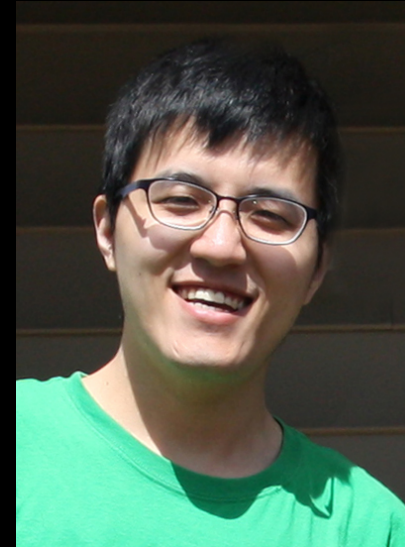
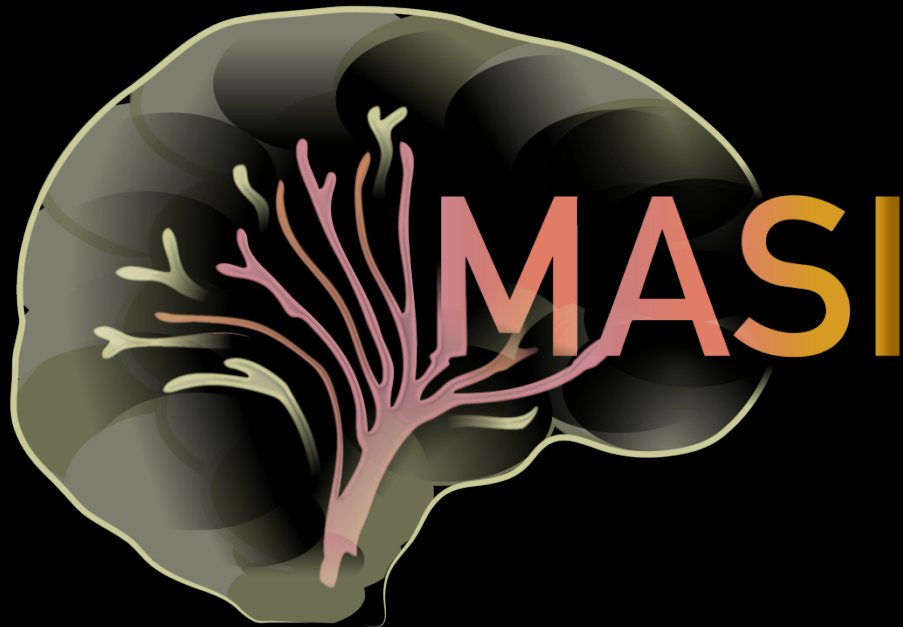


VISE

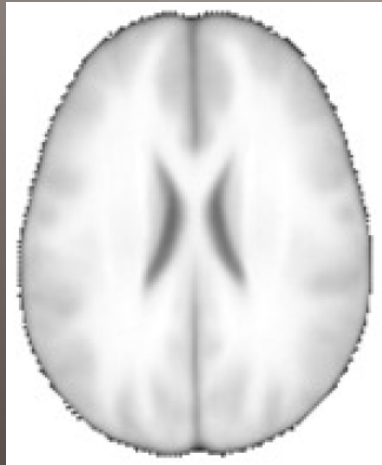


Yuankai Huo, Katherine Swett, Susan M. Resnick,
Laurie E. Cutting, Bennett A. Landman
MICCAI 2015 MAPPING Workshop
October 5, 2015

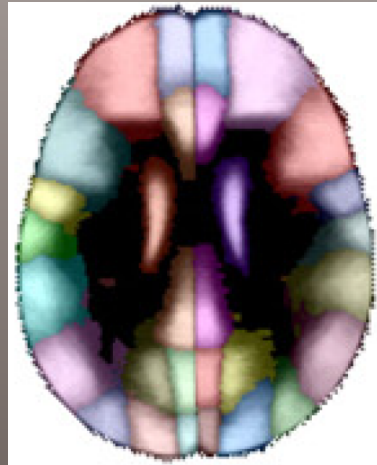
Data-driven Probabilistic Atlases Capture
Whole-brain Individual Variation



Outline



Anatomical
Atlas



Probabilistic
Atlas

Shattuck, et al. NeuroImage. 2008

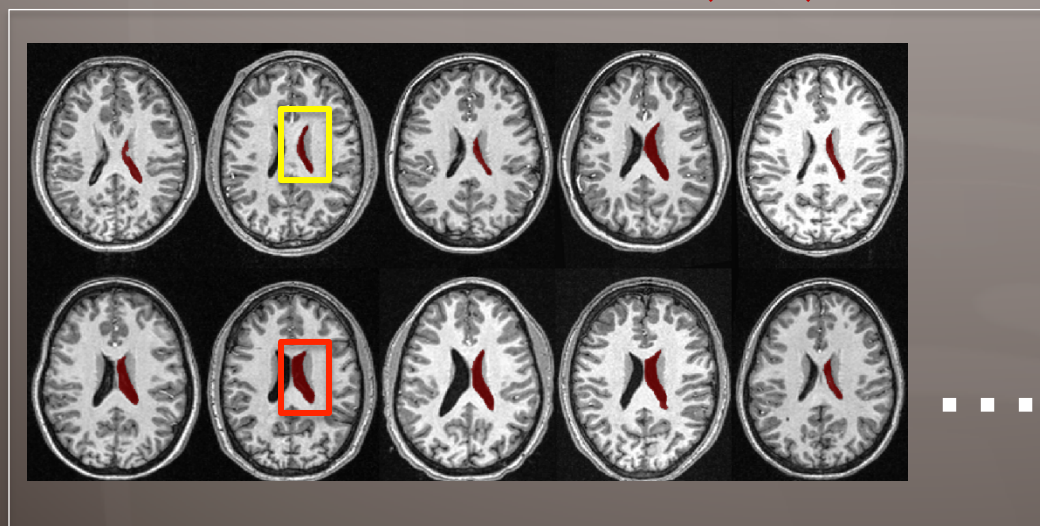
- ❖ Motivation
- ❖ Multi-Atlas Segmentation
- ❖ Learn Dictionary
- ❖ Apply Dictionary
- ❖ Results

Motivation

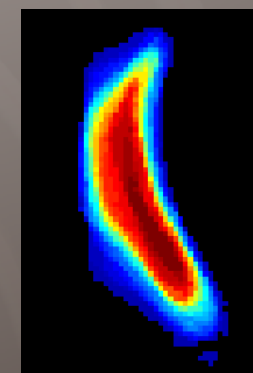
Shattuck, et al. NeuroImage. 2008

- Traditional Way of Making Probabilistic Atlases

Lateral Ventricle (red)



