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Topological Persistence in Computer Vision: Applications to Obstacle Detection and Image Segmentation

Qian Ge

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Outline

- Introduction
- Image Segmentation Framework
- Persistence Homology
- Consensus-based Image Segmentation
- Obstacle Detection of Outdoor Scene
- Conclusion and Future Work

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Image Segmentation

- Image segmentation clusters the image pixels into a set of groups visually distinct and uniform with respect to some properties.
- Region of interest depends on applications.

Image Segmentation

- **Applications**

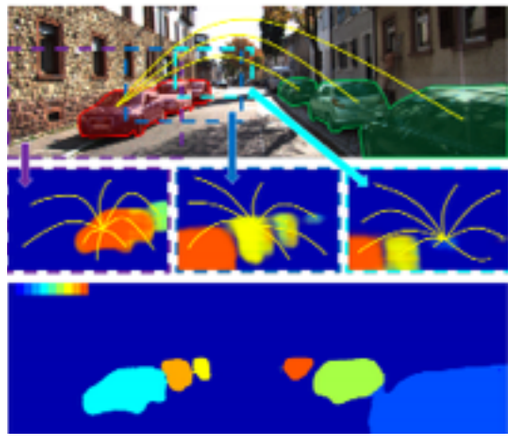
Object Recognition

Object Tracking

Video Surveillance

Image Segmentation

Autonomous Driving



Medical Imaging

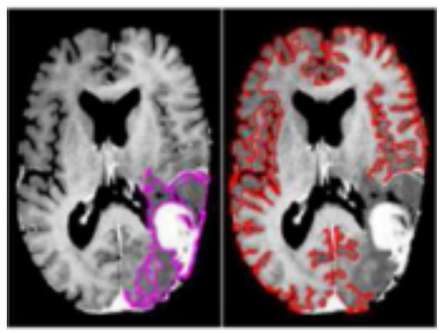


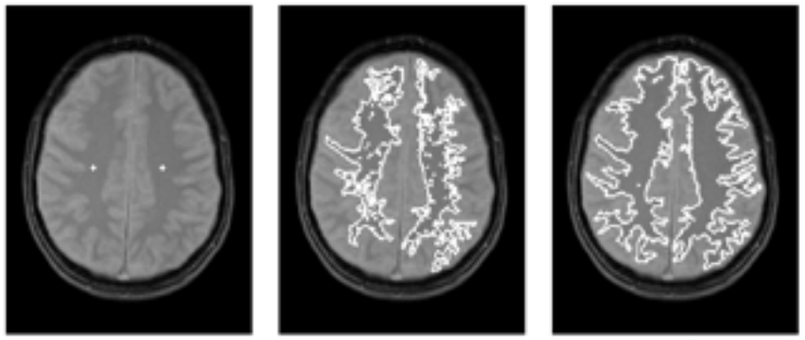
Image Segmentation

- **Grouped by methodology:**

Clustering-based

[DC02]

Region Growing



[JL10]

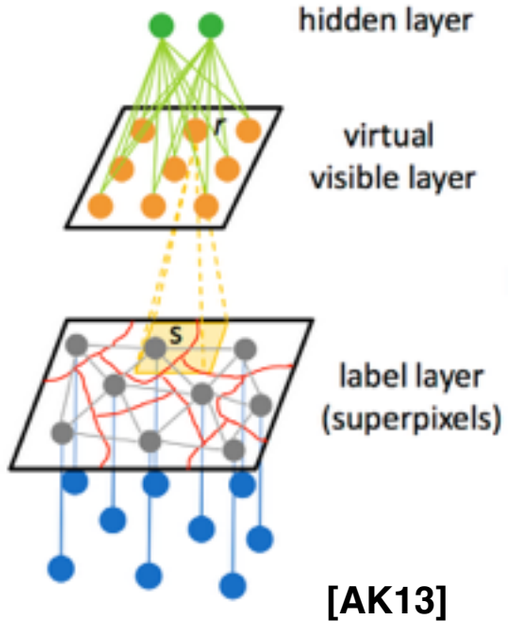
Superpixel-based

[RA12]

Edge-based

http://www.roborealm.com/help/Canny.php

Graph-based



[AK13]

[DC02] Dorin Comaniciu and Peter Meer. 2002. Mean Shift: A Robust Approach Toward Feature Space Analysis. IEEE Trans. Pattern Anal. Mach. Intell. 24, 5 (May 2002), 603-619.
[AK13] A. Kae, K. Sohn, H. Lee and E. Learned-Miller, "Augmenting CRFs with Boltzmann Machine Shape Priors for Image Labeling," 2013 IEEE Conference on Computer Vision and Pattern Recognition, Portland, OR, 2013, pp. 2019-2026.
[JL10] J. L. Rose, T. Grenier, C. Revol-Muller and C. Odet, "Unifying variational approach and region growing segmentation," 2010 18th European Signal Processing Conference, Aalborg, 2010, pp. 1781-1785.
[RA12] Radhakrishna Achanta, Appu Shaji, Kevin Smith, Aurelien Lucchi, Pascal Fua, and Sabine Susstrunk. 2012. SLIC Superpixels Compared to State-of-the-Art Superpixel Methods. IEEE Trans. Pattern Anal. Mach. Intell. 34, 11 (November 2012), 2274-2282.

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Why Robust?

- **Robust to noise, parameter selection, image quality and resolution**

  - Medical images are often polluted noisy.
  - User inputs cannot be the same every time.
  - Outdoor scene images quality varies over time.

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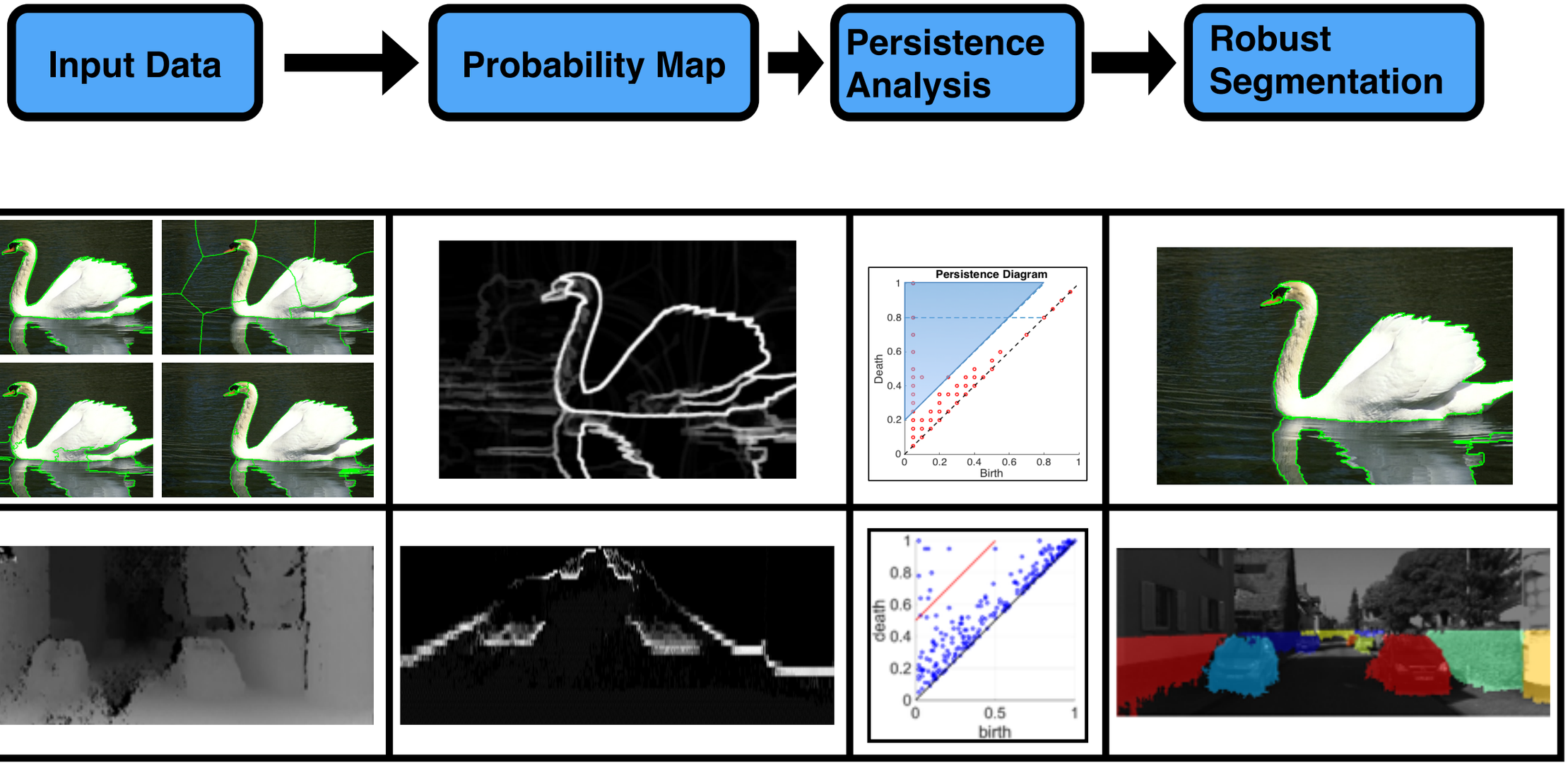
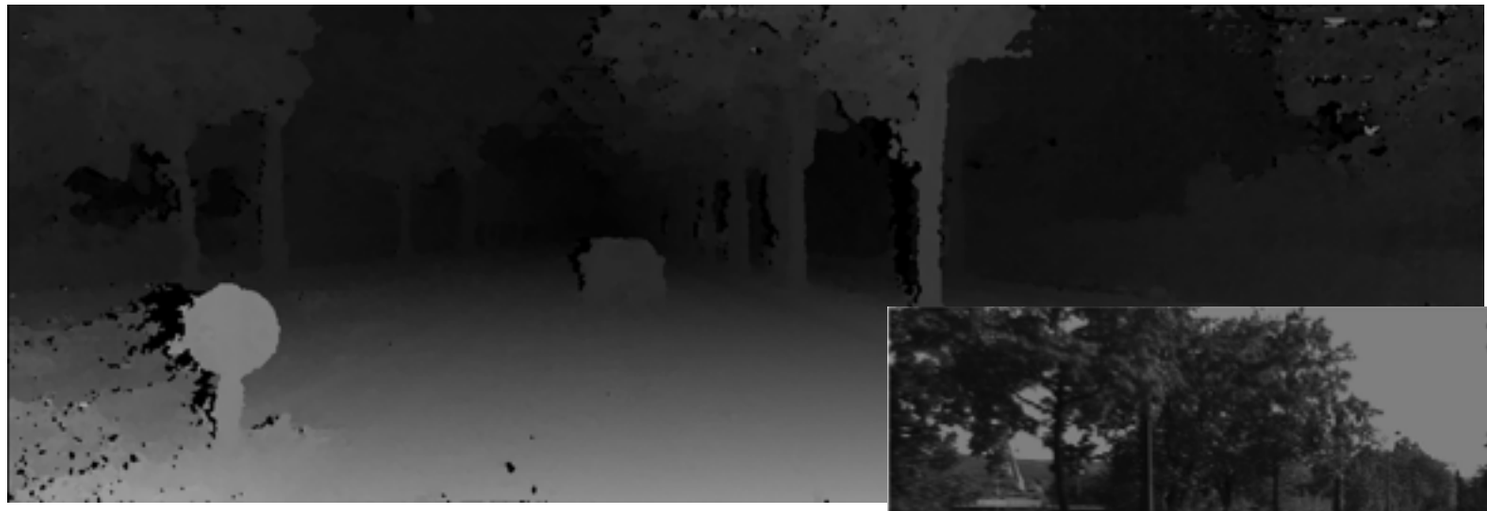
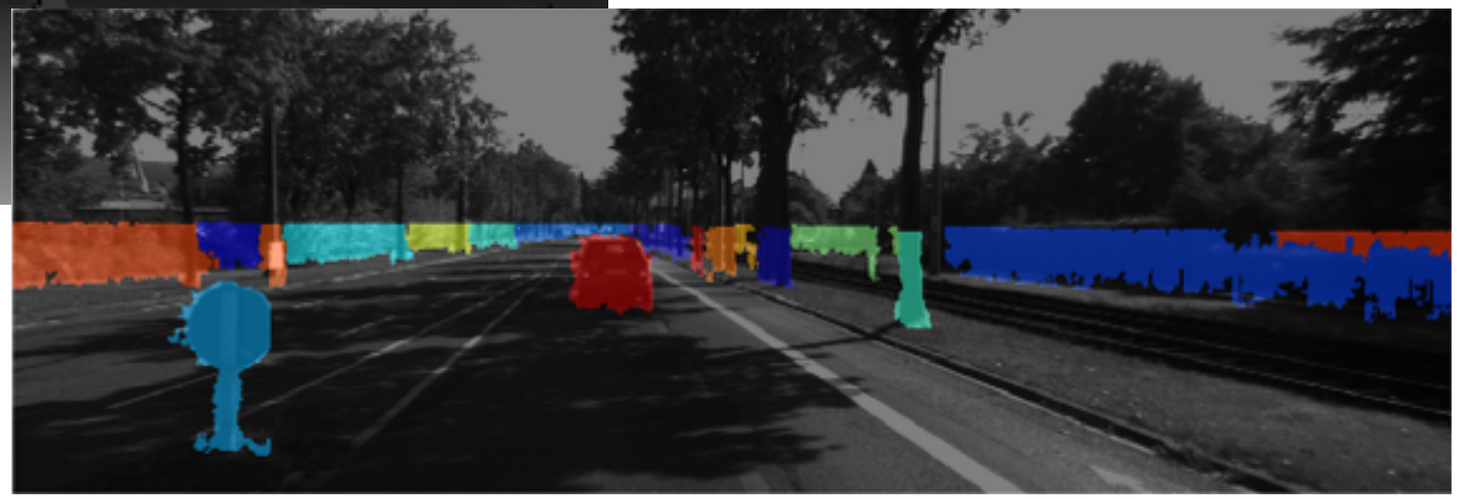
Framework of Robust Segmentation

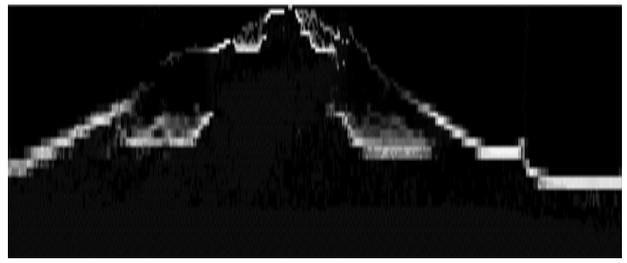


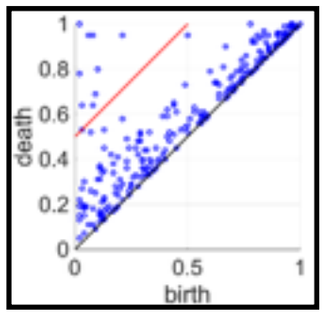
Framework of Robust Segmentation

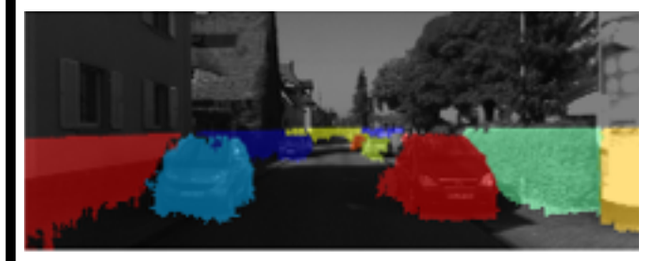
- **Obstacle segmentation of outdoor scene**





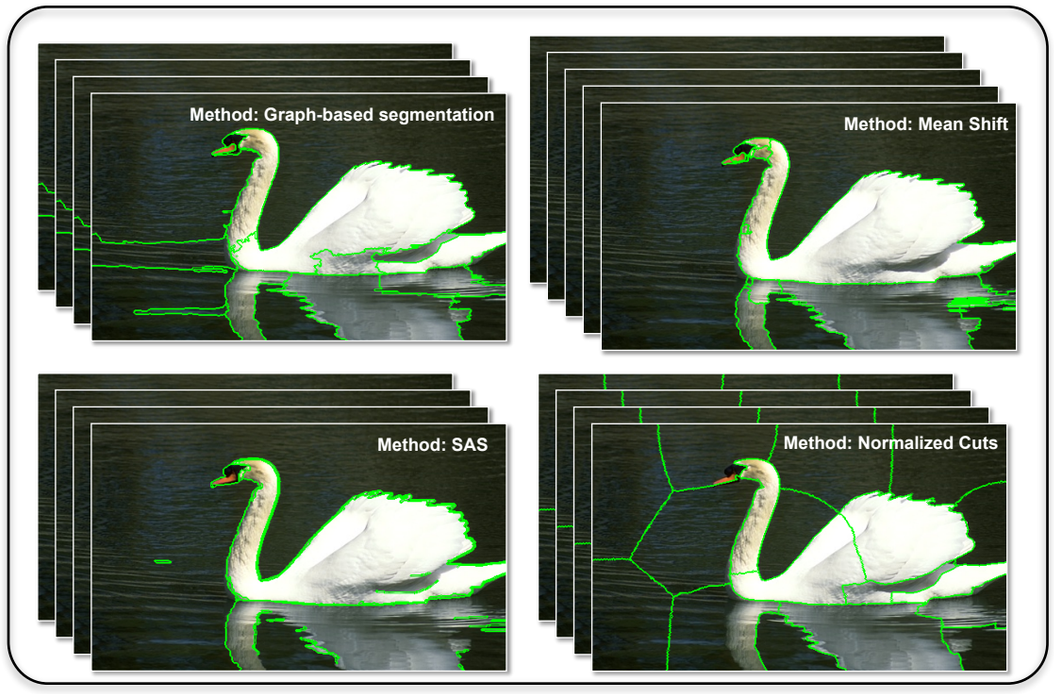


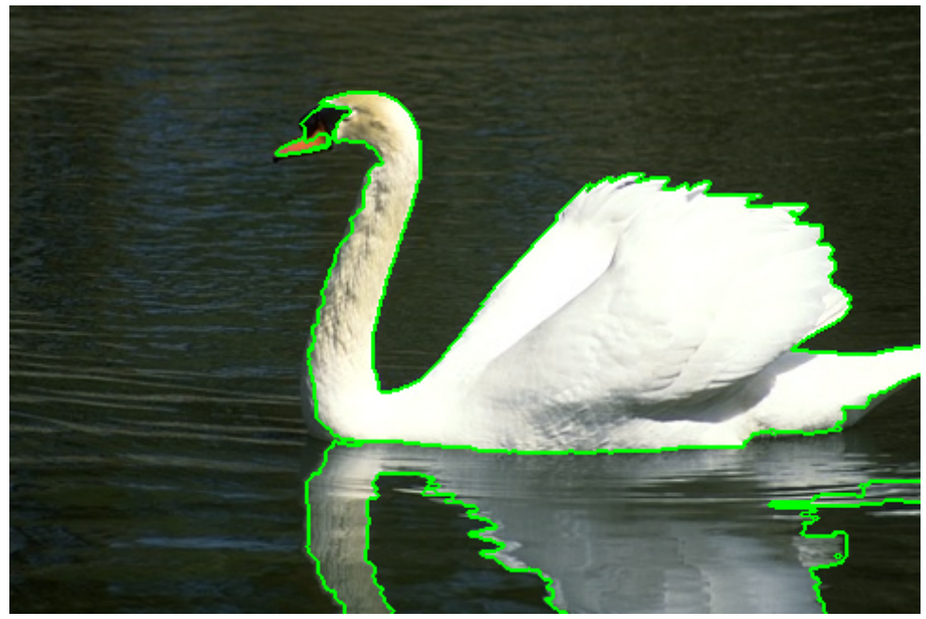


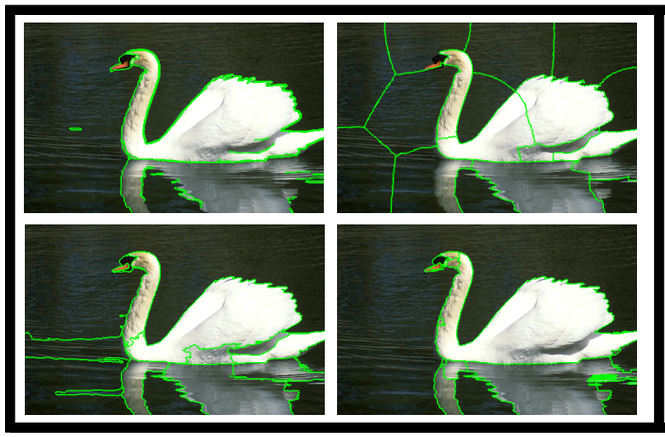


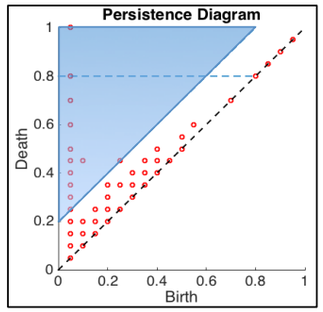
Framework of Robust Segmentation

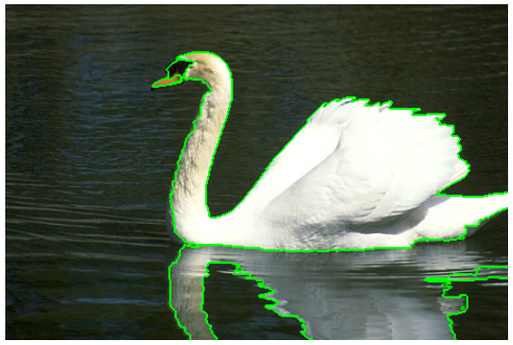
- **Consensus-based image segmentation**











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Contribution

- Present an innovative framework for image segmentation based on topological persistence which is robust to image conditions and parameter selection.
- Applied to obstacle detection in outdoor scene for autonomous driving which is robust to parameter selection.
- Applied to consensus-based image segmentation which is able to get better segmentation results.

