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Topological Persistence in Computer Vision: Applications to Segmentation and Classification

Qian Ge

Outline

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

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**

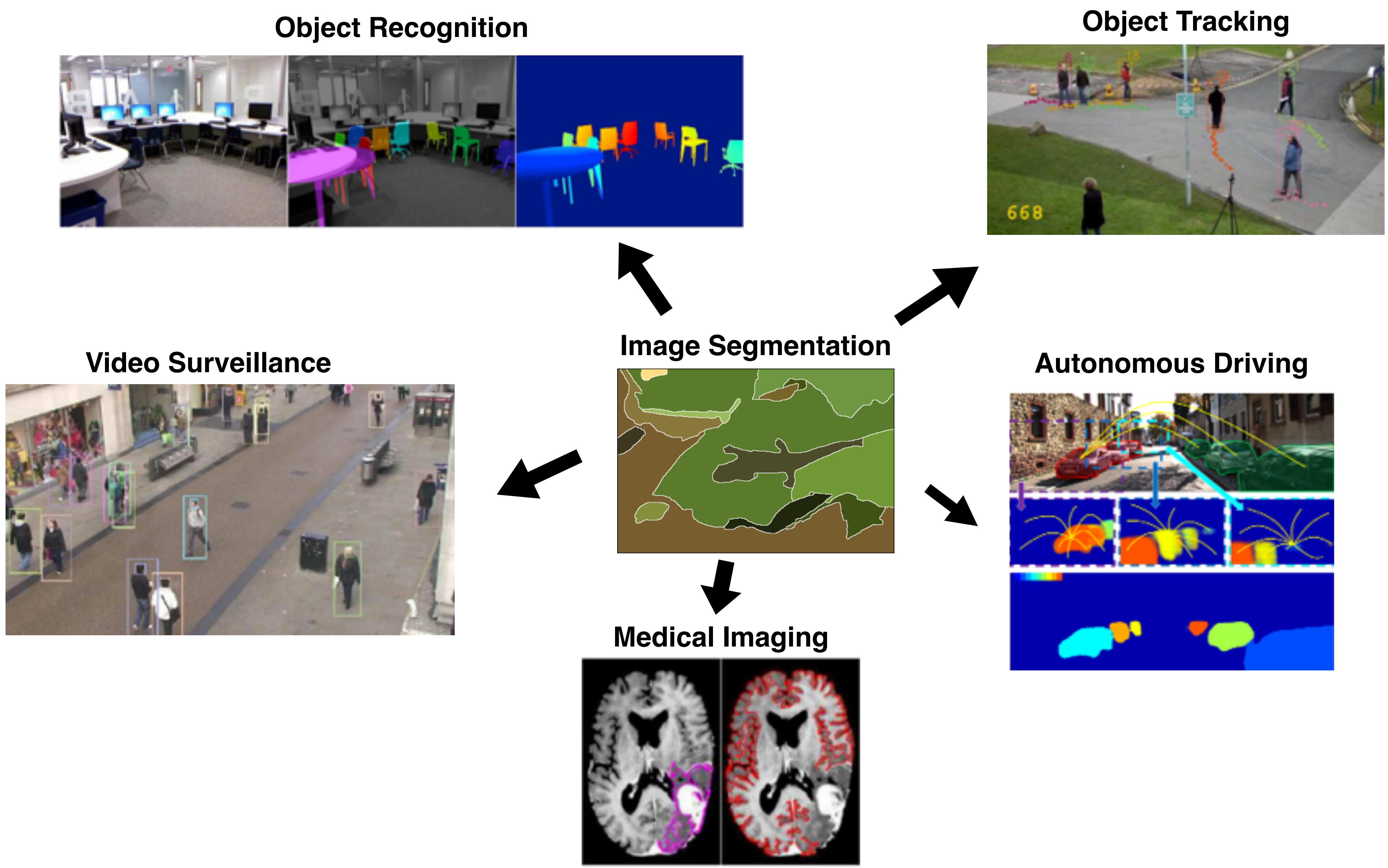


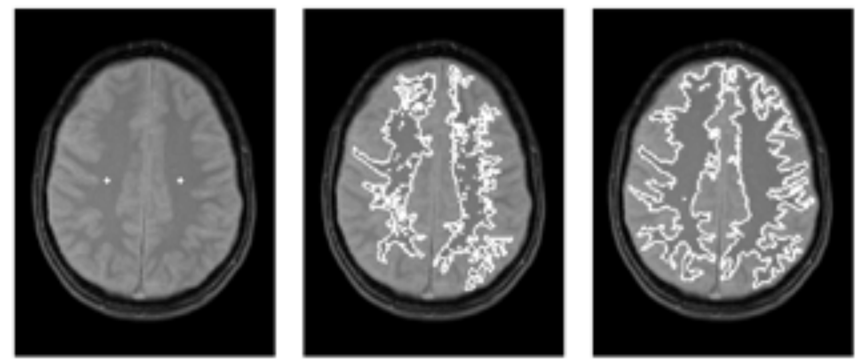
Image Segmentation

- **Grouped by methodology:**

Clustering-based

[DC02]

Region Growing

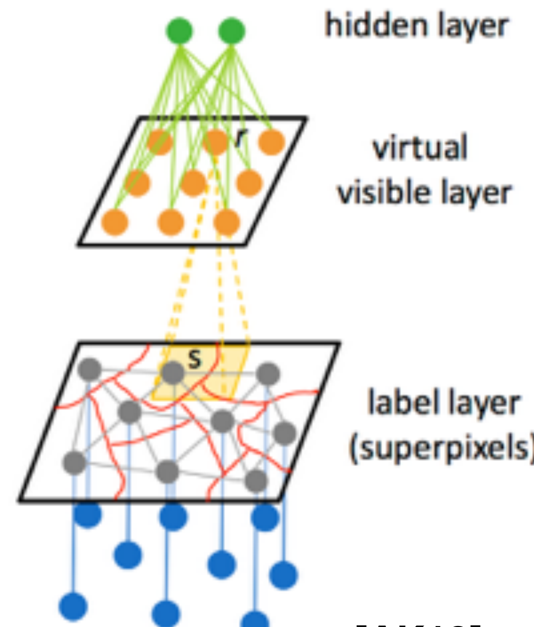


[JL10]

Superpixel-based

[RA12]

Graph-based



[AK13]

Edge-based

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

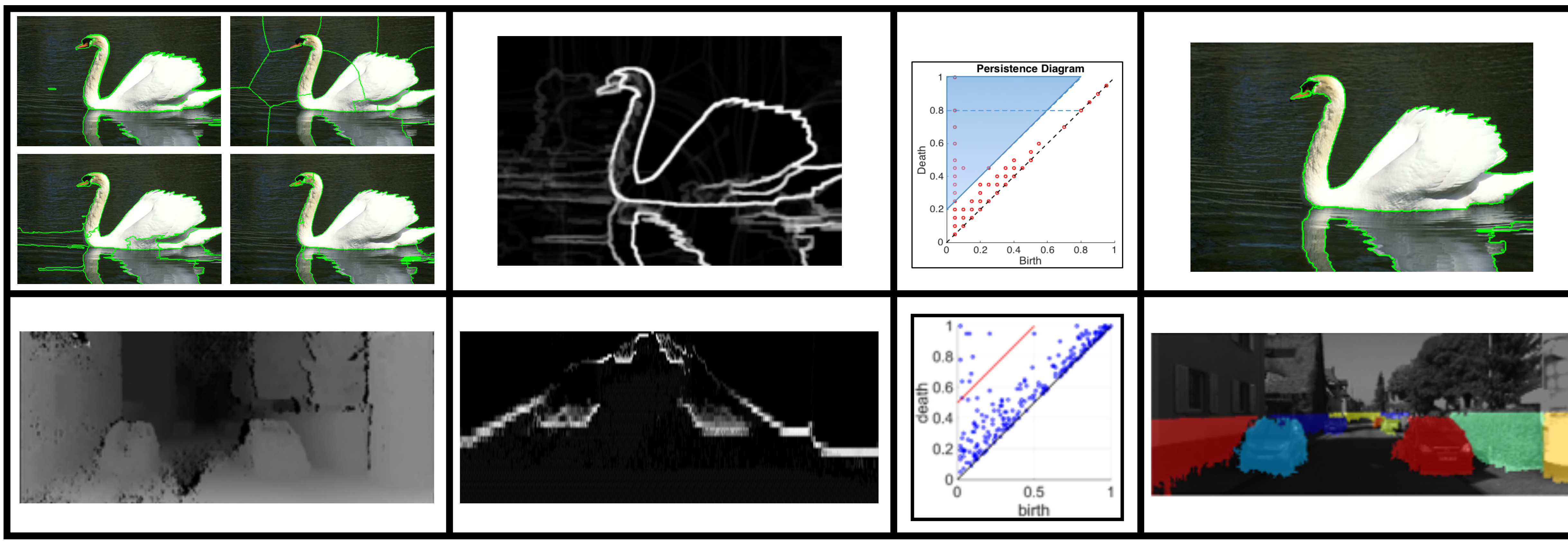
[DC02] Dorin Comaniciu and Peter Meer. 2002. Mean Shift: A Robust Approach Toward Feature Space Analysis. IEEE Trans. Pattern Anal. Mach. Intell. 24, 5 (May 2002), 603-619.
[AK13] A. Kae, K. Sohn, H. Lee and E. Learned-Miller, "Augmenting CRFs with Boltzmann Machine Shape Priors for Image Labeling," 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.

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.

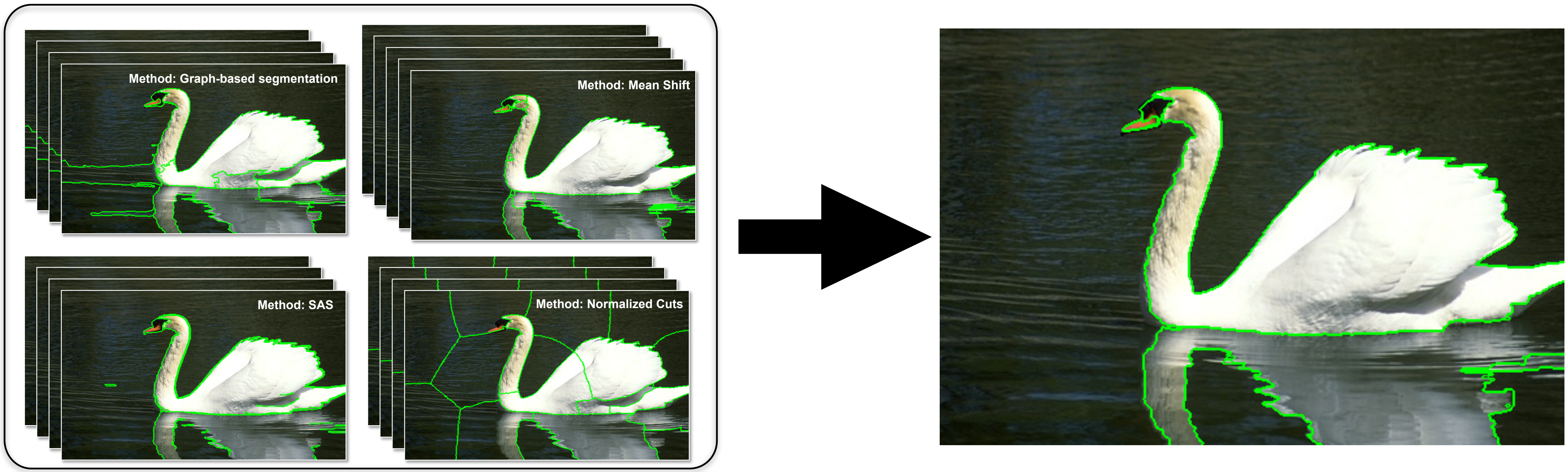
Framework of Robust Segmentation

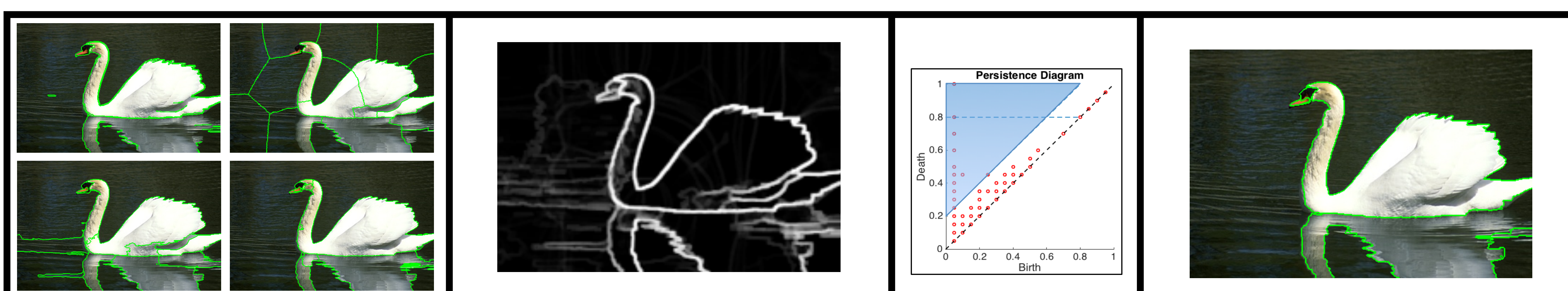
Input Data → **Probability Map** → **Persistence Analysis** → **Robust Segmentation**



Framework of Robust Segmentation

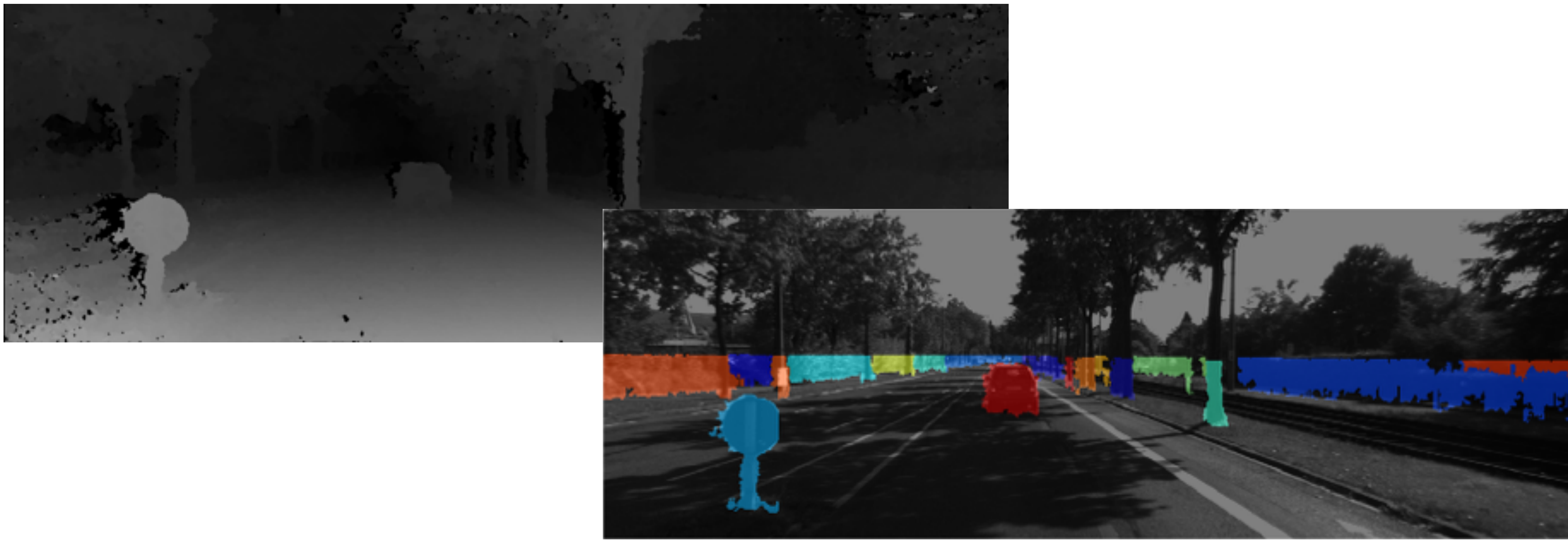
- **Consensus-based image segmentation**

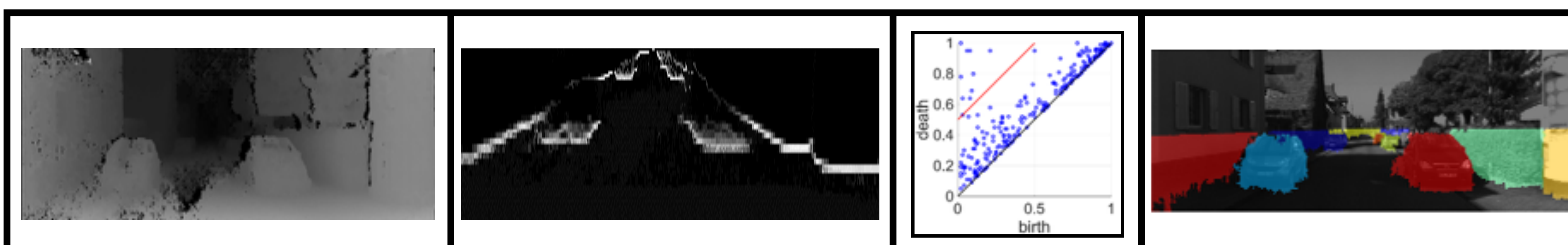




Framework of Robust Segmentation

- **Obstacle segmentation of outdoor scene**



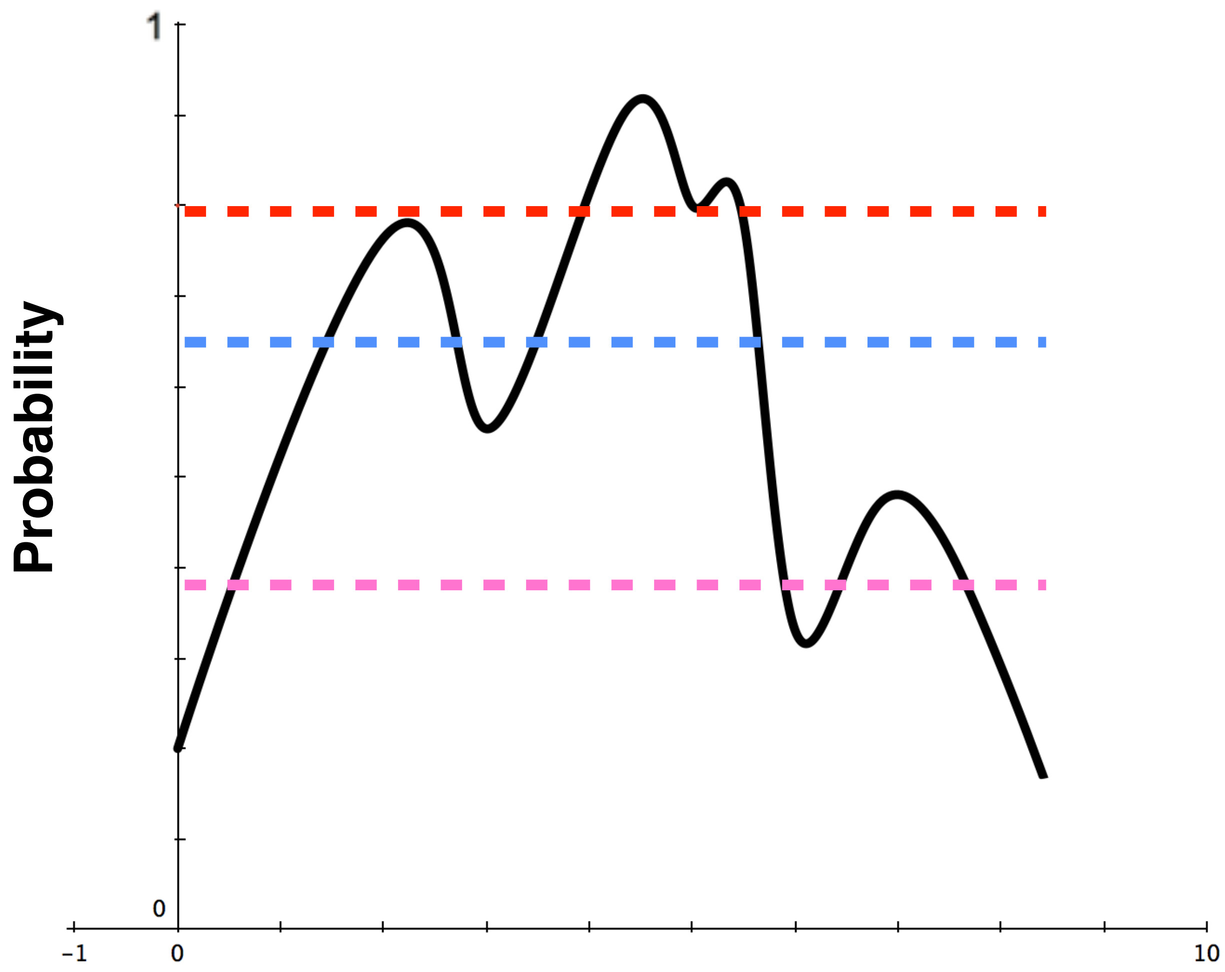


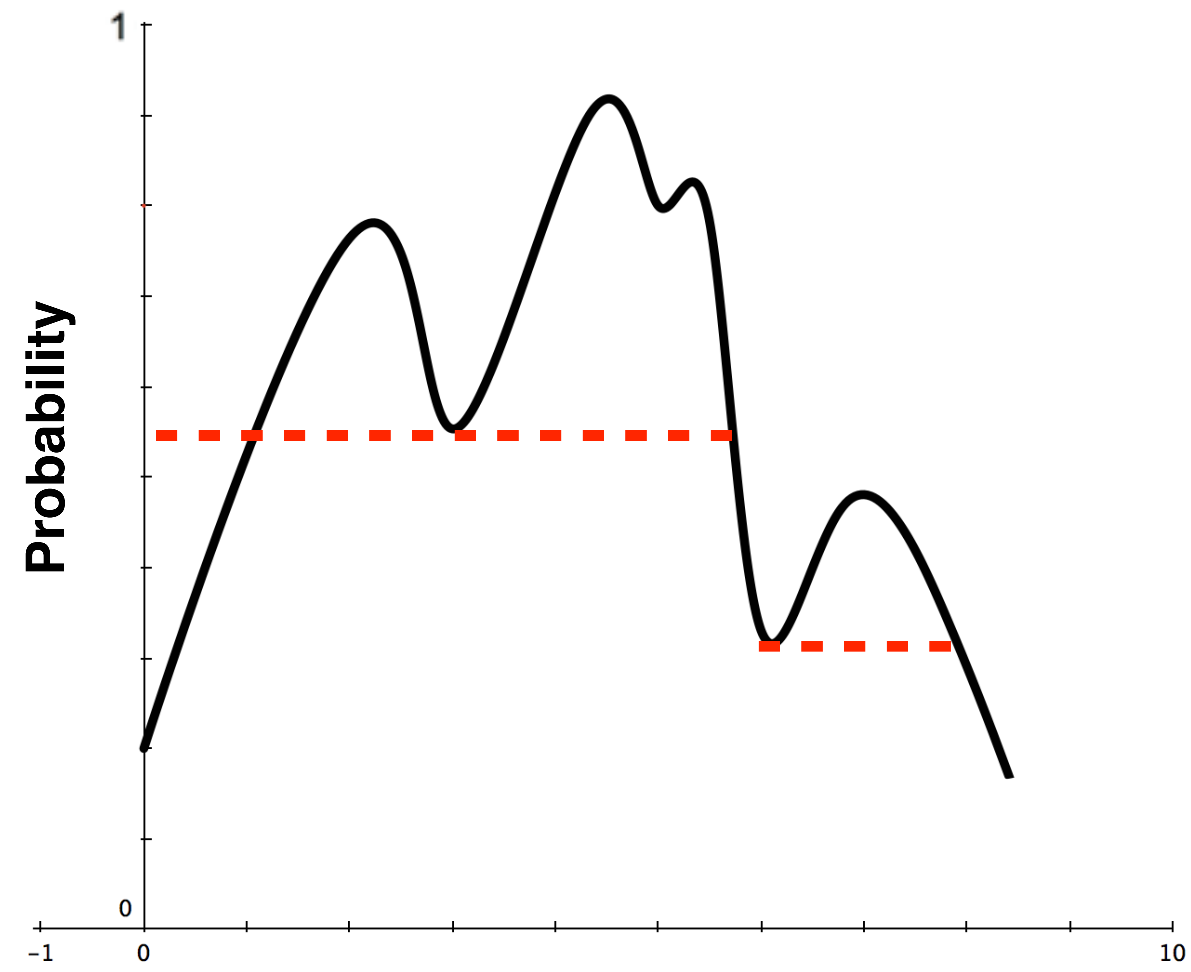
Contribution

- 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.

