Learning How to See the Invisible

A data-driven approach to finding underlying patterns of abnormality in visually normal MR brain images from patients with epilepsy

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Summary

Epilepsy

The Problem

Methods

Results

Discussion

Further Work

Epilepsy

- Common and Serious
- Characterised by recurrent seizures
- First-line treatment with oral medication
- Medication ineffective in 1/3 of cases

Epilepsy

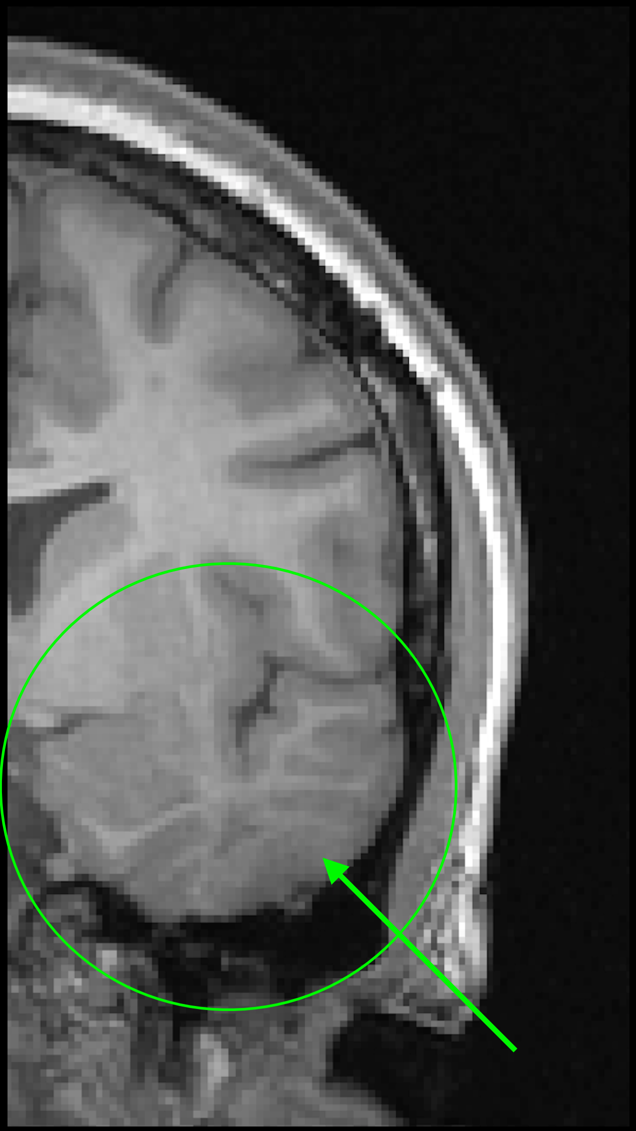
- Drug resistant focal epilepsy is a challenging problem
- Neurosurgery is often considered in these cases
- Aim to remove the ‘epileptogenic’ region of the brain
- Have to find it first…

The Problem

- MRI is normally used to look for these abnormalities
- Abnormality found by a radiologist 2/3 of the time
- …leaving 1/3 of patients ‘MR negative’

The Problem

Healthy



Visible Disease
'MR positive'

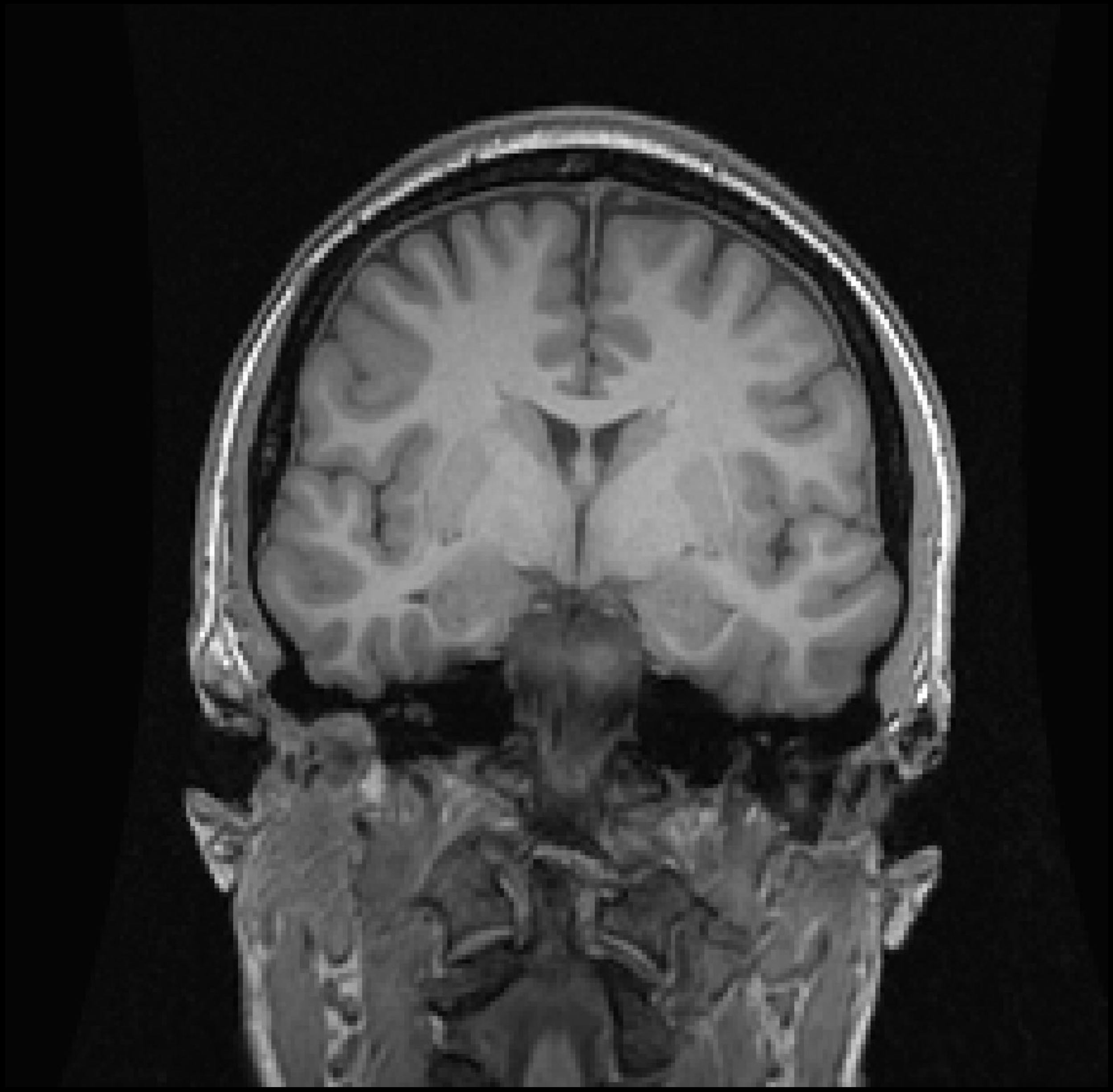
Invisible Disease
'MR negative'

