

# Combining Generative and Discriminative Approaches for Visual Object Class Detection

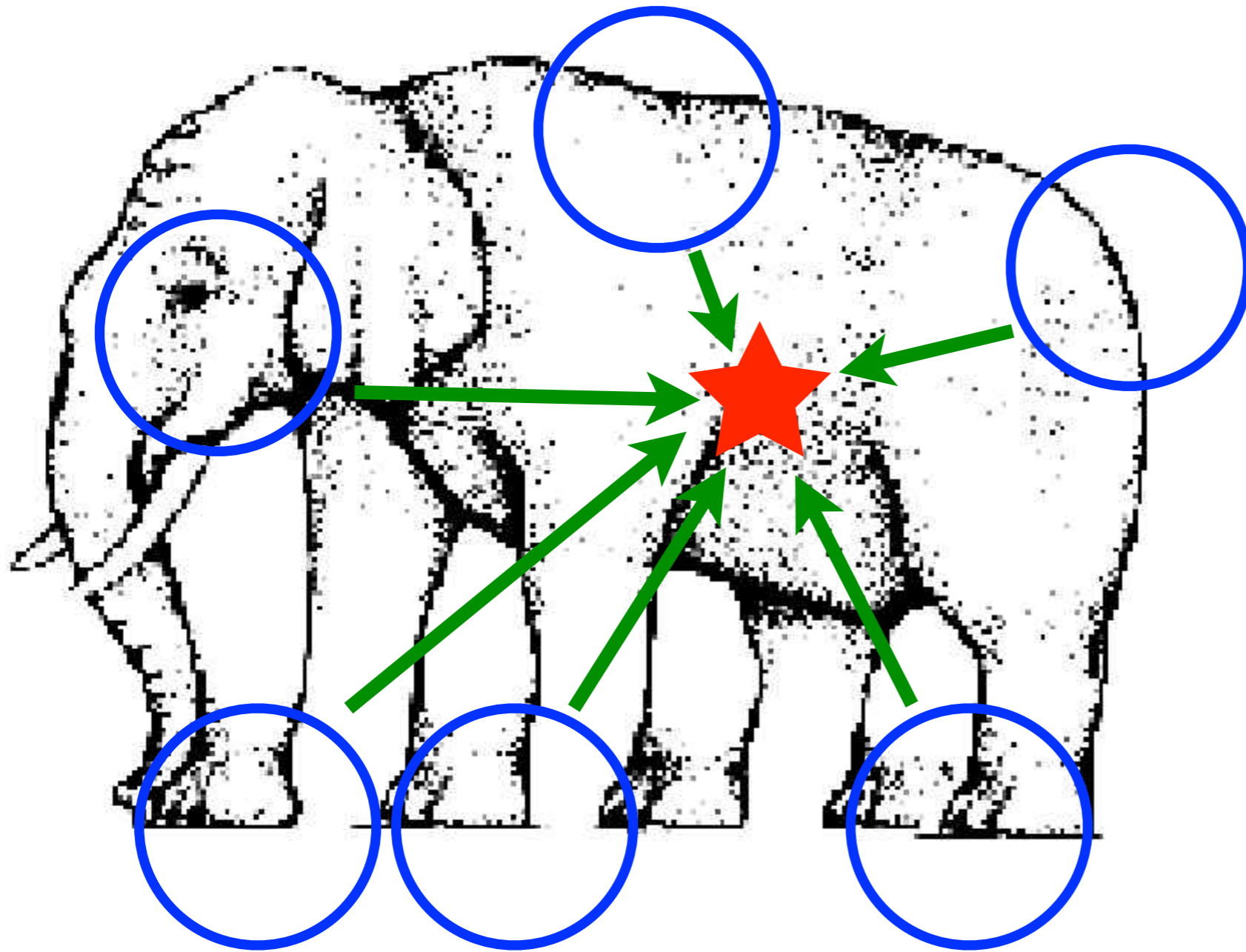
Mario Fritz

# Overview

## Lecture on 3rd March

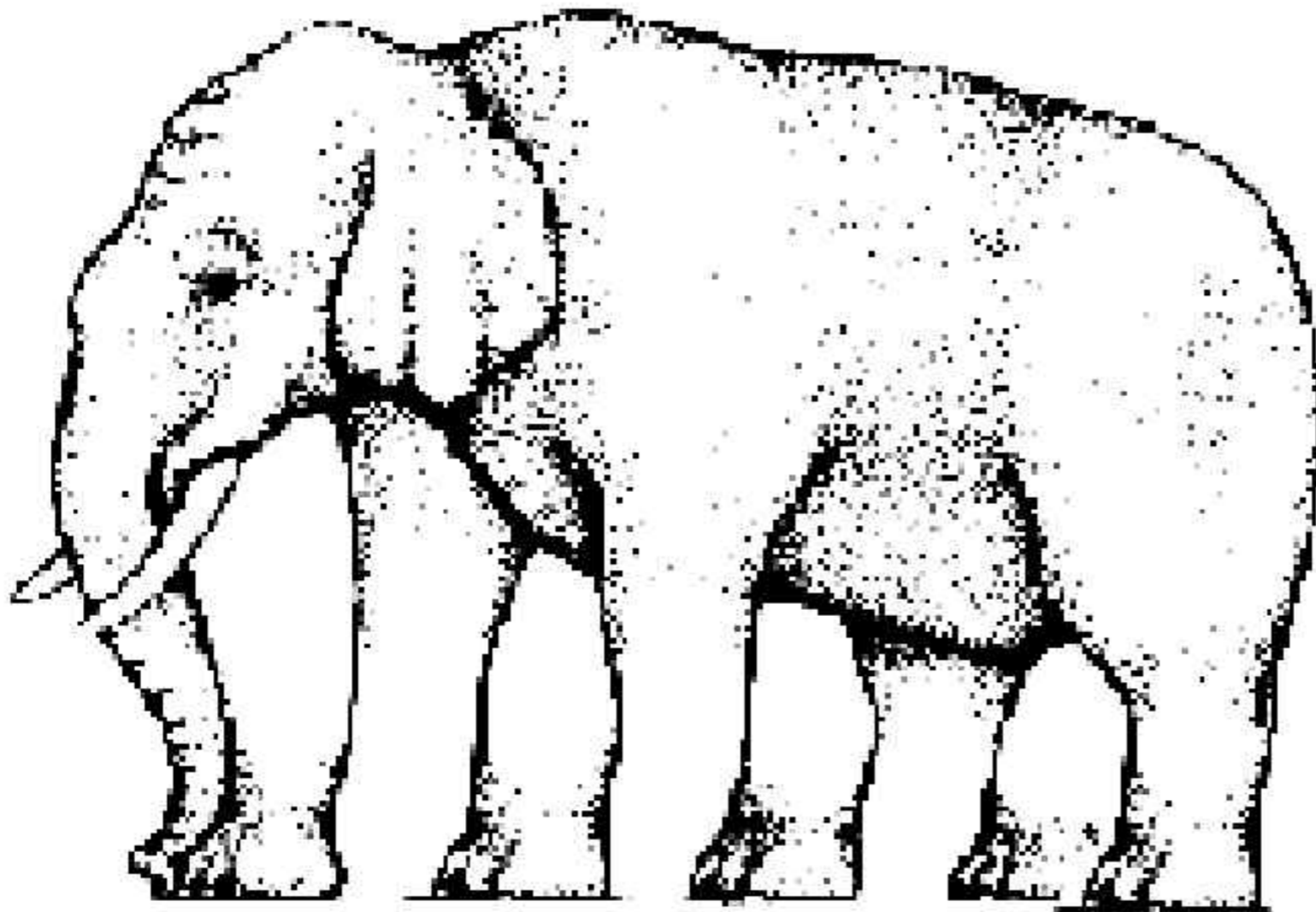
- Motivation from last lecture
  - local vs. global problem
- Recovering global consistency
  - global silhouette verification
- Adding discriminance to the model
  - generative/discriminative model

