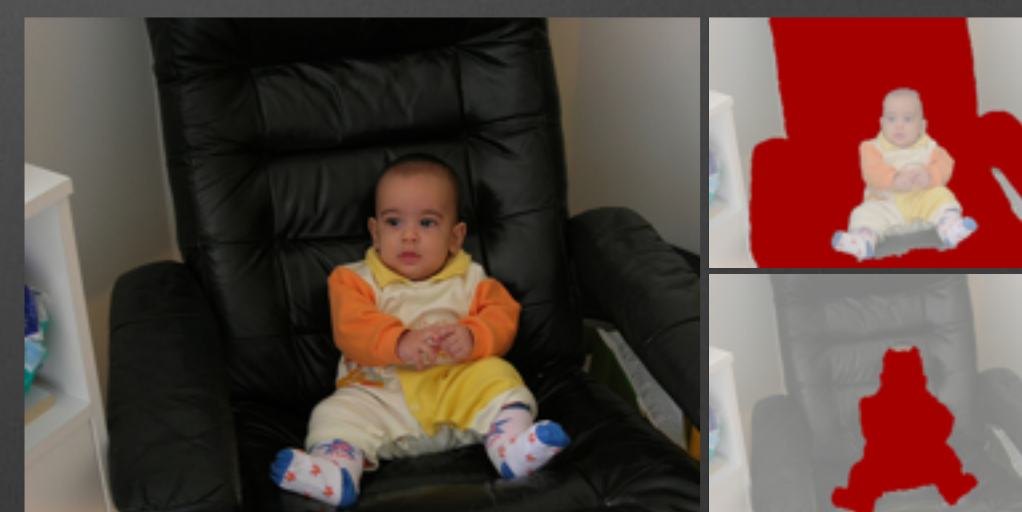
Geodesic Object Proposals

Philipp Krähenbühl
Stanford University

Vladlen Koltun
Adobe Research

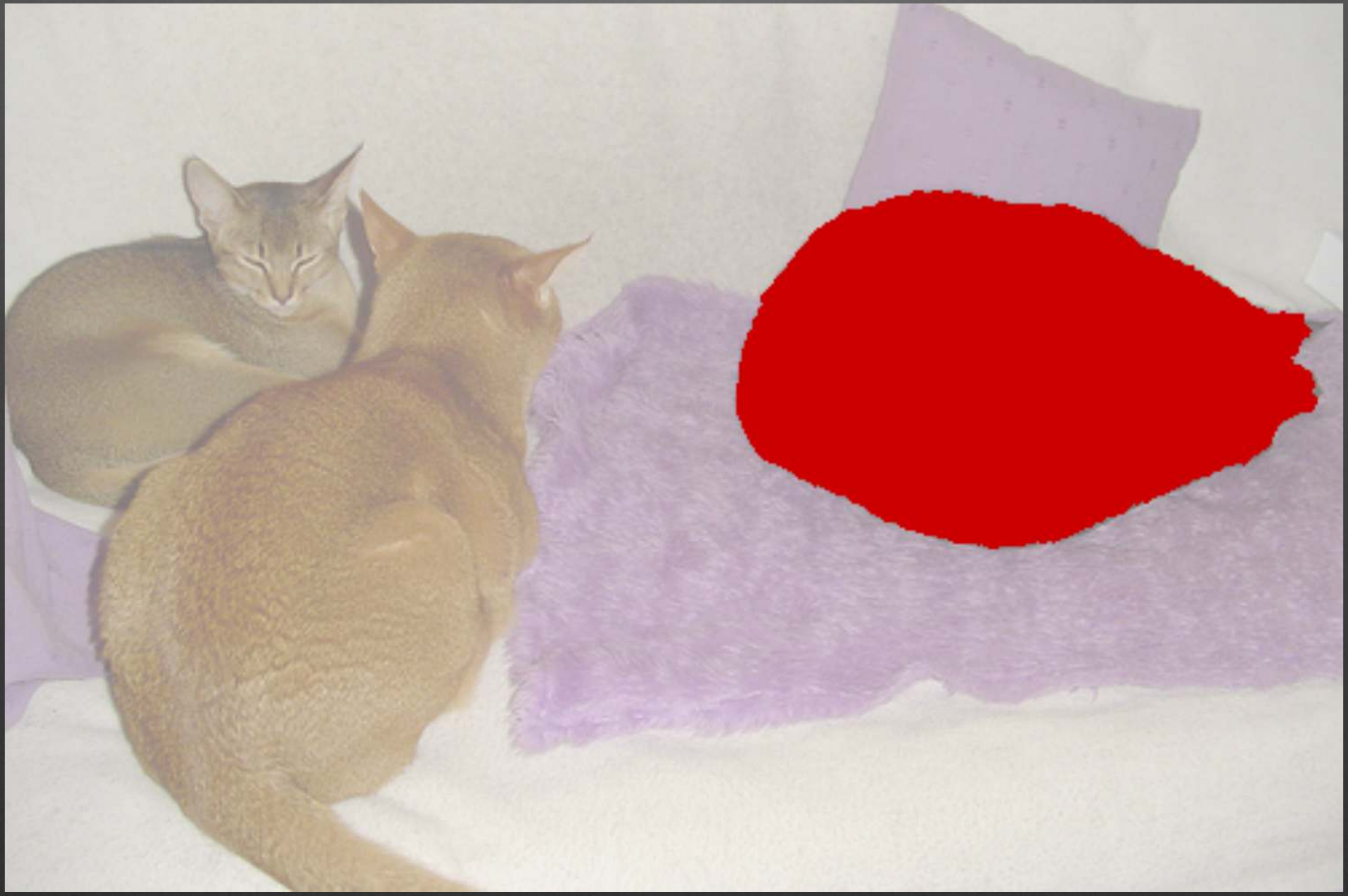


Object Proposals

Find small set of proposals
that includes all objects in a scene

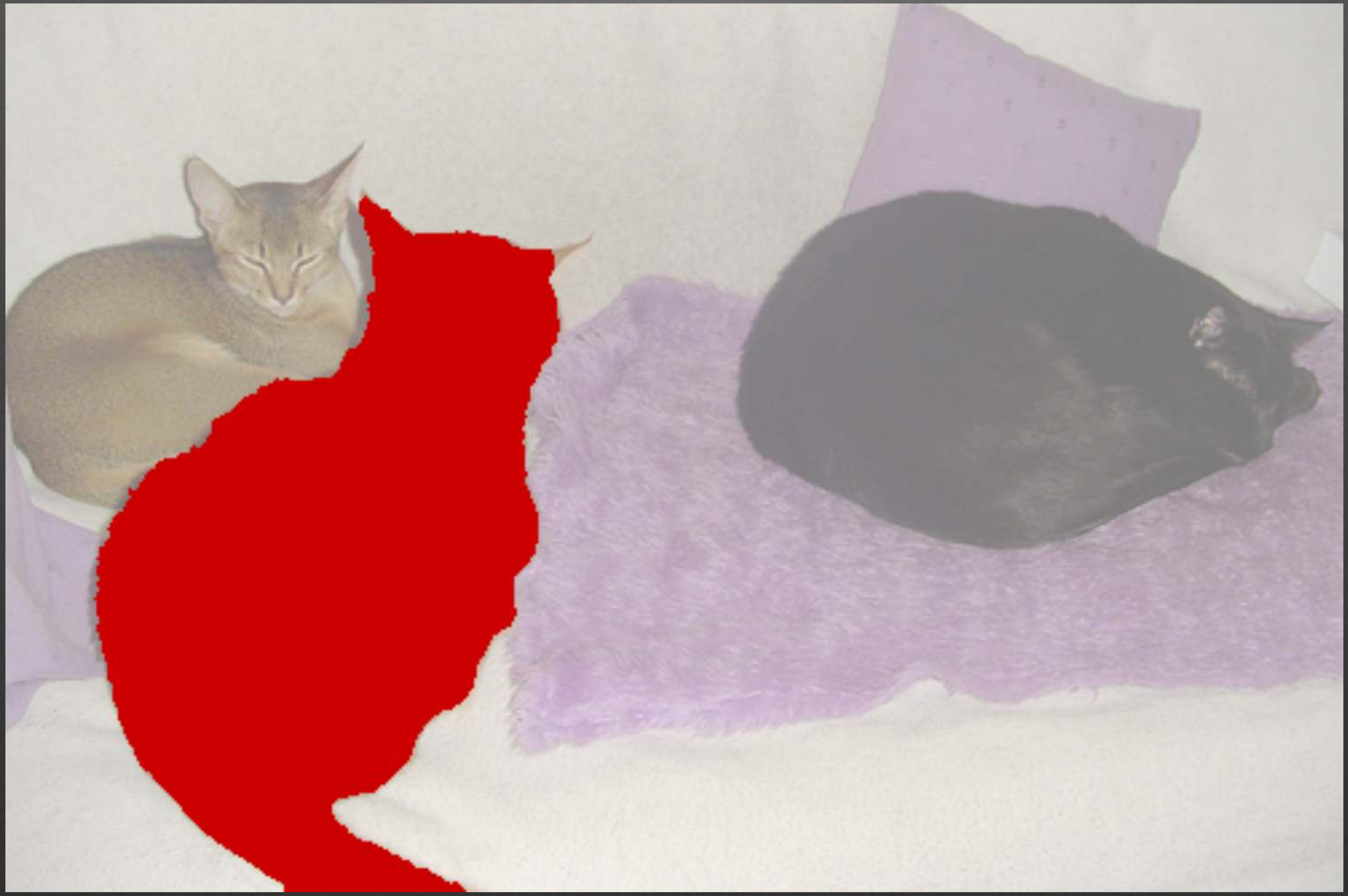
Object Proposals

Find small set of proposals
that includes all objects in a scene



Object Proposals

Find small set of proposals
that includes all objects in a scene



Object Proposals

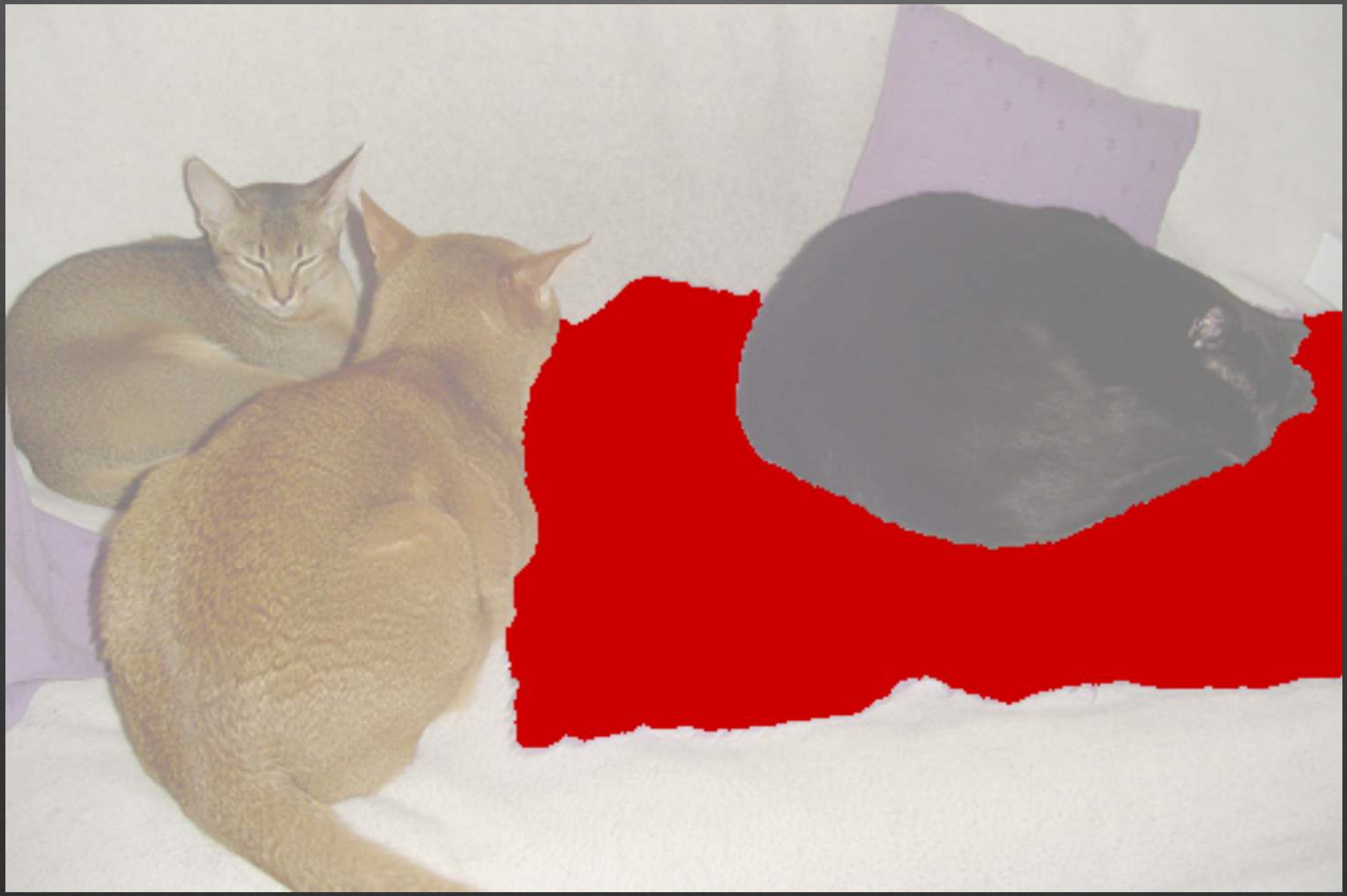
Find small set of proposals
that includes all objects in a scene

Object Proposals

Find small set of proposals
that includes all objects in a scene

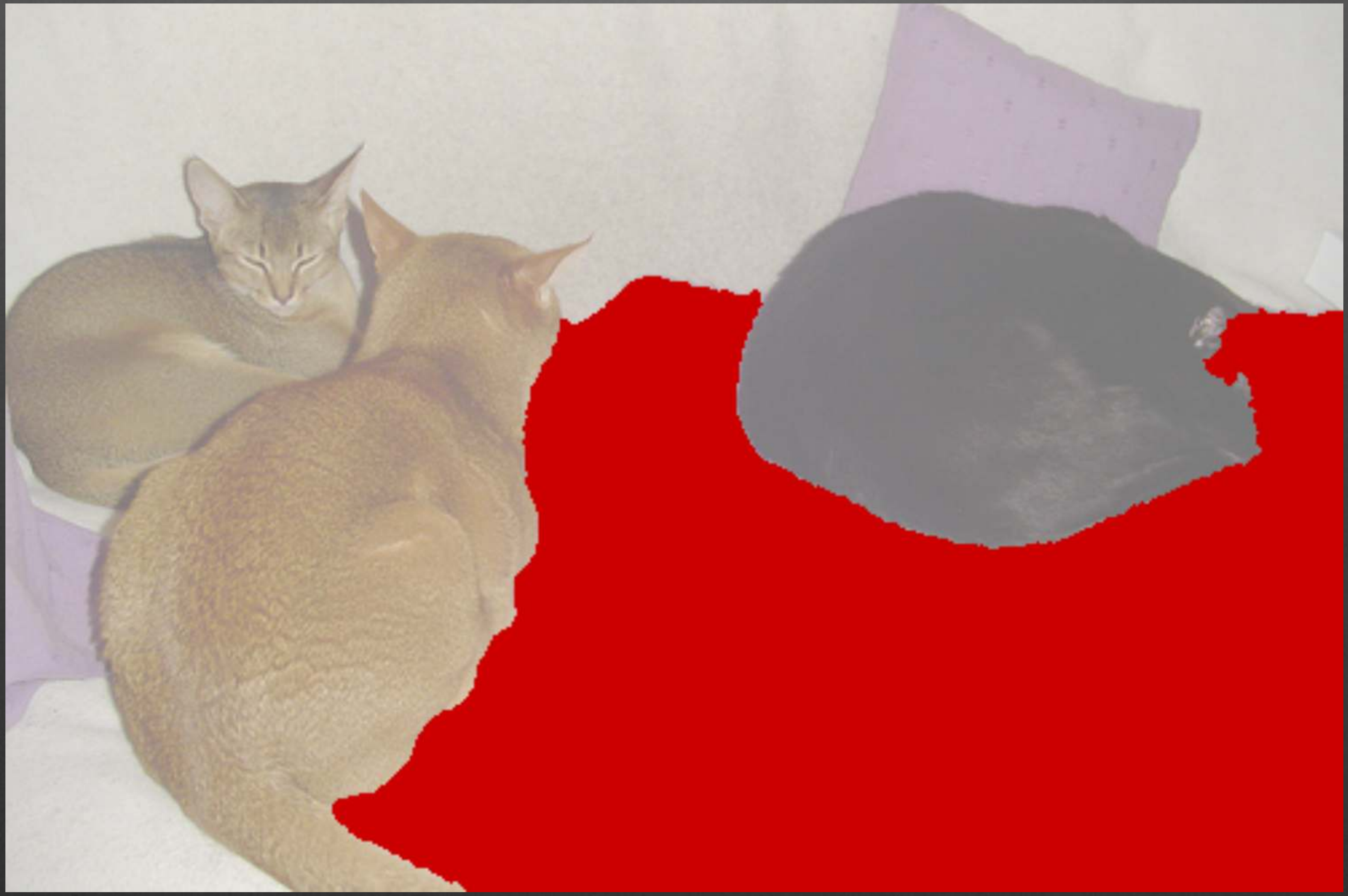
Object Proposals

Find small set of proposals
that includes all objects in a scene



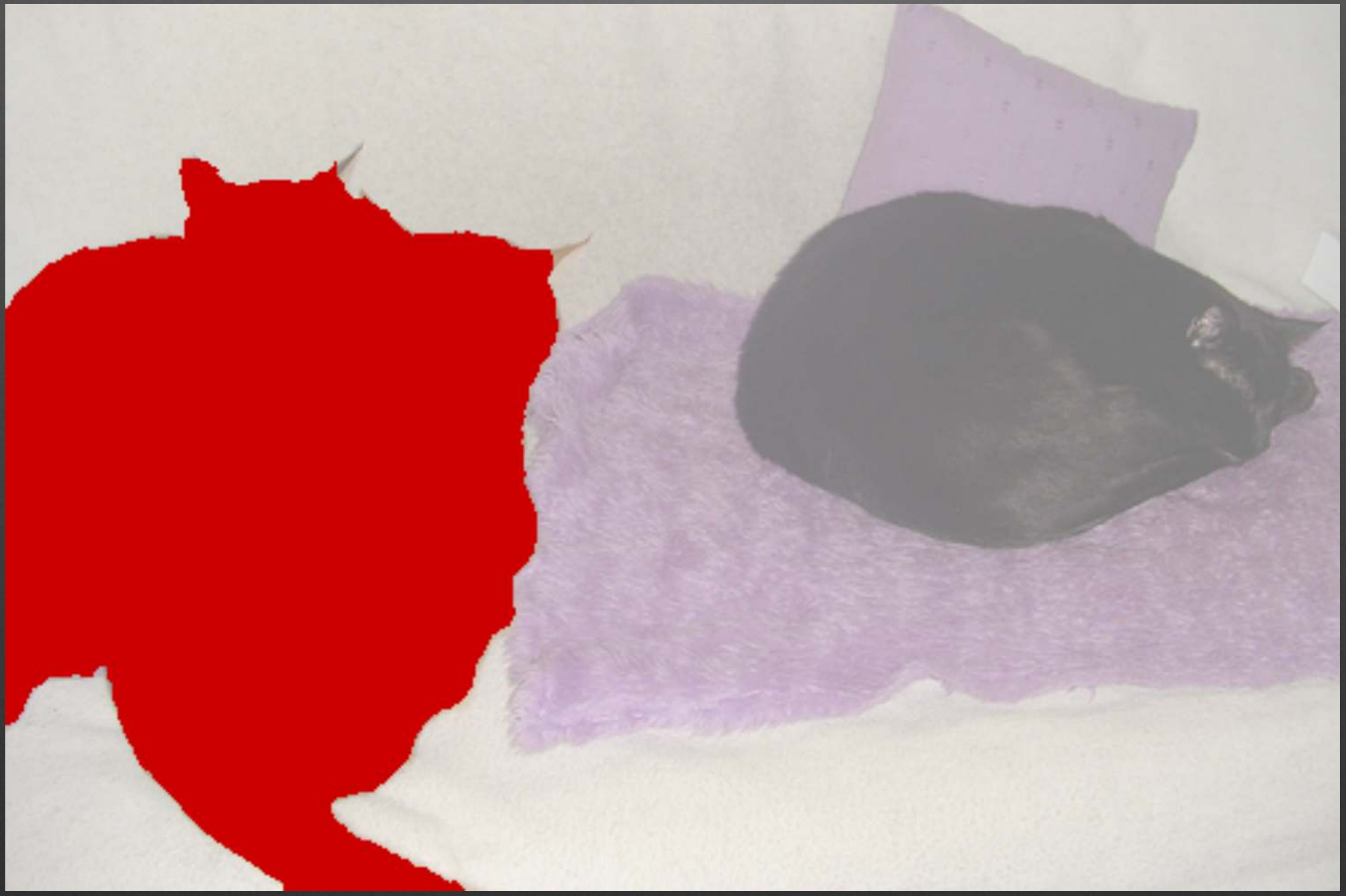
Object Proposals

Find small set of proposals
that includes all objects in a scene



Object Proposals

Find small set of proposals
that includes all objects in a scene



Object Proposals

Bounding Box Proposals

Segment Proposals

Object Proposals

Bounding Box Proposals

Segment Proposals

Object Proposals

Bounding Box Proposals

Segment Proposals

Uses of object proposals

Uses of object proposals

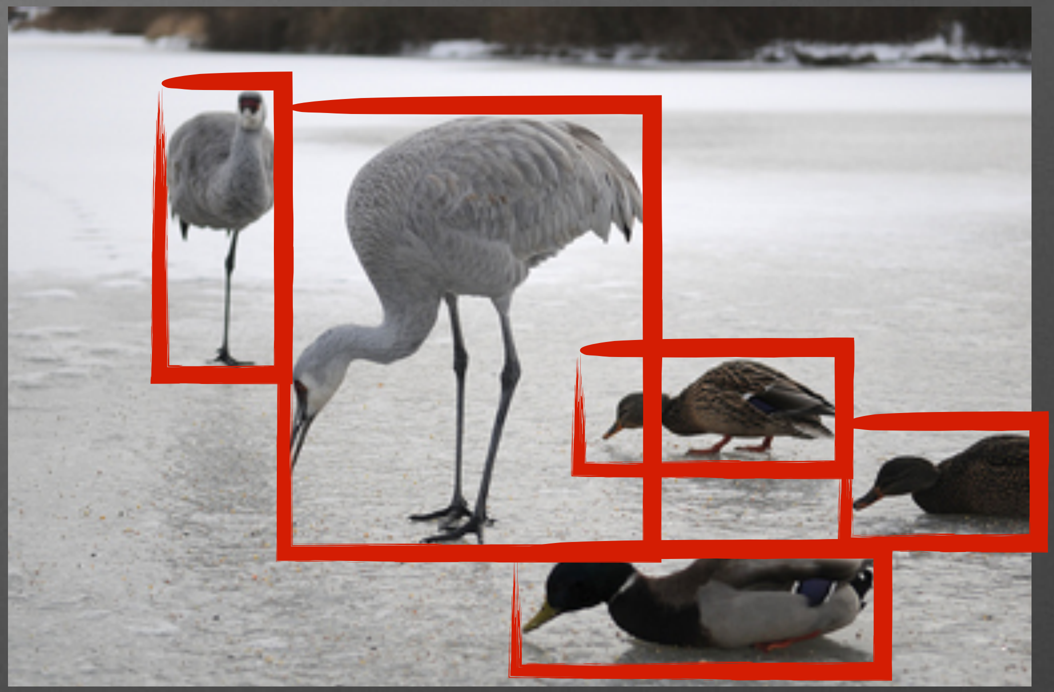
- Object detection

Uses of object proposals

- Object detection

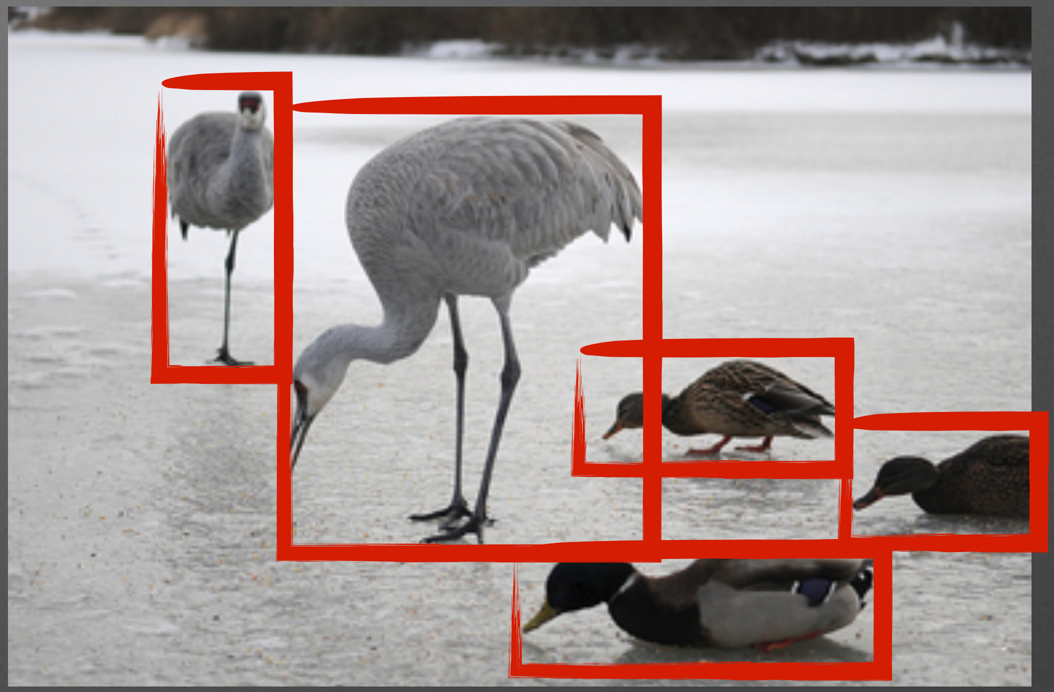
Uses of object proposals

- Object detection



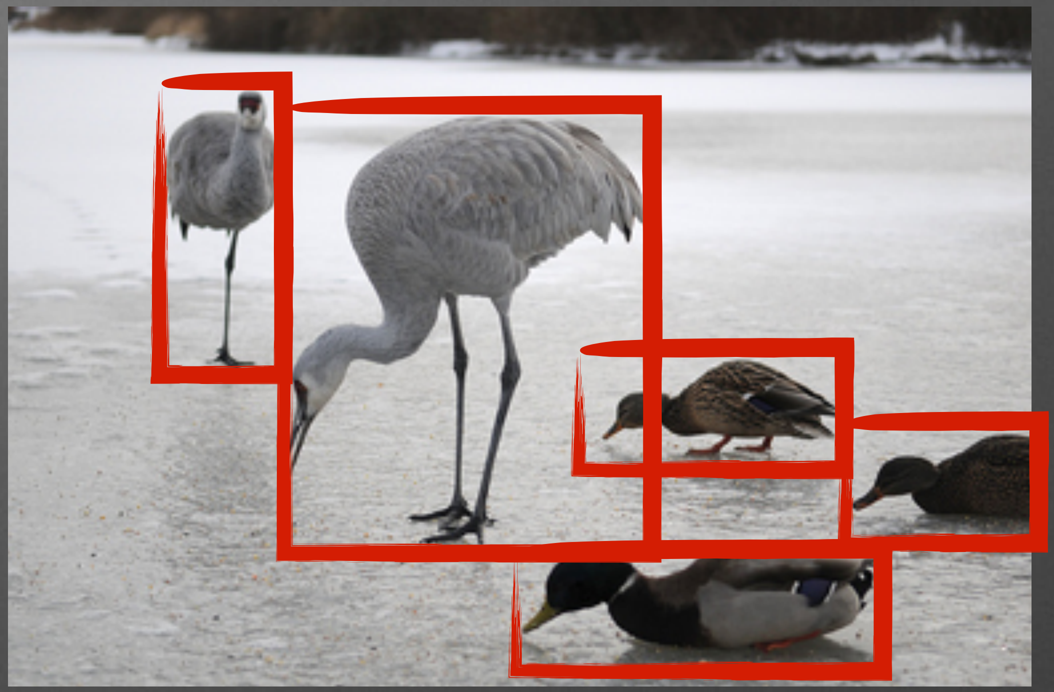
Uses of object proposals

- Object detection
  - faster



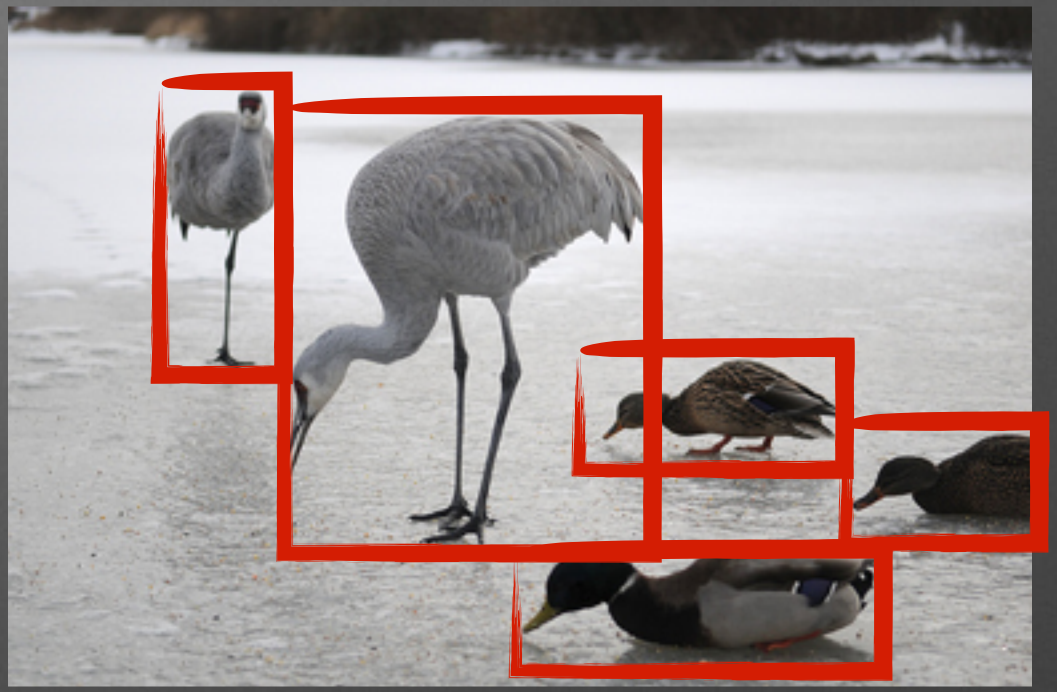
Uses of object proposals

- Object detection
  - faster
  - more expensive features



Uses of object proposals

- Object detection
  - faster
  - more expensive features
  - used in almost all state-of-the art methods



Uses of object proposals

- Object detection
    - faster
    - more expensive features
    - used in almost all state-of-the art methods
- Multi-class image segmentation

Uses of object proposals

- Object detection
  - faster
  - more expensive features
  - used in almost all state-of-the art methods
- Multi-class image segmentation
  - used in state-of-the art

Uses of object proposals

- Object detection
  - faster
  - more expensive features
  - used in almost all state-of-the art methods
- Multi-class image segmentation
  - used in state-of-the art
  - more expressive features

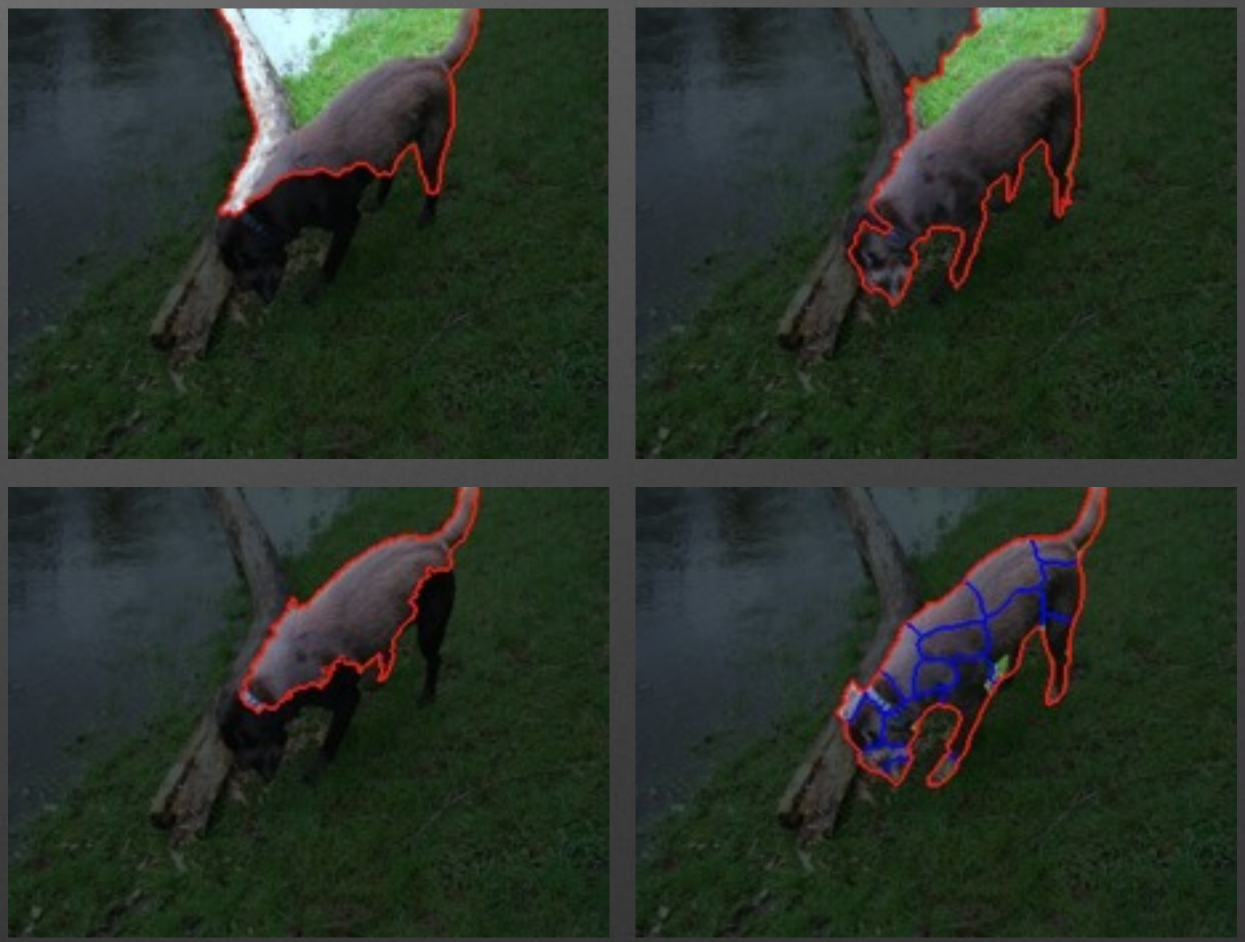
Uses of object proposals

- Object detection
  - faster
  - more expensive features
  - used in almost all state-of-the art methods
- Multi-class image segmentation
  - used in state-of-the art
  - more expressive features