Persistent Homology

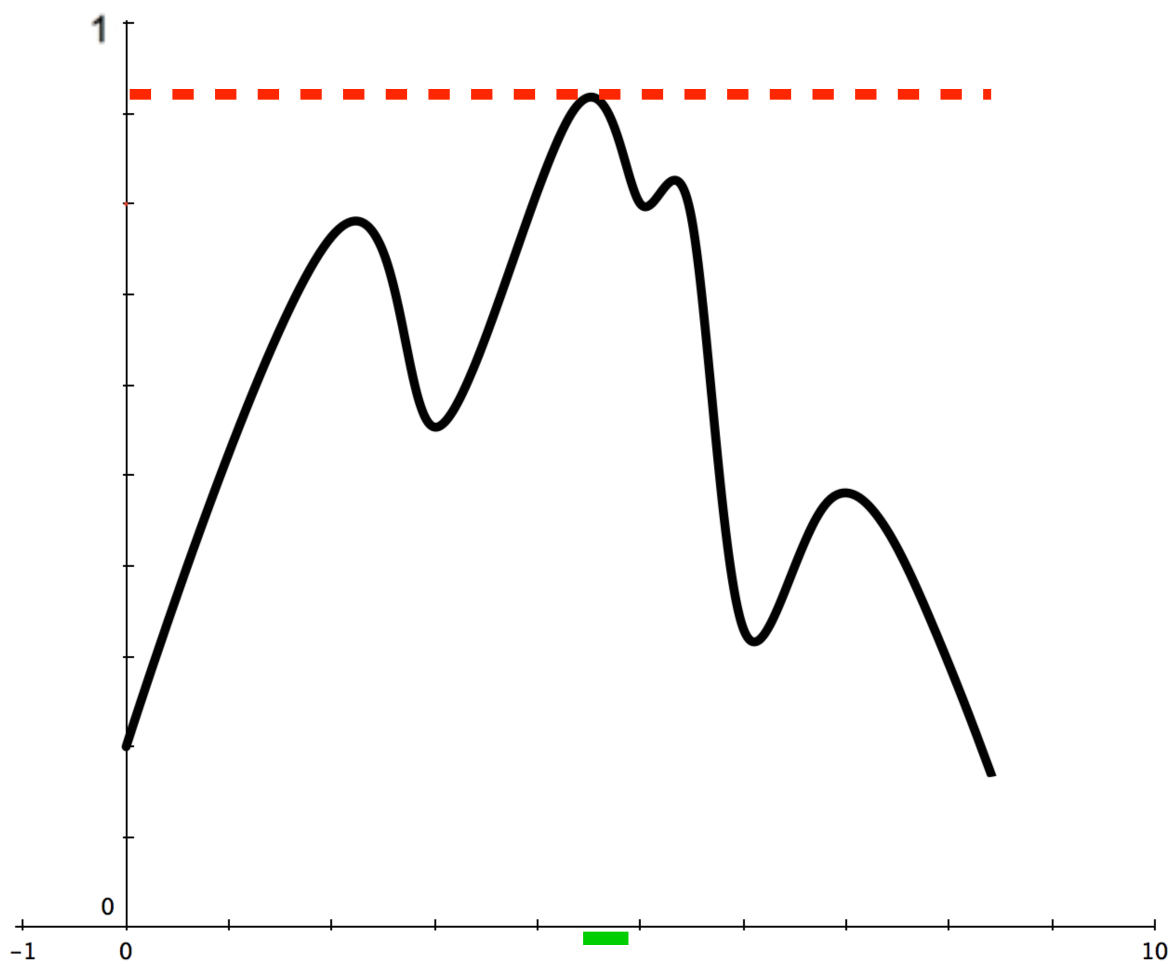
- **For image segmentation, we borrow the concept of persistent homology to extract persistence regions and avoid noise.**