# Complexity of Recognition: Local vs. Global

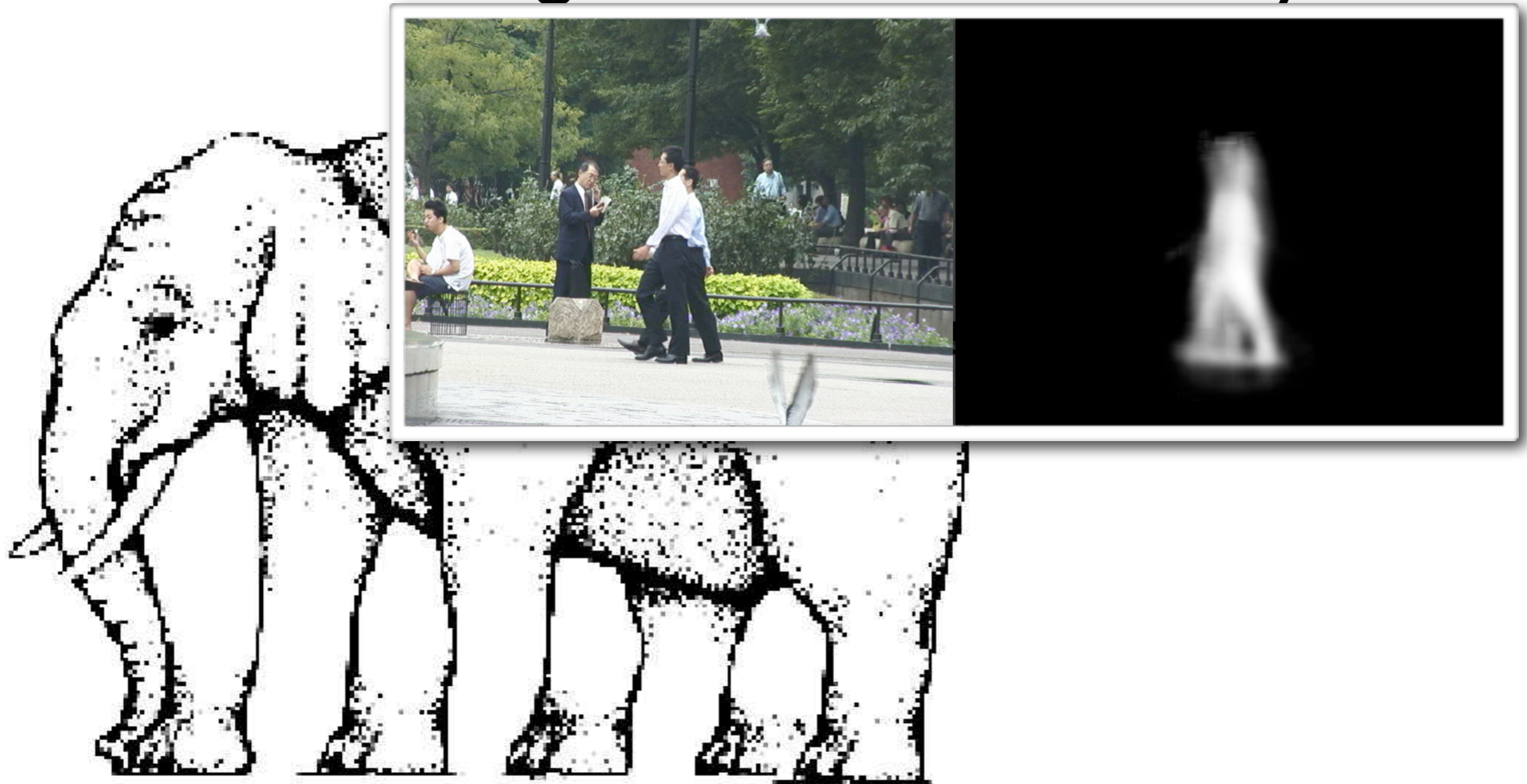


star model

# Complexity of Recognition: Local Voting vs. Global Consistency

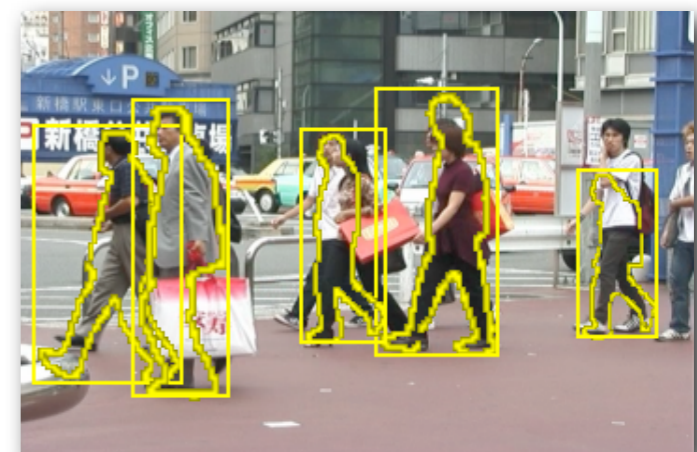
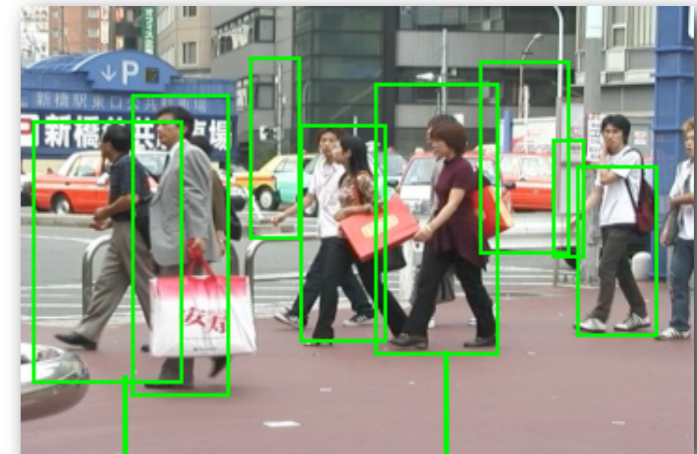


# Complexity of Recognition: Local Voting vs. Global Consistency

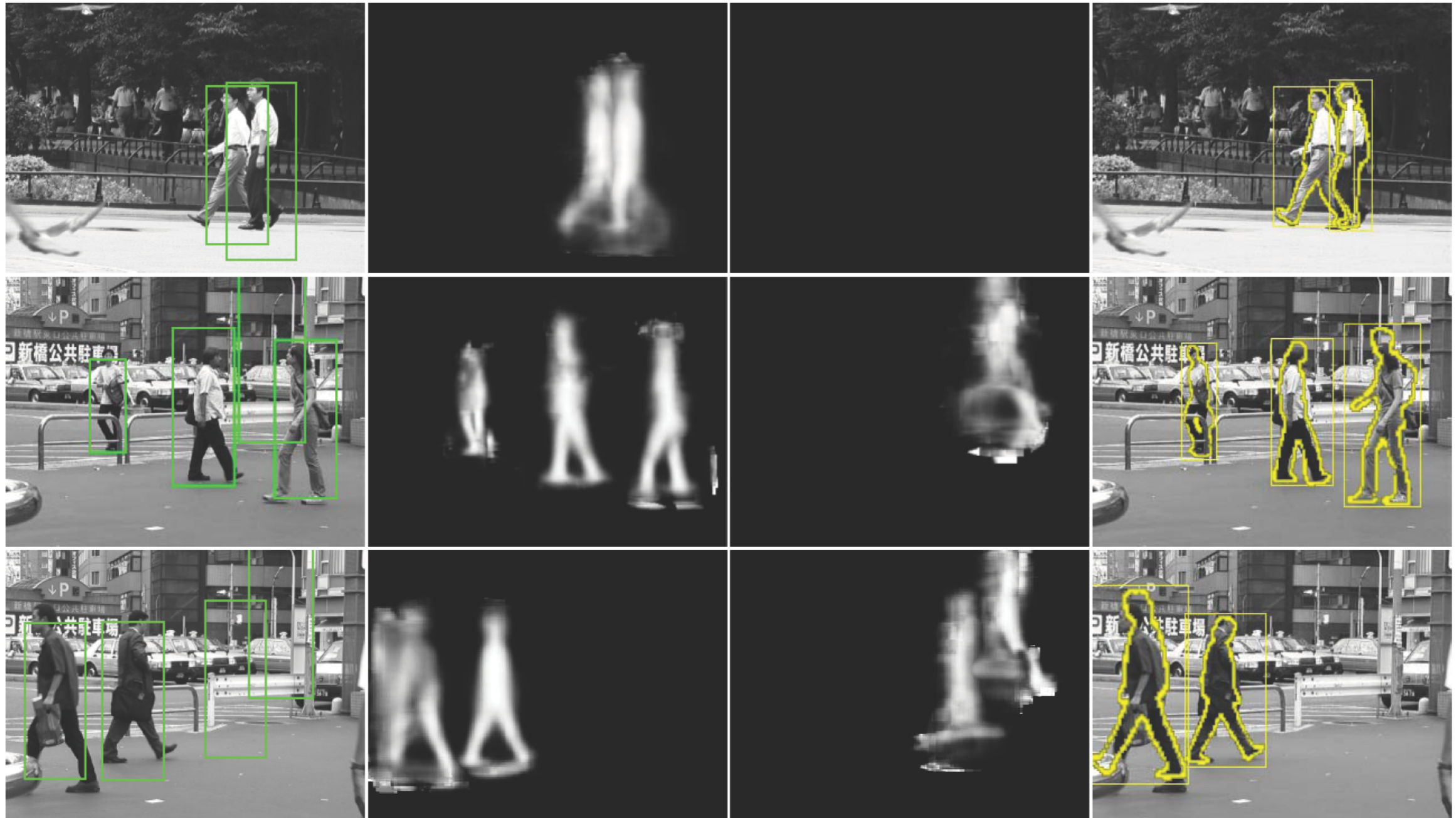


## Global Silhouette Verification [Leibe@CVPR05]

- Initial hypotheses from local features
  - ▶ Implicit Shape Model
- Top-down segmentation for each hypothesis
- Verification using segmentations and global silhouettes
  - ▶ Chamfer verification
  - ▶ Shape constraints for articulated objects