Improving Spatial Support for Objects via Multiple Segmentations

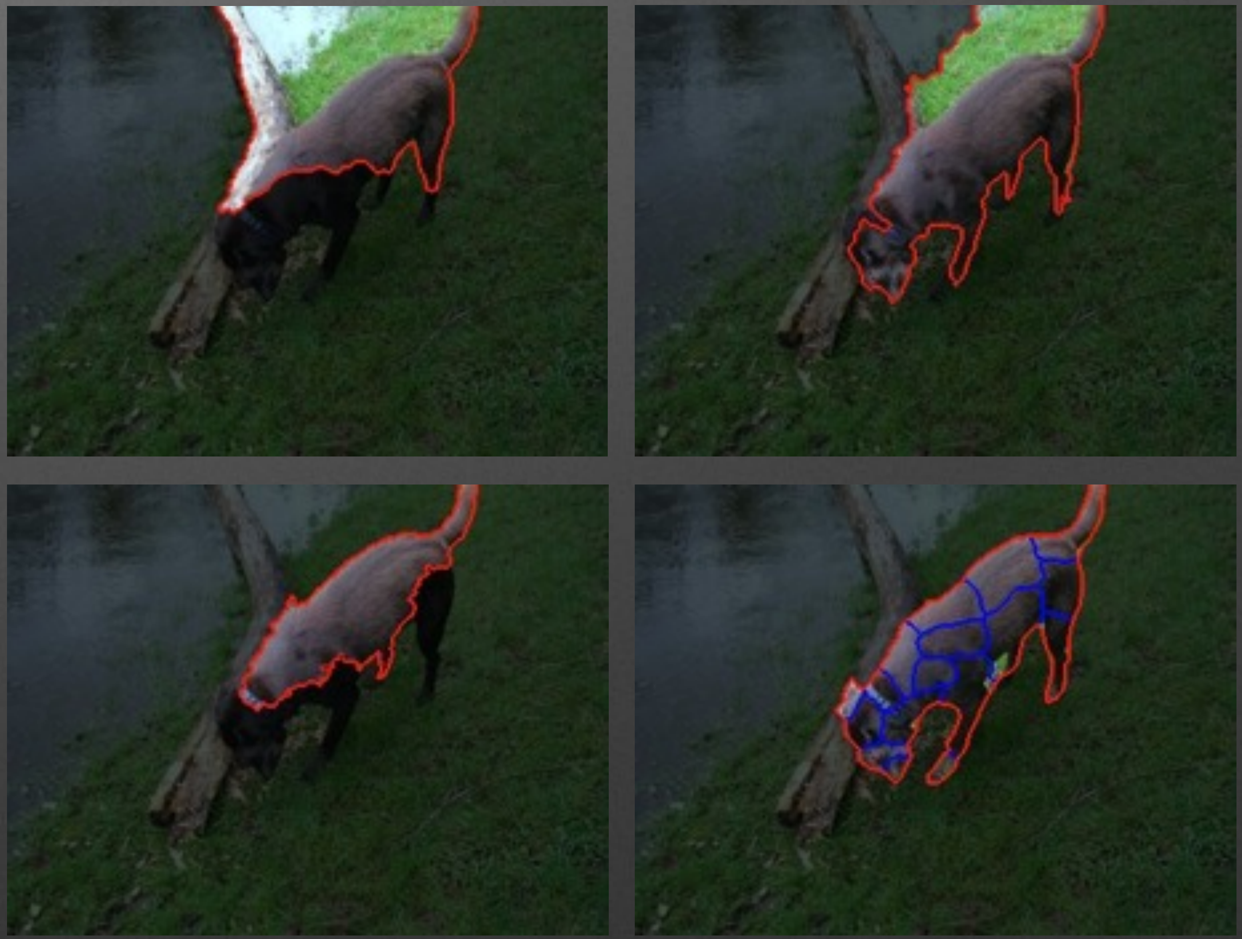
[Malisiewicz and Efros 2007]

- Soup of segments



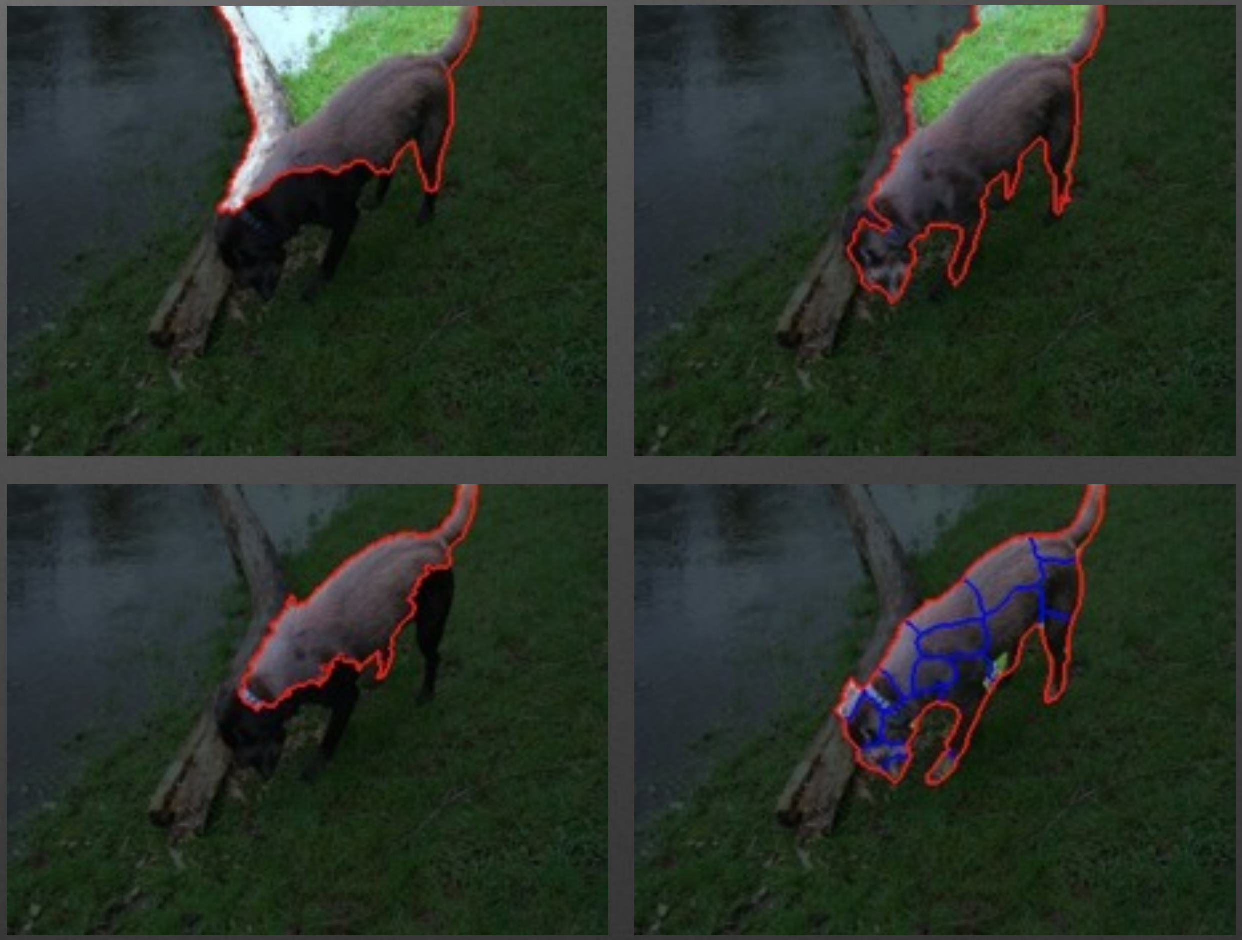
Improving Spatial Support for Objects via Multiple Segmentations
[Malisiewicz and Efros 2007]

- Soup of segments
  - 3 different unsupervised segmentation algorithms



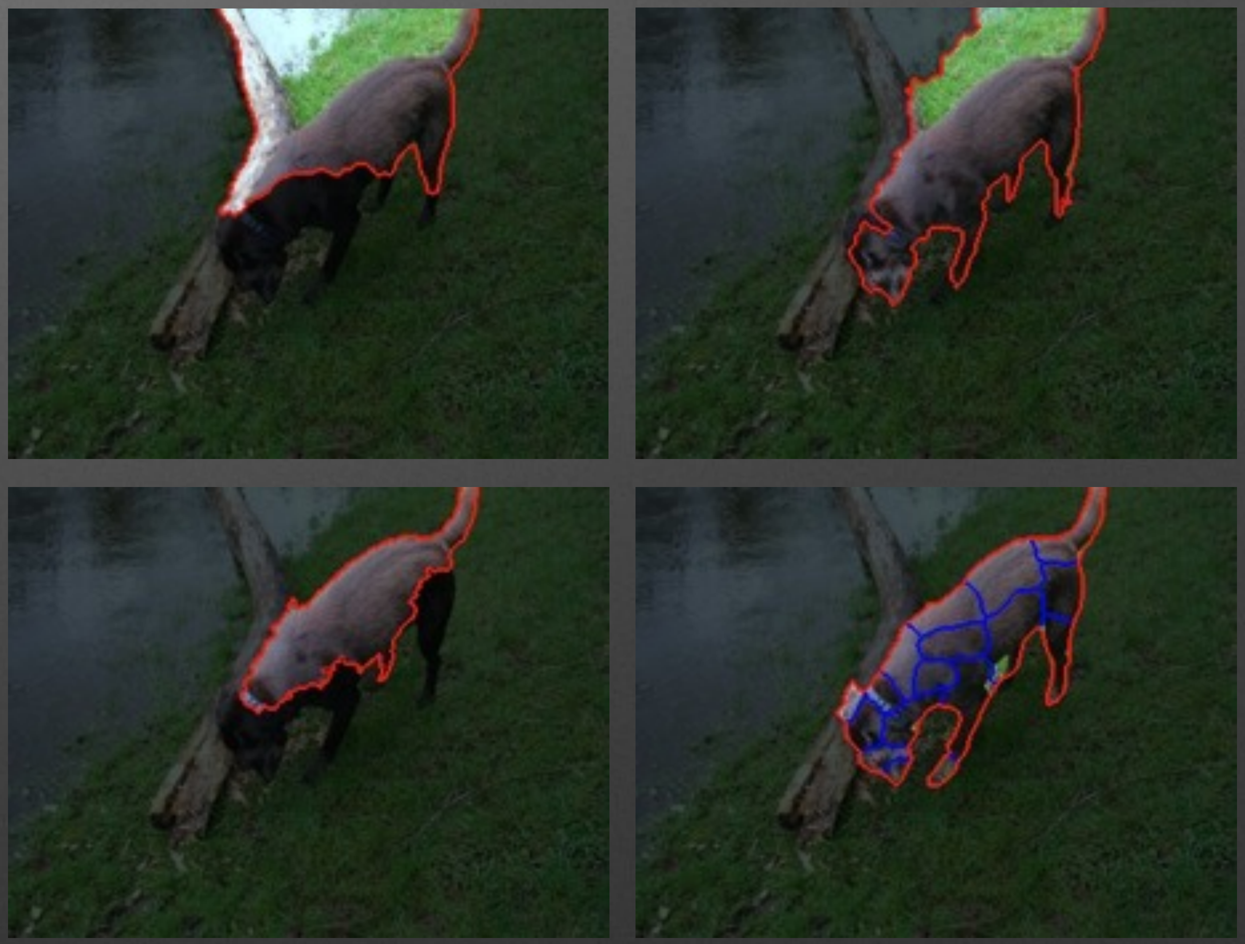
Improving Spatial Support for Objects via Multiple Segmentations
[Malisiewicz and Efros 2007]

- Soup of segments
  - 3 different unsupervised segmentation algorithms
  - vary parameters



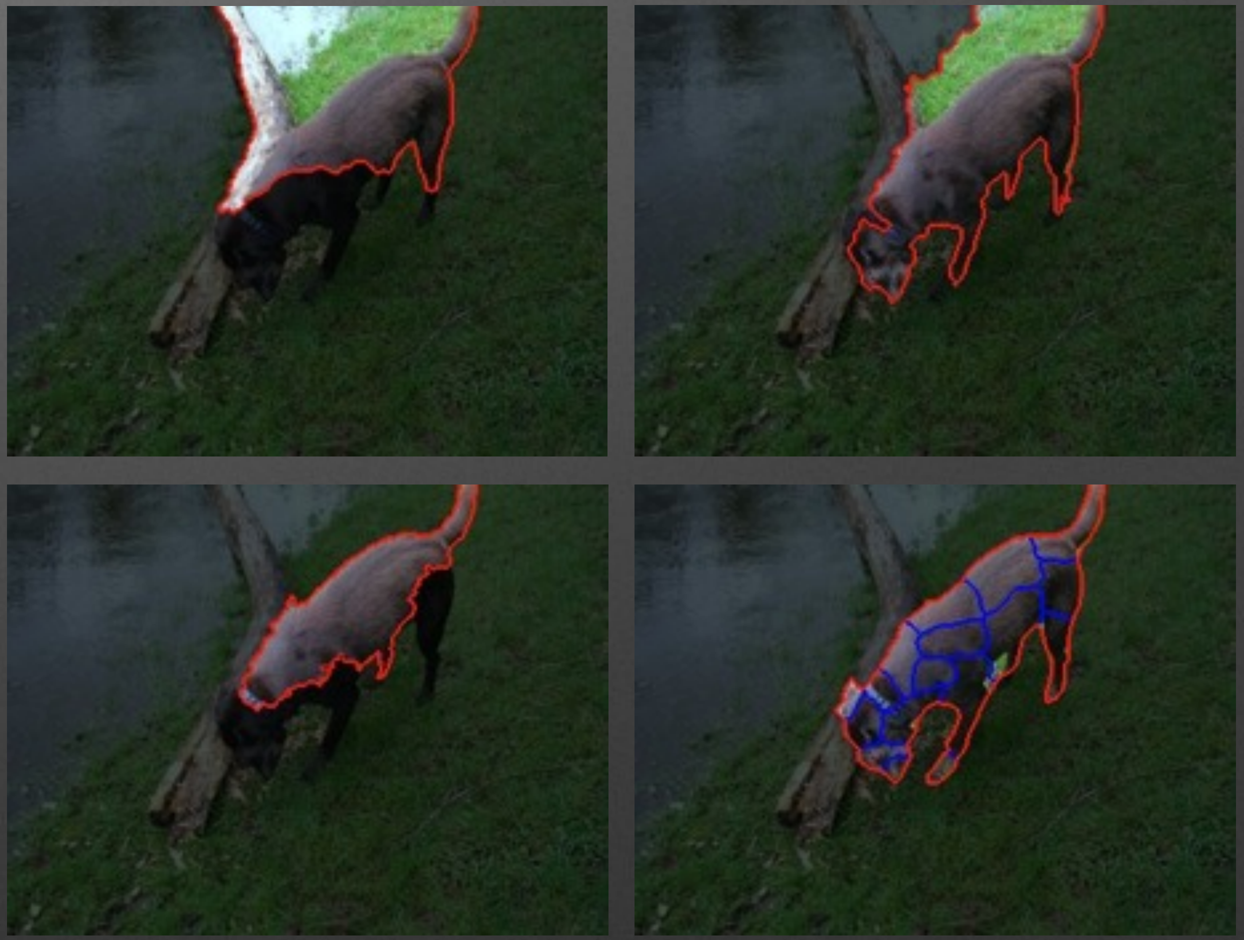
Improving Spatial Support for Objects via Multiple Segmentations
[Malisiewicz and Efros 2007]

- Soup of segments
  - 3 different unsupervised segmentation algorithms
  - vary parameters
  - combination of up to 3 adjacent segments



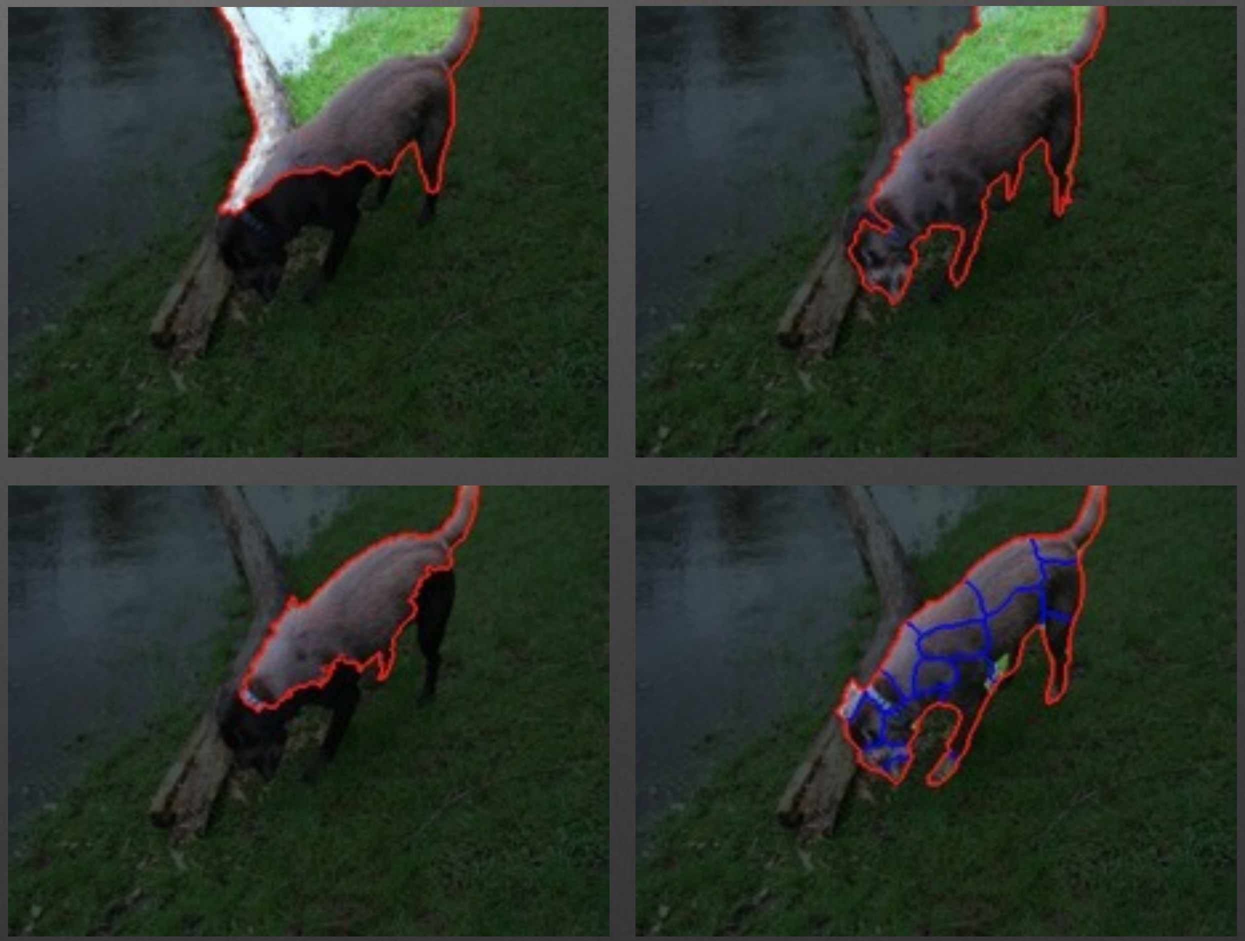
Improving Spatial Support for Objects via Multiple Segmentations
[Malisiewicz and Efros 2007]

- Soup of segments
  - 3 different unsupervised segmentation algorithms
  - vary parameters
  - combination of up to 3 adjacent segments
- Slow (few minutes / image)



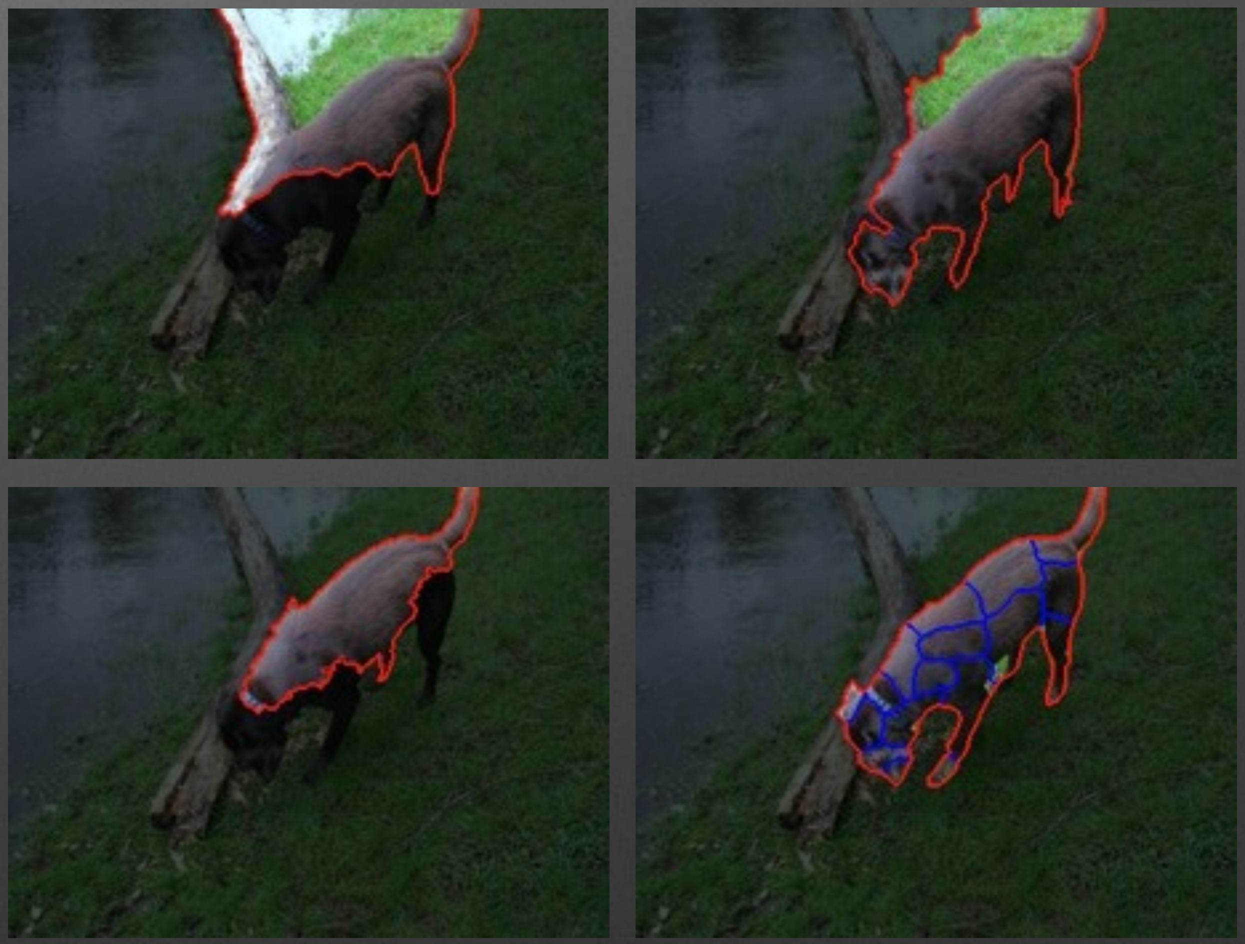
Improving Spatial Support for Objects via Multiple Segmentations
[Malisiewicz and Efros 2007]

- Soup of segments
  - 3 different unsupervised segmentation algorithms
  - vary parameters
  - combination of up to 3 adjacent segments
- Slow (few minutes / image)
- Hard to segment larger objects well



Improving Spatial Support for Objects via Multiple Segmentations
[Malisiewicz and Efros 2007]

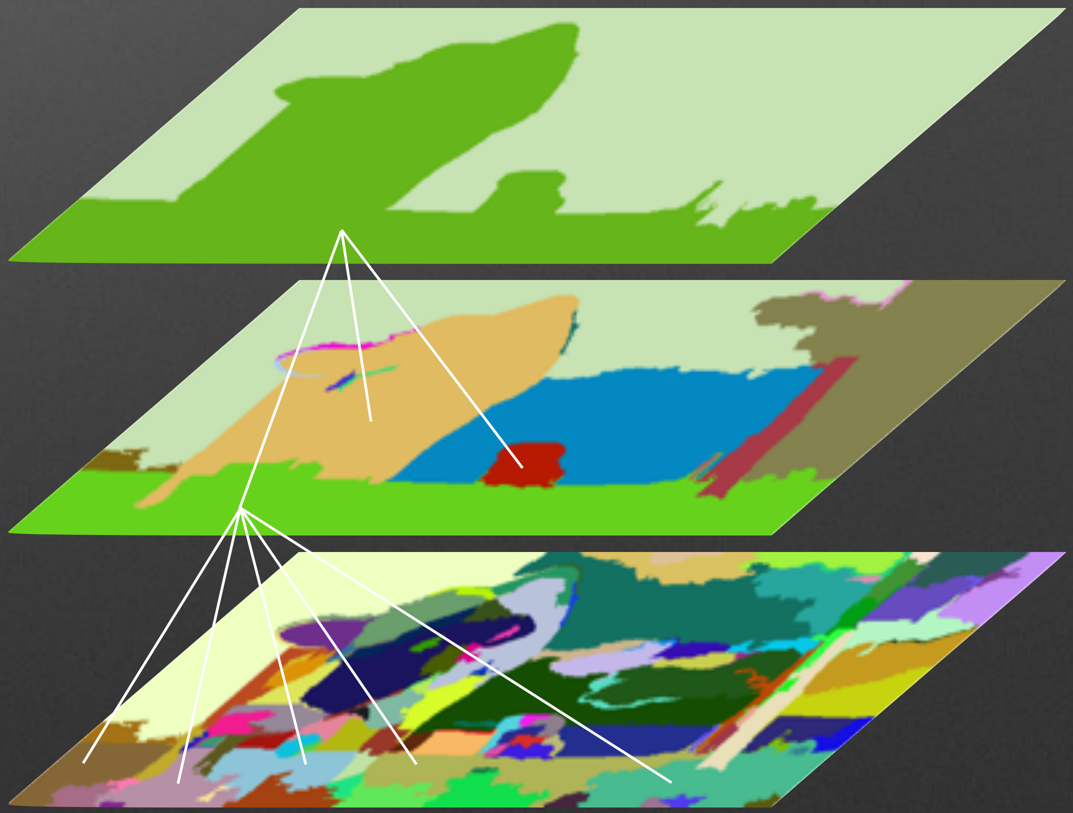
- Soup of segments
  - 3 different unsupervised segmentation algorithms
  - vary parameters
  - combination of up to 3 adjacent segments
- Slow (few minutes / image)
- Hard to segment larger objects well



Segmentation As Selective Search for Object Recognition

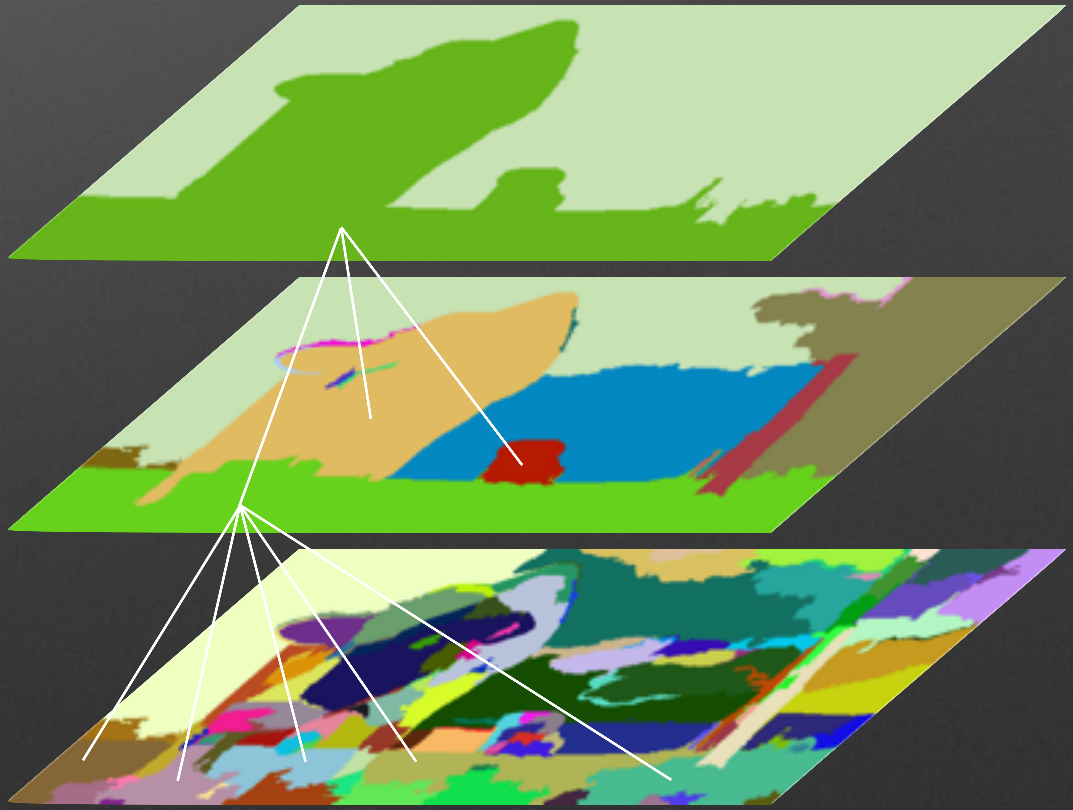
[van de Sande et al. 2011]

- Hierarchical segmentations



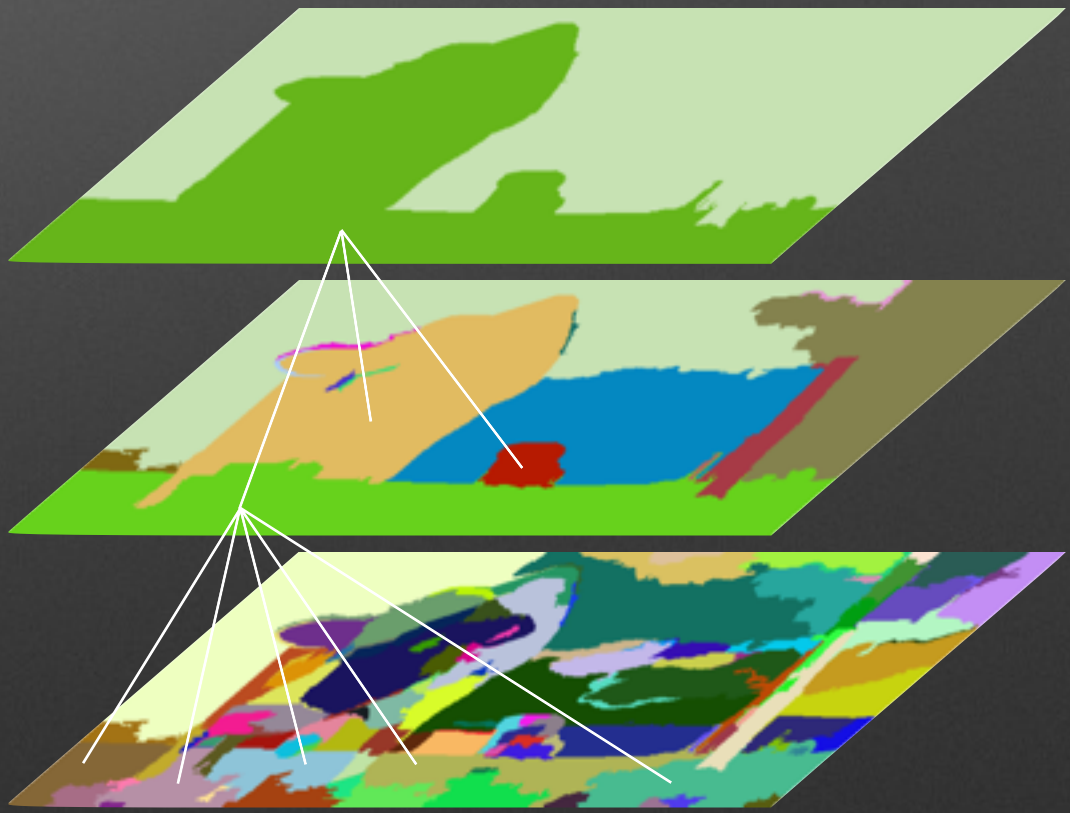
Segmentation As Selective Search for Object Recognition
[van de Sande et al. 2011]

- Hierarchical segmentations
  - same algorithm



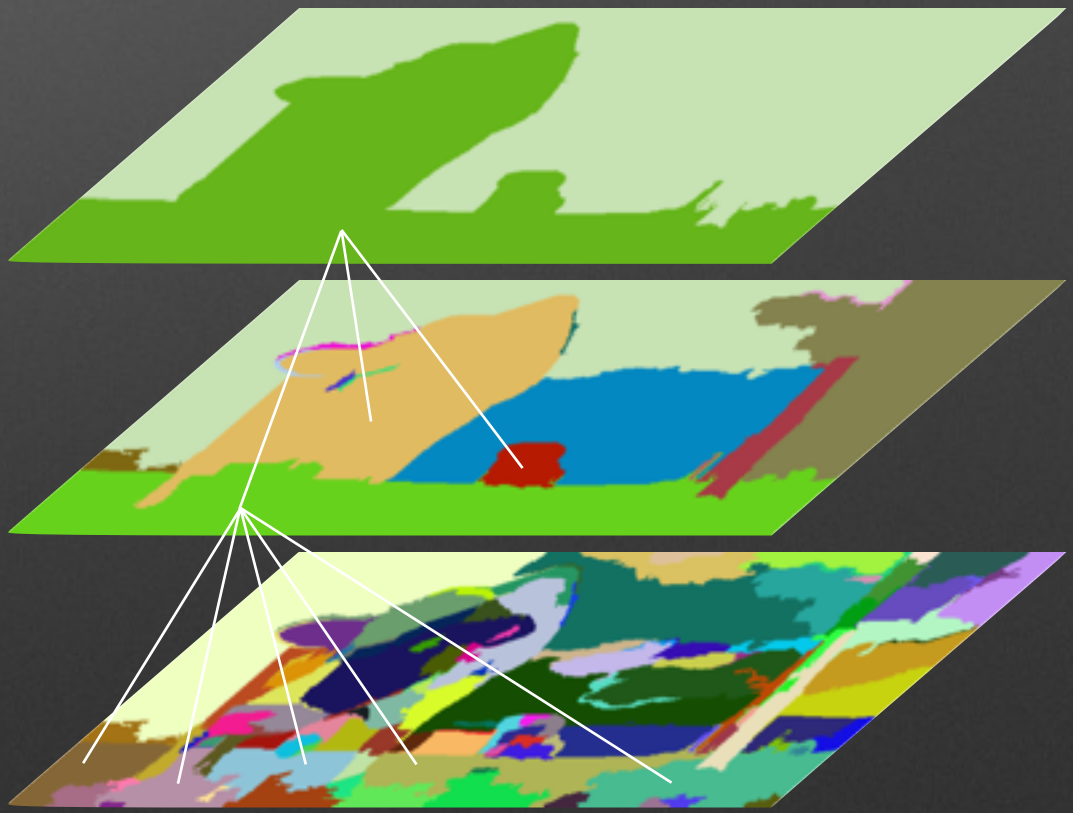
Segmentation As Selective Search for Object Recognition
[van de Sande et al. 2011]

- Hierarchical segmentations
  - same algorithm
  - different parameters and color spaces



Segmentation As Selective Search for Object Recognition
[van de Sande et al. 2011]