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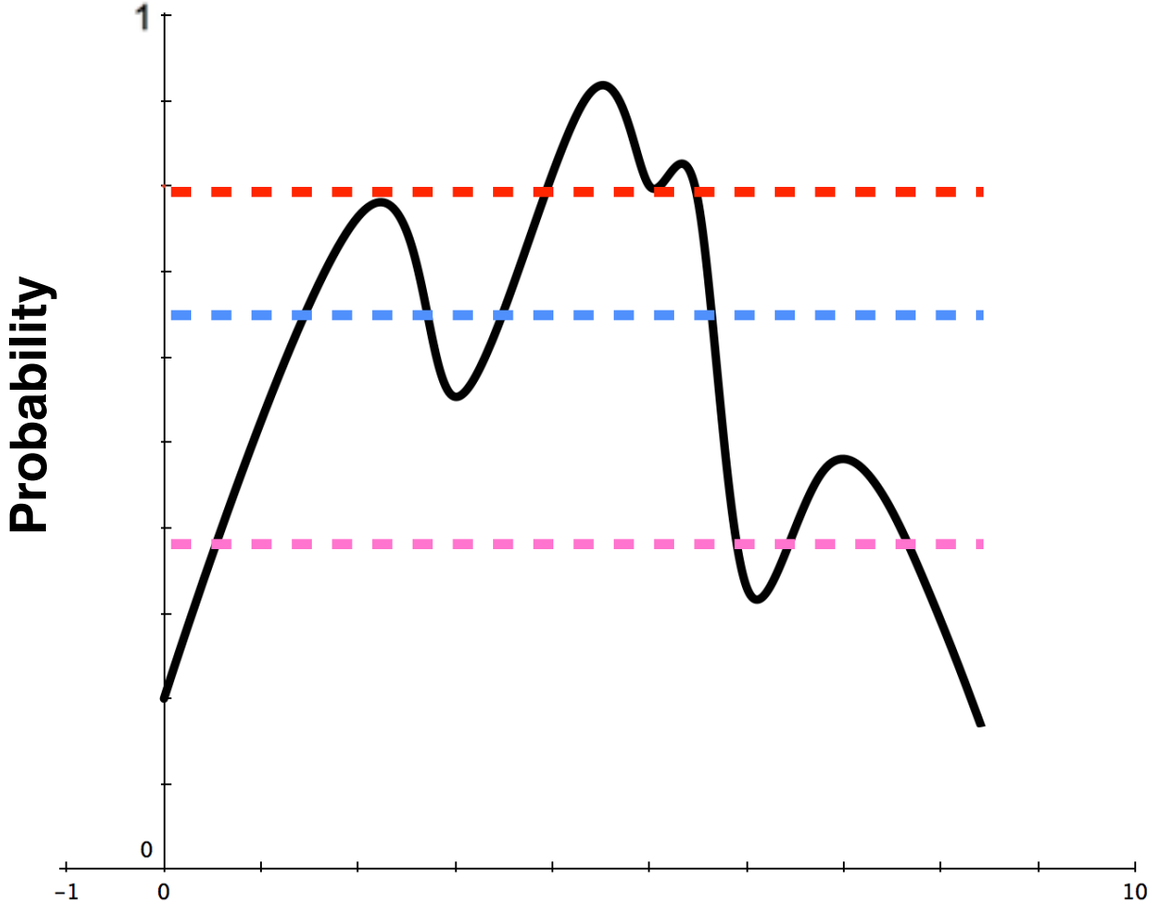
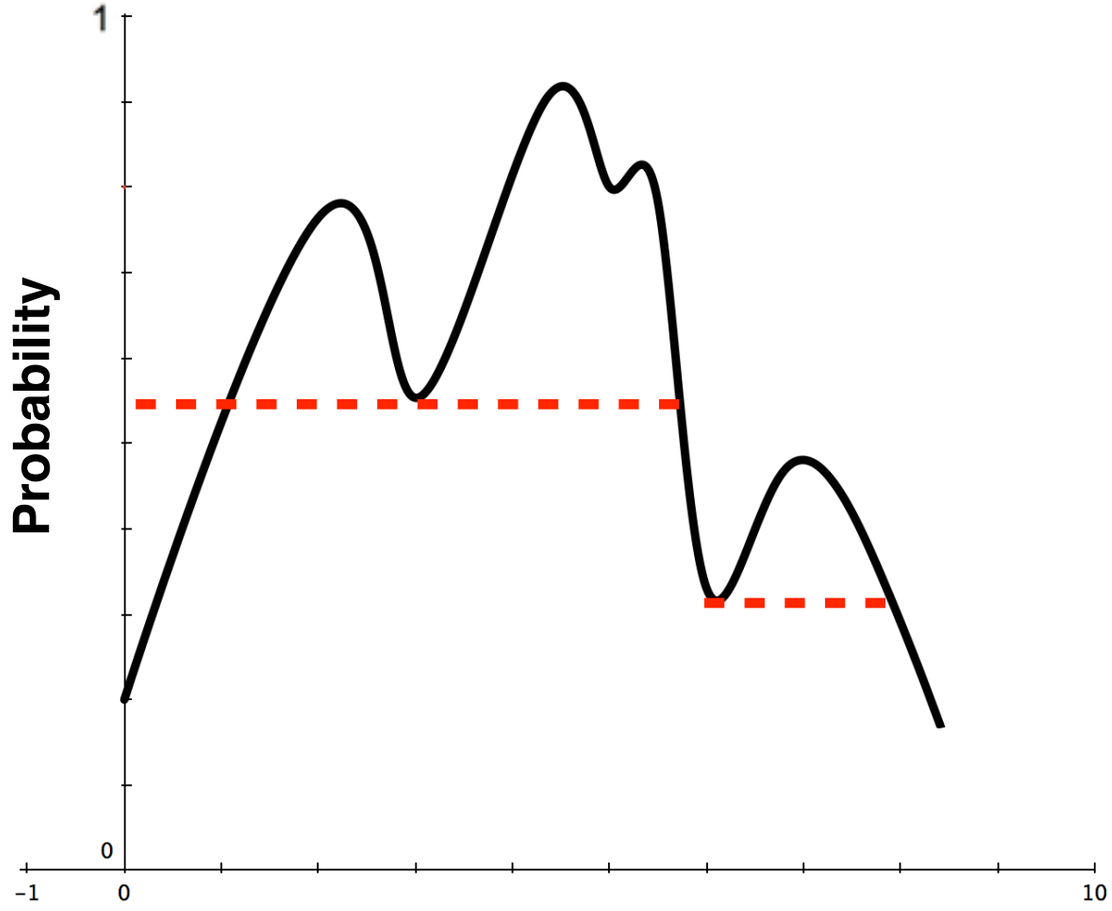
Persistent Homology

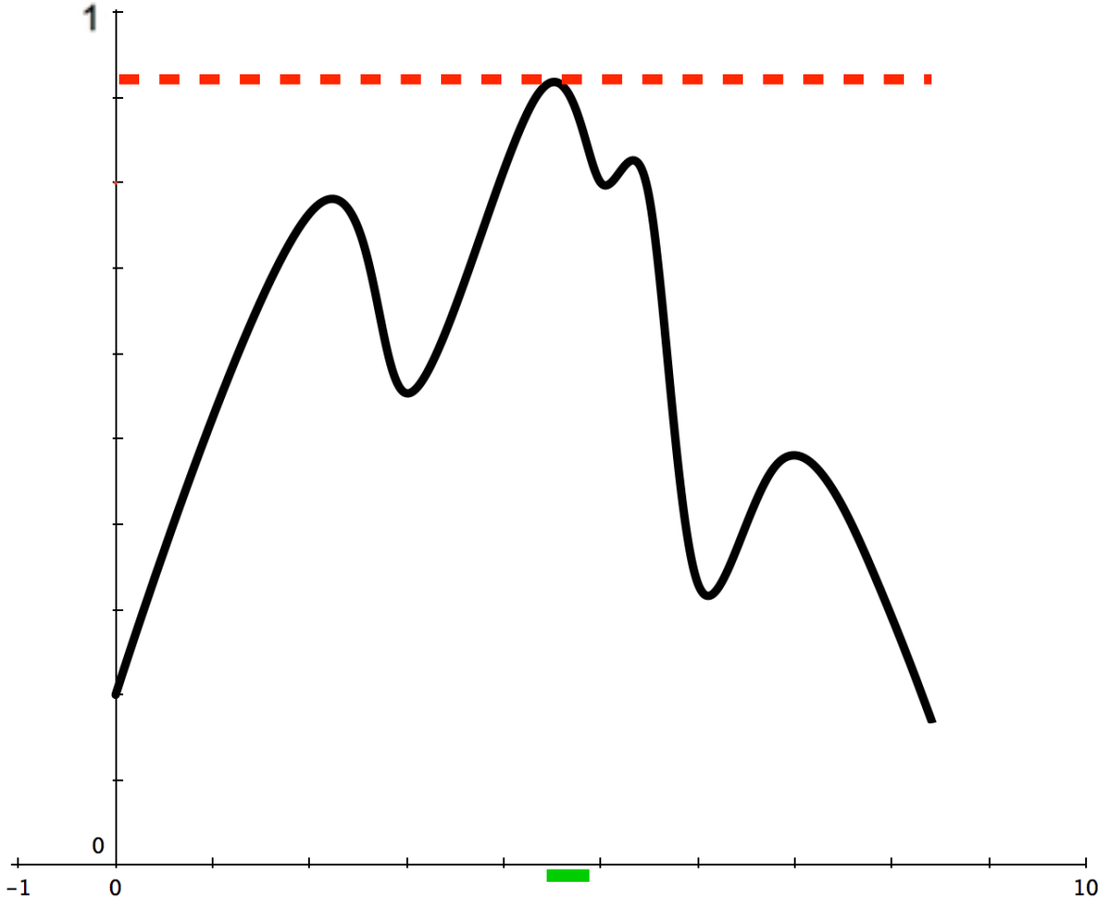
- For image segmentation, we borrow the concept of persistent homology to extract persistence regions and avoid noise.

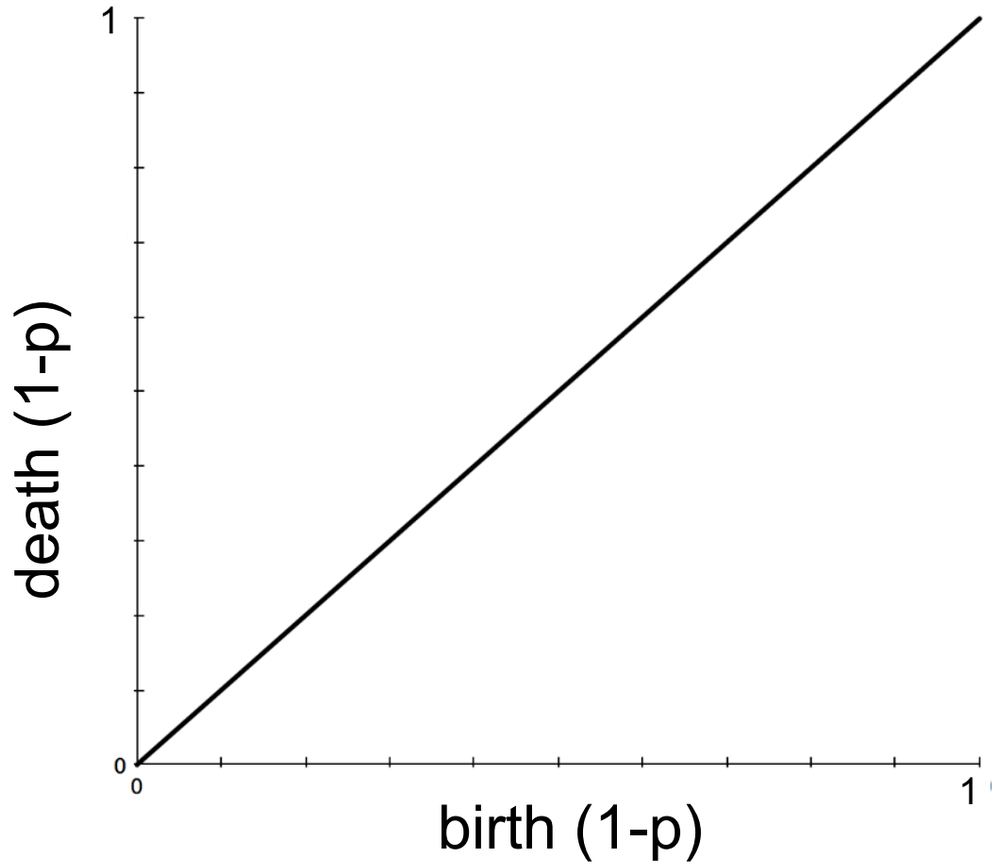




Persistent Homology

- **Topological persistence**





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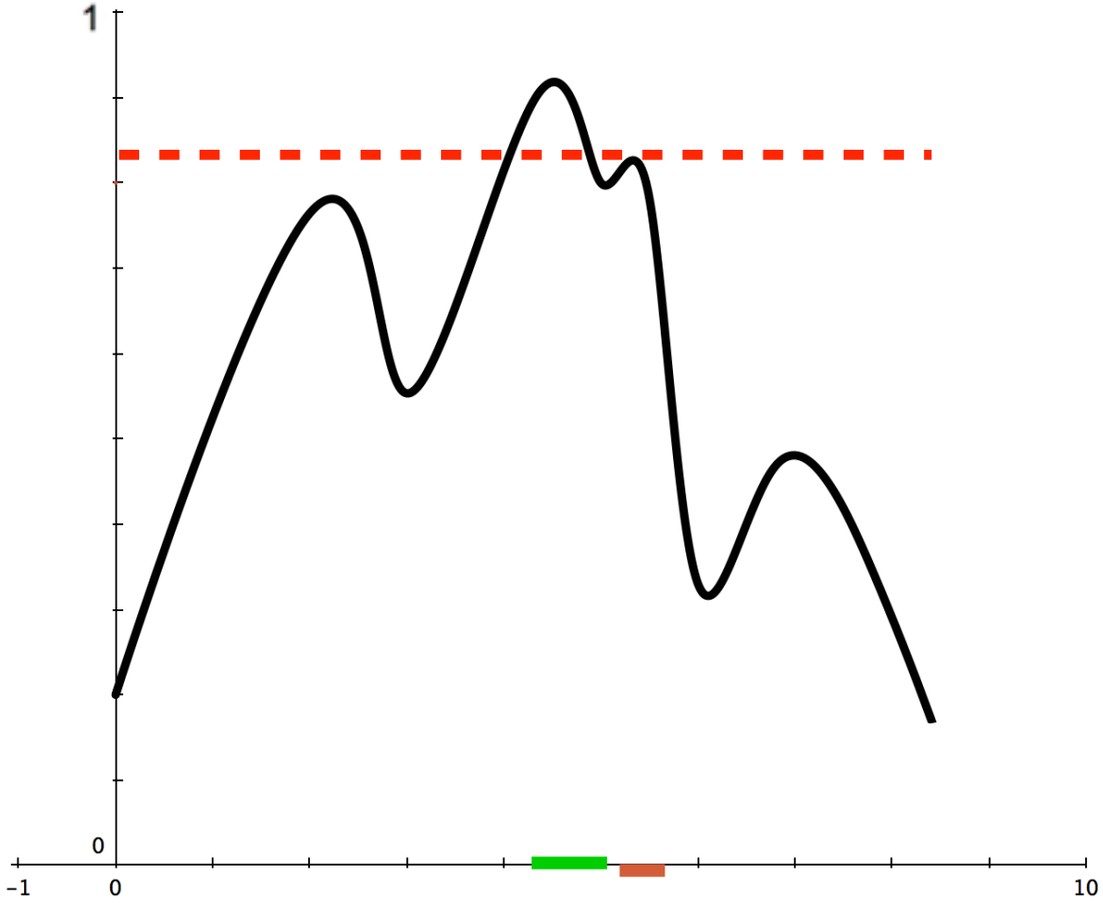
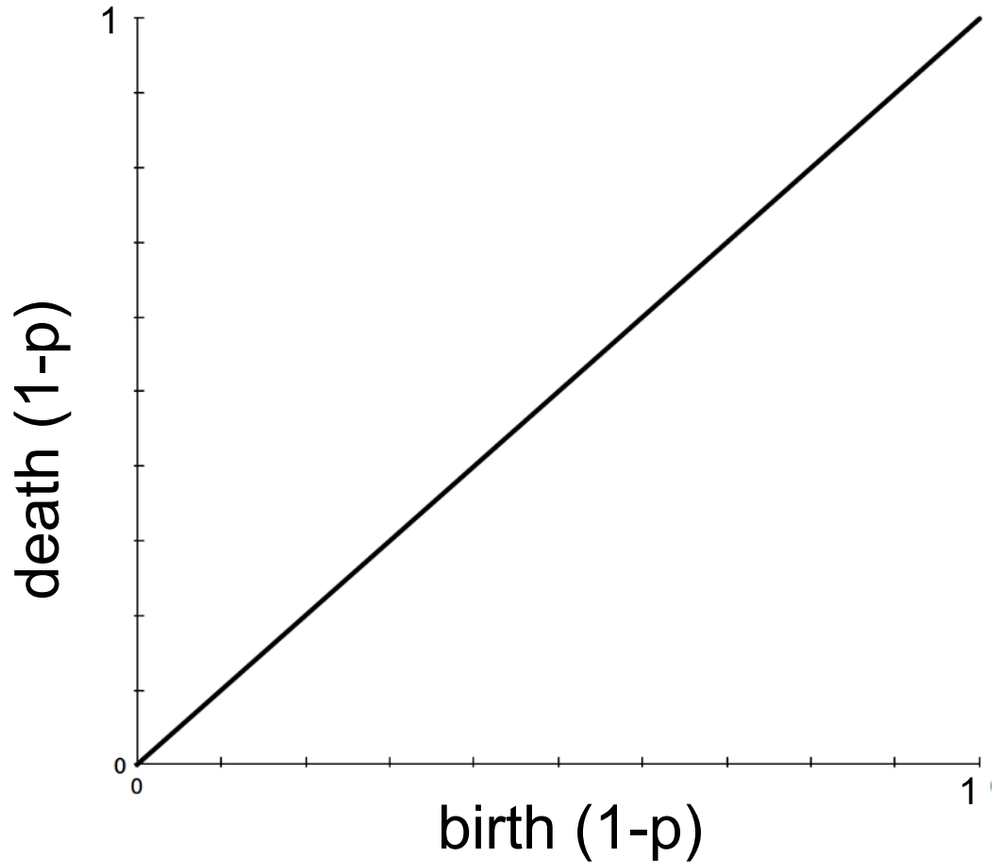
Persistent Homology

- **Topological persistence**





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Persistent Homology

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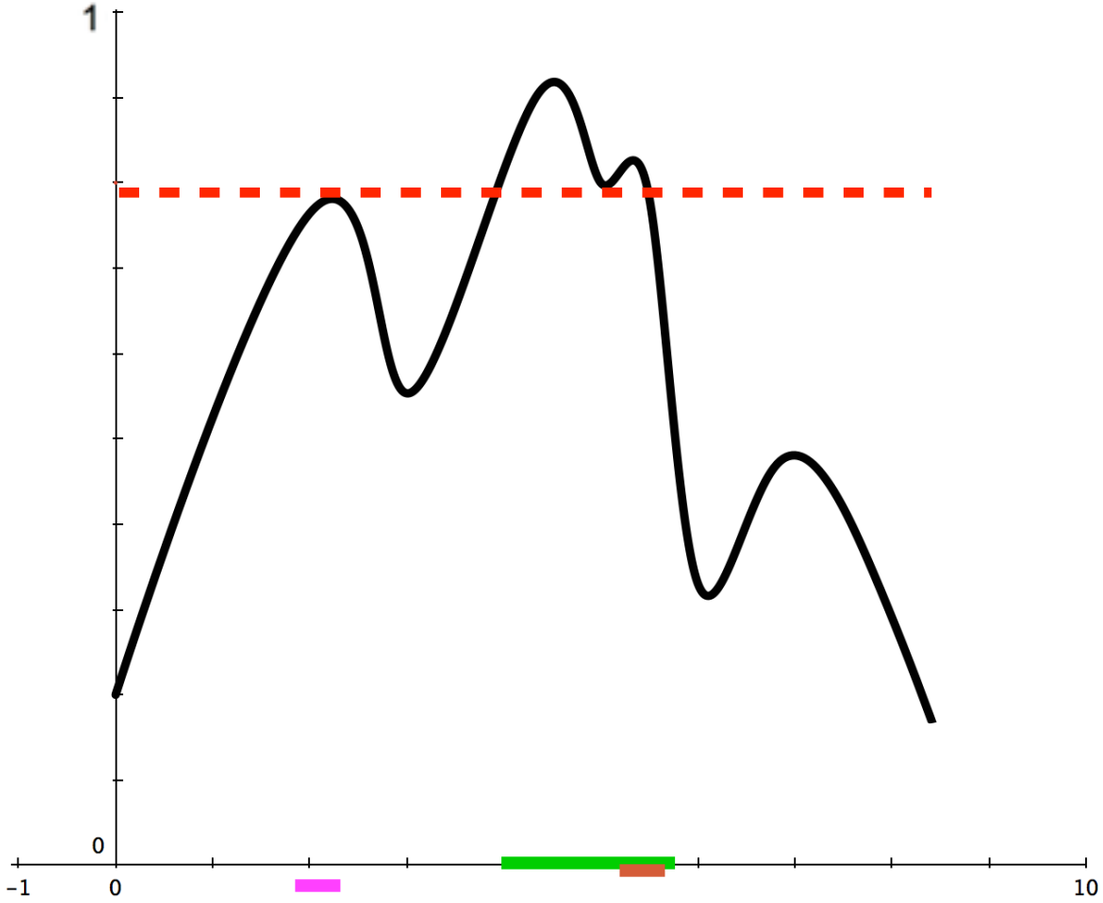

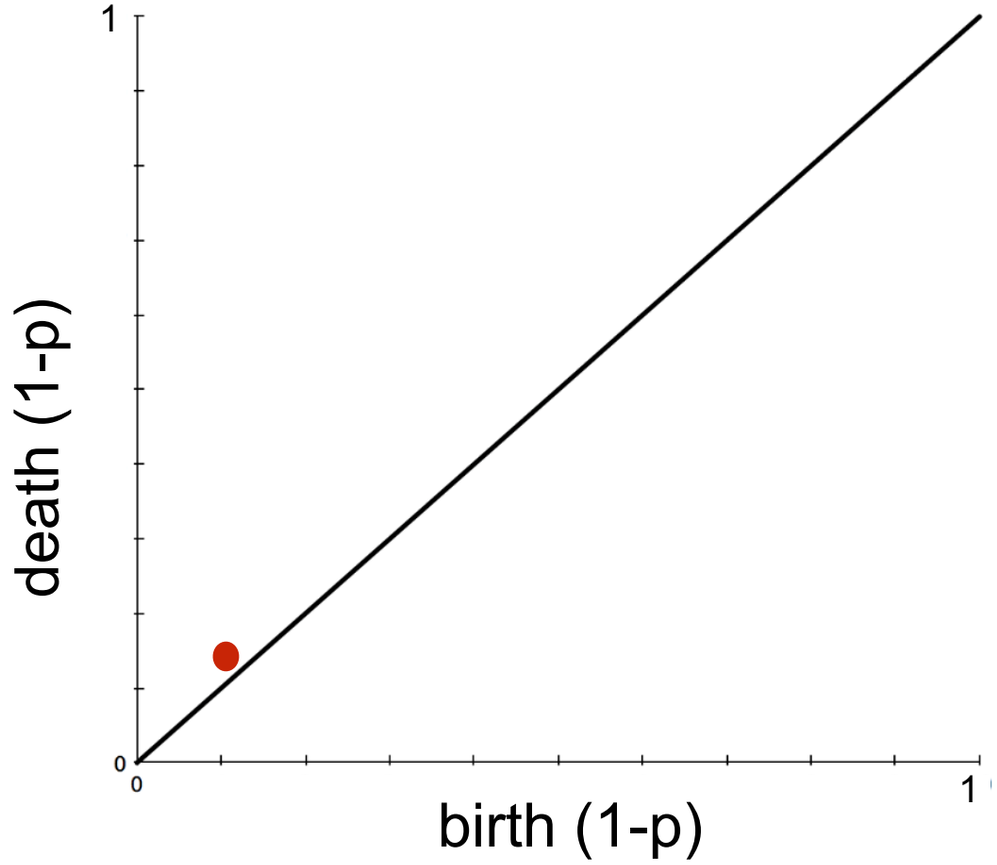

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Persistent Homology

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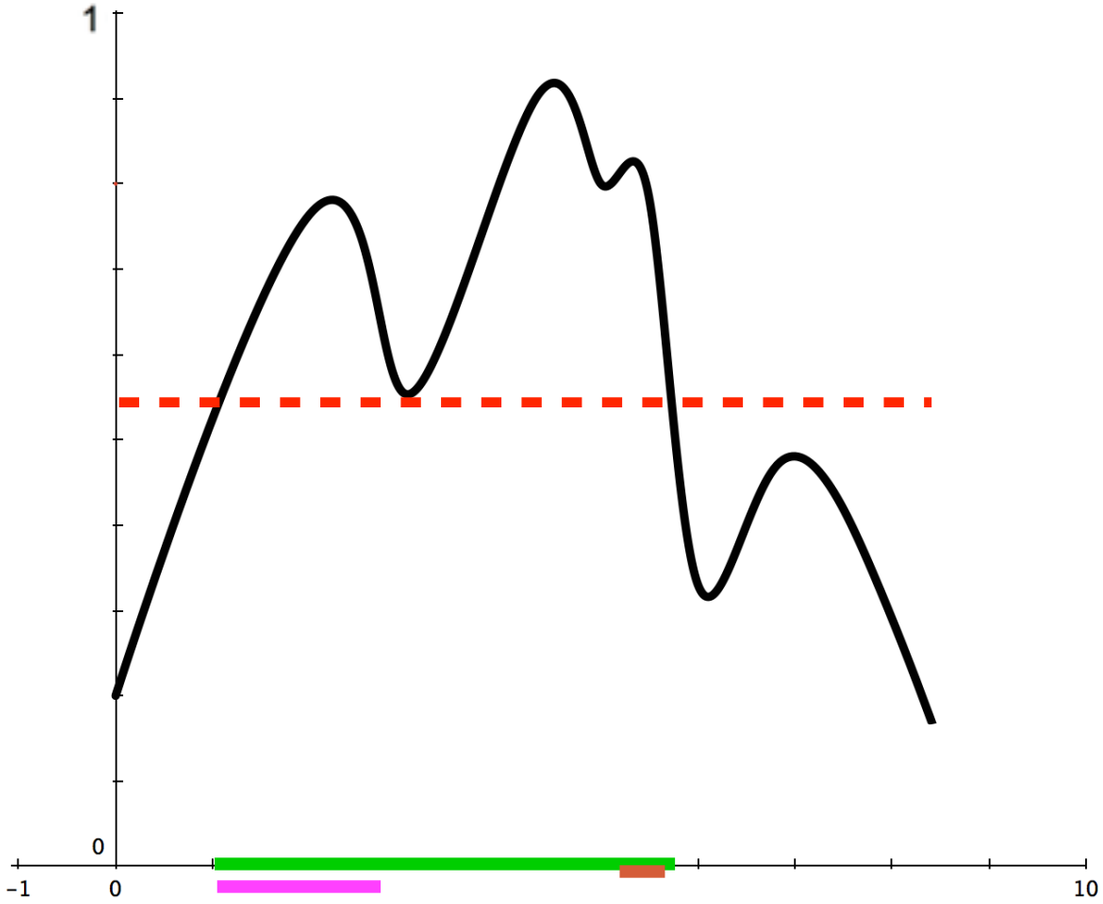

