Lecture 16

Object detection

Administrative

A4 is out

- Due May 23th

A5 is out

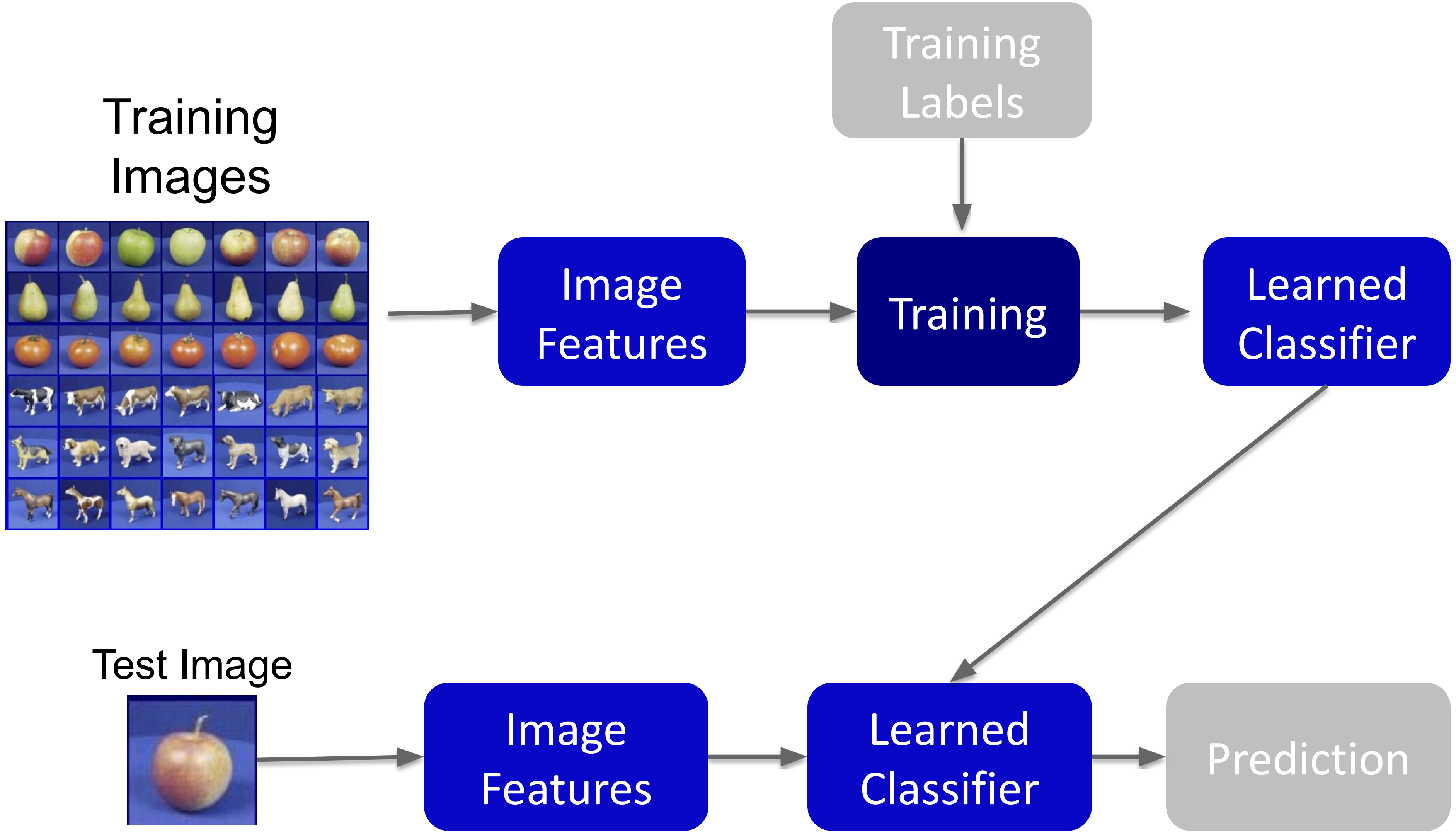
- Due May 30th

Administrative

Recitation this friday

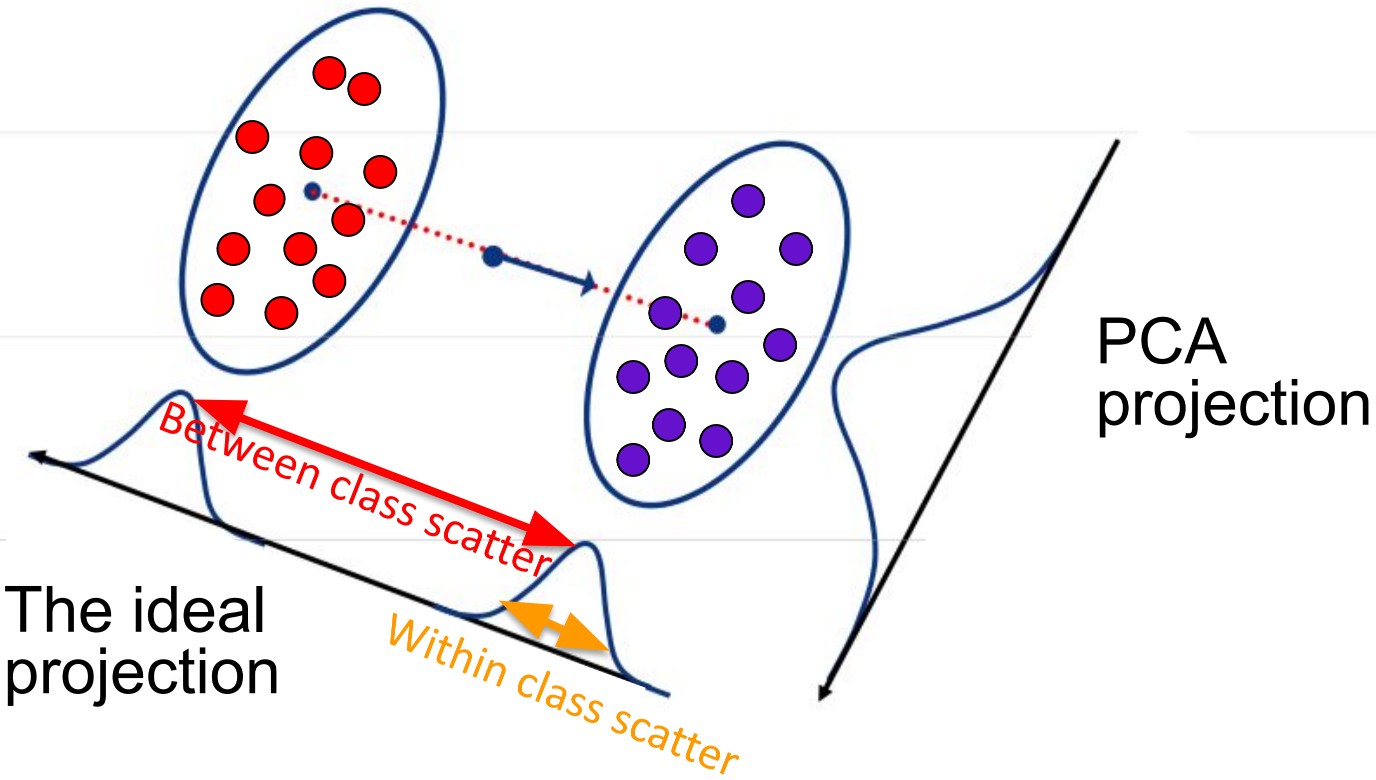
- Recognition review
