Shape Sharing for Object Segmentation

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Problem statement

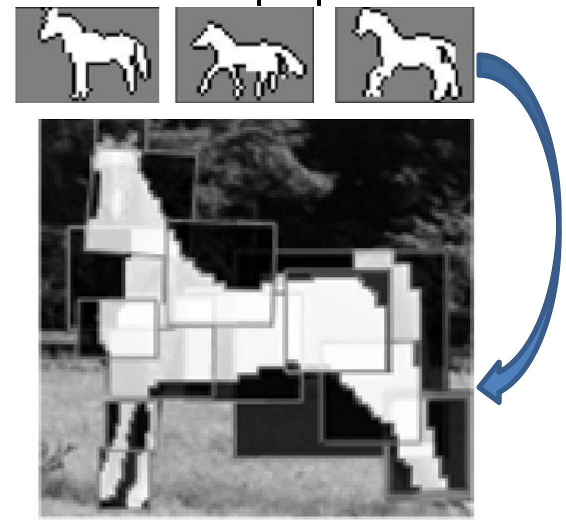
Category-independent object segmentation:
Generate object segments in the image regardless of their categories.

Spectrum of existing approaches

color, textures, edges…

How to model ***top-down*** shape in a ***category-independent*** way?

horse shape priors



Bottom-up

+ coherent mid-level regions
+ applicable to any image
- prone to over/under-segment

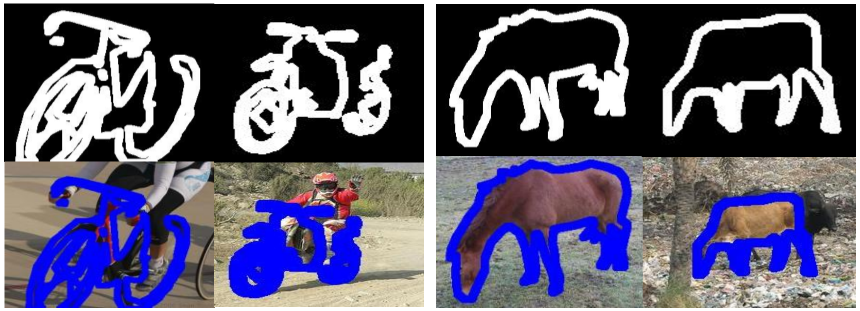
e.g., Malisiewicz and Efros (BMVC 2007),
Arbelaez et al. (CVPR 2009)
Carreira and Sminchisescu (CVPR 2010)
Endres and Hoiem (ECCV 2010)

Class-specific

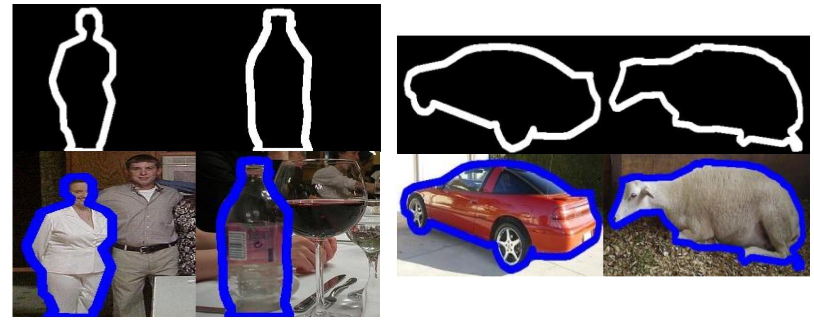
+ robustness to low-level cues
- typically viewpoint specific
- requires class knowledge!

e.g., Active Contours (IJCV 1987)
Borenstein and Ullman (ECCV 2002)
Levin and Weiss (ECCV 2006)
Kumar et.al. (CVPR 2005)