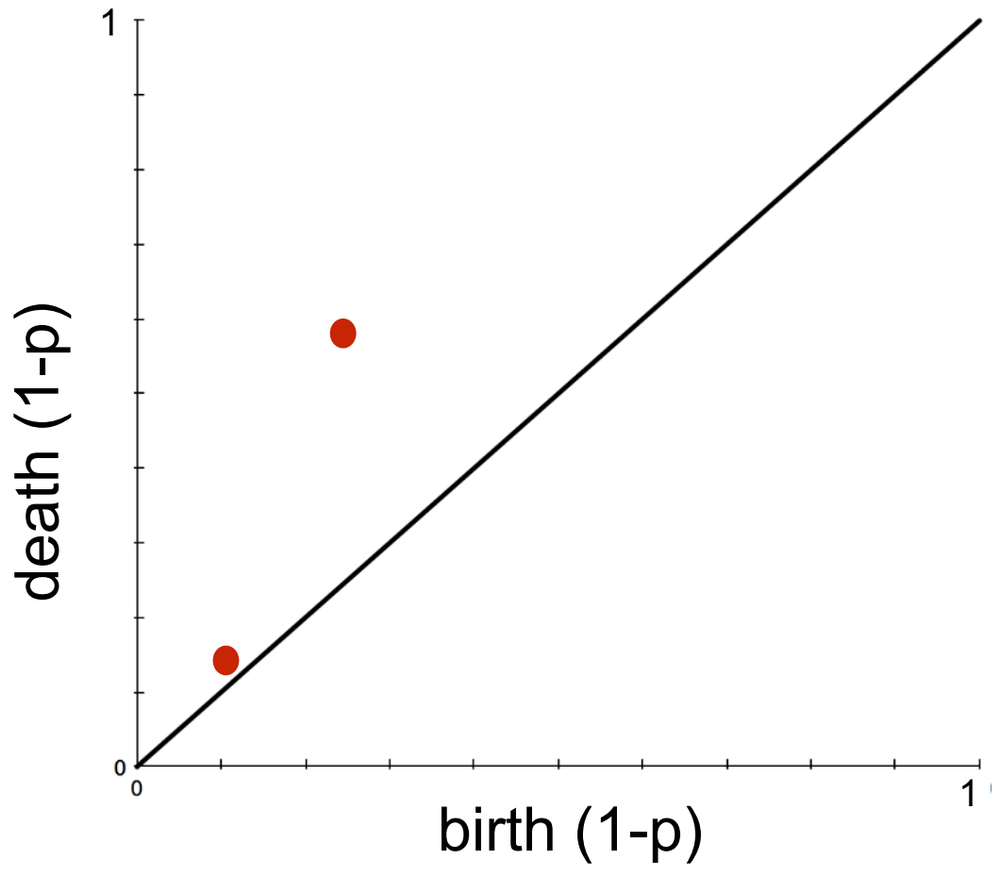

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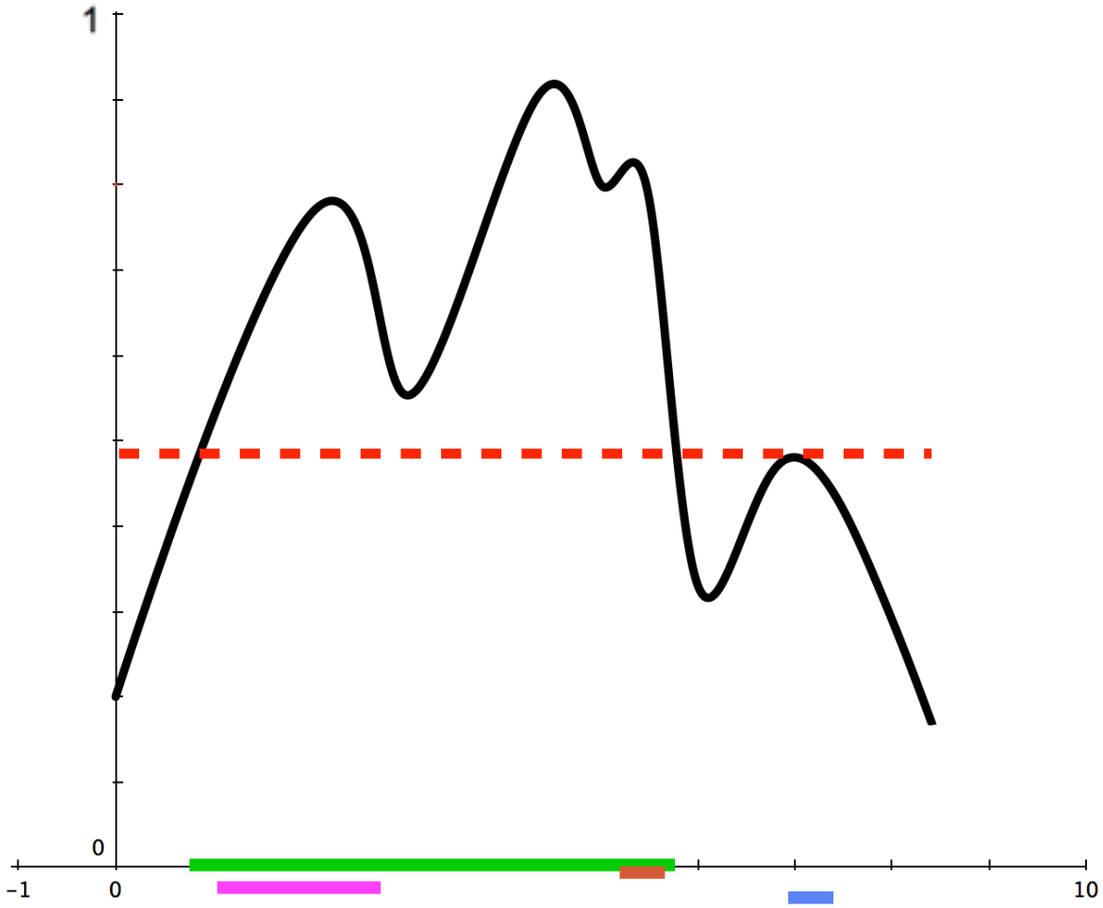
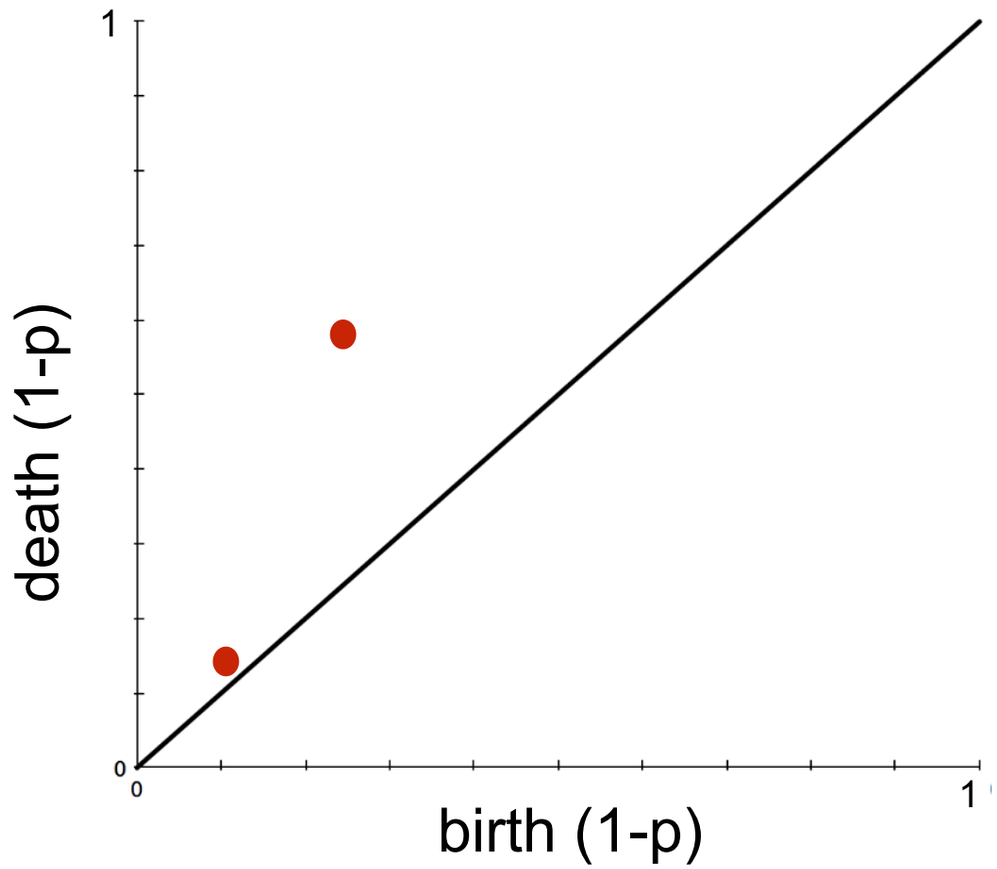
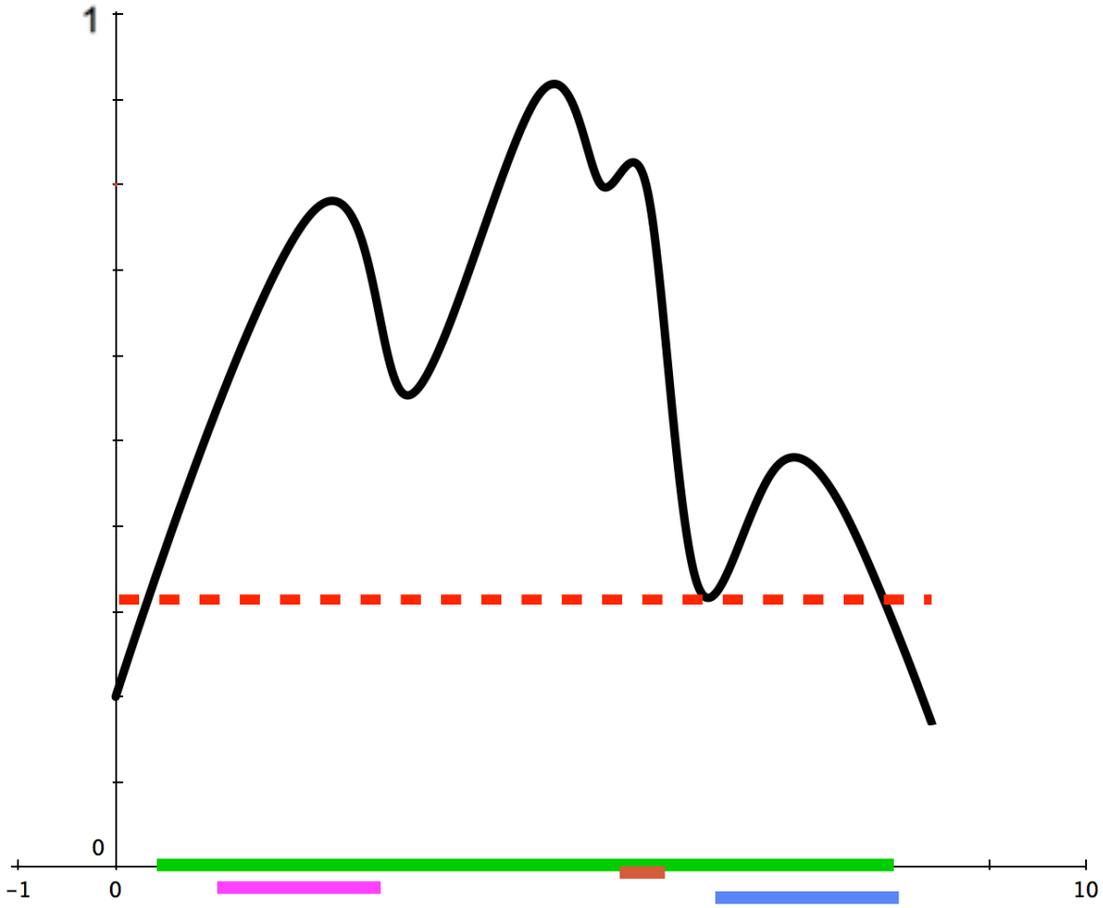
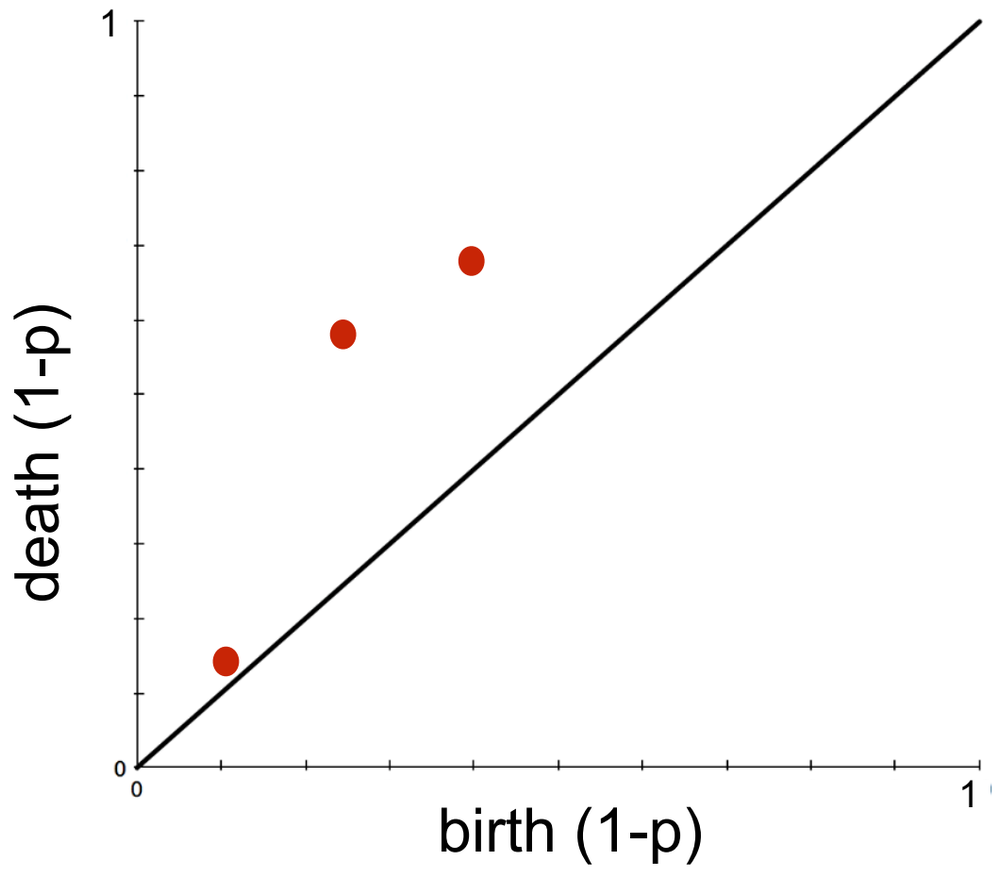




Persistent Homology

- **Topological persistence**





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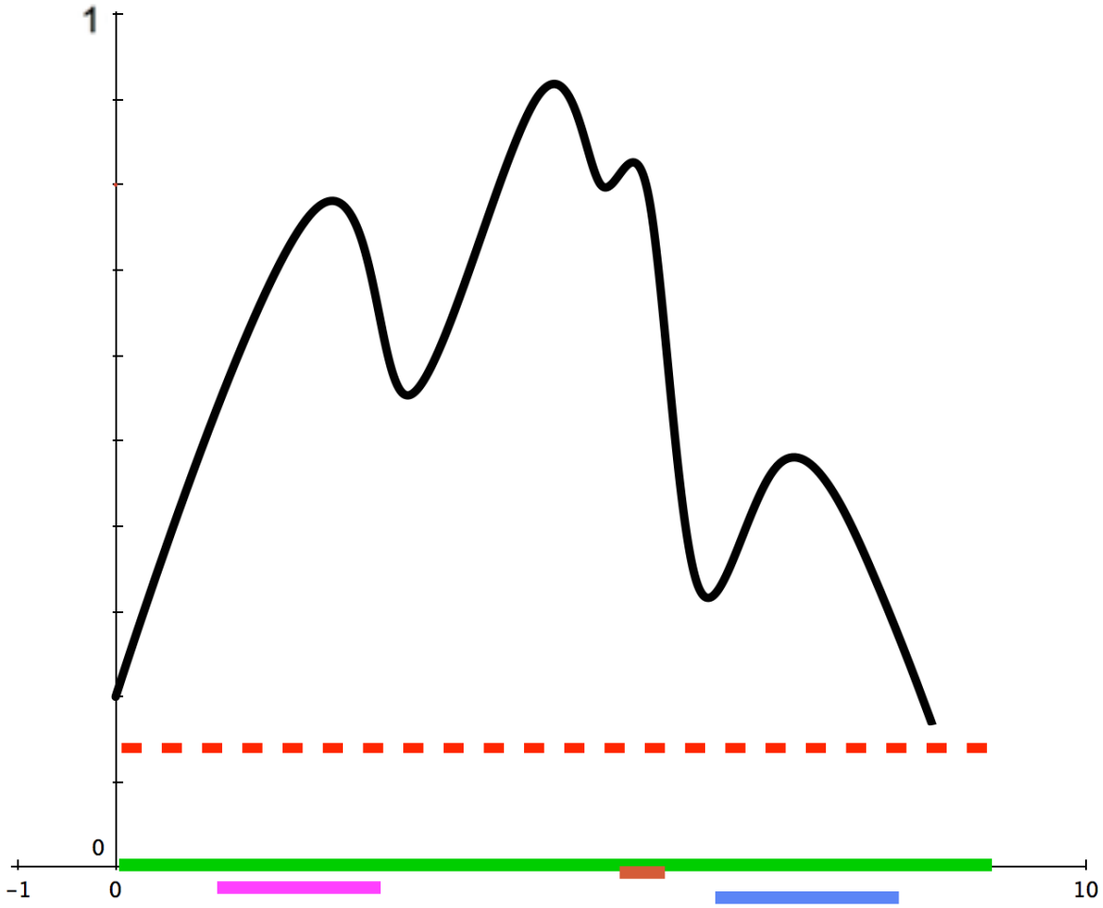
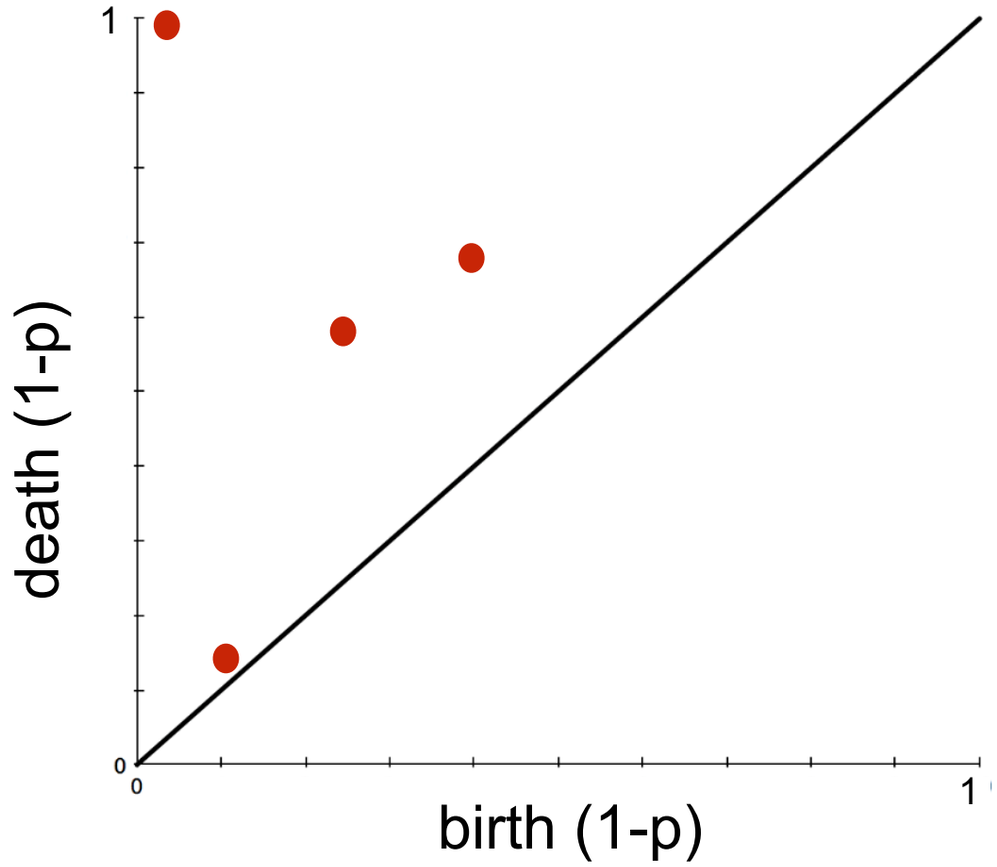
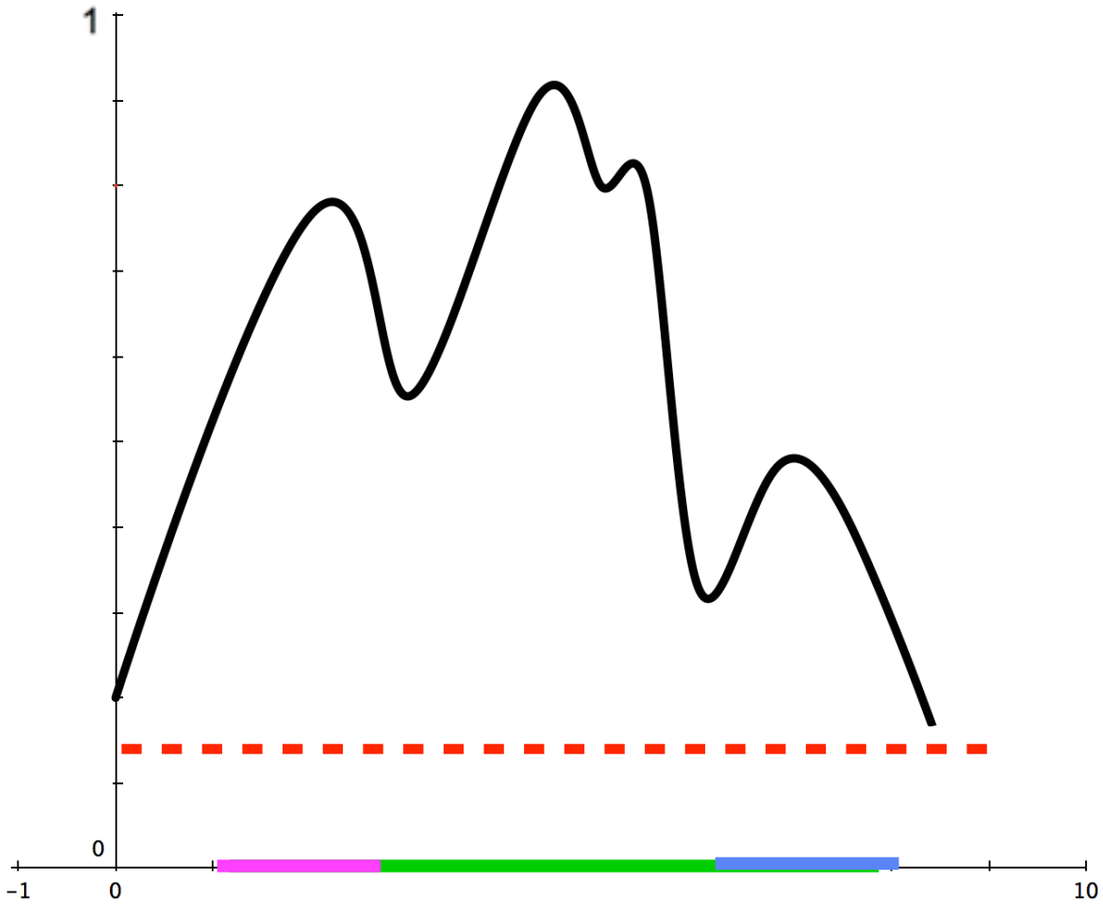
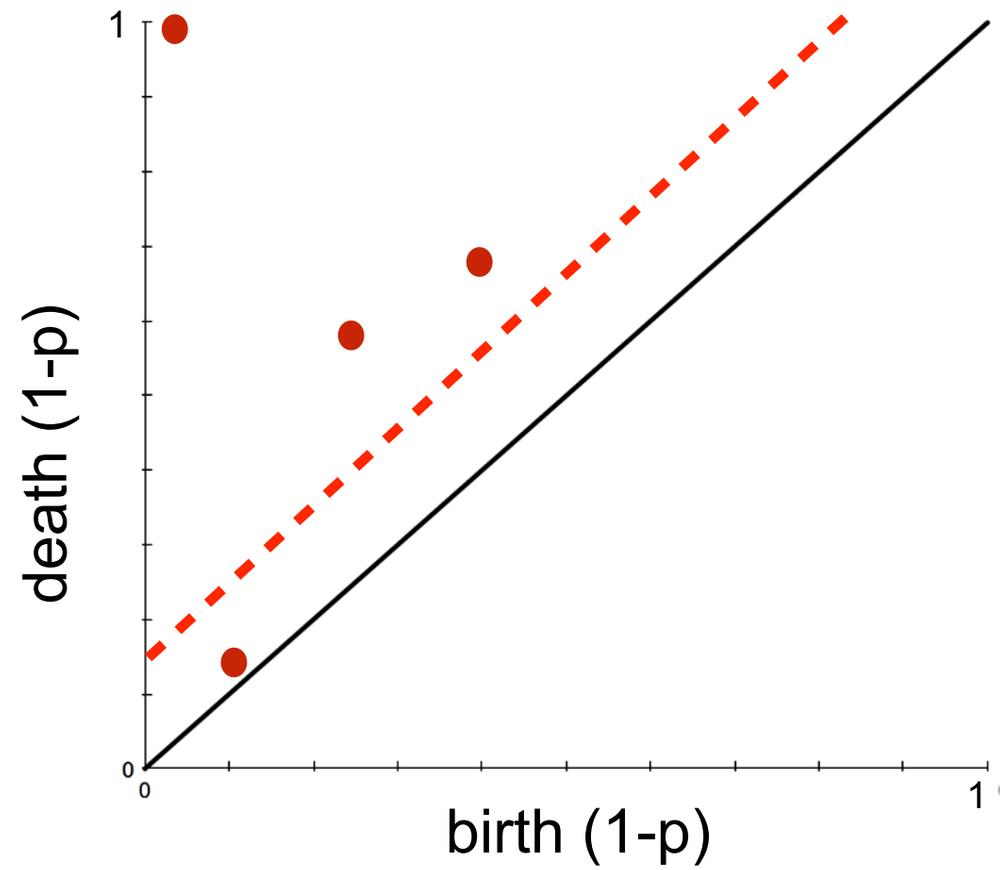




