Lecture:
Object detection

Juan Carlos Niebles and Ranjay Krishna

Stanford Vision and Learning Lab

What we will learn today

- Object detection
  - Task and evaluation
- A simple detector
- Deformable parts model

What we will learn today

- Object detection
  - Task and evaluation
- A simple detector
- Deformable parts model

Object Detection

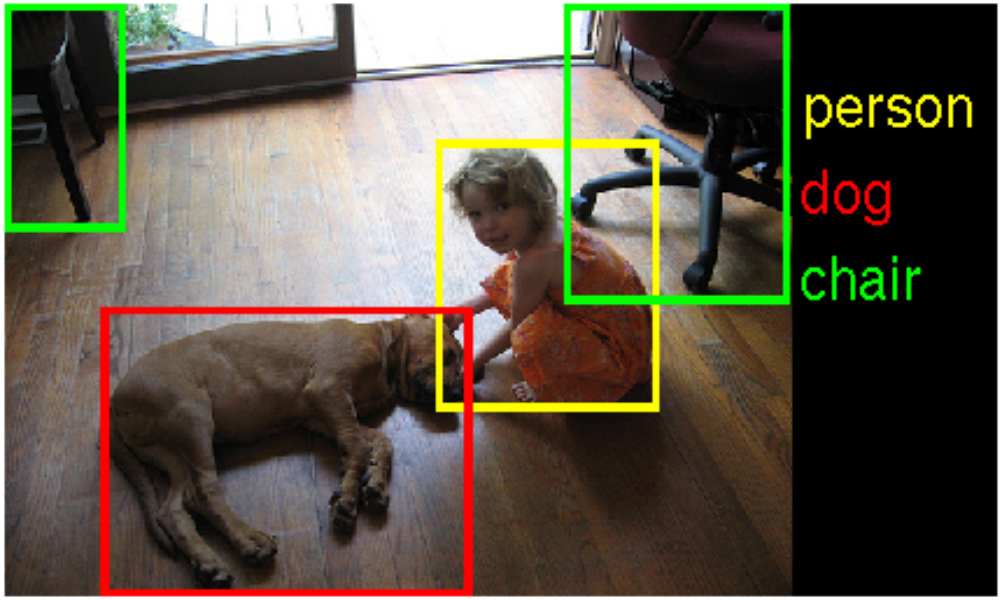
Credit: Flickr user neilalderney123

- What do you see in the image?

Object Detection

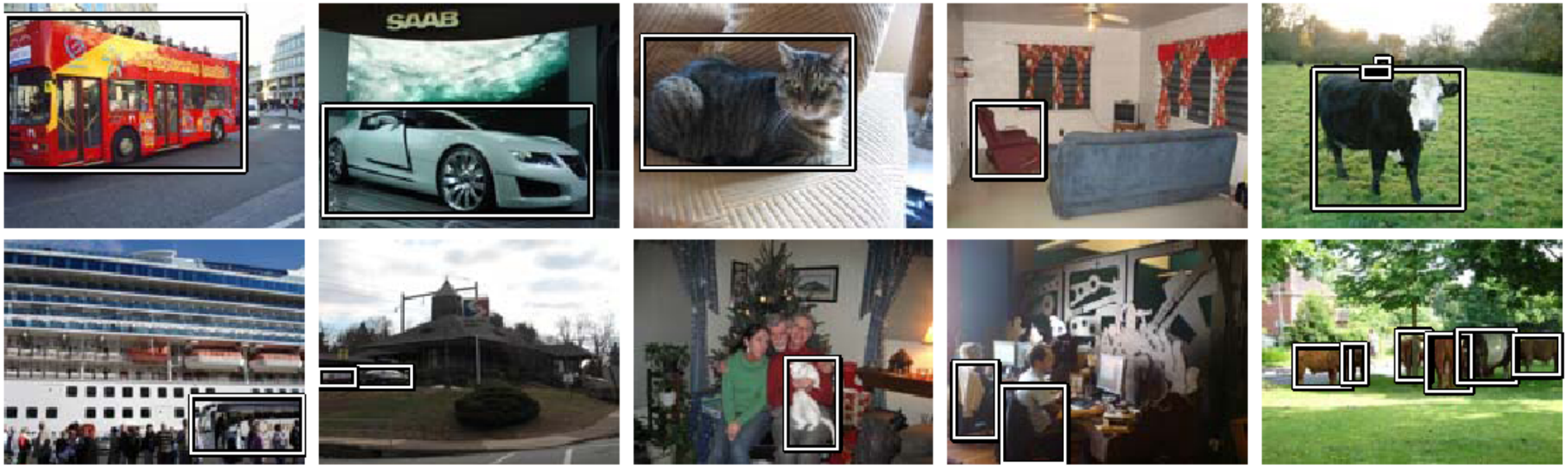
- **Problem**: Detecting and localizing generic objects from various categories, such as cars, people, etc.

- Challenges:
  - Illumination,
  - viewpoint,
  - deformations,
  - Intra-class variability



Object Detection Benchmarks

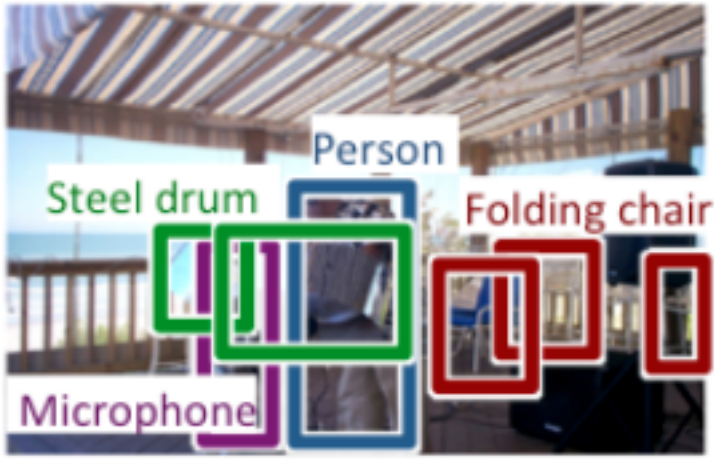
- PASCAL VOC Challenge



- 20 categories
- Annual classification, detection, segmentation, … challenges

Object Detection Benchmarks

- PASCAL VOC Challenge
- ImageNet Large Scale Visual Recognition Challenge (ILSVR)
  - 200 Categories for detection



Object Detection Benchmarks

- PASCAL VOC Challenge
- ImageNet Large Scale Visual Recognition Challenge (ILSVR)
- Common Objects in Context (COCO)
  - 80 Object categories



How do we evaluate object detection?

predictions

ground truth

How do we evaluate object detection?

predictions

ground truth

True positive:

- The overlap of the prediction with the ground truth is MORE than 0.5

How do we evaluate object detection?

predictions

ground truth

True positive:

False positive:

- The overlap of the prediction with the ground truth is LESS than 0.5

How do we evaluate object detection?

predictions

ground truth

True positive:

False positive:

False negative:

- The objects that our model doesn't find

How do we evaluate object detection?

predictions

ground truth

True positive:

False positive:

False negative:

- The objects that our model doesn't find

What is a True Negative?

	Predicted 1	Predicted 0
True 1	true positive	false negative
True 0	false positive	true negative

	Predicted 1	Predicted 0
True 1	true positive	false negative
True 0	false positive	true negative

	Predicted 1	Predicted 0
True 1	TP	FN
True 0	FP	TN

	Predicted 1	Predicted 0
True 1	true positive	false negative
True 0	false positive	true negative

	Predicted 1	Predicted 0
True 1	TP	FN
True 0	FP	TN

	Predicted 1	Predicted 0
True 1	hits	misses
True 0	false alarms	correct rejections

	Predicted 1	Predicted 0
True 1	true positive	false negative
True 0	false positive	true negative

	Predicted 1	Predicted 0
True 1	TP	FN
True 0	FP	TN

	Predicted 1	Predicted 0
True 1	hits	misses
True 0	false alarms	correct rejections

$$precision = \frac{TP}{TP + FP}$$

$$recall = \frac{TP}{TP + FN}$$

How do we evaluate object detection?

predictions

ground truth

True positive: 1
False positive: 2
False negative: 1

So what is the
- precision?
- recall?

Precision versus recall

- Precision:
  - how many of the object detections are correct precision
- Recall:
  - how many of the ground truth objects can the model detect?

In reality, our model makes a lot of predictions with varying scores between 0 and 1

predictions

ground truth

Here are all the boxes that are predicted with score > 0.

This means that our

- Recall is perfect!
- But our precision is BAD!

In reality, our model makes a lot of predictions with varying scores between 0 and 1

predictions

ground truth

There are no boxes that are predicted with score = 1.

This means that our

- Precision is undefined!
- And our recall is BAD!

How do we evaluate object detection?