# Effect of the Verification Stage



## Detections at EER [Leibe@CVPR'05]

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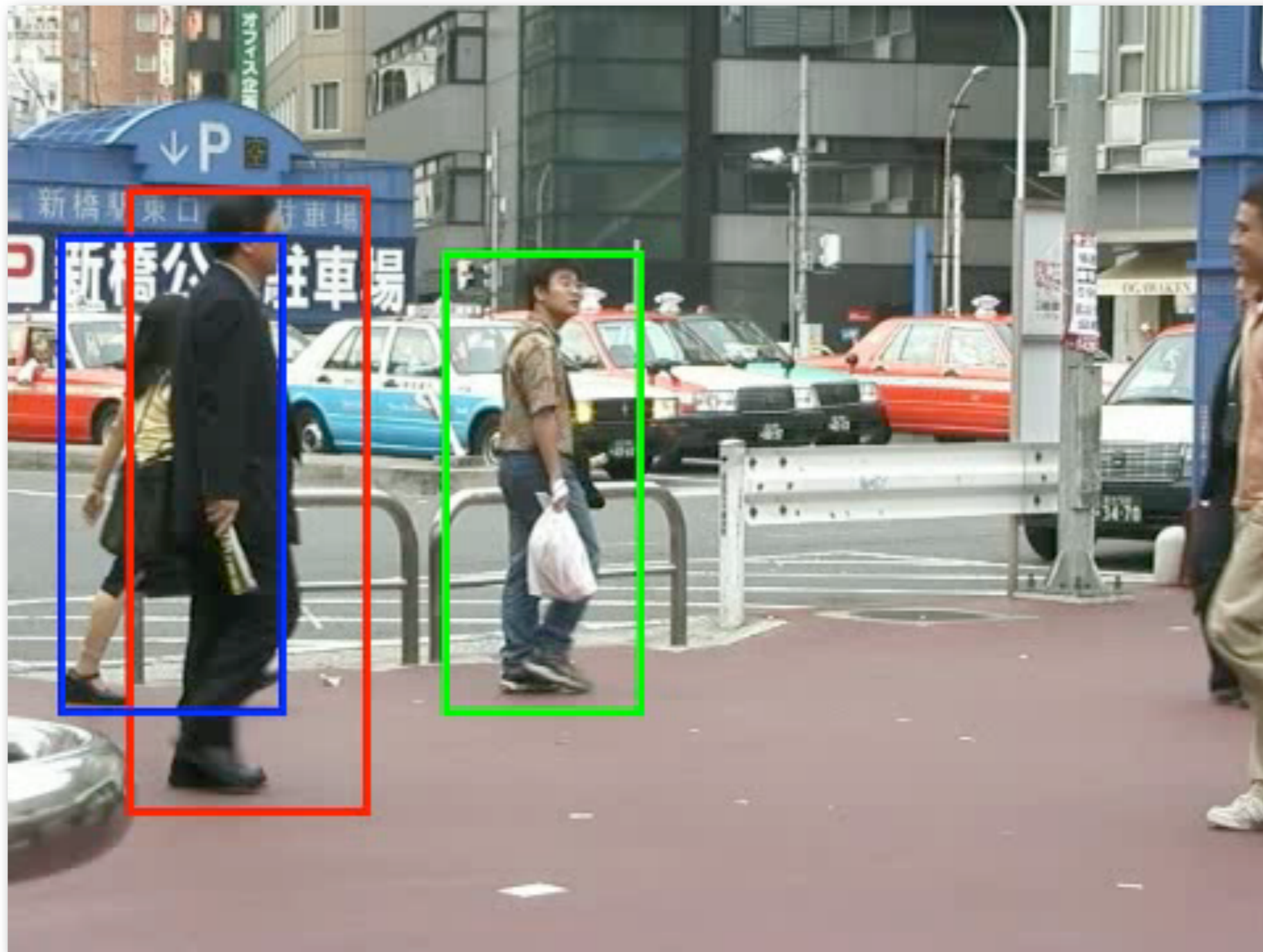


Single-frame detection - no temporal continuity used!



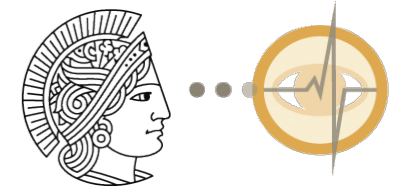
# Tracking individual people... [Seemann, Fritz@CVPR'07]

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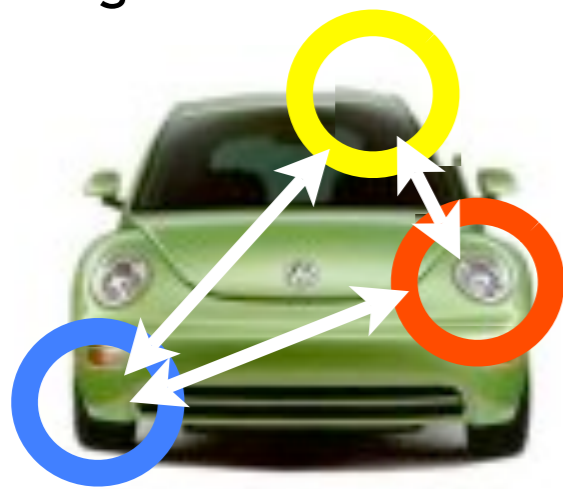
# Combining Generative ISM detector with discriminant SVM

[Fritz'05]



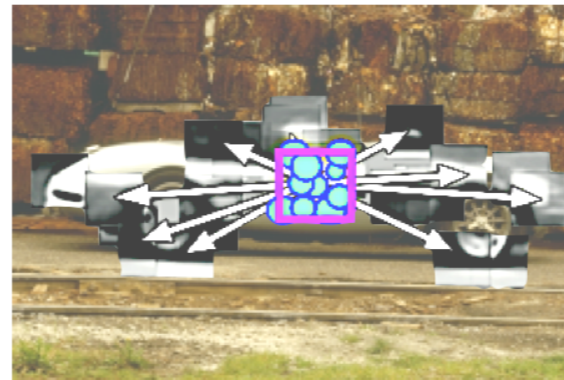
# Modeling Paradigms: Generative vs. Discriminative

Burl'98  
Weber'00 & Perona  
Fergus'03



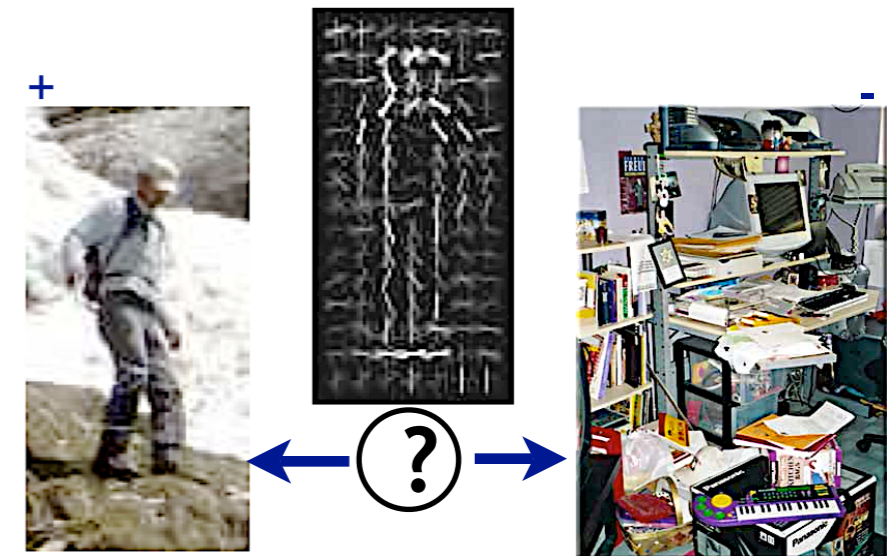
constellation model  
(fully connected)