Persistent Homology

- **Topological persistence**





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Persistent Homology

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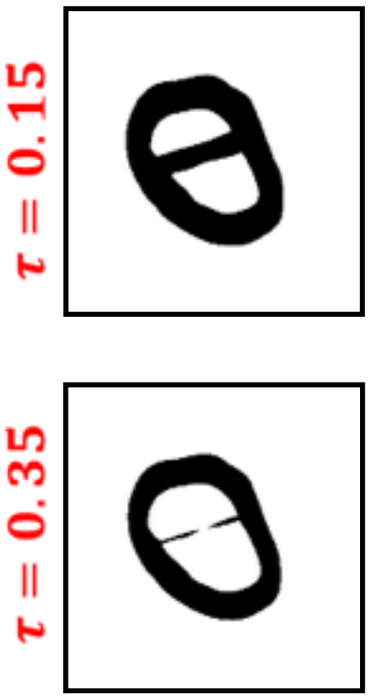
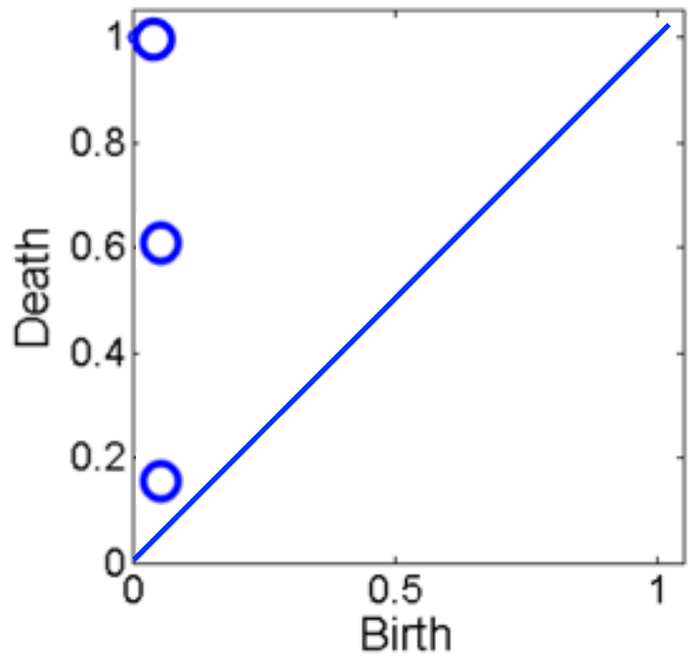
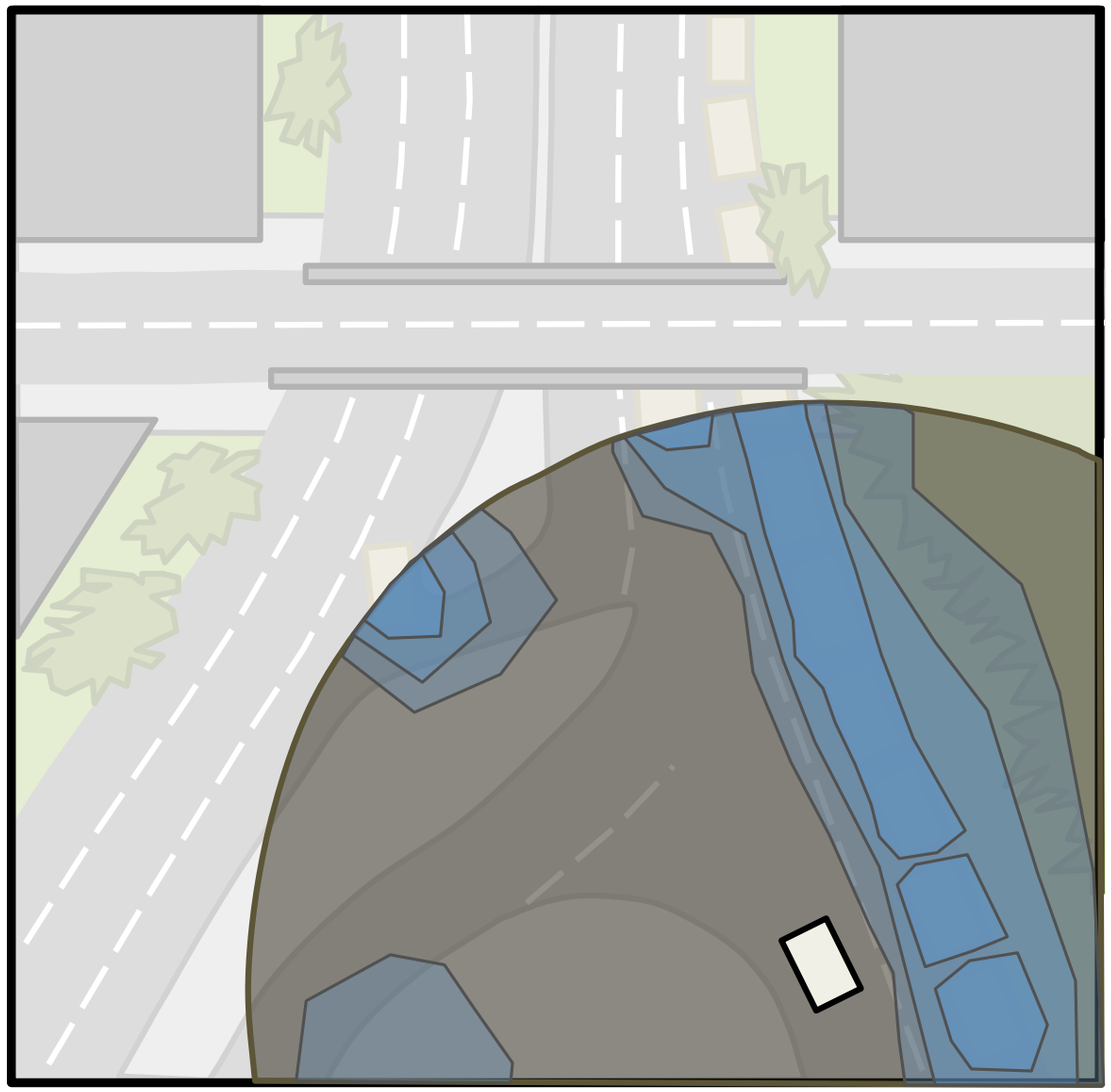
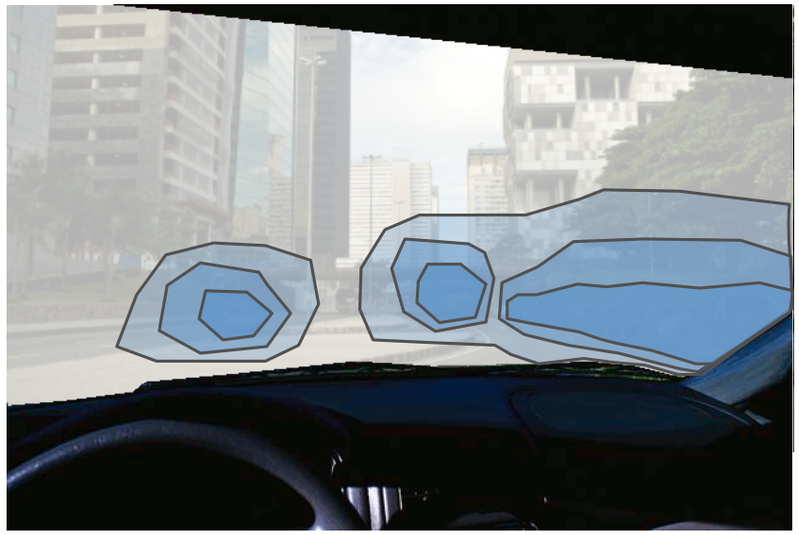




Obstacle Segmentation of Outdoor Scene

- **Vision system for autonomous driving**





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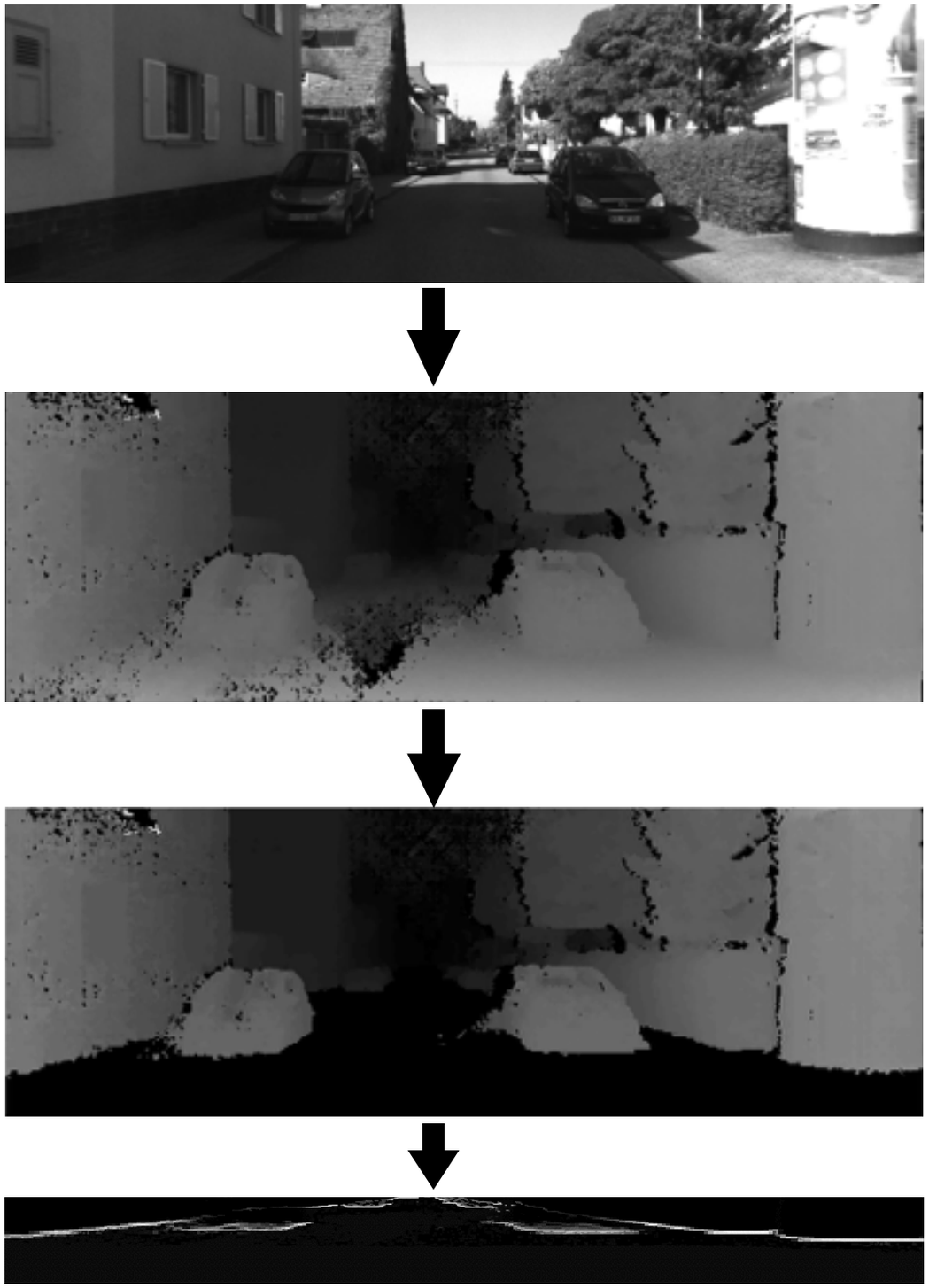
Obstacle Segmentation of Outdoor Scene



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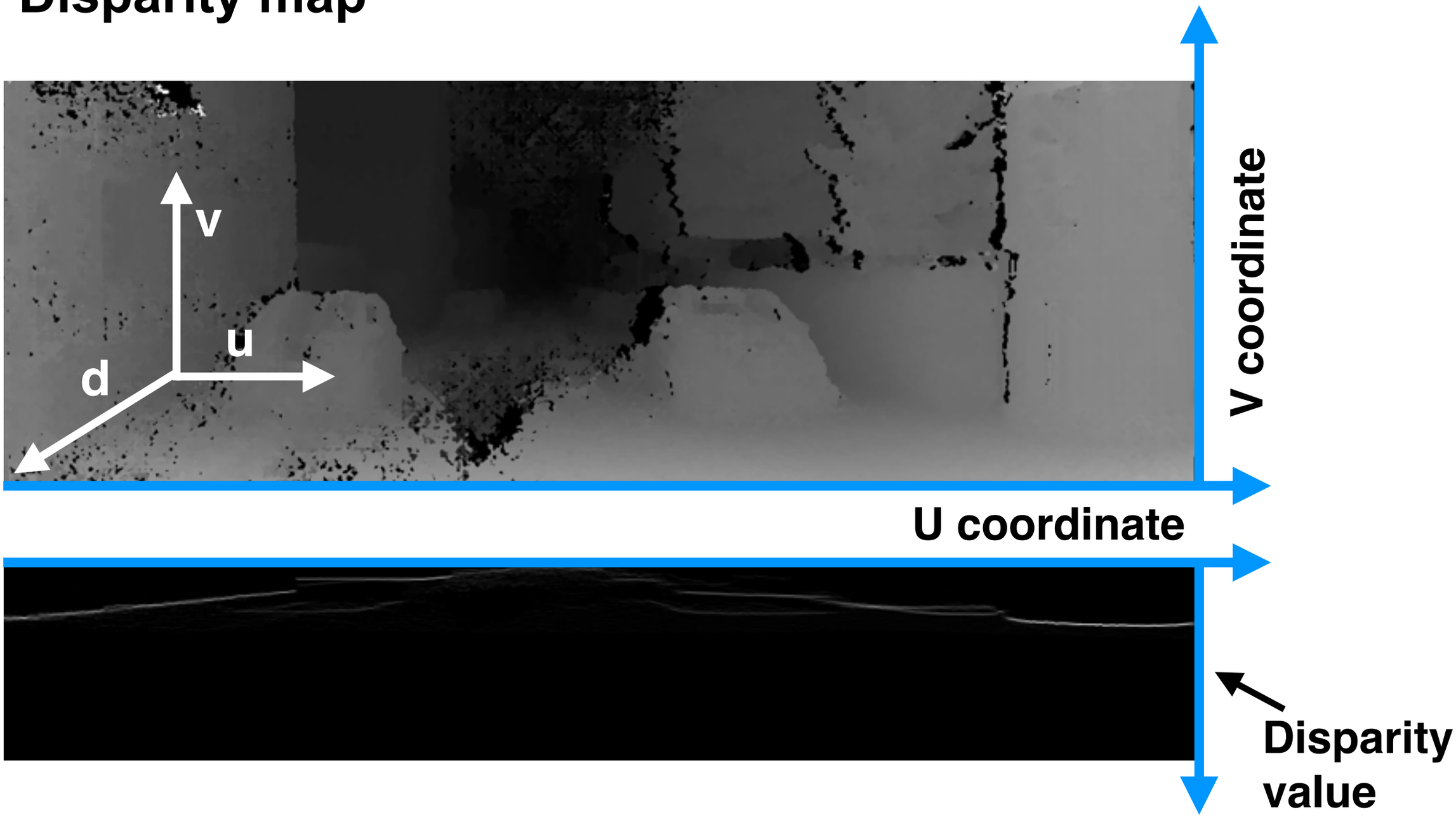
Obstacle Segmentation of Outdoor Scene

- **Disparity map**



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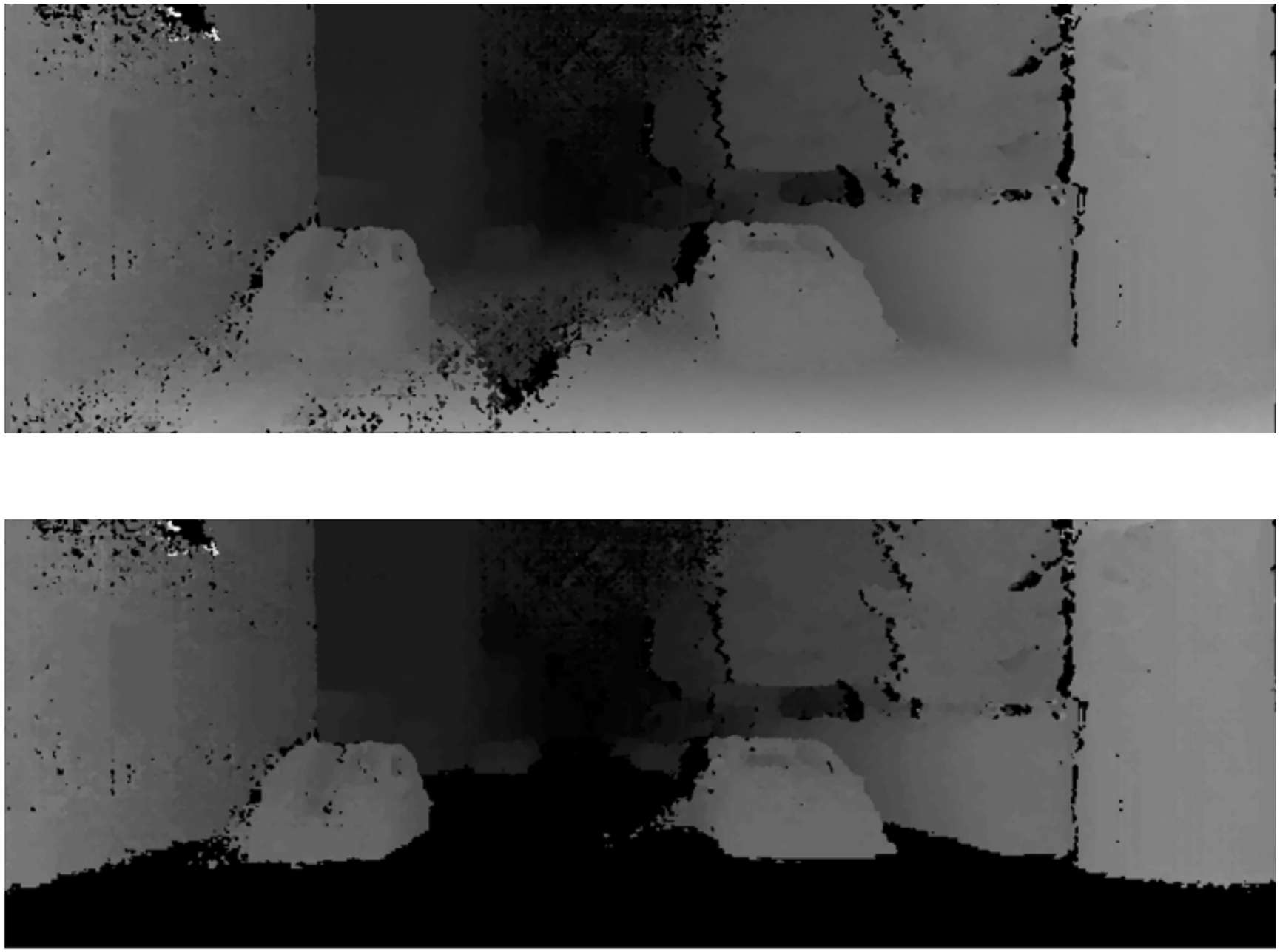
Obstacle Segmentation of Outdoor Scene

