SAIR

Spatial AI & Robotics Lab

CSE 473/573-A

L19: DETECTION

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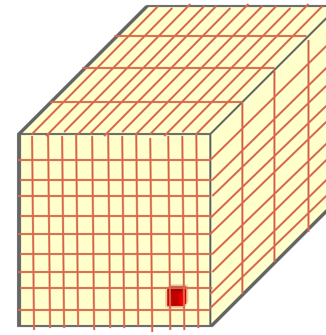
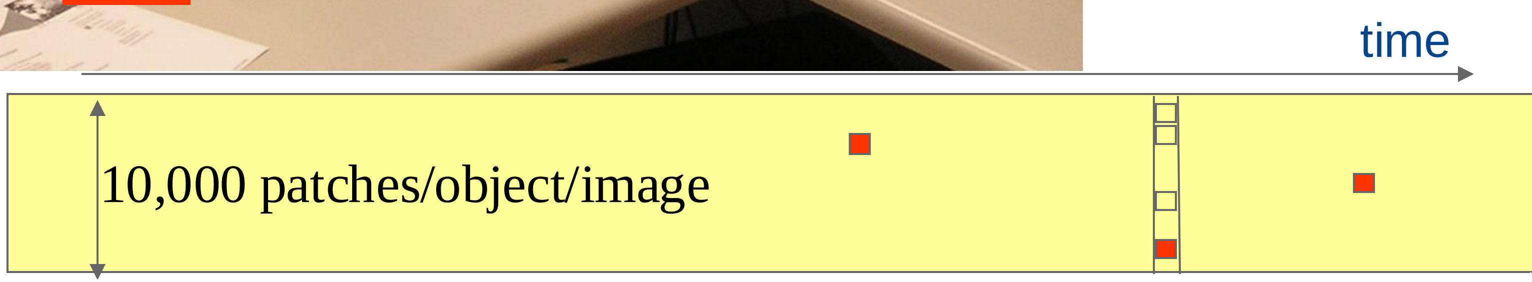
Why is detection hard?



We want to do this
for ~ 1000 objects

1,000,000 images/day



Why is detection hard?

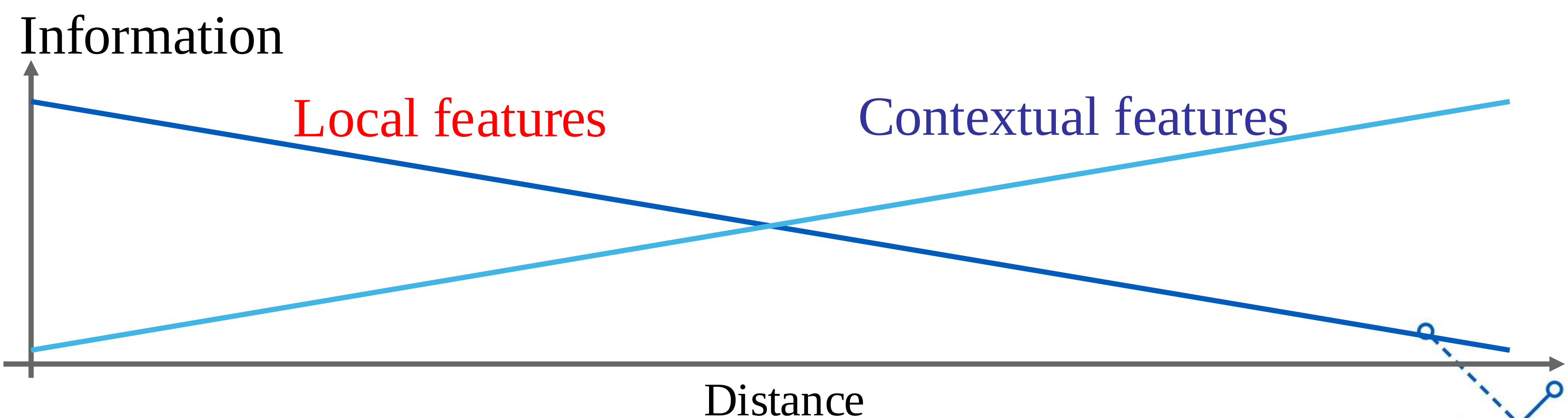
If we have 1000 categories (detectors), and each detector produces 1 false every 10 images, we will have 100 false alarms per image… pretty much garbage…

Slide credit: A. Torralba

Local information is helpful

Slide credit: A. Torralba

Is local information enough?



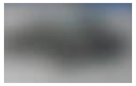
Is local information even enough?

We know there is a keyboard present in this scene even if we cannot see it clearly.

We know there is no keyboard present in this scene

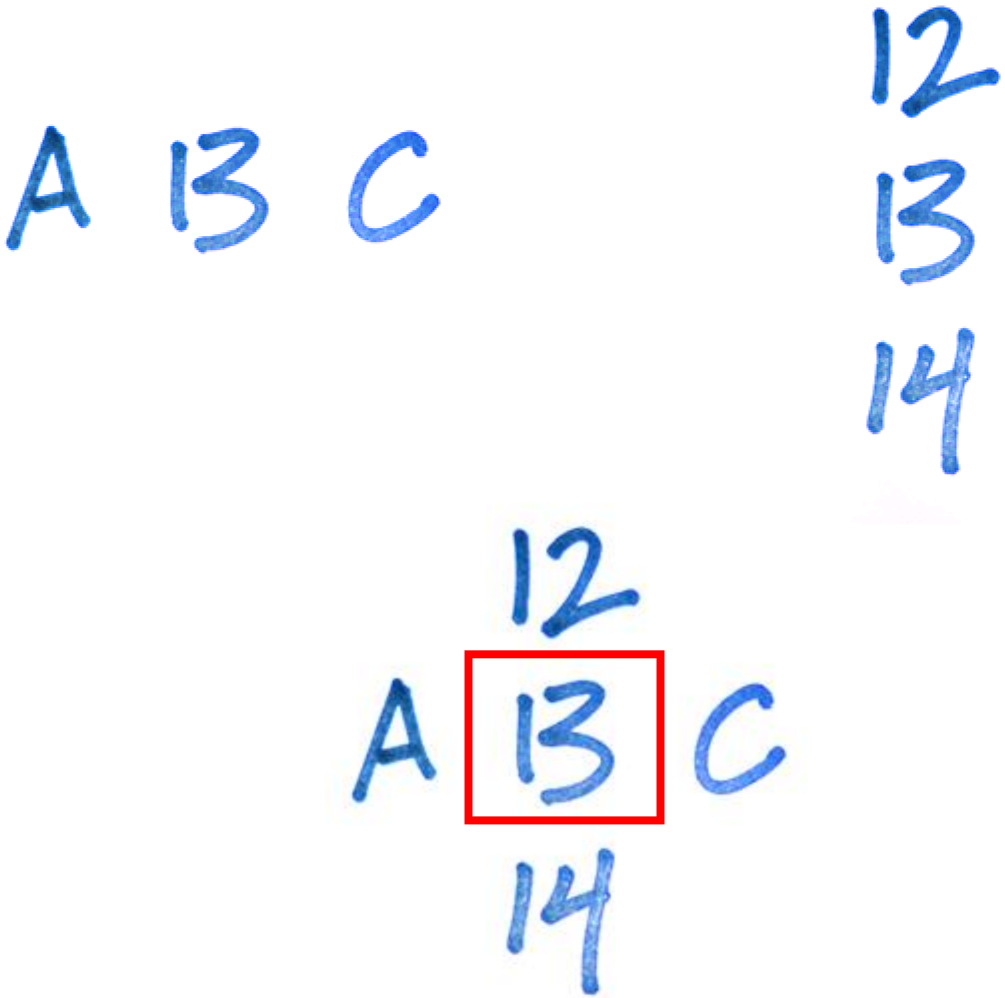
… even if there is one indeed.