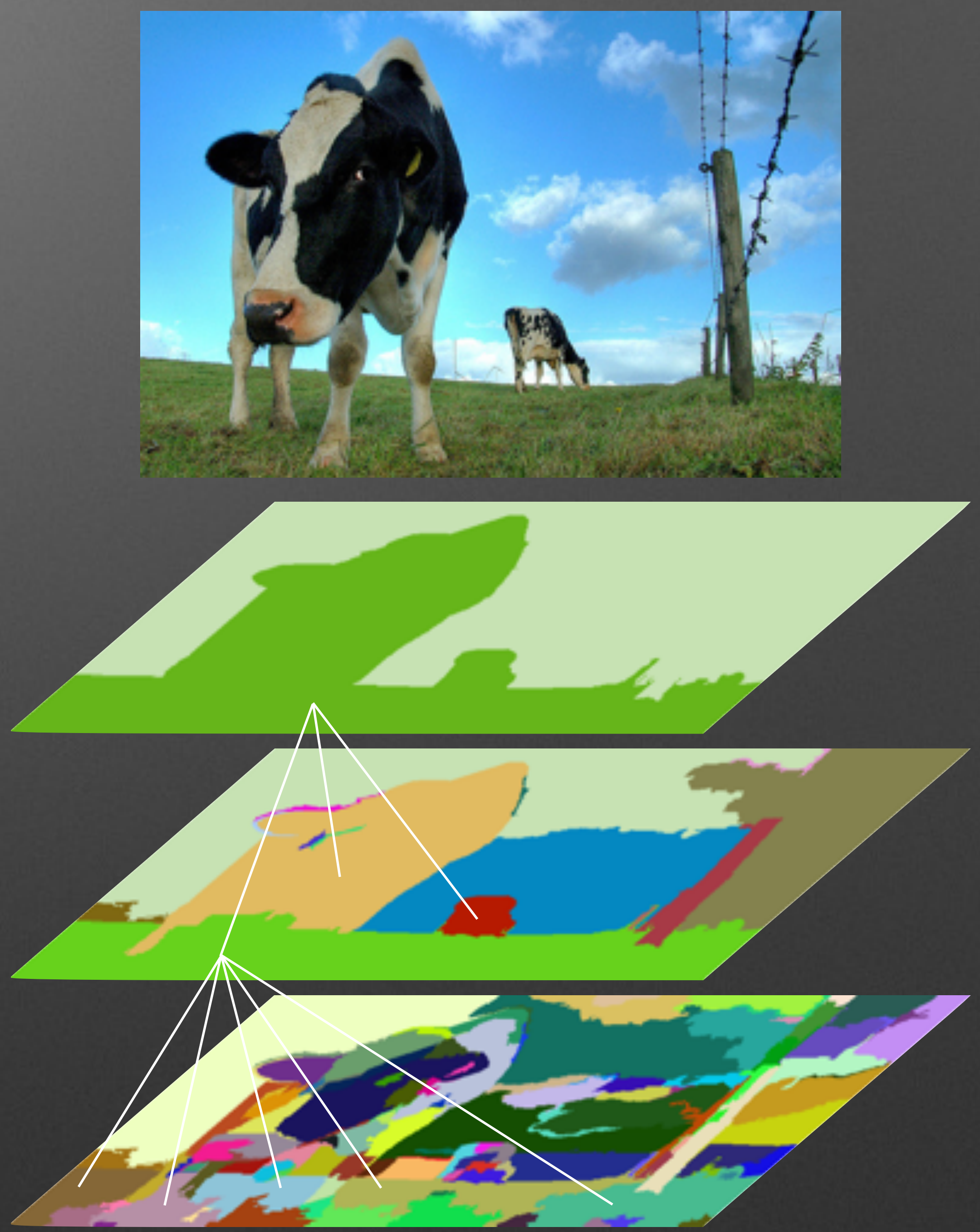
- Hierarchical segmentations
  - same algorithm
  - different parameters and color spaces
- Fast (few seconds / image)



Segmentation As Selective Search for Object Recognition

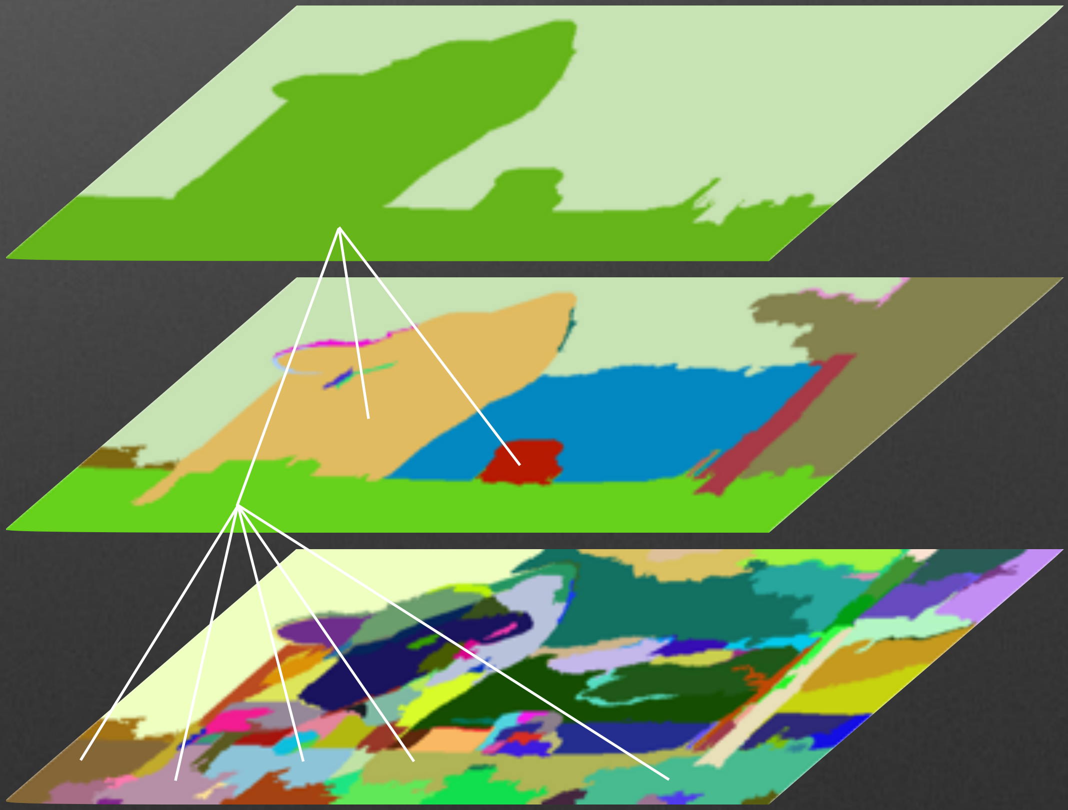
[van de Sande et al. 2011]

- Hierarchical segmentations
  - same algorithm
  - different parameters and color spaces
- Fast (few seconds / image)
- Good bounding box proposals



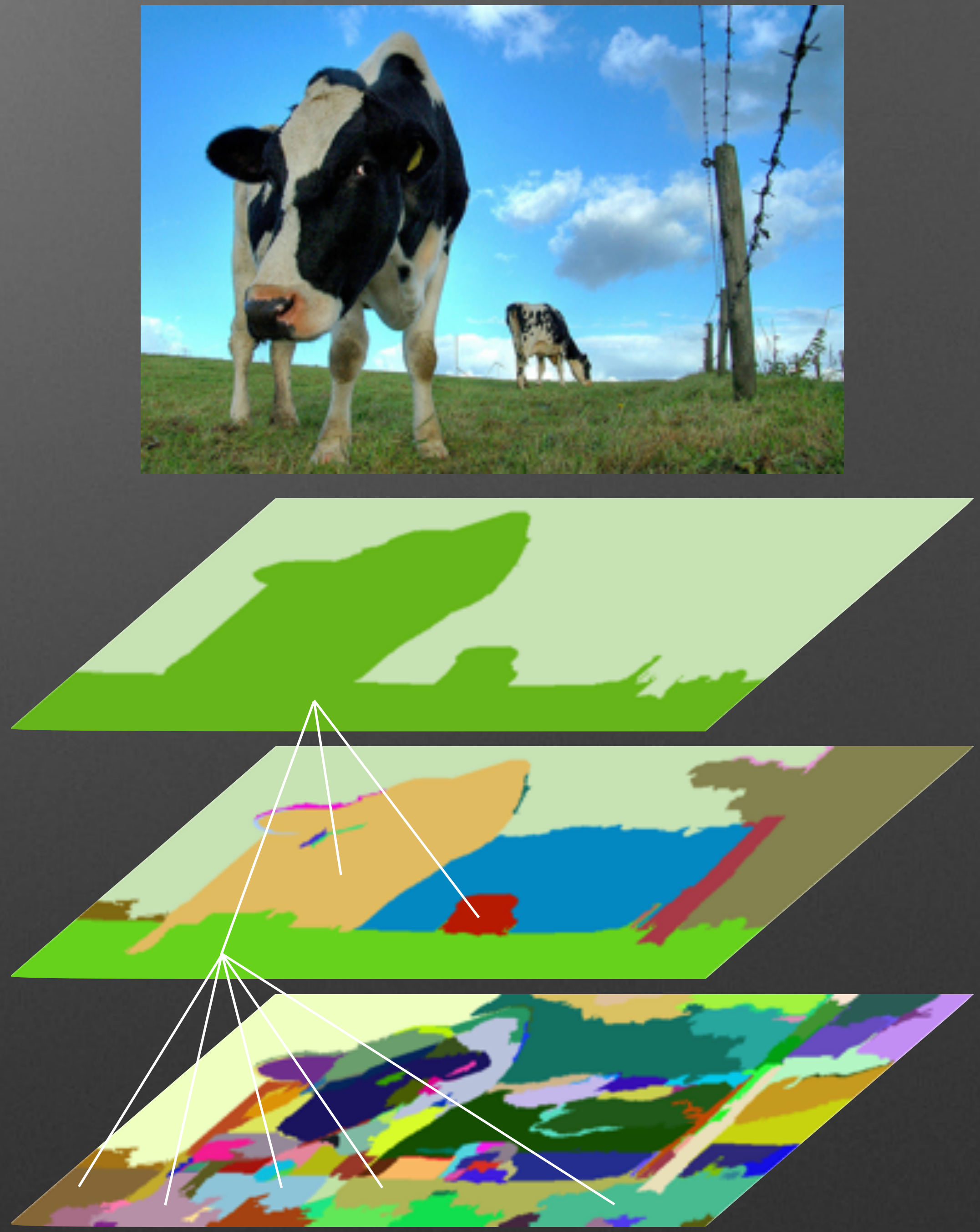
Segmentation As Selective Search for Object Recognition [van de Sande et al. 2011]

- Hierarchical segmentations
  - same algorithm
  - different parameters and color spaces
- Fast (few seconds / image)
- Good bounding box proposals
- OK segment proposals



Segmentation As Selective Search for Object Recognition

[van de Sande et al. 2011]



- Hierarchical segmentations
  - same algorithm
  - different parameters and color spaces
- Fast (few seconds / image)
- Good bounding box proposals
- OK segment proposals

Category Independent Object Proposals
[Endres and Hoiem 2010]

- Series of binary segmentations

Category Independent Object Proposals
[Endres and Hoiem 2010]

- Series of binary segmentations
    - Superpixel CRF model

Category Independent Object Proposals
[Endres and Hoiem 2010]

- Series of binary segmentations
  - Superpixel CRF model
  - Select seeds

Category Independent Object Proposals
[Endres and Hoiem 2010]

- Series of binary segmentations
    - Superpixel CRF model
    - Select seeds
    - Boosted decision tree as unary

Category Independent Object Proposals
[Endres and Hoiem 2010]

- Series of binary segmentations
  - Superpixel CRF model
  - Select seeds
  - Boosted decision tree as unary
  - Pairwise: boundary detector

Category Independent Object Proposals
[Endres and Hoiem 2010]

- Series of binary segmentations
  - Superpixel CRF model
  - Select seeds
  - Boosted decision tree as unary
  - Pairwise: boundary detector
  - Optimize with GraphCuts

Category Independent Object Proposals
[Endres and Hoiem 2010]

- Series of binary segmentations
  - Superpixel CRF model
  - Select seeds
  - Boosted decision tree as unary
  - Pairwise: boundary detector
  - Optimize with GraphCuts
- Good proposals

Category Independent Object Proposals
[Endres and Hoiem 2010]

- Series of binary segmentations
  - Superpixel CRF model
  - Select seeds
  - Boosted decision tree as unary
  - Pairwise: boundary detector
  - Optimize with GraphCuts
- Good proposals
- Slow (100+ sec / image)

Category Independent Object Proposals
[Endres and Hoiem 2010]

- Series of binary segmentations
  - Superpixel CRF model
  - Select seeds
  - Boosted decision tree as unary
  - Pairwise: boundary detector
  - Optimize with GraphCuts
- Good proposals
- Slow (100+ sec / image)

Constrained Parametric Min-Cuts for Automatic Object Segmentation
[Carreira and Sminchisescu 2010]

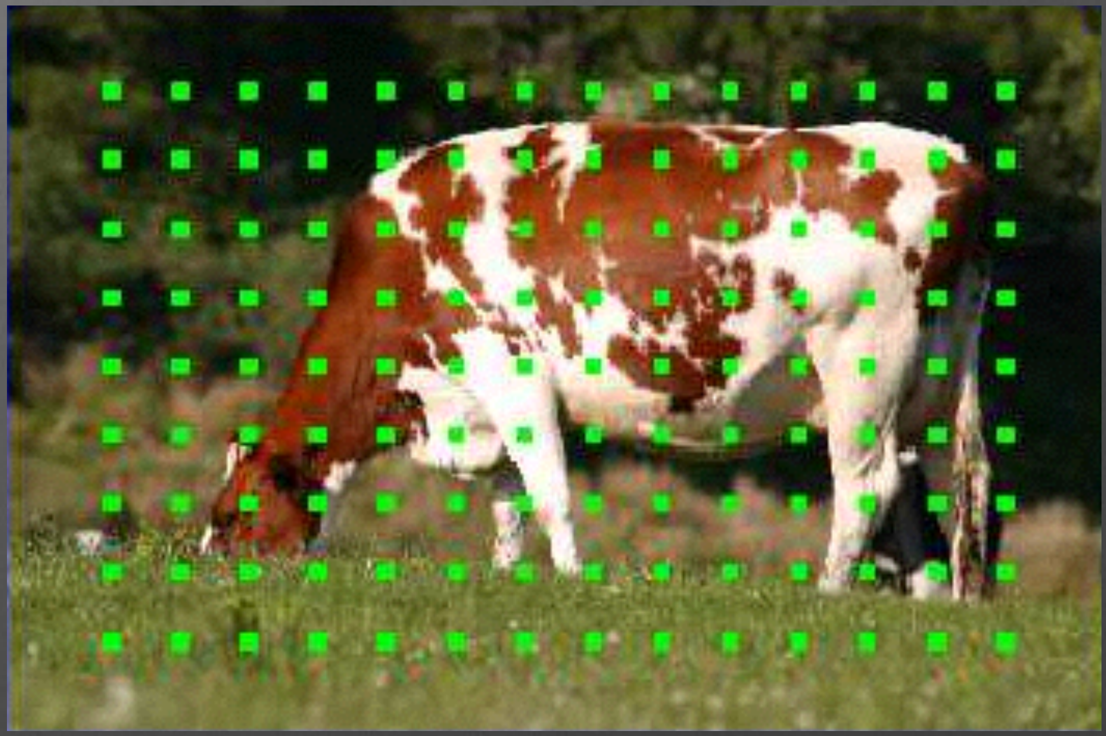
- Series of binary segmentations

Constrained Parametric Min-Cuts for Automatic Object Segmentation
[Carreira and Sminchisescu 2010]

- Series of binary segmentations
  - Pixel CRF model

Constrained Parametric Min-Cuts for Automatic Object Segmentation
[Carreira and Sminchisescu 2010]

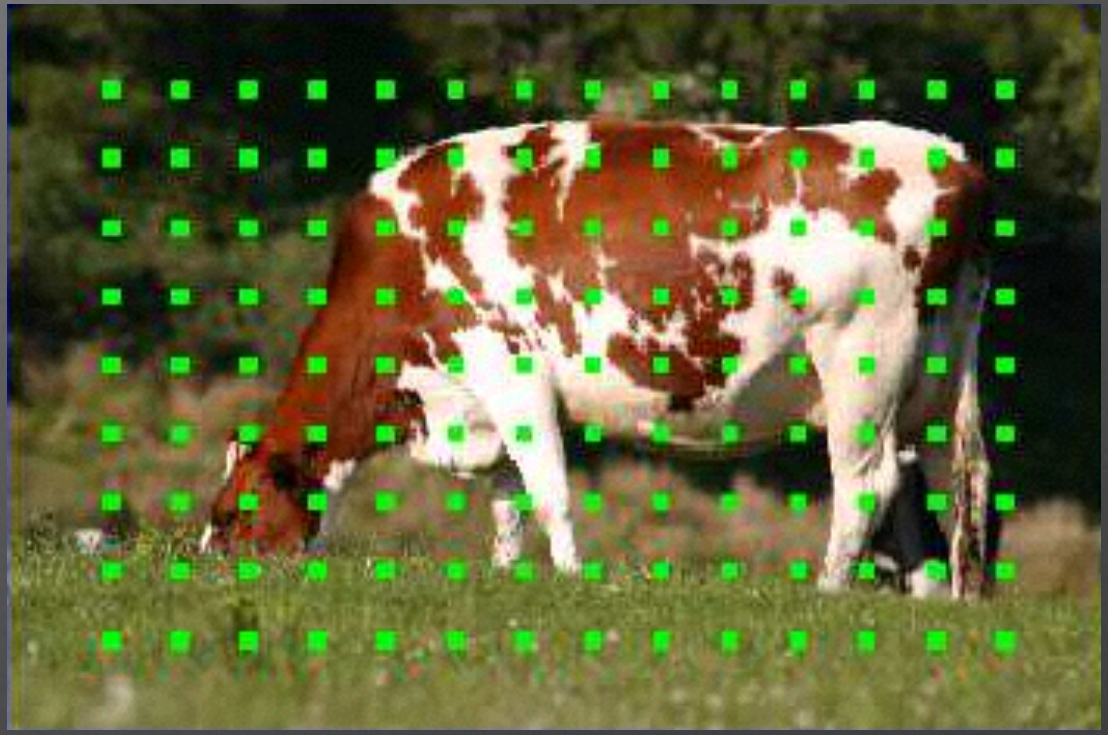
- Series of binary segmentations
  - Pixel CRF model
  - Regularly sampled seeds



Constrained Parametric Min-Cuts for Automatic Object Segmentation

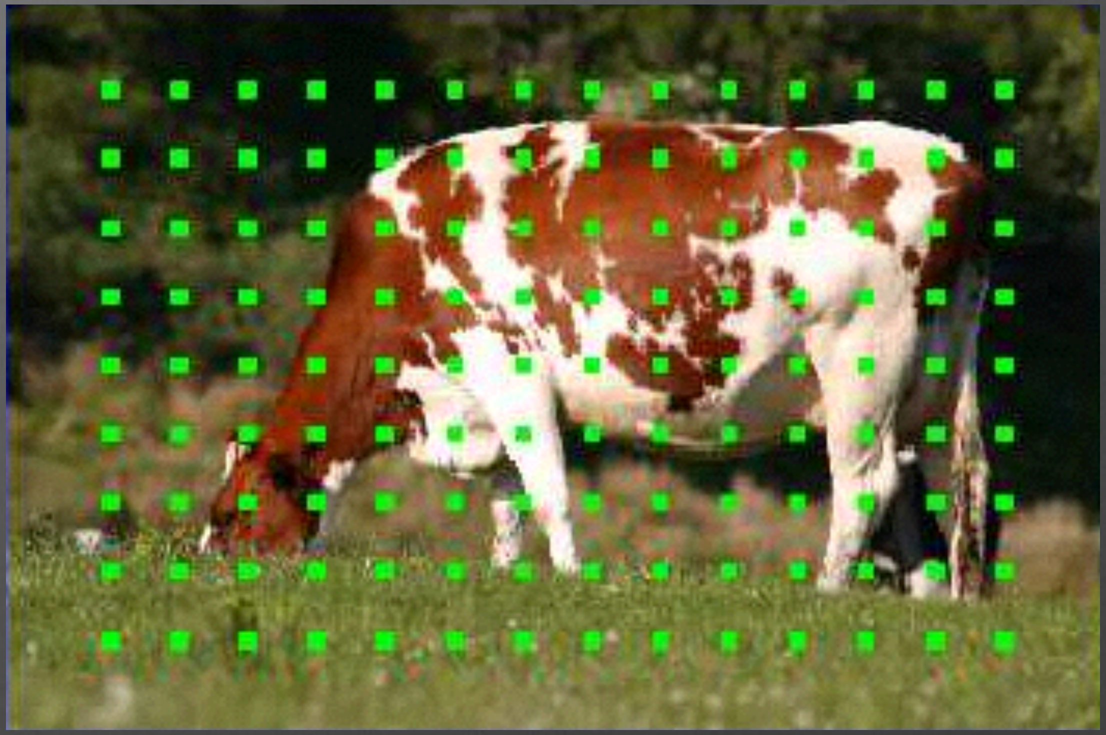
[Carreira and Sminchisescu 2010]

- Series of binary segmentations
  - Pixel CRF model
  - Regularly sampled seeds
  - Color based unary



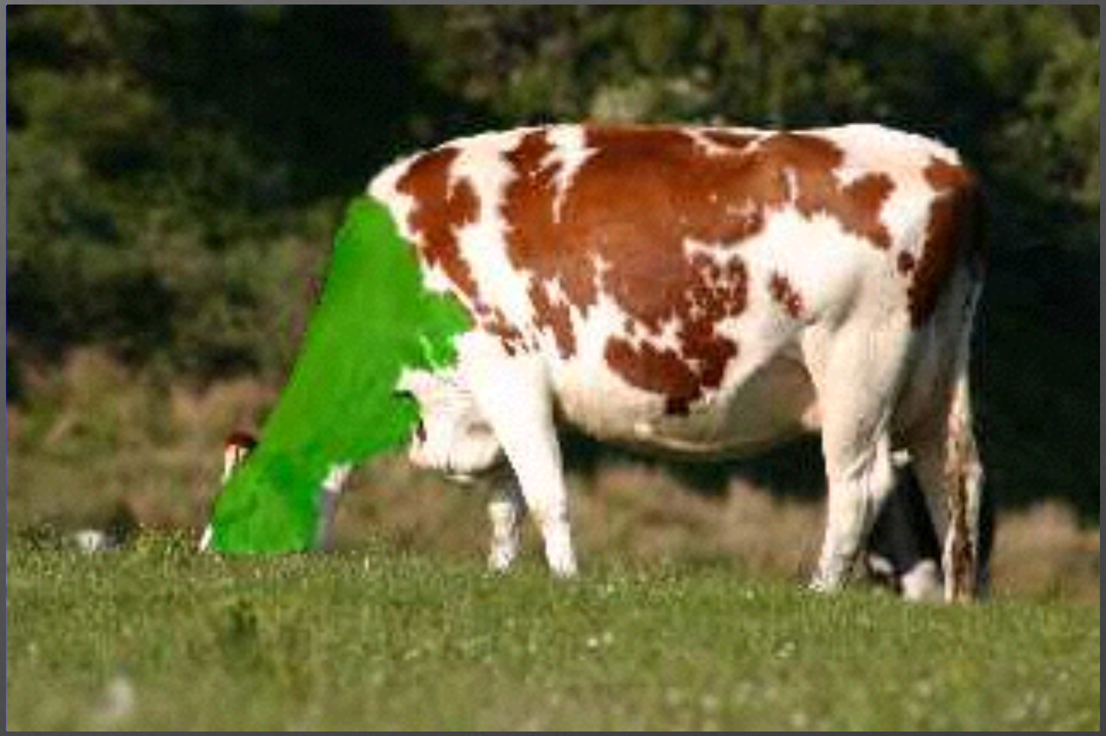
Constrained Parametric Min-Cuts for Automatic Object Segmentation
[Carreira and Sminchisescu 2010]

- Series of binary segmentations
  - Pixel CRF model
  - Regularly sampled seeds
  - Color based unary
  - GraphCuts with pairwise term



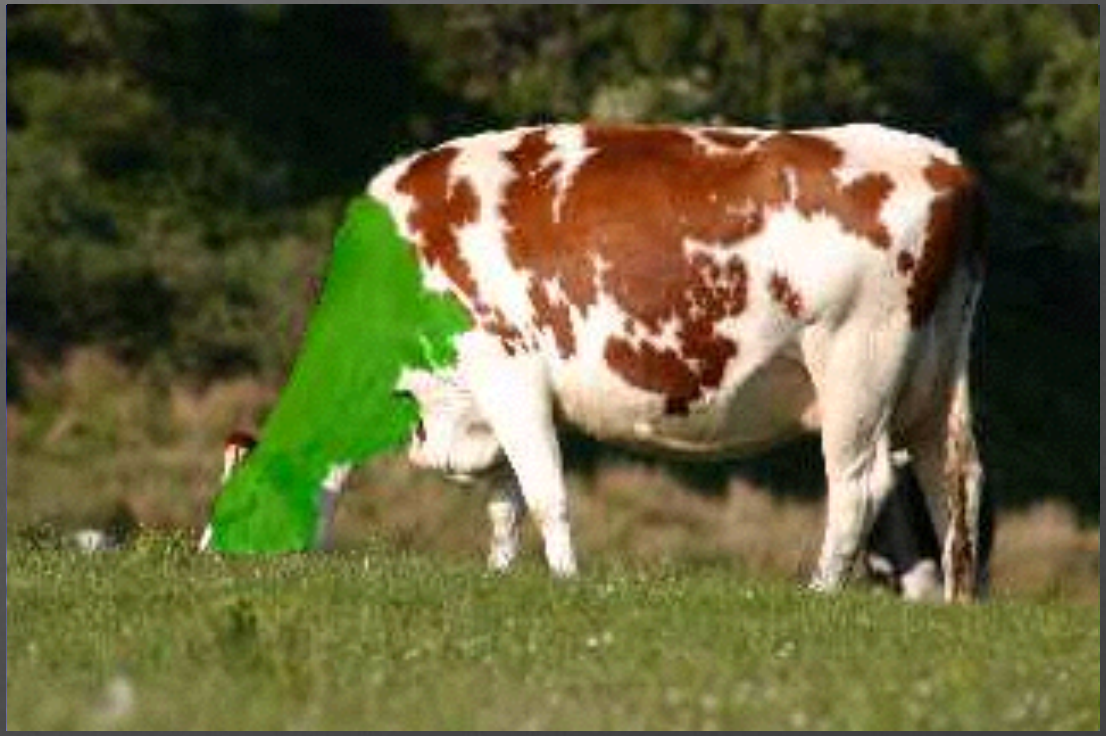
Constrained Parametric Min-Cuts for Automatic Object Segmentation
[Carreira and Sminchisescu 2010]

- Series of binary segmentations
  - Pixel CRF model
  - Regularly sampled seeds
  - Color based unary
  - GraphCuts with pairwise term



Constrained Parametric Min-Cuts for Automatic Object Segmentation
[Carreira and Sminchisescu 2010]

- Series of binary segmentations
  - Pixel CRF model
  - Regularly sampled seeds
  - Color based unary
  - GraphCuts with pairwise term
  - Parametric cut



Constrained Parametric Min-Cuts for Automatic Object Segmentation [Carreira and Sminchisescu 2010]

- Series of binary segmentations
  - Pixel CRF model
  - Regularly sampled seeds
  - Color based unary
  - GraphCuts with pairwise term
  - Parametric cut
    - slowly inflate segmentation

Constrained Parametric Min-Cuts for Automatic Object Segmentation
[Carreira and Sminchisescu 2010]

- Series of binary segmentations
  - Pixel CRF model
  - Regularly sampled seeds
  - Color based unary
  - GraphCuts with pairwise term
  - Parametric cut
    - slowly inflate segmentation

Constrained Parametric Min-Cuts for Automatic Object Segmentation
[Carreira and Sminchisescu 2010]

- Series of binary segmentations
  - Pixel CRF model
  - Regularly sampled seeds
  - Color based unary
  - GraphCuts with pairwise term
  - Parametric cut
    - slowly inflate segmentation
- Best proposals

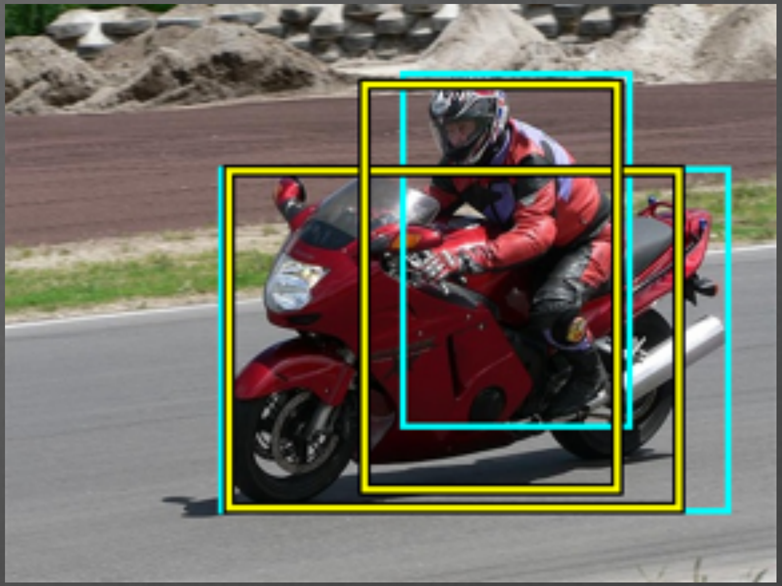
Constrained Parametric Min-Cuts for Automatic Object Segmentation [Carreira and Sminchisescu 2010]

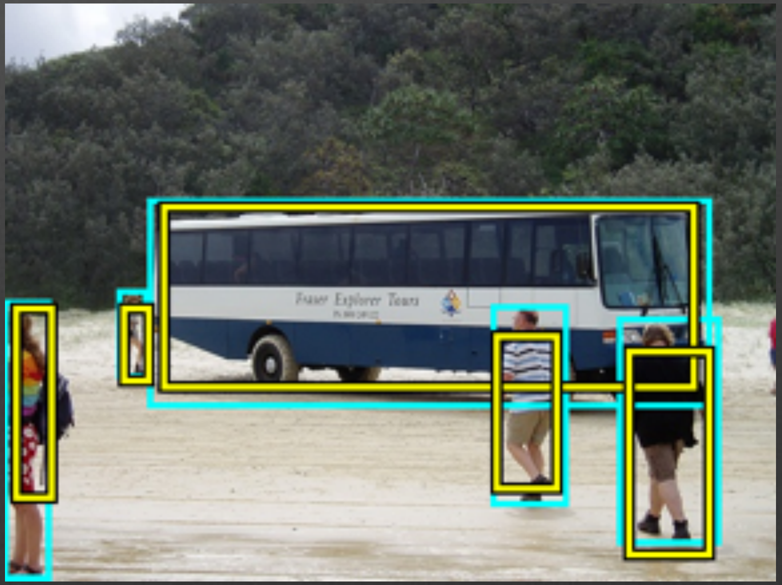
- Series of binary segmentations
  - Pixel CRF model
  - Regularly sampled seeds
  - Color based unary
  - GraphCuts with pairwise term
  - Parametric cut
    - slowly inflate segmentation
- Best proposals
- Slow (200+ sec / image)

Constrained Parametric Min-Cuts for Automatic Object Segmentation [Carreira and Sminchisescu 2010]

- Series of binary segmentations
  - Pixel CRF model
  - Regularly sampled seeds
  - Color based unary
  - GraphCuts with pairwise term
  - Parametric cut
    - slowly inflate segmentation
- Best proposals
- Slow (200+ sec / image)

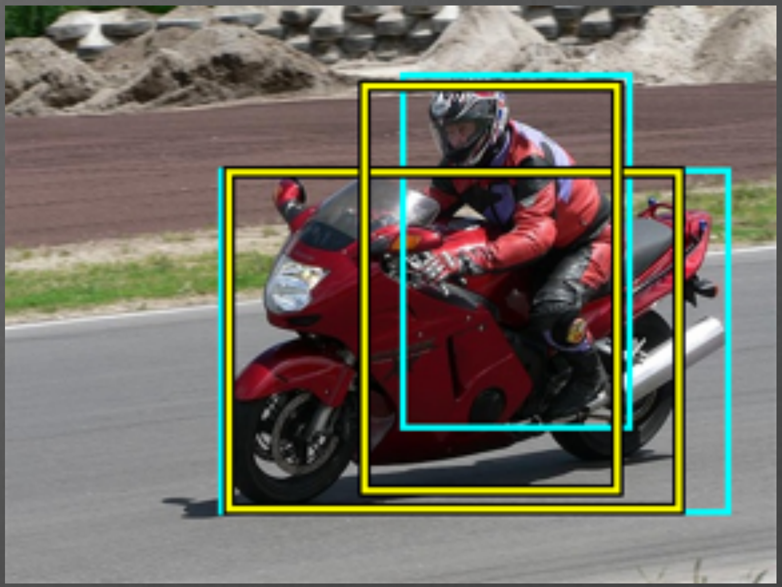
What is an object?
[Alexe et al. 2010]

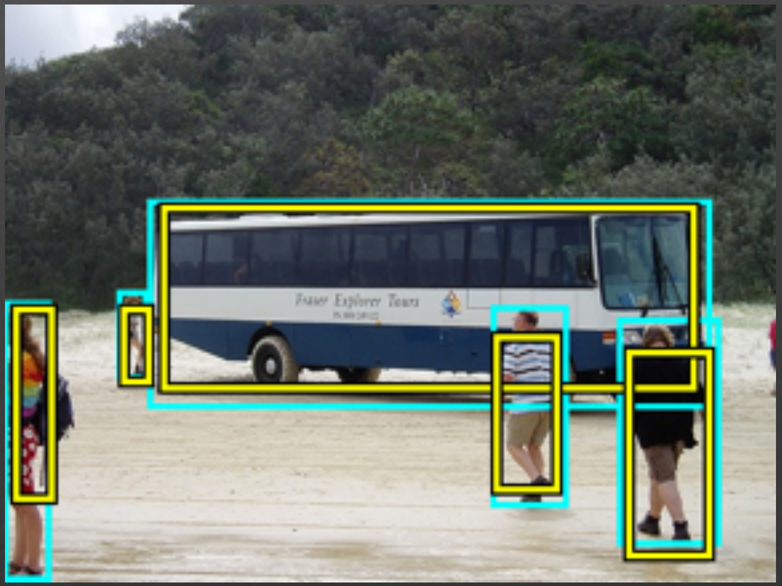




What is an object?
[Alexe et al. 2010]

