Hierarchical Markov Random Fields for Mast Cell Segmentation in Electron Microscopic Recordings

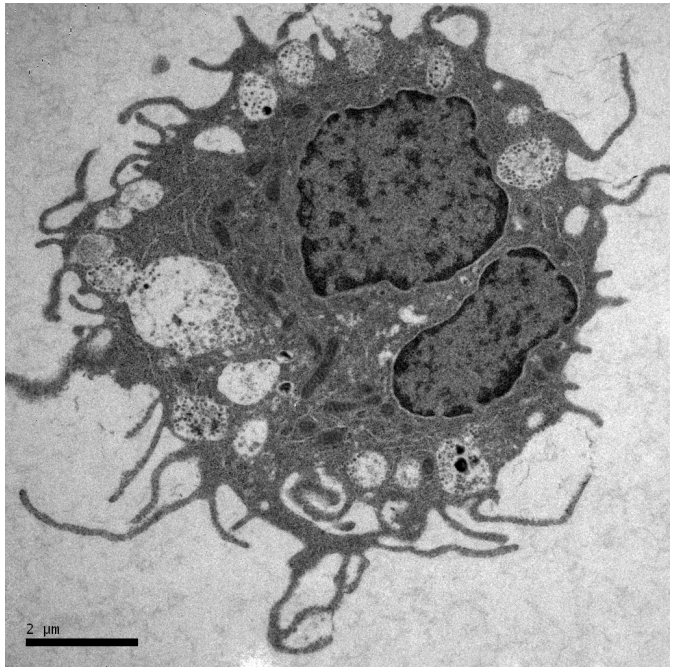
Margret Keuper

Thorsten Schmidt, Marta Rodriguez-Franco, Wolfgang Schamel, Thomas Brox, Hans Burkhardt, Olaf Ronneberger

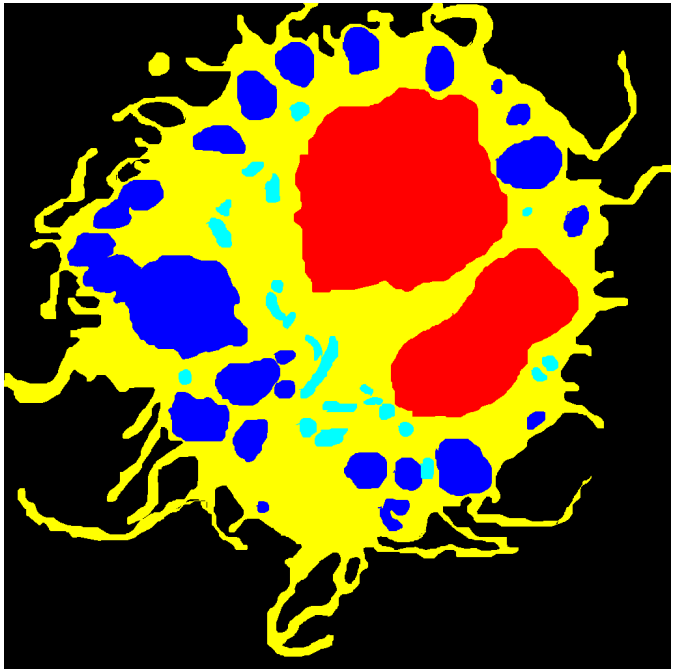
Albert-Ludwigs-Universität Freiburg, Germany

Biological Motivation

Mast Cell Segmentation:
- Quantitatively analyze cell populations (e.g. receptor density)
- Distinguish 5 classes
- Ground truth labeling



EM Recording



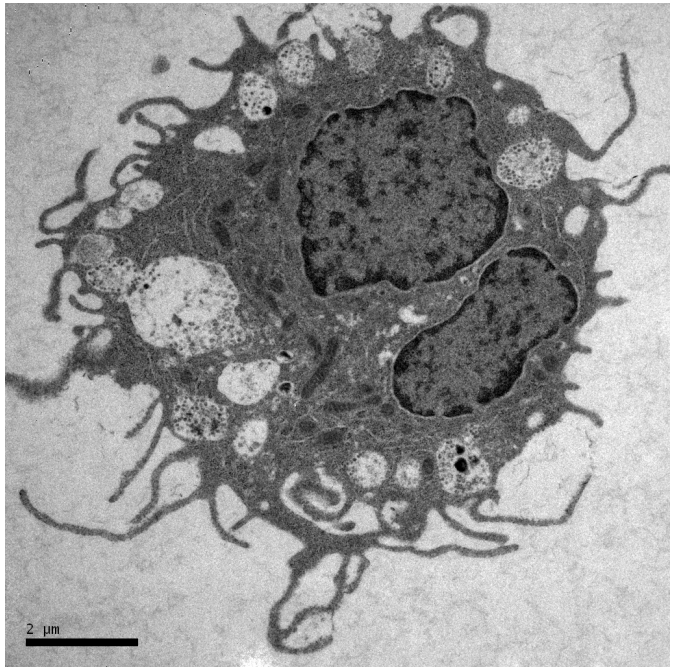
Ground truth

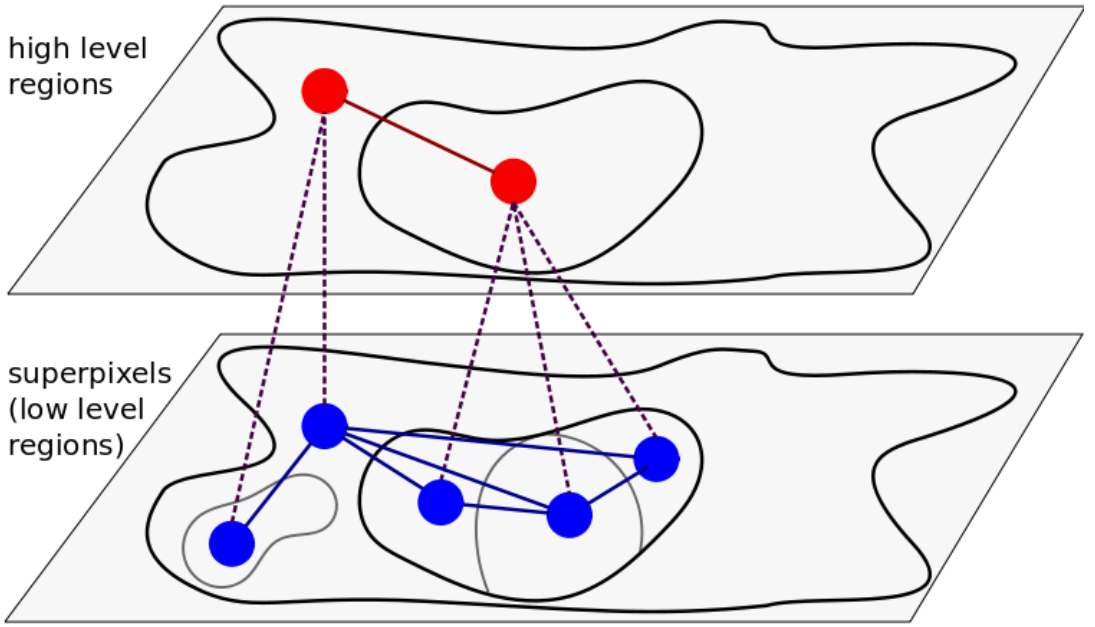
1 background
2 cytoplasm
3 nucleus
4 mitochondria
5 vesicles

