Towards Learning-Based Holistic Brain Image Segmentation

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in collaboration with (A. Toga, P. Thompson et al.)

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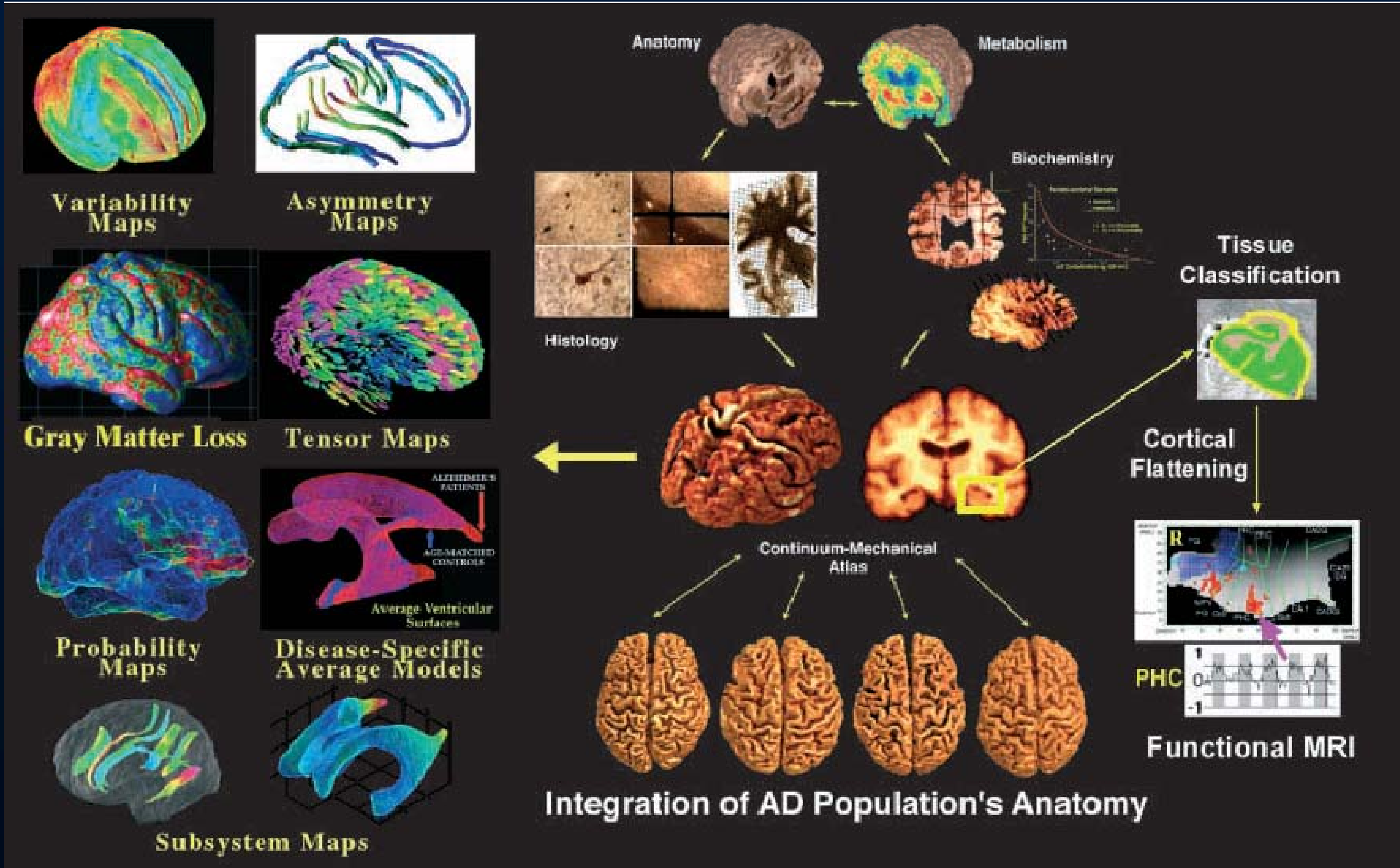
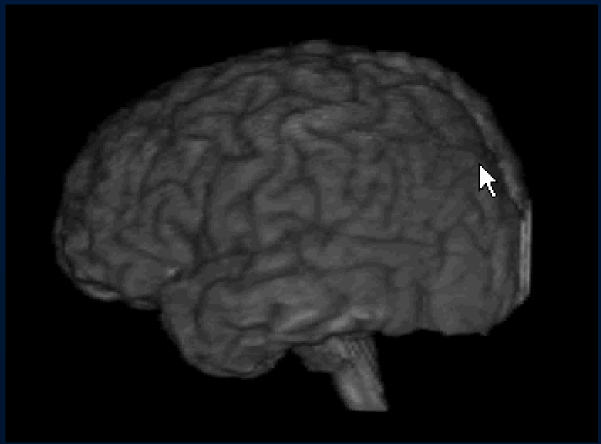
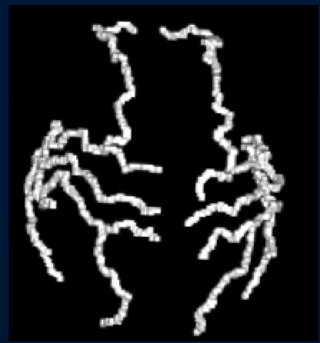
Building A Brain Atlas
(Thompson and Toga 2004)

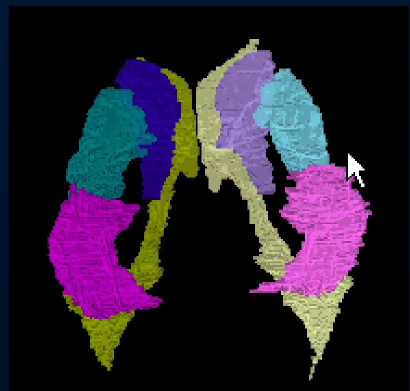


Brain Anatomical Structure Parsing

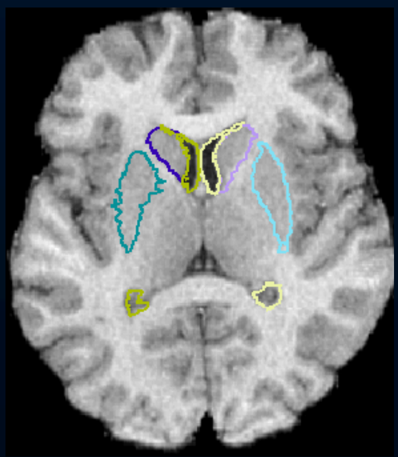


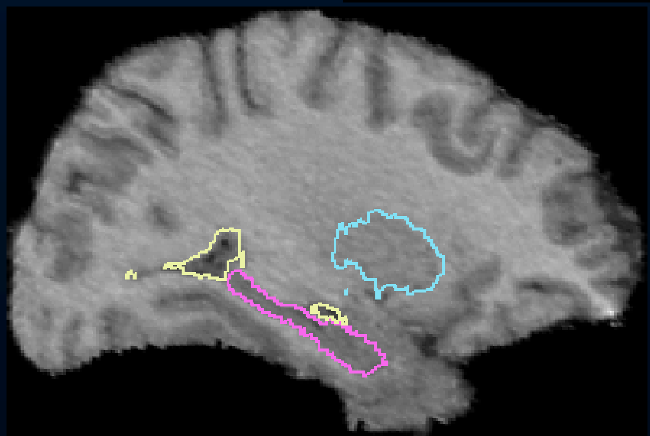


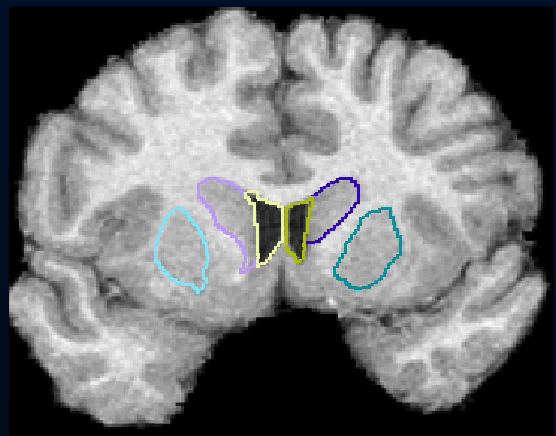
cortical structures: major sulci curves



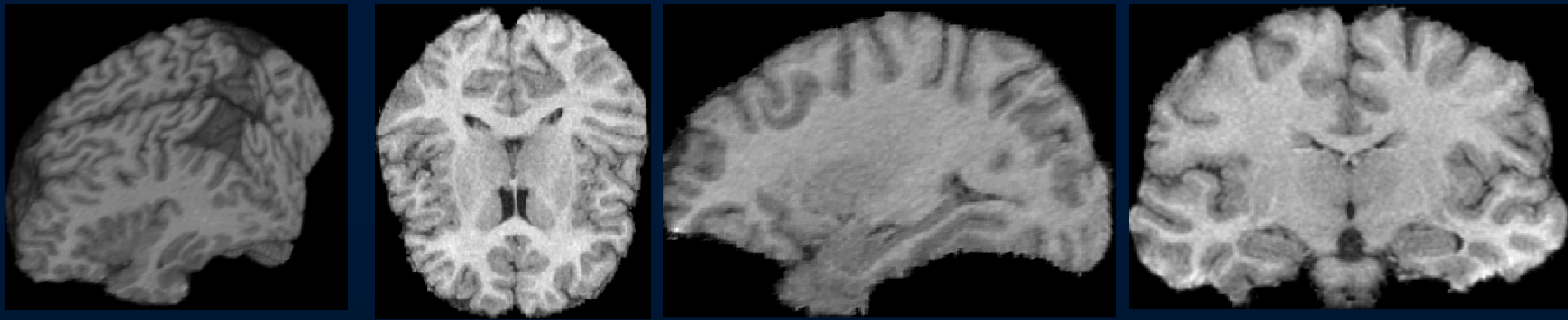
sub-cortical structures







Challenges for Automatic Segmentation



1. Large volume size for high resolution 3d MRI.
2. Very weak intensity patterns. (large inter-class similarity and intra-class variation)
3. Hard to capture 3D shape info due to the high dimension space and limited number of training data.
4. Hard to capture the high-level knowledge and adapt to different protocols.

Existing Work

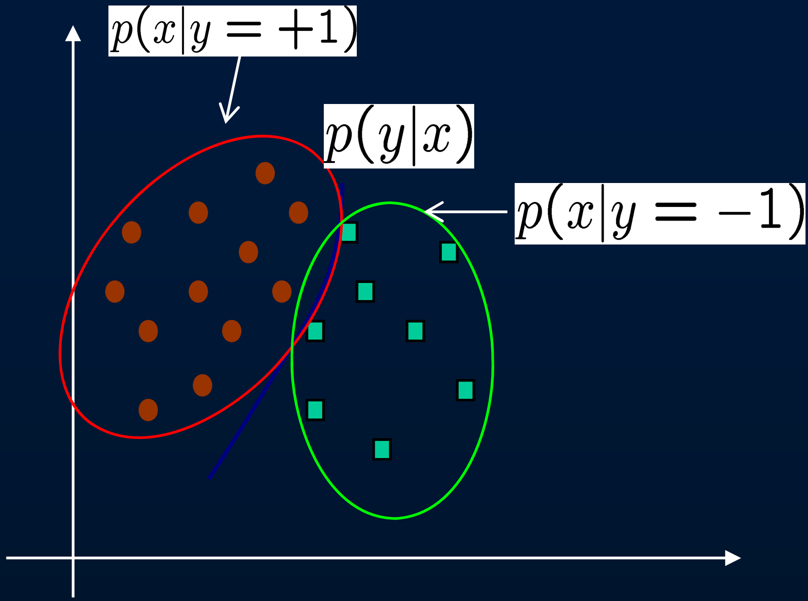
Generative model (shape) driven:

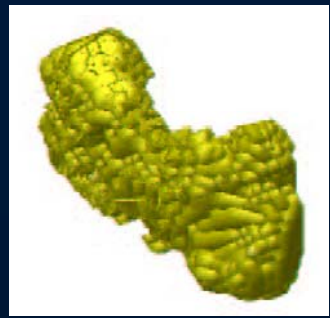
- •Markov random fields (Fischl et al. 2002)
- •Active shape model (Cootes et al. 2001)
- •M-rep (Pizer et al.)
- •Joint PCA shape constraints (Yang et al. 2004)
- •Atlas-based (Li et al. 1993)

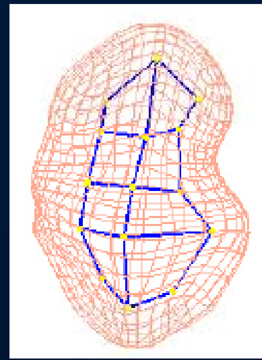
Classification-based (discriminative):