- Jieyu Zhang

So far: A simple recognition pipeline



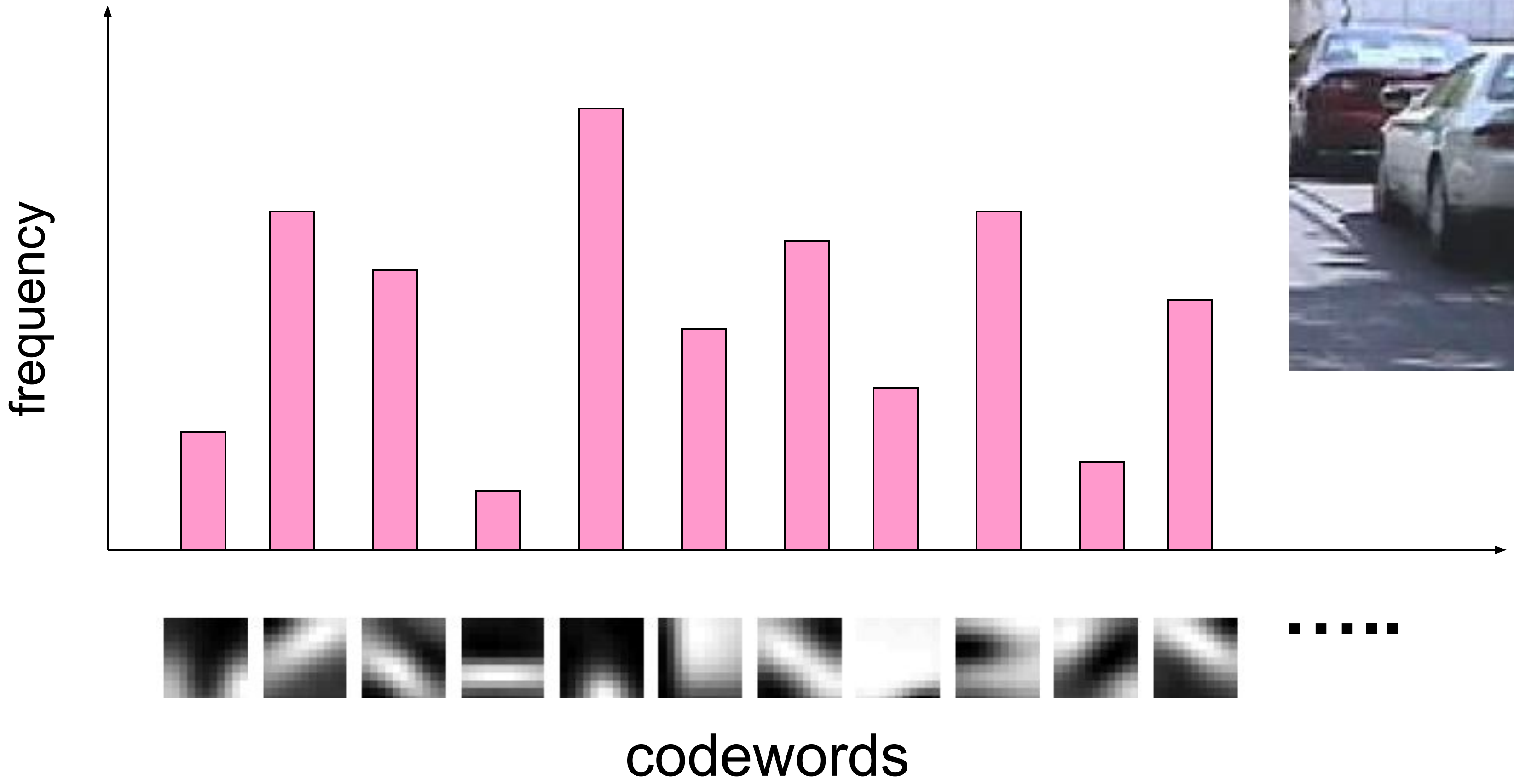
So far: PCA versus LDA

We want a projection that maximizes: $J(w) = \max \dfrac{between\ \ class\ \ scatter}{within\ \ class\ \ scatter}$

