FEATURE-BASED MORPHOMETRY

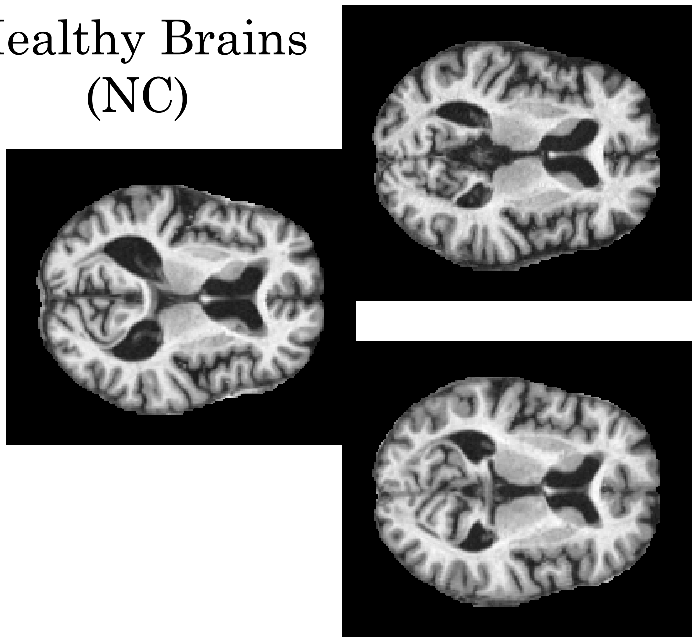
Discovering Group-related Anatomical Patterns

M. Toews, W. M. Wells III, D. L. Collins, T. Arbel

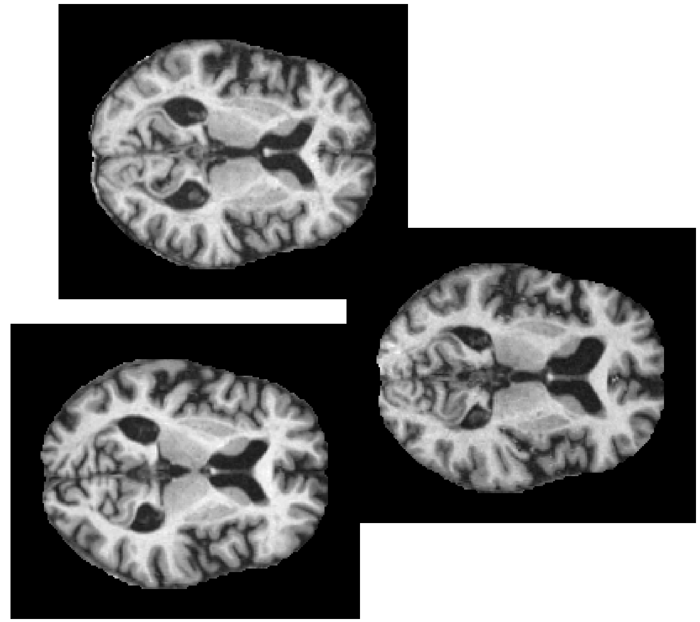
NeuroImage, February, 2010

INTRODUCTION

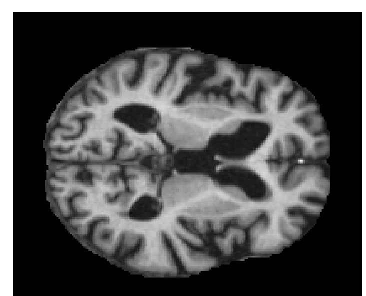
Healthy Brains
(NC)



Brains with Alzheimer's(AD)



A new brain: is it AD or NC?



How do AD and NC brains differ?

What anatomical patterns are characteristic of AD or NC brains?

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INTRODUCTION

- Group Analysis
  - Identify differences between subject groups.
  - Identify group-related structure.
  - Classify new subjects.
- Why?
  - Track disease progression and response to treatment.
    - Image biomarkers of disease
  - Computer-assisted diagnosis.
  - Understanding the neuroanatomical basis for disease.

OUTLINE

- Group Analysis via Morphometry
  - Voxel/Deformation-based
- Feature-based Morphometry
  - Feature extraction
  - Feature-based modeling
  - Analysis

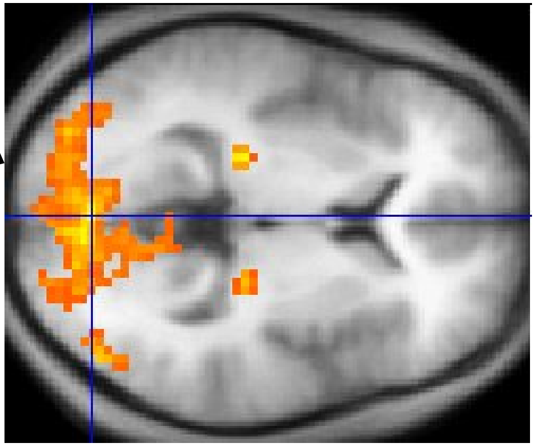
GROUP ANALYSIS VIA MORPHOMETRY

- Voxel/Deformation-based Morphometry

1) Align or spatially normalize subject images
2) Compute statistics across all subjects
3) Identify image regions where statistics differ between groups

Statistical Parametric Map

Orange regions: statistically significant group differences

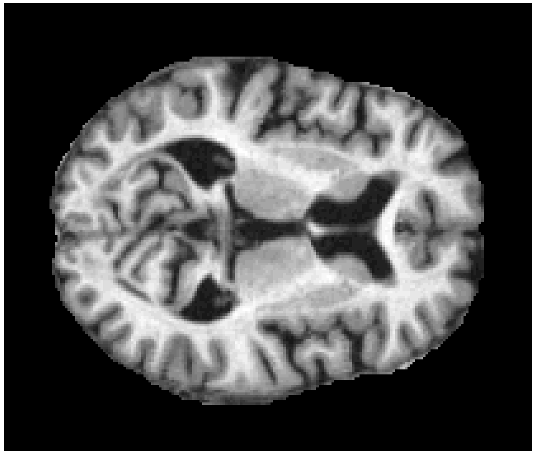


Voxel-based morphometry—the methods
J Ashburner, KJ Friston
Neuroimage, 2000

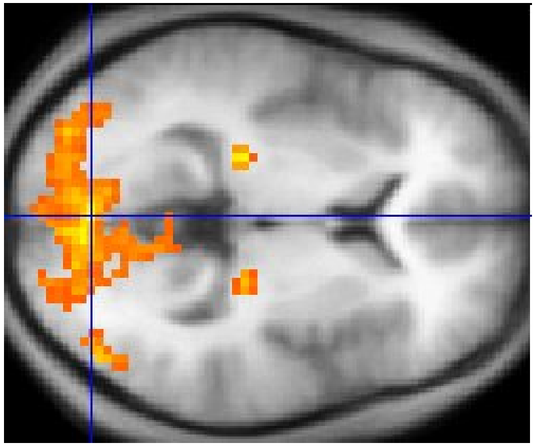
GROUP ANALYSIS VIA MORPHOMETRY

- Are measurements of different tissues being confounded across subjects?
  - One-to-one correspondence between subjects may not exist, e.g. due to disease, natural inter-subject variability.
- What can be said about the differences?
- Group-related structure? Misalignment issues?