- •Knowledge-based (Li et al. 1993)
- •Feature classification (Liu et al. 2004)
- • SVM voxel classification (Lao et al. 2004)

Comparisons



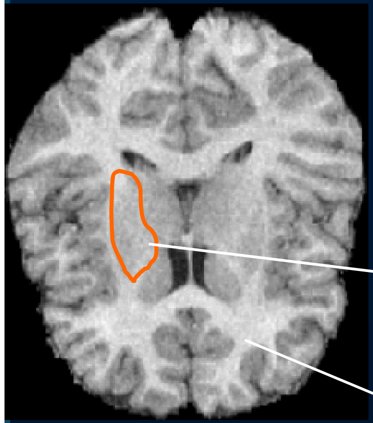

Yang et al. 2004


Pizer et al. 2003

Algorithms	Appearance Model	Shape Model	Inference
Fischl et al. [4]	generative: i.i.d. Gaussians	generative: local constraints	expectation maximization
Yang et al. [5]	generative: i.i.d. Gaussians	generative: PCA on shape	variational method
Pohl et al. [6]	generative: i.i.d. Gaussians	generative: PCA on shape	expectation maximization
Pizer et al. [7]	generative: i.i.d. Gaussians	generative: M-rep on shape	multi-scale gradient descent
Woolrich and Behrens [8]	generative: i.i.d. Gaussians	generative: local constraints	Markov Chain Monte Carlo
Li et al. [9]	discriminative: rule-based	None	rule-based classification
Rohlfing et al. [10]	discriminative: atlas based	somewhat	voxel classification
Descombes et al. [11]	discriminative: extracted features	generative: geometric properties	Markov Chain Monte Carlo
Lao et al. [12]	discriminative: SVM	None	voxel classification
Lee et al. [13]	discriminative: SVM	generative: local constraints	iterated conditional modes

A Bayesian Framework

Input: $\mathbf{V}$ Solution: $W = (R_1, R_2, ..., R_n)$

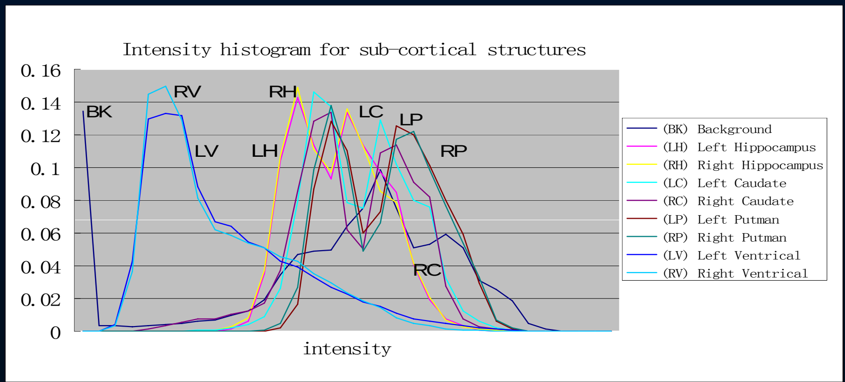


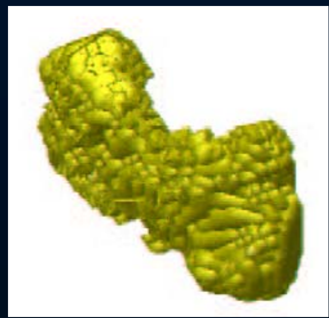
$$p(W|\mathbf{V}) \propto p(\mathbf{V}|W)p(W)$$

$$\propto \prod_{k=1}^{n} p(\mathbf{V}(R_k)|R_k)p(R_k)$$

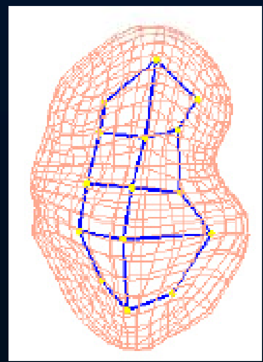
Appearance model

3D shape model





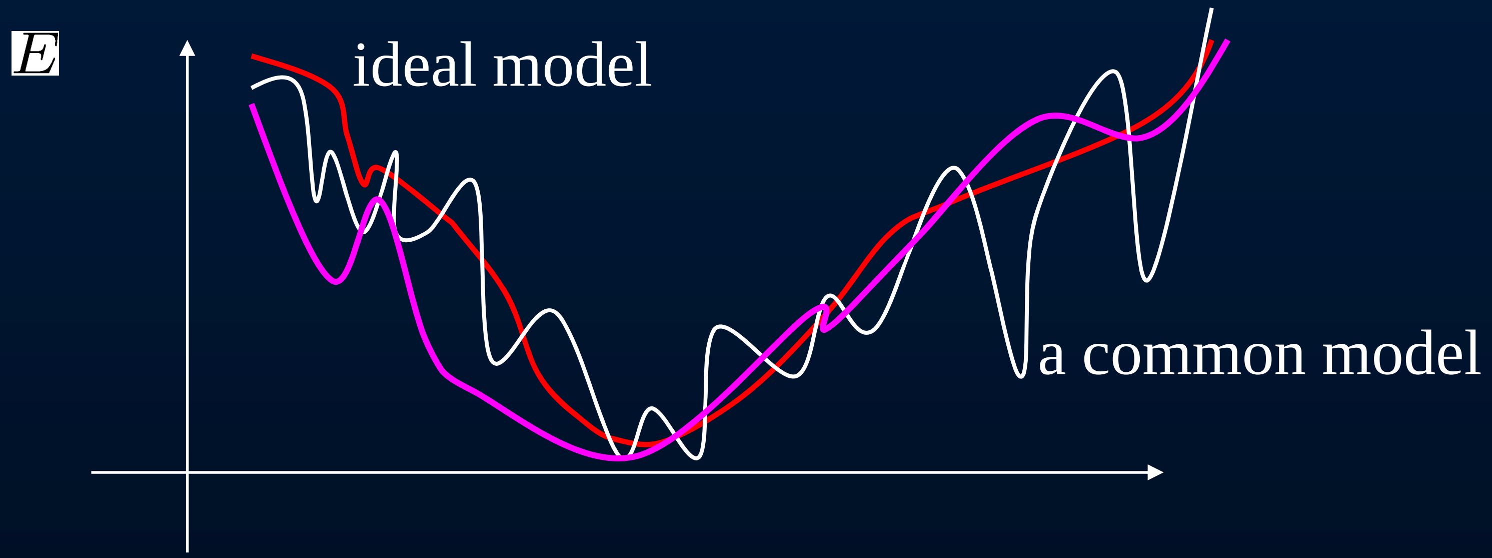
Yang et al. 2004



Pizer et al. 2003

Intensity histograms of different structures

Learning Energy



Are We Getting the Right Model?

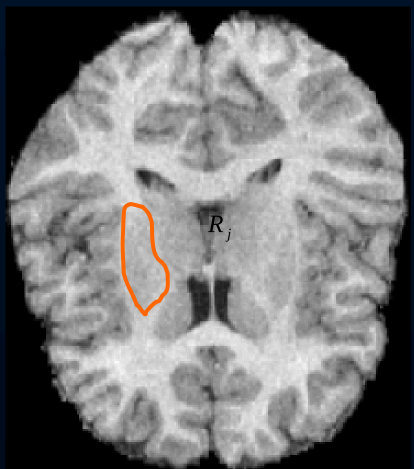
An ideal model: $$p(W|\mathbf{V}) \propto p(\mathbf{V}|W)p(W)$$

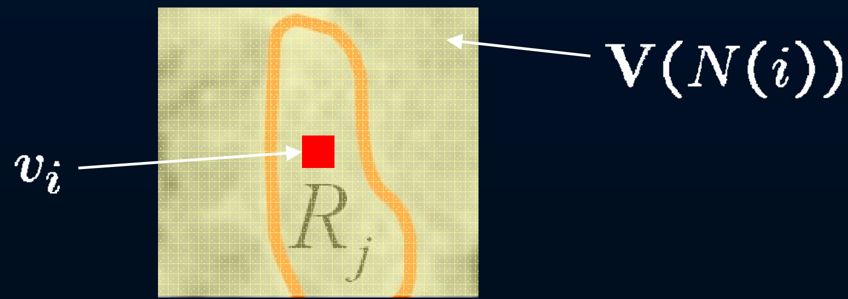
$$E(W,\mathbf{V}) = -\log p(\mathbf{V}|W) - \log p(W)$$

The full generative appearance model p(**V**|W) is very hard to obtain!

$$E_H(W,\mathbf{V}) = -\log \prod_i p(v_i, y_i = j|\mathbf{V}(N(i)/i)) - \log p(W)$$

$$\rightarrow -\log \prod_i p(y_i = j|\mathbf{V}(N(i)) - \log p(W)$$





A discriminative model (classification)!

The Algorithm

Training (given a set of annotated volumes):

(1) Learn multi-class classification model using PBT.

(2) Learn PCA shape model for each structure.

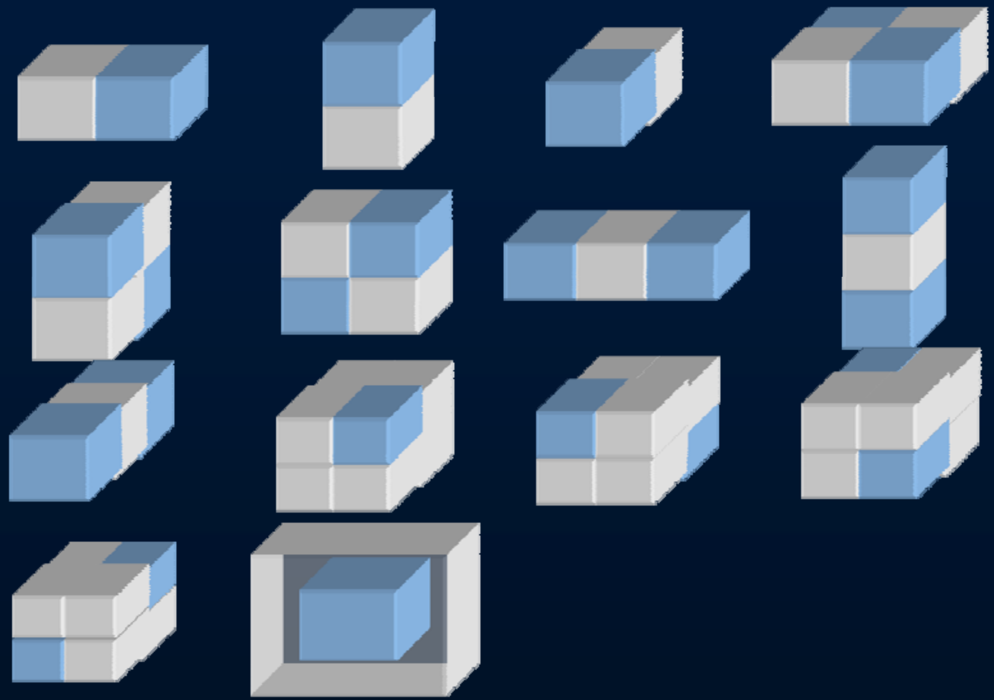
$$E = \alpha_1 \sum_{i=1}^{n} \sum_{s \in R_i} -\log p(l_s = i \,|\, V(N(s)) + \alpha_2 \sum_{i=2} -\log p(S_i) + \alpha_3 \sum_{i=1} -\Lambda(S_i)$$

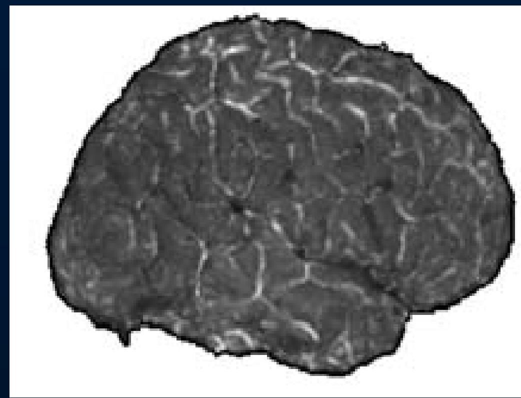
Testing (given a volume)

1. Compute classification using learned PBT.
2. Obtain the initial segmentation.
3. Perform region competition based on the proposed 3D representation.