The Problem

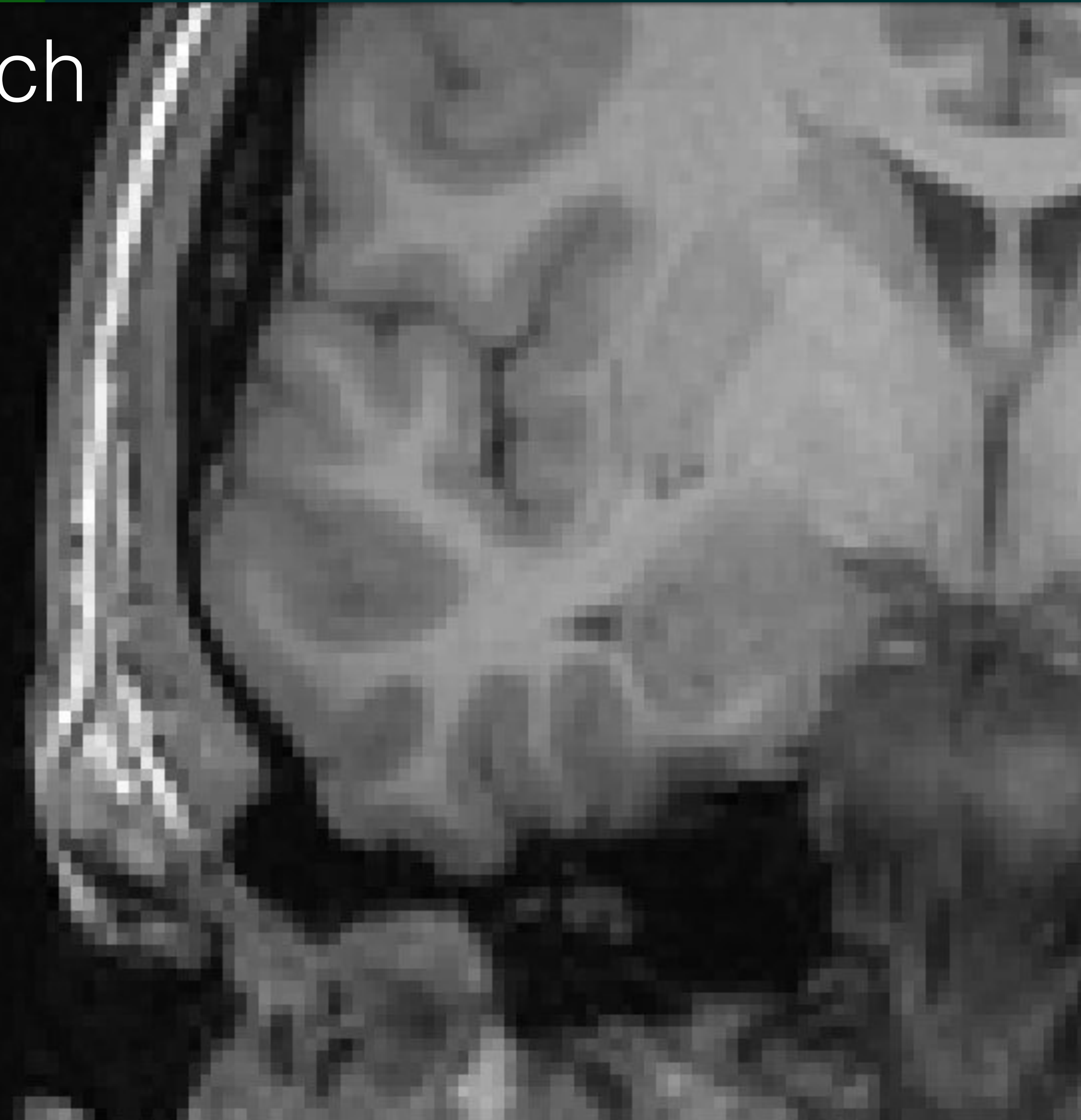
- Are these visually normal MR negative images truly normal?
- Or are the abnormalities within them simply too subtle to see?
- Or in a different pattern from what we expect?

Invisible Disease
'MR negative'

Our Approach



Our Approach



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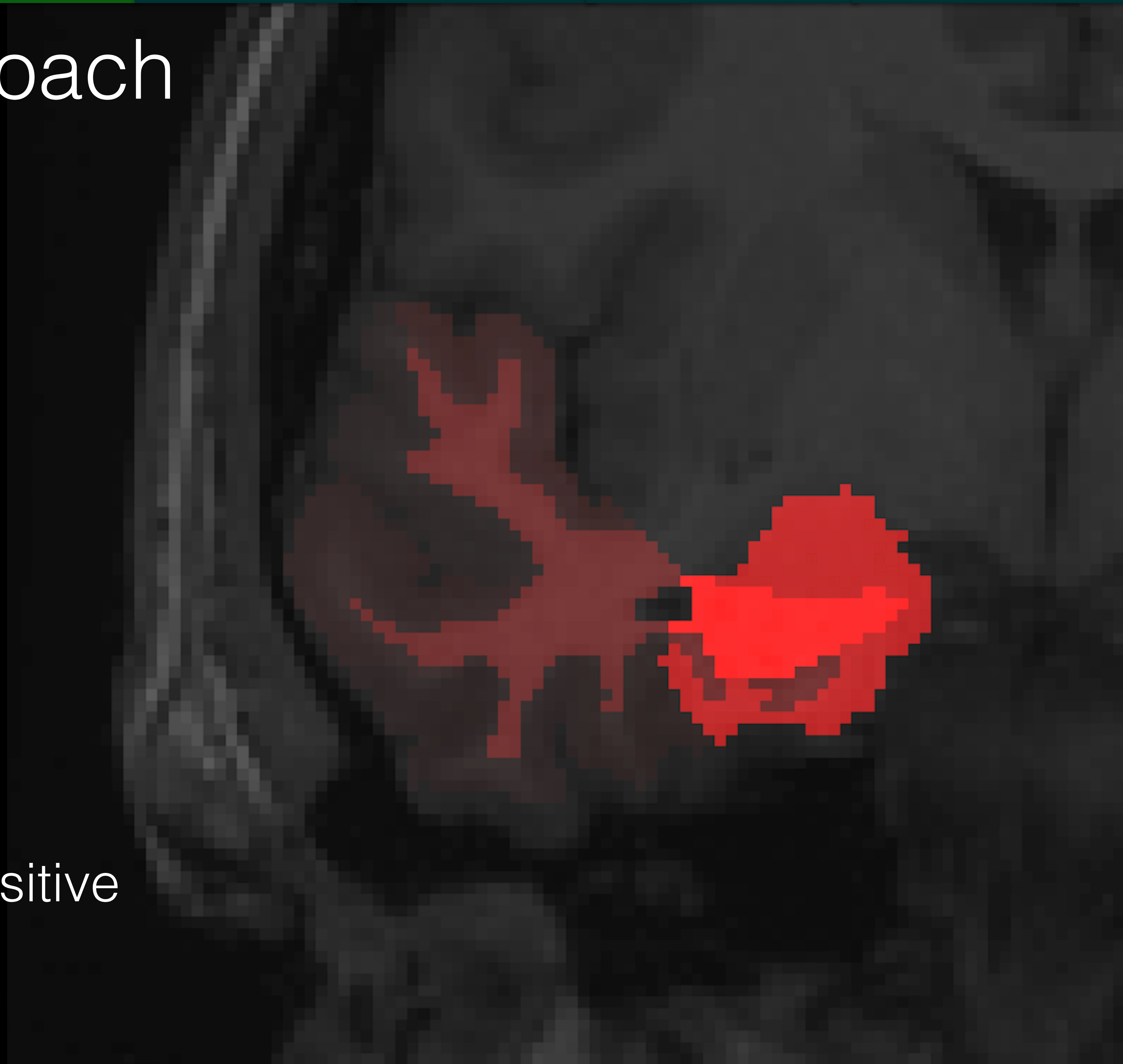
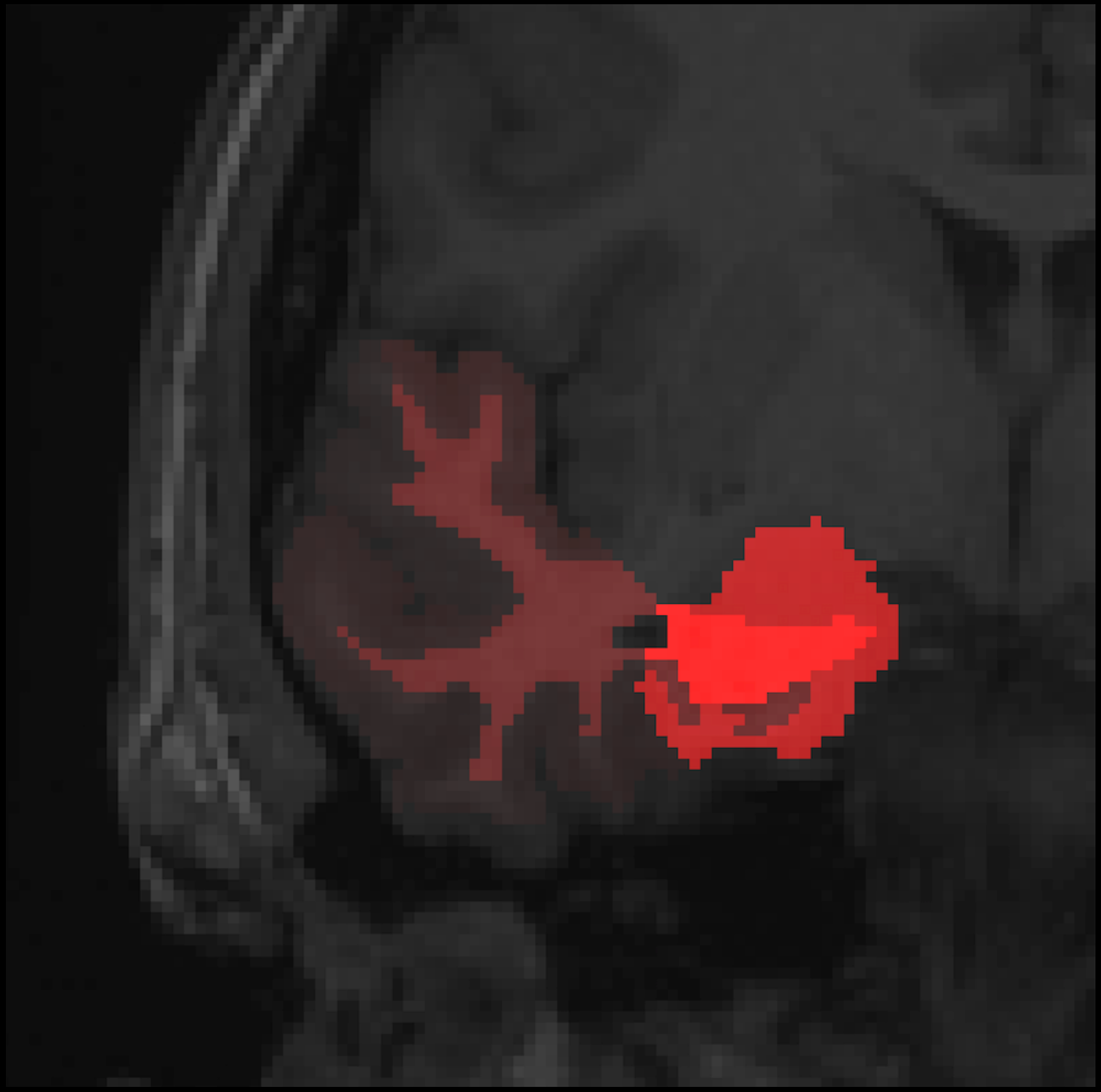


