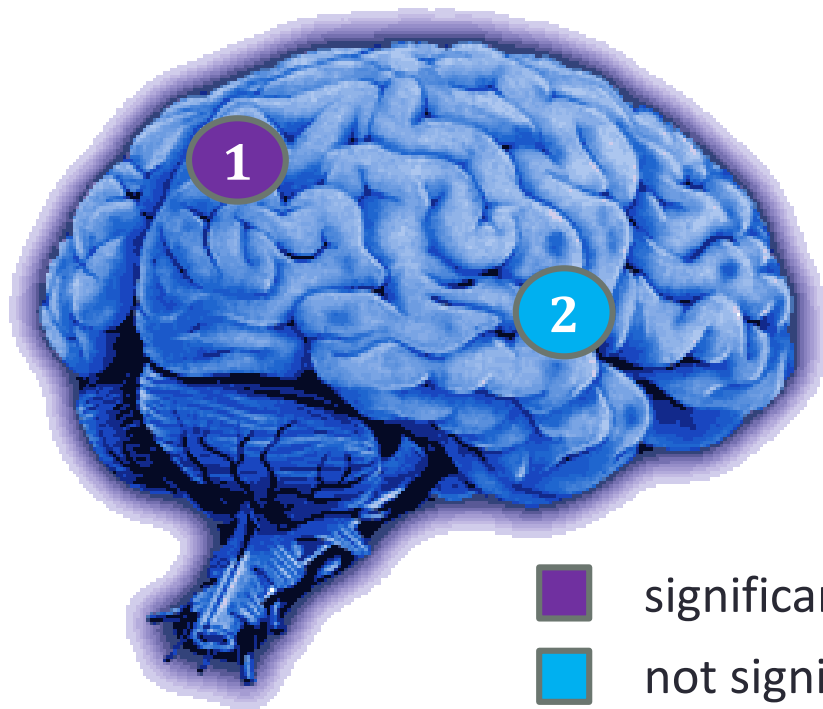
Multivariate Bayes in SPM

Generative Embedding

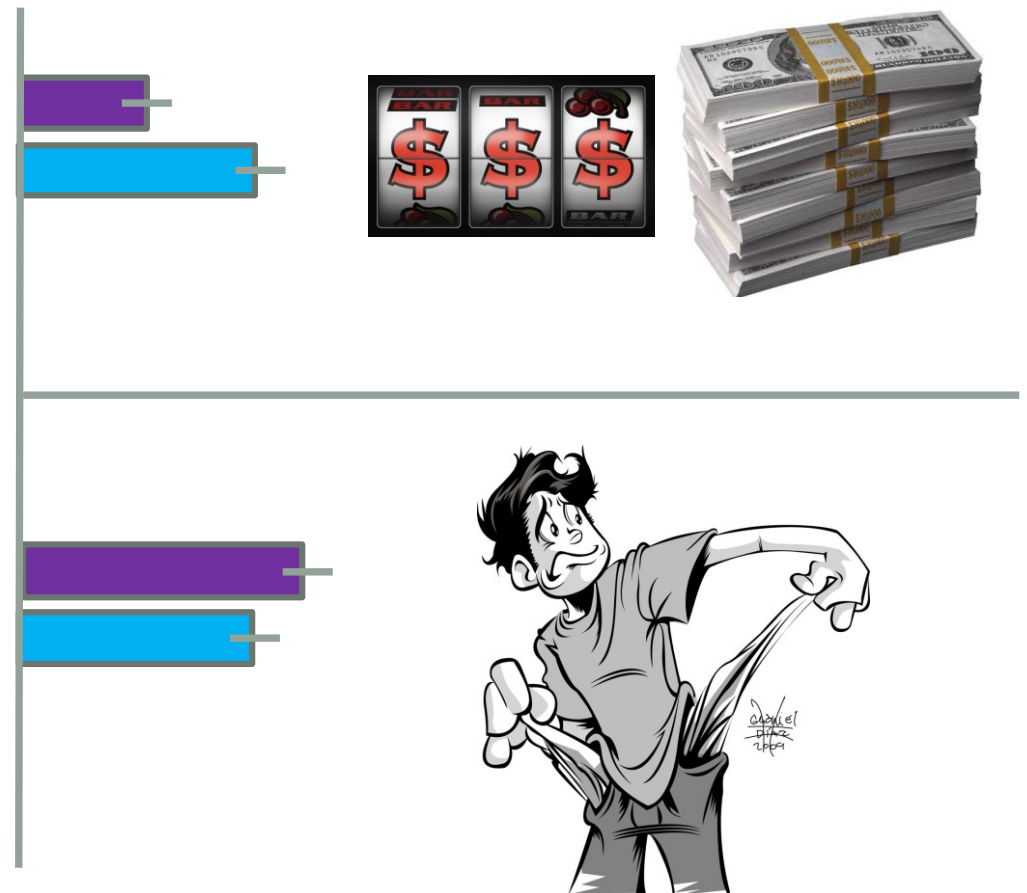


Motivation

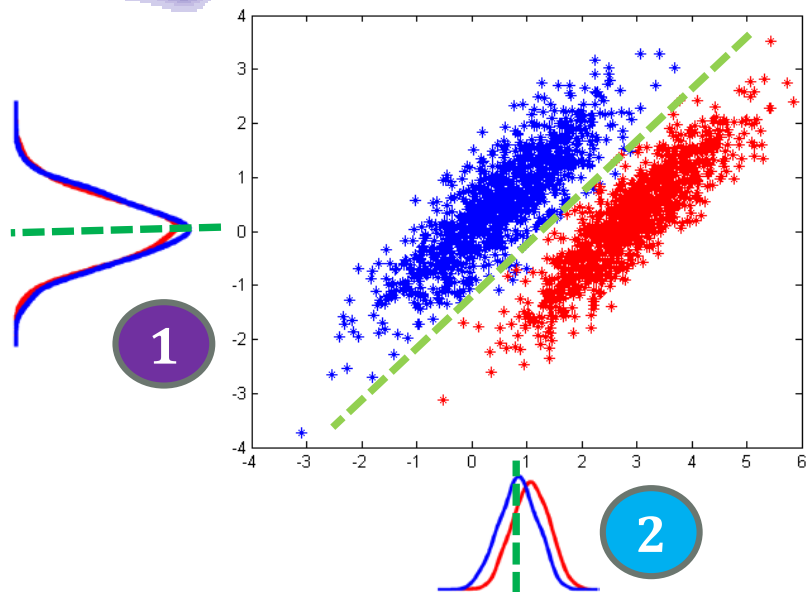
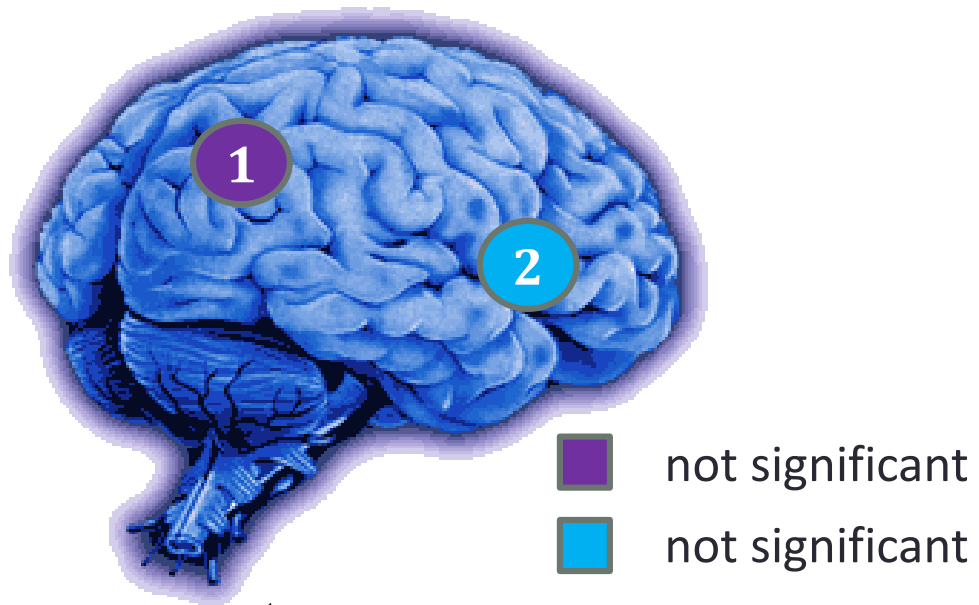
- Local activations – Univariate approach



■ significant
■ not significant



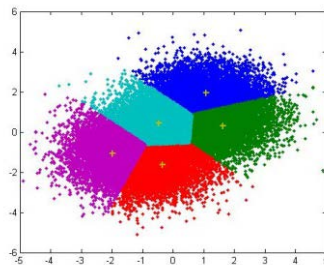
Univariate to Multivariate



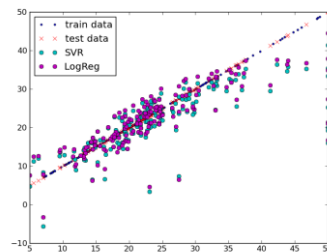
Motivation



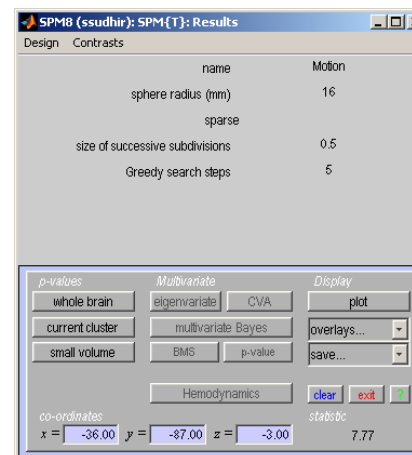
Modelling Terminology



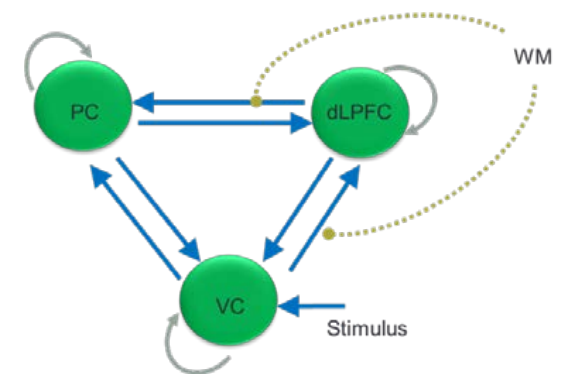
Learning from data



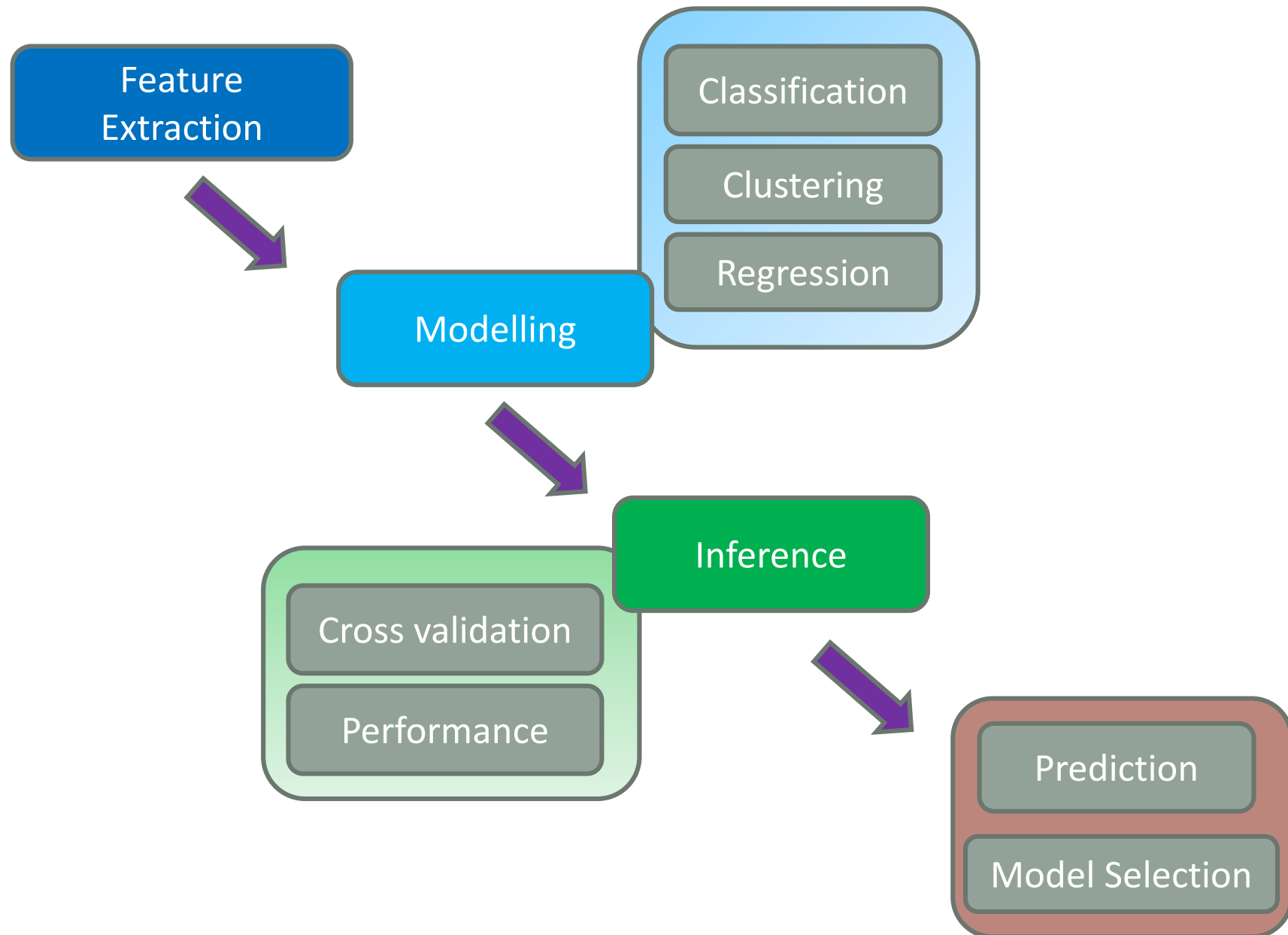
Multivariate Bayes in SPM



Generative Embedding



Steps for analysis

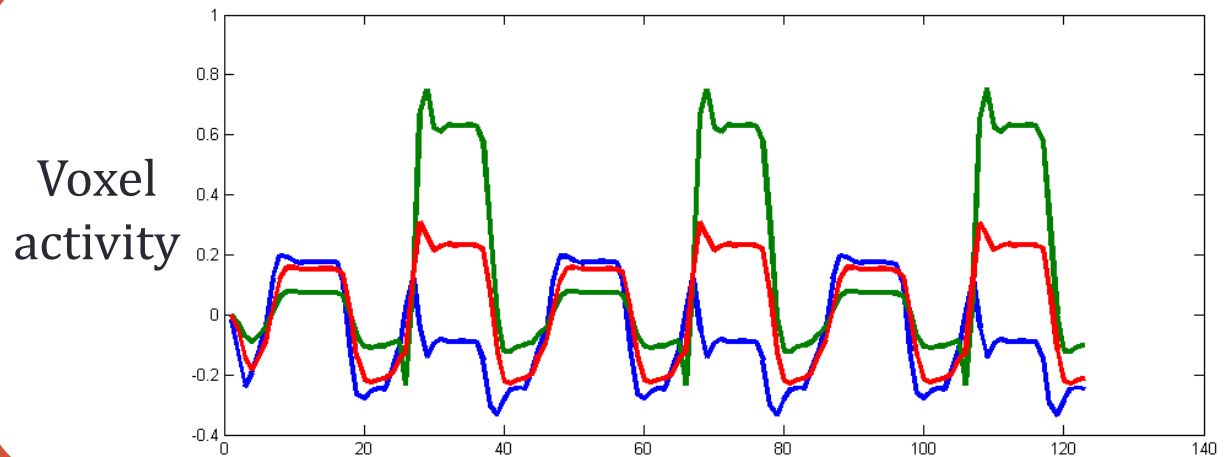


Feature Spaces

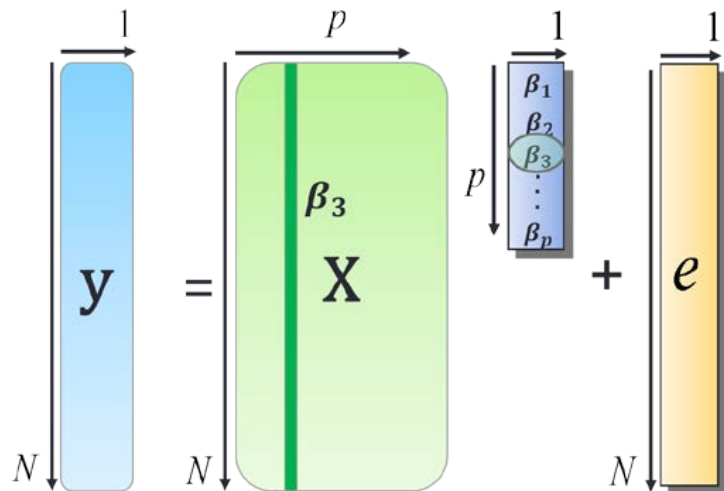
	F_1	F_2	$\cdot$	$\cdot$	$\cdot$	F_p
S_1						
S_2	Data Point or Feature Vector					
$\cdot$						
$\cdot$						
S_N						