Leibe'04 & Schiele



implicit shape model  
(star topology)

e.g. Dalal'05, Viola'01



generic SVM,  
Boosting

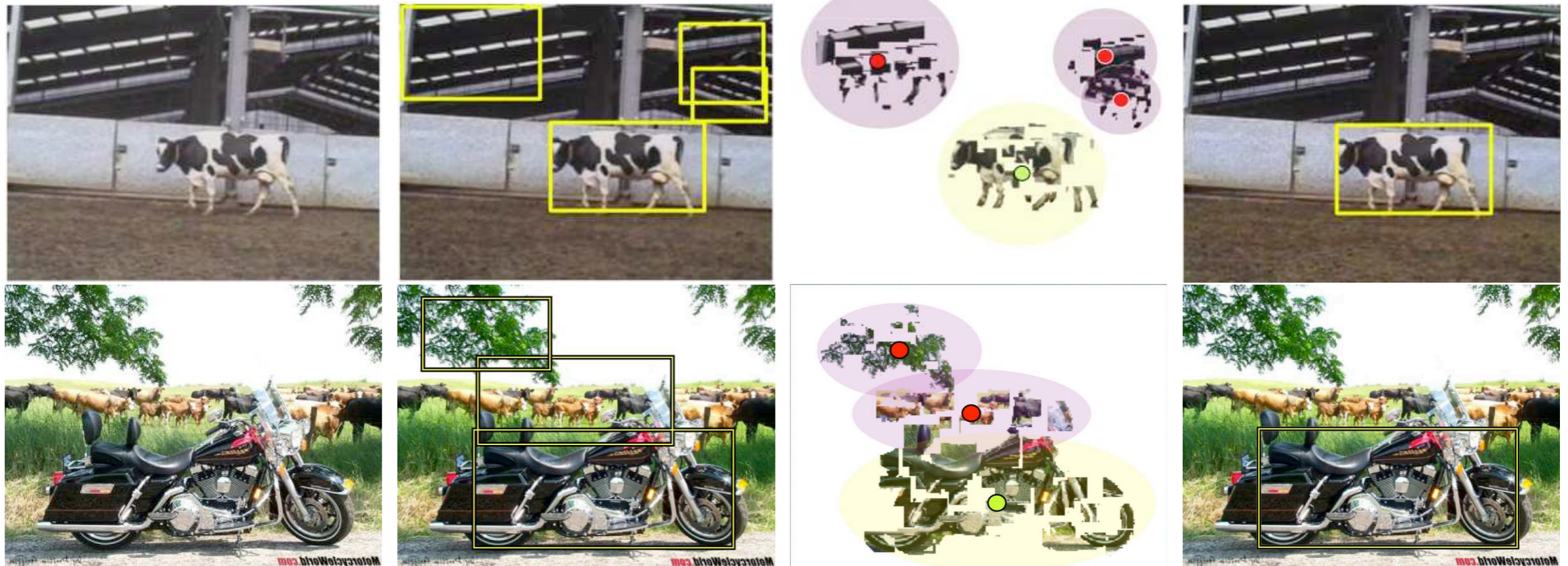
generative model

discriminative model

+ parallel, treat missing data  
- often slow inference

+ focus on differences, precision  
- often large training sets required

# Generative/Discriminative Training [Fritz@ICCV05]



training ISM  
[Leibe04]

detect on  
train/validation  
(generative)

train classifier on  
true/false positive  
(discriminative)

improved  
detector  
(hybrid)

- Ideas:

- ▶ good generalization of generative detector + precision of discriminant classifier
- ▶ simplifying learning problem of classifier (localization, scale, background)
- ▶ sampling structures that get confused

## Local Kernel SVM

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- kernel to match sets of local features [Wallraven03, Caputo04]

$$K(X, Y) = \frac{1}{k} \max_{\Phi, \Psi} \sum_{j=1}^k K_l \left( \left( \vec{x}_{\Phi(j)}, \lambda_{x, \Phi(j)} \right), \left( \vec{y}_{\Psi(j)}, \lambda_{y, \Psi(j)} \right) \right)$$

The diagram shows the equation  $K(X, Y) = \frac{1}{k} \max_{\Phi, \Psi} \sum_{j=1}^k K_l \left( \left( \vec{x}_{\Phi(j)}, \lambda_{x, \Phi(j)} \right), \left( \vec{y}_{\Psi(j)}, \lambda_{y, \Psi(j)} \right) \right)$  with several annotations. A purple arrow points from the text 'maximum over permutations' to the  $\max_{\Phi, \Psi}$  term. A green arrow points from the text 'local feature similarity kernel' to the  $K_l$  term. Two red arrows point from the text 'patch' to the  $\vec{x}_{\Phi(j)}$  and  $\vec{y}_{\Psi(j)}$  terms. Two blue arrows point from the text 'position' to the  $\lambda_{x, \Phi(j)}$  and  $\lambda_{y, \Psi(j)}$  terms.

- greedy approximation of maximum/matching
  - non-mercer kernel
  - but in setting used in practice, kernel matrix is positive definite [Boughorbel04]
-

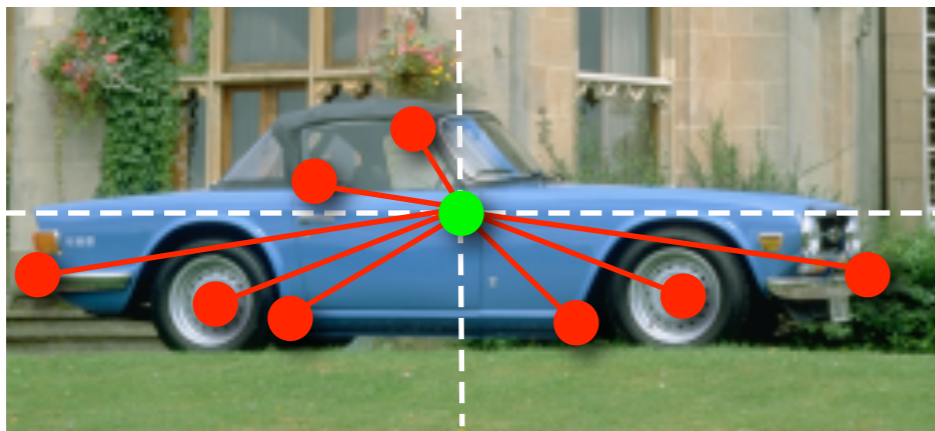
## Local Kernel SVM (2)

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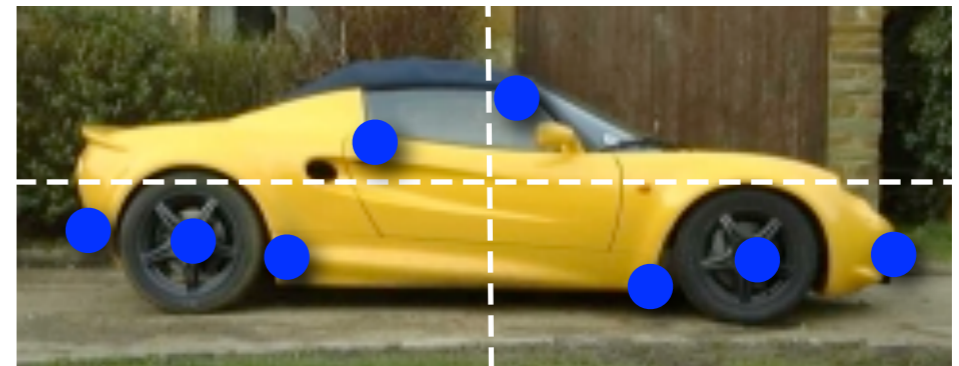
- uses local features similarity kernel:

$$K((\vec{x}, \lambda_x), (\vec{y}, \lambda_y)) = \underbrace{\exp(-\gamma(1 - \langle \vec{x}, \vec{y} \rangle))}_{\text{appearance similarity}} \underbrace{\exp\left(-\frac{(\lambda_x - \lambda_y)^2}{2\sigma^2}\right)}_{\text{position constraint}}$$

- we evaluated directly on codebook representation
  - ▶ across instance learning
- strong shape model
- constraints extends also to relative scale



