Multilevel Segmentation and Integrated Bayesian Model Classification with an Application to Brain Tumor Segmentation

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Main Contribution: A mathematical formulation for incorporating generative models into the calculation of affinities in graph-based segmentation. We extended the Segmentation by Weighted Aggregation algorithm using the proposed model-aware affinities. The implementation is applied to brain tumor segmentation; it is very accurate and extremely efficient (2 minutes for a 256x256x25 volume).

I Segmentation Background

Graph-based Segmentation

Define the problem on a graph: $\mathcal{G} = \{\mathcal{V}, \mathcal{E}\}$

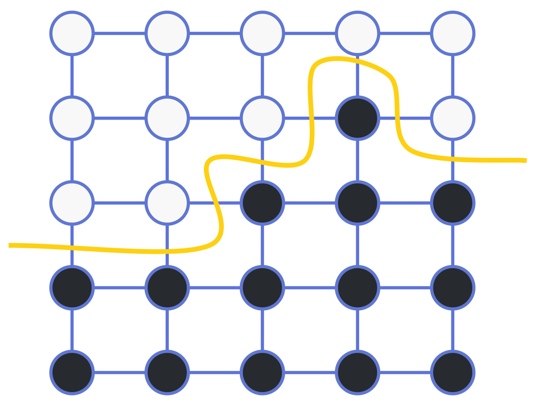
Augment with node statistics s_v and class c_v.

Affinities measured on each edge: $u, v \in \mathcal{V}$

$$w_{uv} = \exp\left(-D(s_u, s_v; \theta)\right)$$

Goal: find cuts that minimize criterion:

$$\Gamma(R) = \frac{\sum_{u \in R, v \notin R} w_{uv}}{\sum_{u,v \in R} w_{uv}}$$



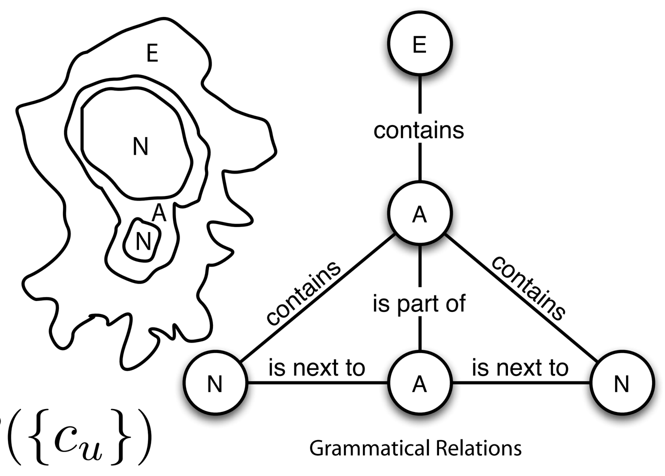
Generative Model-based Segmentation

Define likelihood and prior:

$$P\left(\{s_u | c_u\}\right) P\left(\{c_u\}\right)$$

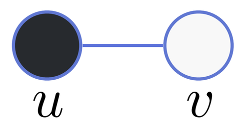
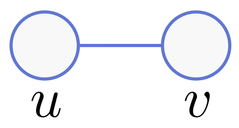
Goal: maximize posterior:

$$\{c_u\}^* = \arg\max\ P(\{c_u\} | \{s_u\})$$
$$\arg\max\ P\left(\{s_u | c_u\}\right) P\left(\{c_u\}\right)$$