Motivation: Semantic Segmentation

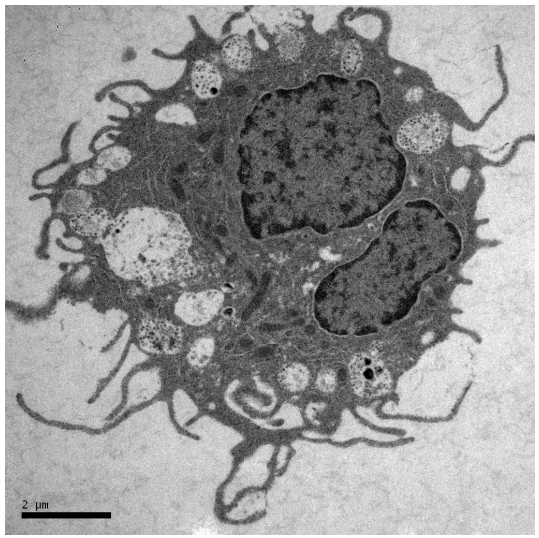
1. Detection AND Segmentation of Regions
2. Semantic Information Needed (SVM + MRF)
3. Cues at different scales

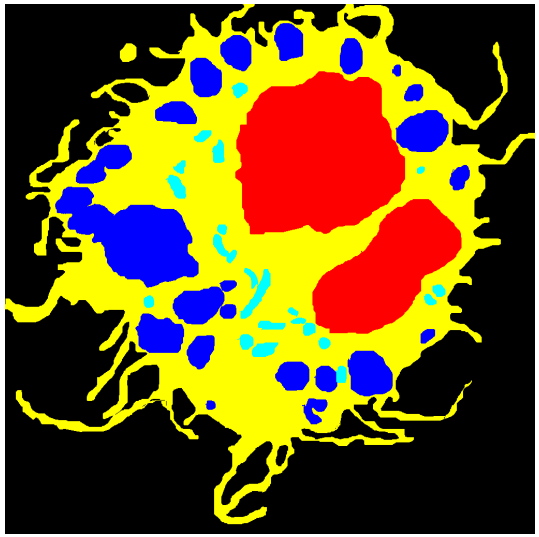
Hierarchy in Semantic Segmentation



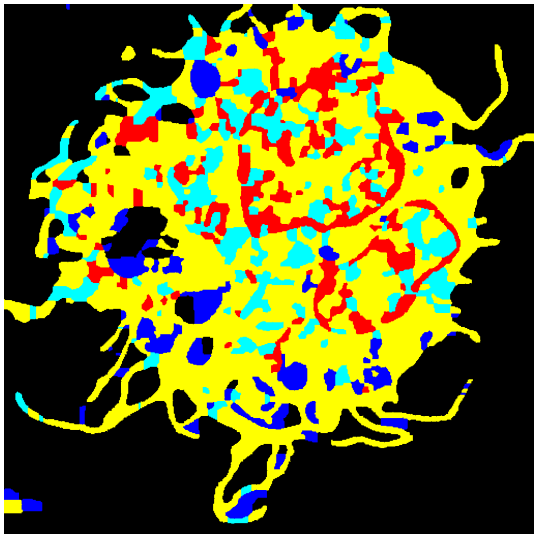


Related Work

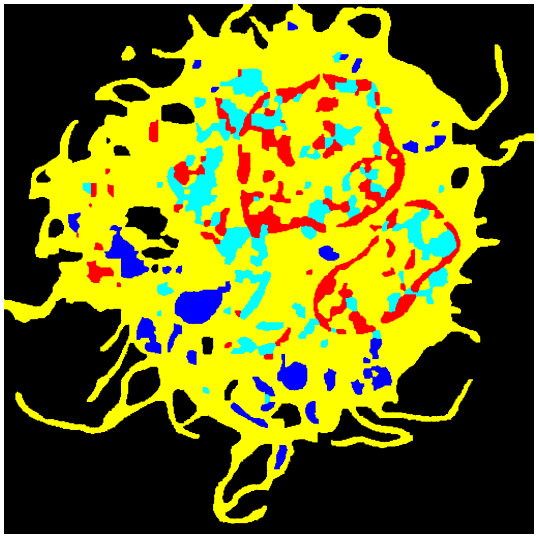




SVM: One vs. One multiclass probabilities

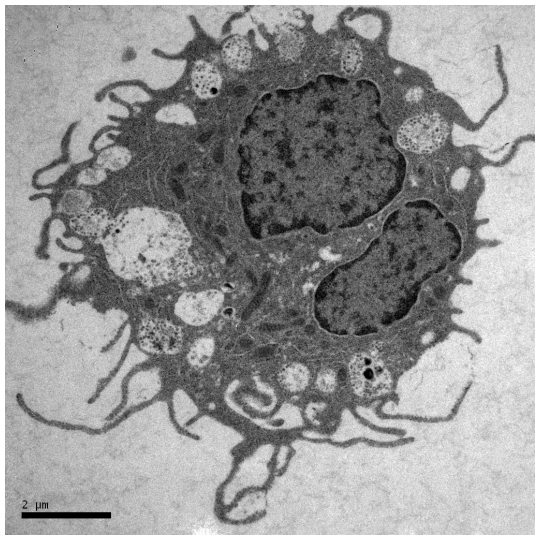


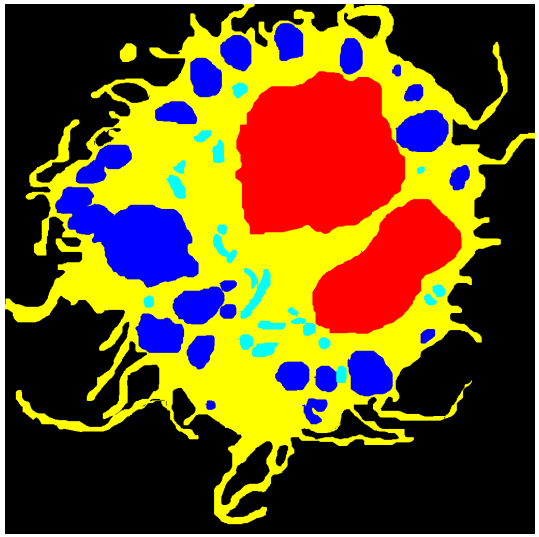
MRF: remove some inconsistencies



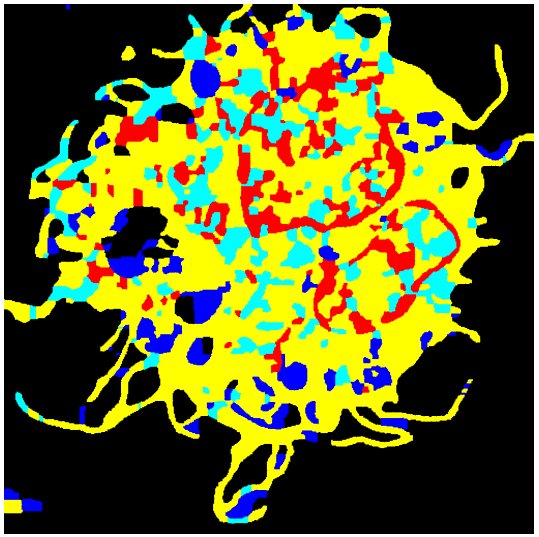
[B. Mičušík and T. Pajdla, CVPR 2007]

Related Work

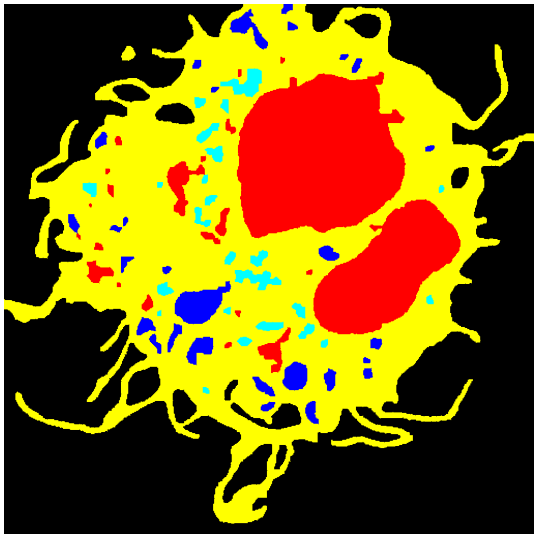




SVM:



MRF + Hierarchy high consistency



Our result

Markov Random Fields

MRF: Undirected Graphical Model
Models Conditional Independence

Graph $G = (V, E)$

Nodes $v \in V$

Edges $E \subseteq \binom{|V|}{2}$

Labels $x_v \in X$

Probability of a labeling:

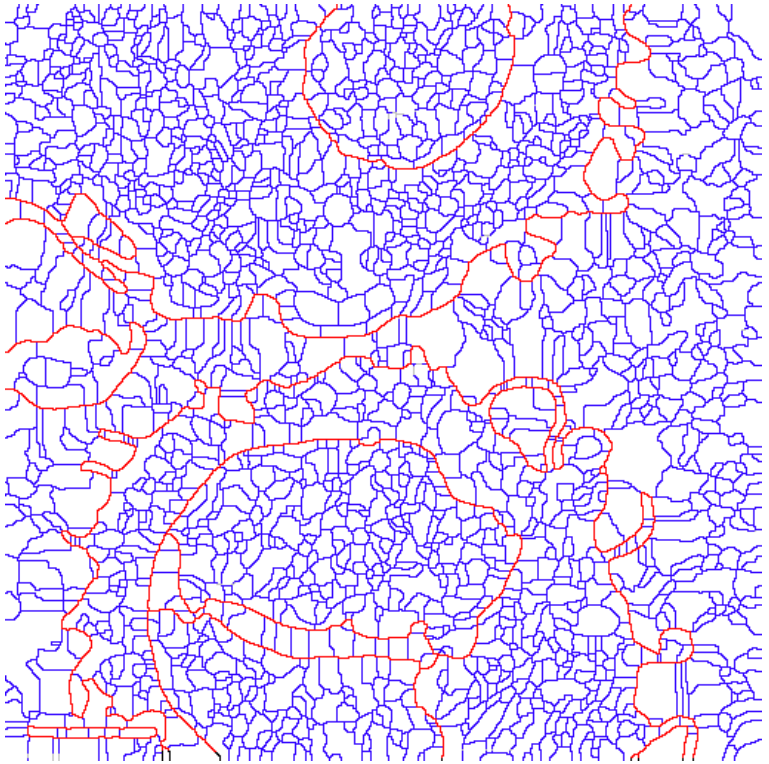
$$p(\mathbf{x}) = \frac{1}{Z} \prod_C \Psi_C(\mathbf{x}_C)$$

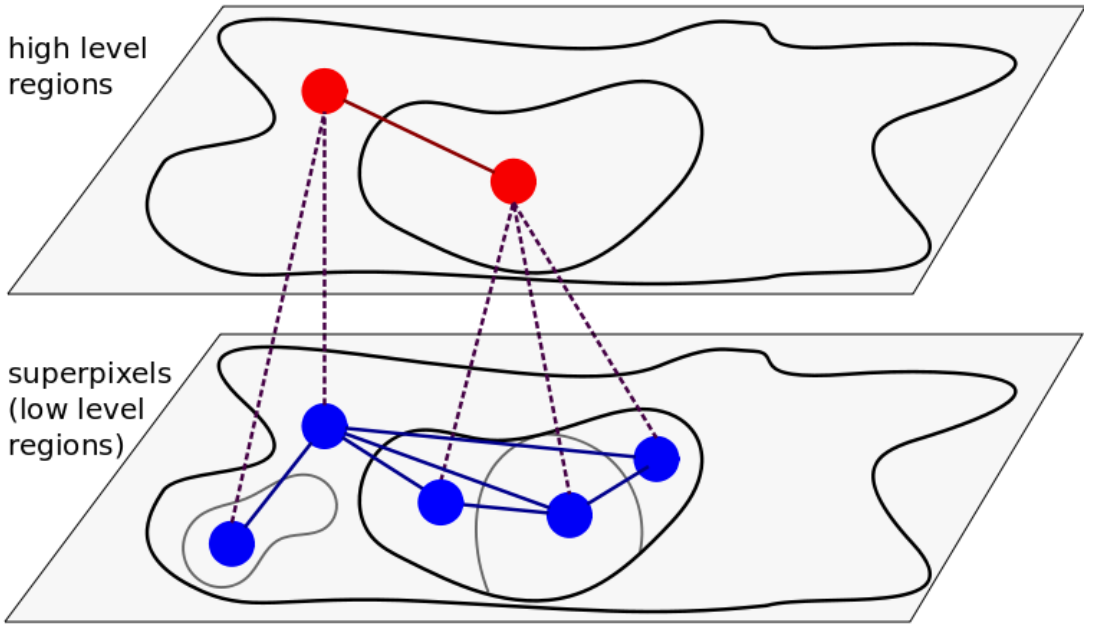
potential functions

Graph Construction

Hierarchical Graph Structure

- low level regions (fine contours)
- high level regions (coarser structures)

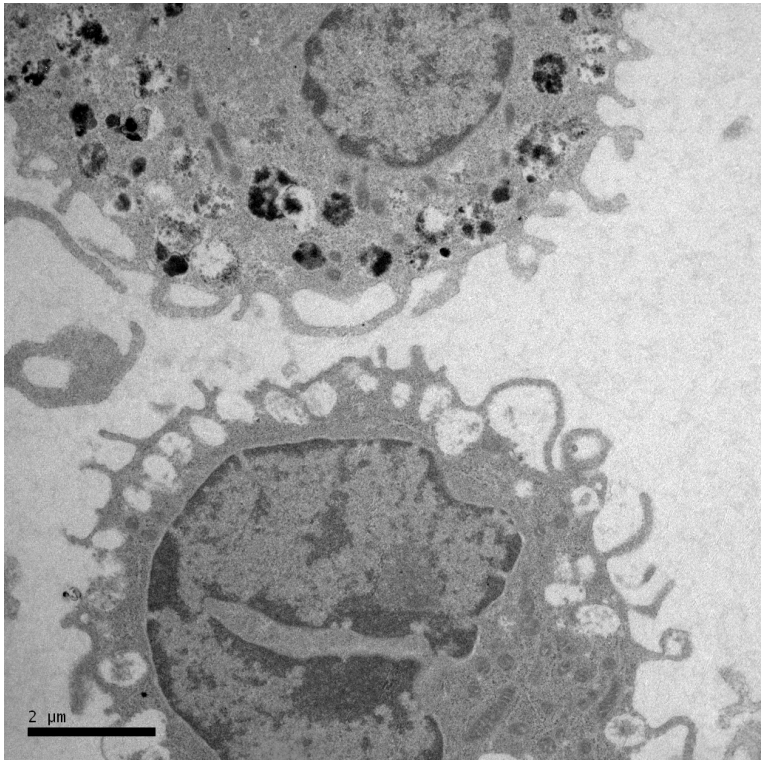




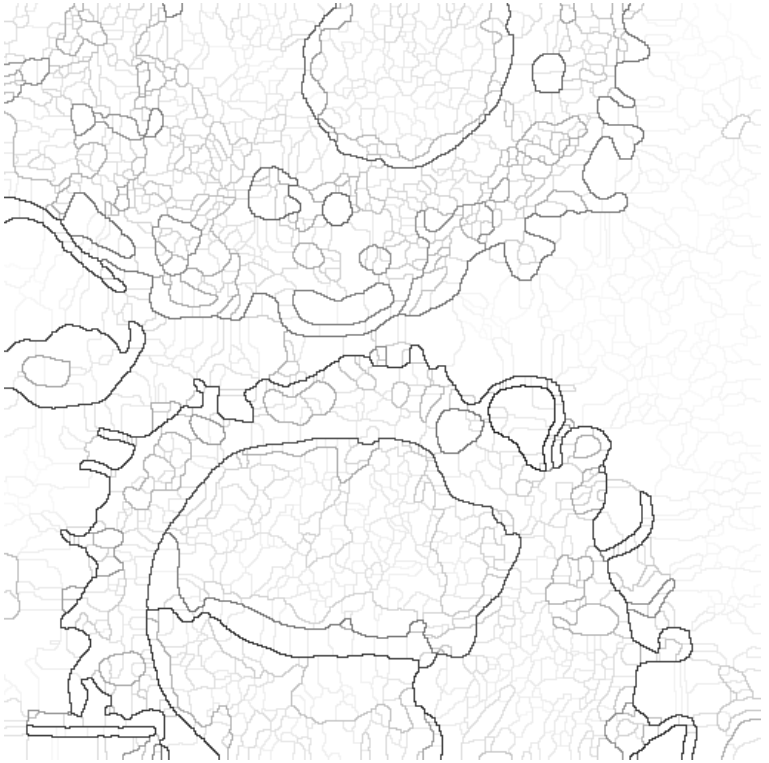
Region Hierarchies

- Built with the Berkeley tool for hierarchical segmentation
- Based on a Contour Detector and Watershed Transform

[Arbelaéz et al.: CVPR , 2009.]



