Can brAIn imaging help Dr House?

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ICNAS INSTITUTO DE CIÊNCIAS NUCLEARES APLICADAS À SAÚDE UNIVERSIDADE DE COIMBRA

CIBIT Coimbra Institute for Biomedical Imaging and Translational Research

FMUC FACULDADE DE MEDICINA UNIVERSIDADE DE COIMBRA

FCTUC FACULDADE DE CIÊNCIAS E TECNOLOGIA UNIVERSIDADE DE COIMBRA

CISUC

Outline

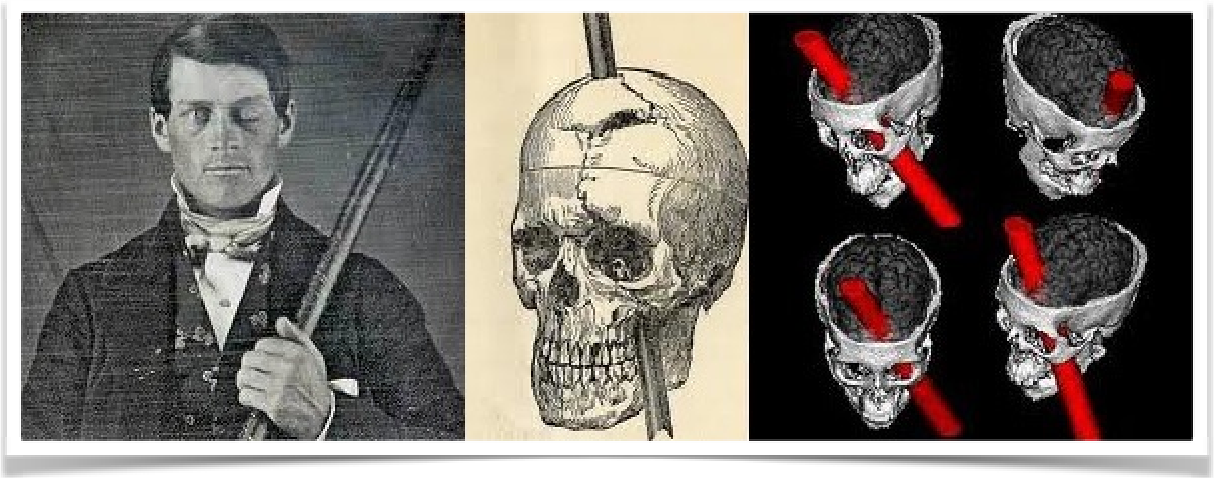
- Neuroimaging
  - Magnetic resonance imaging (MRI)
  - Electroencephalography (EEG)
- Machine learning in neuroimaging
  - Support Vector Machines (SVM)
  - Weightless Neural Networks (WNN)
- Applications of machine learning in neuroimaging
  - Brain function in Autism Spectrum Disorder (ASD)
  - Brain structure in Neurofibromatosis Type 1 (NF1)

Neuroimaging

Neuroimaging

Study of the brain before neuroimaging

Phineas Gage



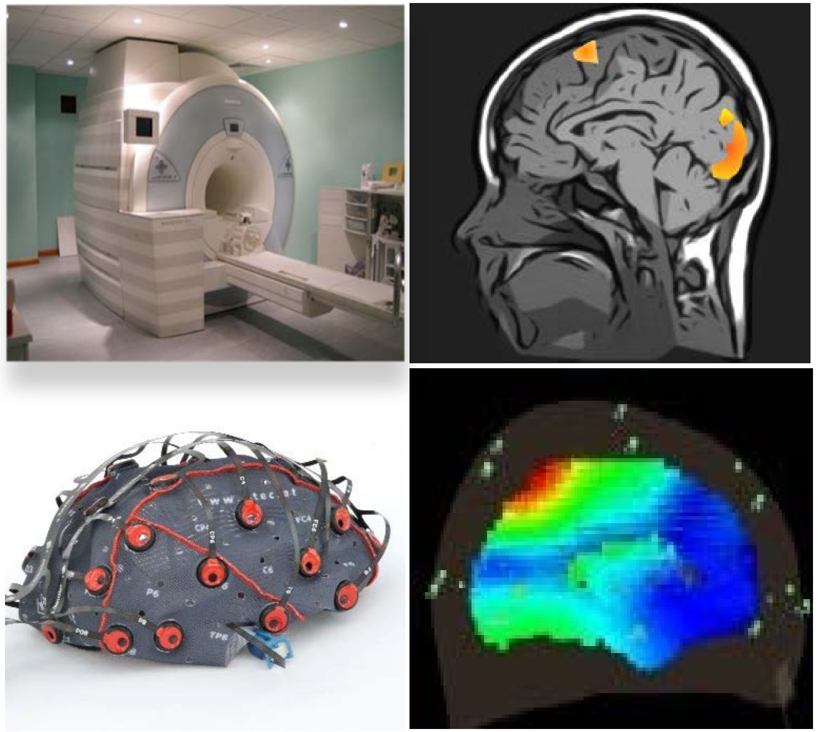
Ratiu, P.; Talos, I. F. (2004) New England Journal of Medicine. doi:10.1056/NEJMicm031024

Background

Neuroimaging

Developments in neuroimaging

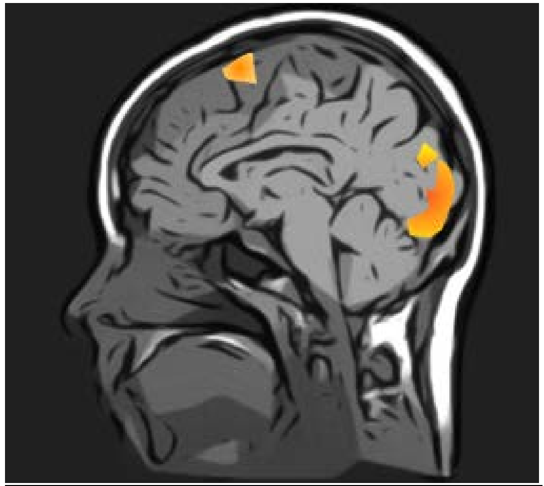
- Information about areas previously unavailable to other imaging techniques
- *Direct* access to brain structure and function
- Identification of neural correlates/functional networks

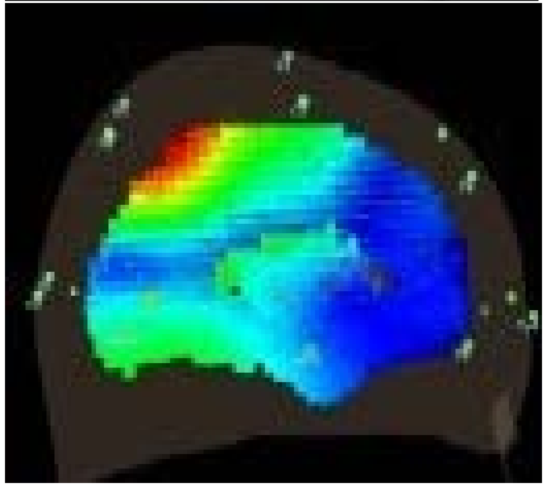


Magnetic Resonance Imaging (MRI) Scanner and Electroencephalography (EEG)