MR positive

Our Approach



MR positive

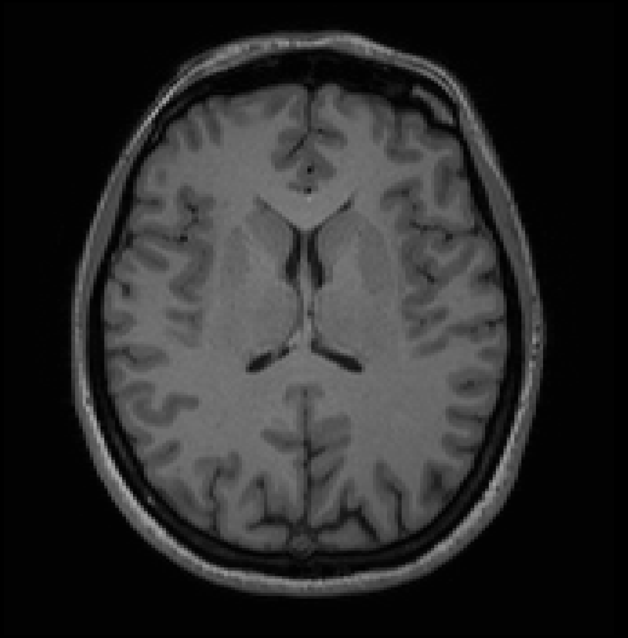
MR negative

Methods

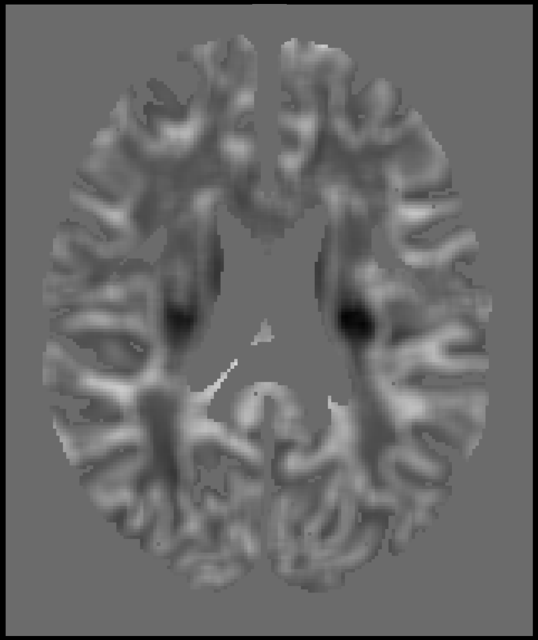
- 82 MR +ve and 26 MR -ve subjects
- All with temporal lobe epilepsy
- Seizure lateralisation known for each subject
- 4 image modalities/types available for each subject
- T1, T2, FLAIR, Junction Map

Methods

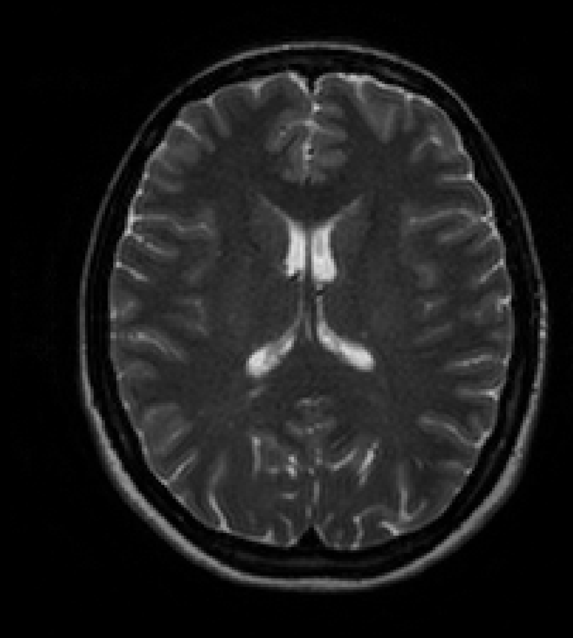
1. Start with the 4 image volumes from each subject