- High dimensionality
- Class/Cluster distributions
- Interpretation

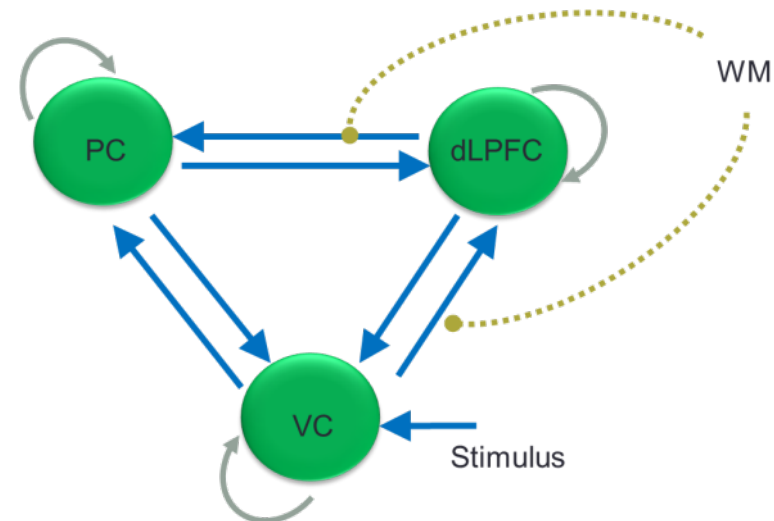
Raw data



Model parameters



GLM – regression coefficients



DCM – connection parameters

Modelling goals

- Prediction



Predictive Density

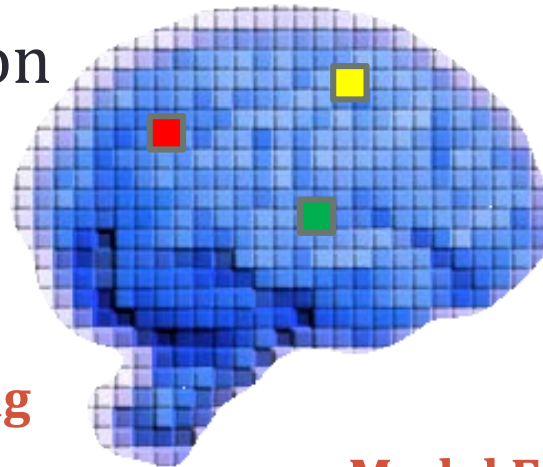
$$p(X_{\text{new}}|Y_{\text{new}}, X, Y) = \int p(X_{\text{new}}|\theta, Y_{\text{new}})q(\theta)d\theta$$



Healthy Brain Severe AD

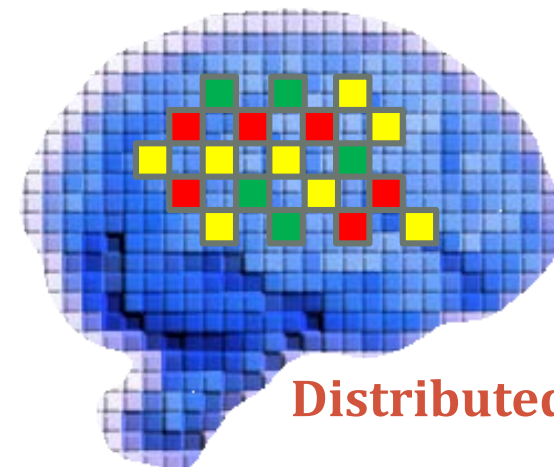


- Model Selection



Sparse Coding

VS

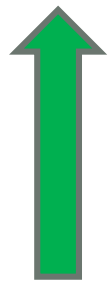


Distributed Coding

Model Evidence

$$p(Y|X) = \int p(Y, \theta|X)d\theta$$

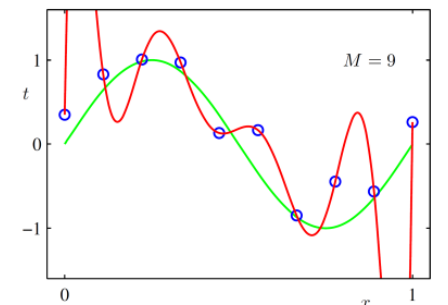
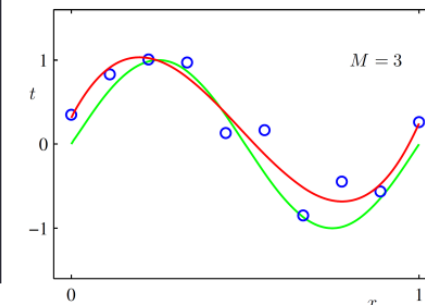
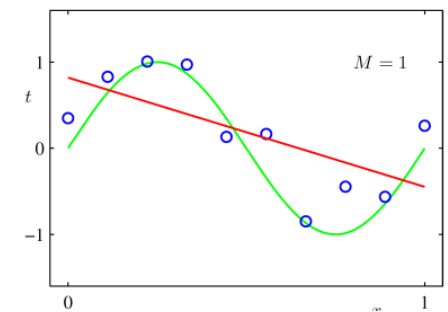
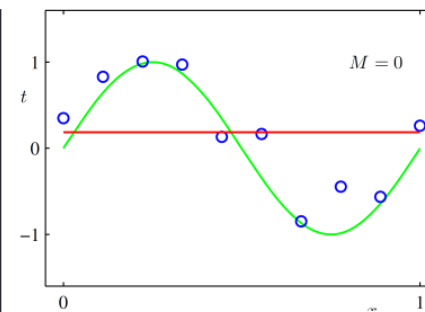
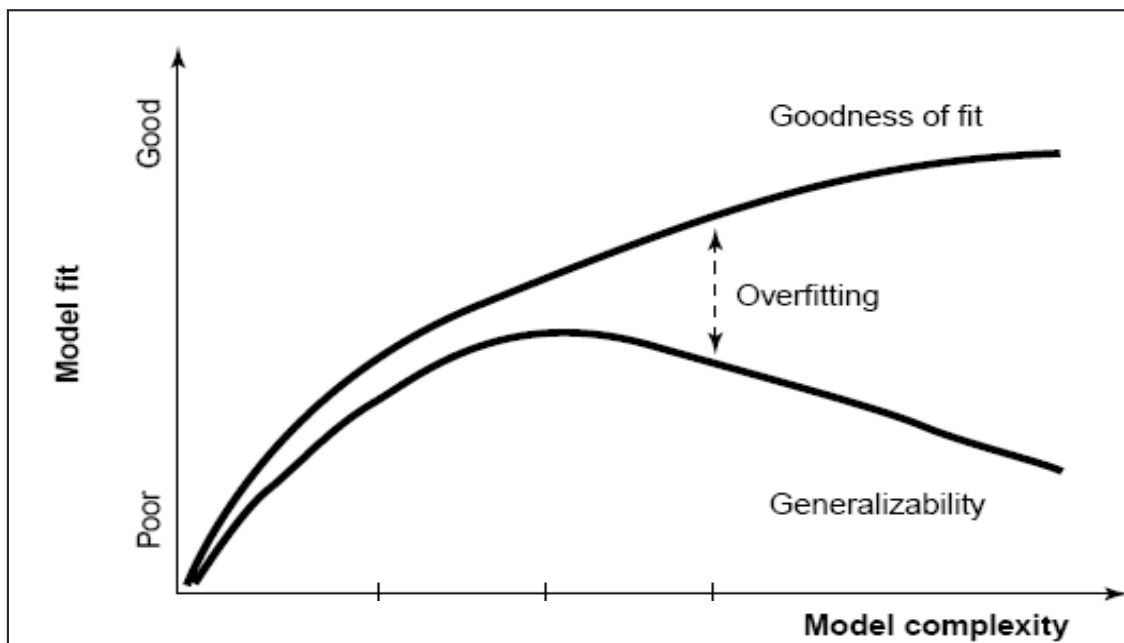
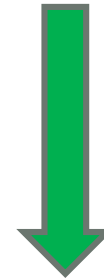
Model Selection - Generalizability



Model
Fit

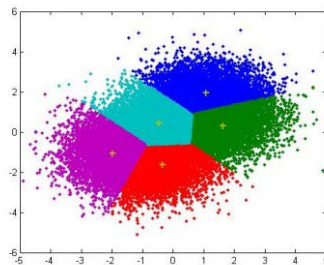


Model
Complexity

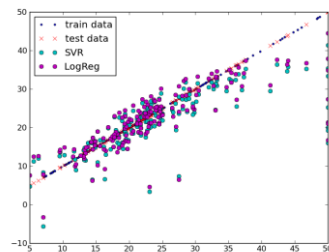


Motivation

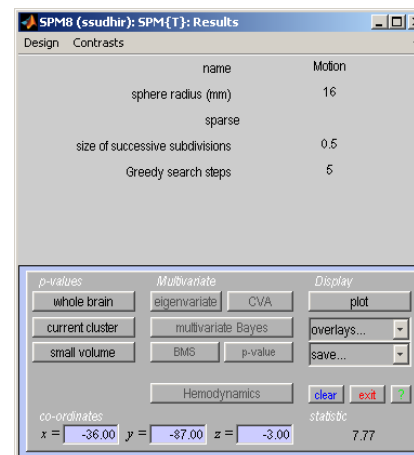
Modelling
Concepts



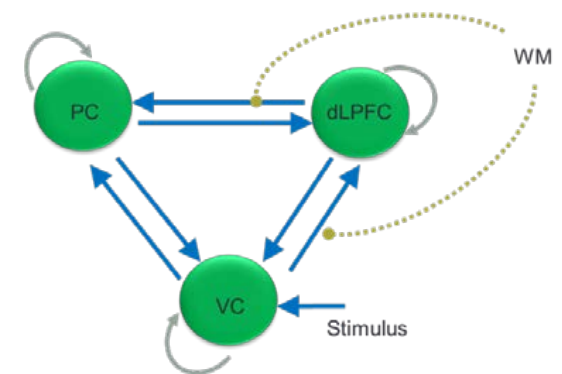
Learning
From Data



Multivariate
Bayes in SPM

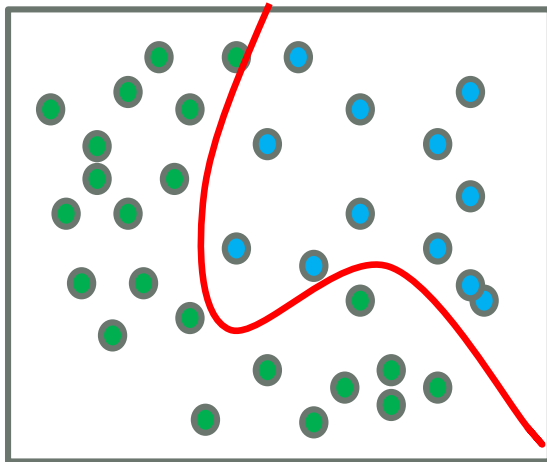


Generative
Embedding

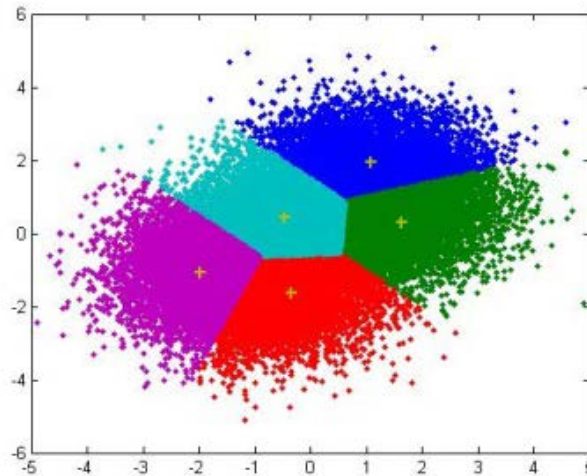


Learning from Data

Supervised
Learning



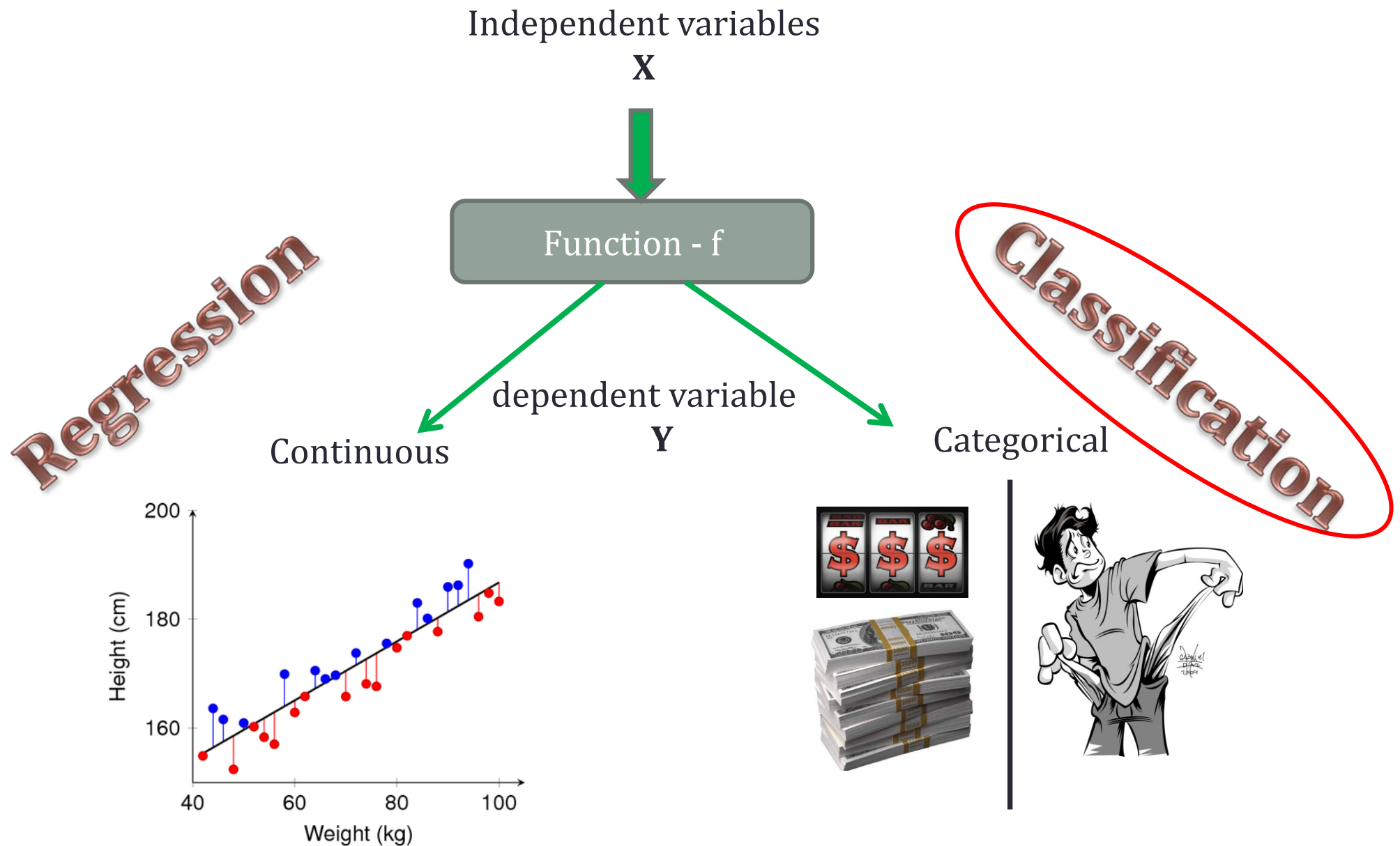
Unsupervised
Learning



Reinforcement
Learning

Semi-supervised
Learning

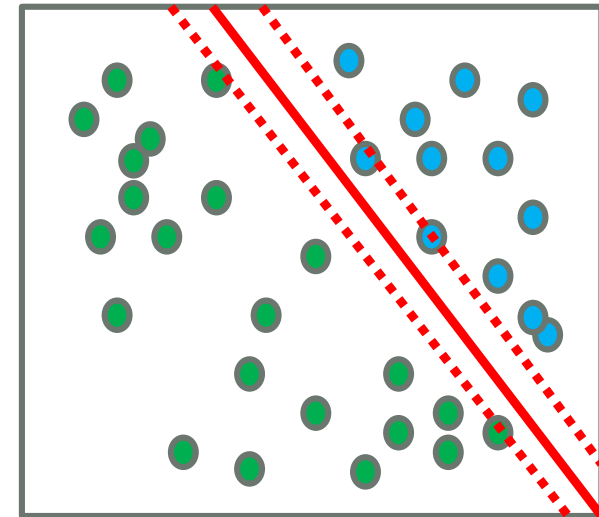
Supervised Learning



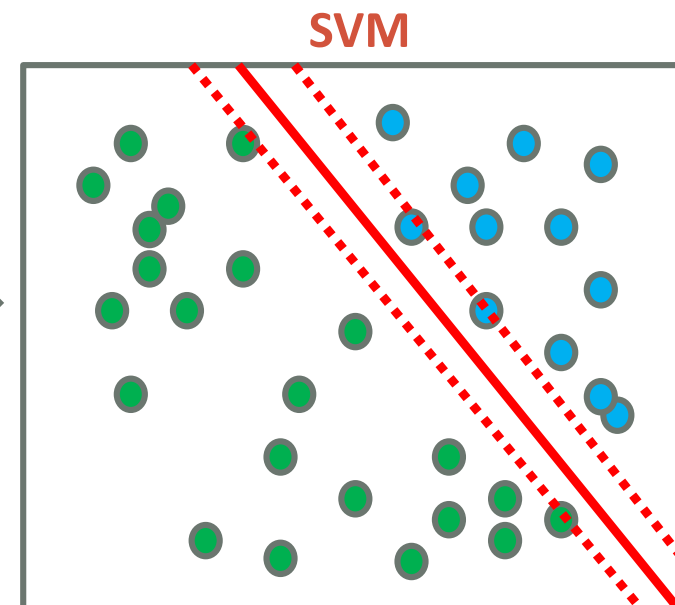
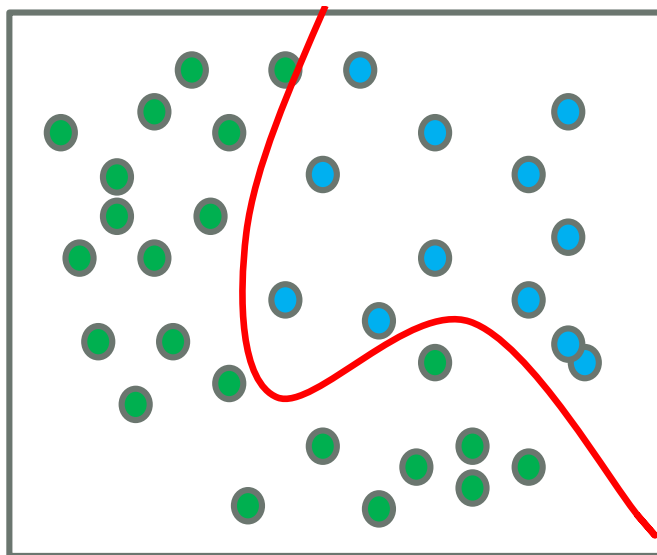
Classification



