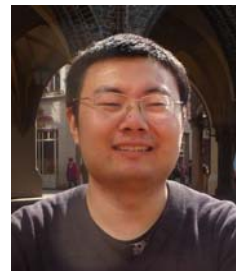


# Ranking Figure-Ground Hypotheses for Object Segmentation

João Carreira, Fuxin Li, Cristian Sminchisescu

*Faculty of Mathematics and Natural Science, INS,  
University of Bonn*

*<http://sminchisescu.ins.uni-bonn.de/>*



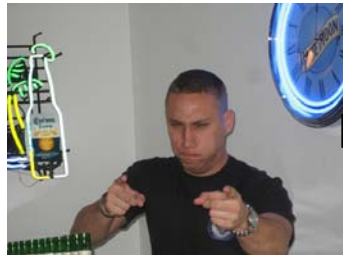
# Principles

- **Avoid early decision making.** Low-level processes should produce plausible segment hypotheses with sufficiently large, non-local spatial scope
- **Exploit mid-level cues.** Some may require the calculation of features over sufficiently large regions (e.g. parallelism, convexity, orientation)
- **Integrate learning and top-down, class information, into bottom-up calculations progressively.** This may still be feasible within a dominantly feed-forward architecture

# Mechanism

- **Multiple figure-ground segment hypotheses** are generated by searching for the breakpoints of constrained min-cut energies, solved at multiple scales on image grid (CPMC)
- **We learn to rank segments.** Ranking uses mid-level, class-independent, visual cues
- **Classification** stage sequentially assigns class labels to segments and resolves conflicts among regions with inconsistent labels

# Computational pipeline



Generate multiple object segment hypotheses

Rank object hypotheses using mid-level cues  
(*Class independent scoring*)

Predict overlap estimate of each segment to specific object class  
(*1 predictor / class*)

- Select segment/class with highest score
- Consolidate by aggregating multiple high-rank segments with large spatial overlap from the same class
- Add result to final segmentation



*Sequentially add segments*

Only segmentation labels used for training/testing. No bounding box information/calculation.