$X$



$Y$

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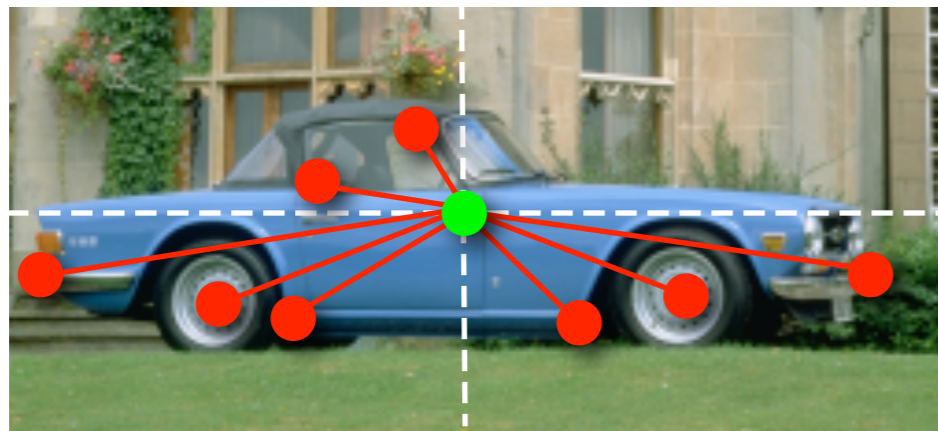
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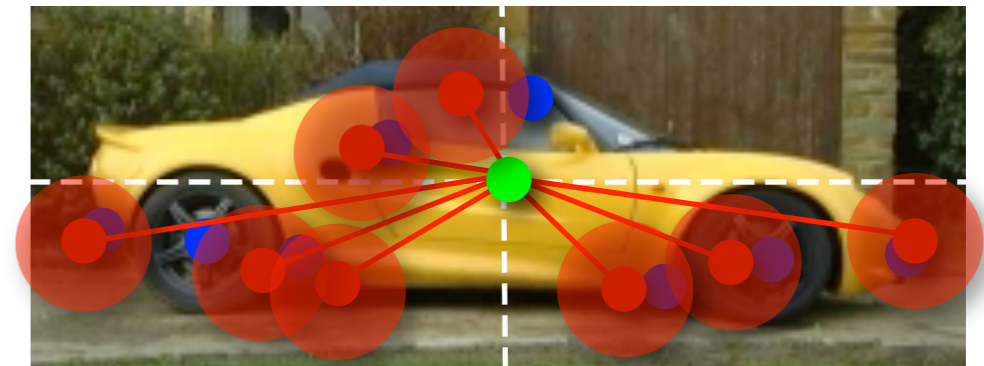
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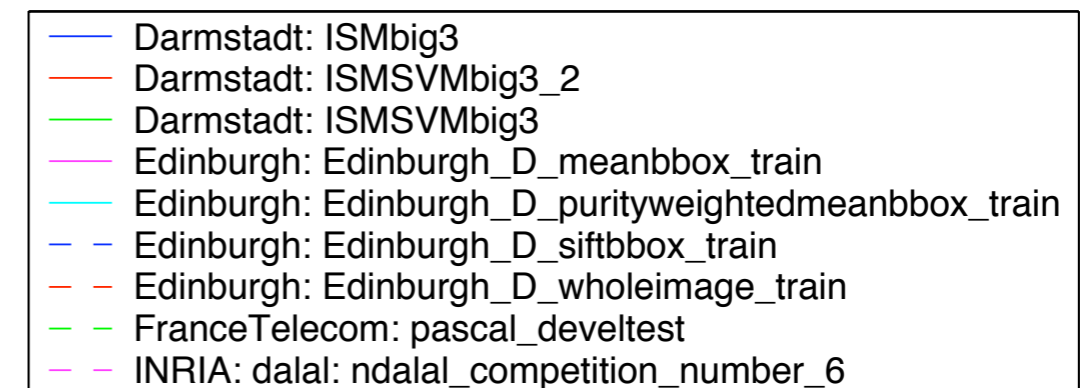
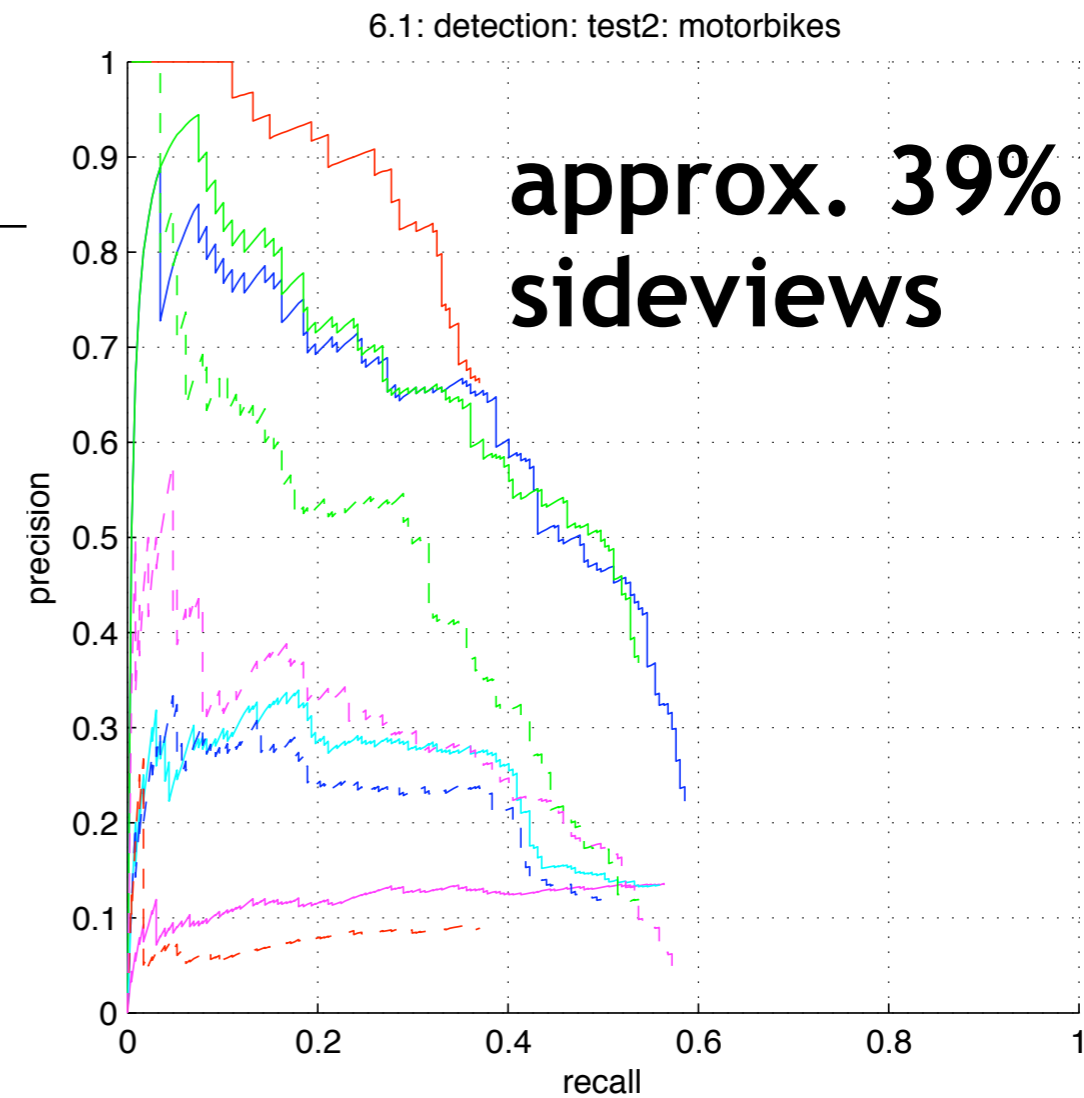
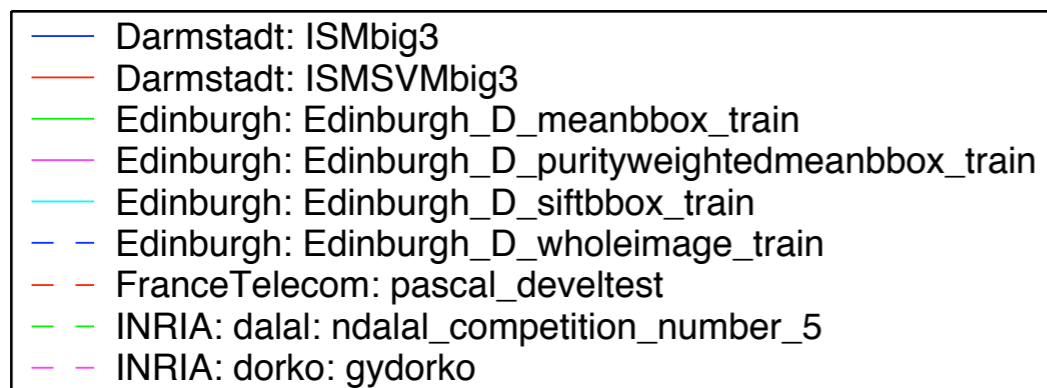
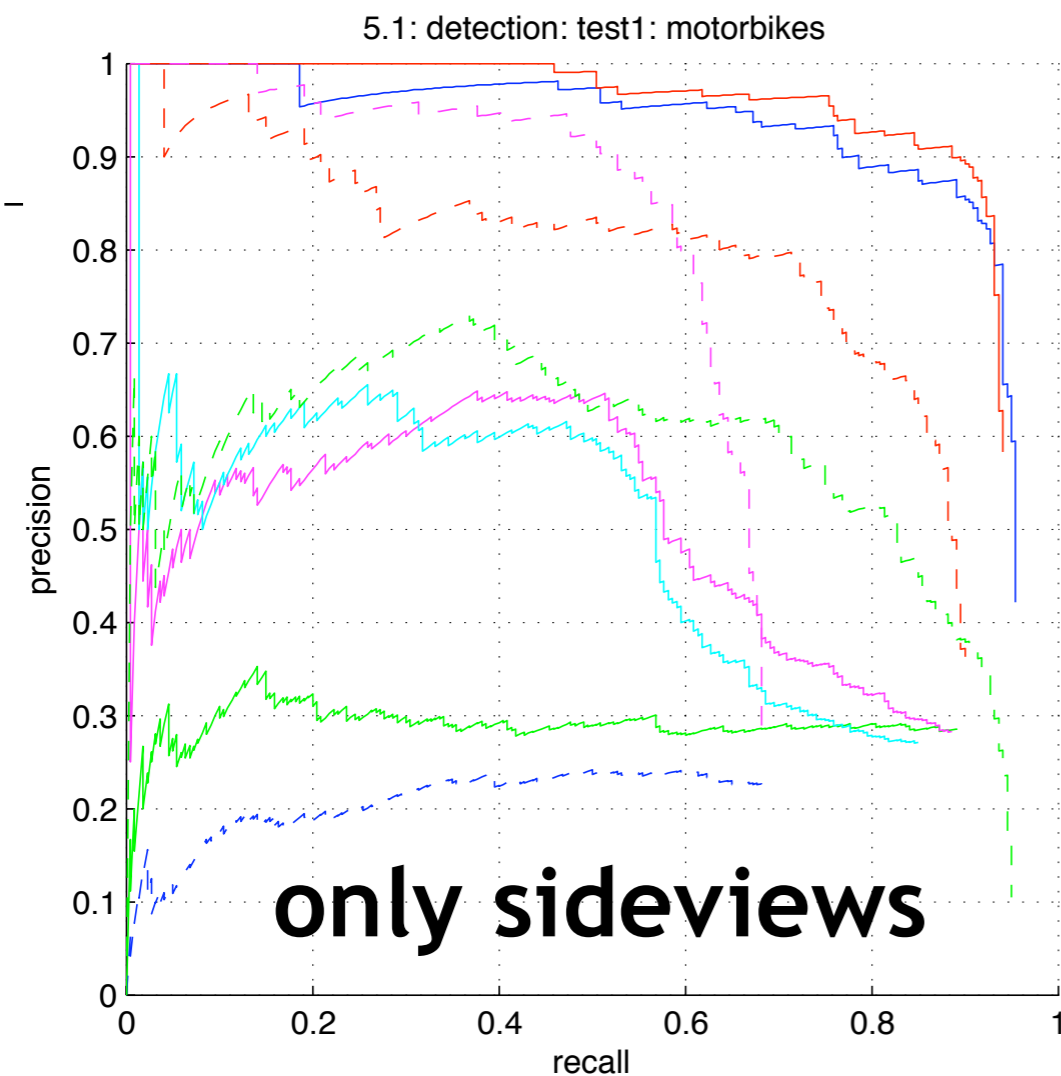
$X$