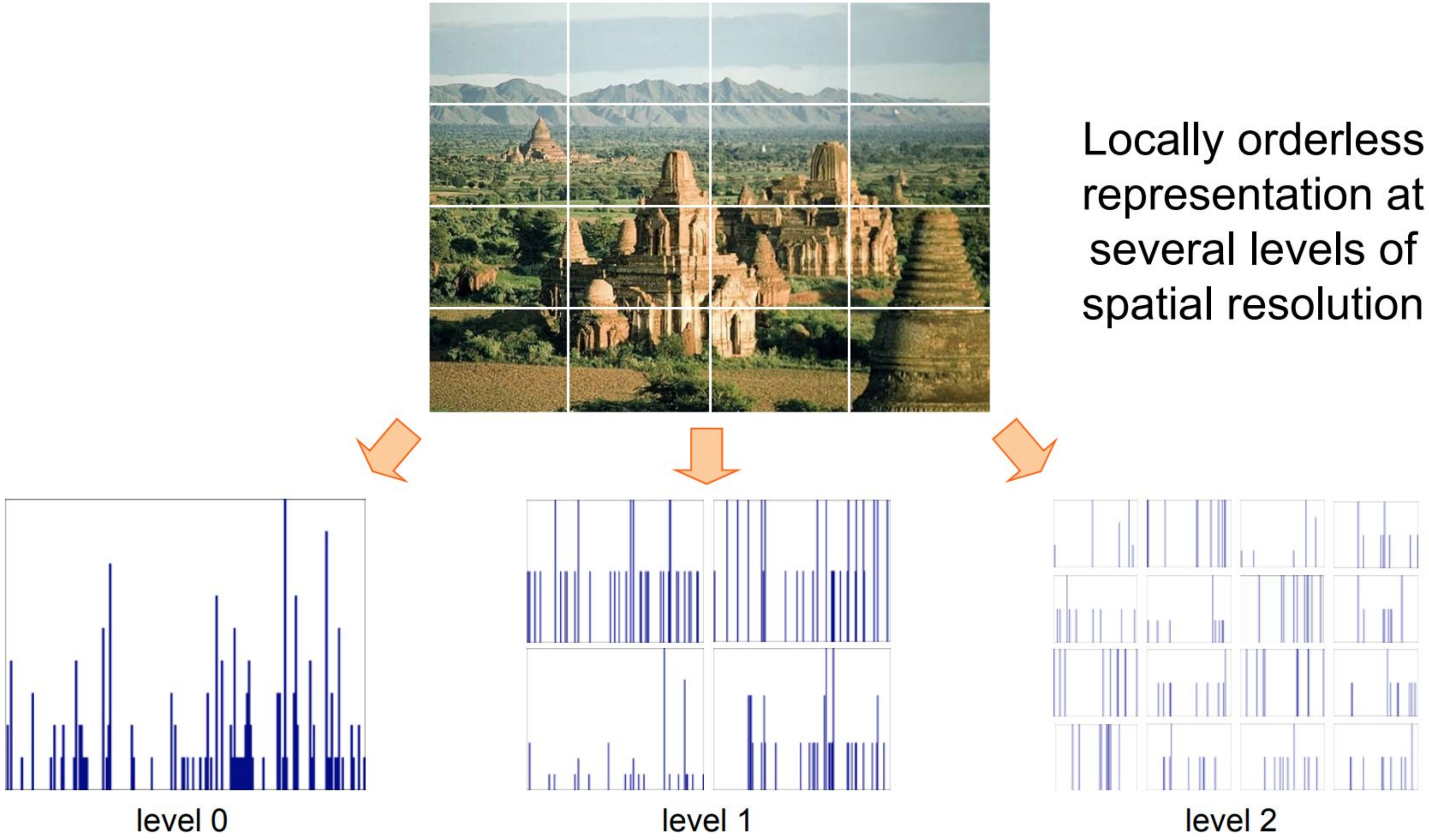


So far: Bag of words features

- Every image now becomes a k-dimensional histogram representation.
- We can use these features for any recognition task.



So far: Bag of words + pyramids



Locally orderless representation at several levels of spatial resolution

Today's agenda

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

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Object Detection

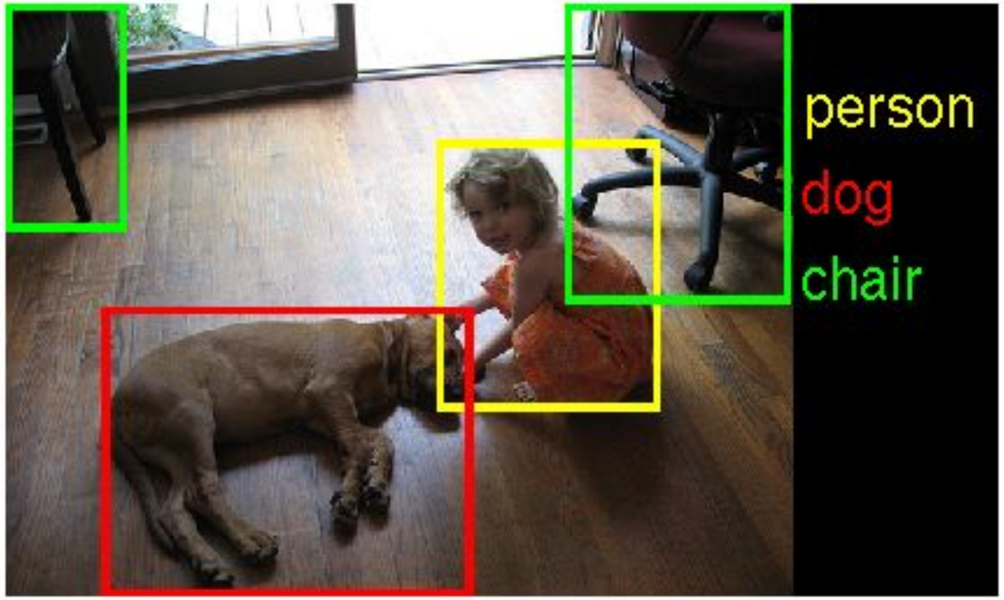
Credit: Flickr user neilalderney123

- What do you see in the image?