Neuroimaging

Comparison between control and clinical groups

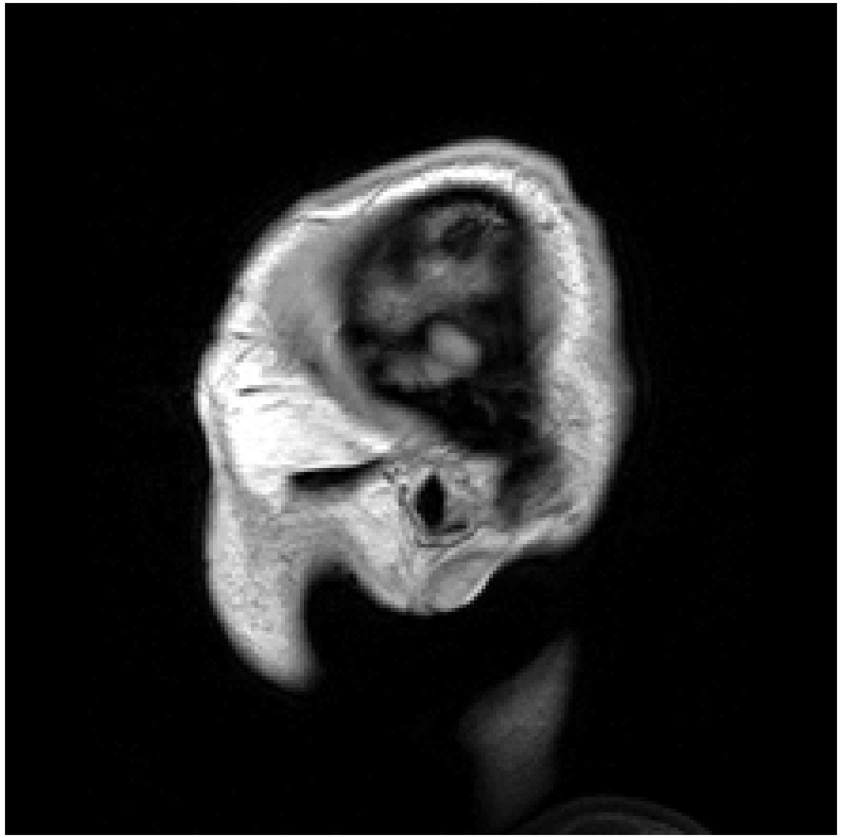


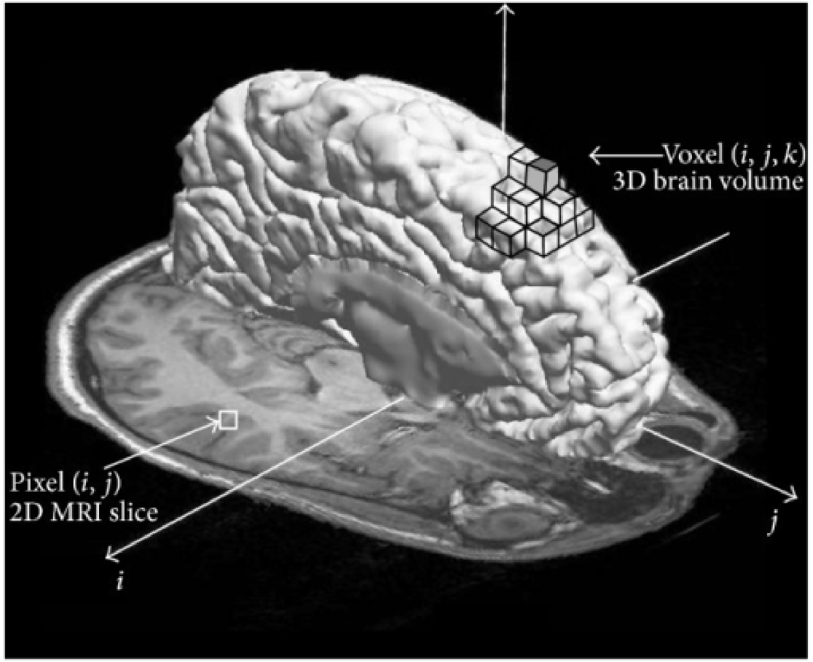


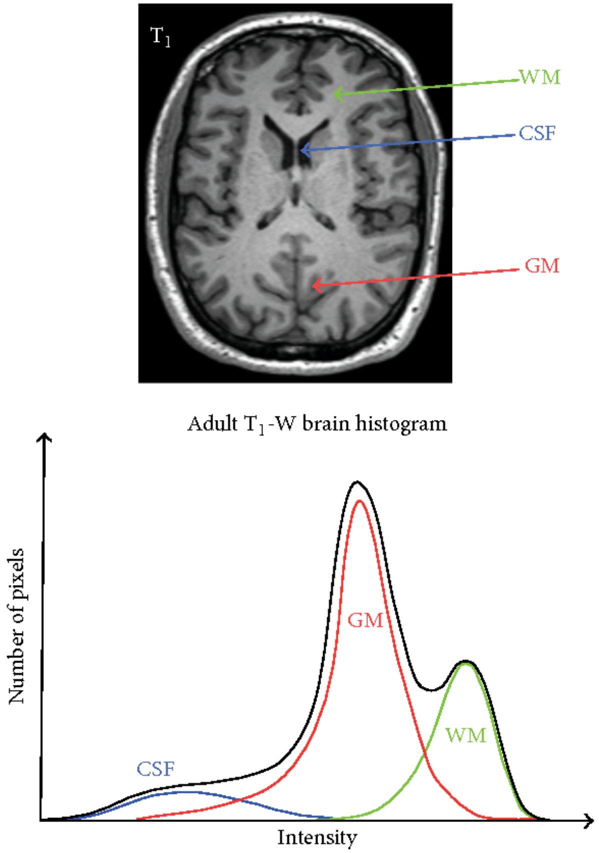
- Observe and understanding brain structural abnormalities or dysfunctions
- Access to the mechanisms involved in structure/function differences
- Creation/development of diagnostic tools/applications
- Creation/development of personalized interventions on the dysfunctional mechanisms

Magnetic Resonance Imaging (MRI)

High quality 2D or 3D images of brain structure (different tissues)





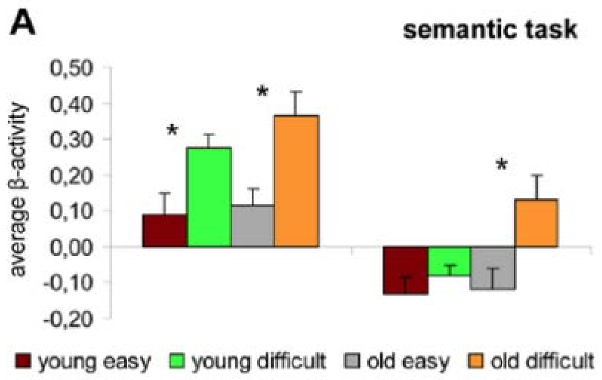


Despotovic et al. (2015), DOI: 10.1155/2015/450341

Standard analysis of MRI data

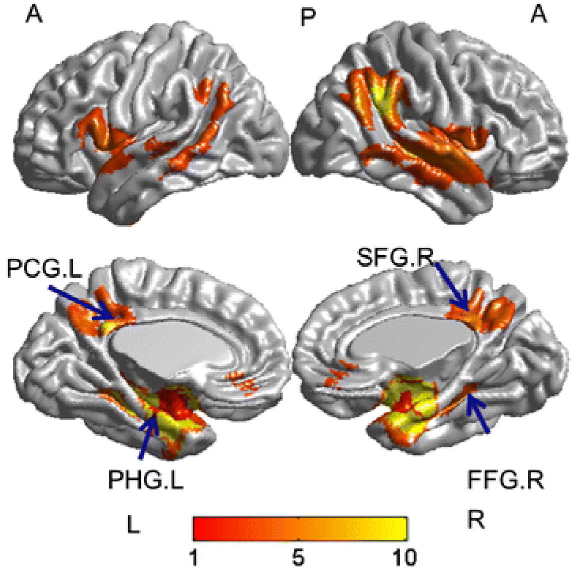
Regions of Interest (ROI) analysis

- High statistical power (no/less correction for multiple comparisons)
- Low exploratory power



Whole-brain analysis

- Low/moderate statistical power (heavy correction for multiple comparisons)
- High exploratory power
- <u>No predictive value</u>

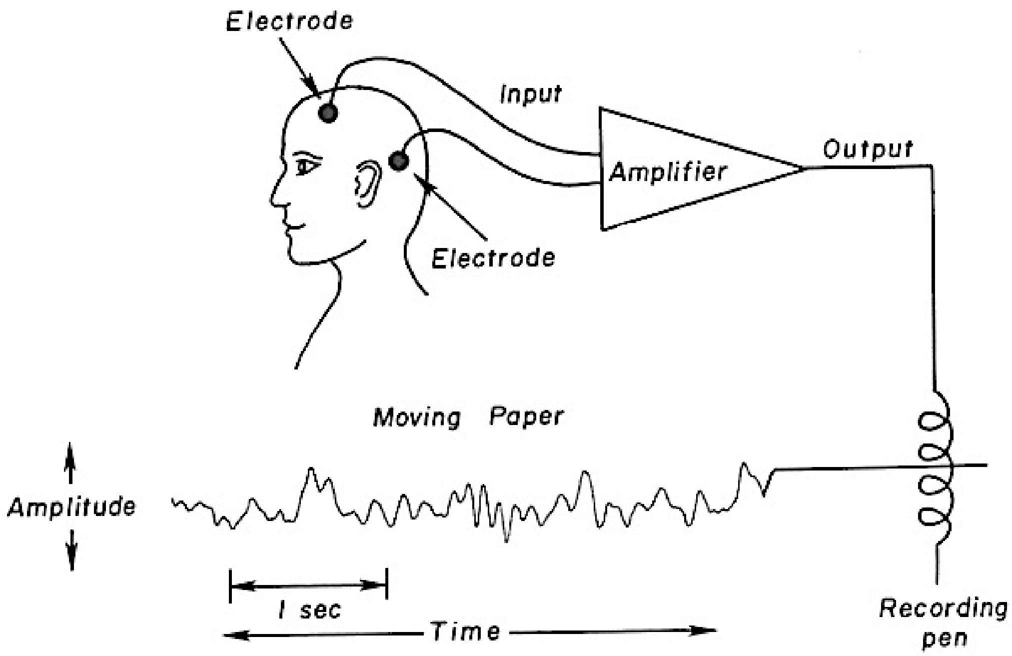


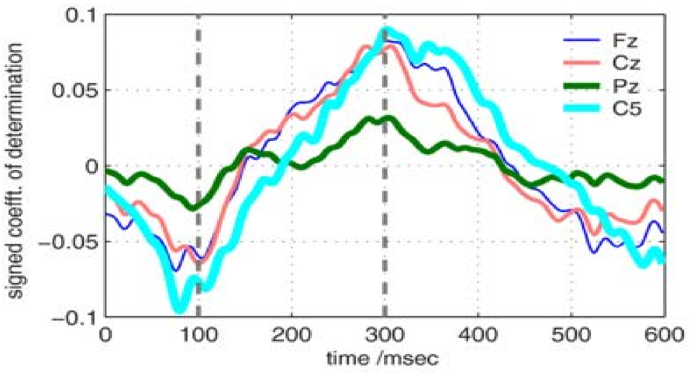
Electroencephalogram (EEG)

