Implicit Shape Model

[Leibe,Schiele04]

Mario Fritz

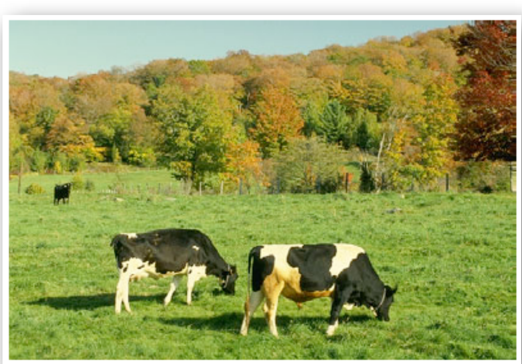
Object Categorization in Real-World Scenes

- How to recognize ANY car





- How to recognize ANY cow




Object Categorization and Segmentation

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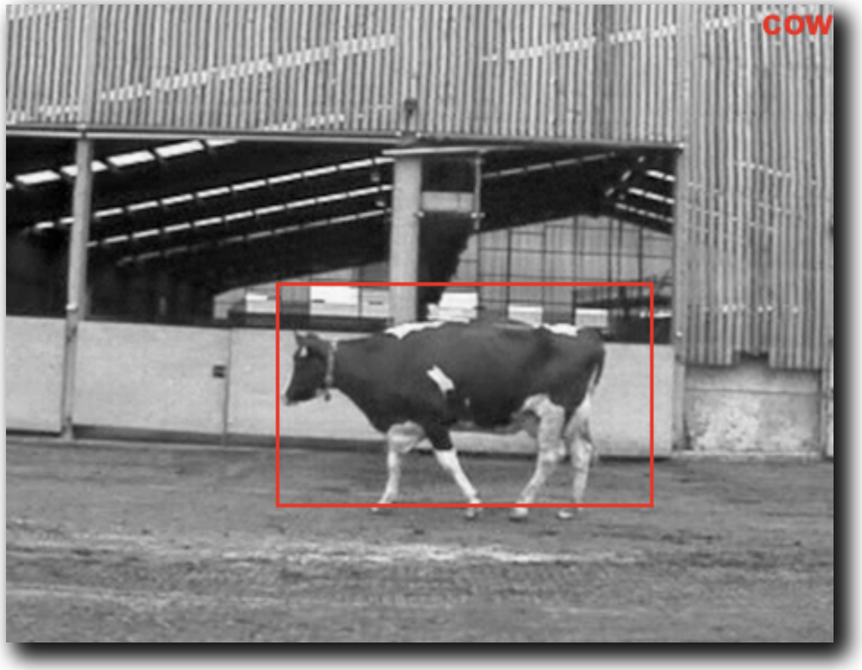

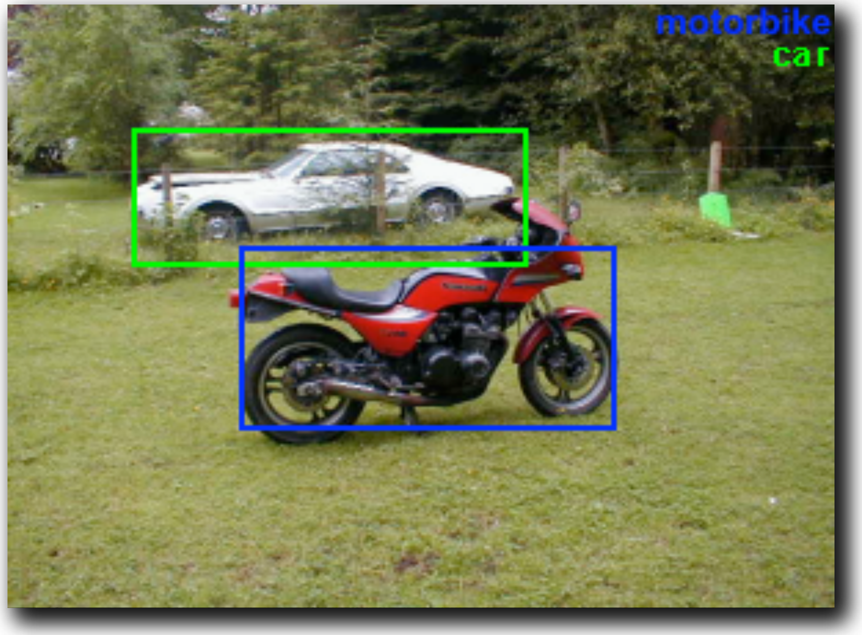

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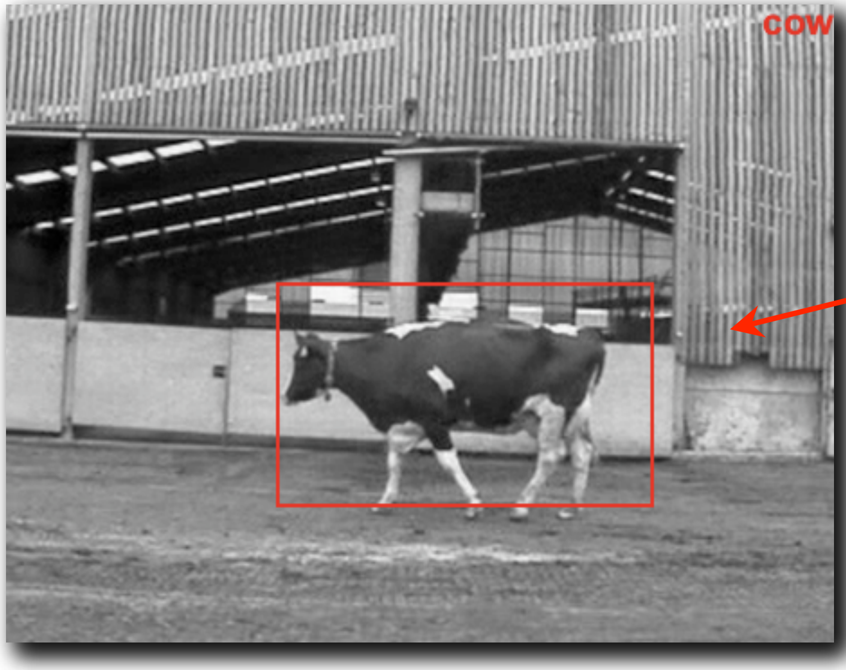

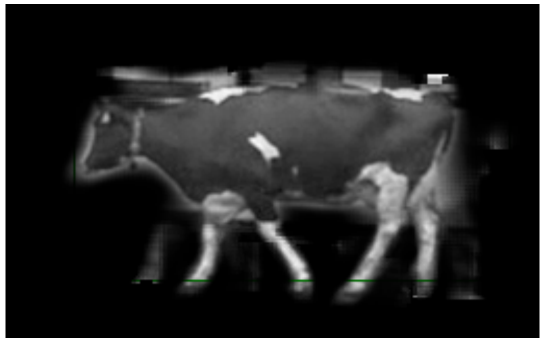

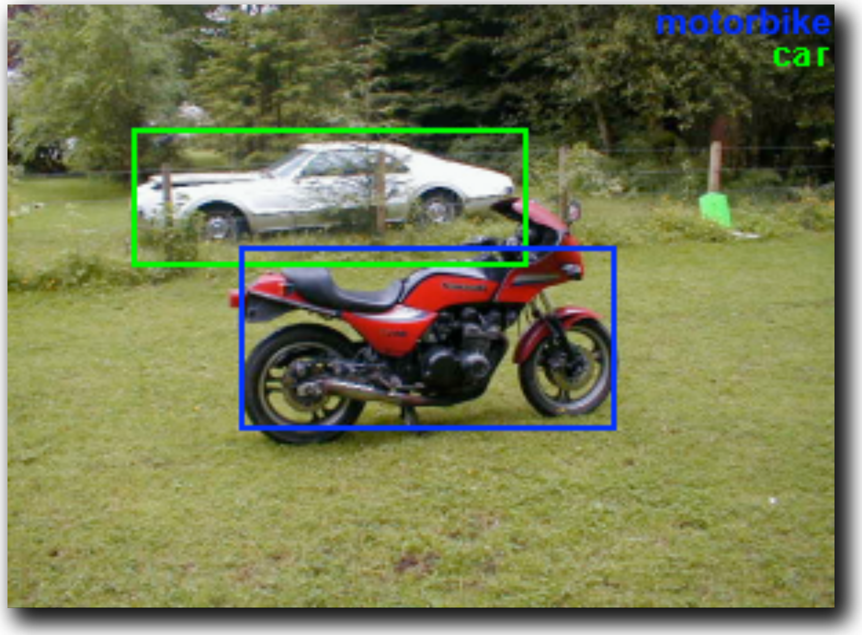

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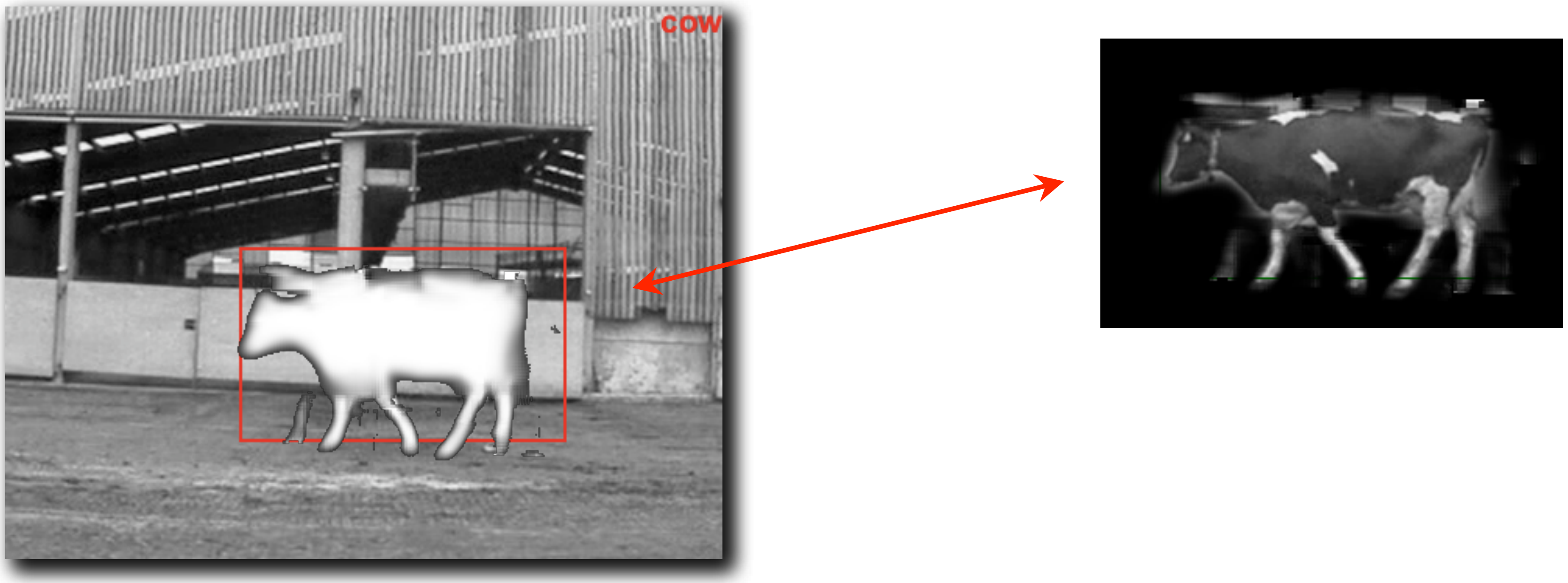

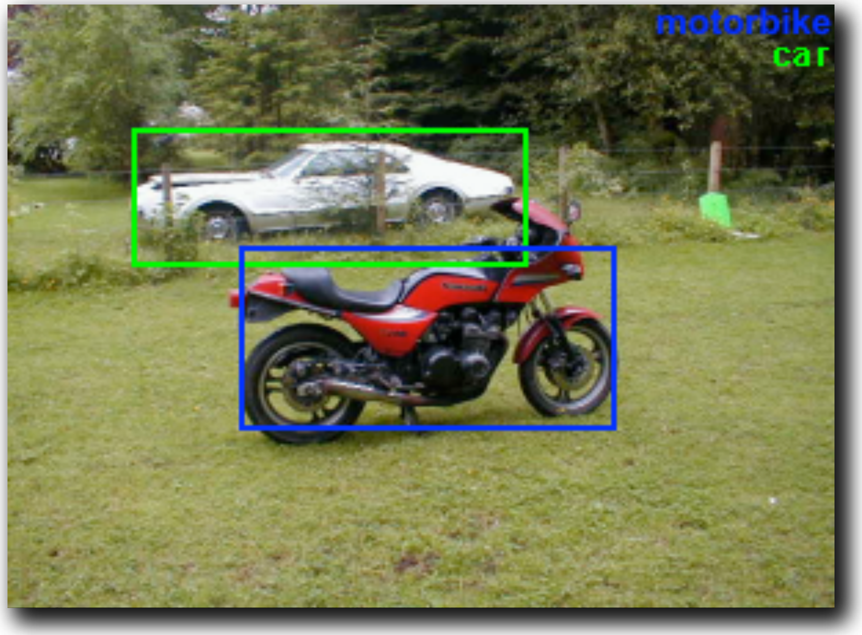

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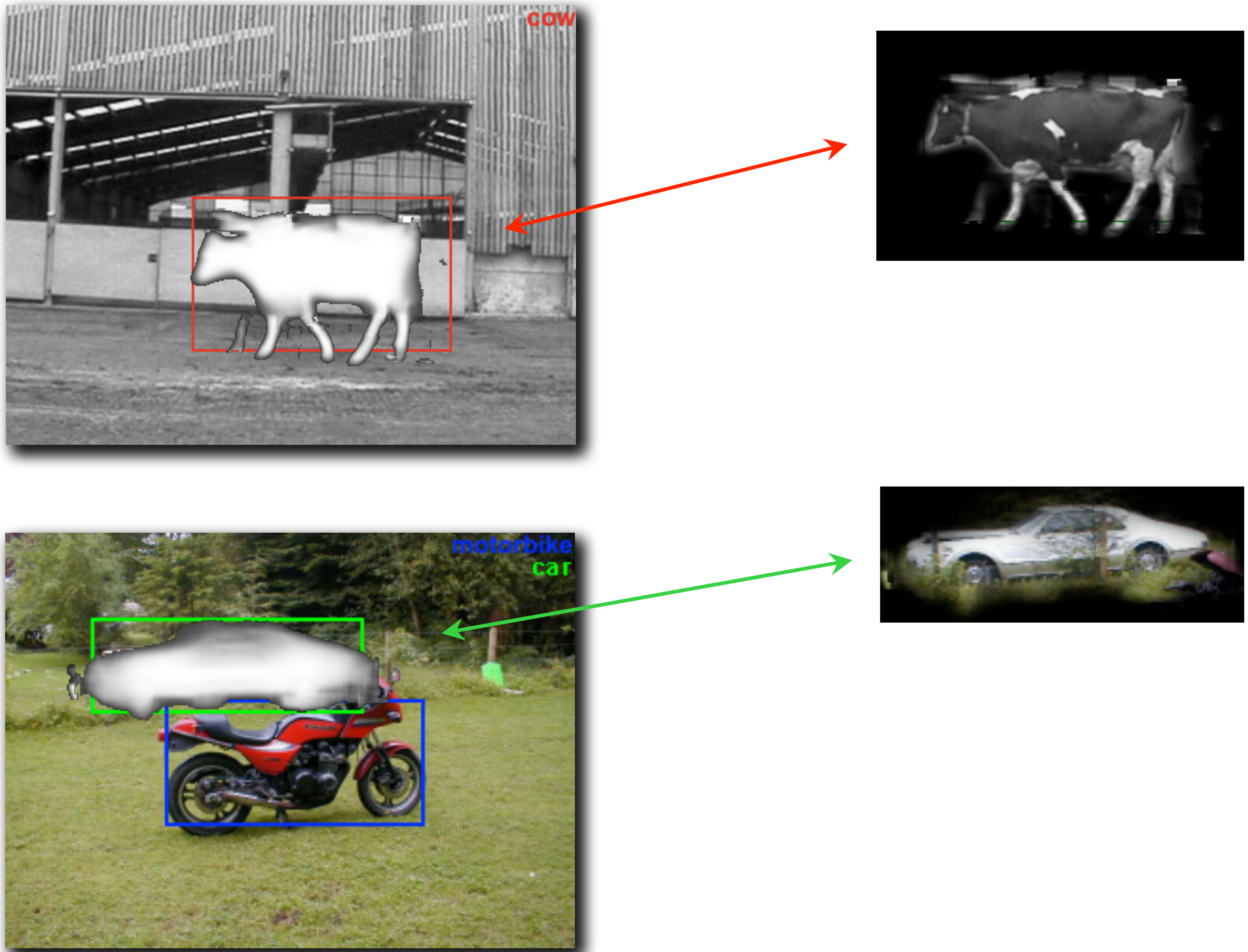