- Generative classifier
- Discriminative classifier



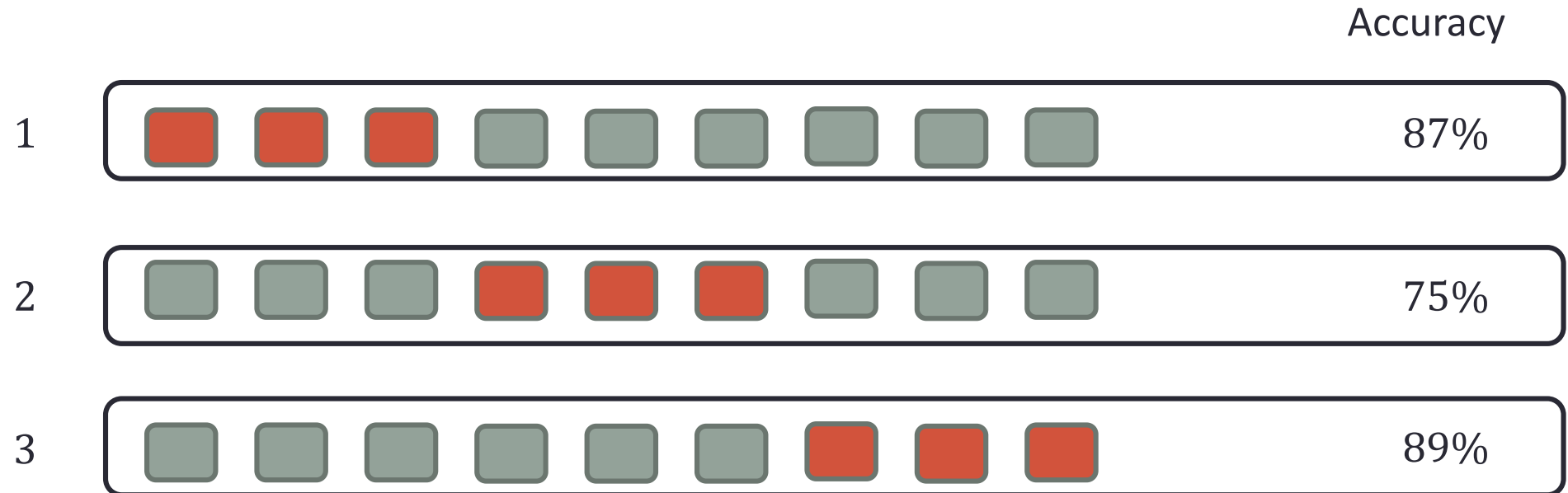
Kernel Methods



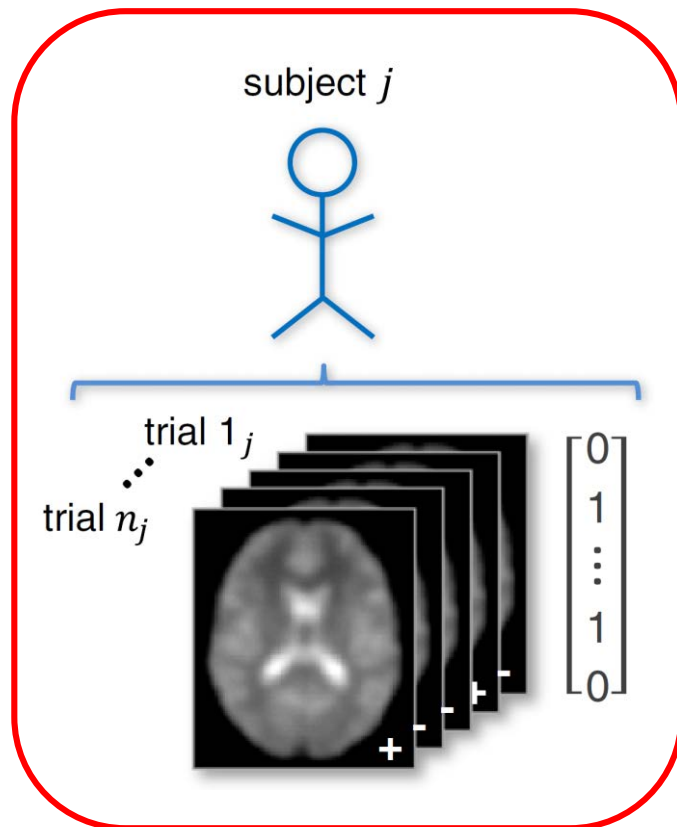
- Kernel Function – $K(x_i, x_j) = \phi(x_i) \cdot \phi(x_j)$

K-fold Cross Validation

- Model Selection
- Performance evaluation



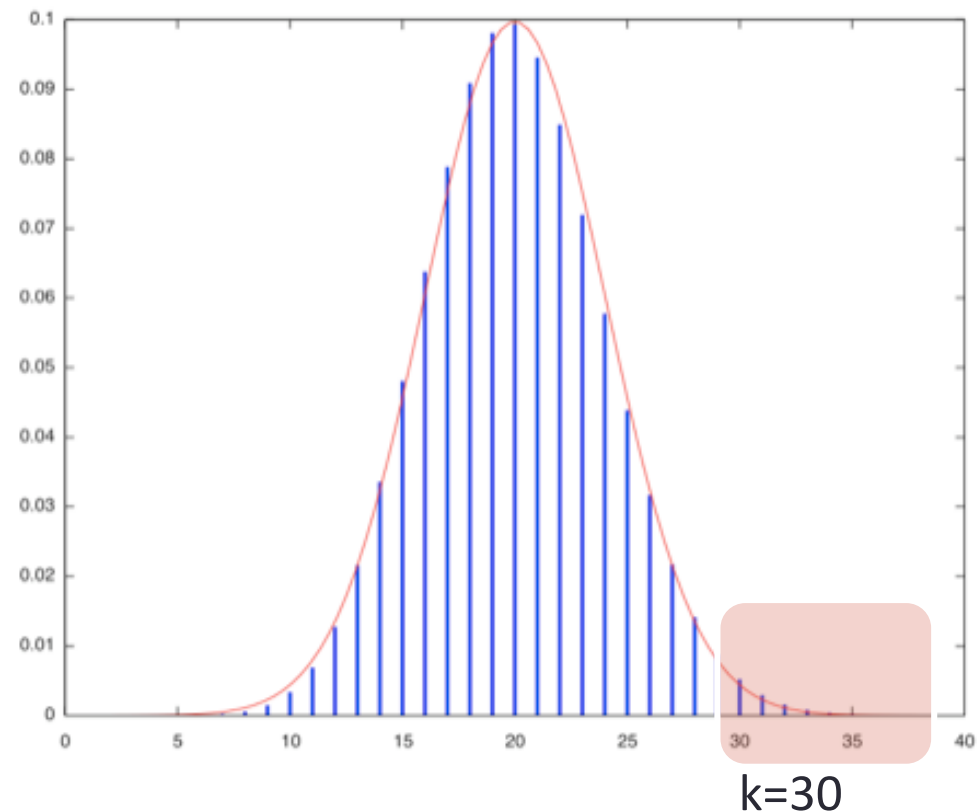
Performance – Single Subject



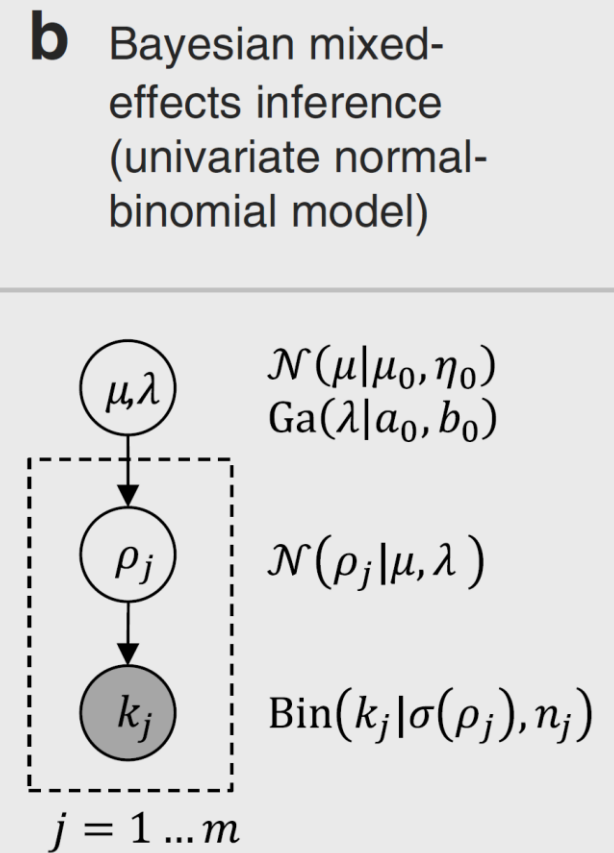
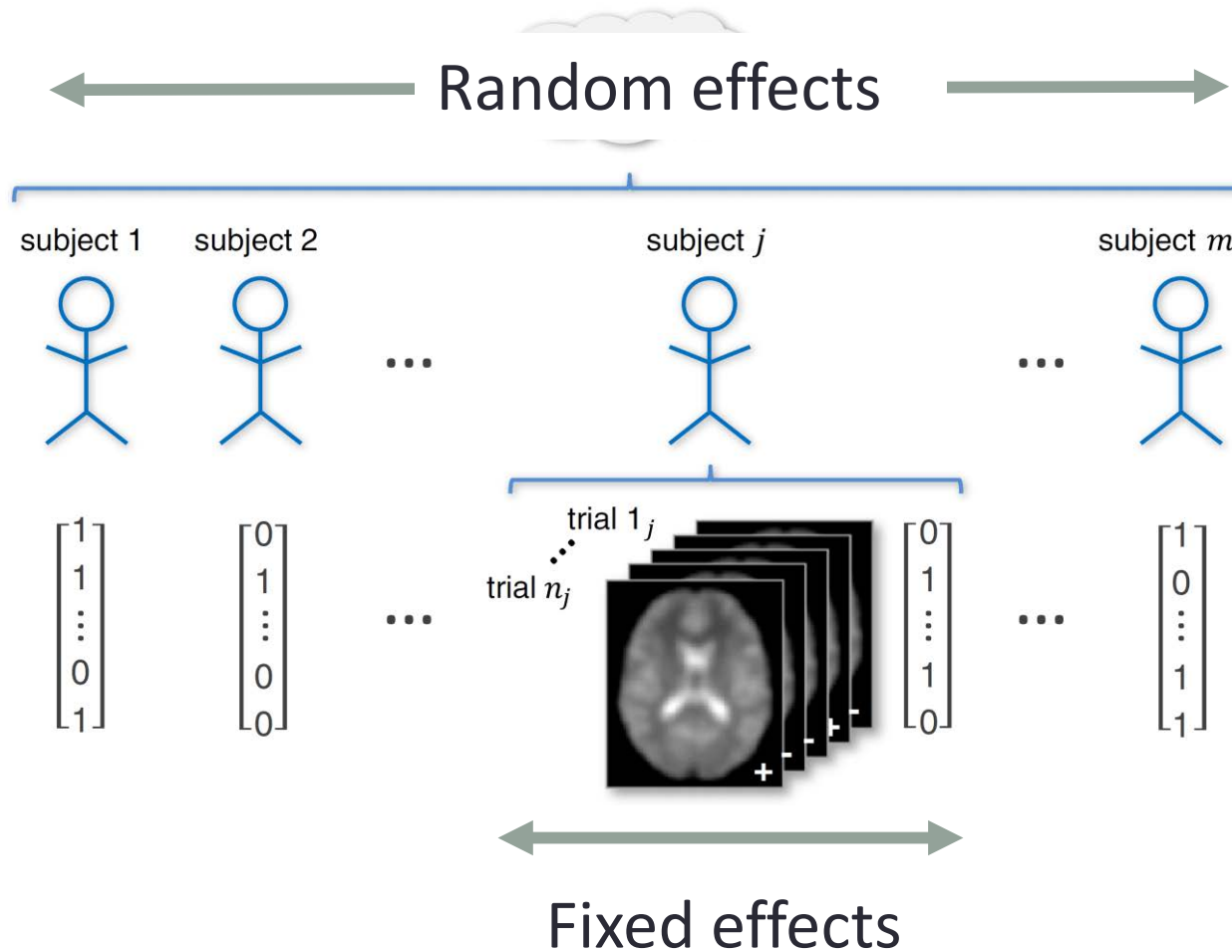
Brodersen et al. 2013, *NeuroImage*

Binomial Test

$$p = P(X \geq k | H_0) = 1 - B(k | n, \pi_0)$$



Performance – Multiple Subjects



<http://www.translationalneuromodeling.org/tapas/>

Using classification for fMRI data

Whole brain



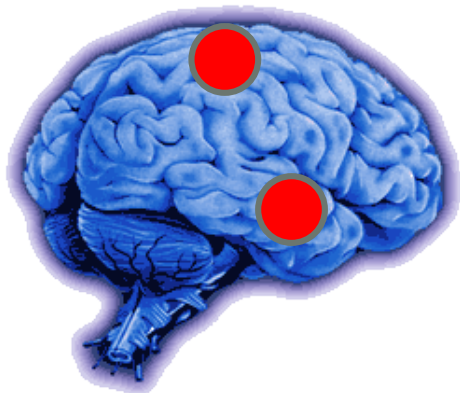
Mourao-Miranda et al. (2005) *NeuroImage*,
Marquand et al. (2010) *NeuroImage*

Searchlight classifier



Kriegeskorte et al. (2006) *PNAS*

Pattern localization

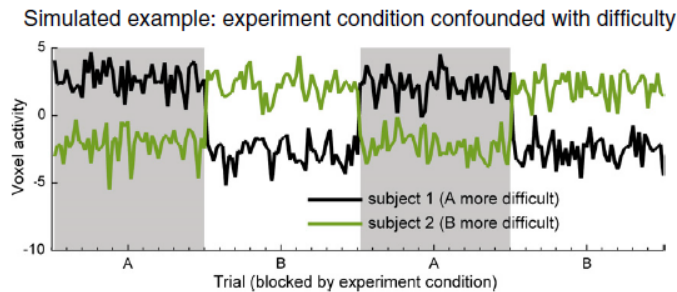


Word Category

Food
Building
People

Pereira et al. (2009) *NeuroImage*, Mitchell et al. (2004) *Machine Learning*

Confound – GLM vs MVPA

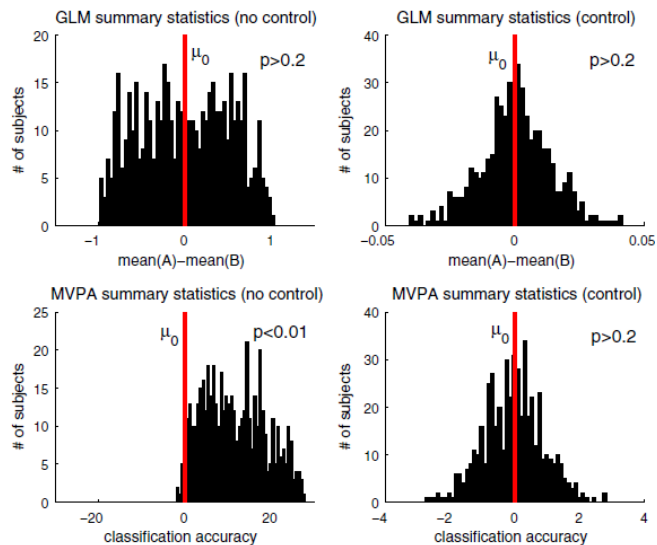


Individual-Subject Summary Statistics

Subject	Experimental Effect (GLM)	Discrimination Success (MVPA)
Subject 1	mean(A)-mean(B) = +4.75	classification accuracy = +13.15, within-minus-across = +3.826
Subject 2	mean(A)-mean(B) = -5.56	classification accuracy = +13.44, within-minus-across = +3.848

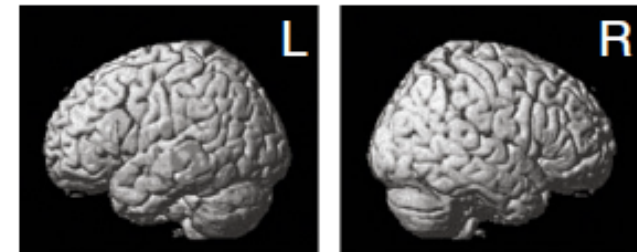
Group Test Statistics (two-tailed t-test)

Experimental Effect (GLM)	Discrimination Success (MVPA)
mean(A)-mean(B): $t_1 = -0.0780$, $p = 0.9504$, n.s.	classification accuracy: $t_1 = 94.0$, $p < 0.01$, sig.