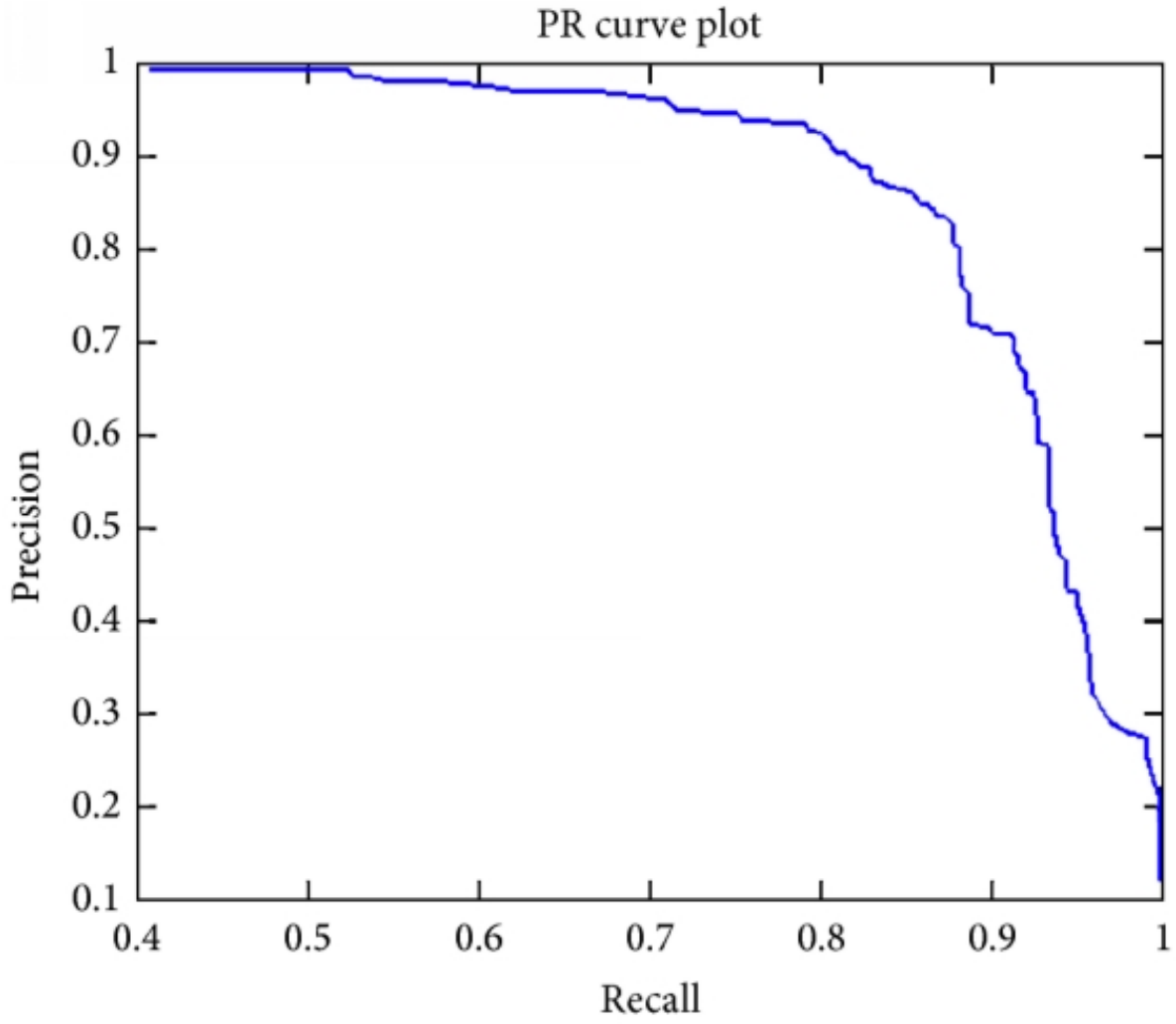
predictions

ground truth

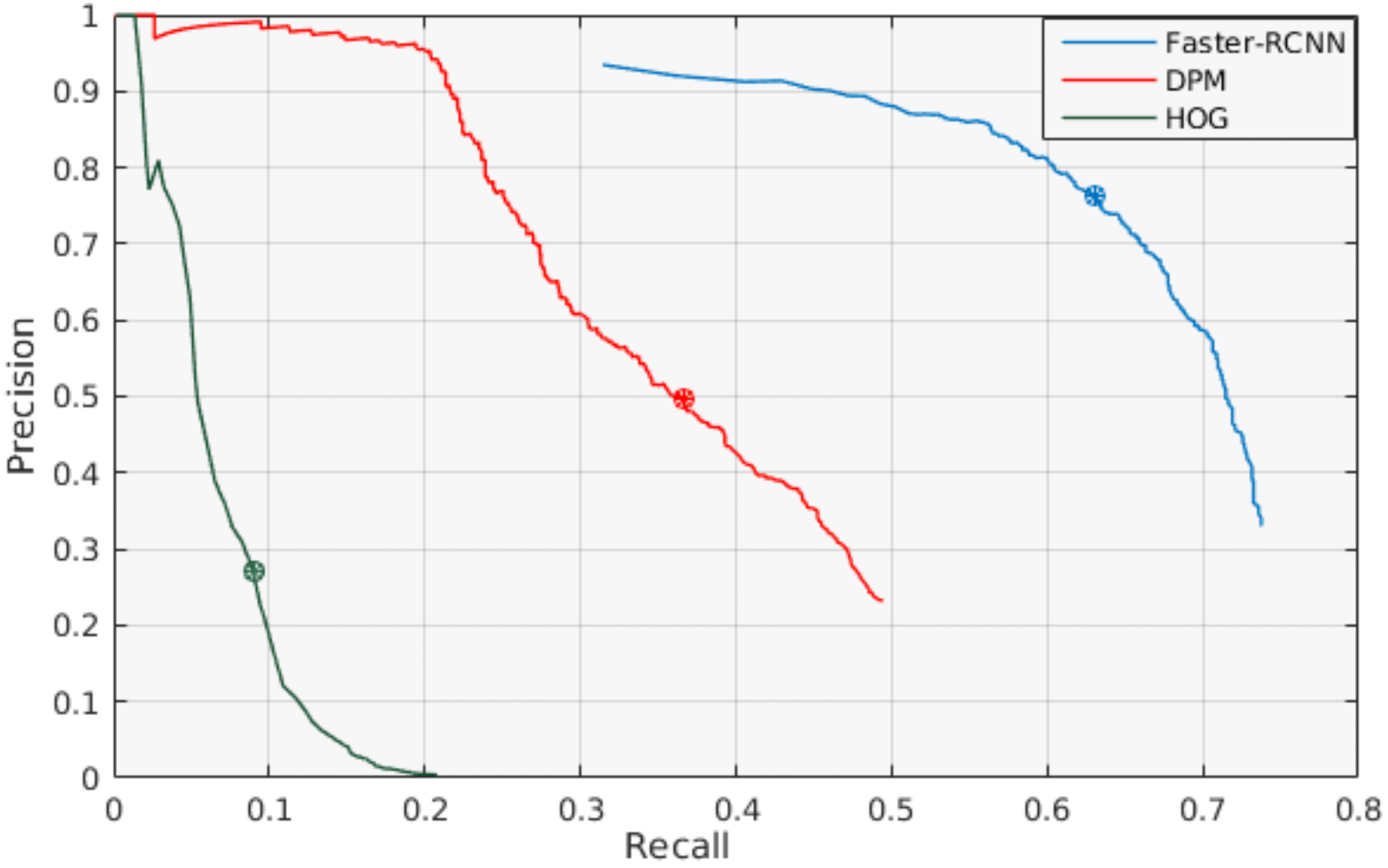
Here are all the boxes that are predicted with score > 0.5

We are setting a threshold of 0.5

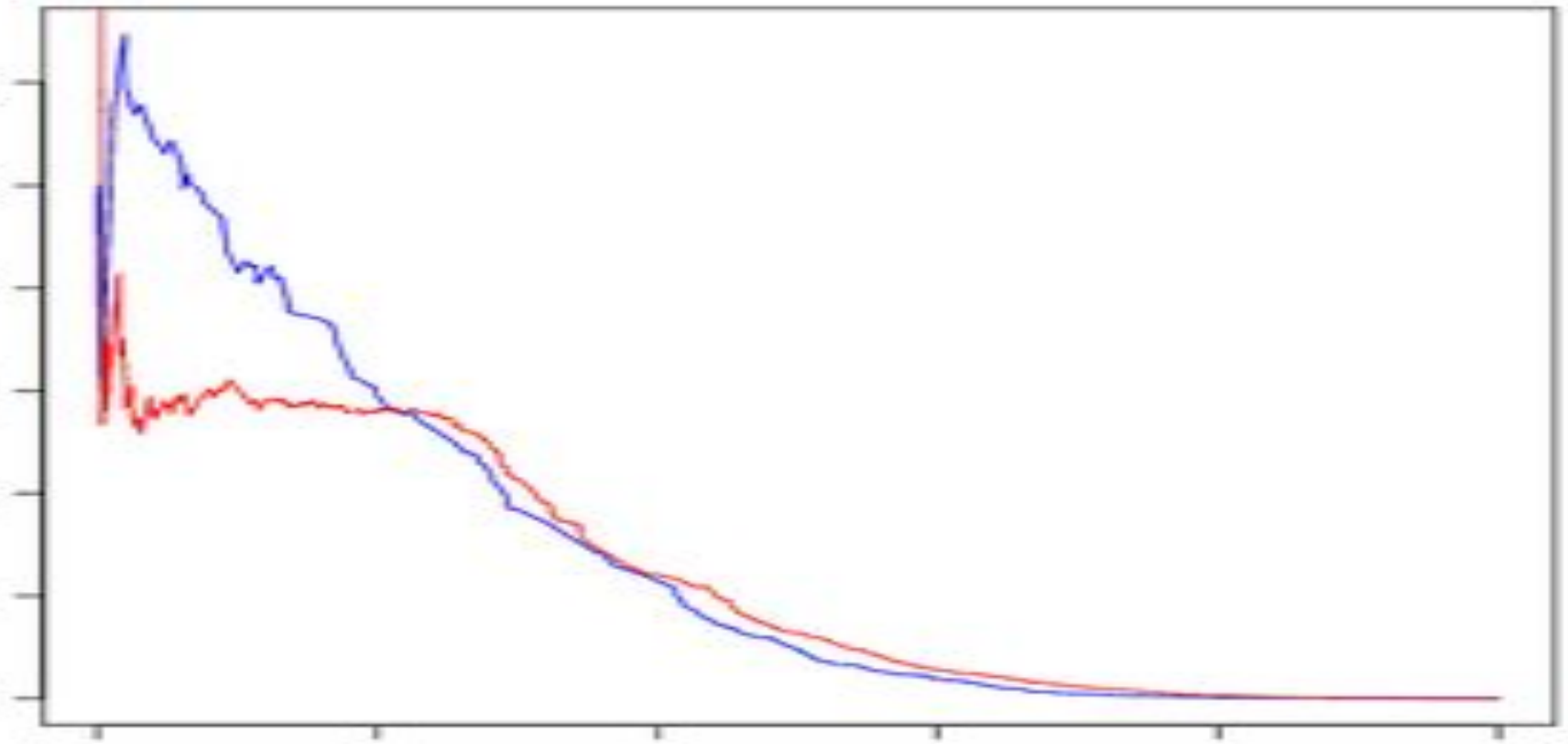
Precision – recall curve (PR curve)



Which model is the best?



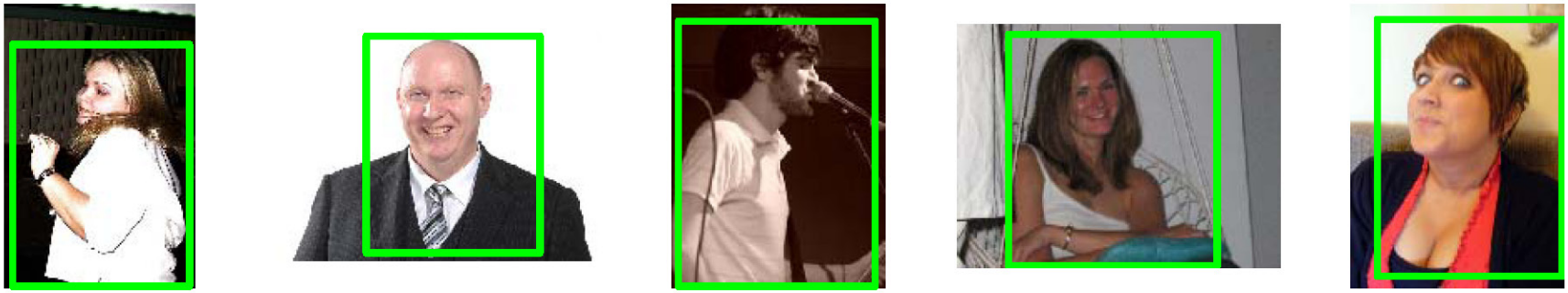
Which model is the best?



True Positives - Person

UoCTTI_LSVM-MDPM

MIZZOU_DEF-HOG-LBP



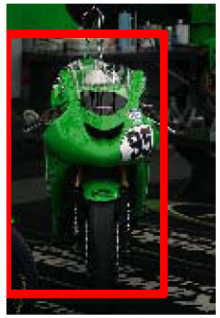
NECUIUC_CLS-DTCT

False Positives - Person

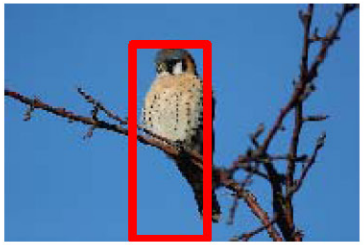
UoCTTI_LSVM-MDPM





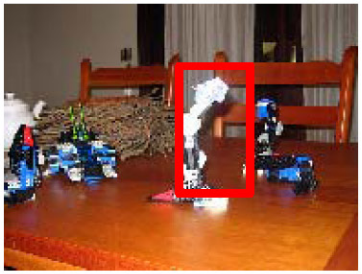


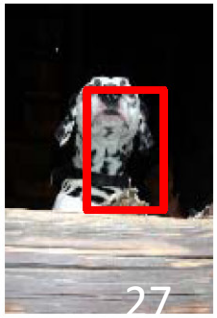
MIZZOU_DEF-HOG-LBP





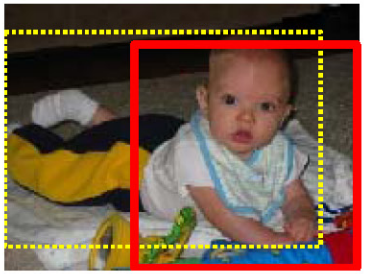
NECUIUC_CLS-DTCT

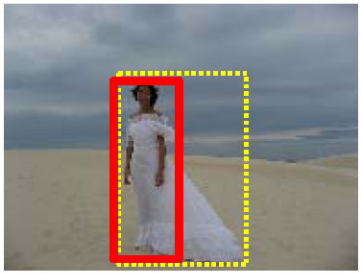
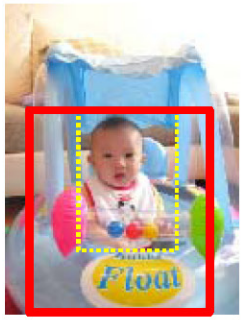