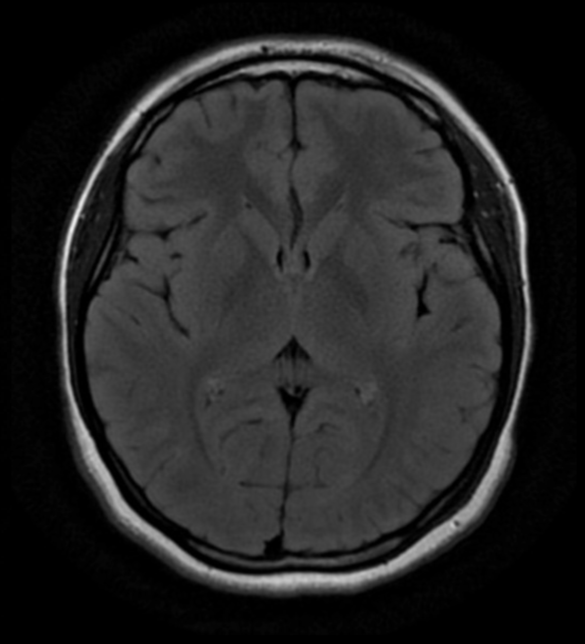
T1



Junction Map



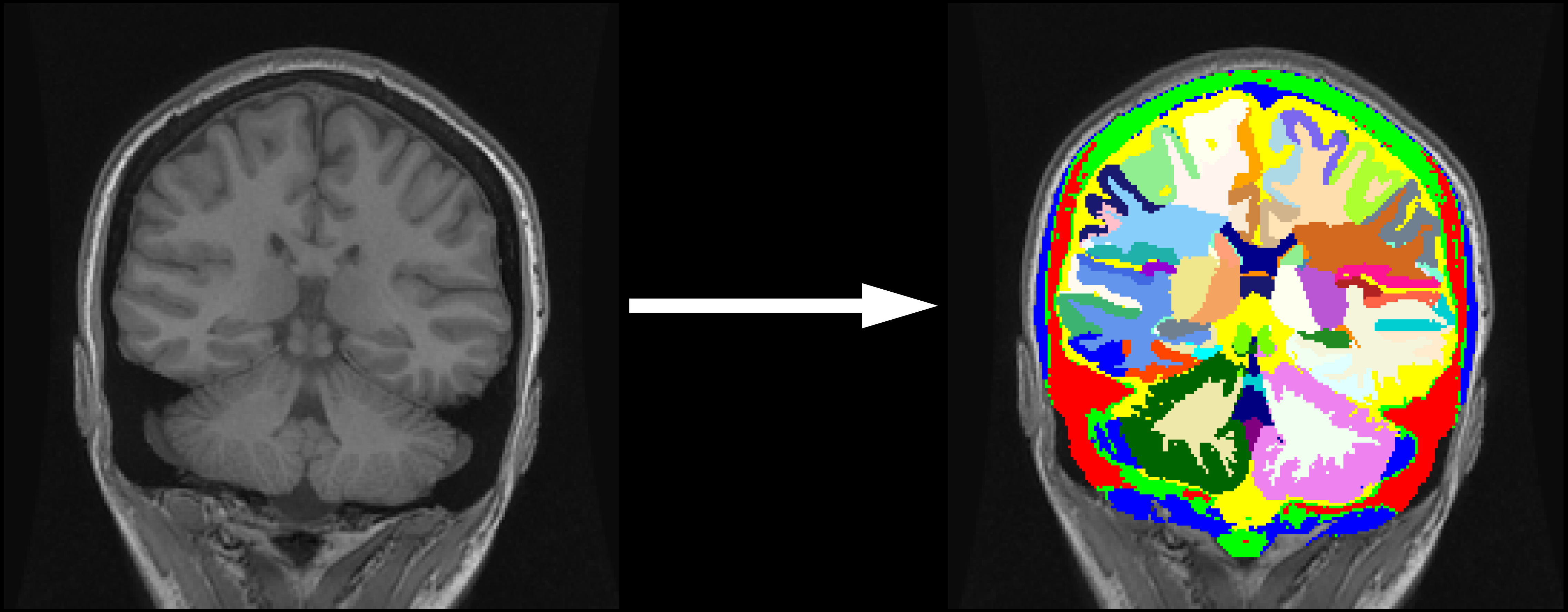
T2



FLAIR

Methods

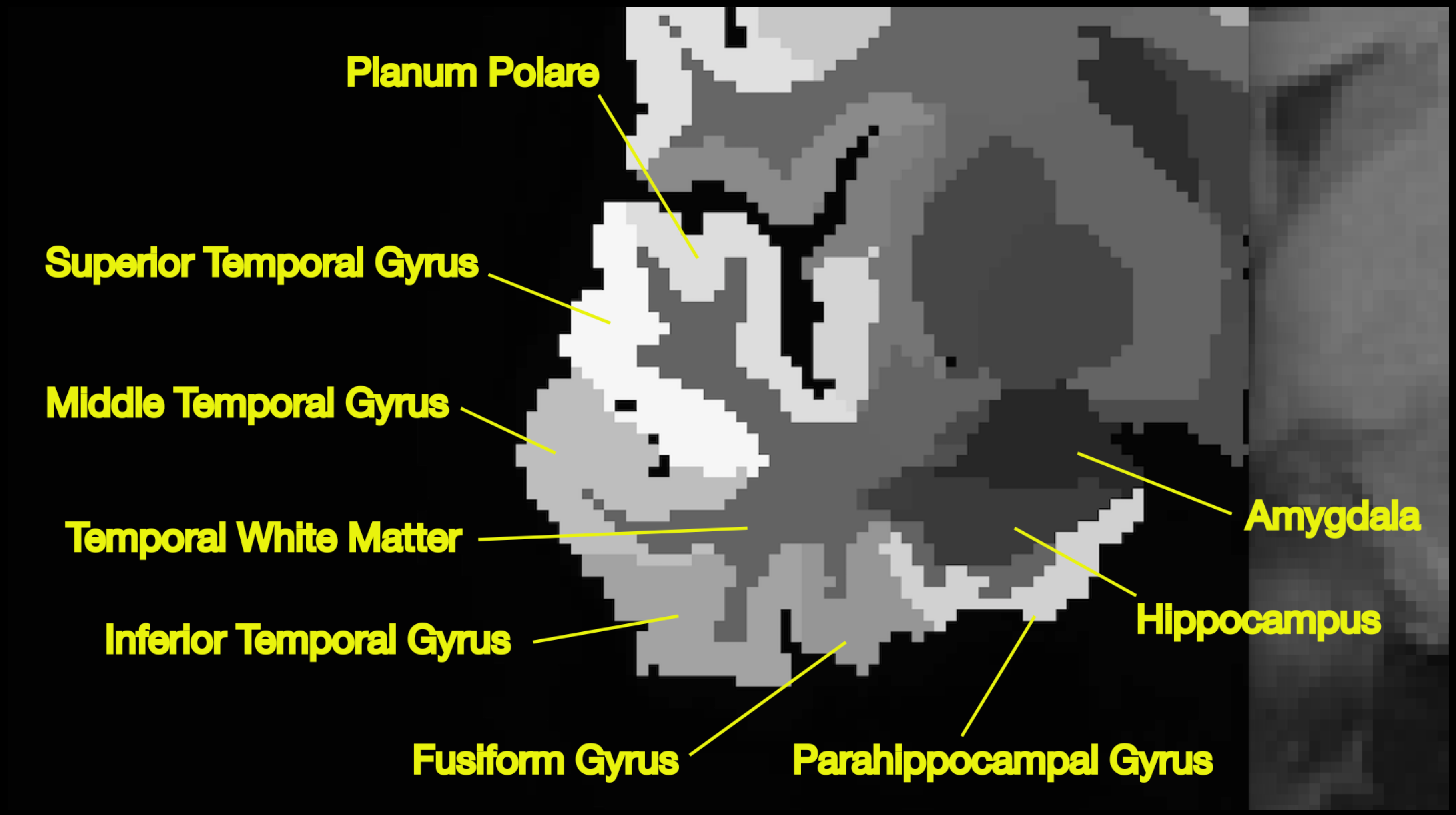
2. Segment out all anatomical regions within images (GIF)



http://cmictig.cs.ucl.ac.uk/wiki/index.php/Full_brain_parcellation_using_Geodesic_Information_Flow

Methods

3. Look specifically at the regions within the temporal lobe



Also:

Entorhinal area

Planum Temorale

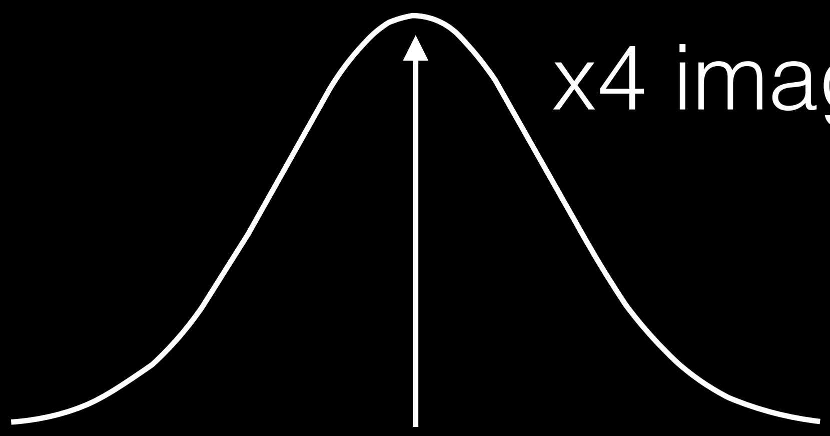
Transverse Temporal Gyrus

Temporal Pole

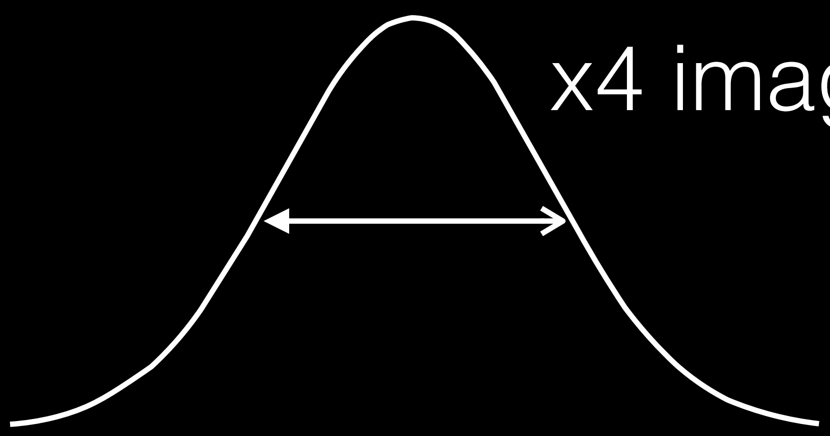
Methods

4. Compute image features from each region within the 13 temporal lobes of each subject

a. Mean Intensity left/right difference



b. Intensity Standard Deviation left/right difference



c. Region volume left/right ratio

Also: Total intracranial volume

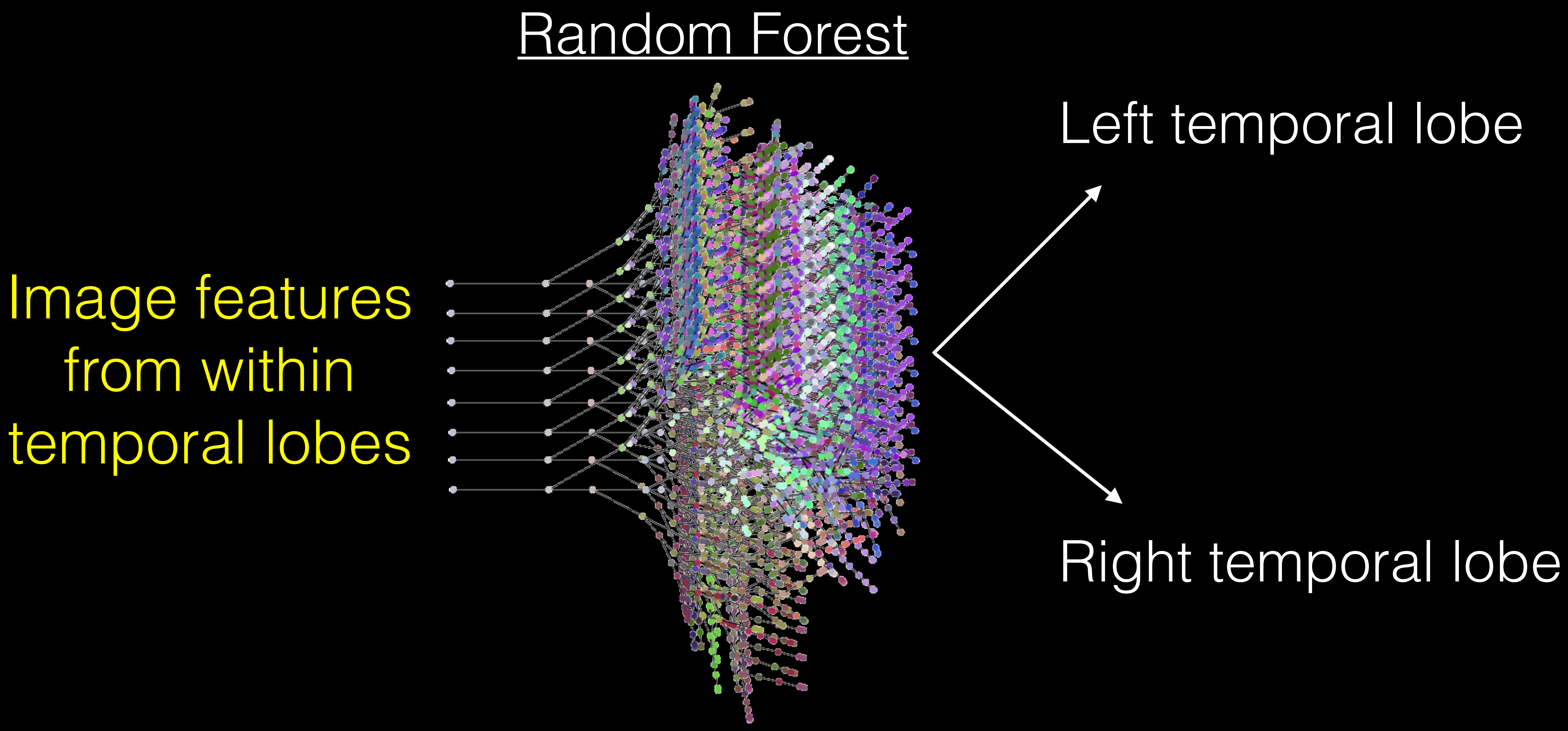
Methods

4. Compute image features from each region within the 13 temporal lobes of each subject

118 features generated per subject

Methods

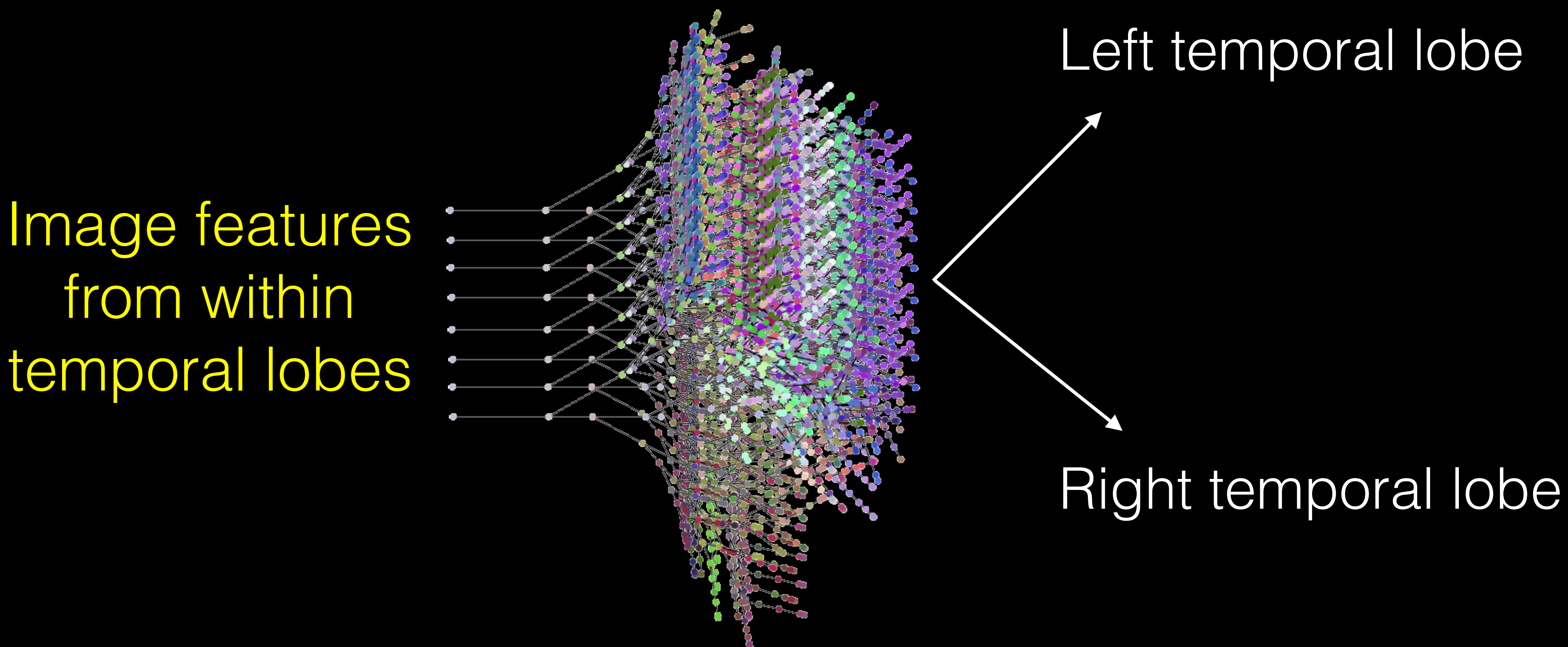
5. Train a random forest classifier on the image features to predict seizure lateralisation