EM Recording



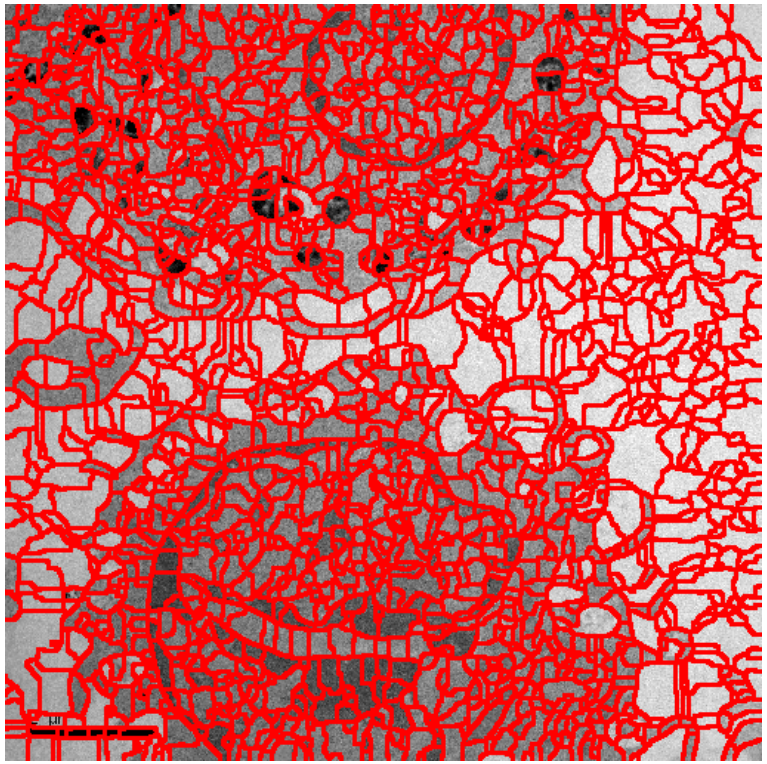
Region Hierarchy

finest regions at 0-level

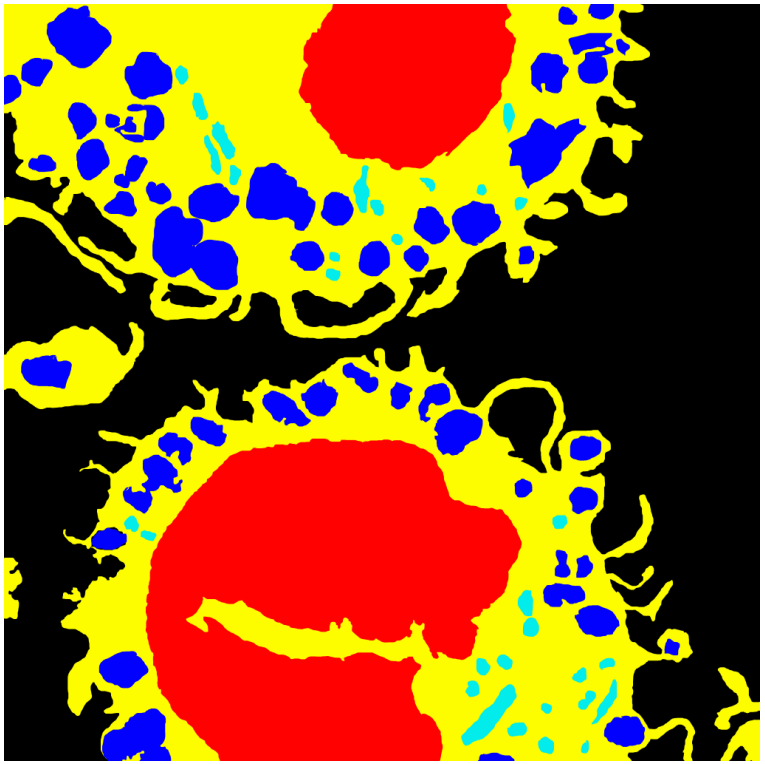
coarse regions at level L/2

Region Hierarchies

- Oversegmentation at finest level
- All classes are separated



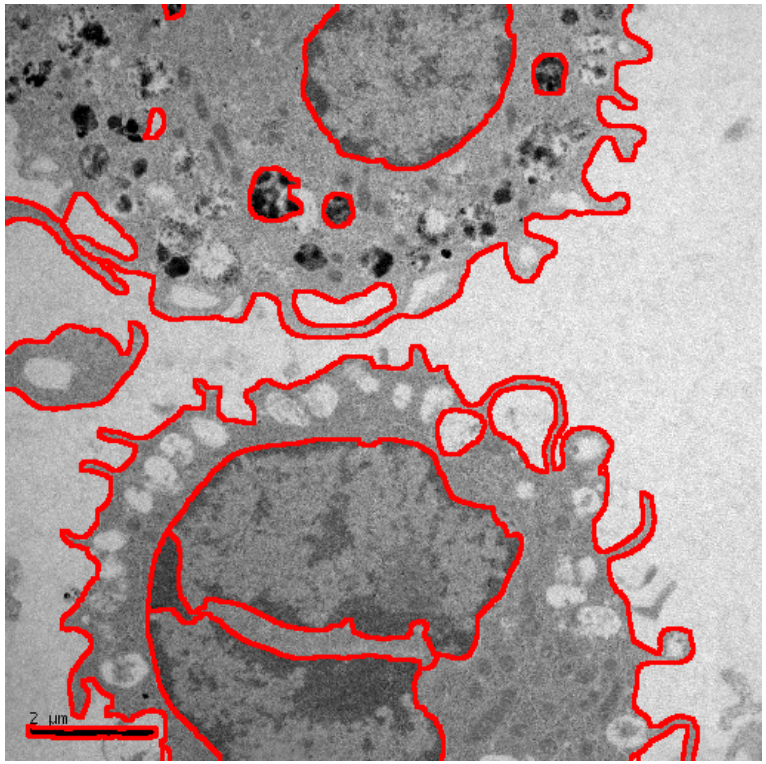
EM Recording with
0-level regions



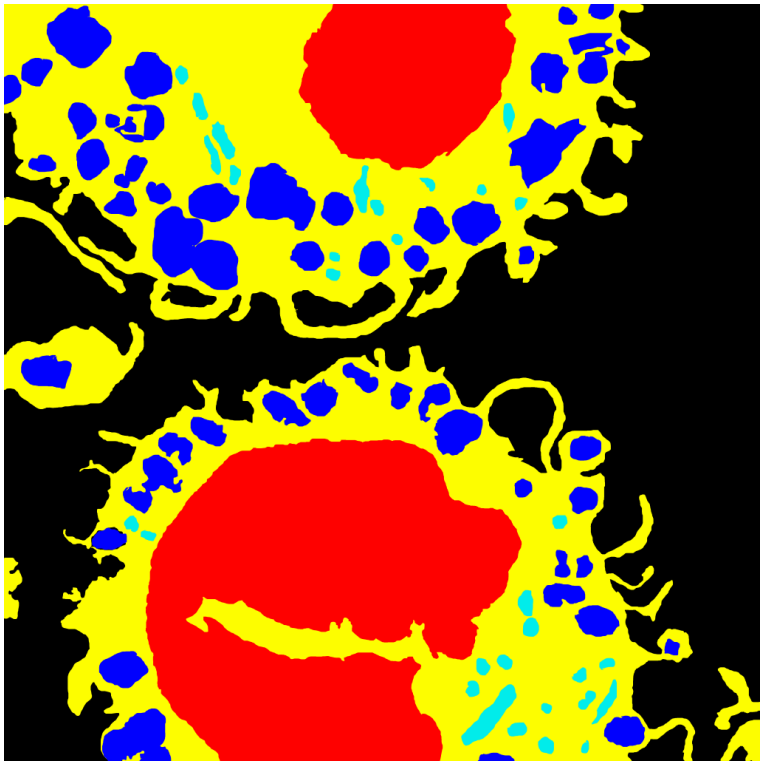
GT annotation

Region Hierarchies

- Missing boundaries at coarser levels
How can we merge the right regions?



EM Recording with
L/2 level regions

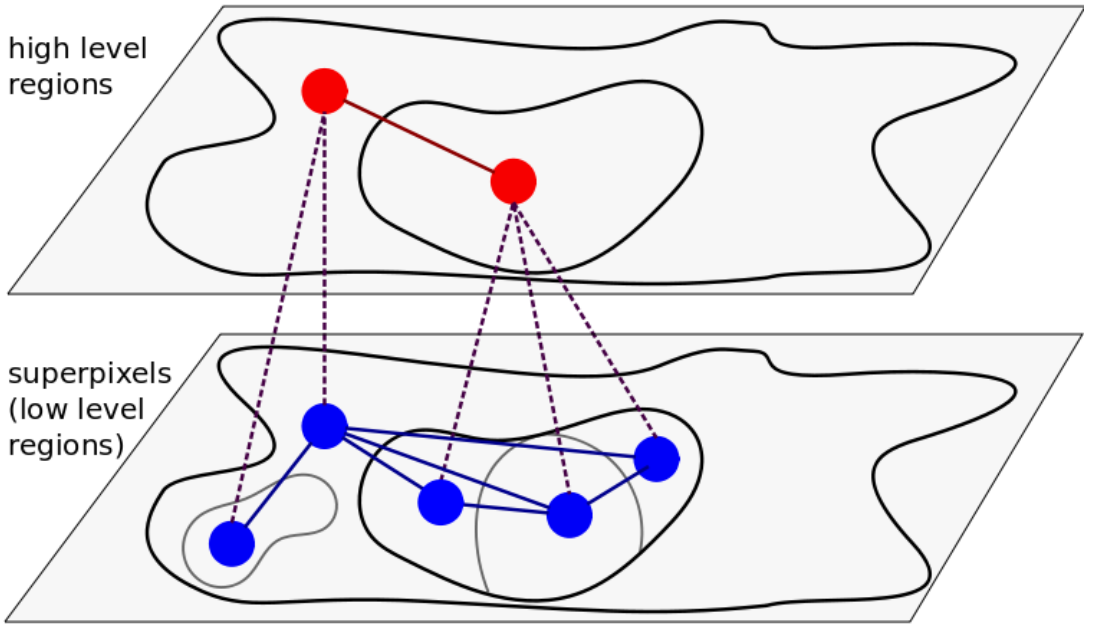


GT annotation

Training Labels

Hierarchical Graph Structure

- Labels at level 0: pixel labels inside the superpixels – we assume there is only one label.
- Labels at level L/2: Generate new labels by the majority vote of the pixels inside the regions.