Object Detection

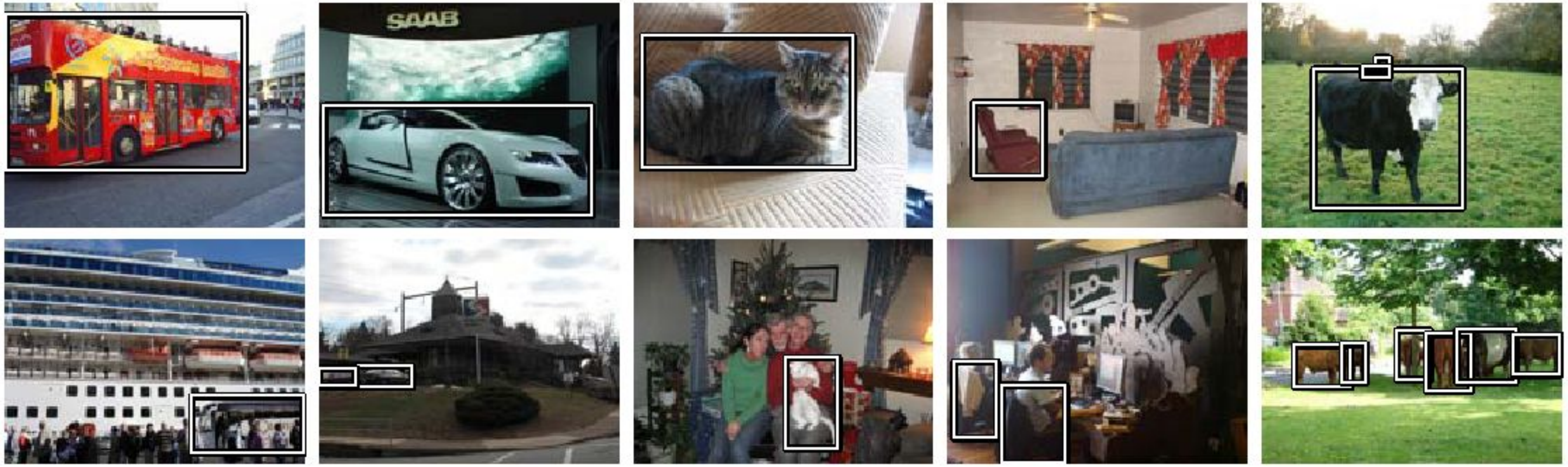
- **Problem**: Detecting and localizing generic objects from various categories, such as cars, people, etc.

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



Object Detection Benchmarks

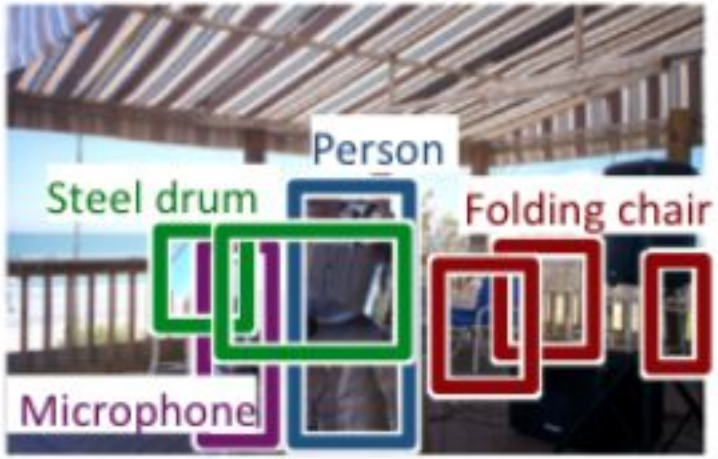
● PASCAL VOC Challenge



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

Object Detection Benchmarks

- PASCAL VOC Challenge
- ImageNet Large Scale Visual Recognition Challenge (ILSVRC)
  - 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?

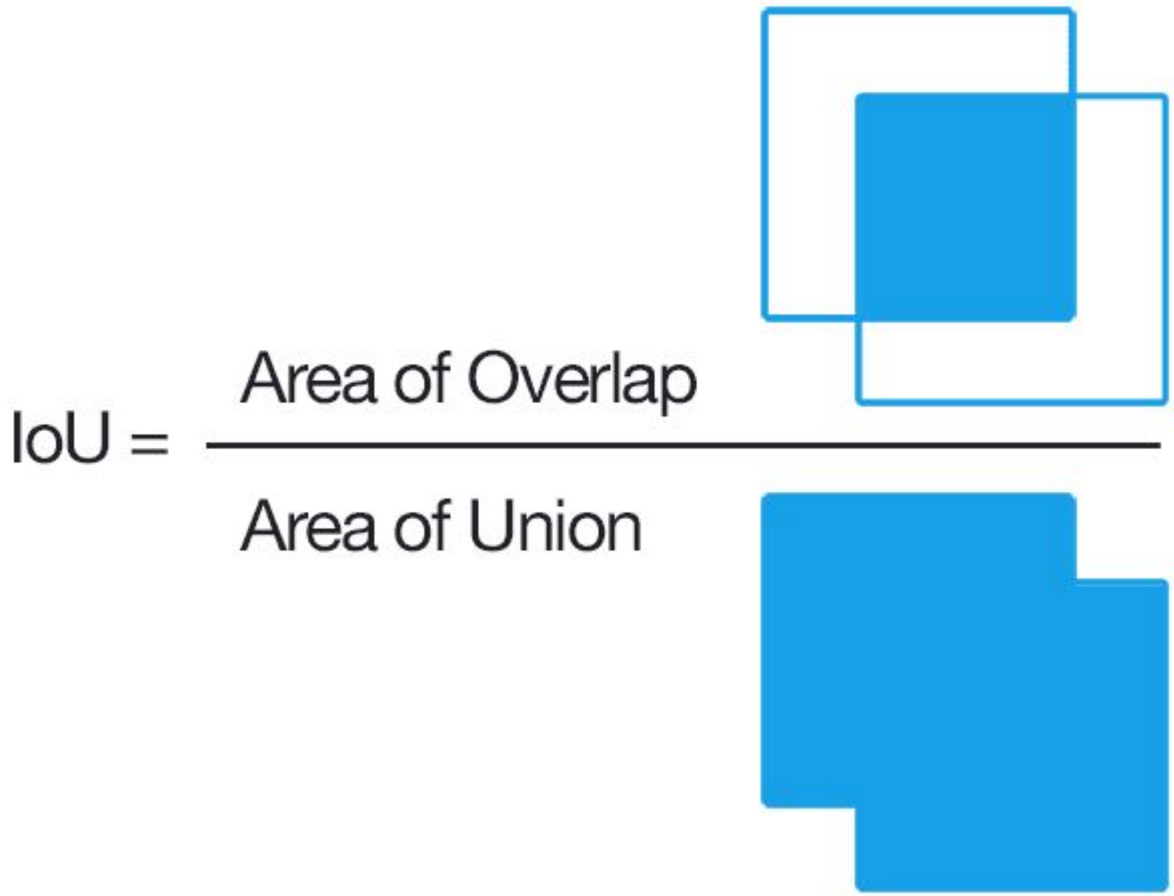
predictions
ground truth

Defining what is a good versus bad detection

IoU is a metric used to decide good from bad predictions.