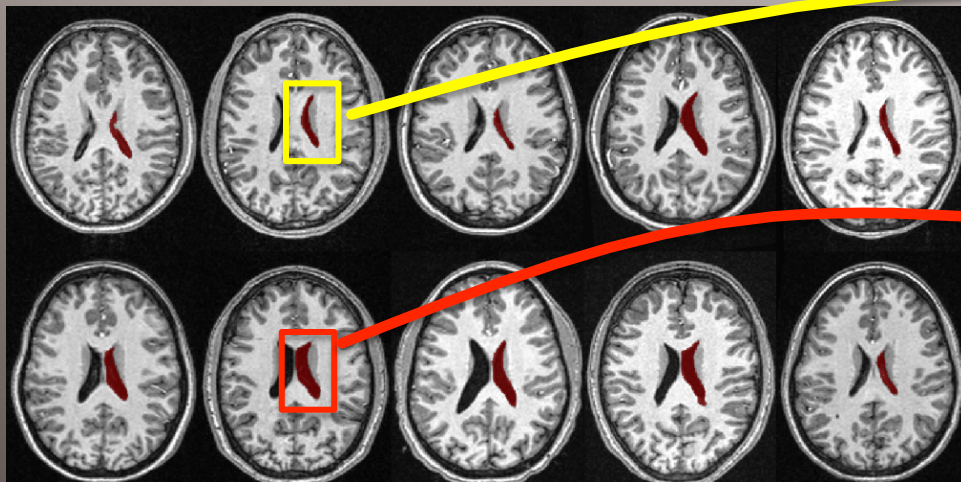
average
→



Prob. Atlas

40 healthy subjects from ADHD200 project (Age 15~17)

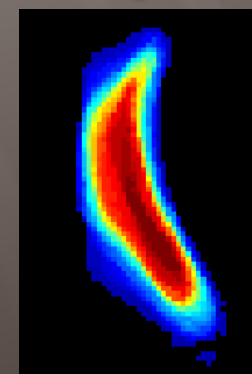
Problem



Can we do better?

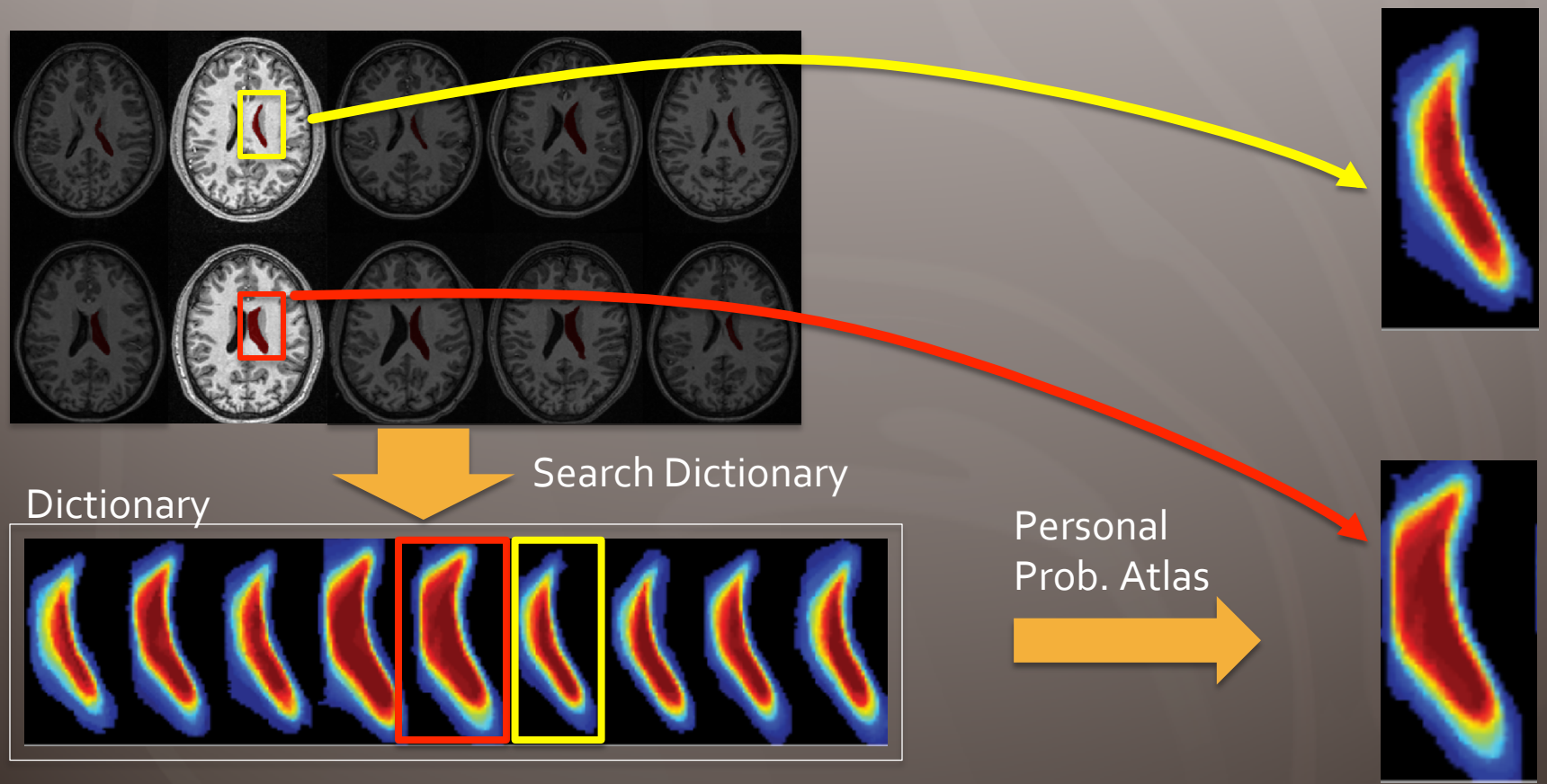
Inter-subject variabilities are large.
Probabilistic atlases are imprecise.

- Is the group based probabilistic atlas representative enough for this group?
- Traditional atlas creation is SLOW.
- Can we change the game with thousands or even more subjects?



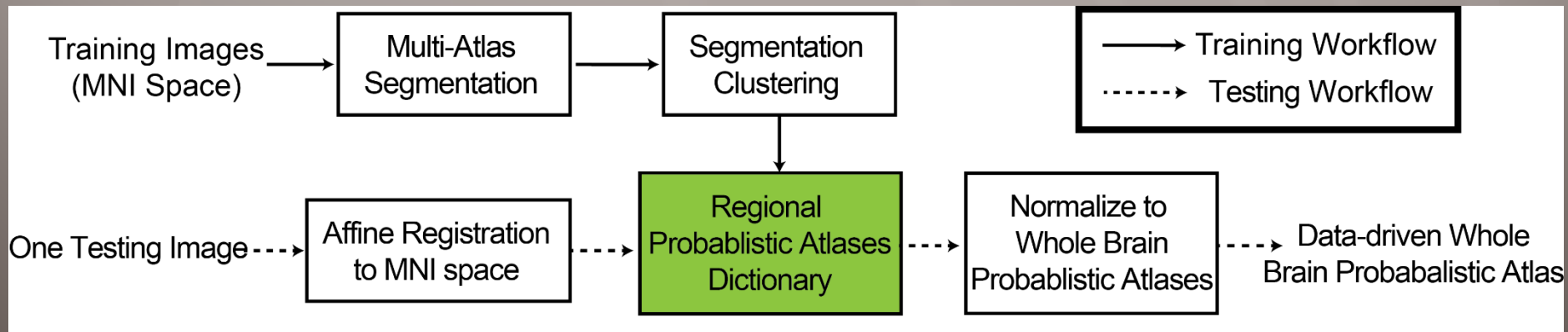
Prob. Atlas

Proposed Method



Workflow & Challenges

Workflow:



Challenges:

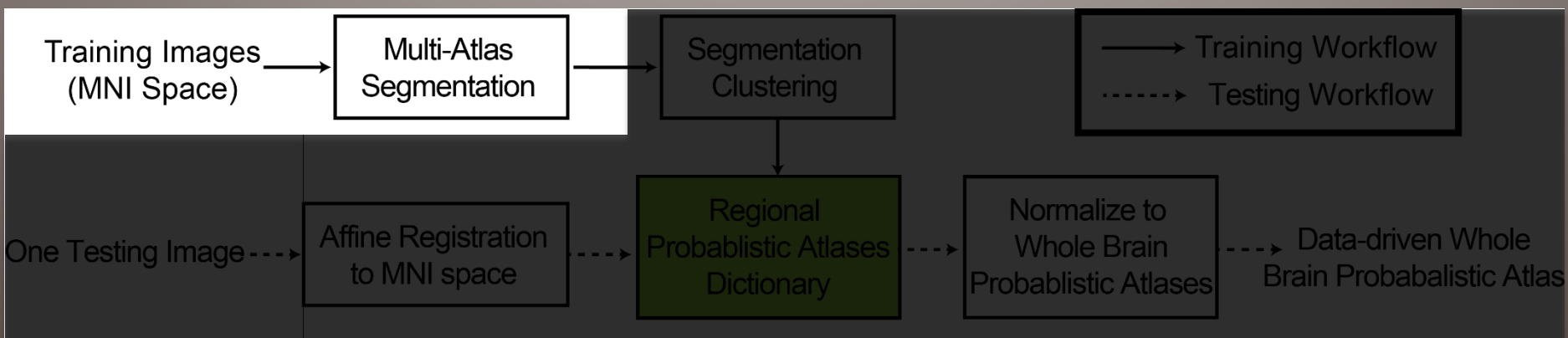
- Accurate Segmentation **(use multi-atlas segmentation)**
- Establish Representative Dictionary **(use large-scale dataset)**
- Quickly Obtain Personal Prob. Atlas on New Subject
(1 affine registration + 12s indexing time)



Multi-Atlas Segmentation

A robust approach for learning labeling algorithms from expertly labeled examples

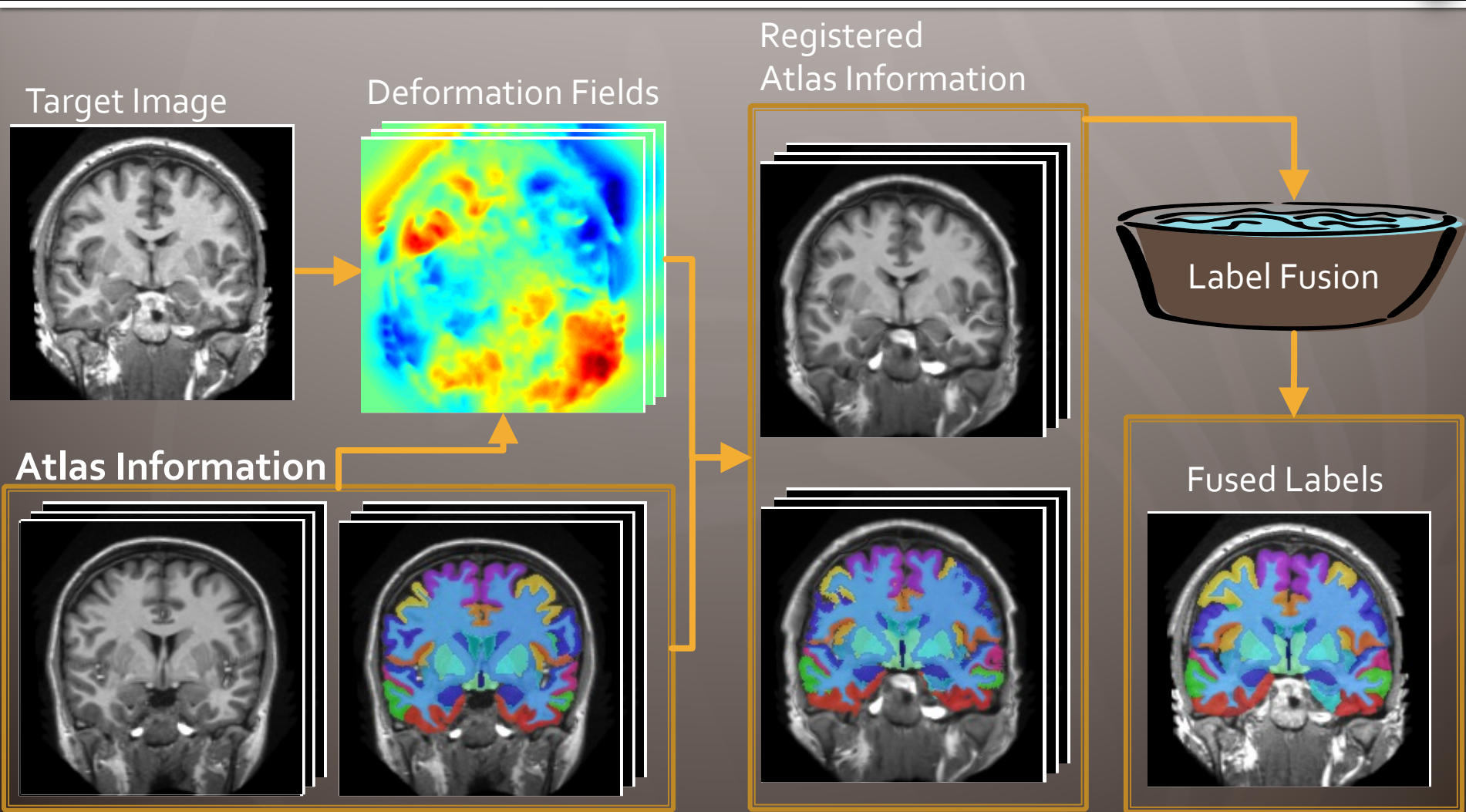
- ❖ Motivation
- ❖ Multi-Atlas Seg.
- ❖ Learn Dictionary
- ❖ Apply Dictionary
- ❖ Results