Features

Around 10,000 features in the candidate pool: Gradients, Curvatures, Haars



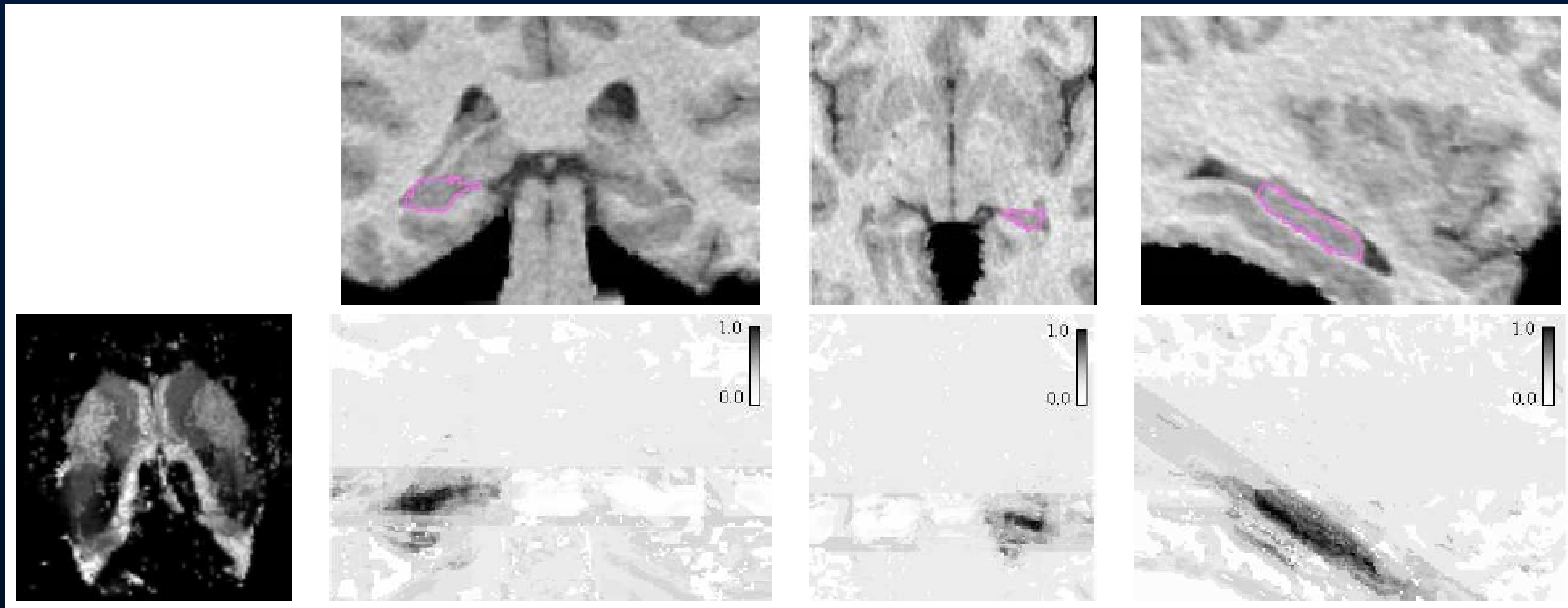


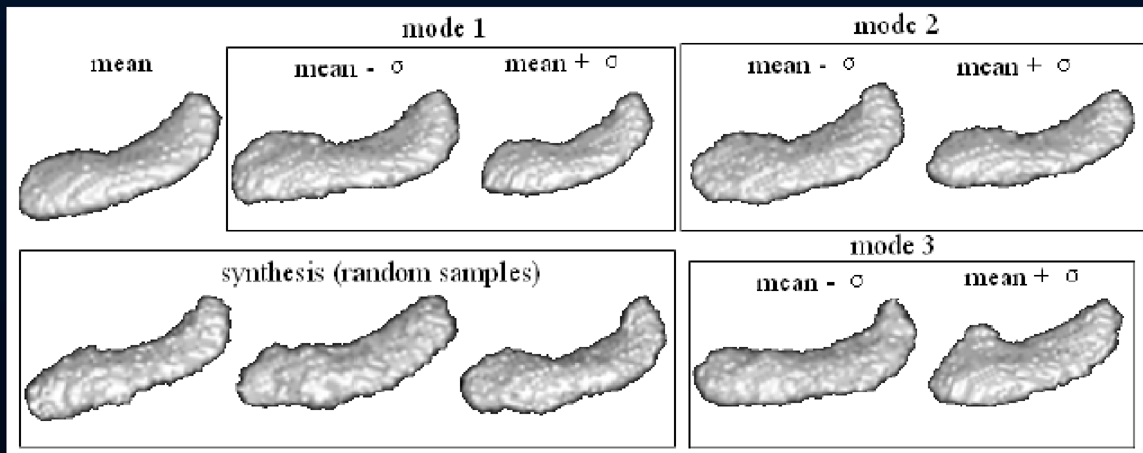
curvatures

(1) Very fast to compute using integral volume.

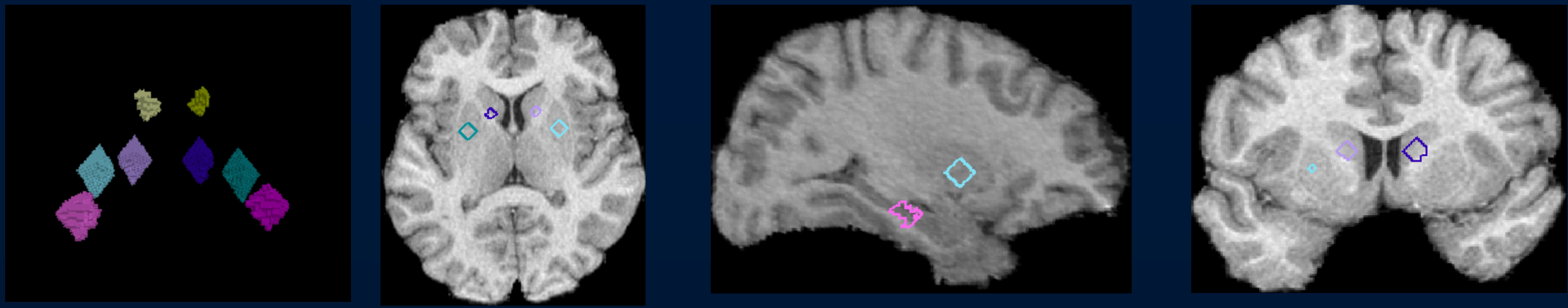
(2) Combine information at different scales.