Affine Alignment



Statistical Parametric Map



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FEATURE-BASED MORPHOMETRY (FBM)

- Avoid modeling image structure that cannot be reliably identified or aligned in all subjects.
  - Assumption of one-to-one correspondence
- Model distinctive anatomical patterns
  - Natural image patterns that might not occur in all subjects
  - E.g. a distinctive pattern of disease-related atrophy

FEATURE-BASED MORPHOMETRY (FBM)

1) Image alignment
2) Feature extraction
3) Feature modeling
4) Group analysis and classification

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FEATURE-BASED MORPHOMETRY (FBM)

1) Image alignment

2) Feature extraction

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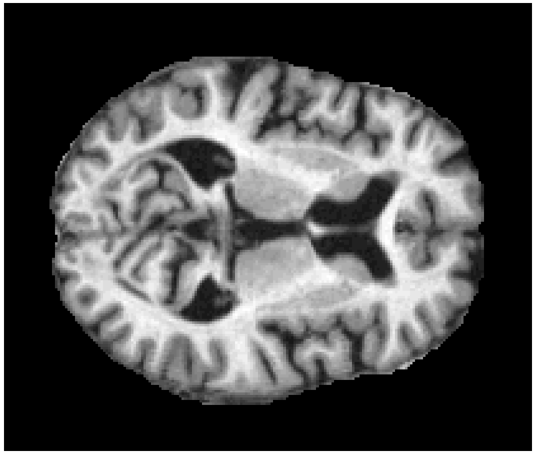
4) Group analysis and classification

INTER-SUBJECT ALIGNMENT

- Approximate alignment
  - Affine, linear
- Assumption:
  - If similar image structures are present in different subjects, they are approximately aligned

Affine Alignment



FEATURE-BASED MORPHOMETRY (FBM)

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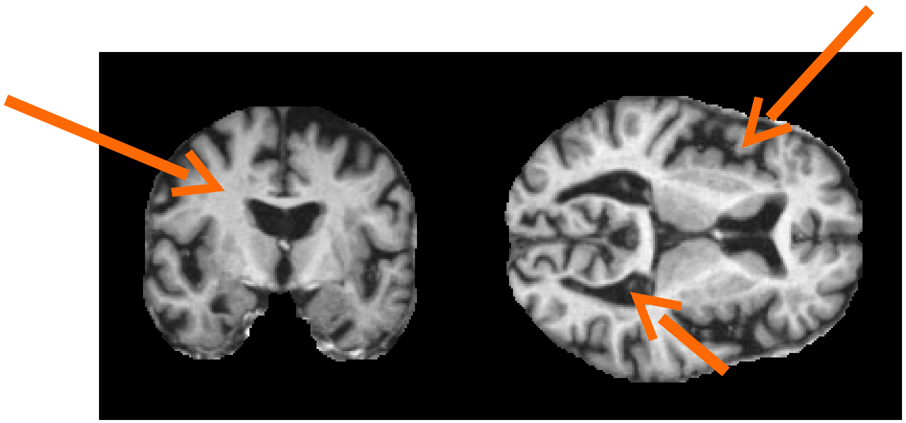
FEATURE EXTRACTION

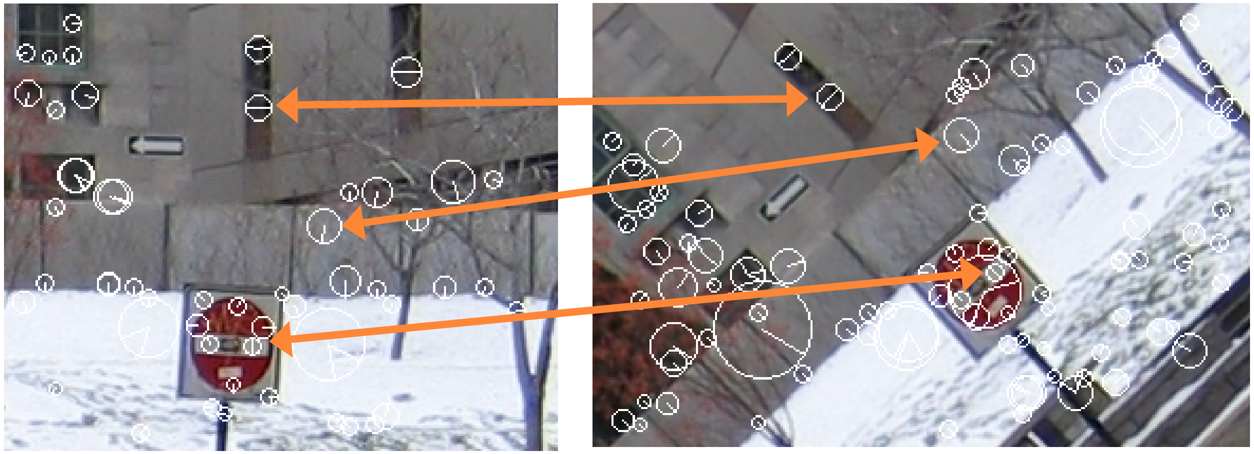
- Goal: automatically identify image patterns/features for group analysis.
- Features should be:
  - Robust to geometrical variation (e.g. spatial misalignment, inter-subject variability)
  - Robust to intensity variation (e.g. scanner non-uniformity)
  - Distinctive in appearance



FEATURE EXTRACTION

- SIFT Features (scale invariant feature transform)
  - Informative, natural image regions (location, scale)
  - Invariant to similarity transform, intensity variations
  - Used to match images of the same scene/object