Our idea:
Shape sharing



Semantically close



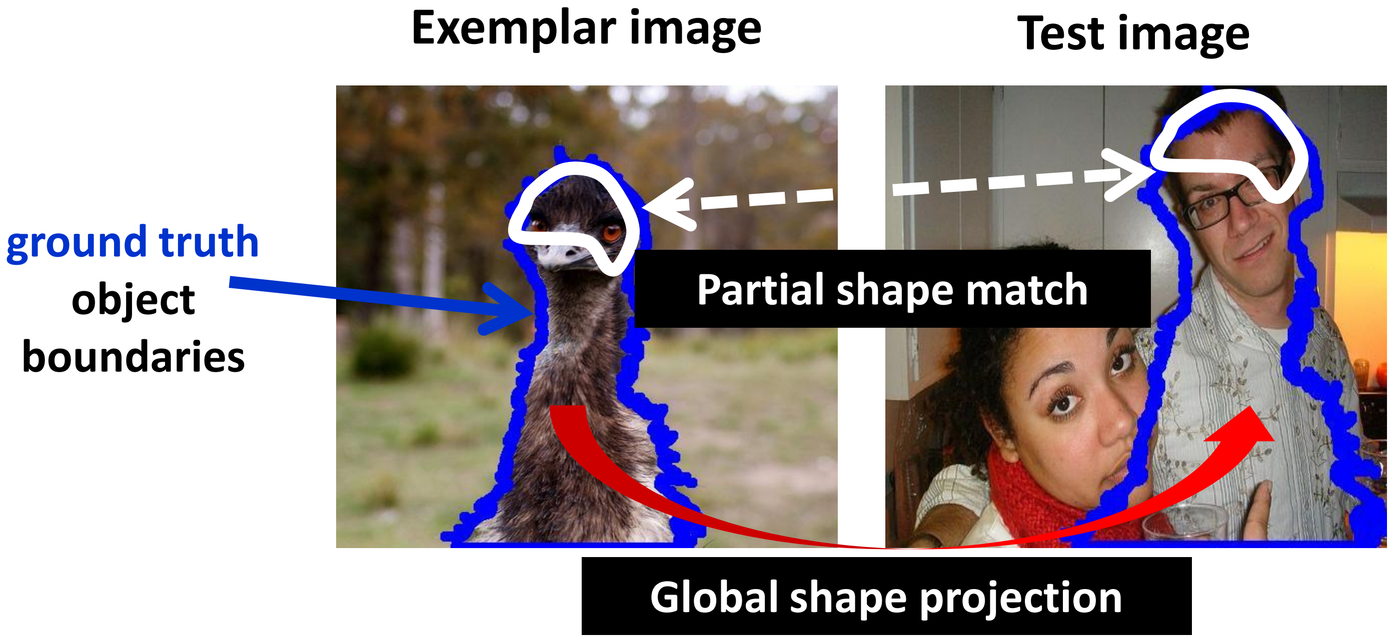
Semantically disparate

Object shapes are shared among different categories.

Shapes from one class can be used to segment another (*possibly unknown*) class:

Enable category-independent shape priors

Basis of approach: transfer through matching



Transfer category-independent shape prior

Projection → Aggregation → Segmentation

Approach: Shape projection

Test image

Projection → Aggregation → Segmentation

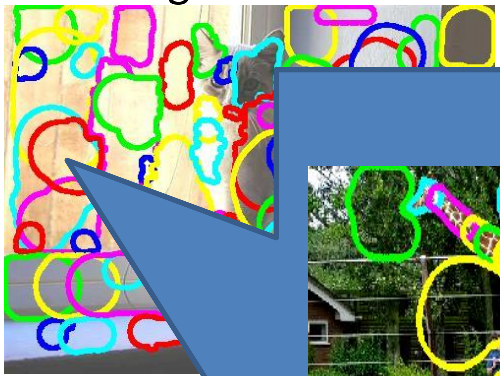
Approach: Shape projection

Test image

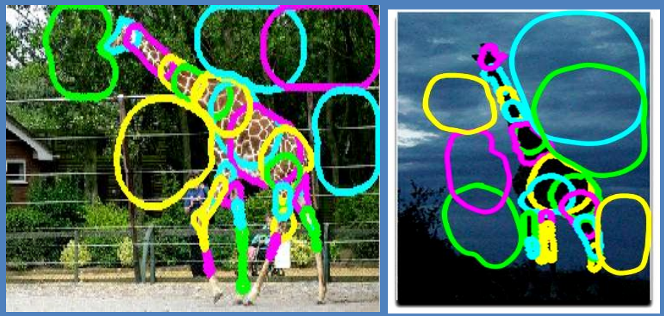
Projection → Aggregation → Segmentation

Approach: Shape projection

Test image

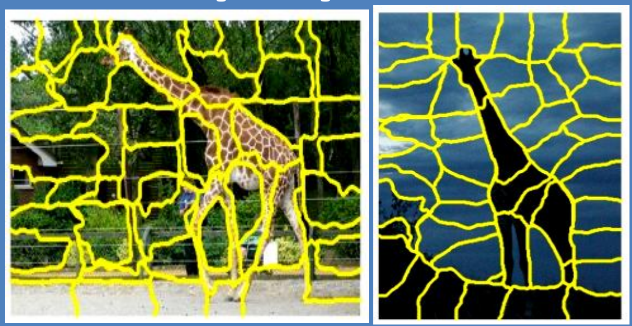


BPLRs



Vs.