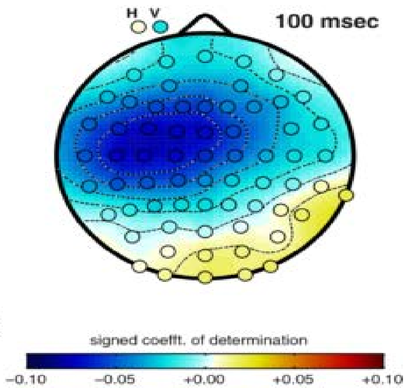
Invented by **Hans Berger** in 1924

Measures **electric activity** along the scalp (head)

Activity which corresponds to neuronal processes







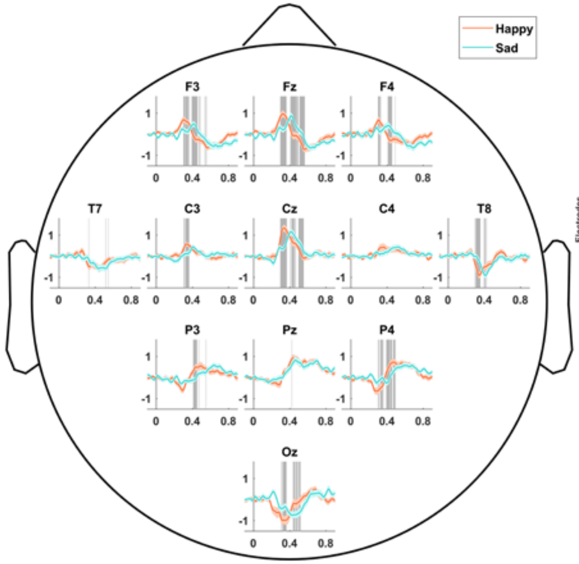
Electroencephalogram (EEG)

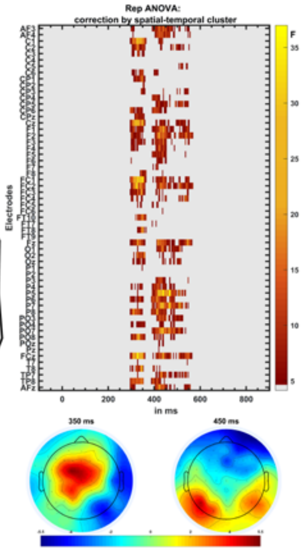
Very good temporal resolution

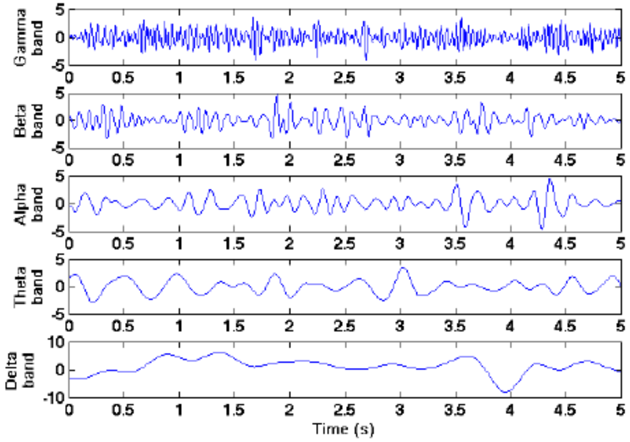
Poor spatial resolution – source reconstruction

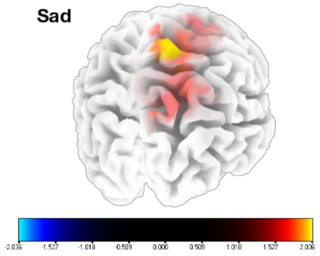
Easily contaminated by noise

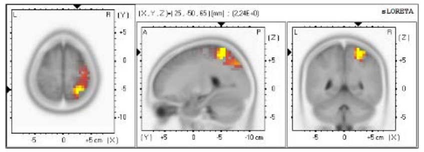
Frequency bands for different mental processes











Machine learning in

Neuroimaging

Machine learning in neuroimaging

Brain imaging

- MRI
- EEG
- …

Machine learning

- Multivariate pattern analysis (MVPA)
- Pattern recognition
- Classification models
- Brain reading

Clinical decision

- Healthy vs. Disease (diagnostic)
- Invisible brain damage (structure)
- Cognitive state/performance (function)
- Clinical score (prognostic)

Learn mathematical decision functions based on statistical information extracted from **known training data** and **predict** (assign a label to) **new unseen data**

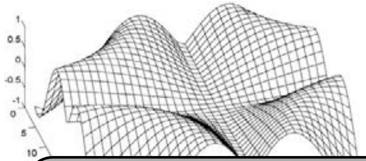
Basic design

Data collection

- Measurements in input space (e.g. image intensity).
- How big is an adequately large sample? **Complex patterns need larger samples to be found…**

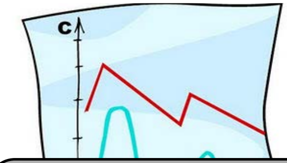
Feature extraction

- Features can be the input variables or characteristics computed from input data.
- It depends on the problem domain: **the features should be interpretable!**



Training of the classifier

- Trade-off between computational cost, biological interpretability and performance.
- Good practice: **do not train the model with test examples** - that is cheating!

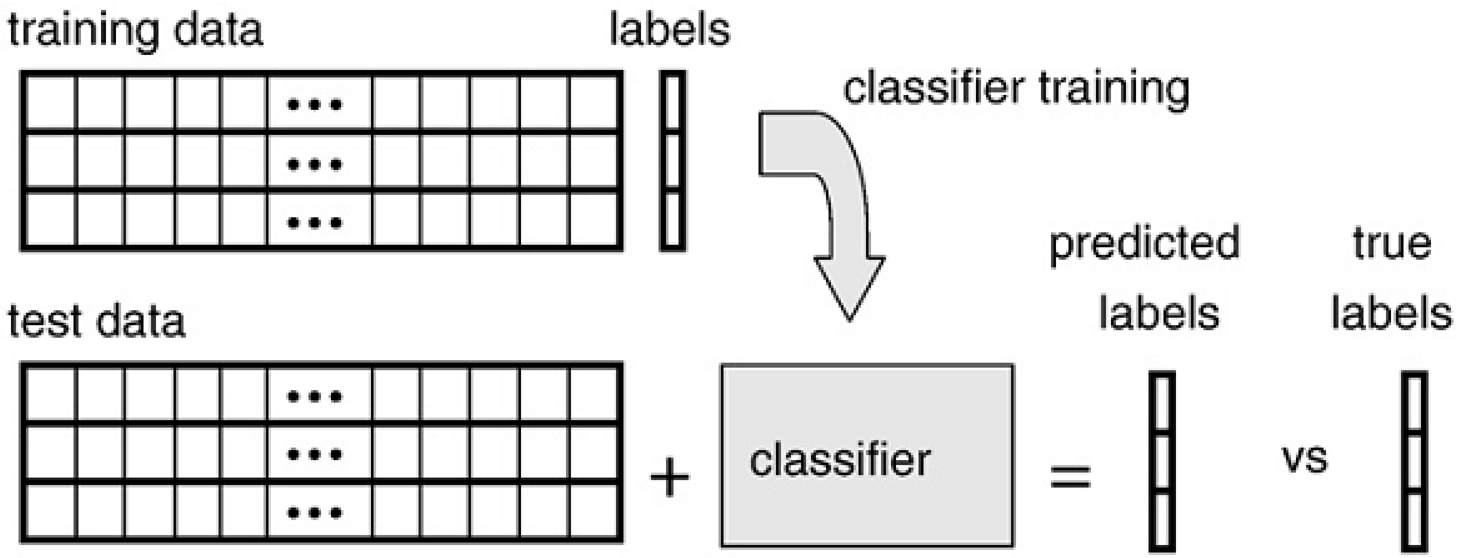


Testing and performance evaluation

- **Measure testing error rate** on unseen data **and adjust**:
- Features
- Model (and parameters)
- Training/testing sample size