Methods

6. Feature importance measurements

Random Forest



Methods

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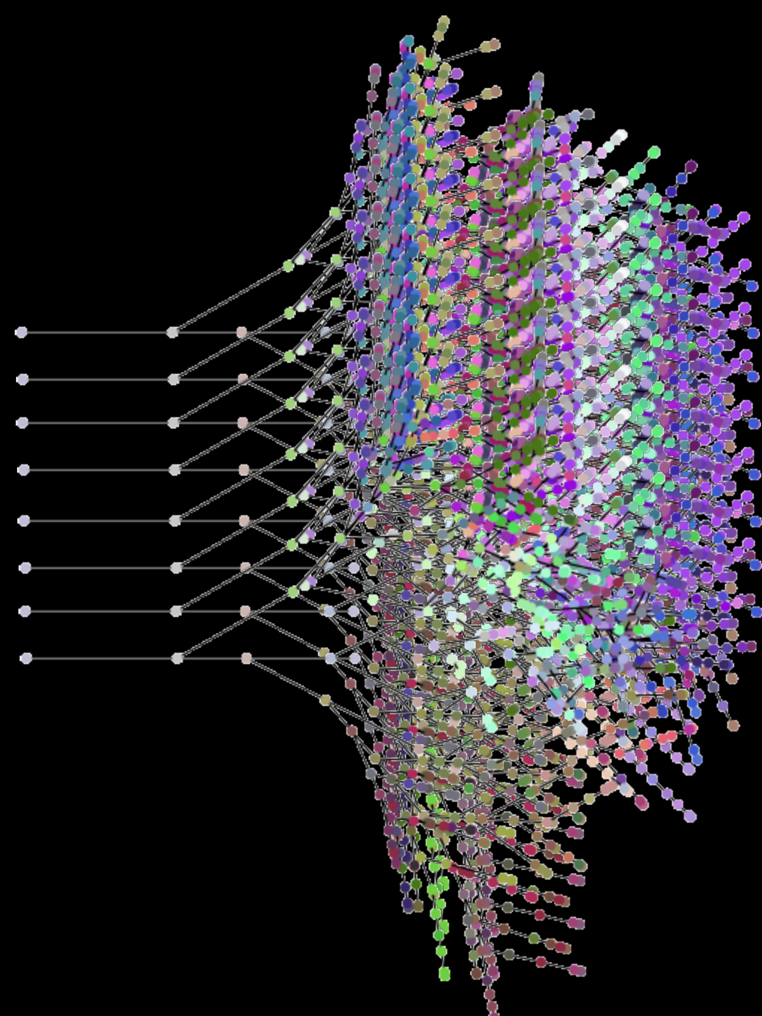
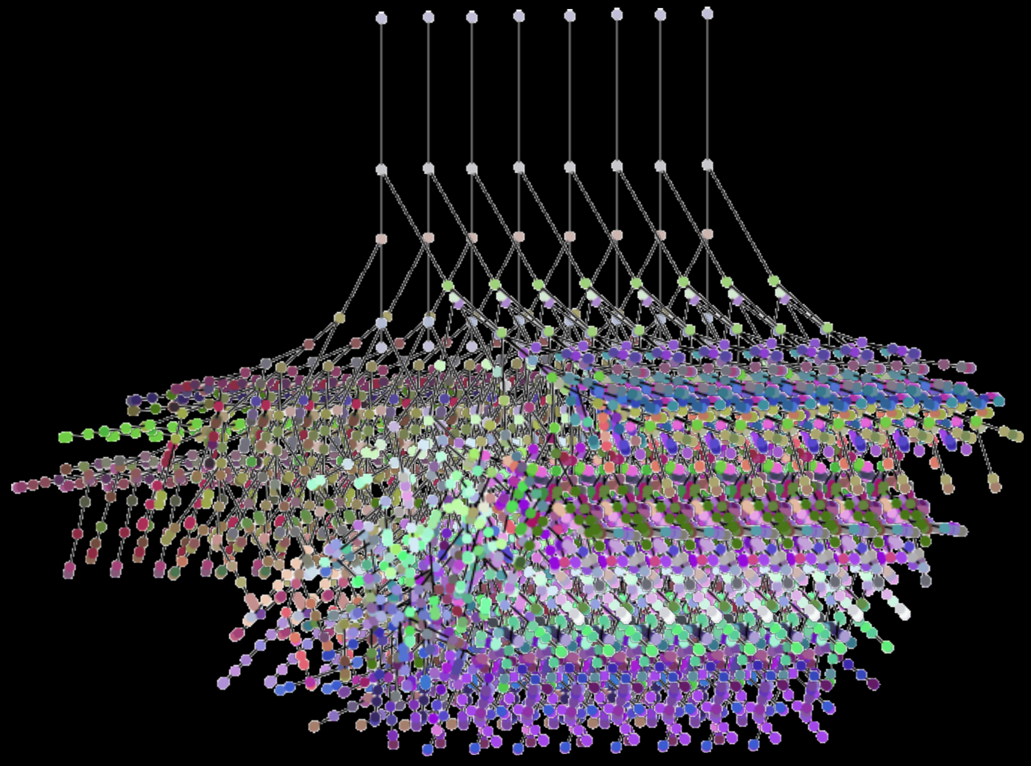


Methods

6. Feature importance measurements



Methods

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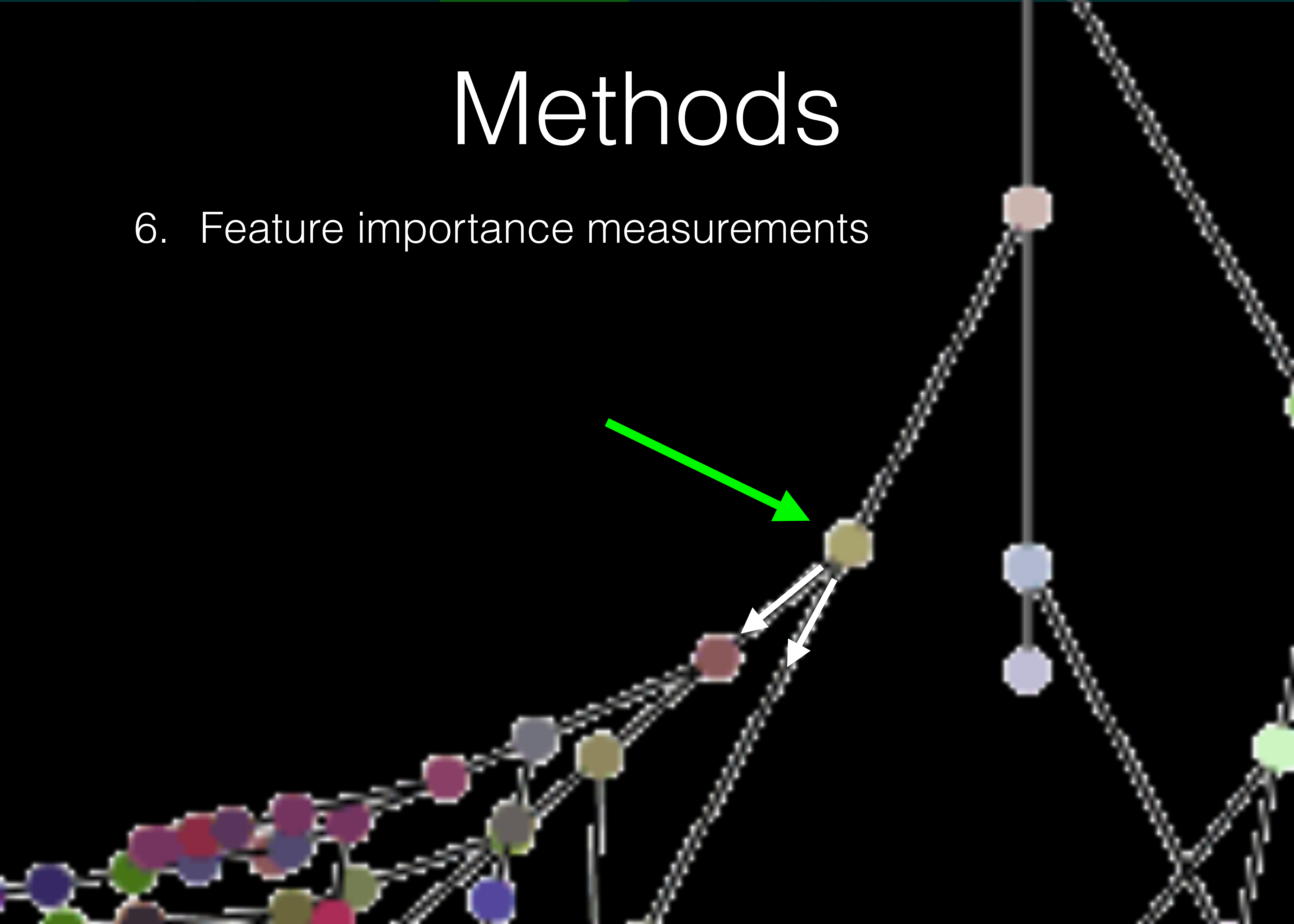

Methods

6. Feature importance measurements

A feature's importance is: *the drop in Gini impurity it provides weighted by the chance of reaching that decision in the tree, averaged across all trees in the forest*

Provides a quantitative measure of the 'usefulness' of each feature for distinguishing between classes

Methods

7. Generate Importance Maps

Visualisations of feature importances created in the form of Importance Maps

Can be thought of as ‘heat maps’ of abnormality

Results

SVM Classification accuracy using features:

MR positive:
Accuracy: 94% (CI 86-98%) using top 3 features

MR negative:
Accuracy: 82% (CI 63-93%) using top 38 features

Results

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Results

MR **positive** subjects

Region	Feature
1) Hippocampus	vol
2) Hippocampus	mean T2
3) Hippocampus	std FLAIR
4) Temporal White Matter	vol
5) Hippocampus	mean FLAIR
6) Hippocampus	std T1
7) Temporal Pole	mean T2
8) Parahippocampal Gyrus	mean T2
9) Amygdala	mean T2
10) Hippocampus	std T2

