Harmonizing sMRI Data via Robust Preprocessing

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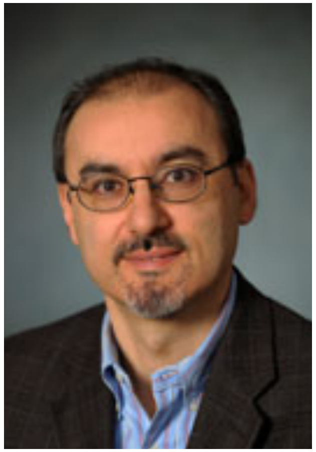
SBIA



SBIA – Neuroimaging Projects

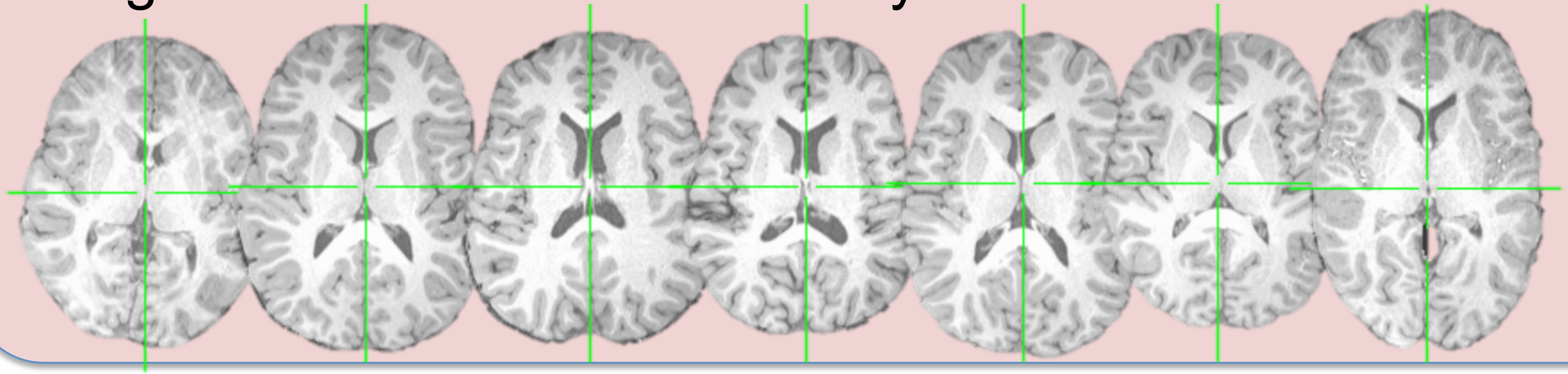
Study	Multi-site	Scanner	Participants
BLSA	No	1.5T/3T	160
SCZ	Yes	1.5T/3T	1081
ADNI	Yes	1.5T	822
PNC	No	3T	1,445
ACCORD	Yes	1.5T	729 (BL) – 511 (FUP)
CARDIA	Yes	3T	~600
NiCK	No	3T	180
Sprint	Yes	3T	640

"*Big Data*" projects:

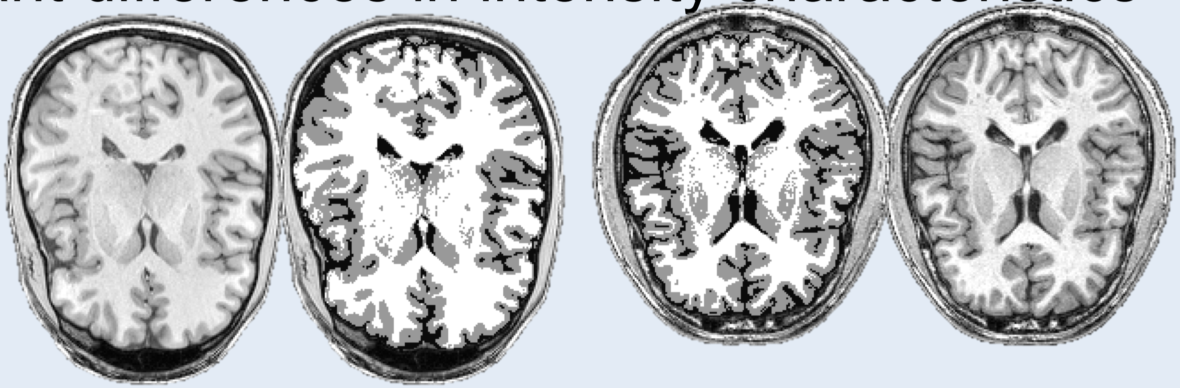
- high sample size
- multi-site
- different imaging protocols

Challenges

- Significant anatomical variability



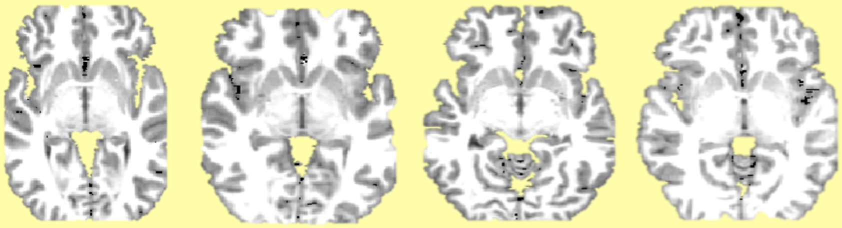
- Significant differences in intensity characteristics



Robust Preprocessing based on Multi-Atlas Framework

Templates (with ground-truth ROI masks)

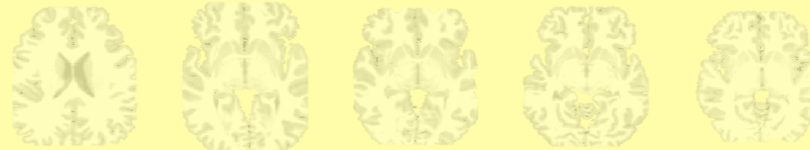
Multiple atlases capturing
- Anatomical variability
- Intensity variability



Robust Preprocessing based on Multi-Atlas Framework

Templates (with ground-truth ROI masks)

Multiple atlases

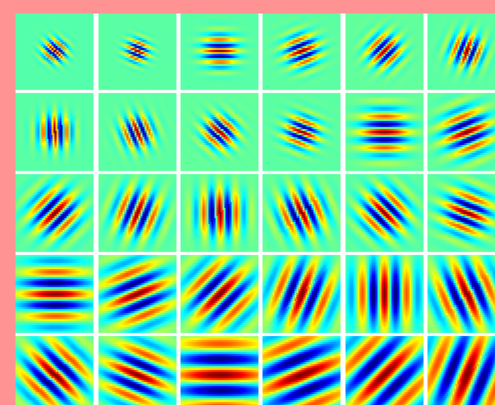


Registration

- Robust
- Efficient

Gabor Features

- Multi-scale information
- Neighborhood information
- Geometry



Robust Preprocessing based on Multi-Atlas Framework

Multiple atlases

Templates (with ground-truth ROI masks)