$Y$

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# Results of Motorbike Detector

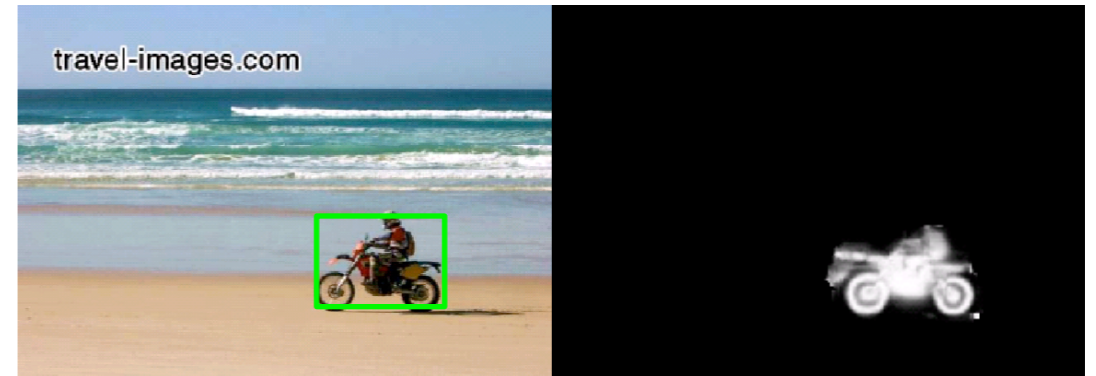
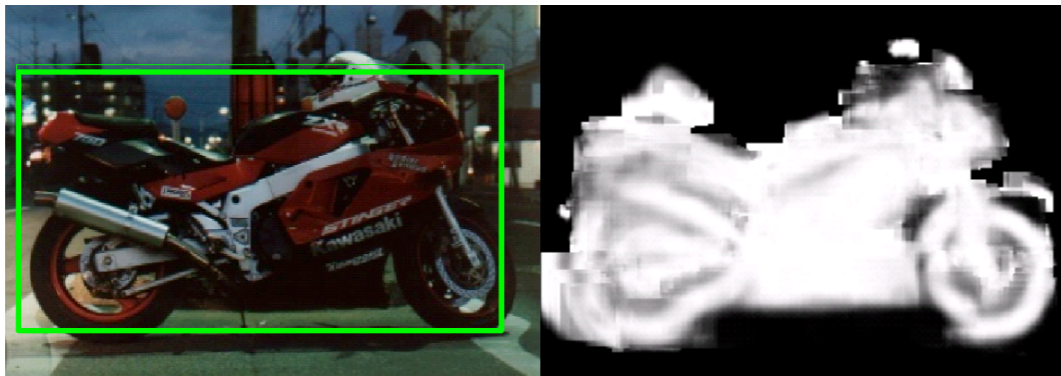
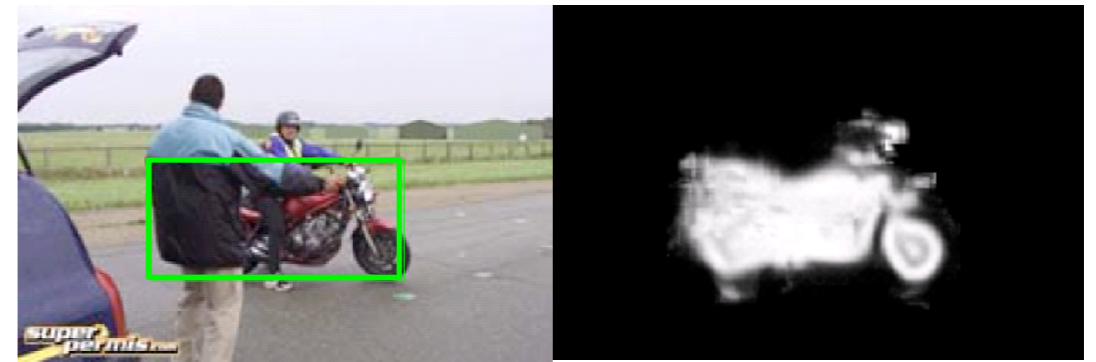
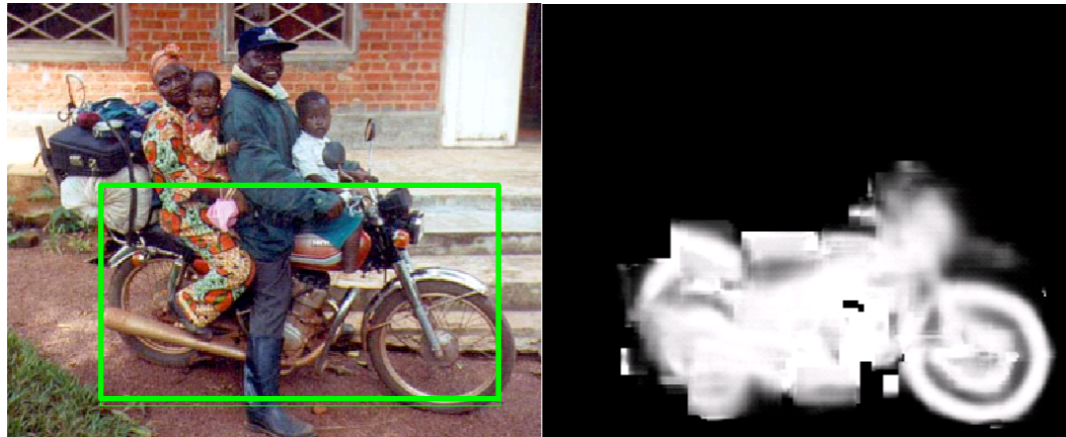