Label	1	2	3	4	5
1'	98%	2%			
2'	8%	75%	1%	1%	15%
3'		3%	97%		

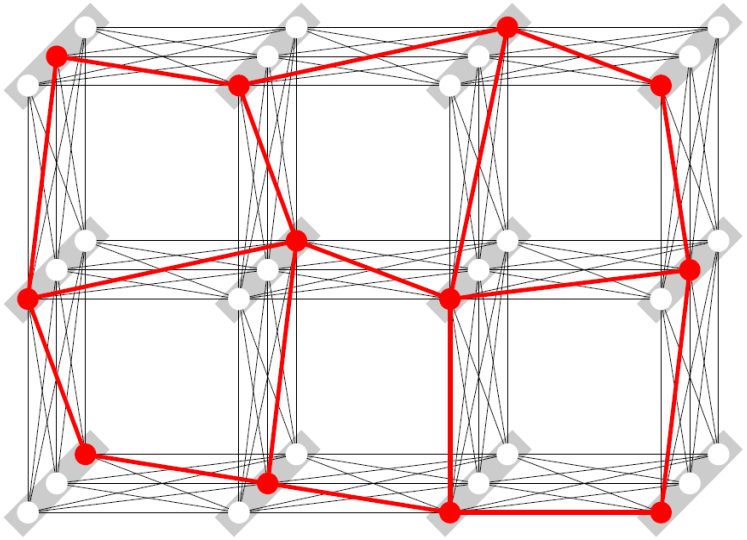
pixel-label distribution d

MAX-SUM Problem

Find MAP of a given MRF
Instance of a MAX-SUM problem:

$$(G, X, \mathbf{g})$$

potentials



[Werner, PAMI, 2007]

Find the set of optimal labelings:

$$\mathcal{L}_{G,X}(\mathbf{g}) = \underset{\mathbf{x} \in X^{|V|}}{\operatorname{argmax}} \; \Sigma_v g_v(x_v) + \Sigma_{v,v'} g_{vv'}(x_v, x_{v'})$$

vertex potentials

edge potentials

Code for MAX-SUM solver from:
http://cmp.felk.cvut.cz/cmp/software/maxsum/.

Vertex Potentials

$$\mathcal{L}_{G,X}(\mathbf{g}) = \underset{\mathbf{x}\in X^{|V|}}{\operatorname{argmax}} \; \Sigma_v g_v(x_v) + \Sigma_{v,v'} g_{vv'}(x_v, x_{v'})$$