Learning by Examples: Multi-Atlas Labeling

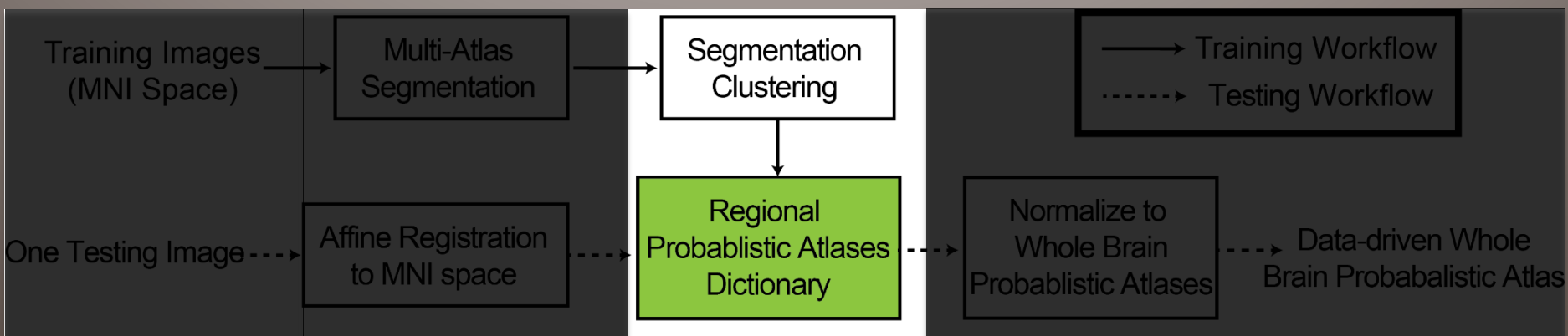


In 2002: Rohlfing, et al. Warfield et al.



Learn Dictionary

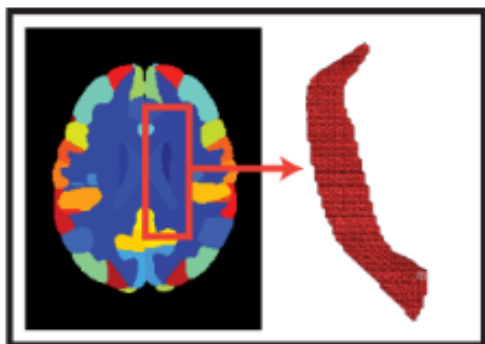
- ❖ Motivation
- ❖ Multi-Atlas Seg.
- ❖ Learn Dictionary
- ❖ Apply Dictionary
- ❖ Results



Define Shape Feature

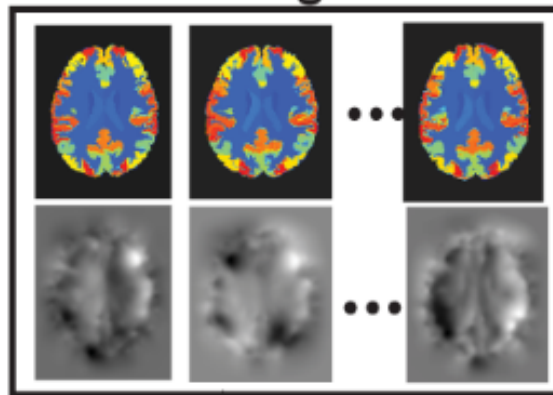
Each Region Has Its Own Shape Model

Mean Segmentation
& Vertices on mesh



\bar{S} \bar{V}^k

Non-rigid Registration
To Mean Segmentation



ϕ_i ϕ_i^{-1}

For Each Region
Volume to Volume
Propagation



Point Distribution Models

V_i^k

- Generate mesh on mean segmentation
- Propagate mesh to each subject
- Obtain meshes on 132 regions for all subjects

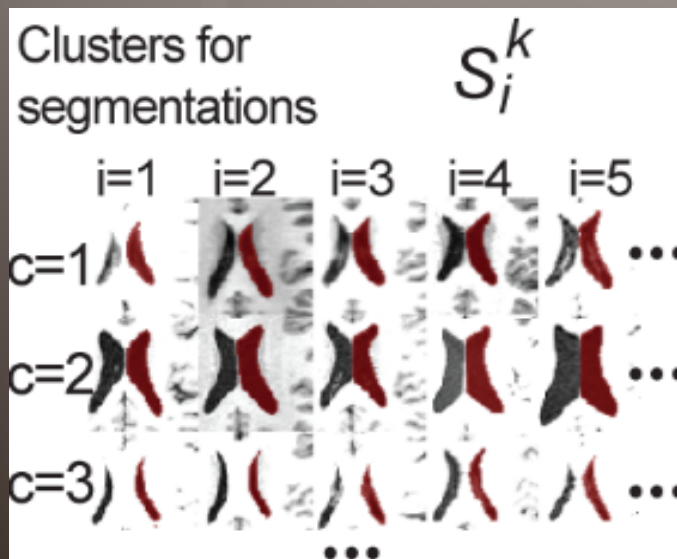
Affinity Propagation Clustering

Clustering for Each Region



- Calculate Euclidean distance between vertices on generated meshes
- Conduct Affinity Propagation (AP) clustering based on the distances