Support Vector Machine - Concept

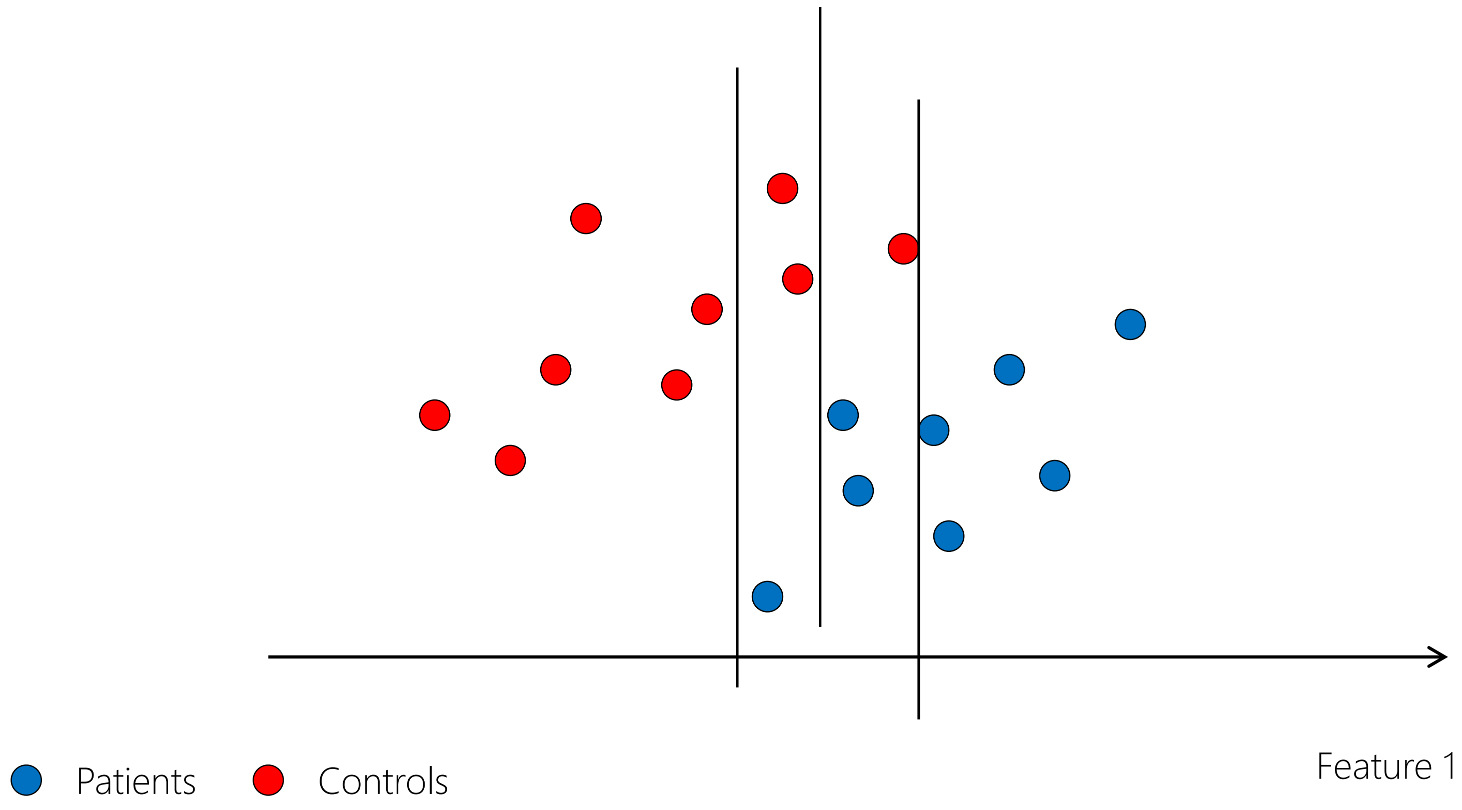
Multivariate Pattern Classifier



Pereira F et al. (2009): Machine learning classifiers and fMRI: A tutorial overview. *Neuroimage*