The multiple personalities of a blob



Slide credit: A. Torralba

The multiple personalities of a blob



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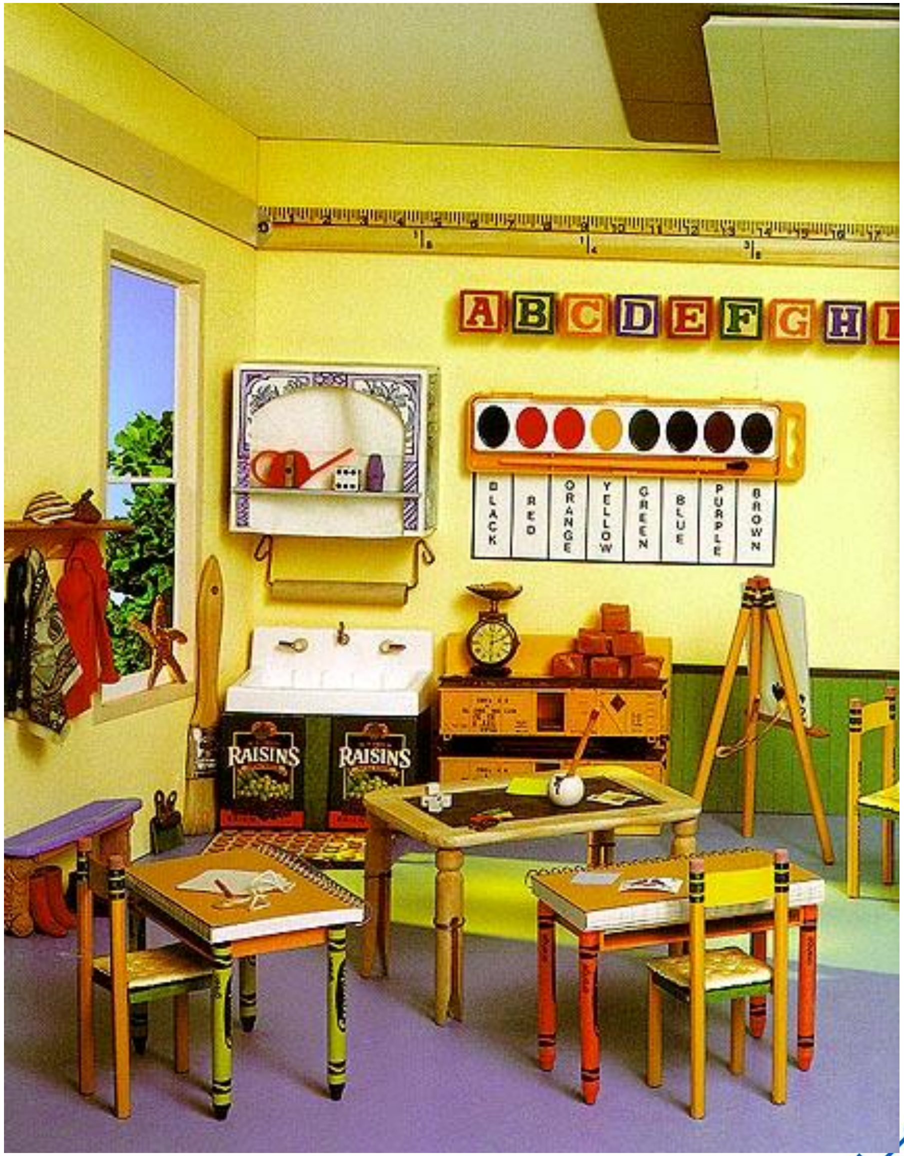
The multiple personalities of a blob



Look-Alikes: The More You Look, the More You See! Joan Steiner, October 17, 2003

Slide credit: A. Torralba

The context challenge

- What are the hidden objects?

Slide credit: A. Torralba

The context challenge

- What are the hidden objects?

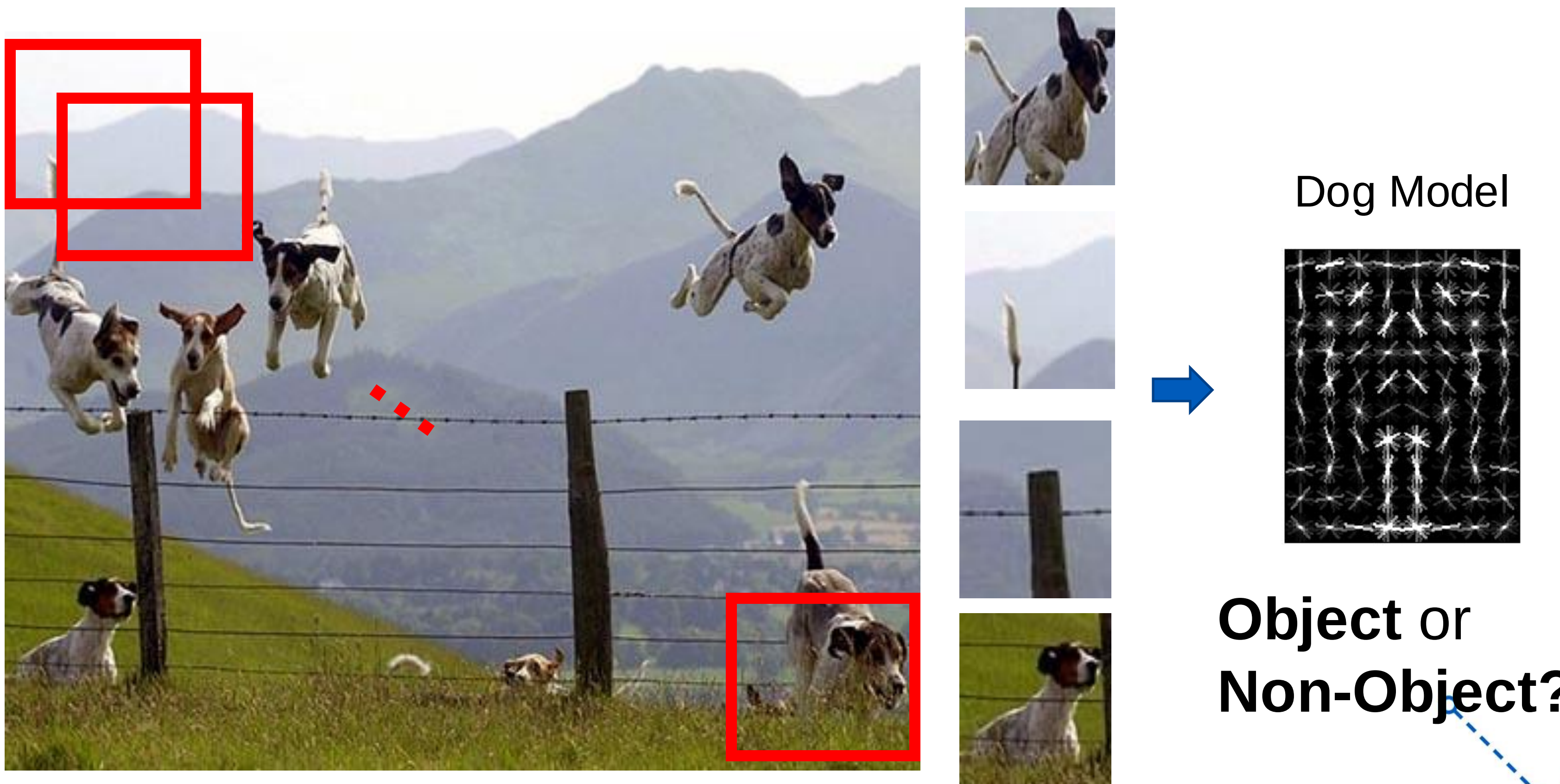
Slide credit: A. Torralba

Object detection vs Scene Recognition

- Objects (even if deformable and articulated) probably have more **consistent shapes** than scenes.
- Scenes can be defined by distribution of “stuff” – materials and surfaces with **arbitrary shape**.
- Objects are **“things” that own their boundaries**
- Bag of words (BoW) were less popular for object detection because they **throw away shape** info.

Object Category Detection

- Focus on object search: "Where is it?"
- Build templates that quickly differentiate object patch from background patch



Challenges in modeling the object class

Illumination

Object pose

Clutter

Occlusions

Intra-class appearance

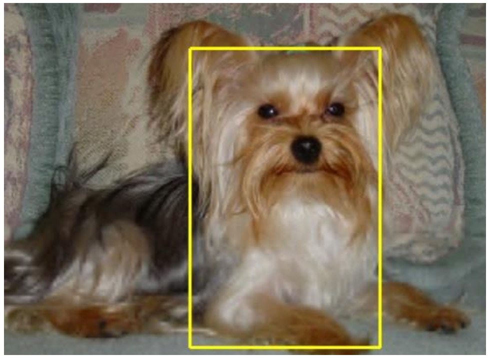
Viewpoint

Slide from K. Grauman, B. Leibe

Challenges in modeling the non-object class

True Detections

Bad Localization



Confused with Similar Object

Misc. Background

Confused with Dissimilar Objects

General Process of Object Recognition

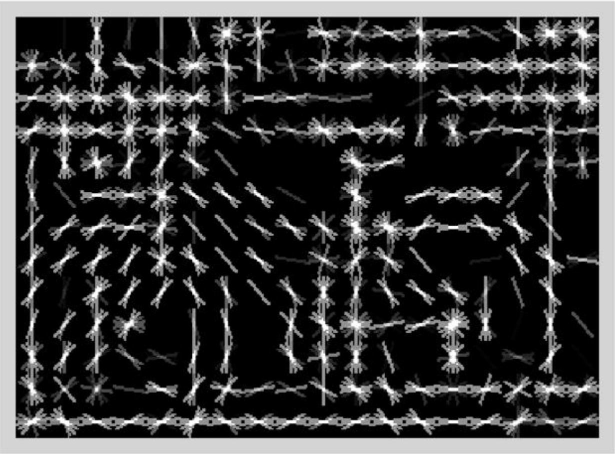
Specify Object Model → Generate Hypotheses → Score Hypotheses → Resolve Detections

What are the object parameters?