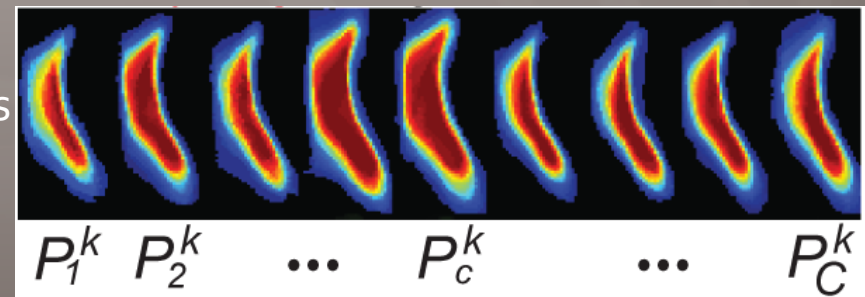
Clusters for One ROI



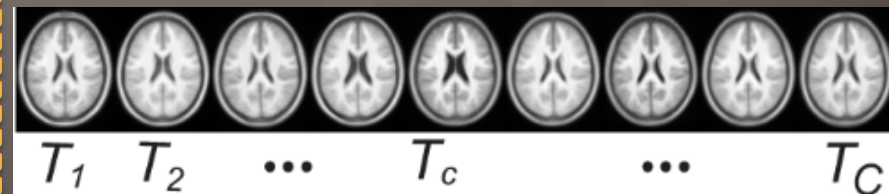
average segmentations

average anatomical images

Regional Probabilistic Atlases



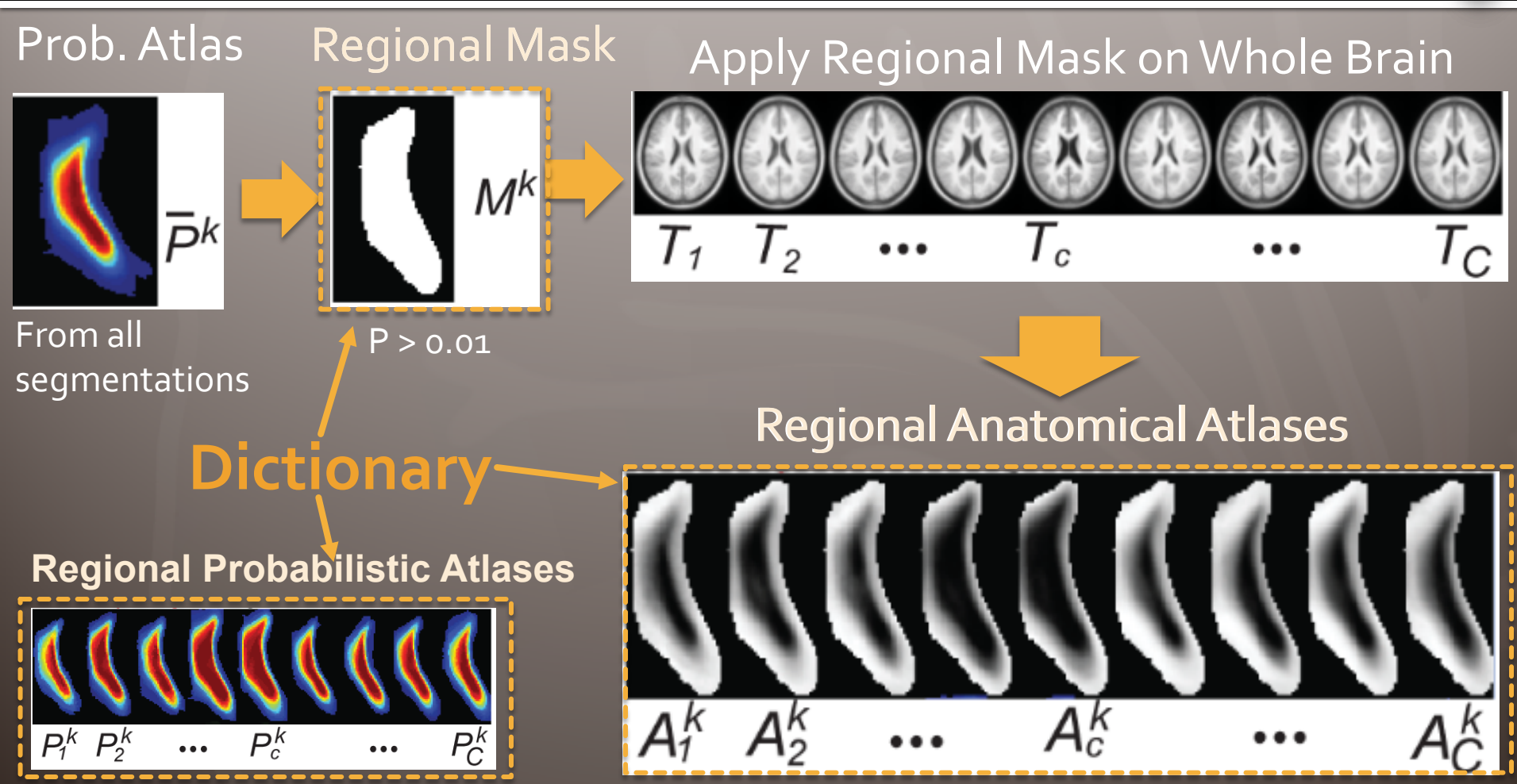
Whole Brain Anatomical Atlases



One atlas per cluster

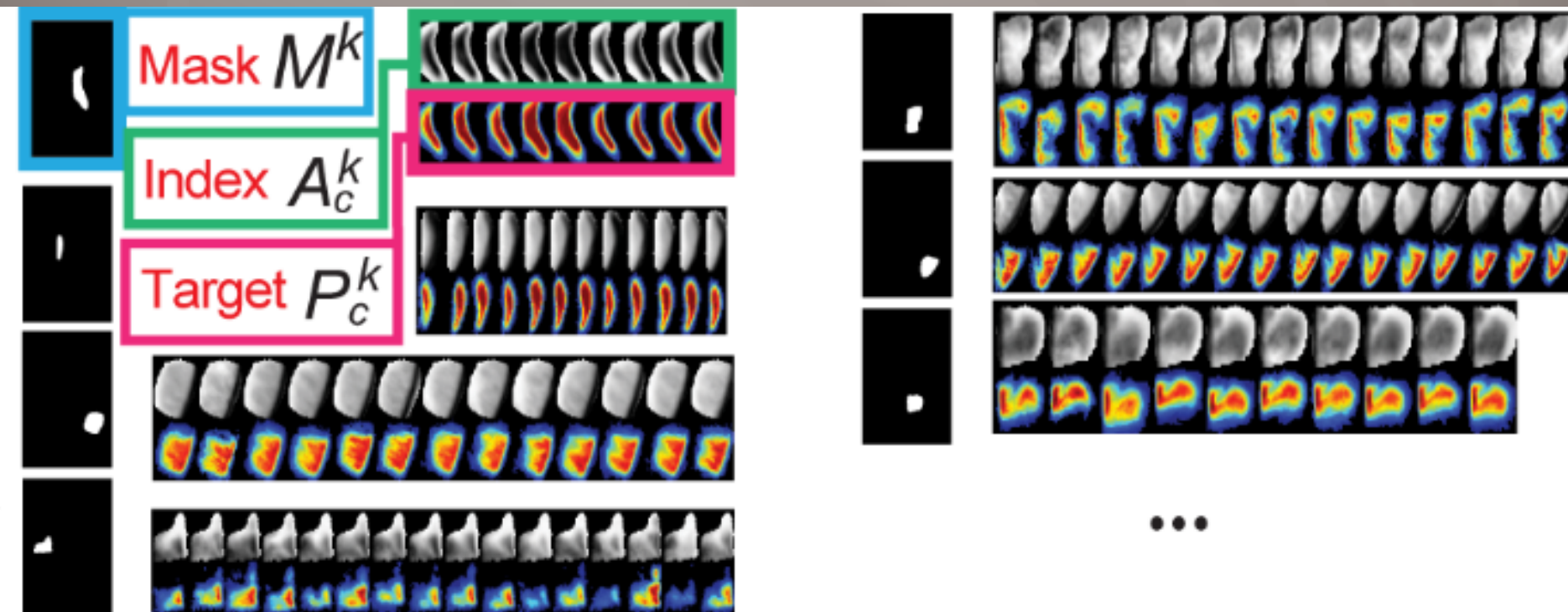
Regional Anatomical Atlases

Obtain Index for the Dictionary



Summary of Dictionary

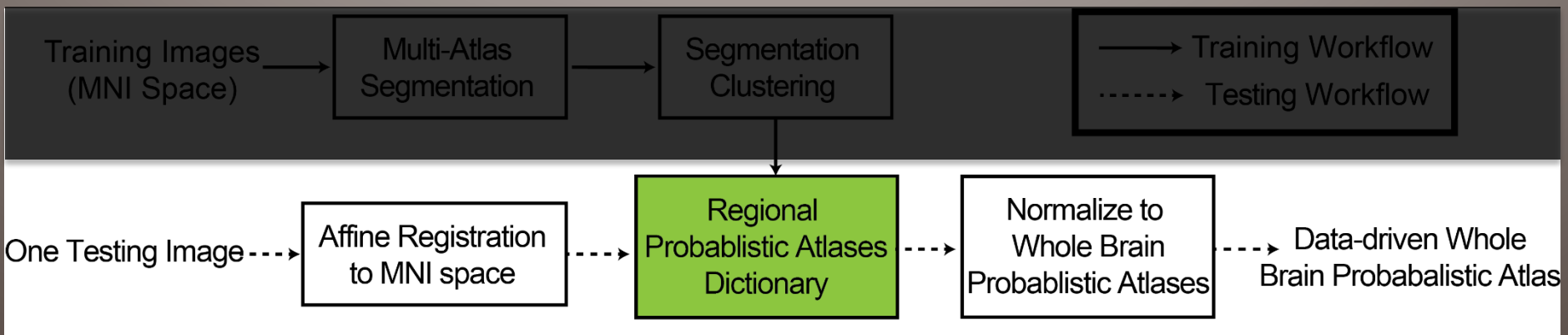
Final Dictionary (132 Regions)