Superpixels



Boundary-Preserving Local Regions (BPLR):

- Distinctively shaped
- Dense
- Repeatable

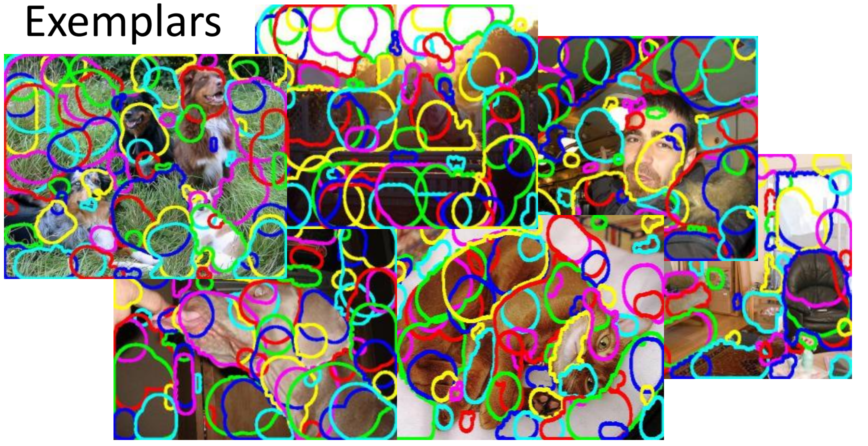
[Kim & Grauman, CVPR 2011]