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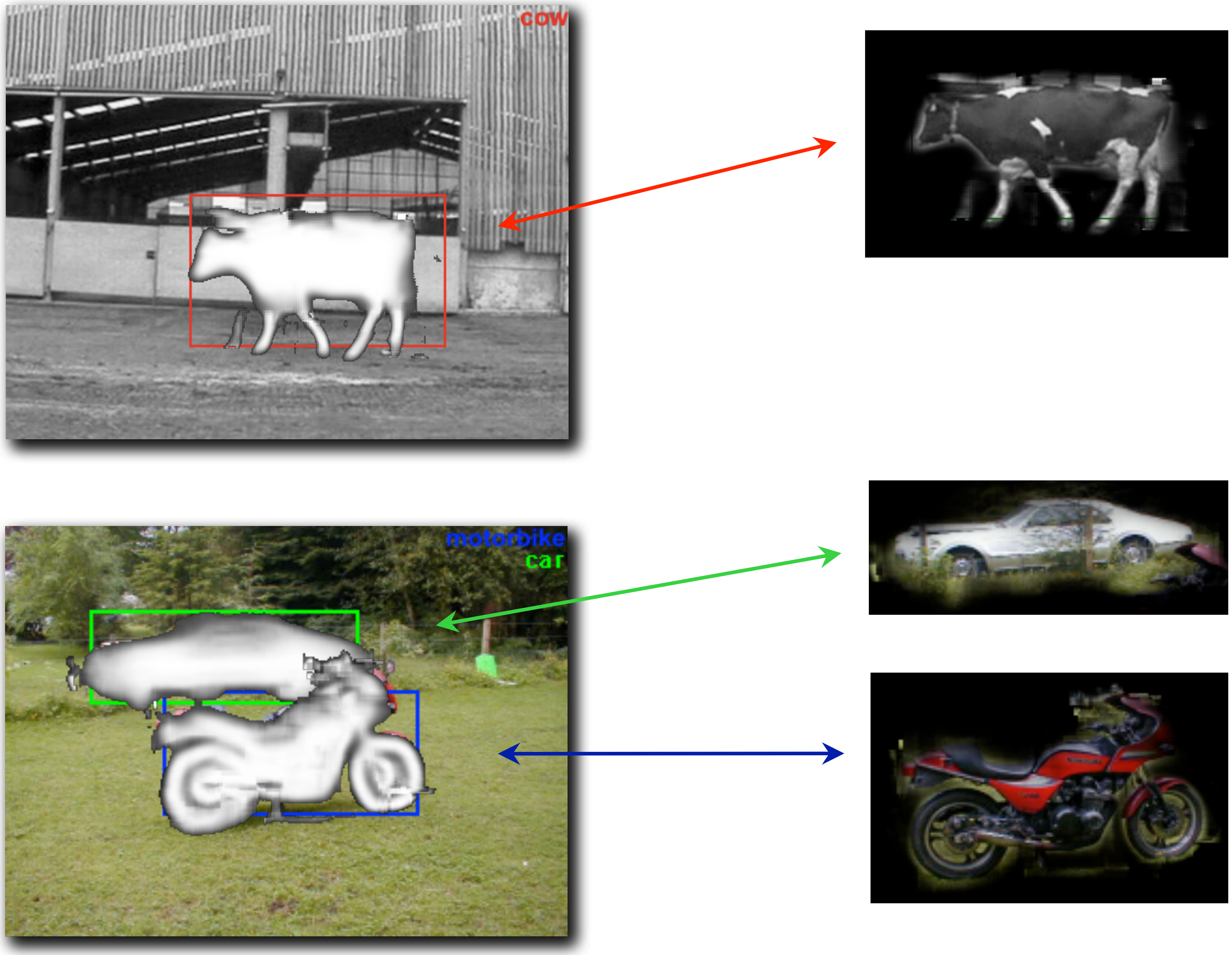
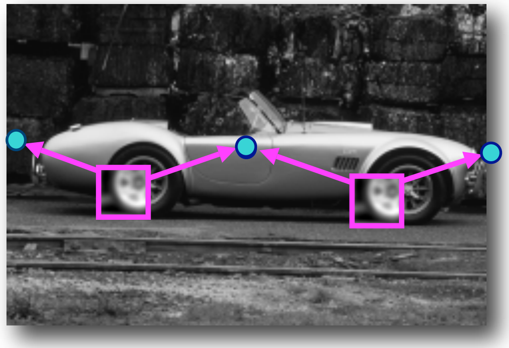


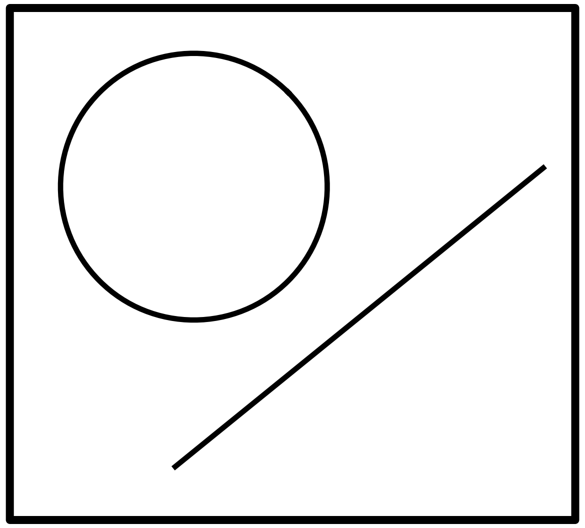
Overview

- **Implicit Shape Model:**
  - Hough transform idea
  - Non-parametric object model
  - Voting scheme for detection
  - Detection and segmentation
  - Limitations and outlook



Hough Transform

- Simple Examle: find lines in image



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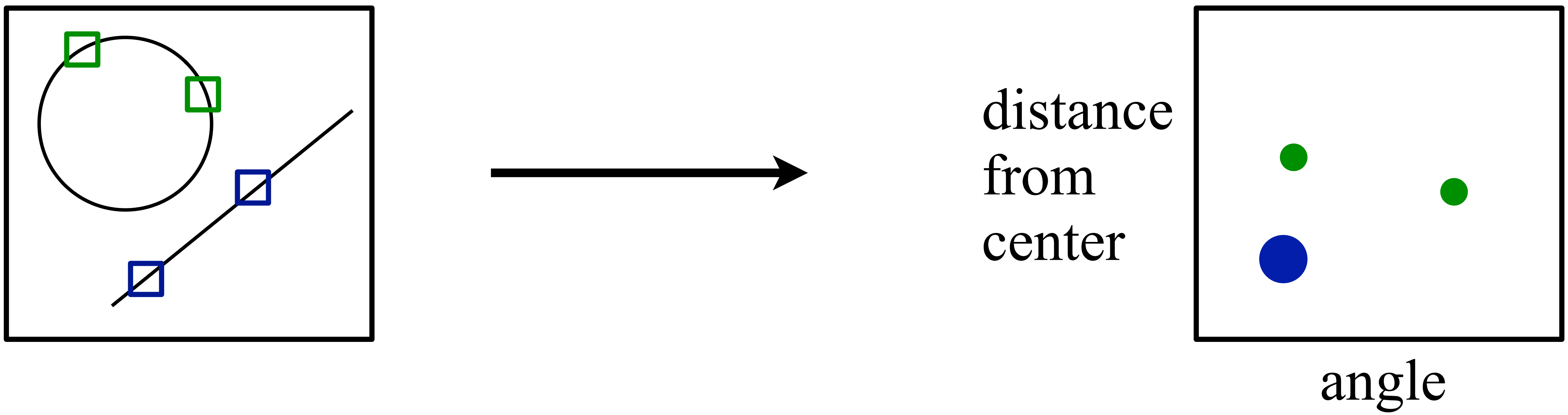

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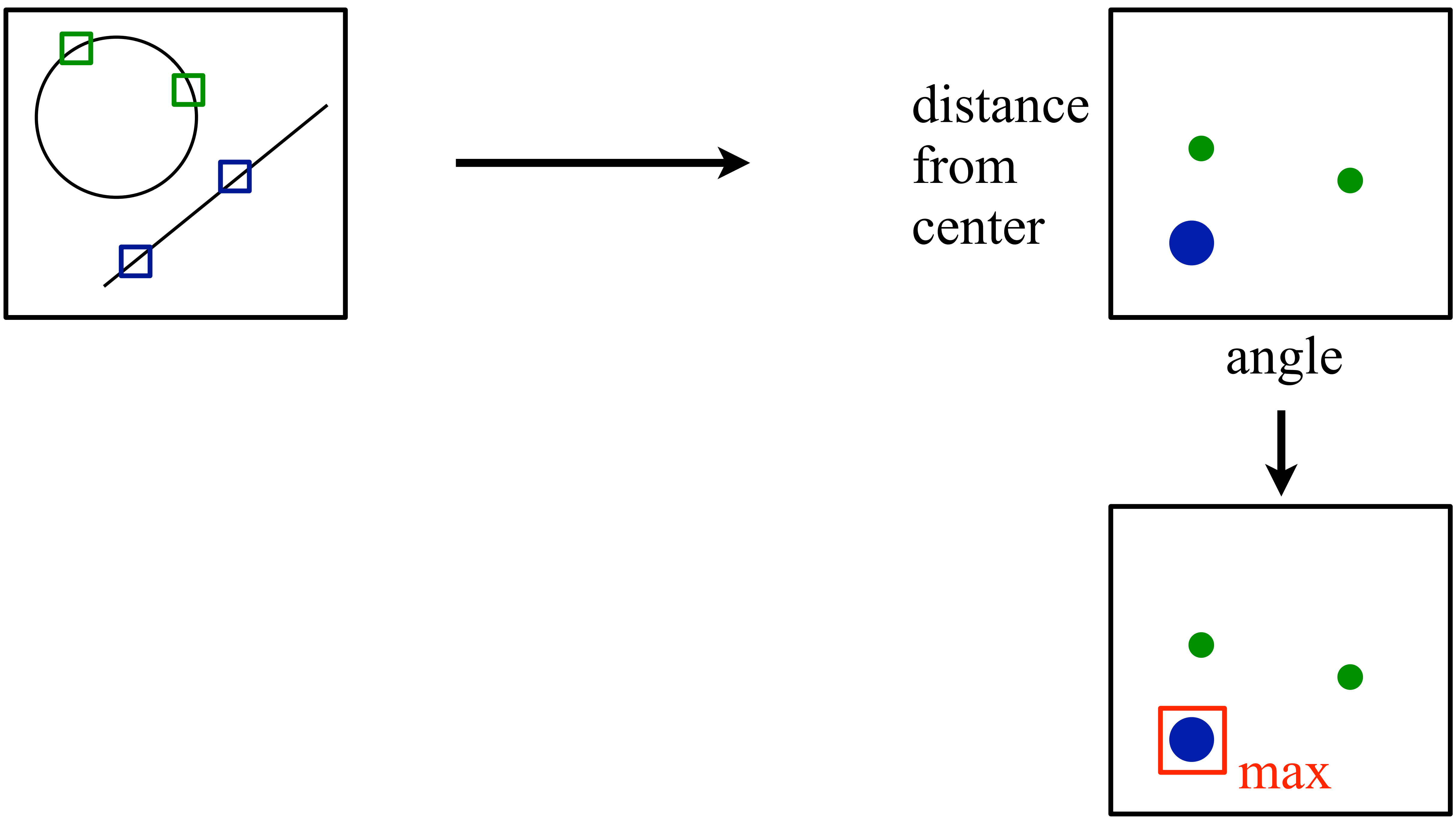