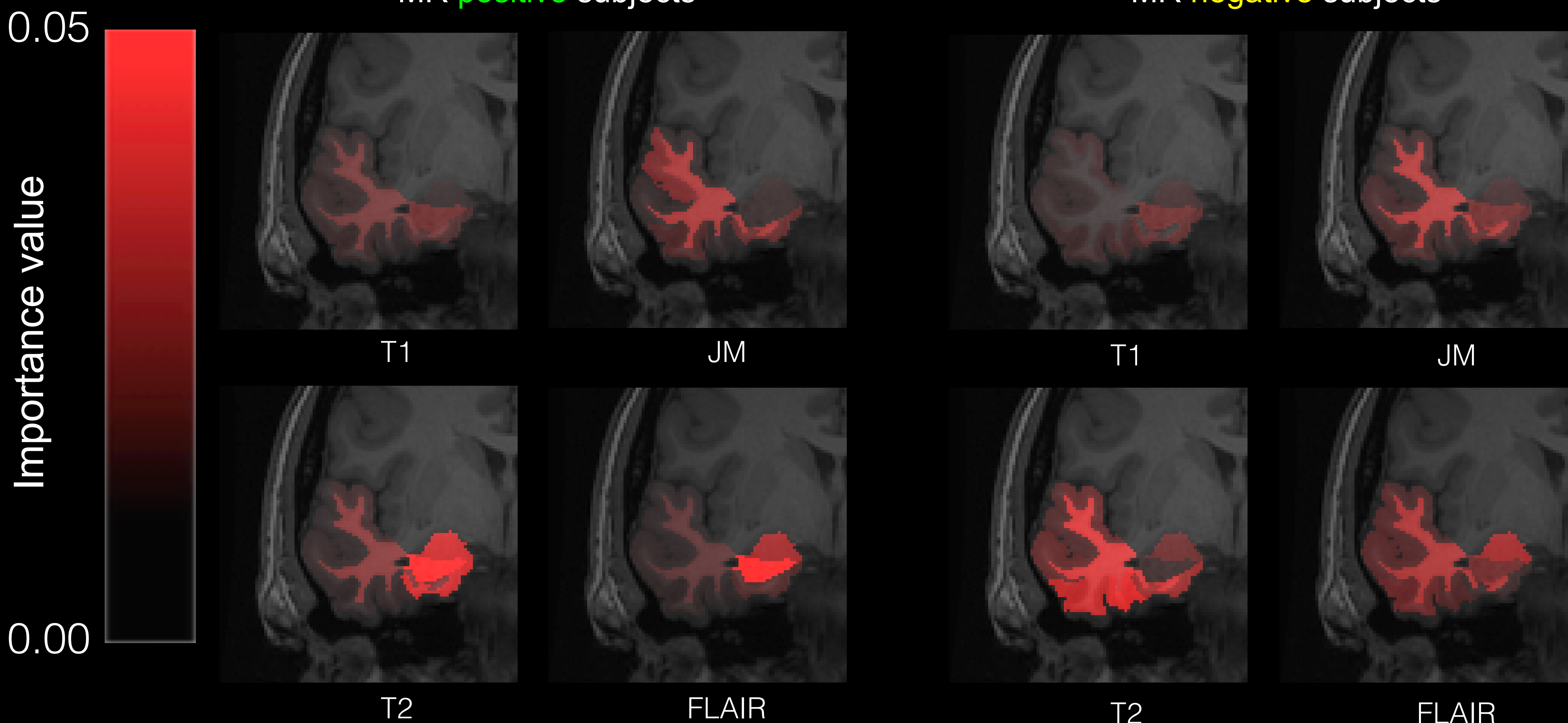
MR **negative** subjects

Region	Feature
1) Amygdala	std T1
2) Fusiform Gyrus	mean T2
3) Temporal White Matter	mean T2
4) Amygdala	std T2
5) Inferior Temporal Gyrus	mean T2
6) Planum Temporale	std T2
7) Hippocampus	std T2
8) Temporal White Matter	mean JM
9) Hippocampus	std T1
10) Amygdala	mean FLAIR

Results

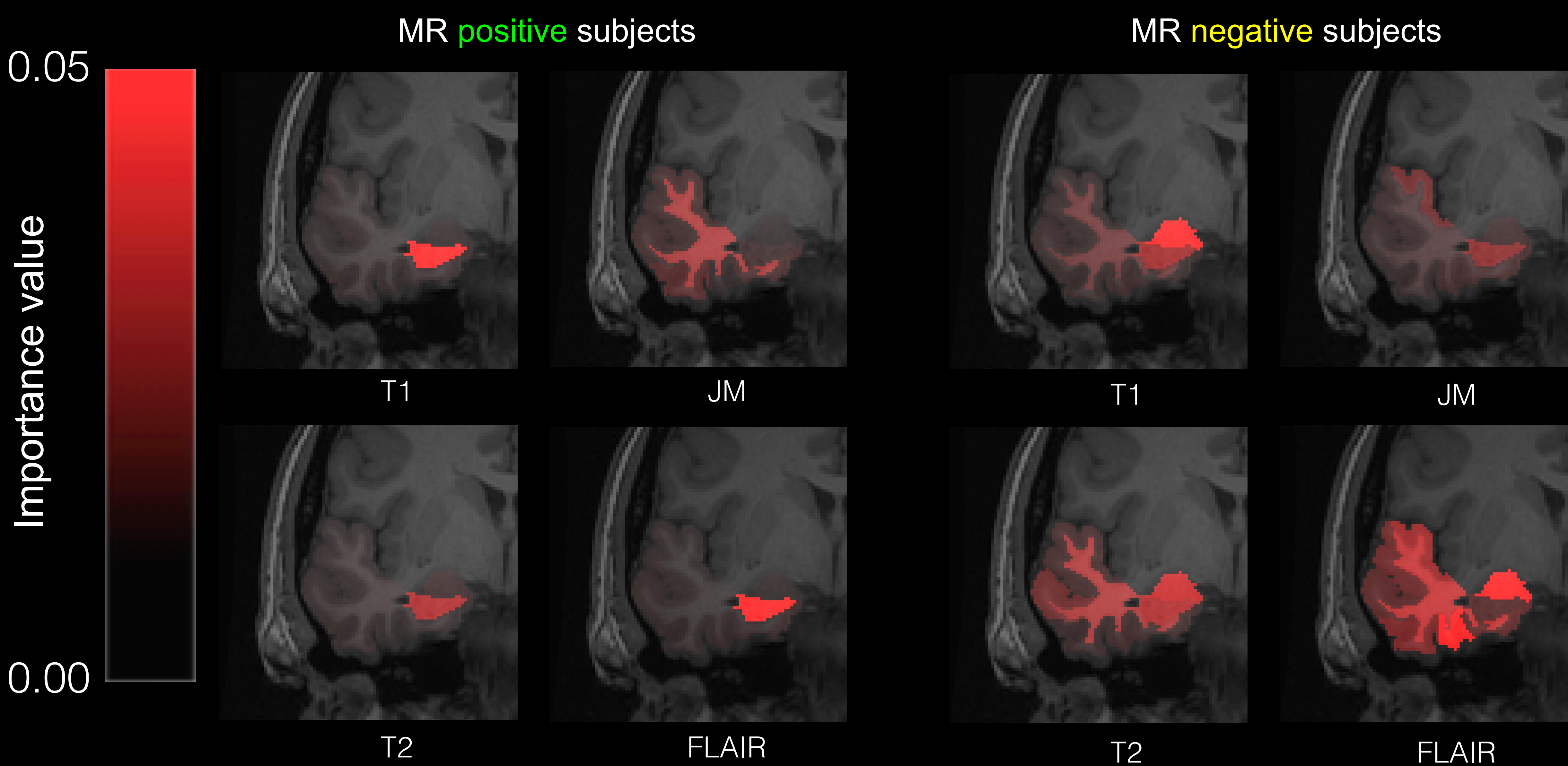
Mean Intensity R - L difference Importance Maps