Specifying an object model

1. Statistical Template in Bounding Box
   - Object is somewhere (x,y,w,h) in image
   - Features defined wrt bounding box coordinates

Image

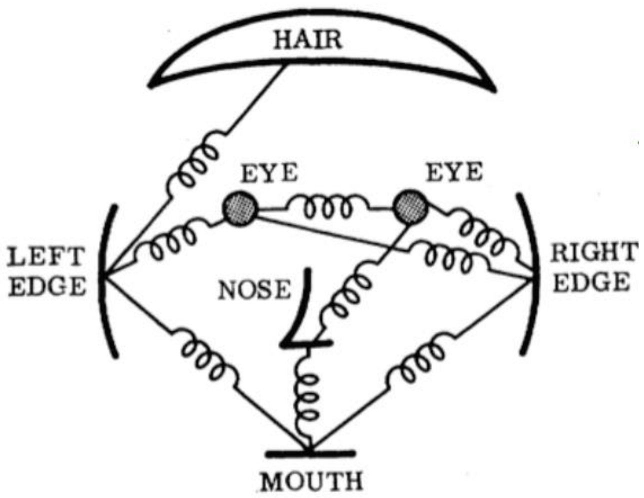


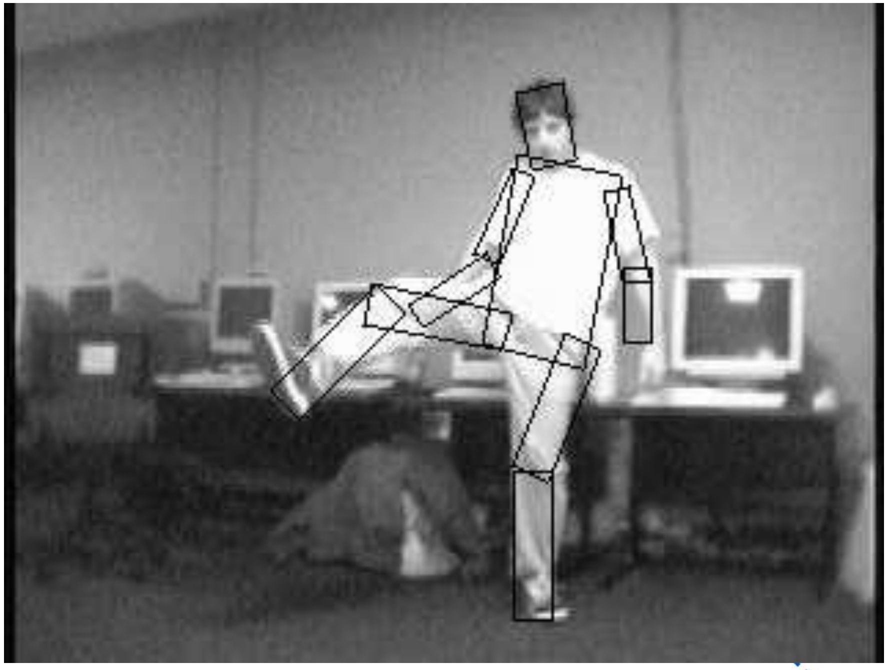
Template Visualization
(HoG features)

Images from Felzenszwalb

Specifying an object model

2. Articulated parts model
    - Object is configuration of parts
    - Each part is detectable



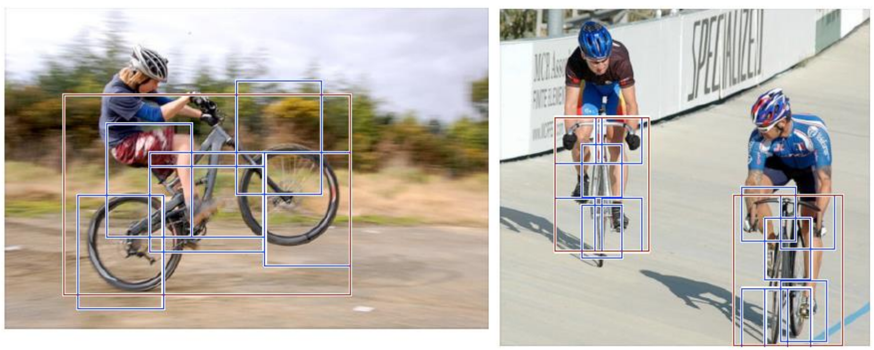


Images from Felzenszwalb

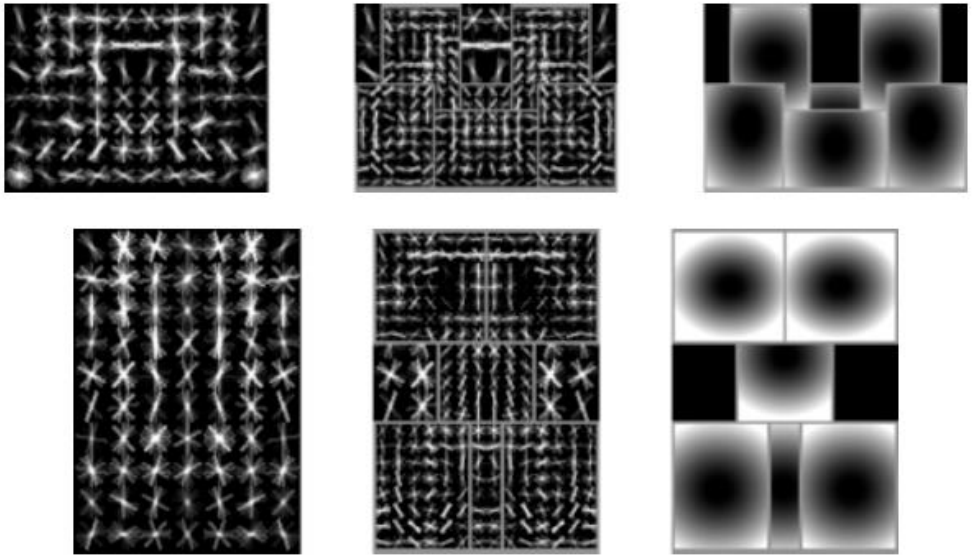
Specifying an object model

3. Hybrid template/parts model

Detections



Template Visualization
HoG features



root filters
coarse resolution

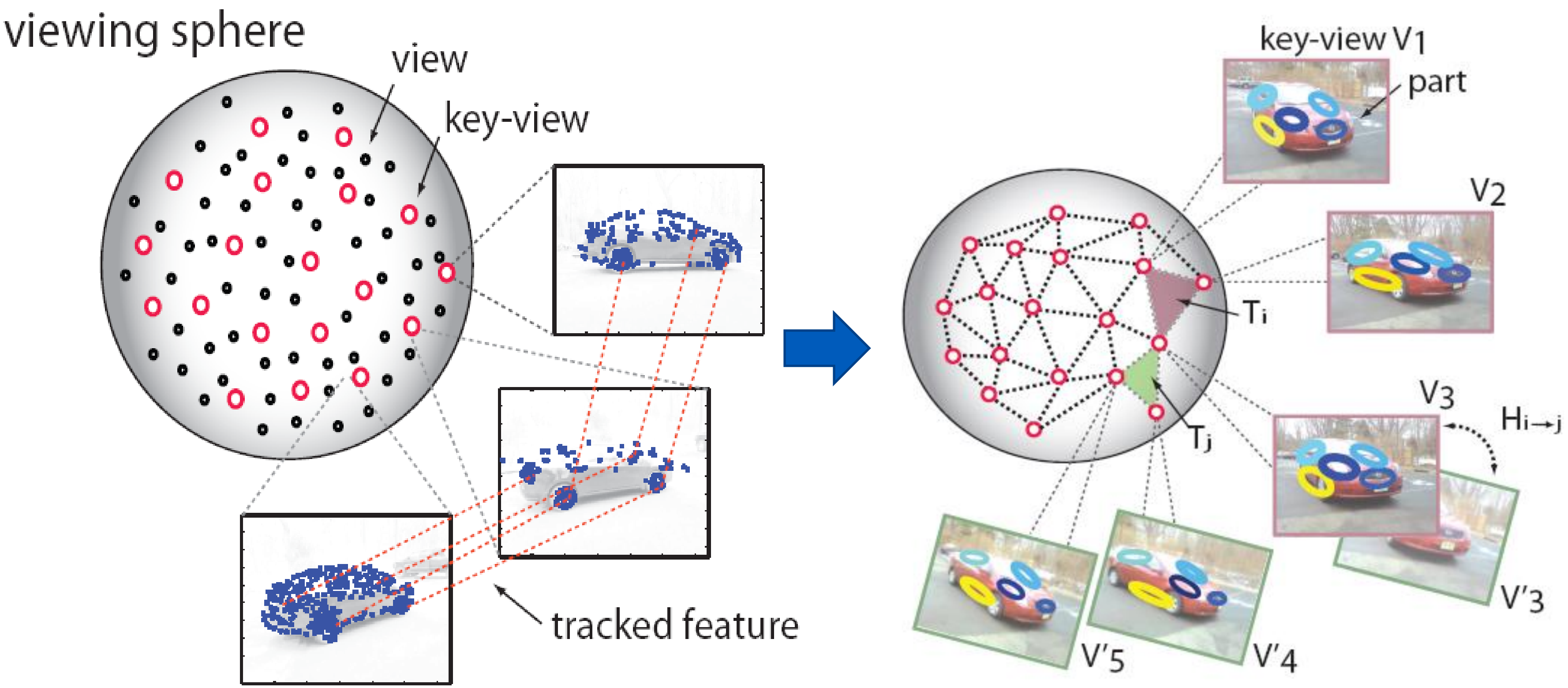
part filters
finer resolution

deformation
models

Felzenszwalb et al. 2008

Specifying an object model

4. 3D-ish model
   - Object is collection of 3D planar patches under affine transformation