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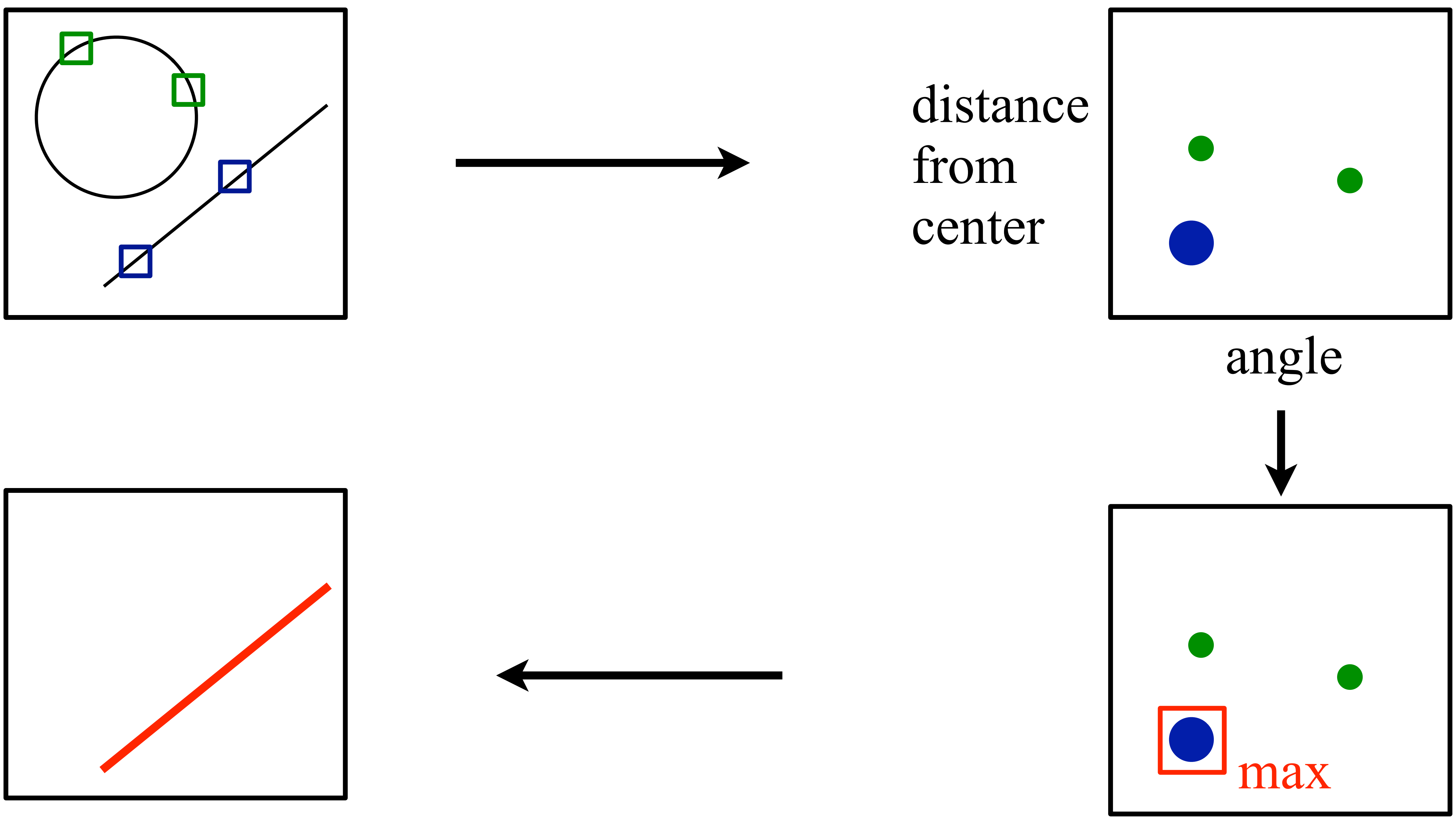
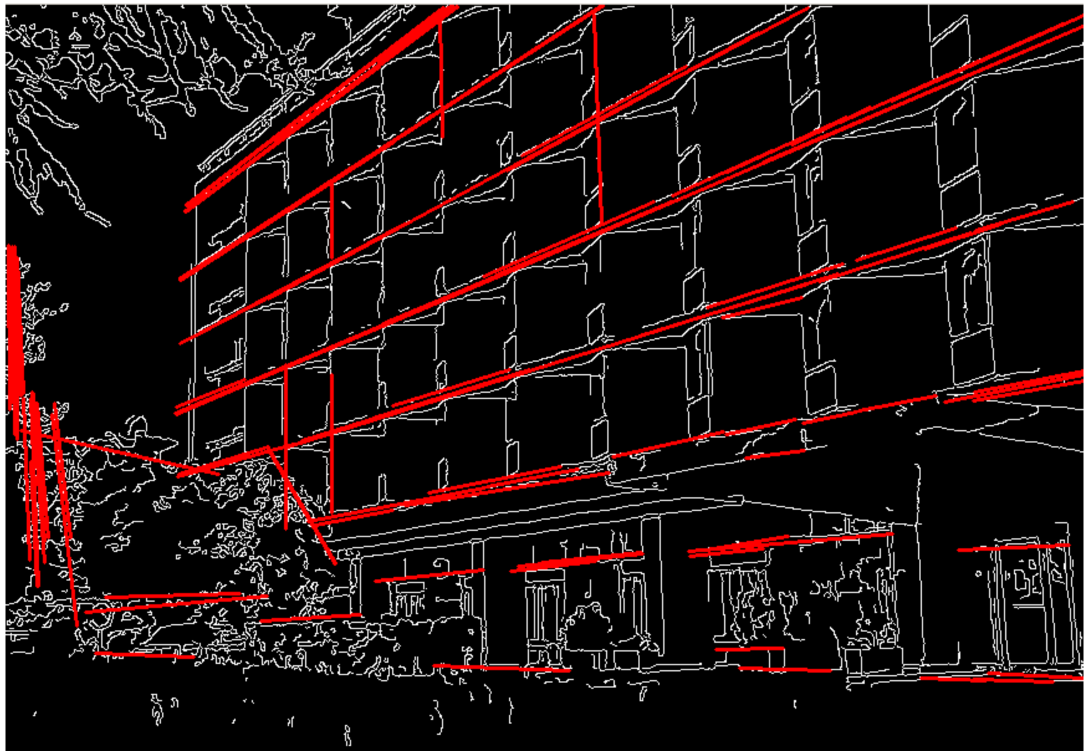


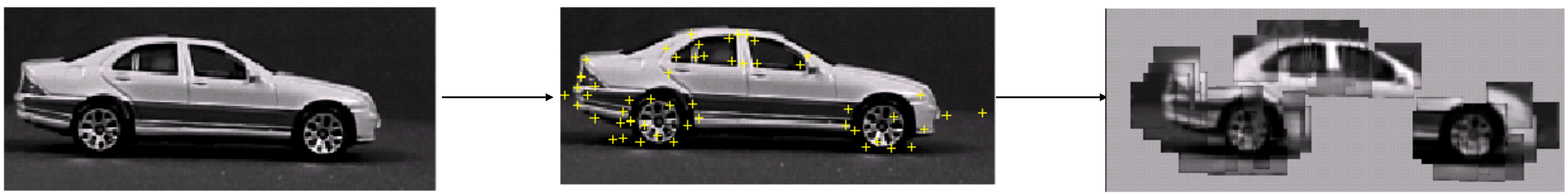
Hough Transform

- **example:**

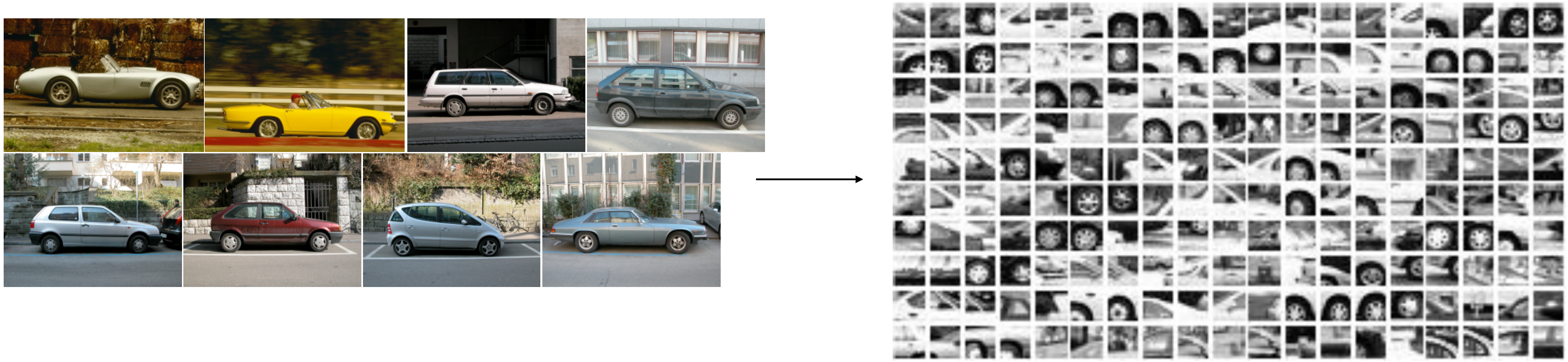


Codebook Representation

- Extraction of local object patches
  - scale-invariant interest points (difference of gaussian)



- Collect patches from whole training set
- Example:



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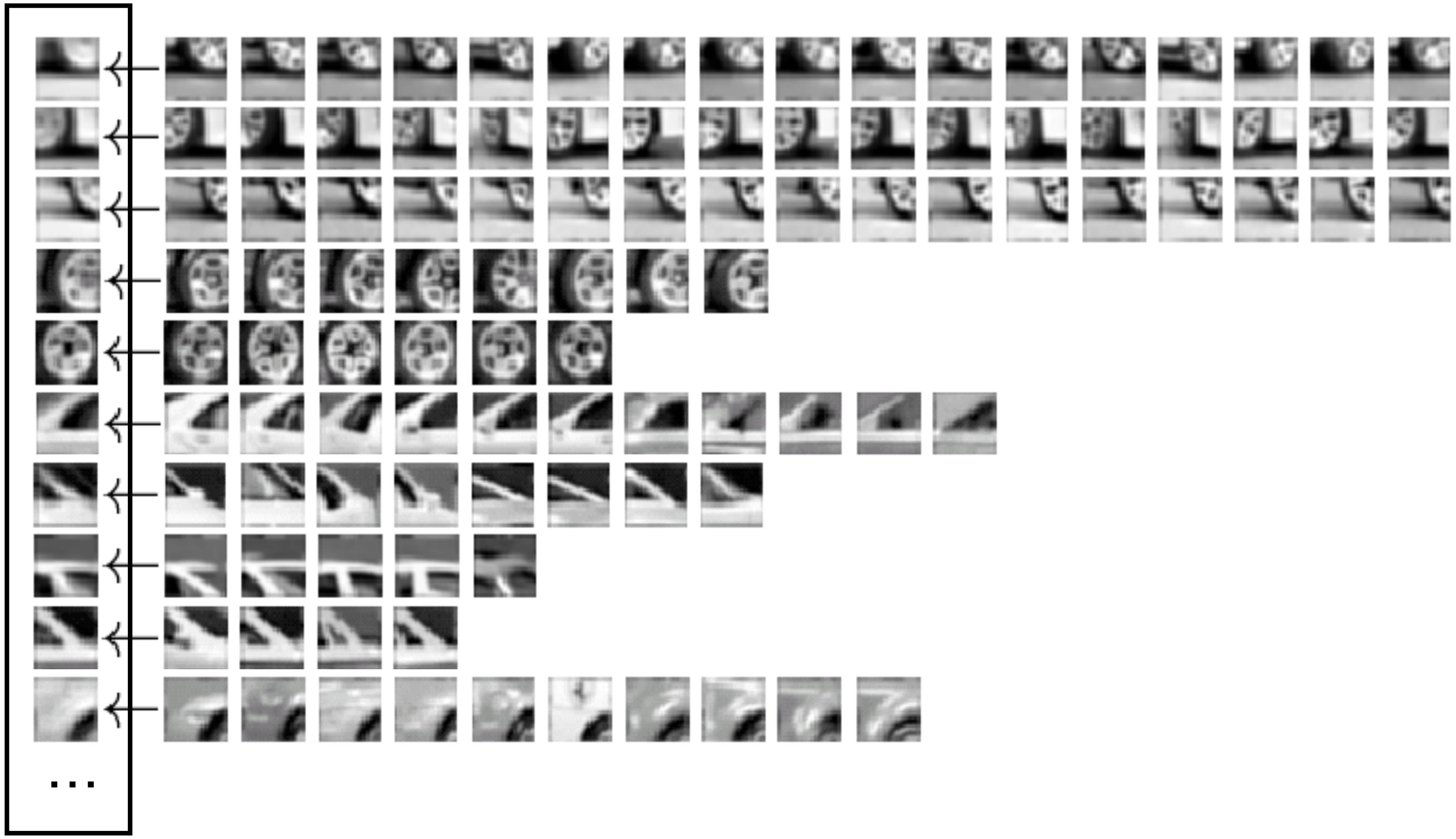
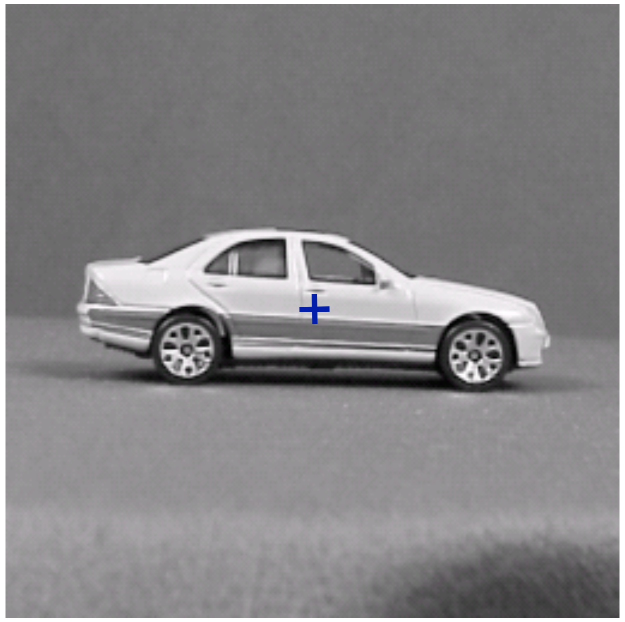


- 50 car images
- only side views were used

Implicit Shape Model (ISM)

- For every codebook entry, store possible “occurrences”



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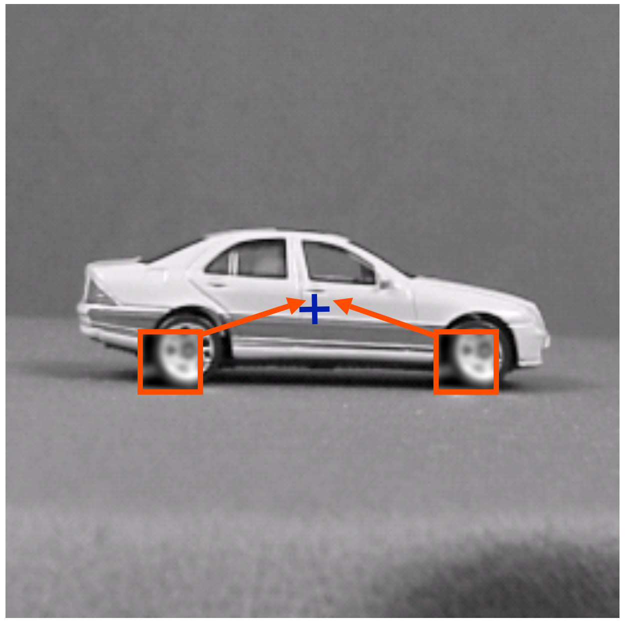

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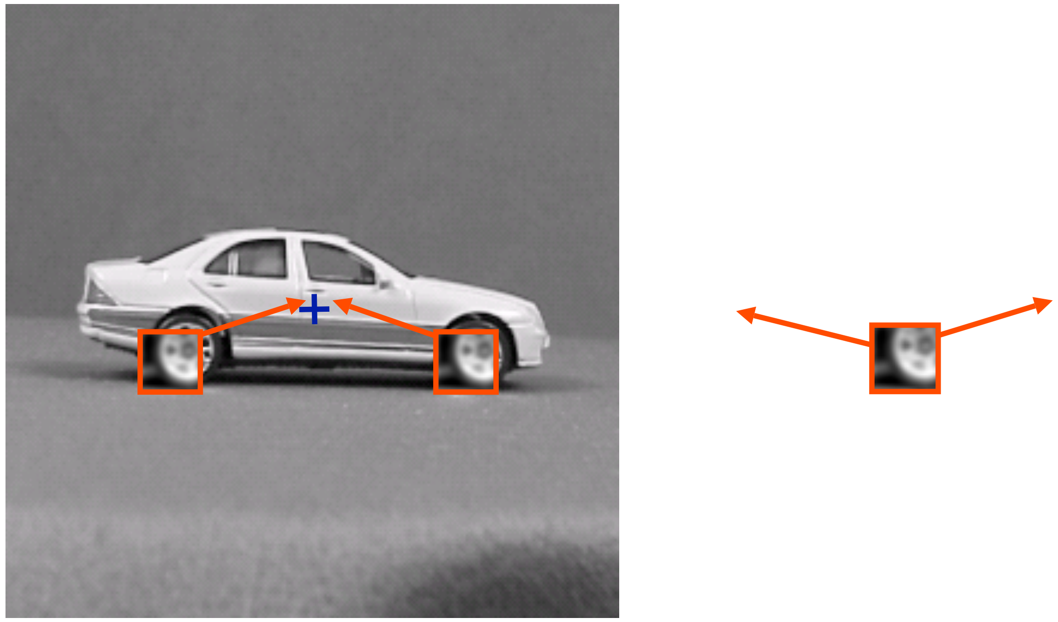