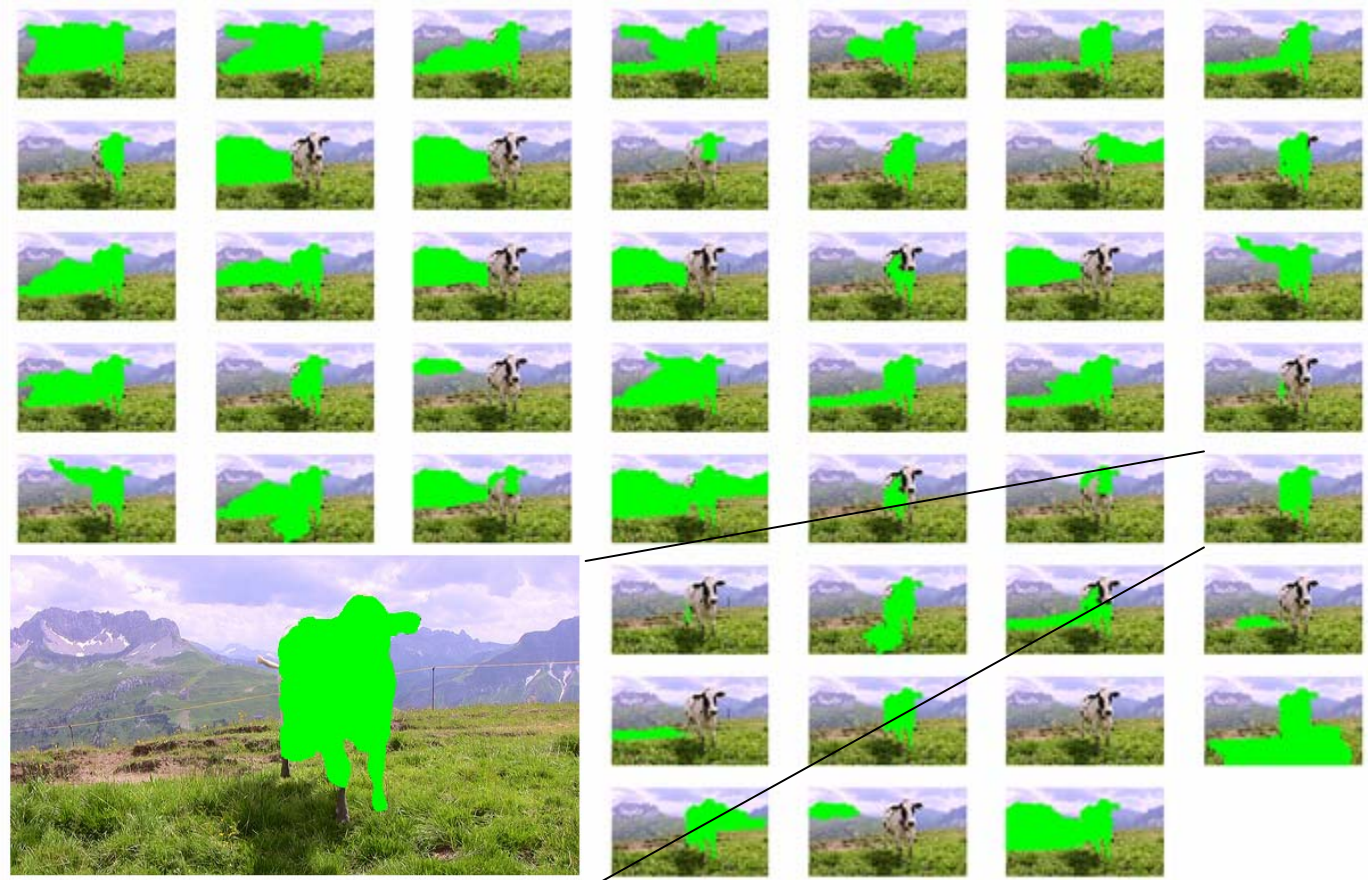
# The appeal of bottom-up figure-ground segmentation



Segments  
obtained by  
our method

But can accurate results be achieved ?

Instead of committing to one segmentation, generate multiple figure-ground hypotheses