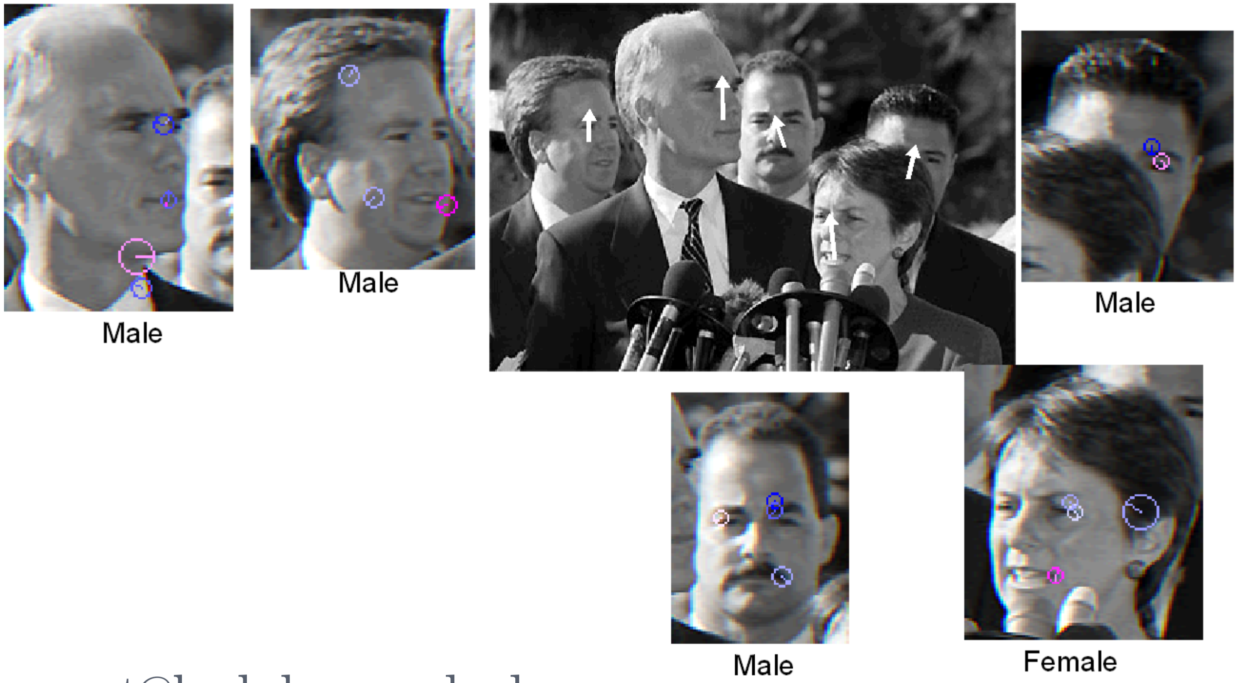
Distinctive Image Features from Scale-Invariant Keypoints
D. G. Lowe, IJCV, 2004.



FEATURE EXTRACTION

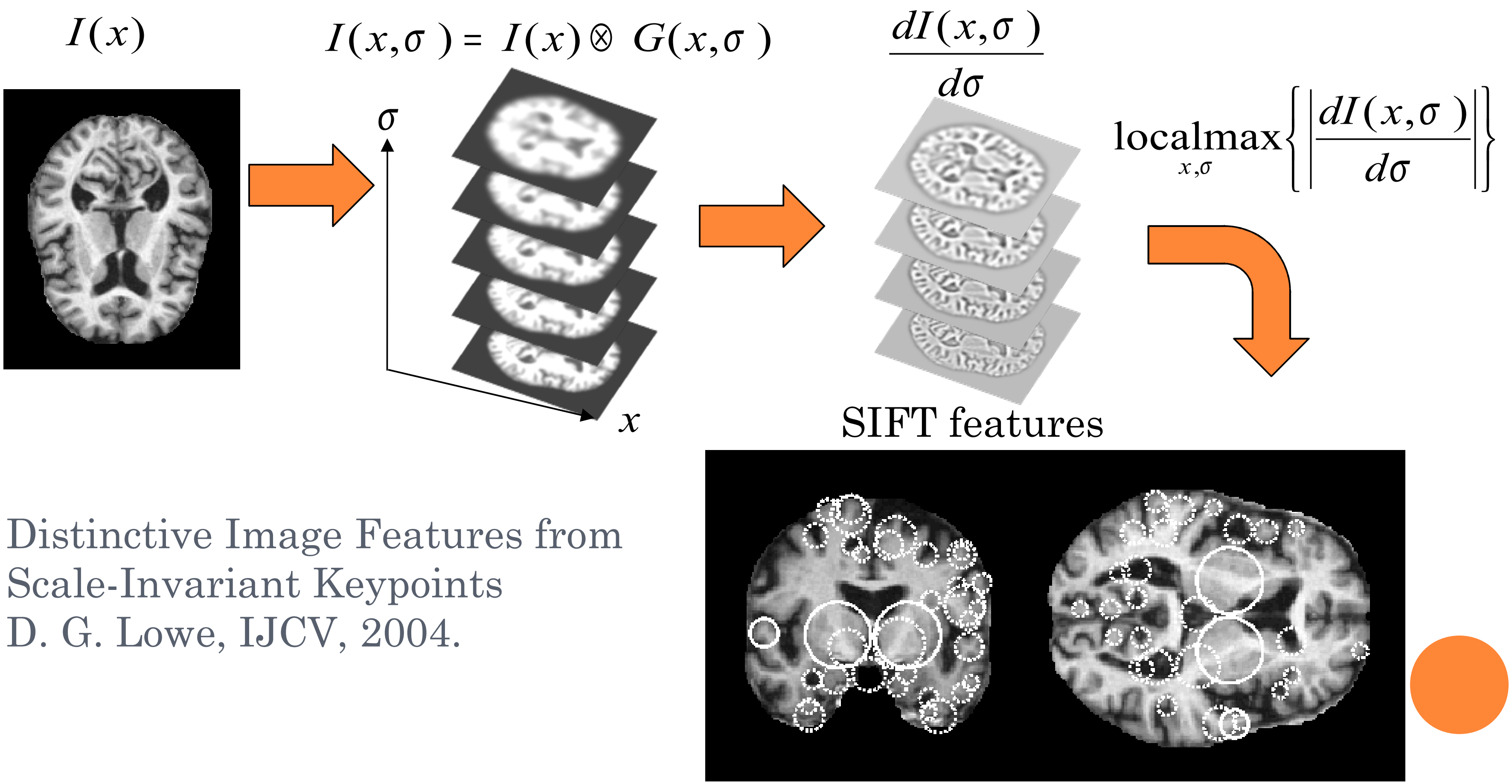
- Can be used to model object classes in natural scenes

Detection, Localization and Sex Classification of Faces from Arbitrary Viewpoints and Under Occlusion.
M. Toews T. Arbel, IEEE TPAMI 2009



FEATURE EXTRACTION

- SIFT: Difference-of-Gaussian (DOG) Scale Space



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MODELING

- Model: the brain as a collage of features.