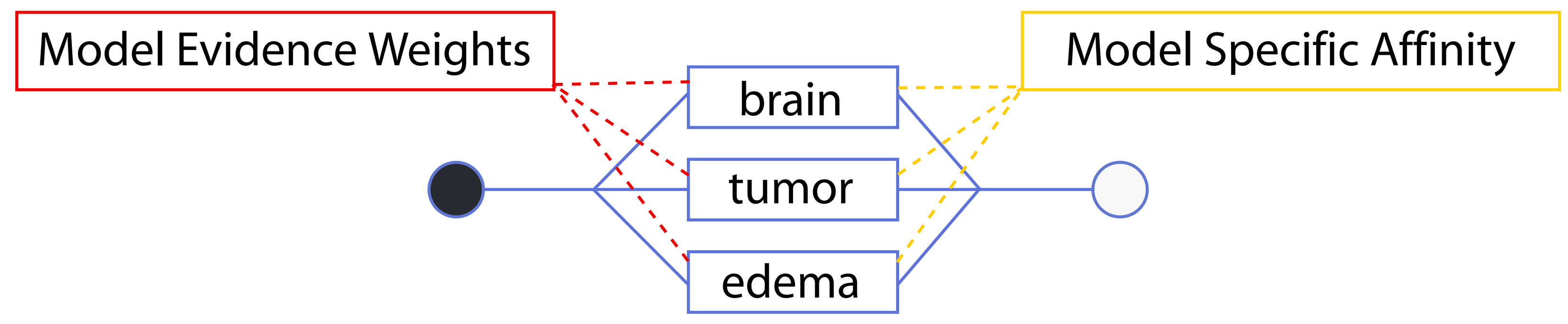


II Bayesian Model-Aware Affinity

Define binary random variable to capture probabilistic region membership:

$X_{uv} = 0$  or $X_{uv} = 1$ 

Incorporate models as hidden variables and marginalize over them:



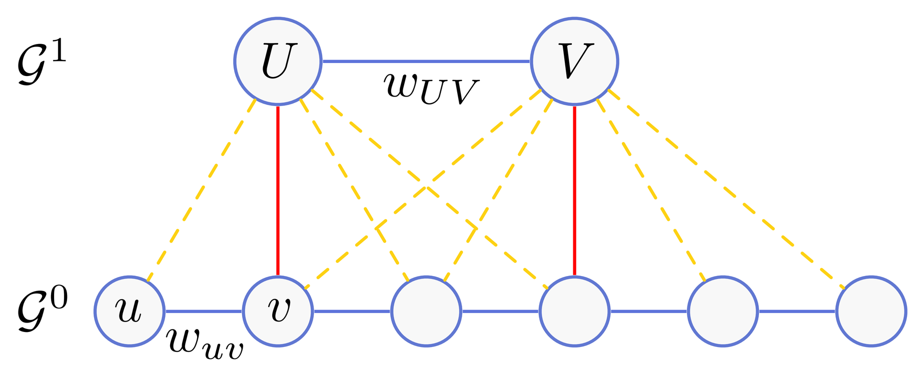
$$P(X_{uv}|s_u, s_v) = \sum_{c_u}\sum_{c_v} P(X_{uv}|s_u, s_v, c_u, c_v) P(c_u, c_v | s_u, s_v) \ ,$$
$$\propto \sum_{c_u}\sum_{c_v} P(X_{uv}|s_u, s_v, c_u, c_v) P(s_u, s_v | c_u, c_v) P(c_u, c_v) \ ,$$
$$= \sum_{c_u}\sum_{c_v} P(X_{uv}|s_u, s_v, c_u, c_v) P(s_u|c_u) P(s_v|c_v) P(c_u, c_v)$$

Model specific affinity is a function of the class variables.

For example: class dependent weighted distance: $$P(X_{uv}|s_u, s_v, c_u, c_v) = \exp\left(-\sum_{m=1}^{M} \theta^m_{c_u c_v} |s^m_u - s^m_v|\right)$$

III Segmentation by Weighted Aggregation

Efficient multiscale process based on algebraic multigrid. Approximates the normalized cut criterion Γ.

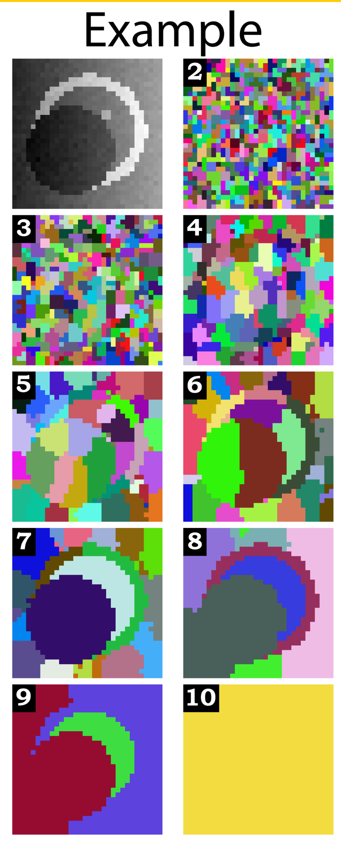


Model-aware affinities modulate multiscale process:

Original SWA $\quad w_{UV} = \hat{w}_{UV} \exp\left(-D(s_U, s_V; \theta)\right)$

SWA with Models $\quad w_{UV} = \hat{w}_{UV} P(X_{UV}|s_U, s_V)$

Example



Gives Output in Multiple Scales

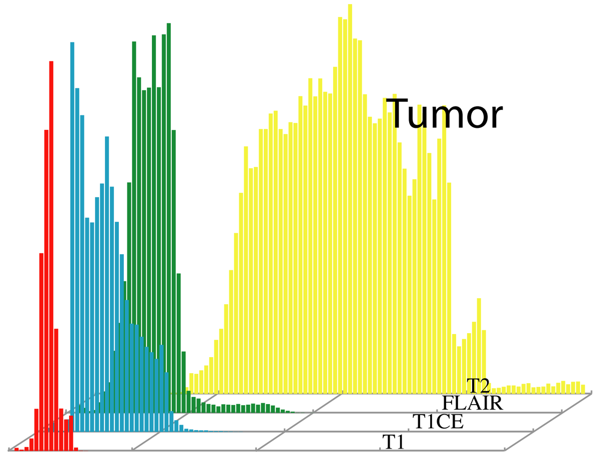
IV Generative Models and Class Likelihood

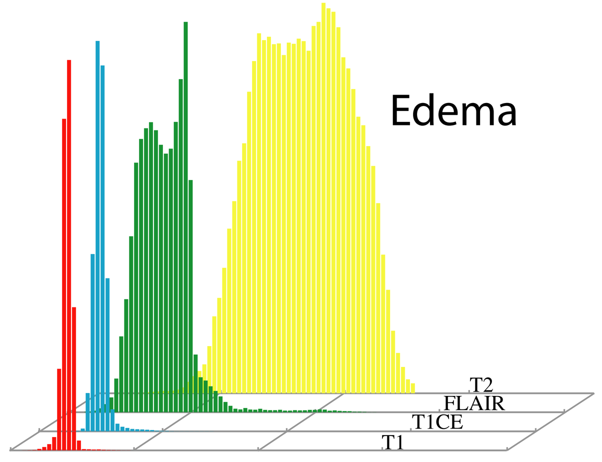
Class label is associated with each node, a by-product of model-aware affinity.

$$c^*_U = \arg\max_{c \in \mathcal{C}} P(s_U|c)$$

Standard SWA gives a segmentation hierarchy but it does not say which elements to select; our integrated model classification provides a selection.

Currently use i.i.d. models: mixture of Gaussians over 4D multichannel image.





V Application to Brain Tumor

Important to quantify tumor size.

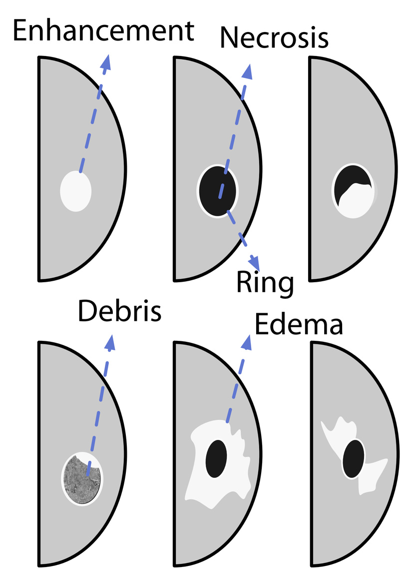
State of the art is manual.

20 Studies: *Glioblastoma Multiforme.*

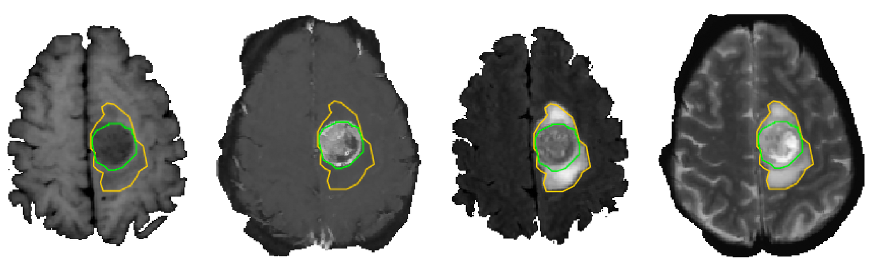
Highly varying in appearance, size, shape and location.

Use of multiple MR channels needed.

All processing in 3D.