Registration

- Robust
- Efficient

Discrete Optimization

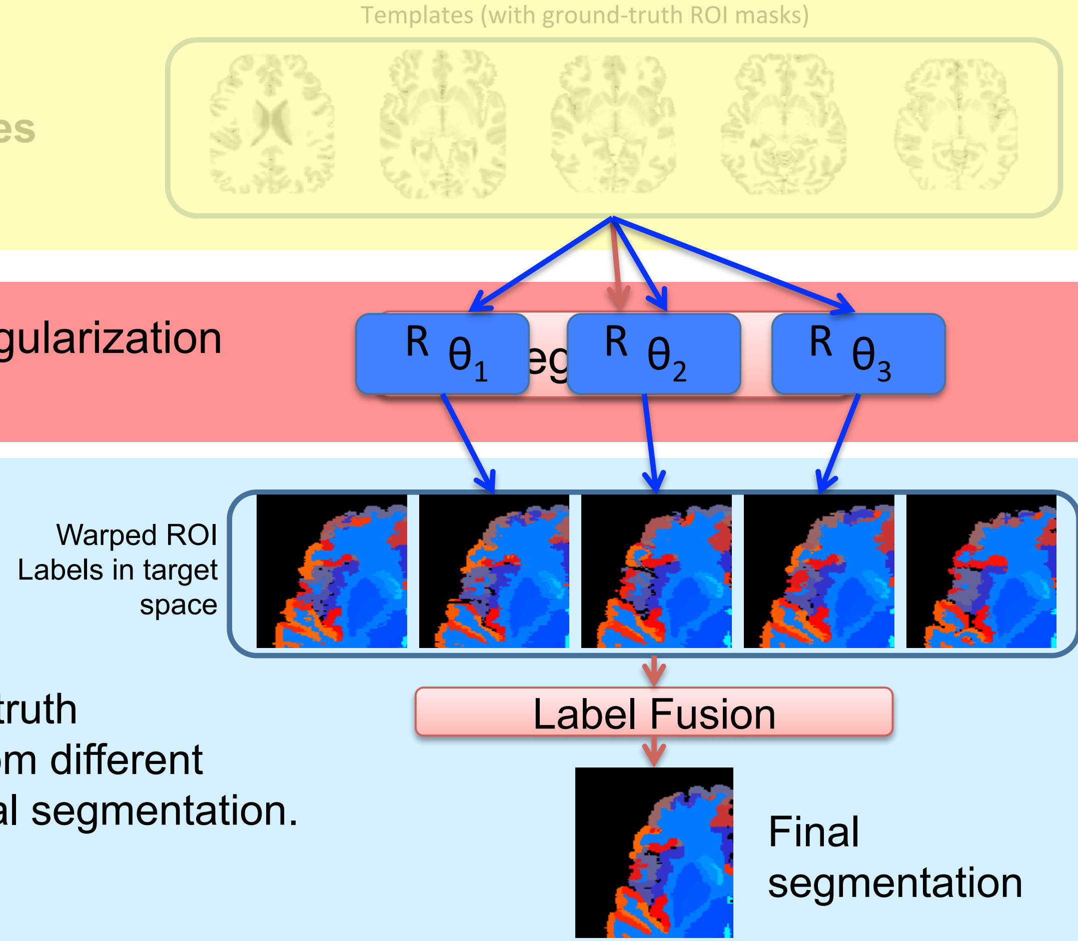
- Markov Random Field theory
- Efficient
- Good optimality guarantees

$$E_{MRF} = \sum_{p \in V} U_P(l_p) + \sum_{(p,q) \in E} P(l_p, l_q)$$

Robust Preprocessing based on Multi-Atlas Framework

Multiple atlases

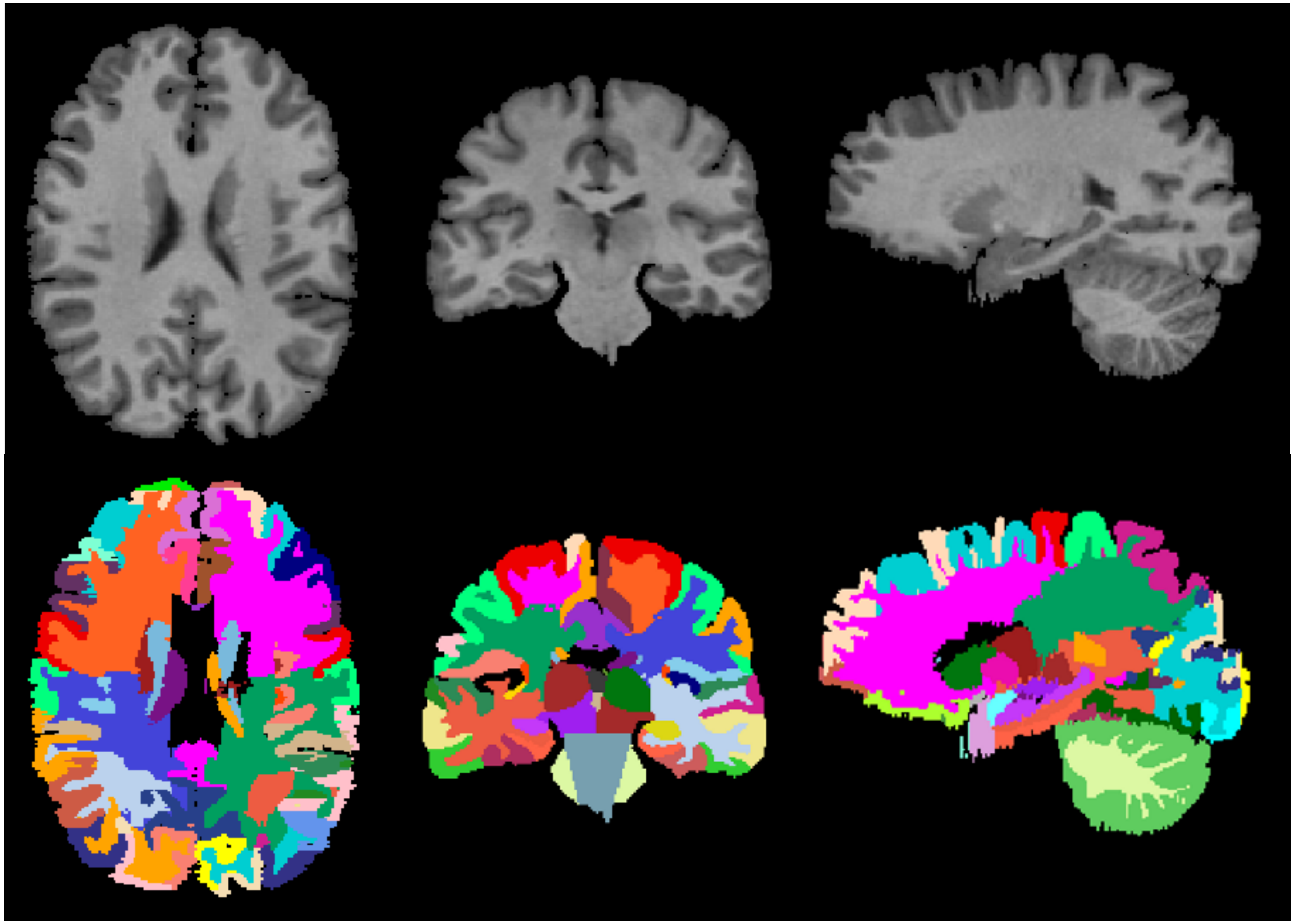
Use **multiple** regularization parameters



Label fusion:

Combine ground-truth segmentations from different sources into a final segmentation.

Hierarchical Multi-Atlas Representation



Doshi, Jimit, et al. "Multi-atlas skull-stripping." *Academic radiology* 20.12 (2013): 1566-1576.