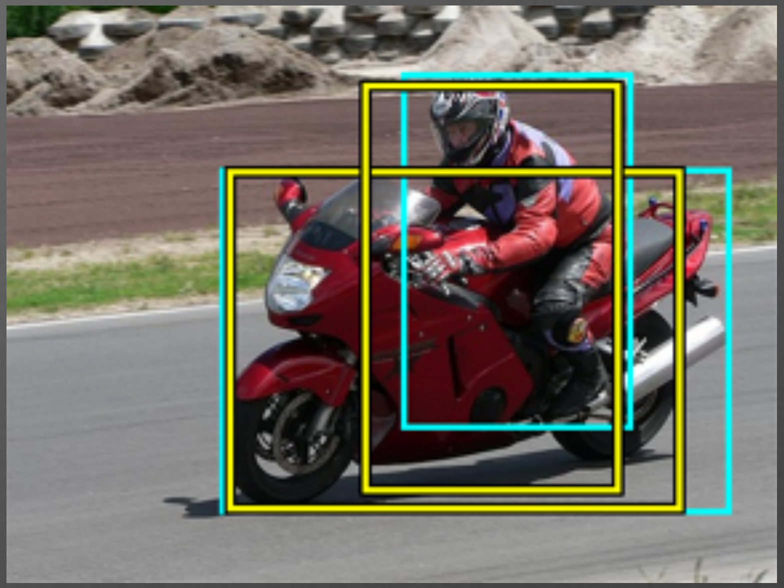
- Bounding box proposals

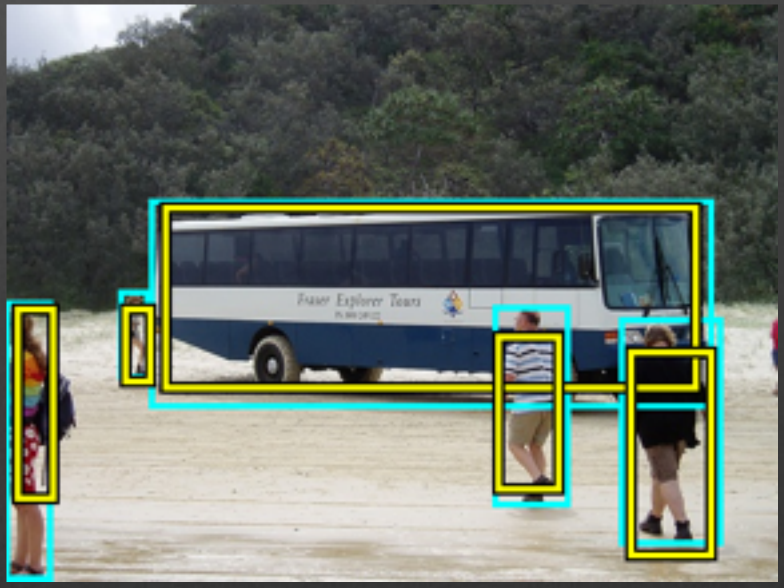




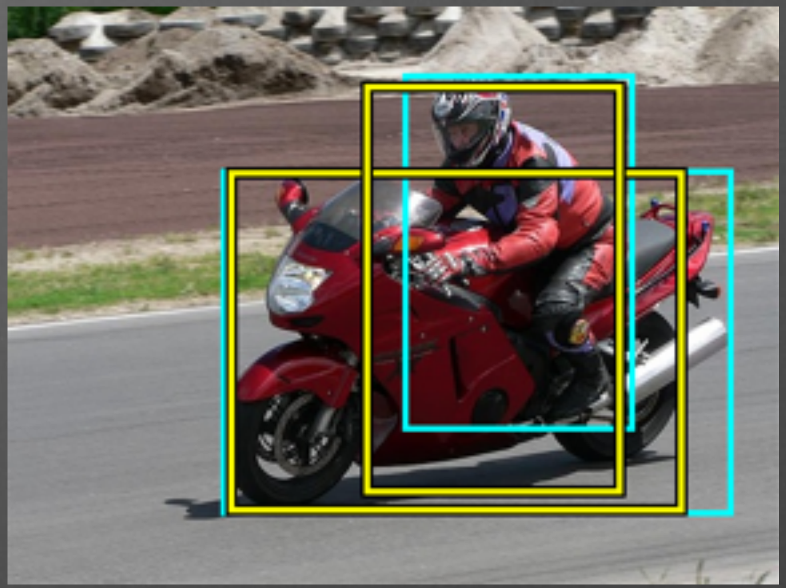
What is an object?
[Alexe et al. 2010]

- Bounding box proposals
    - Train a general classifier for "objectness"

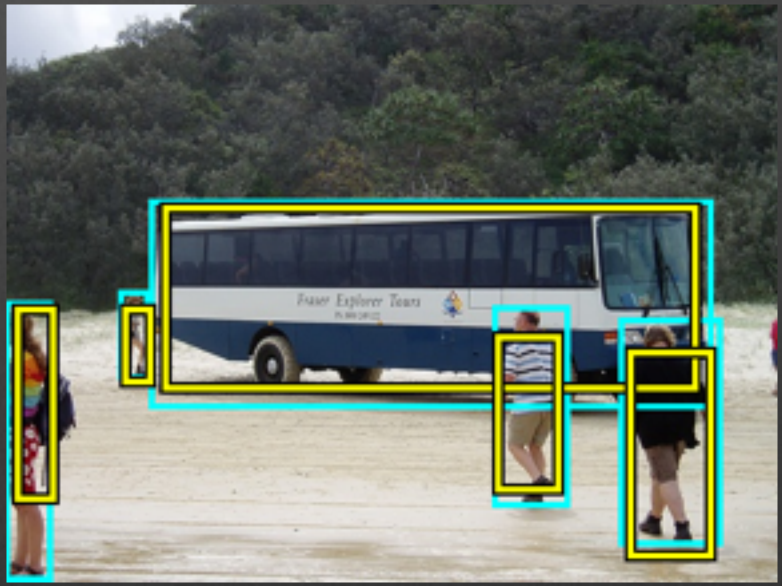




What is an object?
[Alexe et al. 2010]

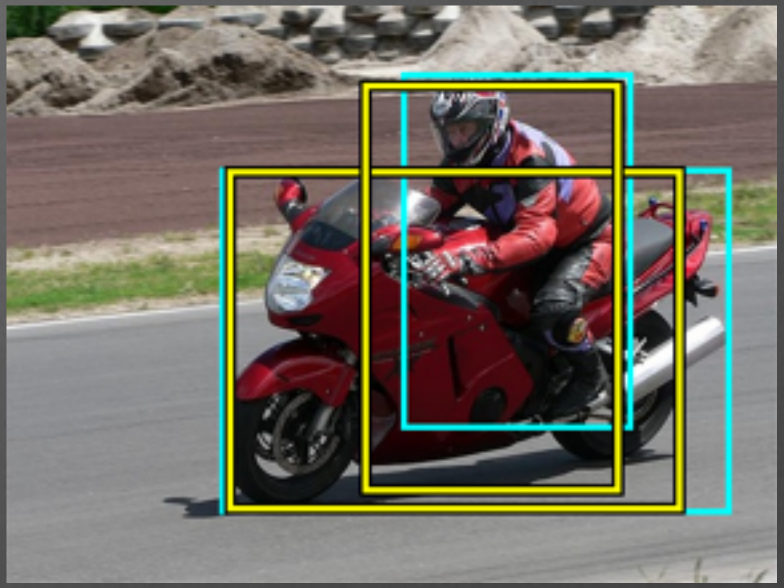


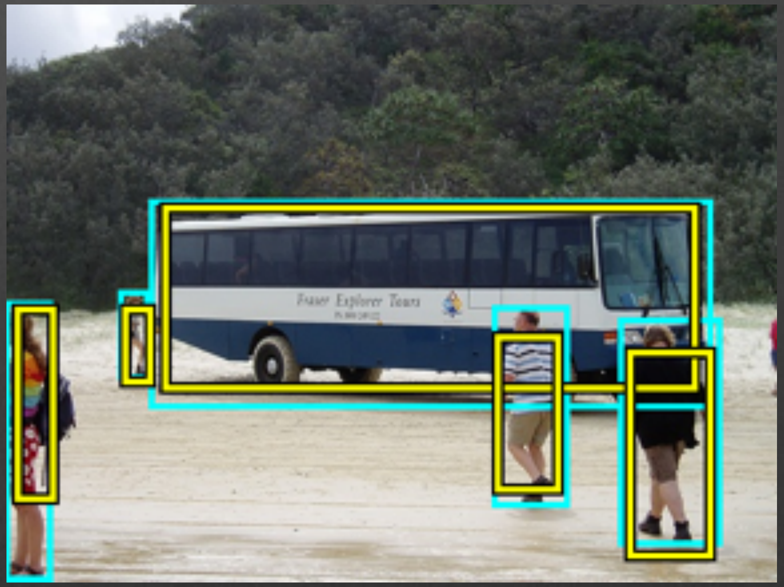
- Bounding box proposals
  - Train a general classifier for "objectness"
- fast (few seconds, BING[1]: few ms)



[1] BING: Binarized Normed Gradients for Objectness Estimation at 300fps [Cheng et al. 2014]

What is an object?
[Alexe et al. 2010]

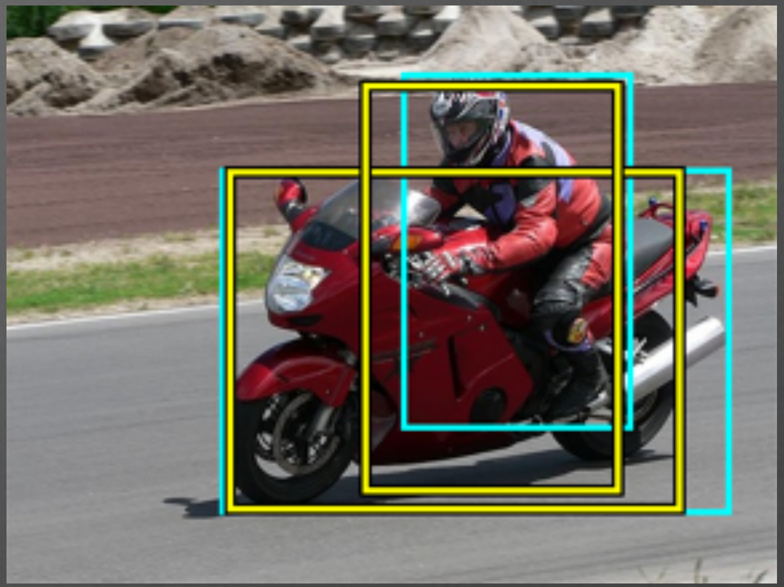


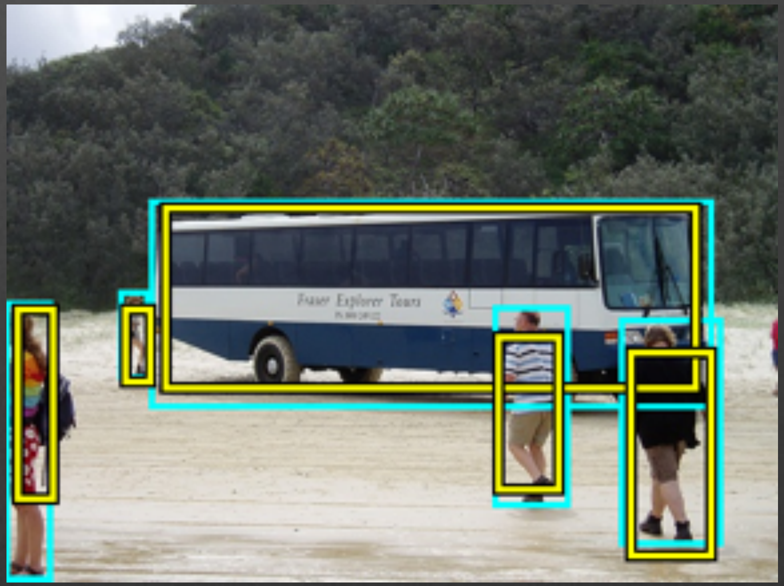


- Bounding box proposals
  - Train a general classifier for "objectness"
- fast (few seconds, BING[1]: few ms)
- Only works for bounding boxes

[1] BING: Binarized Normed Gradients for Objectness Estimation at 300fps [Cheng et al. 2014]

What is an object?
[Alexe et al. 2010]

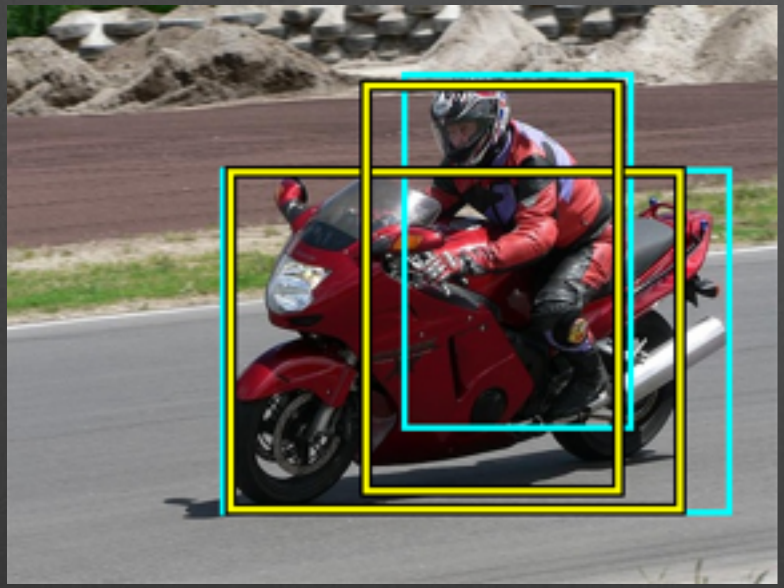
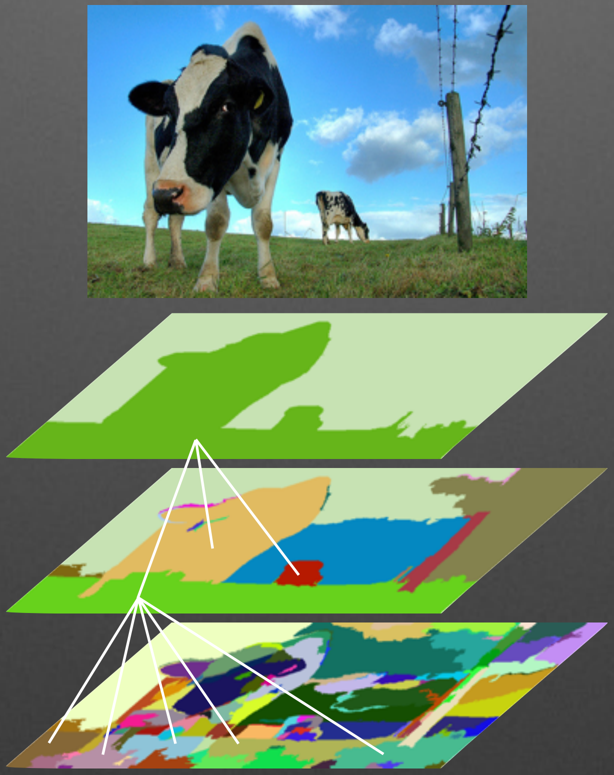




- Bounding box proposals
  - Train a general classifier for "objectness"
- fast (few seconds, BING[1]: few ms)
- Only works for bounding boxes

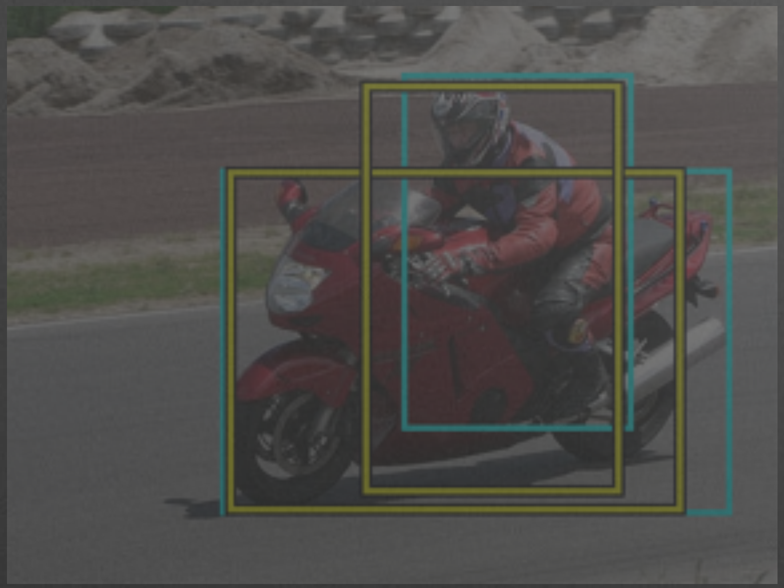
[1] BING: Binarized Normed Gradients for Objectness Estimation at 300fps [Cheng et al. 2014]

Prior work - summary

Objectness	Segmentation based	Seed / GraphCuts
		

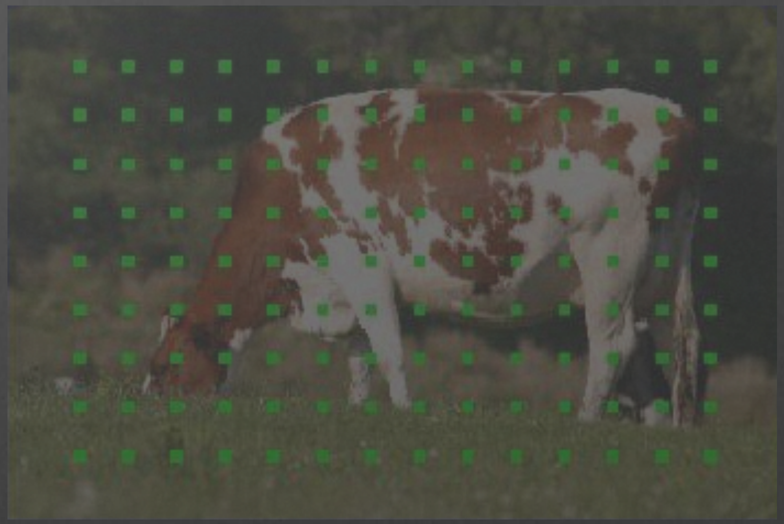
Prior work - summary

Objectness



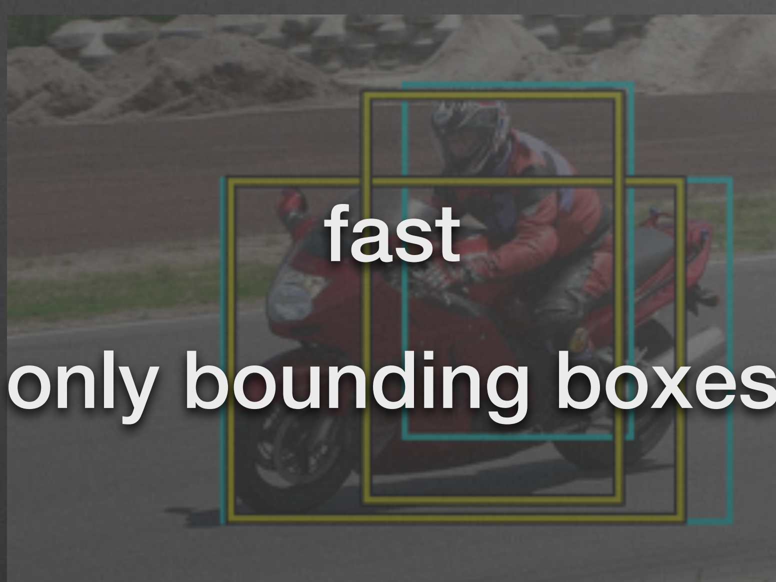
Segmentation based

Seed / GraphCuts



Prior work - summary

Objectness

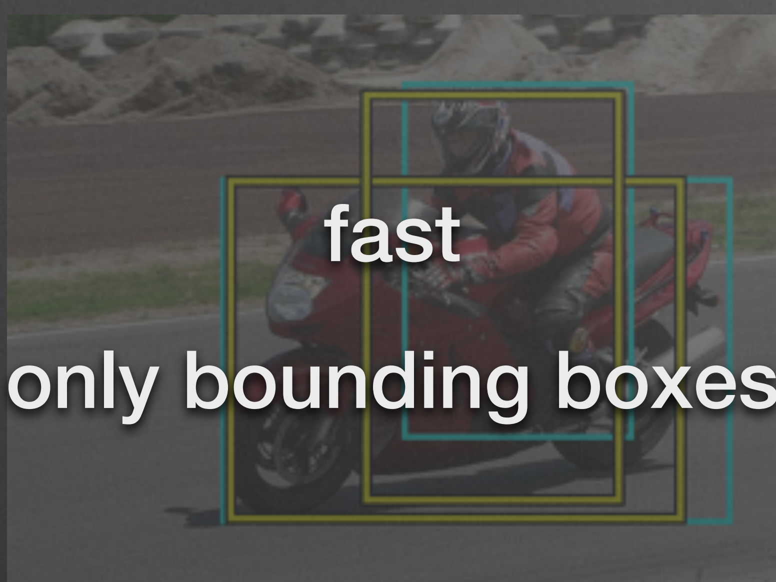


Segmentation based

Seed / GraphCuts

Prior work - summary

Objectness



fast

only bounding boxes

Segmentation based

fast

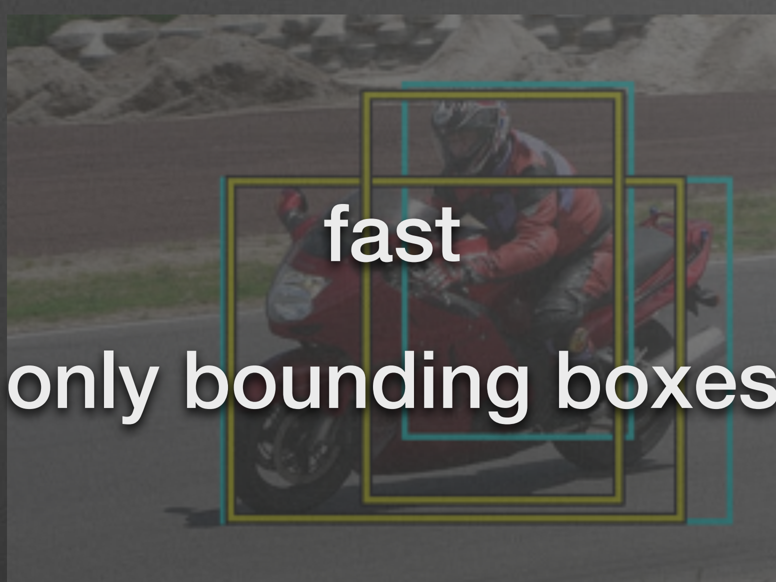
good bounding boxes

OK segmentation

Seed / GraphCuts

Prior work - summary

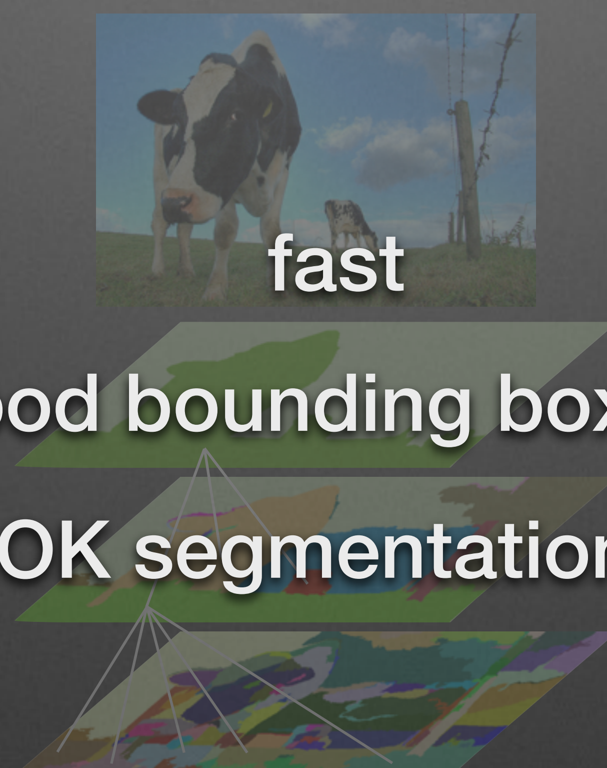
Objectness



fast

only bounding boxes

Segmentation based

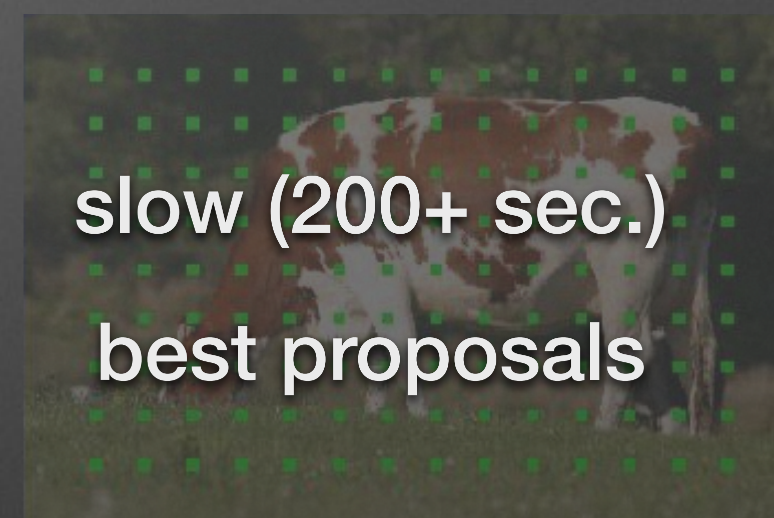


fast

good bounding boxes

OK segmentation

Seed / GraphCuts

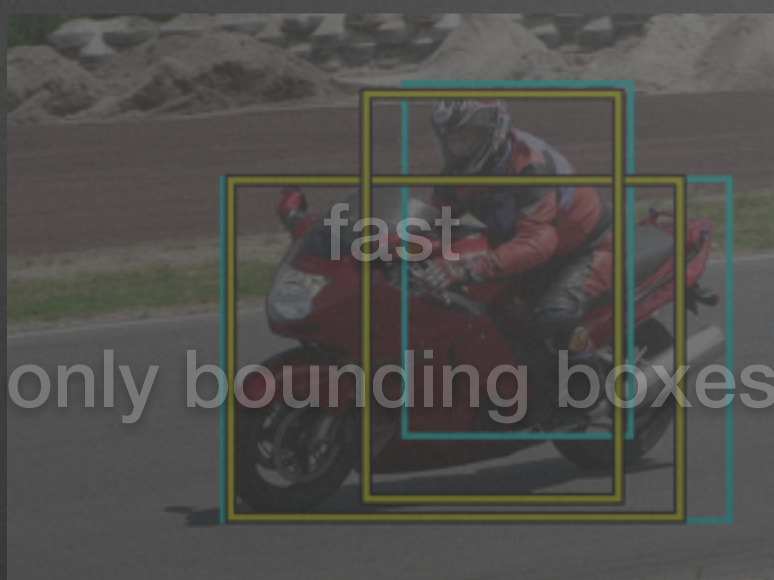


slow (200+ sec.)

best proposals

Prior work - summary

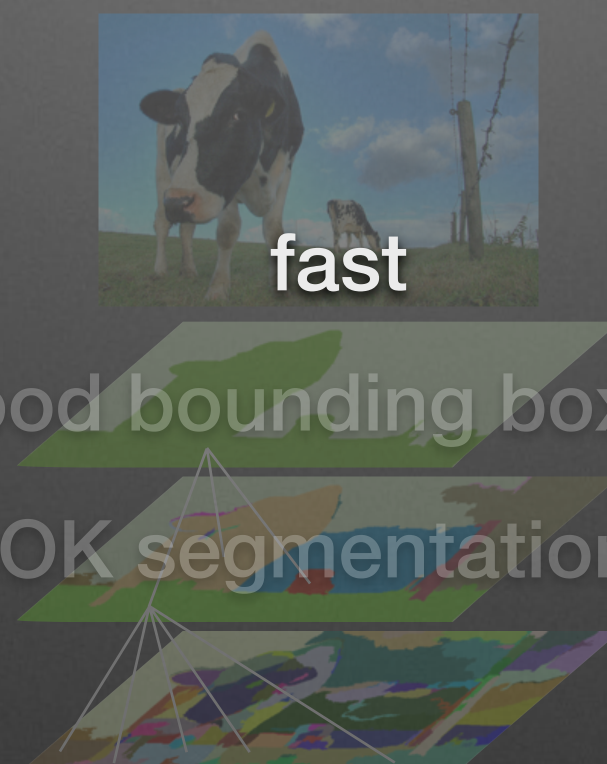
Objectness



fast

only bounding boxes

Segmentation based

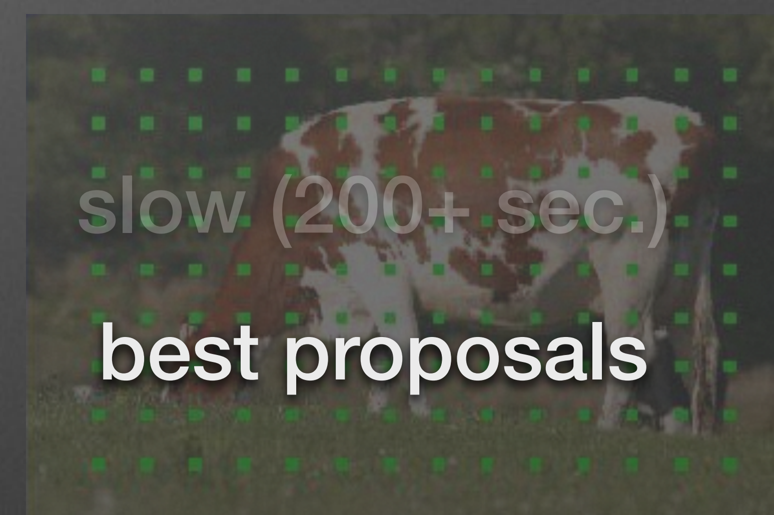


fast

good bounding boxes

OK segmentation

Seed / GraphCuts



slow (200+ sec.)

best proposals

Geodesic image segmentation

Geodesic image segmentation

- (Signed) geodesic distance transform

Geodesic image segmentation

- (Signed) geodesic distance transform
  - Shortest path to background and foreground scribble

Geodesic image segmentation

- (Signed) geodesic distance transform
  - Shortest path to background and foreground scribble
  - small within objects

Geodesic image segmentation

- (Signed) geodesic distance transform
  - Shortest path to background and foreground scribble
  - small within objects
  - large between objects

Geodesic image segmentation

- (Signed) geodesic distance transform
  - Shortest path to background and foreground scribble
  - small within objects
  - large between objects
  - efficient to compute

Geodesic image segmentation

- (Signed) geodesic distance transform
  - Shortest path to background and foreground scribble
  - small within objects
  - large between objects
  - efficient to compute
- State of the art in interactive image and video segmentation[1,2]

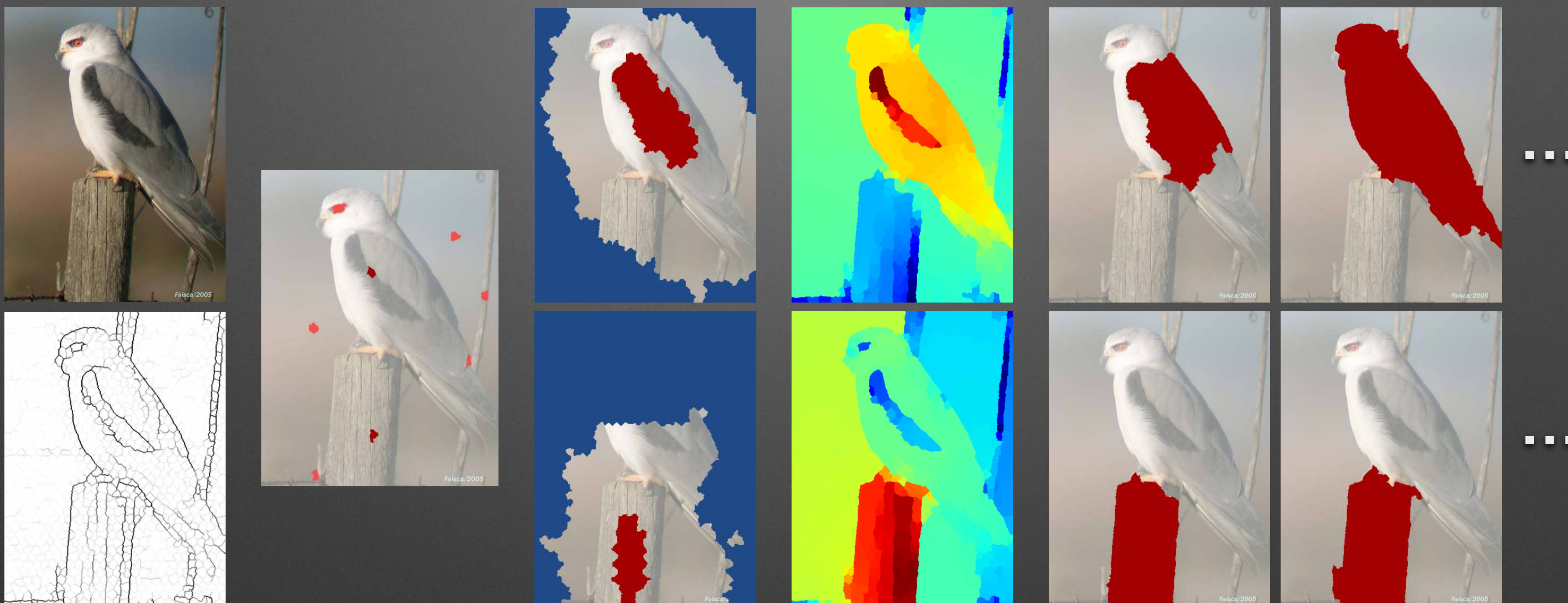
[1] Geodesic Matting: A Framework for Fast Interactive Image and Video Segmentation and Matting [Bai and Sapiro 2008]
[2] Geodesic Image and Video Editing [Criminisi et al. 2011]

Geodesic image segmentation

- (Signed) geodesic distance transform
  - Shortest path to background and foreground scribble
  - small within objects
  - large between objects
  - efficient to compute
- State of the art in interactive image and video segmentation[1,2]

[1] Geodesic Matting: A Framework for Fast Interactive Image and Video Segmentation and Matting [Bai and Sapiro 2008]
[2] Geodesic Image and Video Editing [Criminisi et al. 2011]