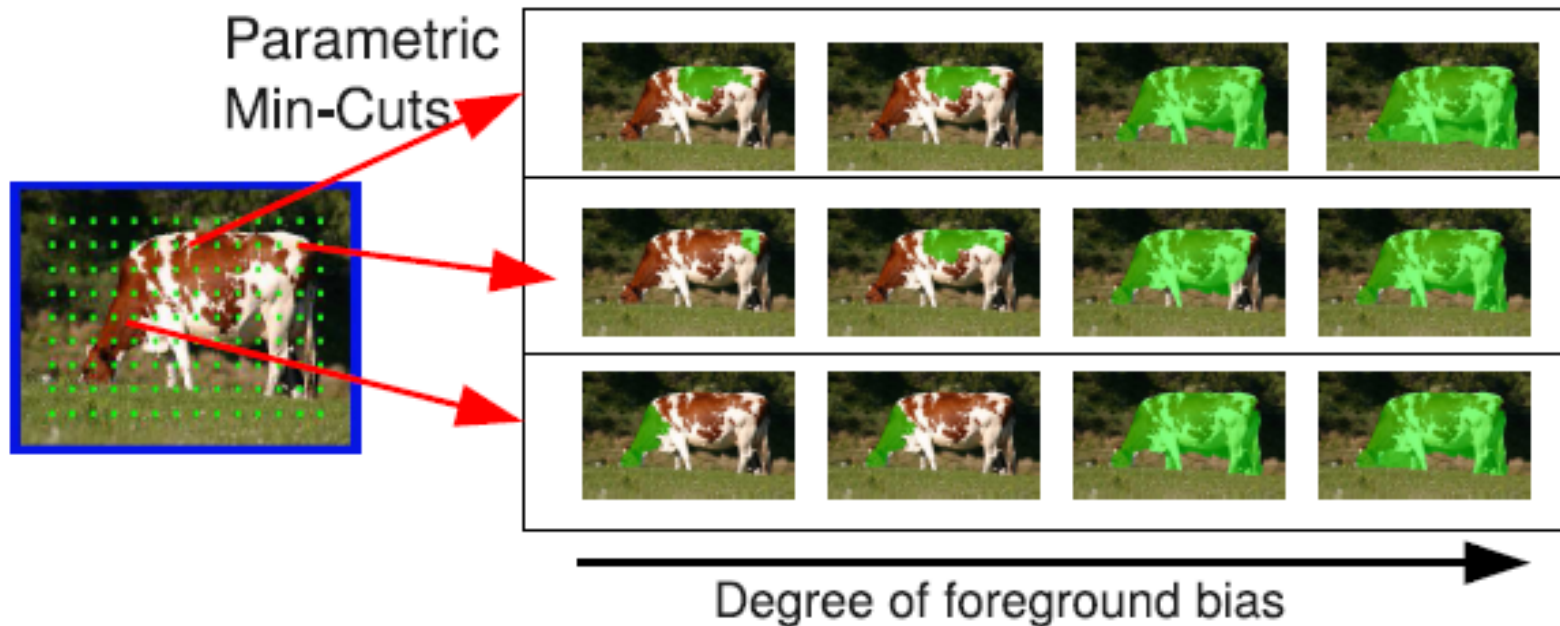


*The challenge is to pull out good segments*

# Constrained Parametric Min-Cuts

$$E(A) = \lambda R(A) + B(A)$$

Design region term in such a way that  $\lambda$  represents the degree of foreground bias (foreground scale)

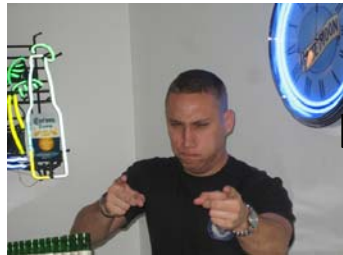


- Solve sequence of constrained min-cut problems on regular grid of seeds. Search for all breakpoints using parametric max flow
- Filter solutions with large spatial overlap (small segments co-exist, notice that the method *does not* particularly favor large segments)





# Computational pipeline



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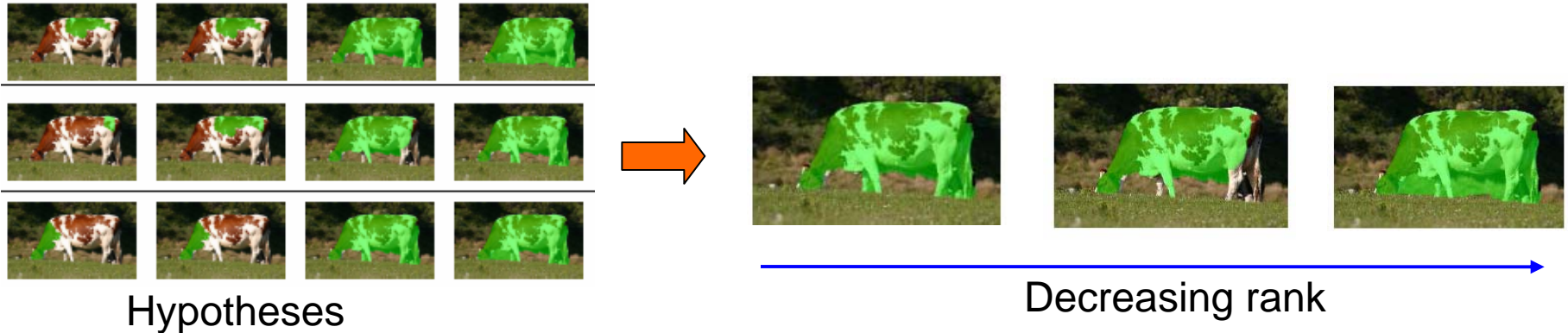
- Select segment/class with highest score
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*Sequentially add segments*

Only segmentation labeling used for training/testing. No bounding box information/calculation.