The Brain
- subject group
- anatomy

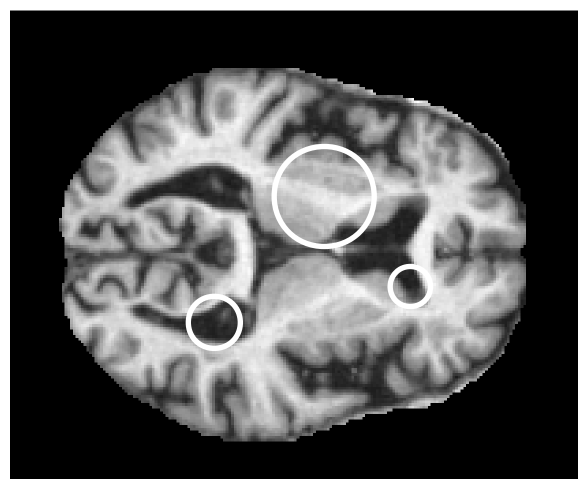
B

$$p(B \mid \{f_i\}) = \frac{p(B)}{p(\{f_i\})} \prod_i p(f_i \mid B)$$

Conditional feature independence

Features
- geometry
- appearance
- occurrence

$f_1 \quad f_2 \quad \ldots$



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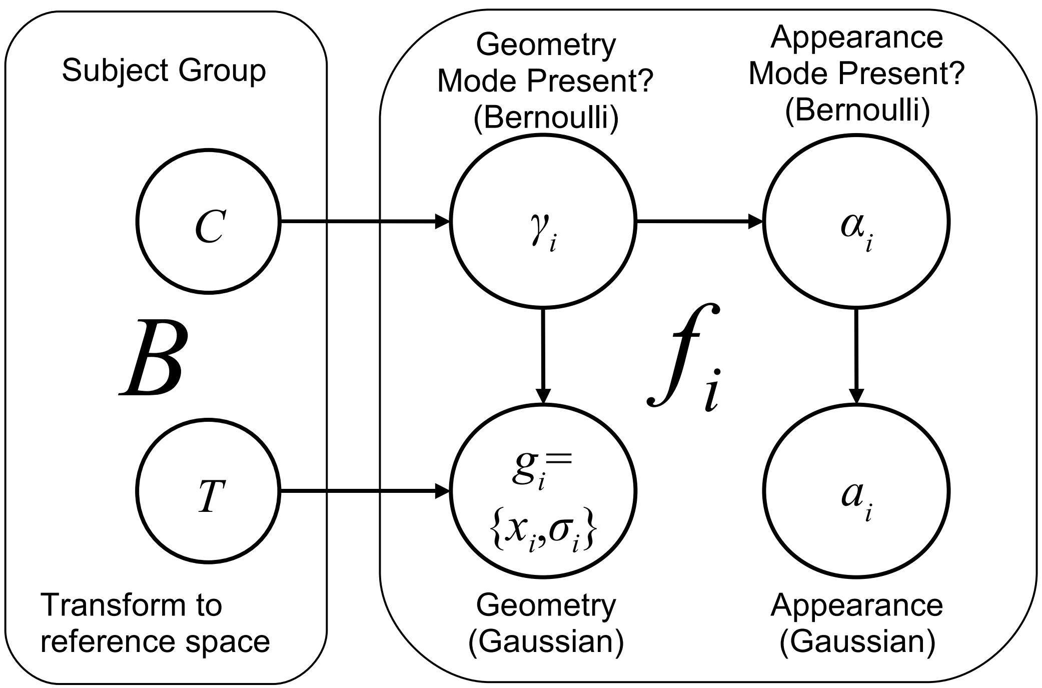
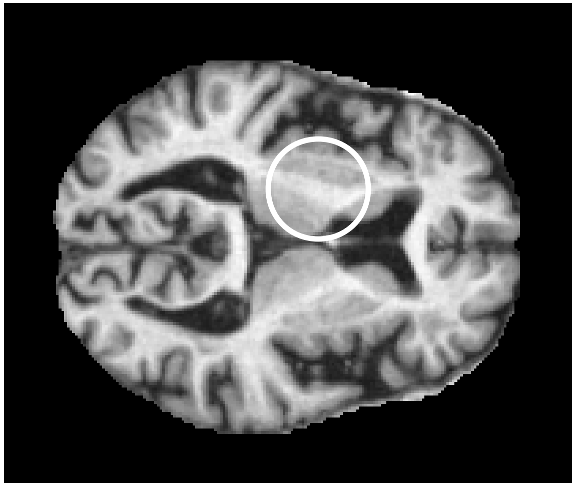
MODELING

- Relationship between a feature and the brain.

$$p(f_i \mid B) = p(\gamma_i \mid C)\,p(g_i \mid \gamma_i, T)\,p(\alpha_i \mid \gamma_i)\,p(a_i \mid \alpha_i)$$





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MODELING

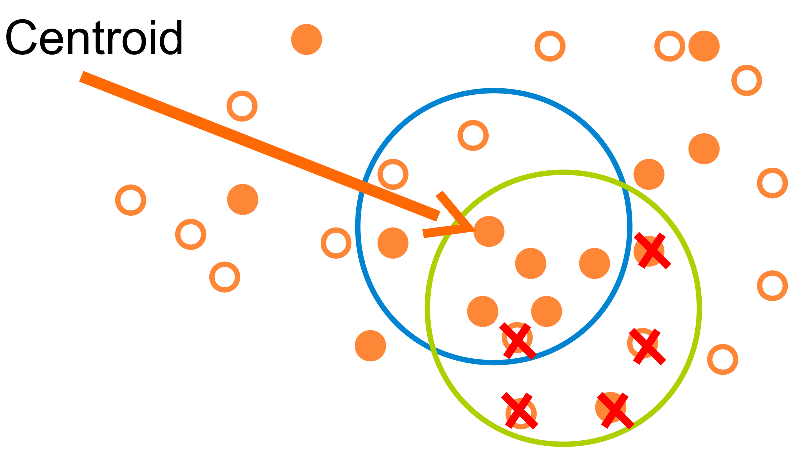
- Model Learning: estimate parameters of conditional feature distributions.
- Cluster features across subjects
  - Similarity in geometry, appearance and group.

● AD ○ NC

1) Geometry: scale/location difference thresholds

2) Appearance/group: intensity difference threshold

Increase while count(●) > count(✗)



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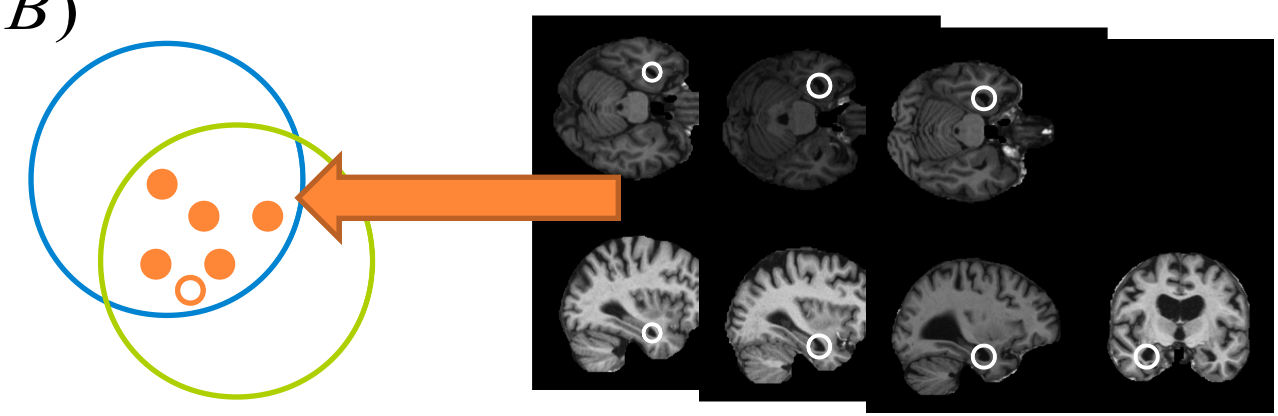
MODELING