General Process of Object Recognition

Specify Object Model

↓

Generate Hypotheses

↓

Score Hypotheses

↓

Resolve Detections

Propose an alignment of the model to the image

Generating hypotheses

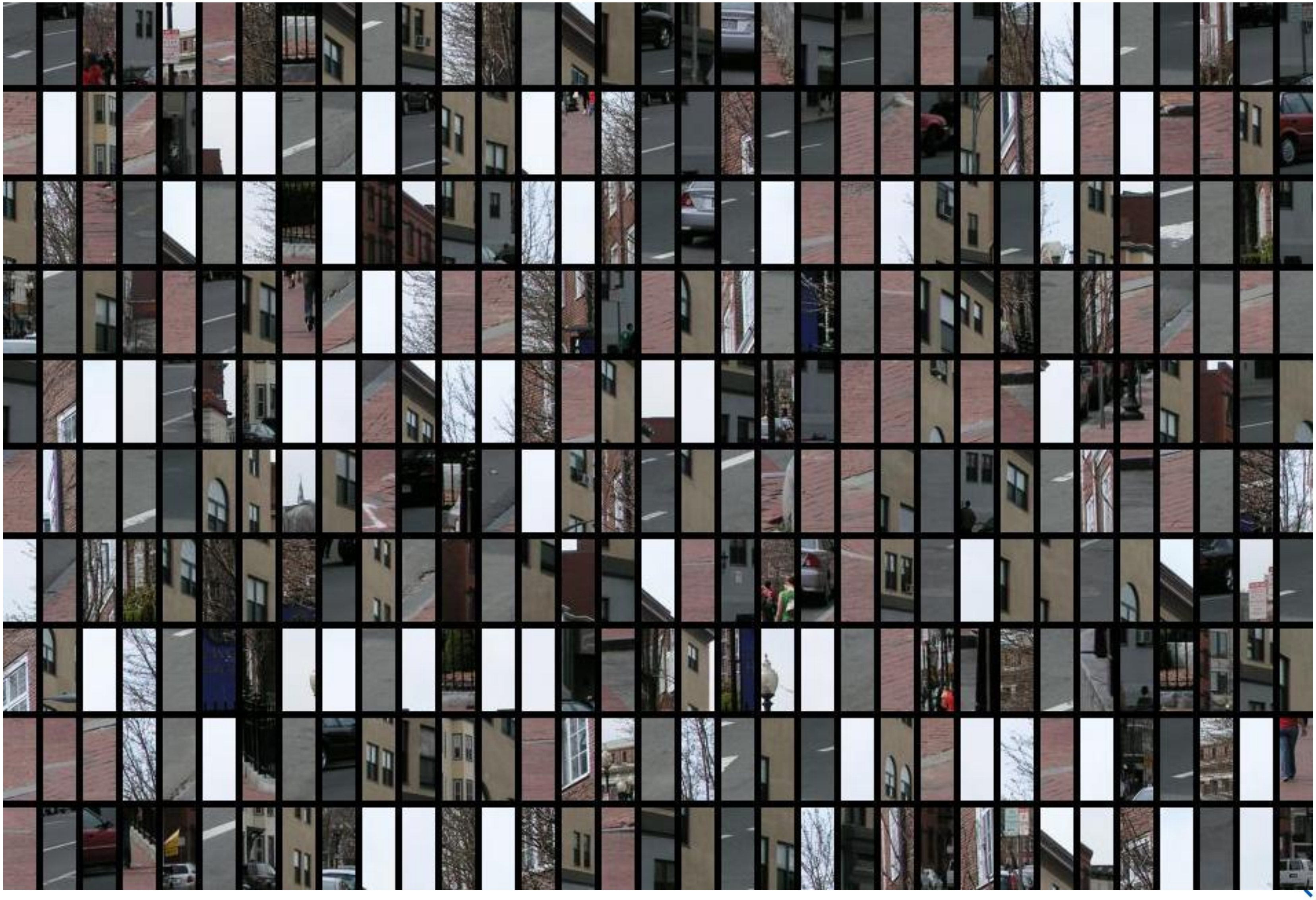
1. Sliding window
   - Test patch at each **location** and **scale**

Generating hypotheses

1. Sliding window
   - Test patch at each **location** and **scale (pyramids)**

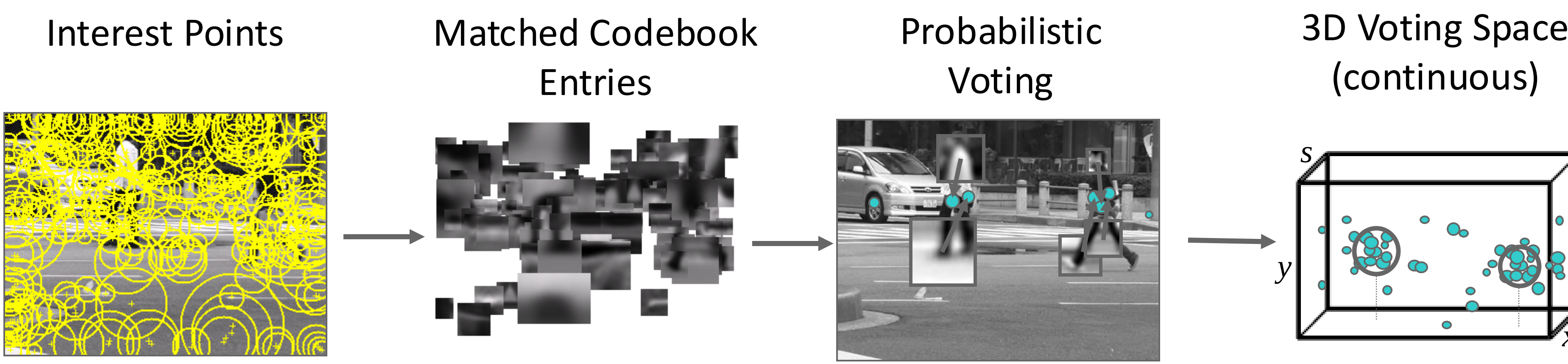
Note – Template did not change size

Each window is separately **classified**



Generating hypotheses

2. Voting from patches/keypoints



ISM model by Leibe et al.