Geodesic object proposals



image, boundary map and superpixels

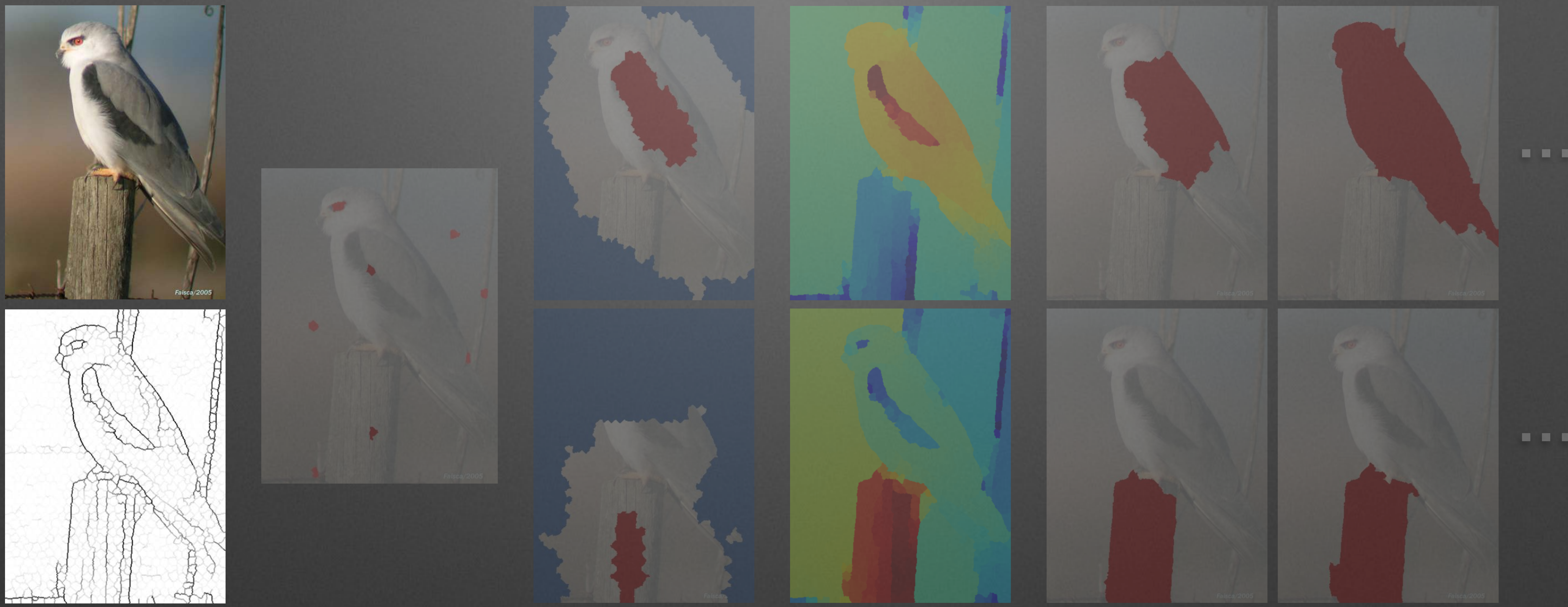
select seeds

foreground background masks

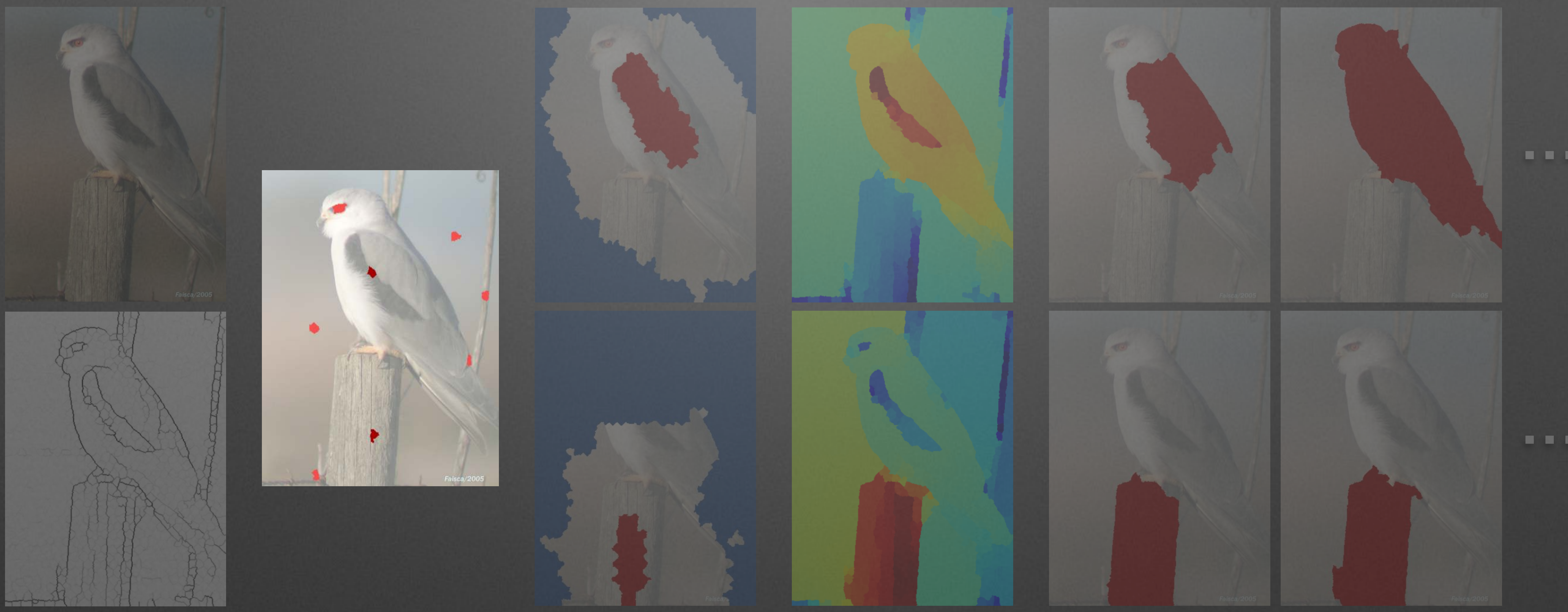
geodesic distance transform

multiple proposals

Geodesic object proposals



Geodesic object proposals



image, boundary map and superpixels

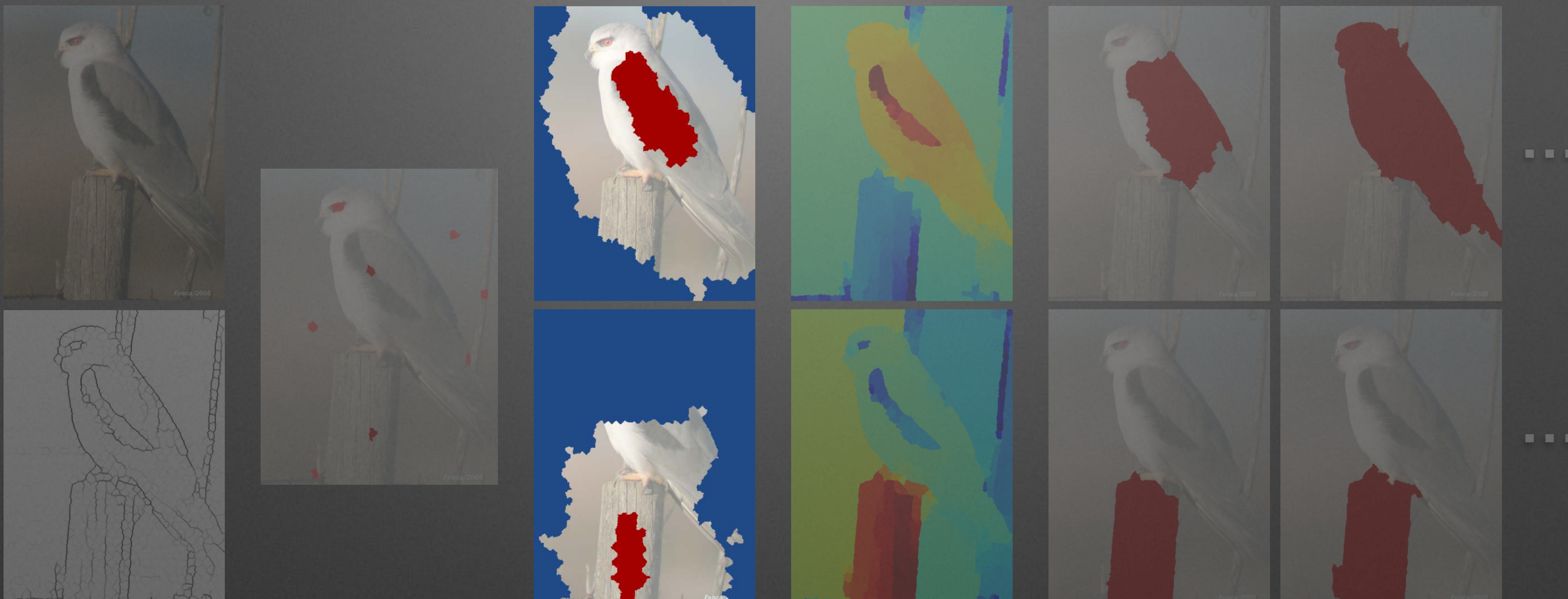
select seeds

foreground background masks

geodesic distance transform

multiple proposals

Geodesic object proposals



image, boundary map and superpixels

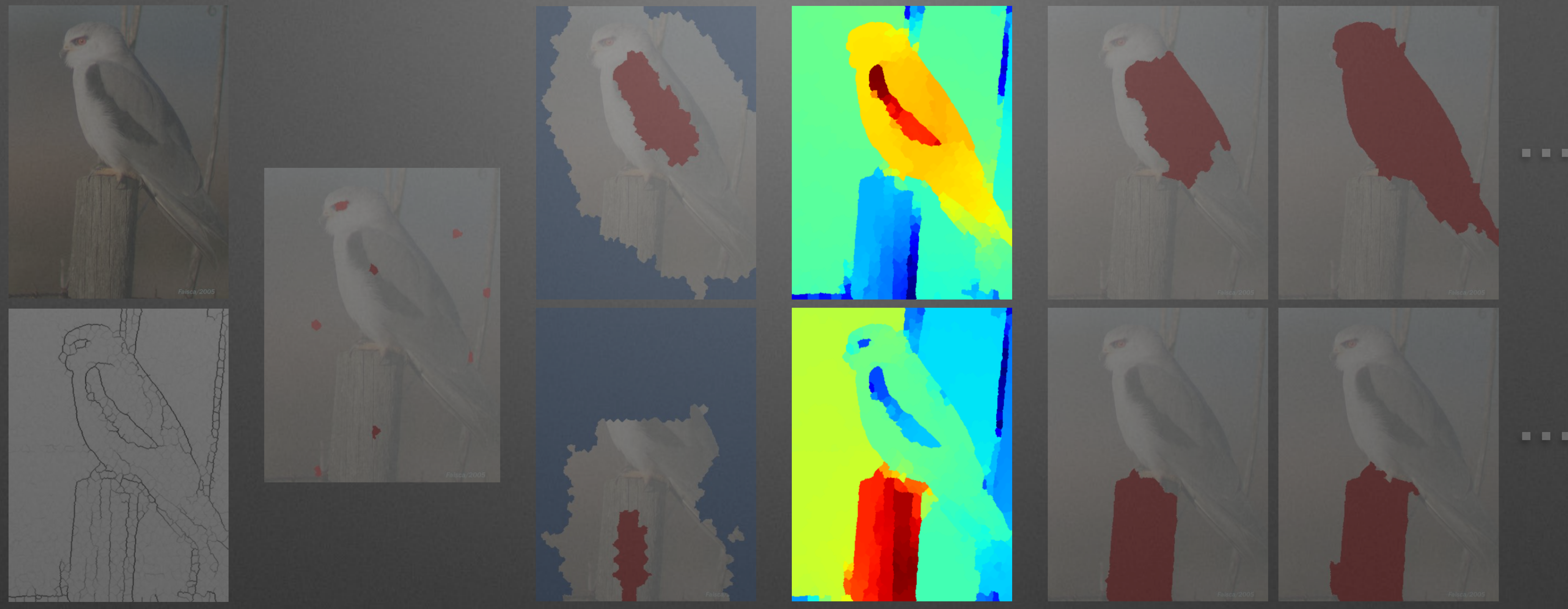
select seeds

foreground background masks

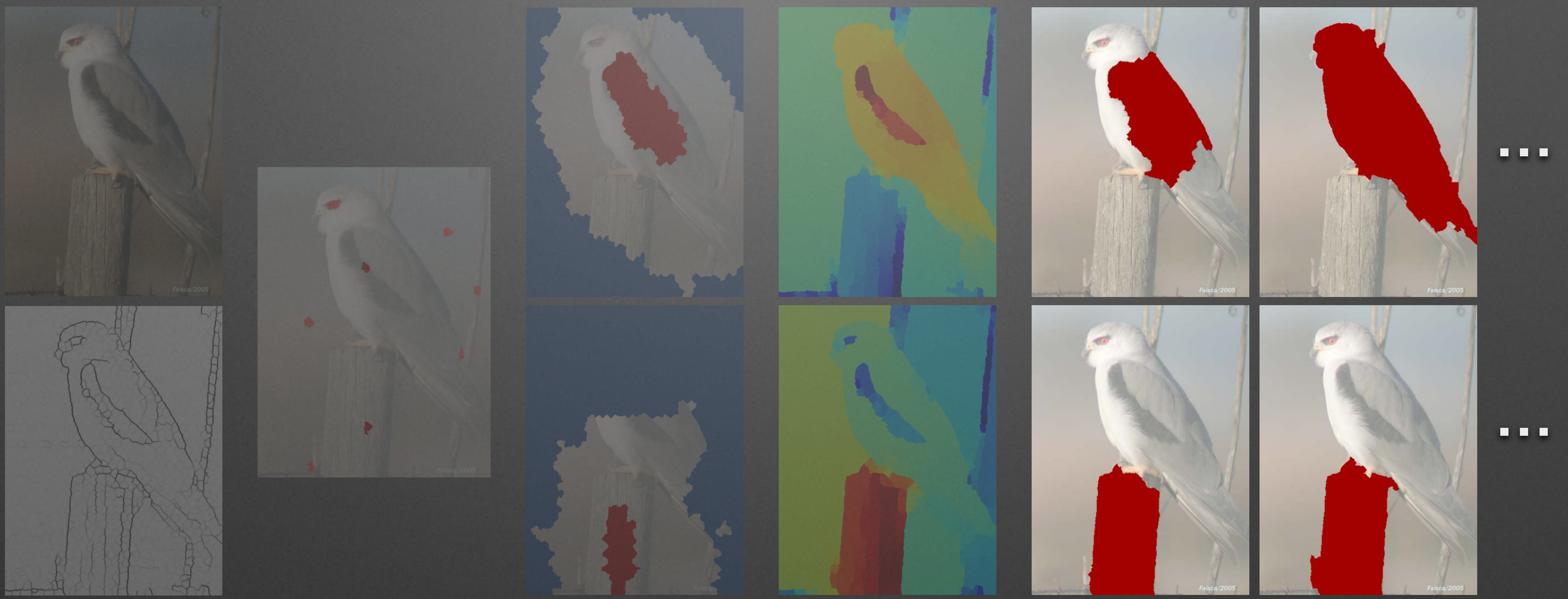
geodesic distance transform

multiple proposals

Geodesic object proposals



Geodesic object proposals



image, boundary map and superpixels

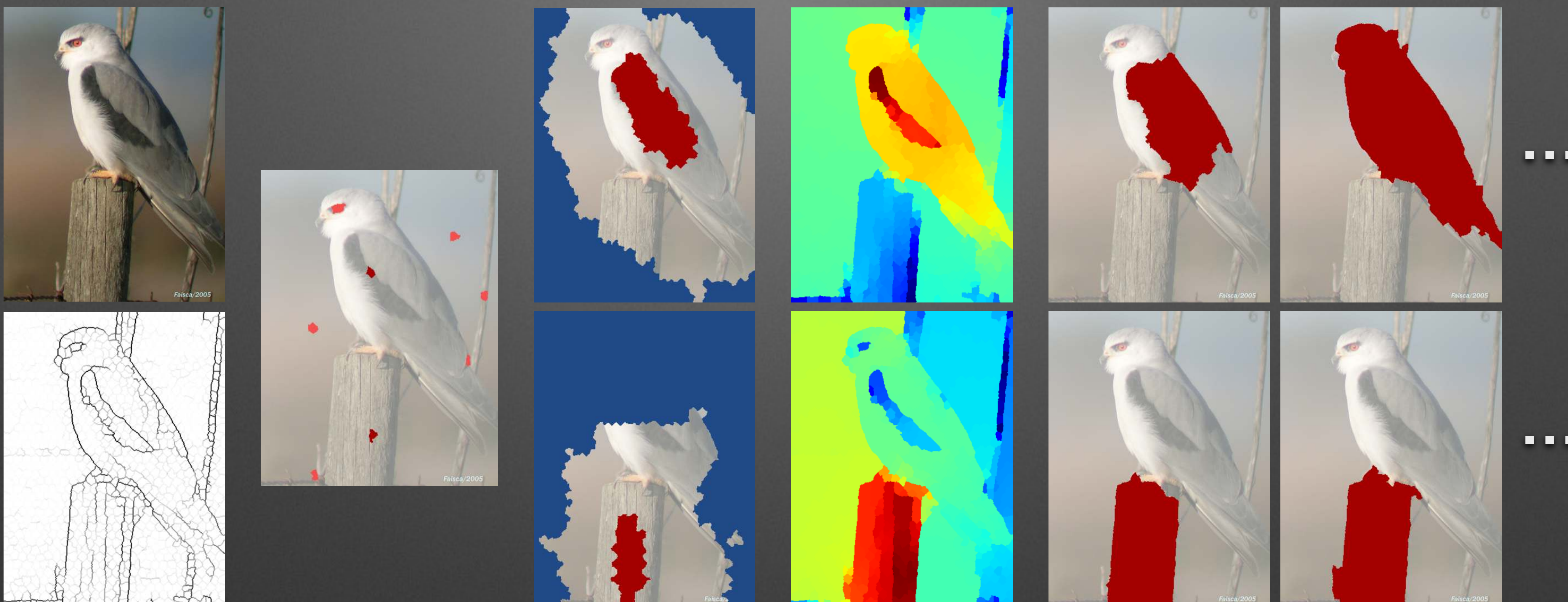
select seeds

foreground background masks

geodesic distance transform

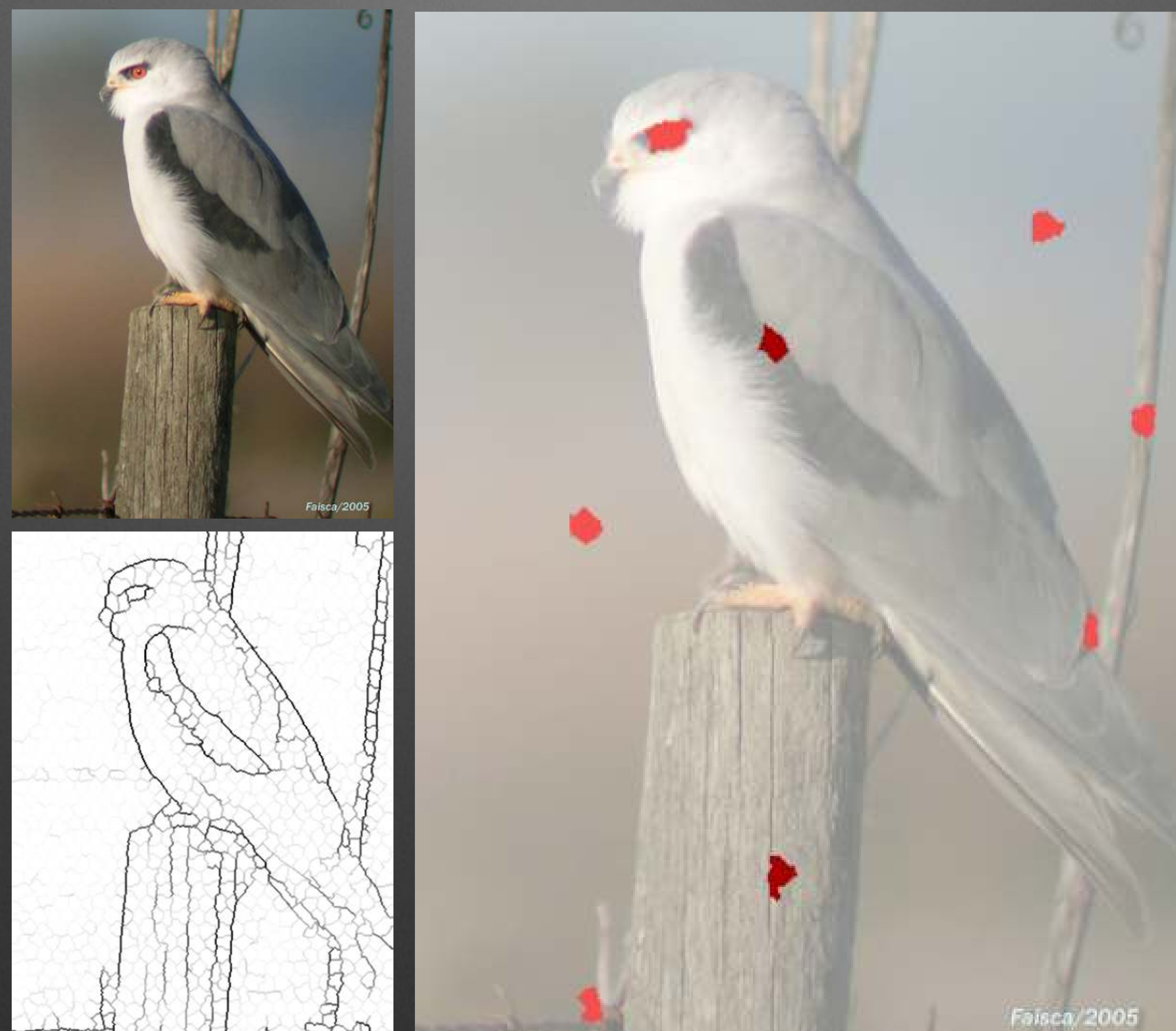
multiple proposals

Geodesic object proposals



image, boundary map and superpixels | select seeds | foreground background masks | geodesic distance transform | multiple proposals

Seed placement



Seed placement

Seed placement

- Place a seed in each object

Seed placement

- Place a seed in each object
- Regular or random sampling

Seed placement

- Place a seed in each object
- Regular or random sampling
  - miss small objects

Seed placement

- Place a seed in each object
- Regular or random sampling
  - miss small objects
- Saliency based sampling

Seed placement

- Place a seed in each object
- Regular or random sampling
  - miss small objects
- Saliency based sampling
  - miss non-salient objects

Seed placement

- Place a seed in each object
- Regular or random sampling
  - miss small objects
- Saliency based sampling
  - miss non-salient objects
- Geodesic placement

Seed placement

- Place a seed in each object
- Regular or random sampling
  - miss small objects
- Saliency based sampling
  - miss non-salient objects
- Geodesic placement
  - regular sampling in geodesic space

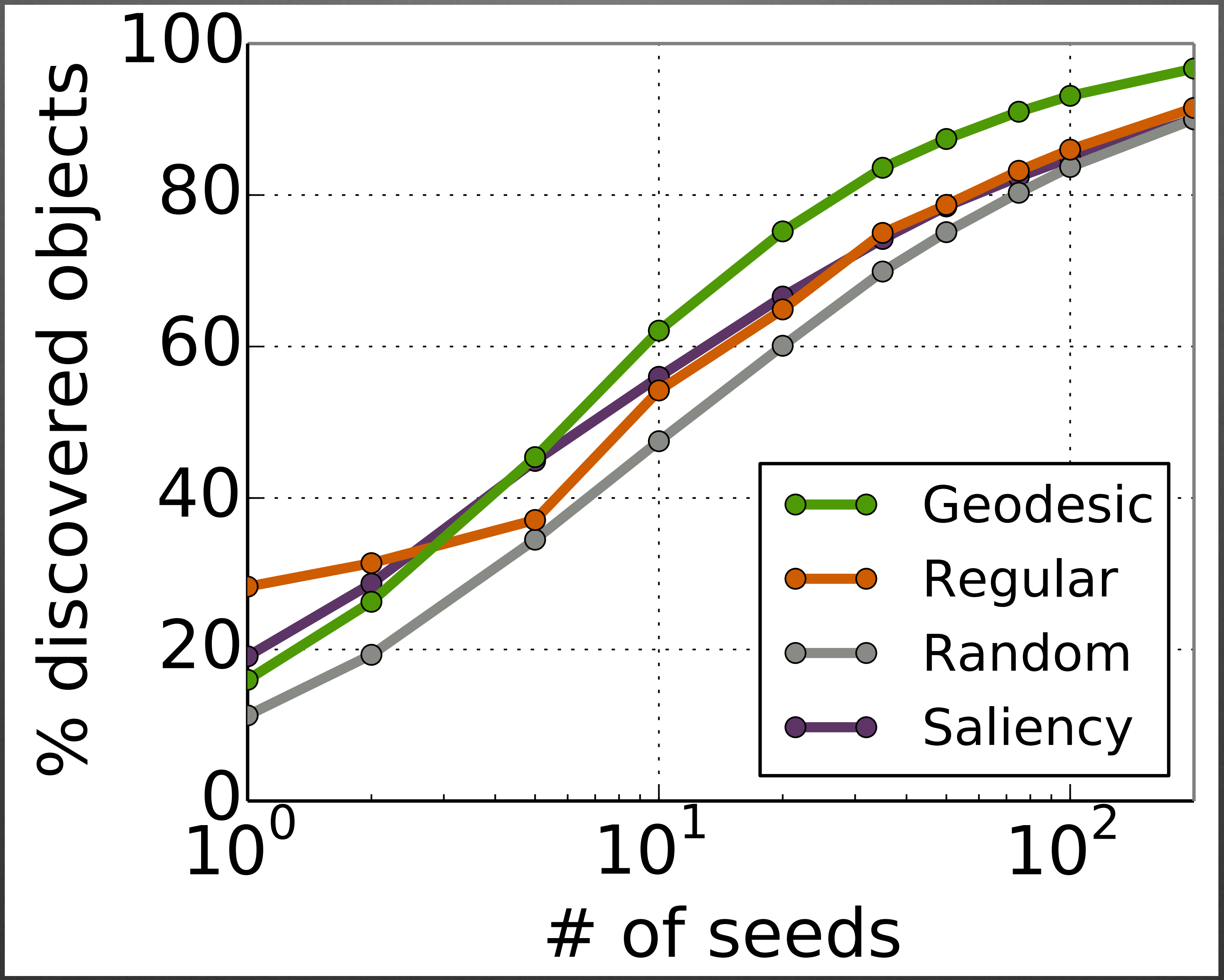
Seed placement

- Place a seed in each object
- Regular or random sampling
    - miss small objects
- Saliency based sampling
    - miss non-salient objects
- Geodesic placement
    - regular sampling in geodesic space
    - greedily place next seed at maximal geodesic distance

Seed placement

- Place a seed in each object
- Regular or random sampling
  - miss small objects
- Saliency based sampling
  - miss non-salient objects
- Geodesic placement
  - regular sampling in geodesic space
  - greedily place next seed at maximal geodesic distance

Seed placement



Mask generation

Mask generation

Mask generation

- No errors in masks

Mask generation

- No errors in masks
  - errors propagate

Mask generation

- No errors in masks
  - errors propagate
- Foreground mask

Mask generation

- No errors in masks
  - errors propagate
- Foreground mask
  - seed

Mask generation

- No errors in masks
  - errors propagate
- Foreground mask
  - seed
- Background mask

Mask generation

- No errors in masks
  - errors propagate
- Foreground mask
  - seed
- Background mask
  - boundary

Mask generation

- No errors in masks
  - errors propagate
- Foreground mask
  - seed
- Background mask
  - boundary
  - empty

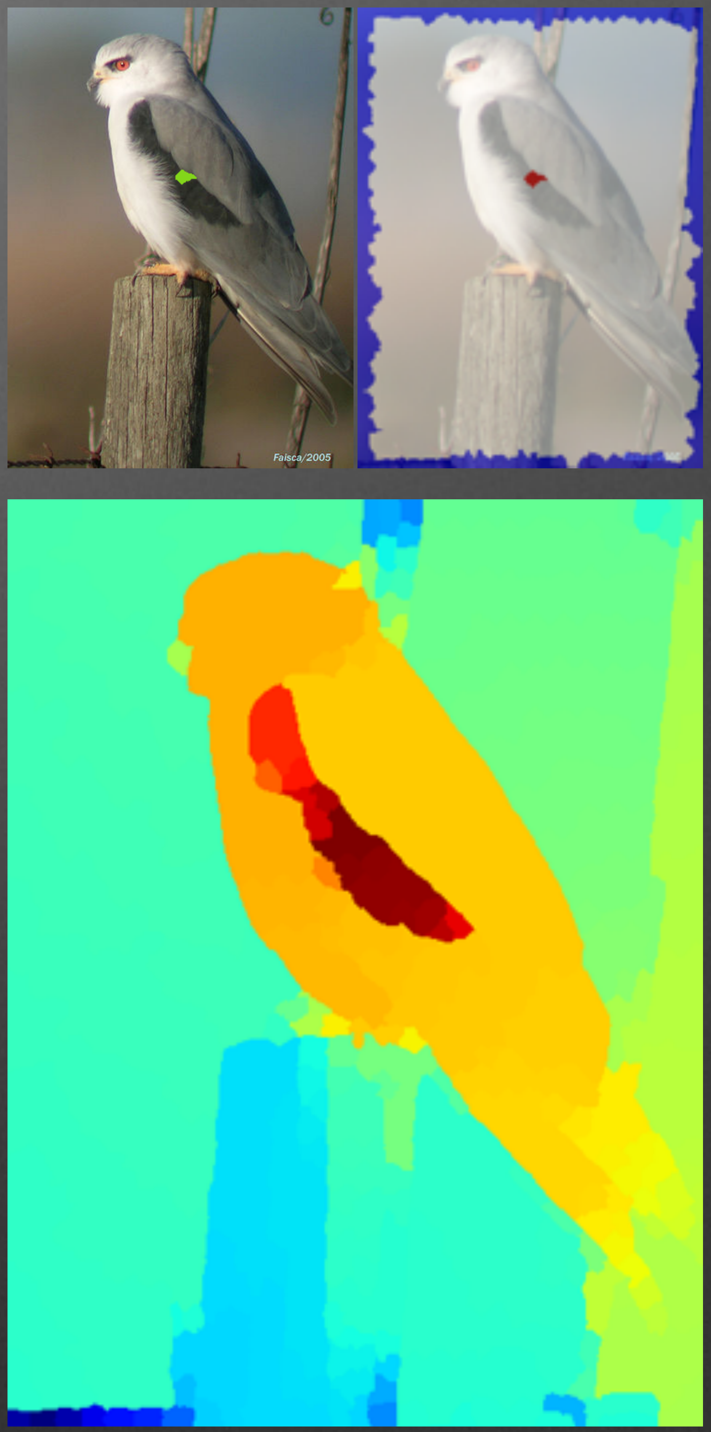
Mask generation

- No errors in masks
  - errors propagate
- Foreground mask
  - seed
- Background mask
  - boundary
  - empty