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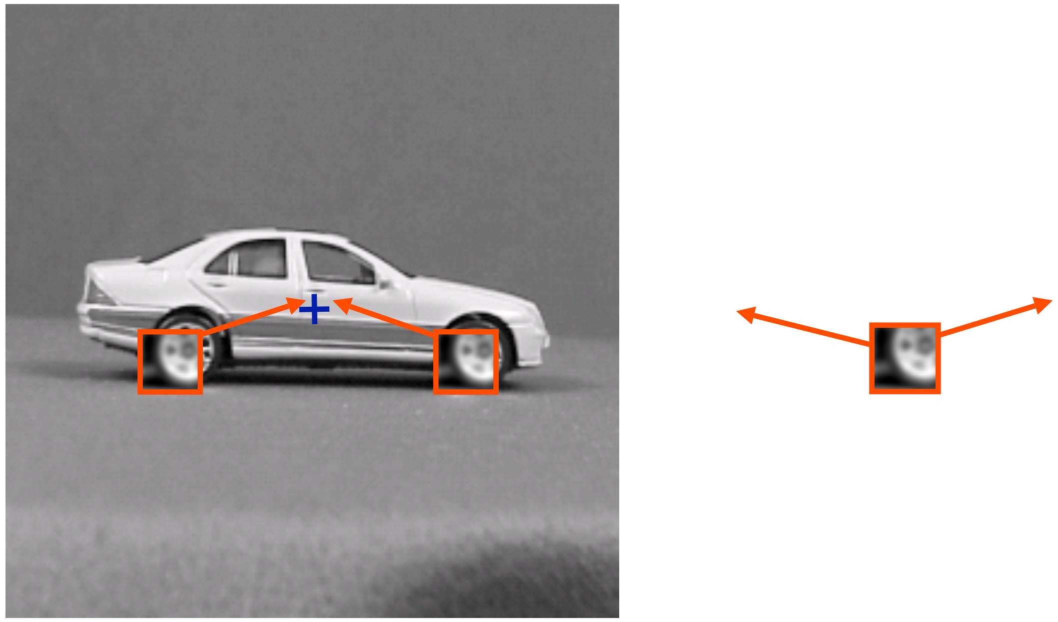

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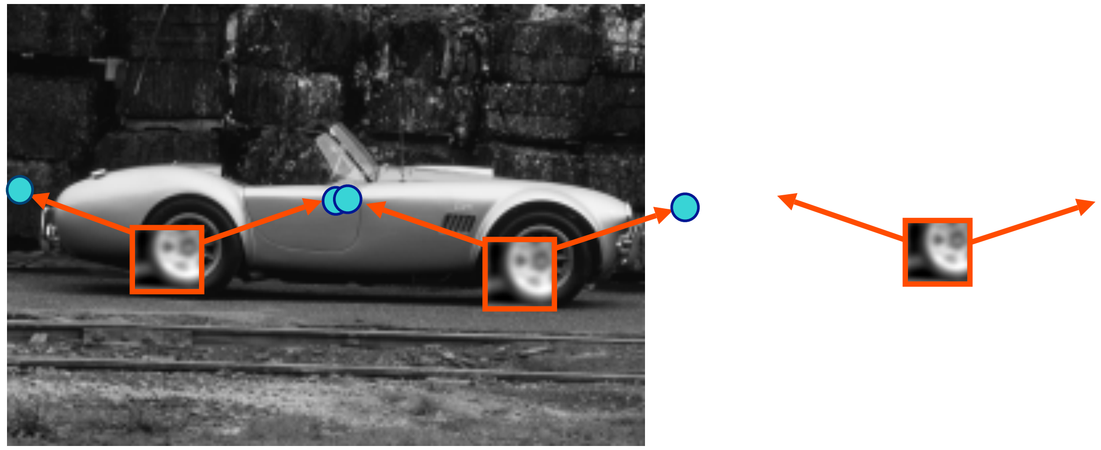
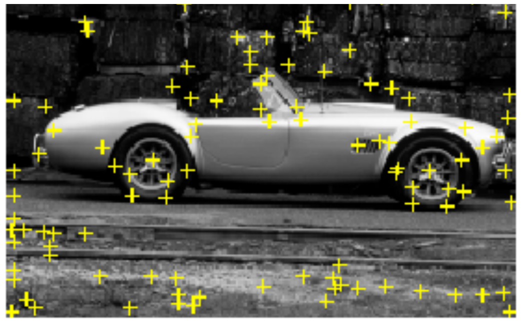


Object Categorization Procedure

Interest Points



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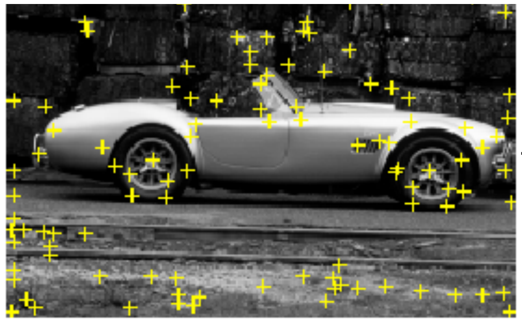
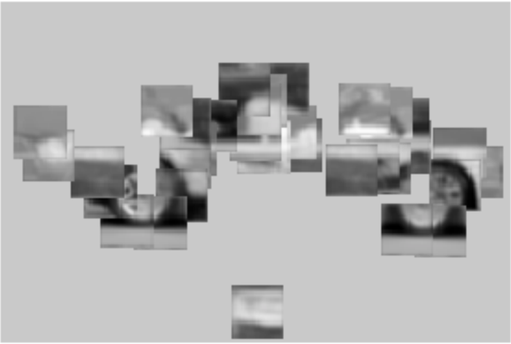


Matched Codebook Entries



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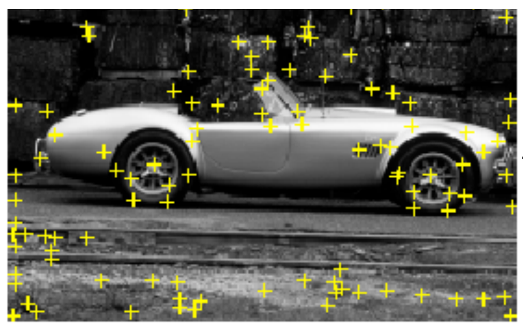

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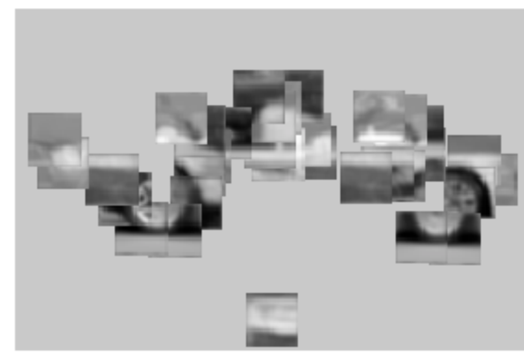
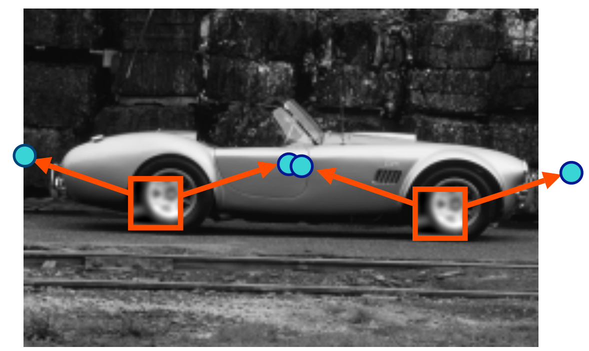
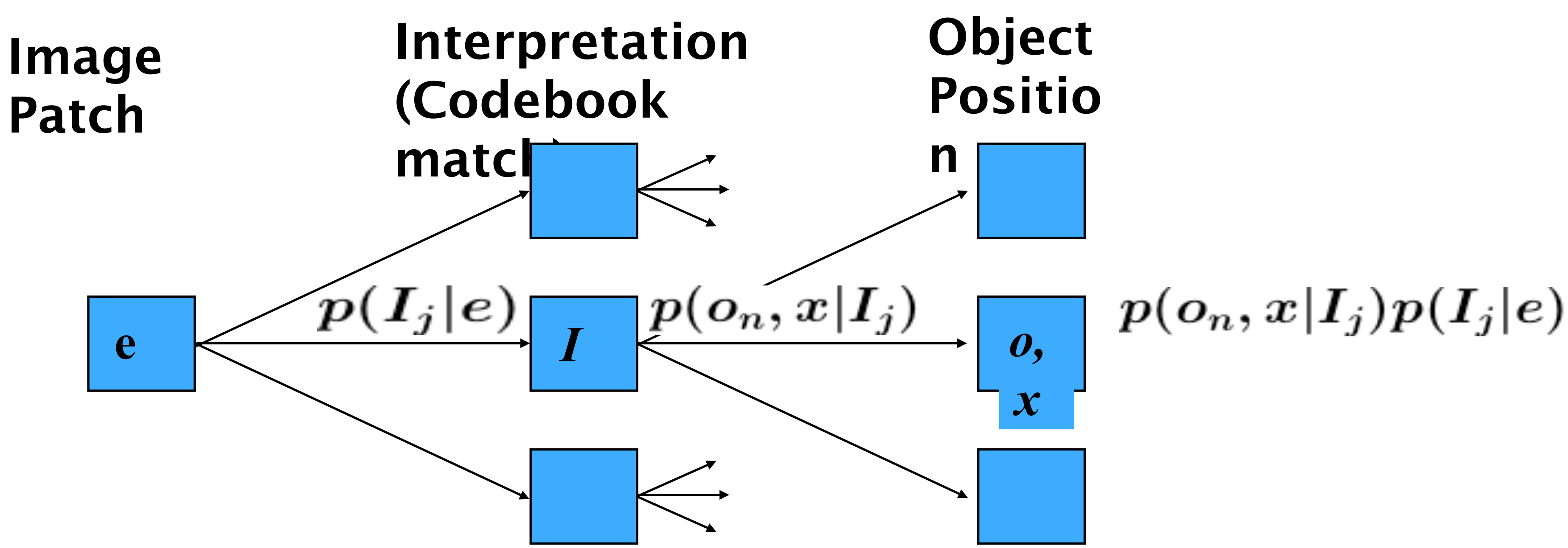


Probabilistic Voting





$$p(o_n, x|e) = \sum_j p(o_n, x|I_j)p(I_j|e)$$

Object Categorization Procedure

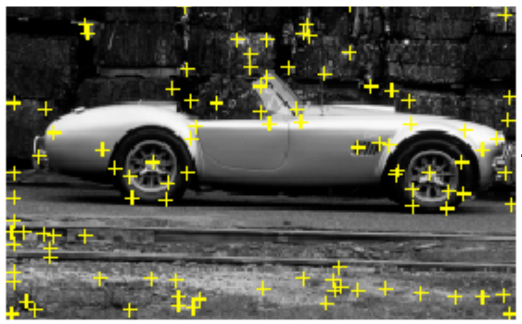
Interest Points

Matched Codebook Entries

Probabilistic Voting

Object Categorization Procedure

Interest Points



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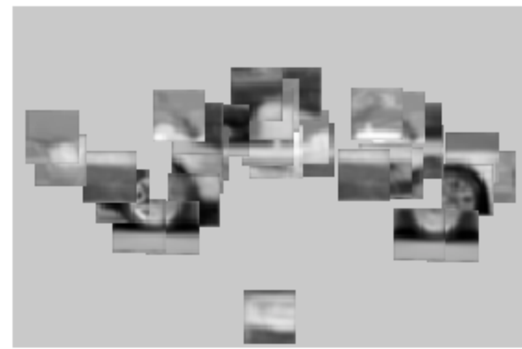

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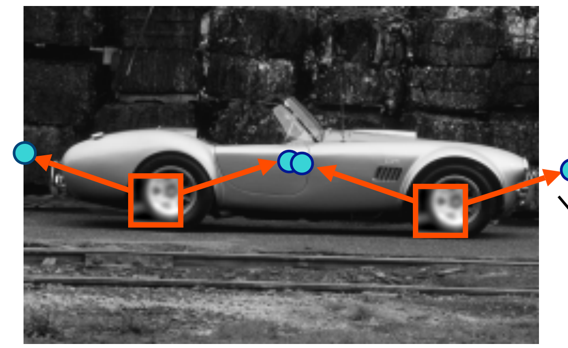
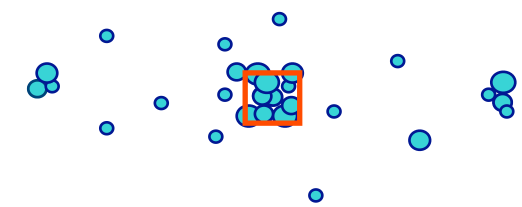
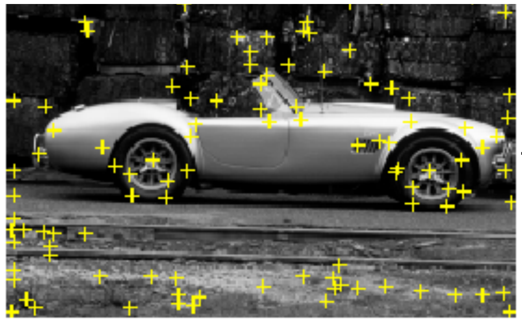




Voting Space (continuous)

Object Categorization Procedure

Interest Points



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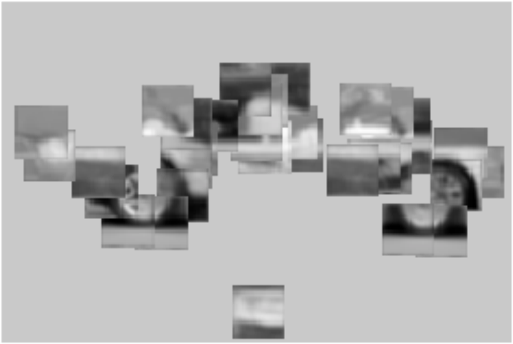