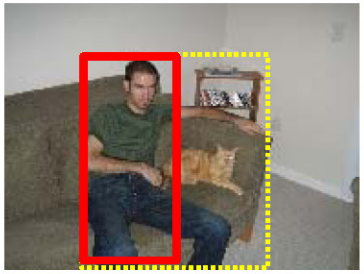

“Near Misses” - Person

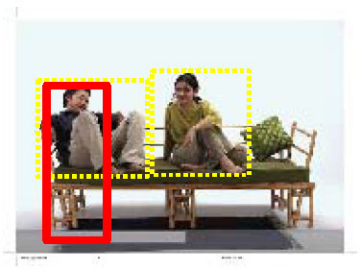
UoCTTI_LSVM-MDPM



MIZZOU_DEF-HOG-LBP



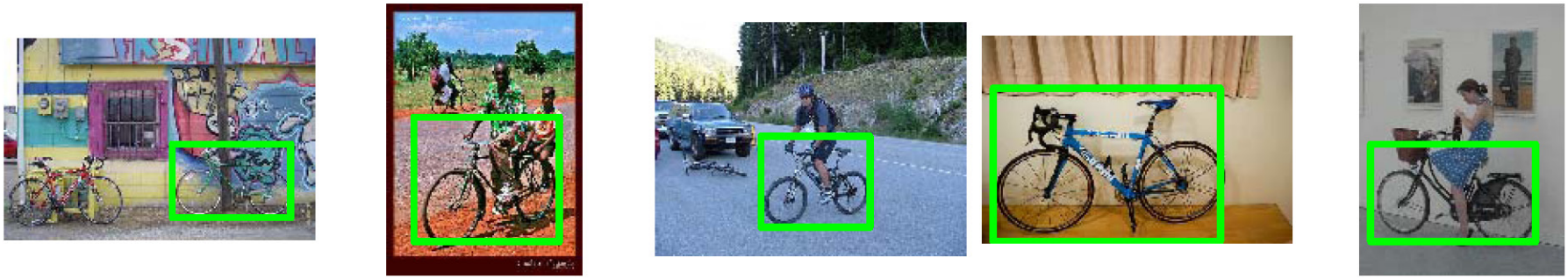

NECUIUC_CLS-DTCT



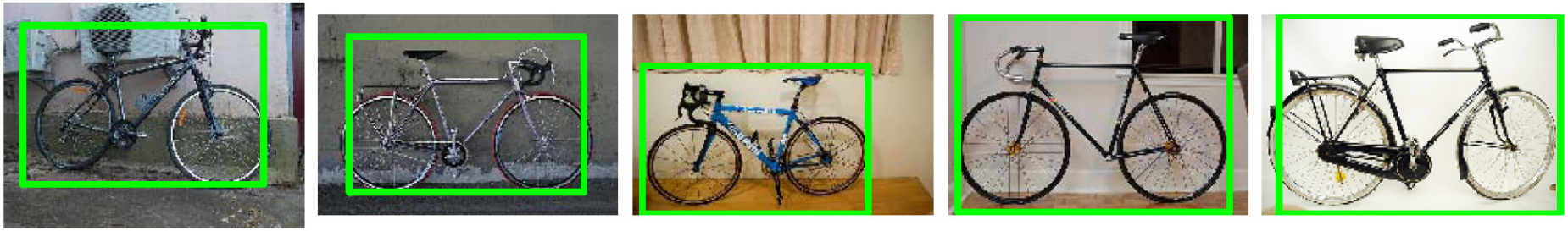


True Positives - Bicycle

UoCTTI_LSVM-MDPM



OXFORD_MKL



NECUIUC_CLS-DTCT

False Positives - Bicycle

UoCTTI_LSVM-MDPM



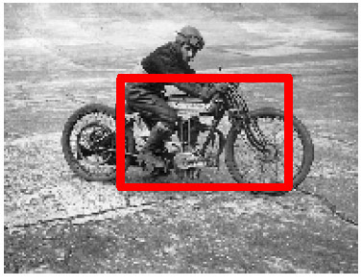


OXFORD_MKL





NECUIUC_CLS-DTCT

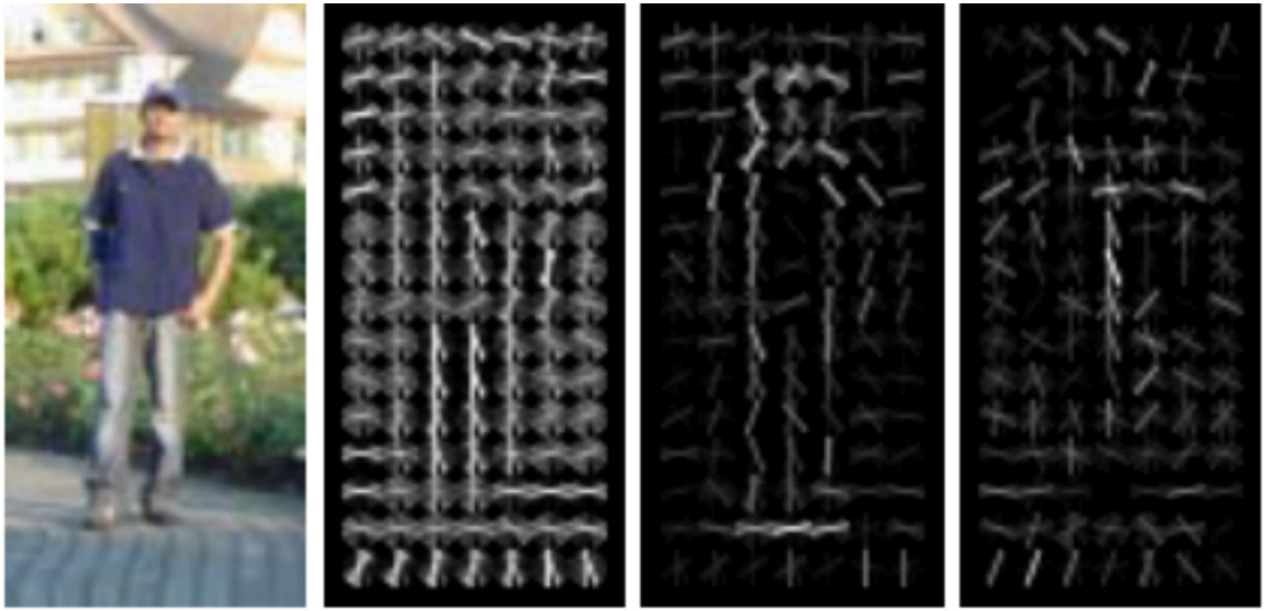

What we will learn today

- Object detection
  - Task and evaluation
- A simple detector
- Deformable parts model

Dalal-Triggs method

sliding window

Recap – HOG features



- Find a HOG template and use as filter

Sliding window + hog features

- Slide through the image and check if there is an object at every location

No person here

Sliding window + hog features

- Slide through the image and check if there is an object at every location

YES!! Person match found

Sliding window + hog features

- But what if we were looking for buses?

No bus found

Sliding window + hog features

- But what if we were looking for buses?

No bus found

Sliding window + hog features

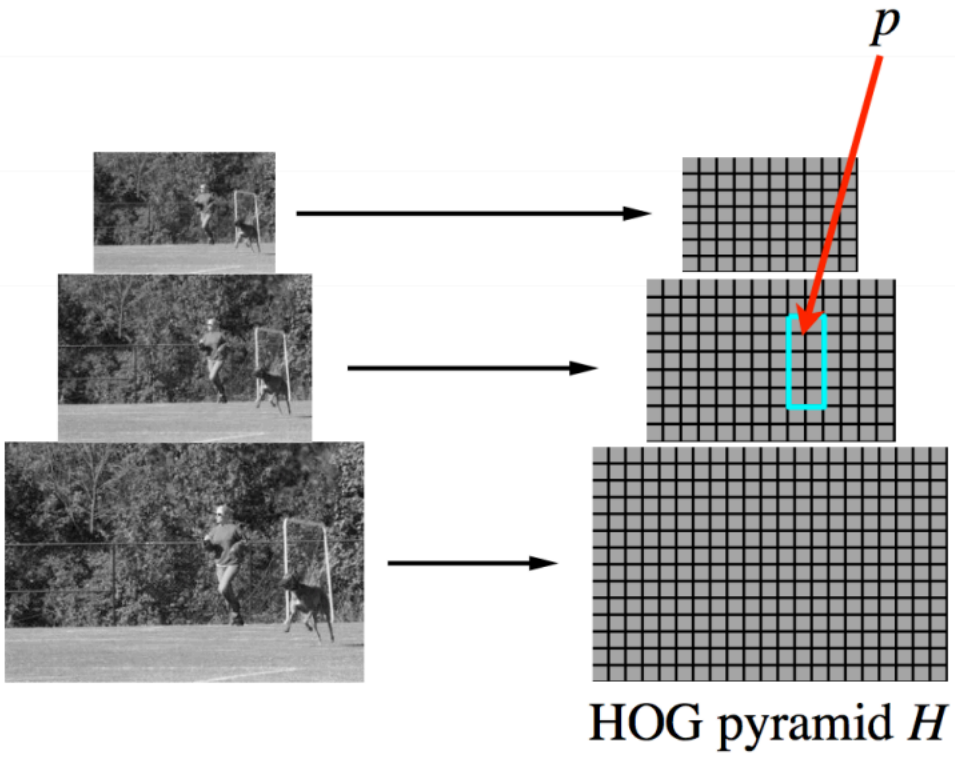
No bus found

- We will never find the object we don't choose our window size wisely!

Sliding window + hog features

- We need to do multi scale sliding window

Create a feature pyramid



Filter F

Score of F at position p is $F \cdot \phi(p, H)$

$\phi(p, H)$ = concatenation of HOG features from subwindow specified by p

What we will learn today

- Object detection
  - Task and evaluation
- A simple detector
- Deformable parts model

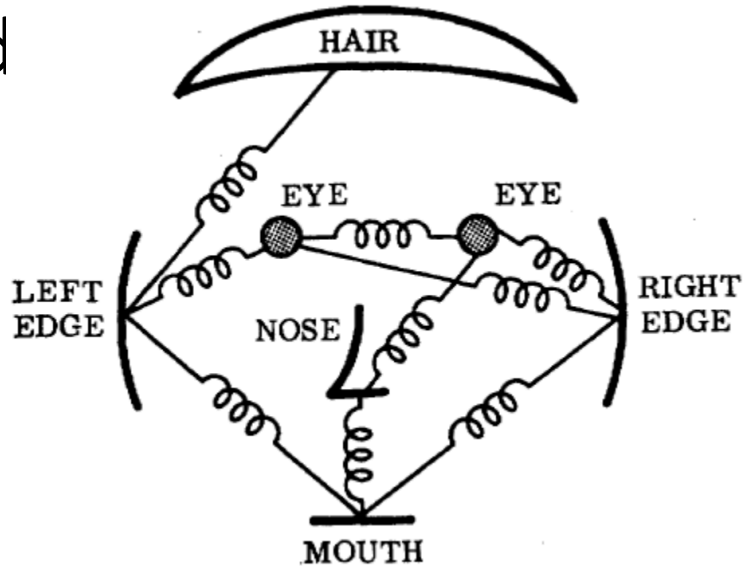
Recap – bag of visual words

- We can present images as a set of words
  - Where each word represents a **part** of the image.

- Can we do the same for objects within those images?

Deformable parts model

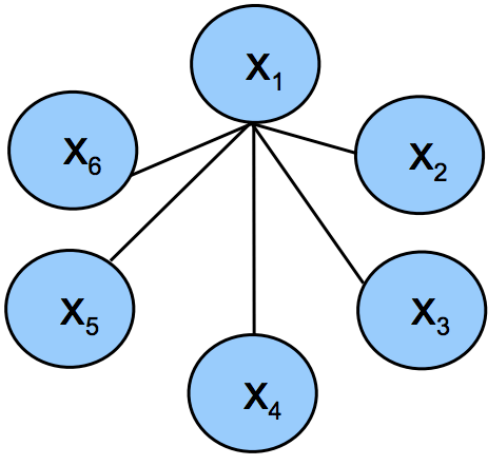
- Represents an object as a collection of parts arranged in a deformable configuration
- Each part represents local appearances
- Spring-like connections between certain pairs of parts

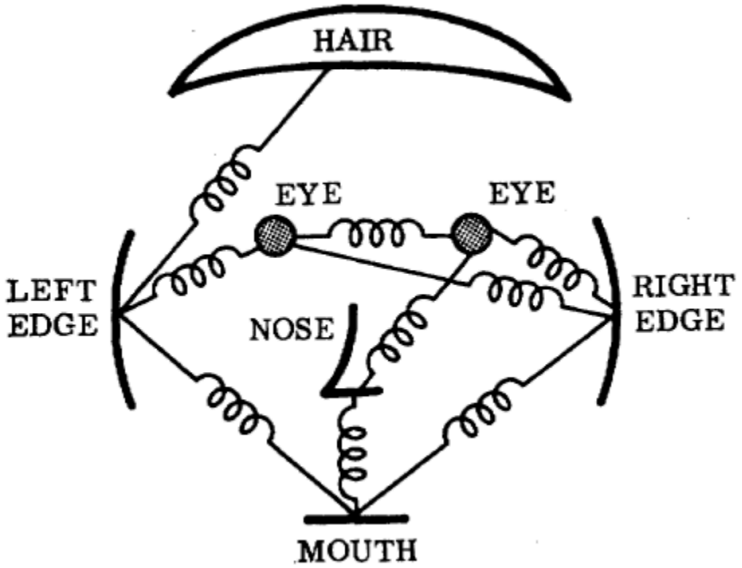


Fischler and Elschlager, Pictoral Structures, 1973

Deformable parts model

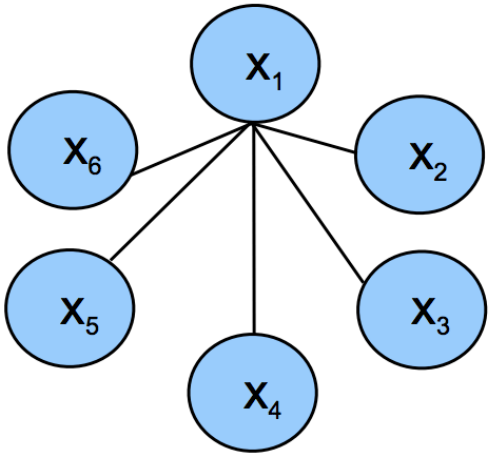
- The parts of an object form pairwise relationships.
- We can model this using a “star model”
  - where every part is defined relative to a root.