Hierarchical Multi-Atlas Representation

TOTALBRAIN	TISSUE_SEG	SUBGROUP_0	SUBGROUP_1	SUBGROUP_2	ROI_NAME
TOTALBRAIN	GM	FRONTAL	FRONTAL_GM	FRONTAL_INFERIOR_GM	Left AOrG anterior orbital gyrus
	GM				Left LOrG lateral orbital gyrus
	GM				Right MOrG medial orbital gyrus
	GM				Right POrG posterior orbital gyrus
	GM			FRONTAL_INSULAR_GM	Left AIns anterior insula
	GM				Left PIns posterior insula
	GM				Right AIns anterior insula
	GM				Right PIns posterior insula
	GM			FRONTAL_LATERAL_GM	Right OpIFG opercular part of the inferior frontal gyrus
	GM				Right OrIFG orbital part of the inferior frontal gyrus
	GM				Right PrG precentral gyrus
	GM				Right SFG superior frontal gyrus
	GM				Right TrIFG triangular part of the inferior frontal gyrus
	GM			FRONTAL_MEDIAL_GM	Left GRe gyrus rectus
	GM				Left MFC medial frontal cortex
	GM				Left MPrG precentral gyrus medial segment
	GM				Right MPrG precentral gyrus medial segment
	GM				Right MSFG superior frontal gyrus medial segment
	GM				Right SCA subcallosal area
	GM				Right SMC supplementary motor cortex
	GM			FRONTAL_OPERCULAR_GM	Left CO central operculum
	GM				Left FO frontal operculum
	GM				Left PO parietal operculum
	GM				Right CO central operculum
	GM				Right FO frontal operculum
	GM				Right PO parietal operculum
	WM		FRONTAL_WM		frontal lobe WM left
	WM				frontal lobe WM right
	GM	PARIETAL	PARIETAL_GM	PARIETAL_LATERAL_GM	Left AnG angular gyrus
	GM				Left PoG postcentral gyrus
	GM				Right PoG postcentral gyrus
	GM				Right SMG supramarginal gyrus
	GM				Right SPL superior parietal lobule
	GM			PARIETAL_MEDIAL_GM	Left MPoG postcentral gyrus medial segment
	GM				Left PCu precuneus
	GM				Right MPoG postcentral gyrus medial segment
	GM				Right PCu precuneus
	WM		PARIETAL_WM		parietal lobe WM left
	WM				parietal lobe WM right

Doshi, Jimit, et al. "Multi-atlas skull-stripping." *Academic radiology* 20.12 (2013): 1566-1576.

Harmonizing BLSA*

*BLSA: Baltimore Longitudinal Study of Aging
America's longest-running scientific study of human aging
Longitudinal scans of hundreds of subjects

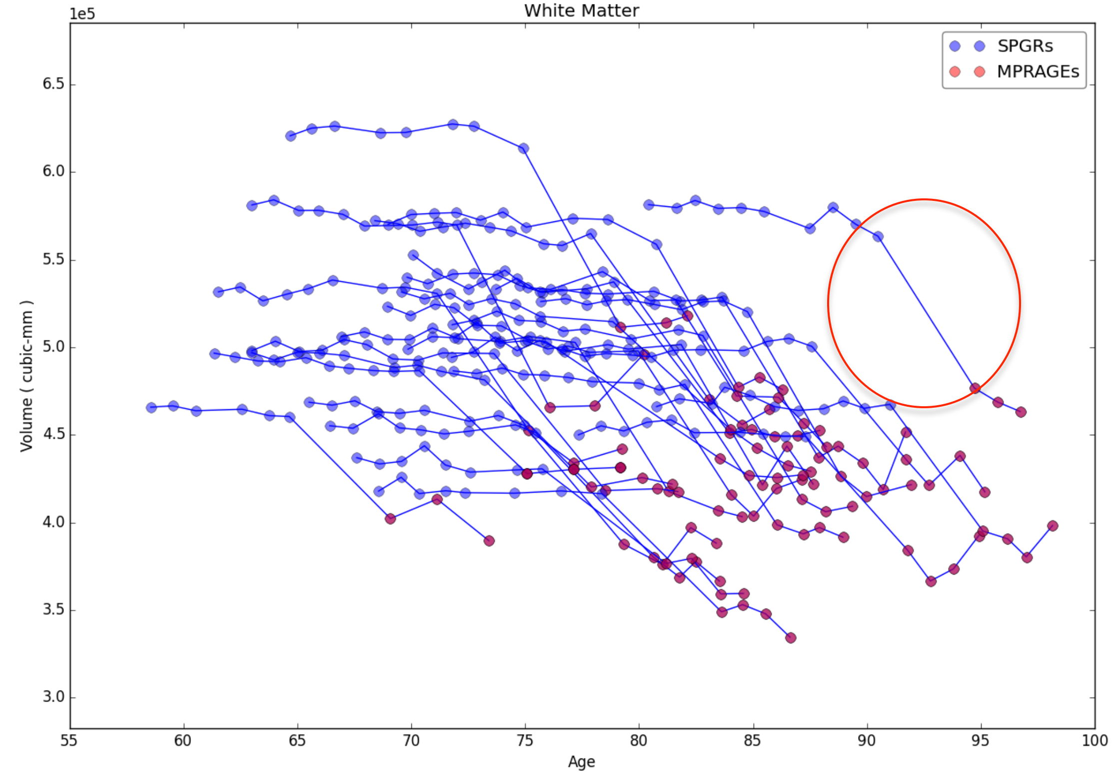
Main challenge:
Scanner change from 1.5T SPGR to 3T MPRAGE

Scanner	1.5T	3T
Participants	160	561
Gender: males (females)	92 (68)	252 (309)
Age: mean ± std (range)	73.79 ± 8.17 (45.64)	71.87±13.00 (69.33)
No of scans	1089	862

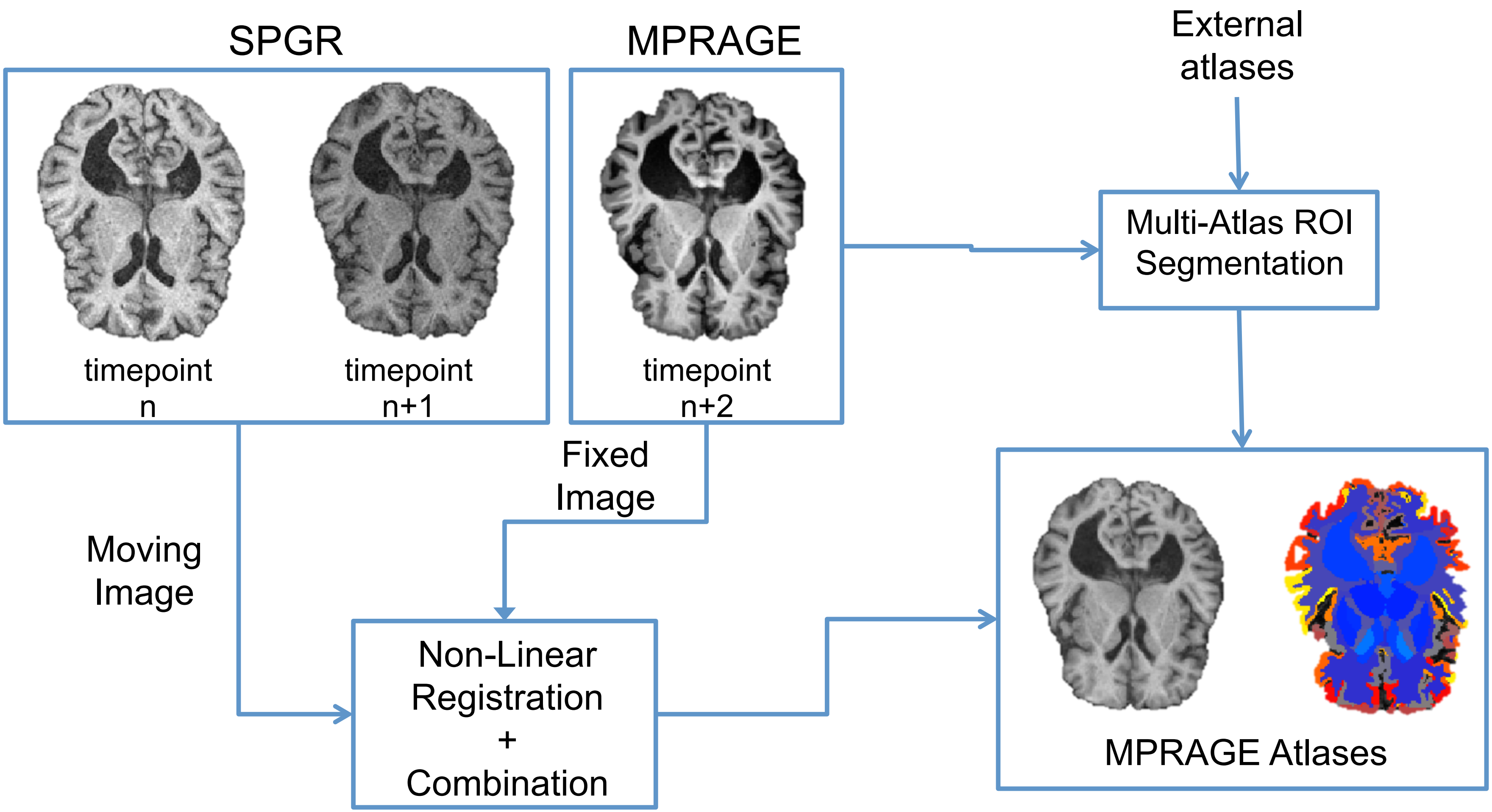
Harmonizing BLSA

Image contrast differences between SPGR and MPRAGE:

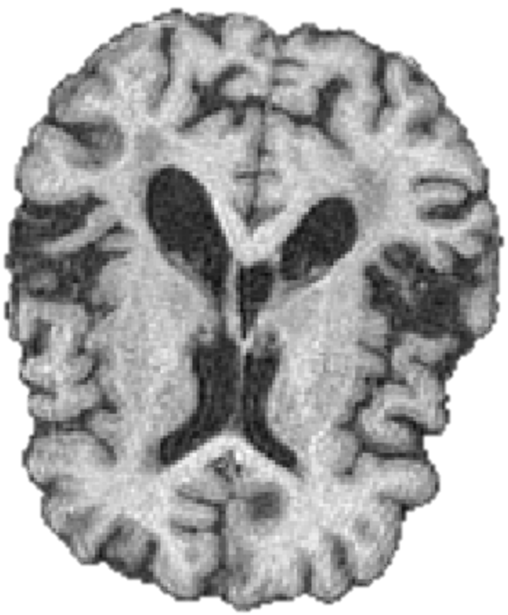
- Lead to under-segmentation
- Solution: adaptive atlas construction



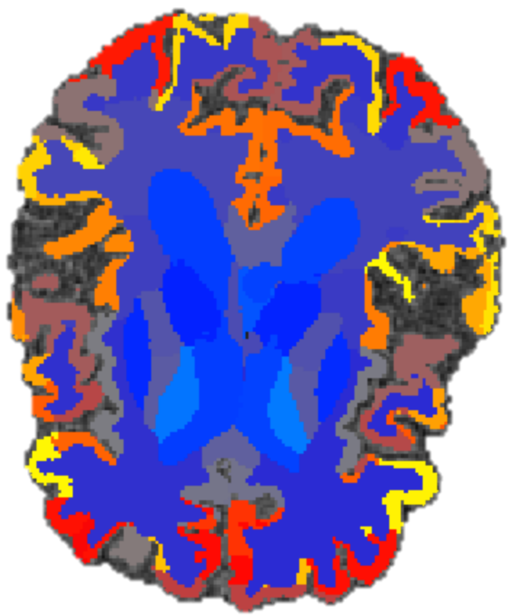
Adaptive Atlas Construction



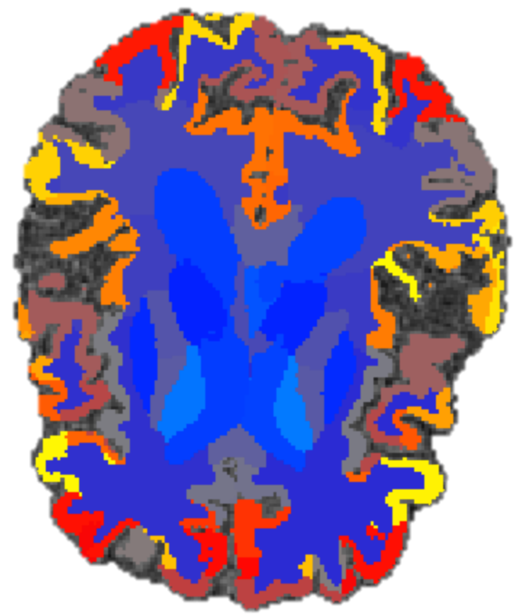
Segmentation Results



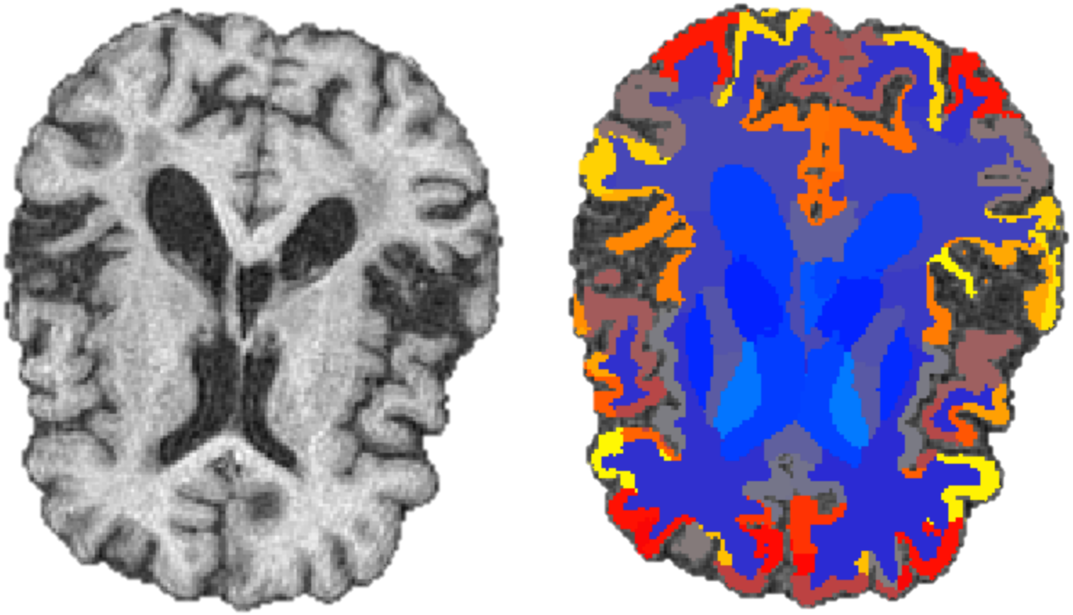
Previous Segmentation