Generating hypotheses

3. Region-based proposal

Endres Hoiem 2010

General Process of Object Recognition

Specify Object Model

↓

Generate Hypotheses

↓

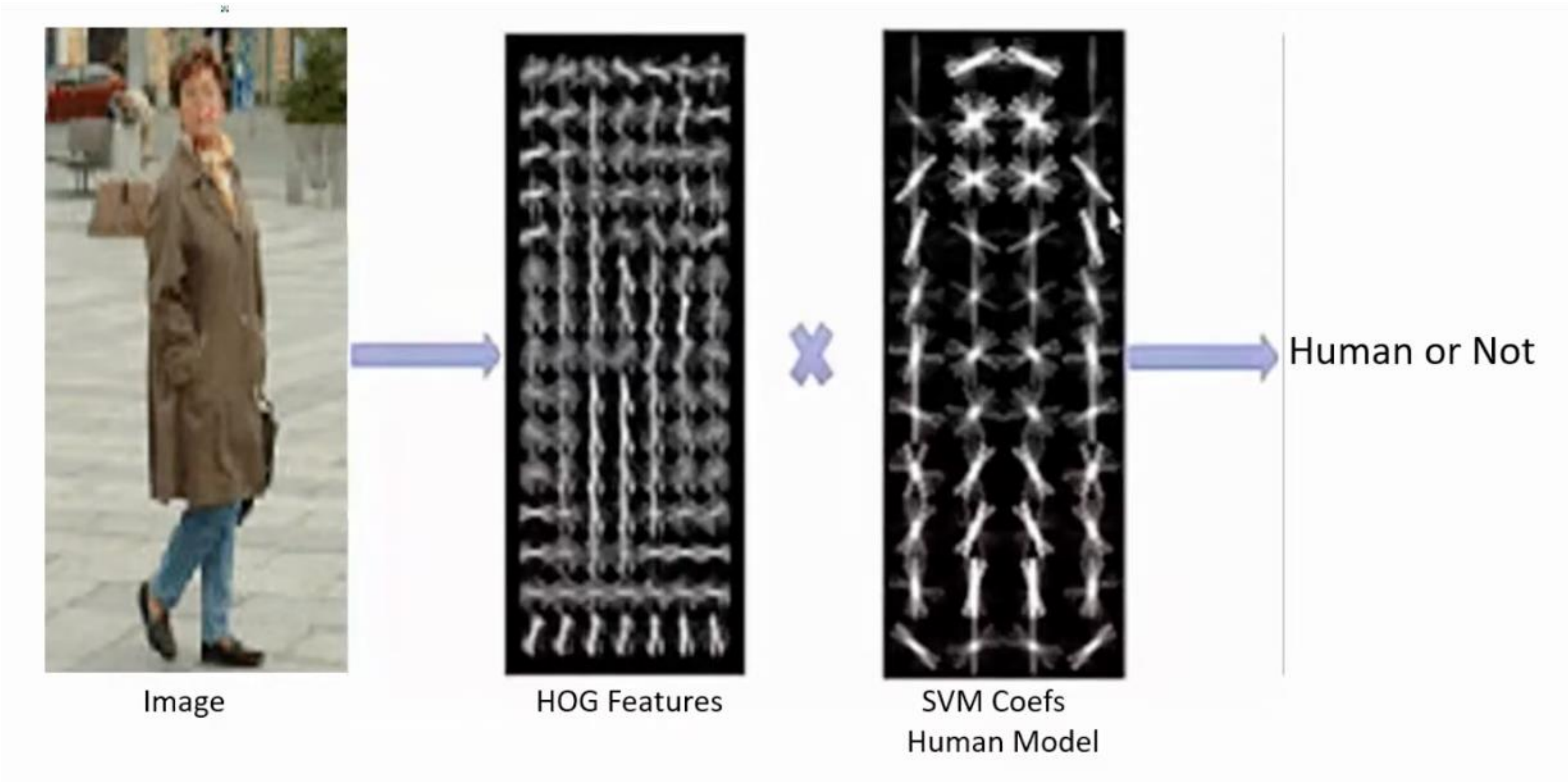
Score Hypotheses

↓

Resolve Detections

Mainly-gradient based features, usually based on summary representation, many classifiers.

HOG + SVM for Object Detection



https://youtu.be/sDByl84n5mY

Histograms of Oriented Gradients for Human Detection, Navneet Dalal, Bill Triggs, International Conference on Computer Vision & Pattern Recognition, 2005