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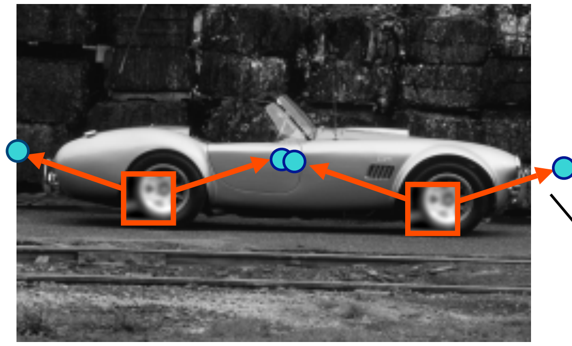

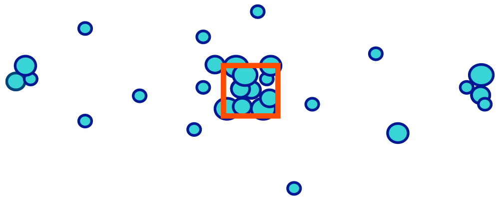

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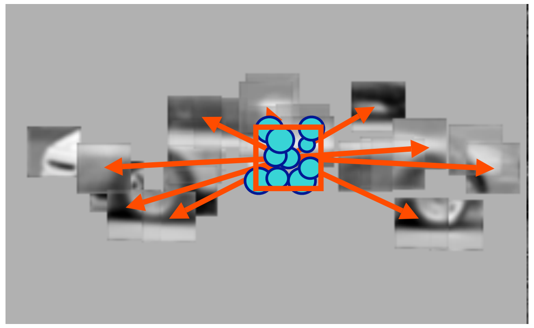
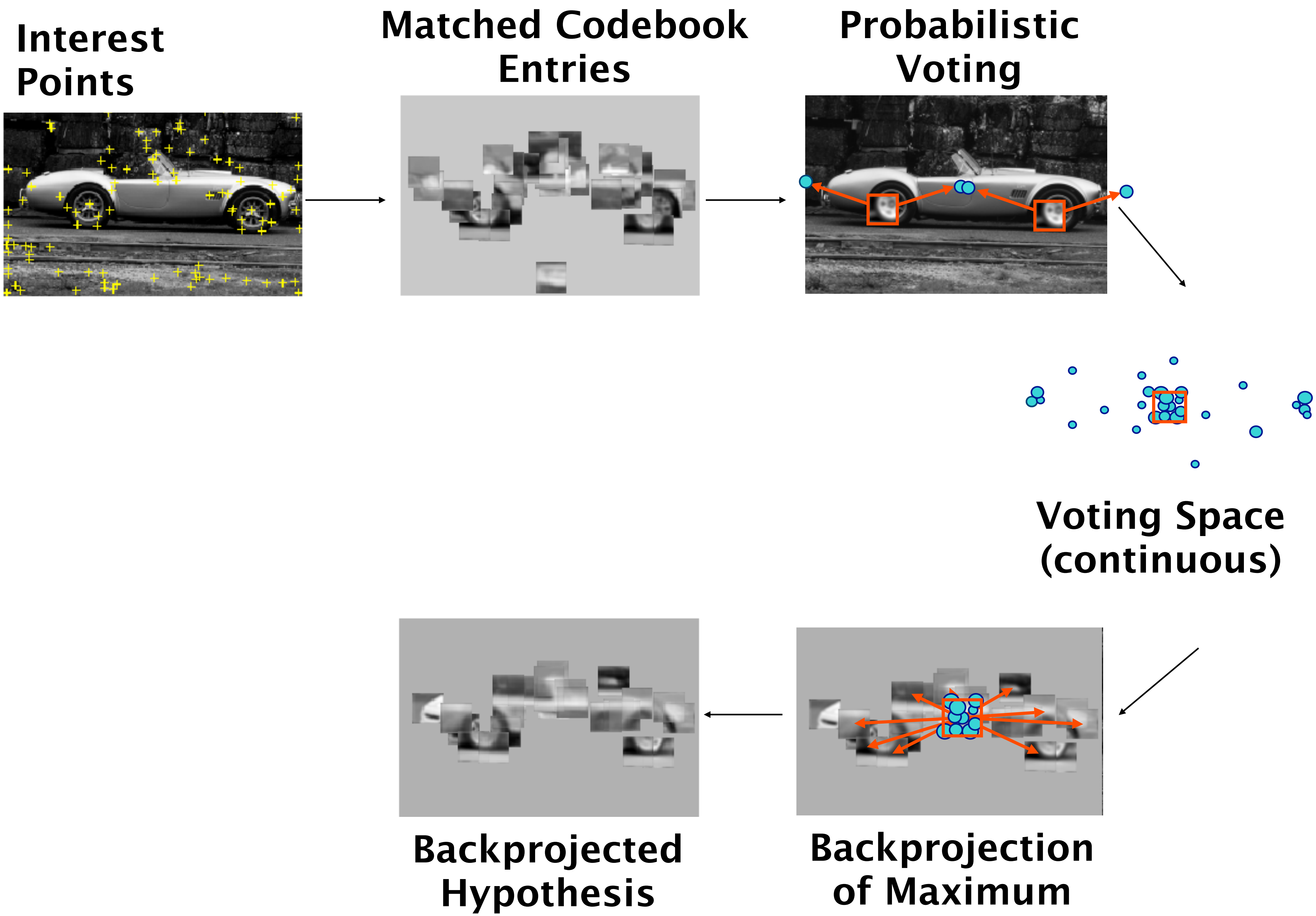


Backprojection of Maximum

Object Categorization Procedure



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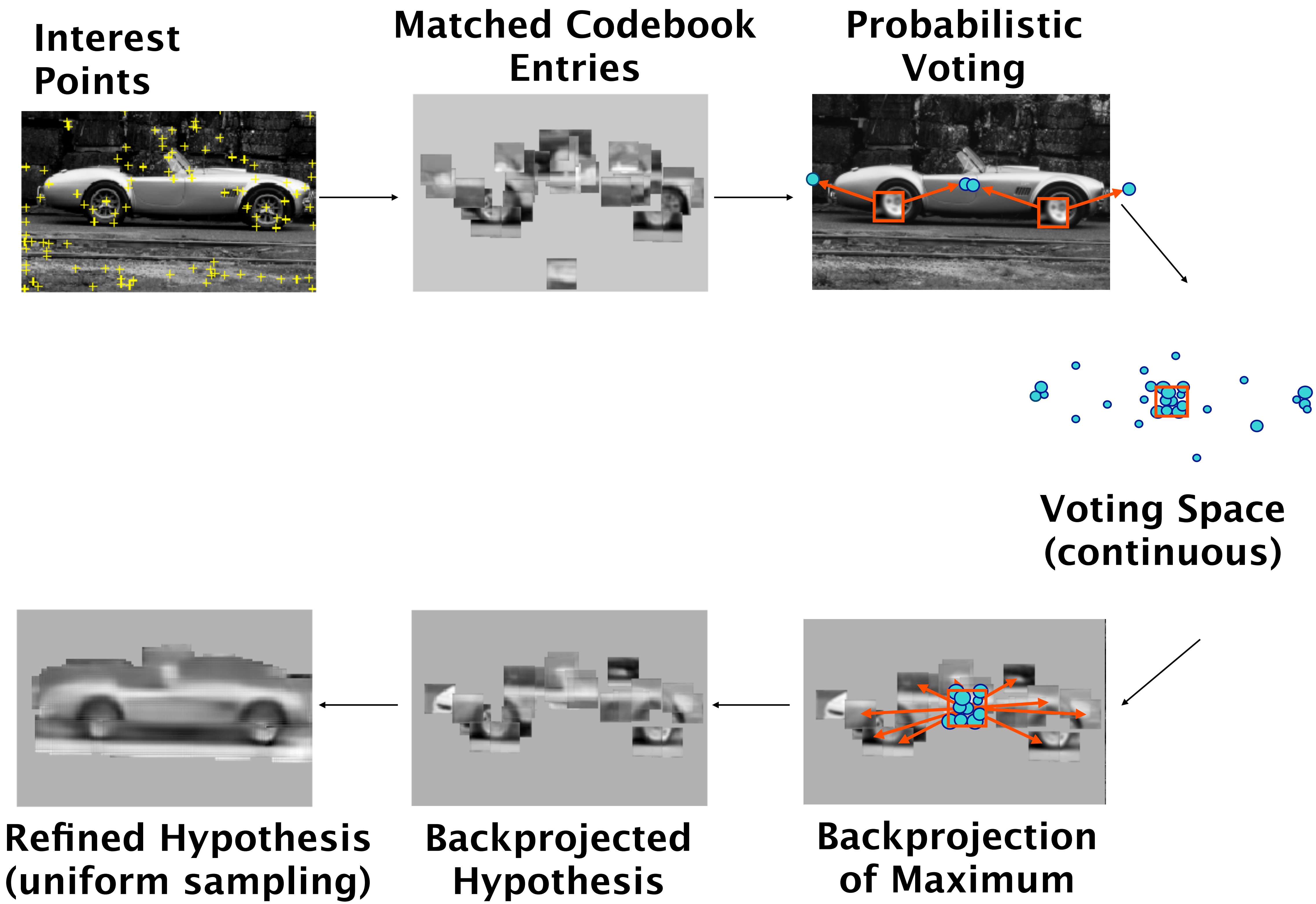

Results on Cows

Results on Cows

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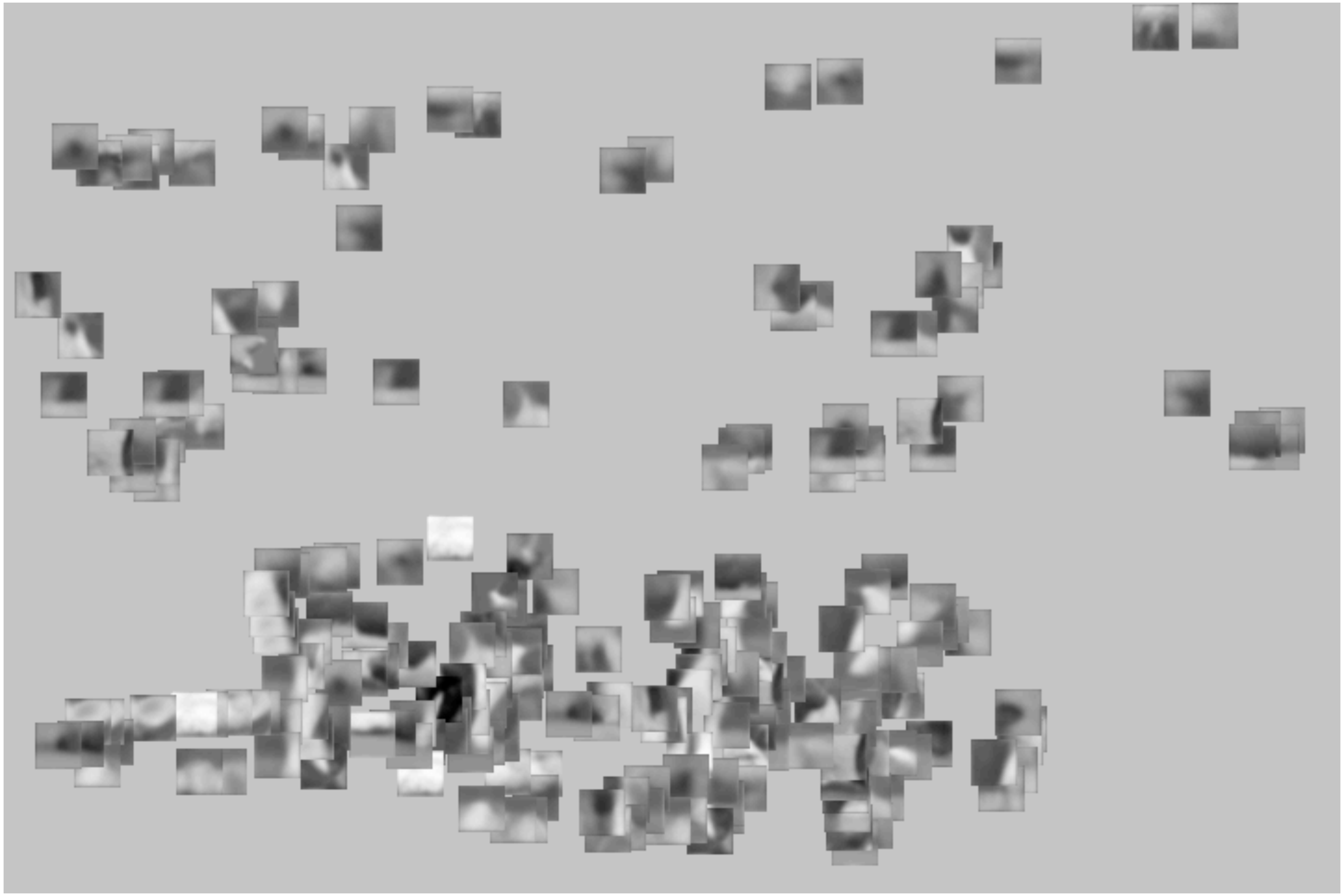

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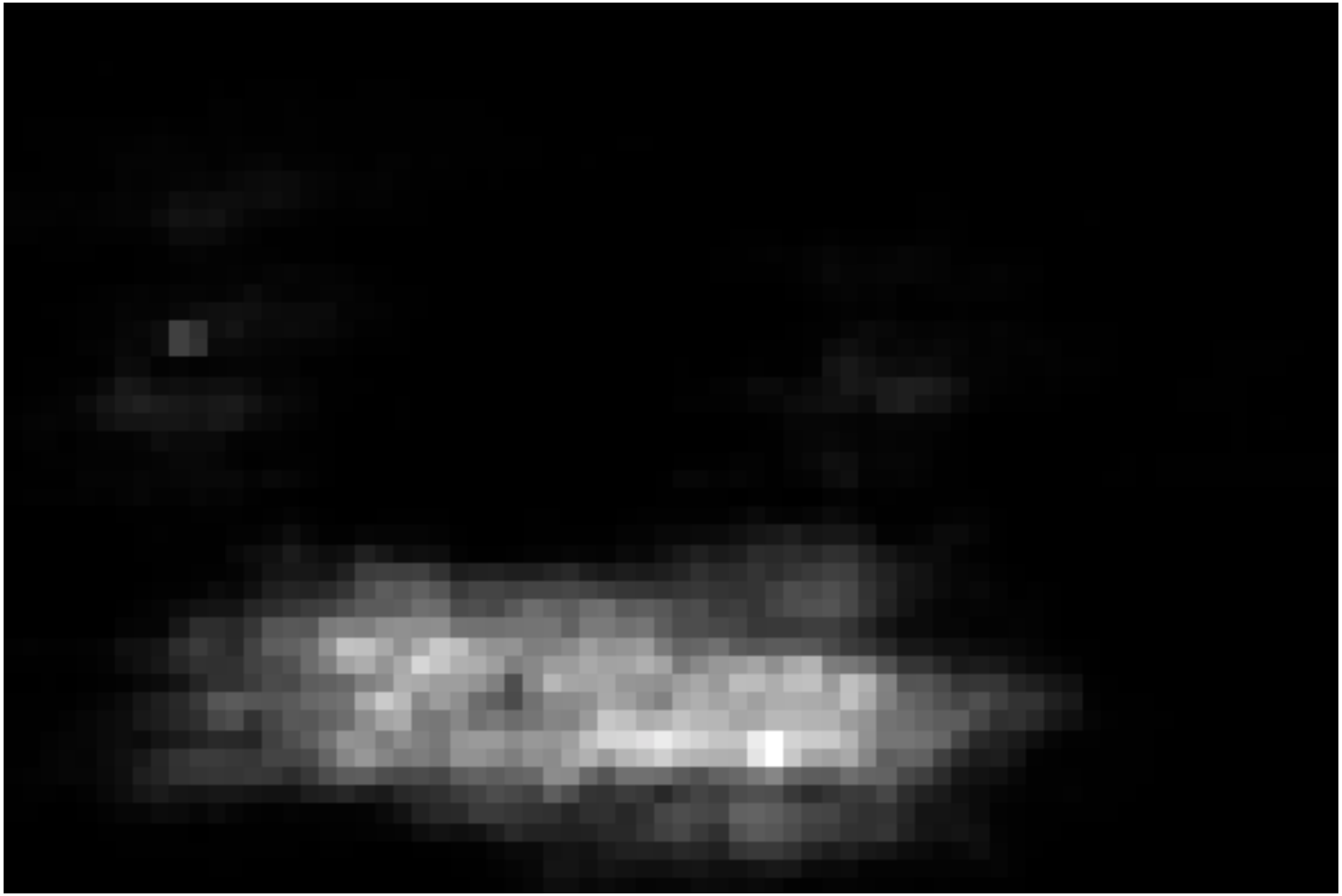