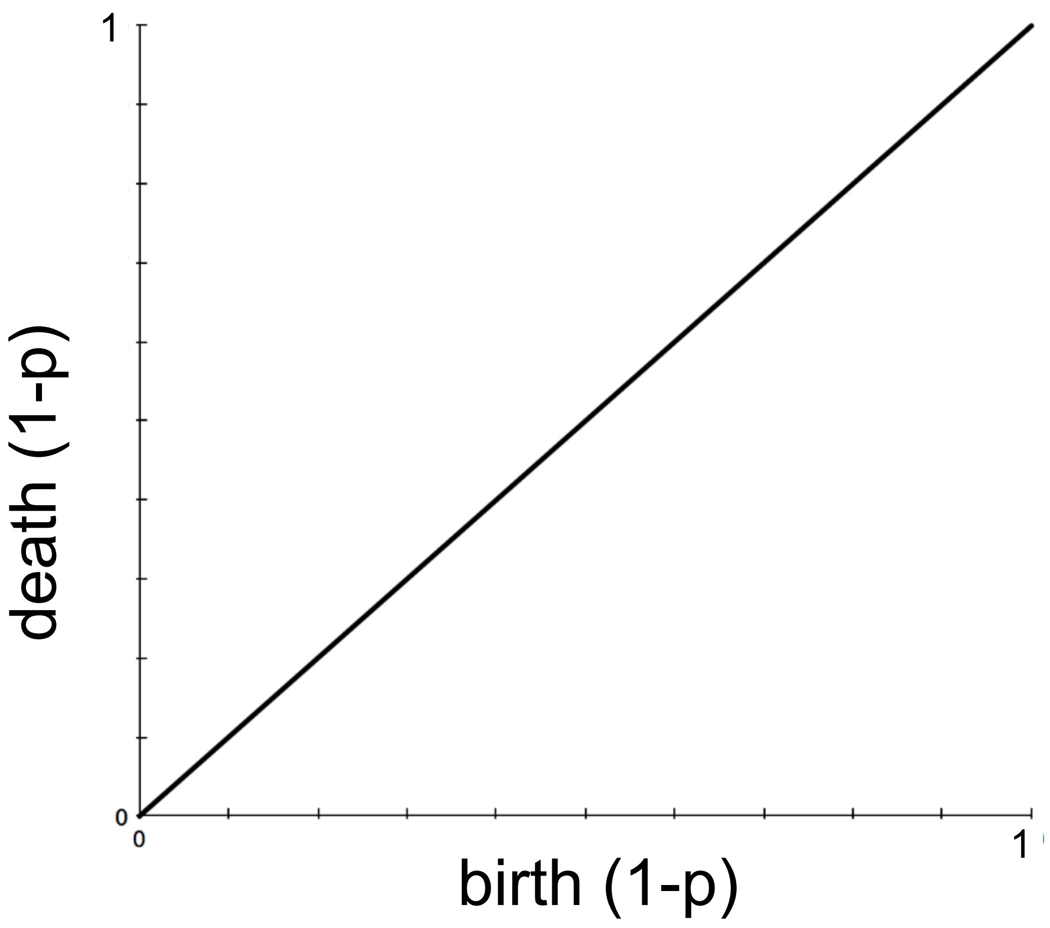




Persistent Homology

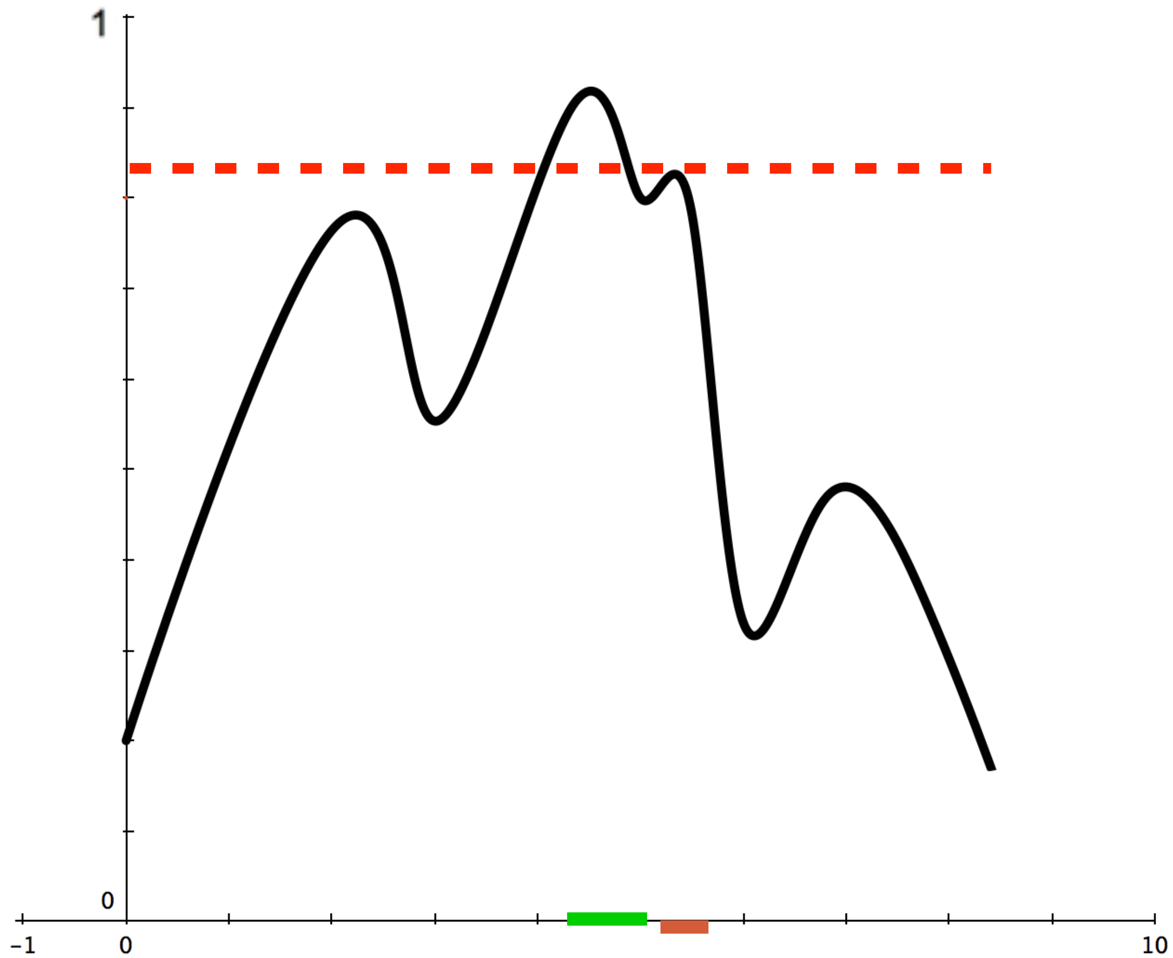
- **Topological persistence**

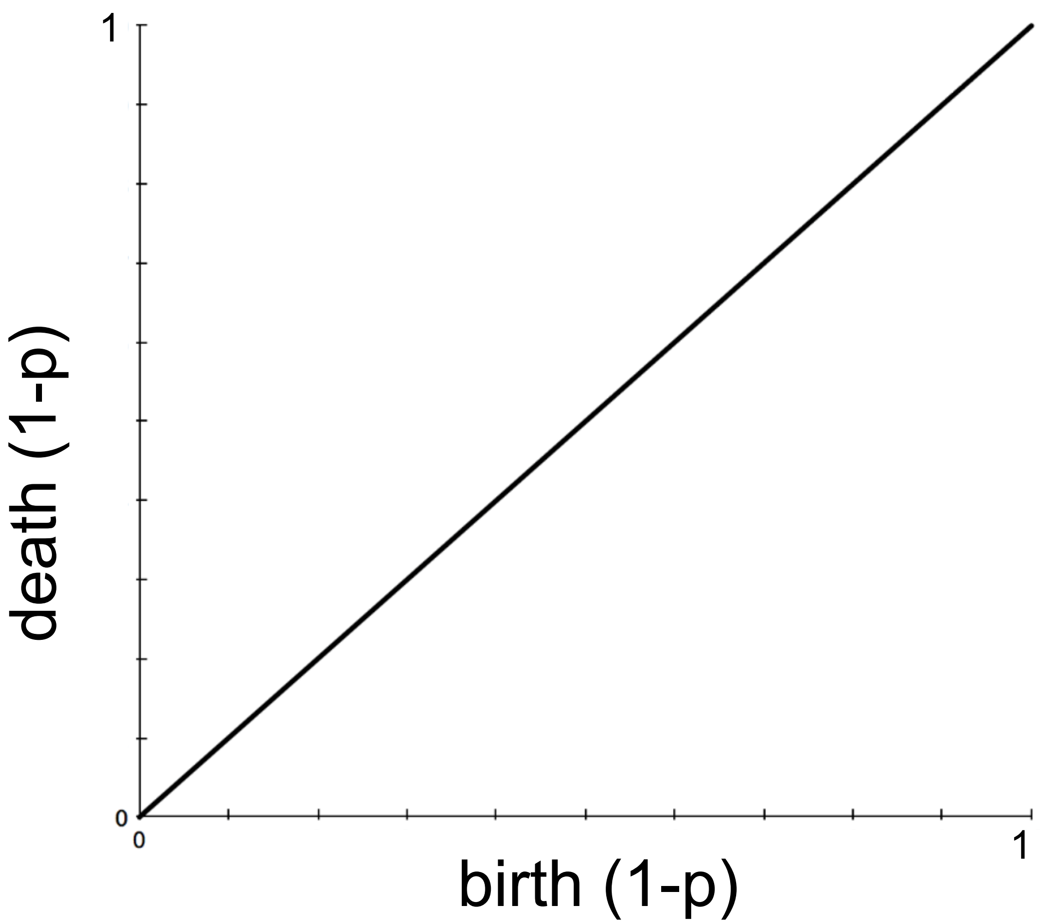




Persistent Homology

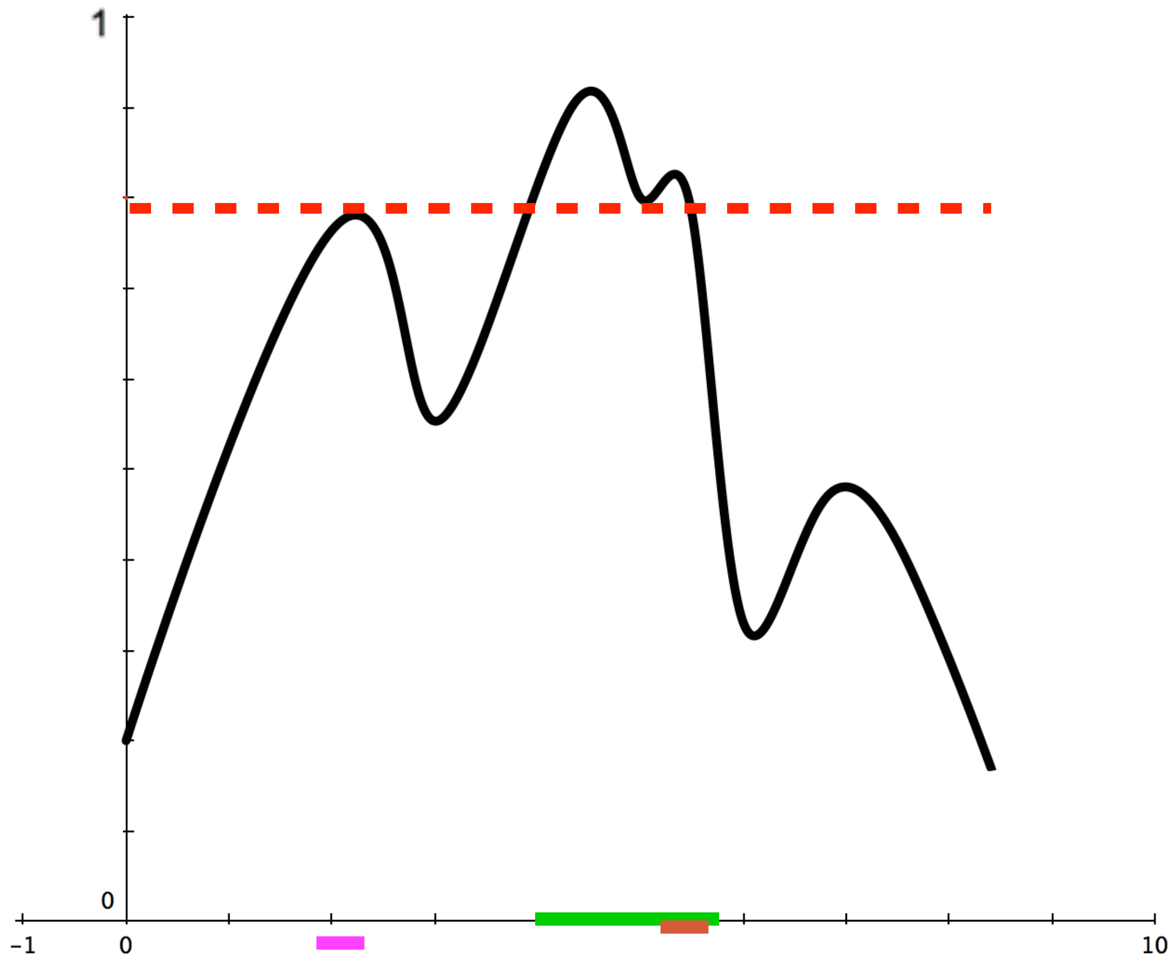
- **Topological persistence**

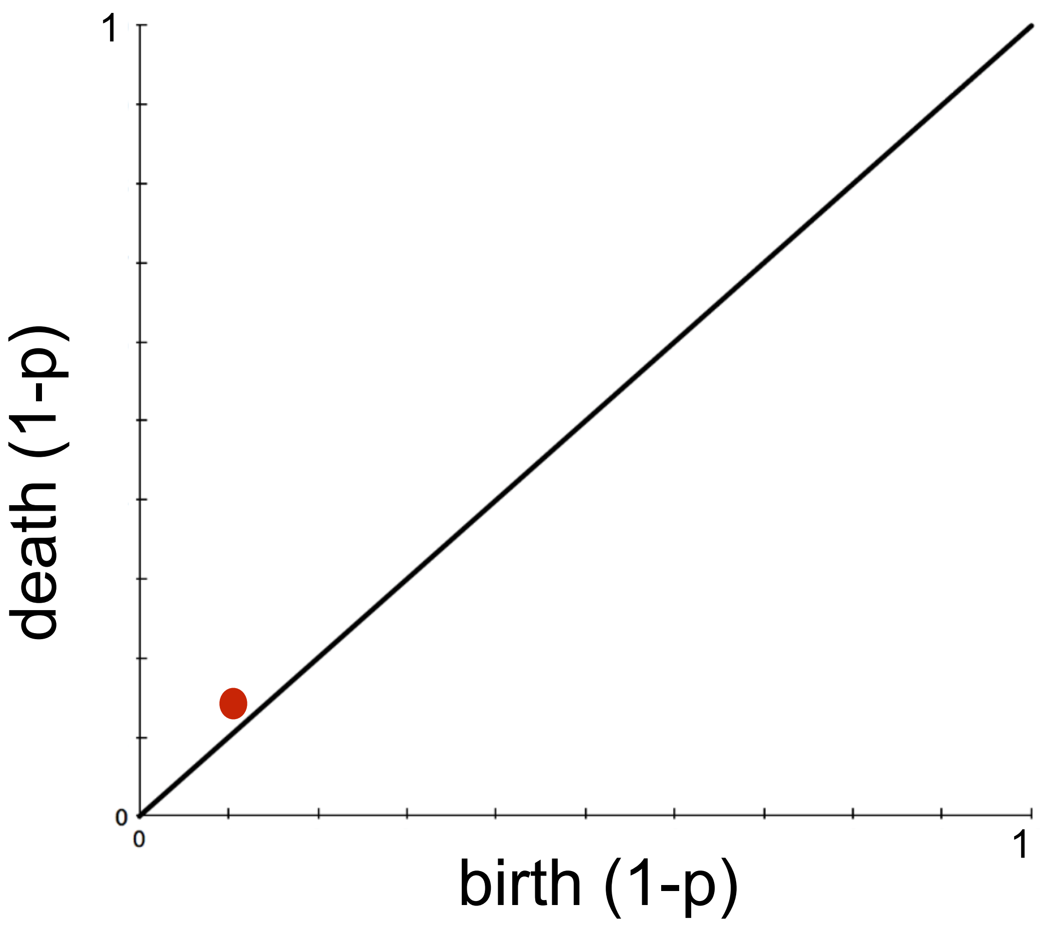




Persistent Homology

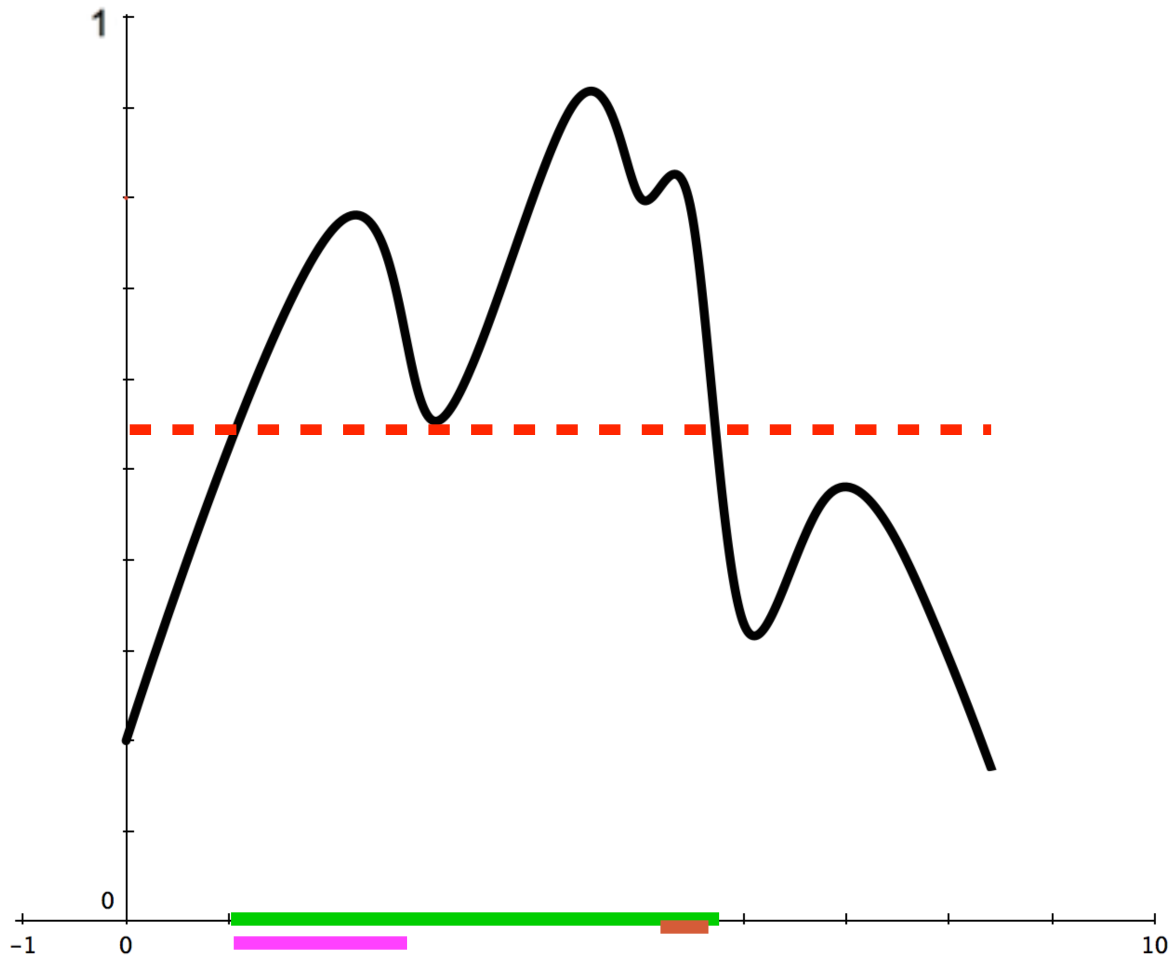
- **Topological persistence**

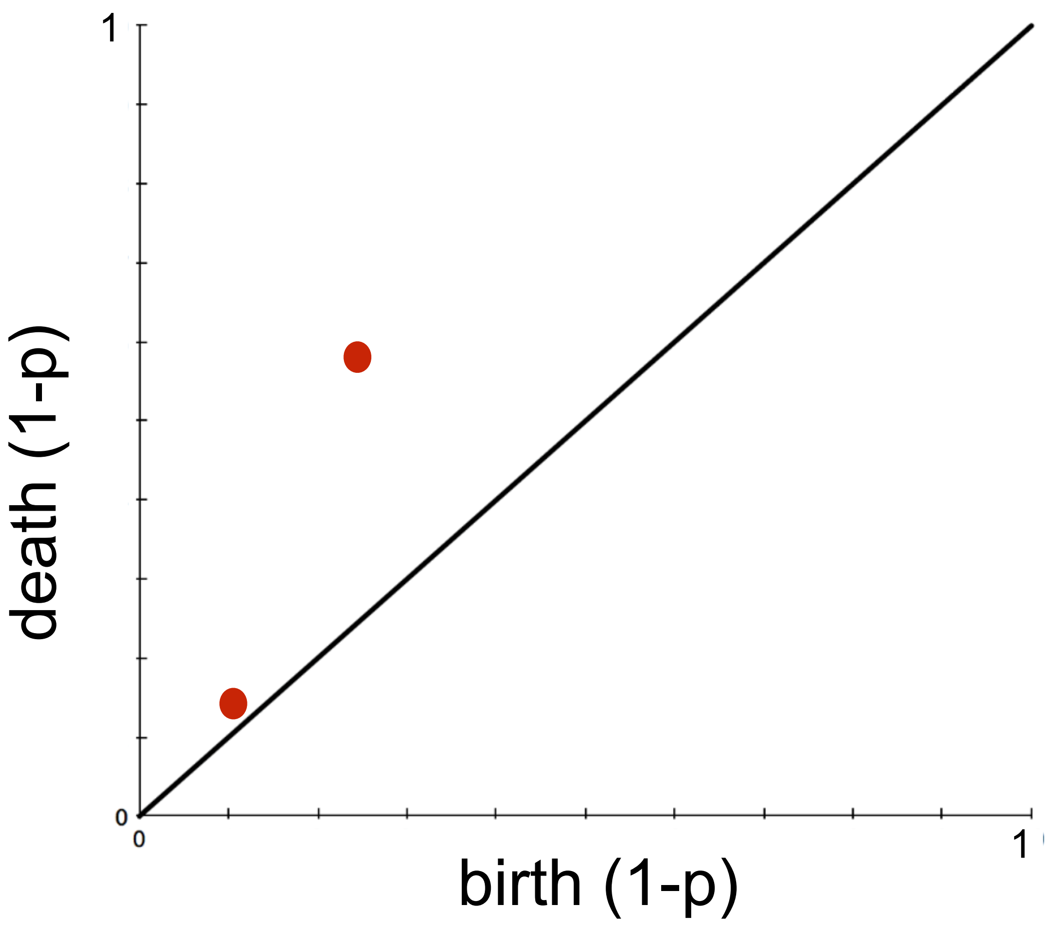




Persistent Homology

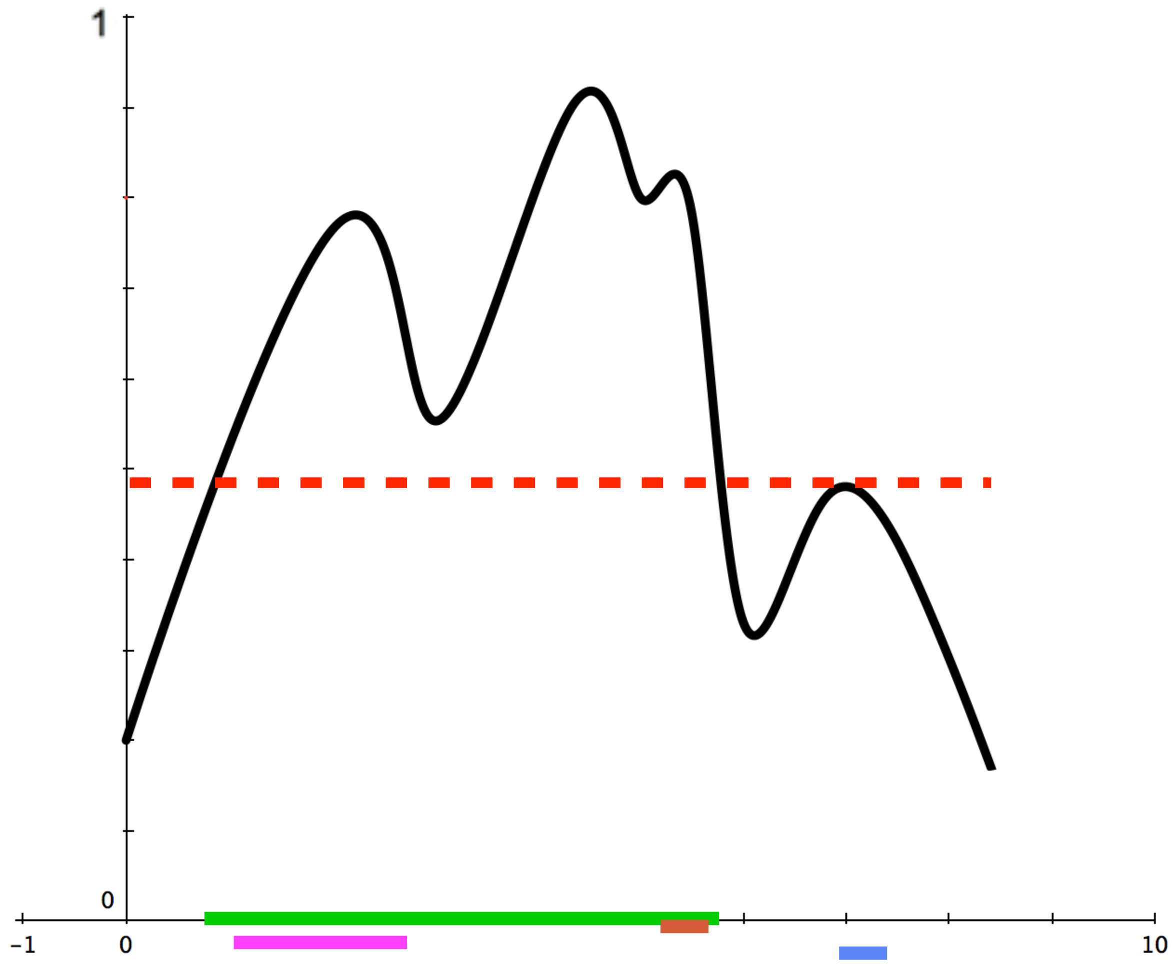
- **Topological persistence**

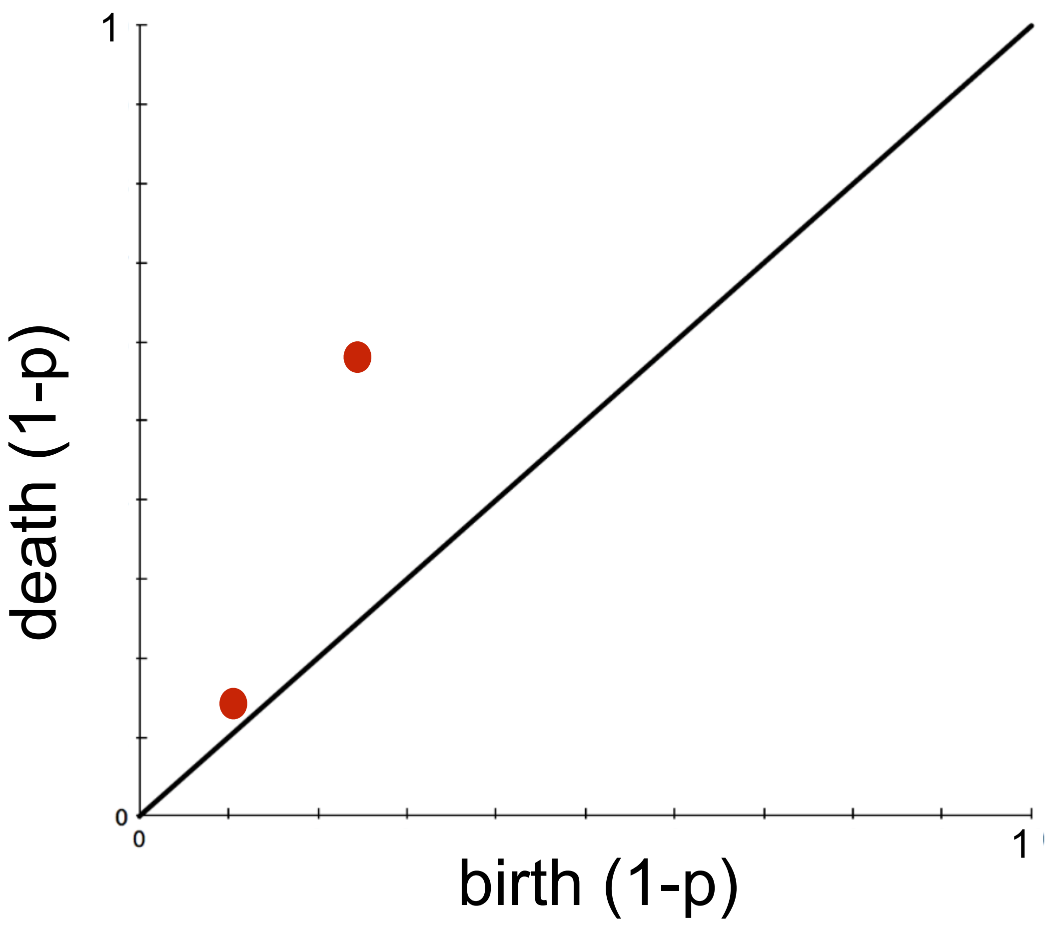




Persistent Homology

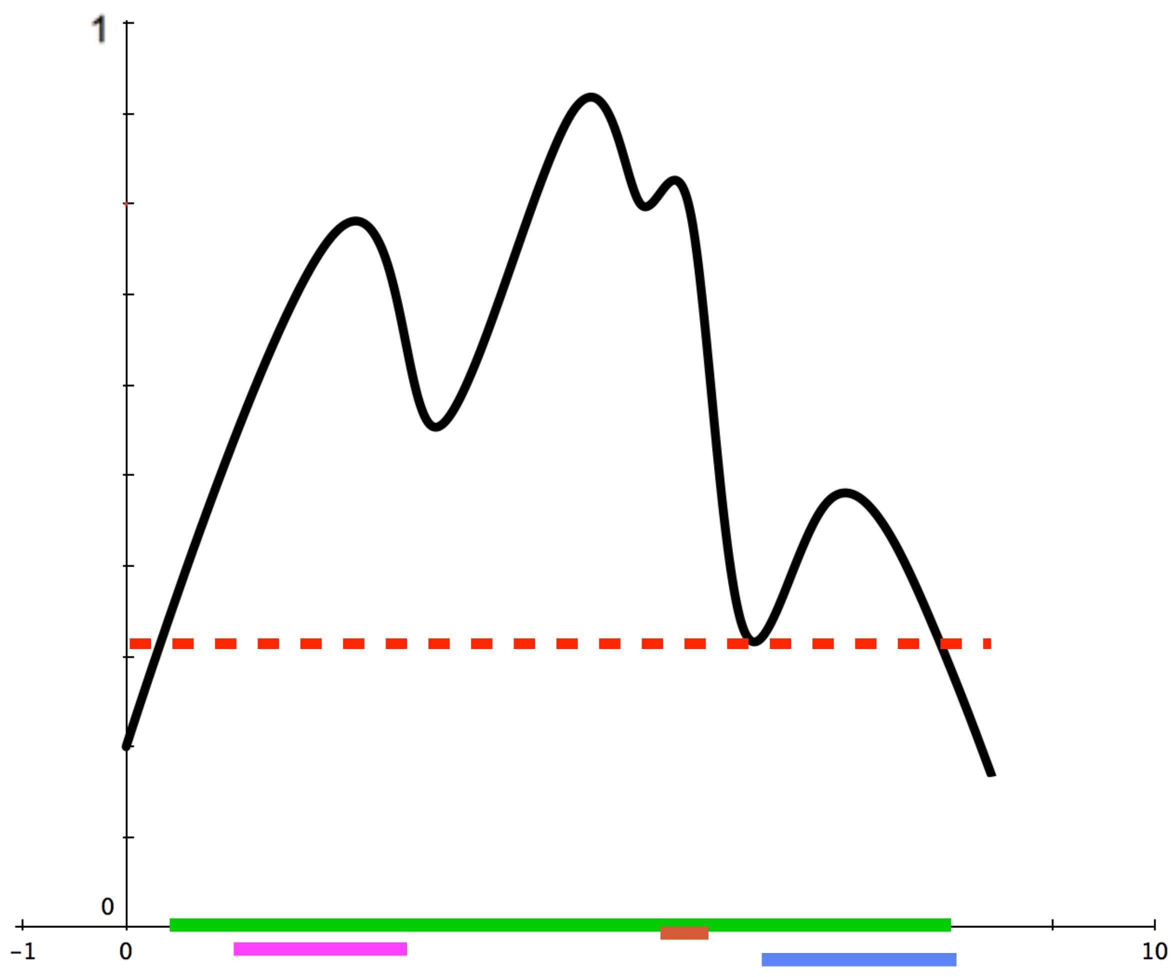
- **Topological persistence**

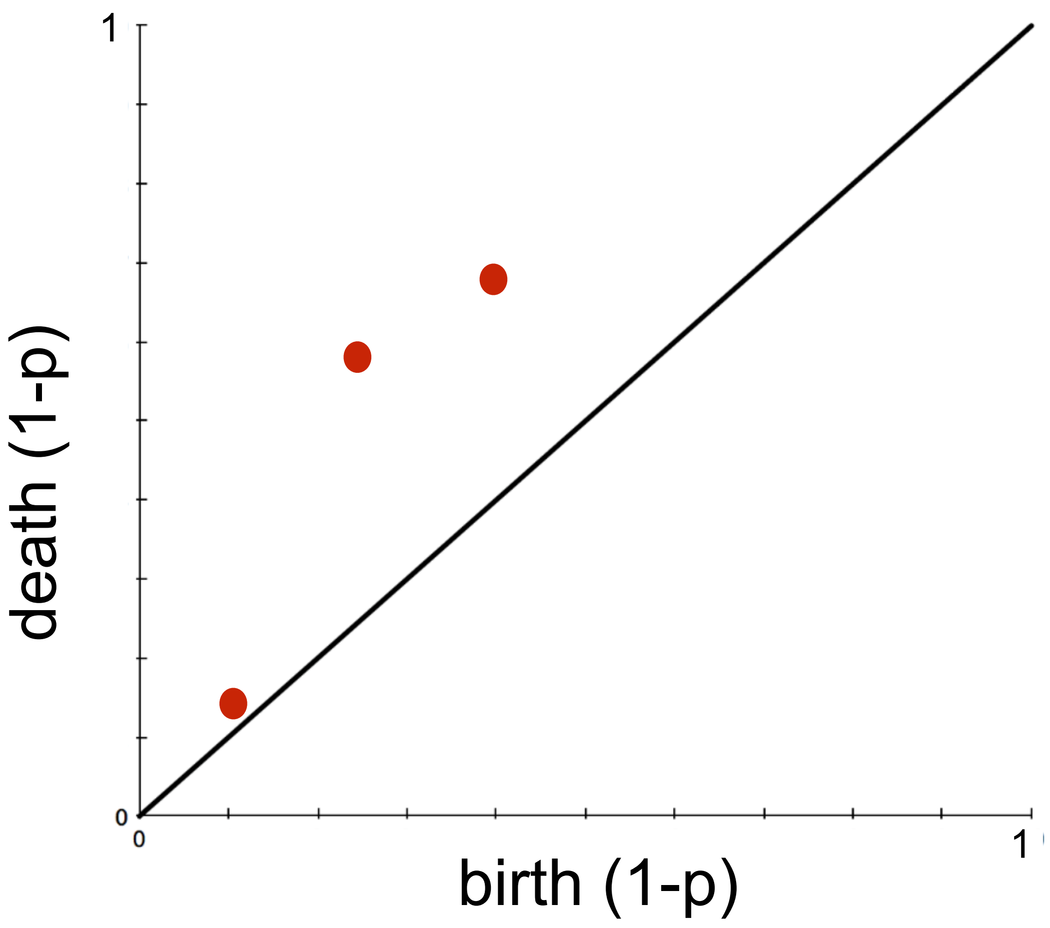




Persistent Homology

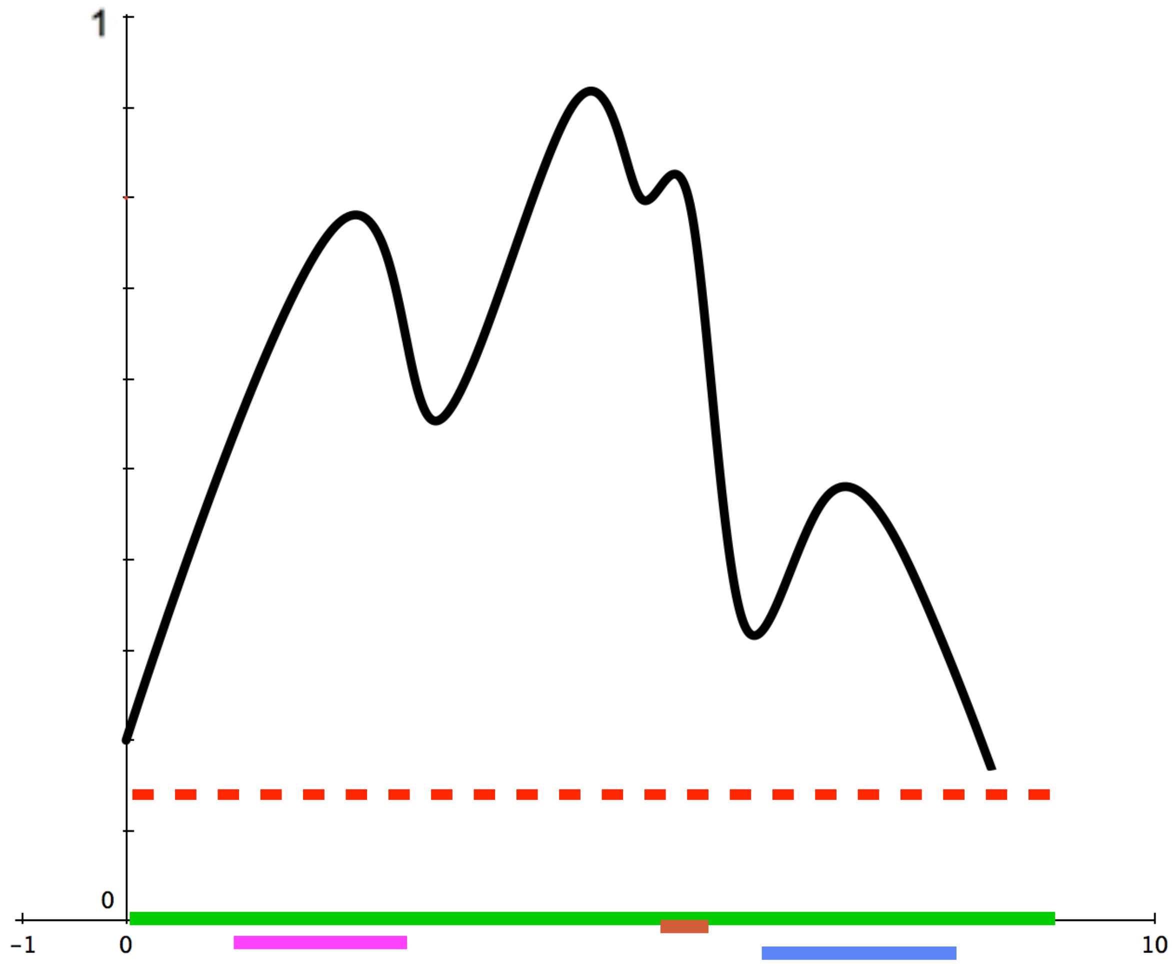
- **Topological persistence**

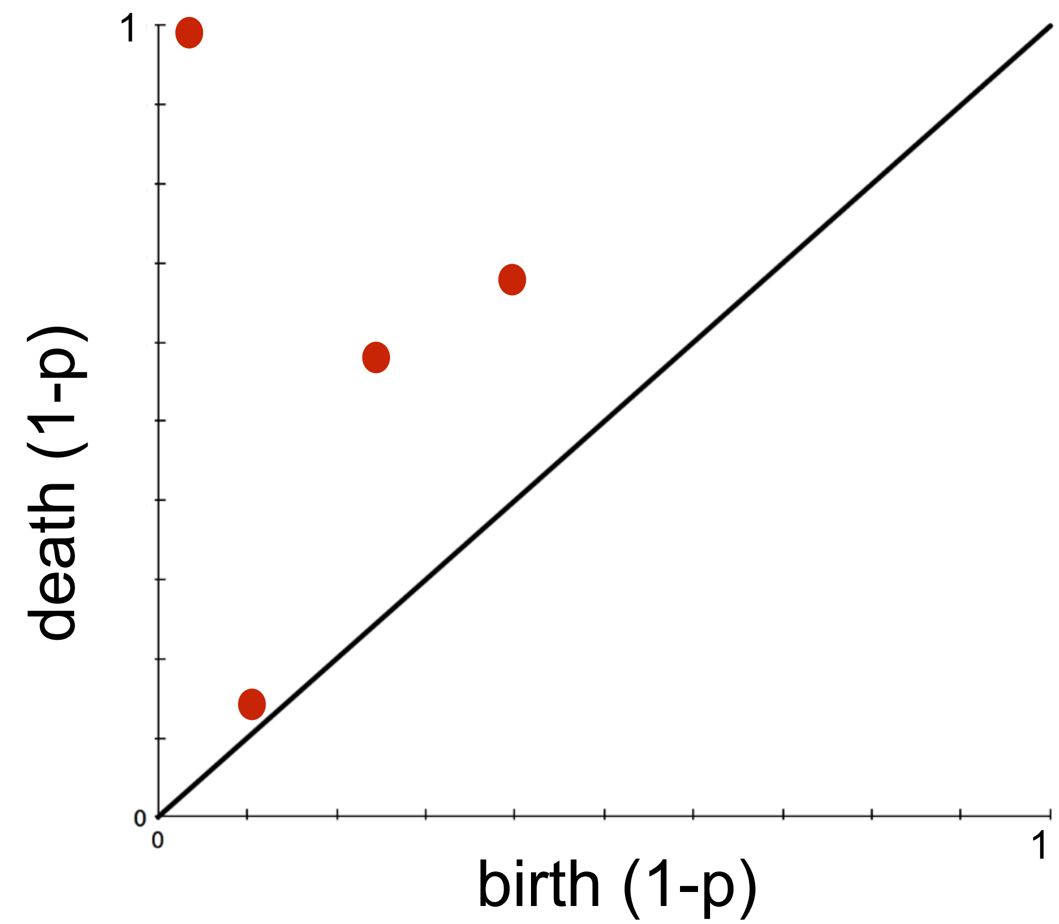




Persistent Homology

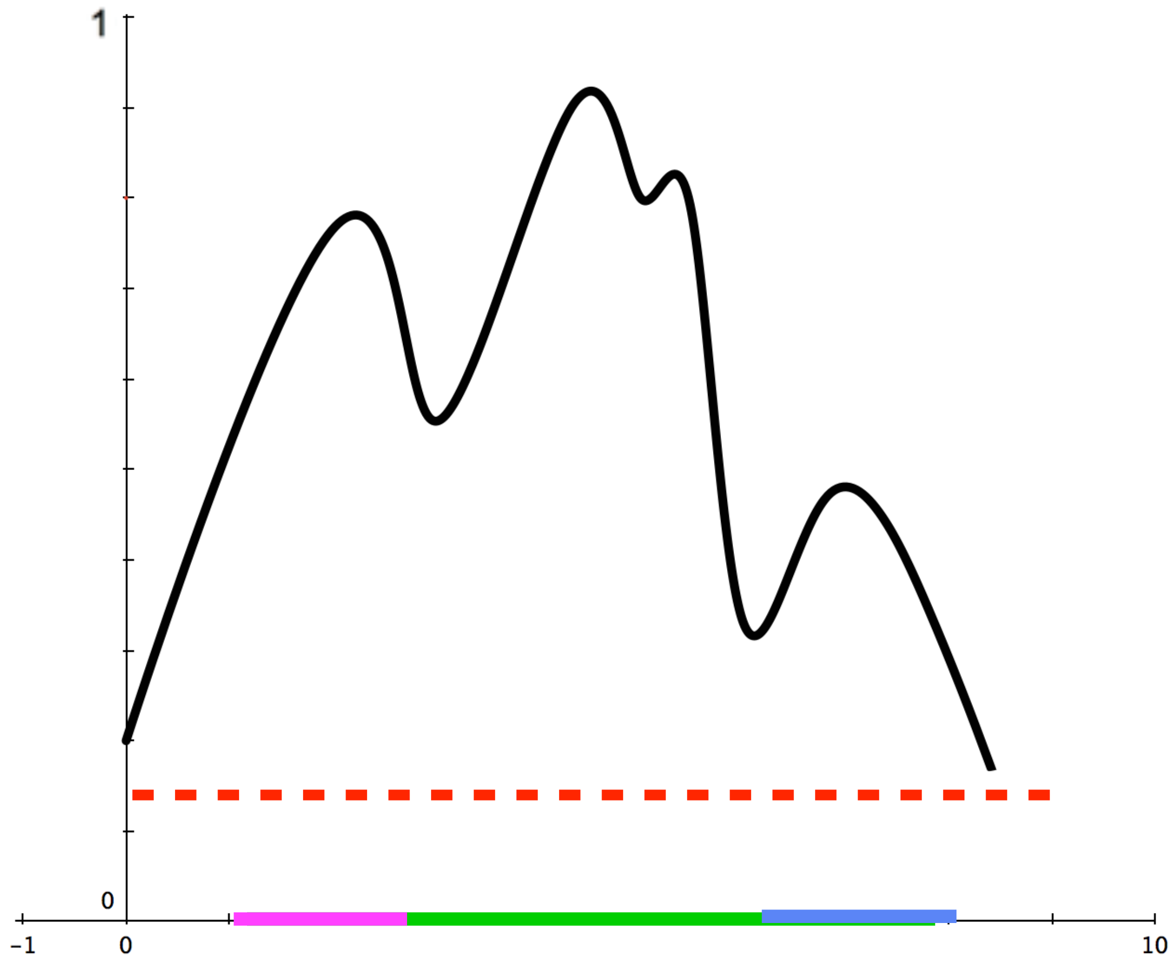
- **Topological persistence**

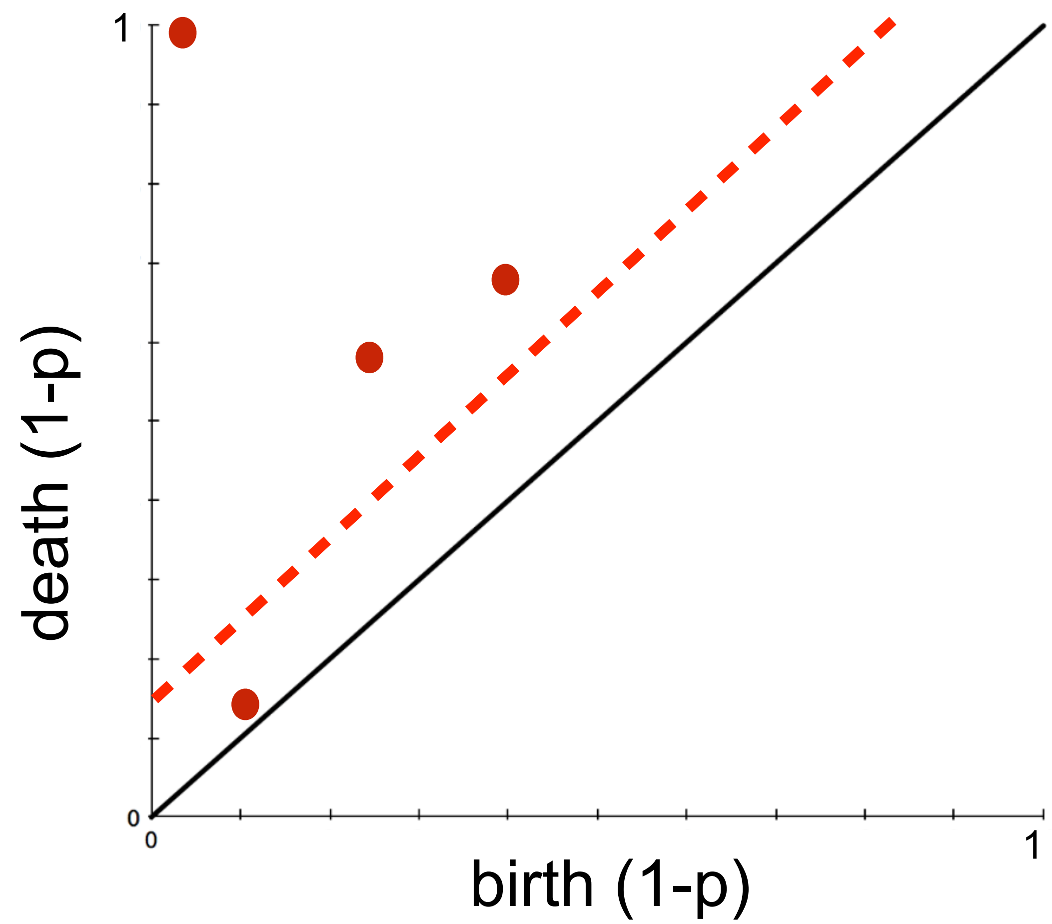




Persistent Homology

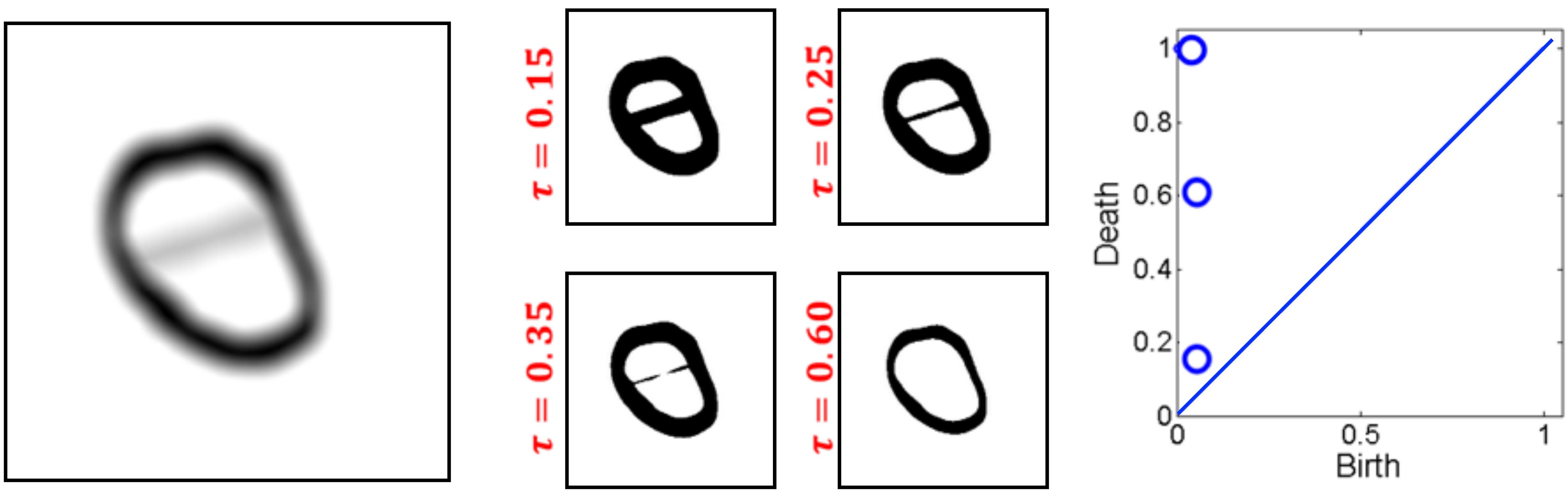
- **Topological persistence**



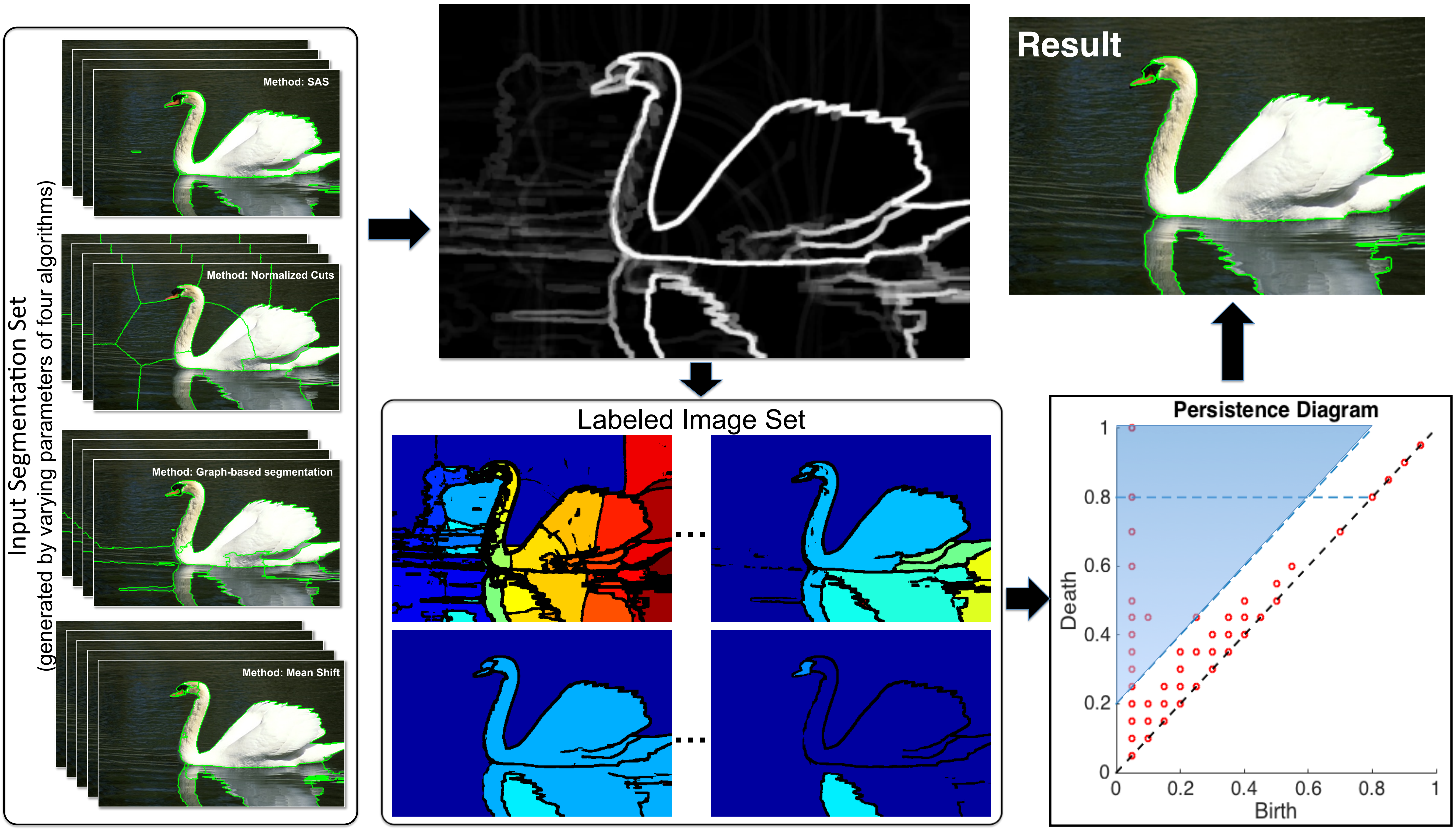


Persistent Homology

- **Topological persistence**

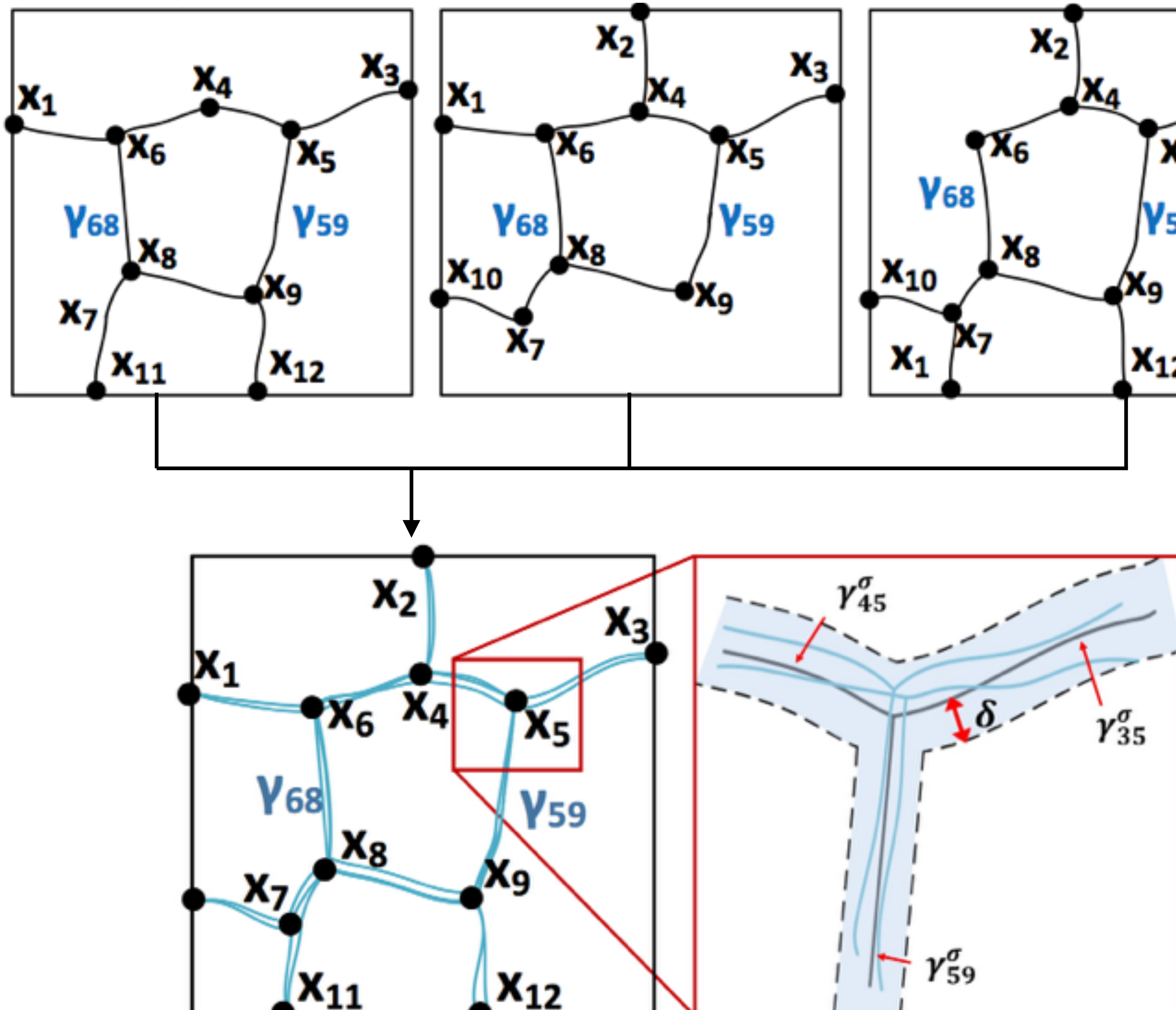


Consensus-based Image Segmentation



Consensus-based Image Segmentation