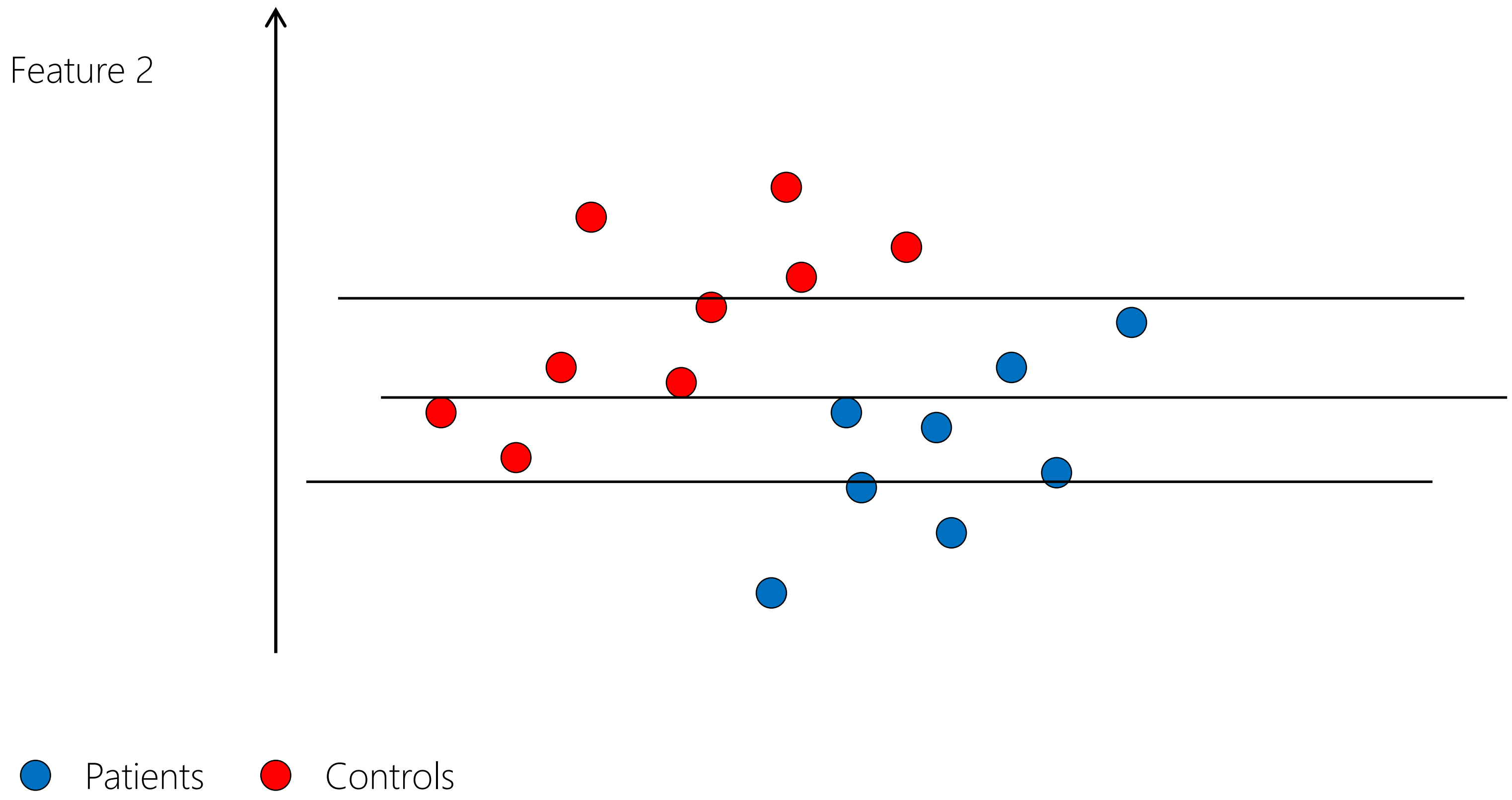
Support Vector Machine - Concept

Discrimination in 1D is not good…



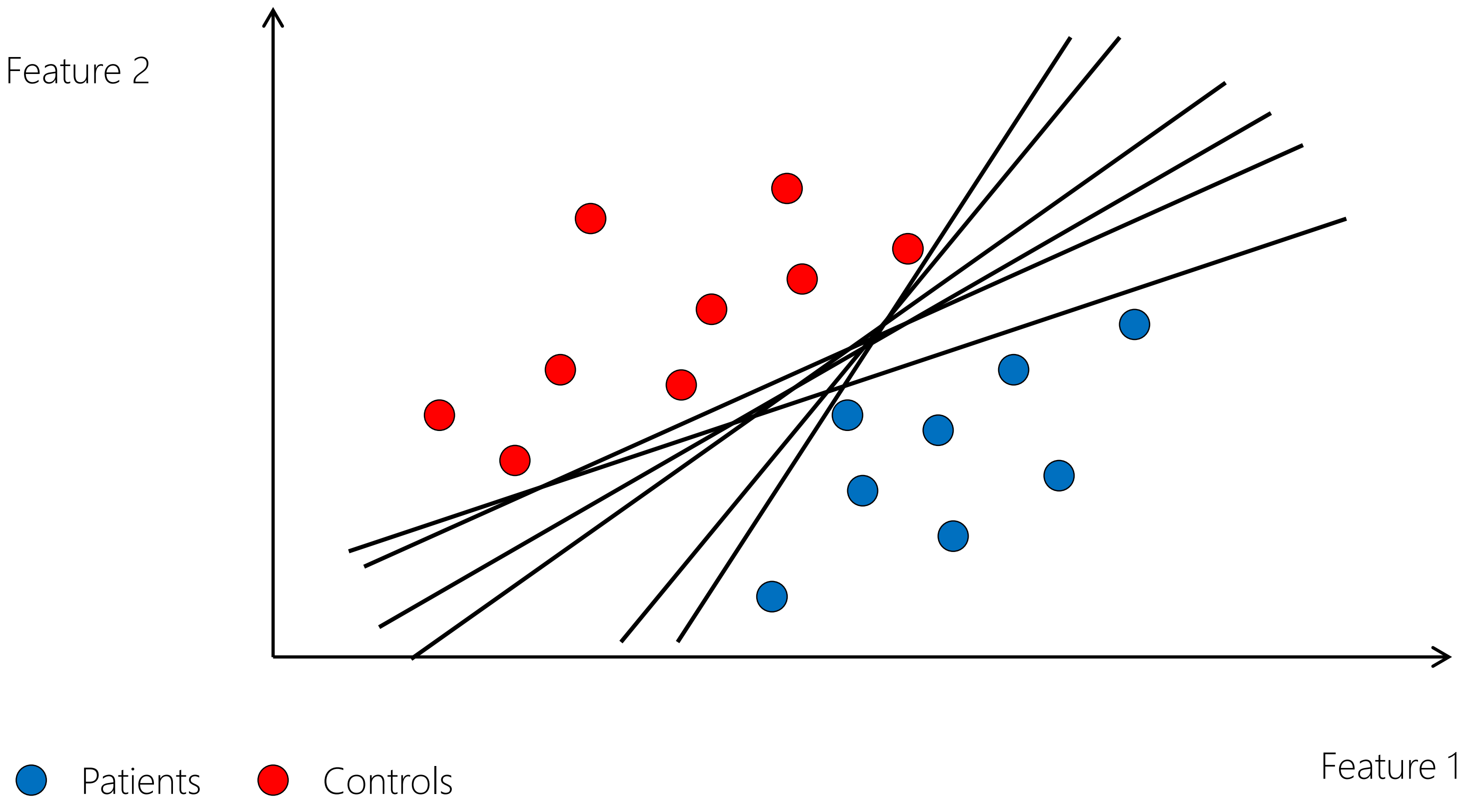
Support Vector Machine - Concept

Discrimination in 1D is not good…



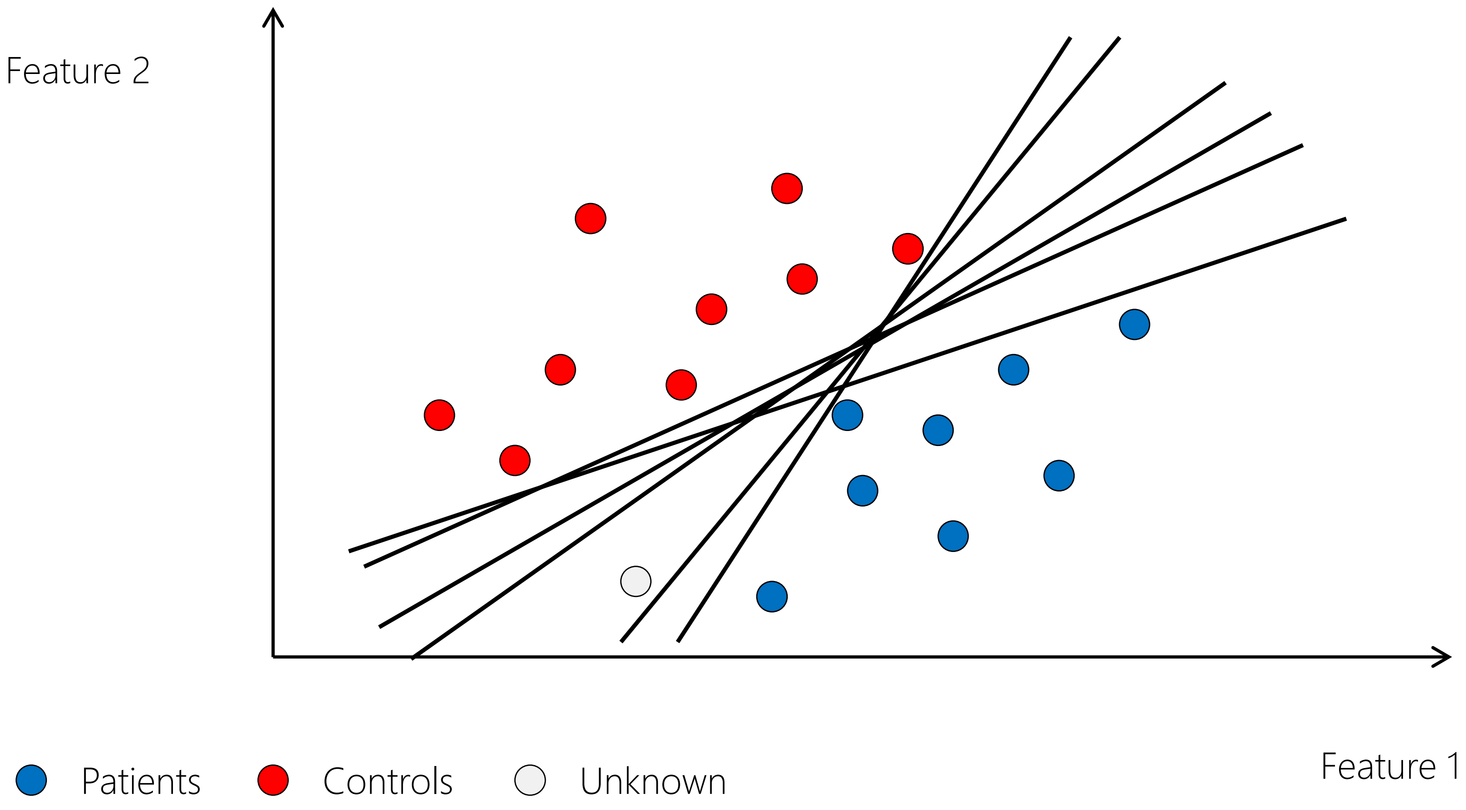
Support Vector Machine - Concept

With 2D we have many possibilities…



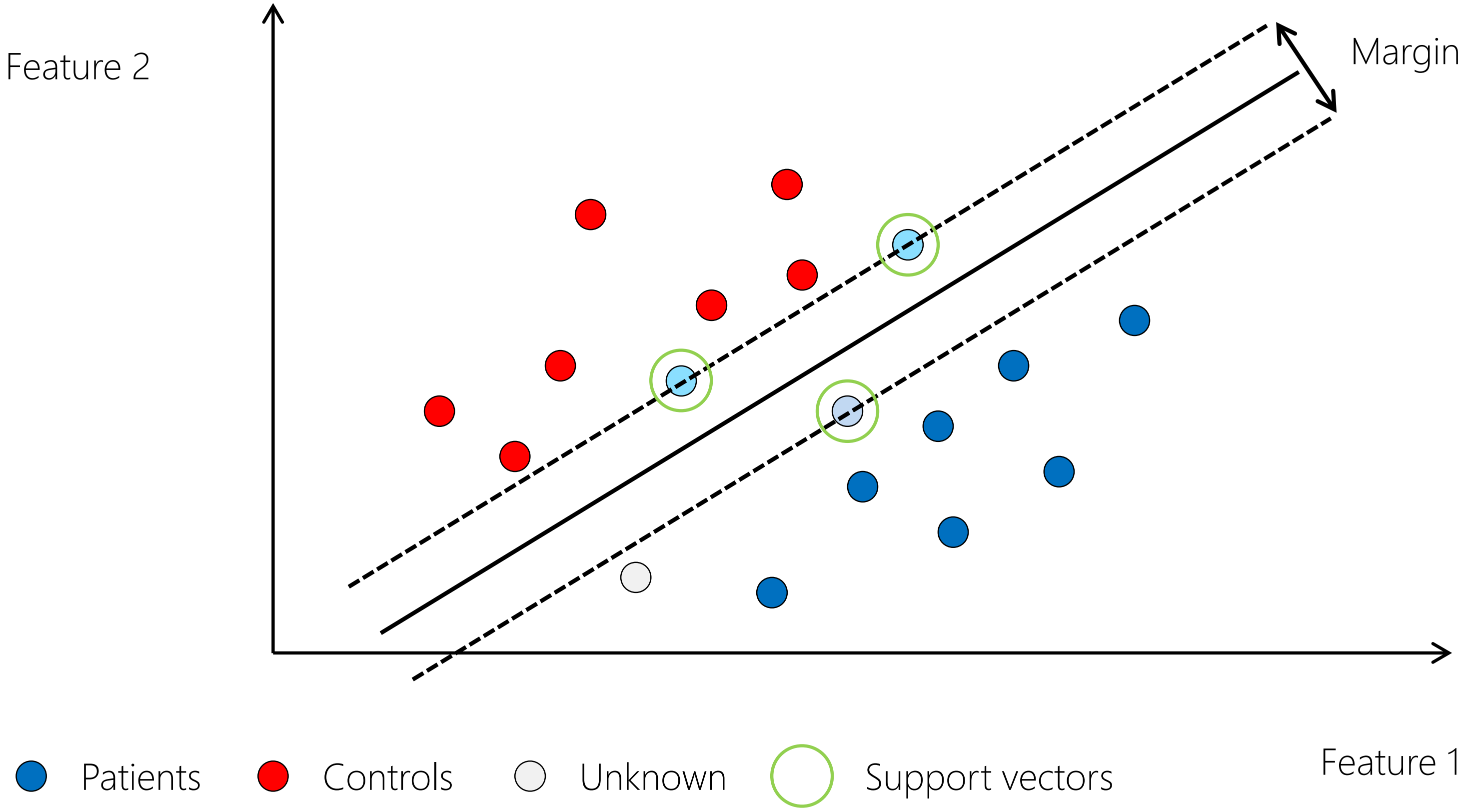
Support Vector Machine - Concept

Which one is best to predict new data?