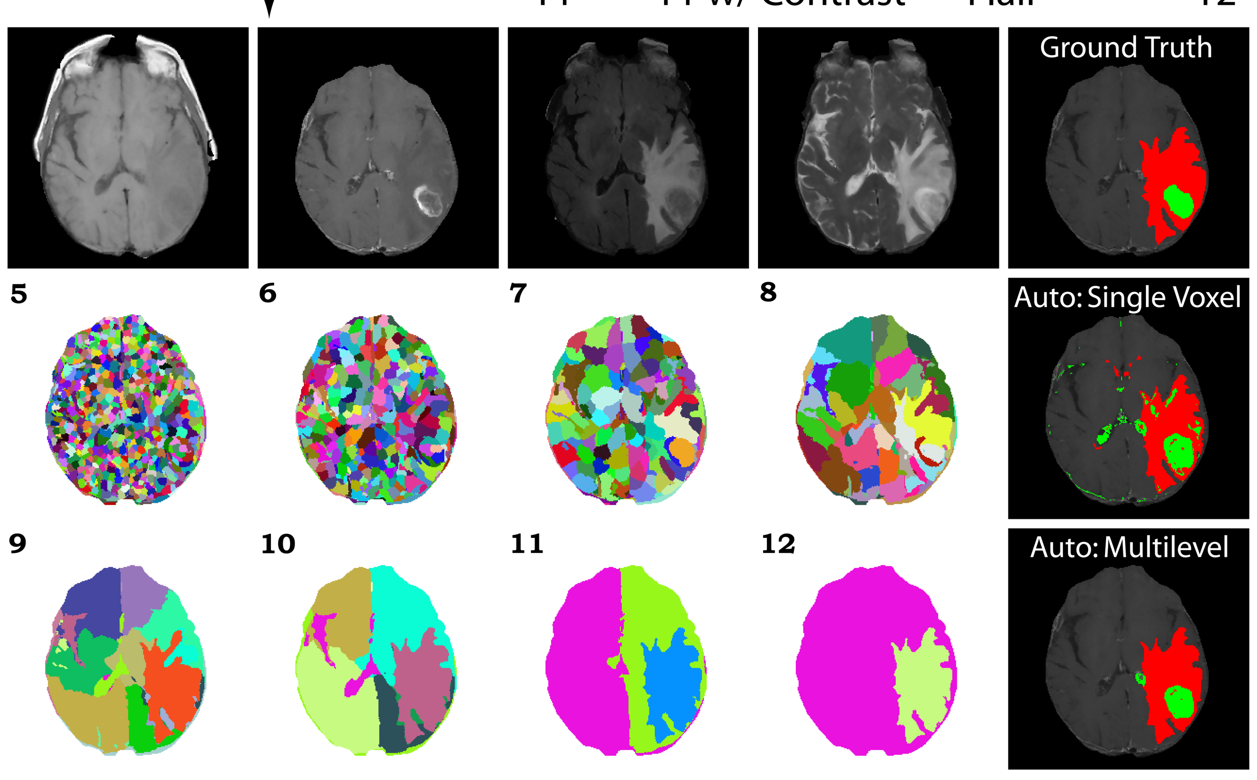


Typical Example:



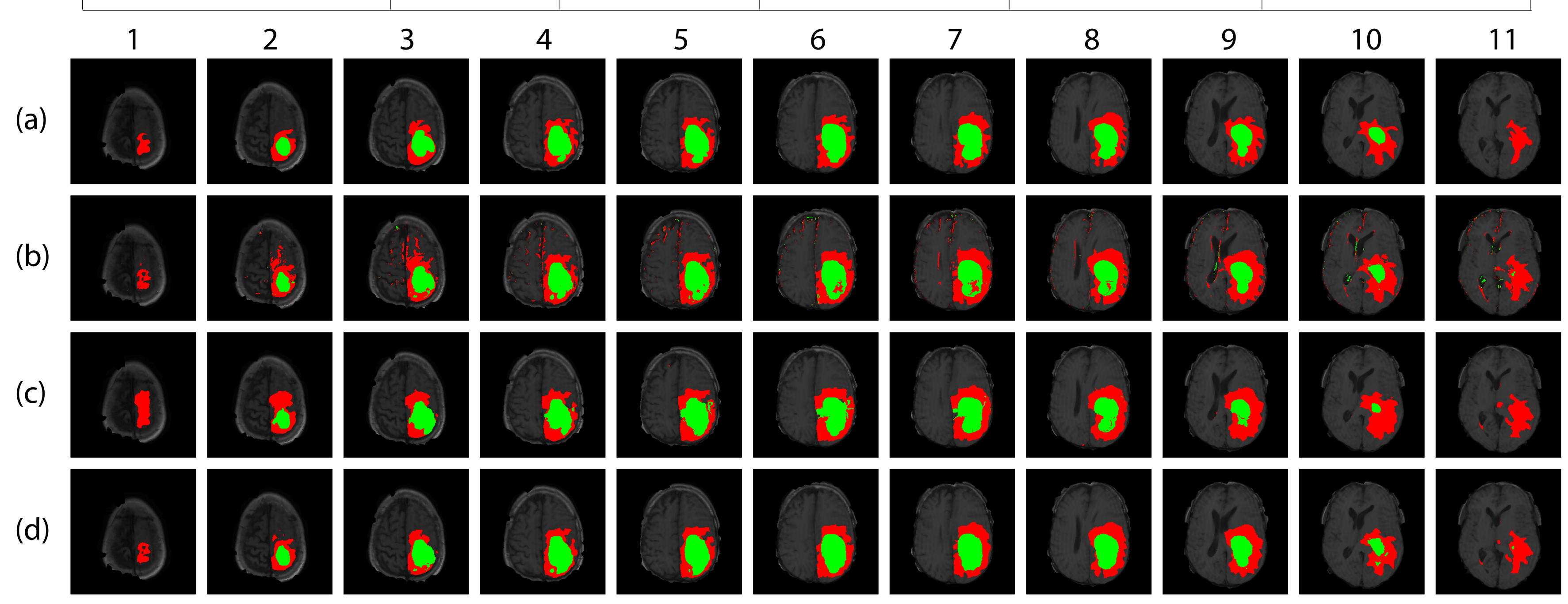
T1 T1 w/ Contrast Flair T2

Hierarchy Example:



Channel weights on the model specific affinity; set from domain knowledge.

	ND, ND	ND, Brain	Brain, Tumor	Brain, Edema	Tumor, Edema
T1	1/3	0	0	0	0
T1 with Contrast	1/3	1/2	1	0	1/2
FLAIR	1/3	1/2	0	1	1/2

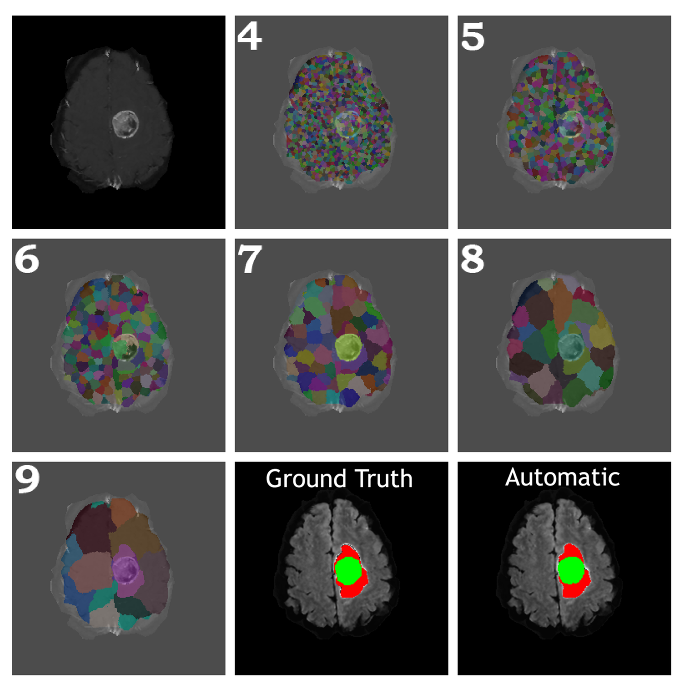


Results on Training Set

Algorithm	Tumor Jac	Tumor Prec	Tumor Rec	Edema Jac	Edema Prec	Edema Rec
Single Voxel Classifier	42%	48%	85%	43%	49%	78%
Saliency-Based Extractor	44%	51%	64%	47%	55%	76%
Model-Based Extractor	62%	75%	81%	54%	66%	72%

Results on Testing Set

Algorithm	Tumor Jac	Tumor Prec	Tumor Rec	Edema Jac	Edema Prec	Edema Rec
Single Voxel Classifier	49%	55%	81%	56%	66%	76%
Saliency-Based Extractor	48%	61%	63%	56%	66%	71%
Model-Based Extractor	66%	80%	79%	61%	78%	71%



Extremely efficient processing; of a 256 x 256 x 25 volume full segmentation and classifcation in about 2 minutes.