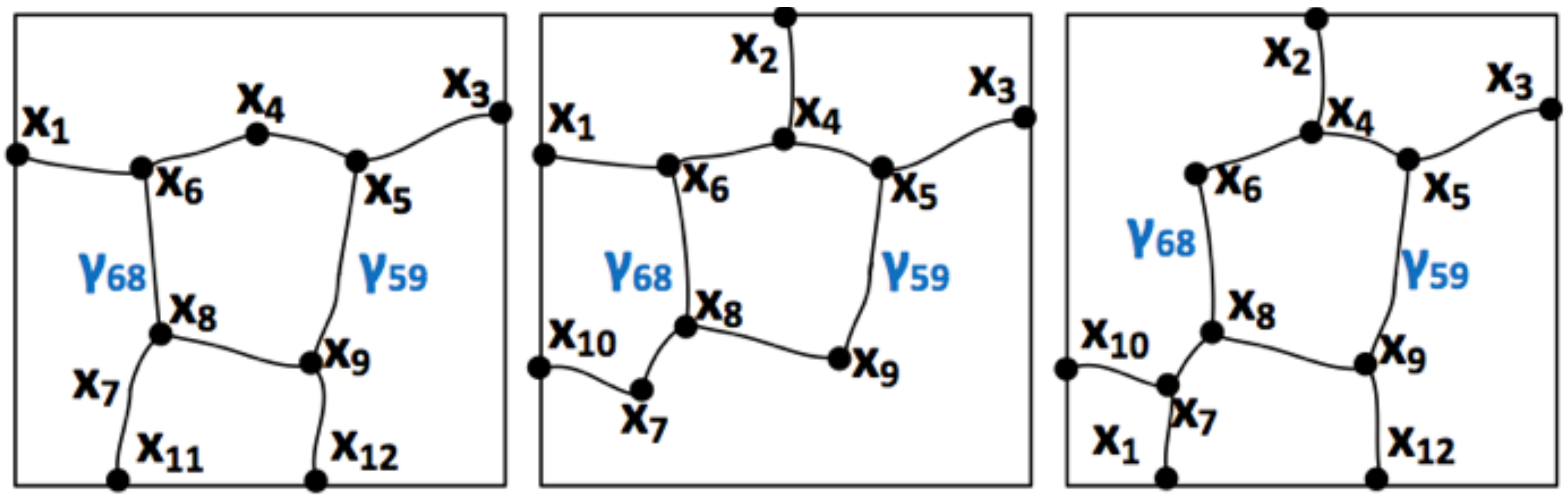
- **Image segmentation model**



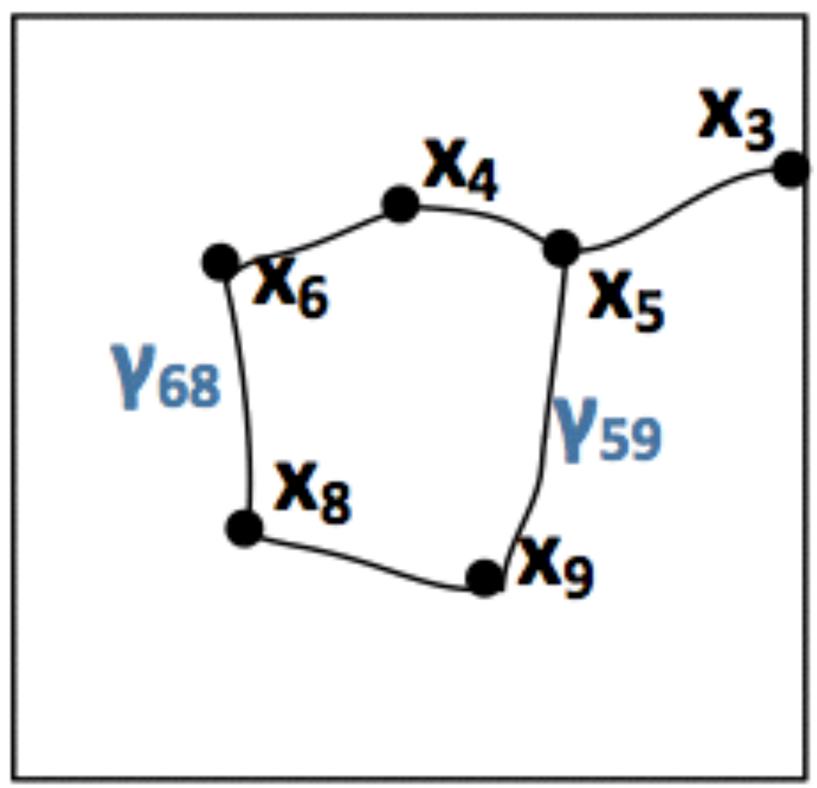
Consensus-based Image Segmentation

- **Image segmentation model**

Input

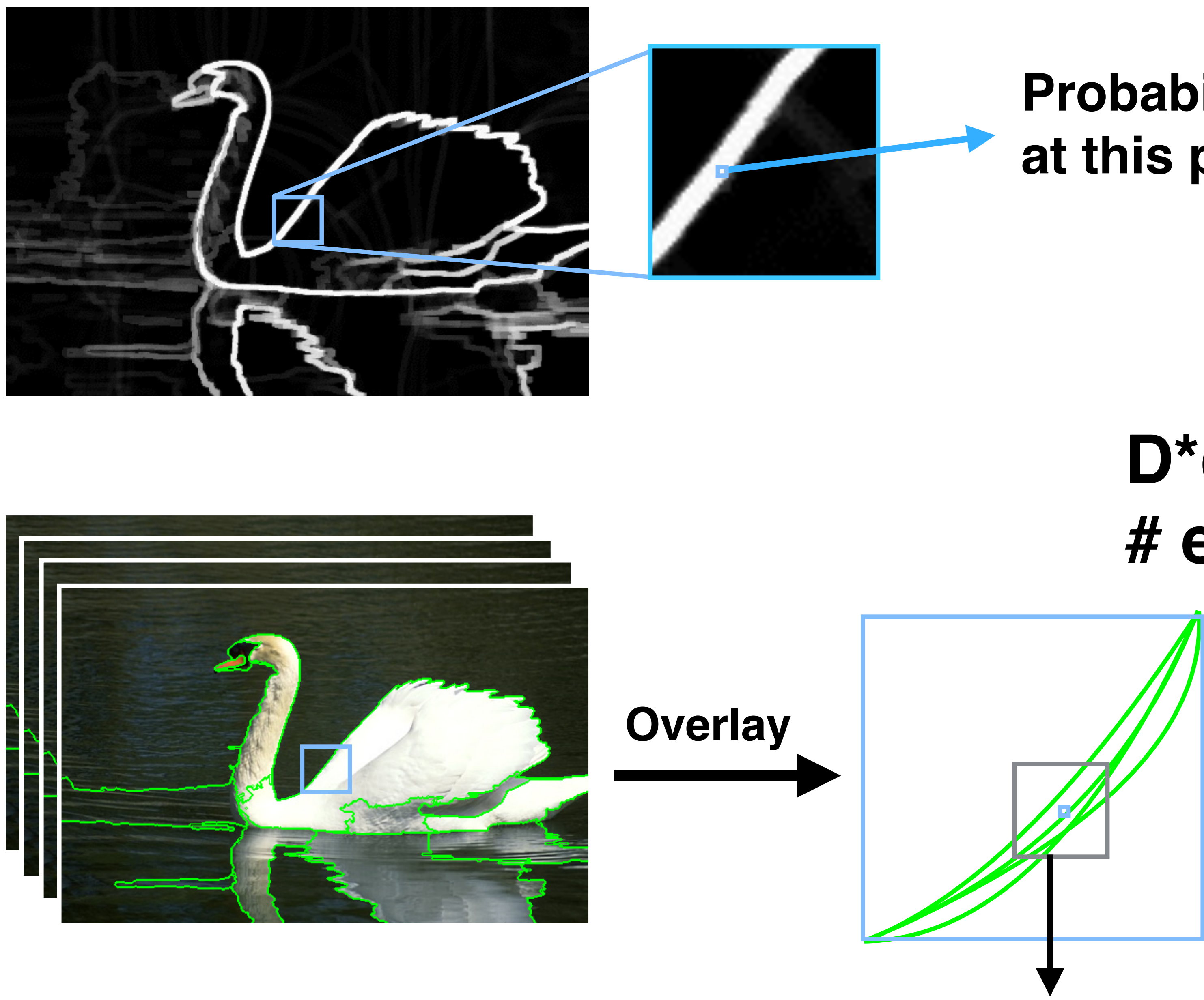


Segmentation Result



Consensus-based Image Segmentation

- **Probability map construction**



Probability of edge at this pixel

D*(X) =
 # edge / # segmentations

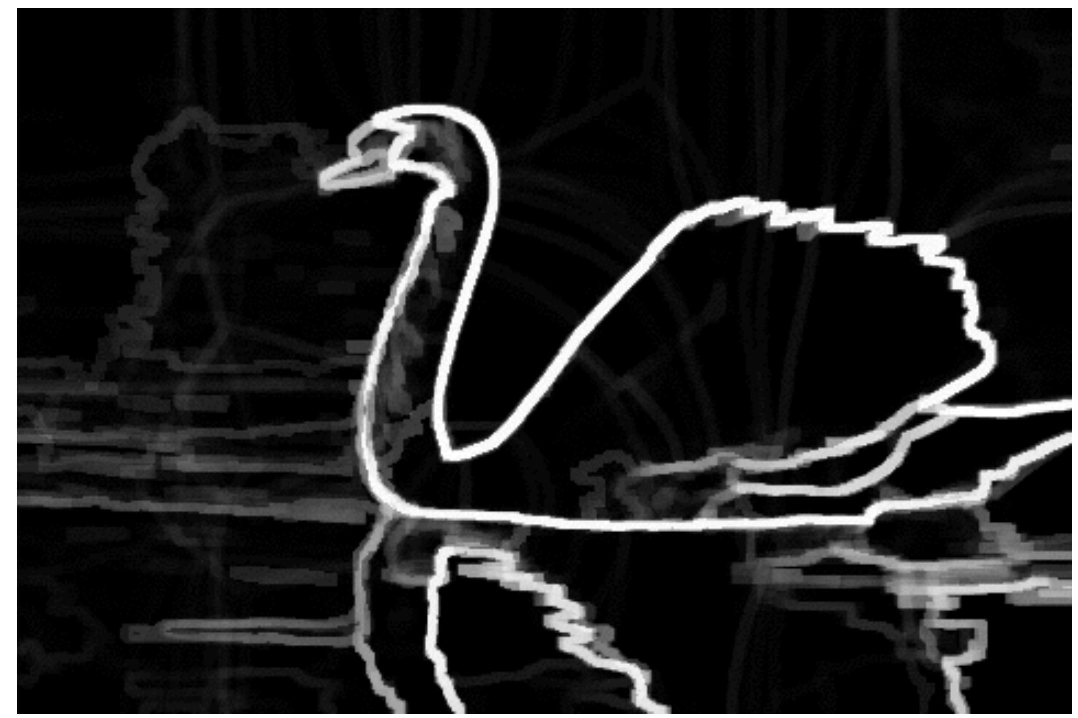
A small patch around pixel X

Consensus-based Image Segmentation

- **Probability map construction**

Connection probability map

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

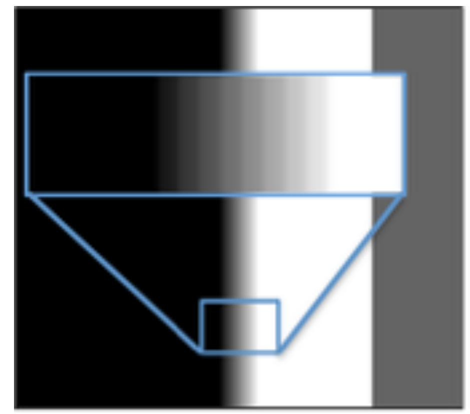


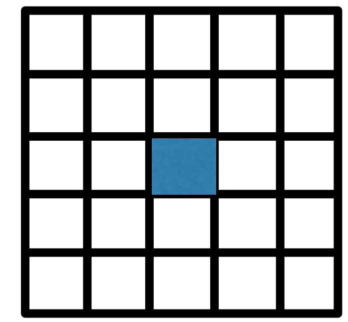
Edge probability map

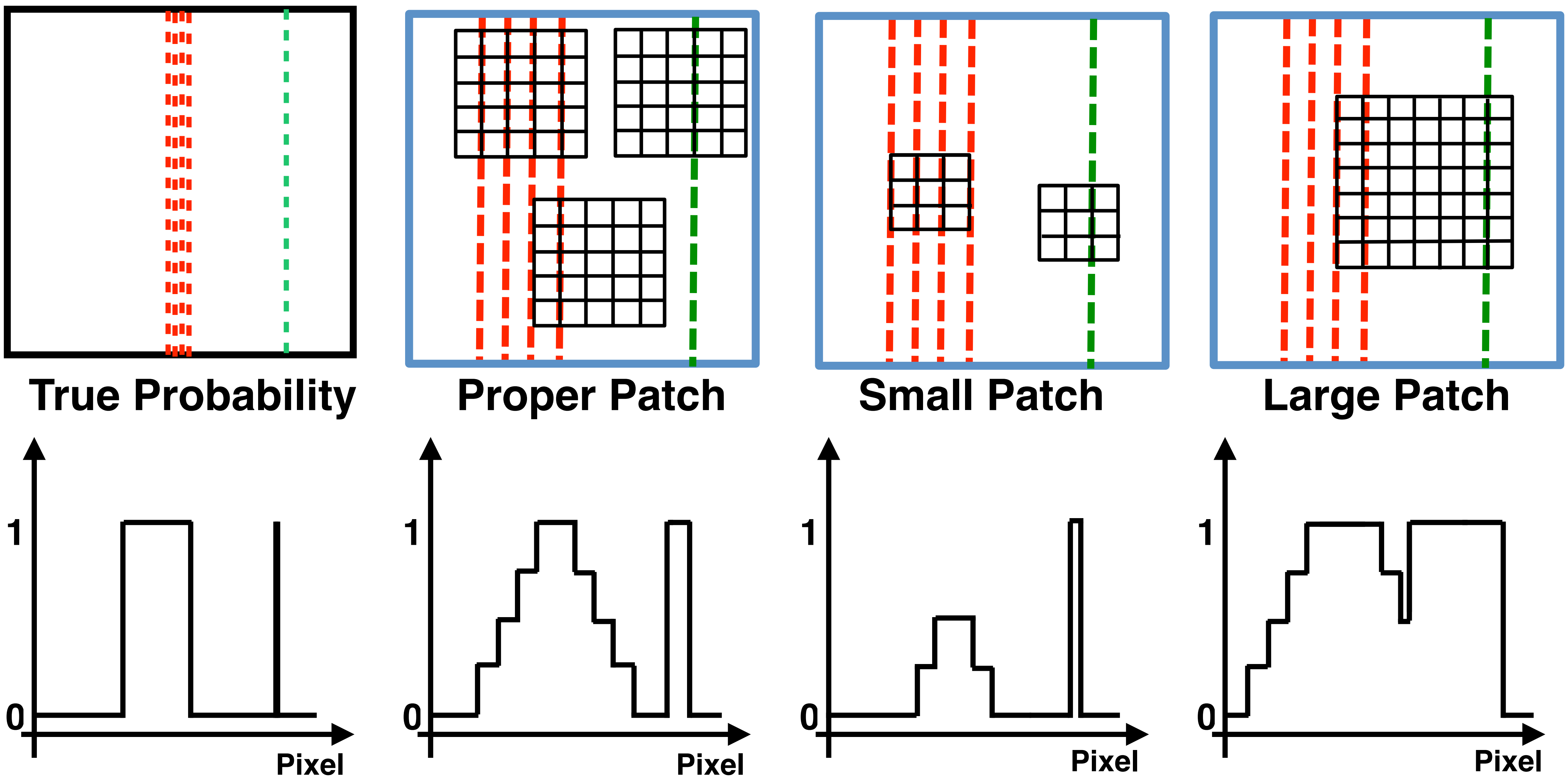
$$D_n^*(x)$$

Consensus-based Image Segmentation

- **Effect of patch size n**

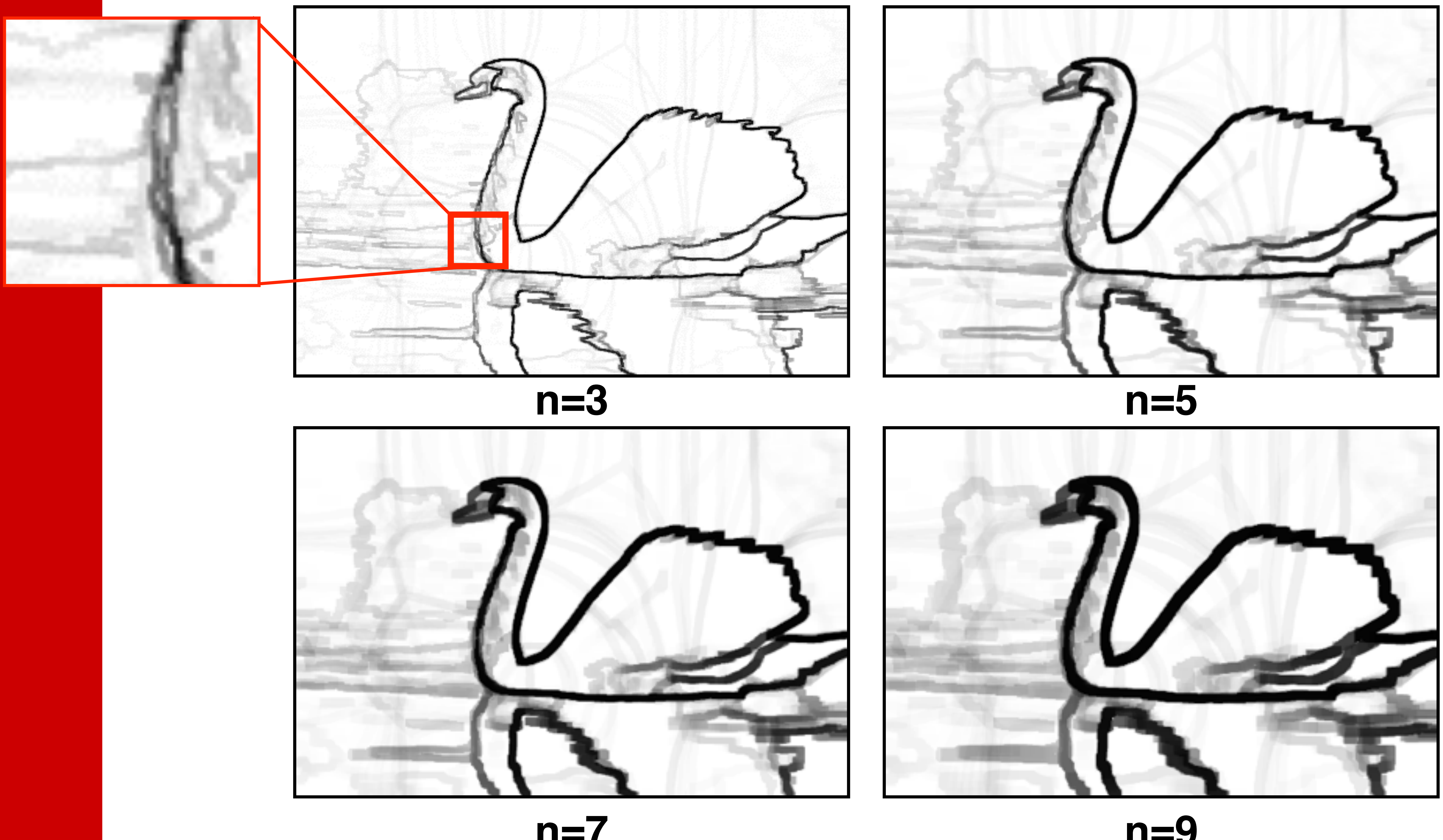






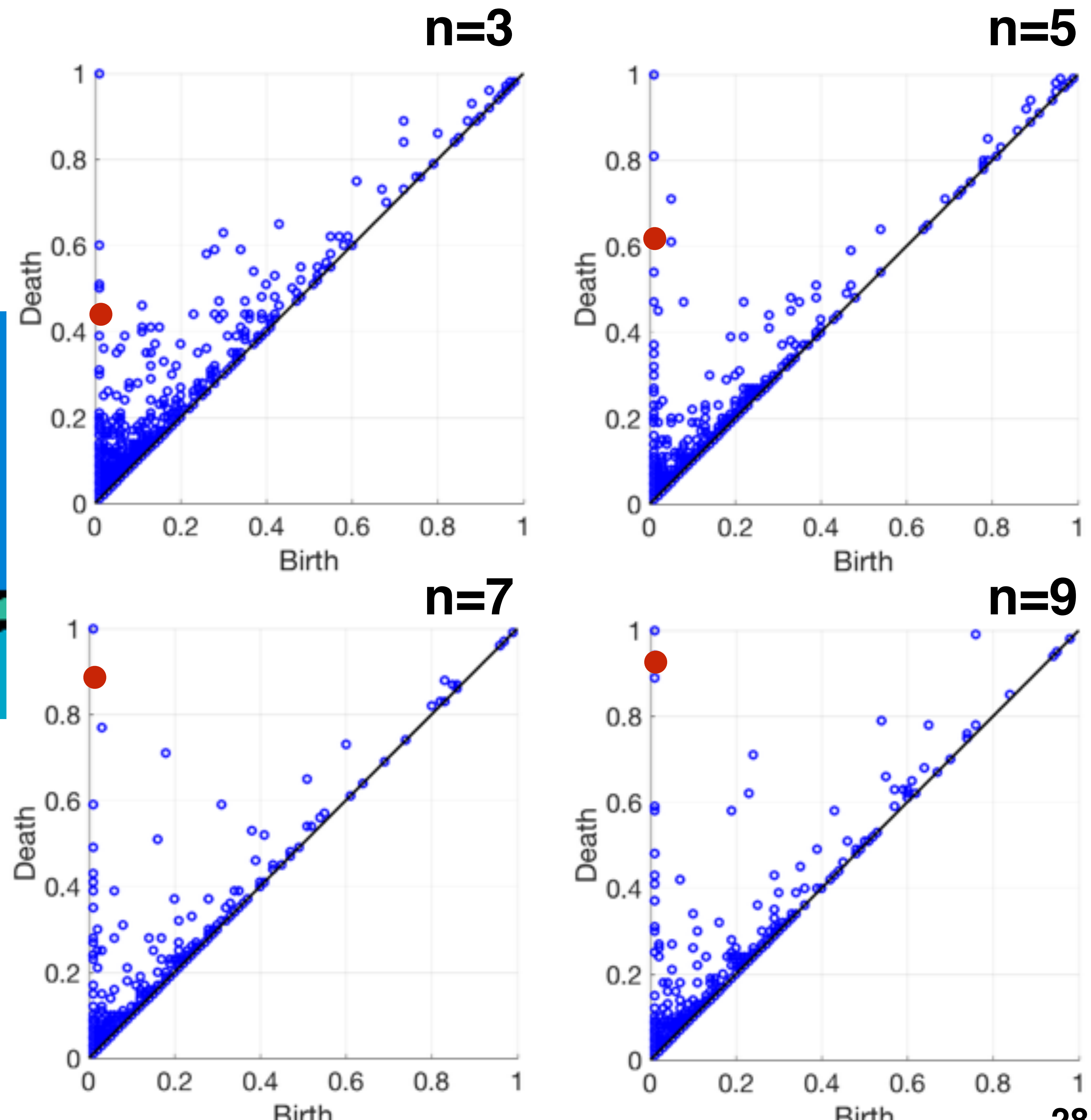
Consensus-based Image Segmentation

- **Effect of patch size n**



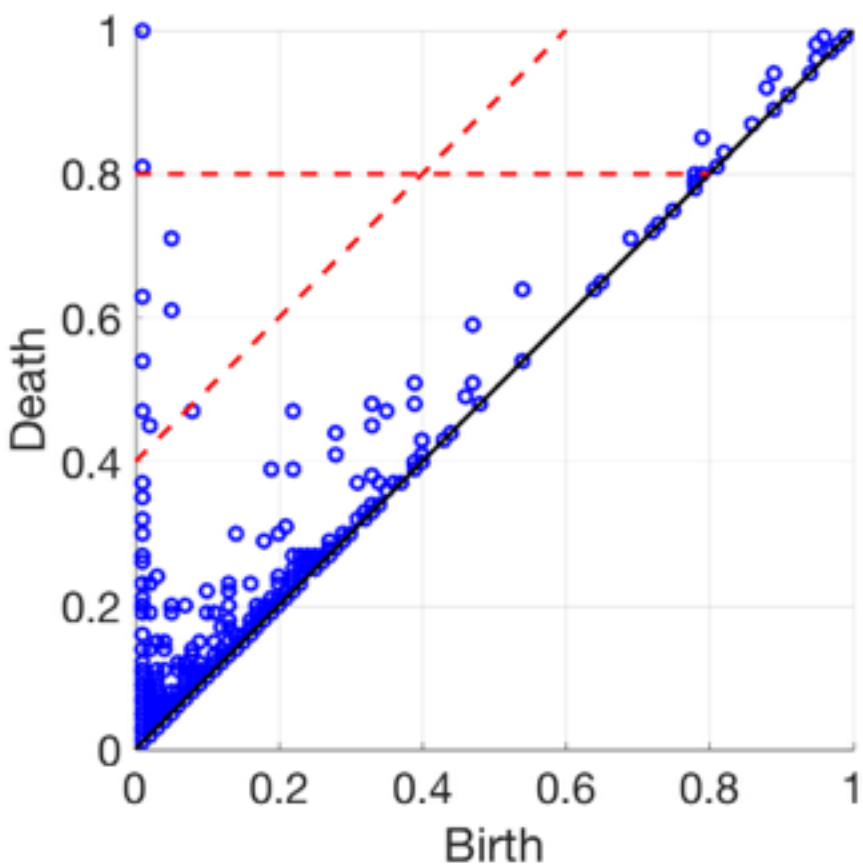
Consensus-based Image Segmentation

- **Persistence diagram**



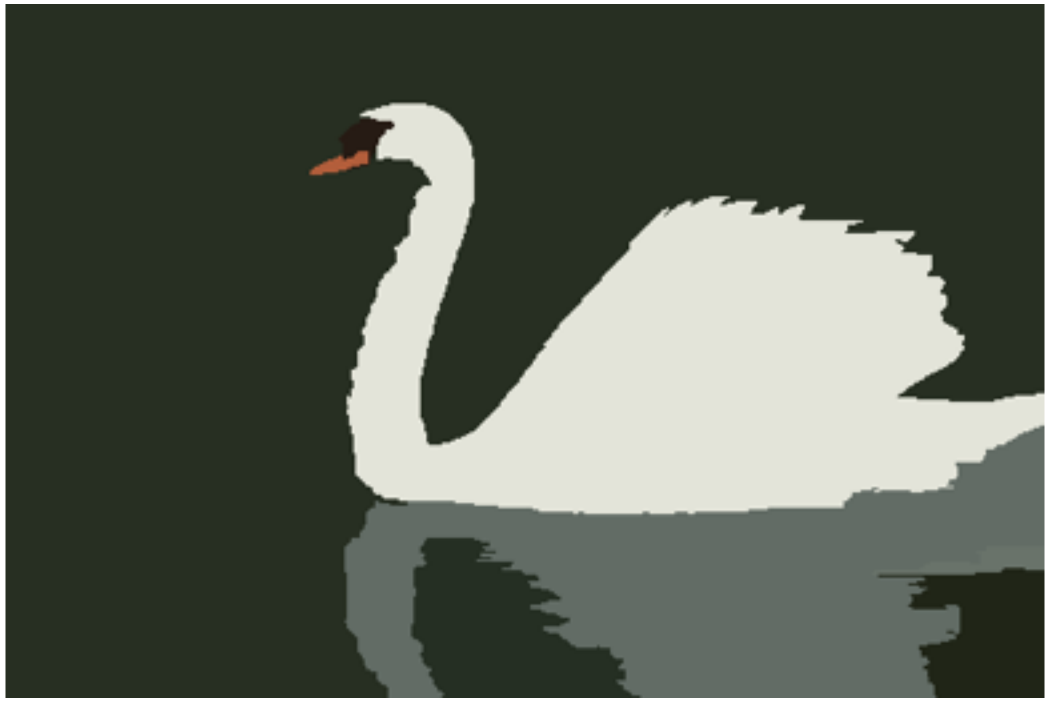
Consensus-based Image Segmentation

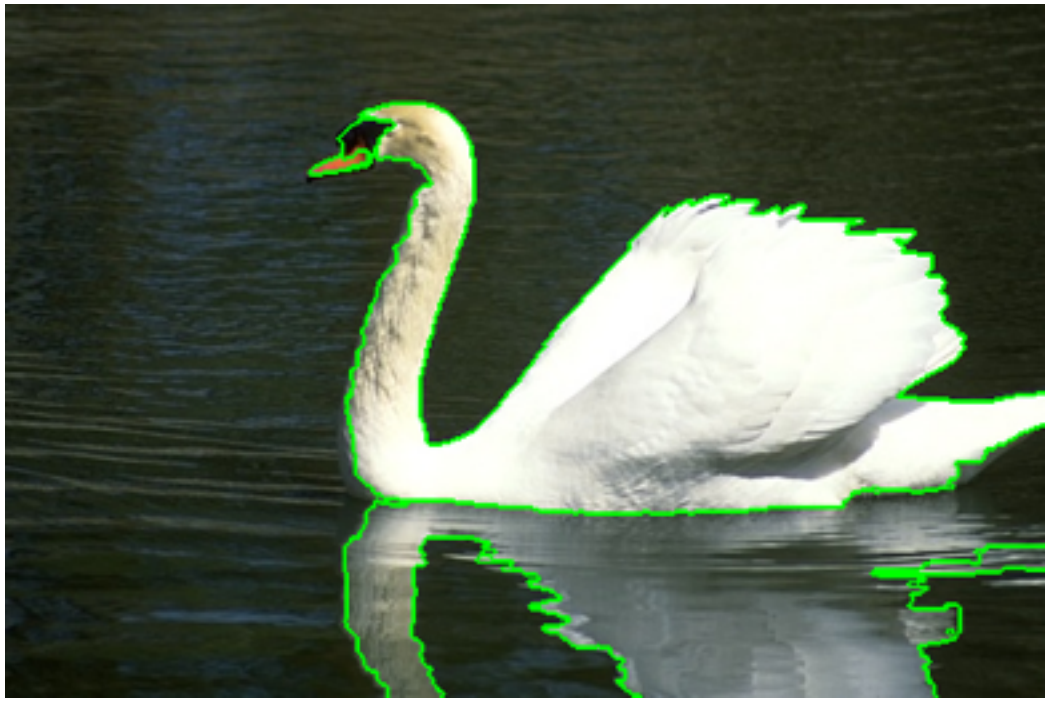
- **Thresholding persistence diagram**
  - **Persistence threshold - extract persistent region and remove noise.**