# Ranking figure-ground hypotheses



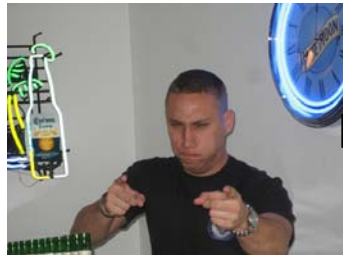
- Hypothesized segments ranked using regression
- Ranking is class-independent (mid-level)
- Features (~2500)
  - *Boundary* – cut, ratio cut, normalized cut
  - *Region* – location, perimeter, area, Euler number, orientation
  - *Gestalt* – convexity, smoothness, symmetry
  - *Appearance/Shape* –BOW, HOG

# Highest ranked segment hypotheses



We learn to discard homogenous `non object-like' segments

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*Sequentially add segments*

Only segmentation labels used for training/testing. No bounding box information/calculation.

# Prediction of segment overlap to class-object

- Support Vector Regression framework
- Each regressor is trained to estimate overlap of foreground segment with object of its class
- Trained with all generated figure segments. For each class, the output training scores of segments that only overlap with other classes (or background) are set to 0



Dataset has plenty of partial views

Training image



Bus: 1.2530



Bus: 0.7462

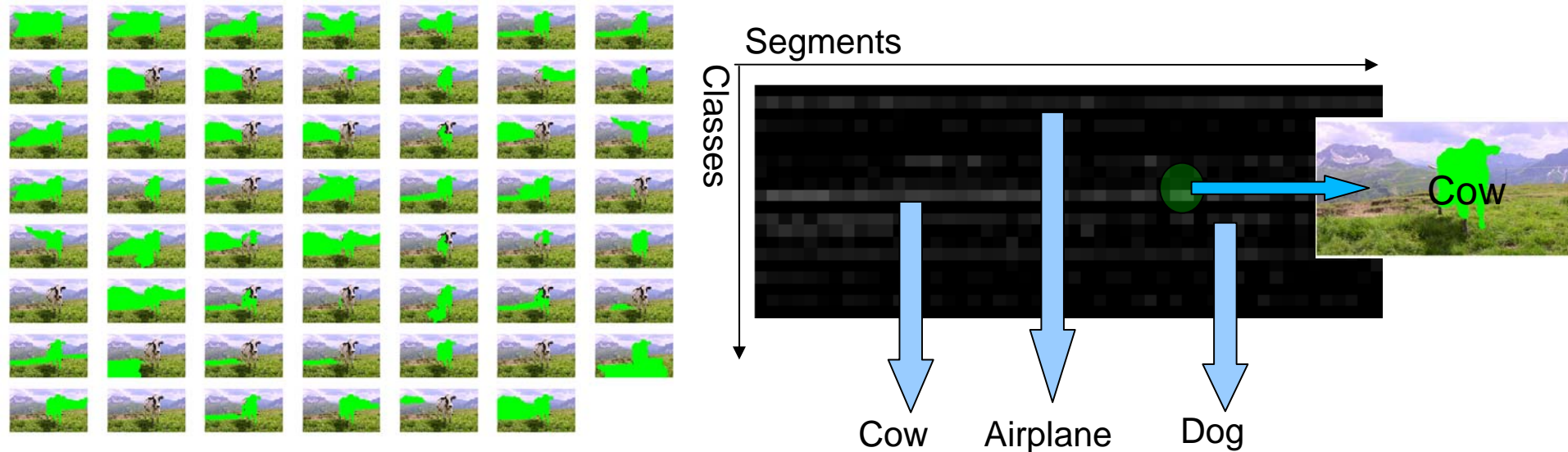


Bus: 0.4332



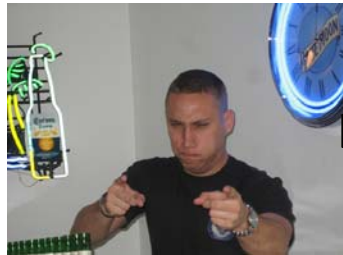
Bus: 0.2081