Adaptive Segmentation

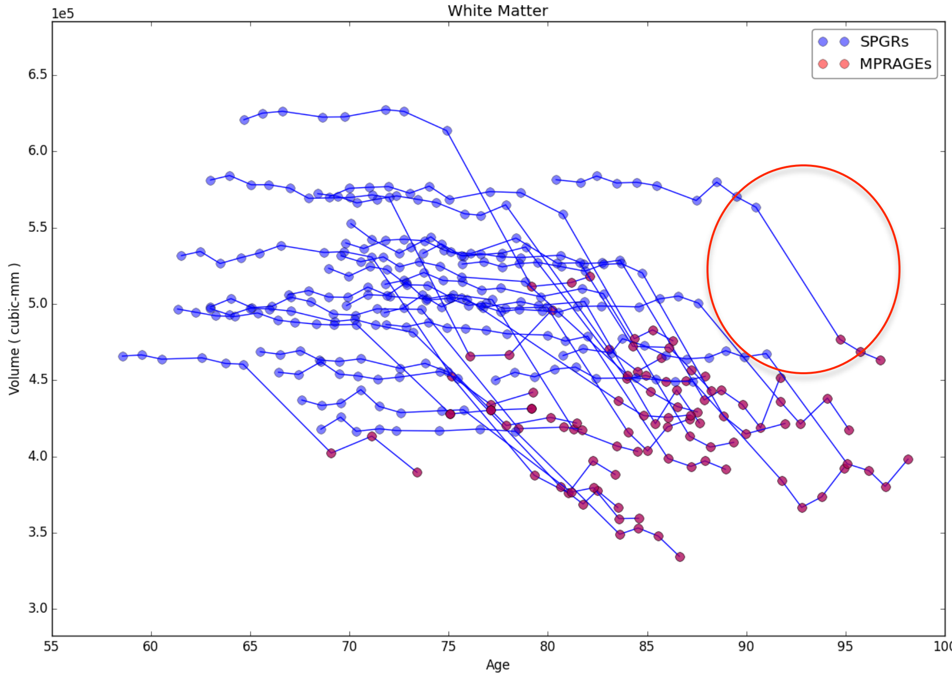


Segmentation Results

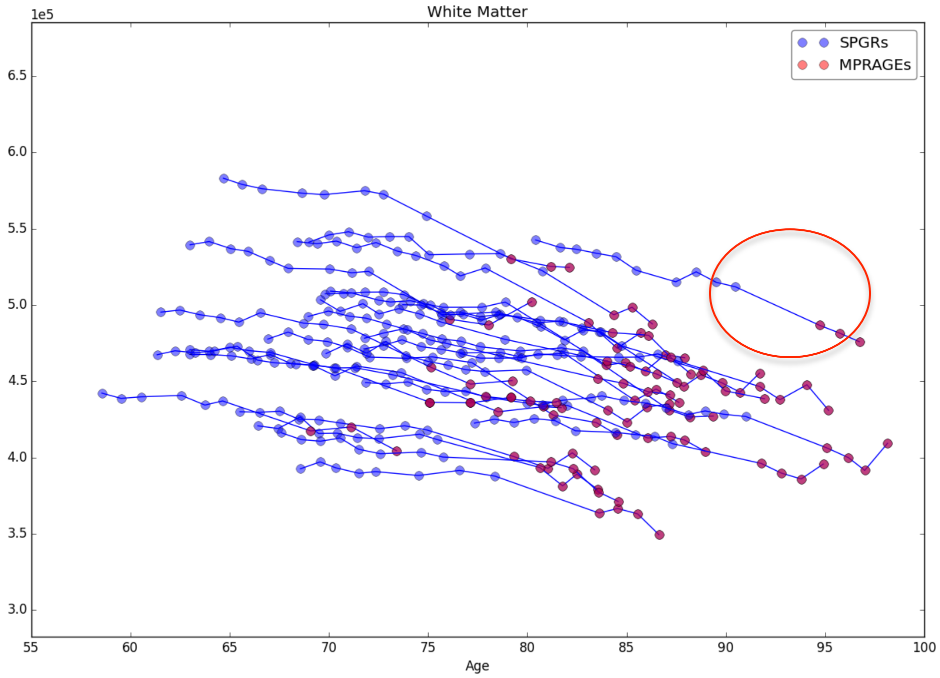


Longitudinal WM Trajectories

Initial

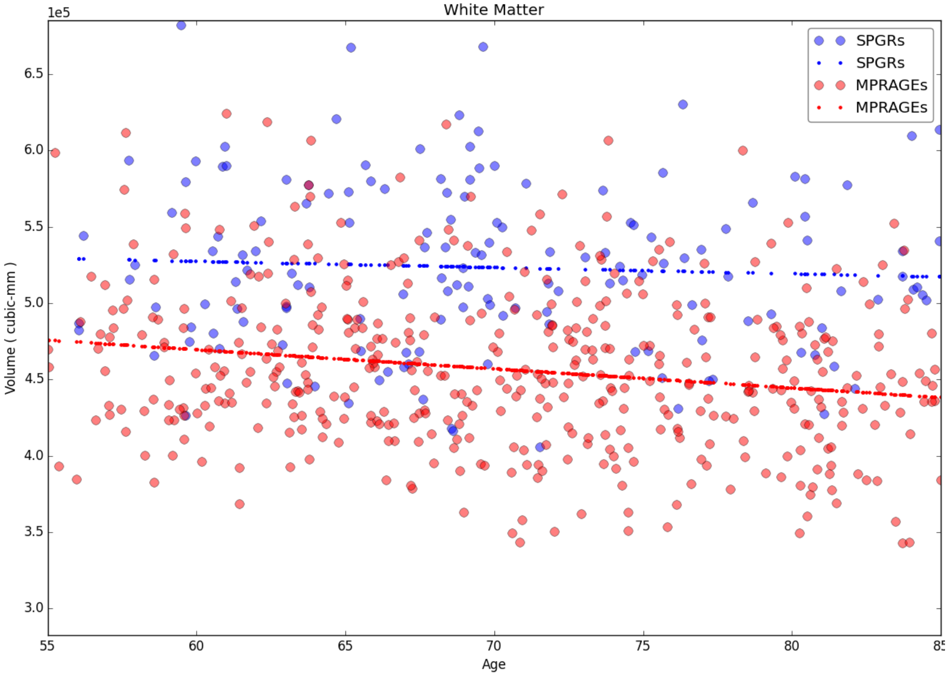


Adaptive

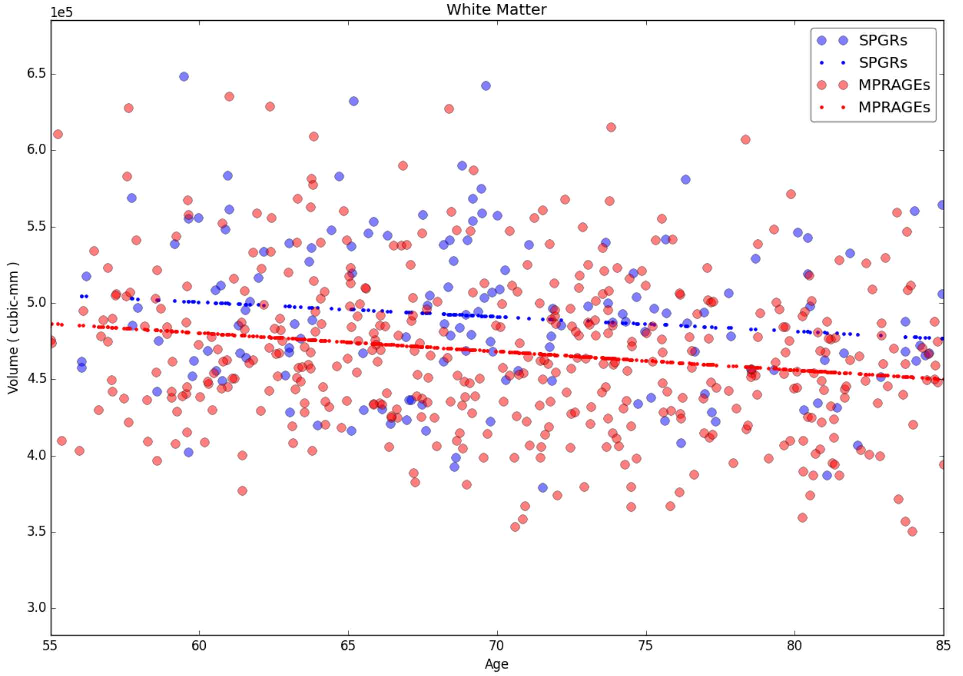


Cross-Sectional WM Trends