General Process of Object Recognition

Specify Object Model

↓

Generate Hypotheses

↓

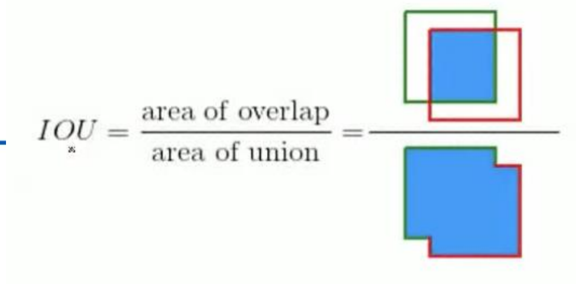
Score Hypotheses

↓

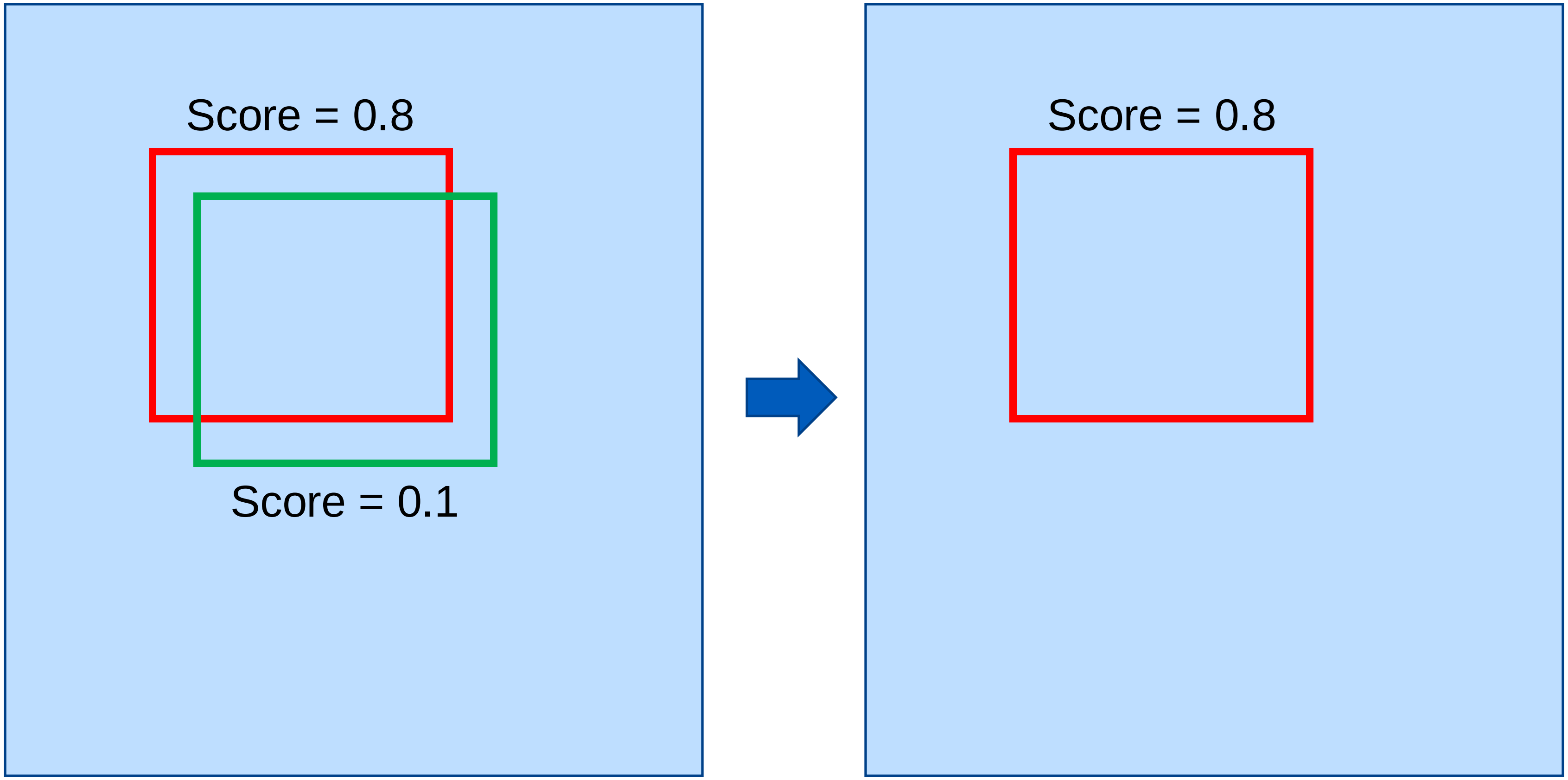
Resolve Detections

Rescore each proposed object based on whole set

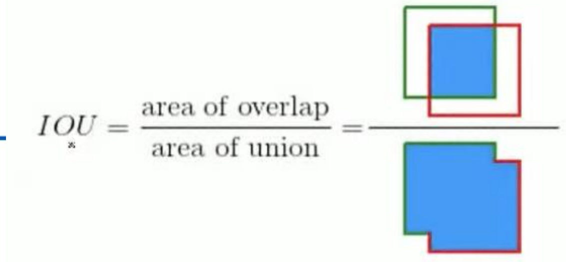
Resolving detection scores



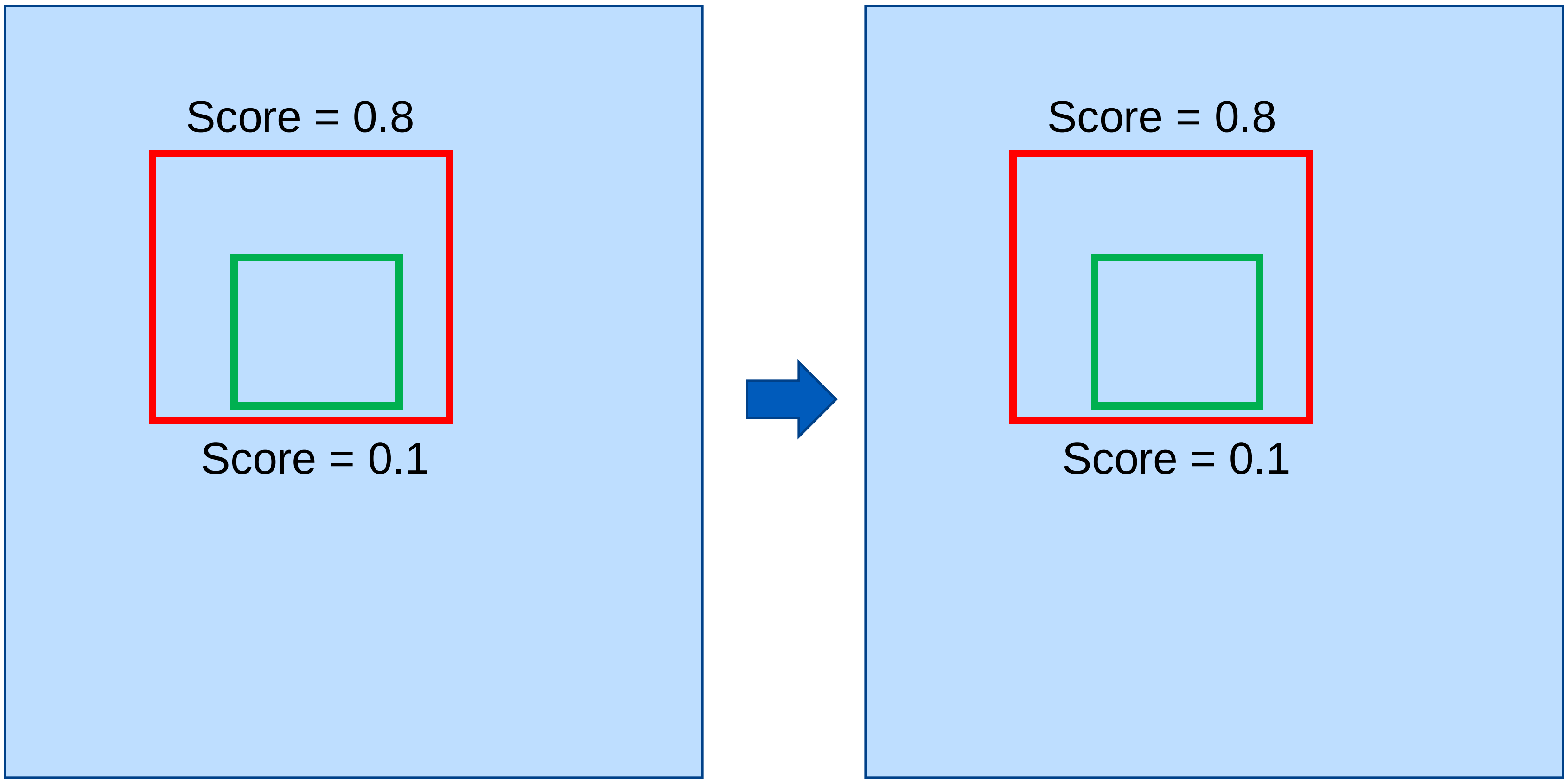
1. Non-max suppression



Resolving detection scores



1. Non-max suppression



"Overlap" score is below some threshold

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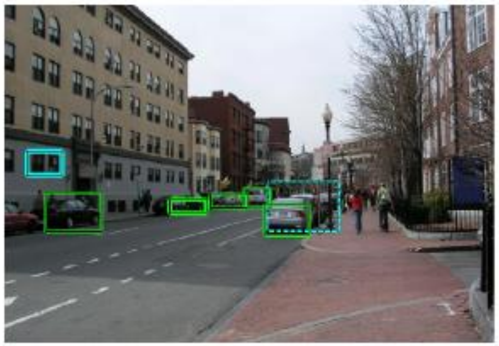
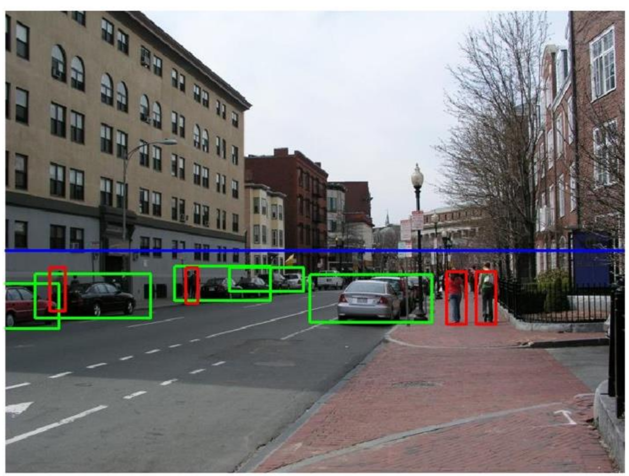
Resolving Detection Scores