MR positive subjects | MR negative subjects



Results

Intensity standard deviation R - L difference Importance Maps

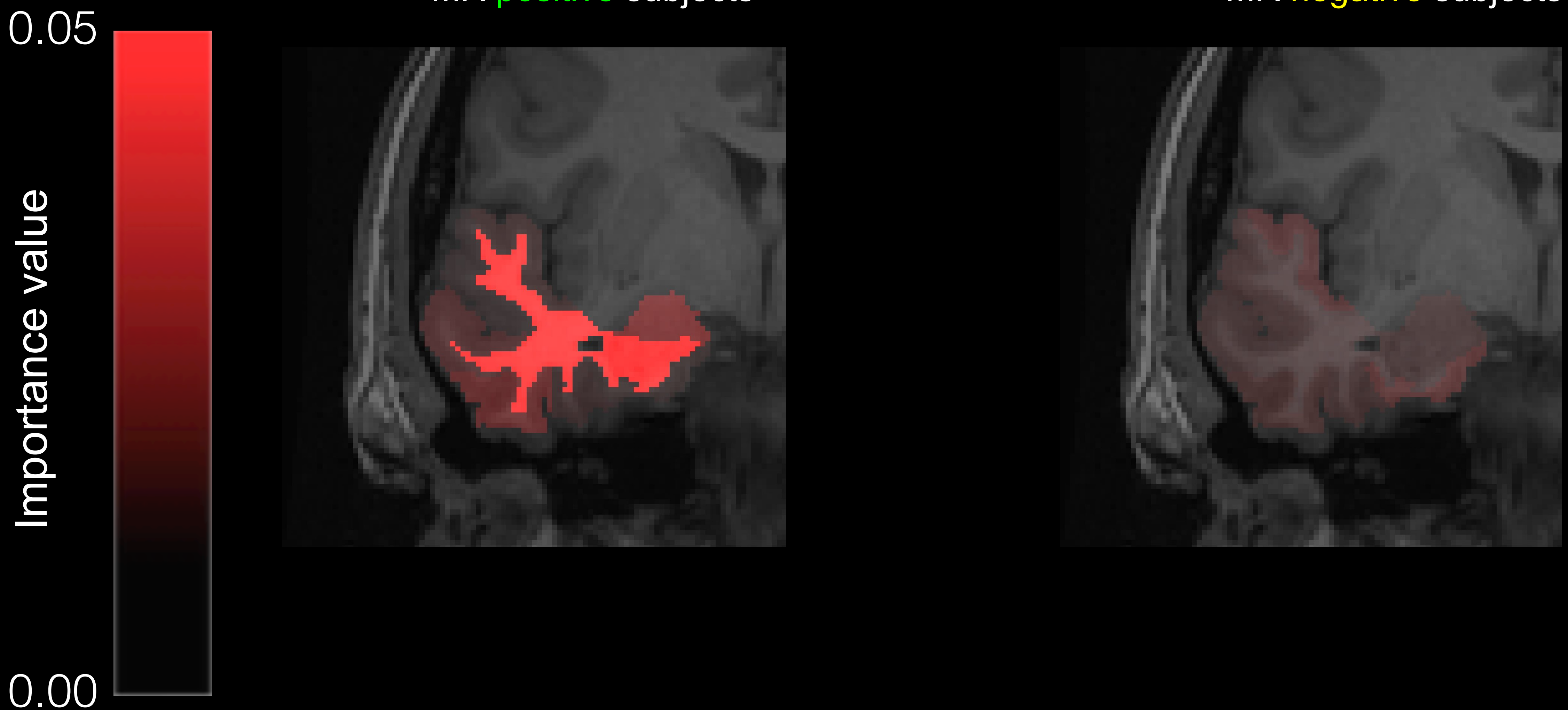


Results

R/L volume ratio Importance Maps

MR positive subjects

MR negative subjects



Discussion

We have demonstrated that:

- MR negative images do contain abnormalities
- These abnormalities seem to lie in a different pattern from those seen in MR positive (visible disease) cases

Discussion

More generally:

- Generates a disease's 'abnormality signature' in imaging investigations
- A training tool for radiologists?

Further Work

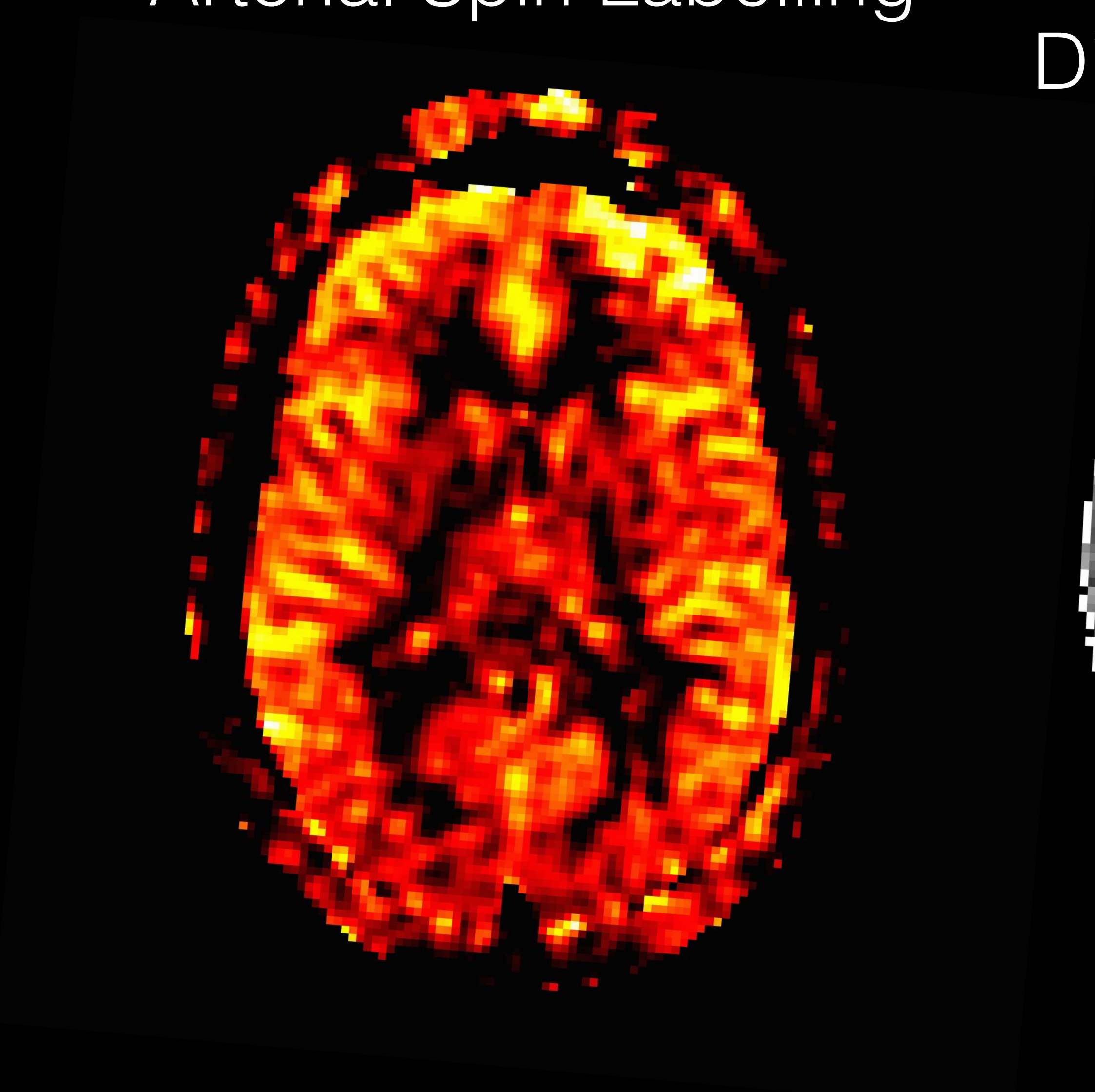
- Could be a way of characterising the amount of extra information novel imaging modalities provide
- The methodology could be applied to other disease processes with subtle or poorly understood visual appearances

Questions

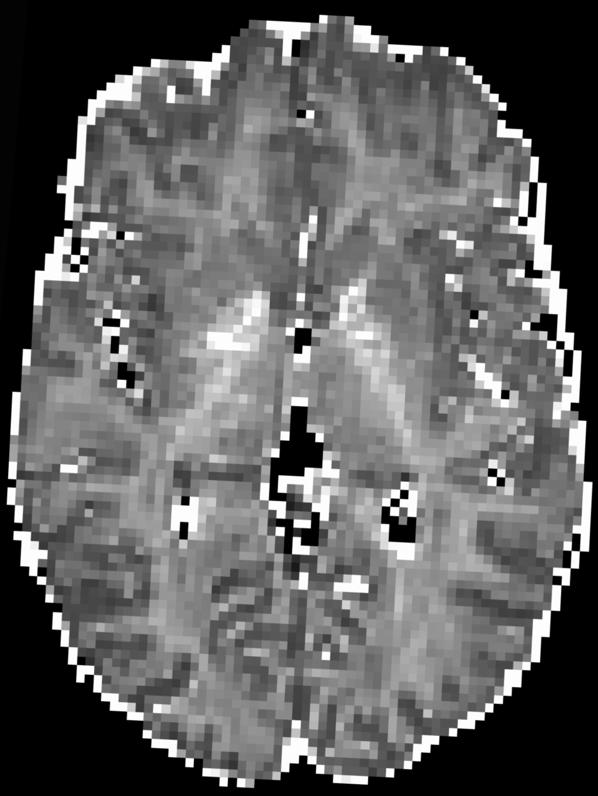
Further Work

Could be a way of characterising the amount of extra information novel imaging modalities provide

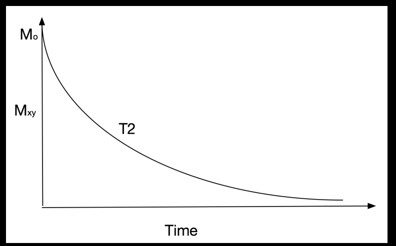
Arterial Spin Labelling

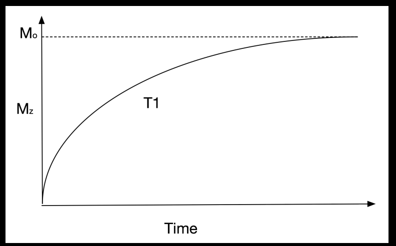


Multi-Compartment Diffusion Modelling



T1, T2 Relaxometry





Sodium Imaging

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