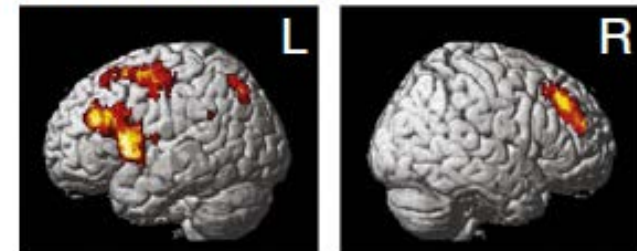


Task Rule (A vs. B)

GLM



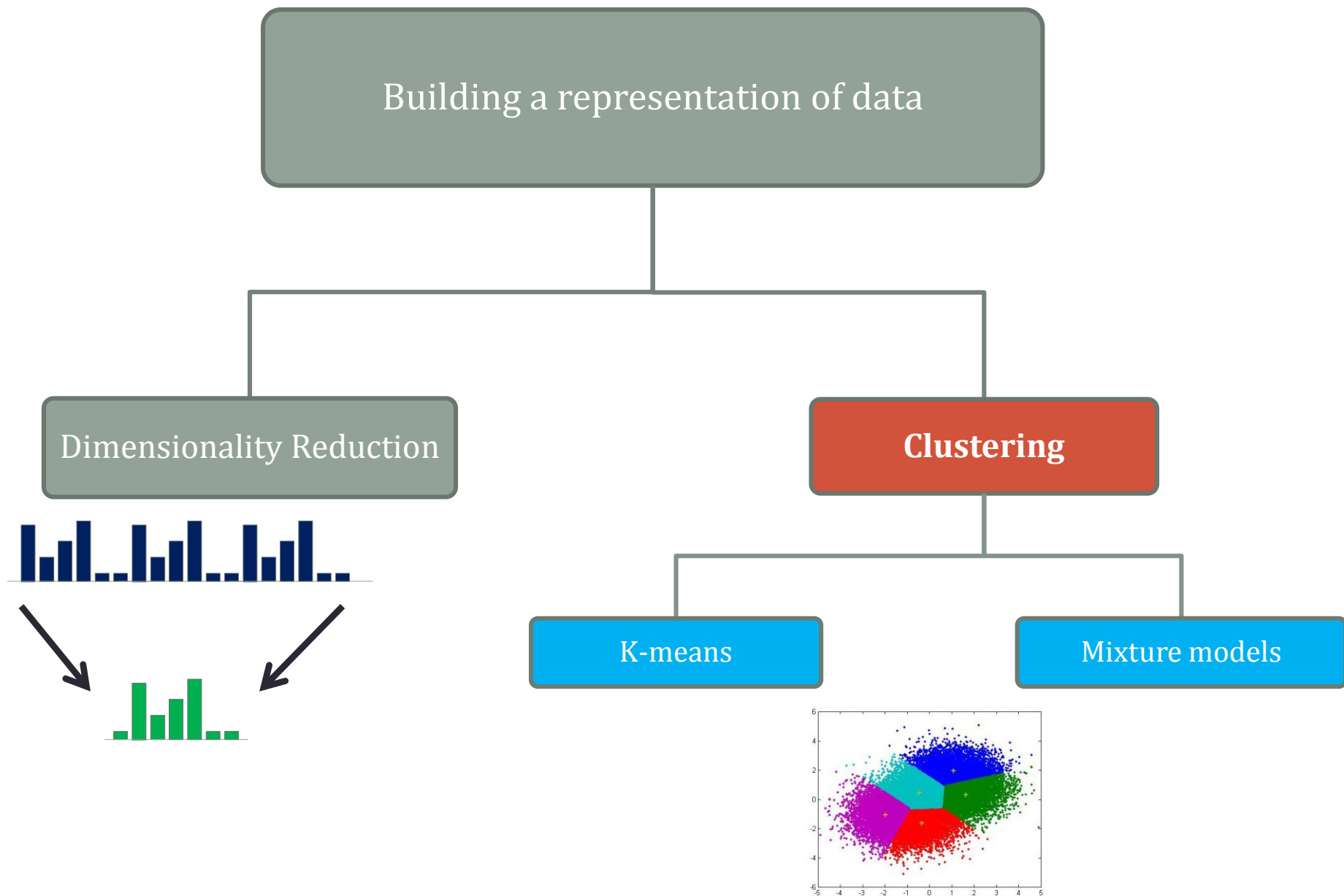
MVPA (no control)



MVPA (after RT regression)

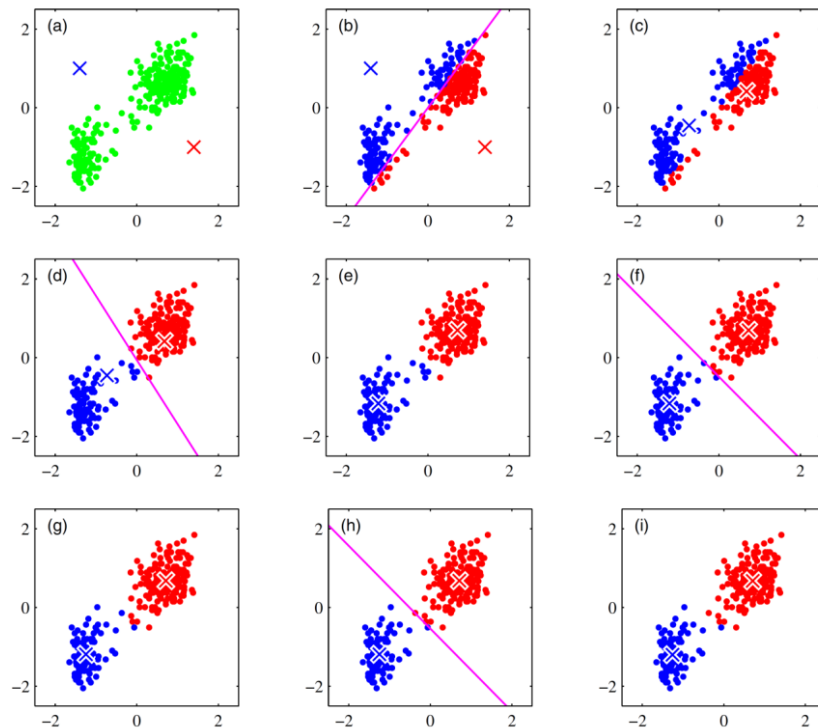


Unsupervised Learning

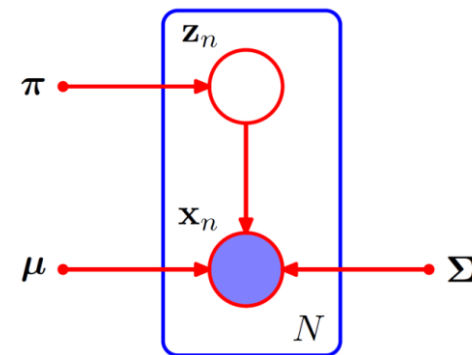


K-means

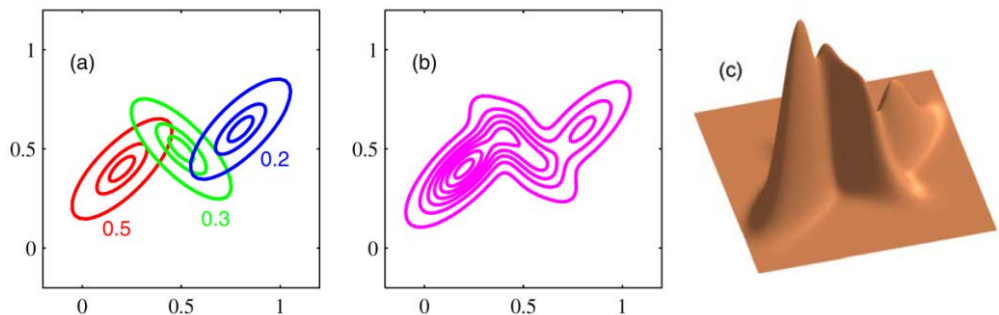
$$\tilde{J} = \sum_{n=1}^N \sum_{k=1}^K r_{nk} \mathcal{V}(\mathbf{x}_n, \boldsymbol{\mu}_k)$$



Mixture of Gaussians

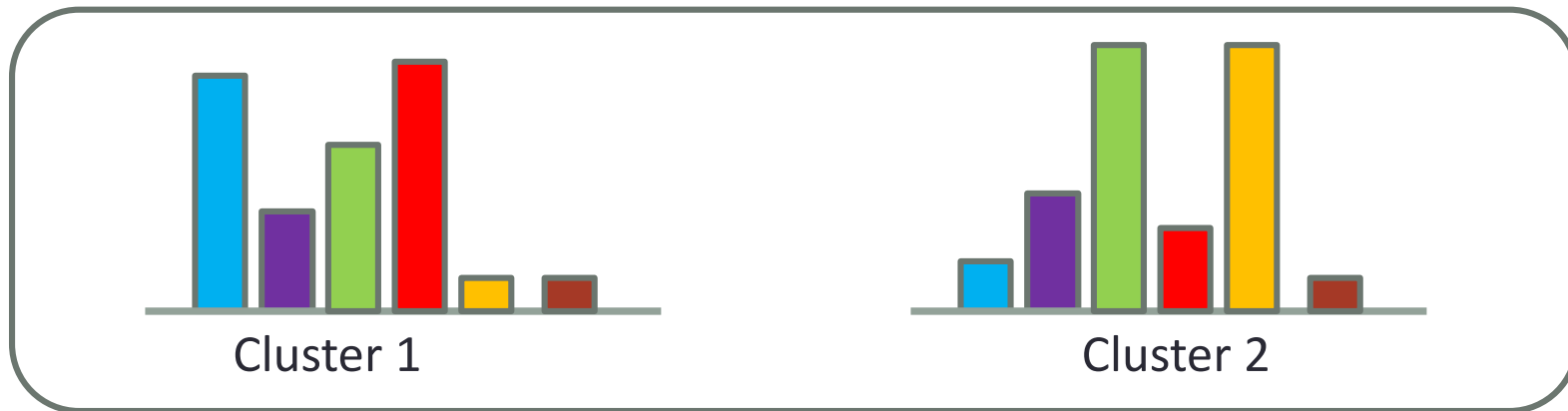


$$p(\mathbf{x}) = \sum_{k=1}^K \pi_k \mathcal{N}(\mathbf{x} | \boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k)$$

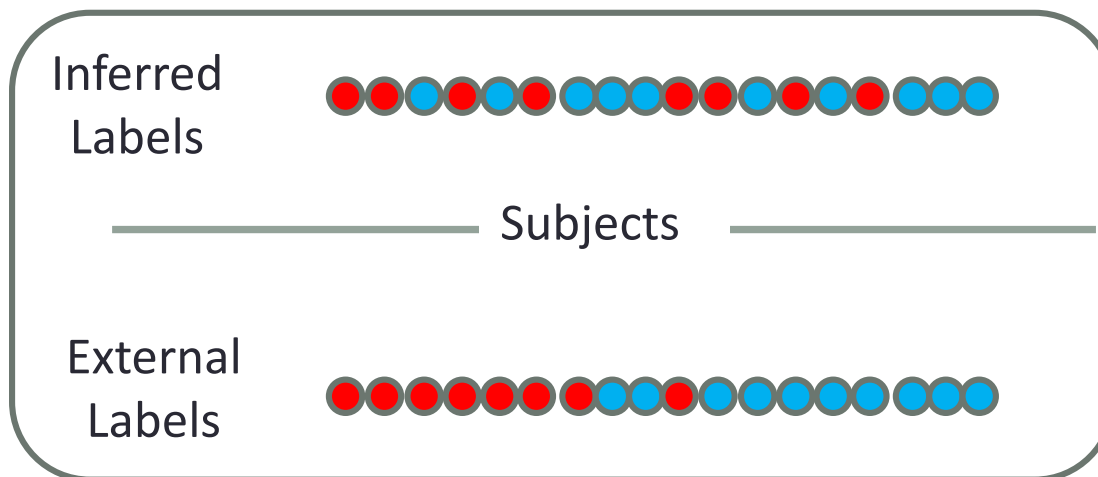


Interpretation

- Cluster parameters



- Internal Criterion – Model Evidence
- External Criterion - Purity



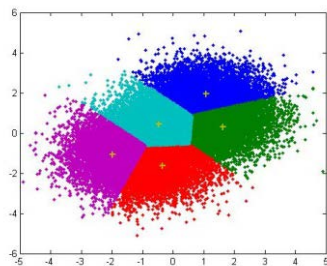
Normalized Mutual Information (NMI)