Given a predicted box and and ground truth box:

IoU = intersection between the two boxes over (divided by) the union of the two

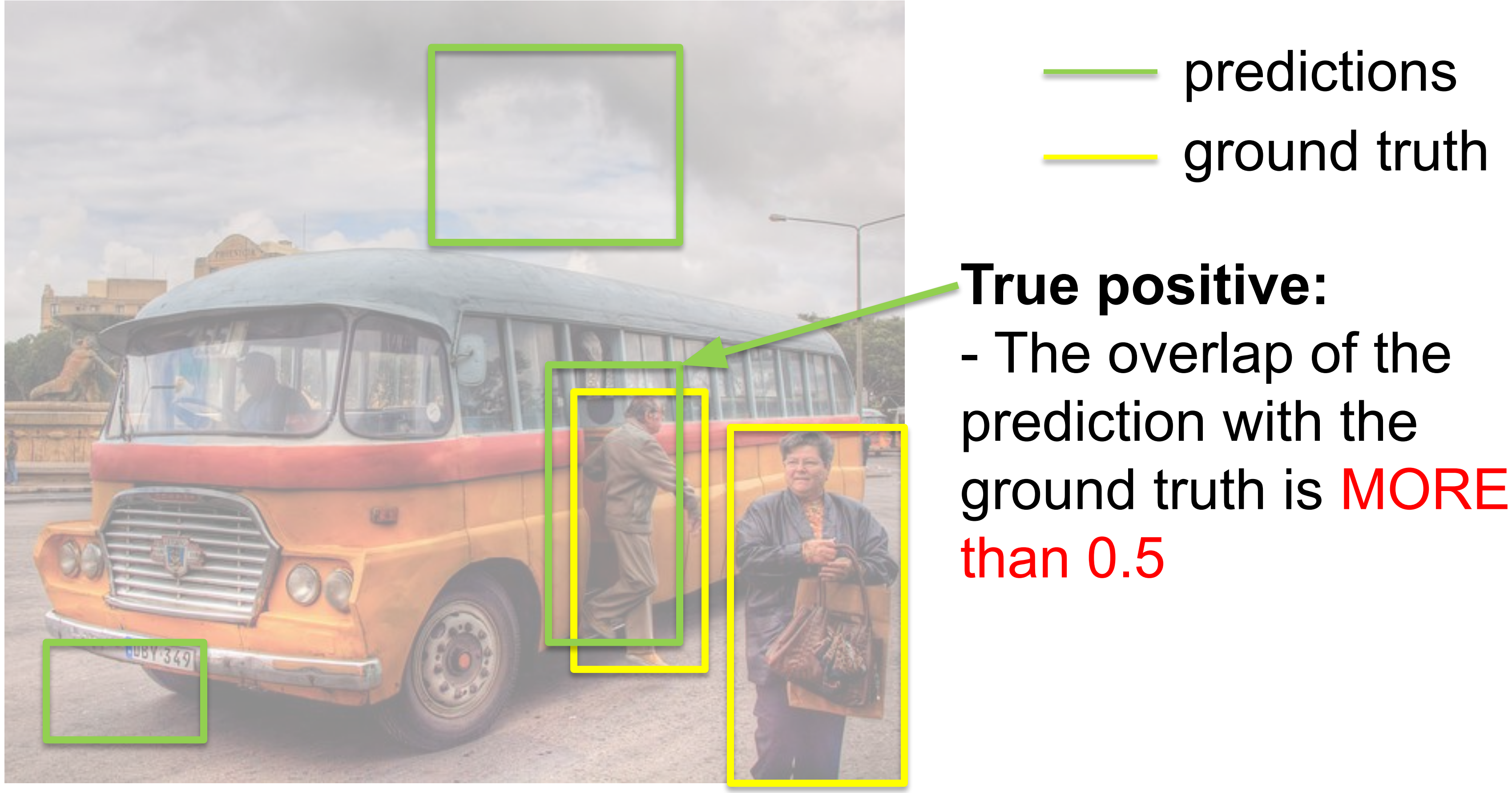


Defining what is a good versus bad detection

We say a prediction was good if it has IoU > 0.5 with any of the ground truth boxes

0.5 is a threshold that is generally accepted as a good heuristic.

How do we evaluate object detection?



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

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

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

How do we evaluate object detection?

predictions

ground truth

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

Q. What is the precision?

How do we evaluate object detection?

predictions
ground truth

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

Q. What is the precision?

Q. What is the recall?

How to intuitively understand precision versus recall

- Precision:
  - how many of the predicted detections are correct?

- Recall:
  - how many of the ground truth objects are detected?

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.

From this, we see that:

- Recall is perfect!
- But our precision 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 using a threshold of 0.5

Q. What happens to precision if threshold is high?

How do we evaluate object detection?