Geodesic segmentation

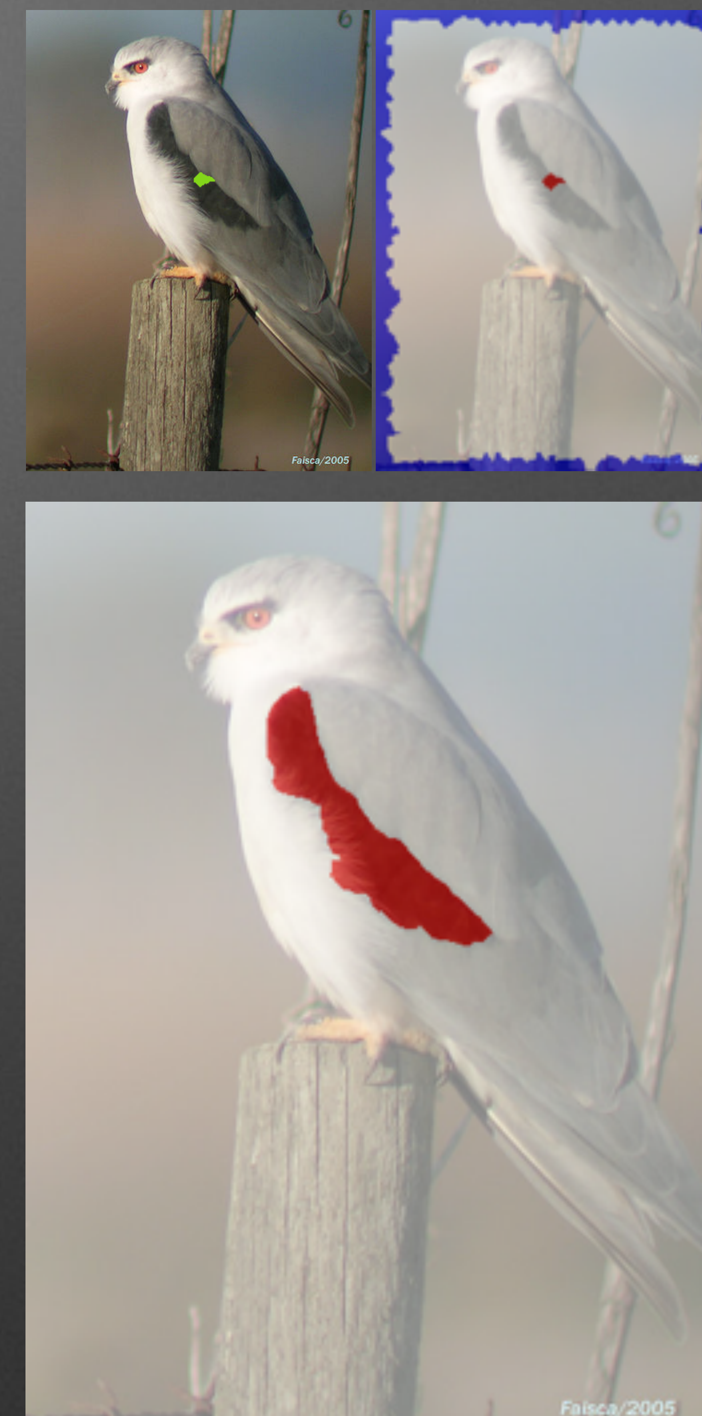
Geodesic segmentation

- Signed geodesic distance transform



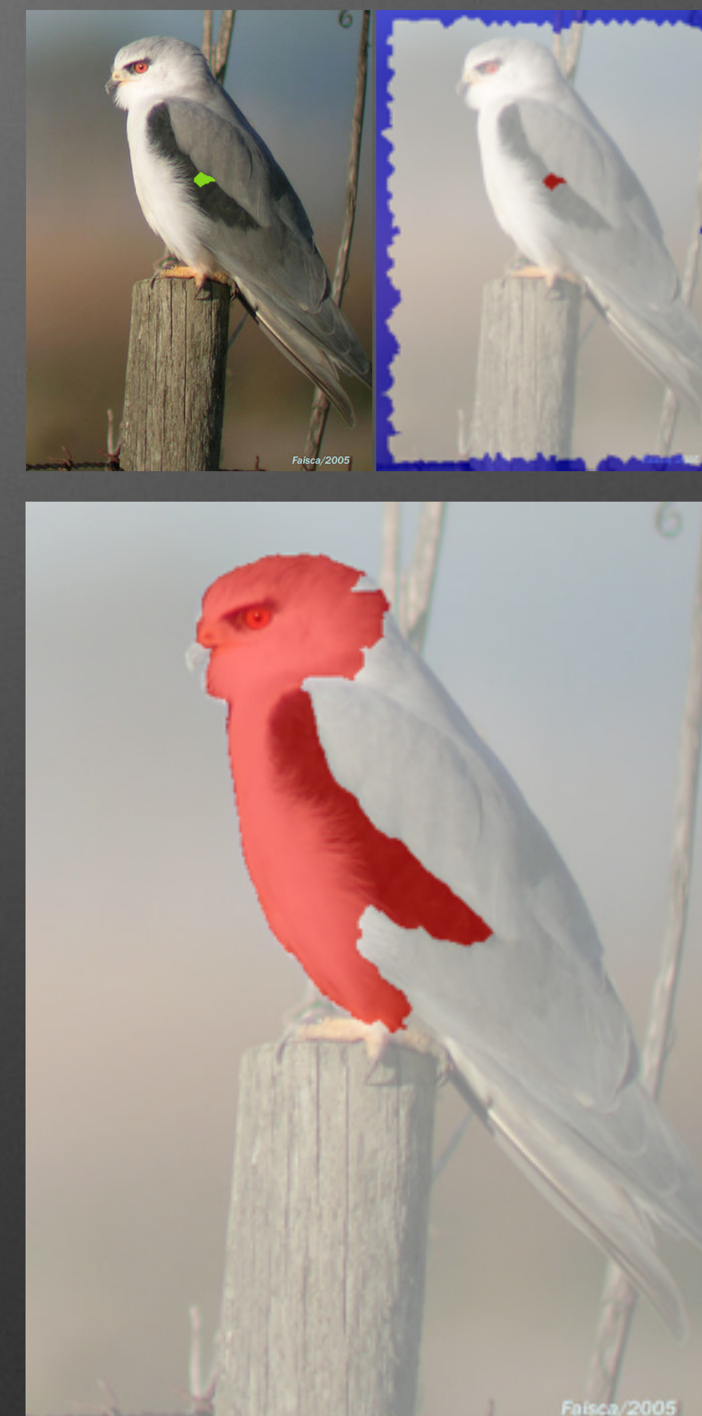
Geodesic segmentation

- Signed geodesic distance transform
- Each level set is a segmentation



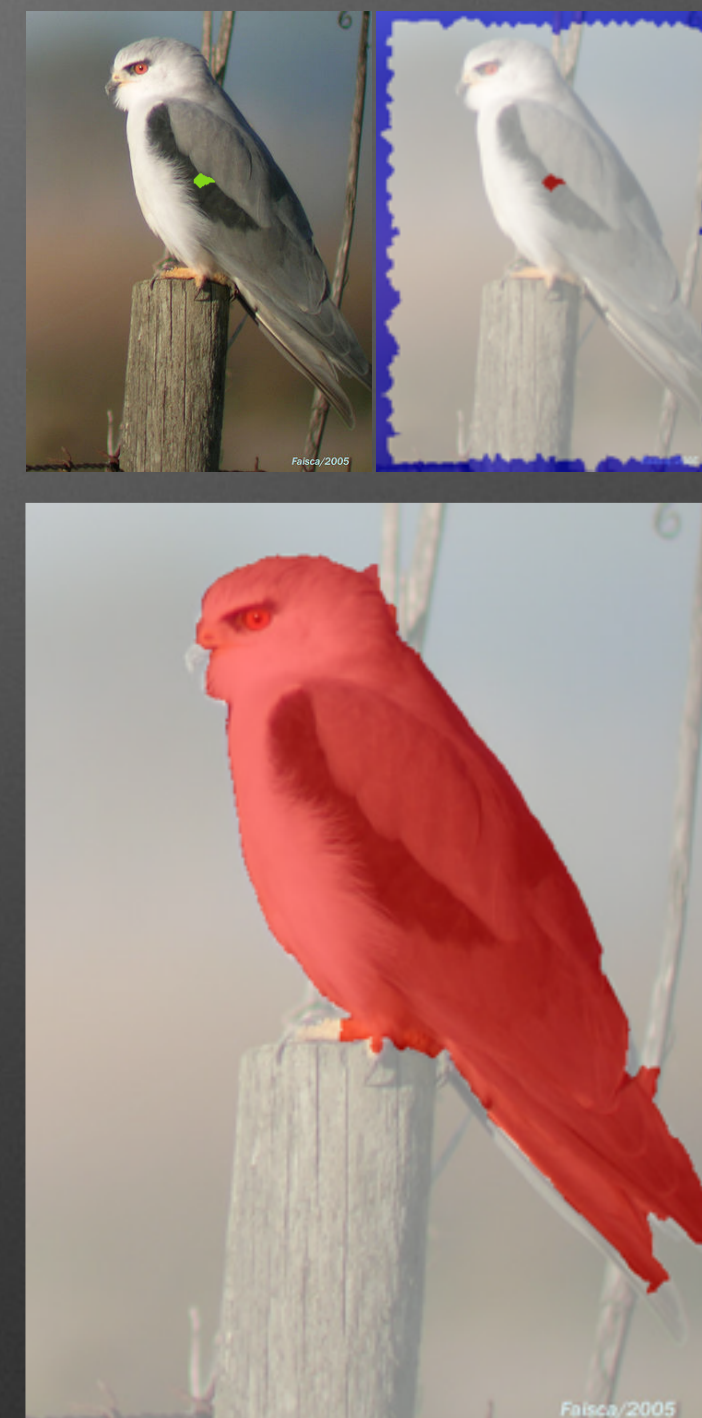
Geodesic segmentation

- Signed geodesic distance transform
- Each level set is a segmentation



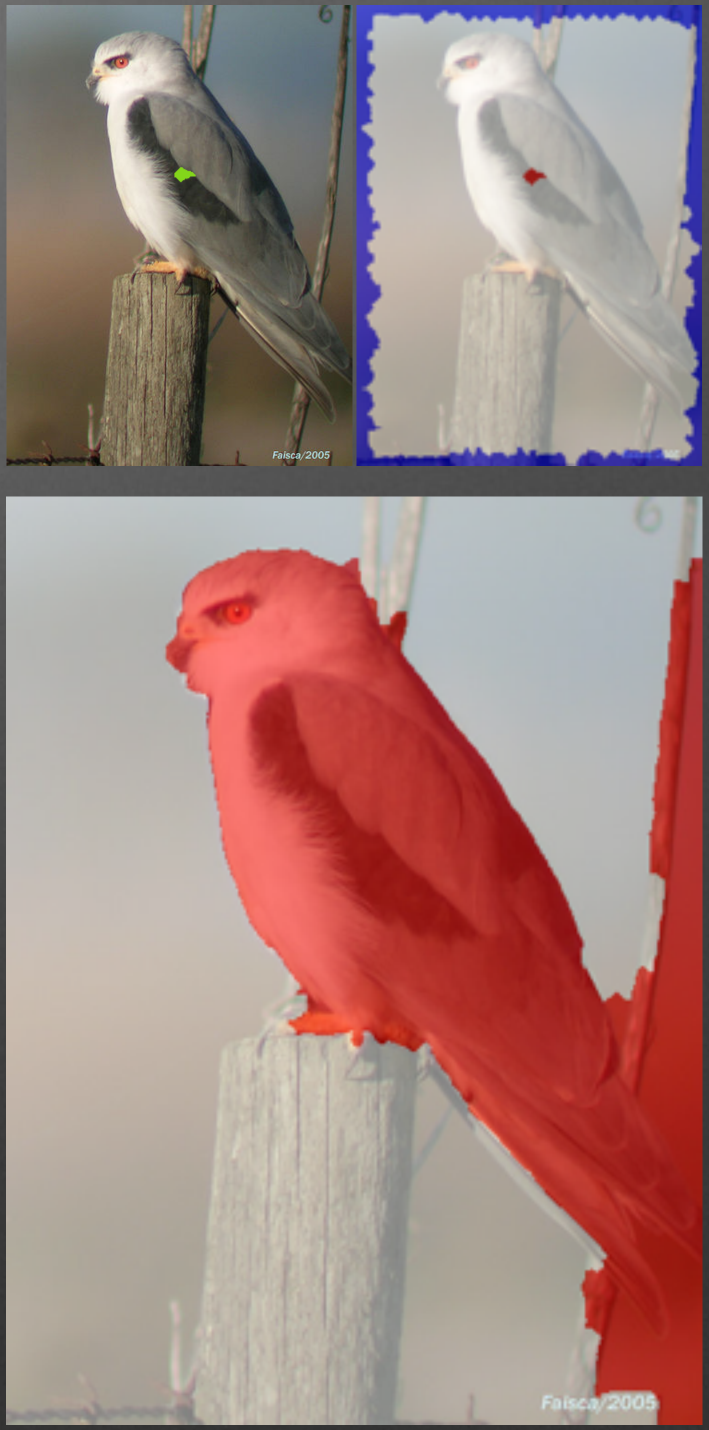
Geodesic segmentation

- Signed geodesic distance transform
- Each level set is a segmentation



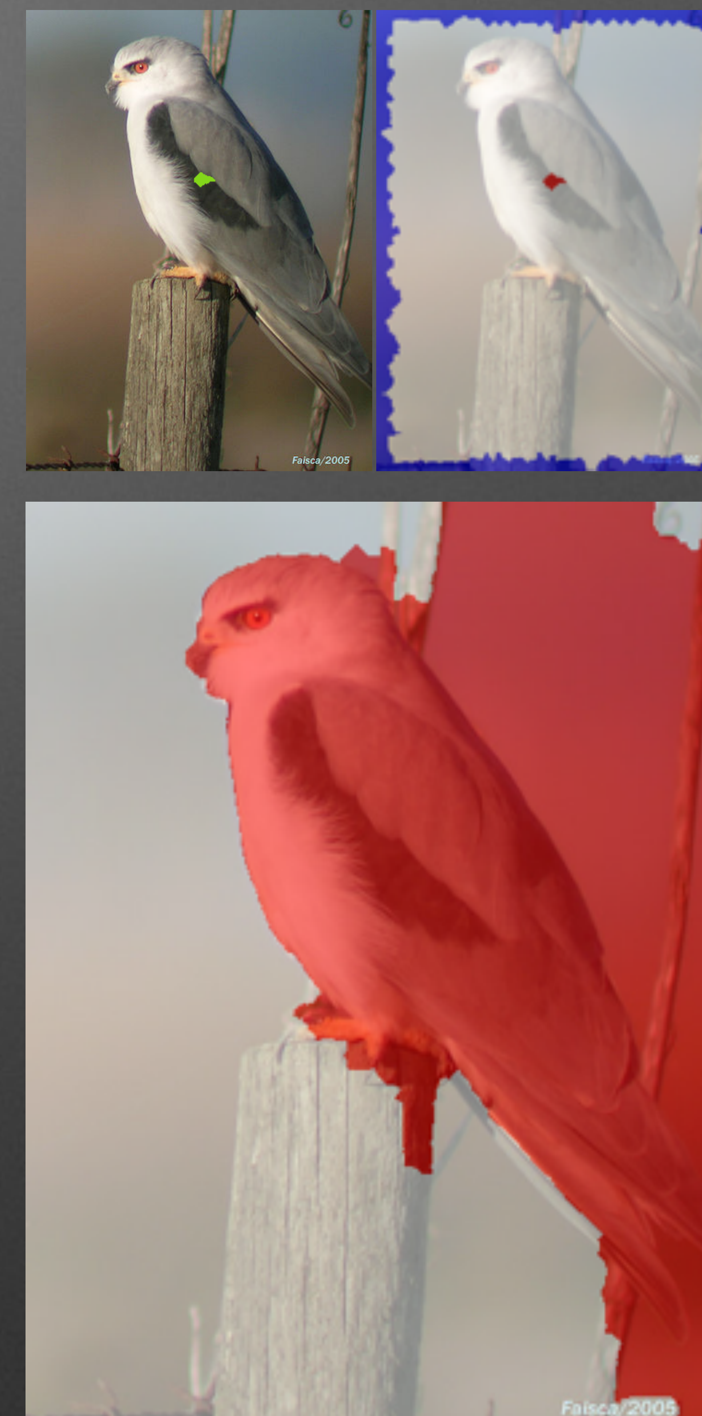
Geodesic segmentation

- Signed geodesic distance transform
- Each level set is a segmentation



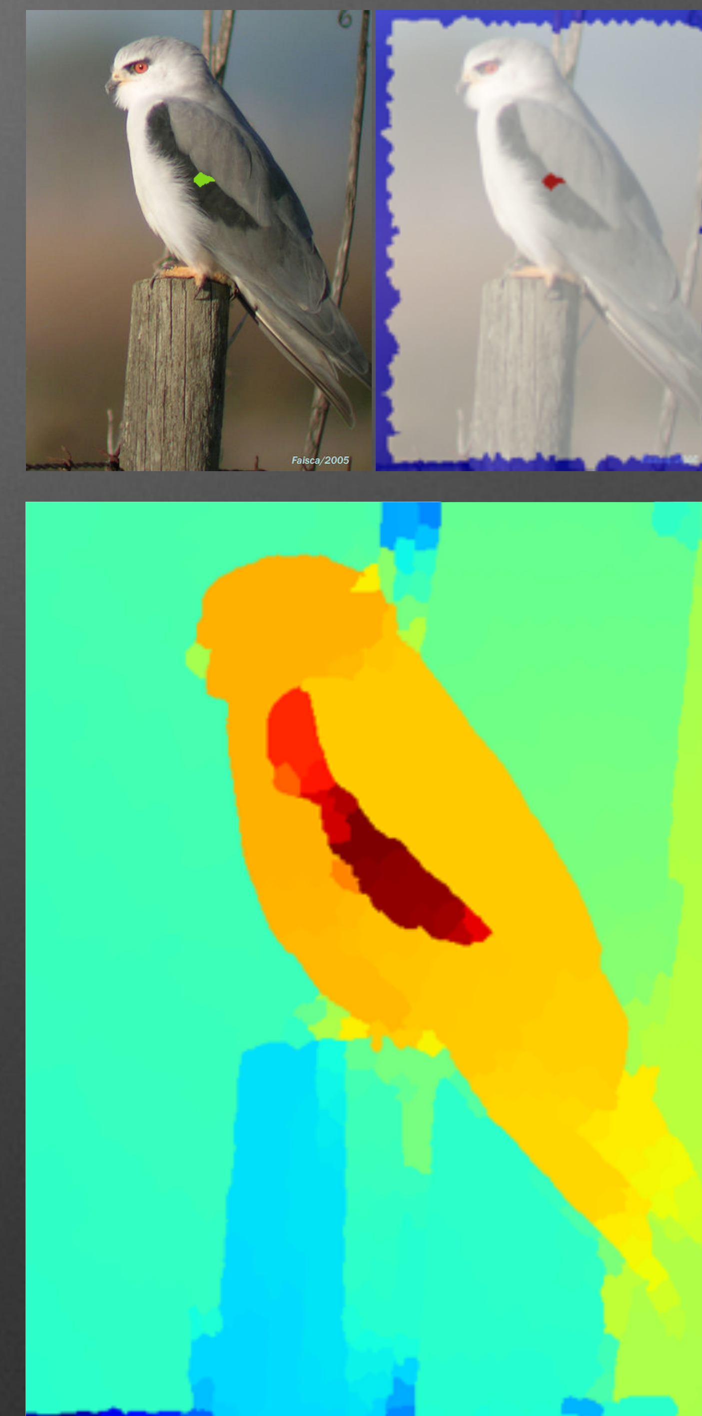
Geodesic segmentation

- Signed geodesic distance transform
- Each level set is a segmentation



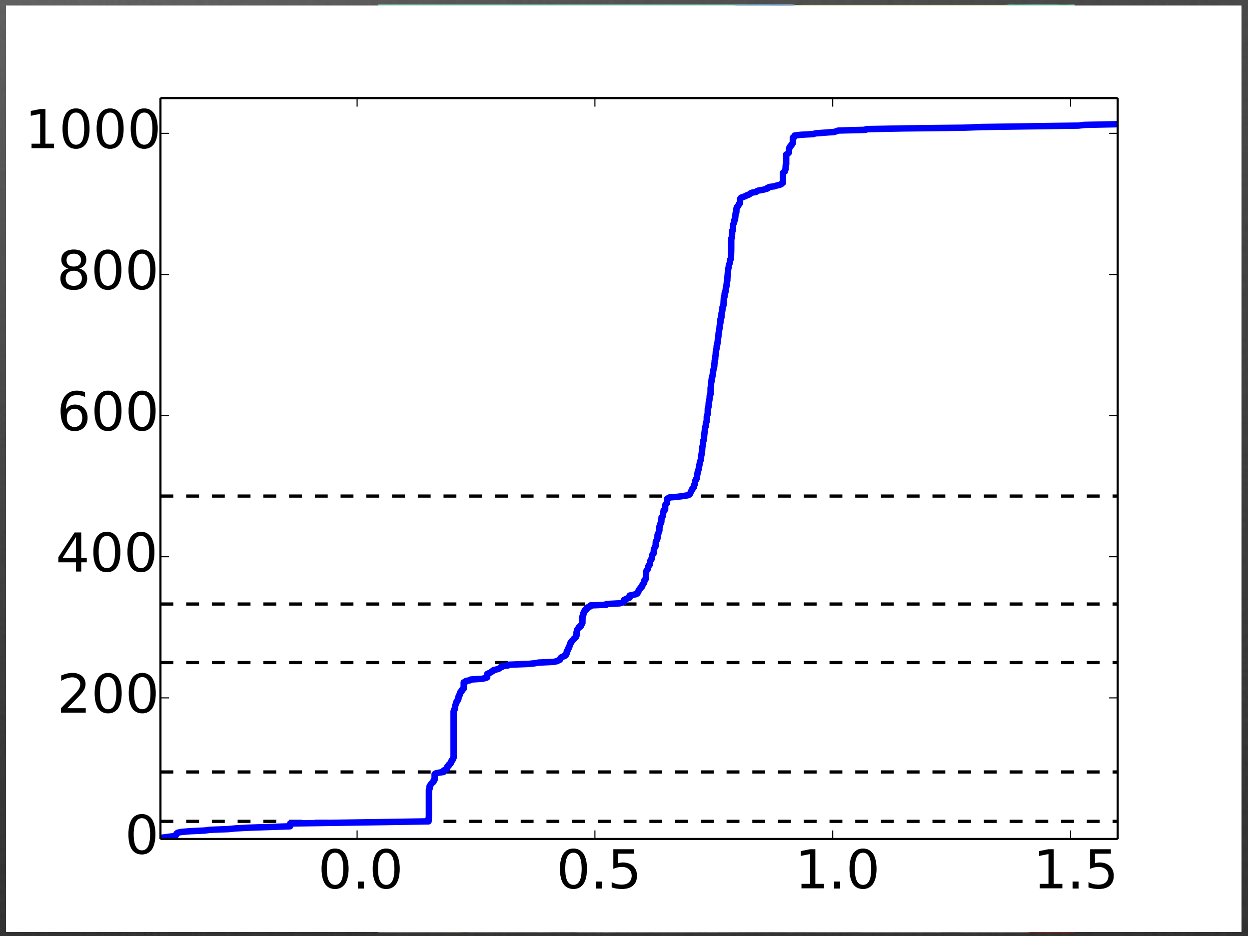
Geodesic segmentation

- Signed geodesic distance transform
- Each level set is a segmentation
- Find critical level sets



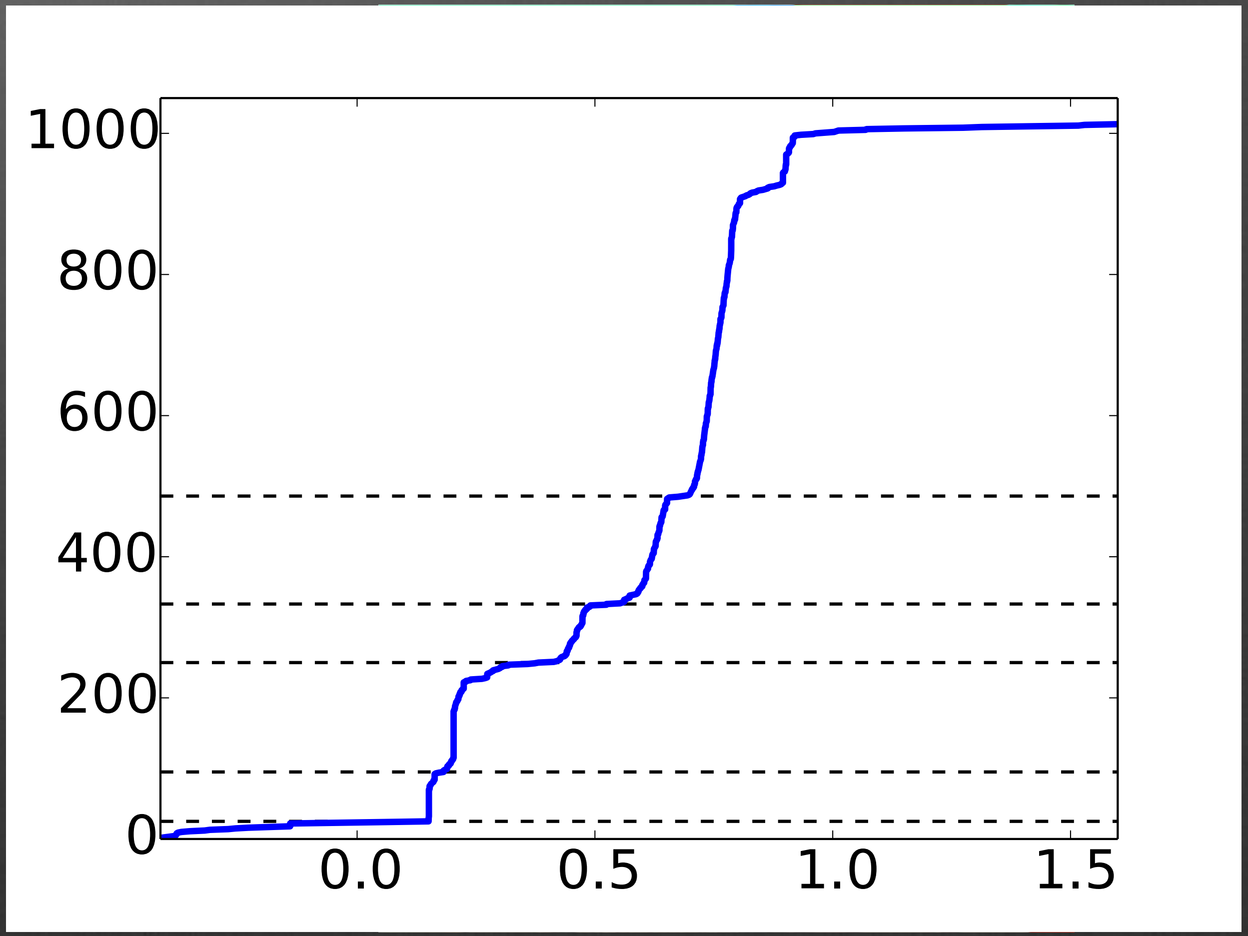
Geodesic segmentation

- Signed geodesic distance transform
- Each level set is a segmentation
- Find critical level sets
  - stationary points in geodesic function



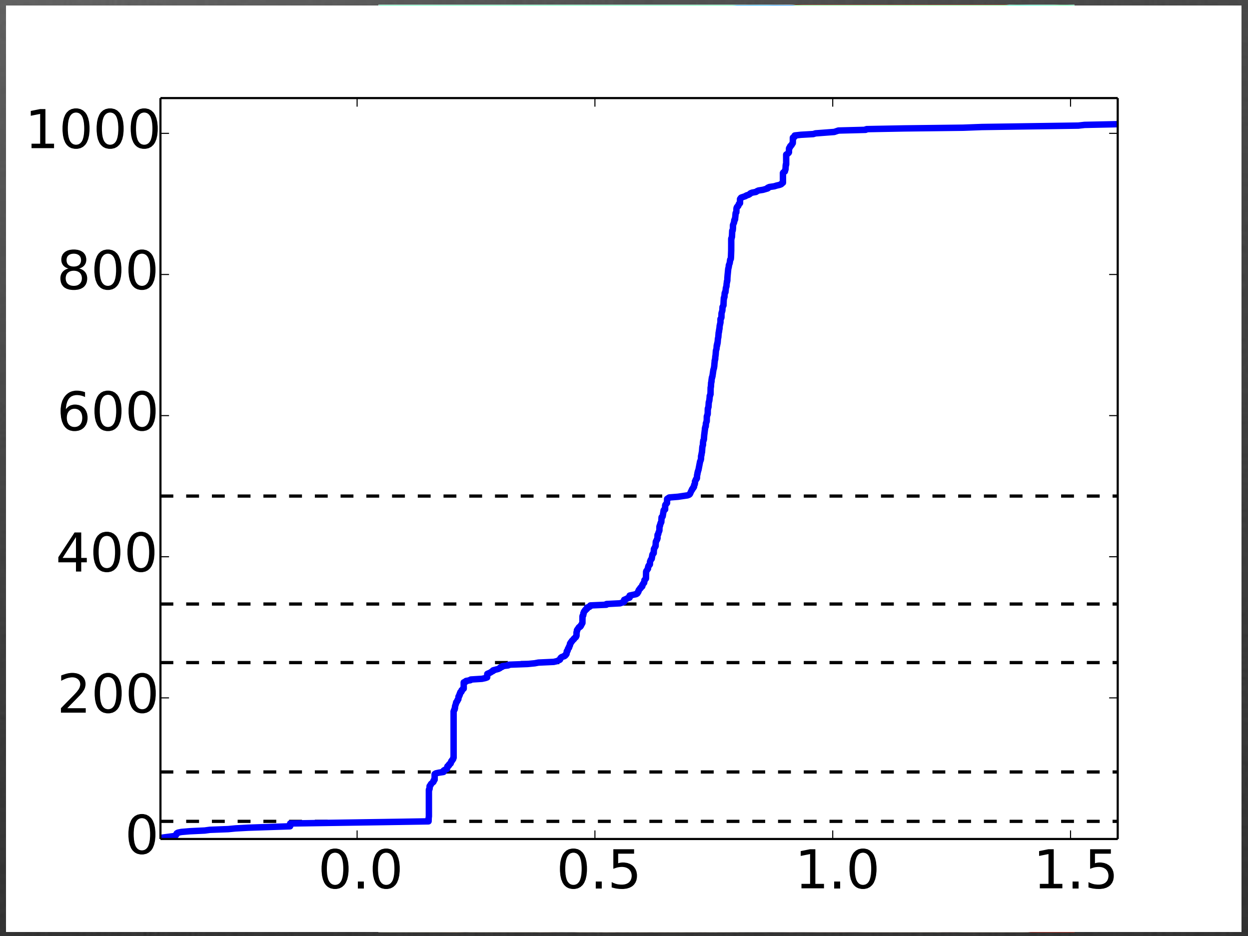
Geodesic segmentation

- Signed geodesic distance transform
- Each level set is a segmentation
- Find critical level sets
  - stationary points in geodesic function
  - evolution of Eikonal equation

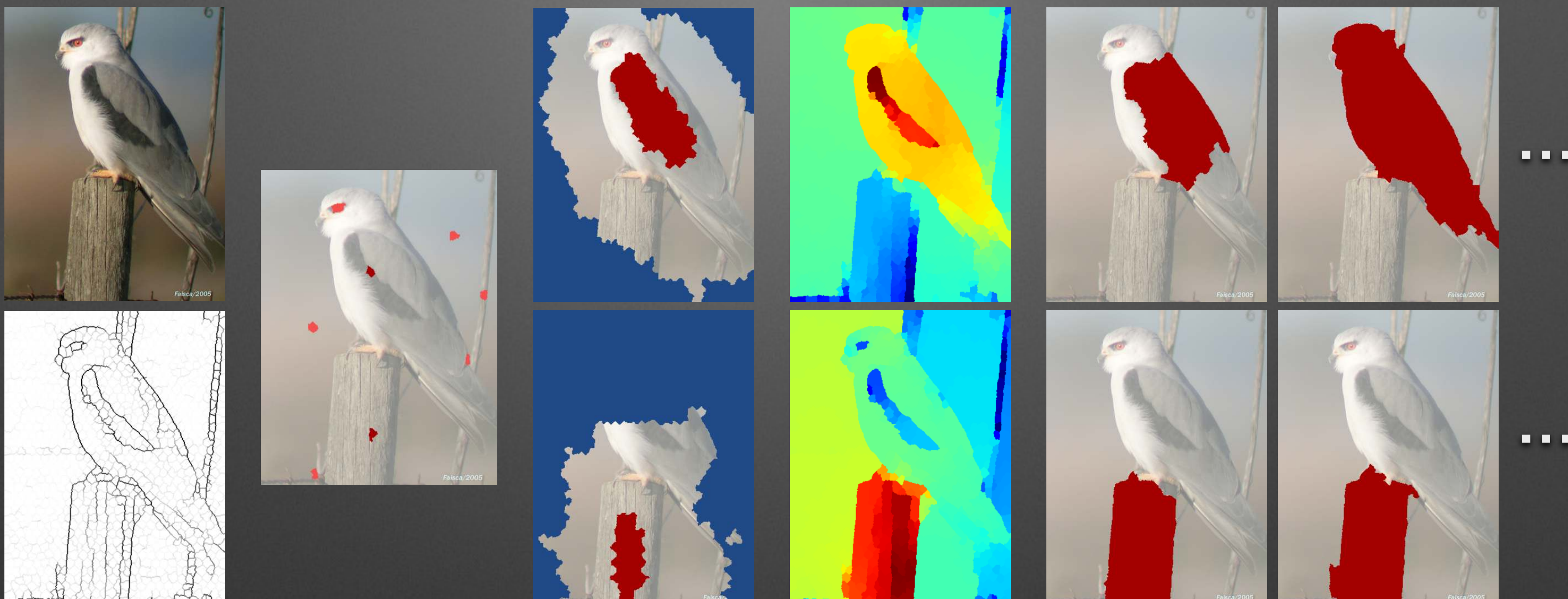


Geodesic segmentation

- Signed geodesic distance transform
- Each level set is a segmentation
- Find critical level sets
  - stationary points in geodesic function
  - evolution of Eikonal equation



Baseline GOP



image, boundary map and superpixels

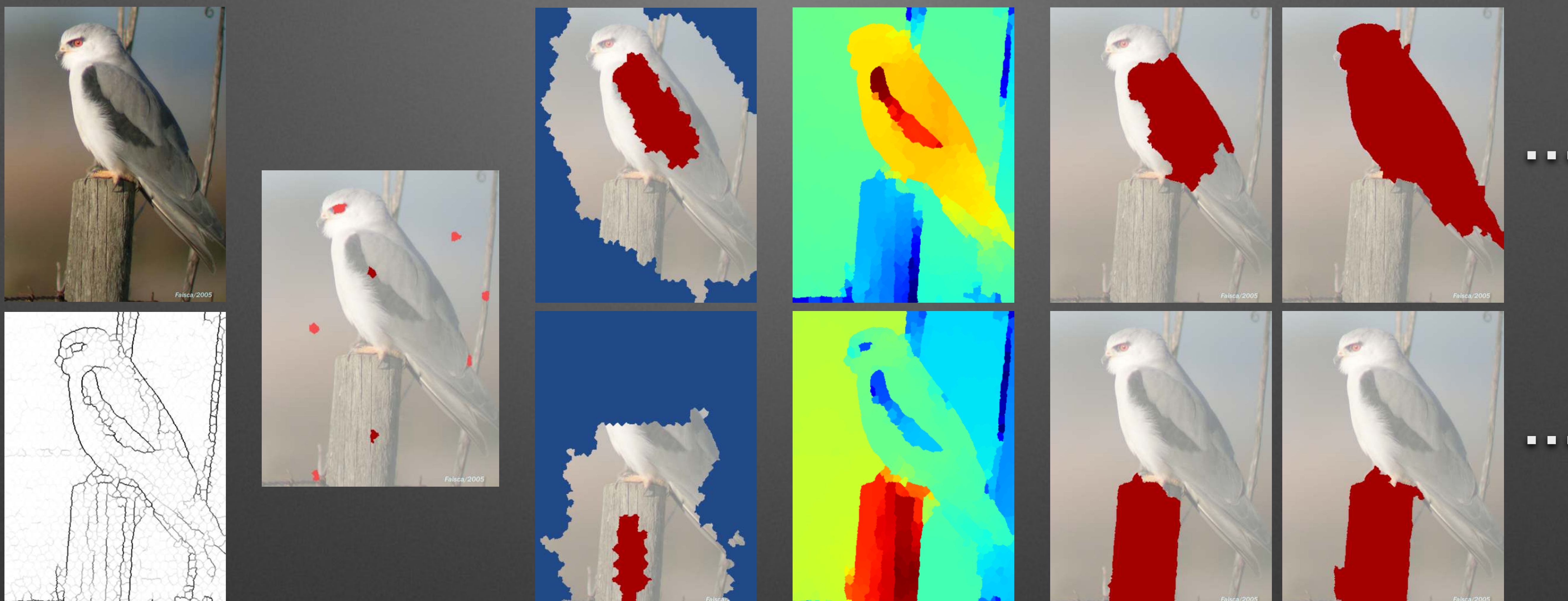
select seeds

foreground background masks

geodesic distance transform

multiple proposals per transform

Learned GOP



image, boundary map and superpixels

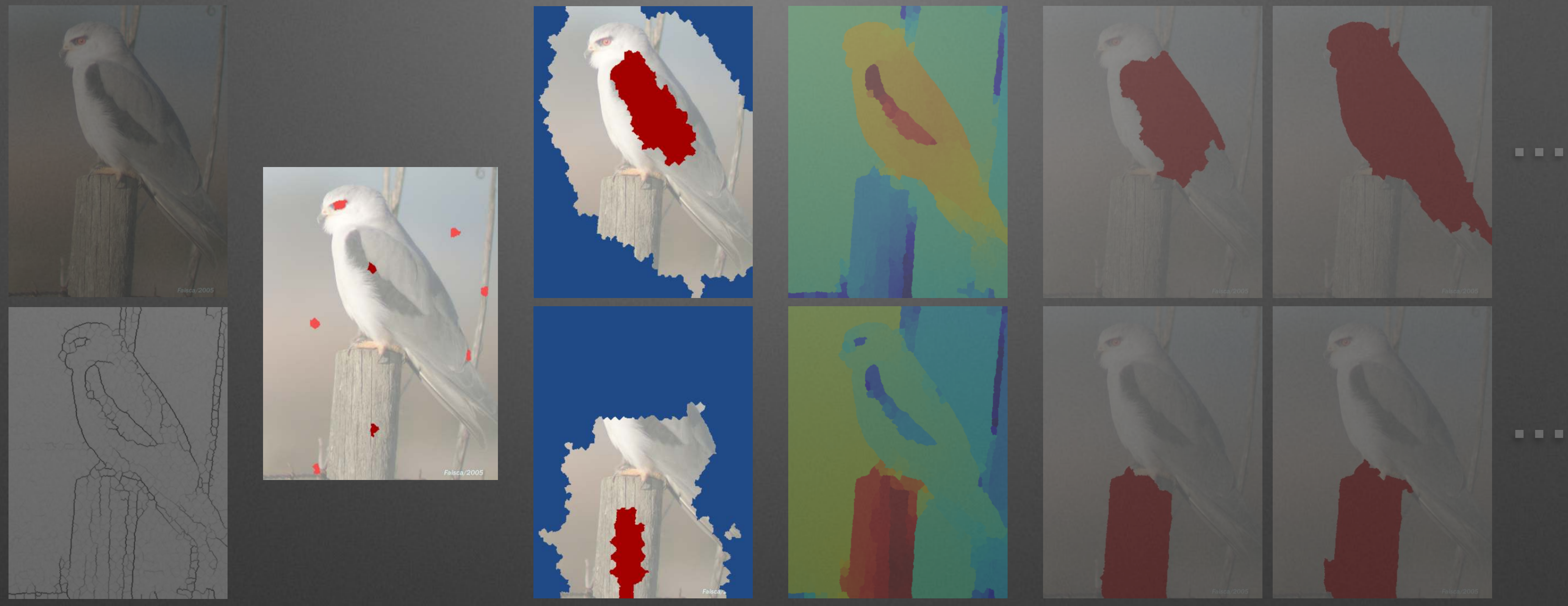
learned seeds

learned masks

geodesic distance transform

multiple proposals per transform

Learned GOP



image, boundary map and superpixels
learned seeds
learned masks
geodesic distance transform
multiple proposals per transform

Results

Results

- VOC 2012 dataset

Results

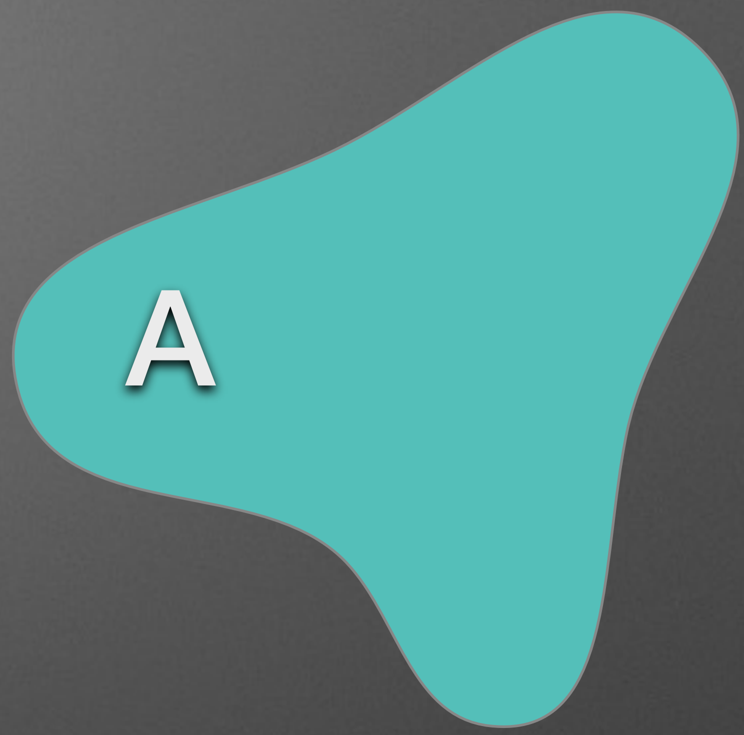
- VOC 2012 dataset
- Evaluation metric

Results

- VOC 2012 dataset
- Evaluation metric
  - overlap $\mathcal{J}(A, B) = \dfrac{|A \cap B|}{|A \cup B|}$