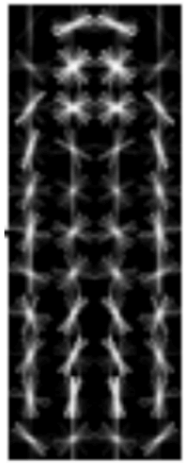
Detecting a person with their parts

- For example, a person can be modelled as having a head, left arm, right arm, etc.
- All parts can be modelled relative to the global person detector



Deformable parts model

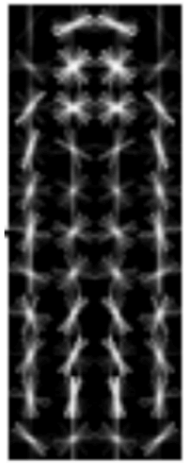
- Mixture of deformable part models
- Each component has global component + deformable parts



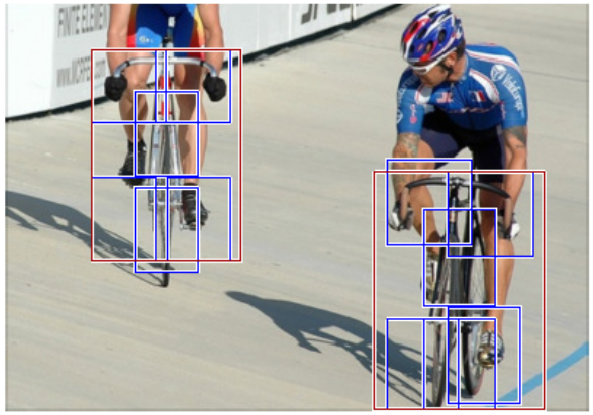
- Part filters have finer details

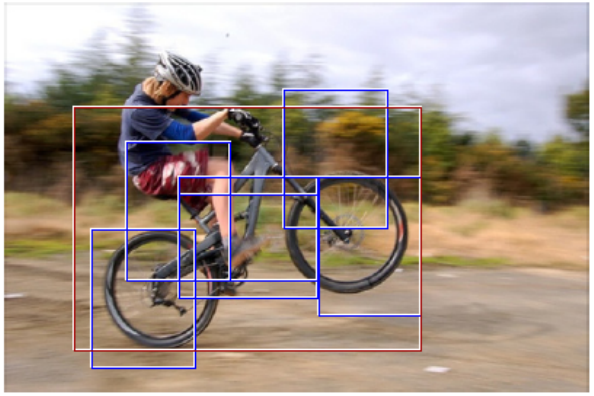
Deformable parts model

- Each model will have a global filter. And a set of part filters. Here is an example of a global person filter with it's 'head' part filter:

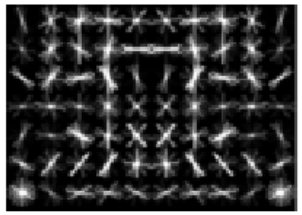


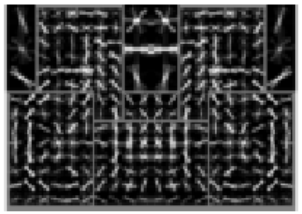
Two-component bicycle model

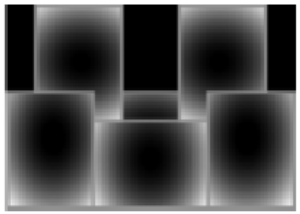




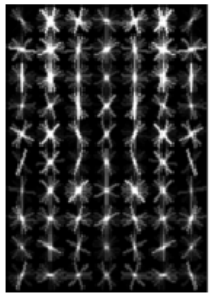
"side" component

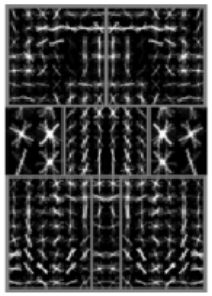


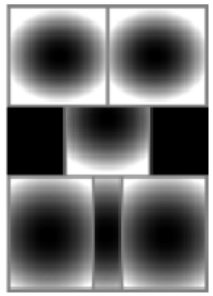




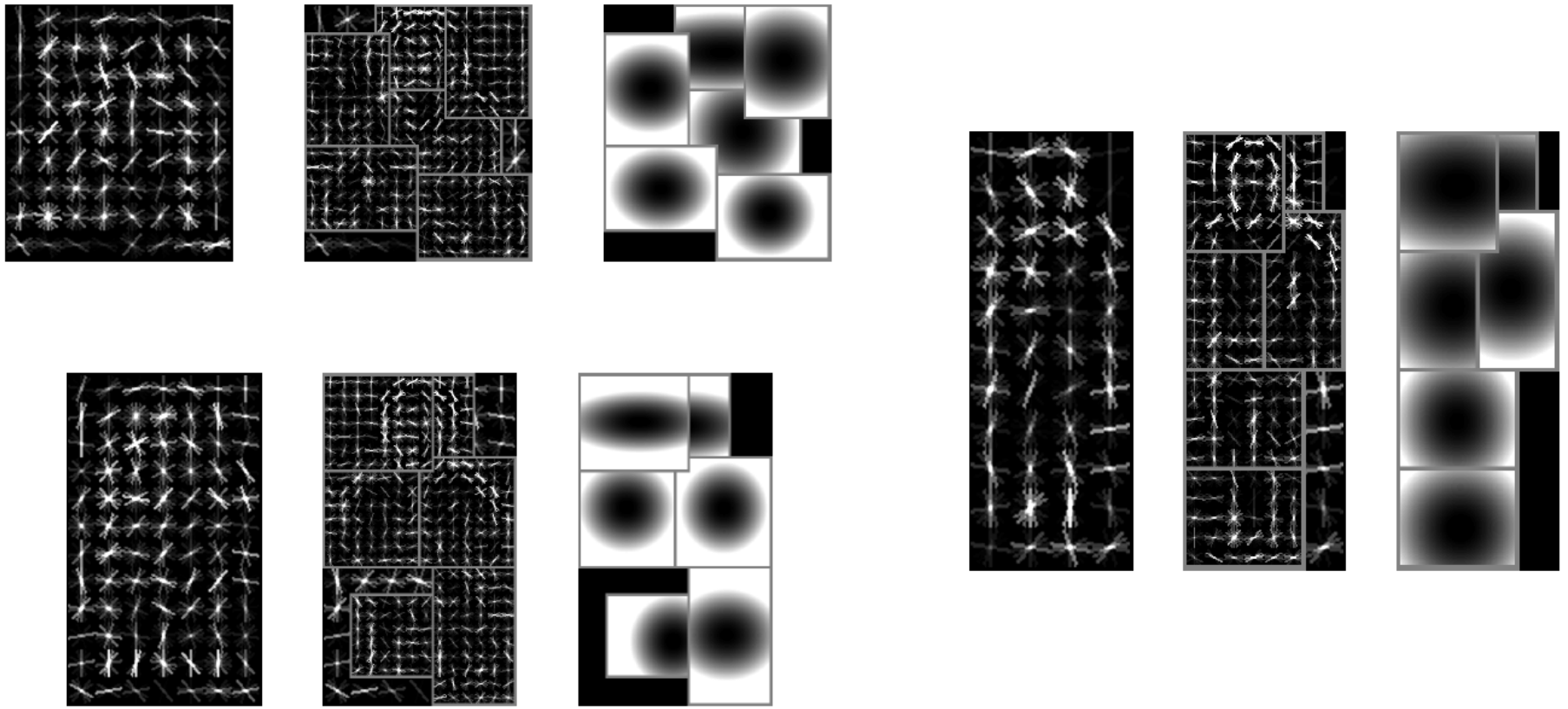
"frontal" component







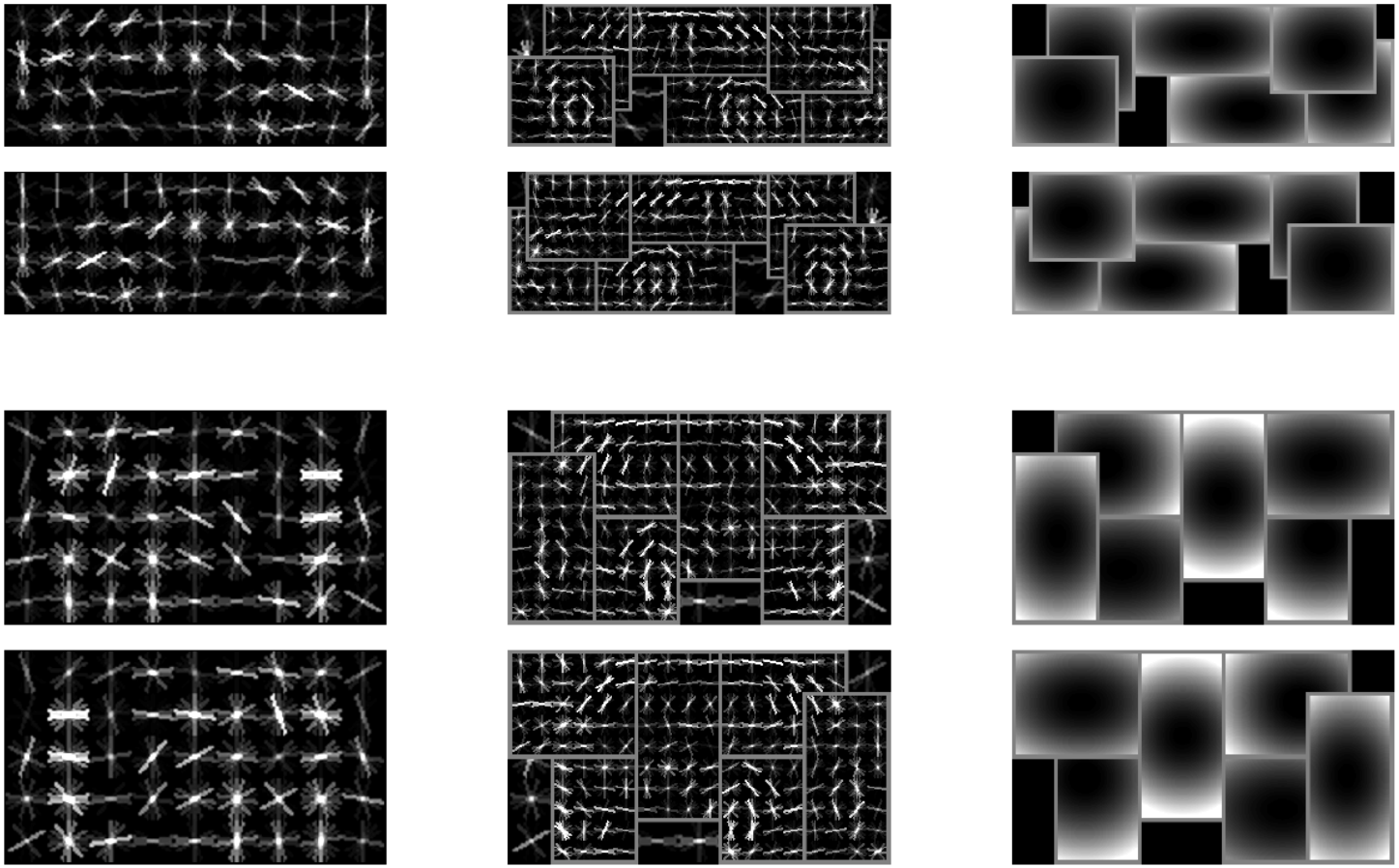
Six-component person model



Six-component car model

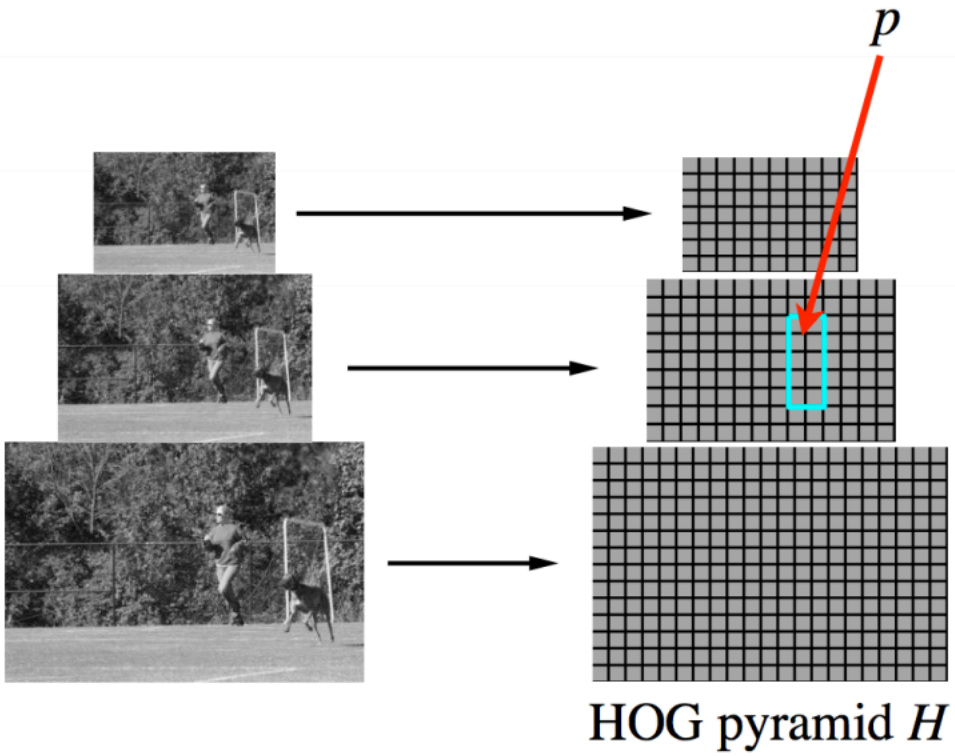
side view

frontal view



root filters (coarse) part filters (fine) deformation models

Remember from Dalal and Triggs



Filter F

Score of F at position p is $F \cdot \phi(p, H)$

$\phi(p, H)$ = concatenation of HOG features from subwindow specified by p

Deformable parts model

- A model for an object with n parts is a $(n+2)$ tuple:

$$(F_0, P_1, \cdots, P_n, b)$$

Root filter — Model for 1st part — Bias term

- Each part-based model defined as:

$$(F_i, v_i, d_i)$$

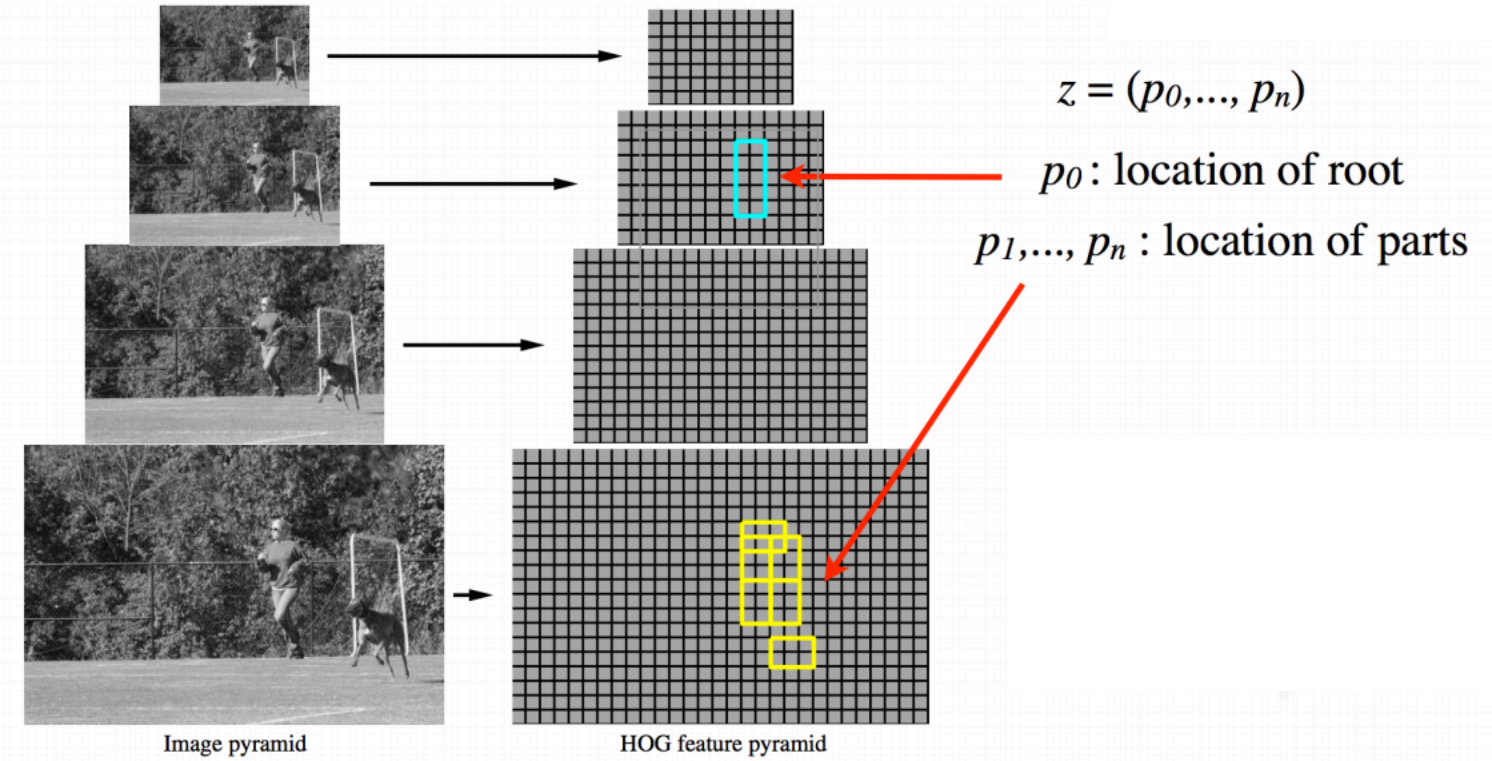
F_i filter for the *i*-th part

v_i "anchor" position for part *i* relative to the root position

d_i defines a deformation cost for each possible placement of the part relative to the anchor position

Deformable parts calculates a score for each part along with a global score

$p_i = (x_i, y_i, l_i)$ specifies the level and position of the *i*-th filter



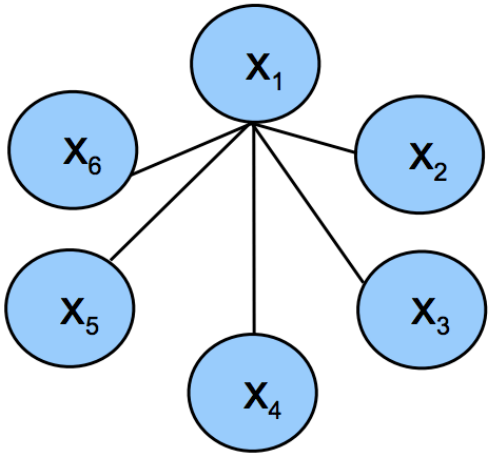
Calculating the score for a detection

The score for a detection is defined as the score for the global detector minus the sum of deformation costs for each part.

This means that if a detection's parts are really far away from where they should be, it's probably a false positive.

Calculating the score for a detection

The score for a detection is defined as the score for the global detector minus the sum of deformation costs for each part.



Calculating the score for a detection

The score for a detection is defined as the score for the global detector minus the sum of deformation costs for each part.

$$detection\ score$$
$$= \prod_{i=0}^{n} F_i \, \phi(p_i, H) - \sum_{i=1}^{n} d_i \, (dx_i, dyi, dx_i^2, dyi^2)$$

Calculating the score for a detection

$$detection\ score = \prod_{i=0}^{n} F_i\, \phi(p_i, H) - \sum_{i=1}^{n} d_i\, (dx_i, dyi, dx_i^2, dyi^2)$$

Scores for each part filter + global filter (same as Dalal and Triggs).

Calculating the score for a detection

$$detection\ score = \prod_{i=0}^{n} F_i\, \phi(p_i, H) - \sum_{i=1}^{n} d_i\, (dxi, dyi, dx_i^2, dyi^2)$$

The deformation costs for each part. dx_i measures the distance in the x-direction from where part$_i$ should be. dy_i measures the same in the y-axis direction. d_i is the weight associated for part$_i$ that penalizes the part for being away.

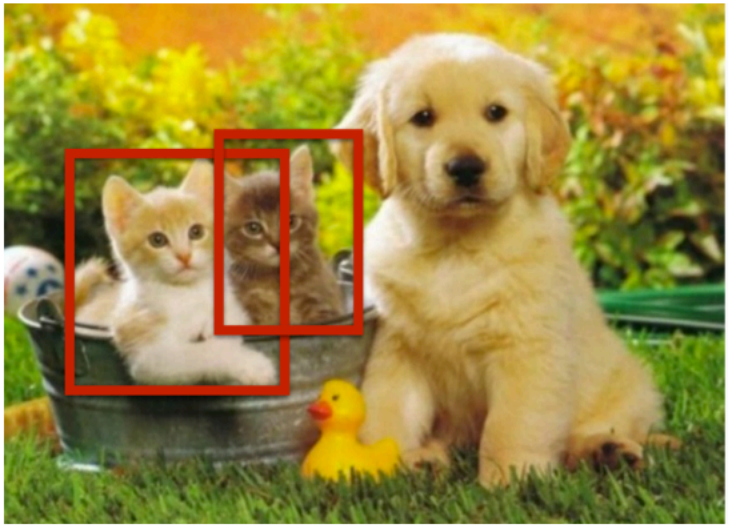
Calculating the score for a detection

$$detection\ score = \prod_{i=0}^{n} F_i\, \phi(p_i, H) - \sum_{i=1}^{n} d_i\, (dxi, dy_i, dx_i^2, dyi^2)$$

If d_i = (0, 0, 1, 0). What does this mean?