Initial



Adaptive

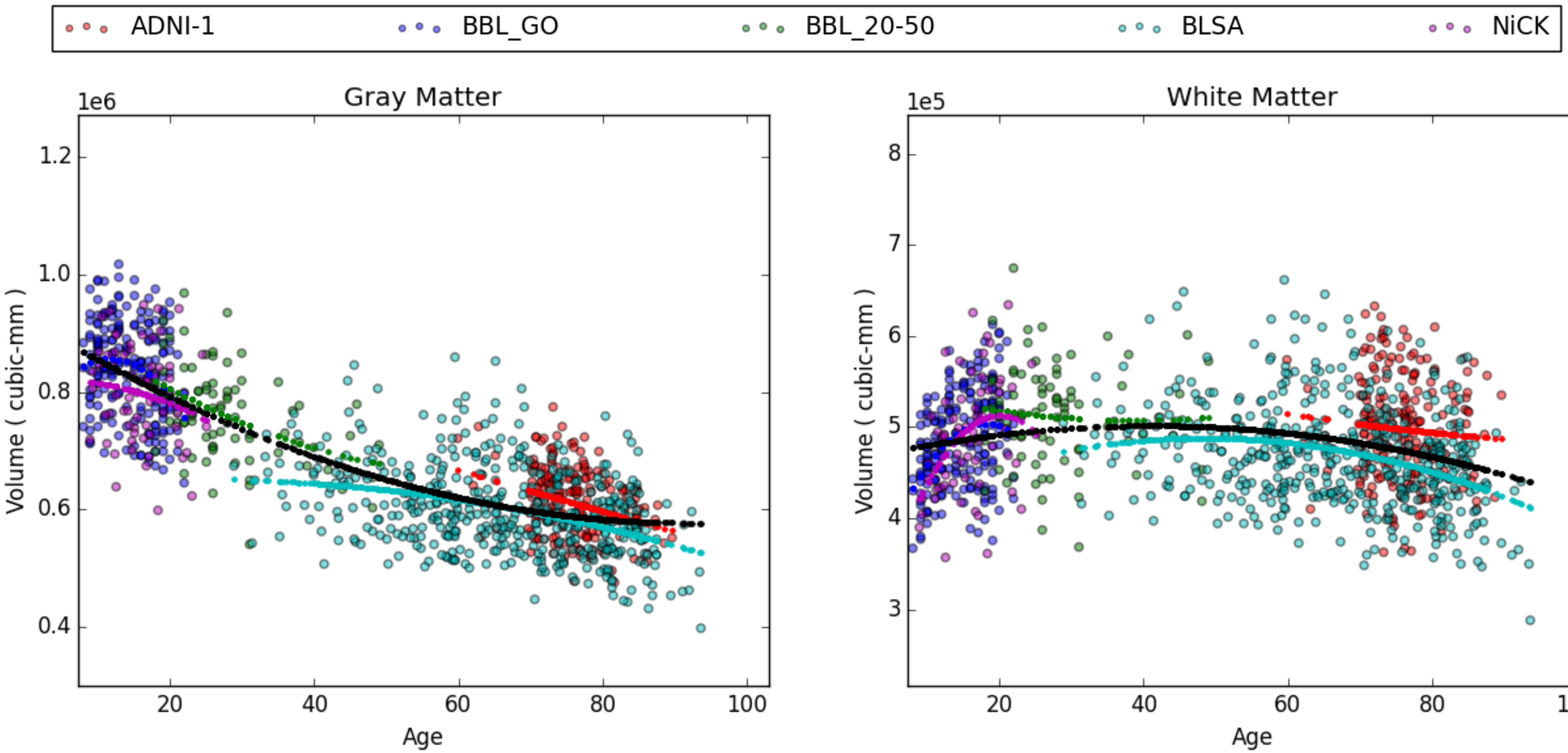


Normative Brain Dataset

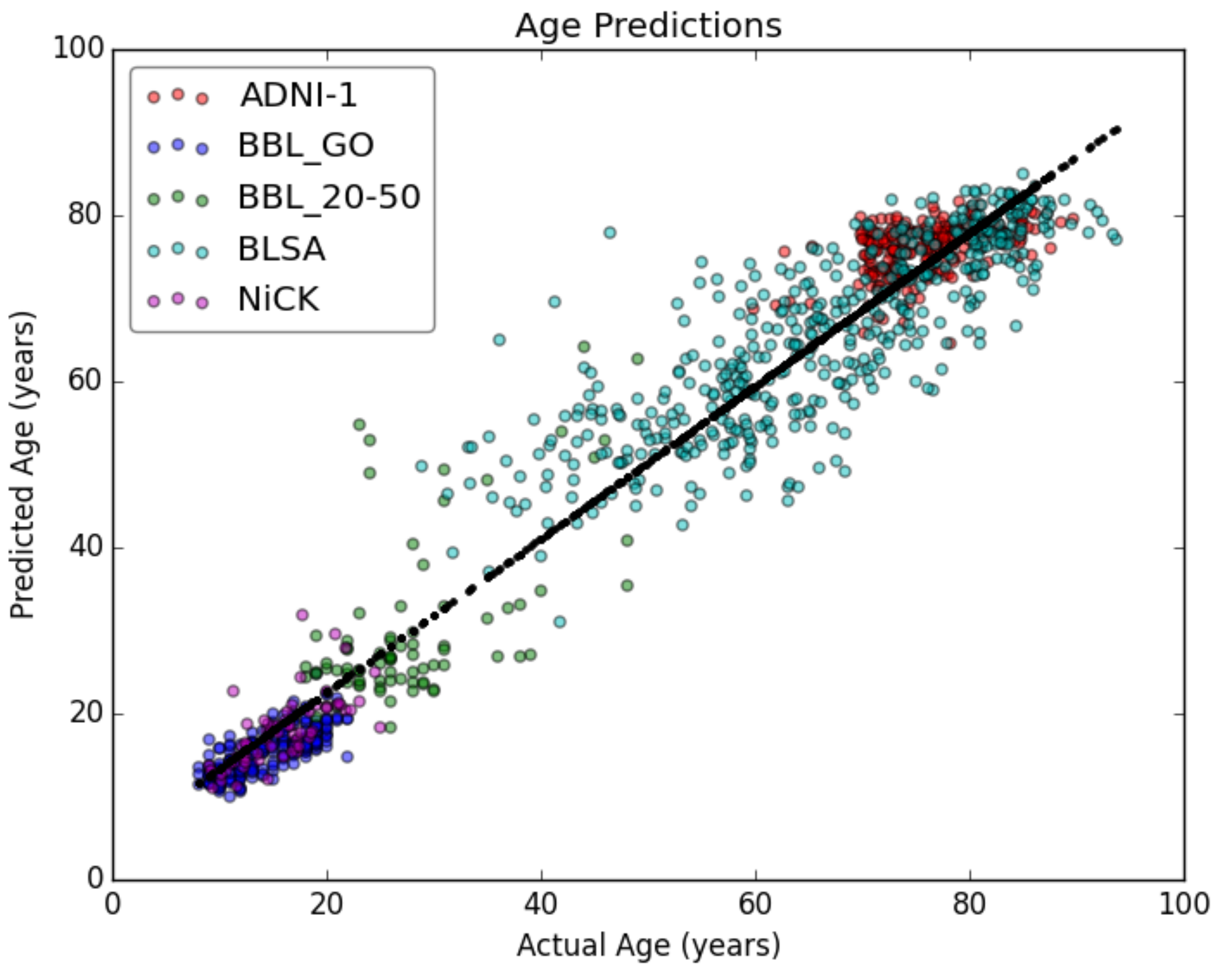
Main objective: Combining control subjects from different studies and extracting robust imaging features for the analysis of structural brain age-related change across life span.