Projection → Aggregation → Segmentation

Approach: Shape projection

Test image

Exemplars

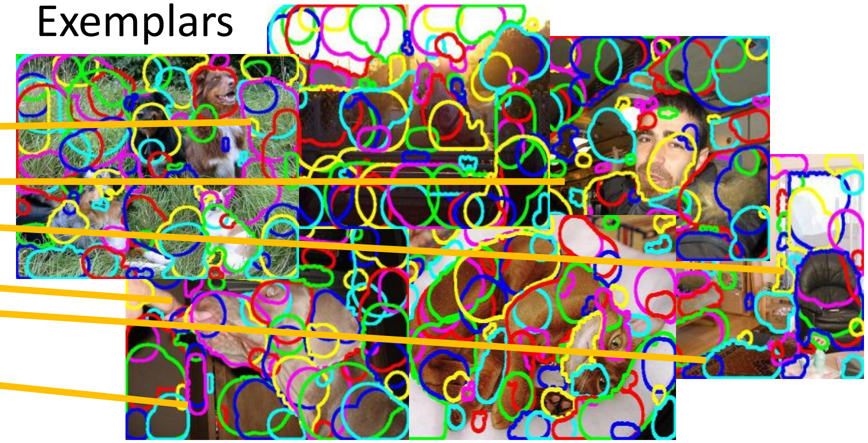


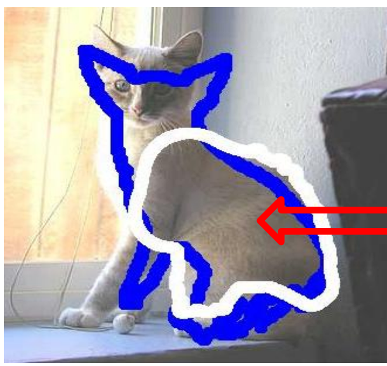
Projection → Aggregation → Segmentation

Approach: Shape projection

Test image

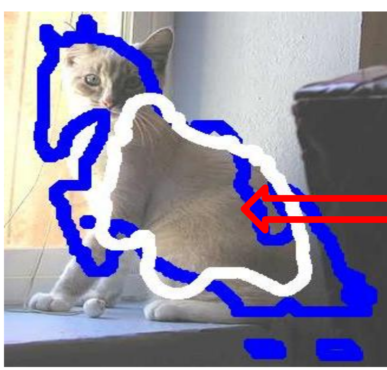
Exemplars





Matched Exemplar 1

Shape projections via similarity transform of BPLR matches

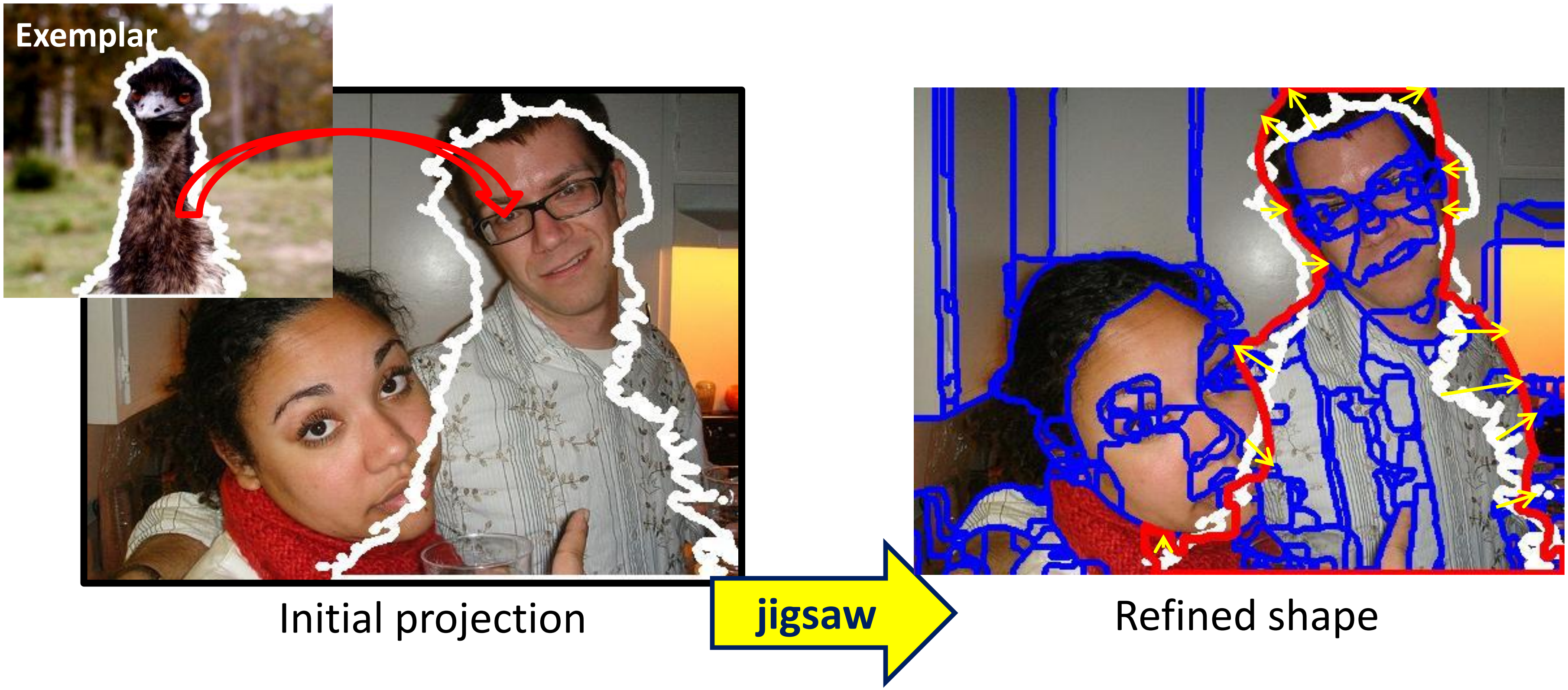


Matched Exemplar 2

Shape hypotheses

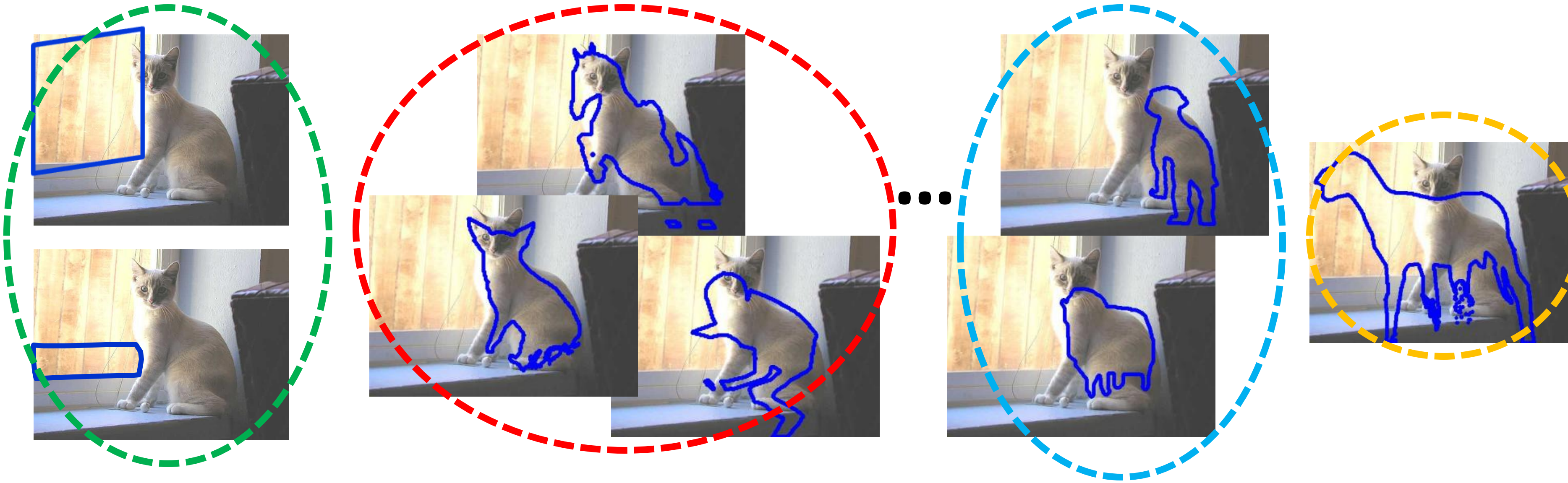
Projection → Aggregation → Segmentation

Approach: Refinement of projections



- Align with bottom-up evidence
- Include superpixels where majority of pixels overlap projection