predictions

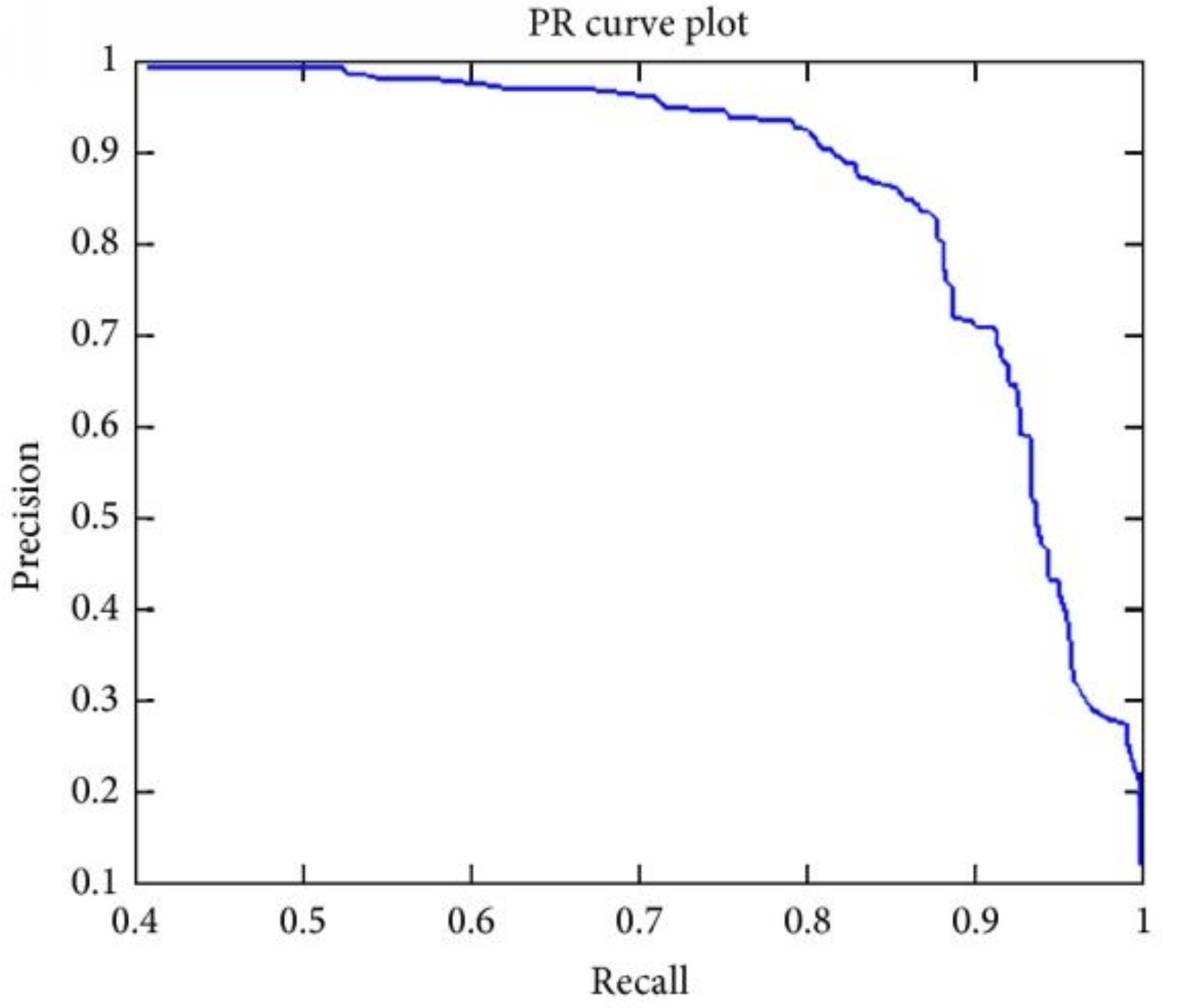
ground truth

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

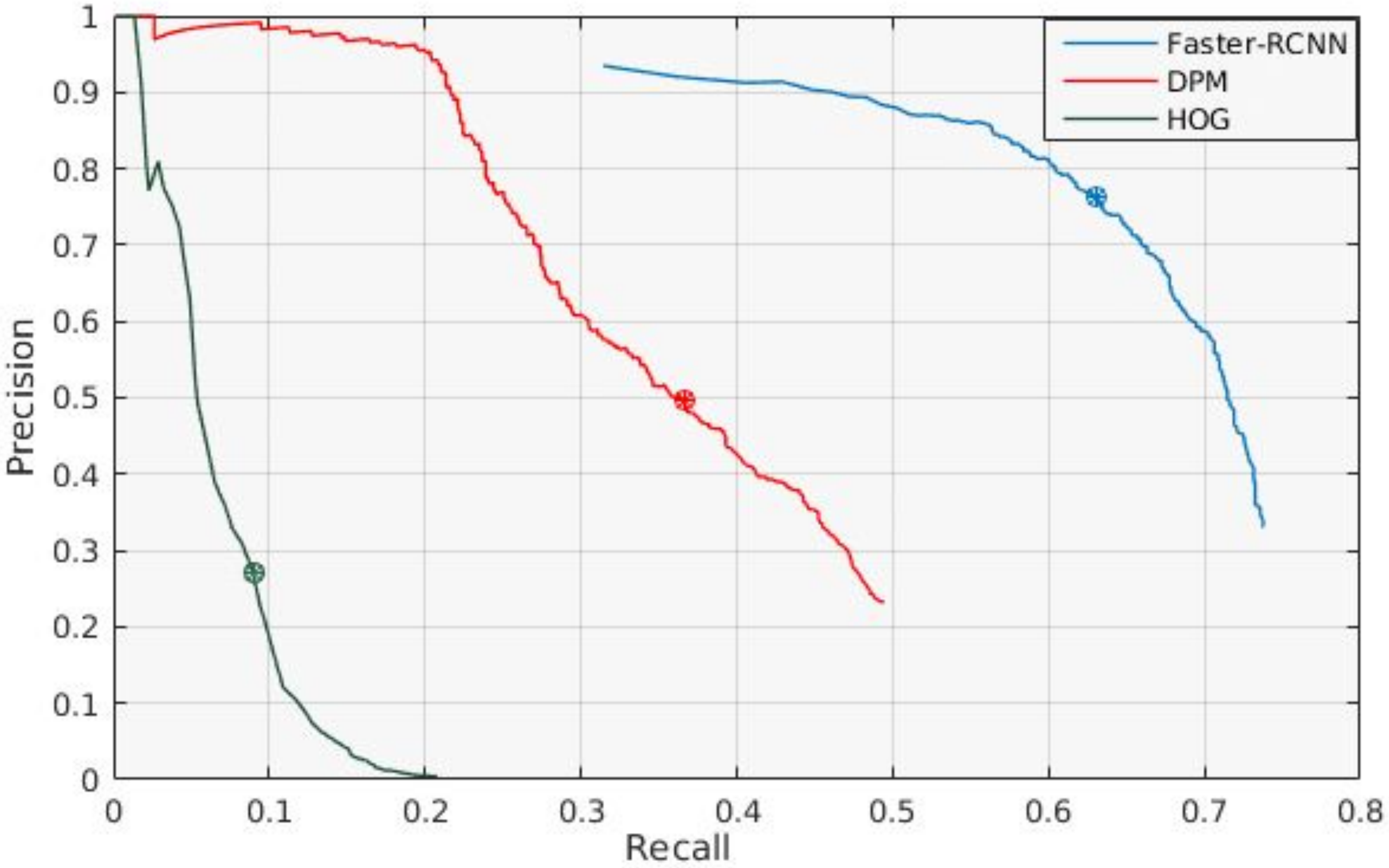