- **Ground Segmentation**



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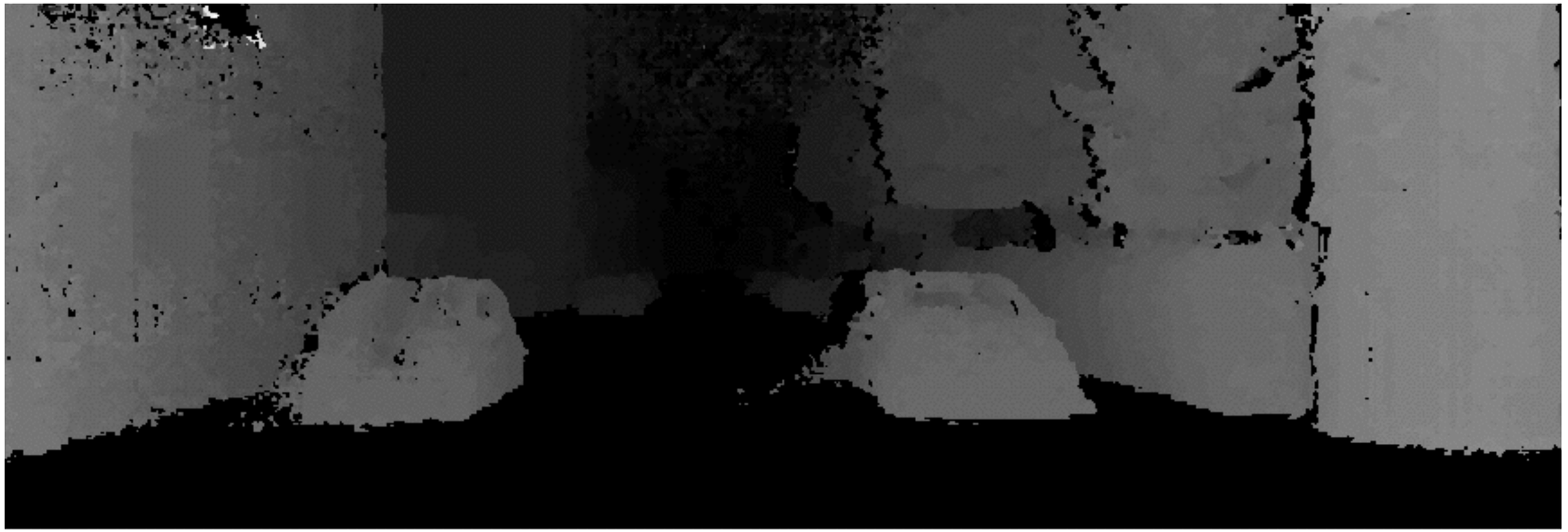
Obstacle Segmentation of Outdoor Scene

- **Occupancy computation**



M. Perrollaz, J.-D. Yoder, A. Ne`gre, A. Spalanzani, and C. Laugier, “A visibility-based approach for occupancy grid computation in disparity space,” *Intelligent Transportation Systems, IEEE Transactions on*, vol. 13, no. 3, pp. 1383–1393, 2012

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Obstacle Segmentation of Outdoor Scene

- **Occupancy computation**

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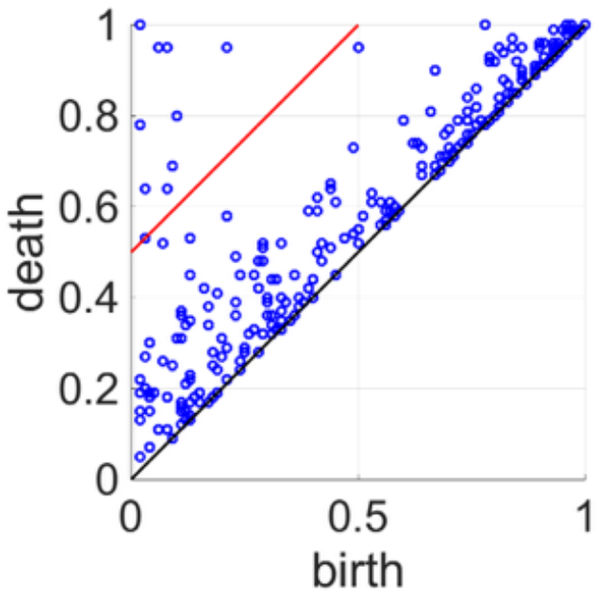
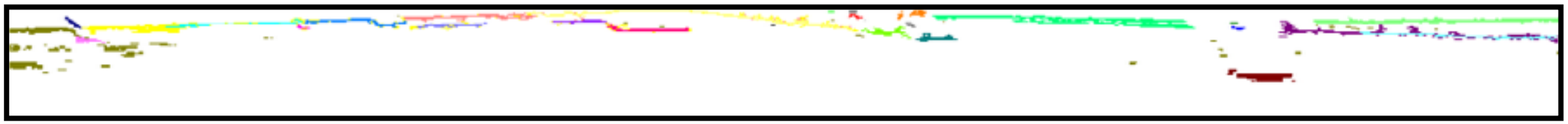
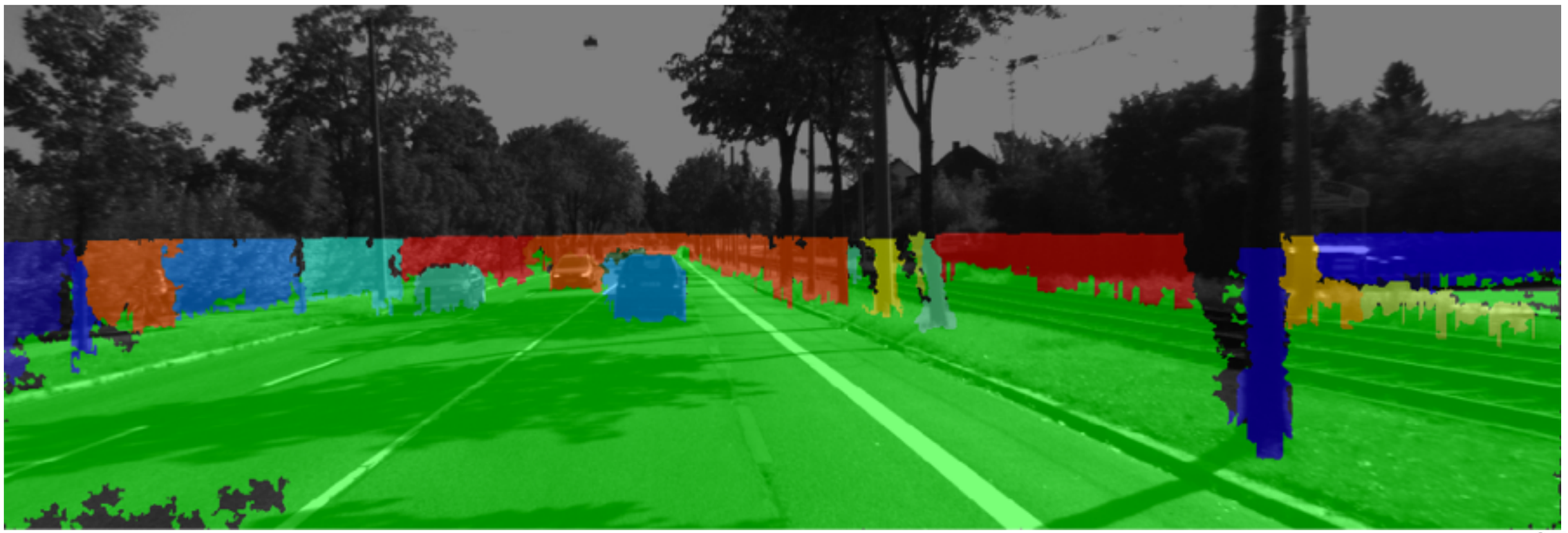
Obstacle Segmentation of Outdoor Scene

- **Persistence region extraction**







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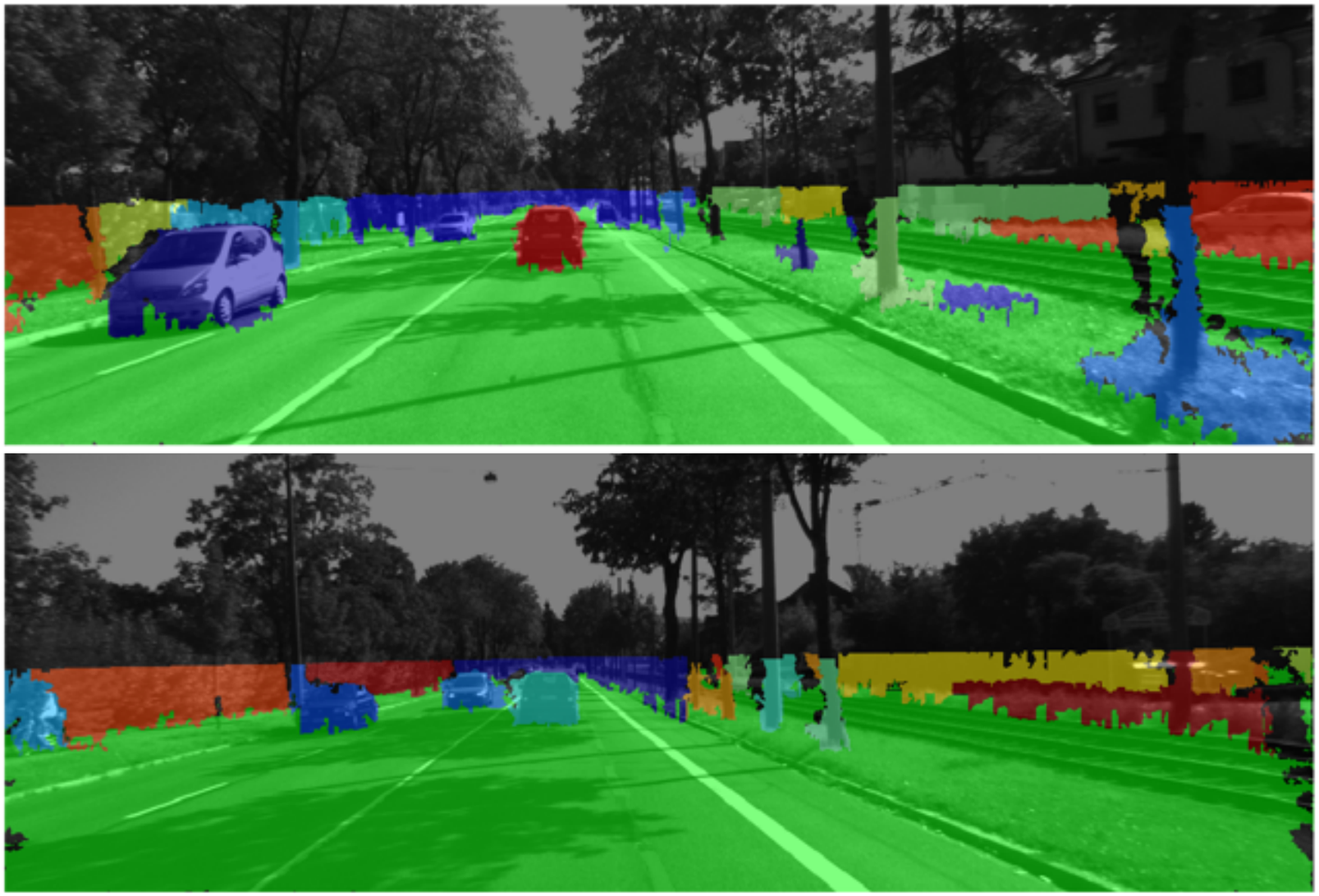
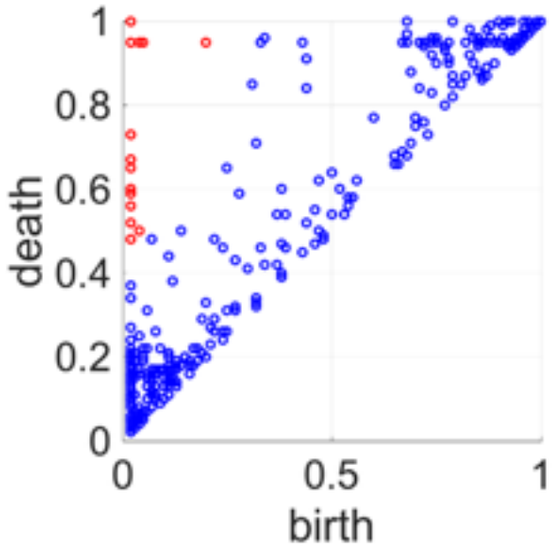
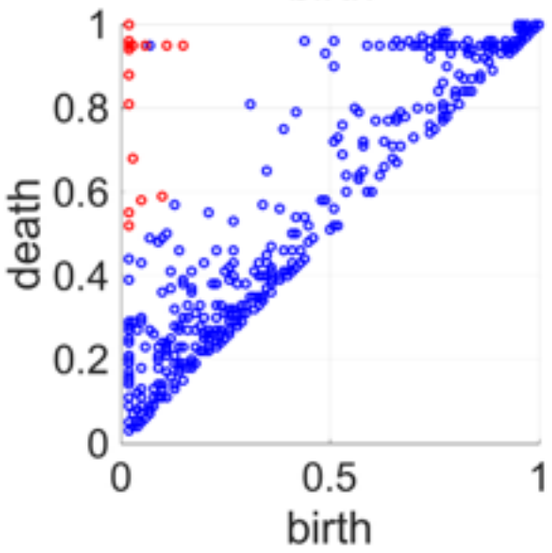
Obstacle Segmentation of Outdoor Scene

- **Experiment**
  - **Dataset - KITTI Vision Benchmark Suite**
  - **Persistence threshold = 0.45**







Obstacle Segmentation of Outdoor Scene

- **Experiment**
  - **Dataset - KITTI Vision Benchmark Suite**
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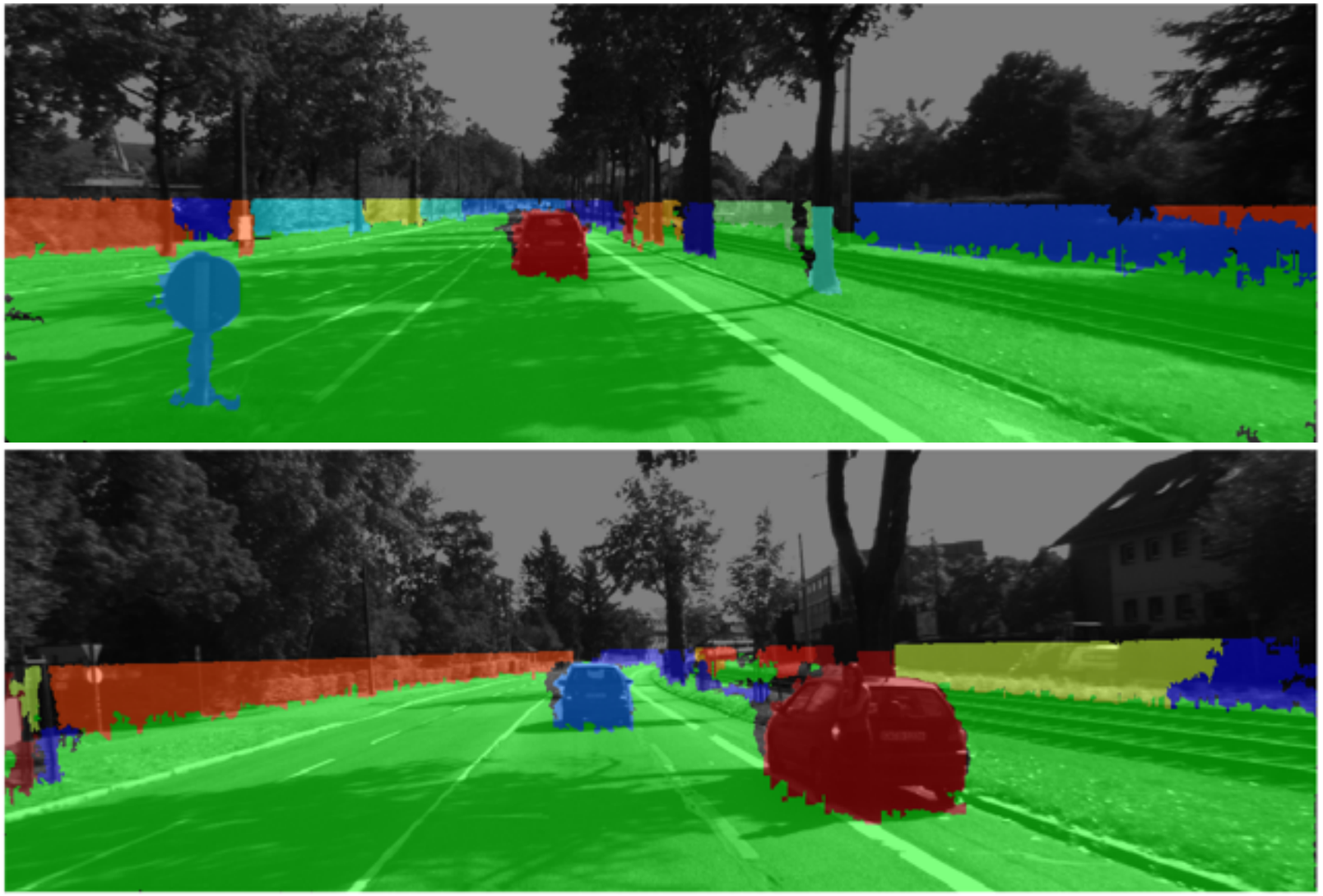

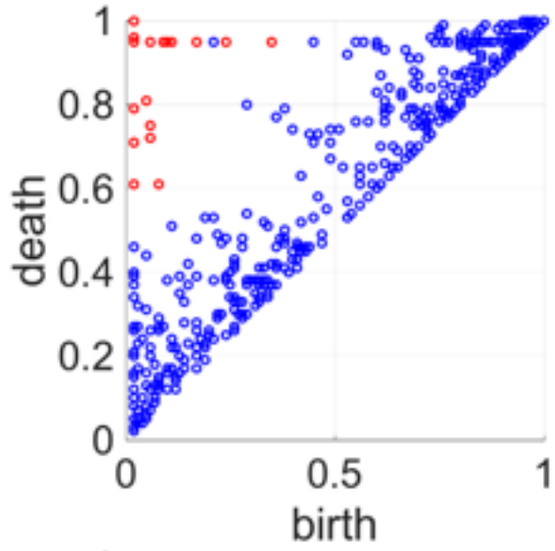

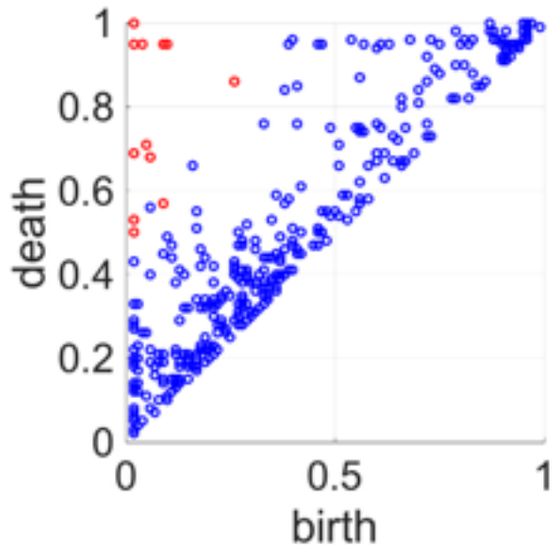

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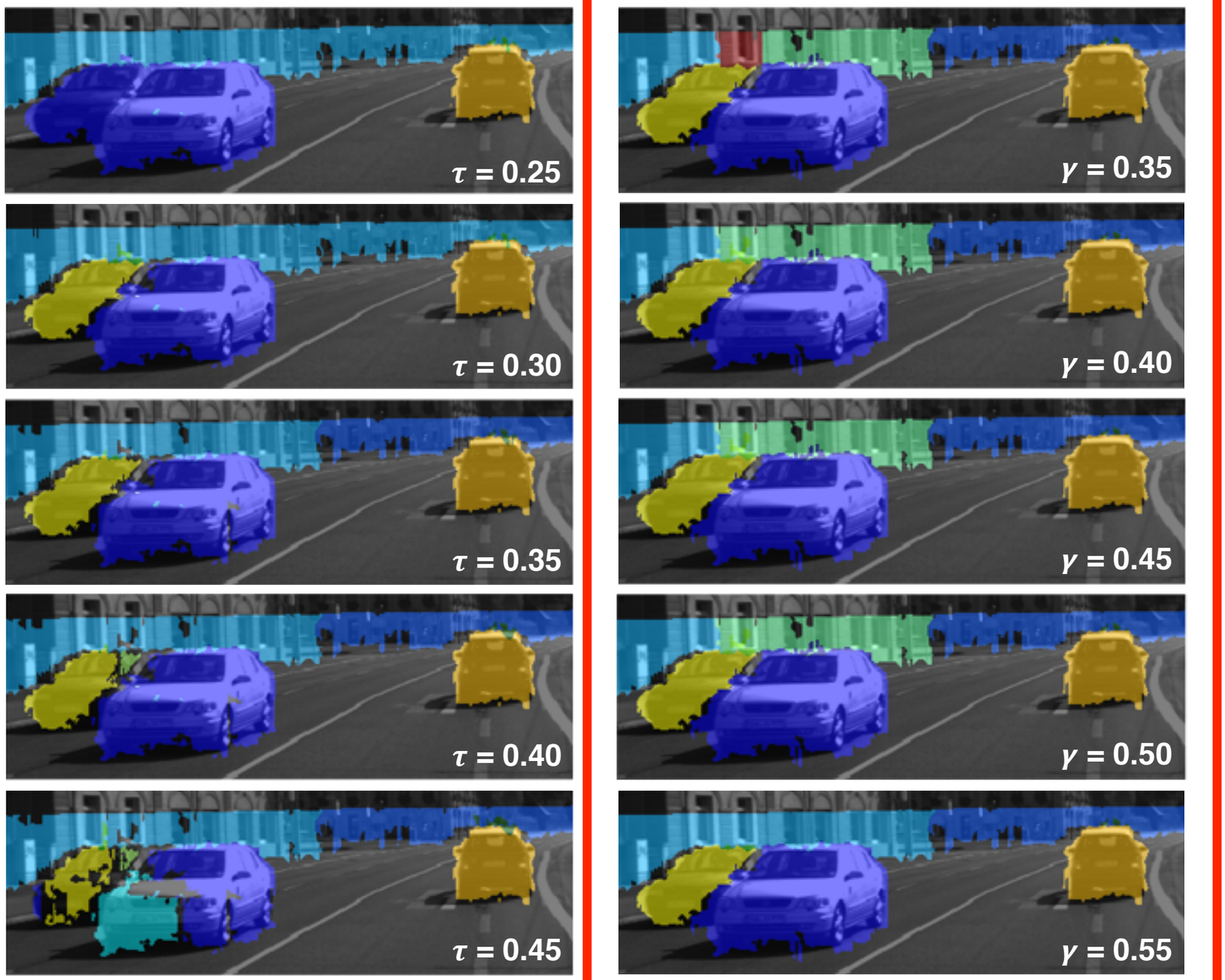
Obstacle Segmentation of Outdoor Scene

- **Experiment - Compare with simple thresholding**
  - **Changing thresholding parameters**