Results on Cows

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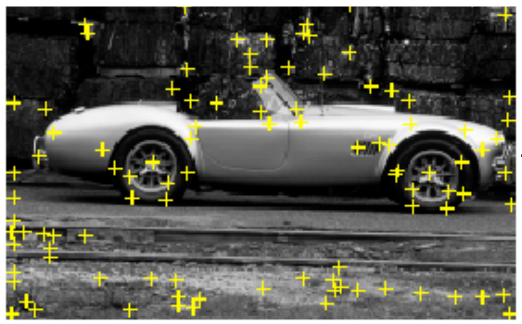
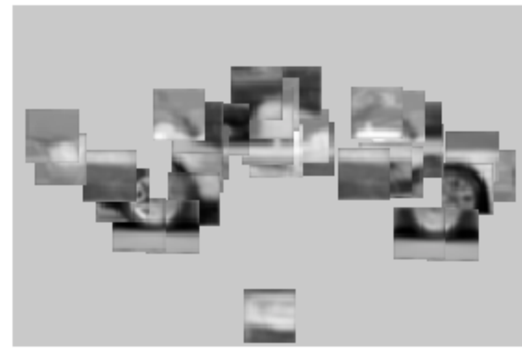
Object Categorization Procedure

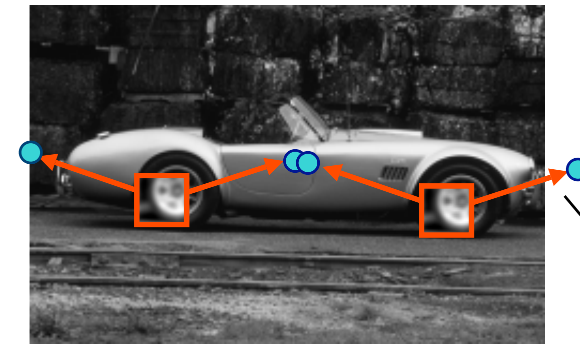
Interest Points

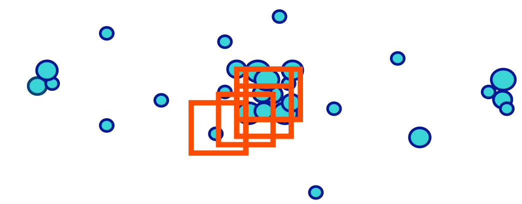


Matched Codebook Entries



Probabilistic Voting





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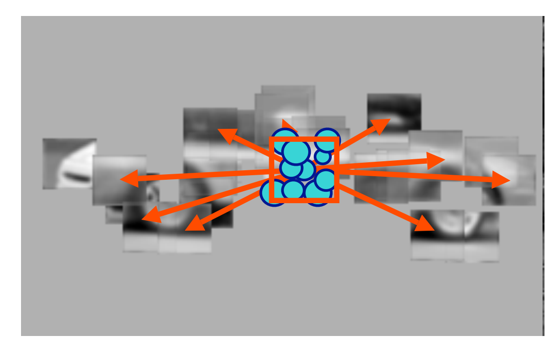

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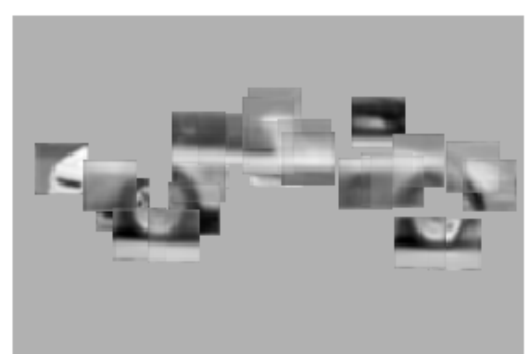
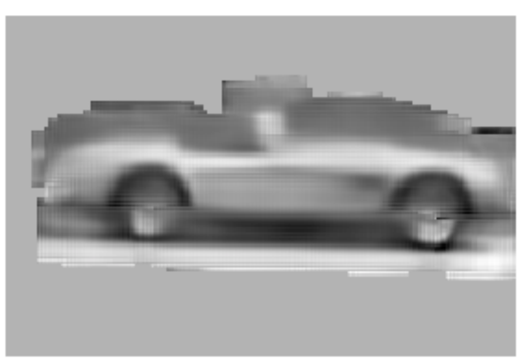
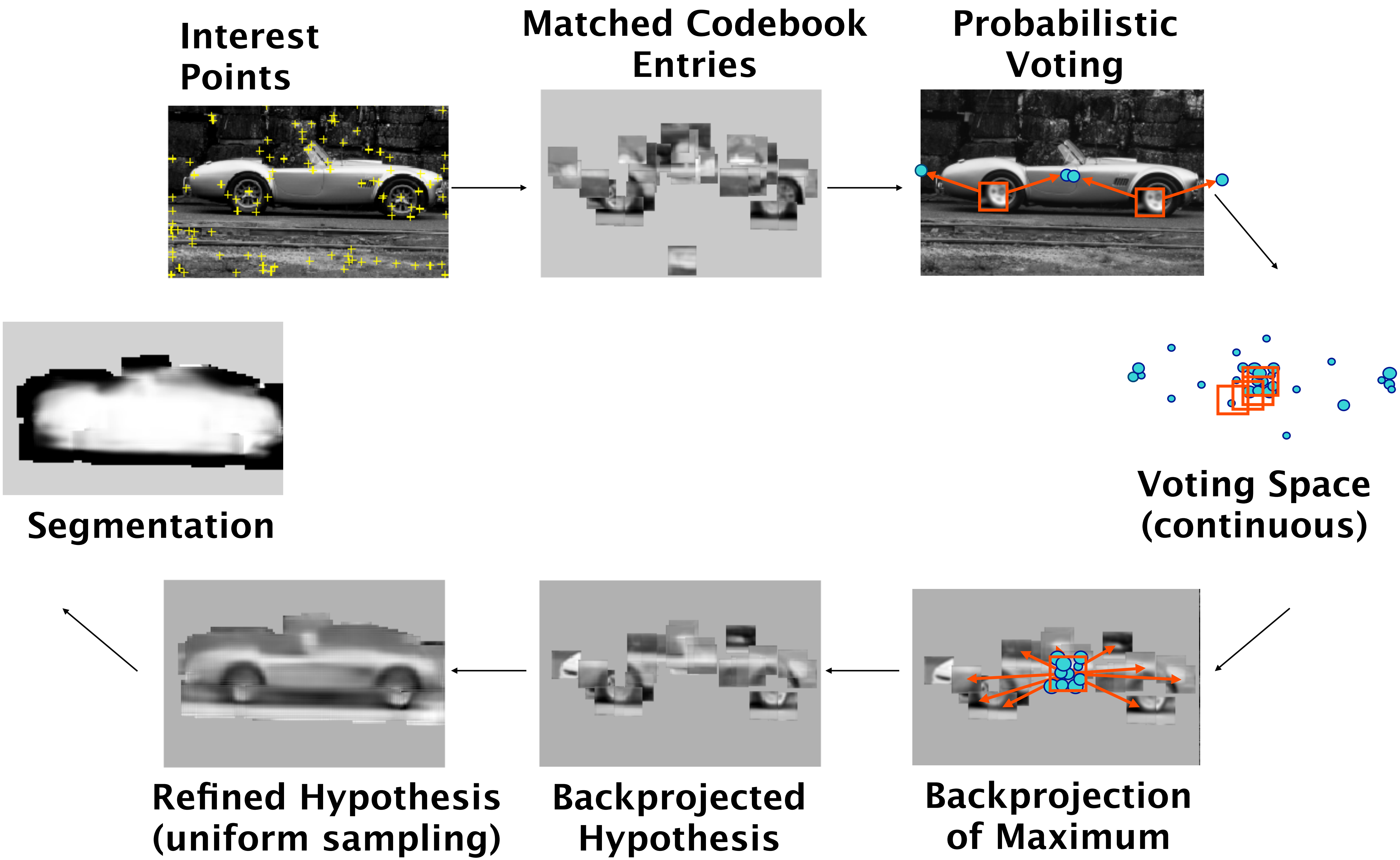


Backprojected Hypothesis



Refined Hypothesis (uniform sampling)

Object Categorization Procedure



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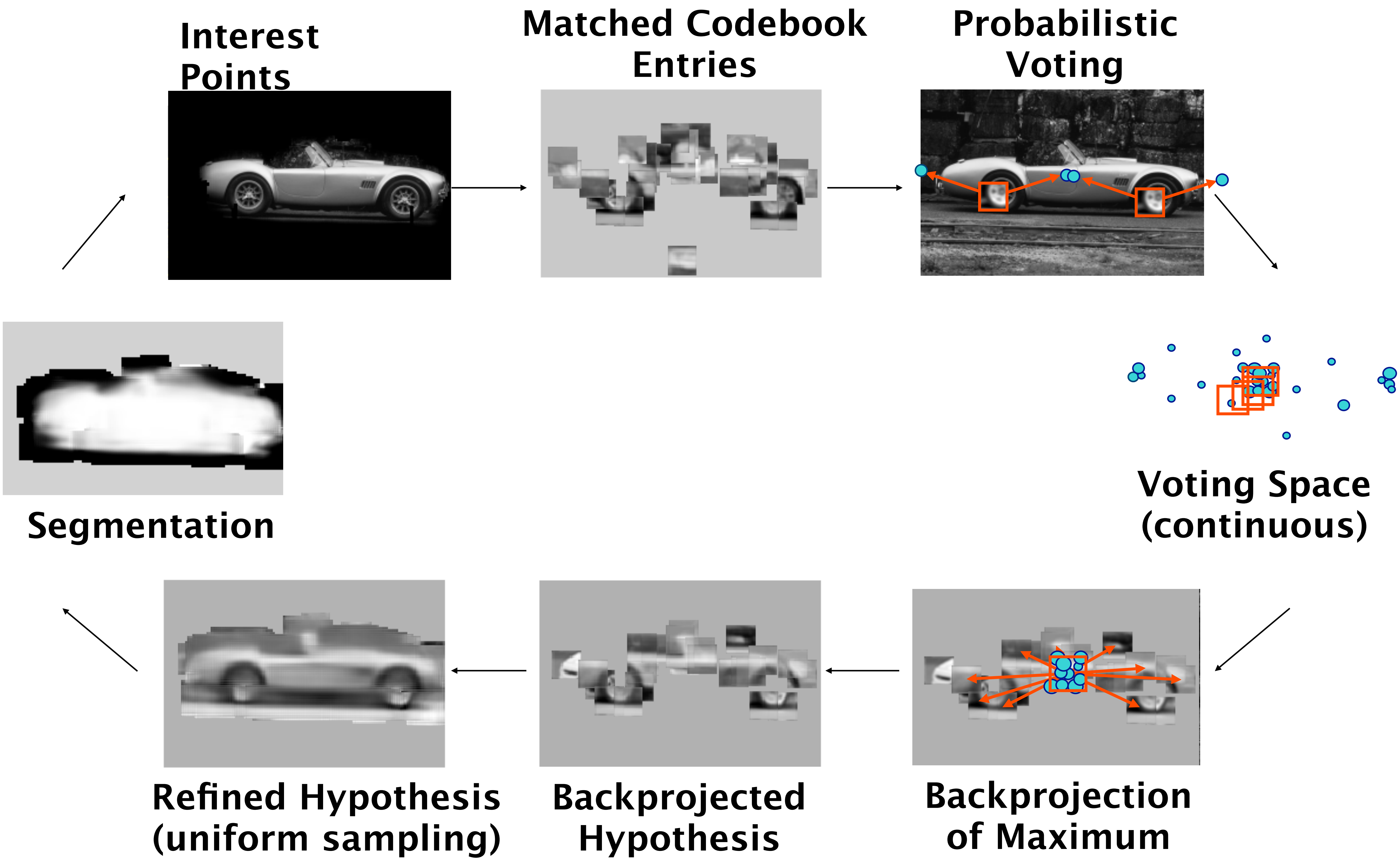
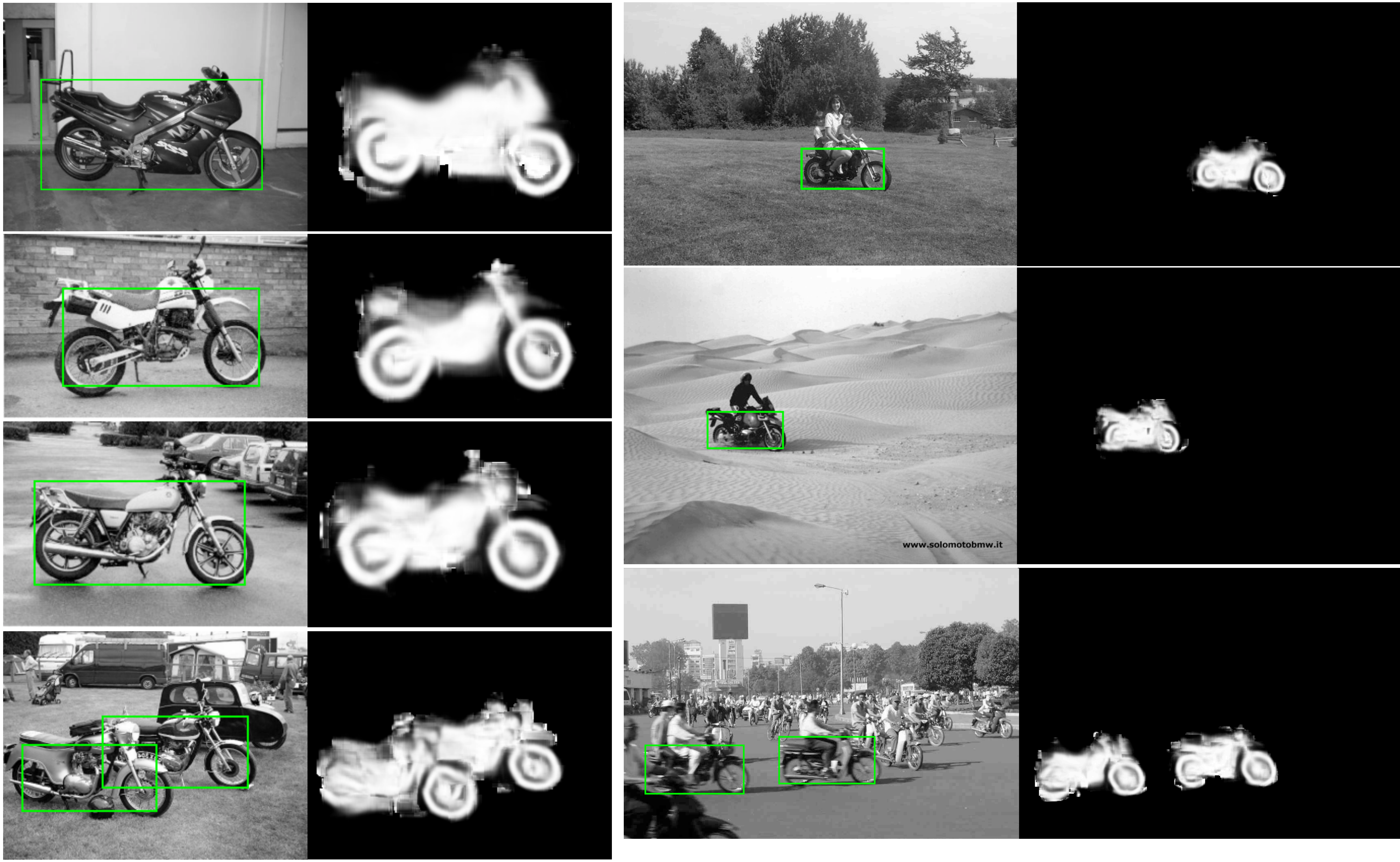