We are using a threshold of 0.5

Q. What happens to recall if threshold is high?

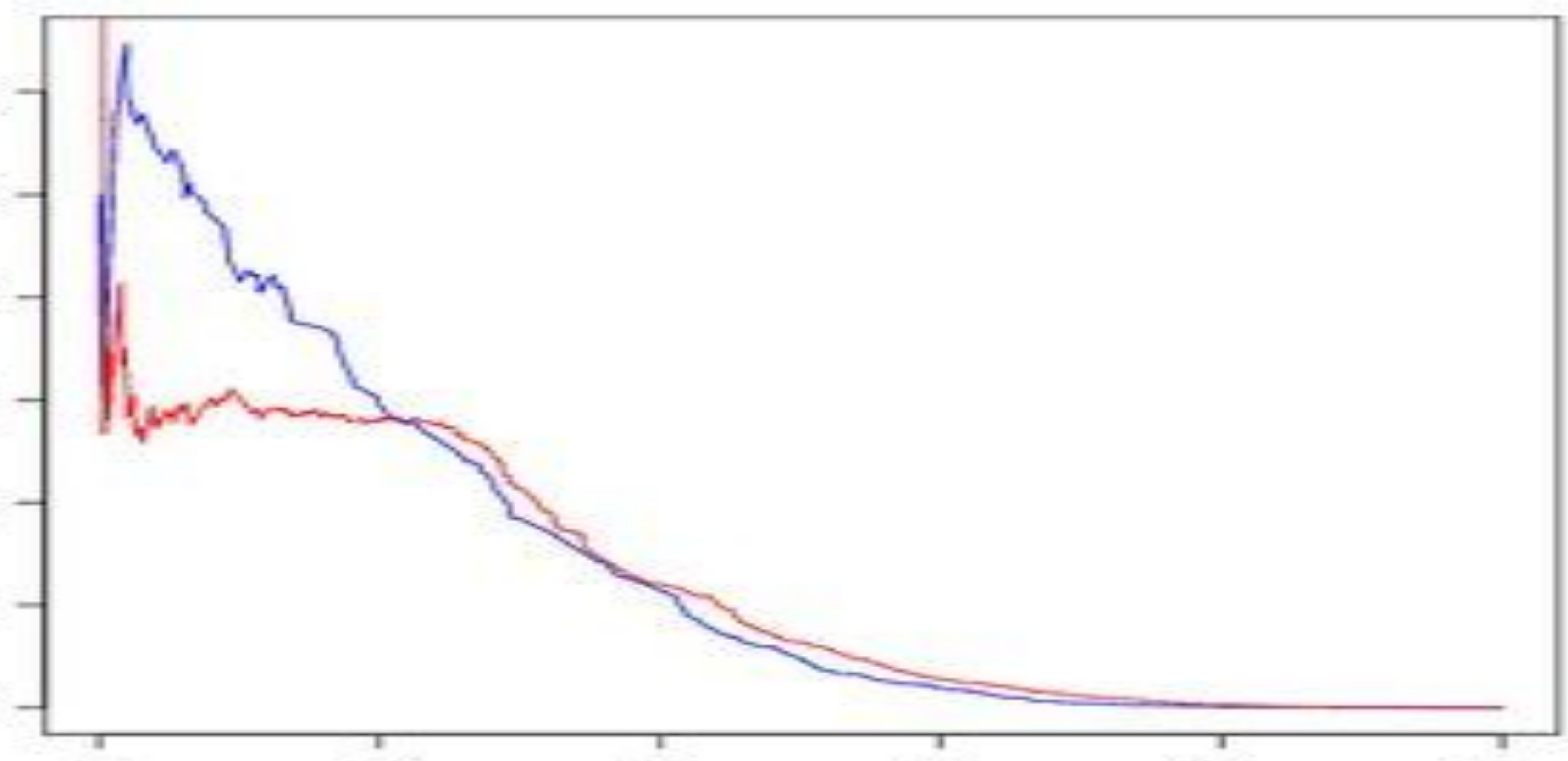
Precision – recall curve (PR curve)