- SVM adds desired precision to ISM
- high precision and recall for sideviews

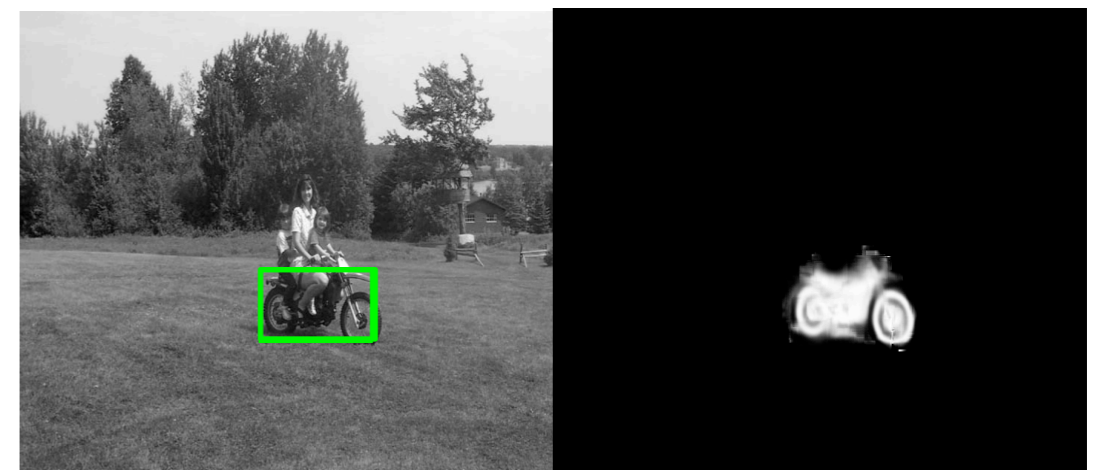
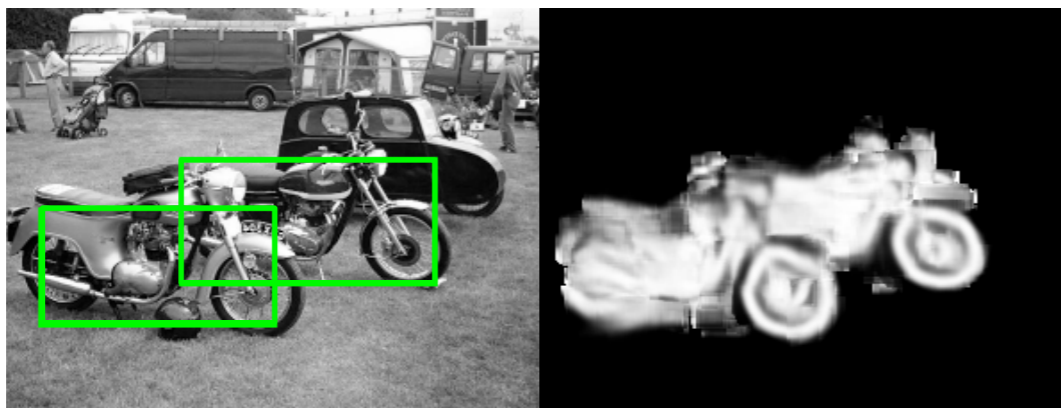