# Prediction of segment overlap to each object class



- One predictor for all visual aspects of each class, evaluates only regions that can plausibly contain objects of interest
- Shape and appearance features on both segment/foreground and background (contour and internal BOW SC, HOG, CSIFT)
- MKL regression framework (8 kernels)

# Computational pipeline



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*Sequentially add segments*

Only segmentation labels used for training/testing. No bounding box information/calculation.

# Increasing segmentation robustness

- Find k other segments with largest overlap, from the class of top-scoring segment
- Generate final solution by weighted combination



Cow: 0.2836 Dog: 0.1496



Cow 0.3062 Dog: 0.1460



Cow: 0.2971 Airplane 0.1847



Cow: 0.2960 Airplane: 0.1786



Cow 0.2830 Horse 0.1532

On each pixel: weighted  
sum of scores



Cow: 0.89276



# Sequential segment classification



Segment #1:  
TV/Monitor 1.6037



Segment #2:  
TV/Monitor 1.7132



Segment #3:  
TV/Monitor 1.3615



Segment #4:  
Chair 0.50904

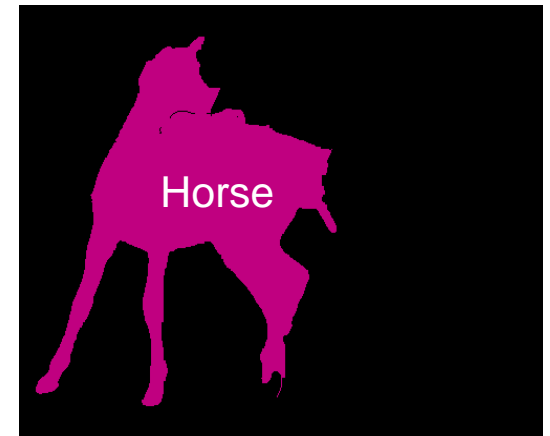
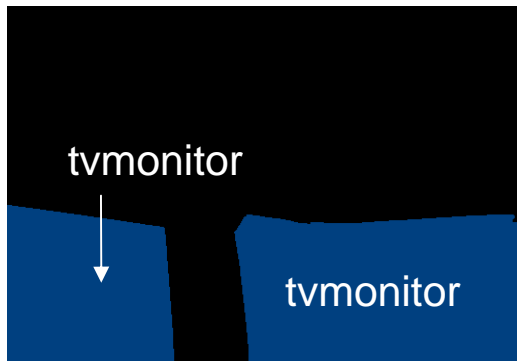


Learned threshold

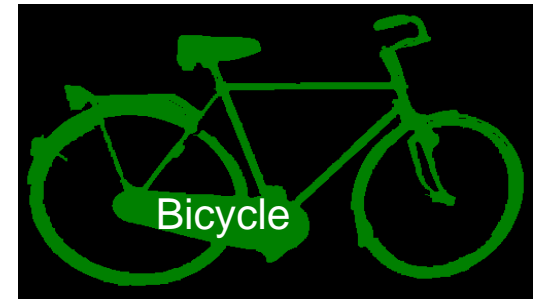
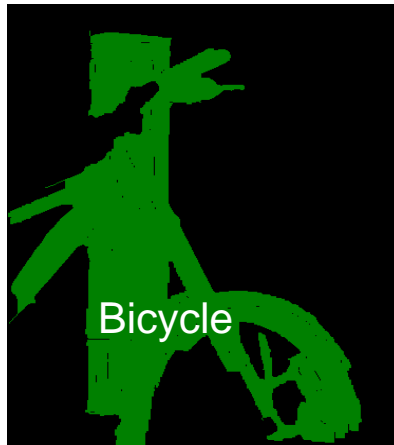