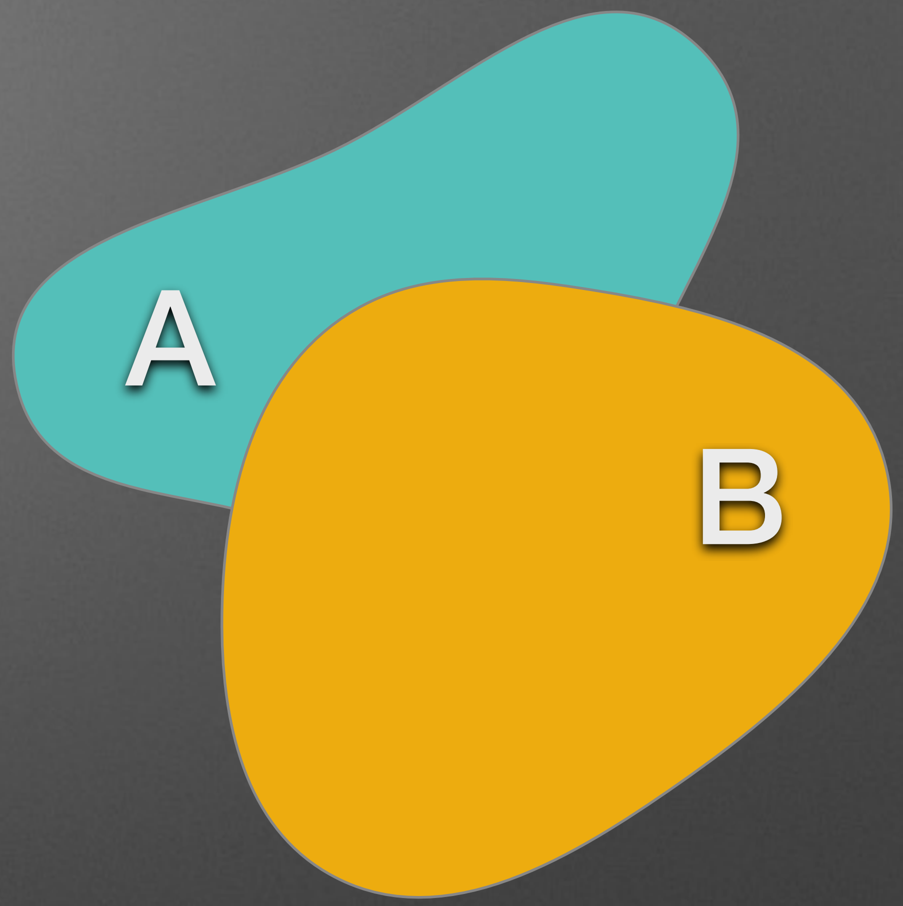
Results

- VOC 2012 dataset
- Evaluation metric
  - overlap $\mathcal{J}(A, B) = \frac{|A \cap B|}{|A \cup B|}$



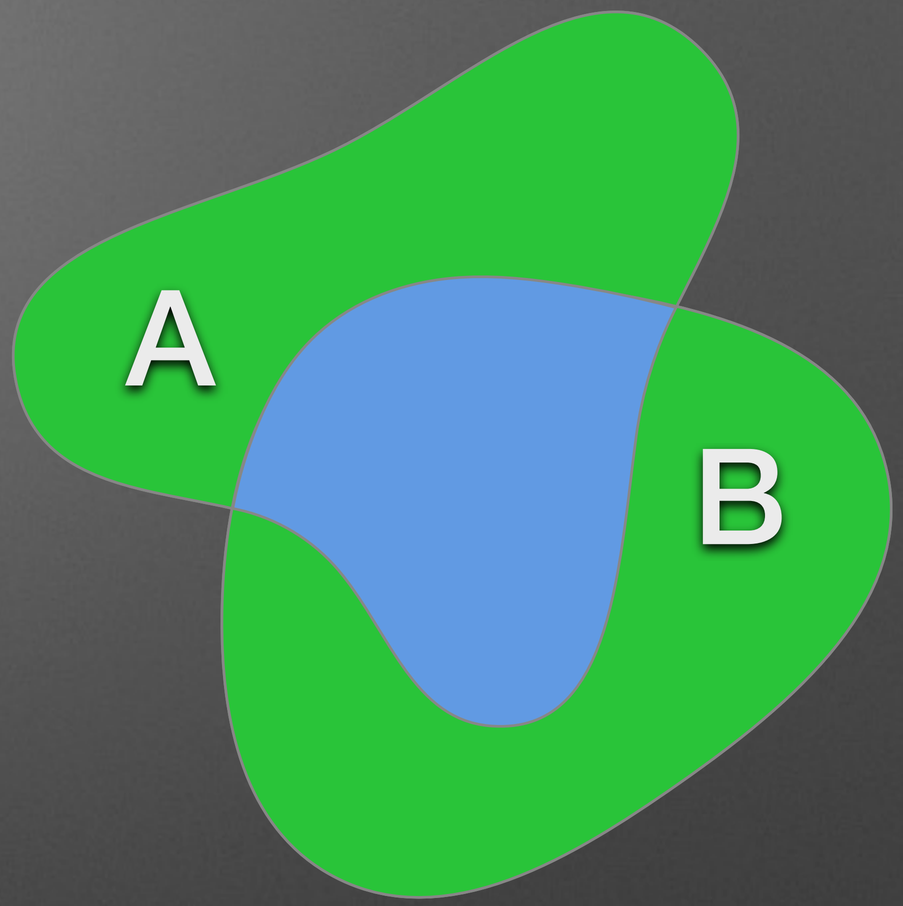
Results

- VOC 2012 dataset
- Evaluation metric
  - overlap $\mathcal{J}(A, B) = \frac{|A \cap B|}{|A \cup B|}$



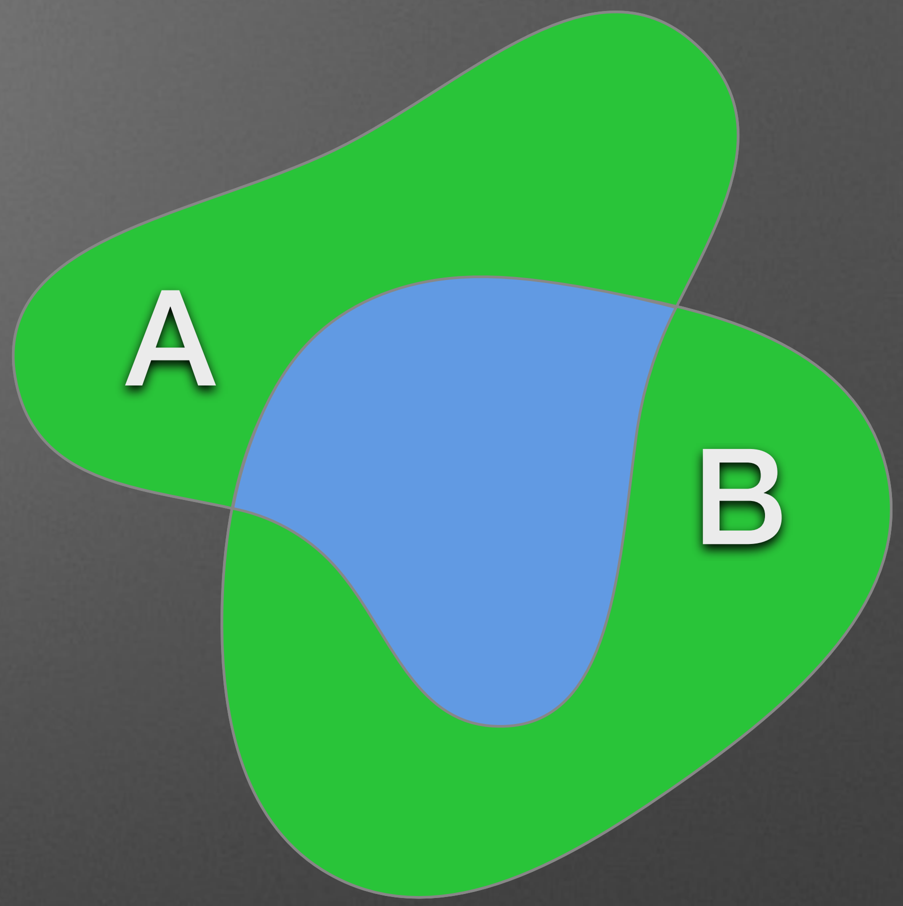
Results

- VOC 2012 dataset
- Evaluation metric
  - overlap $\mathcal{J}(A, B) = \frac{|A \cap B|}{|A \cup B|}$



Results

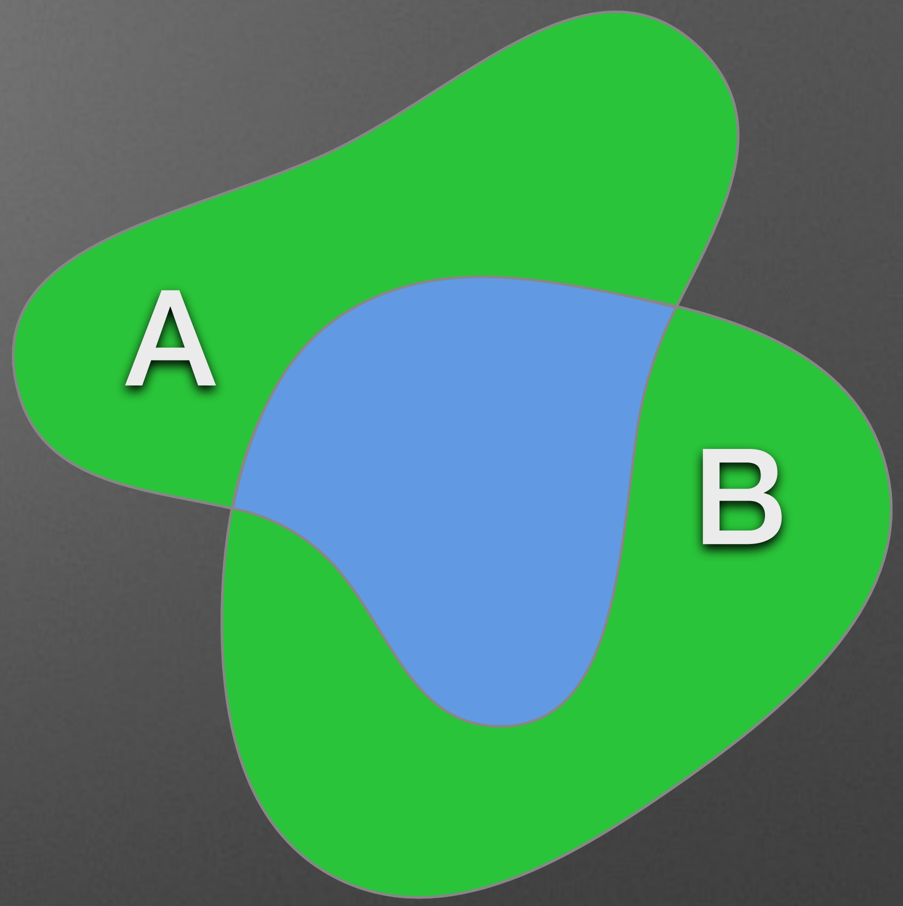
- VOC 2012 dataset
- Evaluation metric
  - overlap $\mathcal{J}(A, B) = \dfrac{|A \cap B|}{|A \cup B|}$
  - best overlap $b(O_k) = \max_P \mathcal{J}(O_k, P)$



Results

- VOC 2012 dataset
- Evaluation metric
  - overlap $\mathcal{J}(A,B) = \dfrac{|A \cap B|}{|A \cup B|}$
  - best overlap $b(O_k) = \max_P \mathcal{J}(O_k, P)$
  - Average best overlap (ABO)

$$\frac{1}{N}\sum_k b(O_k)$$



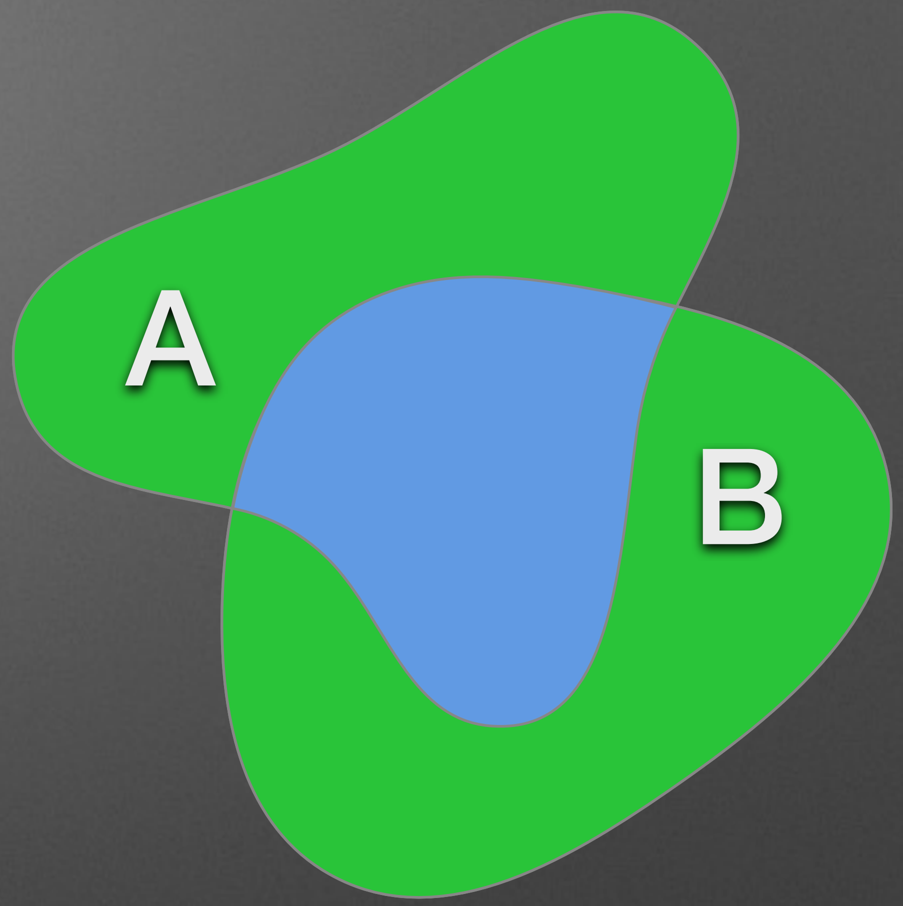
Results

- VOC 2012 dataset
- Evaluation metric
  - overlap $\mathcal{J}(A, B) = \frac{|A \cap B|}{|A \cup B|}$
  - best overlap $b(O_k) = \max_P \mathcal{J}(O_k, P)$
  - Average best overlap (ABO)

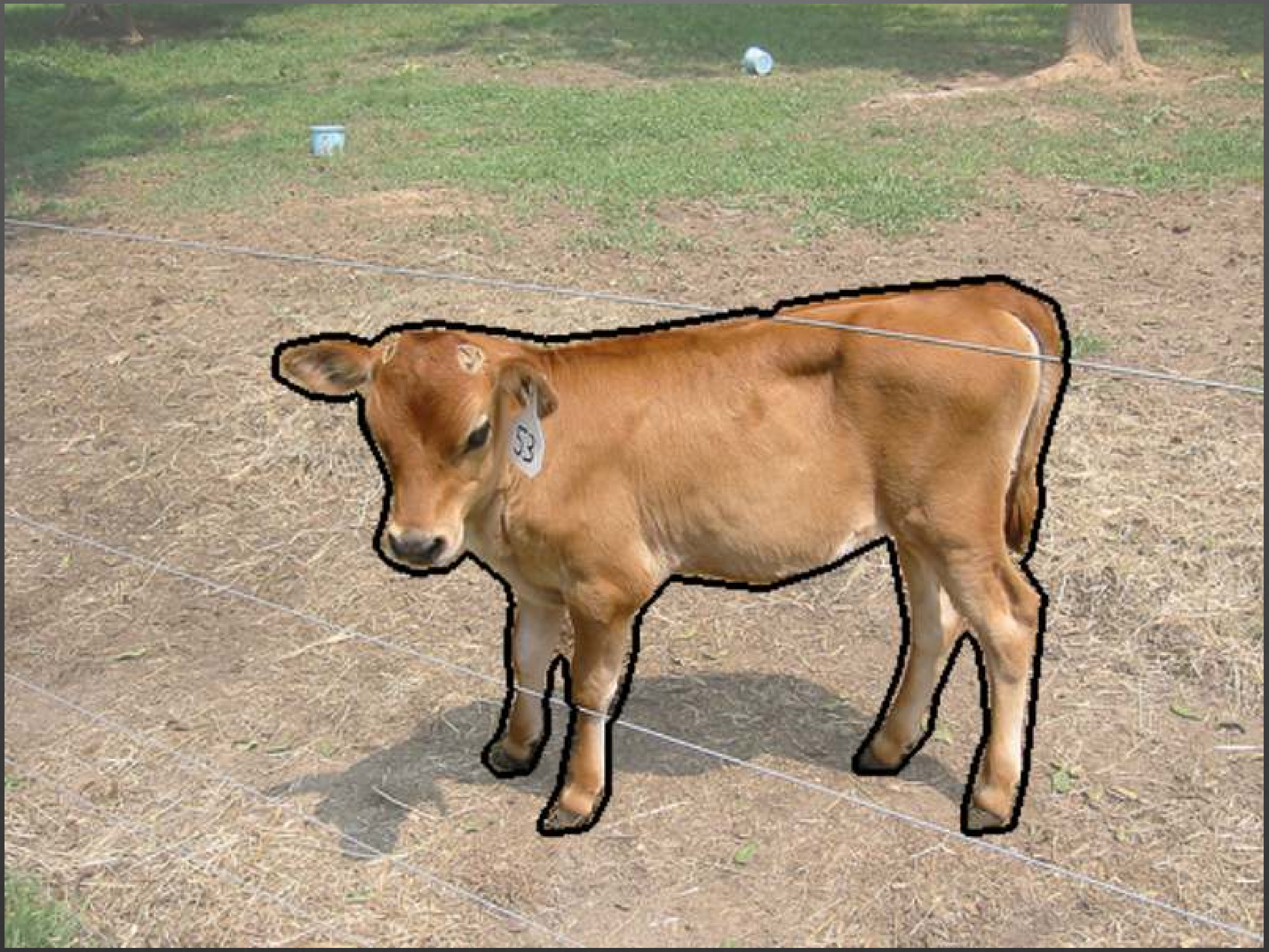
$$\frac{1}{N} \sum_k b(O_k)$$

  - α-recall

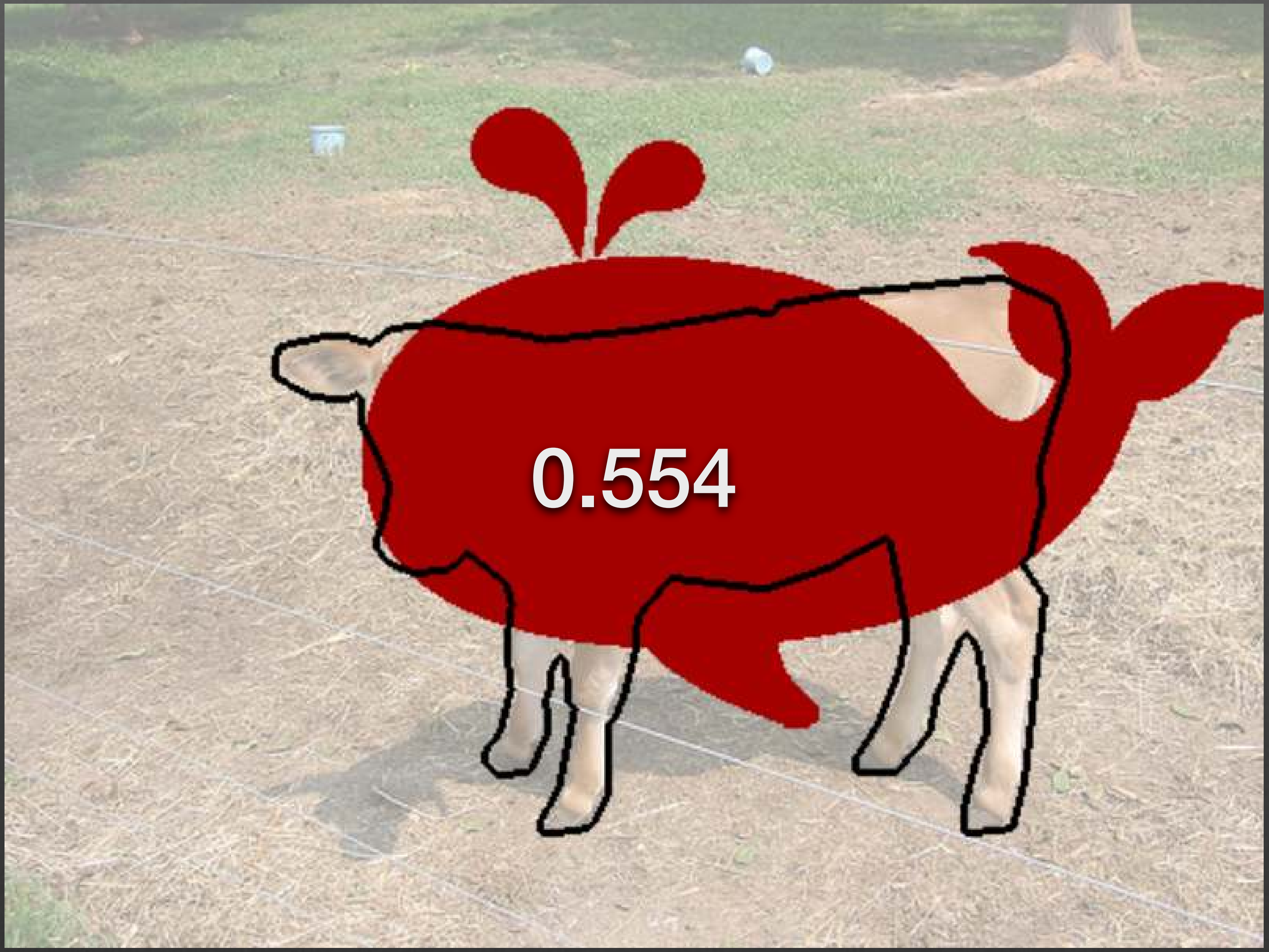
$$\frac{1}{N} \sum_k [b(O_k) > \alpha]$$



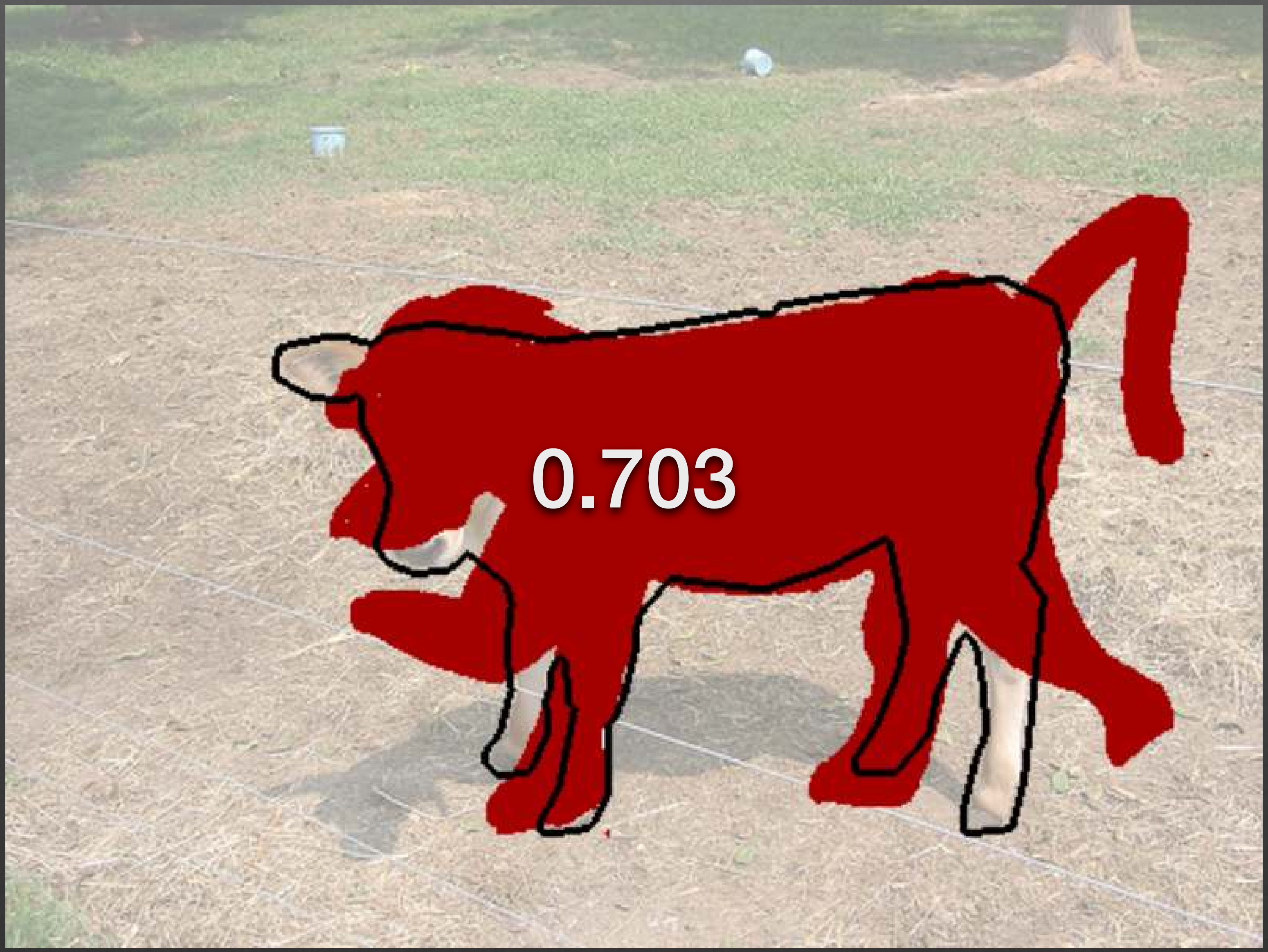
What does overlap mean?



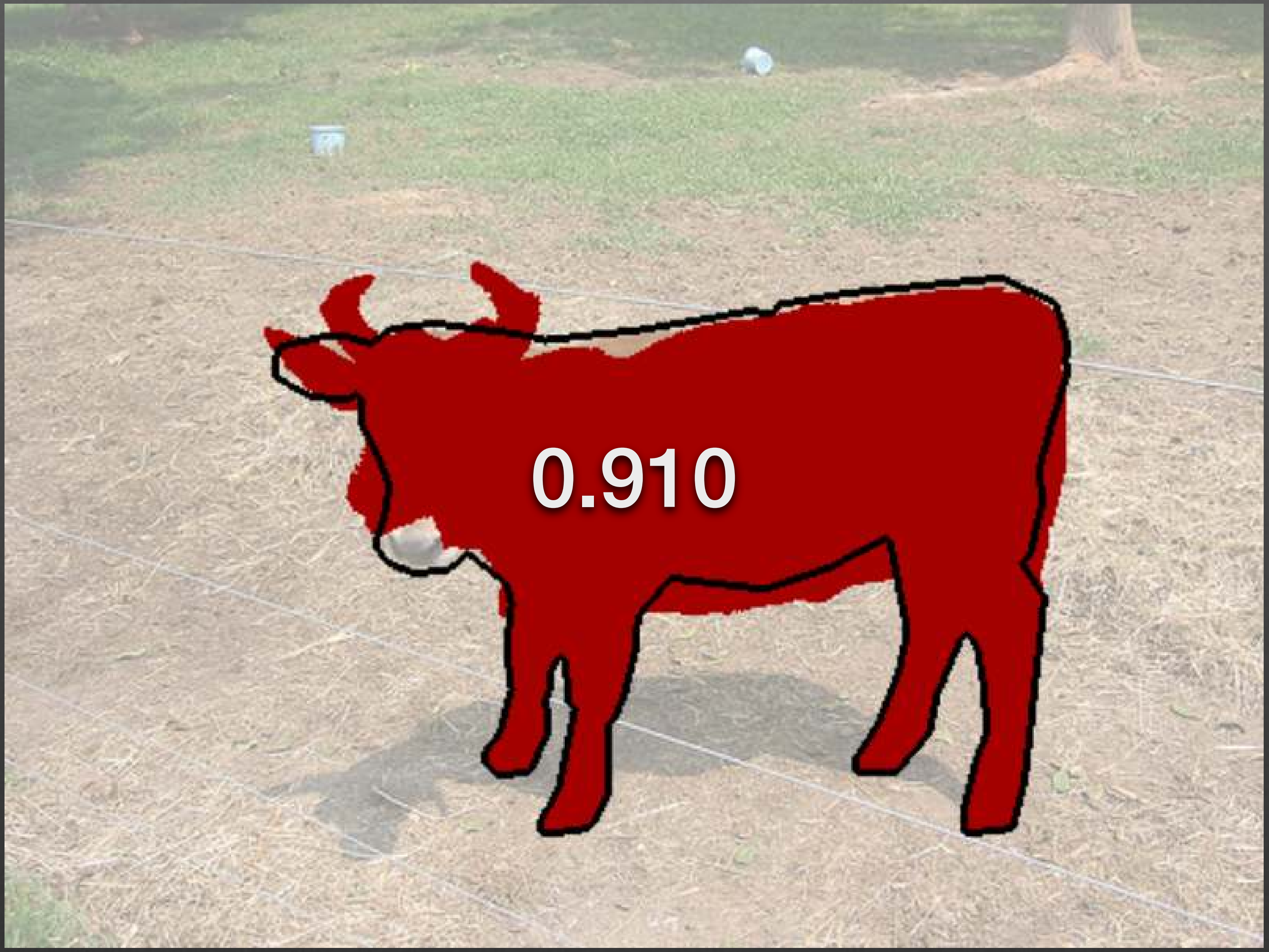
What does overlap mean?



What does overlap mean?



What does overlap mean?



Segmentation results

METHOD	# PROP.	ABO	50%-RECALL	70%-RECALL	TIME

Segmentation results

METHOD	# PROP.	ABO	50%-RECALL	70%-RECALL	TIME
CPMC	646	0.703	0.784	**0.609**	252s

Segmentation results


METHOD	# PROP.	ABO	50%-RECALL	70%-RECALL	TIME
CPMC	646	0.703	0.784	**0.609**	252s
Baseline GOP	653	0.712	0.833	**0.622**	0.6s

Segmentation results

METHOD	# PROP.	ABO	50%-RECALL	70%-RECALL	TIME
CPMC	646	0.703	0.784	**0.609**	252s
Baseline GOP	653	0.712	0.833	**0.622**	0.6s
Learned GOP	652	0.720	0.844	**0.632**	1.0s

Segmentation results

METHOD	# PROP.	ABO	50%-RECALL	70%-RECALL	TIME
CPMC	646	0.703	0.784	**0.609**	252s
Baseline GOP	653	0.712	0.833	**0.622**	0.6s
Learned GOP	652	0.720	0.844	**0.632**	1.0s

Segmentation results

METHOD	# PROP.	ABO	50%-RECALL	70%-RECALL	TIME
CPMC	646	0.703	0.784	**0.609**	252s
Baseline GOP	653	0.712	0.833	**0.622**	0.6s
Learned GOP	652	0.720	0.844	**0.632**	1.0s
Cat-Ind OP	1536	0.718	0.820	**0.624**	119s

Segmentation results


METHOD	# PROP.	ABO	50%-RECALL	70%-RECALL	TIME
CPMC	646	0.703	0.784	**0.609**	252s
Baseline GOP	653	0.712	0.833	**0.622**	0.6s
Learned GOP	652	0.720	0.844	**0.632**	1.0s
Cat-Ind OP	1536	0.718	0.820	**0.624**	119s
Baseline GOP	1090	0.727	0.847	**0.644**	0.65

Segmentation results


METHOD	# PROP.	ABO	50%-RECALL	70%-RECALL	TIME
CPMC	646	0.703	0.784	**0.609**	252s
Baseline GOP	653	0.712	0.833	**0.622**	0.6s
Learned GOP	652	0.720	0.844	**0.632**	1.0s
Cat-Ind OP	1536	0.718	0.820	**0.624**	119s
Baseline GOP	1090	0.727	0.847	**0.644**	0.65
Learned GOP	1199	0.741	0.865	**0.673**	1.1s

Segmentation results

METHOD	# PROP.	ABO	50%-RECALL	70%-RECALL	TIME
CPMC	646	0.703	0.784	**0.609**	252s
Baseline GOP	653	0.712	0.833	**0.622**	0.6s
Learned GOP	652	0.720	0.844	**0.632**	1.0s
Cat-Ind OP	1536	0.718	0.820	**0.624**	119s
Baseline GOP	1090	0.727	0.847	**0.644**	0.65
Learned GOP	1199	0.741	0.865	**0.673**	1.1s

Segmentation results

METHOD	# PROP.	ABO	50%-RECALL	70%-RECALL	TIME
CPMC	646	0.703	0.784	**0.609**	252s
Baseline GOP	653	0.712	0.833	**0.622**	0.6s
Learned GOP	652	0.720	0.844	**0.632**	1.0s
Cat-Ind OP	1536	0.718	0.820	**0.624**	119s
Baseline GOP	1090	0.727	0.847	**0.644**	0.65
Learned GOP	1199	0.741	0.865	**0.673**	1.1s
Sel Search	4374	0.735	0.891	**0.597**	2.6s

Segmentation results


METHOD	# PROP.	ABO	50%-RECALL	70%-RECALL	TIME
CPMC	646	0.703	0.784	**0.609**	252s
Baseline GOP	653	0.712	0.833	**0.622**	0.6s
Learned GOP	652	0.720	0.844	**0.632**	1.0s
Cat-Ind OP	1536	0.718	0.820	**0.624**	119s
Baseline GOP	1090	0.727	0.847	**0.644**	0.65
Learned GOP	1199	0.741	0.865	**0.673**	1.1s
Sel Search	4374	0.735	0.891	**0.597**	2.6s
Baseline GOP	2089	0.744	0.867	**0.673**	0.9s

Segmentation results

METHOD	# PROP.	ABO	50%-RECALL	70%-RECALL	TIME
CPMC	646	0.703	0.784	**0.609**	252s
Baseline GOP	653	0.712	0.833	**0.622**	0.6s
Learned GOP	652	0.720	0.844	**0.632**	1.0s
Cat-Ind OP	1536	0.718	0.820	**0.624**	119s
Baseline GOP	1090	0.727	0.847	**0.644**	0.65
Learned GOP	1199	0.741	0.865	**0.673**	1.1s
Sel Search	4374	0.735	0.891	**0.597**	2.6s
Baseline GOP	2089	0.744	0.867	**0.673**	0.9s
Learned GOP	2286	0.756	0.877	**0.699**	1.4s

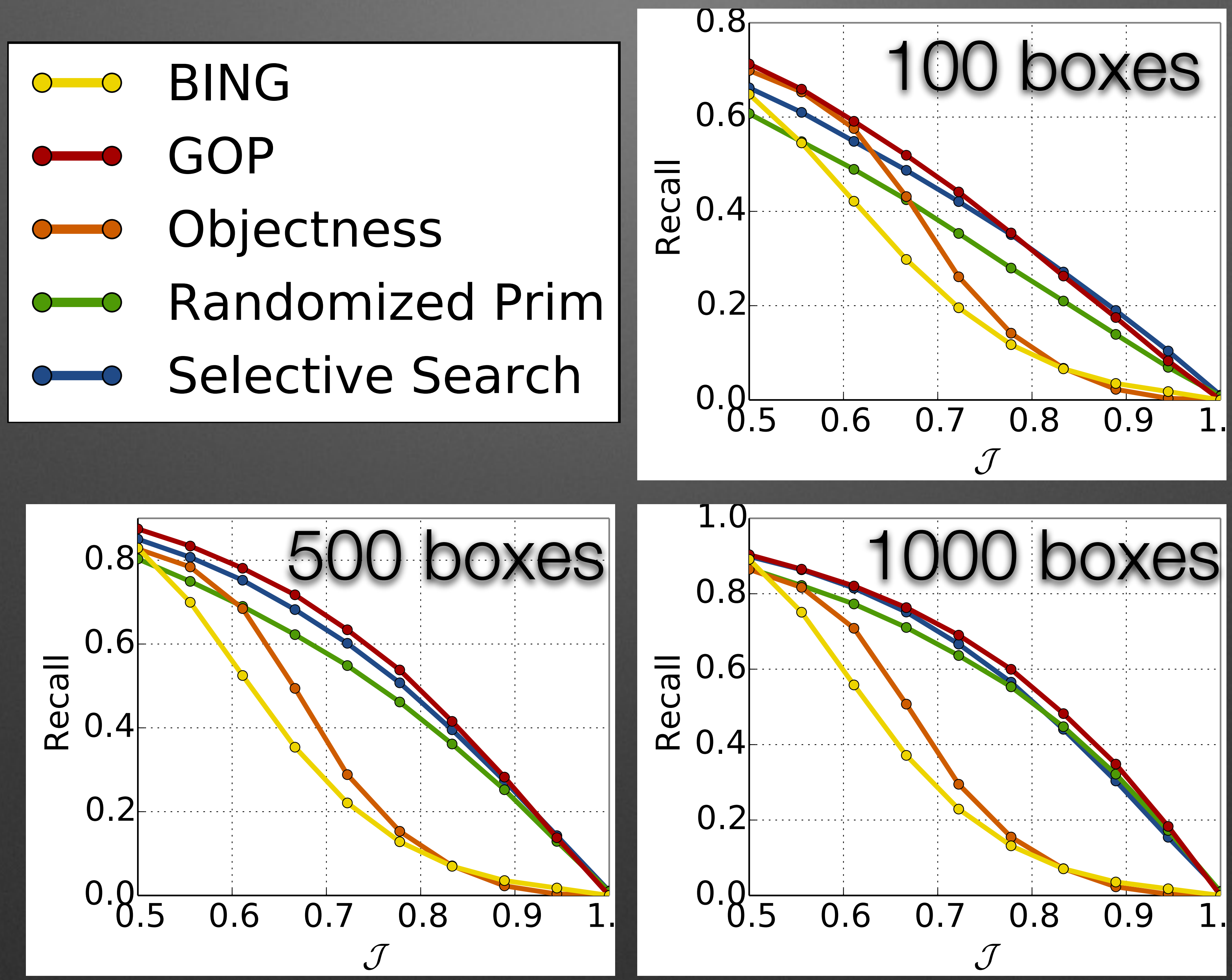
Segmentation results

METHOD	# PROP.	ABO	50%-RECALL	70%-RECALL	TIME
CPMC	646	0.703	0.784	**0.609**	252s
Baseline GOP	653	0.712	0.833	**0.622**	0.6s
Learned GOP	652	0.720	0.844	**0.632**	1.0s
Cat-Ind OP	1536	0.718	0.820	**0.624**	119s
Baseline GOP	1090	0.727	0.847	**0.644**	0.65
Learned GOP	1199	0.741	0.865	**0.673**	1.1s
Sel Search	4374	0.735	0.891	**0.597**	2.6s
Baseline GOP	2089	0.744	0.867	**0.673**	0.9s
Learned GOP	2286	0.756	0.877	**0.699**	1.4s
Baseline GOP	3958	0.756	0.881	**0.699**	1.2s

Segmentation results

METHOD	# PROP.	ABO	50%-RECALL	70%-RECALL	TIME
CPMC	646	0.703	0.784	**0.609**	252s
Baseline GOP	653	0.712	0.833	**0.622**	0.6s
Learned GOP	652	0.720	0.844	**0.632**	1.0s
Cat-Ind OP	1536	0.718	0.820	**0.624**	119s
Baseline GOP	1090	0.727	0.847	**0.644**	0.65
Learned GOP	1199	0.741	0.865	**0.673**	1.1s
Sel Search	4374	0.735	0.891	**0.597**	2.6s
Baseline GOP	2089	0.744	0.867	**0.673**	0.9s
Learned GOP	2286	0.756	0.877	**0.699**	1.4s
Baseline GOP	3958	0.756	0.881	**0.699**	1.2s
Learned GOP	4186	0.766	0.889	**0.715**	1.7s

Bounding box results



Bounding box results

	VOLUME UNDER SURFACE (VUS)

Bounding box results

	VOLUME UNDER SURFACE (VUS)
BING	0.278

Bounding box results

	VOLUME UNDER SURFACE (VUS)
BING	0.278
Objectness	0.324

Bounding box results

	VOLUME UNDER SURFACE (VUS)
BING	0.278
Objectness	0.324
Randomized Prim	0.511

Bounding box results

	VOLUME UNDER SURFACE (VUS)
BING	0.278
Objectness	0.324
Randomized Prim	0.511
Selective Search	0.528

Bounding box results

	VOLUME UNDER SURFACE (VUS)
BING	0.278
Objectness	0.324
Randomized Prim	0.511
Selective Search	0.528
GOP	0.546

COCO dataset - segments

COCO dataset - segments

METHOD	# PROP.	50%-REC.	70%-REC.