Balanced purity

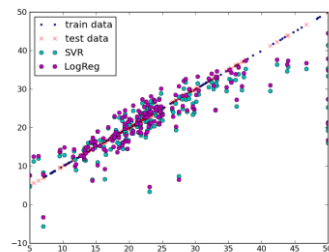
Rand Index

Motivation

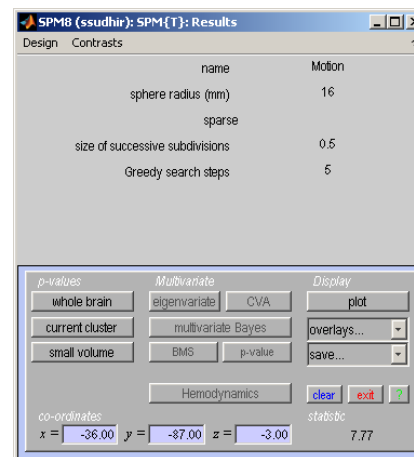
Modelling



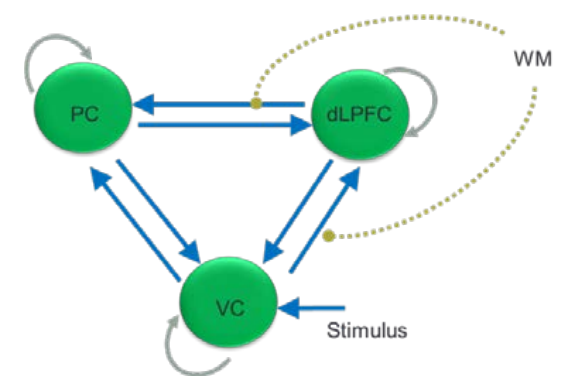
Learning
from Data



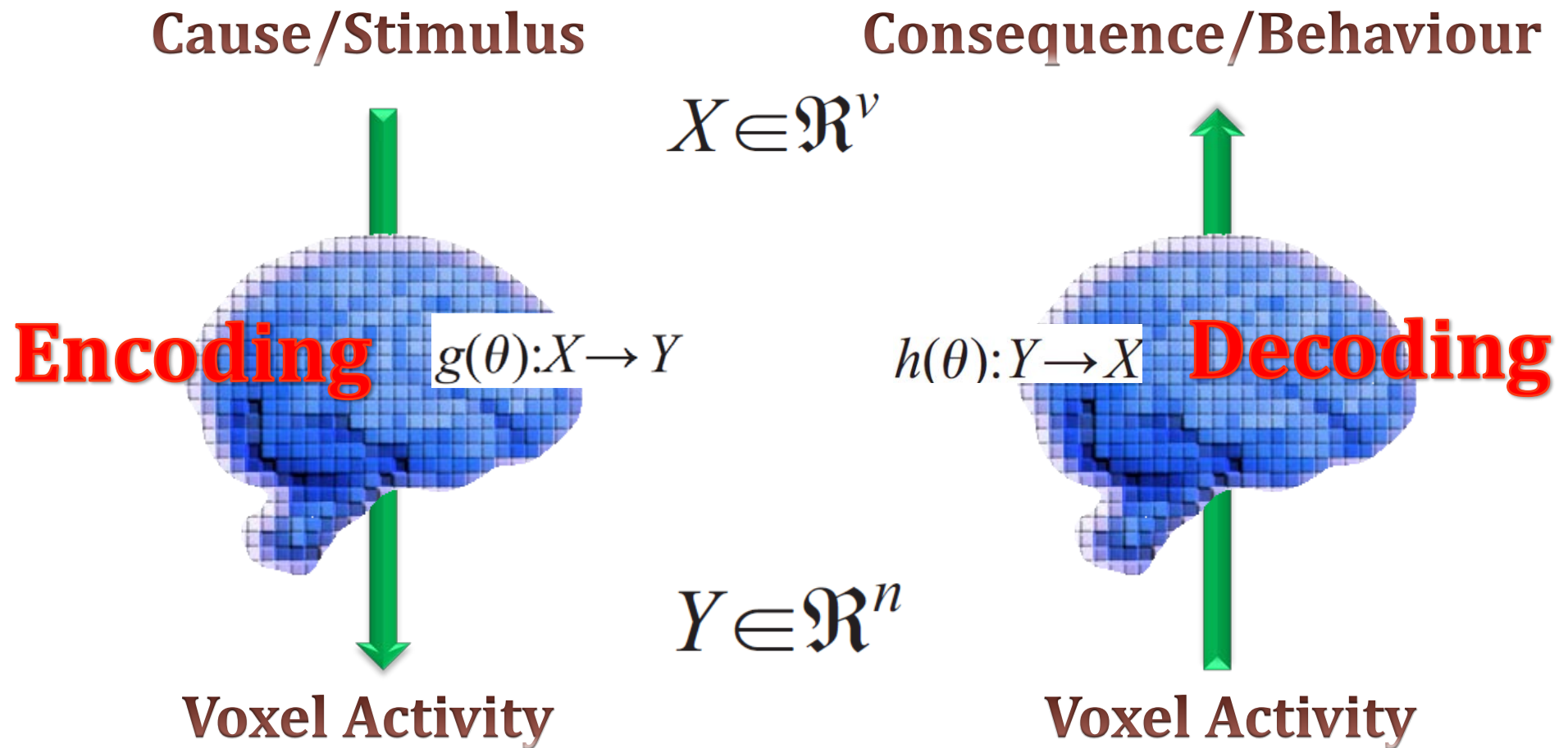
Multivariate
Bayes in SPM



Generative
Embedding



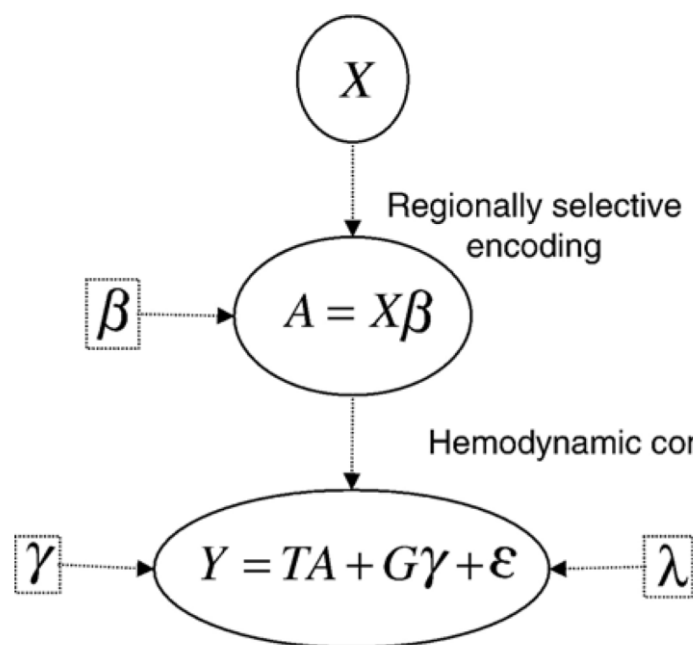
Encoding Vs Decoding Models



Encoding Vs Decoding

Encoding models

X as a cause

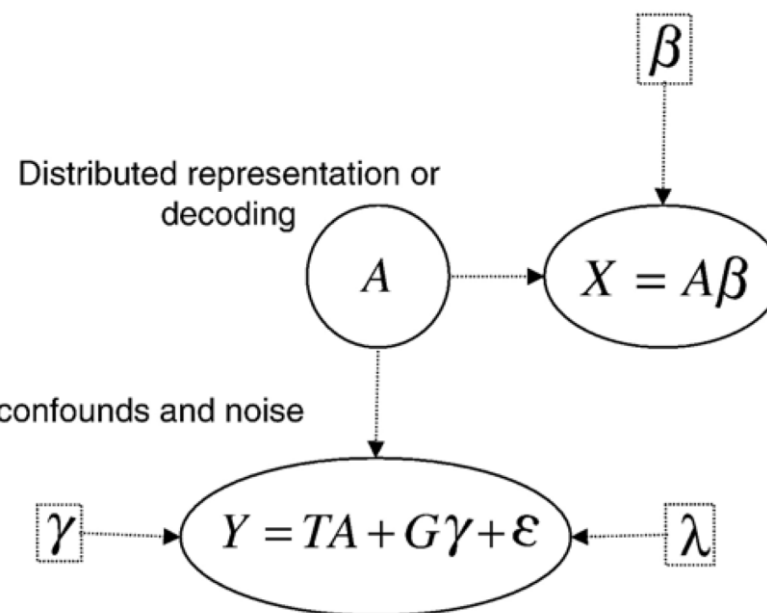


$$g(\theta): X \rightarrow Y$$

$$Y = TX\beta + G\gamma + \varepsilon$$

Decoding models

X as a consequence

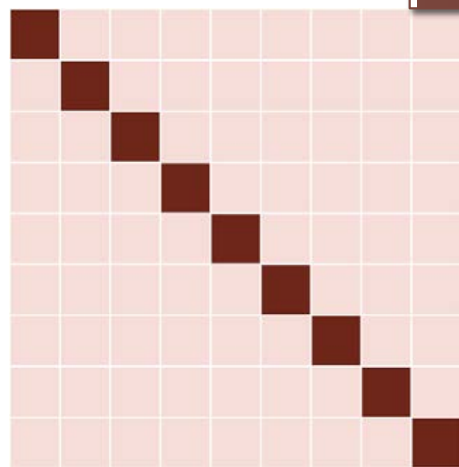


$$g(\theta): Y \rightarrow X$$

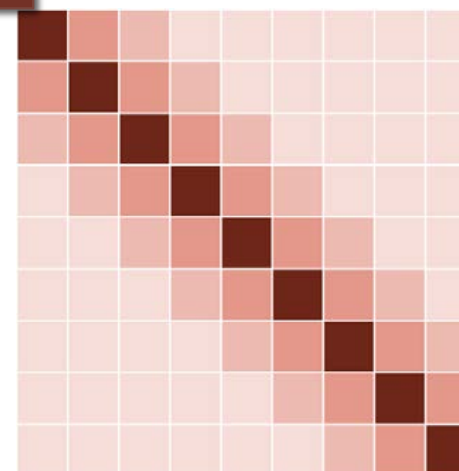
$$TX = Y\beta - G\gamma\beta - \varepsilon\beta$$

Coding hypotheses

Sparse vectors



Spatial vectors

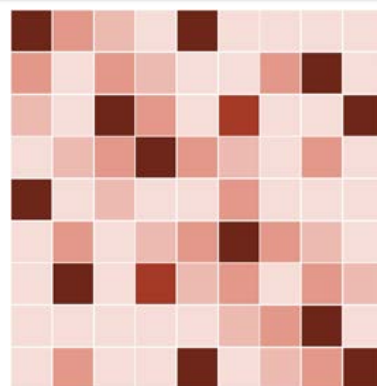


Smooth vectors

Distributed vectors

Singular vectors
of data

$$UDV^T = RY^T$$



Support vectors

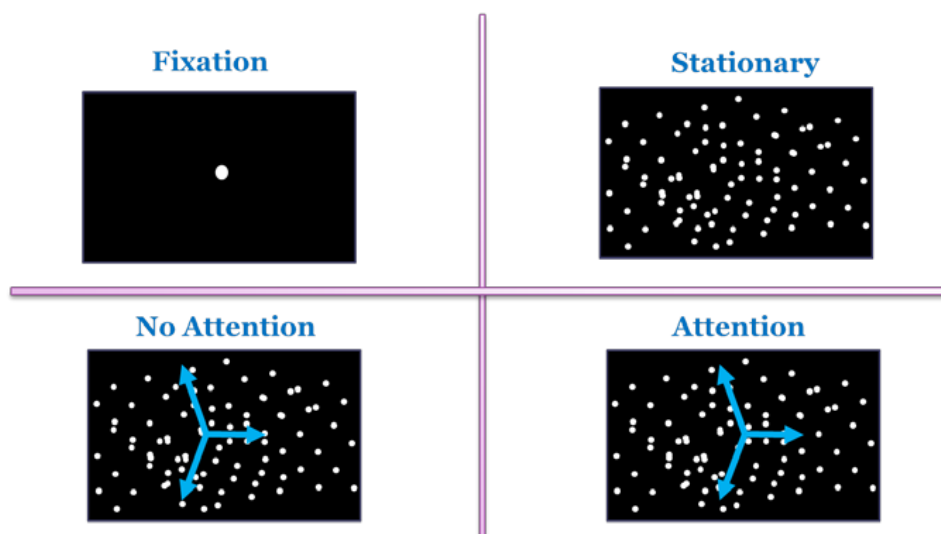
$$U = RY^T$$

Bayesian decoding of motion

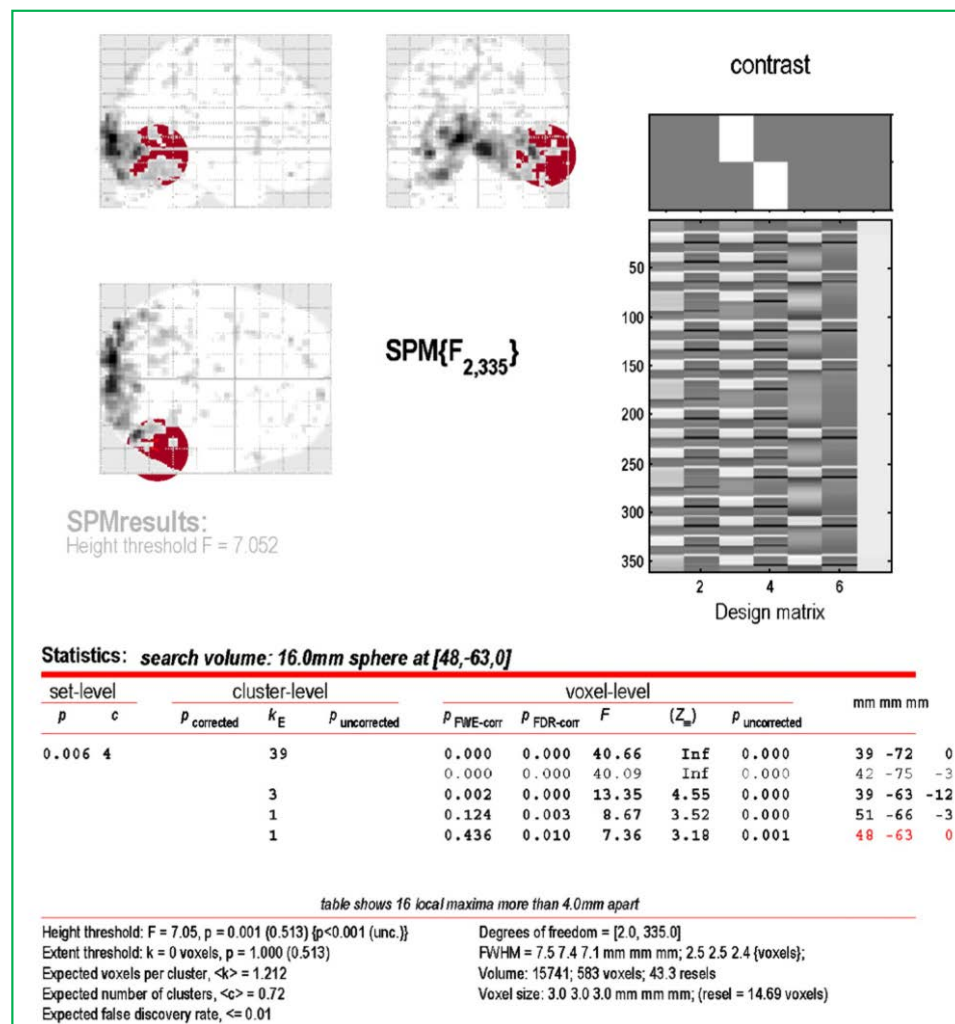
Attention to motion dataset - Büchel & Friston 1999 Cerebral Cortex

Experimental factors:

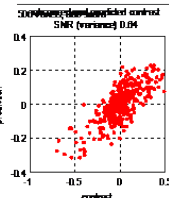
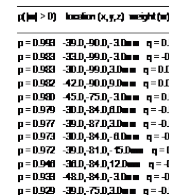
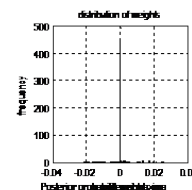
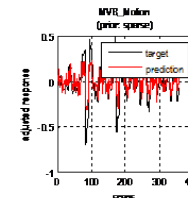
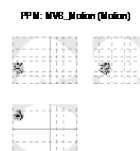
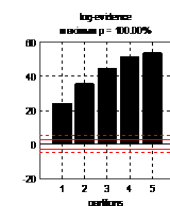
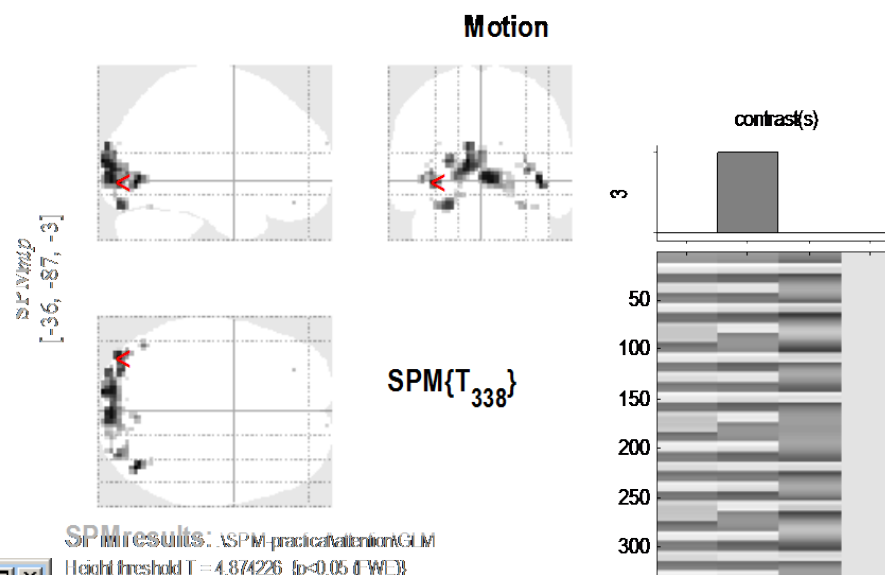
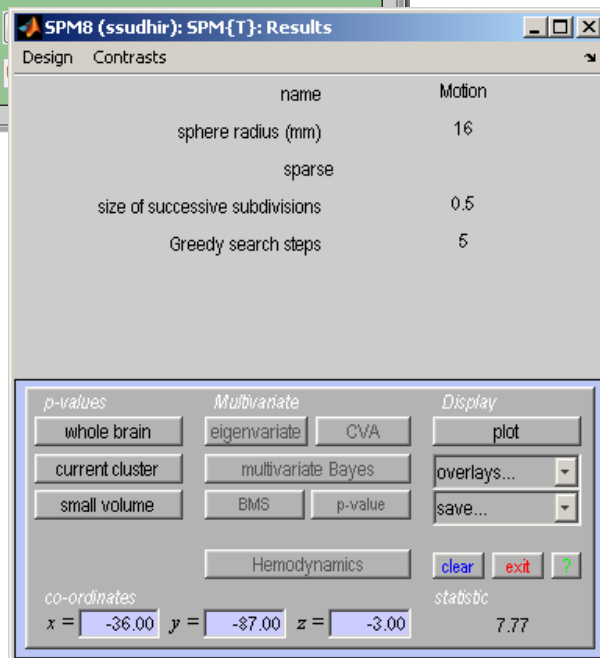
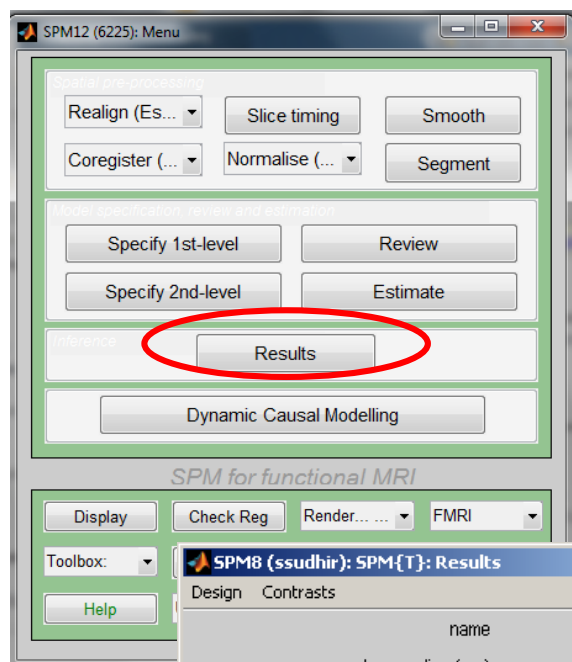
1. Photic
2. Motion
3. Attention



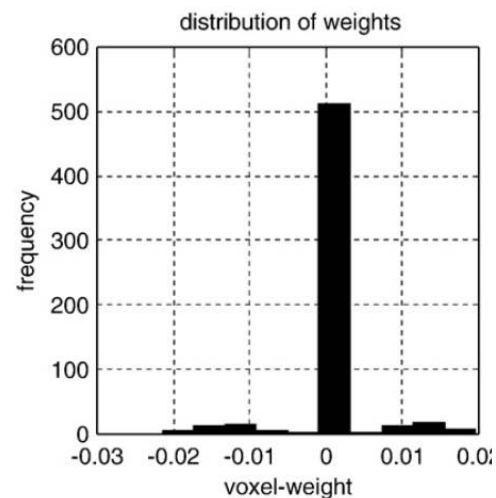
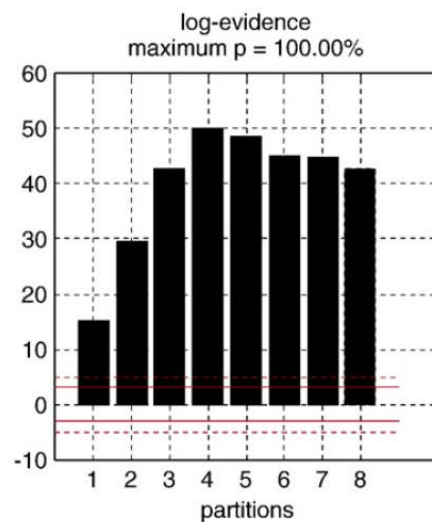
MOVING DOTS