Approach: Aggregating projections

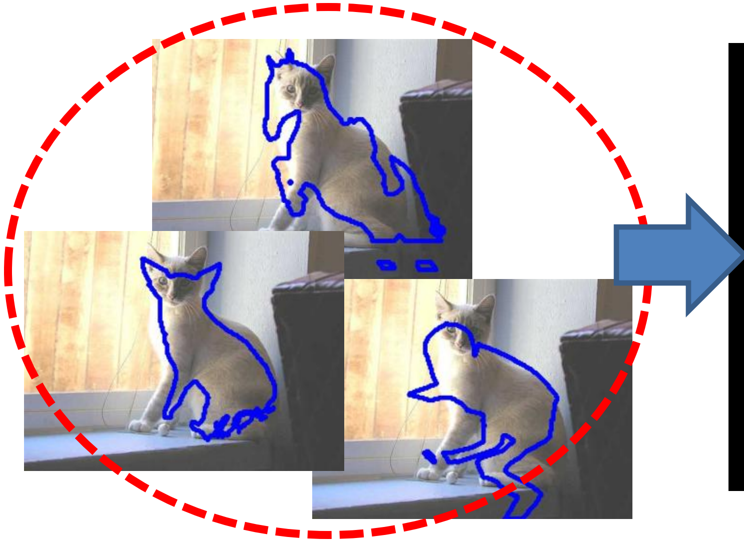


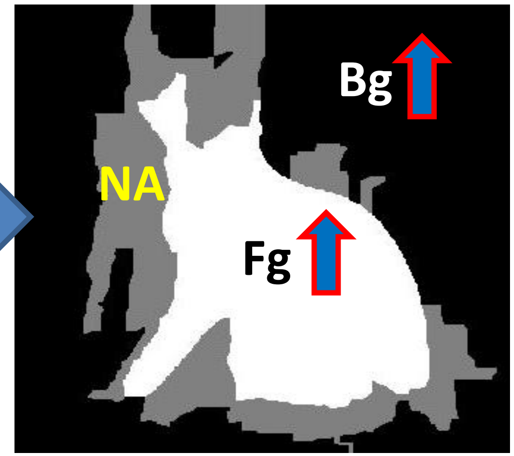
Grouping based on overlap

Exploit partial agreement from multiple exemplars

Projection → Aggregation → **Segmentation**

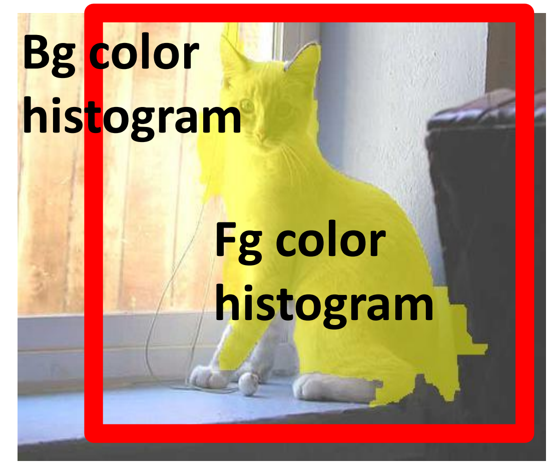
Approach: Segmentation





Shape likelihood

+



Color likelihood

$$E(y) = \sum_{p_i \in \mathcal{P}} \boxed{D_i(y_i)} + \sum_{i,j \in \mathcal{N}} V_{i,j}(y_i, y_j) \qquad y_i \in \{0 \ (\mathrm{bg}), 1 \ (\mathrm{fg})\}$$

Data term

Smoothness term

Graph-cut optimization

Approach: Multiple segmentations

Compute multiple segmentations by varying foreground bias:

$$D_i(y_i, \lambda) = \begin{cases} D_i(y_i) + \lambda & \text{if } y_i = 1 \\ D_i(y_i) - \lambda & \text{if } y_i = 0 \end{cases}$$

Parameter controlling
data term bias

Output:

...

Carreira and Sminchisescu,
CPMC: Automatic Object Segmentation Using Constrained Parametric Min-Cuts PAMI 2012.

Experiments

Exemplar database:

PASCAL 2010 segmentation task training set (20 classes, 2075 objects)

Test datasets:

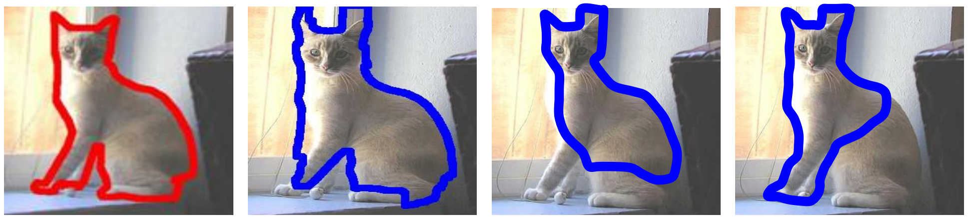
- PASCAL 2010 segmentation task validation set (20 classes, 964 images)
- Berkeley segmentation dataset (natural scenes and objects, 300 images)