COCO dataset - segments

METHOD	# PROP.	50%-REC.	70%-REC.
Sel Search	6504	0.717	**0.369**

COCO dataset - segments


METHOD	# PROP.	50%-REC.	70%-REC.
Sel Search	6504	0.717	**0.369**
Baseline GOP	6106	0.704	**0.426**

COCO dataset - segments

METHOD	# PROP.	50%-REC.	70%-REC.
Sel Search	6504	0.717	**0.369**
Baseline GOP	6106	0.704	**0.426**
Learned GOP	6264	0.717	**0.447**

COCO dataset - segments


METHOD	# PROP.	50%-REC.	70%-REC.
Sel Search	6504	0.717	**0.369**
Baseline GOP	6106	0.704	**0.426**
Learned GOP	6264	0.717	**0.447**

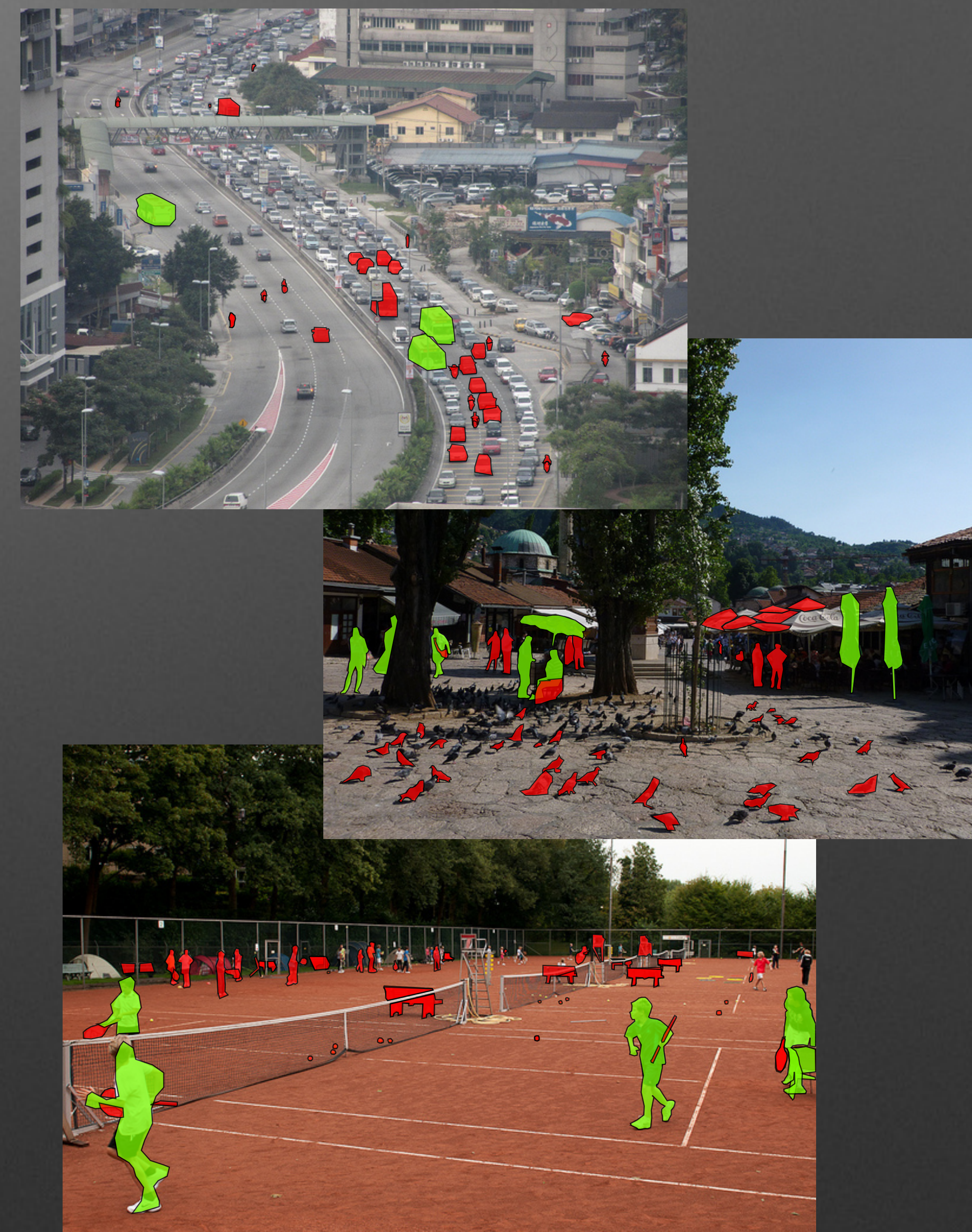
LARGE OBJECTS ≥ 25

COCO dataset - segments

METHOD	# PROP.	50%-REC.	70%-REC.
Sel Search	6504	0.717	**0.369**
Baseline GOP	6106	0.704	**0.426**
Learned GOP	6264	0.717	**0.447**

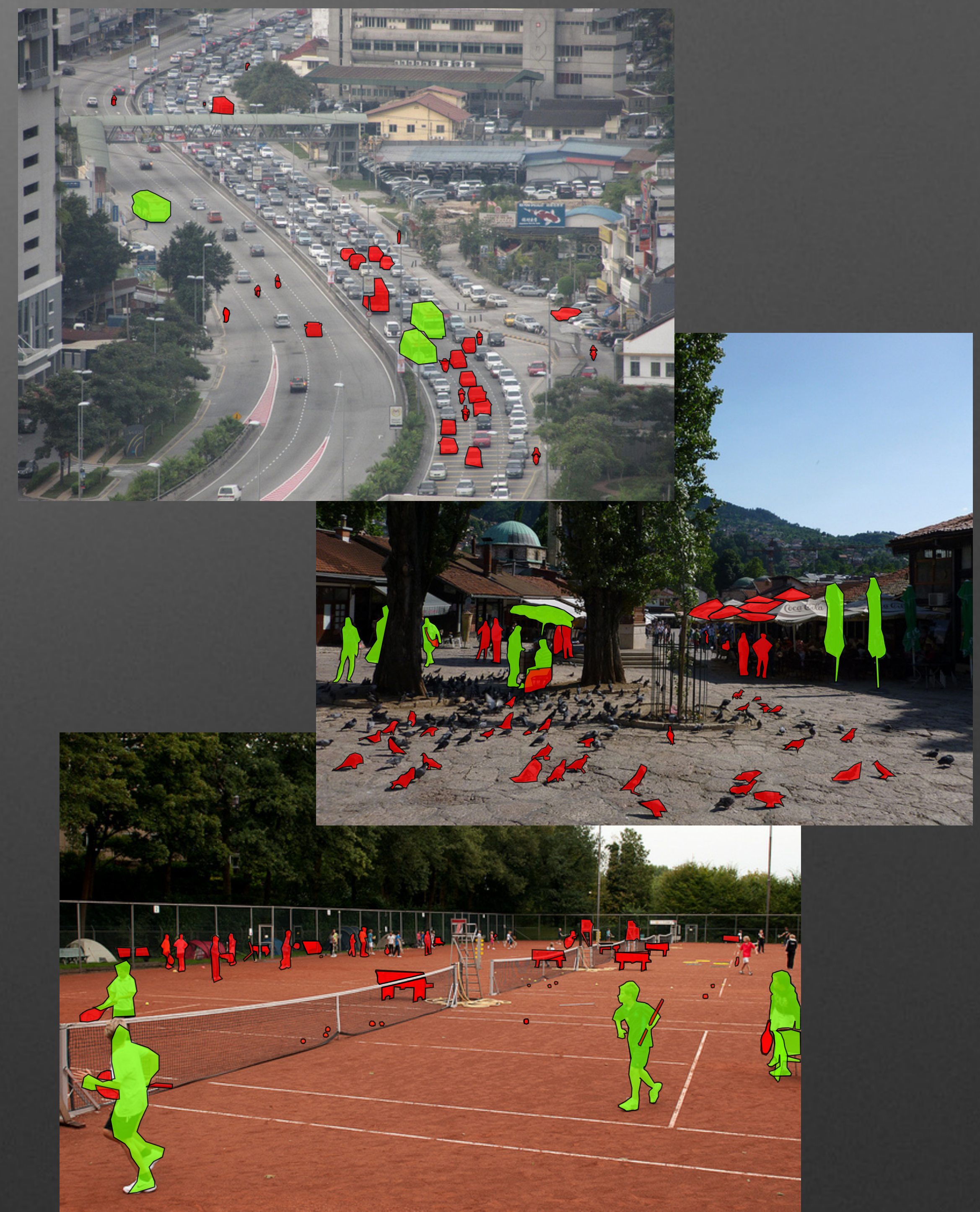
LARGE OBJECTS ≥ 25			
Sel Search	6504	0.810	**0.442**



COCO dataset - segments

METHOD	# PROP.	50%-REC.	70%-REC.
Sel Search	6504	0.717	**0.369**
Baseline GOP	6106	0.704	**0.426**
Learned GOP	6264	0.717	**0.447**

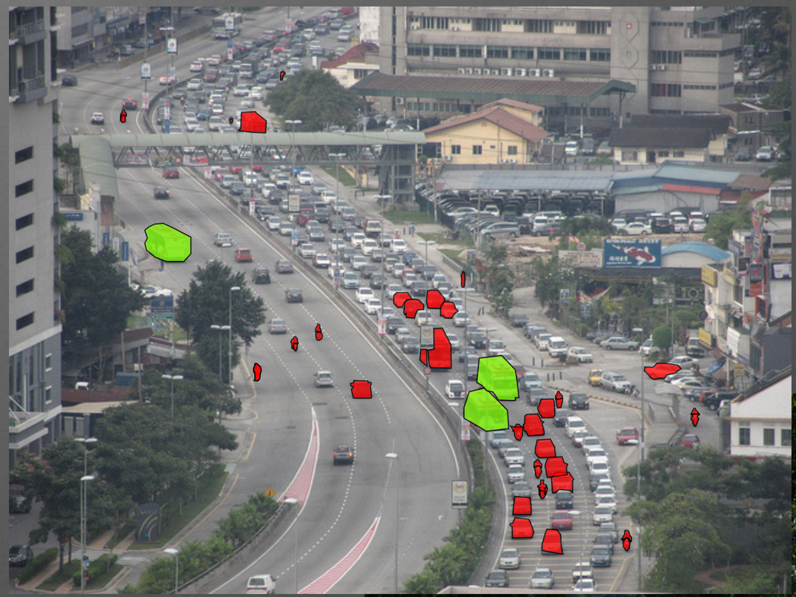
LARGE OBJECTS ≥ 25			
Sel Search	6504	0.810	**0.442**
Baseline GOP	6106	0.882	**0.582**

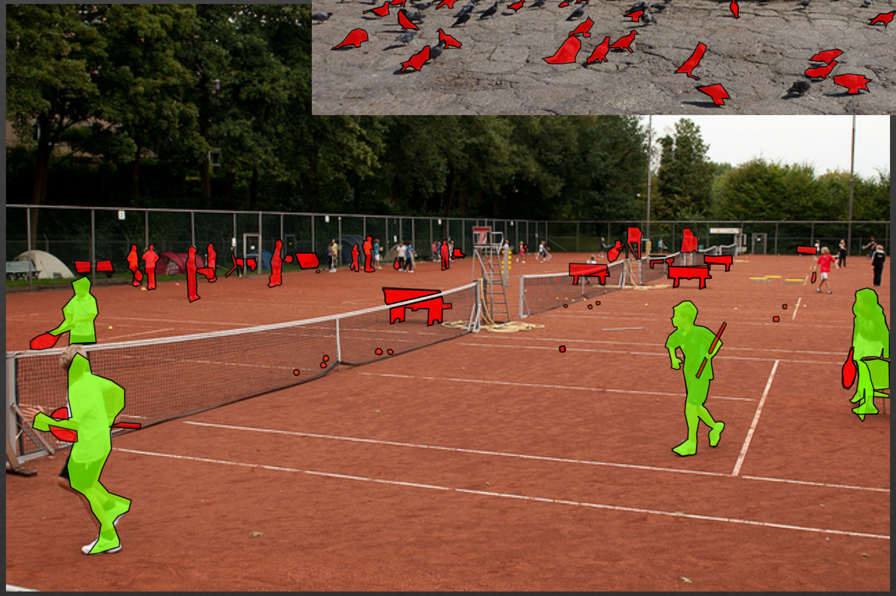


COCO dataset - segments


METHOD	# PROP.	50%-REC.	70%-REC.
Sel Search	6504	0.717	**0.369**
Baseline GOP	6106	0.704	**0.426**
Learned GOP	6264	0.717	**0.447**

LARGE OBJECTS ≥ 25			
Sel Search	6504	0.810	**0.442**
Baseline GOP	6106	0.882	**0.582**
Learned GOP	6264	0.891	**0.609**



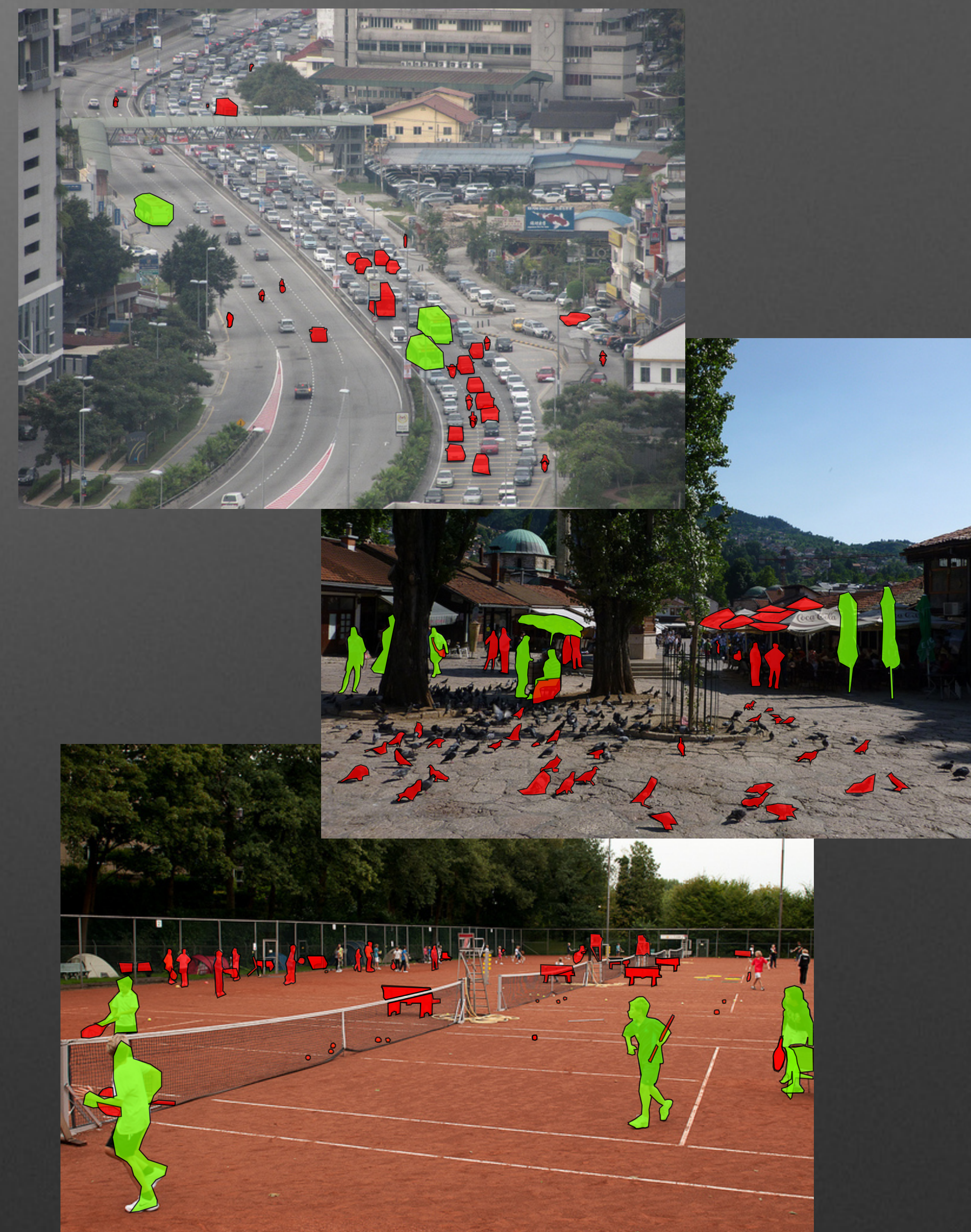


COCO dataset - segments

METHOD	# PROP.	50%-REC.	70%-REC.
Sel Search	6504	0.717	**0.369**
Baseline GOP	6106	0.704	**0.426**
Learned GOP	6264	0.717	**0.447**

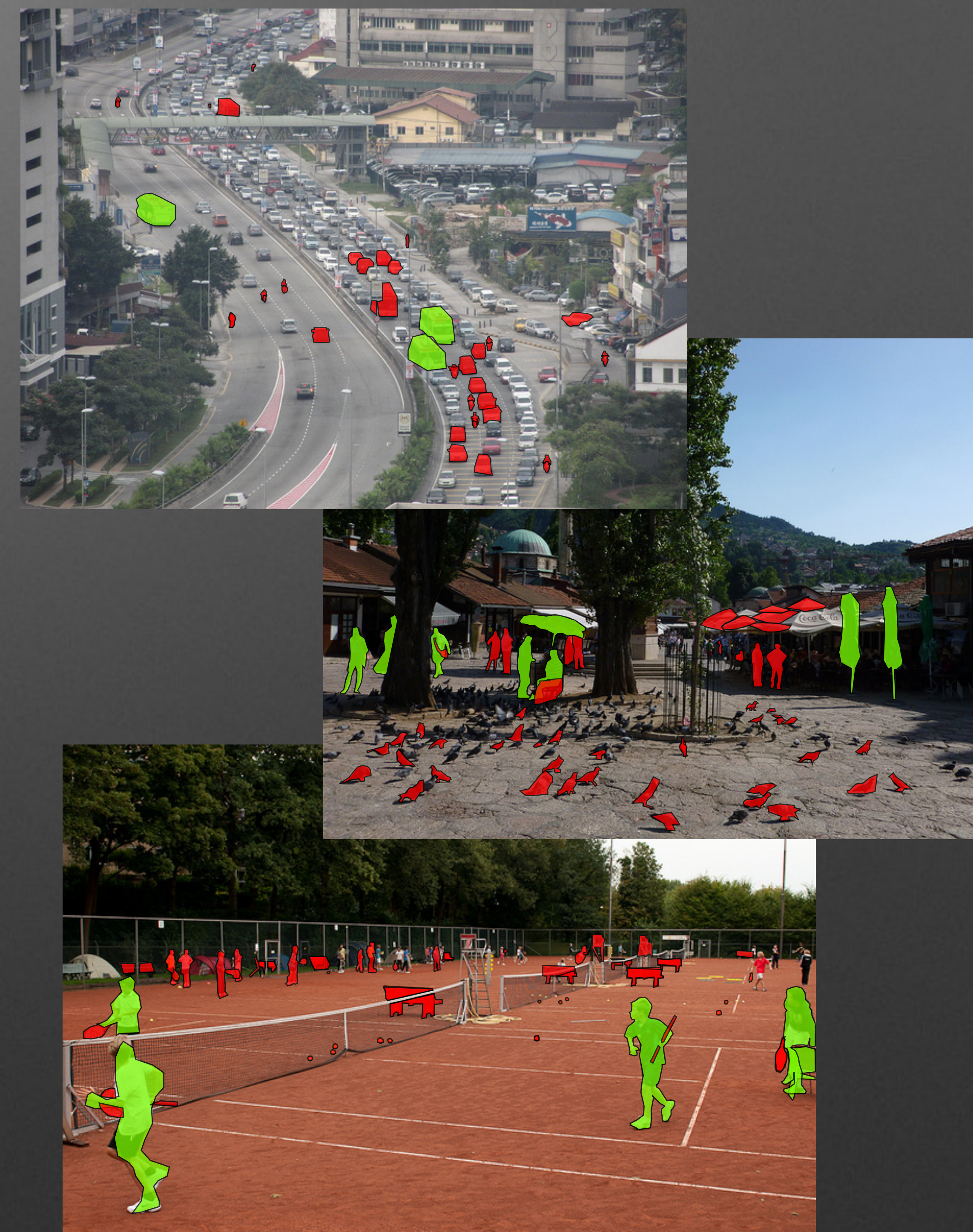
LARGE OBJECTS ≥ 25			
Sel Search	6504	0.810	**0.442**
Baseline GOP	6106	0.882	**0.582**
Learned GOP	6264	0.891	**0.609**

SMALL OBJECTS < 25



COCO dataset - segments

METHOD	# PROP.	50%-REC.	70%-REC.
Sel Search	6504	0.717	**0.369**
Baseline GOP	6106	0.704	**0.426**
Learned GOP	6264	0.717	**0.447**
LARGE OBJECTS ≥ 25			
Sel Search	6504	0.810	**0.442**
Baseline GOP	6106	0.882	**0.582**
Learned GOP	6264	0.891	**0.609**
SMALL OBJECTS < 25			
Sel Search	6504	0.525	**0.219**

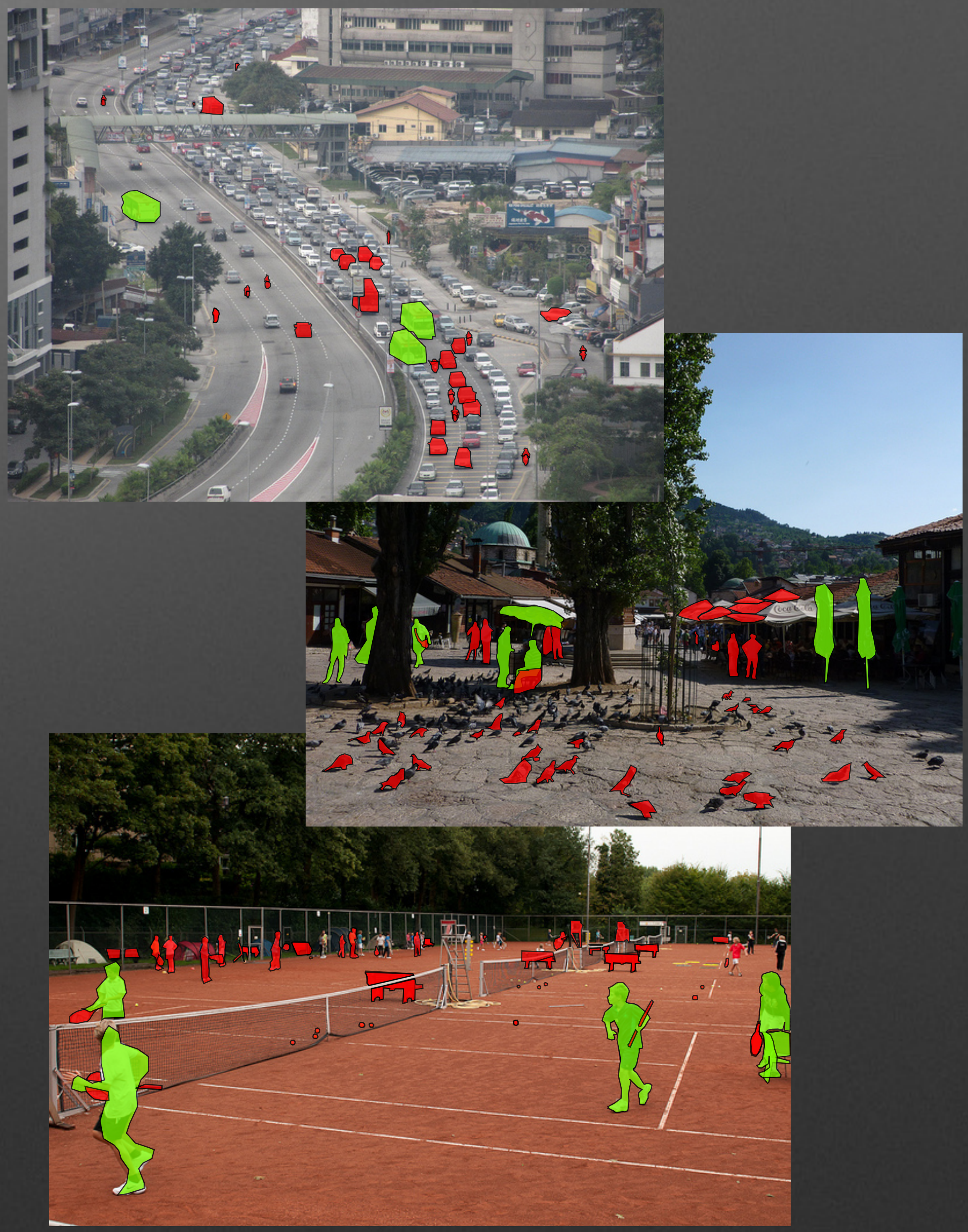


COCO dataset - segments


METHOD	# PROP.	50%-REC.	70%-REC.
Sel Search	6504	0.717	**0.369**
Baseline GOP	6106	0.704	**0.426**
Learned GOP	6264	0.717	**0.447**

LARGE OBJECTS ≥ 25			
Sel Search	6504	0.810	**0.442**
Baseline GOP	6106	0.882	**0.582**
Learned GOP	6264	0.891	**0.609**

SMALL OBJECTS < 25			
Sel Search	6504	0.525	**0.219**
Baseline GOP	6106	0.337	**0.106**

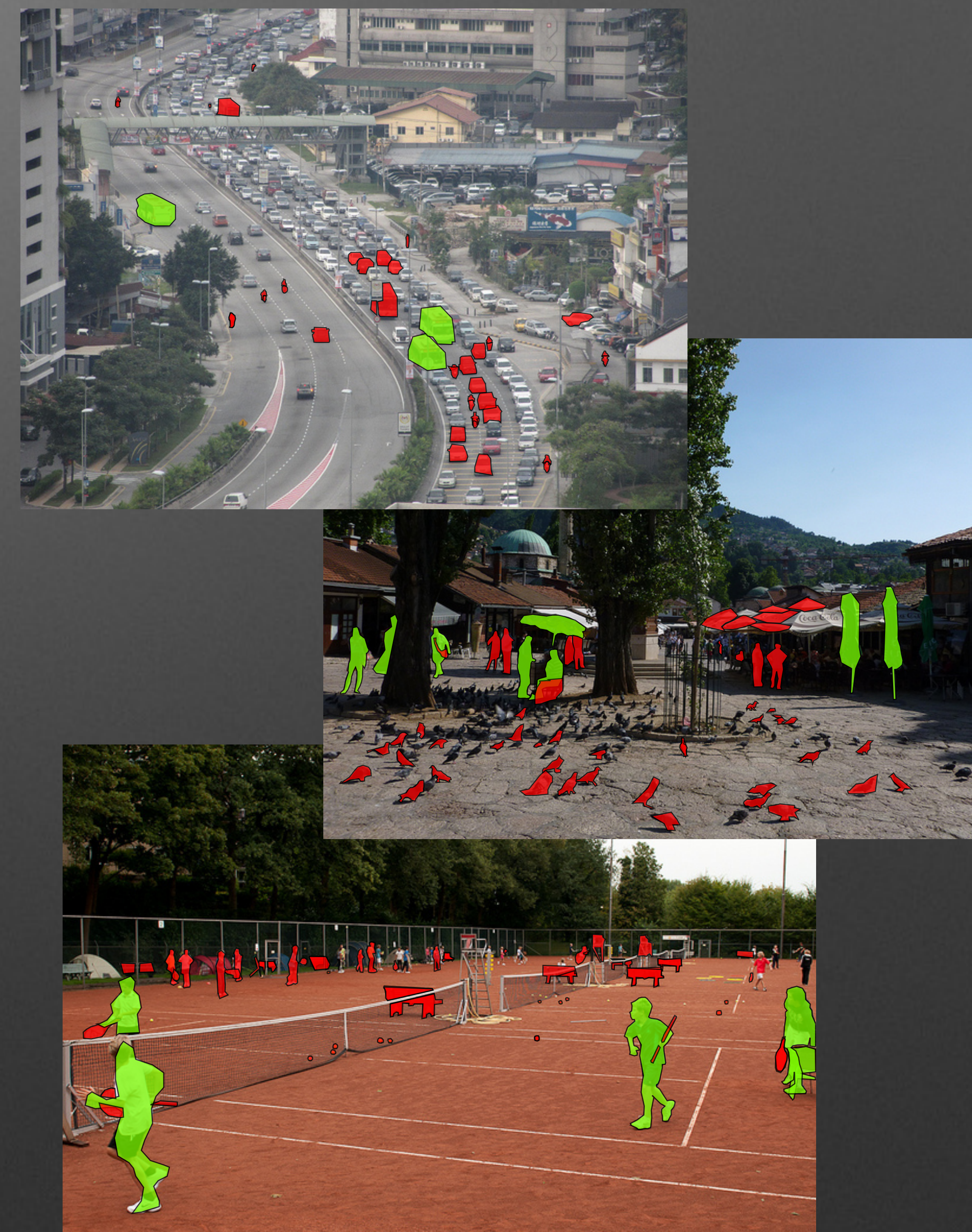


COCO dataset - segments

METHOD	# PROP.	50%-REC.	70%-REC.
Sel Search	6504	0.717	**0.369**
Baseline GOP	6106	0.704	**0.426**
Learned GOP	6264	0.717	**0.447**

LARGE OBJECTS ≥ 25			
Sel Search	6504	0.810	**0.442**
Baseline GOP	6106	0.882	**0.582**
Learned GOP	6264	0.891	**0.609**

SMALL OBJECTS < 25			
Sel Search	6504	0.525	**0.219**
Baseline GOP	6106	0.337	**0.106**
Learned GOP	6264	0.356	**0.112**



Summary

Summary

- Geodesic Object Proposals

Summary

- Geodesic Object Proposals
    - fast

Summary

- Geodesic Object Proposals
  - fast
  - good segment proposals

Summary

- Geodesic Object Proposals
  - fast
  - good segment proposals
  - good bounding box proposals

Summary

- Geodesic Object Proposals
  - fast
  - good segment proposals
  - good bounding box proposals
- Future work

Summary

- Geodesic Object Proposals
  - fast
  - good segment proposals
  - good bounding box proposals
- Future work
  - small objects

Summary

- Geodesic Object Proposals
  - fast
  - good segment proposals
  - good bounding box proposals
- Future work
  - small objects
  - learn proposals directly from data

Questions

C++, Python and Matlab Code:
http://www.philkr.net/home/gop