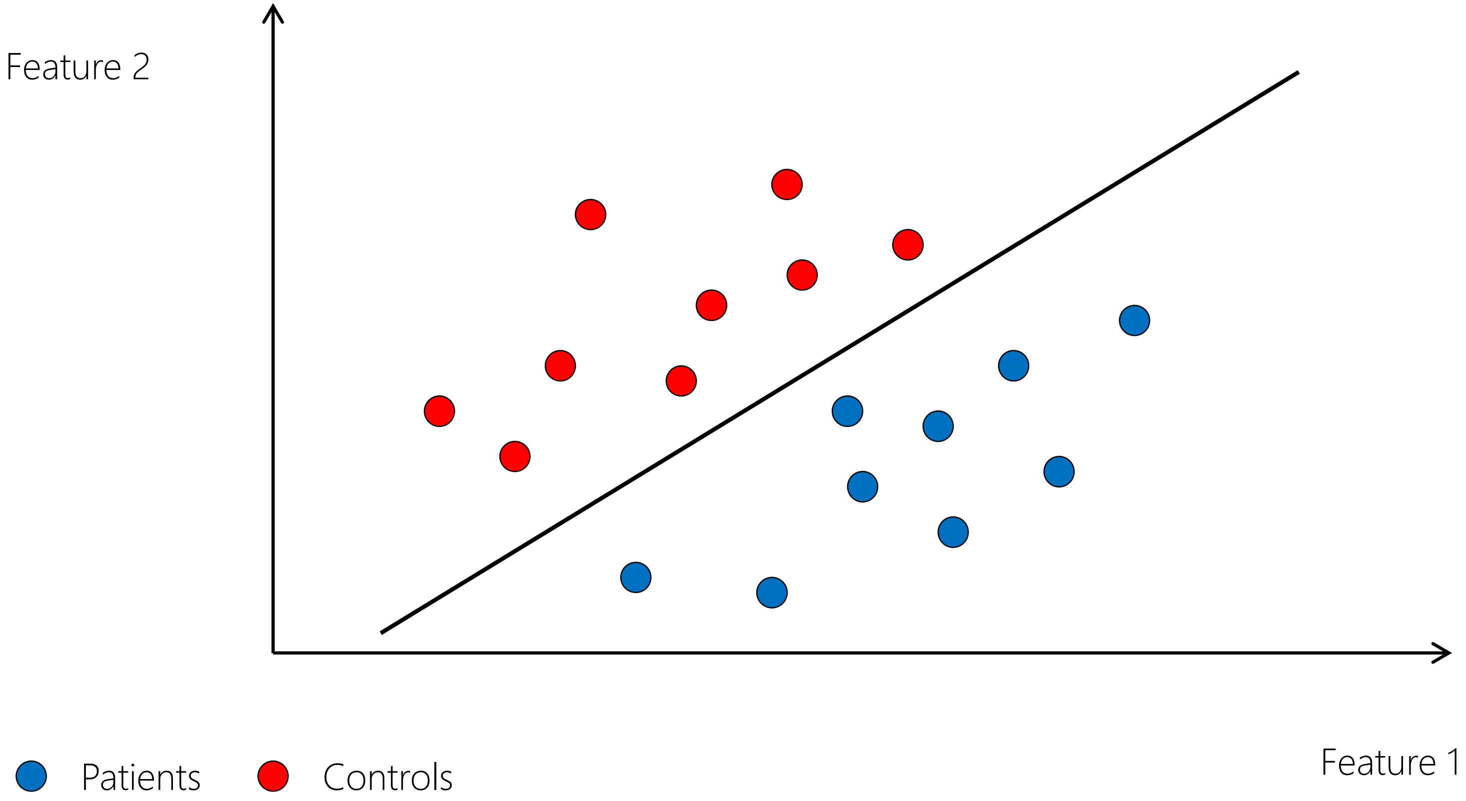
Support Vector Machine - Concept

SVM → Largest margin → Optimal separation → Better generalization



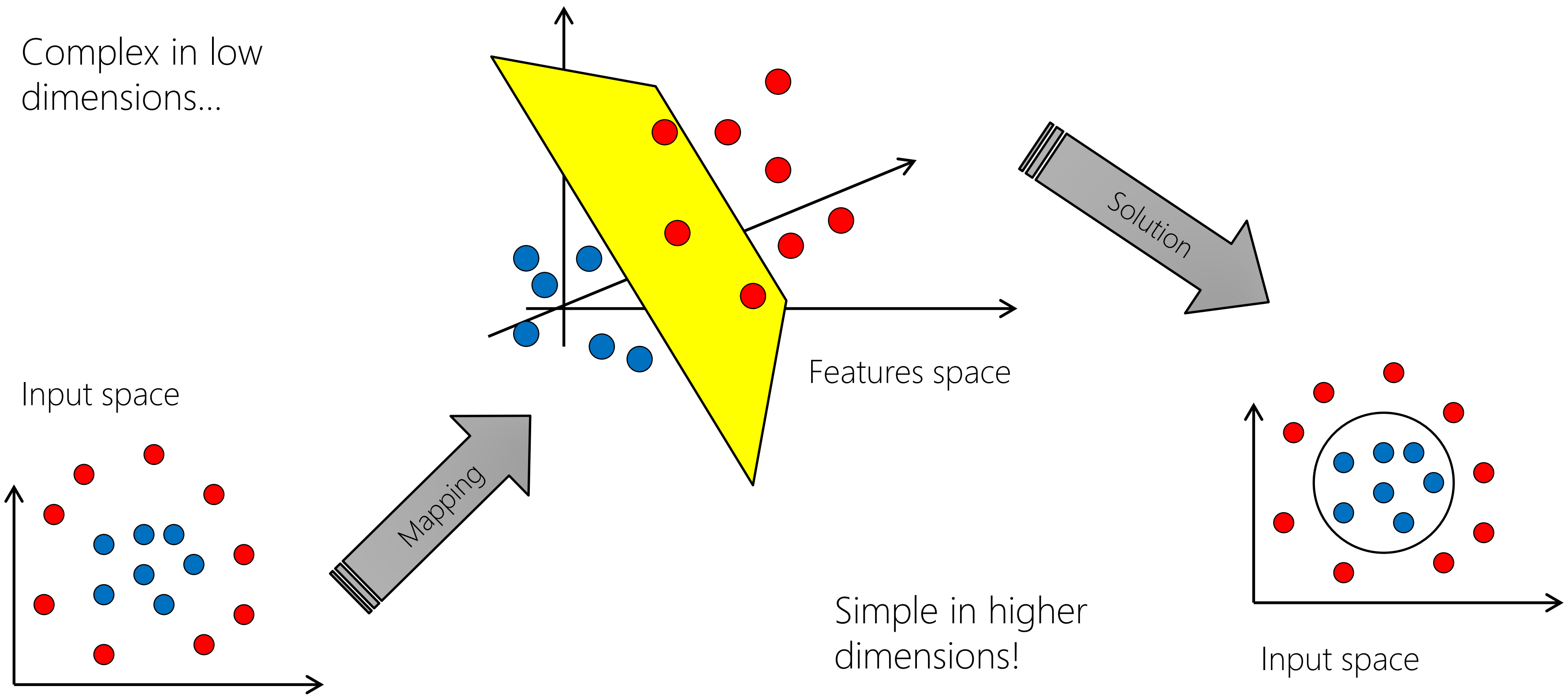
Support Vector Machine - Concept

Ok, this example was easy…



Support Vector Machine - Concept

In harder cases use the ***kernel trick***



Weightless Neural Networks (WNN)

Convert features to **binary representation**

One discriminant per class

Discriminant = list of memories

Ramdomly map bits to memories

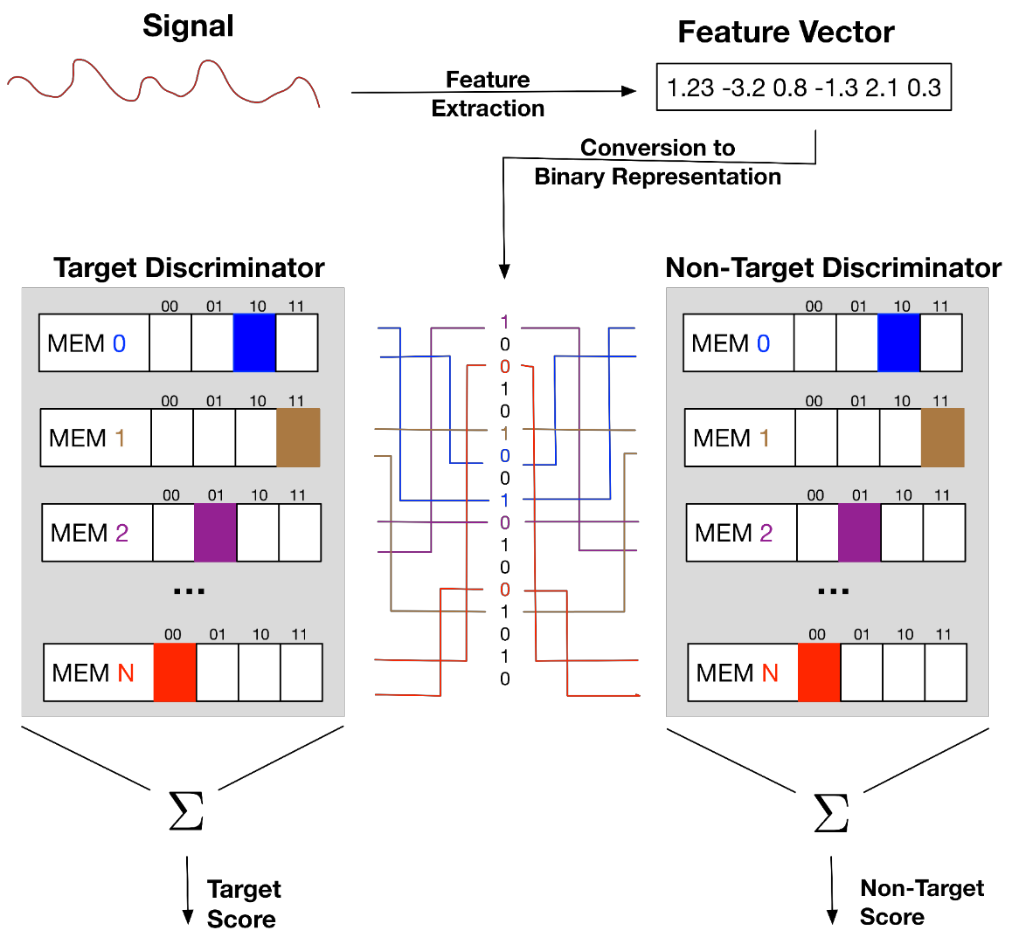
Train phase:

Count bit patterns from the training exemples

Test phase:

Get counts from each discriminant (class)

Label the case with the **discriminant with higher count**



Applications of machine learning

in Neuroimaging

Brain function in Autism Spectrum Disorder (ASD)

Machine learning approaches to neuroimaging

Mental Imagery of Facial Expressions

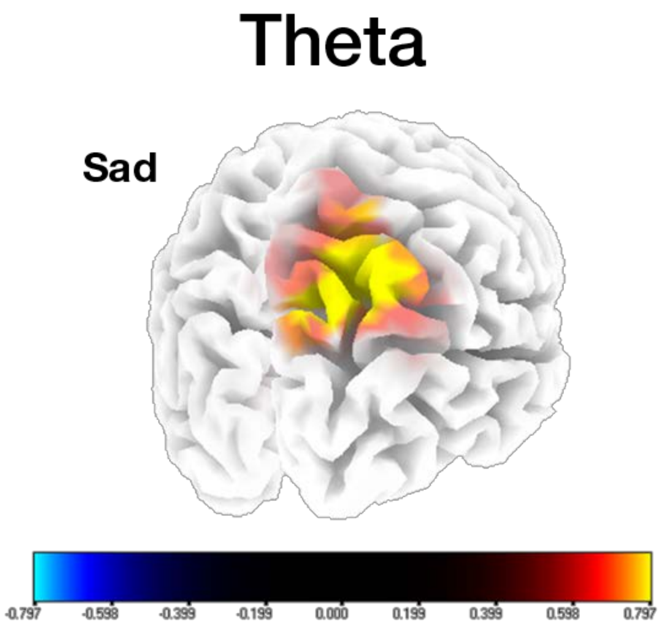
ASD reveal several **Facial Expression processing deficits**

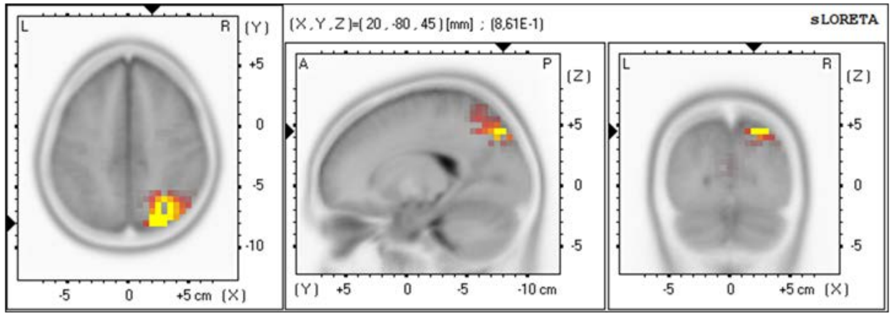
But EEG studies present **inconsistent results**

There are also **deficits on pretend play and imagery**

We created a task that combines both:

mental imagery of facial expressions

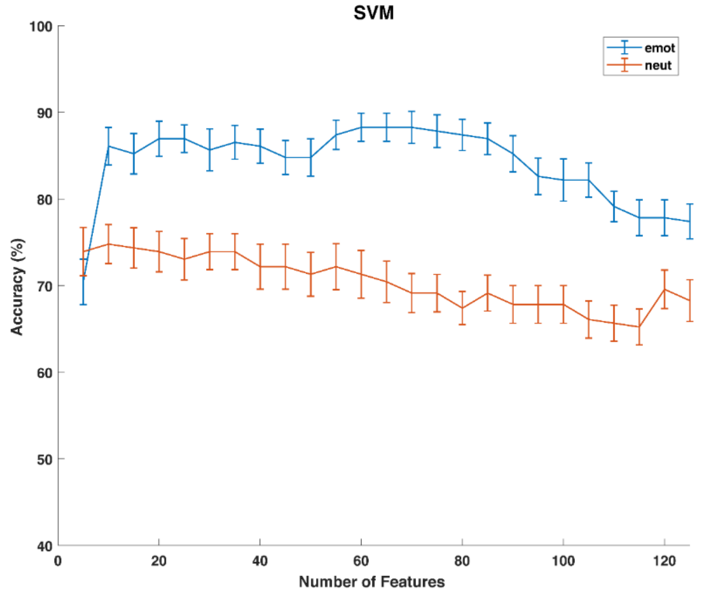


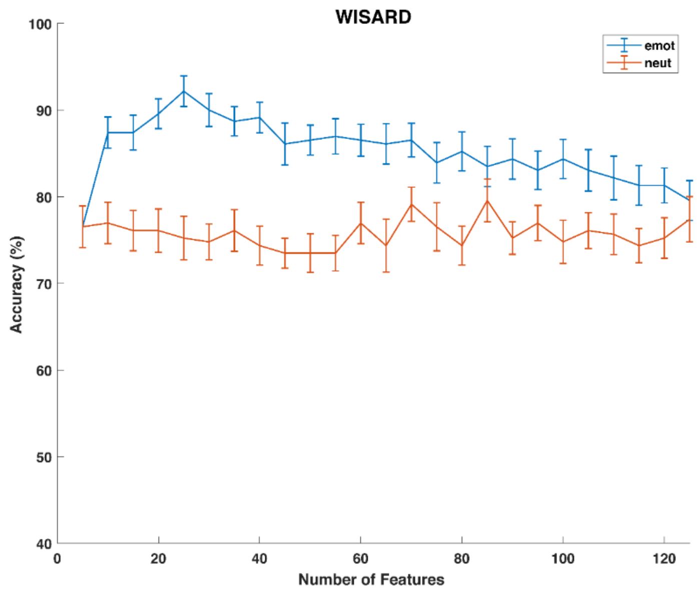


Biomarkers of Facial Expression Imagery Deficit

Characteristics / features of the signal that are related to the disorder

Can be used as diagnosis and interventional biomarker





TYPE	CLASS.	ACCURACY	SPECIFICITY	SENSITIVITY RECALL	PRECISION	F1 SCORE
EMOT	**SVM**	85,5% (1,3)	**95,8% (1,3)**	75,3% (3,1)	**96,2% (1,2)**	82,6% (1,9)
	WiSARD	**92,4% (1,0)**	93,7% (1,7)	**91,1% (1,8)**	94,6% (1,4)	**92,1% (1,1)**
NEUT	**SVM**	75,0% (2,1)	**83,2% (2,8)**	66,8% (4,1)	82,0% (2,8)	72,2% (2,8)
	WiSARD	**78,4% (2,1)**	81,6% (2,8)	**75,3% (3,1)**	**82,4% (2,4)**	**77,0% (2,4)**

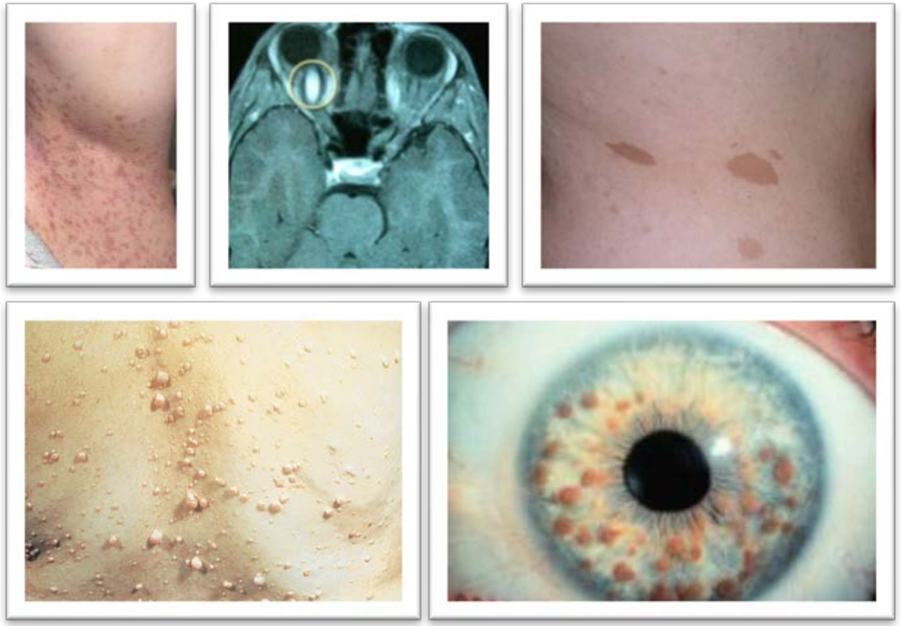
Brain structure in Neurofibromatosis Type 1 (NF1)

Machine learning approaches to neuroimaging

Background

Genetic disorder characterized by impaired cognitive function and brain anomalies, megalencephaly being the most apparent.