Motorbikes: Detection/Segmentation Results



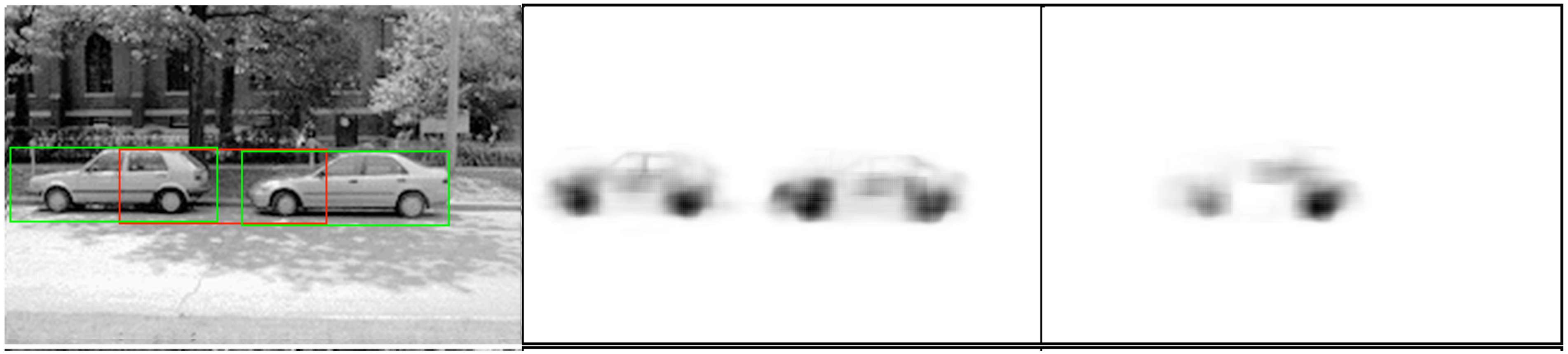
Results on New Sequences

- **Object Detections**

Results on New Sequences

- Segmentation

Segmentation Based Hypothesis Verification



- **Secondary hypotheses**
  - Desired property of algorithm! $\Rightarrow$ robustness to occlusion
  - Standard solution: reject based on bounding box

    $\Rightarrow$ Problematic - may lead to missing detections!

    $\Rightarrow$ Use segmentations to resolve ambiguities instead defining costs and savings for acceptance of hypotheses

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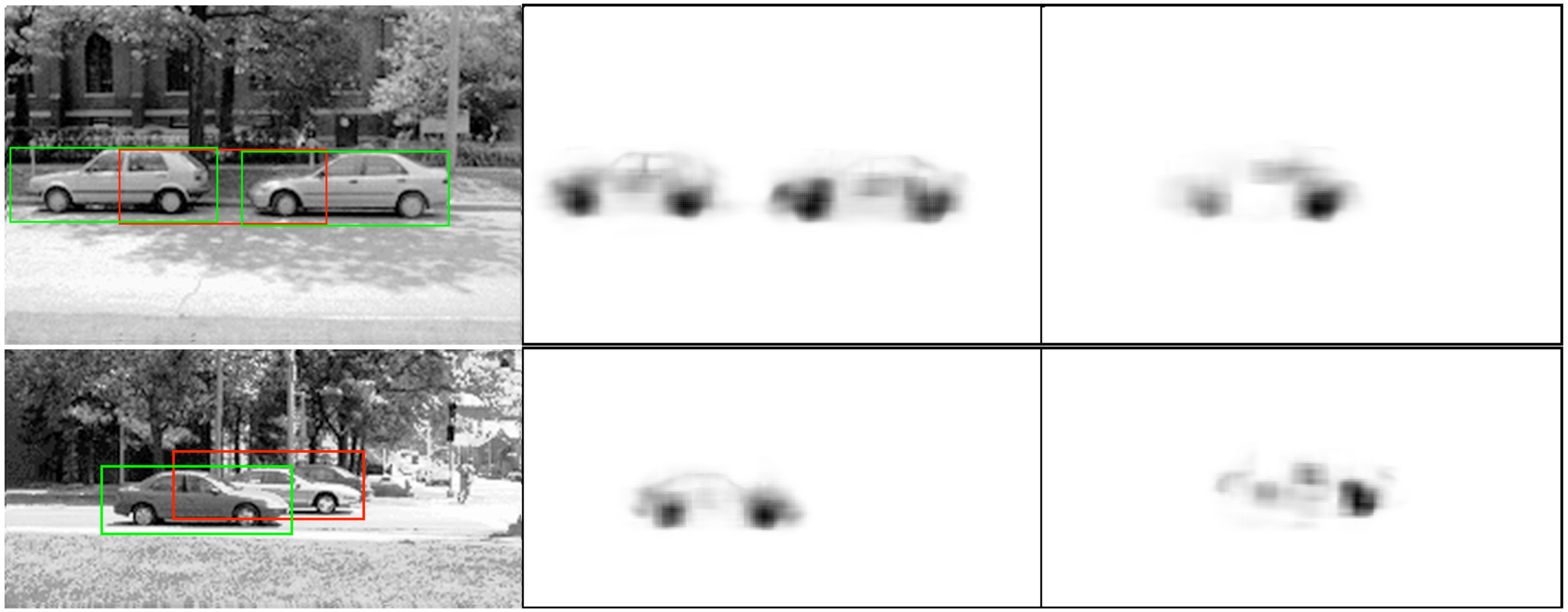

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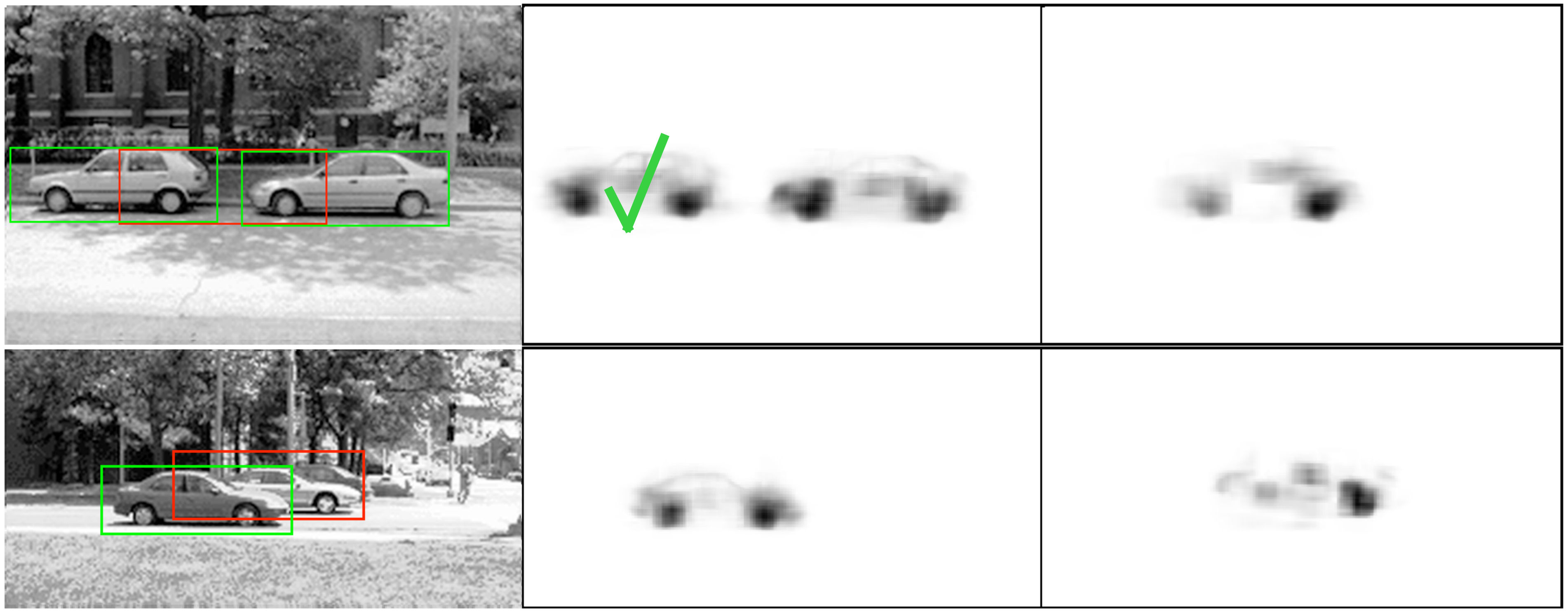

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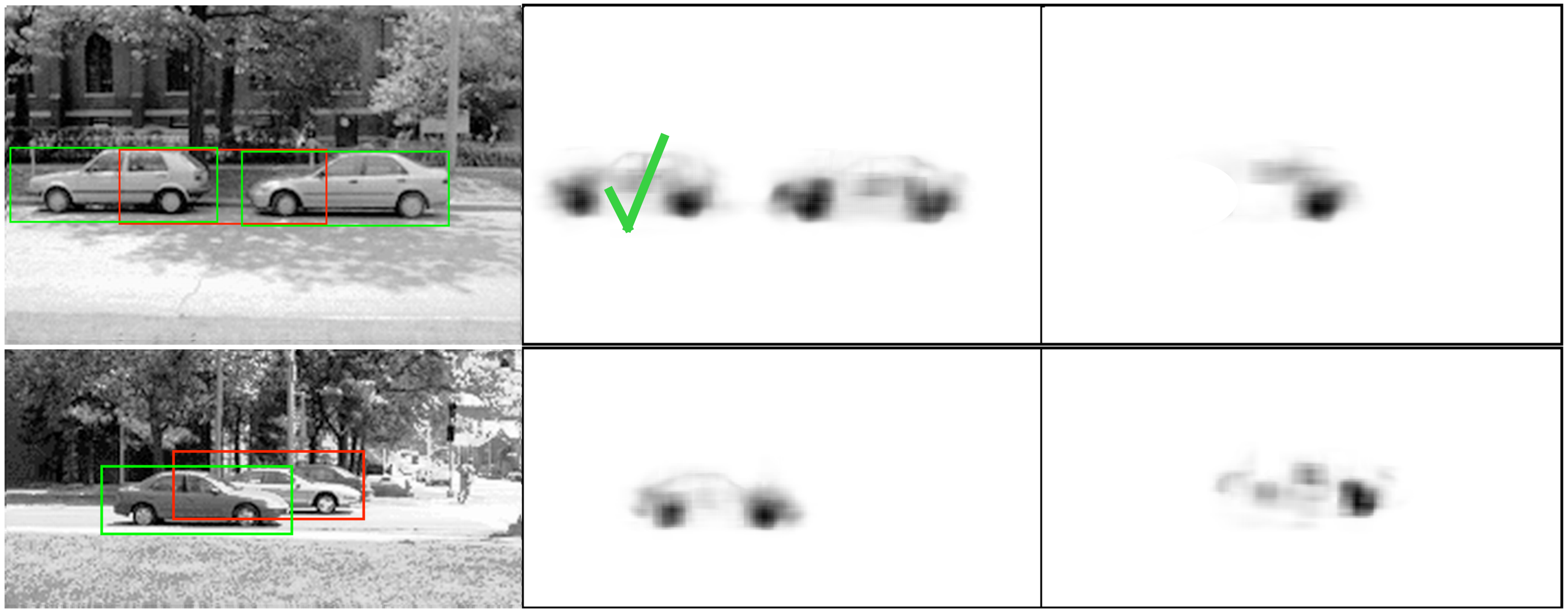

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Formalization in MDL Framework

- **Savings of a hypothesis**

$$S_h = K_0 S_{area} - K_1 S_{model} - K_2 S_{error}$$

- **with**
  - S_{area} **: #pixels** N **in segmentation**
  - S_{model}**: model cost, assumed constant**
  - S_{error} **: estimate of error, according to**

$$S_{error} = \sum_{\mathbf{p} \in Seg(h)} (1 - p(\mathbf{p} = \mathit{figure} | h))$$

- **Savings of *combined* hypothesis**

$$S_{h_1 \cup h_2} = S_{h_1} + S_{h_2} - S_{area}(h_1 \cap h_2) + S_{error}(h_1 \cap h_2)$$