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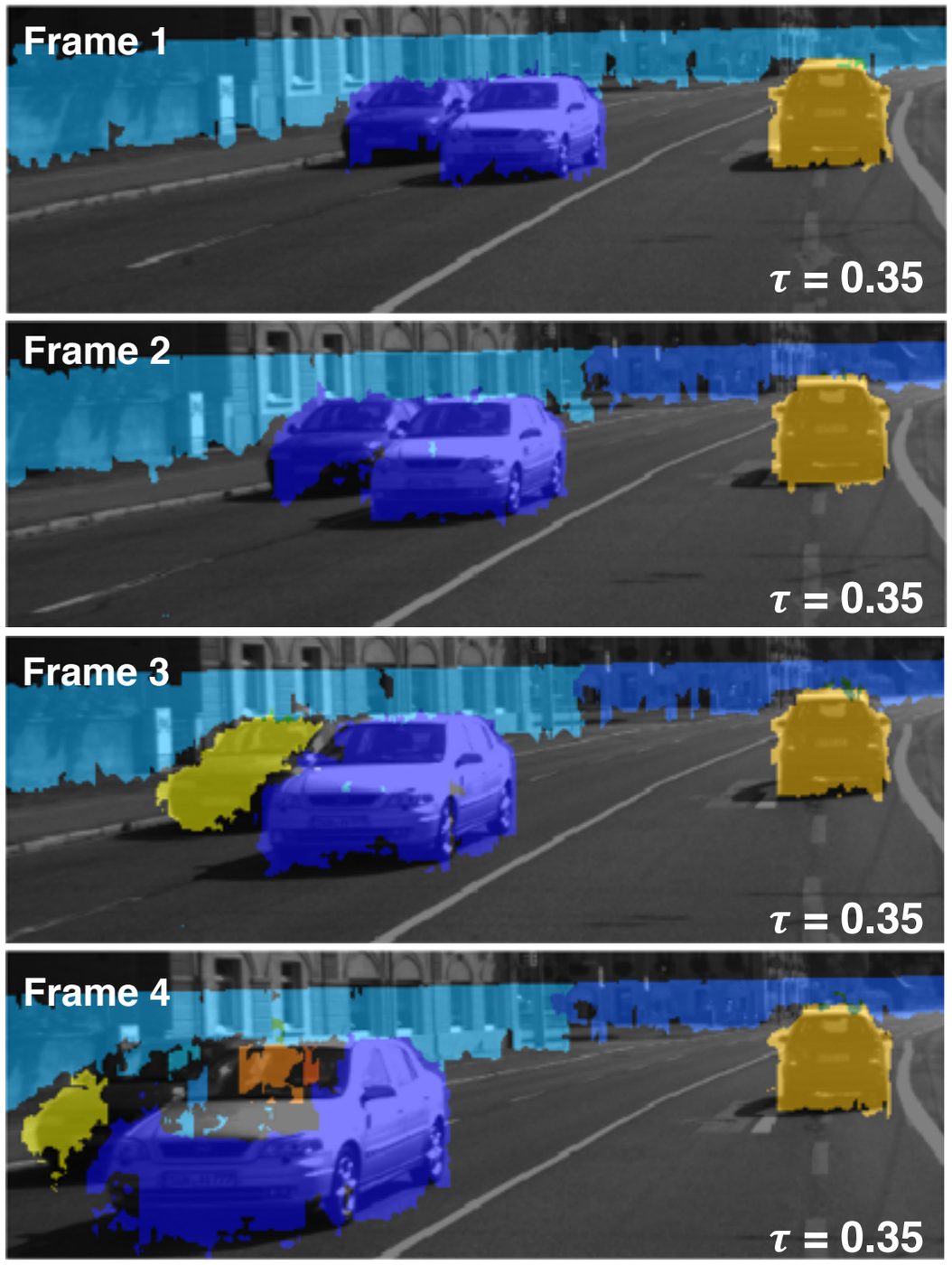
Obstacle Segmentation of Outdoor Scene

- **Experiment - Compare with simple thresholding**
  - **Changing images with the same threshold**



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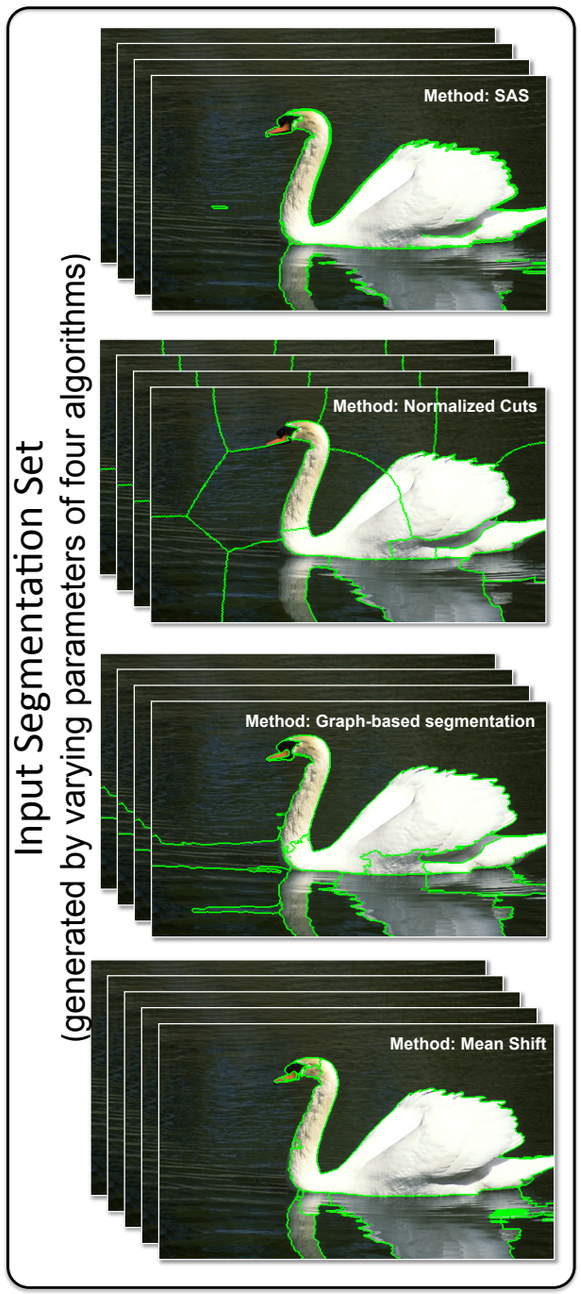
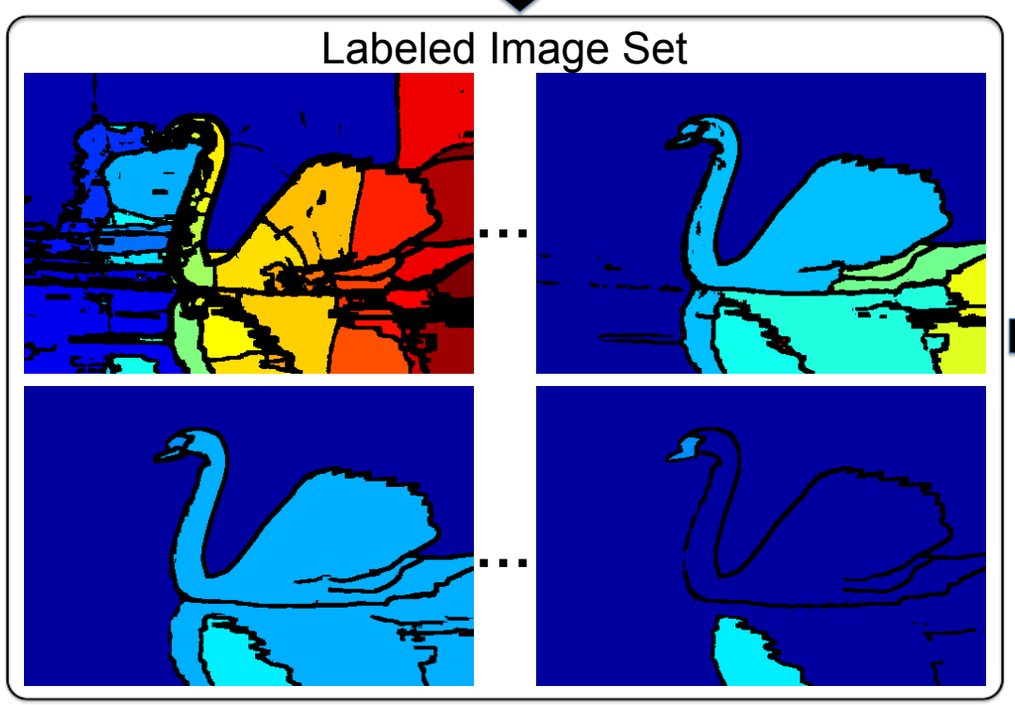
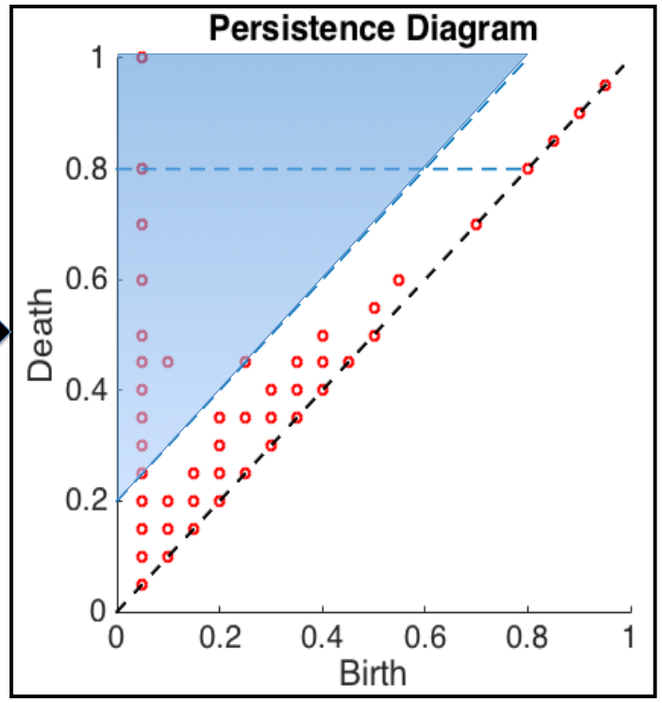
Consensus-based Image Segmentation

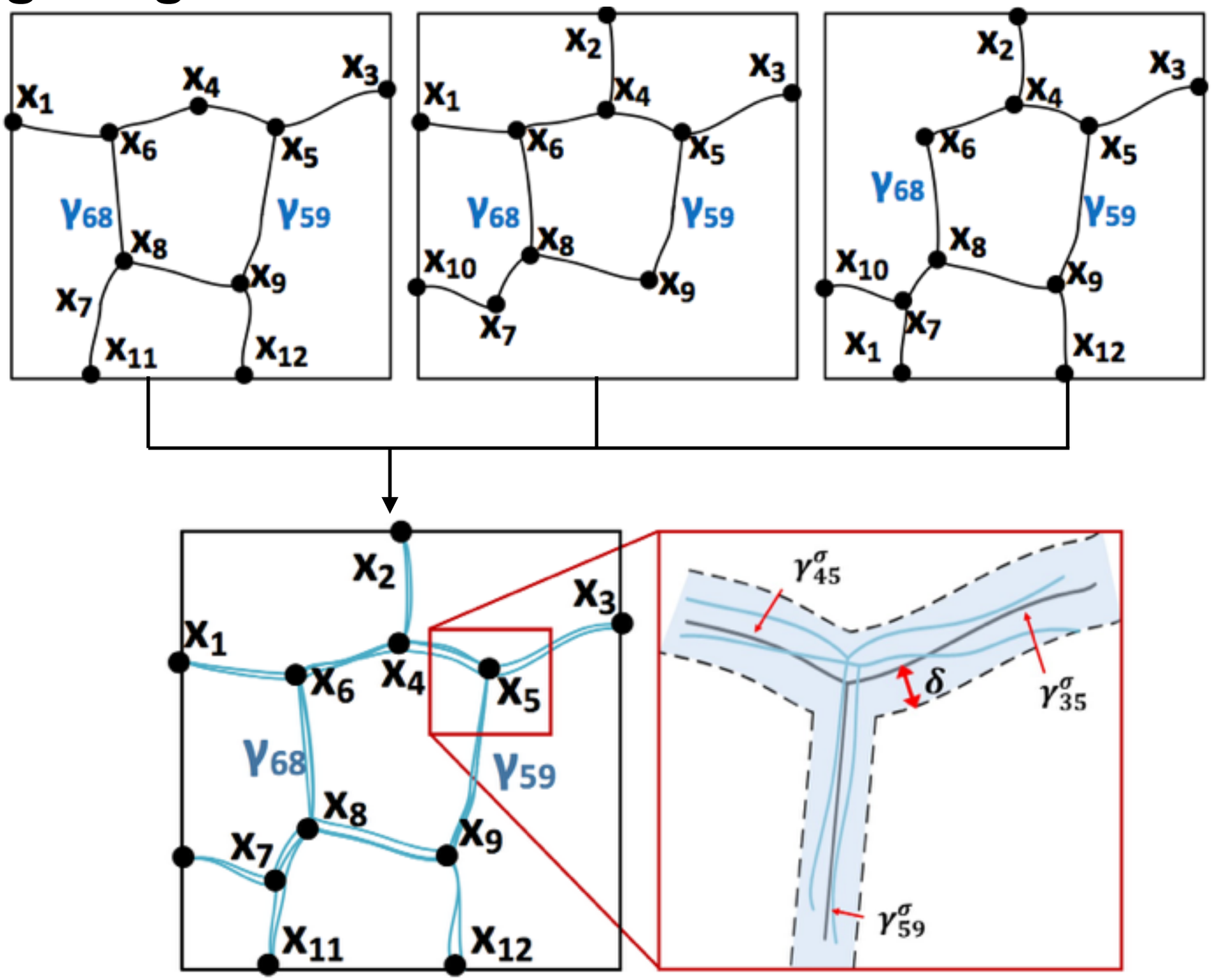






Consensus-based Image Segmentation

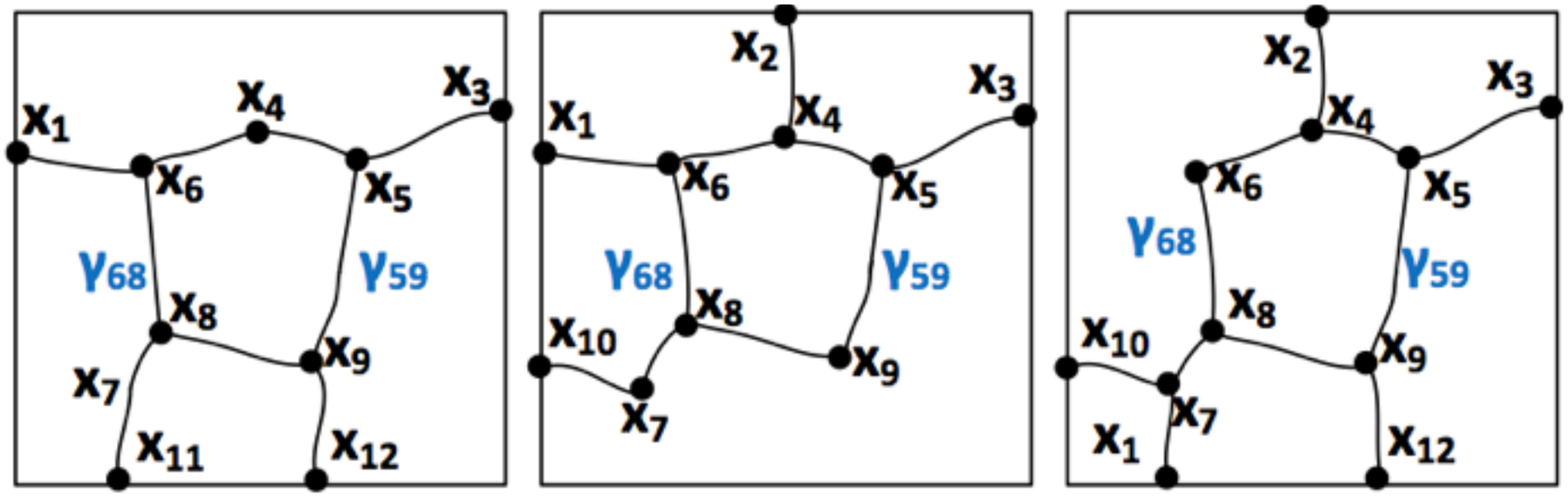
- **Image segmentation model**



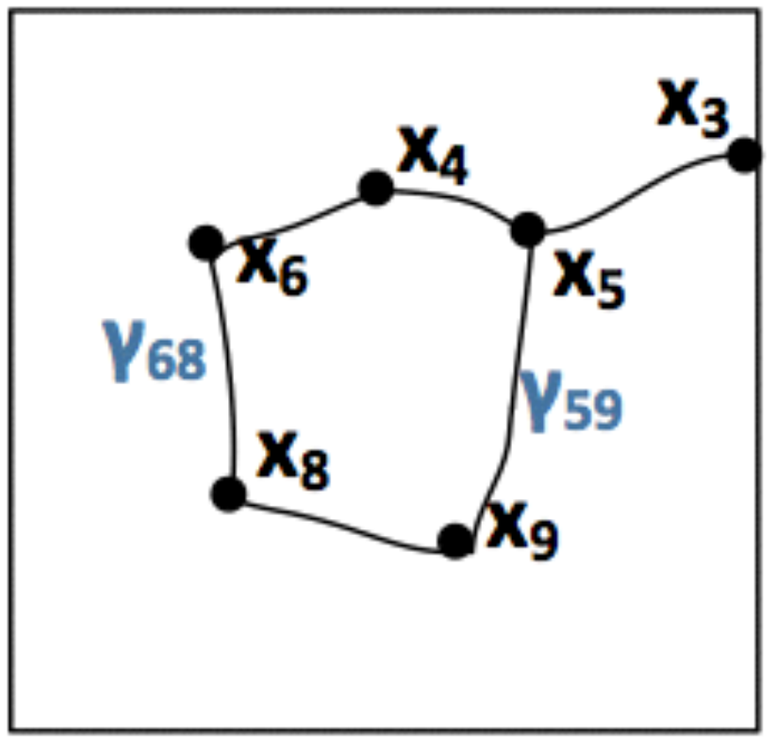
Consensus-based Image Segmentation

- **Image segmentation model**

Input

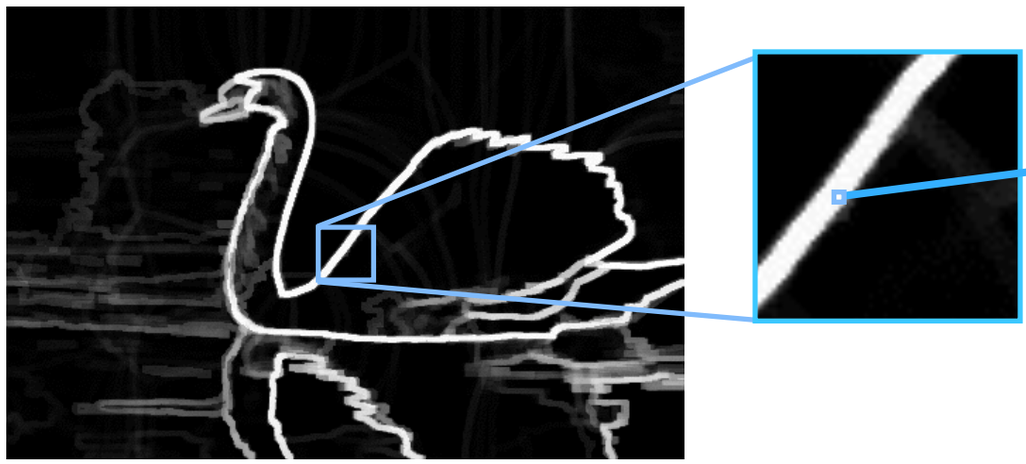


Segmentation Result



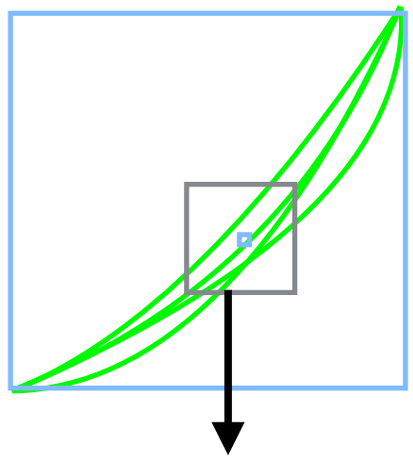
Consensus-based Image Segmentation

- **Probability map construction**



Probability of edge at this pixel

Overlay



D*(X) = # edge / # segmentations

A small patch around pixel X

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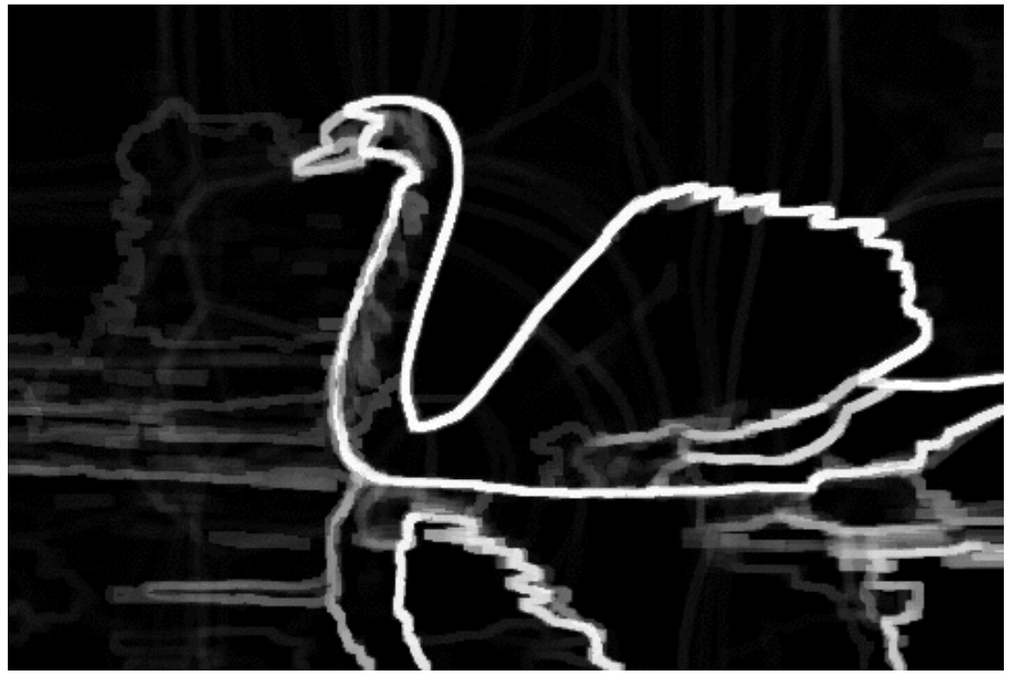
Consensus-based Image Segmentation