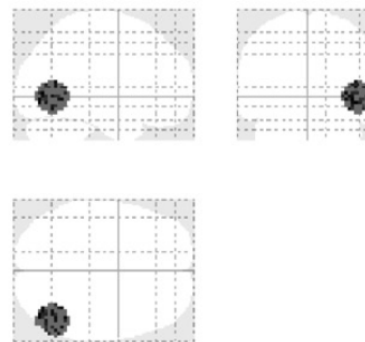
Multivariate Bayes in SPM



Results



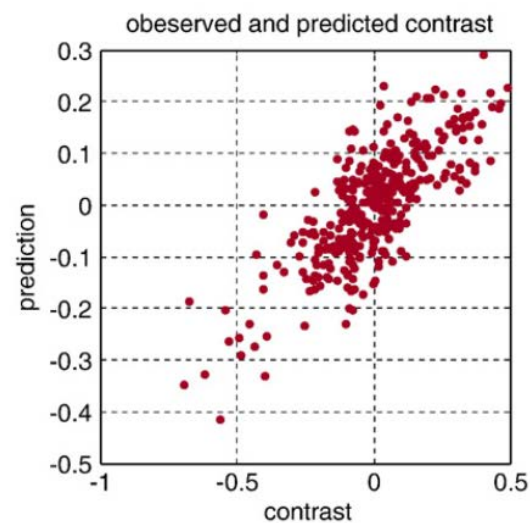
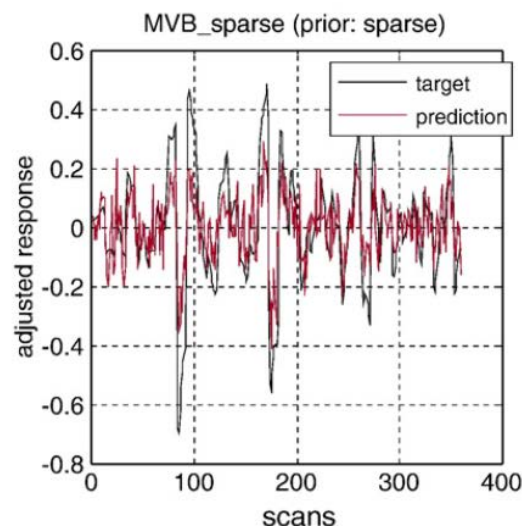
MVB_sparse (motion)



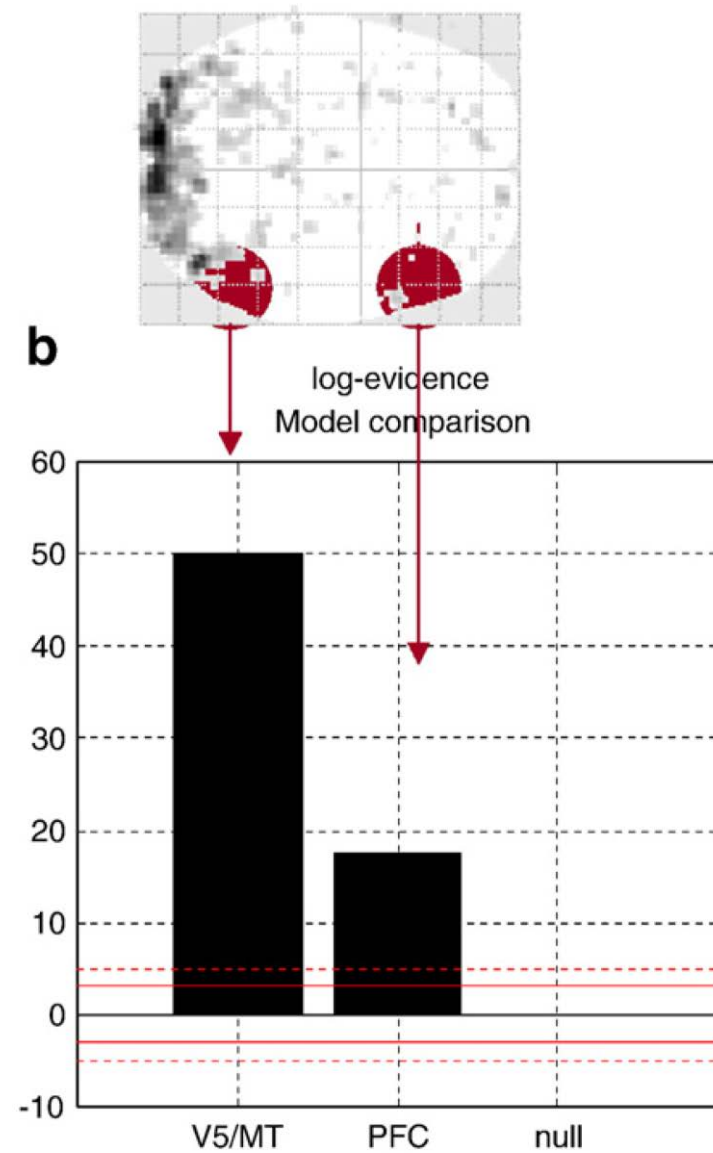
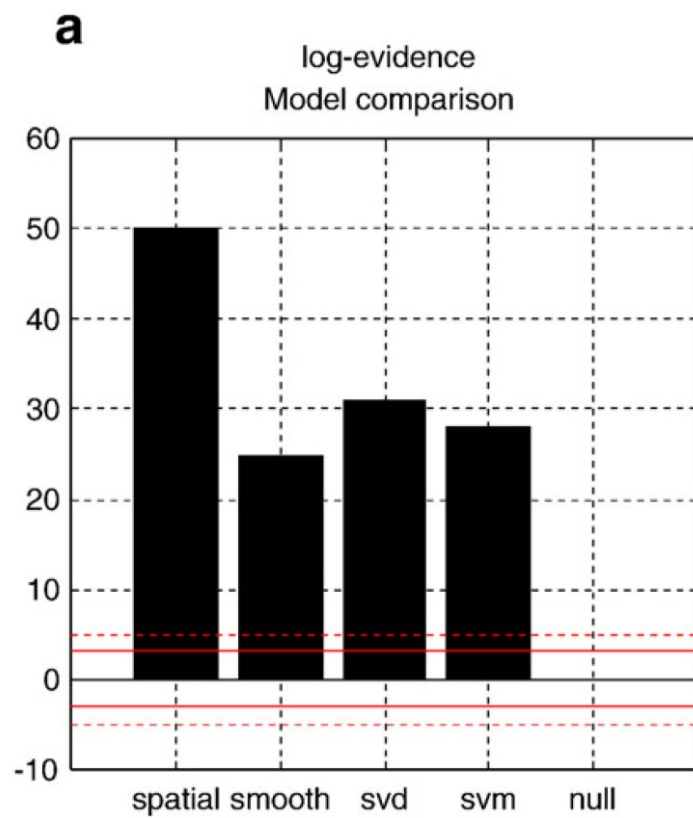
Posterior probabilities at maxmia

p(lwl > 0)	location (x,y,z)	weight (w)
p = 0.991	48,-78,0mm	q = -0.0208;
p = 0.977	48,-72,-3mm	q = -0.0215;
p = 0.973	36,-72,3mm	q = 0.0185;
p = 0.972	45,-51,9mm	q = 0.0188;
p = 0.968	39,-66,-6mm	q = -0.0180;
p = 0.966	42,-54,-3mm	q = -0.0168;
p = 0.963	45,-75,-6mm	q = 0.0196;
p = 0.954	54,-54,9mm	q = 0.0154;
p = 0.947	63,-60,3mm	q = -0.0161;
p = 0.945	42,-63,0mm	q = 0.0150;
p = 0.942	60,-60,-9mm	q = -0.0136;
p = 0.942	36,-57,6mm	q = -0.0167;

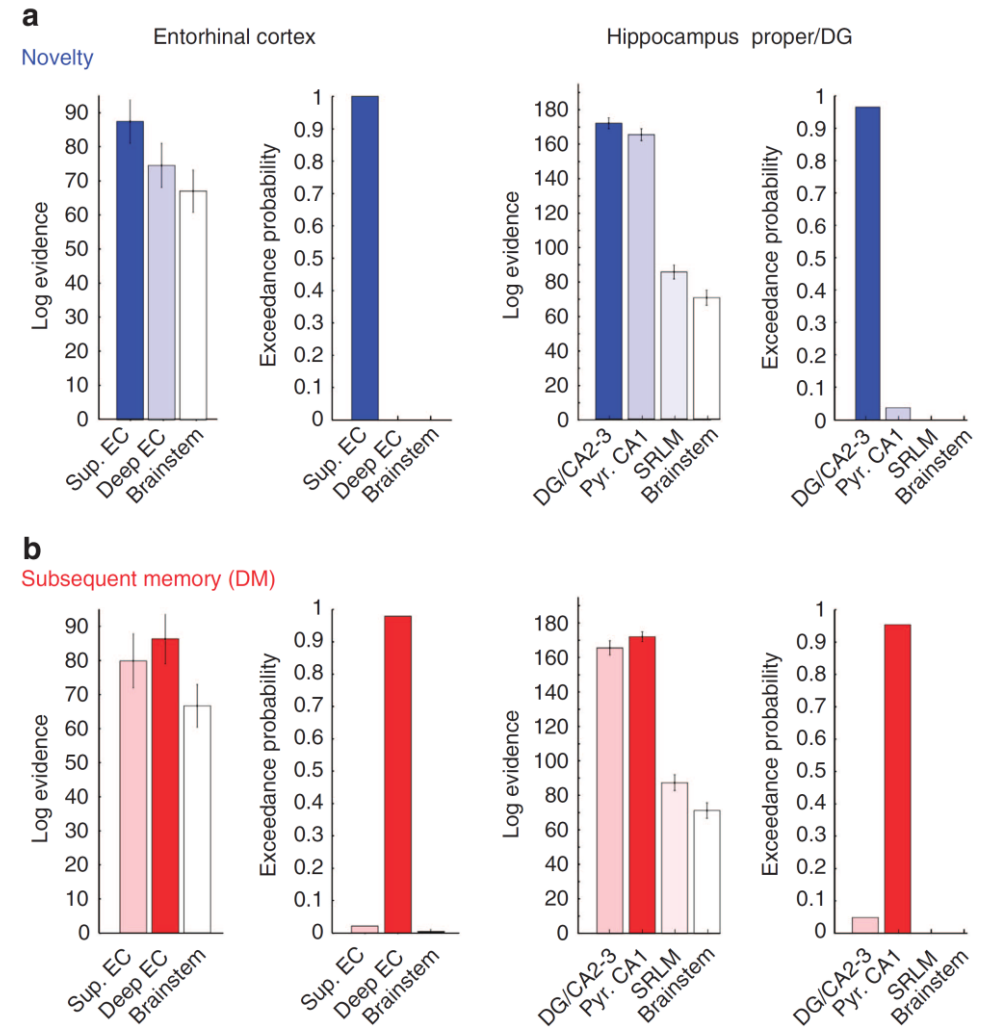
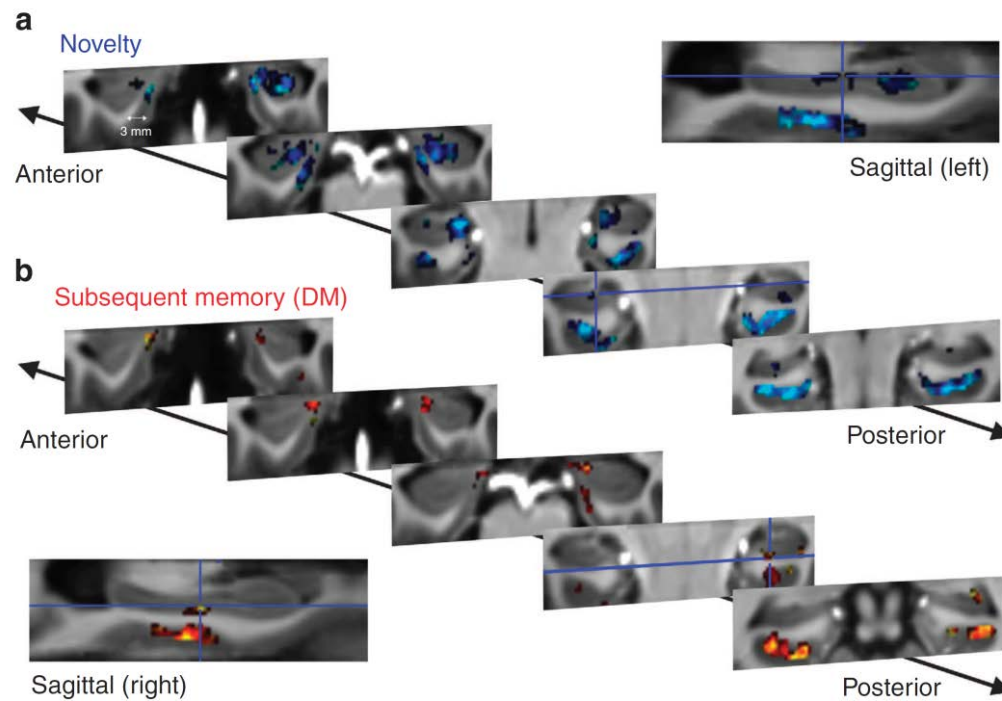
583 voxels; 360 scans



Results

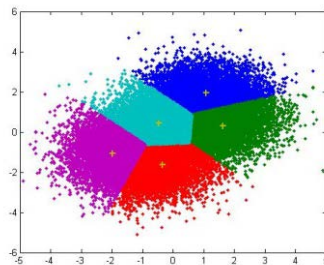


Laminar activity related to novelty and episodic encoding

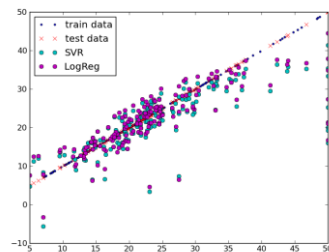


Motivation

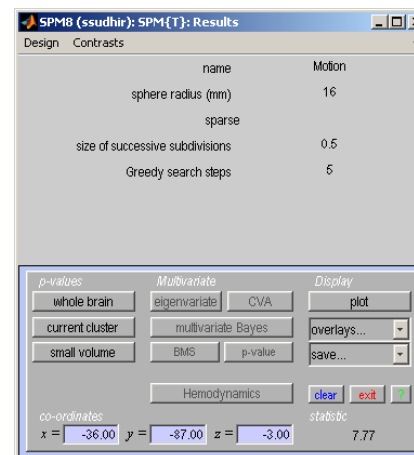
Modelling
Principles



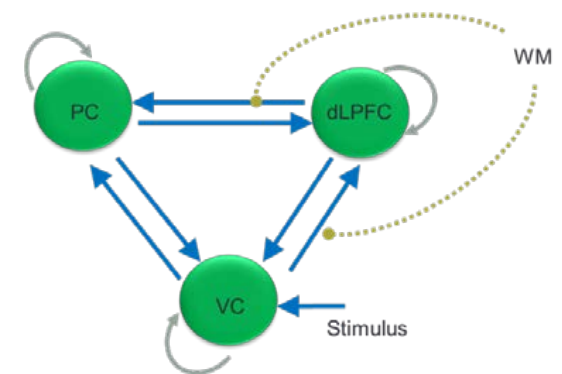
Learning
from Data

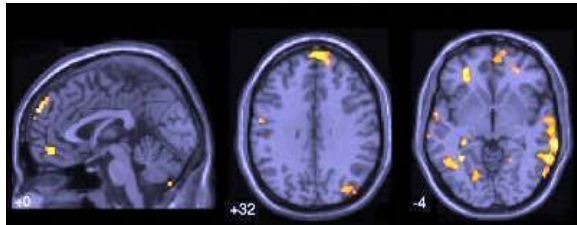


Multivariate
Bayes in SPM

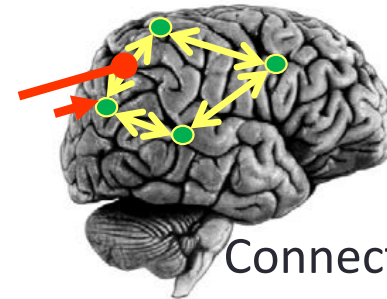


Generative
Embedding

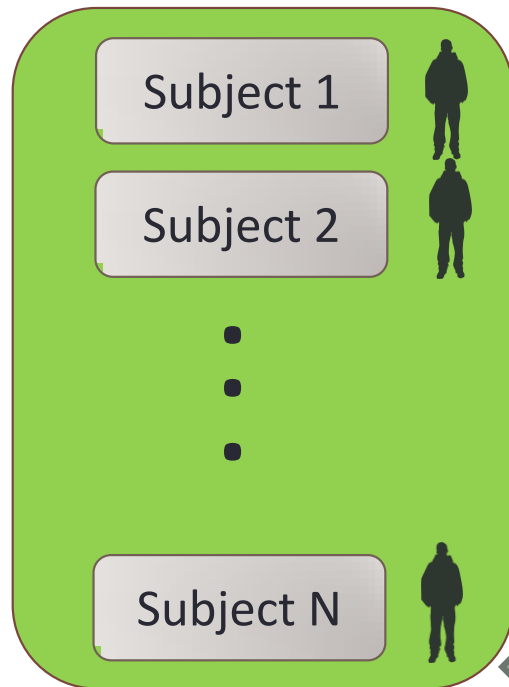




Voxel activity



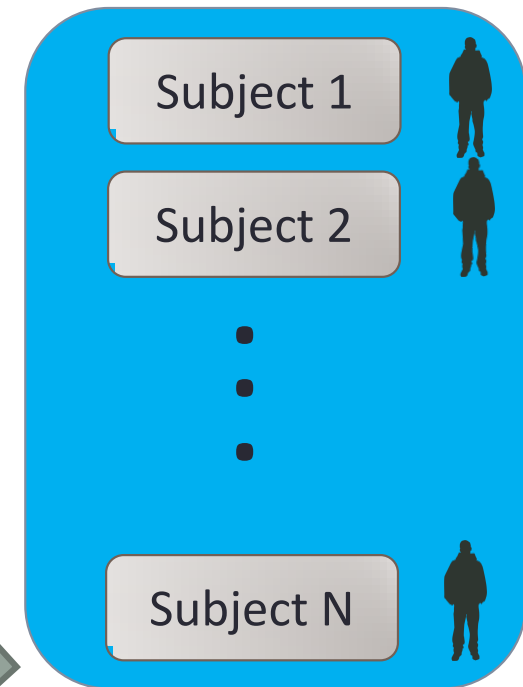
Connectivity



Dynamic causal
model (DCM)