Study	Scanner	Subjects	Gender	Age (Years)
			Male/Female	Mean ± SD (range)
BLSA	1.5T	468	220/248	66.40 ± 13.91 (65)
BBL_GO	3T	201	101/100	14.51 ± 3.79 (14)
BBL_20-50	1.5T	79	41/38	28.22 ± 7.52 (31)
ADNI	1.5T	215	109/106	75.83 ± 5.03 (30)
NiCK	3T	66	35/31	15.89 ± 3.90 (16)

ROI Volumes across Life Span



Age Prediction Across Life Span



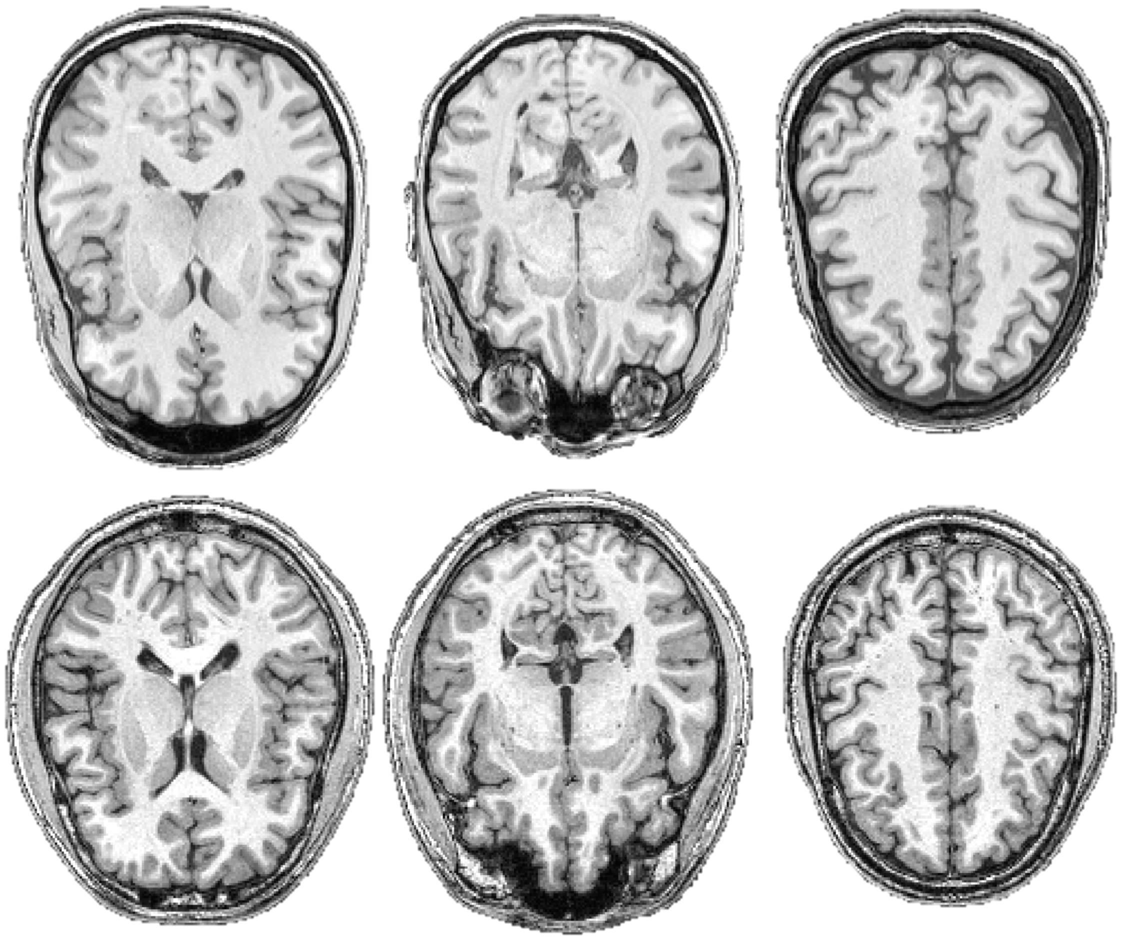
Harmonizing SCZ Study

Data Site	Scanner	Diagnosis	Subjects	Gender	Age (Years)
				Male/Female	Mean ± SD (range)
Penn	3T	SCZ	138	86/52	35.38 ± 11.34 (13-60)
		NC	132	63/69	31.80 ± 12.89 (12-65)
China	3T	SCZ	144	73/71	30.35 ± 9.52 (14-59)
		NC	169	79/90	31.63 ± 10.54 (17-57)
Munich	1.5T	SCZ	165	123/42	31.35 ± 9.66 (18-65)
		NC	177	123/54	31.48 ± 9.16 (18-61)
Brazil	1.5T	SCZ	62	45/17	27.74 ± 8.00 (18-50)
		NC	94	53/41	30.21 ± 8.40 (18-50)
TOTAL		SCZ	509	327/182	31.73 ± 10.18 (13-65)
		NC	572	318/254	31.39 ± 10.41 (12-65)