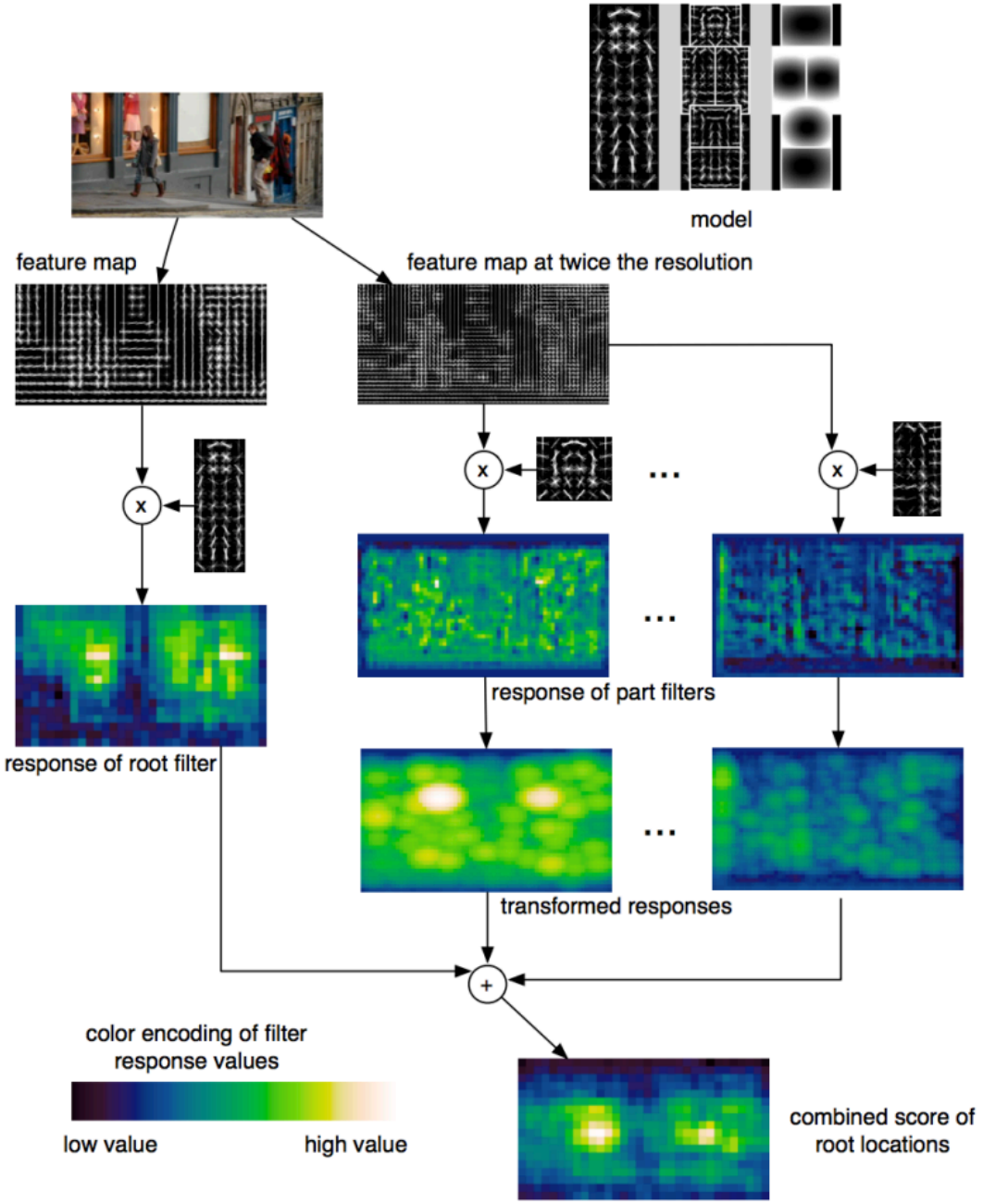
Detection pipeline

- So, to make a detection, we use the sliding window technique and use the global filter first.
- Whenever, the global filters detects an object, we use the part filters to calculate it's score.



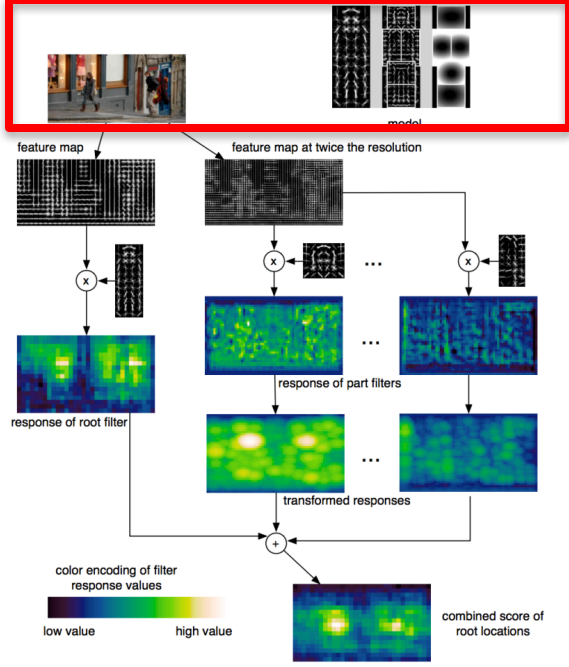
Overall detection pipeline

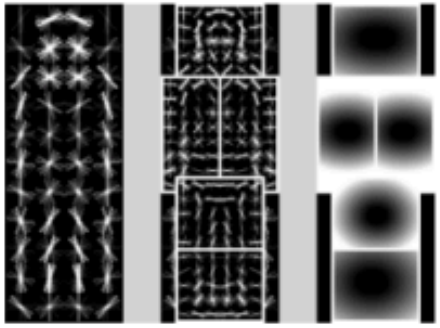
Let's break this down



Detection pipeline

First, make sure you have filters for the global and the parts: F_i



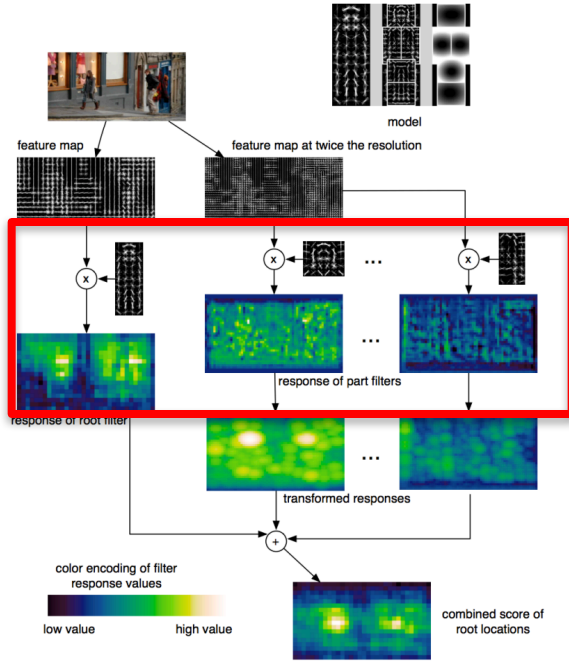


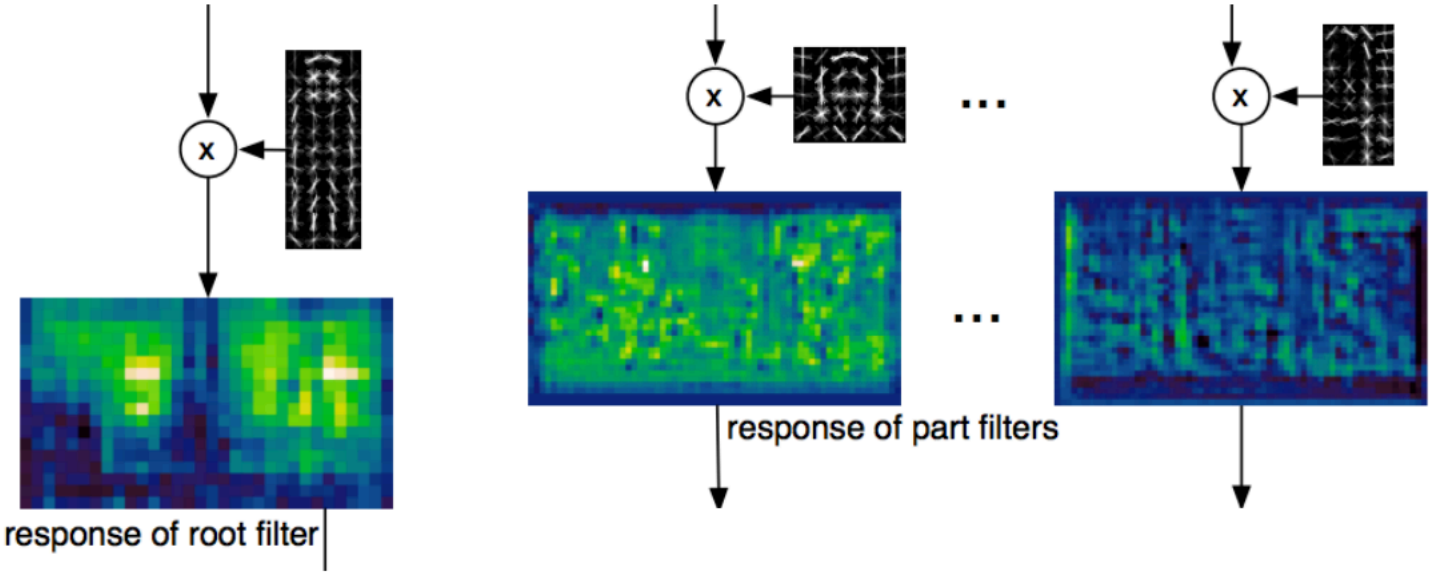
model

Detection pipeline

Apply the filters:

$$\prod_{i=0}^{n} F_i \, \phi(p_i, H)$$

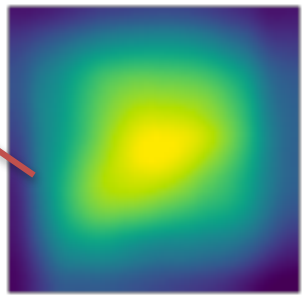




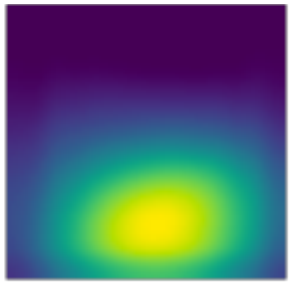
Transformation

Given the location for the detected head, we can guess where the body should be.

The body should be in the direction calculated from the root person filter.



head

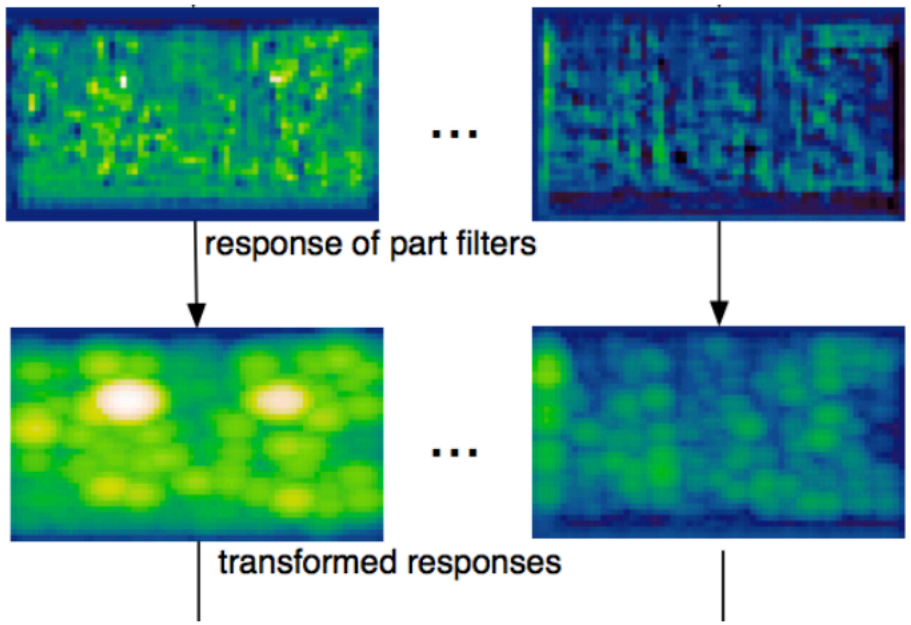


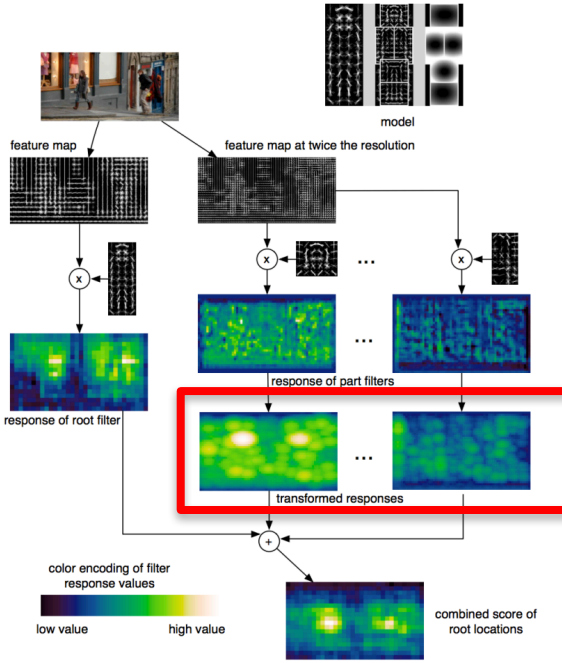
body

Detection pipeline

Now apply the spatial costs:

$$detection\ score = \prod_{i=1}^{n} F_i \, \phi(p_i, H) - \sum_{i=1}^{n} d_i \, (dxi, dyi, dxi^2, dyi^2)$$