- **Probability map construction**

Connection probability map

$$1 - D_n^*(x)$$

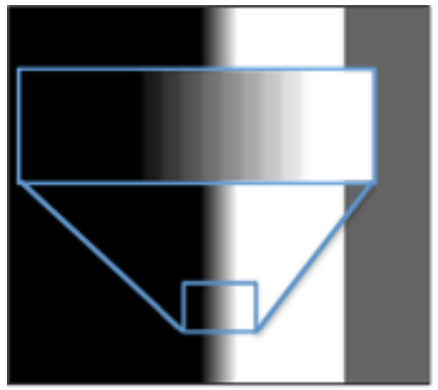


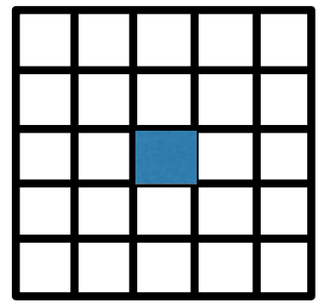
Edge probability map

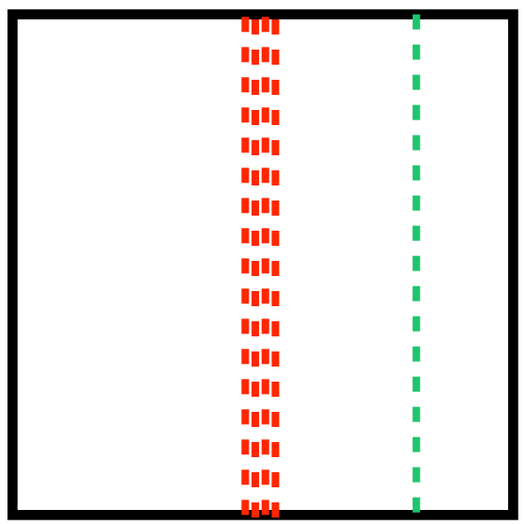
$$D_n^*(x)$$

Consensus-based Image Segmentation

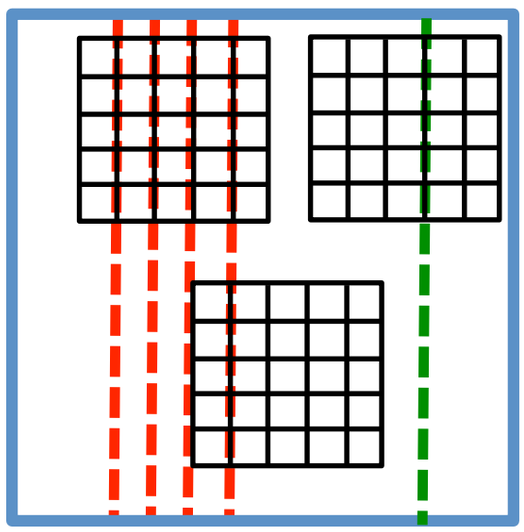
- **Effect of patch size n**



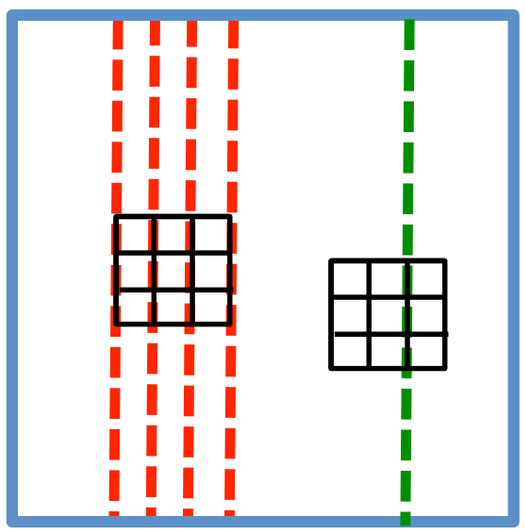




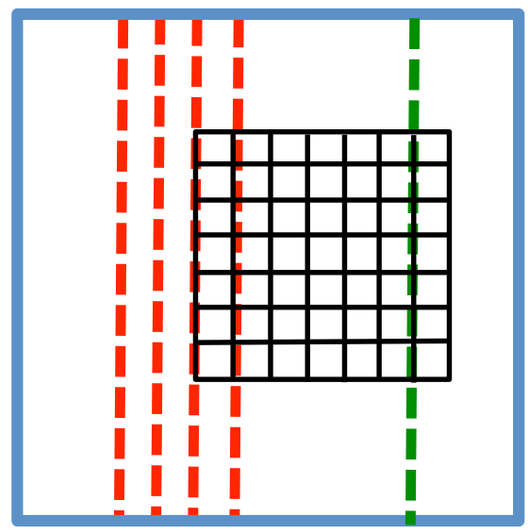
True Probability



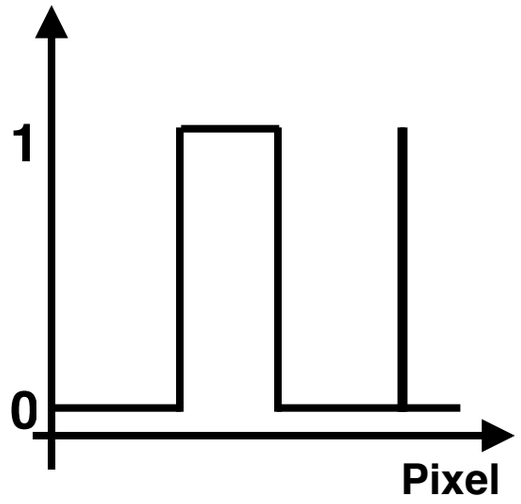
Proper Patch

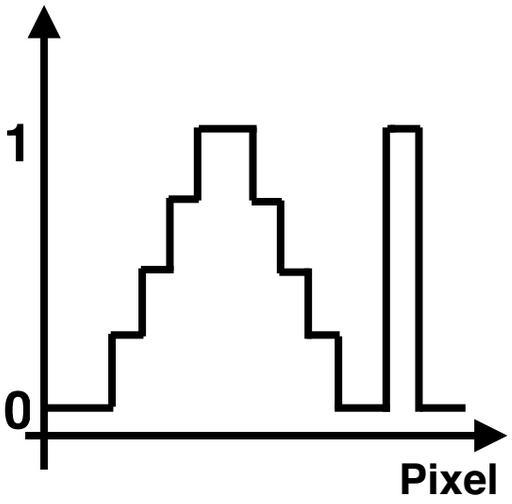


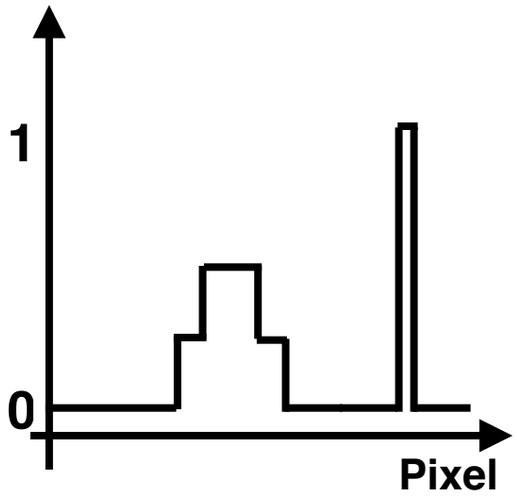
Small Patch

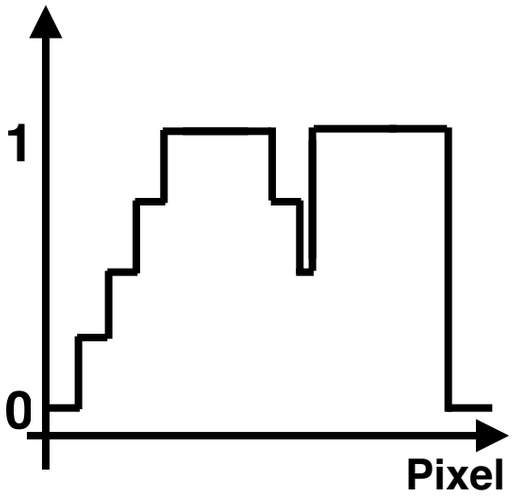


Large Patch









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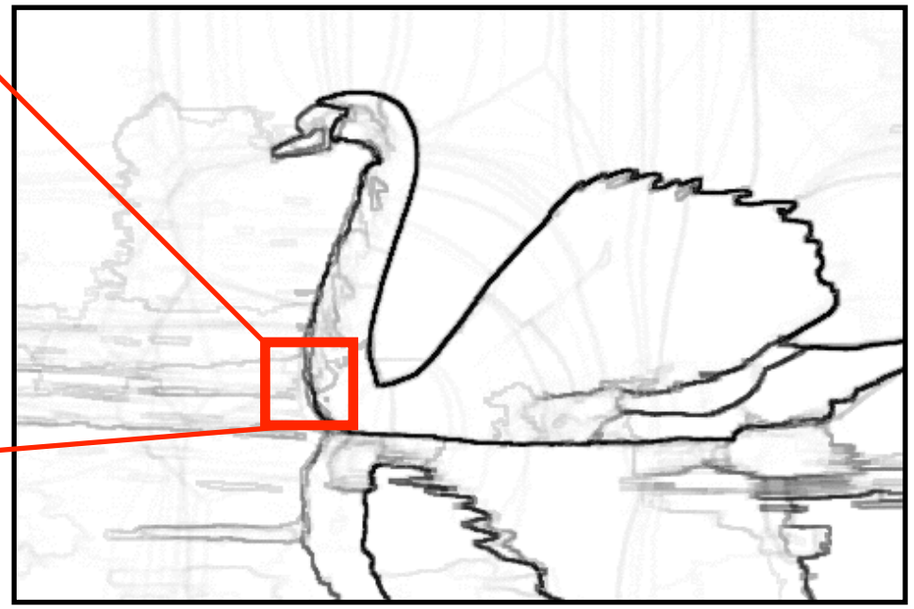
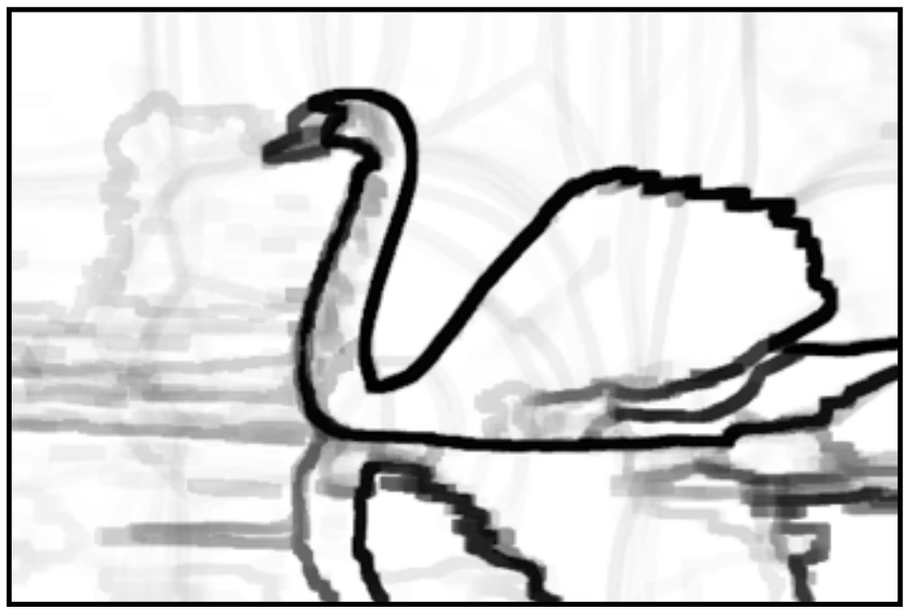
Consensus-based Image Segmentation

- **Effect of patch size n**

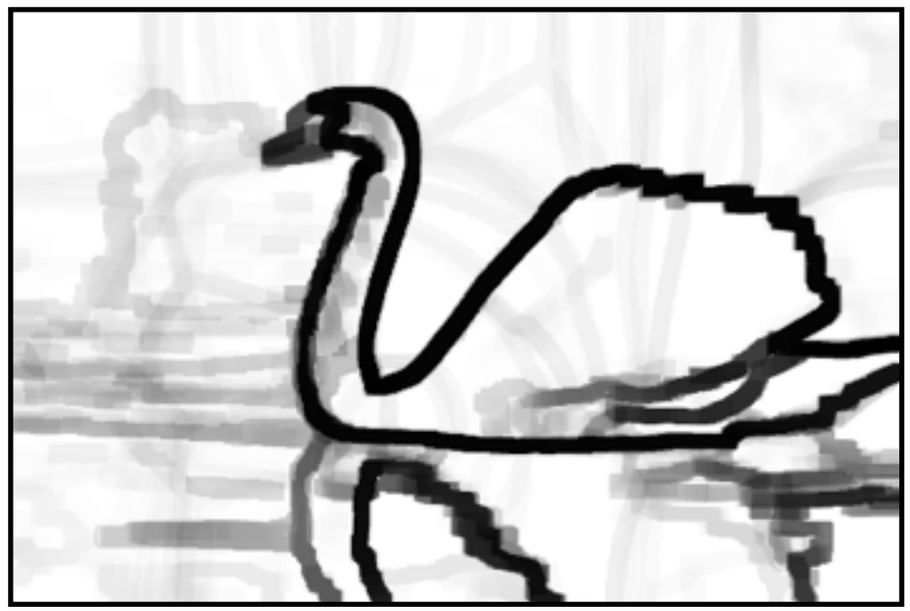


n=3

n=5



n=7



n=9

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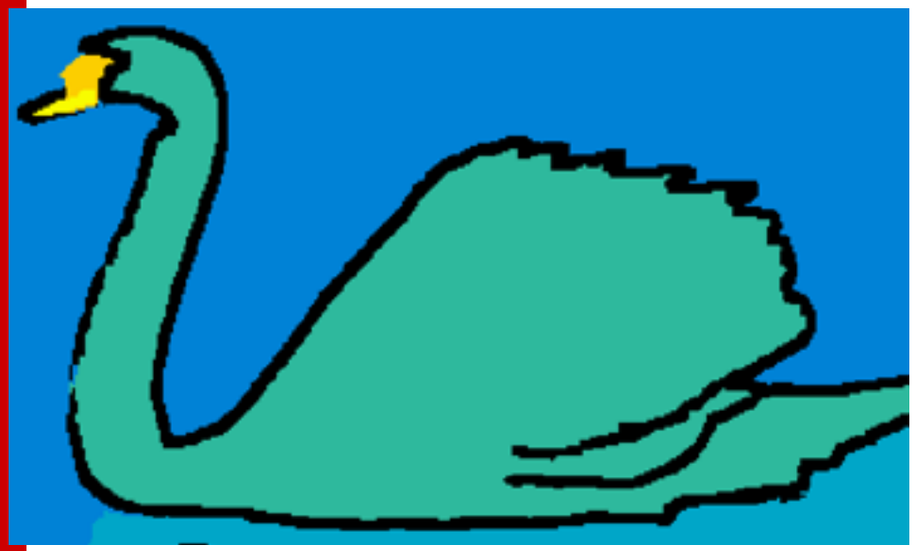
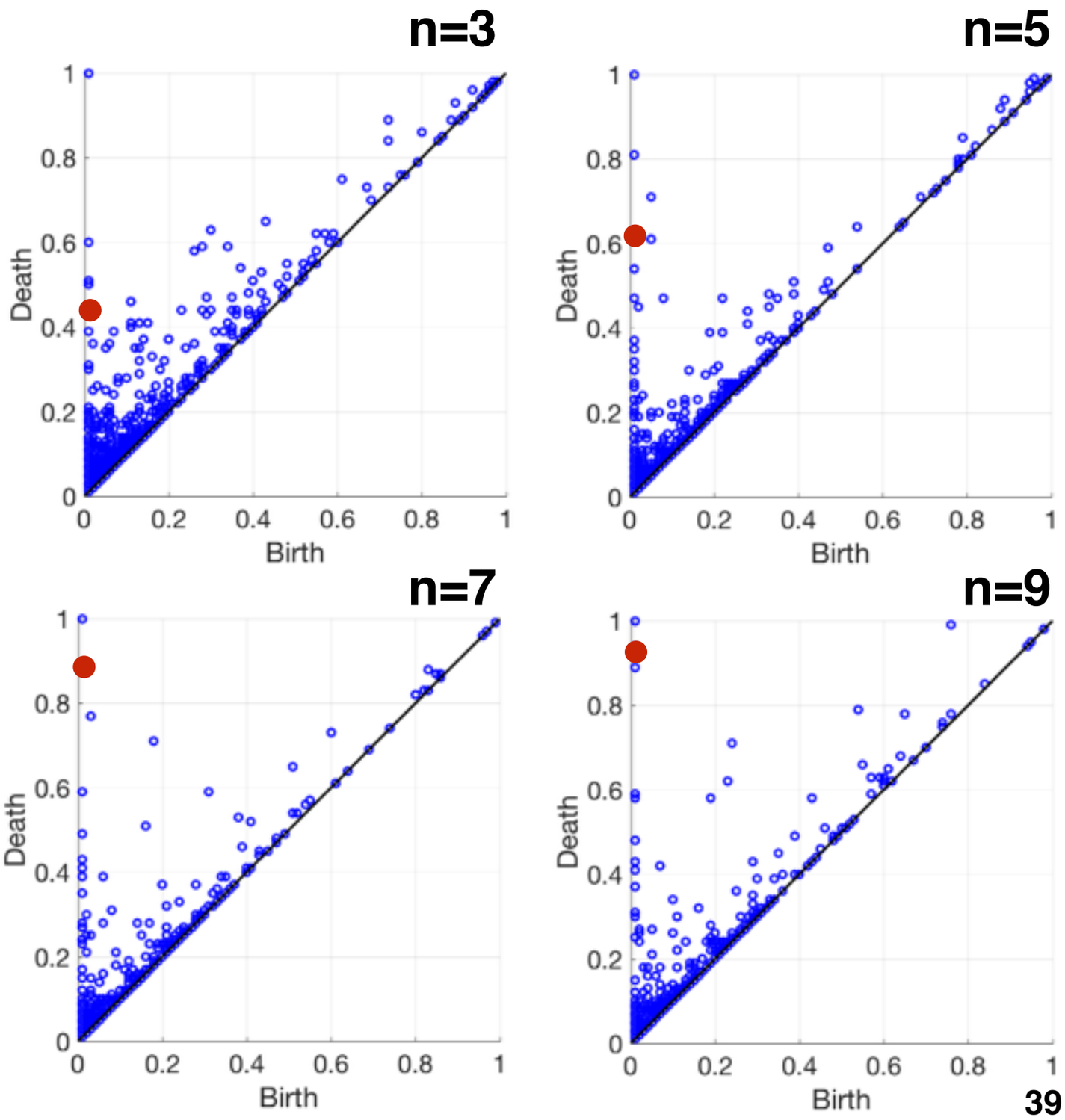
Consensus-based Image Segmentation

- **Persistence diagram**





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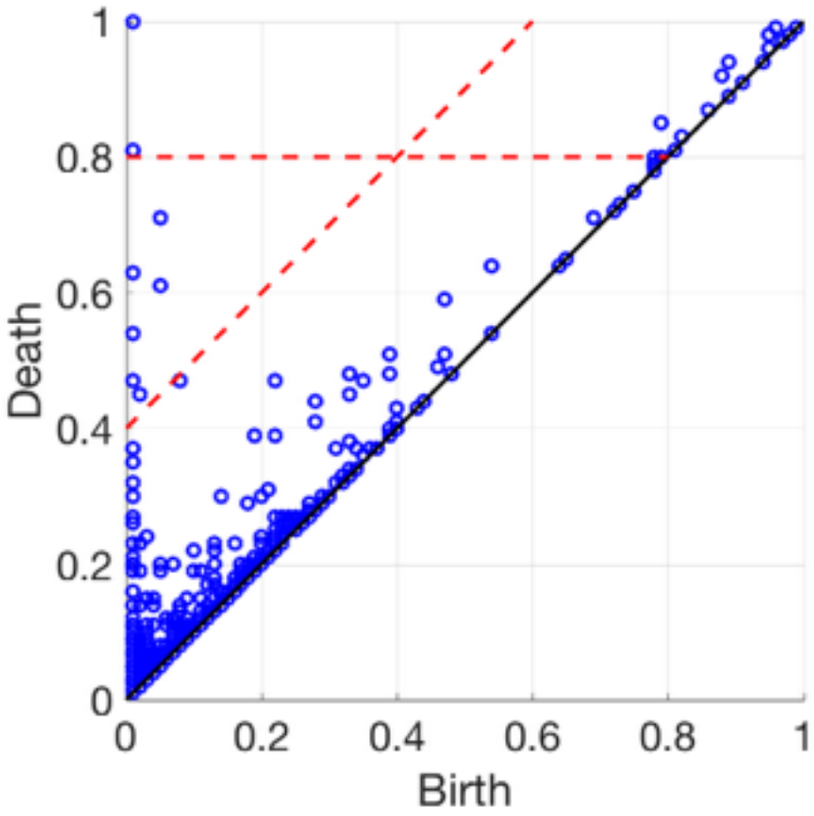
Consensus-based Image Segmentation

- **Thresholding persistence diagram**
  - **Persistence threshold - extract persistent region and remove noise.**
  - **Probability threshold - make sure capture edges being present in high probability.**



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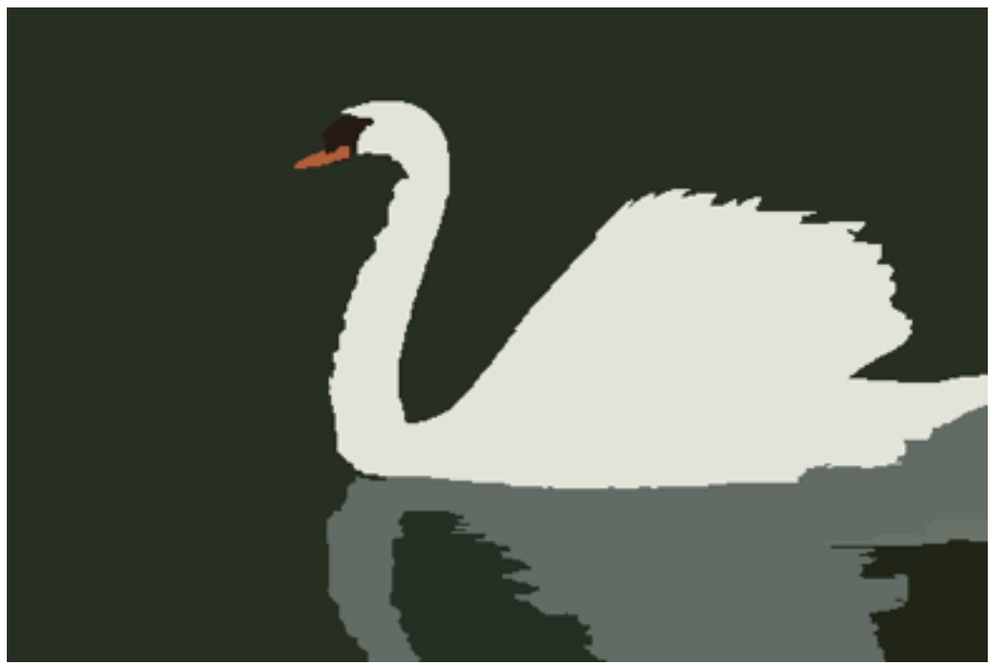
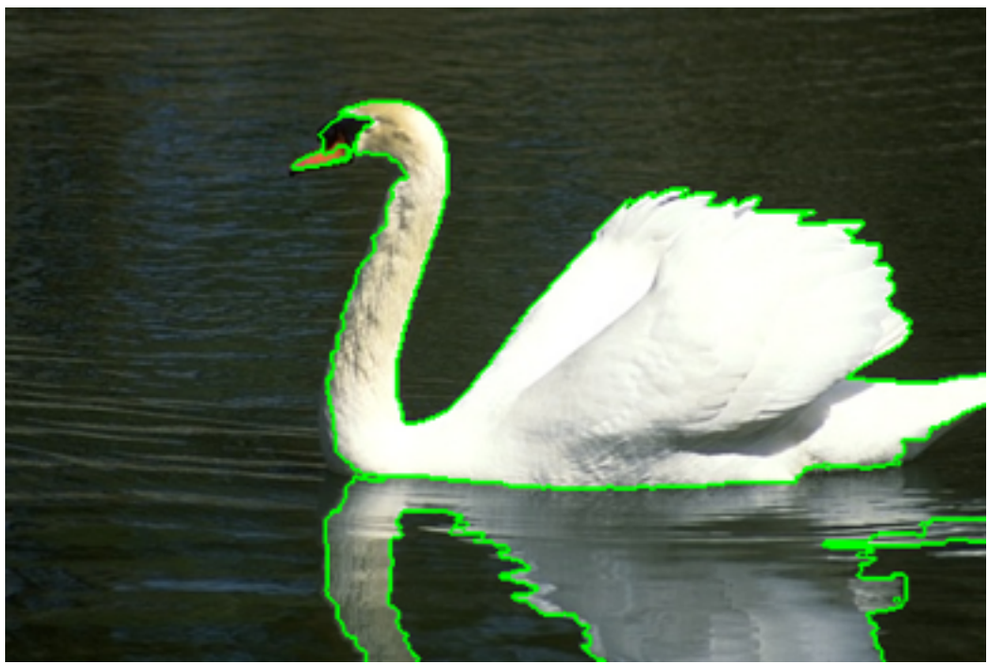
Consensus-based Image Segmentation