Baselines:

- CPMC
  [Carreira and Sminchisescu, PAMI 2012]
- Object proposals
  [Endres and Hoiem, ECCV 2012]
- gPb+owt+ucm
  [Arbelaez et al., PAMI 2011]

Evaluation metric:

Best covering score w.r.t # of segments



Ground truth **0.92** 0.75 0.71 •••

Best covering score: 0.92

Segmentation quality

Approach	Covering (%)	Num of segments
Shape sharing (Ours)	**84.3**	1448
CPMC [Carreira and Sminchisescu]	81.6	1759
Object proposals [Endres and Hoiem]	81.7	1540
gPb-owt-ucm [Arbelaez et al.]	62.8	1242

PASCAL 2010 dataset

Approach	Covering (%)	Num of segments
Shape sharing (Ours)	**75.6**	1449
CPMC [Carreira and Sminchisescu]	74.1	1677
Object proposals [Endres and Hoiem]	72.3	1275
gPb-owt-ucm [Arbelaez et al.]	61.6	1483

Berkeley segmentation dataset

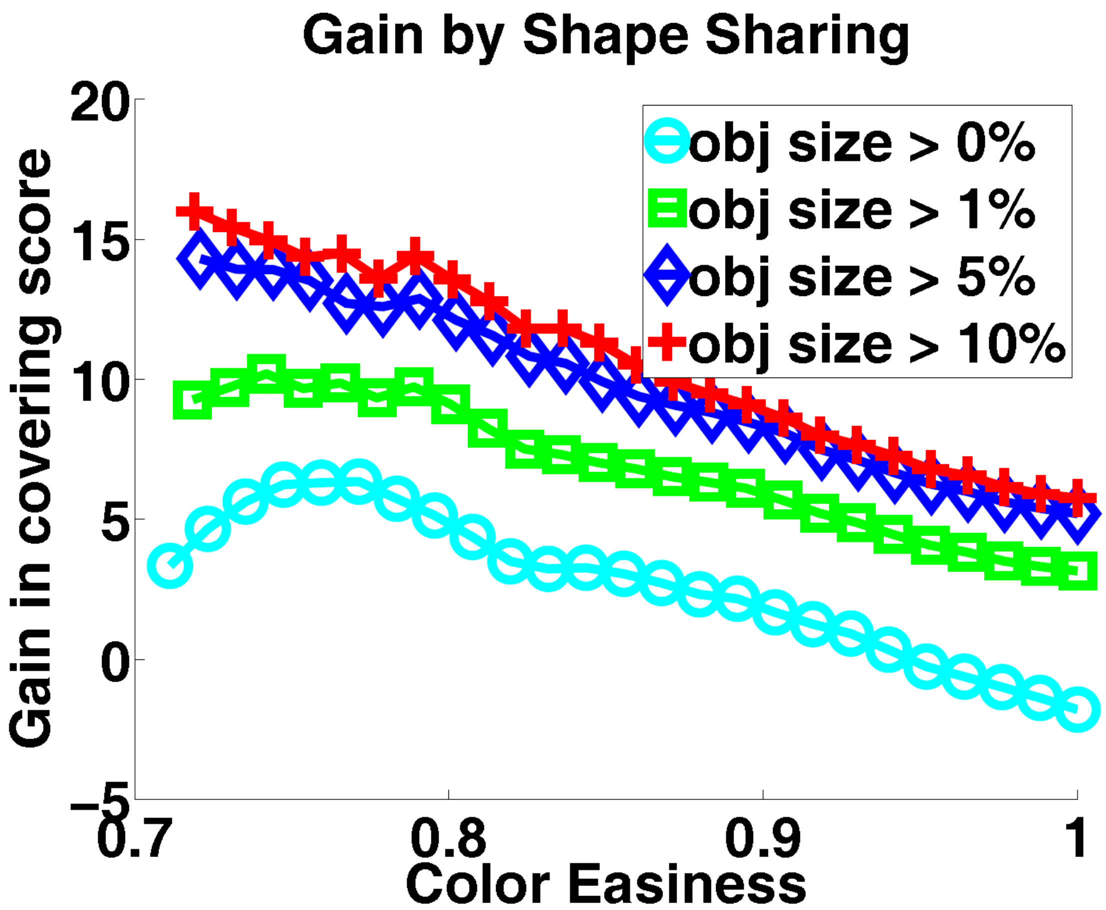
*Exemplars = PASCAL

When does shape sharing help most?