# Motorbike Detection/Segmentation on Pascal05

test 2

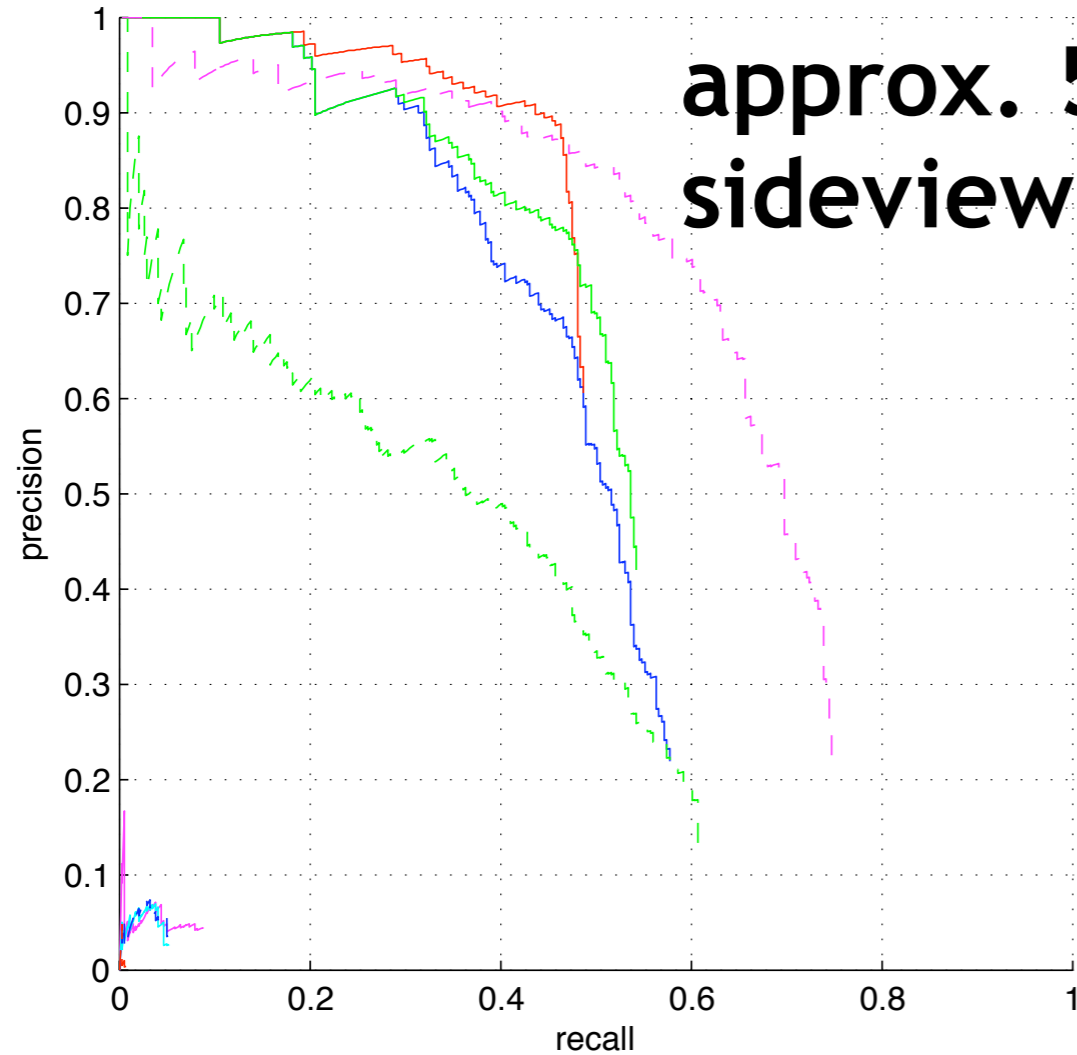


test 1

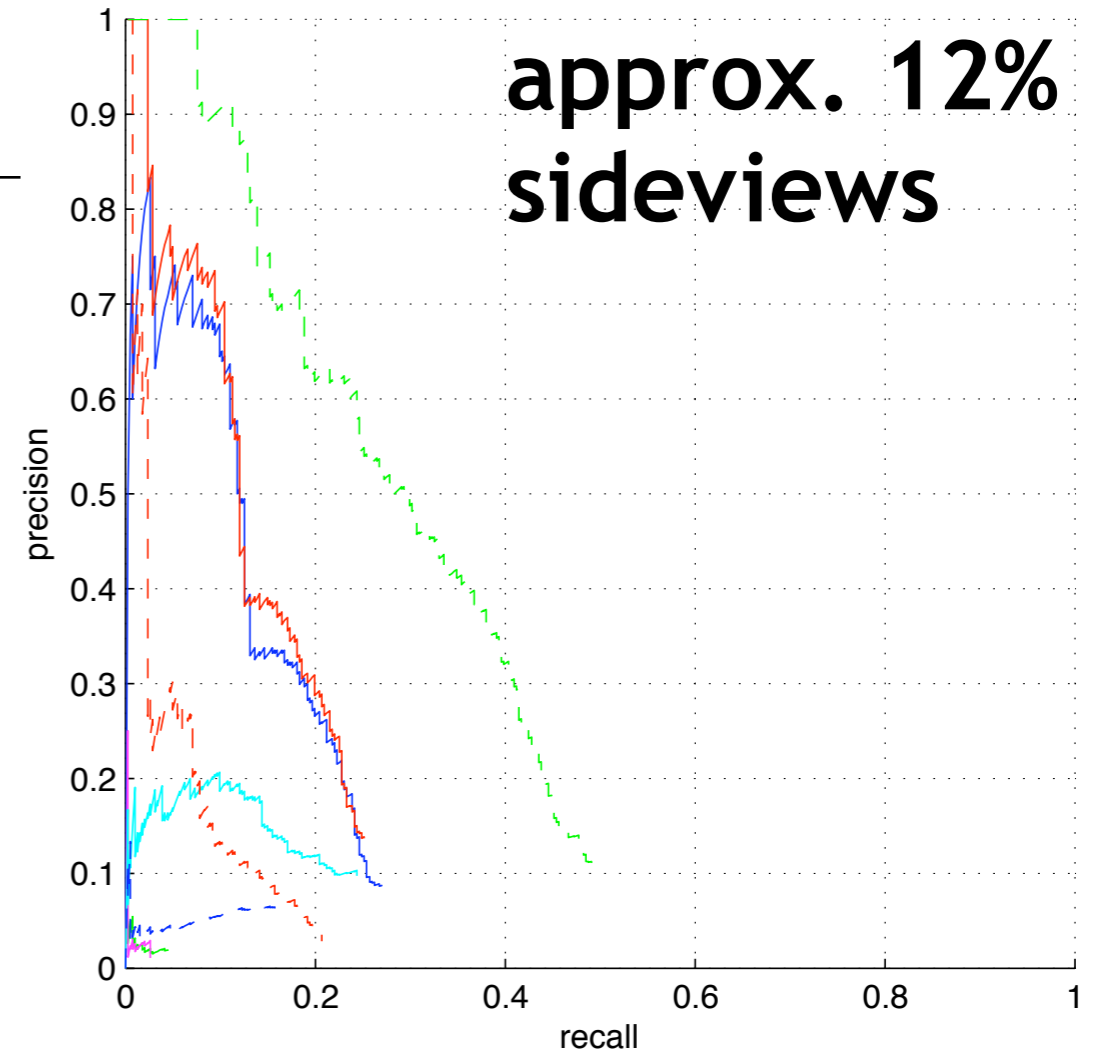


# Results on Car Detection

5.4: detection: test1: cars



6.4: detection: test2: cars



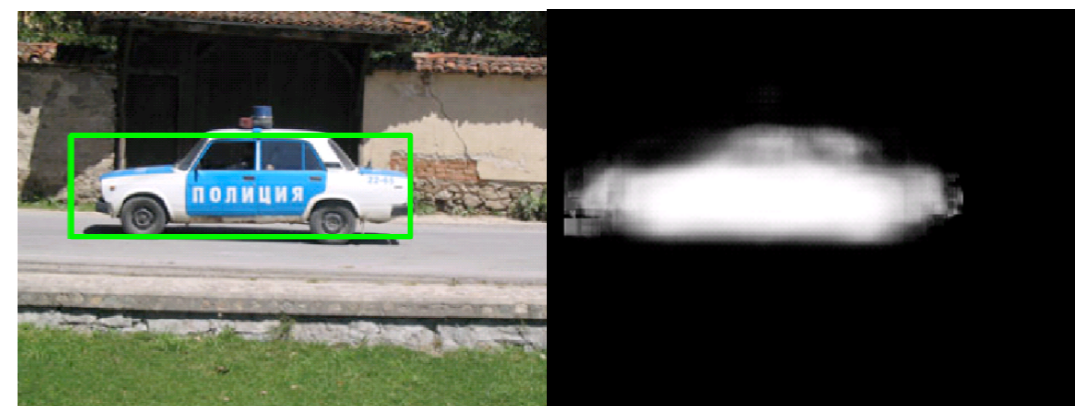
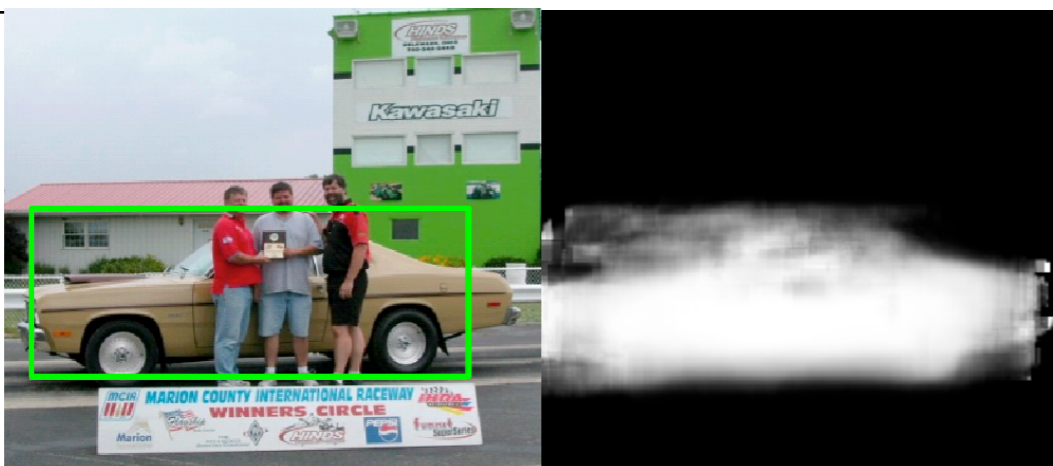
- Darmstadt: ISMbig4
- Darmstadt: ISMSVMbig4\_2
- Darmstadt: ISMSVMbig4
- - Edinburgh: Edinburgh\_D\_meanbbox\_train
- Edinburgh: Edinburgh\_D\_purityweightedmeanbbox\_train
- - Edinburgh: Edinburgh\_D\_siftbbox\_train
- - Edinburgh: Edinburgh\_D\_wholeimage\_train
- - FranceTelecom: pascal\_develtest
- - INRIA: dalal: ndalal\_competition\_number\_5

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- - Edinburgh: Edinburgh\_D\_wholeimage\_train
- - FranceTelecom: pascal\_develtest
- - INRIA: dalal: ndalal\_competition\_number\_6

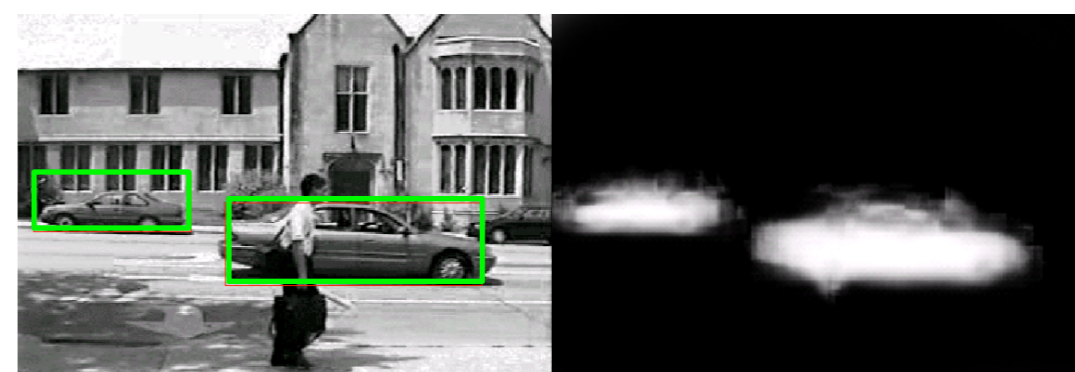
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# Car Detection/Segmentation on Pascal05

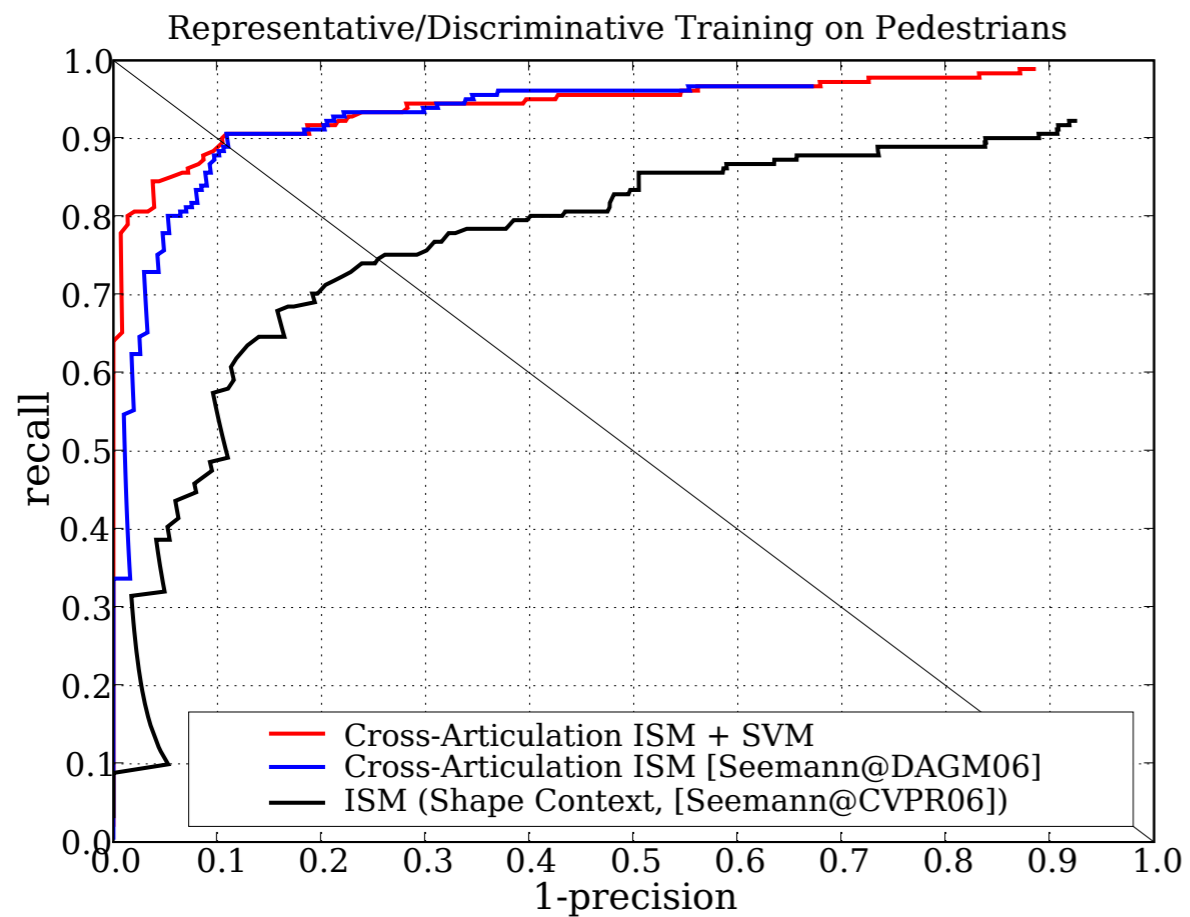
test 2



test 1



# Improving Pedestrian Detection by Generative/ Discriminant Training



- single shot/no groundplane
- improved precision
- first false positives at 65% recall