Challenges: Contrast Difference

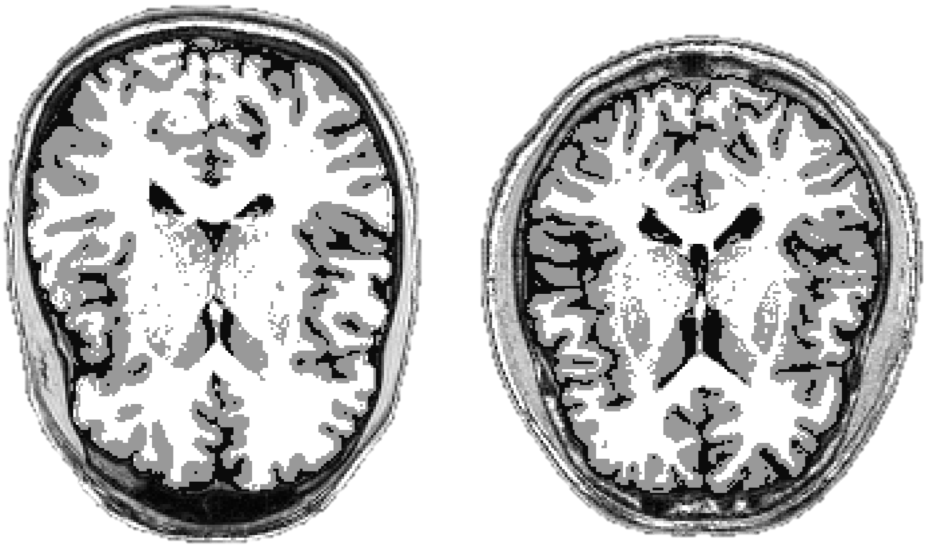
Penn

China

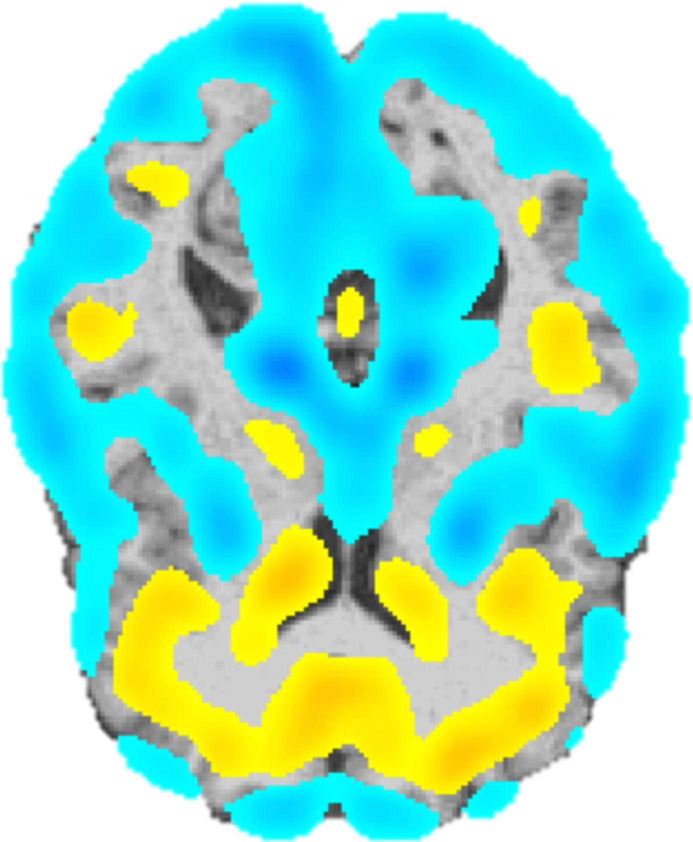


Dataset Differences

GM-WM-CSF Segmented Images



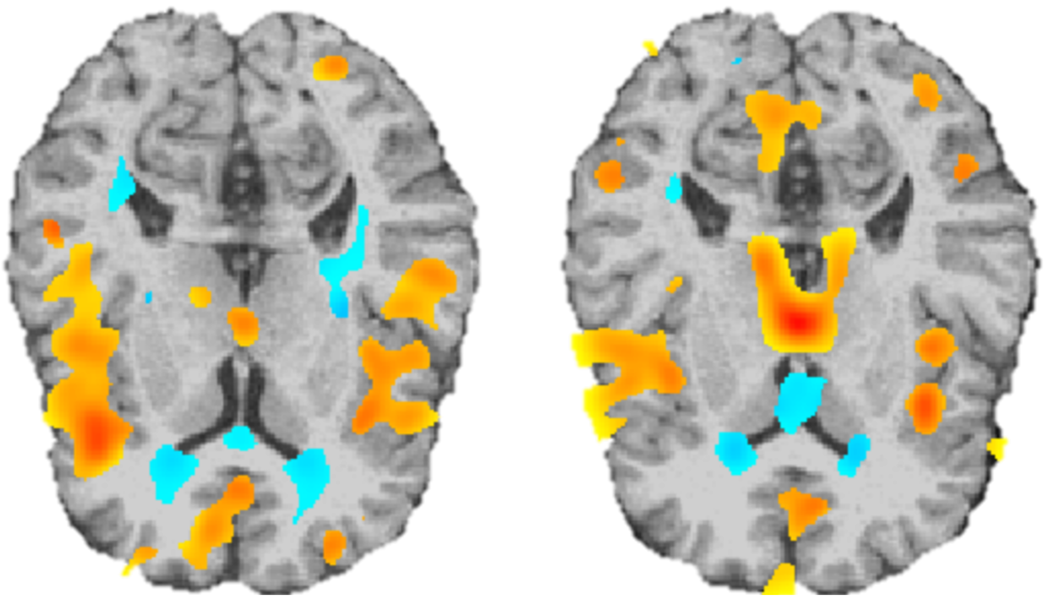
VBM comparison of dataset control GM



Blue: Penn less GM
Yellow: Penn more GM

Harmonizing by CN Means

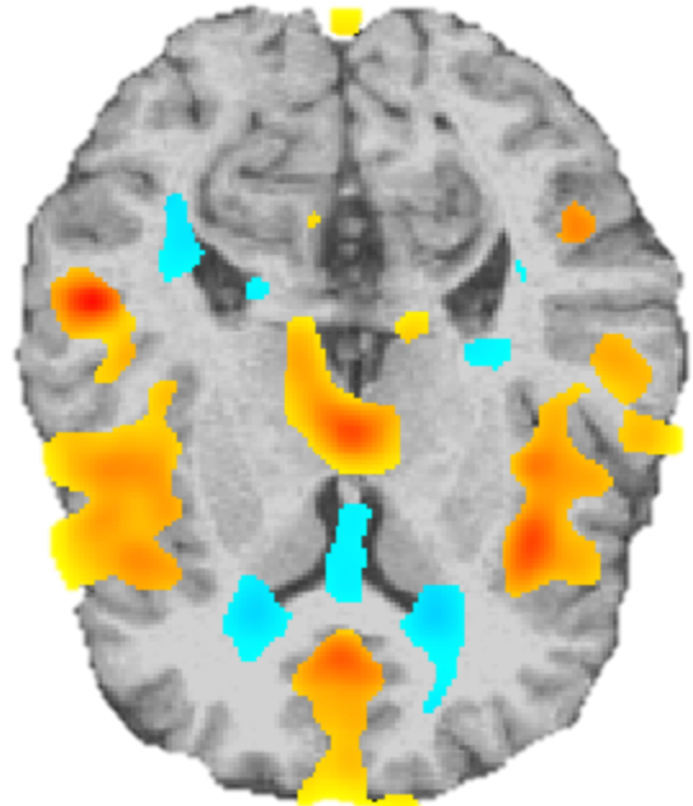
VBM Comparison of NC vs SCZ within each dataset



Penn China

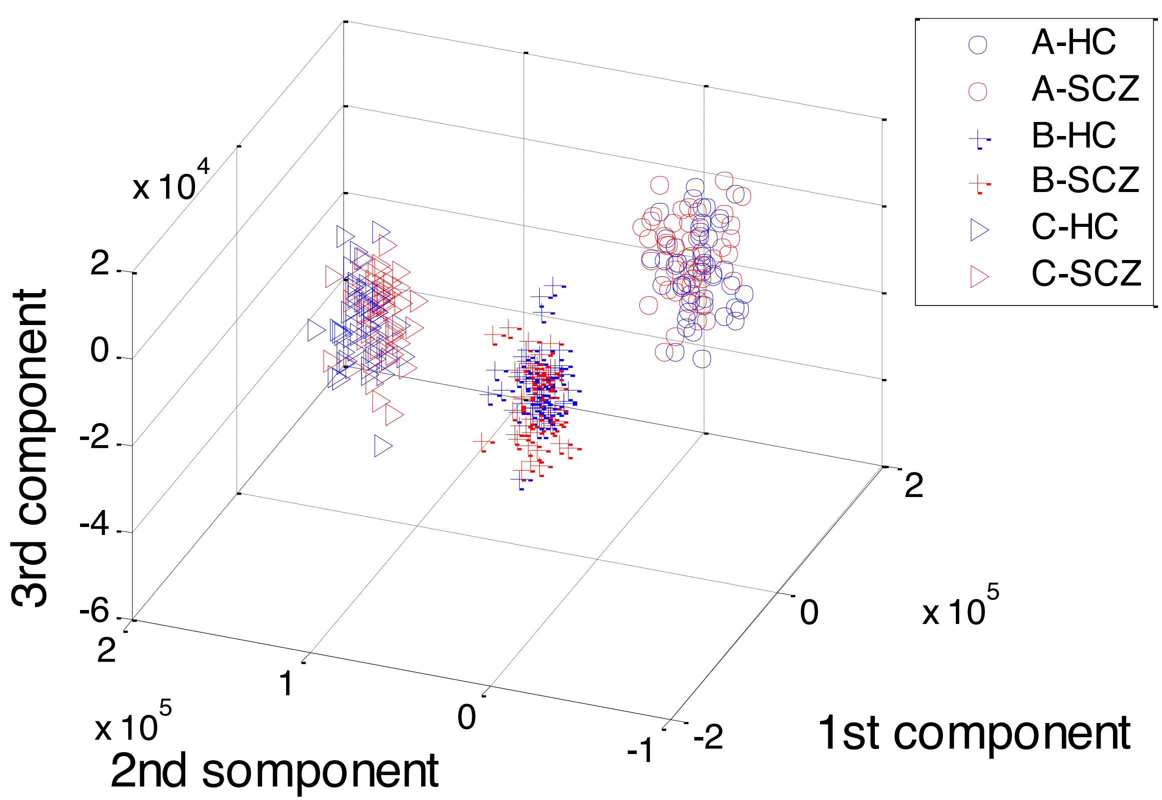
Key
Blue: Control GM < SCZ GM
Yellow: Control GM > SCZ GM

VBM Comparison of NC vs SCZ for Pooled Datasets



Classification Accuracy

Demographic information



Classification accuracy

Site	SVM	GLM+SVM
A	72	76
B	67	74
C	68	84

a: Pearson Chi-square test. b: Two-sample t-test.

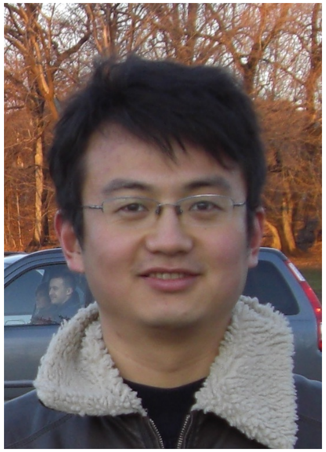
Conclusions

- Important challenges associated with harmonizing shared resources
  - Anatomical variability
  - Different intensity properties
- Robust preprocessing removes important confounding variation
- Simple statistical models help
- Can we do more ?
  - Machine learning approaches based on multi-task learning
  - Machine learning techniques that model explicitly the confounding factors

Credits

C. Davatzikos

G. Erus



T. Zhang

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