- High dimensionality
- Class/Cluster distributions
- Interpretation



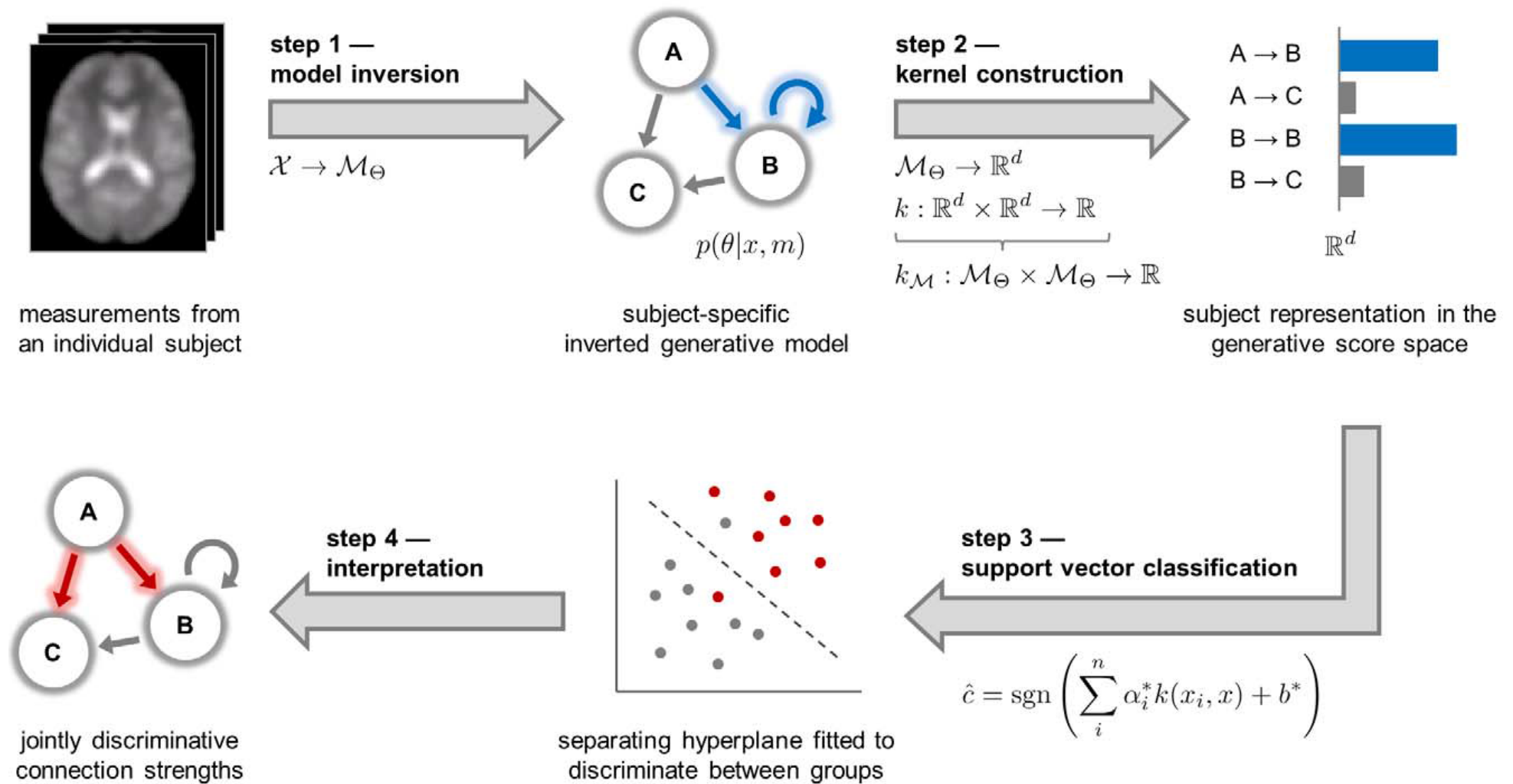
Classification
Clustering

Group 1

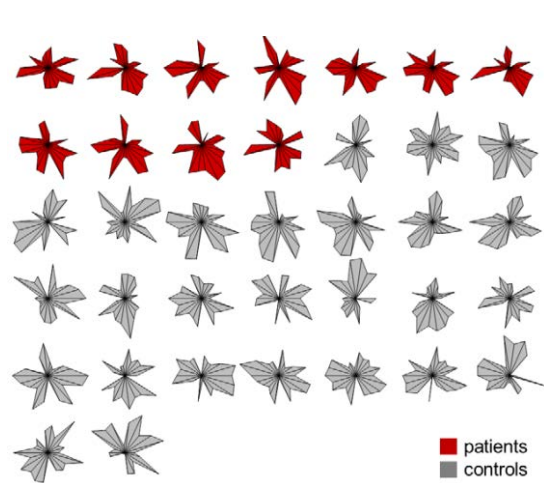
Group 2



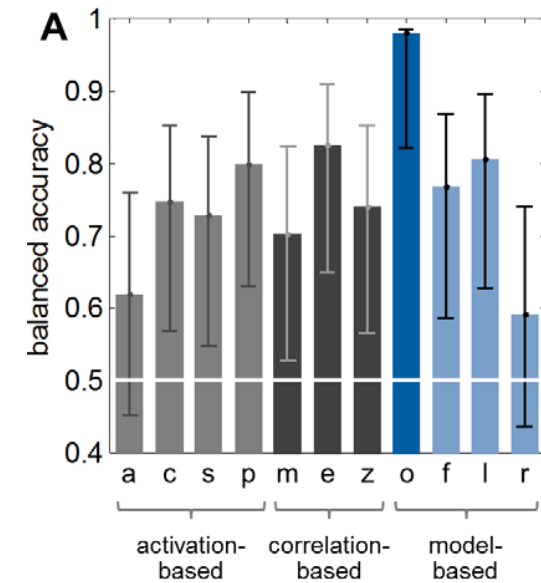
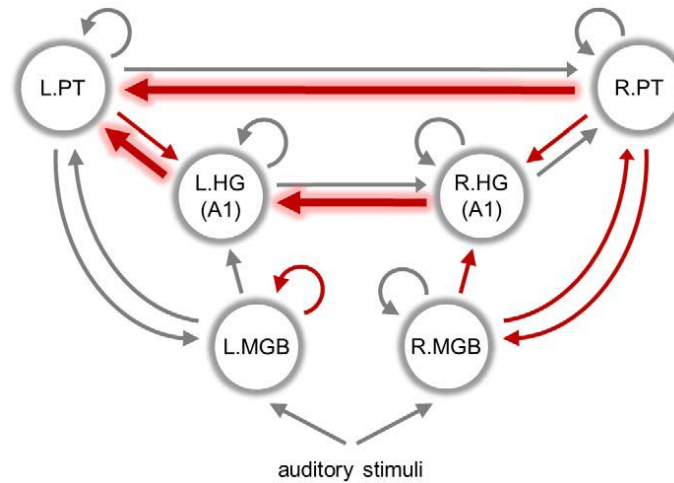
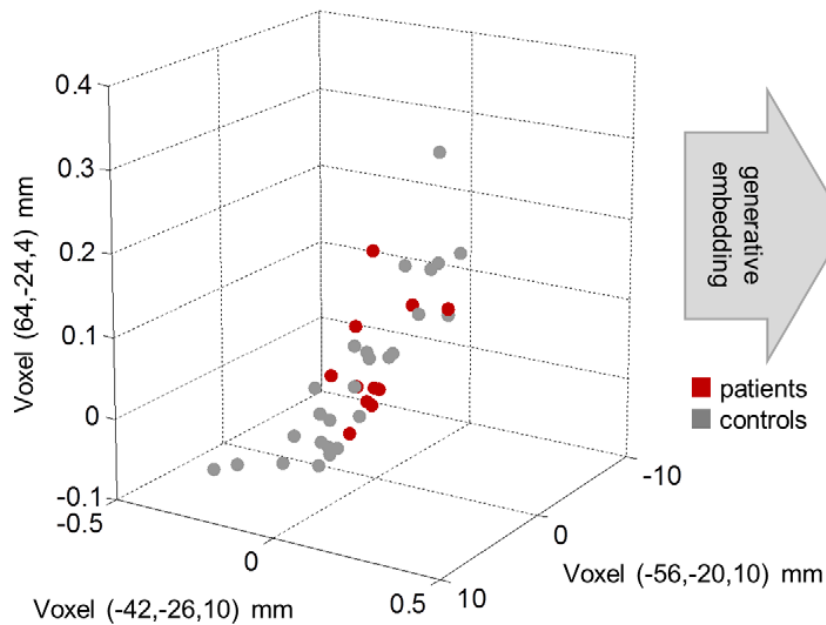
Generative Embedding - Classification



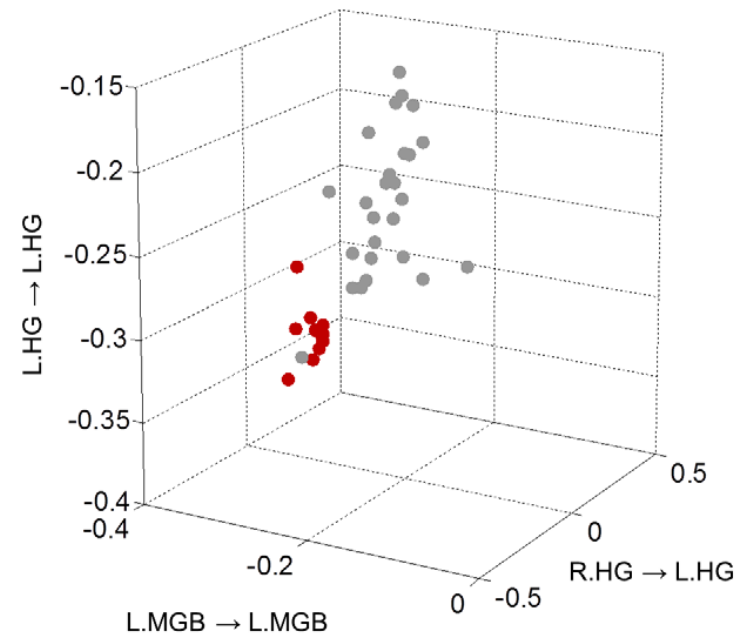
DCM - Speech processing



Voxel-based feature space

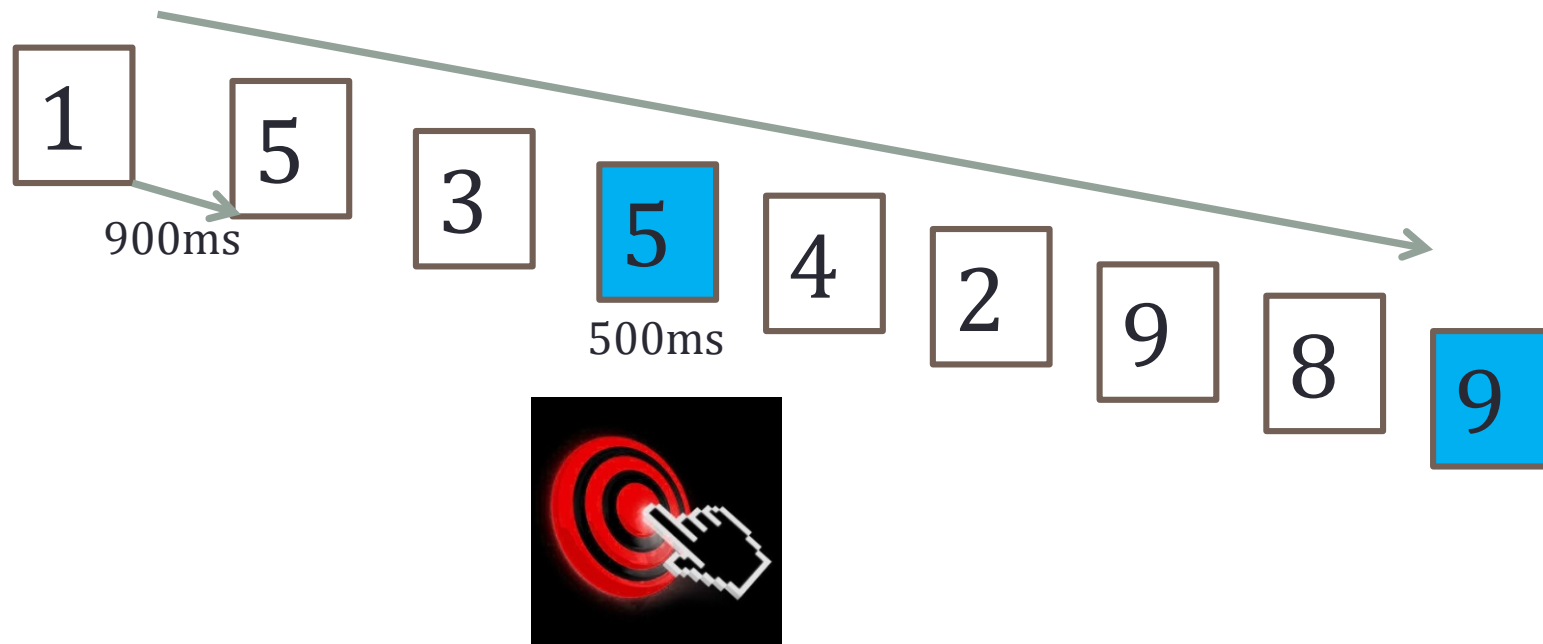


Generative score space

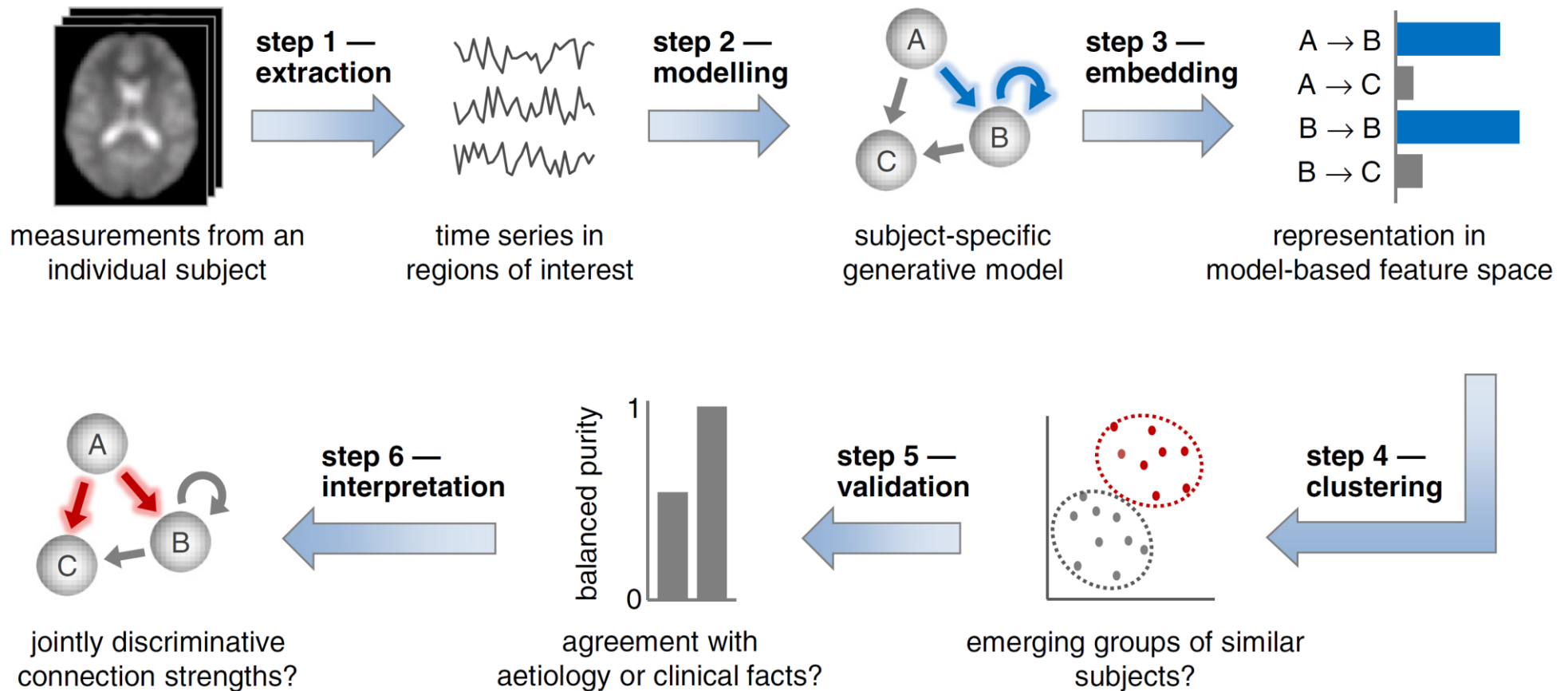


Working memory - fMRI

- 41 Schizophrenia patients (DSM IV, ICD 10), 42 controls
- Visual numeric n-back working memory task