Discriminative and Generative Models Learned

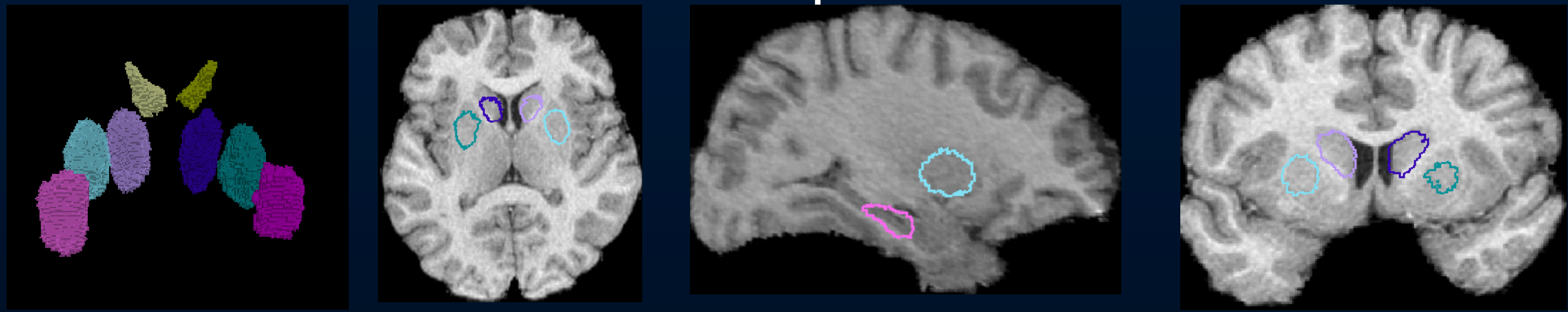




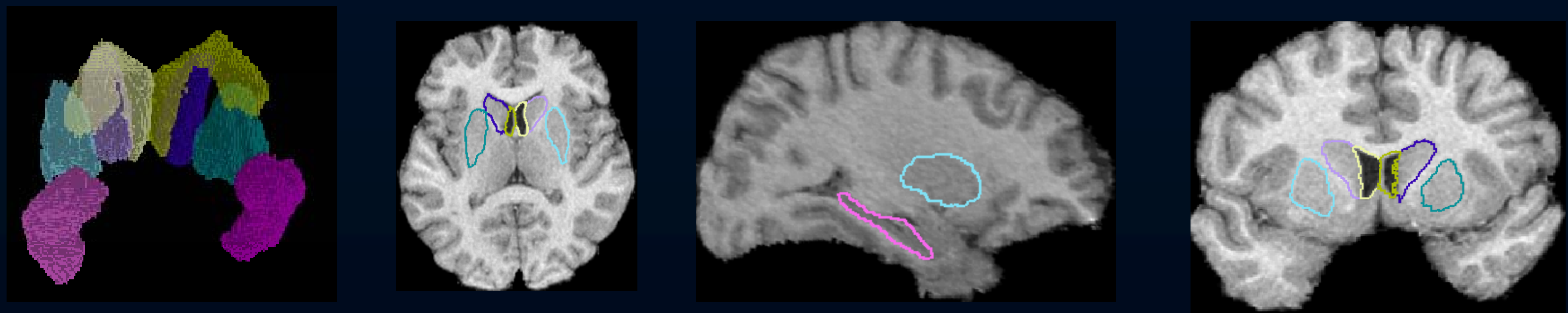
Results



Step=1

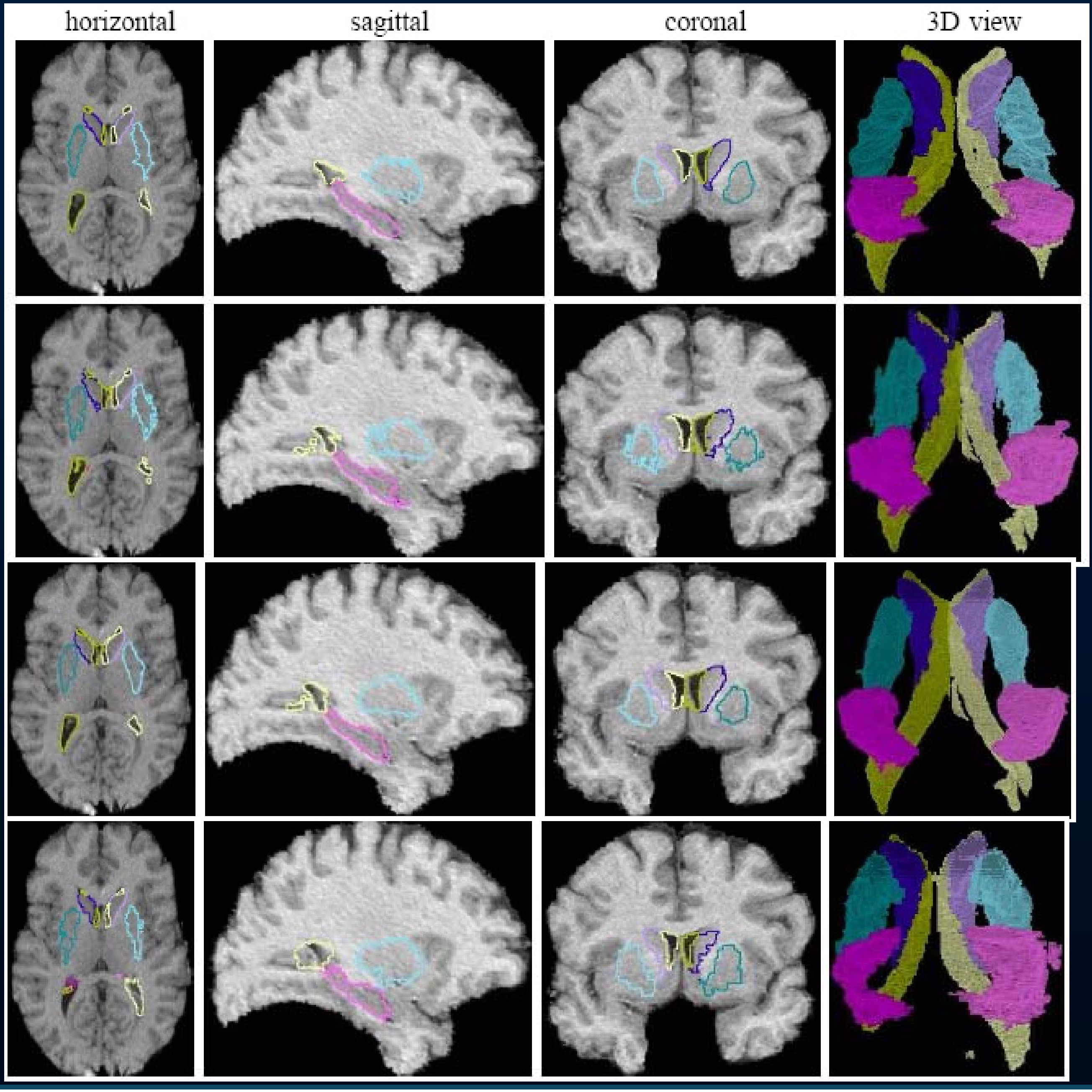


Step=2



Step=3

Results on The Testing Data



manual

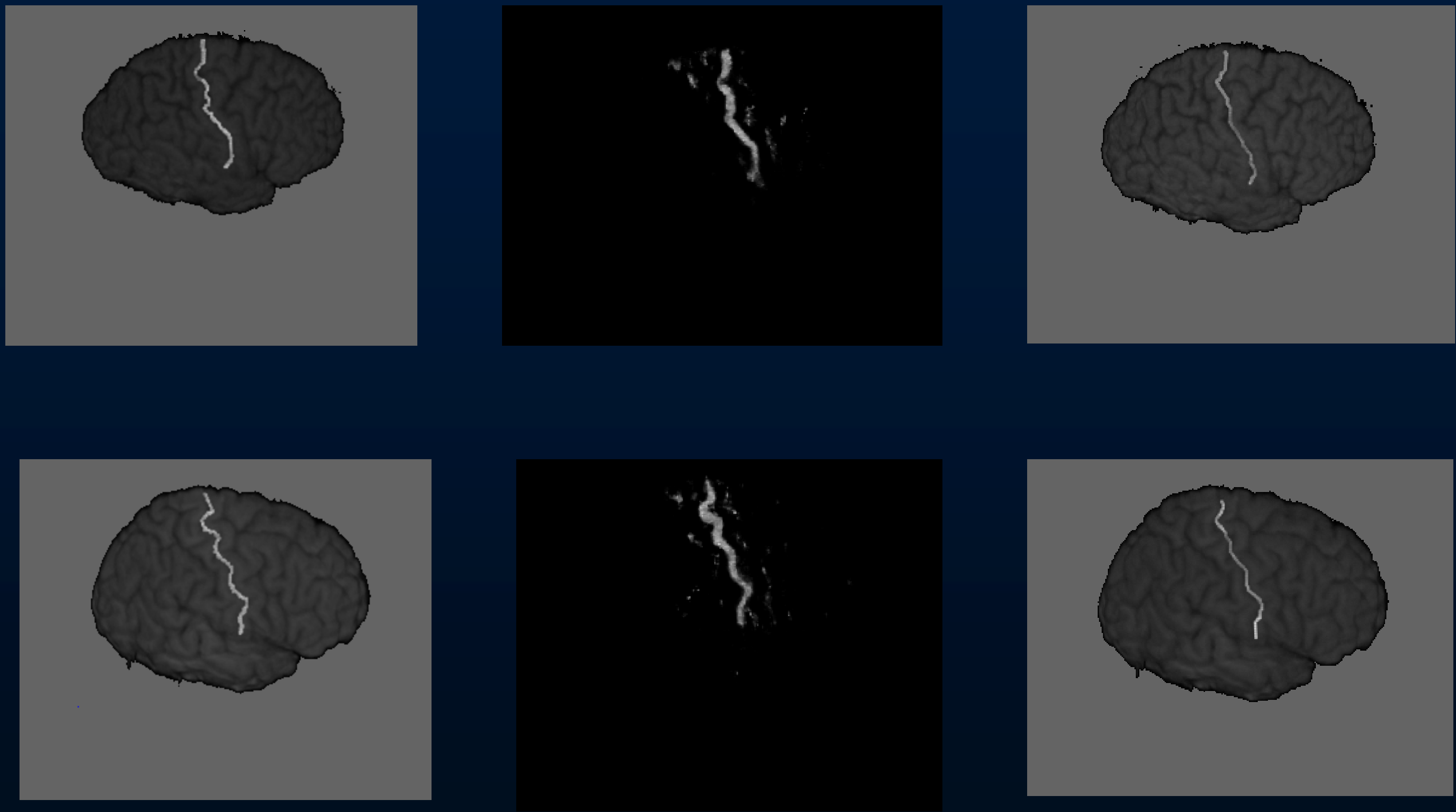
discriminative
model only

hybrid model

FreeSurfer
Fishl. et al.

Sulci-Detection

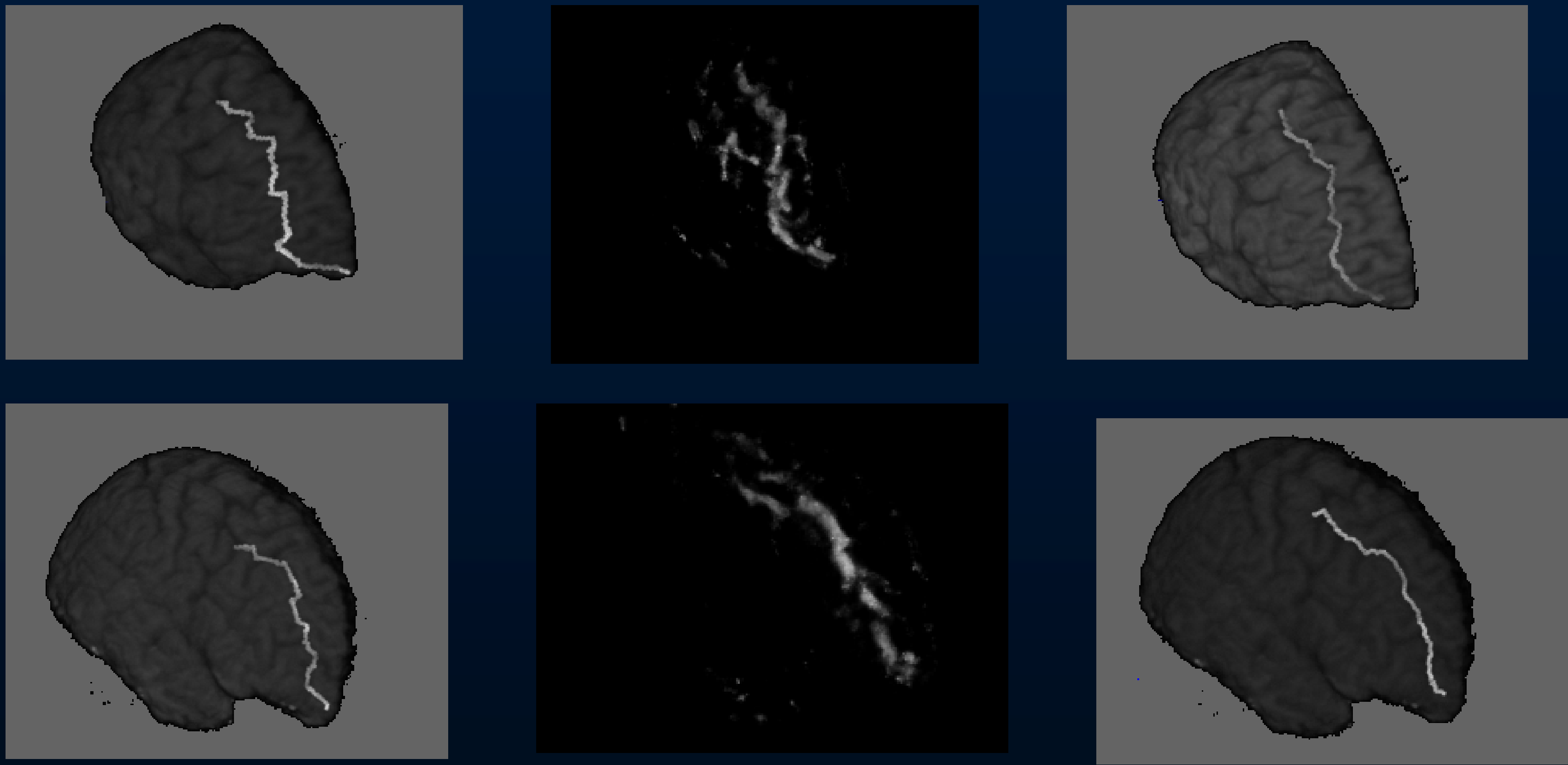
True | Prob | Result



Results on Training set: Central sulcus

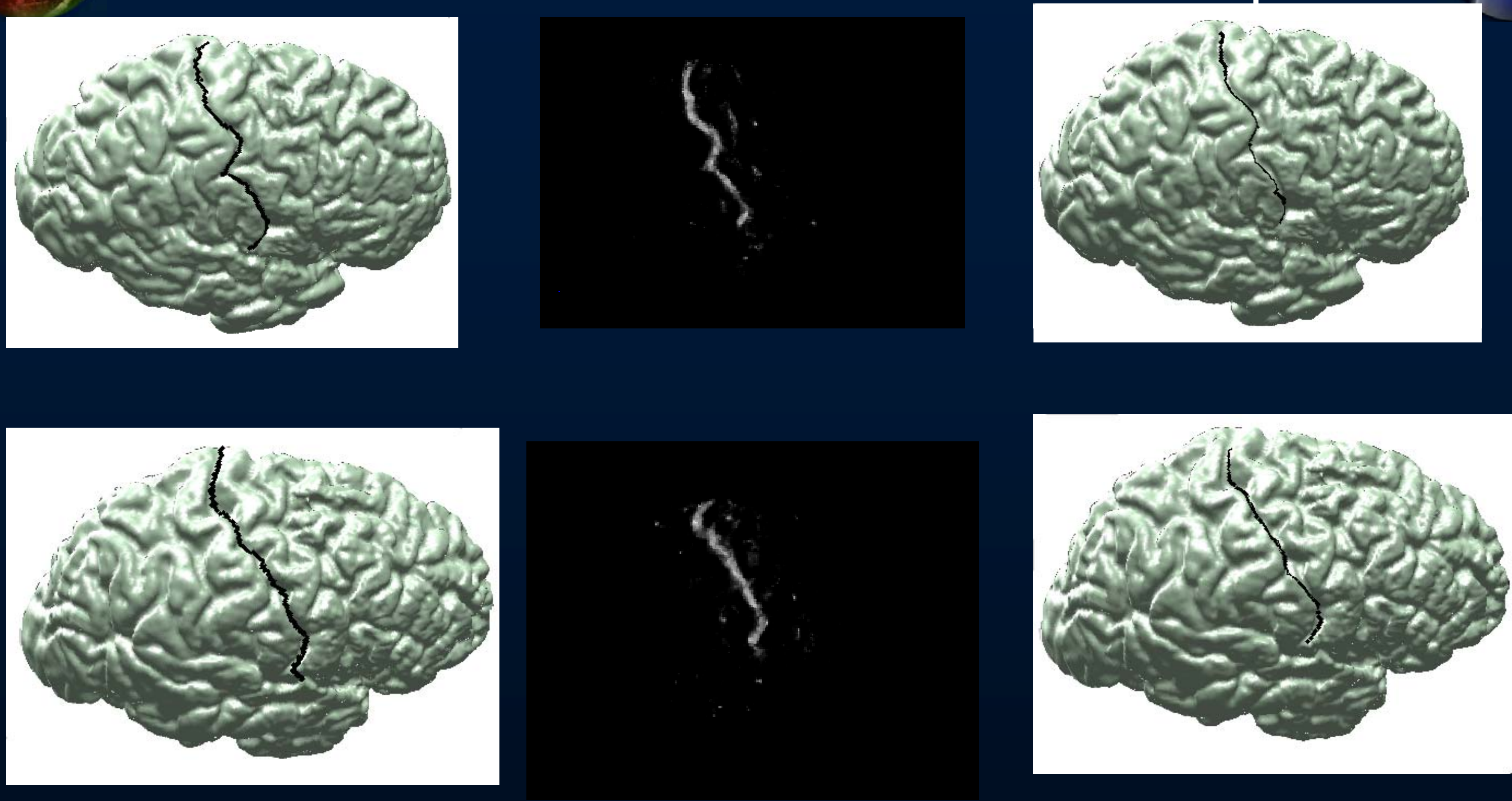
Results

True Prob Result



Results on Testing set: Superior Frontal sulcus

True | Prob | Result



Results on Training set: central sulci on surface

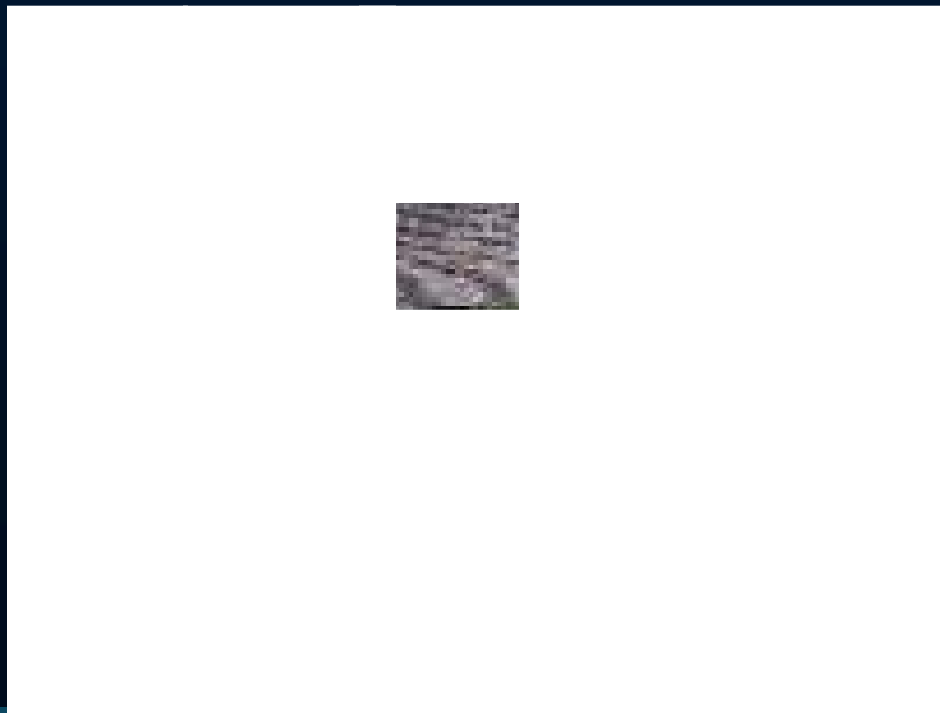
Disadvantages:

- The models only capture the appearance variation in terms of local image “patch” and the joint statistics of different structures are not captured.
- The global shape model is not play the significant role.

Seamless combine context and shape with complex appearance

Context

For object recognition, contexts come in from both **within-object** (parts) and **between-objects** (configurations).



Challenges

$$p(Y|X) \propto p(X|Y)p(Y)$$

Modeling:

It is often very hard to learn p(X|Y) and p(Y) for complex patterns.

Computing:

Computing for the optimal solution that maximizes the posterior is not an easy task. A desired algorithm should bb both efficient and effective.

We are looking for the joint statistics of p(Y|X), “context”.

Problems with MRFs, BP, and CRFs

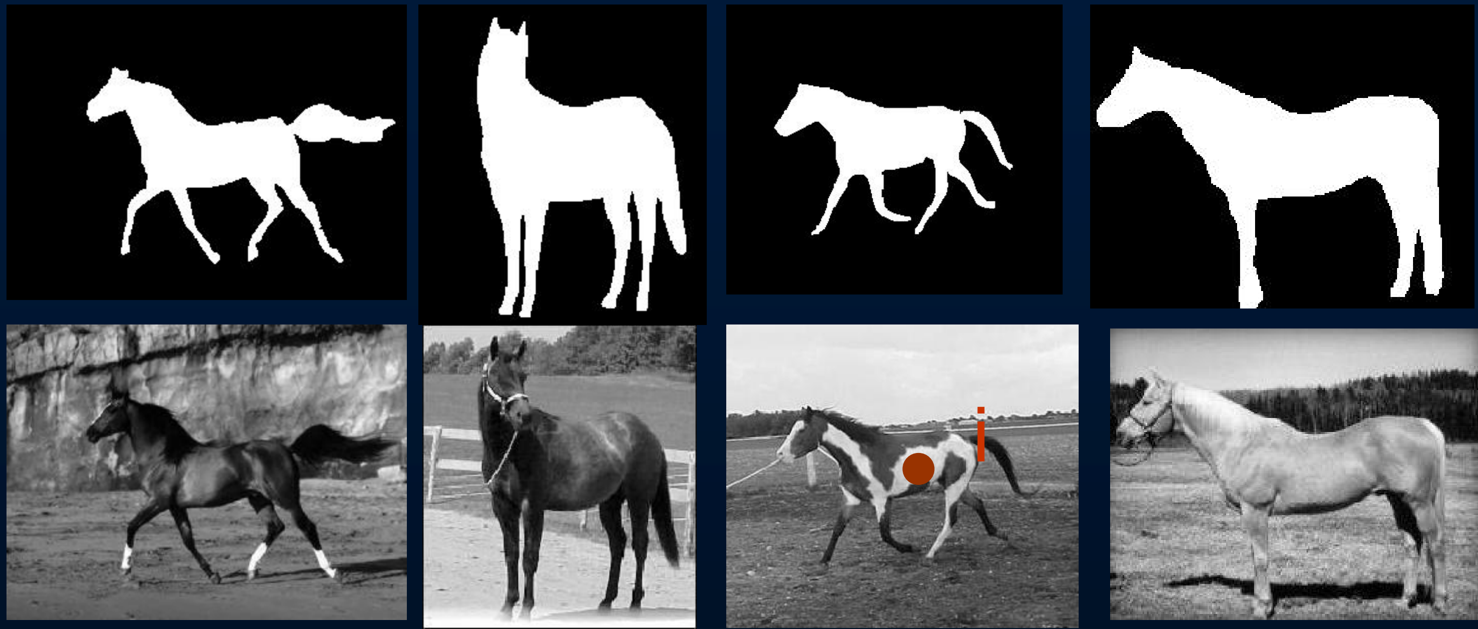
- Use fixed topology on limited number of neighborhood connections (context).
- Usually slow and it takes many steps for the message to propagate.
- Not guaranteed to find the global optimal solution.
- Modeling and computing processes are separate (maybe an advantage in some situations).