  - **Probability threshold - make sure capture edges being present in high probability.**



Consensus-based Image Segmentation

- **Segmentation obtained by color-based region growing**





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Consensus-based Image Segmentation

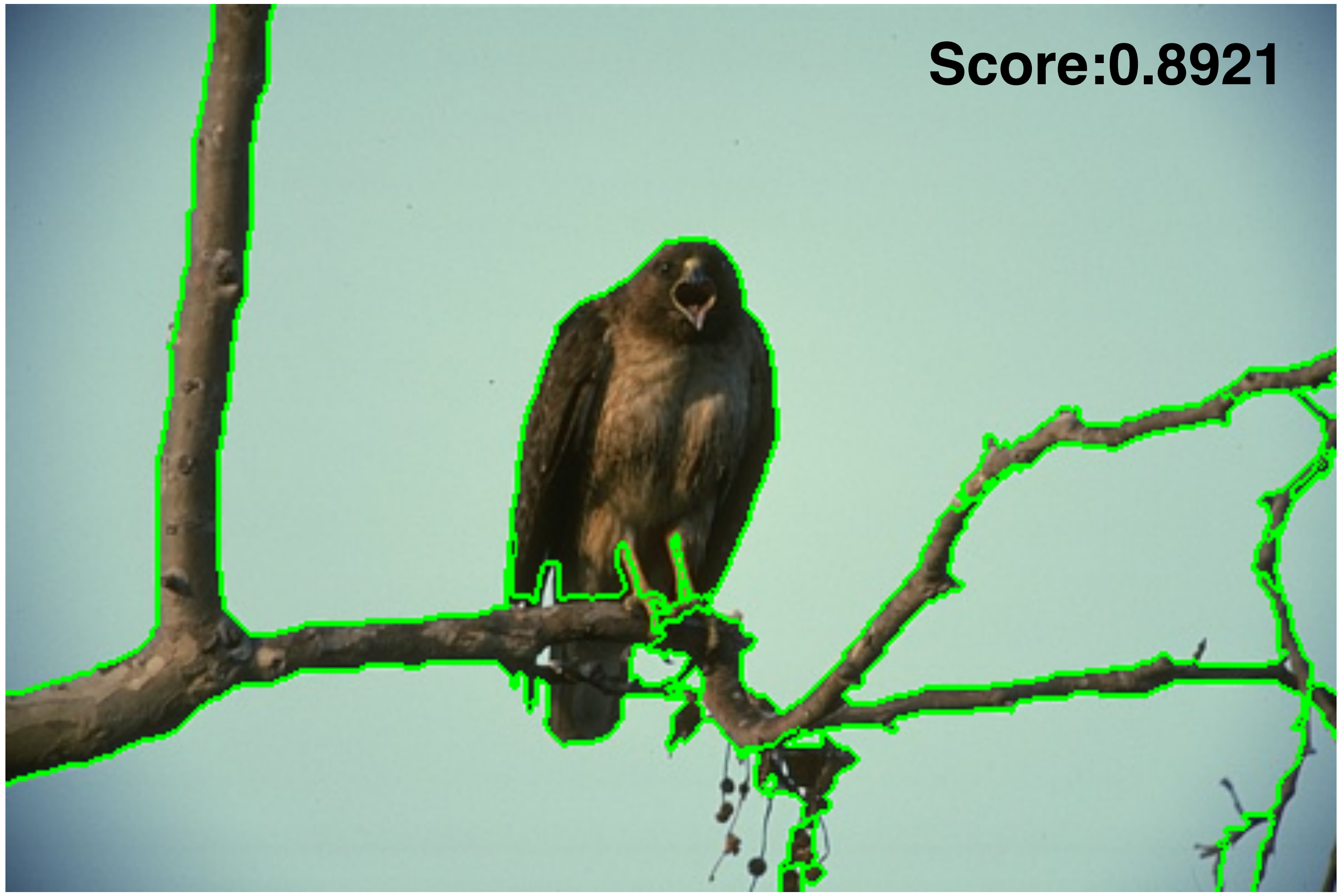
- **Experiment - Input set generation**
  - Dataset - Berkeley Segmentation Database
  - Four input algorithms: SAS, Normalized Cuts, Graph-based and Mean Shift
    - SAS: number of region varying from 5 to 30
    - Normalized Cuts: number of region varying from 5 to 30
    - Graph-based: σ varying from 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

Consensus-based Image Segmentation

- **Experiment - Result**

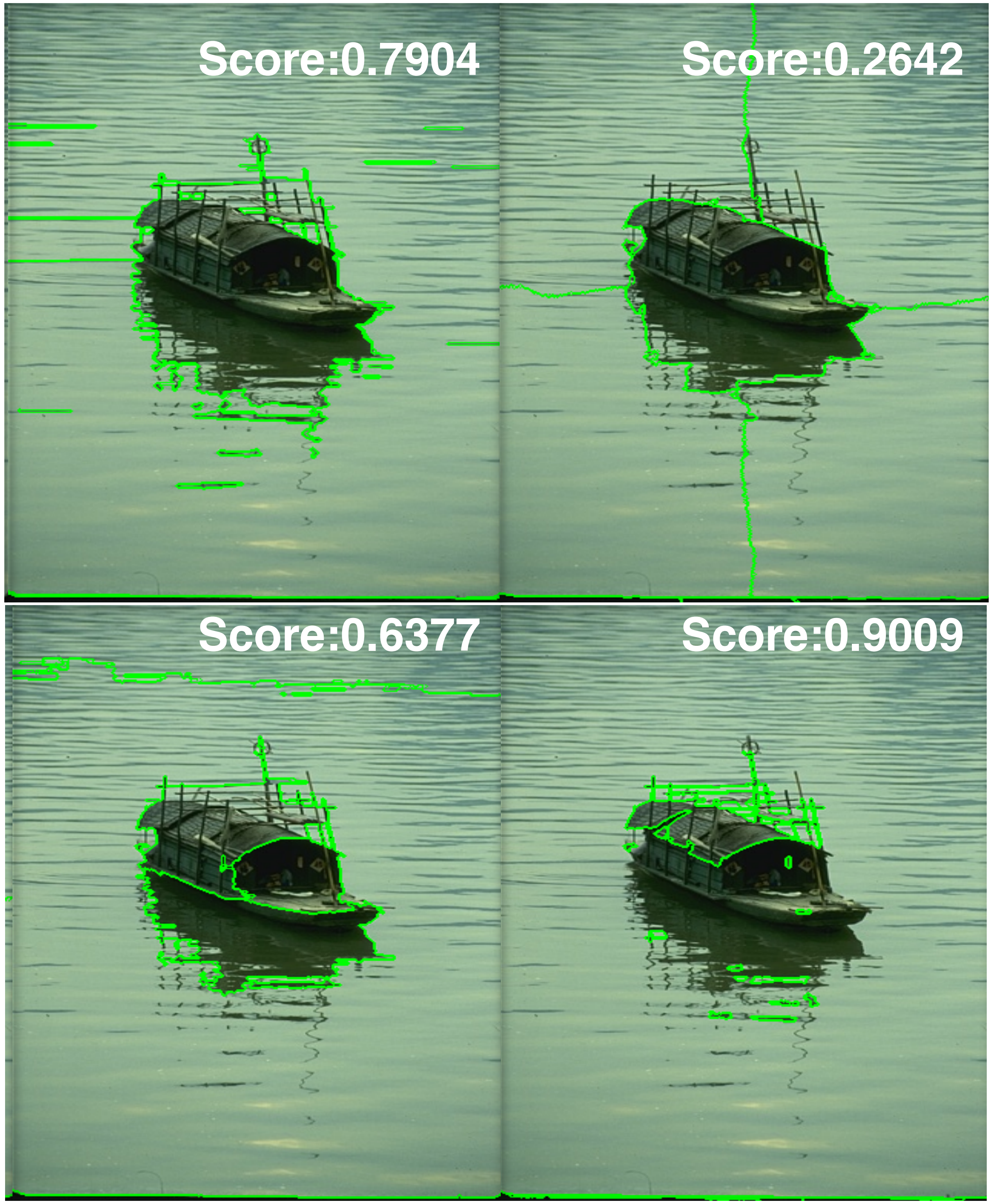
Consensus-based Image Segmentation

- **Experiment - Result**



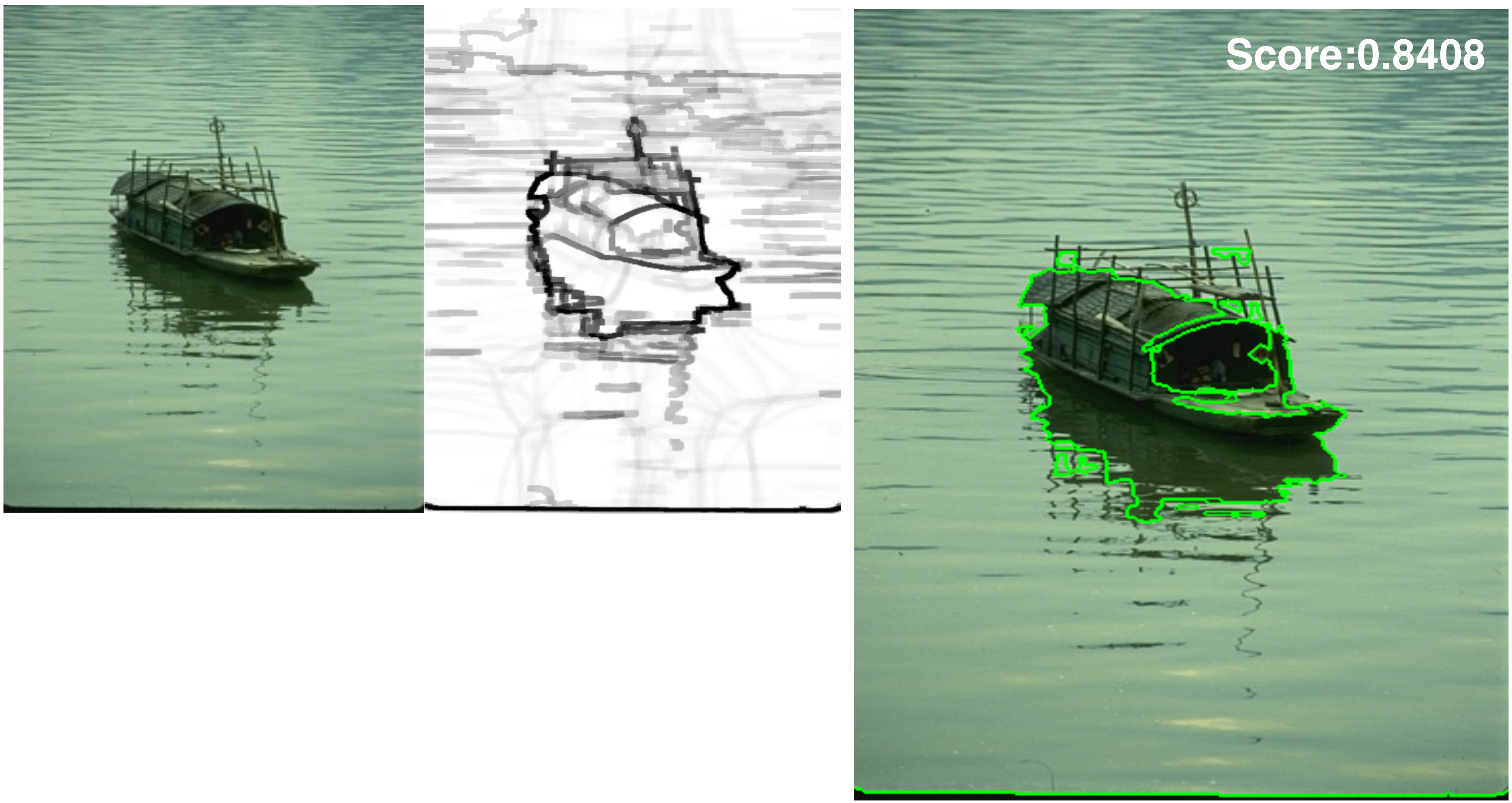
Consensus-based Image Segmentation

- **Experiment - Result**



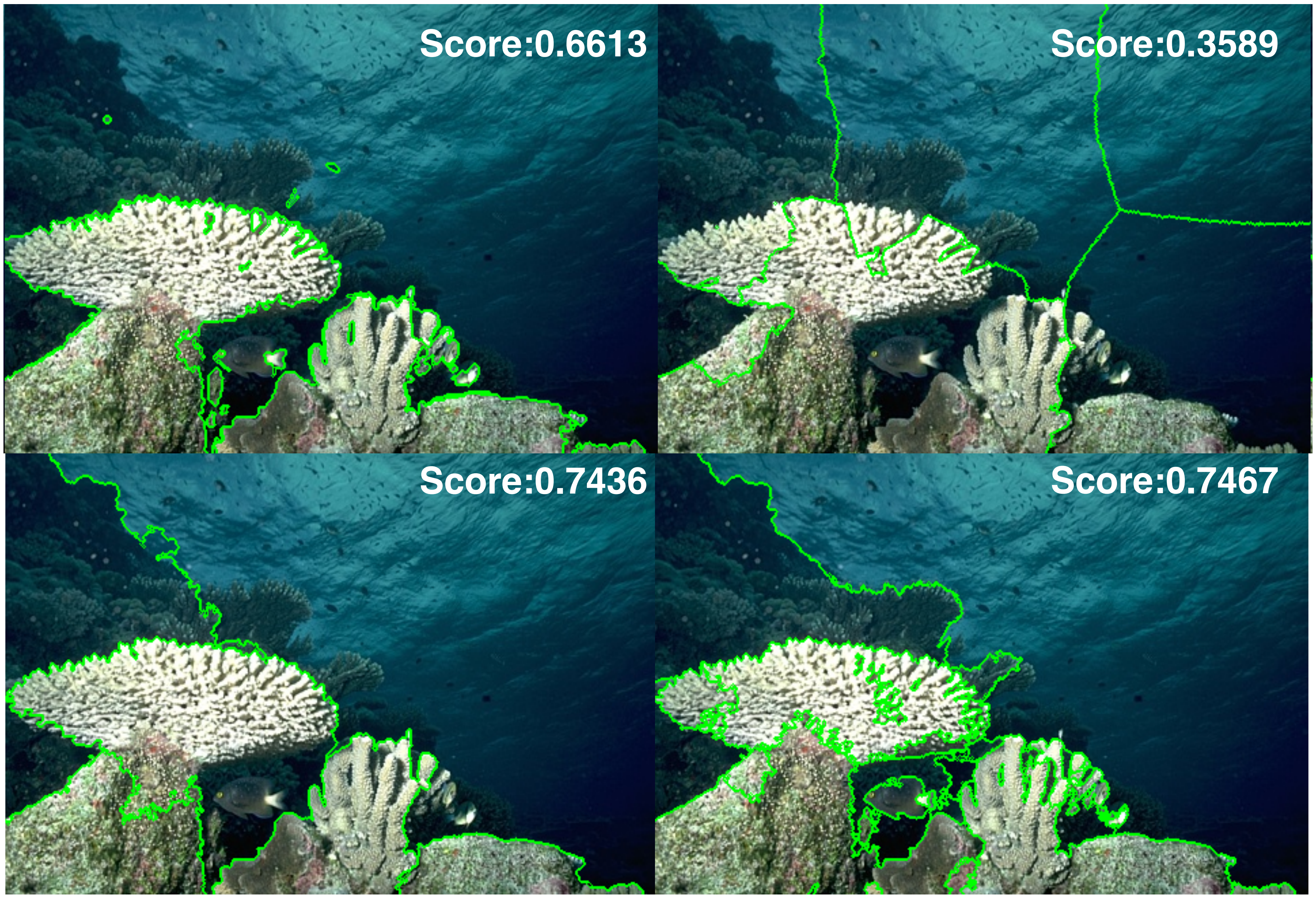
Consensus-based Image Segmentation

- **Experiment - Result**



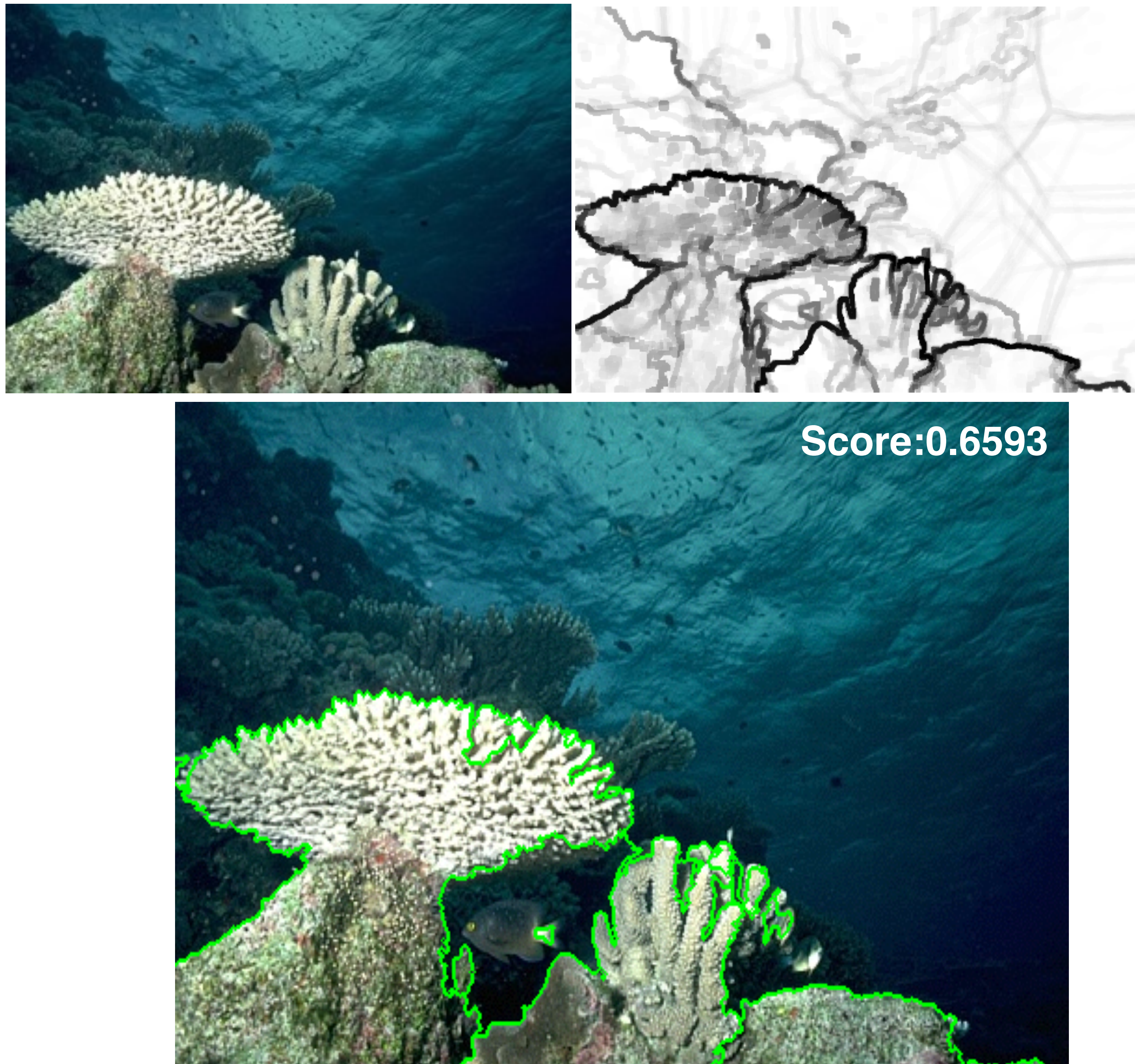
Consensus-based Image Segmentation

- **Experiment - Result**



Consensus-based Image Segmentation

- **Experiment - Result**



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Consensus-based Image Segmentation