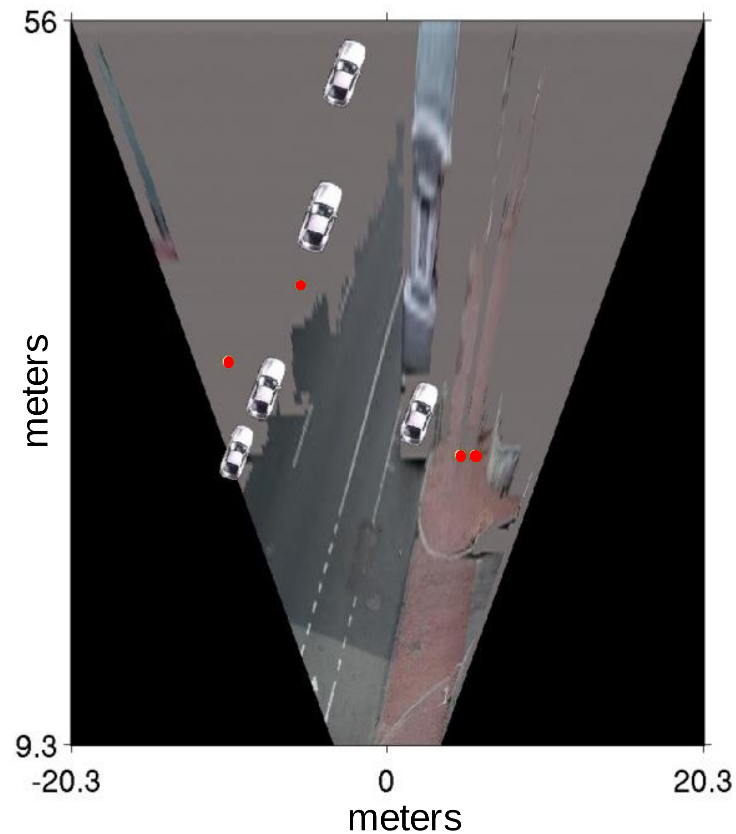
2. Context/reasoning



(g) Car Detections: Local

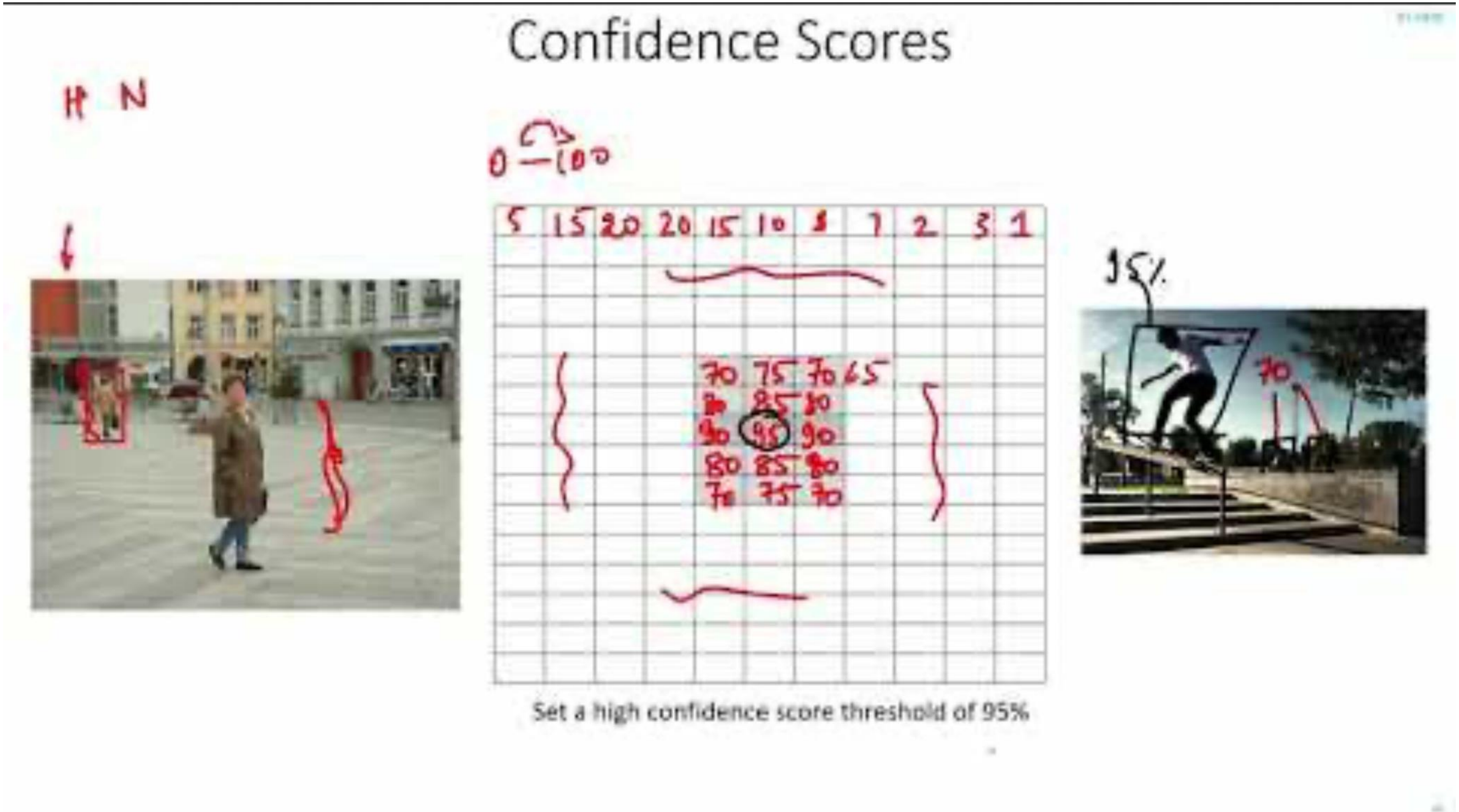
(h) Ped Detections: Local





Hoiem et al. 2006

Non-Max Suppression



How to measure performance?

- Precision – How precise are the answers you gave?
  - (# Relevant)/(# Total Returned)

- Recall – How many did you find of the ones that could be found?
  - (# Relevant)/(# Total Relevant)

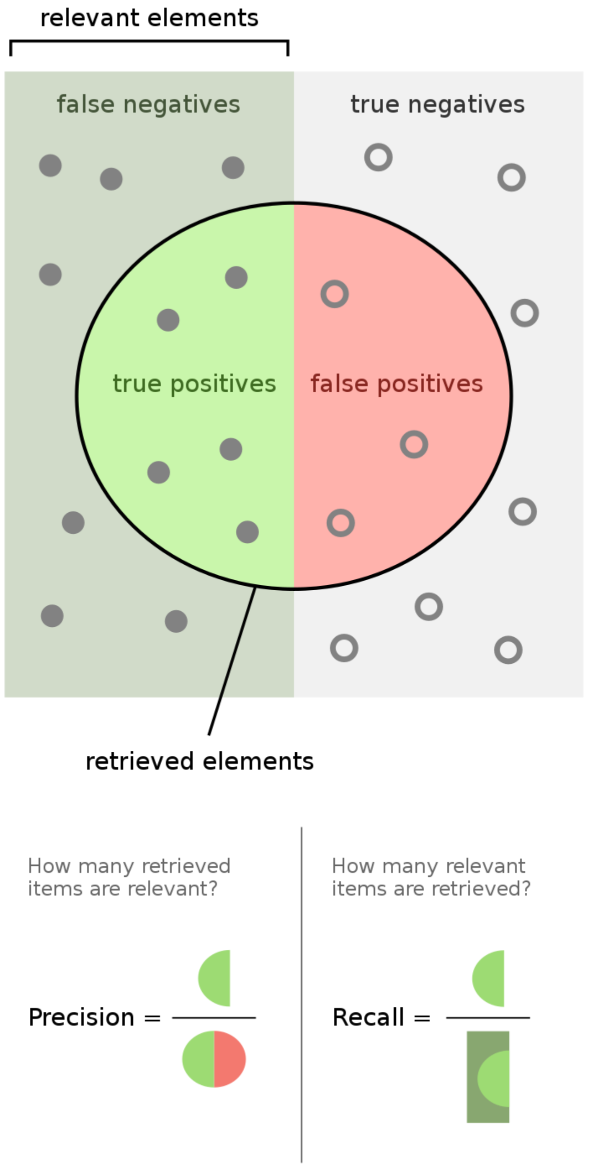
- F Measure – Harmonic Mean of Precision and Recall
  - (2*Precision*Recall)/(Precison+Recall)

Precision, Recall, F1 (Recap)

$$\text{Precision} = \frac{\text{True Positive}}{\text{Predicted Positive}}$$

$$\text{Recall} = \frac{\text{True Positive}}{\text{Actual Positive}}$$

$$F_1 = \frac{2}{\text{recall}^{-1} + \text{precision}^{-1}} = 2\frac{\text{precision} \cdot \text{recall}}{\text{precision} + \text{recall}}$$



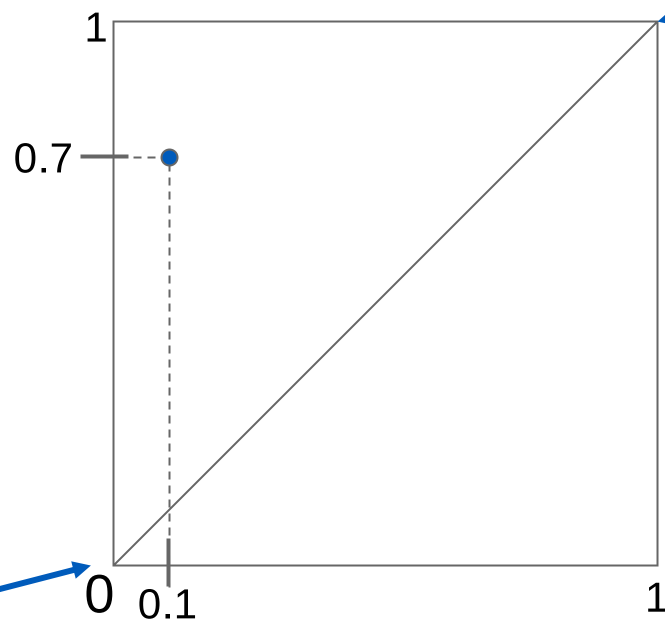
ROC curve (Recap)

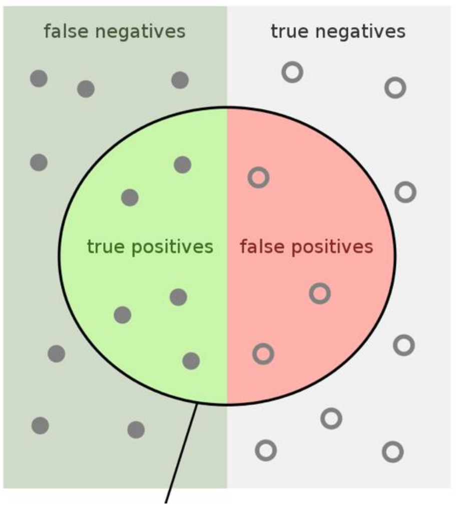
- How can we measure the performance of a feature matcher?

Lowest threshold
all pairs as match

Recall = 

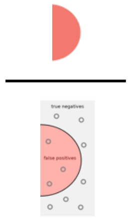
True Positive Rate $\dfrac{\#\,TP}{\#\,TP + FN}$





Highest threshold
no match

False Positive Rate $\dfrac{\#\,FP}{\#\,FP + TN}$

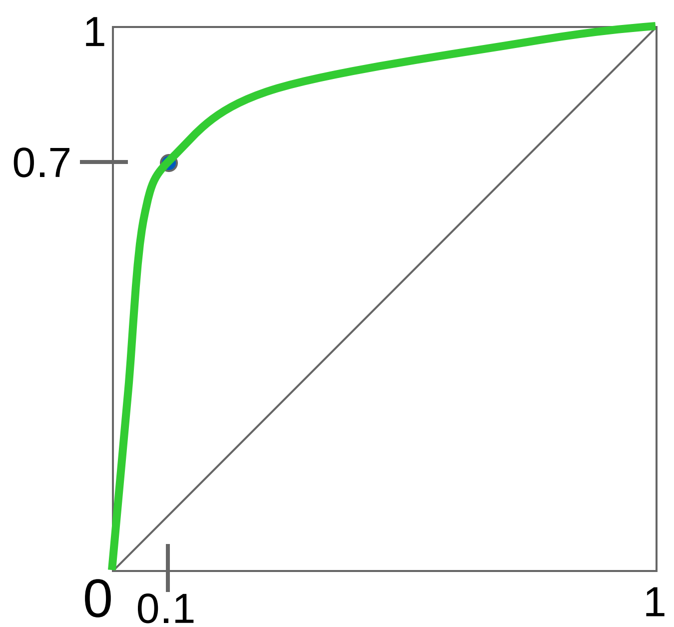
Fallout = 

ROC curve (Recap)

ROC Curves (Receiver Operator Characteristic)

- Generated by counting # correct/incorrect matches, for different thresholds.
- Want to maximize area under the curve (AUC)
- Useful for comparing different feature matching methods.