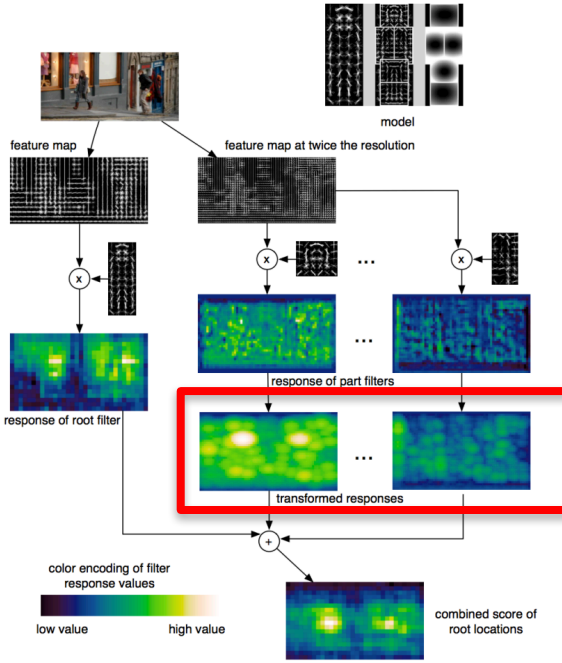


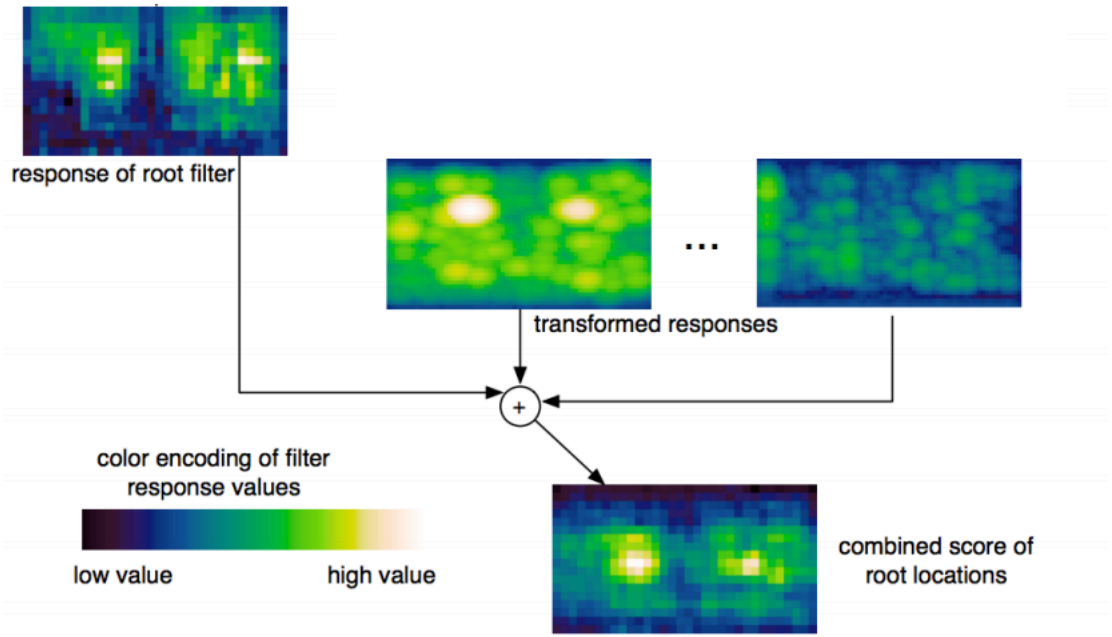
Detection pipeline

Now add the global filter:

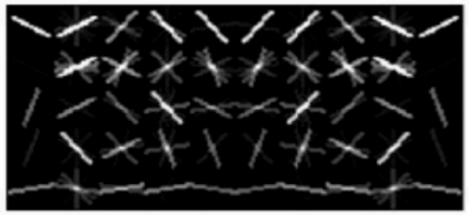
$$detection\ score$$

$$= F_0 + \sum_{i=1}^{n} F_i \cdot \phi(p_i, H) - \sum_{i=1}^{n} d_i \cdot (dxi, dyi, dxi^2, dyi^2)$$