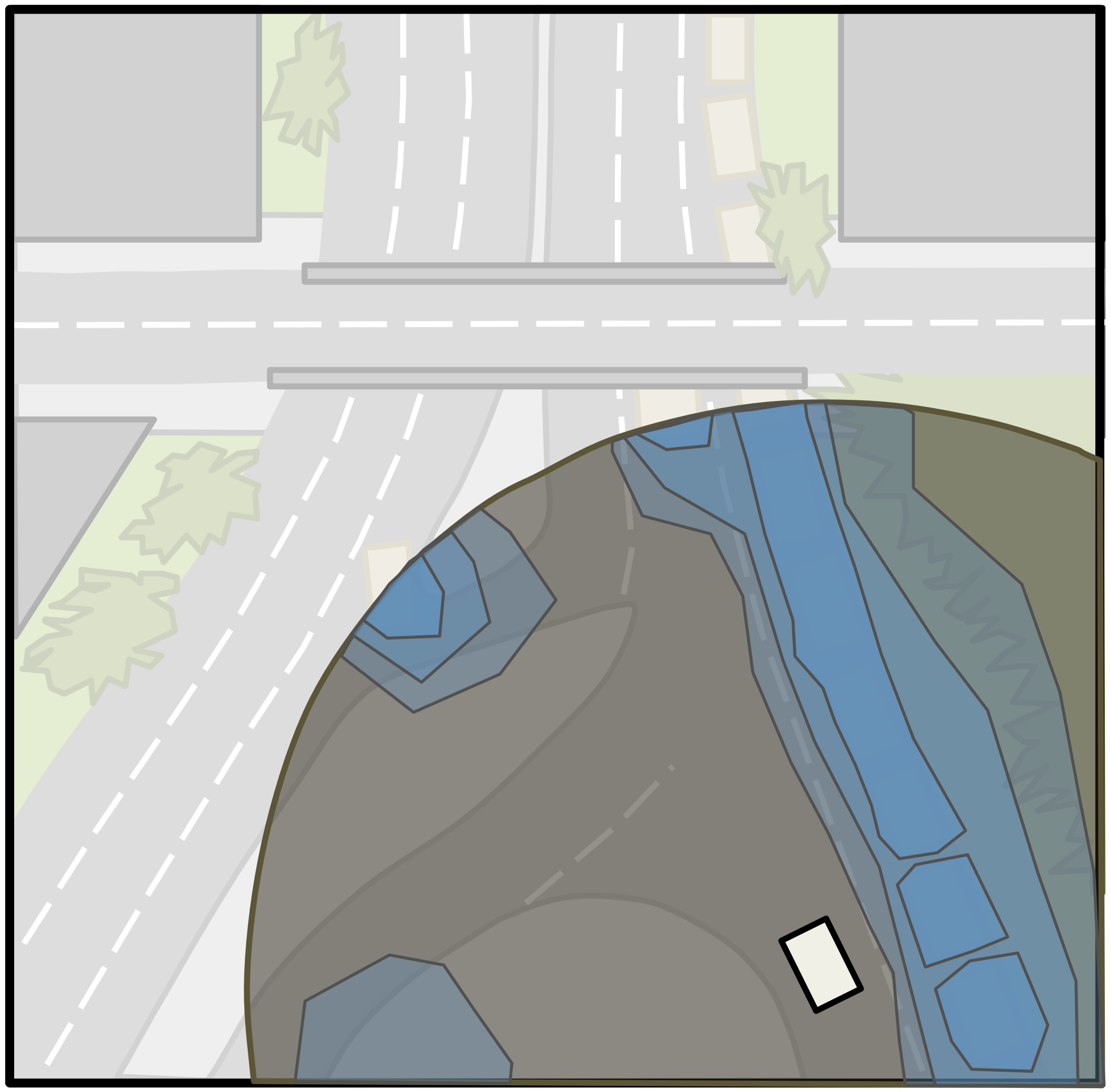
- **Experiment - Result**
  - RSC - Coverage score
  - VoI - Variation of information

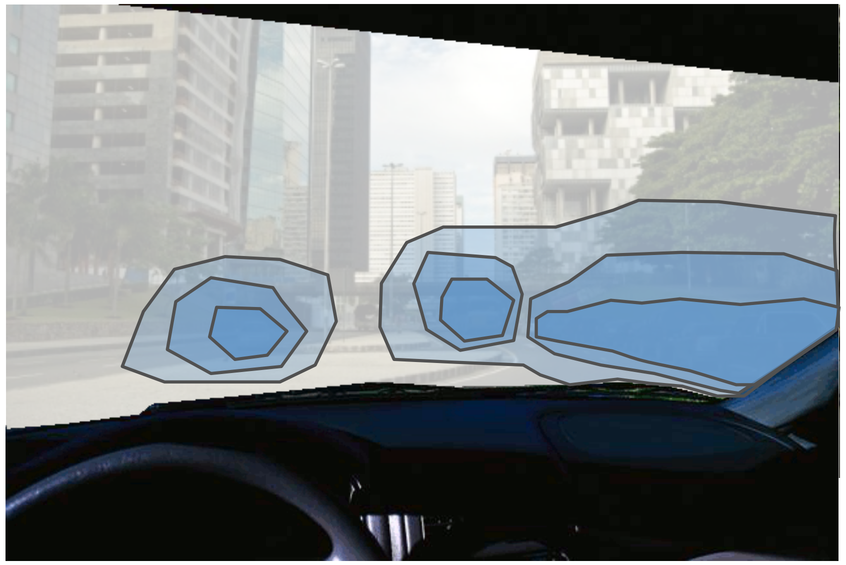
Methods	Graph	NCuts	SAS	Mean Shift
RSC	0.5359	0.3970	0.5325	0.5540
VoI	2.1128	2.3515	1.8251	1.8946

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**

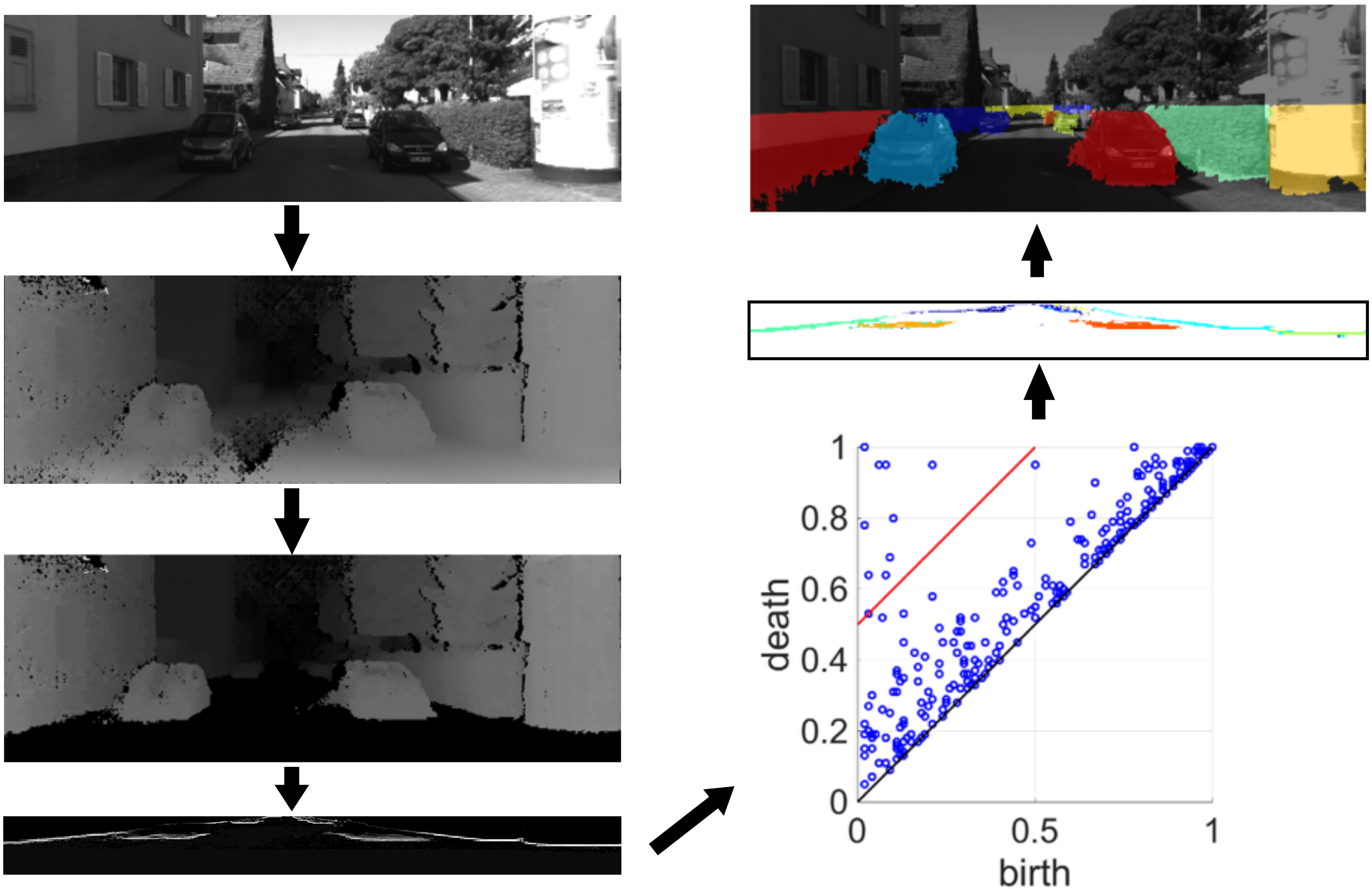
Obstacle Segmentation of Outdoor Scene

- **Vision system for autonomous driving**



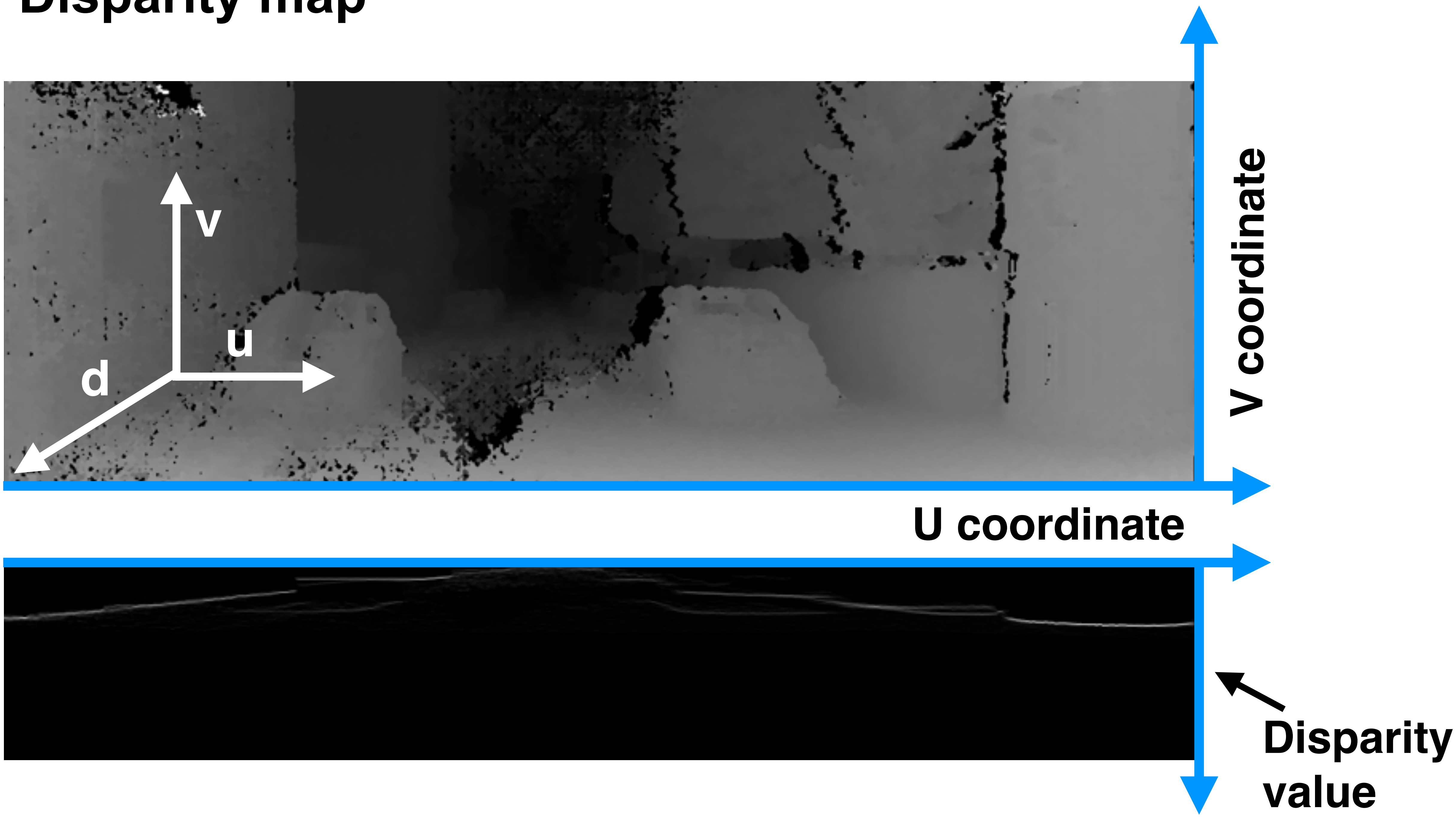


Obstacle Segmentation of Outdoor Scene



Obstacle Segmentation of Outdoor Scene

- **Disparity map**

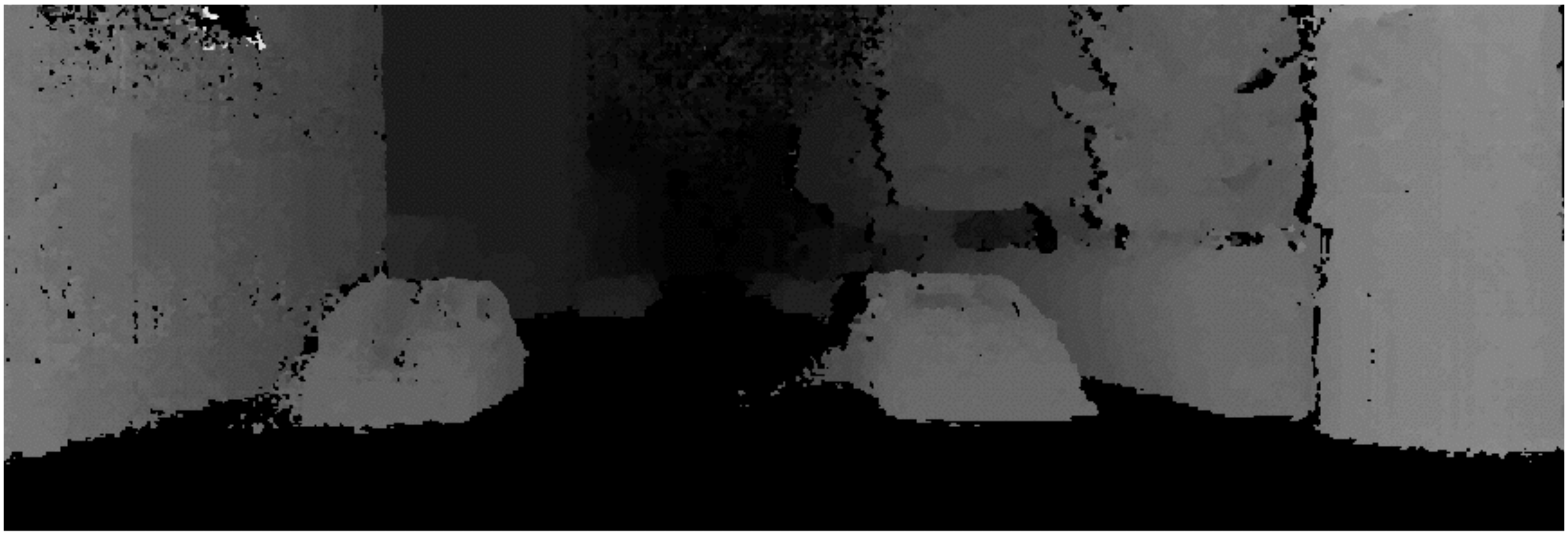


Obstacle Segmentation of Outdoor Scene

- **Ground Segmentation**

Obstacle Segmentation of Outdoor Scene

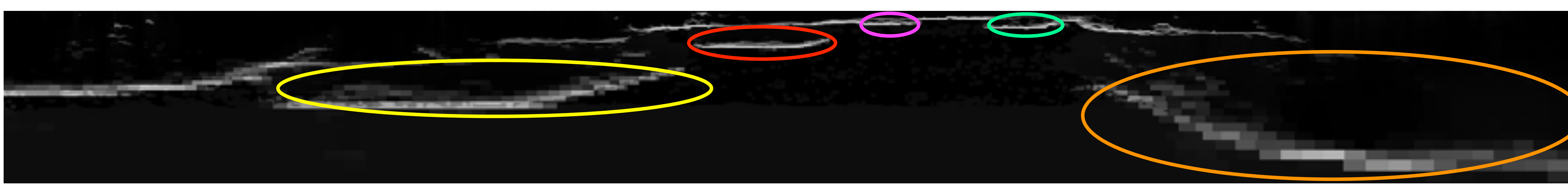
- **Occupancy computation**



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

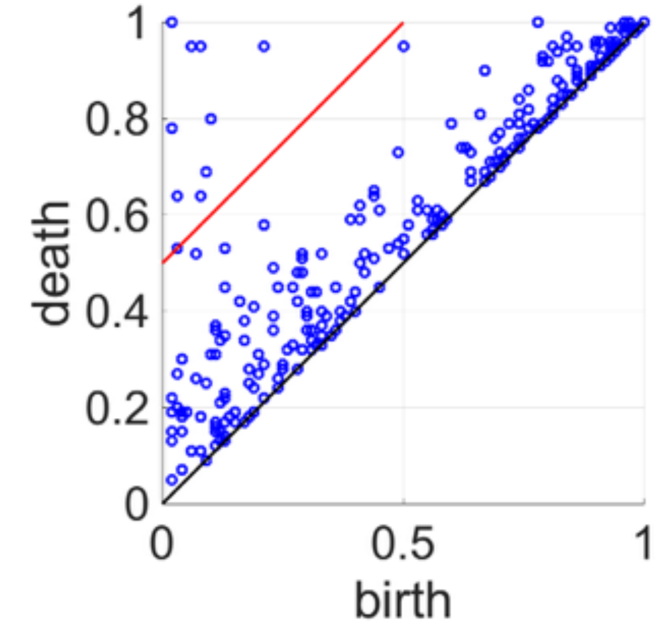
Obstacle Segmentation of Outdoor Scene

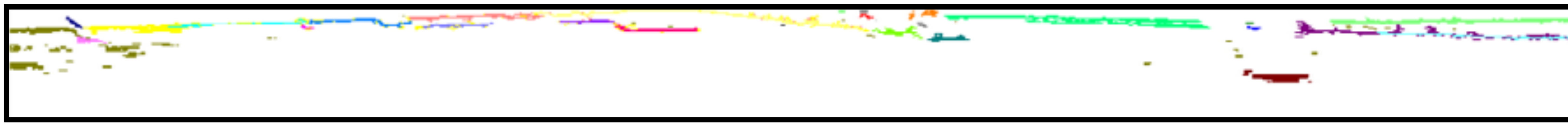
- **Occupancy computation**

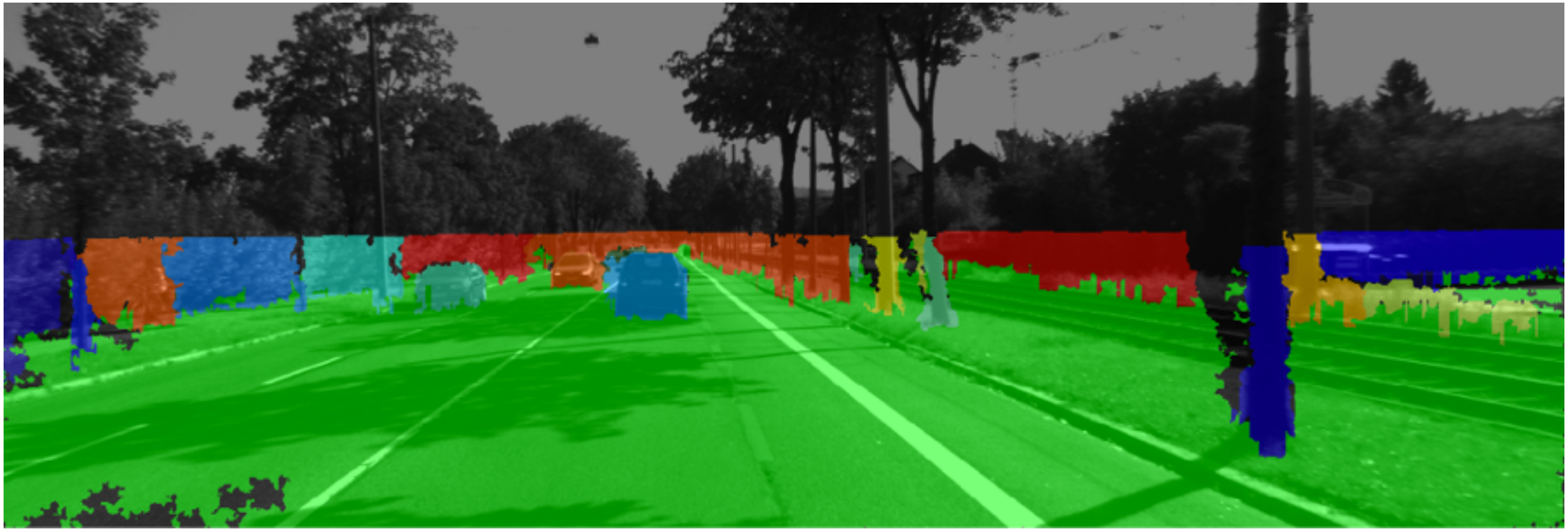


Obstacle Segmentation of Outdoor Scene

- **Persistence region extraction**

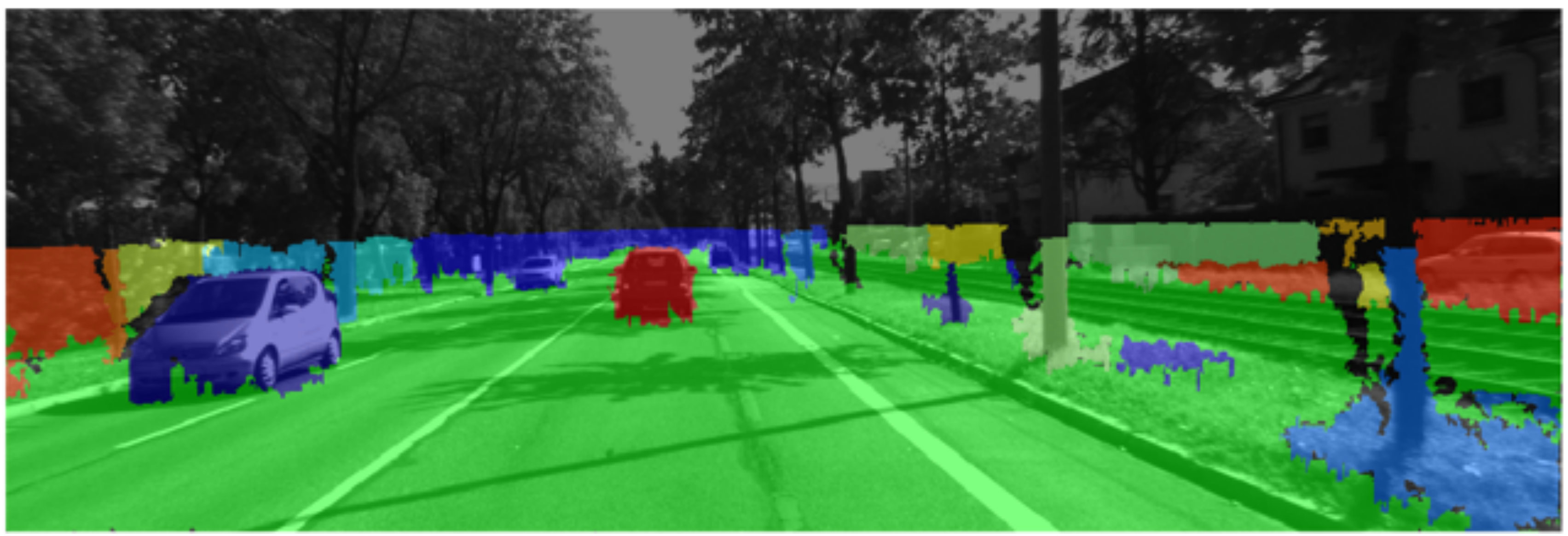


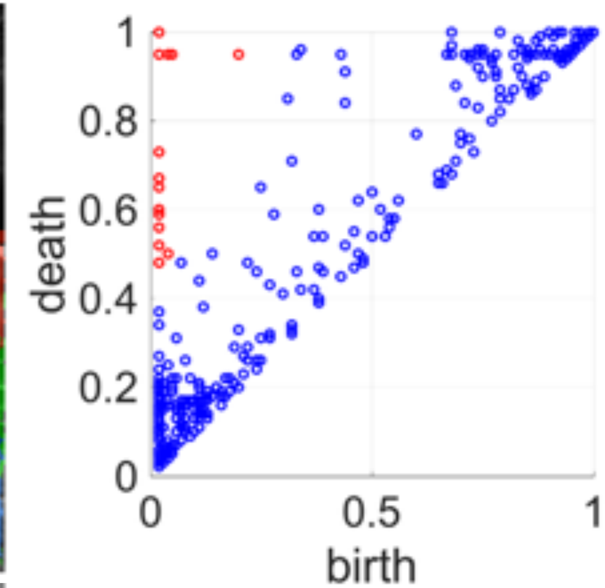


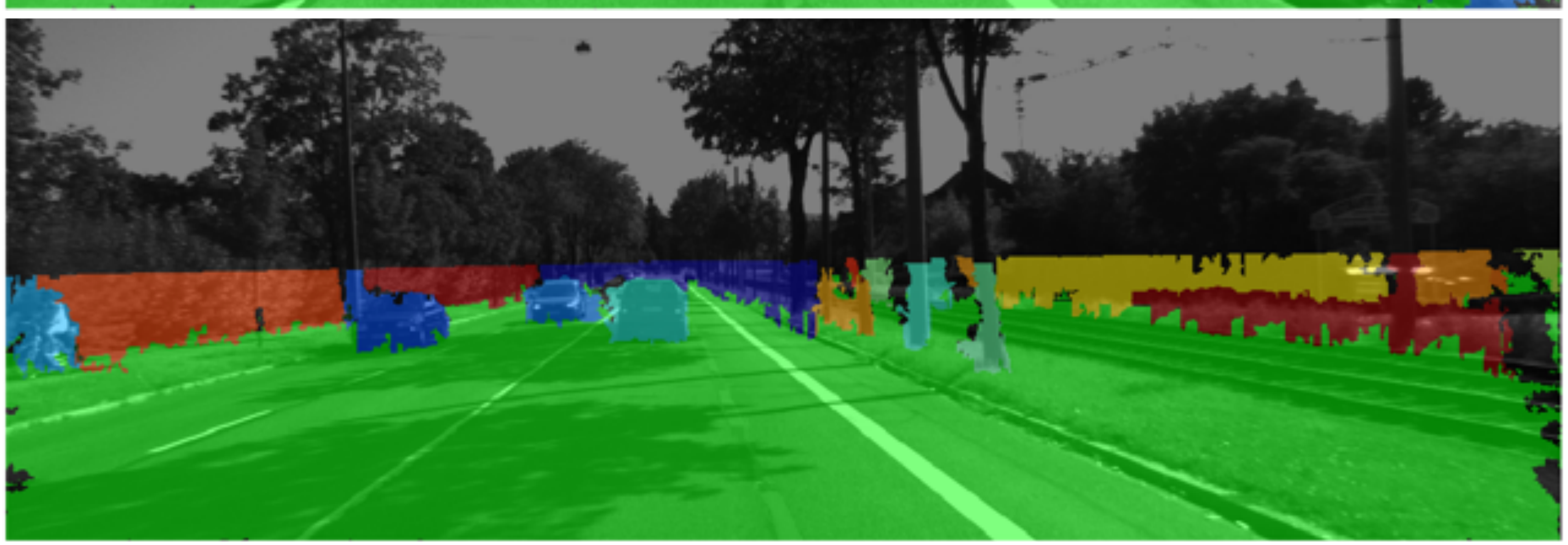


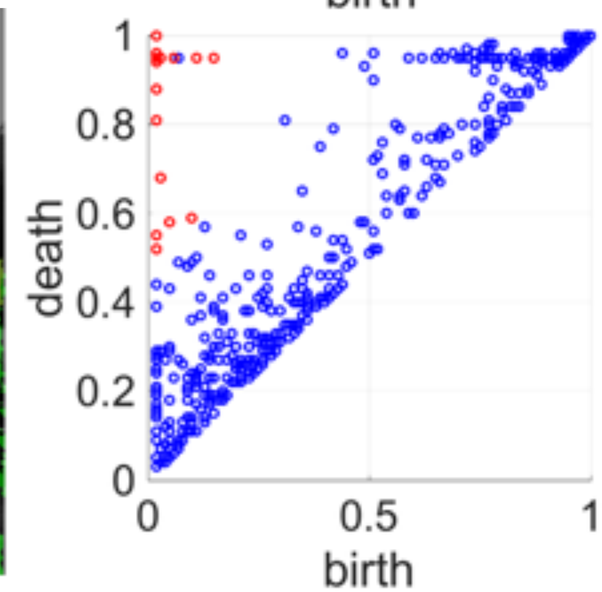
Obstacle Segmentation of Outdoor Scene

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









Obstacle Segmentation of Outdoor Scene

- **Experiment**
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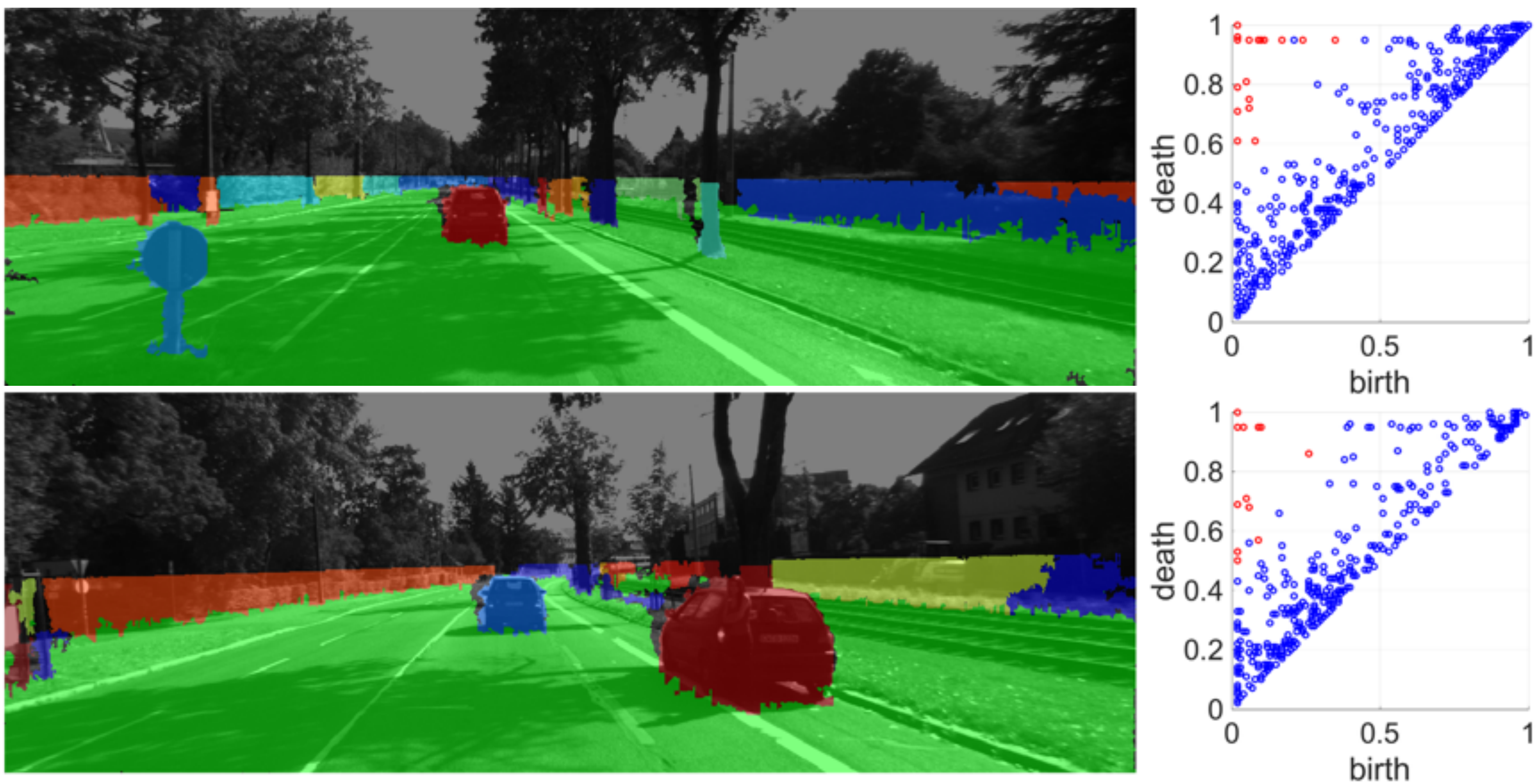
  - **Persistence threshold = 0.45**