- Each cluster represents:
  - Observations of the same group-related anatomical structure in different subjects.
  - Samples of the same underlying model feature f_i

● AD ○ NC

$$p(f_i \mid B)$$



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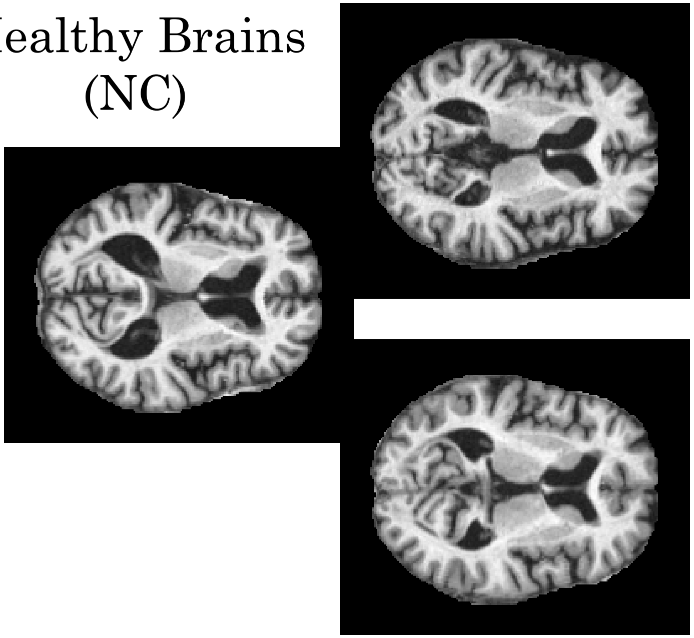
ANALYSIS

Healthy Brains
(NC)



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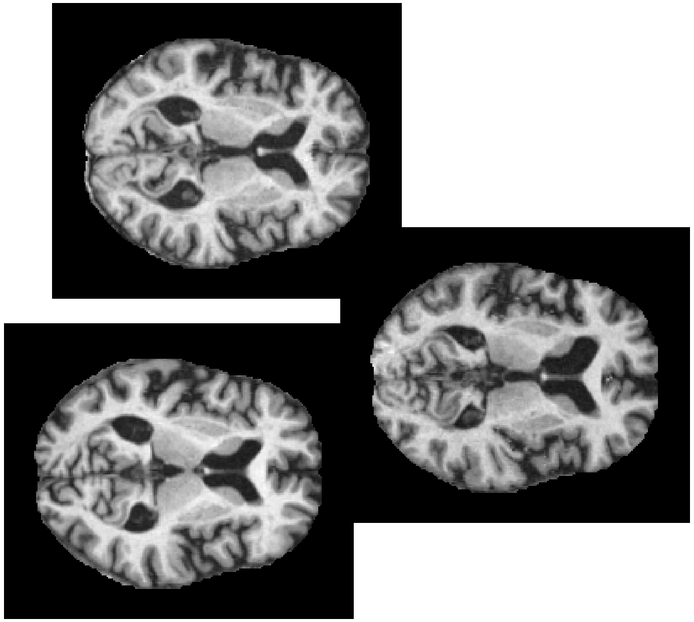
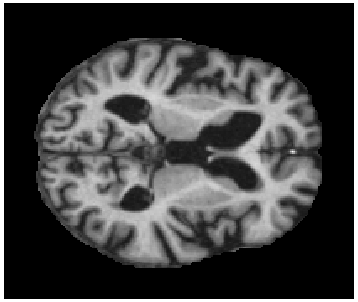


A new brain: is it AD or NC?



How do AD and NC brains differ?

What anatomical patterns are
characteristic of AD or NC brains?

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ANALYSIS

- Feature/group co-occurrence statistics
  - 150 subjects: 75 AD + 75 NC

Group \ Occurrence	f_i	$\overline{f_i}$
AD	**54**	21
NC	35	40

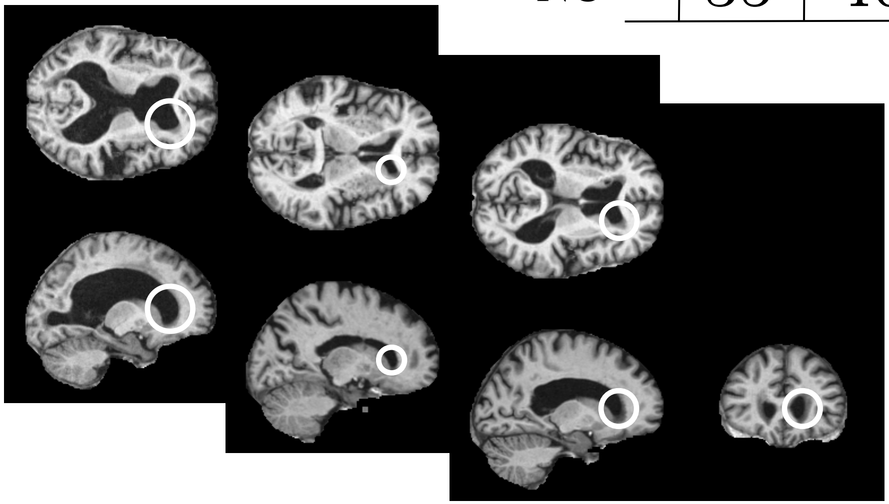
$$p(f_i \mid AD) = \frac{54}{150} = .36$$

$$p(f_i \mid NC) = \frac{35}{150} = .23$$

Likelihood Ratio:

$$\frac{p(f_i \mid AD)}{p(f_i \mid NC)} = \frac{54}{35} = 1.5$$

Feature f_i



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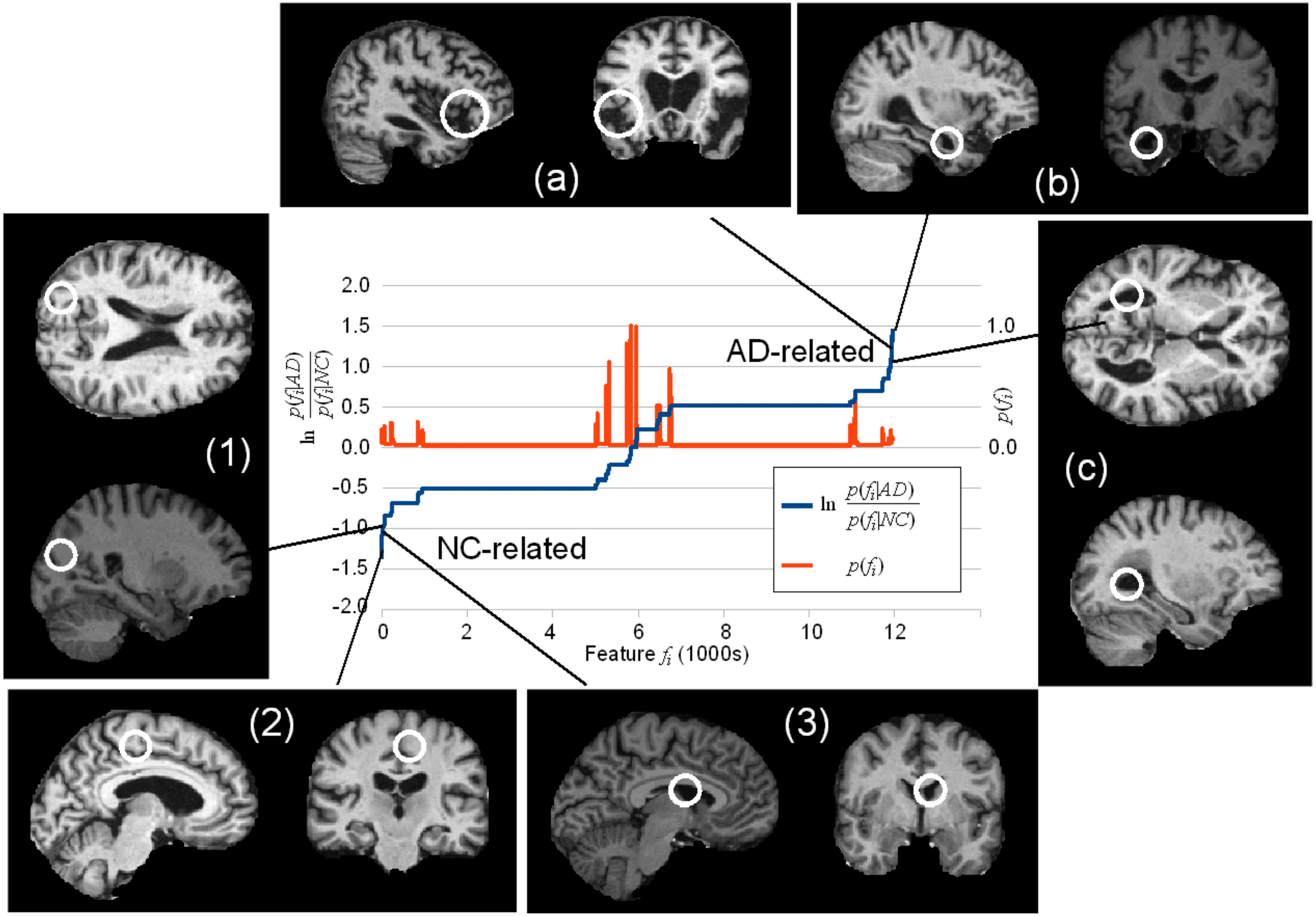
ANALYSIS: LIKELIHOOD RATIO



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ANALYSIS

- Feature significance
  - Fischer's Exact Test
- Group wise significance
  - False Discovery Rate

Group \ Occurrence	f_i	$\bar{f}_i$
AD	**54**	21
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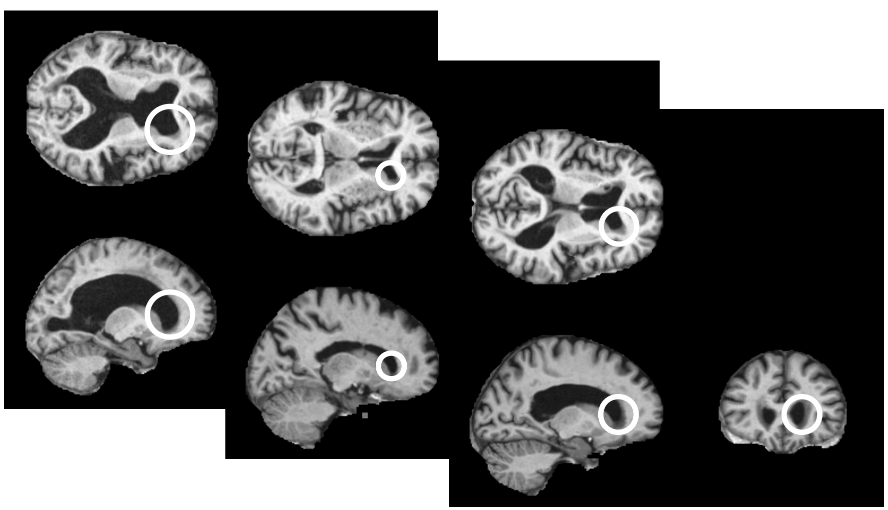
Feature f_i



The control of the false discovery rate in multiple testing under dependency
Y. Benjamini, Y. Hochberg. Ann. Stat. 2001.

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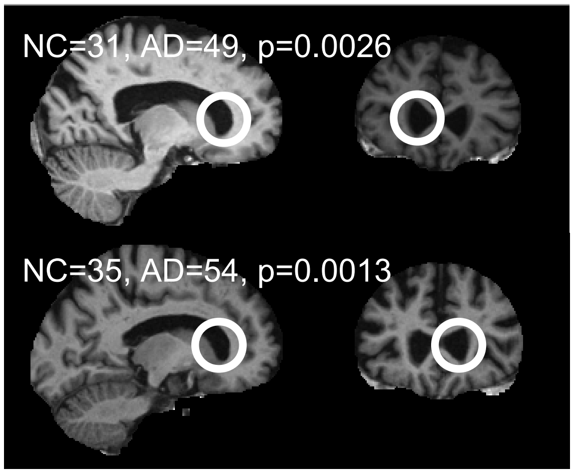
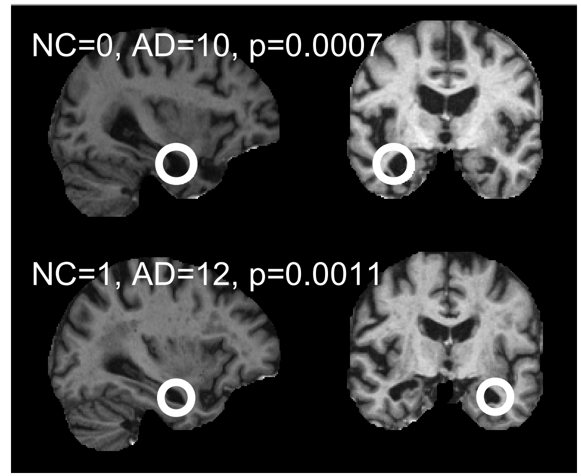
ANALYSIS: AD-RELATED FEATURES