However the gross brain anatomy appears normal.



Subtle and widespread differences in NF1 brain are challenges to:

Region-of-interest analysis (low exploratory power)

Voxel-based morphometry (low statistical power)

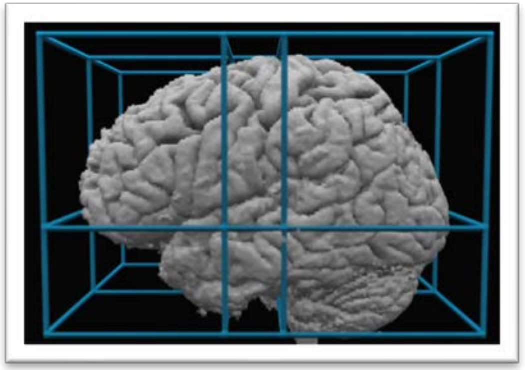
Next logical step: **Multivariate pattern analysis (SVM) with MRI data**

SVM approach

Can we discriminate NF1 patients from controls based on patterns on neuroanatomical data?

High-resolution MRI data

Spatial normalization (inter-subject comparison)



Tissue segmentation (Grey Matter and White Matter)

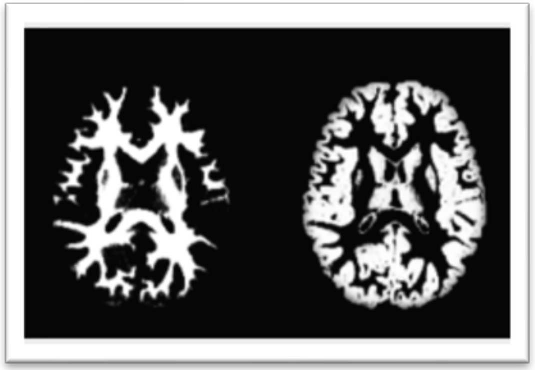
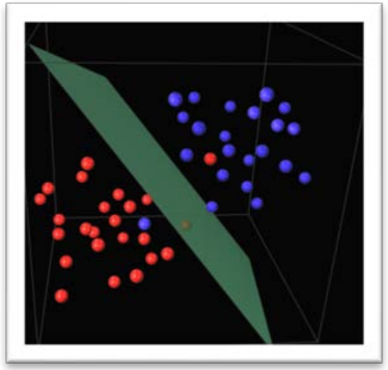


Image classification

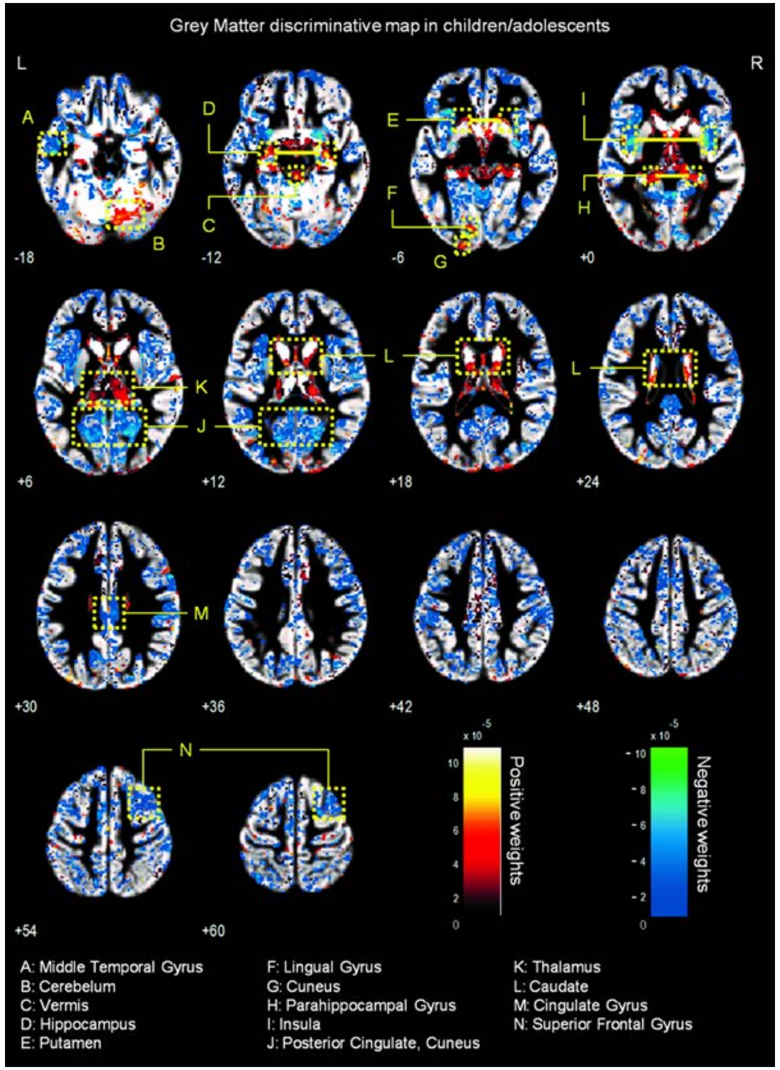


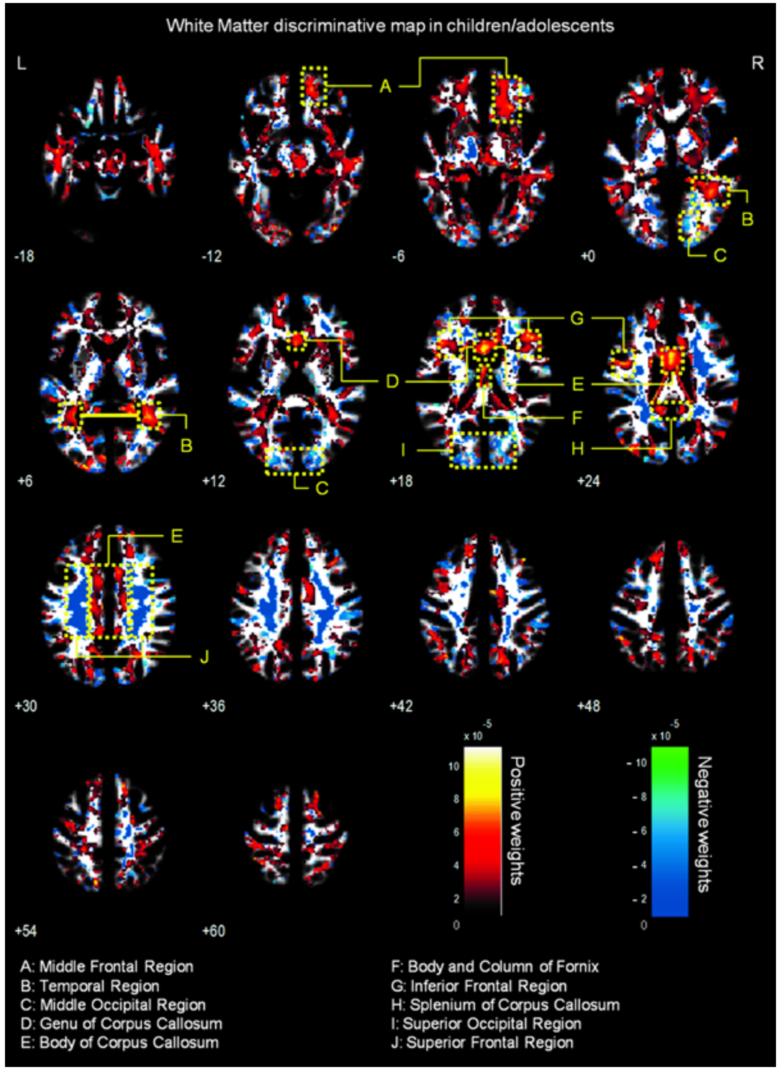
Features: Tissue volume (GM or WM) in each voxel

Label: NF1 (positive class) or control (negative class)

Diagnostic and neuroscientific tool (classification weights)

Performance	GM	WM
Accuracy	93.60%	91.96%
Sensitivity	91.65%	89.64%
Specificity	95.56%	94.28%





Take home messages

Machine learning extends traditional analysis of neuroimaging data.

Can be used for binary (or multiclass) output – diagnostic.

Can be used for development of outcome measures – clinical scores, symptom severity.

Interpretable features can be useful for widespread clinical application.

Machine learning features can guide new basic research about underlying mechanisms.

Thank you!

Questions?