- Segmentation obtained by color-based region growing





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Consensus-based Image Segmentation

- **Experiment - Input set generation**
  - **Dataset - Berkeley Segmentation Database**
  - **Four input algorithms: SAS, Normalized Cuts, Graph-based and Mean Shift**
    - **SAS: number of region varying from 5 to 30**
    - **Normalized Cuts: number of region varying from 5 to 30**
    - **Graph-based: σ varying from 0.4 to 0.8, k varying from 500 to 5000**
    - **Mean Shift: k1 varying from 2 to 15, k2 varying from 7 to 15**
  - **238 input segmentations in total**
  - **Probability are weighted by number of input from each algorithm**

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Consensus-based Image Segmentation

- **Experiment - Result**

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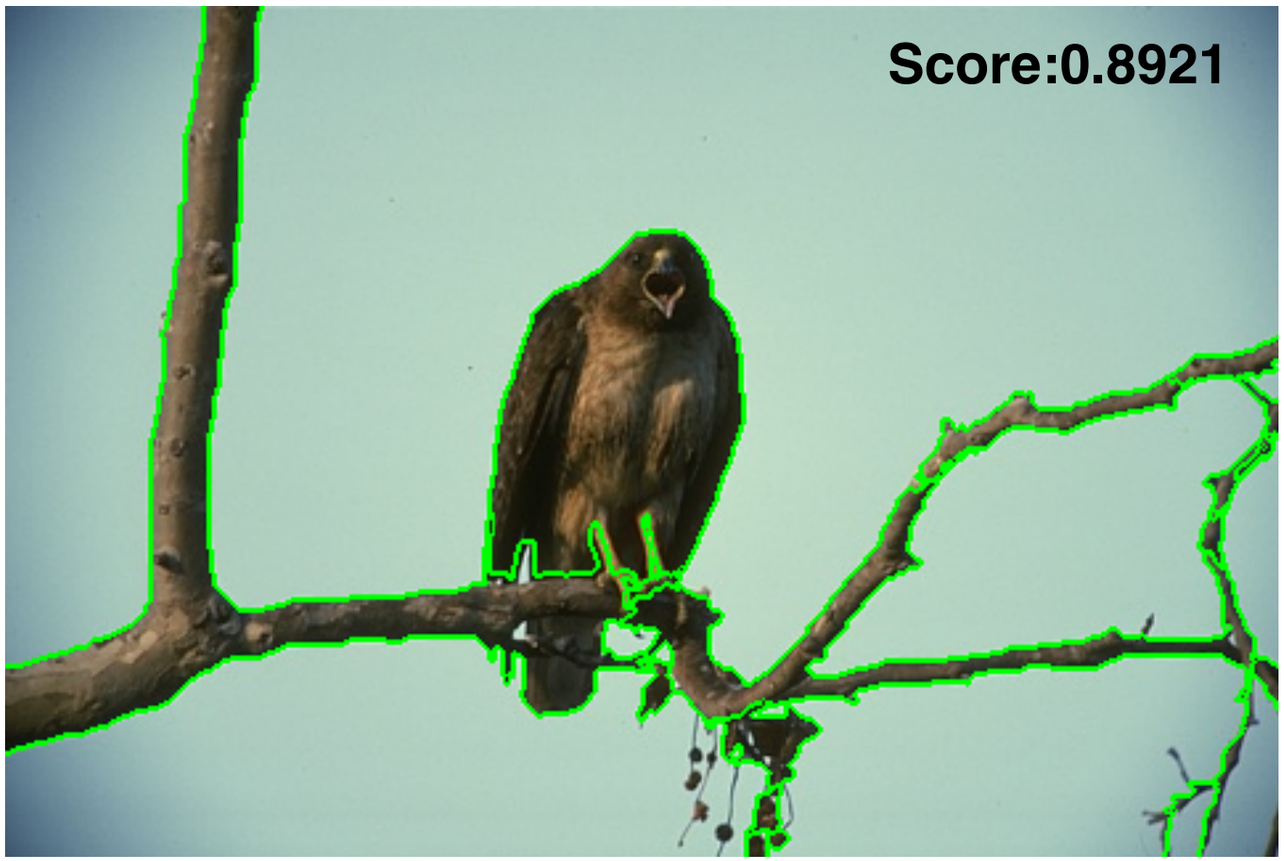
Consensus-based Image Segmentation

- **Experiment - Result**



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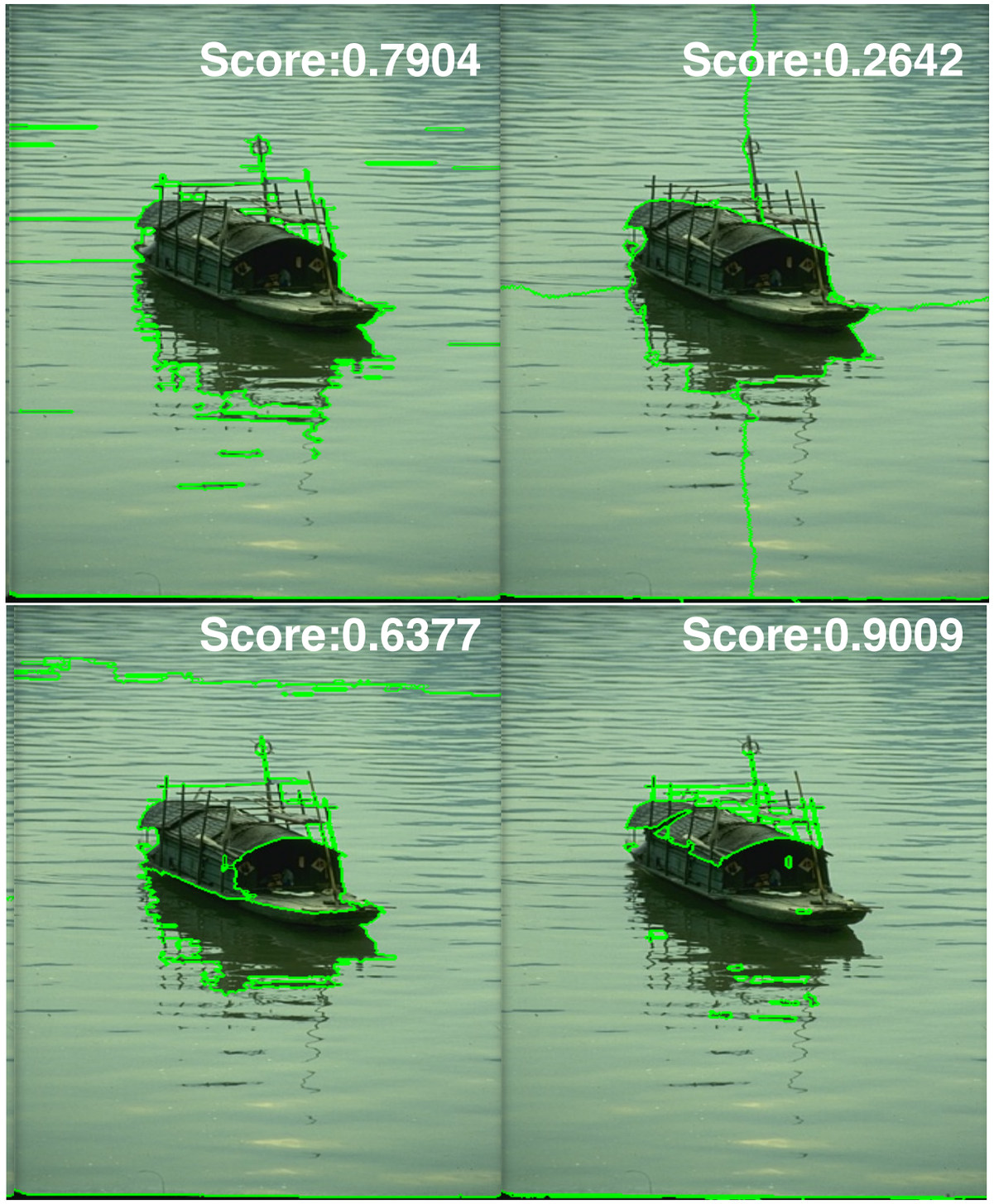
Consensus-based Image Segmentation

- **Experiment - Result**



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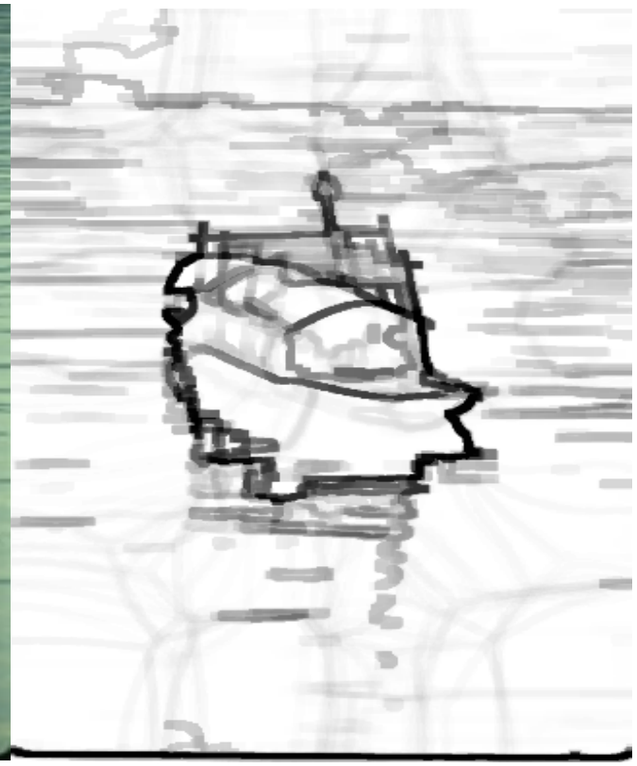
Consensus-based Image Segmentation

- **Experiment - Result**



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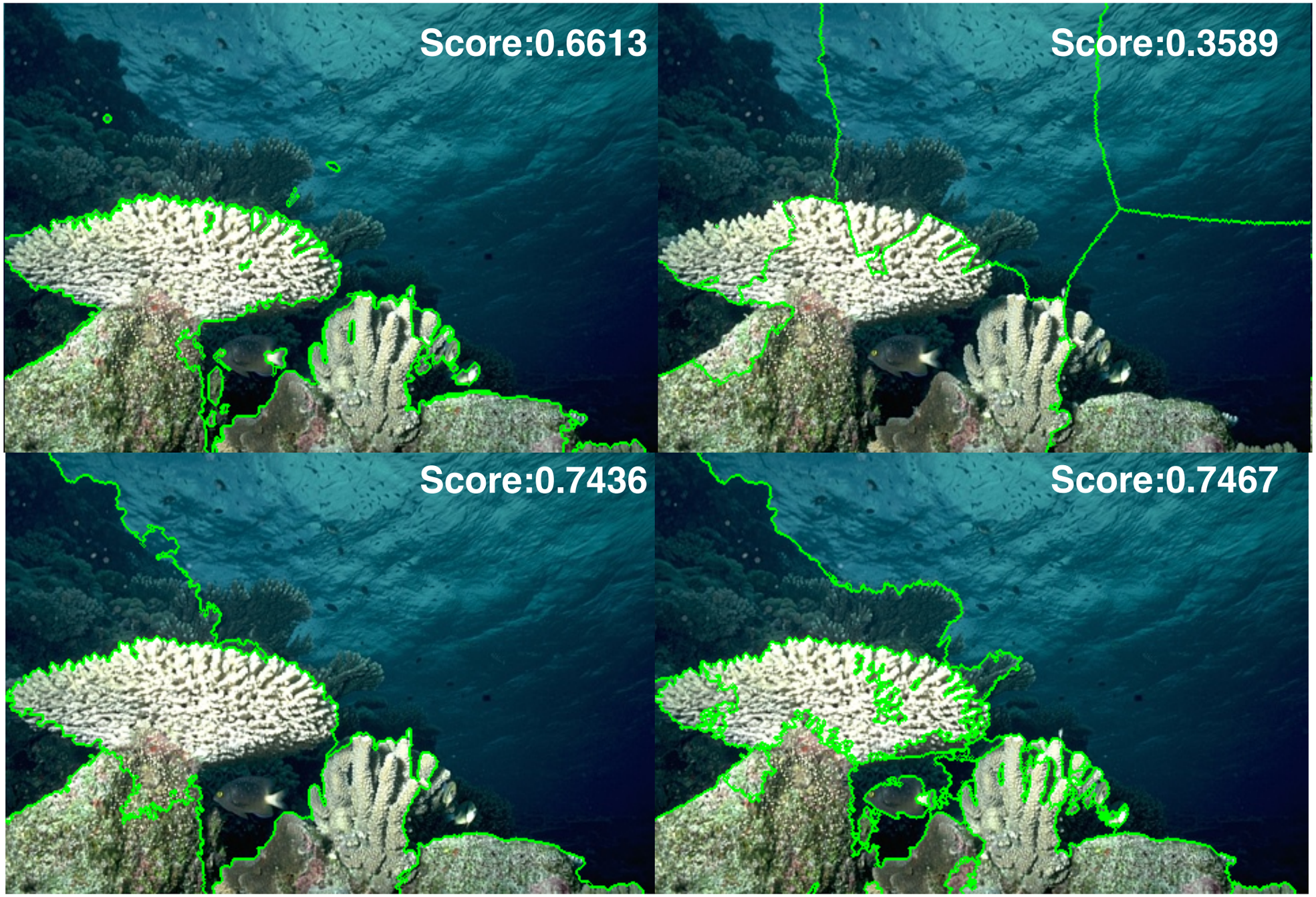
Consensus-based Image Segmentation

- **Experiment - Result**



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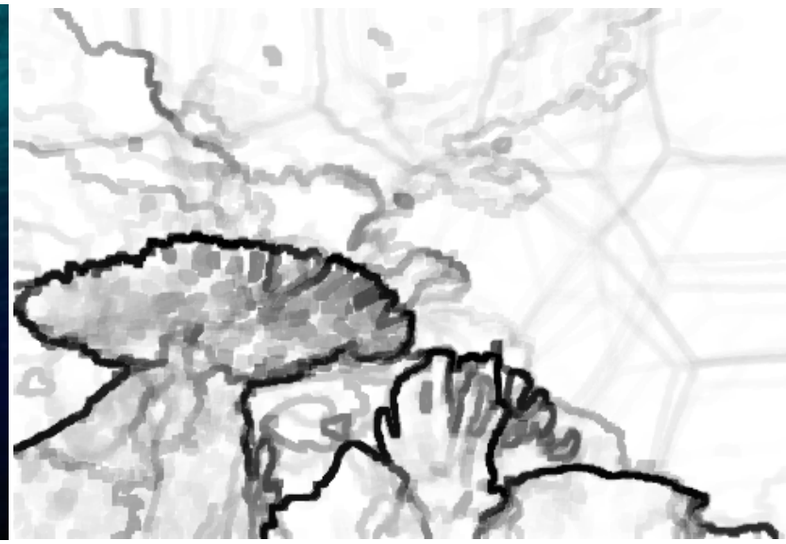
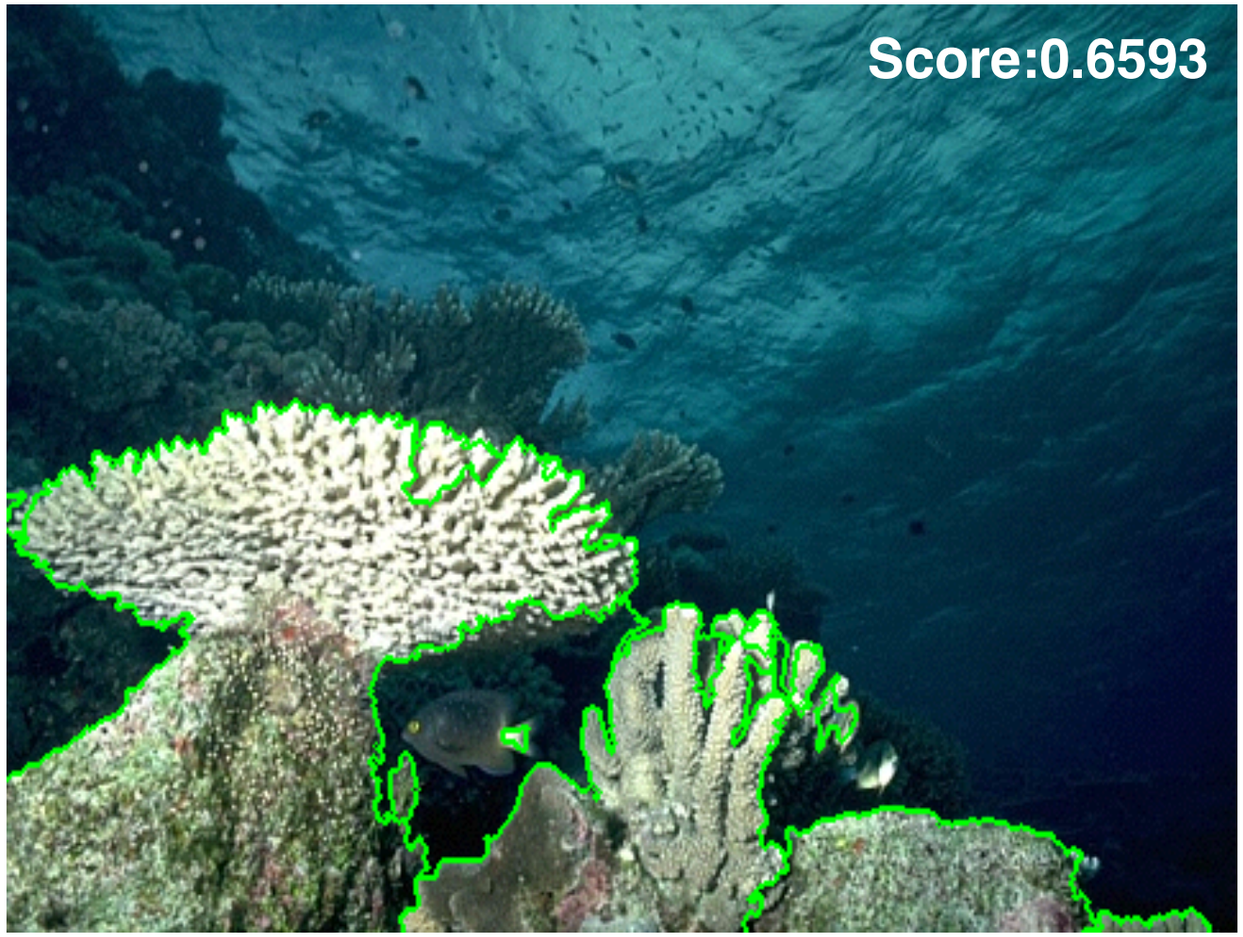
Consensus-based Image Segmentation

- **Experiment - Result**





Consensus-based Image Segmentation

- **Experiment - Result**
  - RSC - Coverage score
  - VoI - Variation of information

Methods	Graph	NCuts	SAS	Mean Shift
RSC	0.5359	0.3970	0.5325	0.5540
VoI	2.1128	2.3515	1.8251	1.8946

Methods	Consensus-base			
	$\tau = 0.30$	$\tau = 0.35$	$\tau = 0.40$	$\tau = 0.45$
RSC	**0.5982**	**0.6085**	**0.5725**	**0.5731**
VoI	**1.7070**	**1.6700**	**1.7600**	**1.7930**

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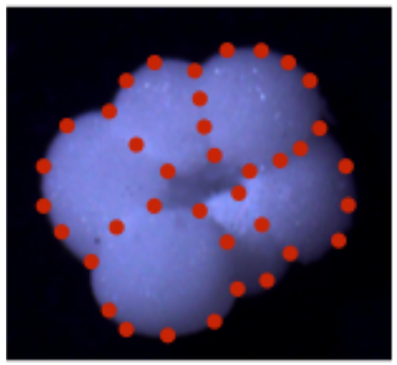
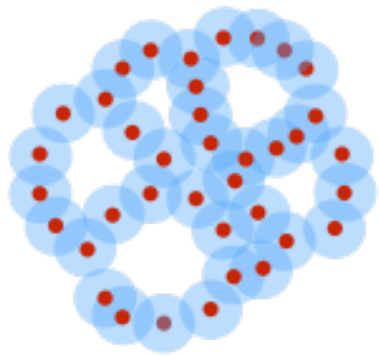
Conclusion

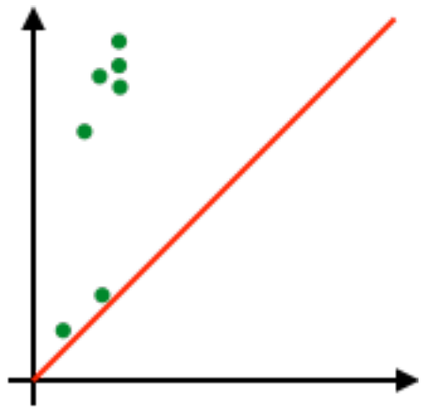
- Present an innovative framework for image segmentation based on topological persistence which is robust to image conditions and parameter selection.
- Applied to consensus-based image segmentation which is able to get better segmentation results.
- Applied to obstacle detection in outdoor scene for autonomous driving which is robust to parameter selection.

Future work

- **Work has to be done before graduation**
  - More experiments to demonstrate the robustness of the segmentation using topological persistence.
  - Extend the mathematical formulation of this work in order to provide guarantees of performance.
  - Collect image data of different species of foraminifera (forams) and apply topological persistence theory on the dataset to segment the structure of each forams as well as identify forams species.







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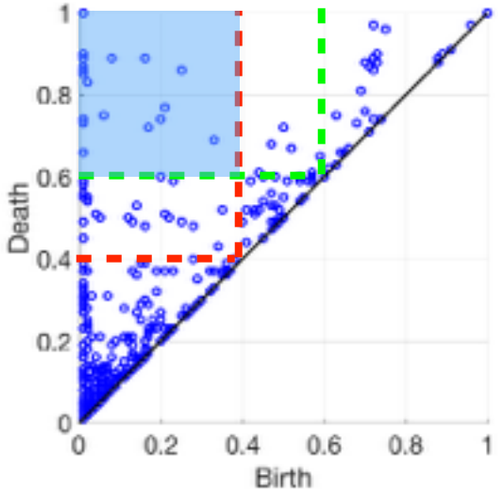
Future work

- **Extension**
  - Find a better parameter selection strategy for consensus-based image segmentation.



  - Refine the obstacle segmentation using Markov Random Field.

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Publication

1. **Q.Ge** and E. Lobaton, "**Consensus-Based Image Segmentation via Topological Persistence**," Intl. Workshop on Differential Geometry in Computer Vision and Machine Learning (DIFF-CVML) at CVPR, 2016.
2. S. Chattopadhyay, **Q. Ge**. C. Wei and E. Lobaton, "**Robust Multi-Target Tracking in Outdoor Traffic Scenarios via Persistence Topology based Robust Motion Segmentation**," IEEE Global Conf. on Signal and Information Processing (GlobalSIP), 2015.
3 .C. Wei, **Q. Ge**, S. Chattopadhyay, and E. Lobaton, "**Robust Obstacle Segmentation based on Topological Persistence in Outdoor Traffic Scenes**," IEEE Symposium Series on Computational Intelligence (SSCI), 2014.
4. **Q. Ge**, N. Lokare, and E. Lobaton, "**Non-Rigid Image Registration under non-Deterministic Deformation Bounds**," Intl. Symposium on Medical Information Processing and Analysis (SIPAIM), 2014.
5. N. Lokare, **Q. Ge**, W. Snyder, Z. Jewell, S. Allibhai, and E. Lobaton, "**Manifold Learning Approach to Curve Identification with Applications to Footprint Segmentation**," IEEE Symposium Series on Computational Intelligence (SSCI), 2014.

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Thanks!