vertex potentials

edge potentials

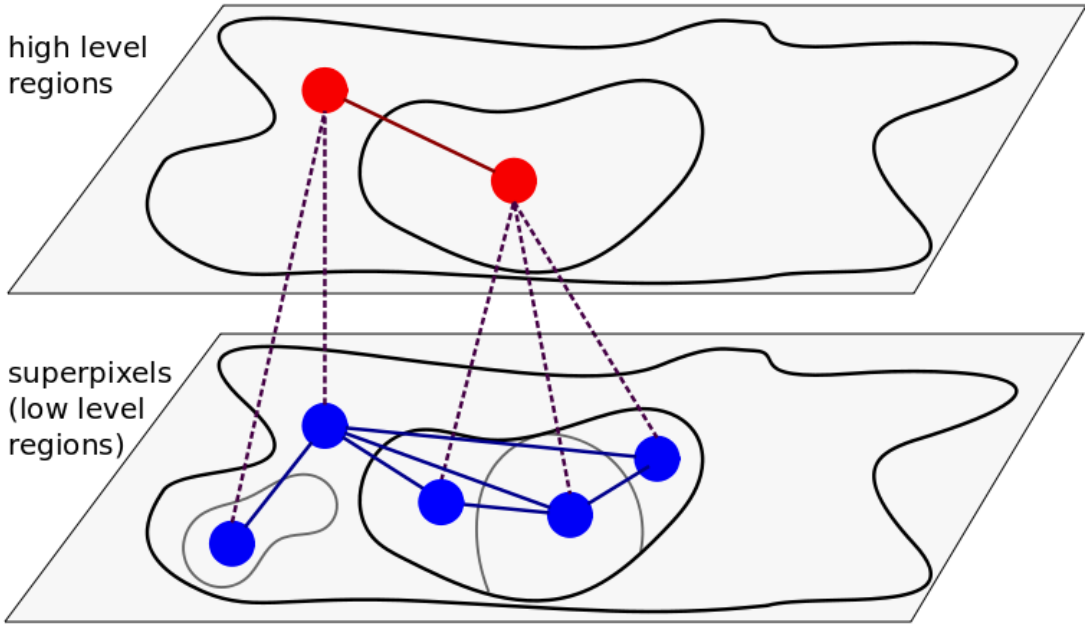
Probabilities from SVM decision values

$$g_v(x_v) = p(x_v) = p(x|\mathbf{f}(v))$$

label

region

feature vector for the region



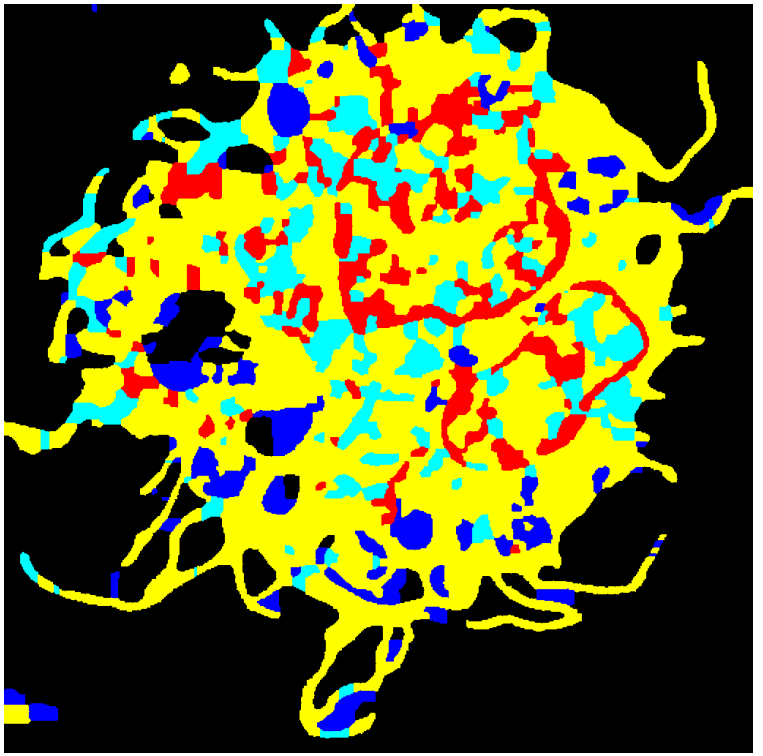
Vertex Potentials

Features:

- Gabor Features
- Mean intensity inside a region
- Variance of the intensity inside a region

SVM:

- One vs one SVM for all classes
- Multiclass Probabilities from One vs. One SVM [Wu et al., JMLR, 2004]



SVM classification result

Edge Potentials

$$\mathcal{L}_{G,X}(\mathbf{g}) = \underset{\mathbf{x}\in X^{|V|}}{\operatorname{argmax}} \; \Sigma_v g_v(x_v) + \Sigma_{v,v'} g_{vv'}(x_v, x_{v'})$$

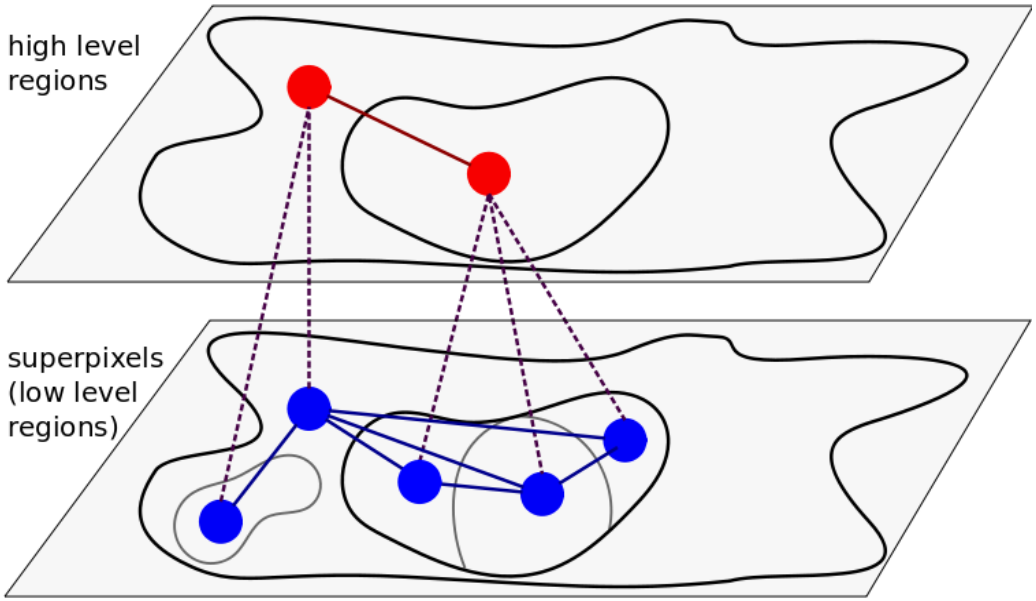
vertex potentials

edge potentials

Intra-Level Edge Potentials
pixel adjacency ratio AR:

average number of boundary pixels between label x_v and label $x_{v'}$:

$$g_{vv'}(x_v, x_{v'}) = \frac{2 \cdot \mathrm{AR}(x_v, x_{v'})}{\sum_{x_{v''}} \mathrm{AR}(x_v, x_{v''}) + \sum_{x_{v''}} \mathrm{AR}(x_{v''}, x_{v'})}$$



Edge Potentials

$$\mathcal{L}_{G,X}(\mathbf{g}) = \underset{\mathbf{x}\in X^{|V|}}{\operatorname{argmax}} \; \Sigma_v g_v(x_v) + \Sigma_{v,v'} g_{vv'}(x_v, x_{v'})$$

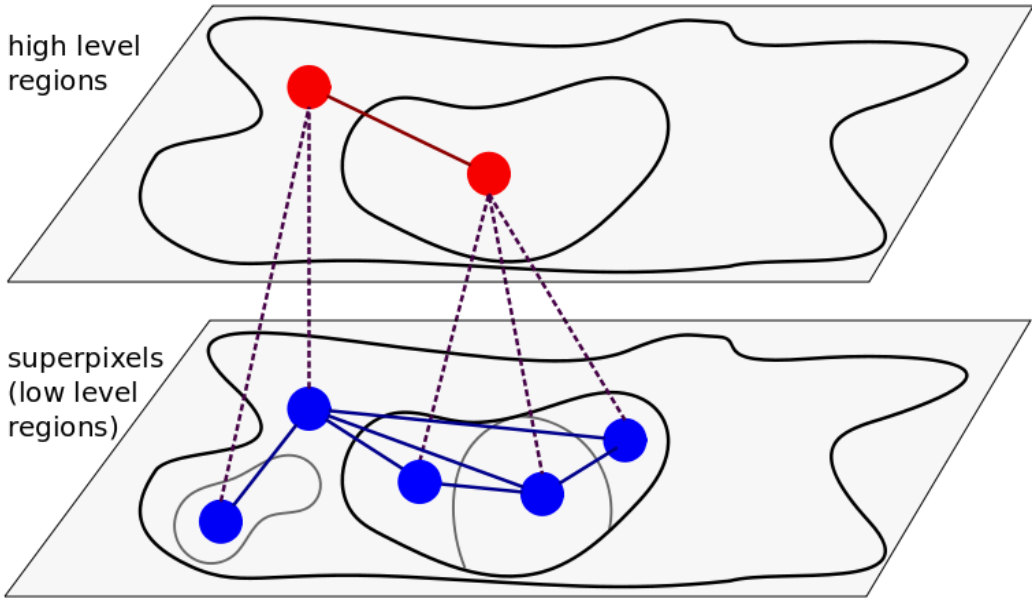
vertex potentials

edge potentials

Inter-Level------- Edge Potentials
Based on the High-level
Region Label Distribution d:

Label	1	2	3	4	5
1'	98%	2%			
2'	8%	75%	1%	1%	15%
3'		3%	97%		

$$g_{\bar{v}v}(x_{\bar{v}}, x_v) = d_{x_{\bar{v}}, x_v}$$



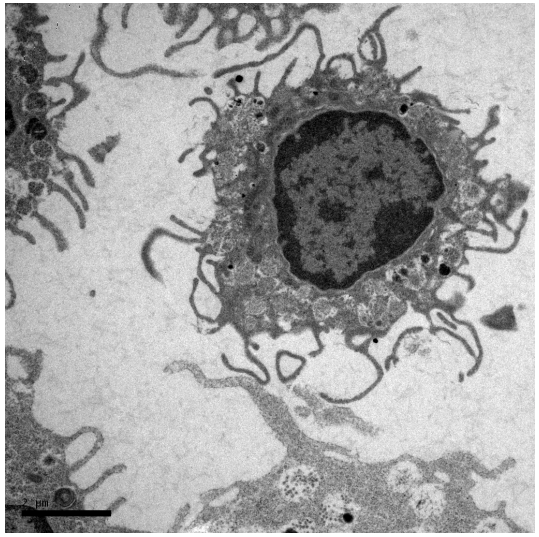
Experiments

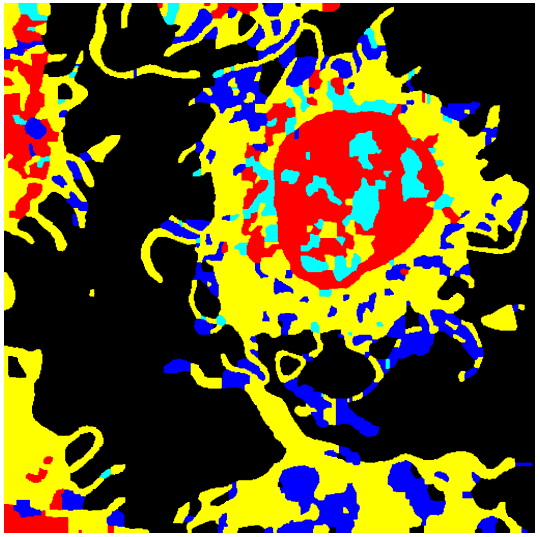
- 27 Transmission Electron Microscopic Recordings

- Manually annotated with 5 labels:
  - Background
  - Cytoplasm
  - Nucleus
  - Mitochondria
  - Vesicles

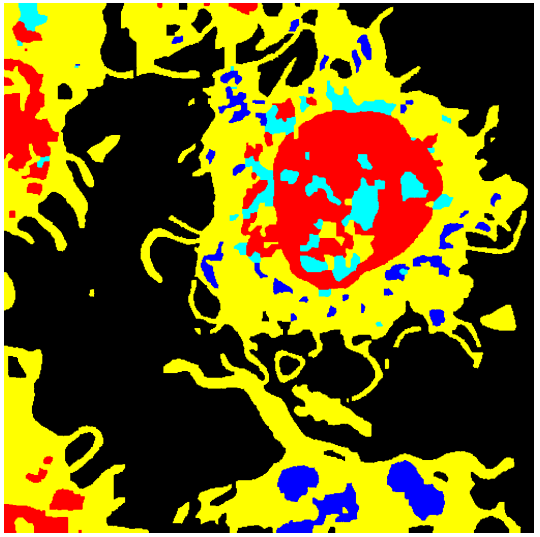
- Compare: (threefold cross-validation)
  - SVM-only Classification
  - MRF without Hierarchy
  - Hierarchical MRF