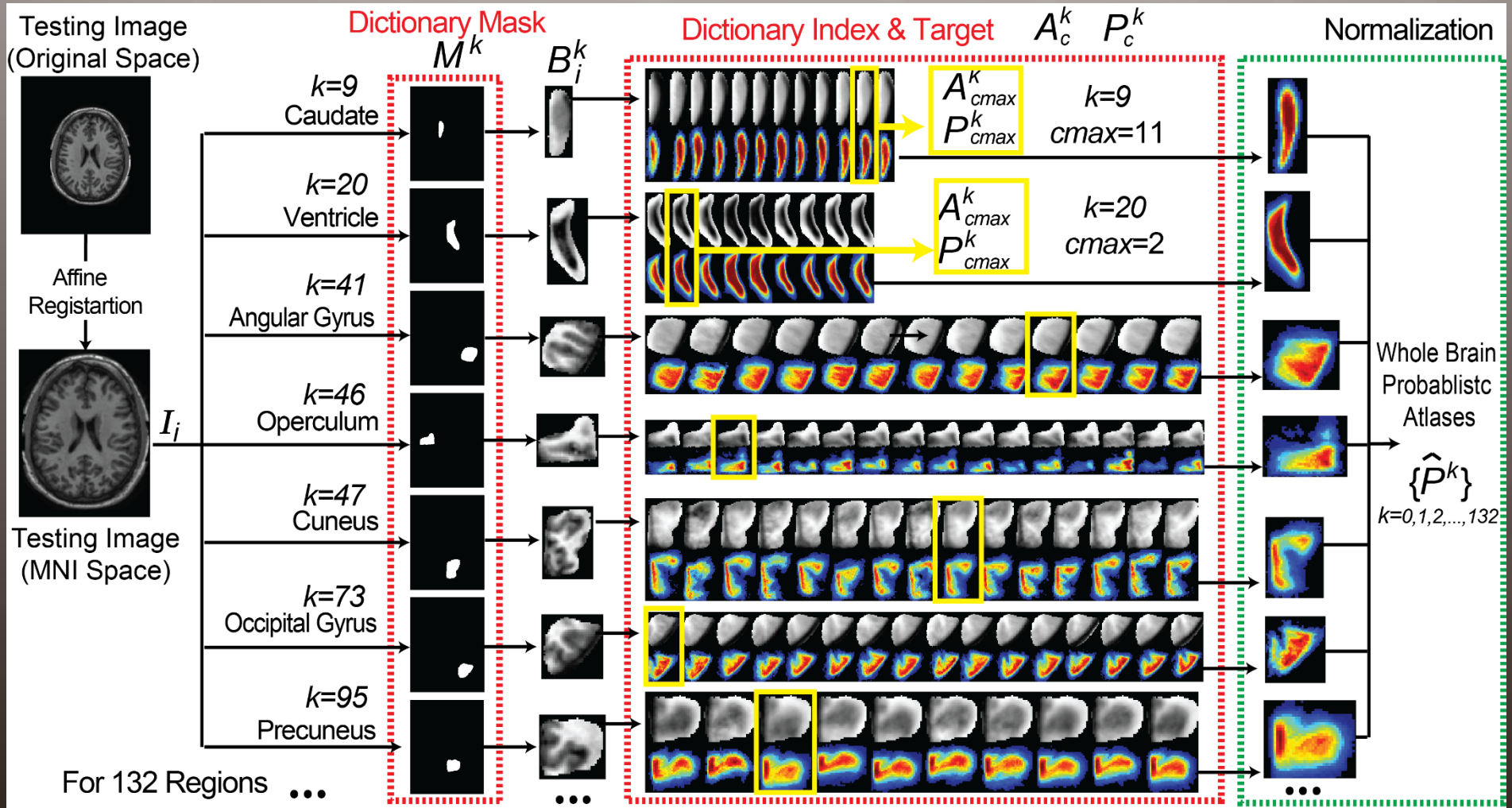


Apply Dictionary

- ❖ Motivation
- ❖ Multi-Atlas Seg.
- ❖ Learn Dictionary
- ❖ Apply Dictionary
- ❖ Results



Generate Personal Prob. Atlas



Data & Results

- ❖ Motivation
- ❖ Multi-Atlas Seg
- ❖ Learn Dictionary
- ❖ Apply Dictionary
- ❖ Results



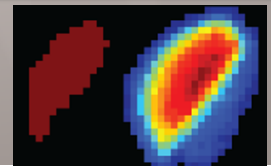
Table 1. Data summary of Training Set 720 and Testing Set

	Study	Site	Sex (1 is male)	Age (years)	Scanner (Tesla)	Training (number)	Testing (number)
1	BLSA	NIA	1, 2	29~45	3T	40	0
2	Cutting	Vanderbilt	1, 2	20~30	3T	40	37
3	ABIDE	NYU	1, 2	15~32	3T	40	0
4	IXI	Guys	1	20~45	1.5T	40	22
5	IXI	Guys	2	20~45	1.5T	40	20
6	IXI	HH	1, 2	20~45	3T	40	47
7	IXI	IOP	1, 2	20~45	1.5T	40	0
8	ADHD200	NYU	1, 2	15~17	3T	40	0
9	ADHD200	NeuroIM	1, 2	15~26	3T	40	0
10	ADHD200	Pittsburgh	1, 2	15~20	3T	40	0
11	fcon_1000	Beijing	1	20~26	3T	40	23
12	fcon_1000	Beijing	2	20~26	3T	40	61
13	fcon_1000	Cambridge	1	20~25	3T	40	17
14	fcon_1000	Cambridge	2	21~25	3T	40	39
15	fcon_1000	ICBM	1, 2	19~45	3T	40	0
16	fcon_1000	NewYork	1, 2	20~45	3T	40	52
17	fcon_1000	Oulu	1, 2	20~23	1.5T	40	63
18	NKI_rockland	Rockland	1, 2	15~45	3T	40	35
	OASIS with manual segmentation		1, 2	18~90	3T	0	45
					Total	720	461