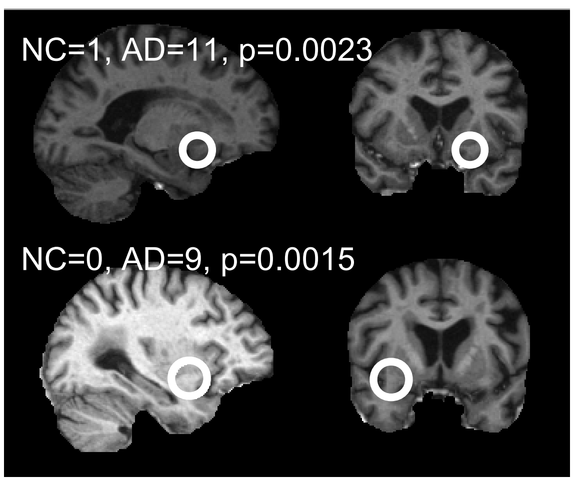
Symmetric

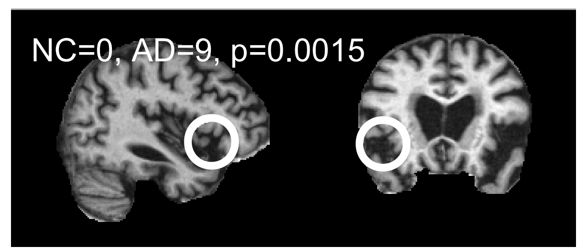


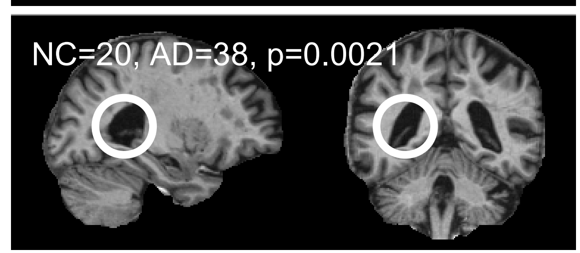


Symmetric

Symmetric







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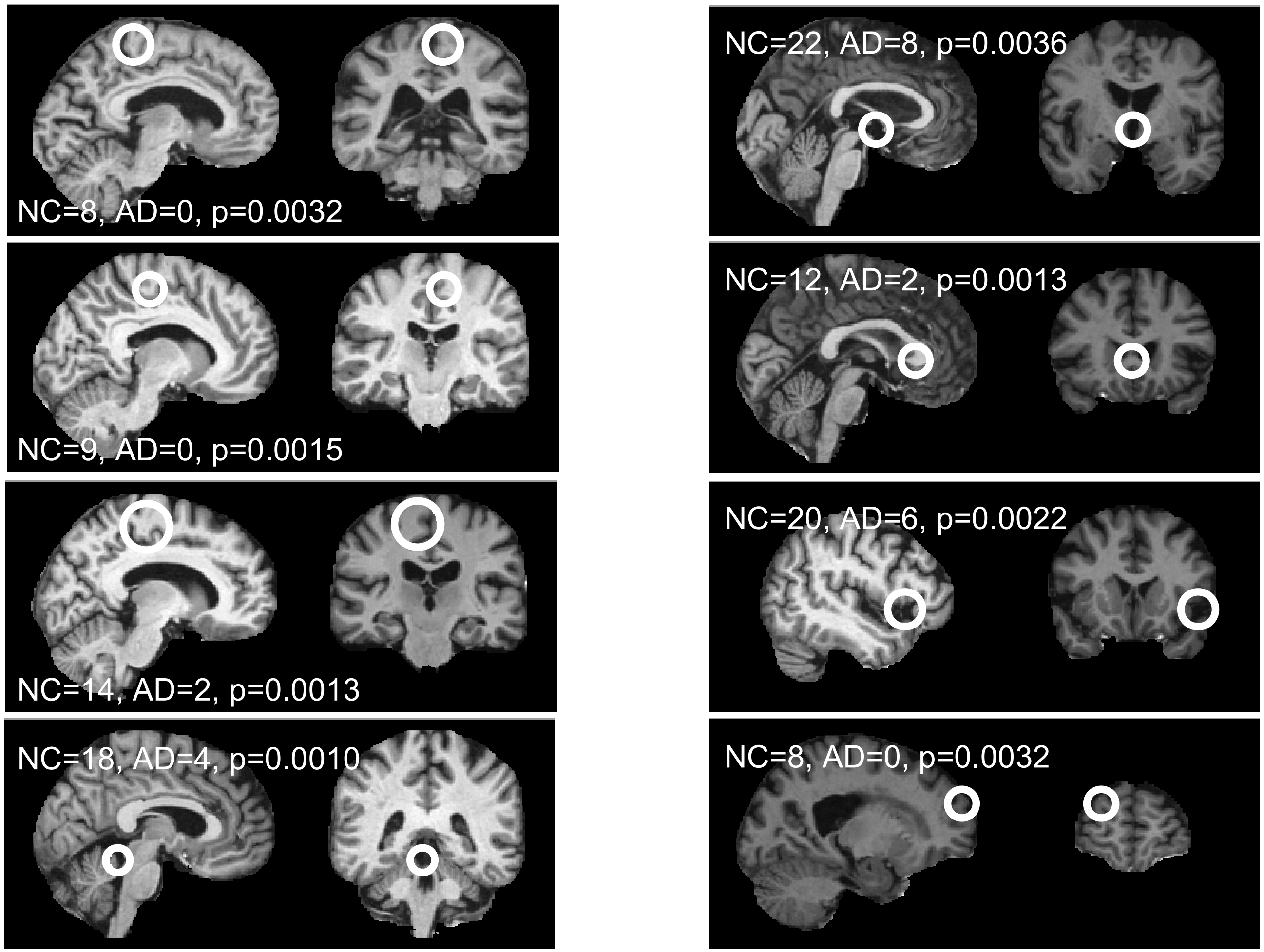
ANALYSIS: NC-RELATED FEATURES



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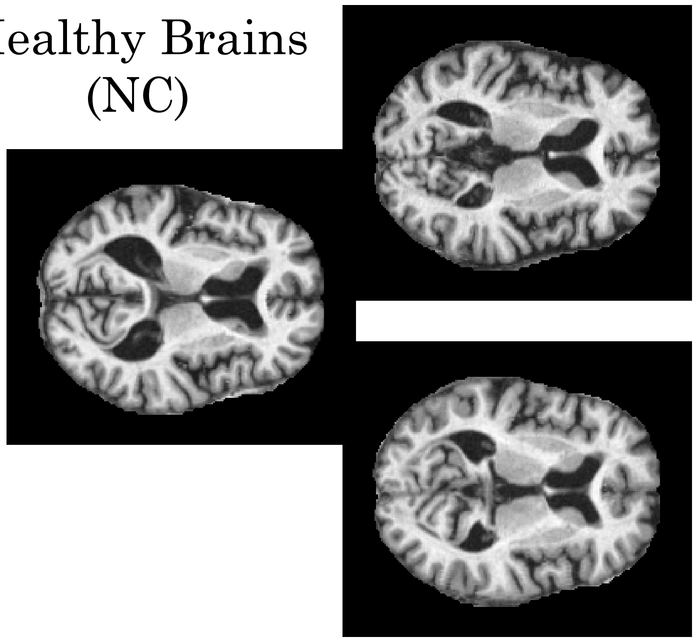
CLASSIFICATION