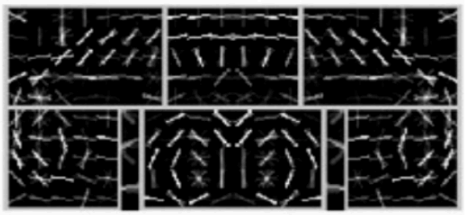




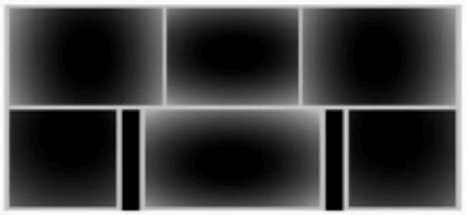
DPM - bicycle



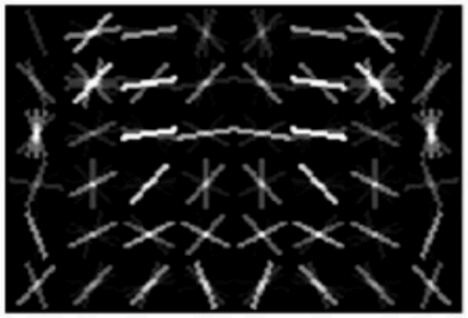
root filters
coarse resolution

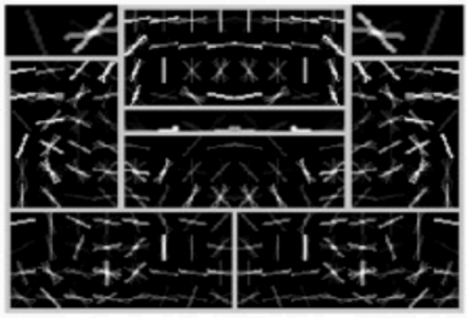


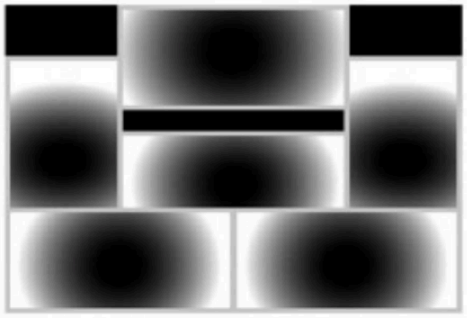
part filters
finer resolution



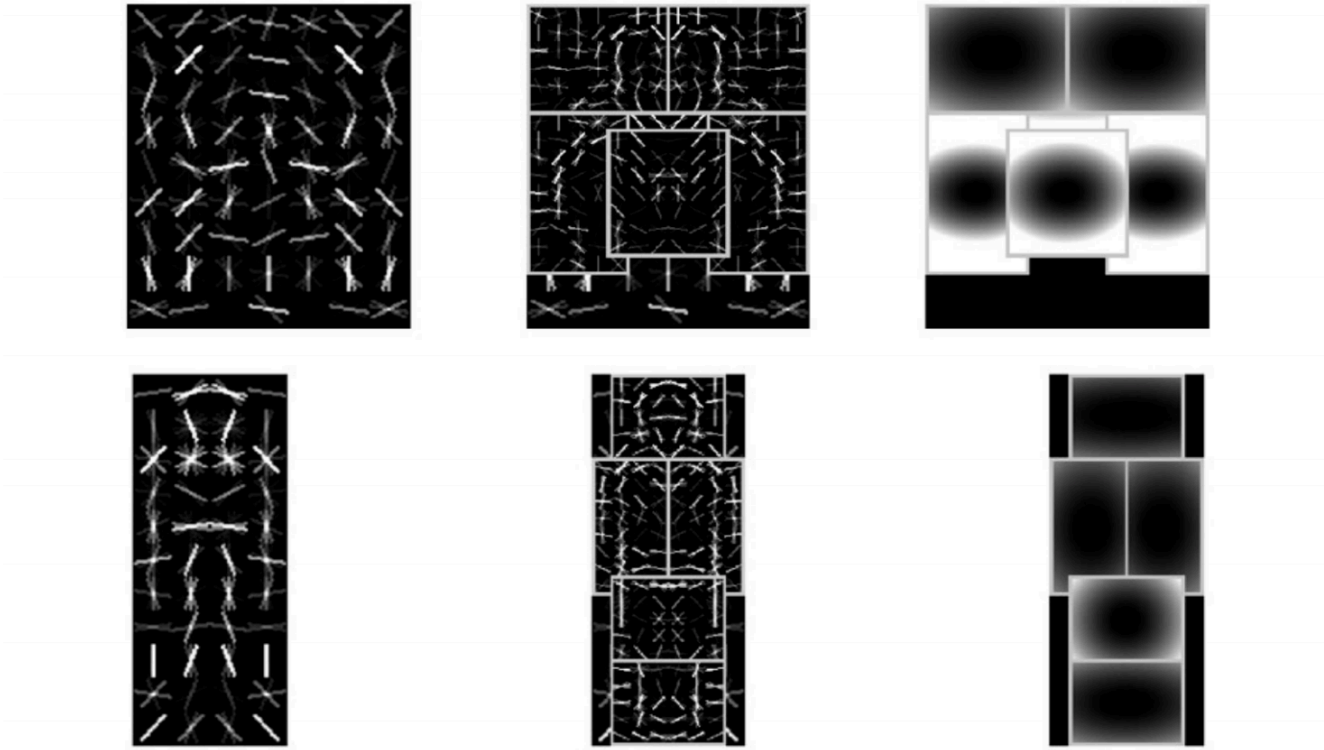
deformation
models



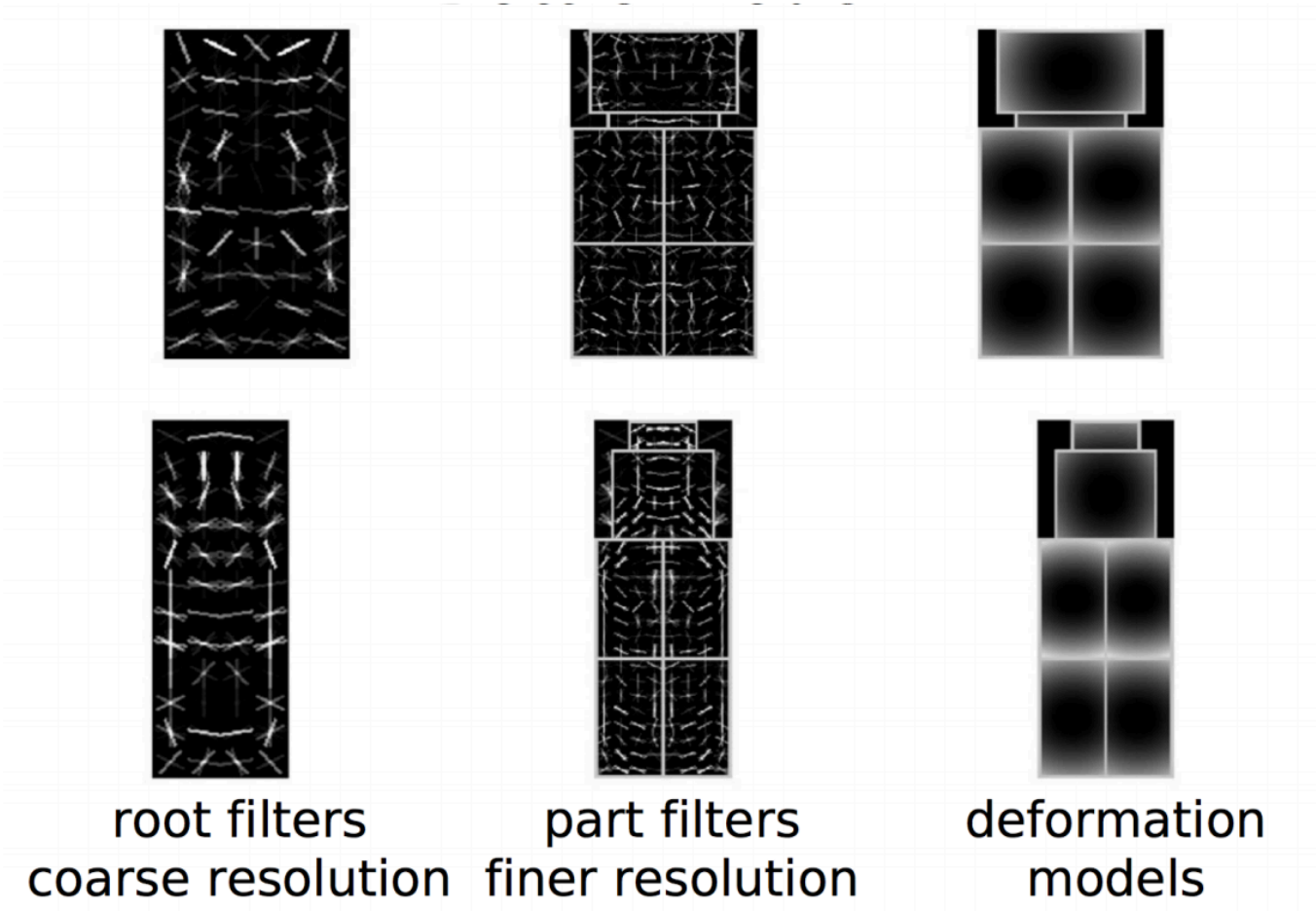




DPM - person

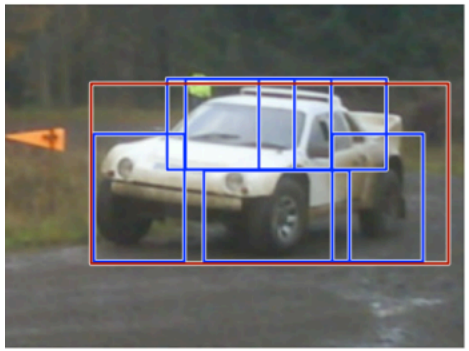
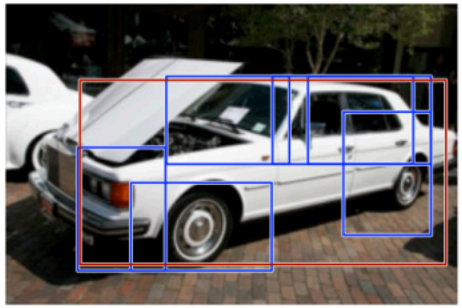

root filters
coarse resolution
part filters
finer resolution
deformation
models

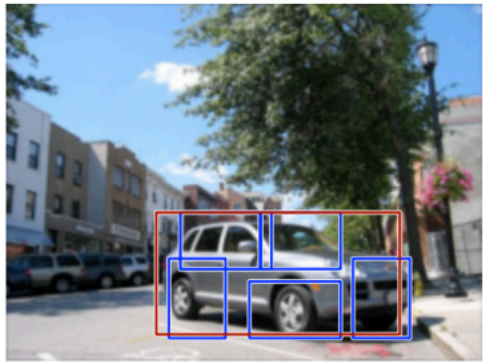
DPM - bottle


root filters
coarse resolution
part filters
finer resolution
deformation
models

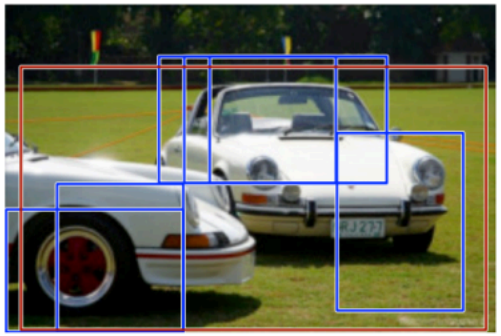
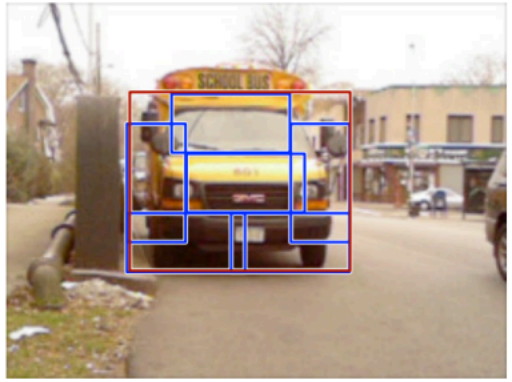
Results – car detection

high scoring true positives

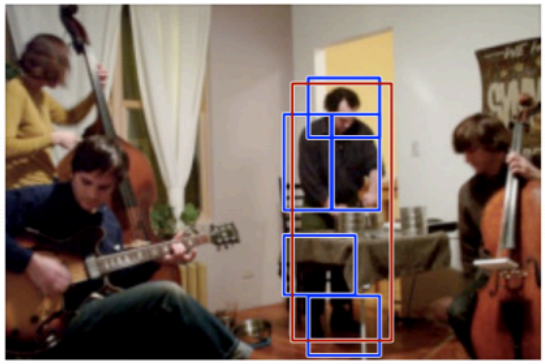


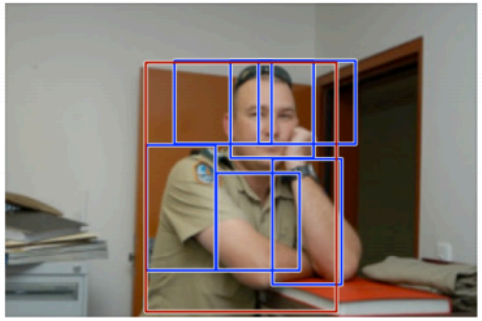
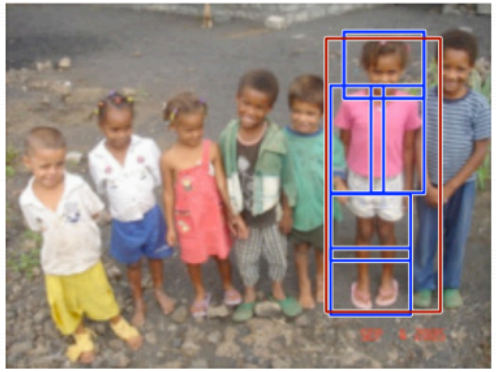
high scoring false positives

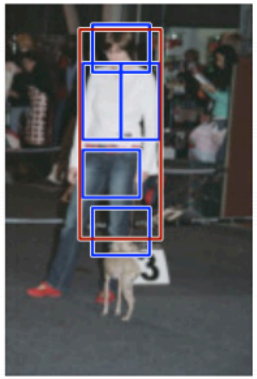
Results – Person detection

high scoring true positives



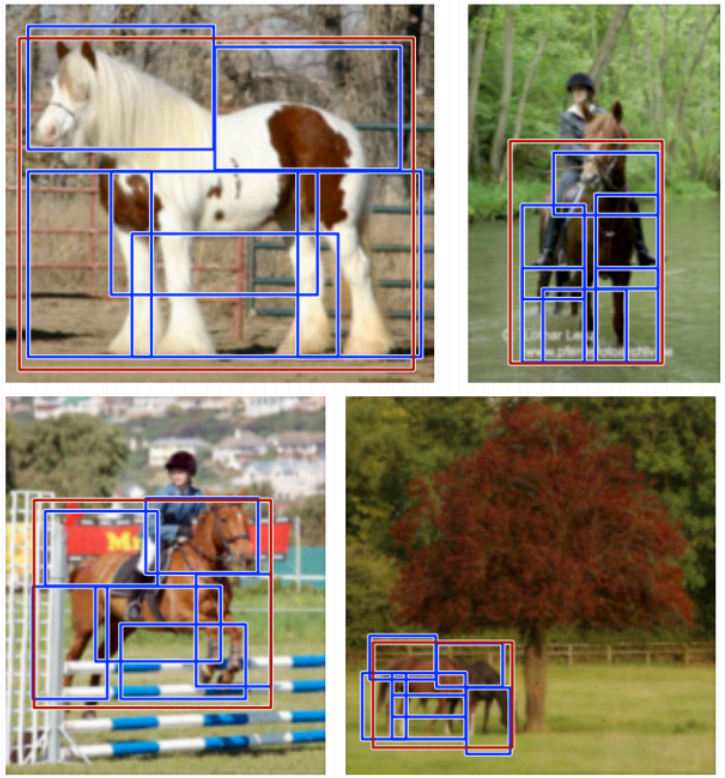



high scoring false positives
(not enough overlap)

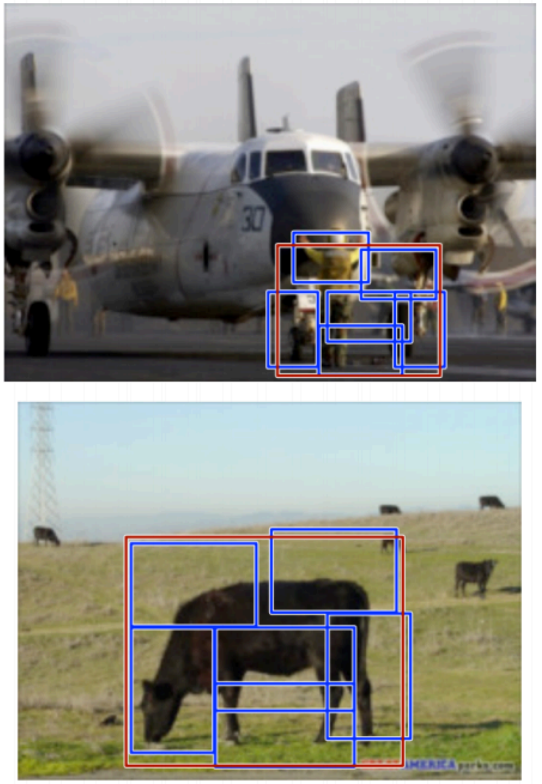



Results – horse detection

high scoring true positives



high scoring false positives

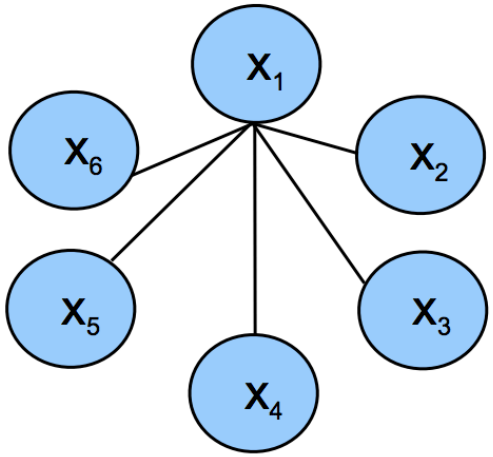


DPM - discussion

- Approach
  - Manually selected set of parts - Specific detector trained for each part
  - Spatial model trained on part activations
  - Evaluate joint likelihood of part activations
- Advantages
  - Parts have intuitive meaning.
  - Standard detection approaches can be used for each part.
  - Works well for specific categories.
- Disadvantages
  - Parts need to be selected manually
  - Semantically motivated parts sometimes don't have a simple appearance distribution
  - No guarantee that some important part hasn't been missed
- When switching to another category, the model has to be rebuilt from scratch.

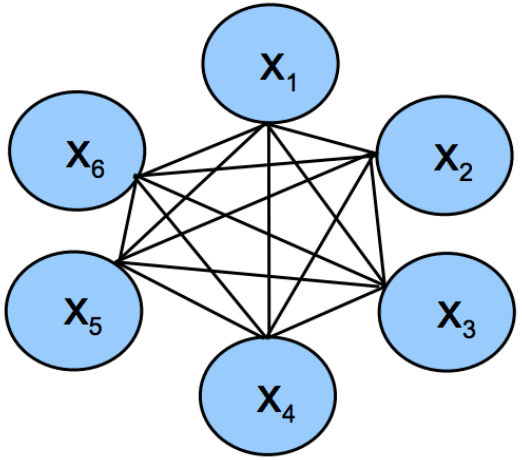
Extensions - From star shaped model to constellation model

"Star" shape model



- e.g. ISM (Implicit Shape Model)
- Parts mutually independent
- Recognition complexity: O(NP)
- Method: Generalized Hough Transform

Fully connected shape model



- e.g. Constellation Model
- Parts fully connected
- Recognition complexity: $O(N^P)$
- Method: Exhaustive search

What we have learned today

- Object detection
  - Task and evaluation
- A simple detector
- Deformable parts model