ROC curve

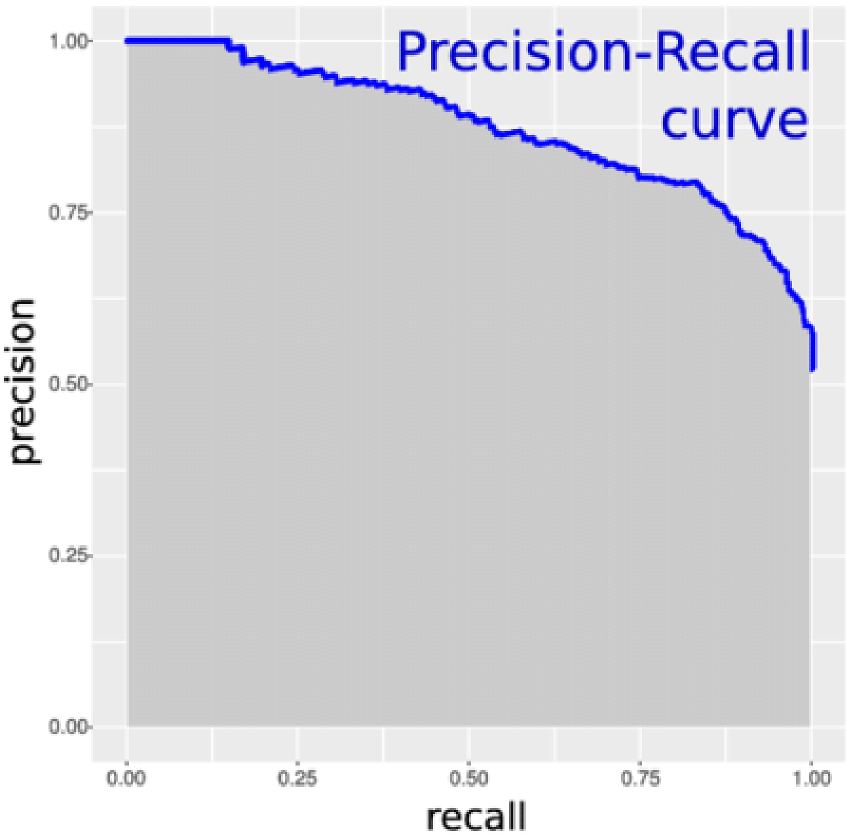


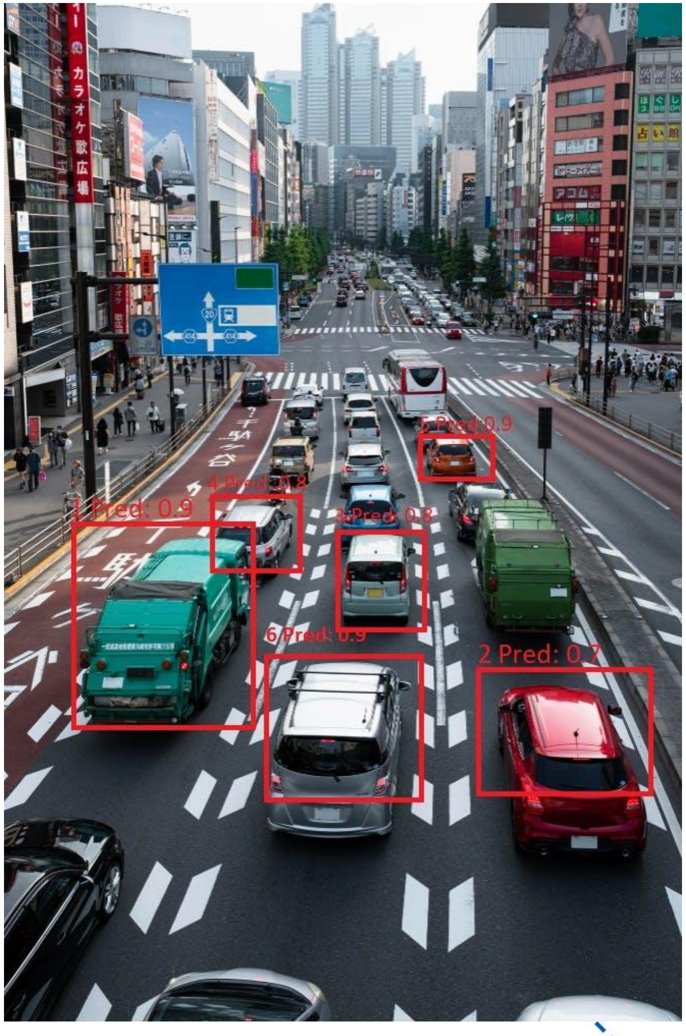
true positive rate $\dfrac{\#\,TP}{\#\,TP + FN}$

false positive rate $\dfrac{\#\,FP}{\#\,FP + TN}$

Precision and Recall Curve (PR curve)

precision = #relevant / #returned
recall = #relevant / #total relevant

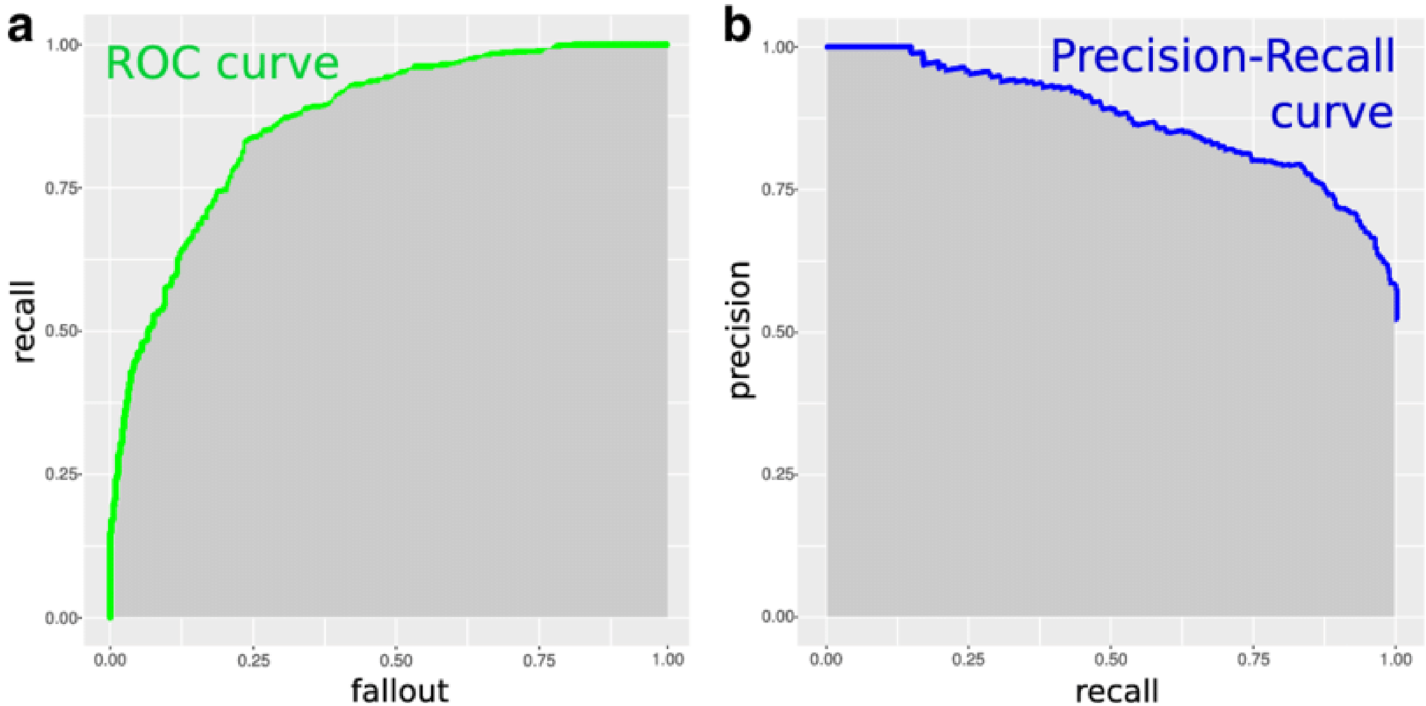




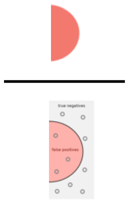
Slide credit: Ondrej Chum

ROC curve VS. PR curve

Recall = 



Precision = 

Fallout = 

Recall = 

ROC curve VS. PR curve

- ROC Curves (Lecture 4)
  - summarize the trade-off between the **true positive rate** and **false positive rate** for a predictive model using different probability thresholds.
- PR curves
  - summarize the trade-off between the **true positive rate** and the **positive predictive value** for a predictive model using different probability thresholds.

ROC curve VS. PR curve

- ROC: good for balanced datasets/classes.
- PR curves: appropriate for **imbalanced datasets**.
- If the proportion of positive to negative instances changes in a test set, the ROC curves will not change, so do not depend on class distributions.
- ROC “weights” equally true positives and true negatives (not expected sometimes, e.g., place recognition).

More explanation