Results

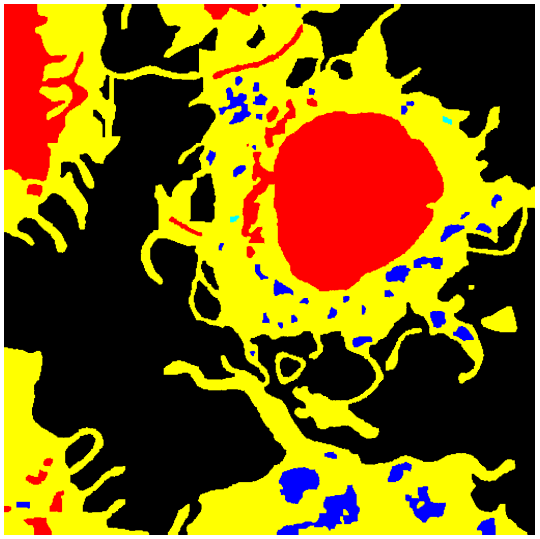




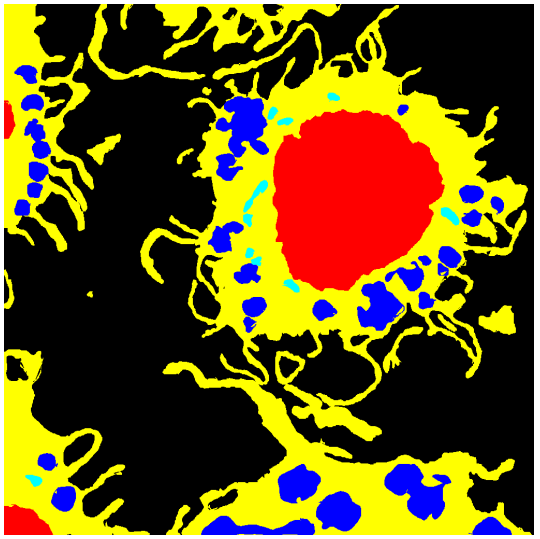
SVM



SVM + MRF

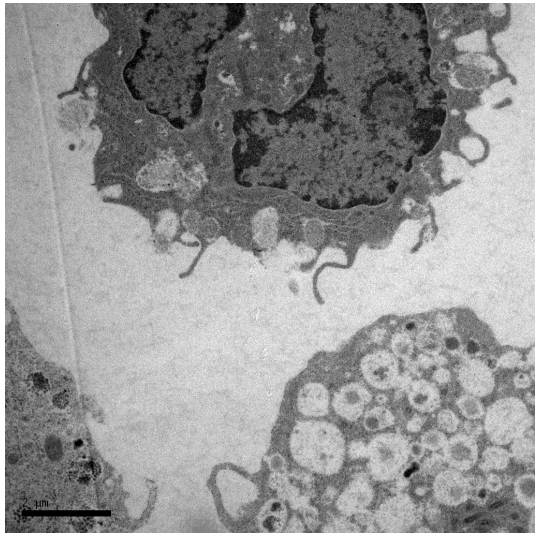


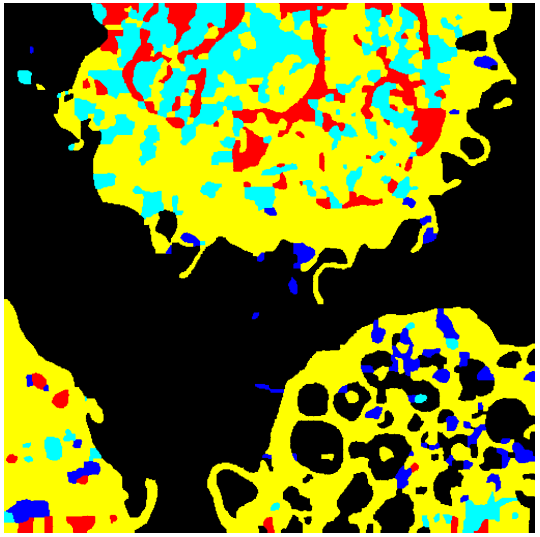
SVM + HMRF



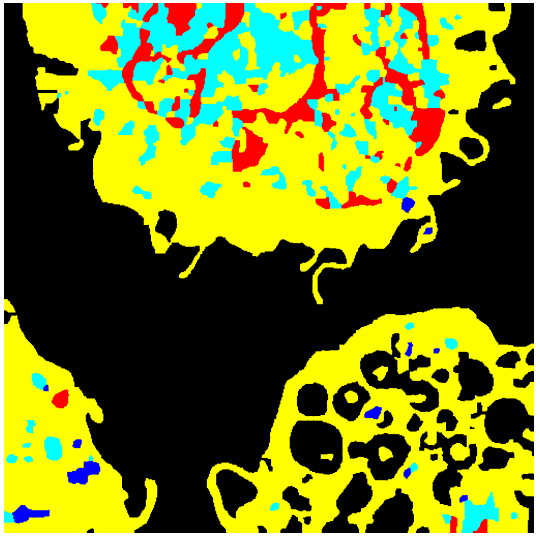
Ground Truth

Limitations

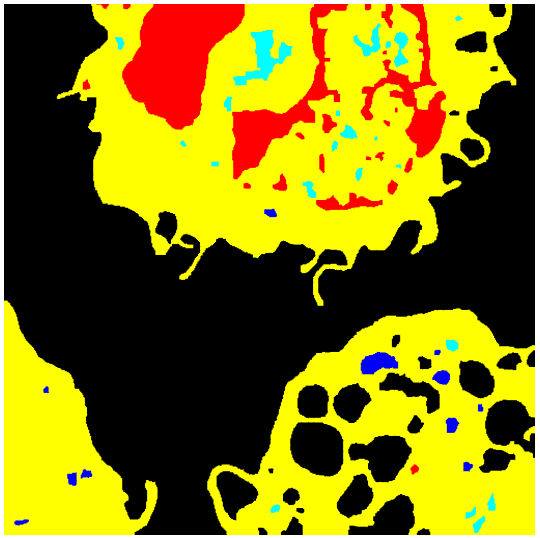




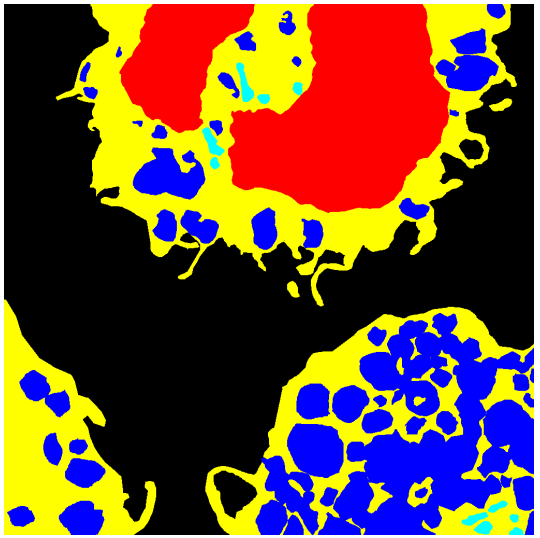
SVM



SVM + MRF



SVM + HMRF



Ground Truth

Results

Class-wise accuracy of the different methods.

	Back-ground	Cyt	Nucleus	Mito	Vesicles
HMRF	**87.3%**	**61.7%**	**31.8%**	8.1%	10.9%
MRF	83.5%	58.6%	21.9%	**10.8%**	14.9%
SVM	85.2%	57.3%	22.2%	9.5%	**17.6%**

Overall accuracy:

HMRF	**65.42%**
MRF	61.5%
SVM	60.5%

accuracy:

$$\frac{\mathrm{tp}}{\mathrm{tp}+\mathrm{fp}+\mathrm{fn}}$$

precision:

$$\frac{\mathrm{tp}}{\mathrm{tp}+\mathrm{fp}}$$

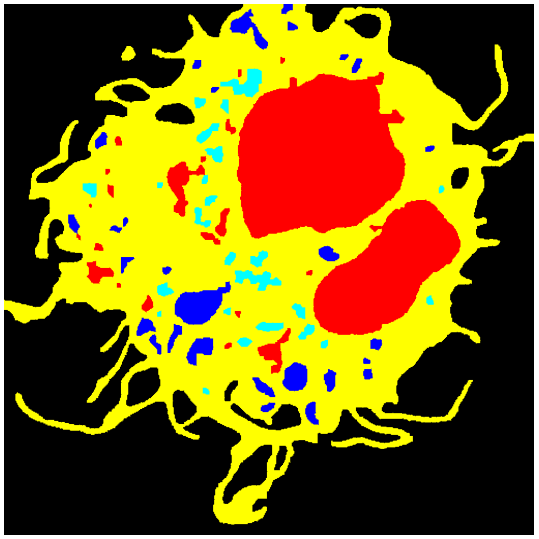
recall:

$$\frac{\mathrm{tp}}{\mathrm{tp}+\mathrm{fn}}$$

Precision and Recall of the HMRF-method.

	Back-ground	Cyt	Nucleus	Mito	Vesicles
precision	**93.3%**	**67.4%**	**55.5%**	22.7%	69.3%
recall	93.3%	89.1%	40.4%	**18.2%**	11.9%

Conclusion



- Hierarchical Graph structure leads to much higher consistency
- Convincing results for background, cytoplasm and nucleus

Outlook

- Evaluation on a larger dataset
- Generate Benchmark from the data

Literatur

[1] P. Arbelaéz, M. Maire, C. Fowlkes, and J. Malik, “From contours to regions: An empirical evaluation,” in Proc. of the CVPR , 2009.

[2] Vladimir N. Vapnik, Statistical Learning Theory , Wiley-Interscience, 1998.

[3] B. Mičušík and T. Pajdla, “Multi-label image segmentation via max-sum solver,” in Proc. of the CVPR , 2007.

[4] T. Werner, “A linear programming approach to maxsum problem: A review,” Trans. on PAMI , vol. 29/7, pp. 1165–1178, 2007.

[5] Y Boykov and V. Kolmogorov, “An experimental comparison of min-cut/max-flow algorithms for energy minimization in vision,” Trans. on PAMI , vol. 26/9, pp. 1124–1137, 2004.

[6] H. Chang, M. Auer, and B. Parvin, “Structural annotation of em images by graph cut,” in IEEE Int. Symp. On Biomedical Imaging-from nano to macro (ISBI) . 2009, IEEE Computer Society.

[7] C. D’Elia, G. Poggi, and G. Scarpa, “A tree-structured markov random field model for bayesian image segmentation,” Trans. on IP , vol. 12/10, pp. 1259–1273, 2003.

[8] N. Plath, M. Toussaint, and S. Nakajima, “Multi-class image segmentation using conditional random fields and global classification,” in Proceedings of the 26th Annual International Conference on Machine Learning , New York, NY, USA, 2009, ICML ’09, pp. 817–824, ACM.

[9] J. Reynolds and K. Murphy, “Figure-ground segmentation using a hierarchical conditional random field,” in Proceedings of the Fourth Canadian Conference on Computer and Robot Vision , 2007.

[10] J. Shotton, M. Johnson, and R. Cipolla, “Semantic texton forests for image categorization and segmentation,” in Proc. of the CVPR , 2008.

[11] M. Maire, P. Arbelaéz, C. Fowlkes, and J. Malik, “Using contours to detect and localize junctions in natural images,” in Proc. of the CVPR , 2008.

[12] T.-F. Wu, C.-J. Lin, and R. C. Weng, “Probability estimates for multi-class classification by pairwise coupling.,” Journal of Machine Learning Research , vol. 5, pp. 975–1005, 2004.

[13] http://cmp.felk.cvut.cz/cmp/software/maxsum/.