After combination

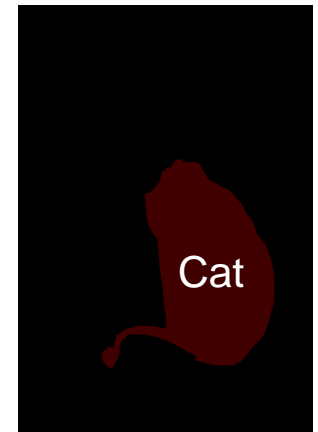
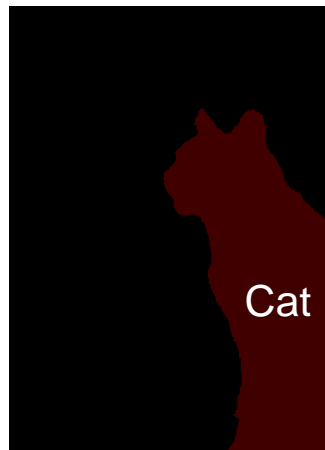
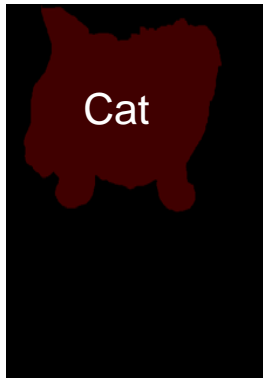
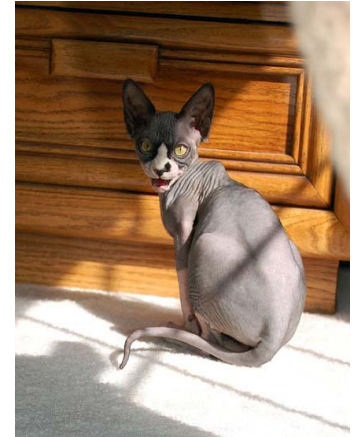
# Results: success stories



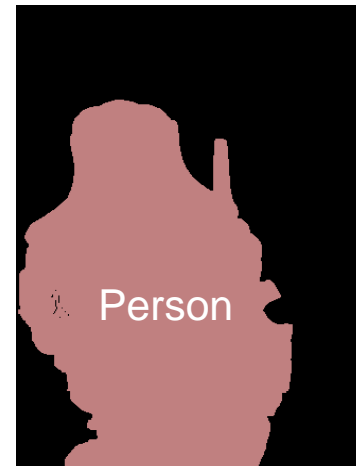
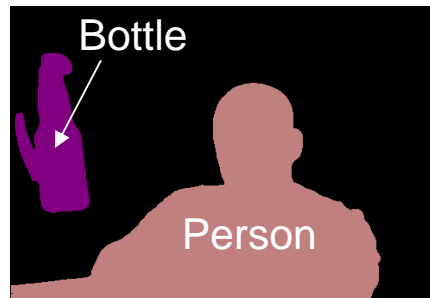
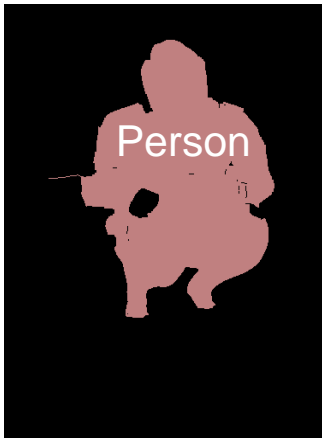
# Success stories – bikes and motorbikes