Gain as a function of color easiness and object size

Easy to segment by color

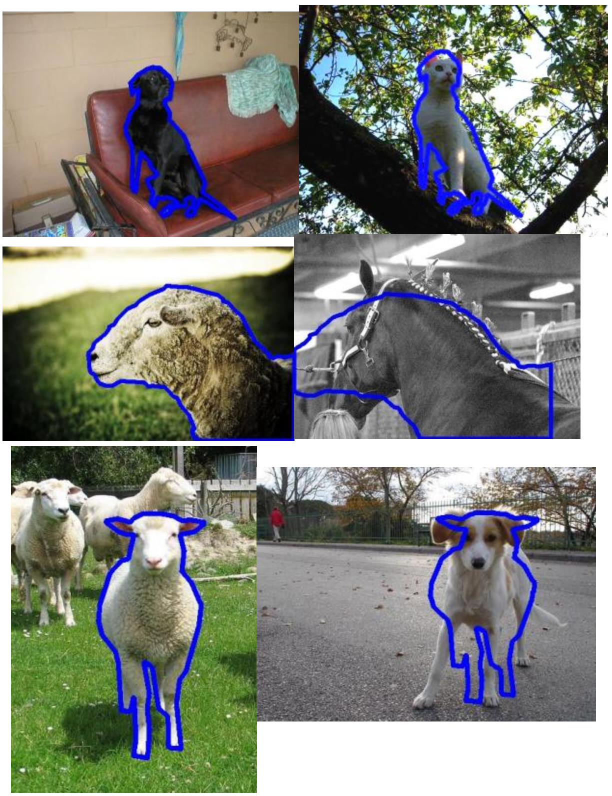
Hard to segment by color

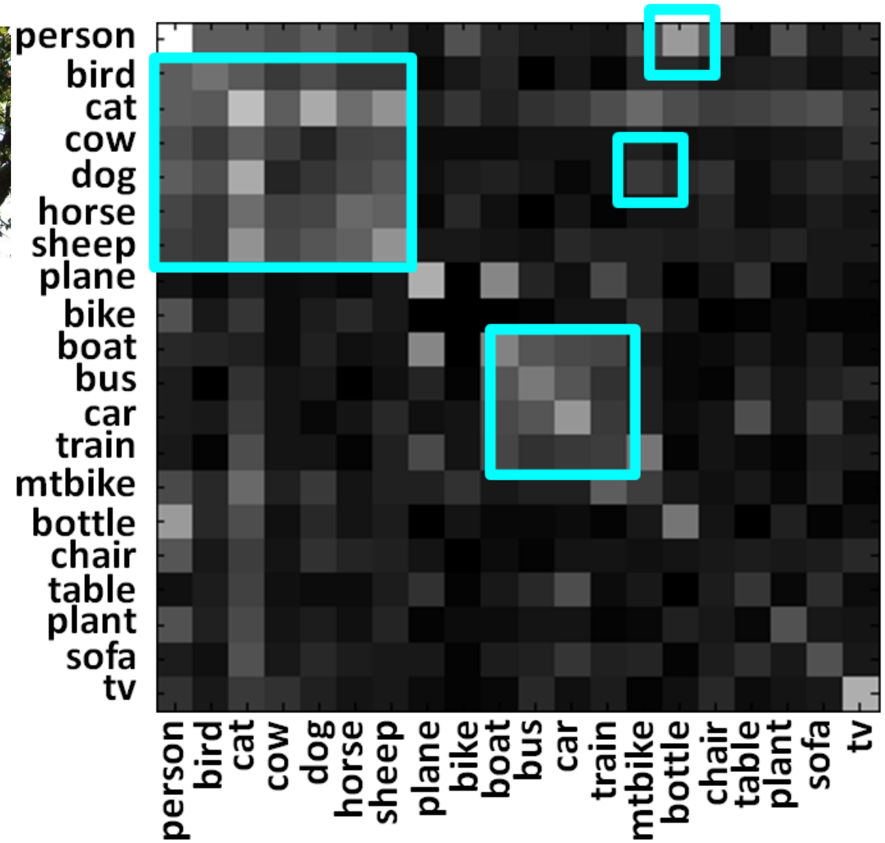


Compared to CPMC [Carreira and Sminchisescu., PAMI 2012]

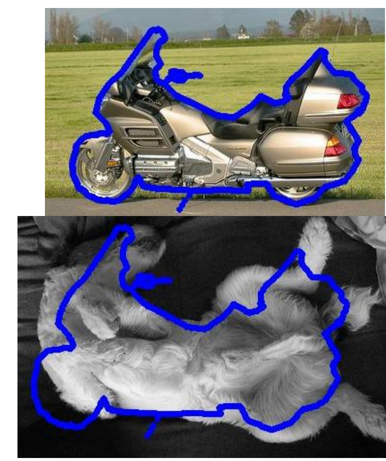
Which classes share shapes?