Auto-Context

Target $p(Y|X)$ directly

Y_j

X_j

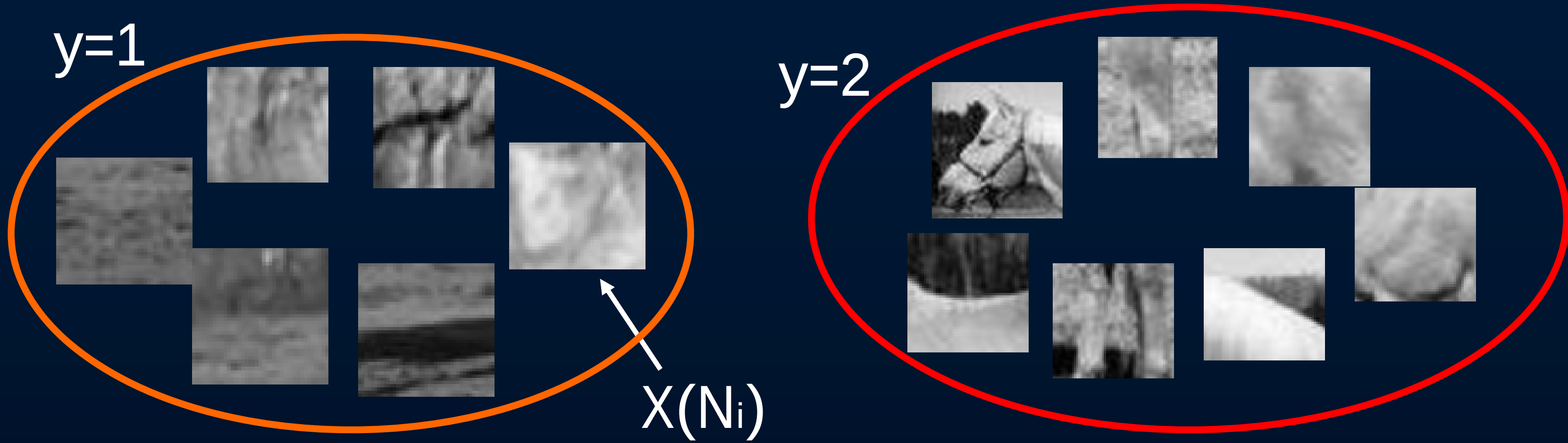


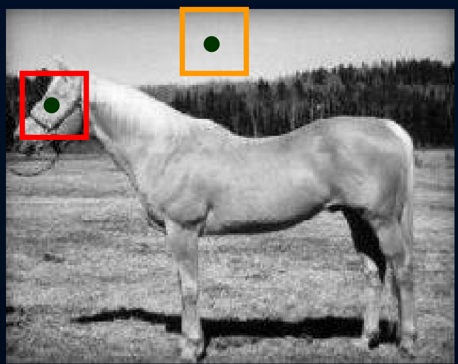
To learn $p(y_i|X)$

$$p(y_i|X) = \int p(y_i, y_{-i}|X) dy_{-i}$$

A Classification Approach

Training Set: $S = \{(y_i, X(N_i)), i = 1..n\}$

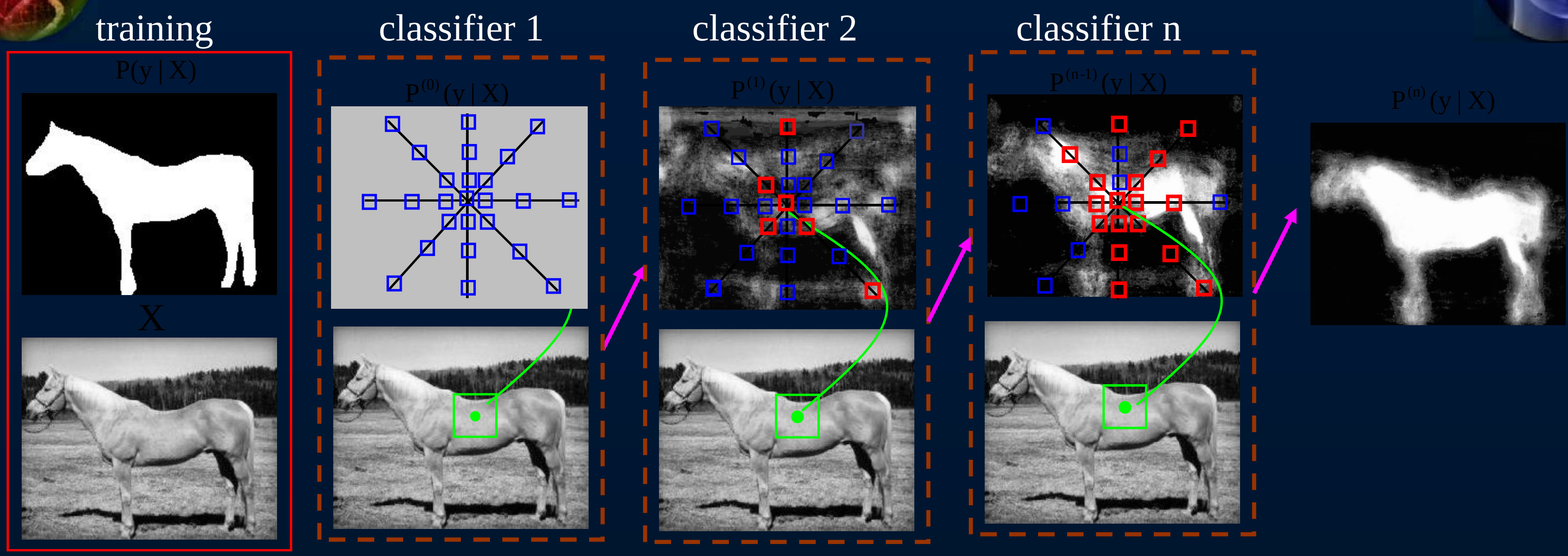




$$p(y = k|X(N)) = \frac{e^{F_k(X(N))}}{\sum_{k=1}^{K} e^{F_k(X(N))}}$$

$$\sum_{k=1}^{K} F_k(X(N)) = 0$$

Auto-Context



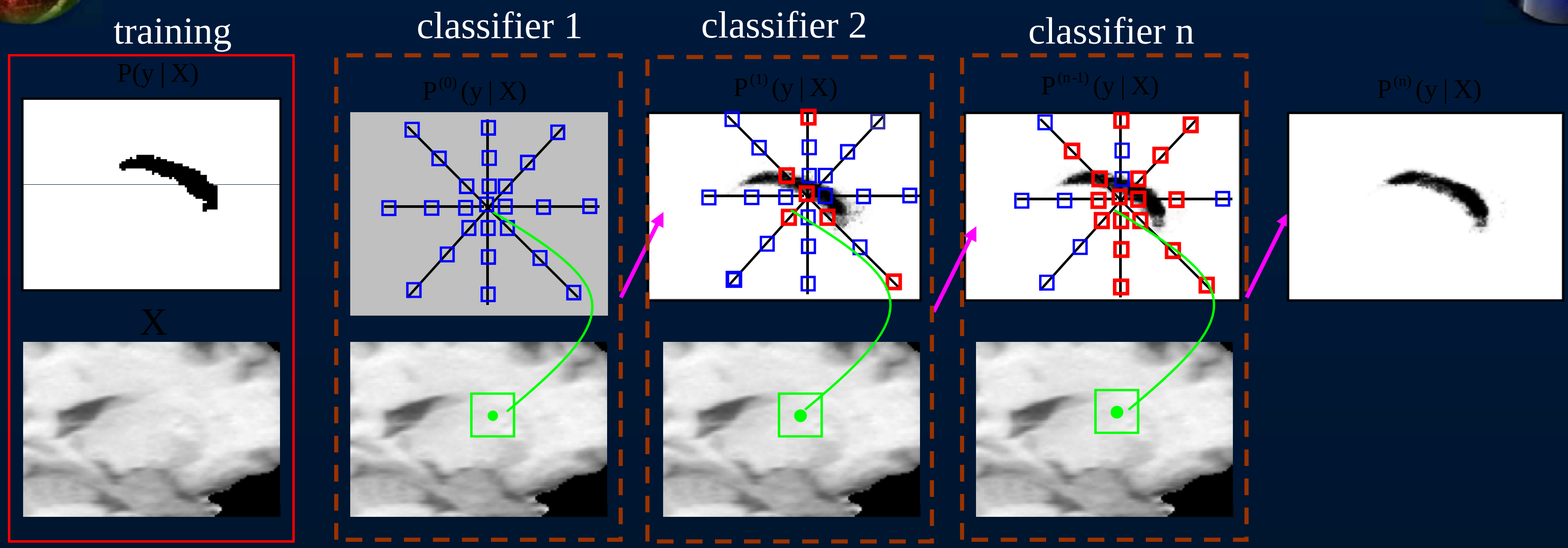
$$p^{(n)}(y_i | X(N_i), \mathbf{P}^{(n-1)}(i)) \rightarrow p(y_i, X) = \int p(y_i, y_{-i}, X) dy_{-i}$$

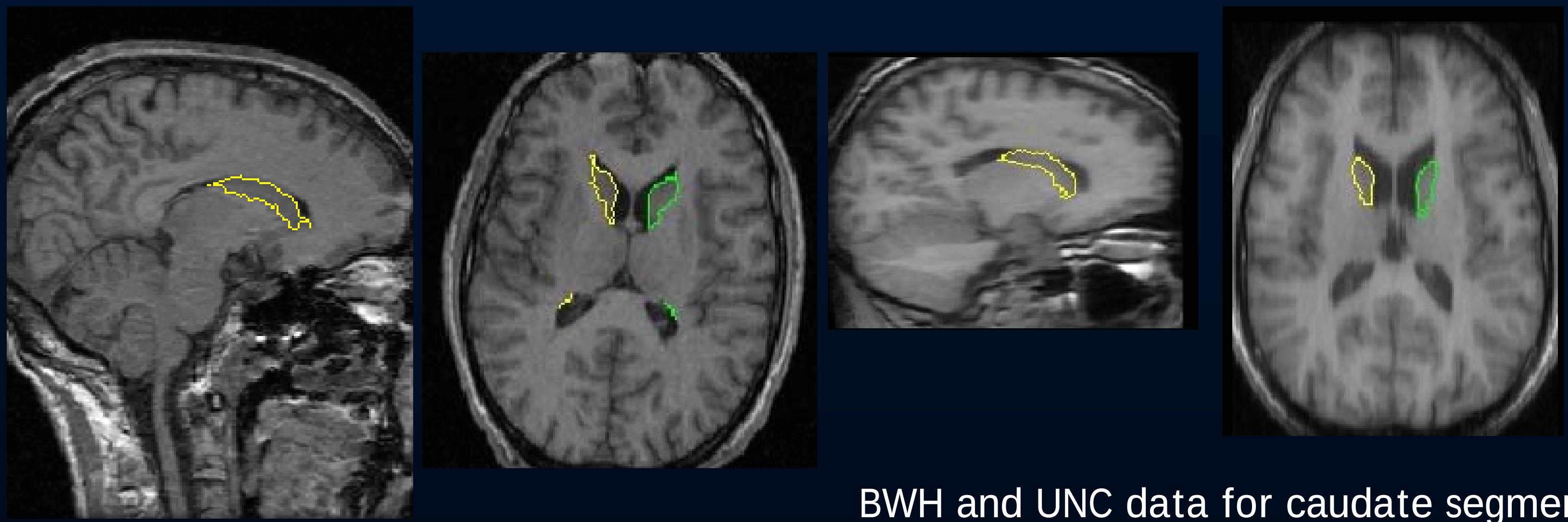
Features:

(1) appearances on X(N), 20,000 Gradients, Gabor, Haar at different scales

(2) context (shape) on P, 10,000 on a fairly large neighborhood

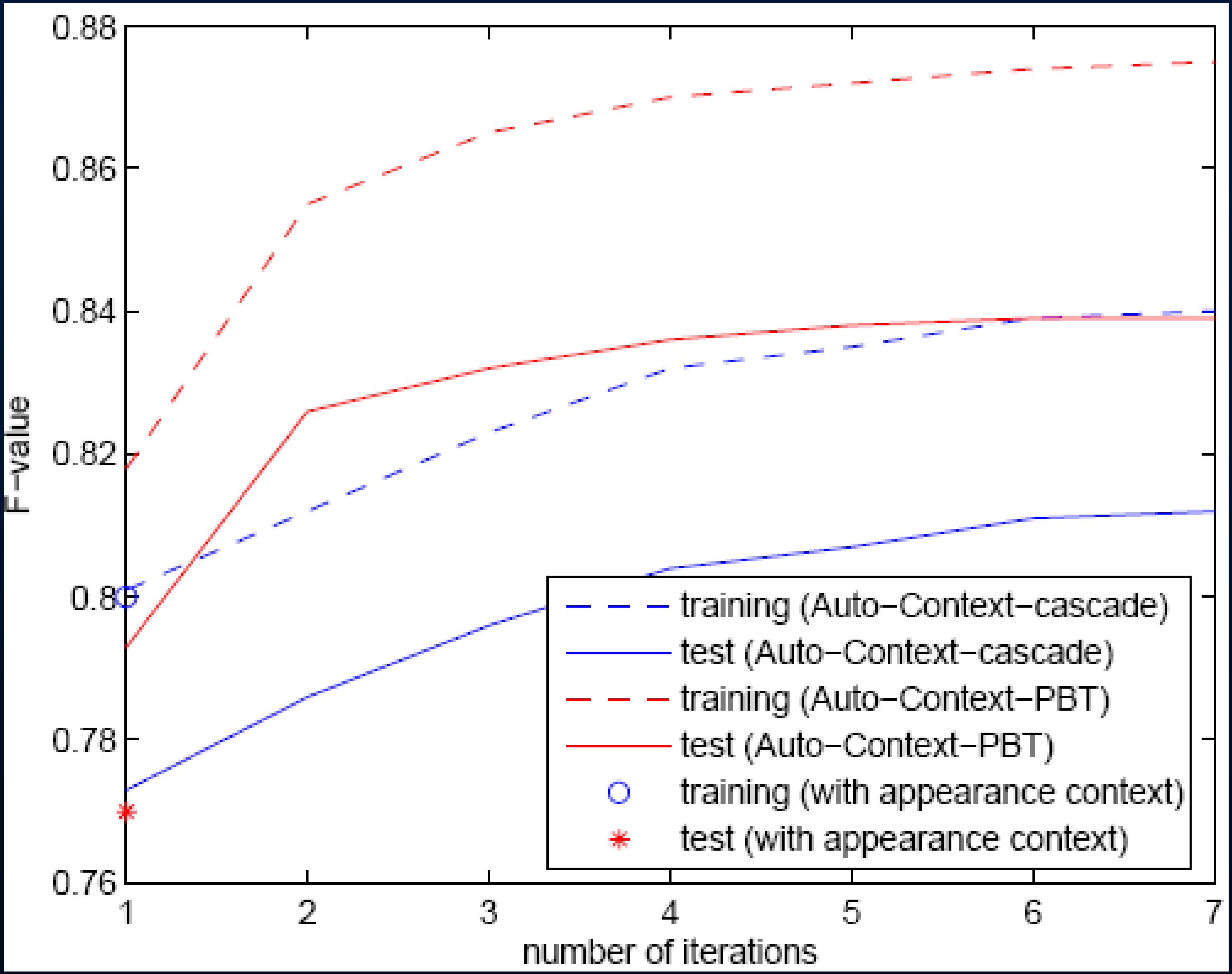
Segmenting Caudate





BWH and UNC data for caudate segmentation

Comparisons with Segmentation Methods



MICCAI

Workshop on 3D Segmentation in the Clinic:

- A Grand Challenge -

MICCAI 2007 BRISBANE AUSTRALIA

For more Information: www.MICCAI.org	Welcome!	Date: 29. October '07 Location: Brisbane, Australia
Home	10th International Conference on Medical Image Computing an	

- News
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Compare your algorithm to others:

Tune it with supplied training data

Evaluate it on specific test images

Get objective results

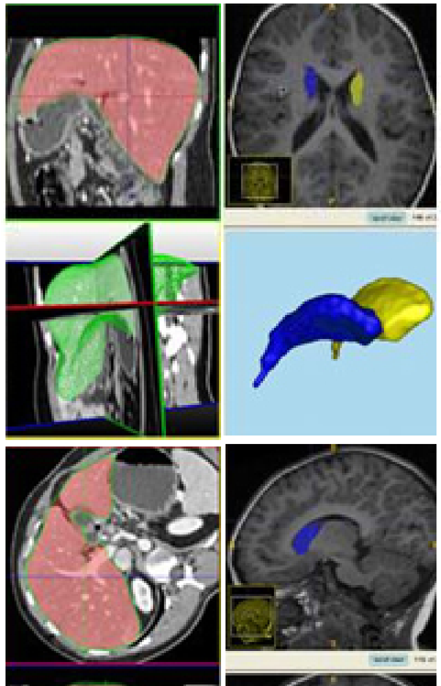
Win prizes, fame and glory

[Read workshop proceedings]()

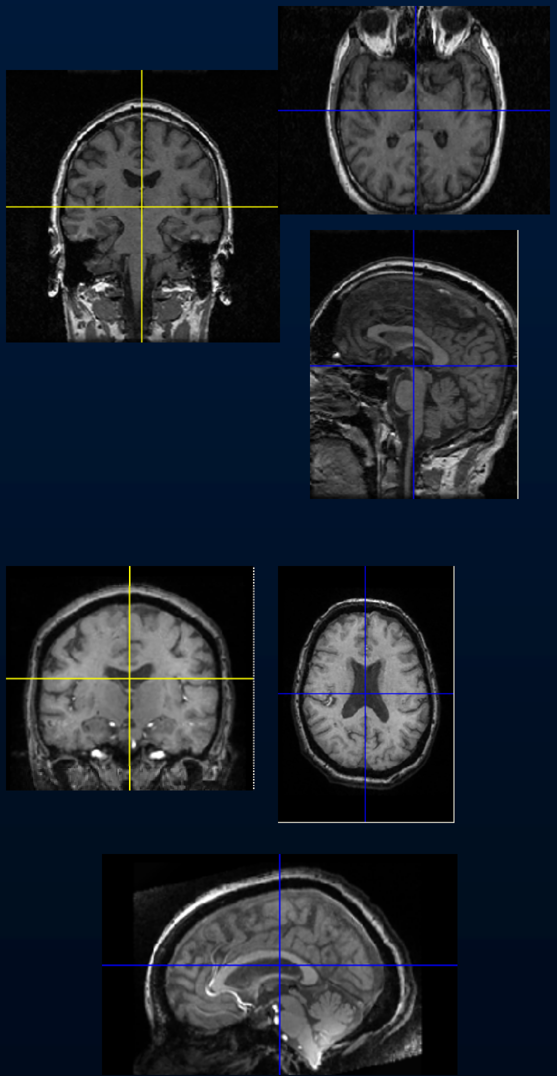
The workshop is over but the Challenge continues:

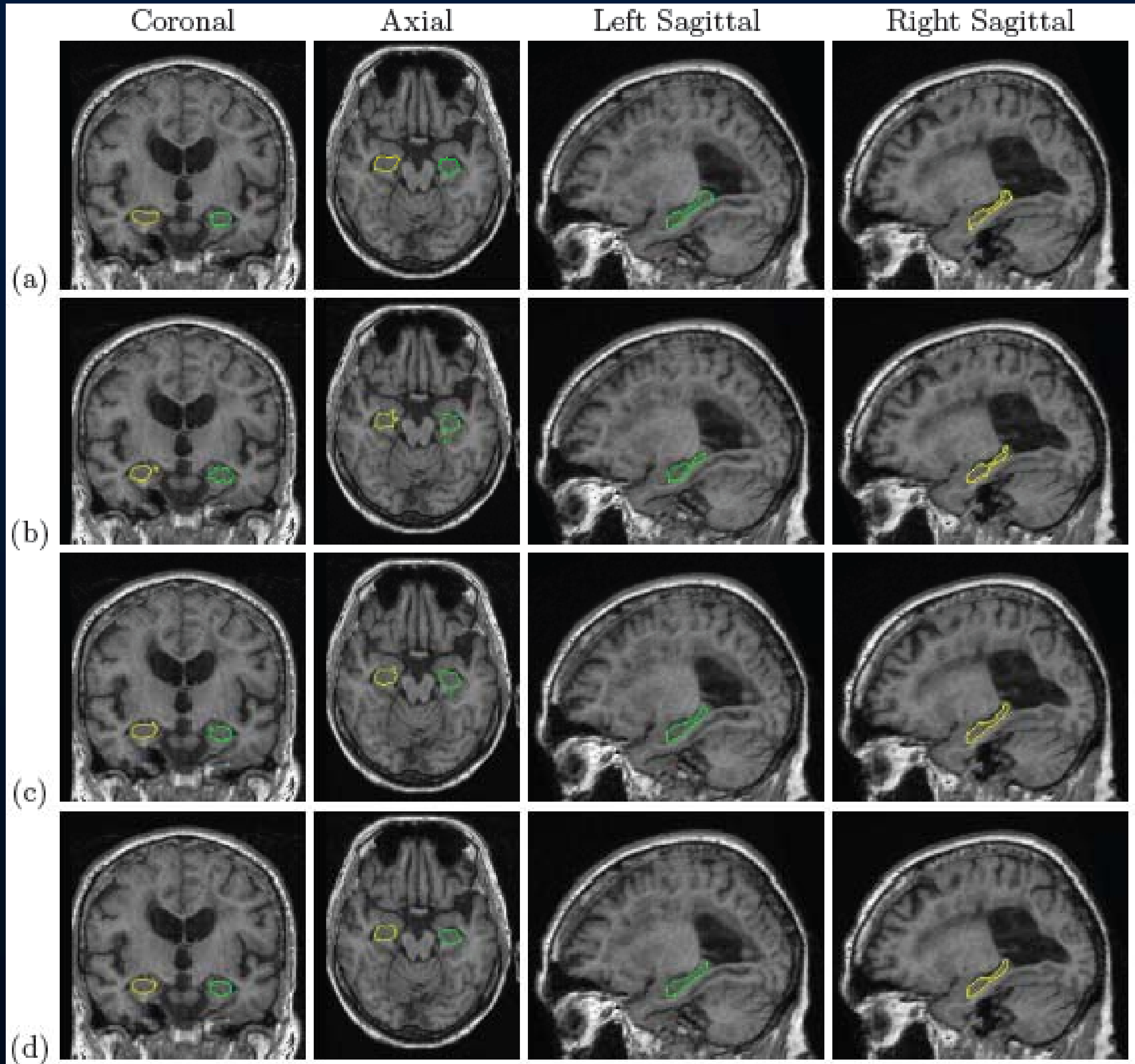
[Online Caudate Segmentation]()

[Online Liver Segmentation]()



Grand Challenge Competition





Grand Challenge Competition

Case	OE	Score	VD	Score	AD	Score	RMSD	Score	MD	Score	Total
UNC Ped	40.35	74.62	-23.21	59.46	0.86	68.25	1.21	78.38	5.64	83.41	72.82
UNC Eld	38.75	75.63	-17.23	69.77	0.75	72.15	1.14	79.64	6.79	80.02	75.44
BWH PNL	41.76	73.73	-26.62	53.78	1.51	49.10	3.50	42.05	25.27	28.41	49.42
Average All	40.84	74.31	-23.93	58.30	1.22	57.89	2.53	57.45	17.33	50.62	59.71

Hybrid Model

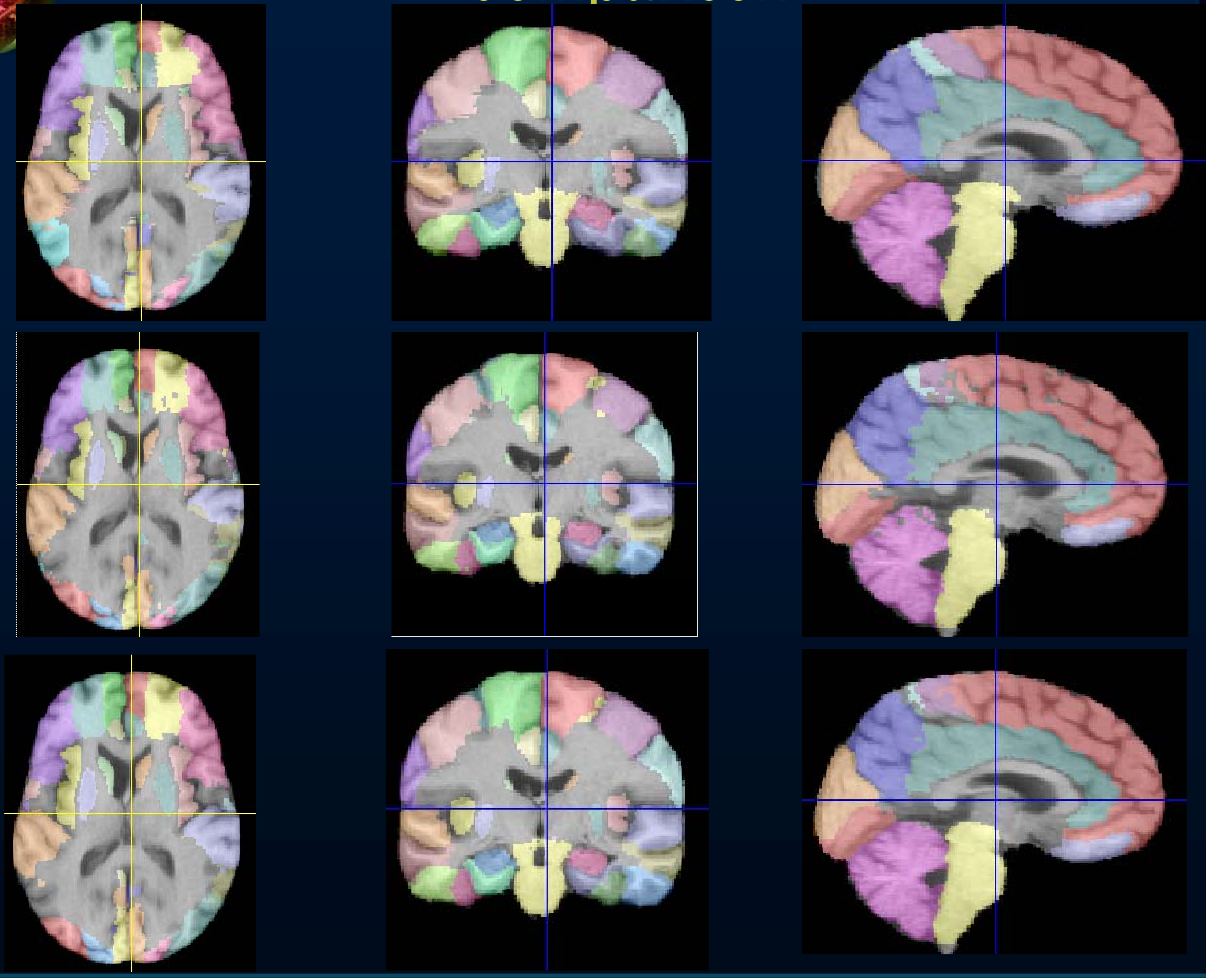
UNC Ped	33.42	78.98	-12.05	76.50	0.68	74.76	1.09	80.47	12.09	64.44	75.03
UNC Eld	36.79	76.86	-0.69	80.04	0.72	73.37	1.31	76.53	17.61	48.21	71.00
BWH PNL	32.07	78.50	-13.62	74.42	1.17	76.55	1.75	76.45	12.83	62.26	73.64
Average All	33.34	78.26	-10.60	76.03	0.97	75.51	1.52	77.31	13.67	59.78	73.38

Auto-Context

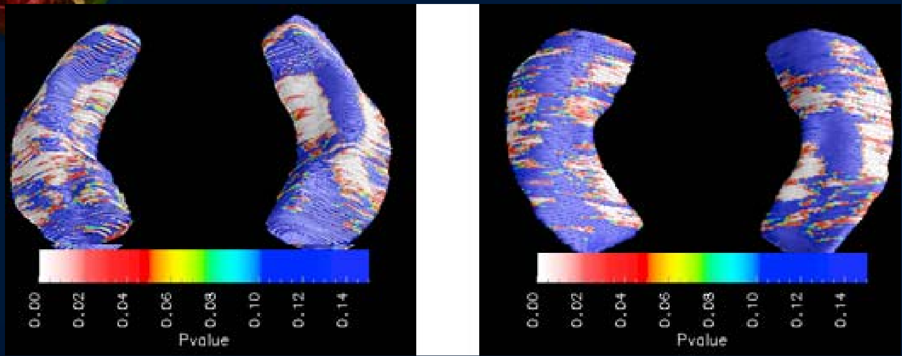
Test/Re-Test	UNC 03 [mm^3]	UNC 04 [mm^3]	UNC 09 [mm^3]	UNC 11 [mm^3]	UNC 17 [mm^3]	UNC 18 [mm^3]	UNC 21 [mm^3]	UNC 22 [mm^3]	UNC 24 [mm^3]	UNC 25 [mm^3]	Mean [mm^3]	Stdev [mm^3]	COV [%]
Left	3008	2896	2965	2862	2849	2917	2844	2836	3078	3041	2930	88	3.0
Right	2908	2980	2948	2806	2825	2971	2845	2889	3125	3059	2936	103	3.5
Total	-										-	-	3.3

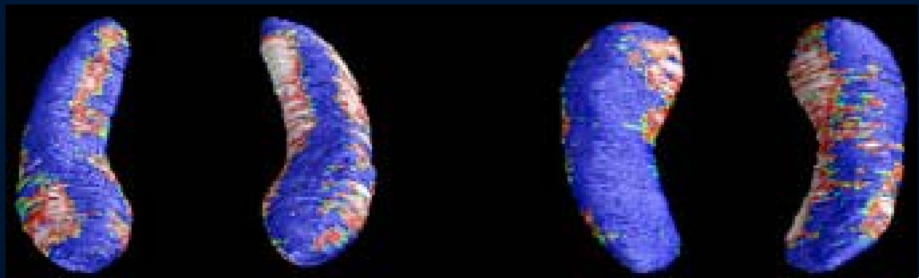
Table 2. The volumetric measurements of the 10 data sets of the same young adult acquired on 5 different scanners within 60 days. The coefficient of variation (COV = standard deviation / average, last column) indicates the stability of the algorithm in a test/re-test situation including scanner variability.