- **-> greedy optimization of total savings**

Extension to Scale Invariance

Extension to Scale Invariance

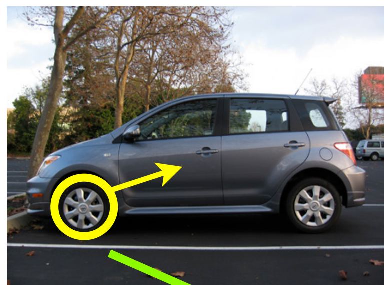
Extension to Scale Invariance

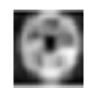
scale = 0.75

scale = 3.71

Extensions to Scale Invariance

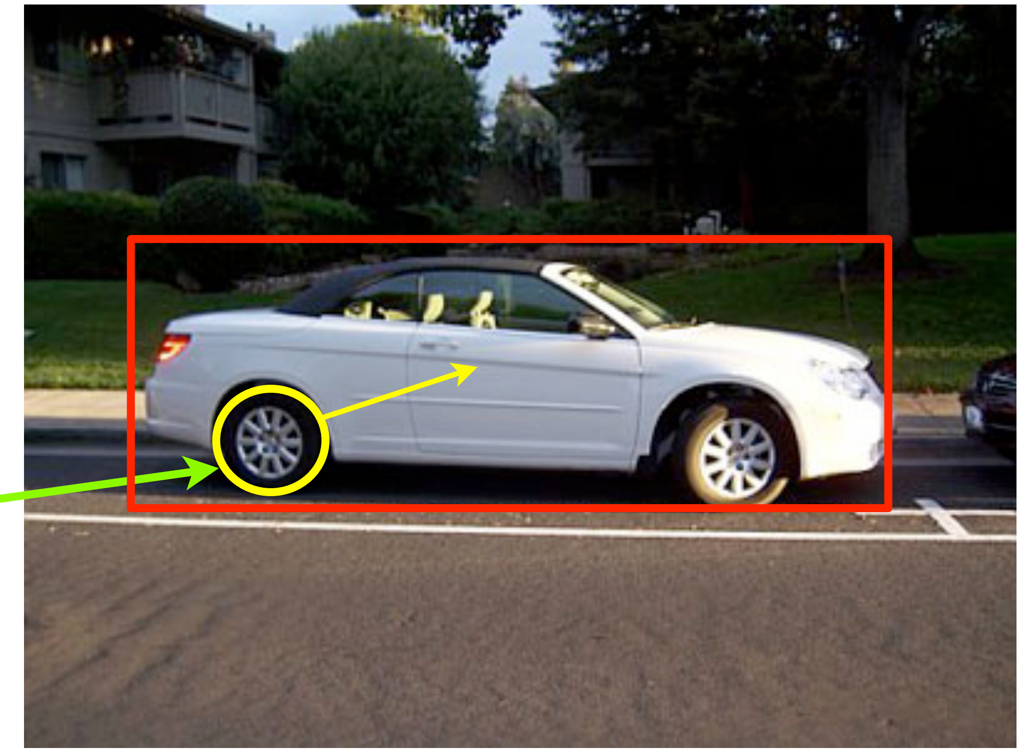
train





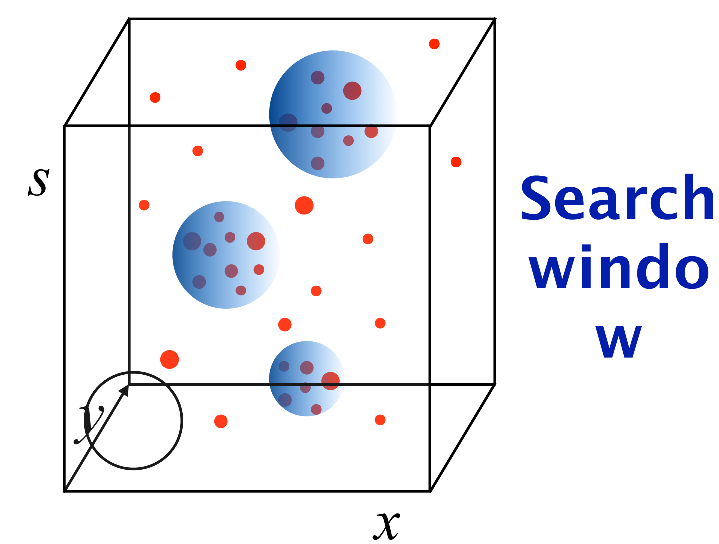
codebook entry

test



- **Generate scale votes**
  - Scale as 3rd dimension in voting space

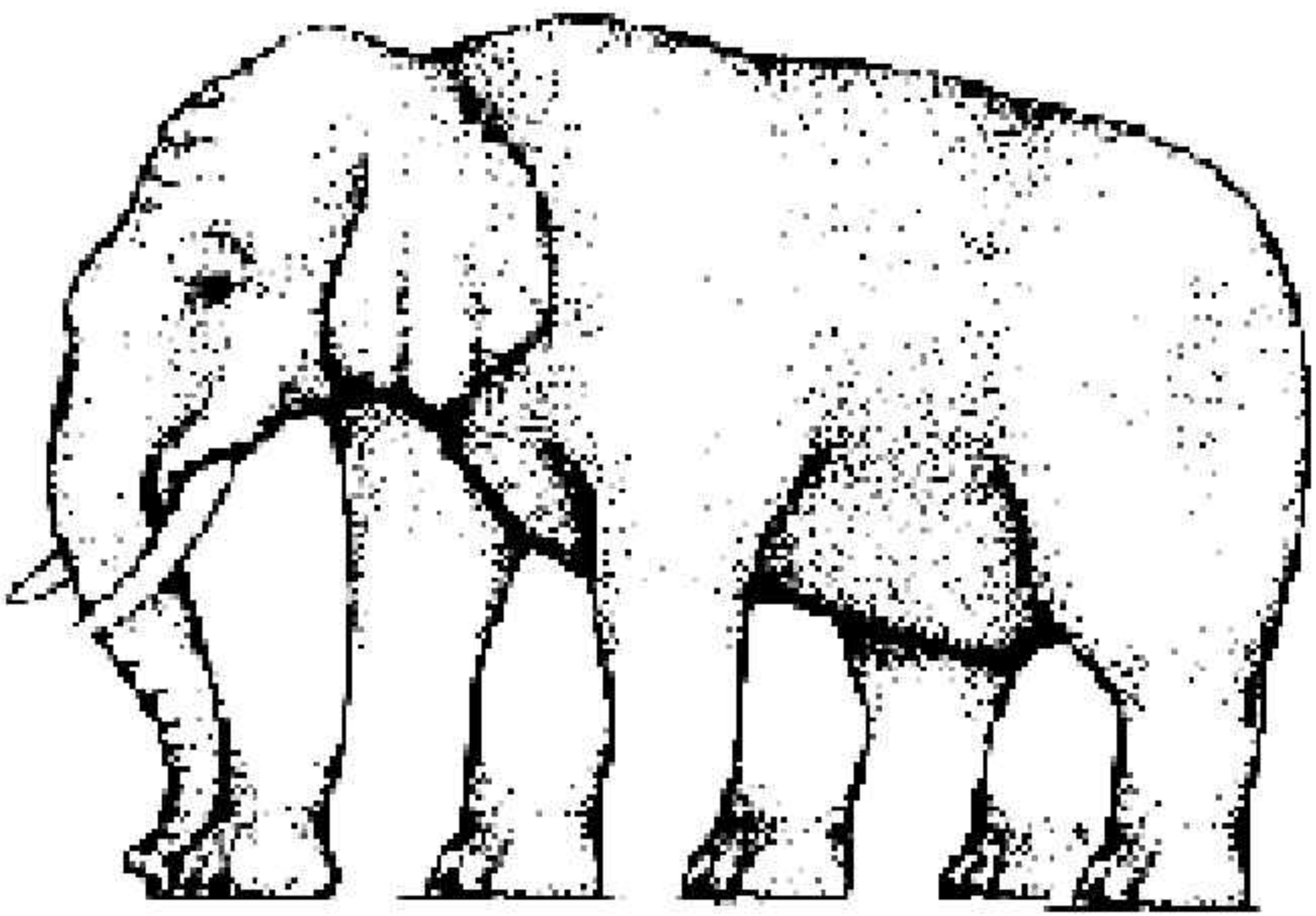
$$
\begin{aligned}
x_{vote} &= x_{img} - x_{occ}(s_{img}/s_{occ}) \\
y_{vote} &= x_{img} - y_{occ}(s_{img}/s_{occ}) \\
s_{vote} &= (s_{img}/s_{occ})
\end{aligned}
$$



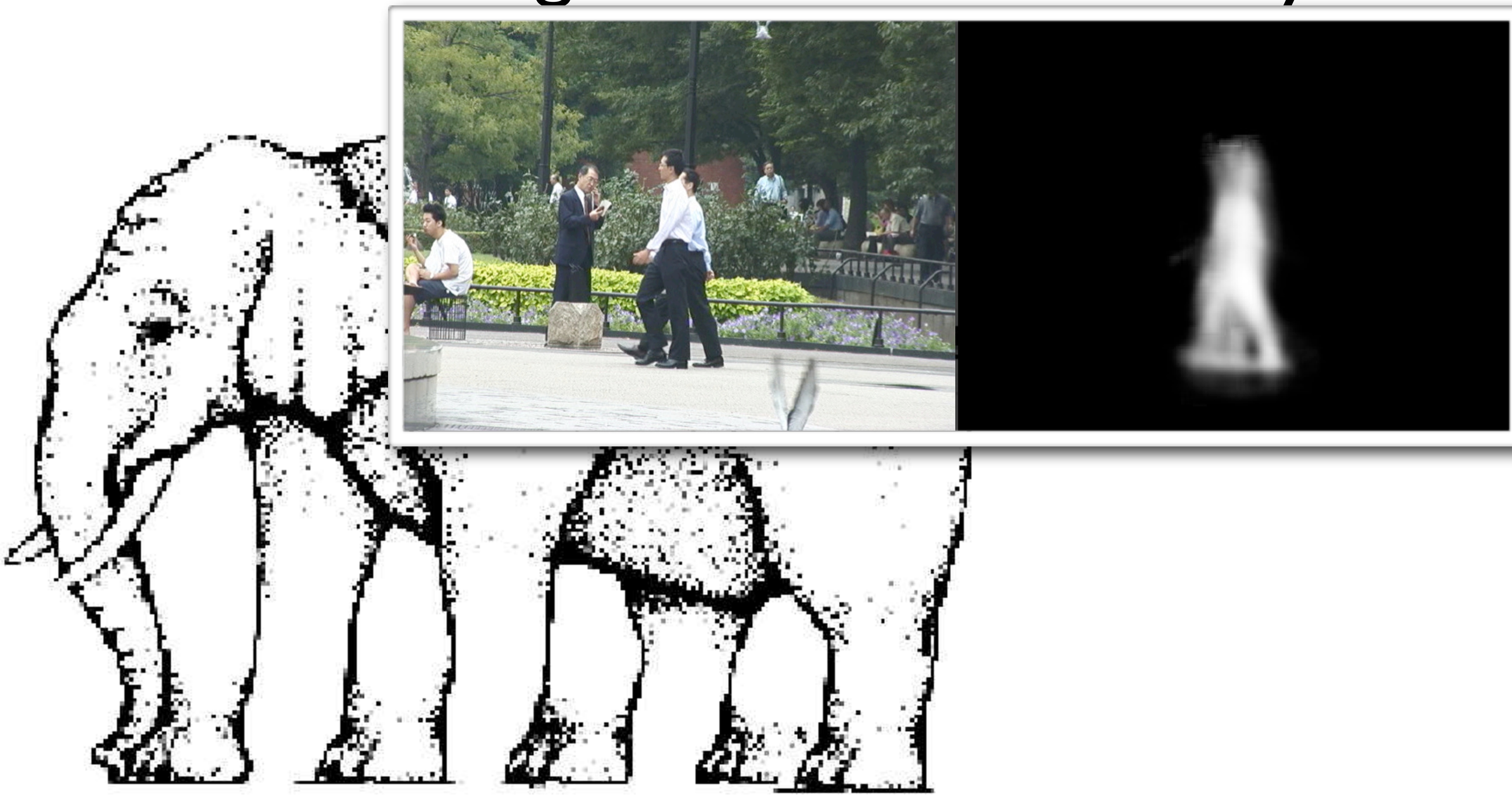
  - Search for maxima in 3D voting space

Extension to Rotation Invariance [Mikolajczyk06]

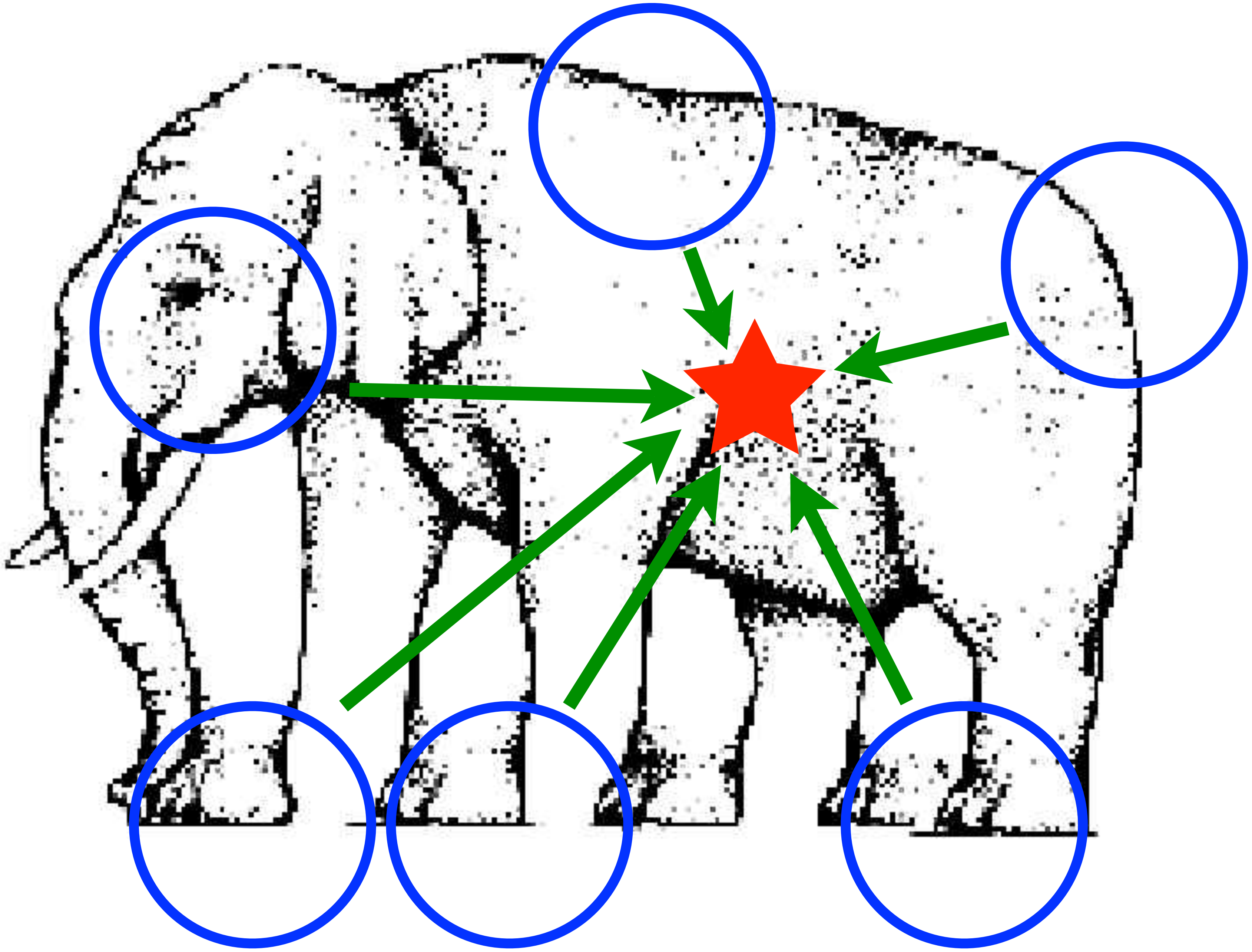
Complexity of Recognition: Local Voting vs. Global Cosistency



Complexity of Recognition: Local Voting vs. Global Cosistency



Complexity of Recognition: Local vs. Global



star model

Outlook to Lecture on 3rd March

- Recovering global consistency
- Adding discriminance to the model