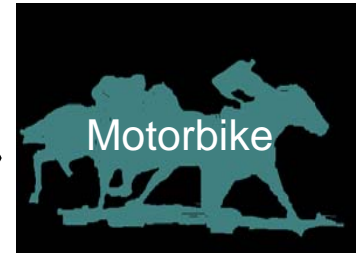
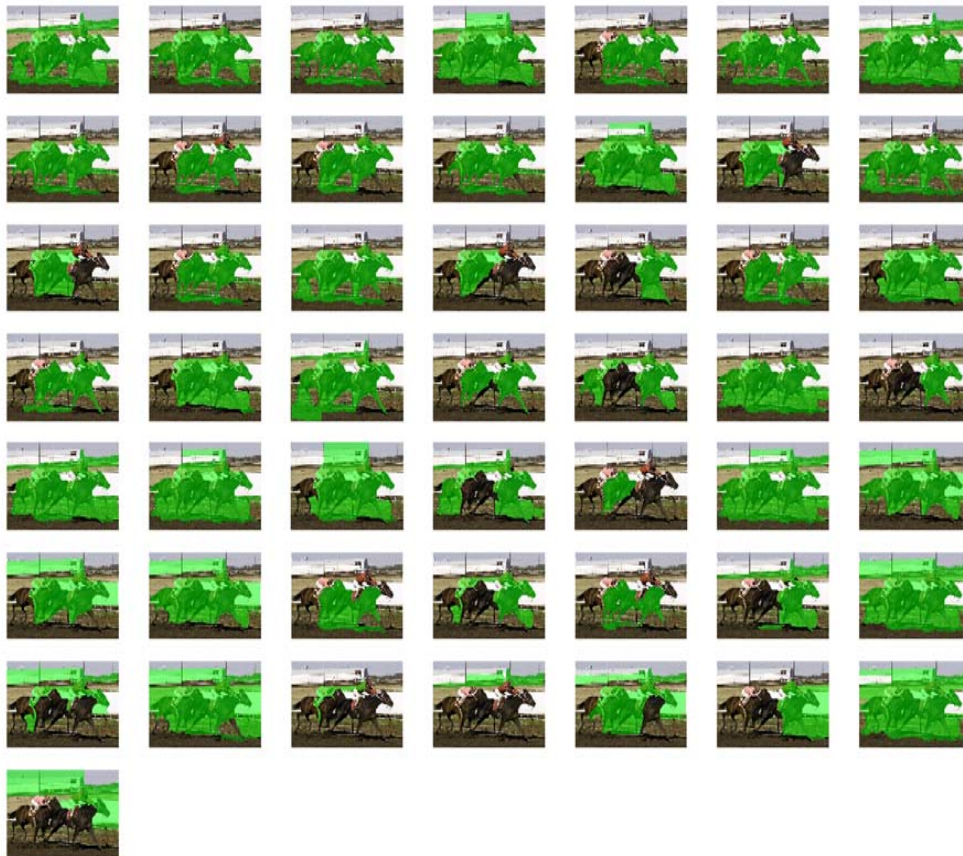
# Success stories - cats



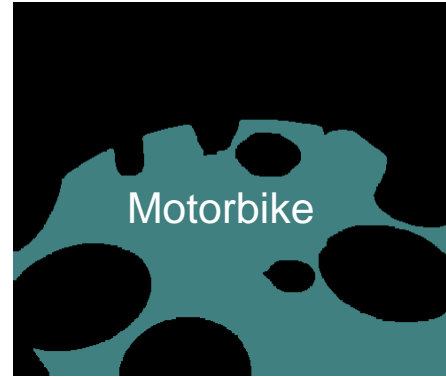
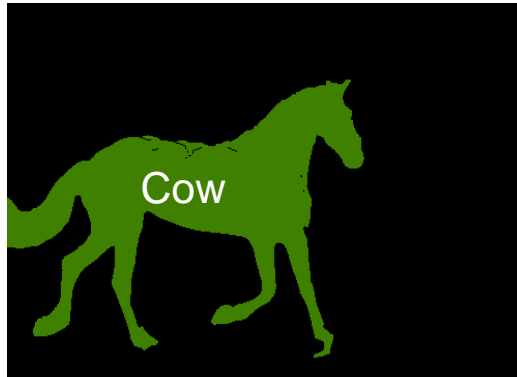
# Success stories - people