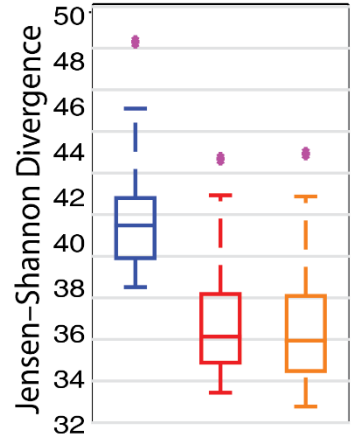
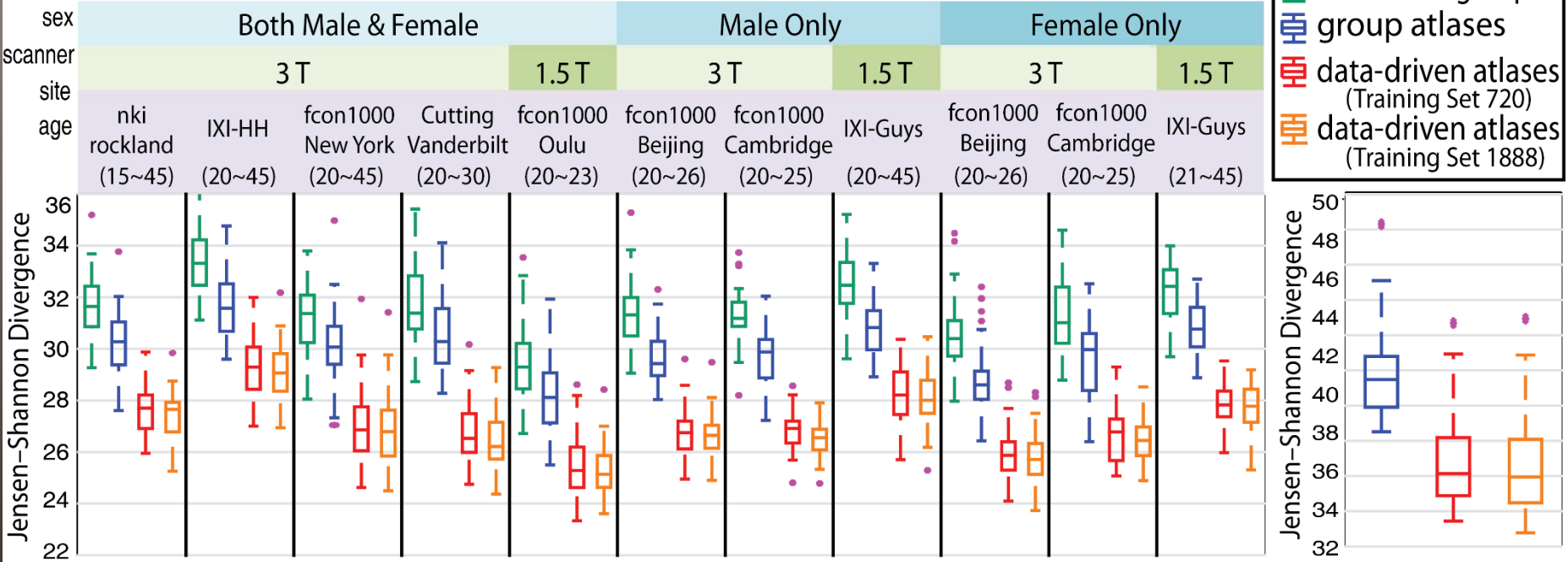
“Training Set 1888” has 1168 more training data than “Training Set 720”.
They both use the same testing data.

Quantitative Results

Similarity of spatial distributions between segmentations and different probabilistic atlases.



Jensen-Shannon Divergence



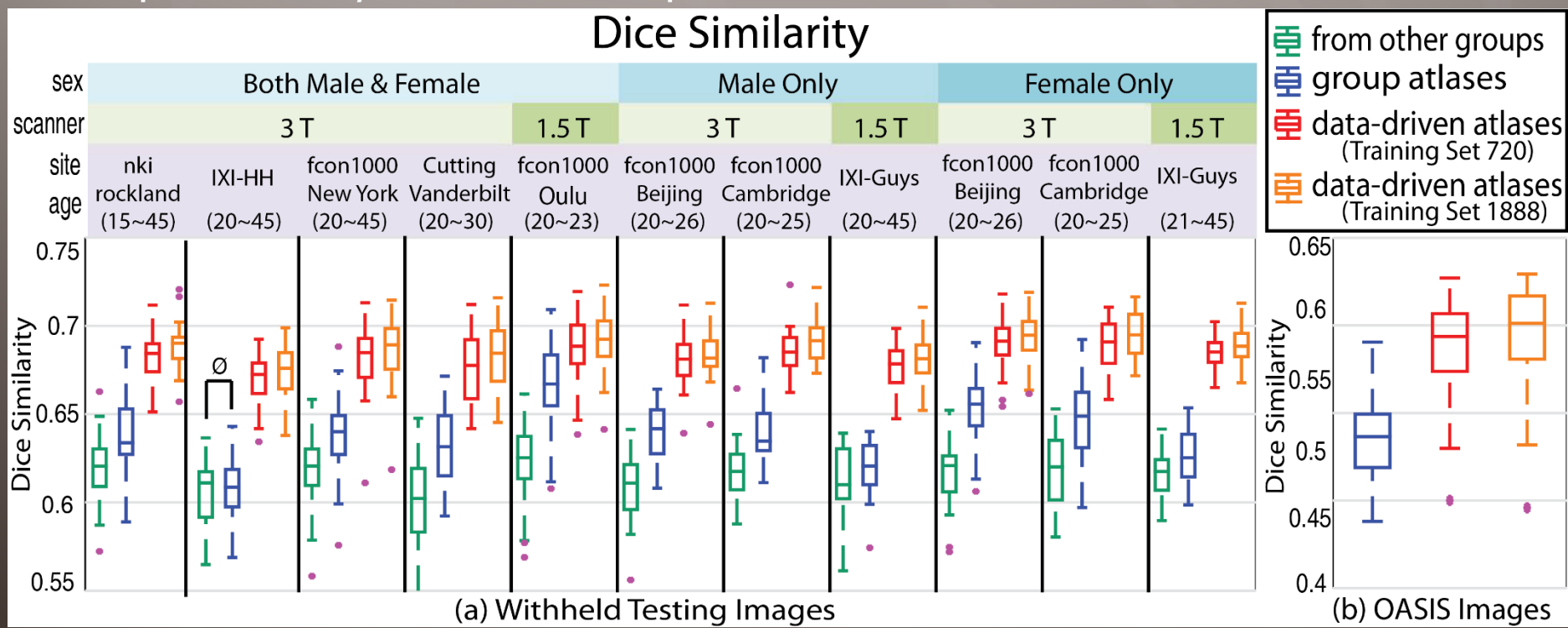
(a) Withheld Testing Images

(b) OASIS Images

(a) shows the results of withheld testing images with multi-atlas segmentations
 (b) indicates the results from 45 OASIS with manual segmentations (leave one out)