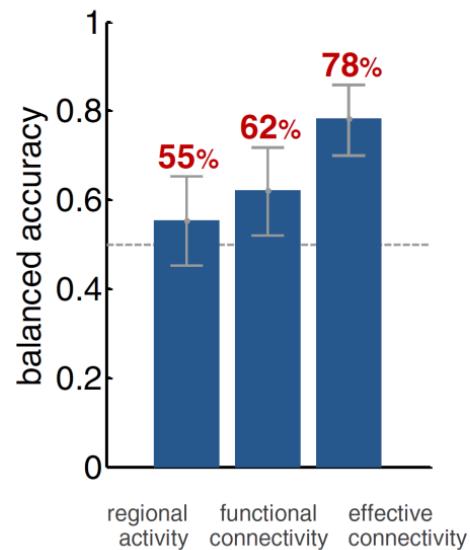


Model based clustering

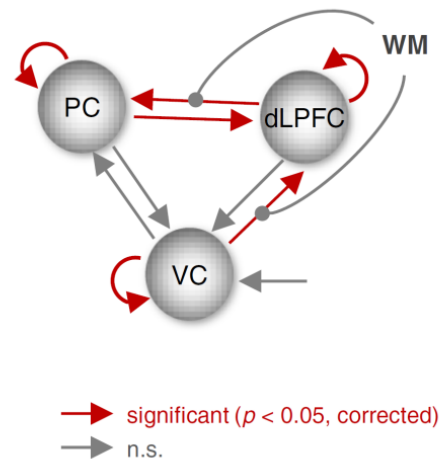


Results – Healthy vs Schizophrenic

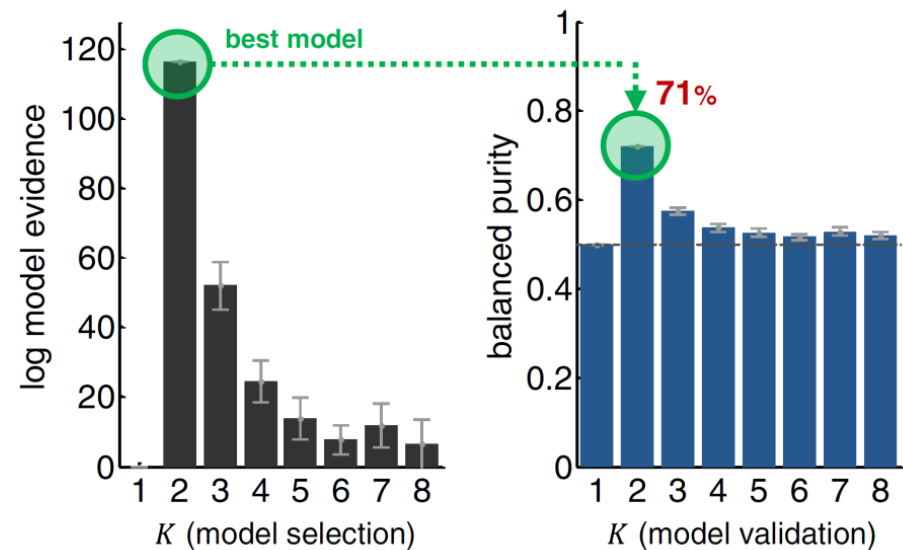
a supervised learning:
SVM classification



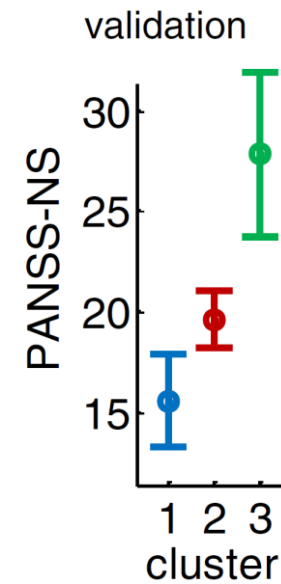
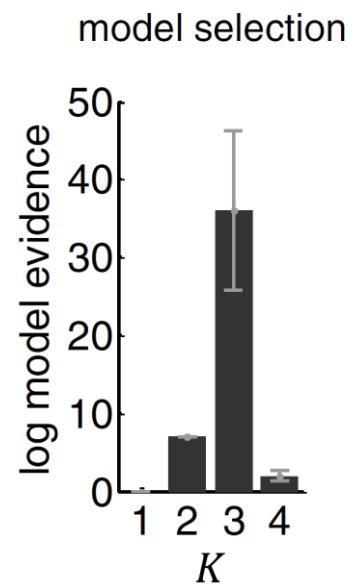
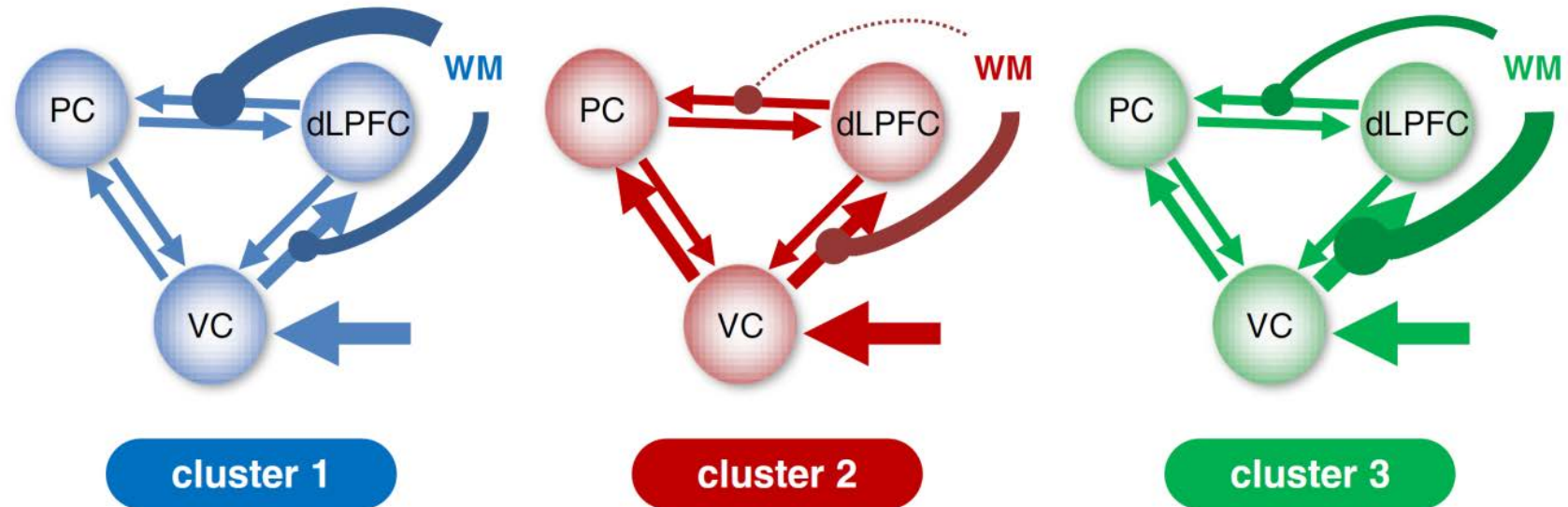
b discriminative
model parameters



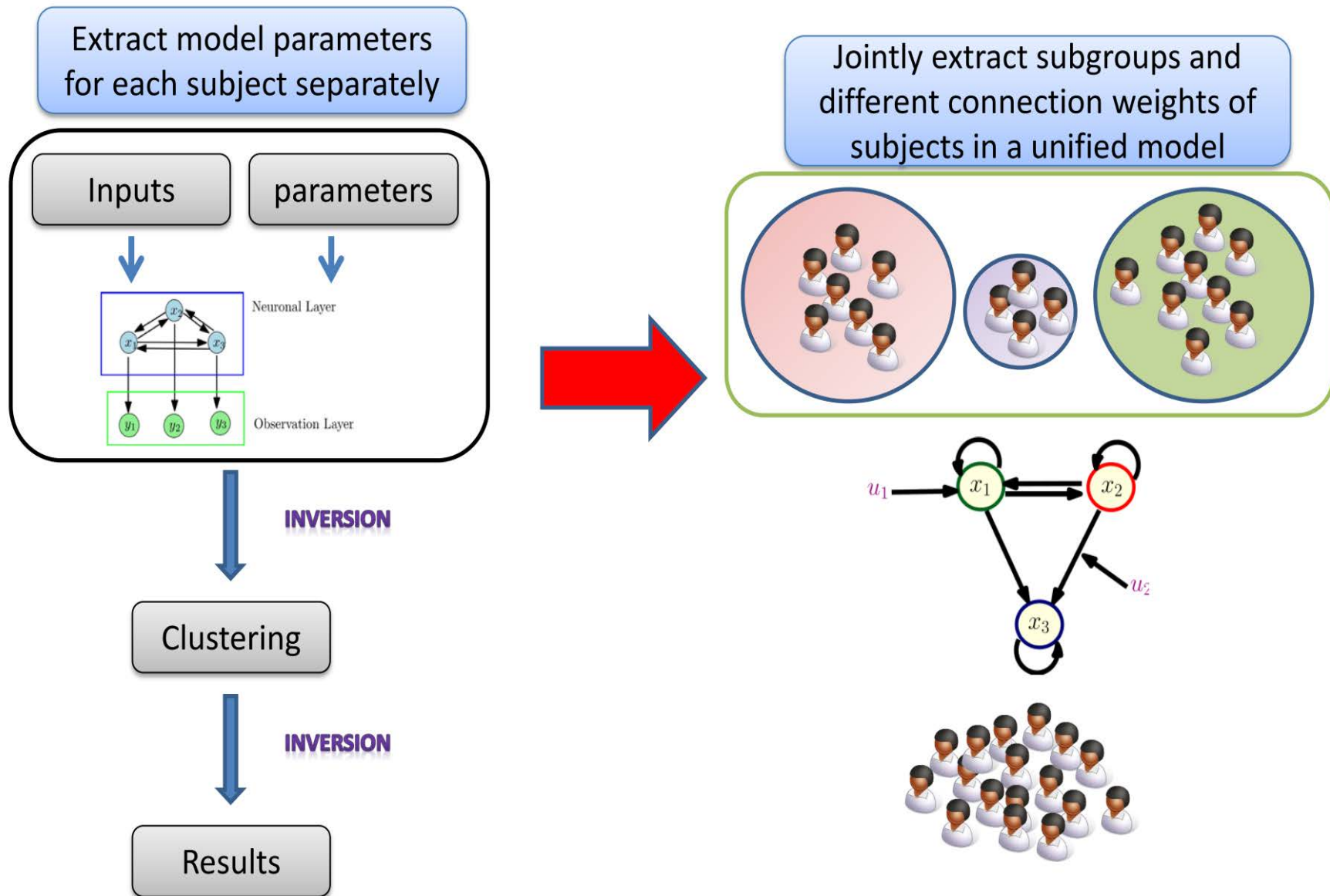
c unsupervised learning:
variational GMM clustering (using effective connectivity)



Results – Schizophrenia patients

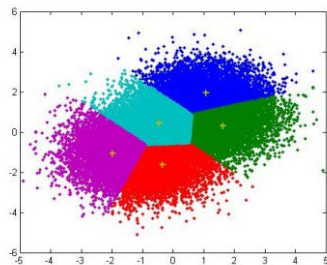


Unified model for identifying subgroups

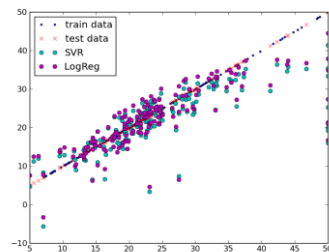


Summary

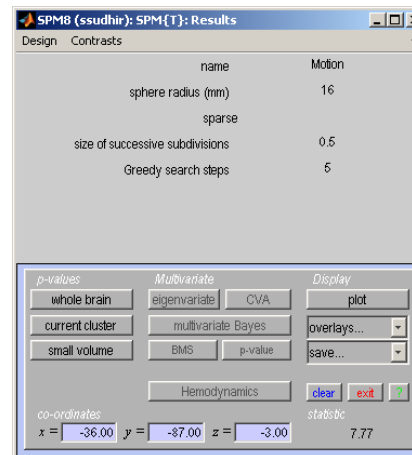
Modelling
Principles



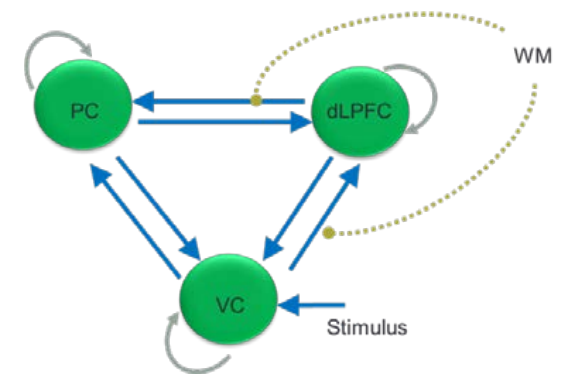
Learning
from Data



Multivariate
Bayes in SPM

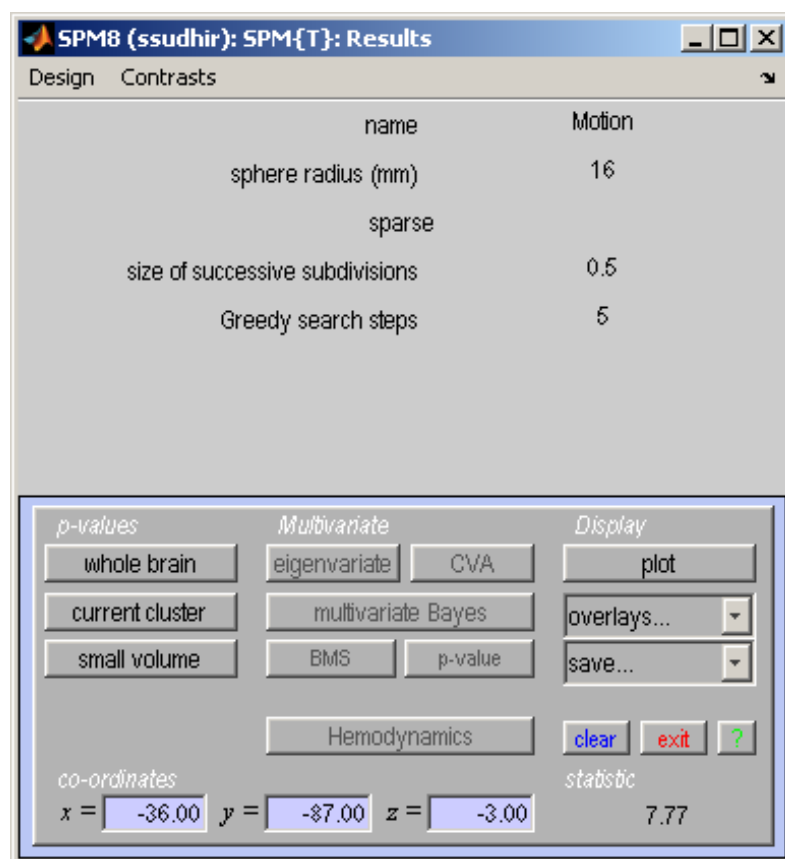


Generative
Embedding

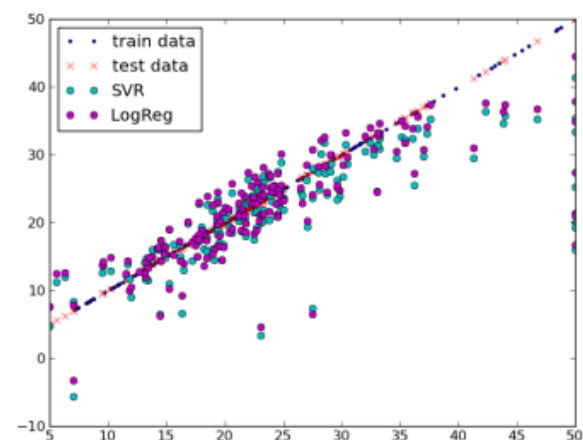


Practicals

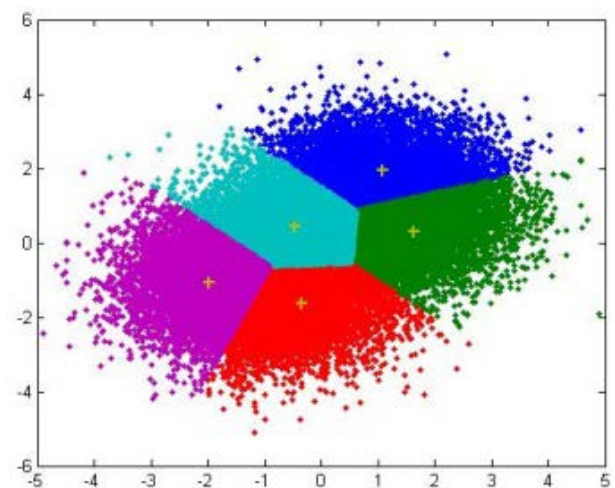
- Multivariate Bayes in SPM



- Classification



- Clustering



Thank you