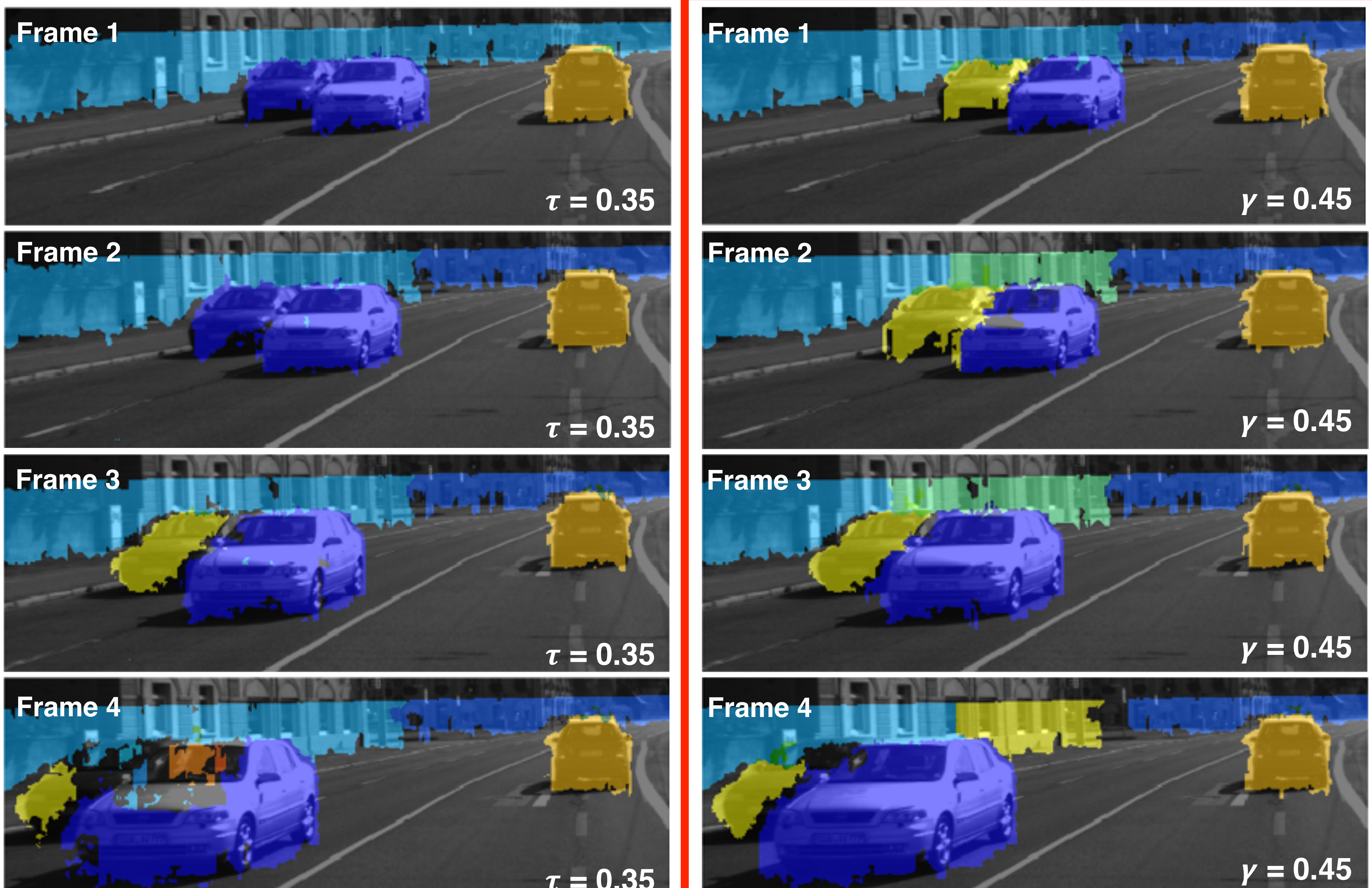


Obstacle Segmentation of Outdoor Scene

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

Obstacle Segmentation of Outdoor Scene

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

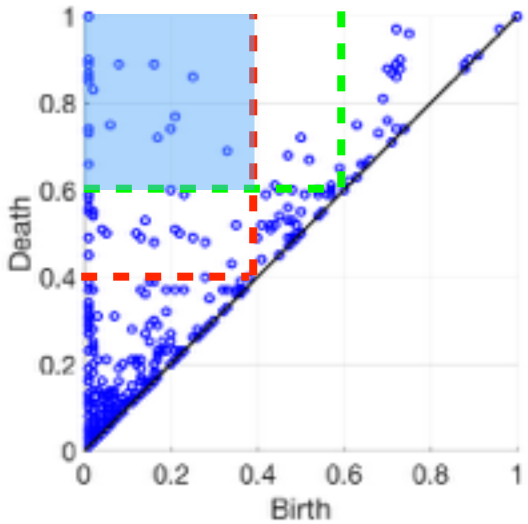


Conclusion

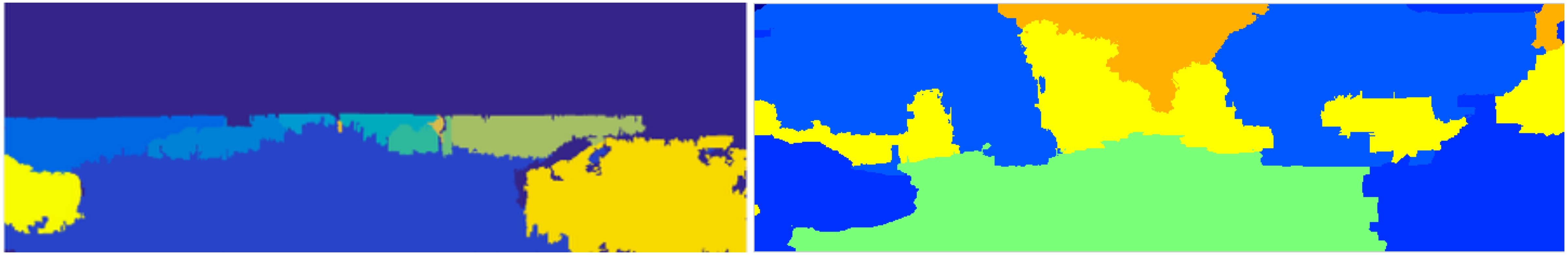
- Present an innovative framework for image segmentation based on topological persistence which is robust to image conditions and parameter selection.
- Applied to consensus-based image segmentation which is able to get better segmentation results.
- Applied to obstacle detection in outdoor scene for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

Future work

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



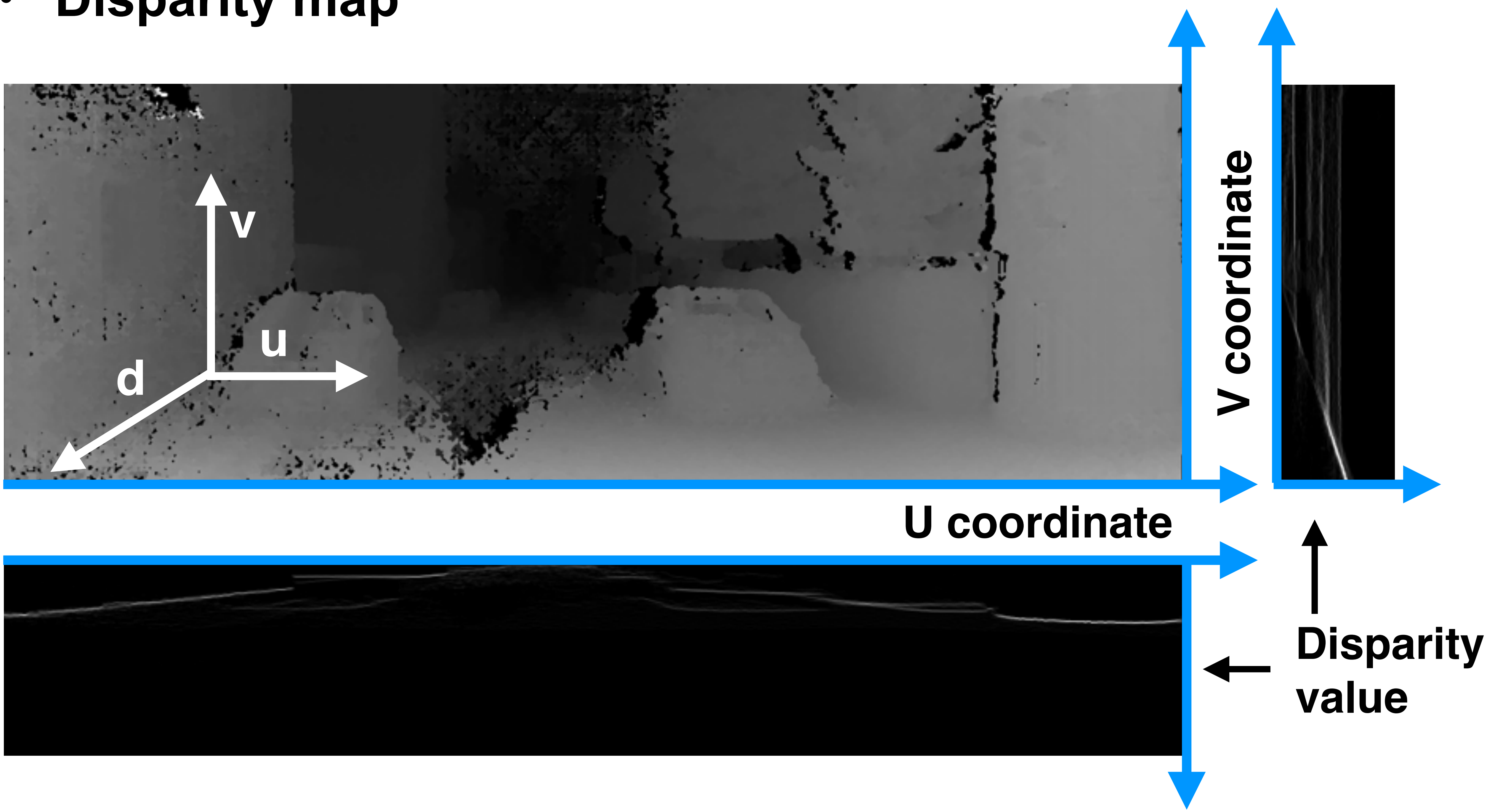
  - Refine the obstacle segmentation using Markov Random Field.



Thanks!

Obstacle Segmentation of Outdoor Scene

- **Disparity map**



Persistent Homology

- Homology is motivated by the observation that two shapes can be distinguished by their holes

D

- One connected component
- One hole

B

- One connected component
- Two holes

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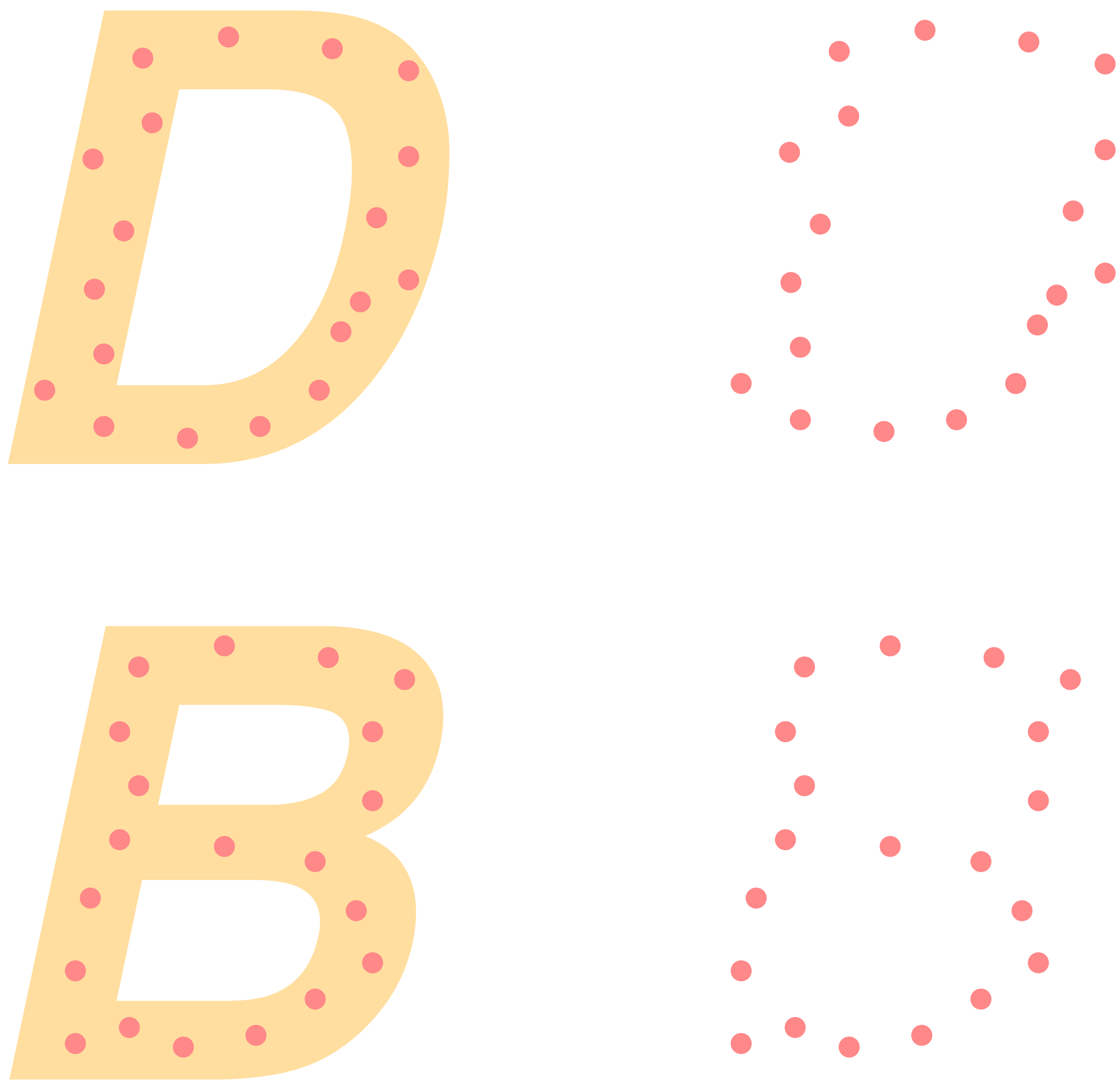
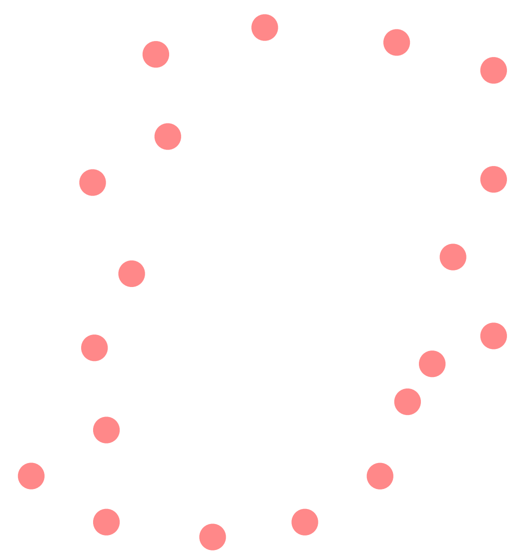
Persistent Homology

- **Sample topological space by point cloud**



Persistent Homology

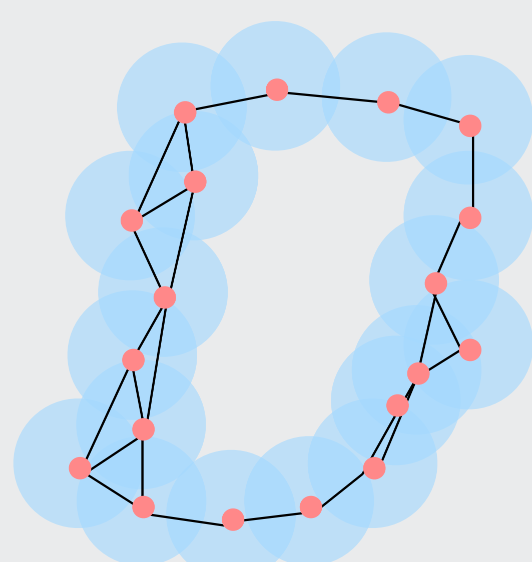


Describe

Dim0 - Connected Component

Dim1 - Hole

Simplicial Complex

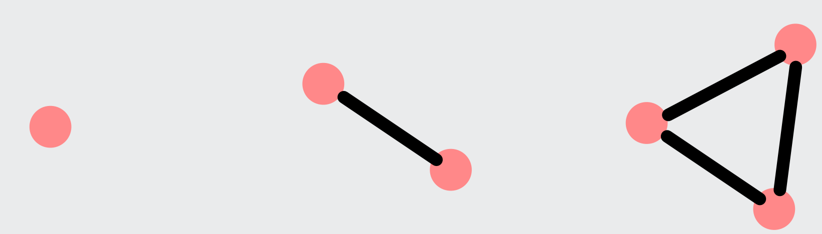


Vietoris-Rips complex

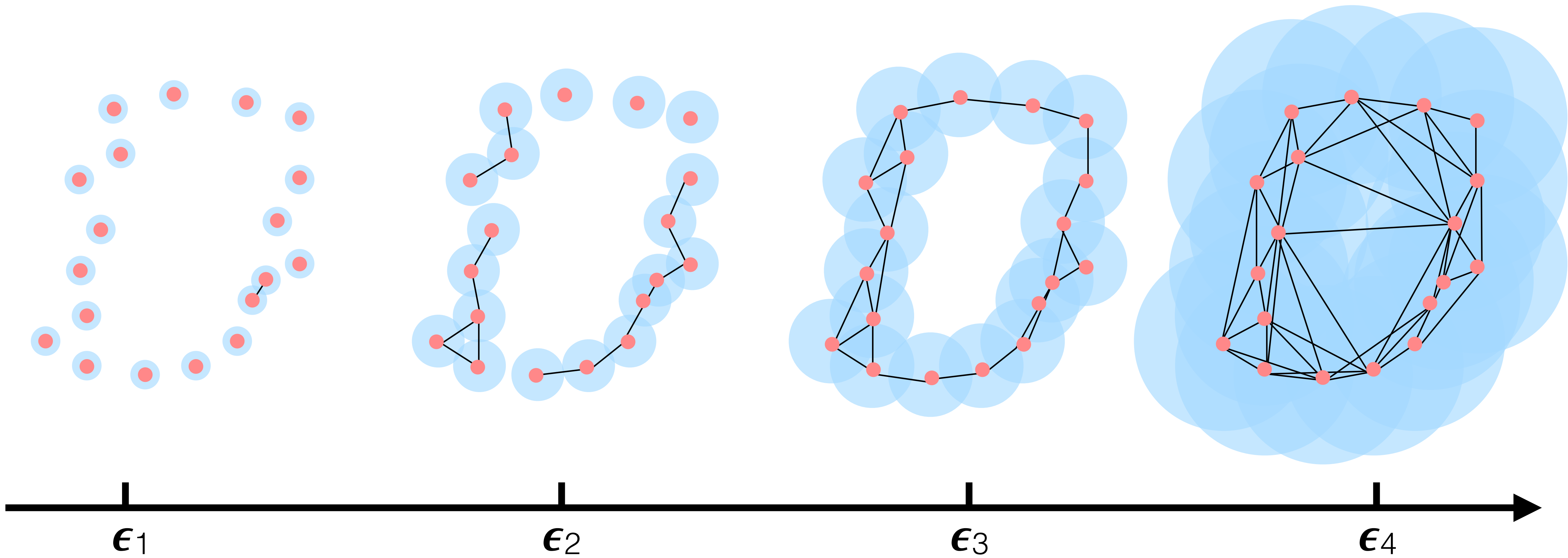
Finite Collection

Simplex

0-simplex **1-simplex** **2-simplex**



Persistent Homology



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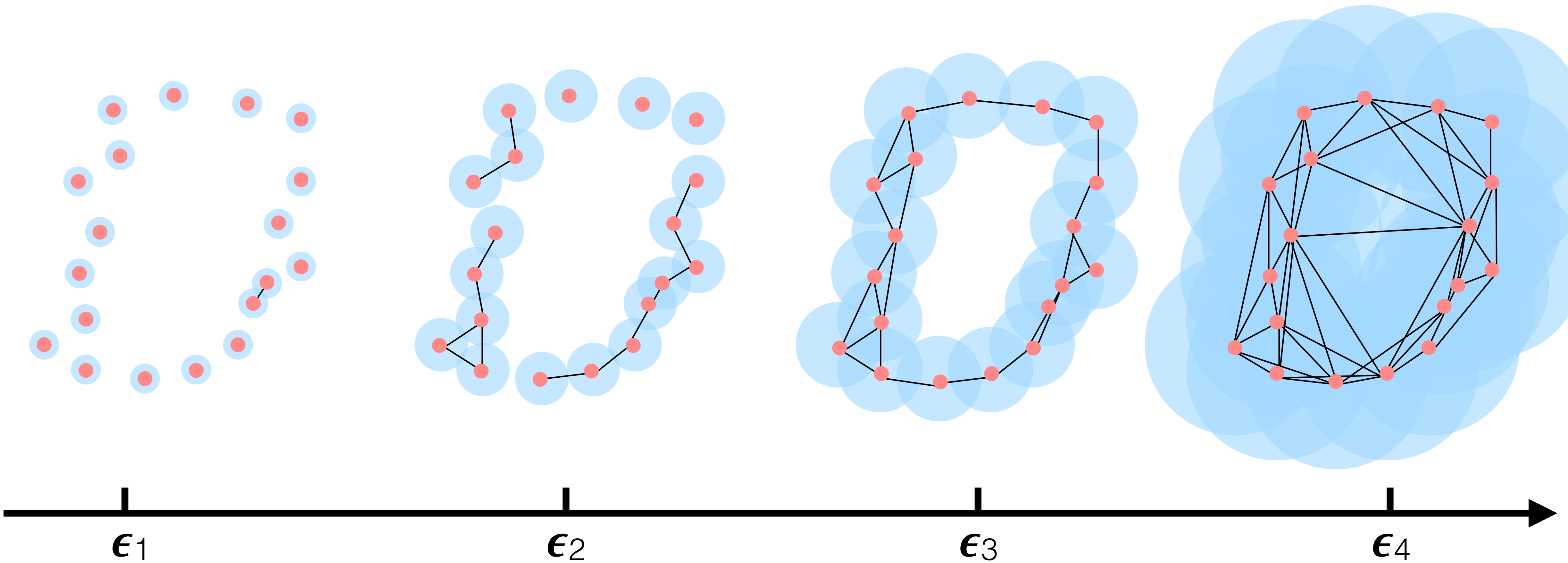
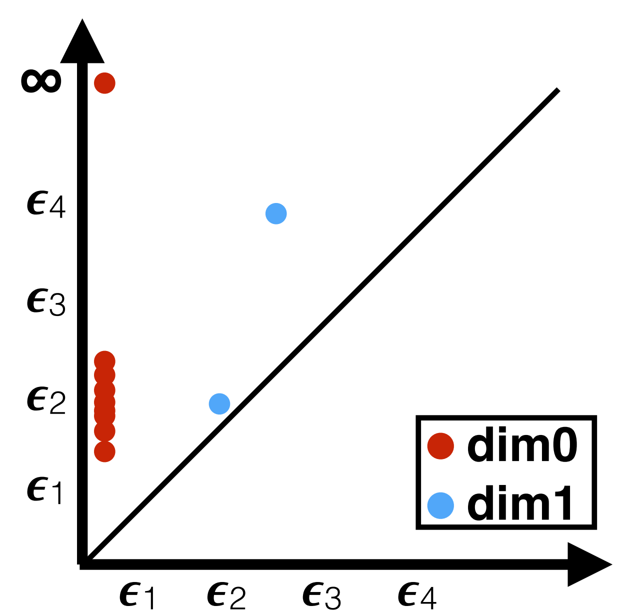
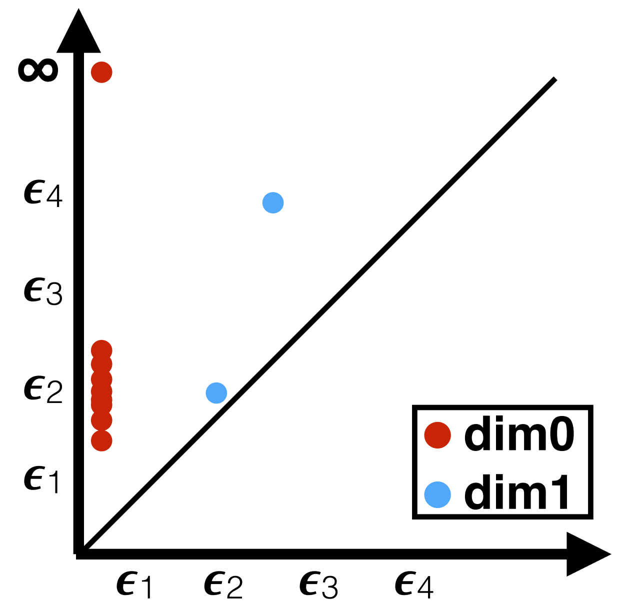
Persistent Homology