Healthy Brains
(NC)



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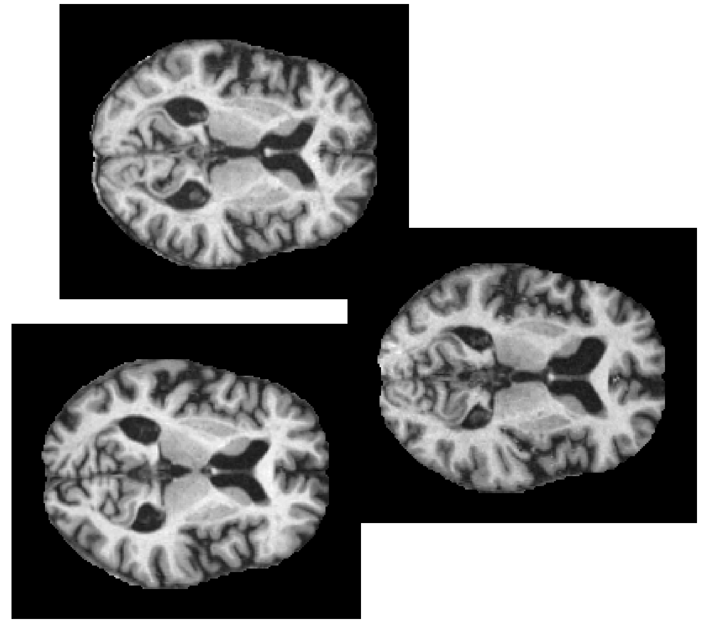

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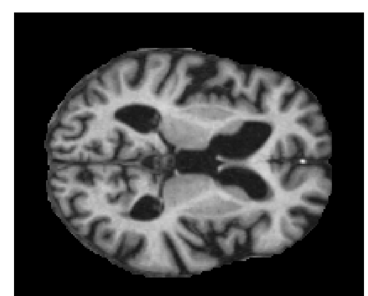

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What anatomical patterns are characteristic of AD or NC brains?

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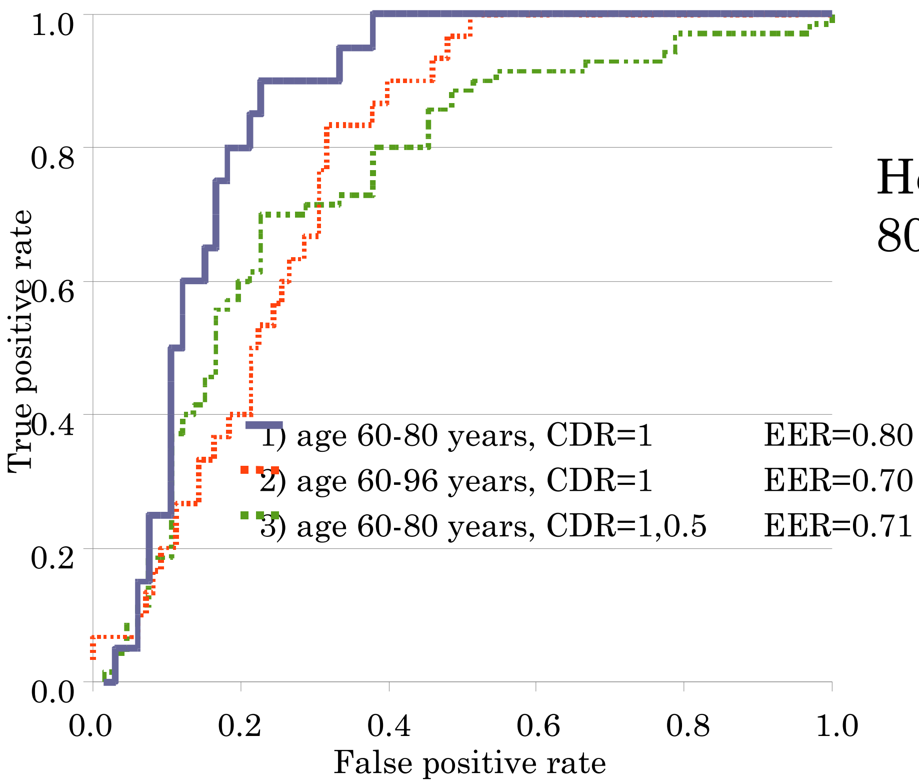
CLASSIFICATION

1) Extract features from a new subject image.
2) Fit image features to model features
   - Learned thresholds in geometry & appearance.
3) Estimate most probable subject group, Bayes decision ratio:

$$\frac{p(AD \mid \{f_i\})}{p(NC \mid \{f_i\})} = \frac{p(AD)}{p(NC)} \prod_i \underbrace{\frac{p(f_i \mid AD)}{p(f_i \mid NC)}}_{\text{Likelihood Ratio}}$$

CLASSIFICATION

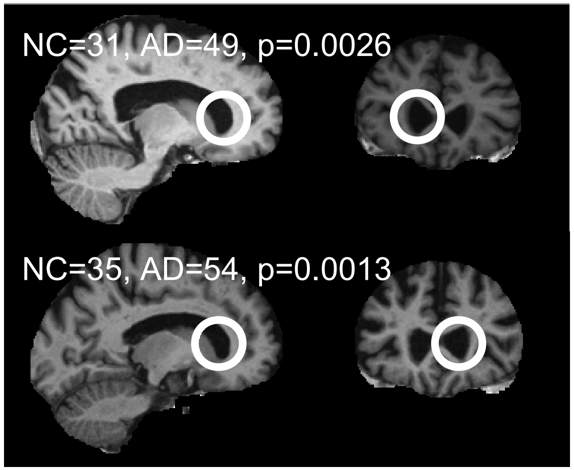
- Leave-one-out classification
  - Elderly subjects or mild dementia are difficult



Healthy vs. Mild Dementia, 80% classification rate.

FBM: SUMMARY

- The brain as a collection of discrete features
  - Do no have to occur in all subjects
  - Avoid assuming of one-to-one correspondence
- Identify group-related features
- Classify new subjects



FBM: FUTURE

- Image modalities
  - Structure: T1, T2, PD, CT, …
  - Connectivity: DW imagery, FA maps, …
  - Function: fMR imagery, …
- Subject groups
  - Disease, age, genes (SNPs), …
- Alternative features
  - Many scale-invariant feature types exist
  - Combine different features to highlight different aspects of anatomy
- Alternative models
  - Potential feature dependencies

ACKNOWLEDGEMENTS

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  - William M. Wells III, Harvard Medical School
  - D. Louis Collins, Montreal Neurological Institute
  - Tal Arbel, McGill University
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- MR Data
  - Open Access Series of Imaging Studies (OASIS): Cross-sectional MRI Data in Young, Middle Aged, Nondemented, and Demented Older Adults. D. S. Marcus et al., J. of Cog. Neurosci., Vol 19, 2007