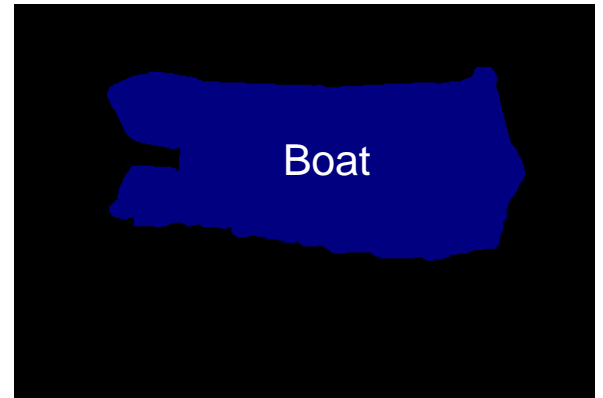
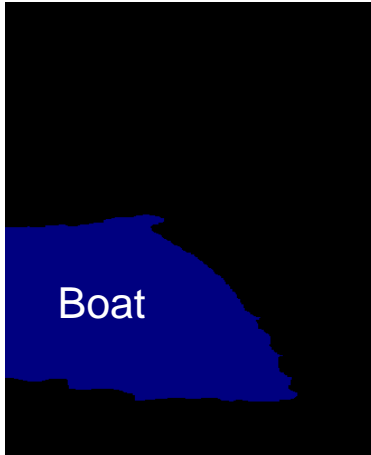
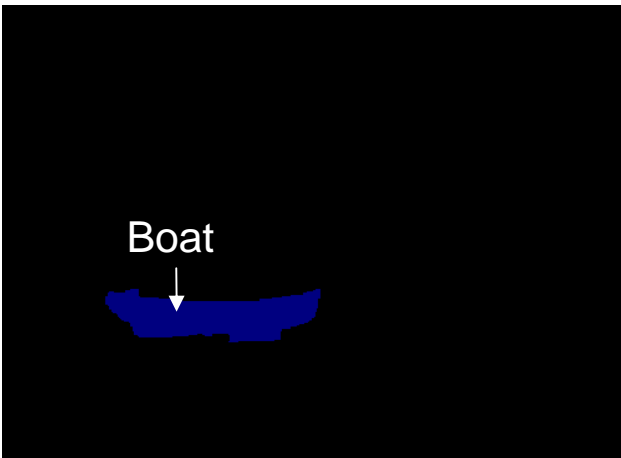
# Failure modes - wrong segments



# Failure modes - wrong classification



# A peculiarity - reflections





# Discussion

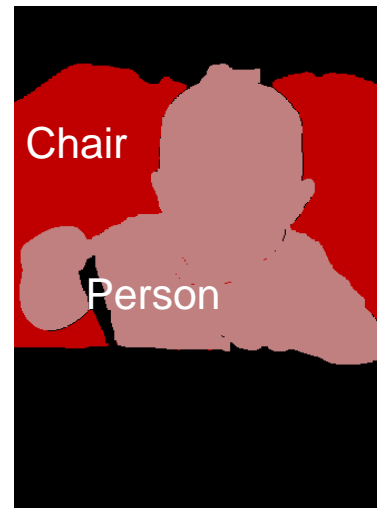
## Pros

- Small number of classification decisions
- Can use global object shape features
- Context as additional feature
- One regressor for all visual aspects of each category
- Learn partial object views from full views



## Cons

- Reliant on reasonable segmentability
- May learn “intertwined” object classes – people on horses and bikes. Depending on the goal, this can be a feature...



# Conclusions

- Segmentation-recognition pipeline
  - Ranking and sequential classification of multiple segmentation hypotheses, generated using Constrained Parametric Minimum Cuts (CPMC)
- Winning segmentation entry in VOC 2009
- Future work
  - Integrate information from bounding box detectors
  - Closer integration of learning in the segmentation-recognition loop