Persistence Diagram

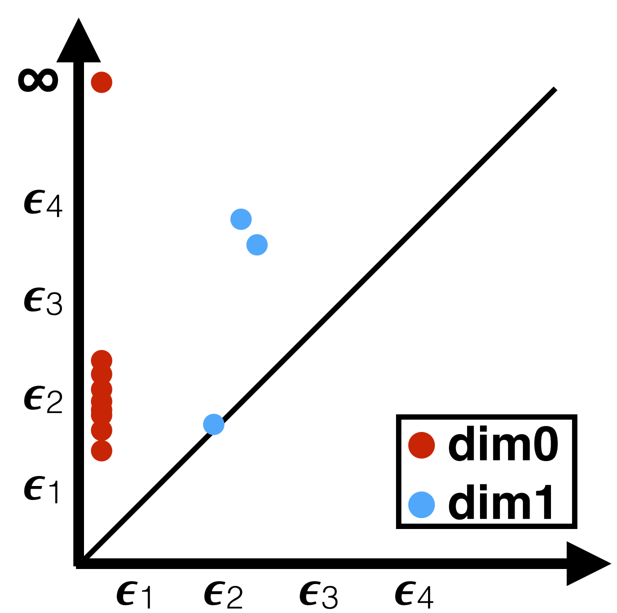


Persistent Homology



One connected component

One hole

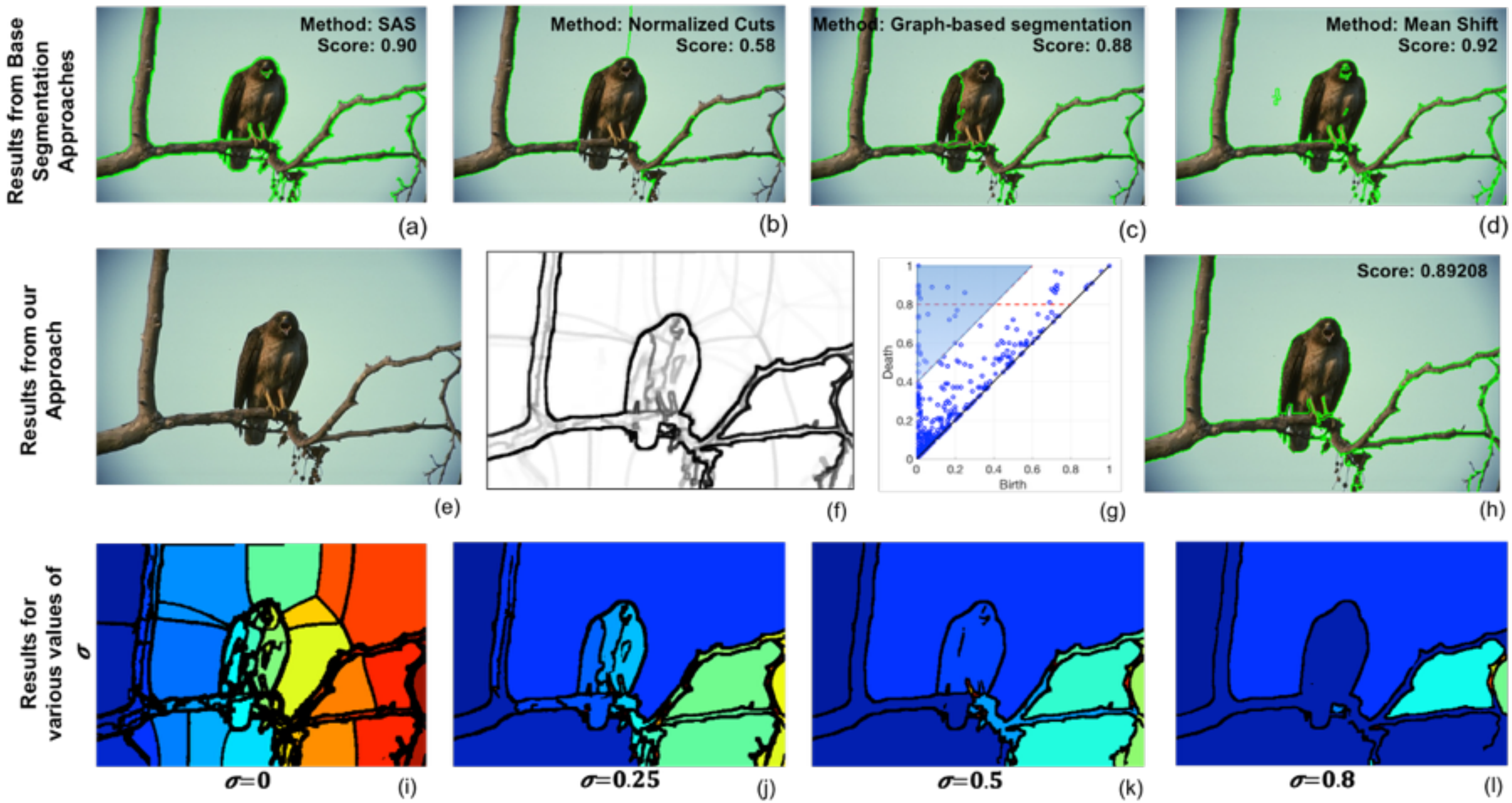


One connected component

Two holes

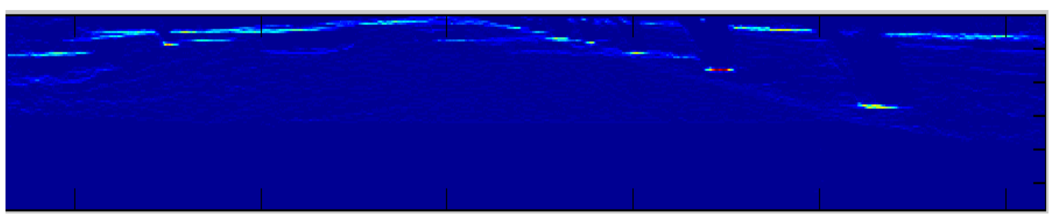
Consensus-based Image Segmentation

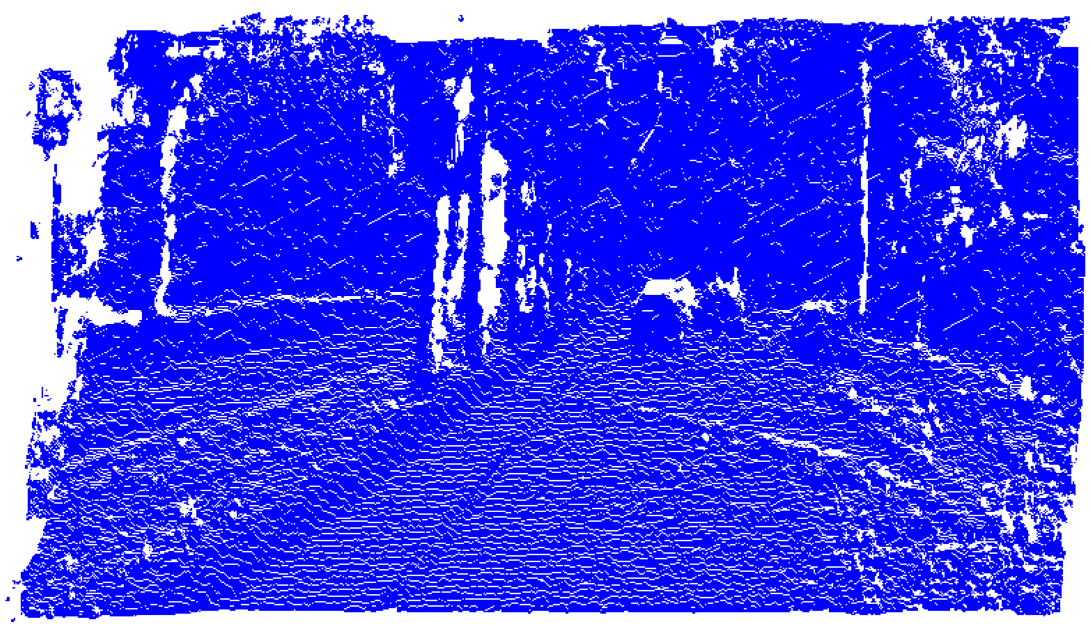
- **Experiment - Result**



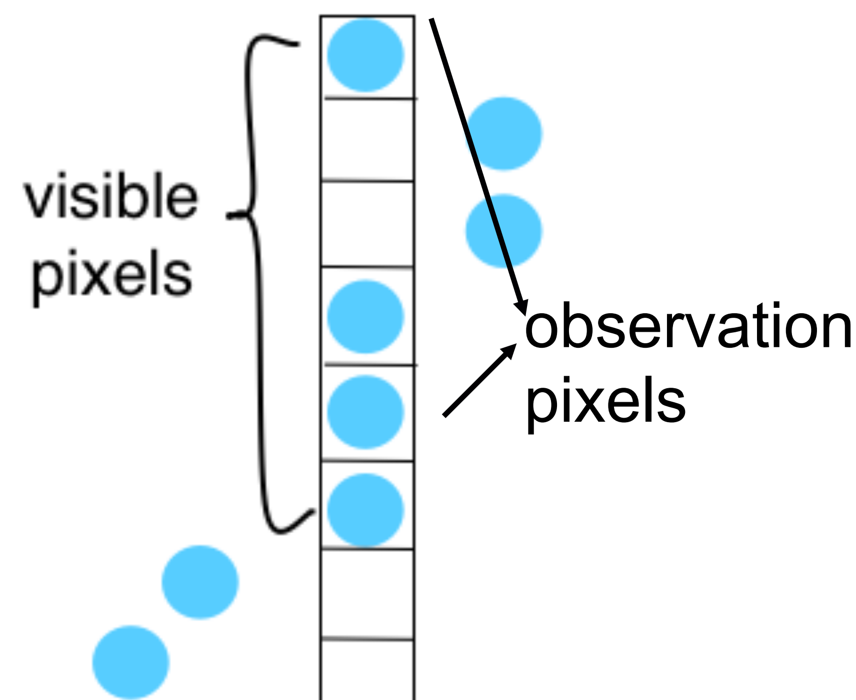
Obstacle Segmentation of Outdoor Scene

- **Occupancy computation**





One column in point cloud



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

Obstacle Segmentation of Outdoor Scene

- **Occupancy computation**

$$P(O_s) = \sum_{v,c} P(V_s = v, C_s = c) P(O_s | V_s = v, C_s = c)$$

$$P(V_s = 1) = N_v(s)/N_p(s)$$

$$P(C_s = 1) = 1 - e^{-\lambda \frac{N_O(s)}{N_v(s)}}$$

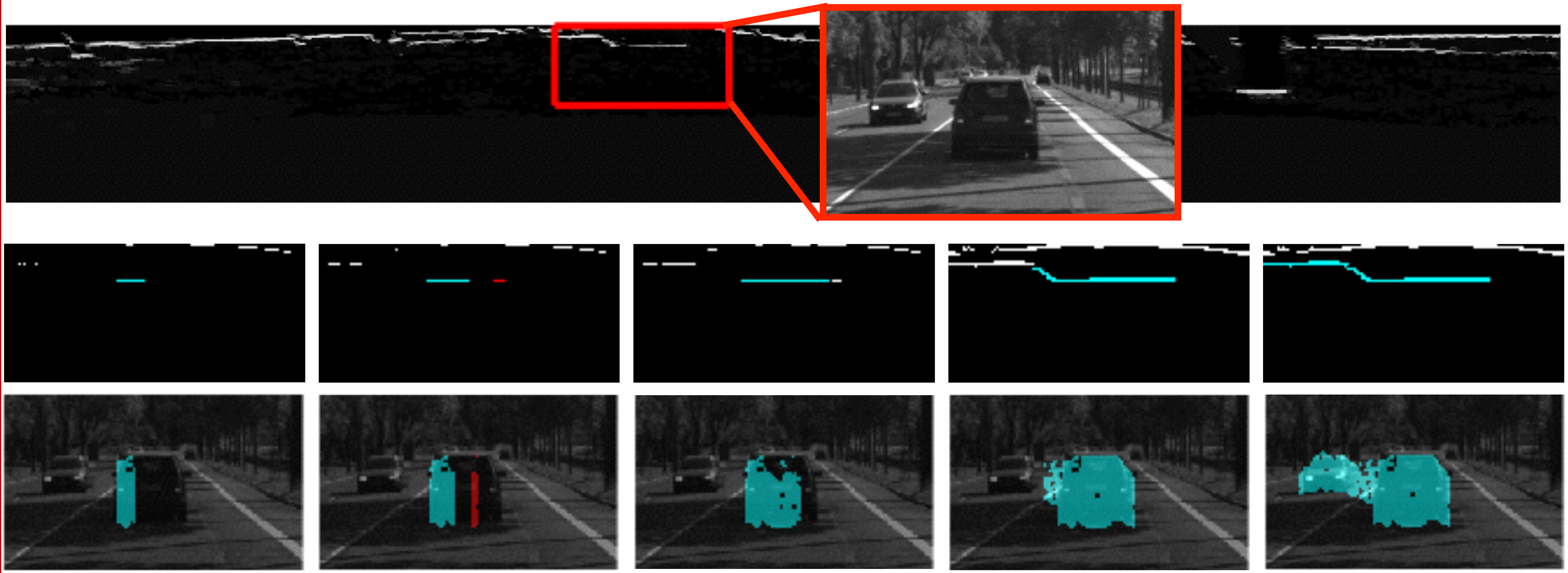
Let $P_v := N_v(s)/N_p(s)$ and $P_o := N_o(s)/N_v(s)$. Then, we have

$$P(O_s) = P(V_s)P(C_s)(1 - P_{FP}) + P(V_s)(1 - P(C_s))P_{FN} + \frac{1}{2}(1 - P(V_s))$$
$$= (\frac{1}{2} - P_{FP})P_v + (P_{FP} + P_{FN} - 1)P_v e^{-\lambda P_0} + \frac{1}{2}$$

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

Obstacle Segmentation of Outdoor Scene

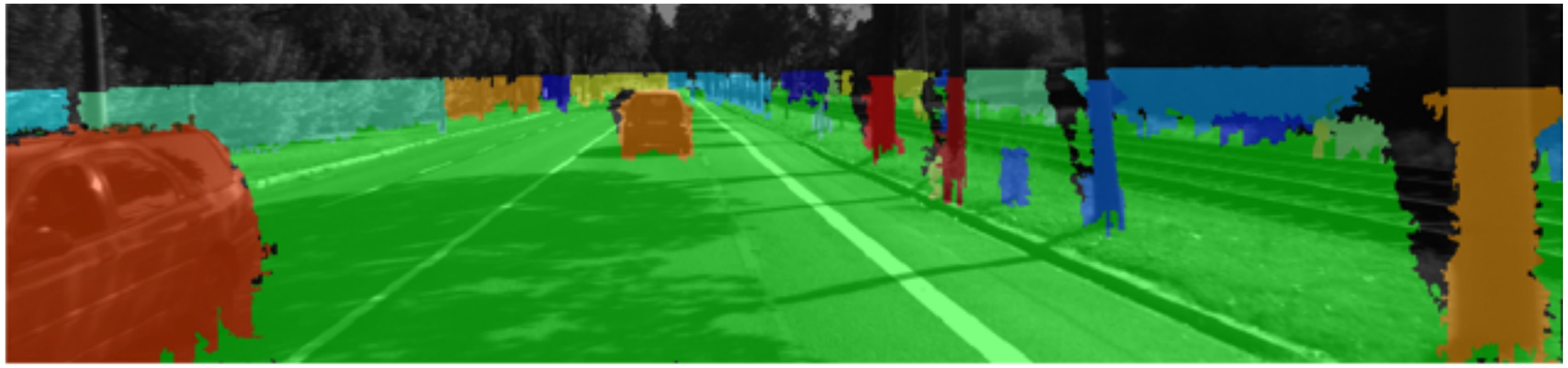
- **Persistence region extraction**



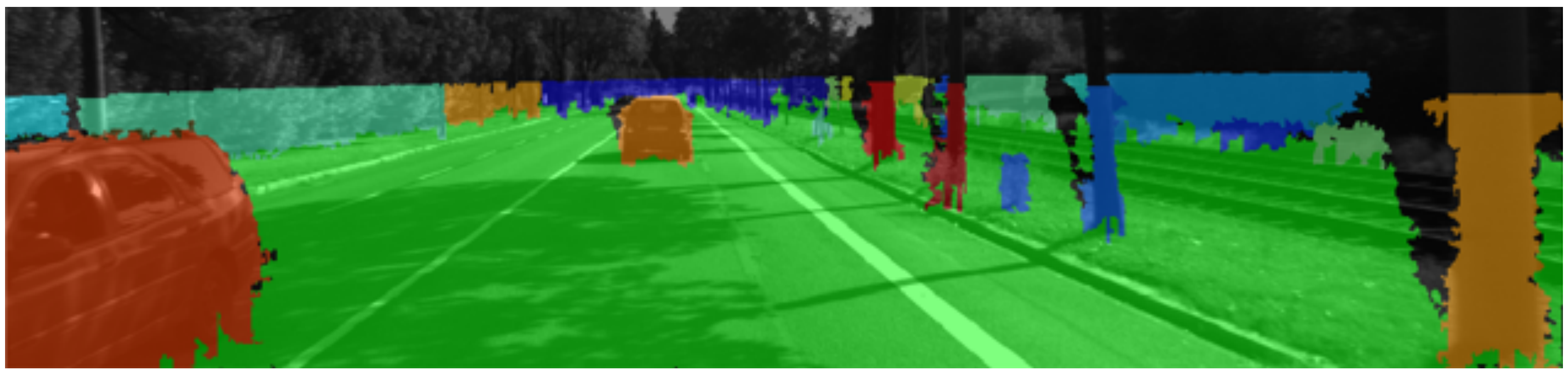
τ = 0.02 τ = 0.03 τ = 0.10 τ = 0.53 τ = 0.51

Obstacle Segmentation of Outdoor Scene

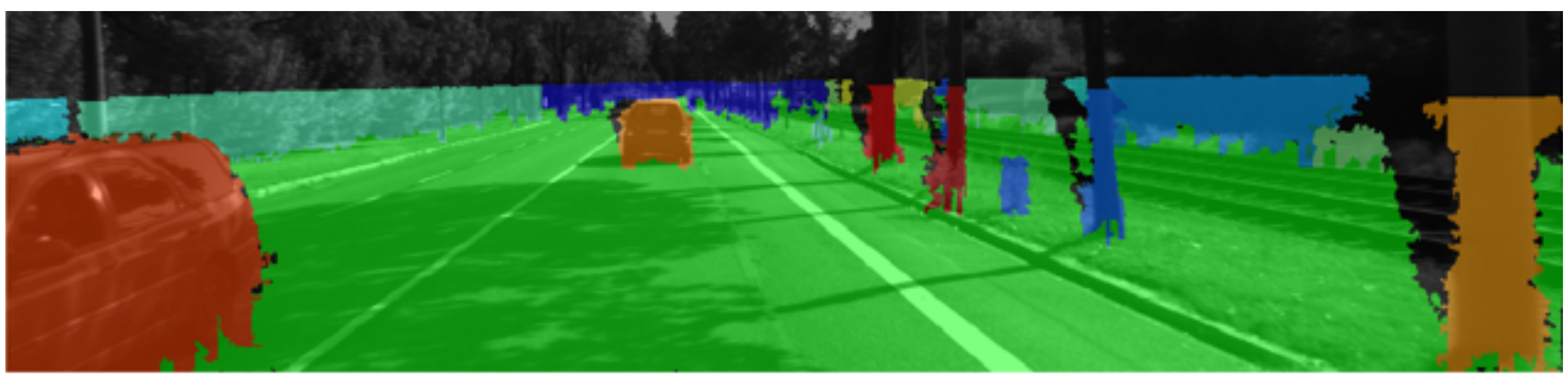
- **Experiment - Effect of parameter**



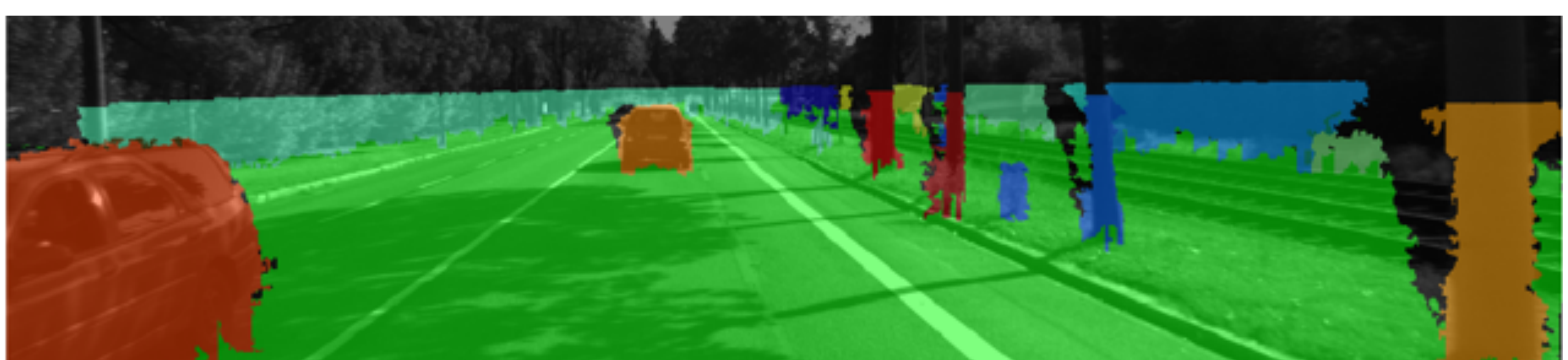
$\gamma = 0.30$



$\gamma = 0.40$



$\gamma = 0.50$



$\gamma = 0.60$

Consensus-based Image Segmentation

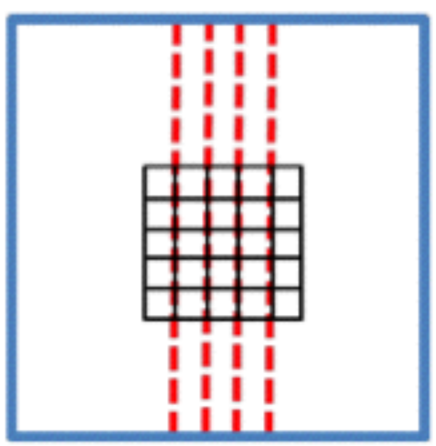
- **Effect of patch size n**

Let 2σ be the range of perturbation of an edge.

Case 1

$n-2 \geq 2\delta, D_n^*(x) = p_{ij}.$

The range can be covered by a single patch.



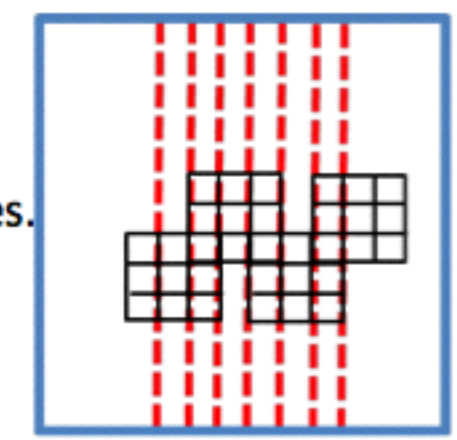
Case 2

$n-1 < 2\delta,$

$p_{ij}/m \leq D_n^*(x) < p_{ij},$

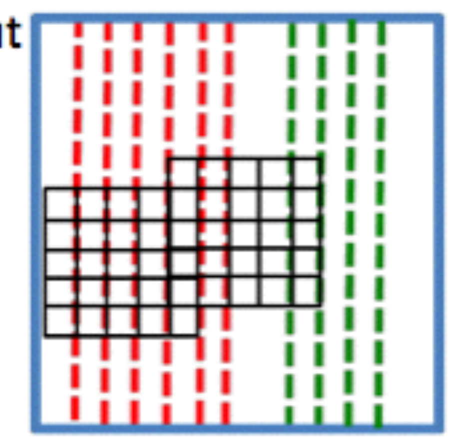
where $m = [(2\delta+1)/(n-1)].$

The range can be covered by m patches.



Case 3

Perturbation range of two edges n-1 pixels away from each other can be identified without the influence of other edges.



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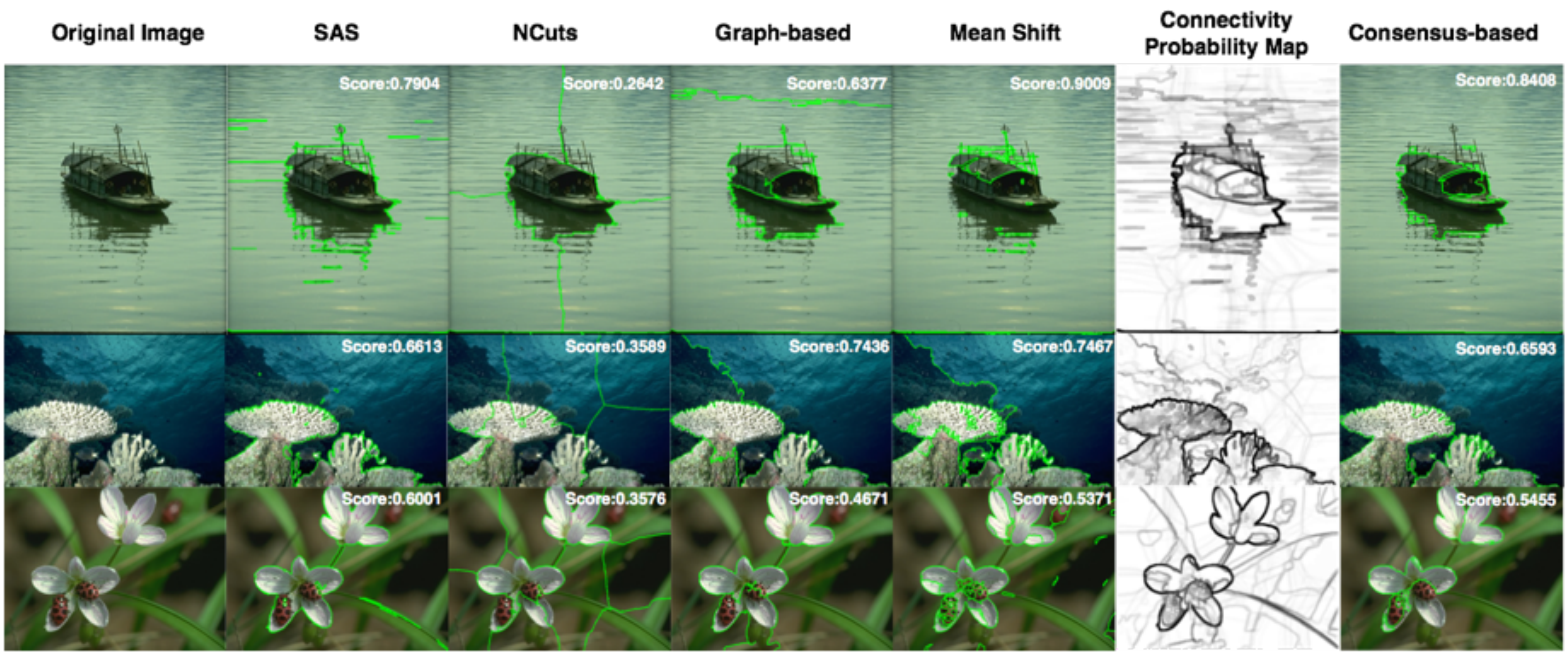
Consensus-based Image Segmentation

- **Experiment - Result**



Obstacle Segmentation of Outdoor Scene

- **Stereo vision setup**