Animals





Semantically disparate

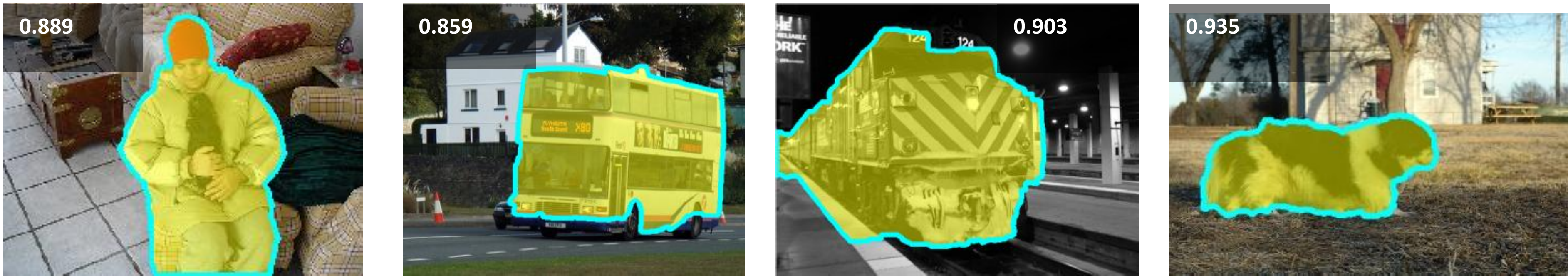


Unexpected pose variations

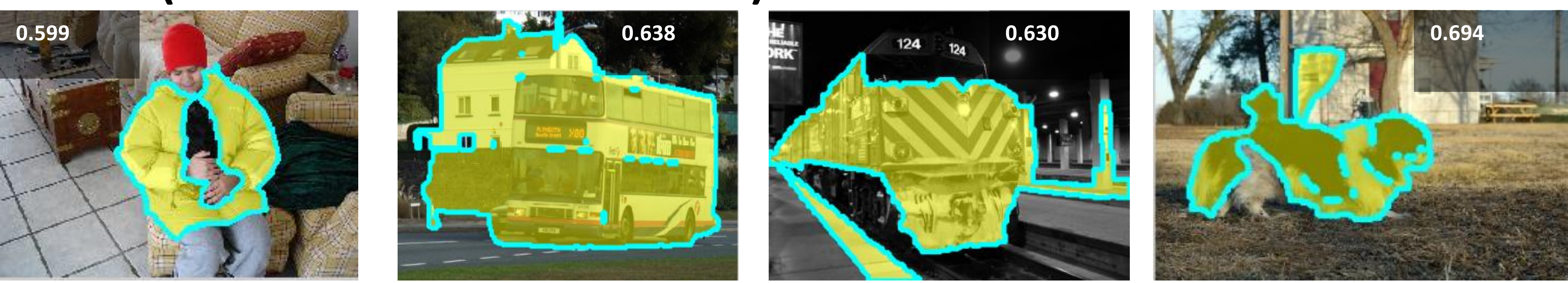
Vehicles

Example results (good)

Shape sharing (ours)



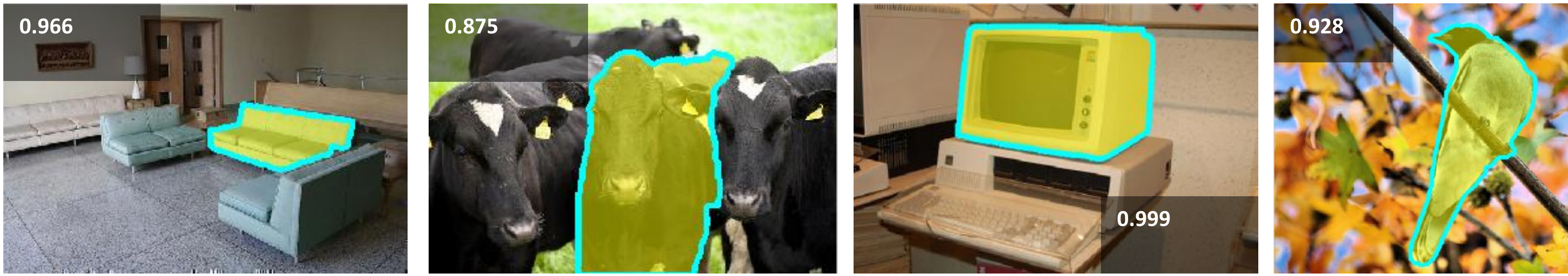
CPMC (Carreira and Sminchisescu)



Objects with diverse colors

Example results (good)

Shape sharing (ours)



CPMC (Carreira and Sminchisescu)

Objects confused by surrounding colors

Example results (failure cases)

Shape sharing (ours)

CPMC (Carreira and Sminchisescu)

Shape sharing: highlights

Top-down shape prior in a category-independent way

- Non-parametric transfer of shapes across categories
- Partial shape agreement from multiple exemplars
- Multiple hypothesis approach
- Most impact for heterogeneous objects

Code will be available soon:
http://vision.cs.utexas.edu/projects/shapesharing