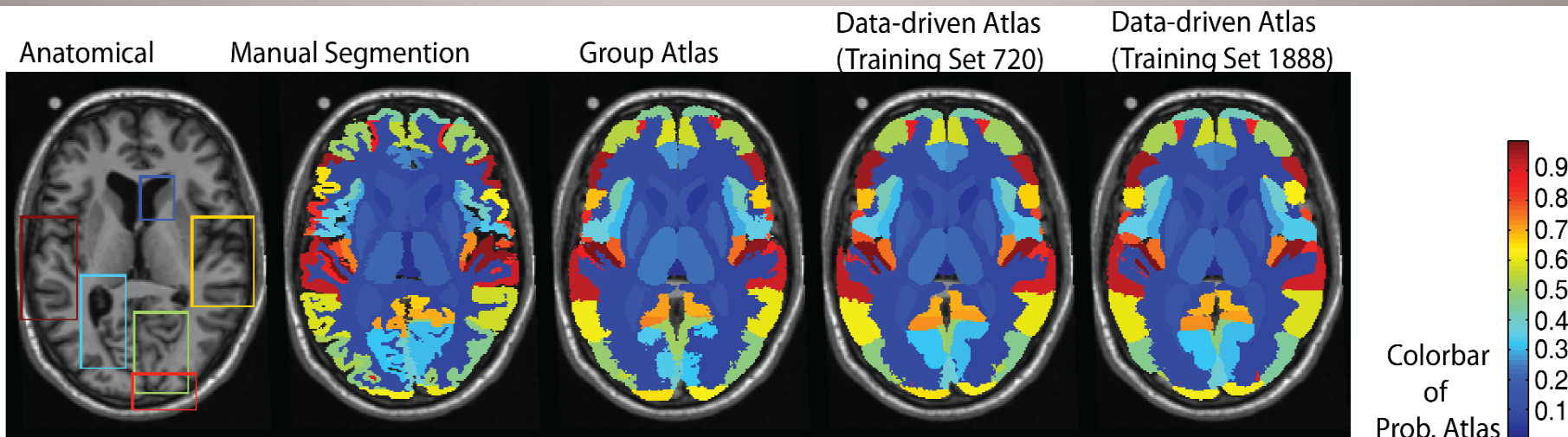
Segmentation Results

Conduct “naive segmentation” (select label with highest probability) to different probabilistic atlases



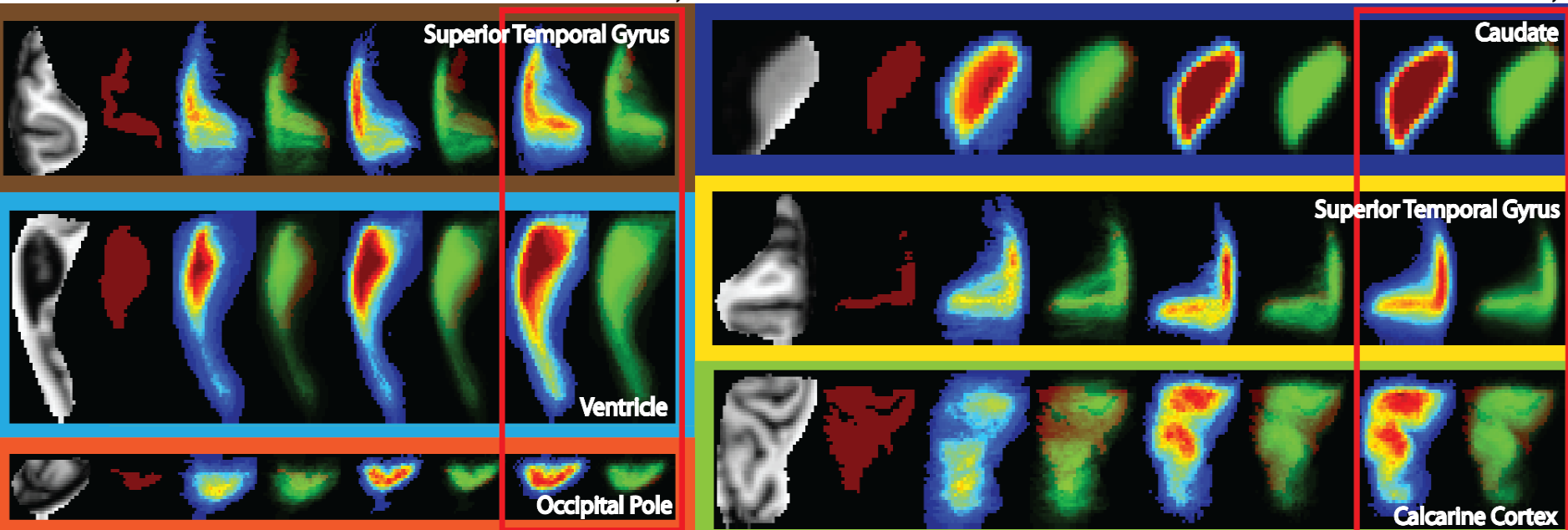
(a) Agreement of withheld testing images with multi-atlas segmentations
 (b) Validation with 45 OASIS with manual segmentations (leave one out)

Segmentations and Overlay



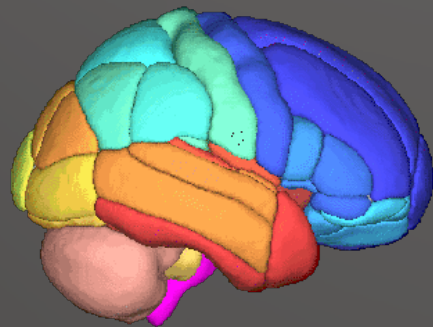
Prob. Atlas Overlay

Prob. Atlas Overlay

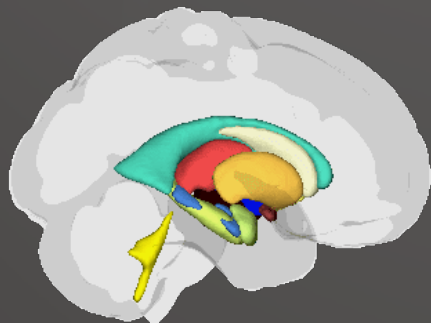


Anatomical ManualSeg. Group Atlas Data-driven Atlas (Training Set 720) Data-driven Atlas (Training Set 1888) Anatomical ManualSeg. Group Atlas Data-driven Atlas (Training Set 720) Data-driven Atlas (Training Set 1888)

Conclusion



- The framework uses the large-scale heterogeneous data to achieve personal specific probabilistic atlases.
- This work provides a new perspective of using data-driven scheme rather than the traditional group based methods.
- The large-scale scheme with 1888 training images performs better than the smaller 720 training images.
- The approach achieves low computational cost.



Asman, MedIA, 2014

Thank you. Questions?

- Made possible by
 - NIH R03EB012461, R01EB006193, UL1RR024975, UL1TR000445, P30CA068485, R01EB15611, 5R01MH098098, 1R21NS064534, R21EY024036, 5T32EY007135
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