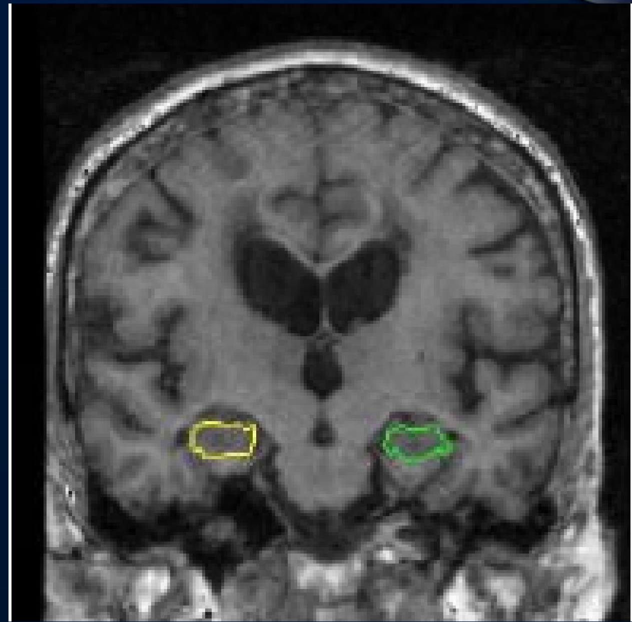
Comparison

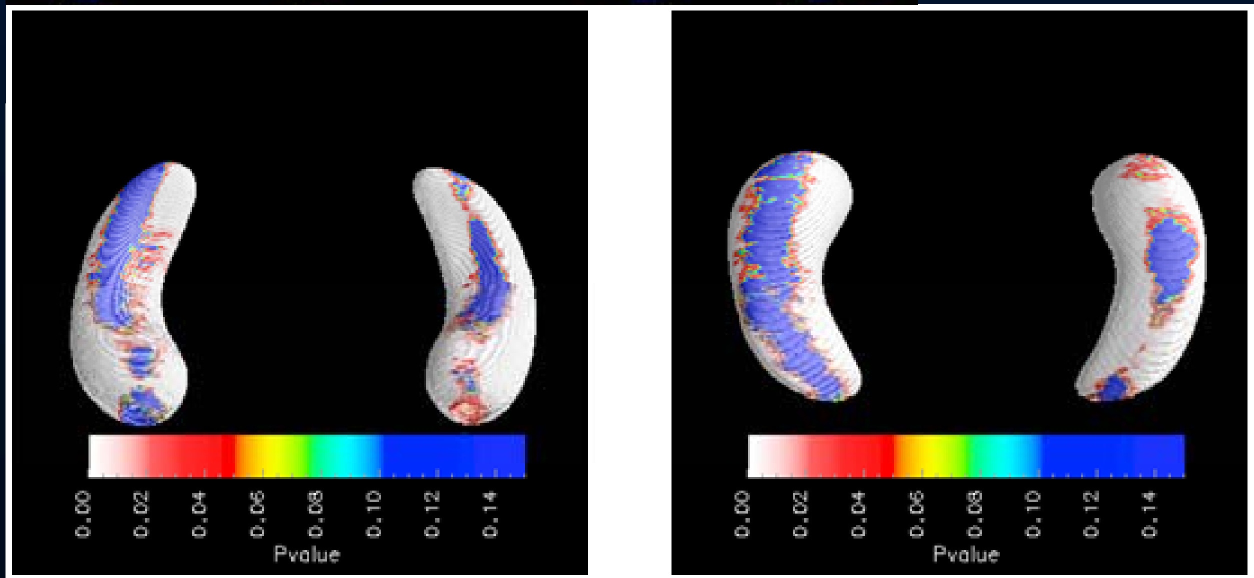


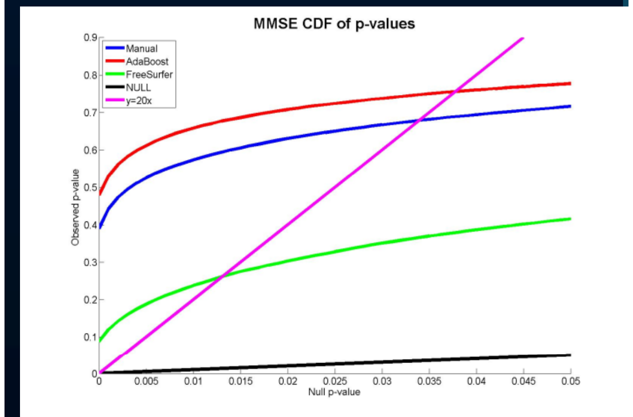
Hippocampus Image Segmentation (Morra l.)







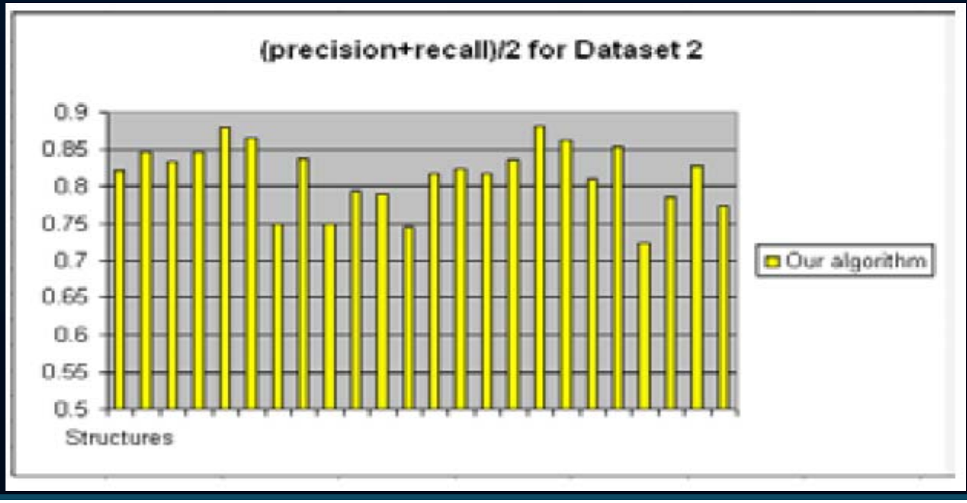




More Results

Manual Delineation

Automatic Segmentation



Convergence of Auto-Context

Theorem: The turbo context algorithm monotonically decreases the training error.

$$\epsilon_t = -\sum_i \log p^{(t)}(y_i | X(i), \mathbf{P}^{(t-1)}(i))$$

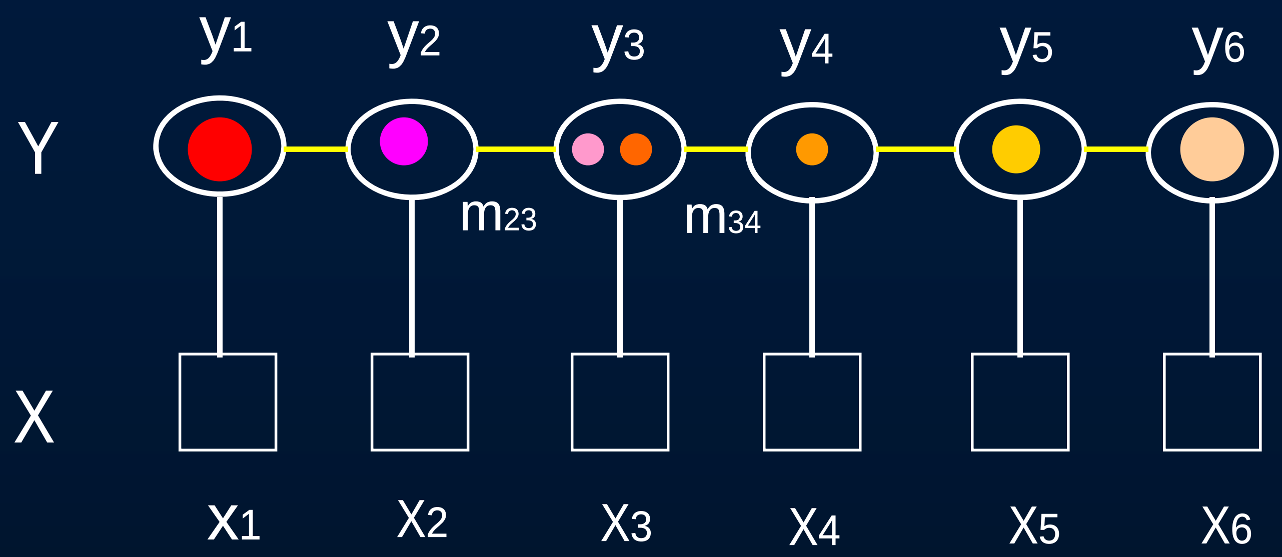
$$p^{(t)}(y_i | X(i), \mathbf{P}^{(t-1)}(i)) = \frac{e^{F_k^{(t)}(X(i), \mathbf{P}^{(t-1)}(i))}}{\sum_{k=1}^{K} e^{F_k^{(t)}(X(i), \mathbf{P}^{(t-1)}(i))}}$$

$$\epsilon_{t-1} = -\sum_i \log \mathbf{P}^{(t-1)}(i)(y_i)$$

And:

$$p^{(t)}(y_i | X(i), \mathbf{P}^{(t-1)}(i)) = \mathbf{P}^{(t-1)}(i)(y_i)$$

Belief Propagation on (MRFs, CRFs)

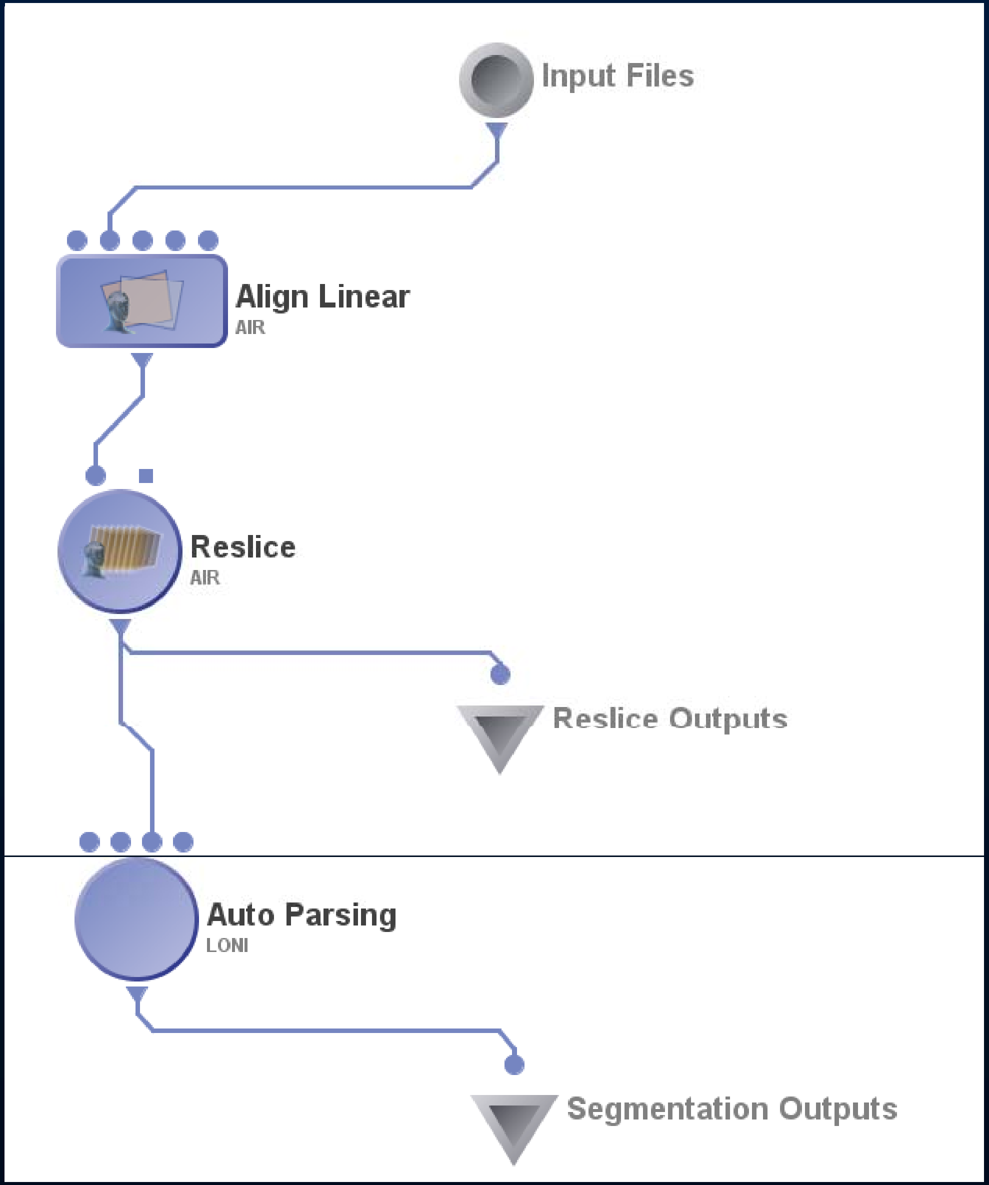


$$p(Y|X) = \frac{1}{Z} \prod_i \phi_i(x_i|y_i) \prod_{(i,j)} \psi(y_i, y_j)$$

$$p_i(y_i) = \frac{1}{Z}\phi_i(y_i) \prod_{j \in N(i)} m_{ji}(y_i)$$

$$m_{ij}(y_j) \leftarrow \sum_{y_i} \phi_i(y_i)\psi_{i,j}(y_i, y_j) \prod_{k \in N(i)\backslash j} m_{ki}(y_i)$$

Brain Parser Pipeline



Conclusions for Auto-Context

Advantages:

- Learns low-level and context model in an integrated framework.
- Very easy to implement.
- Significantly faster than MCMC and BP (30~50 seconds) on MRFs or CRFs.
- General and avoid heavy algorithm design.
- Learning and computing use the same procedures.
- Can be applied in other domains.

Conclusions for Auto-Context

Disadvantages:

- Require training for different problems.
- Explicit high-level information is not included.
- Training time might be long. (half day to a week)
- Require all labeled data (fully supervised).

Thank you!

Questions?