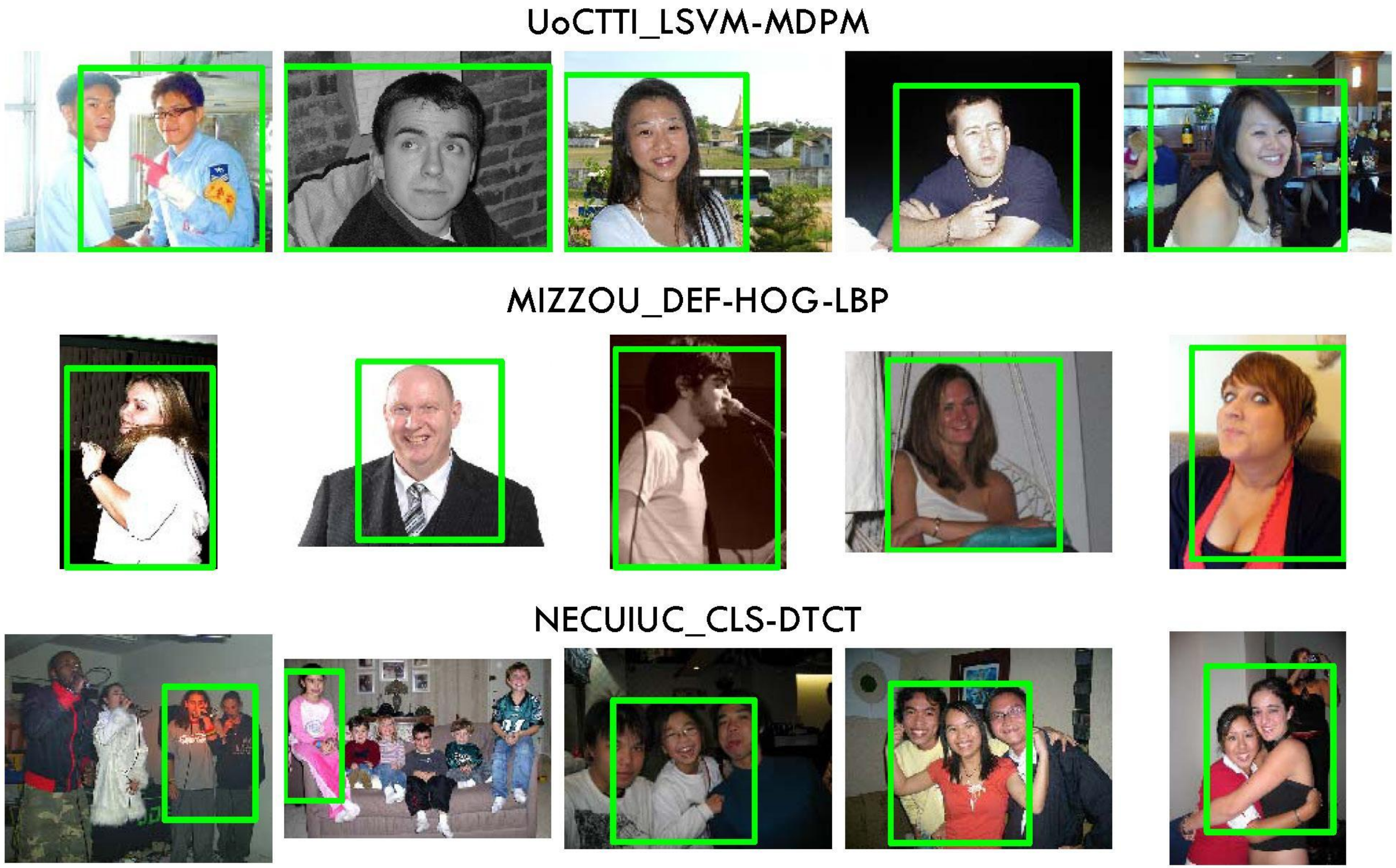
Which model is the best?



Which model is the best?



True positives - detecting person



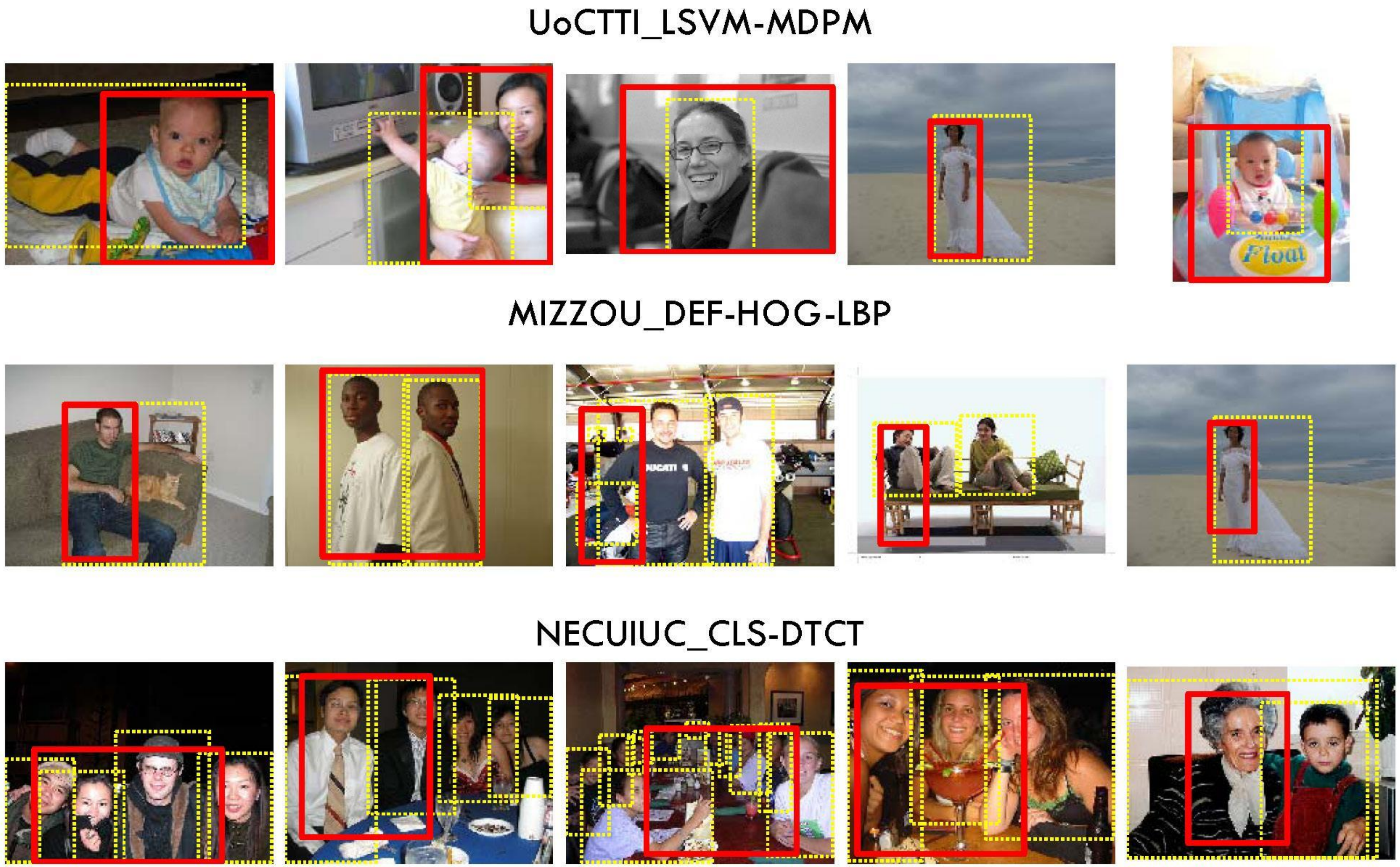
False positives - detecting person

UoCTTI_LSVM-MDPM

MIZZOU_DEF-HOG-LBP

NECUIUC_CLS-DTCT

Near misses: IoU falls short of 0.5



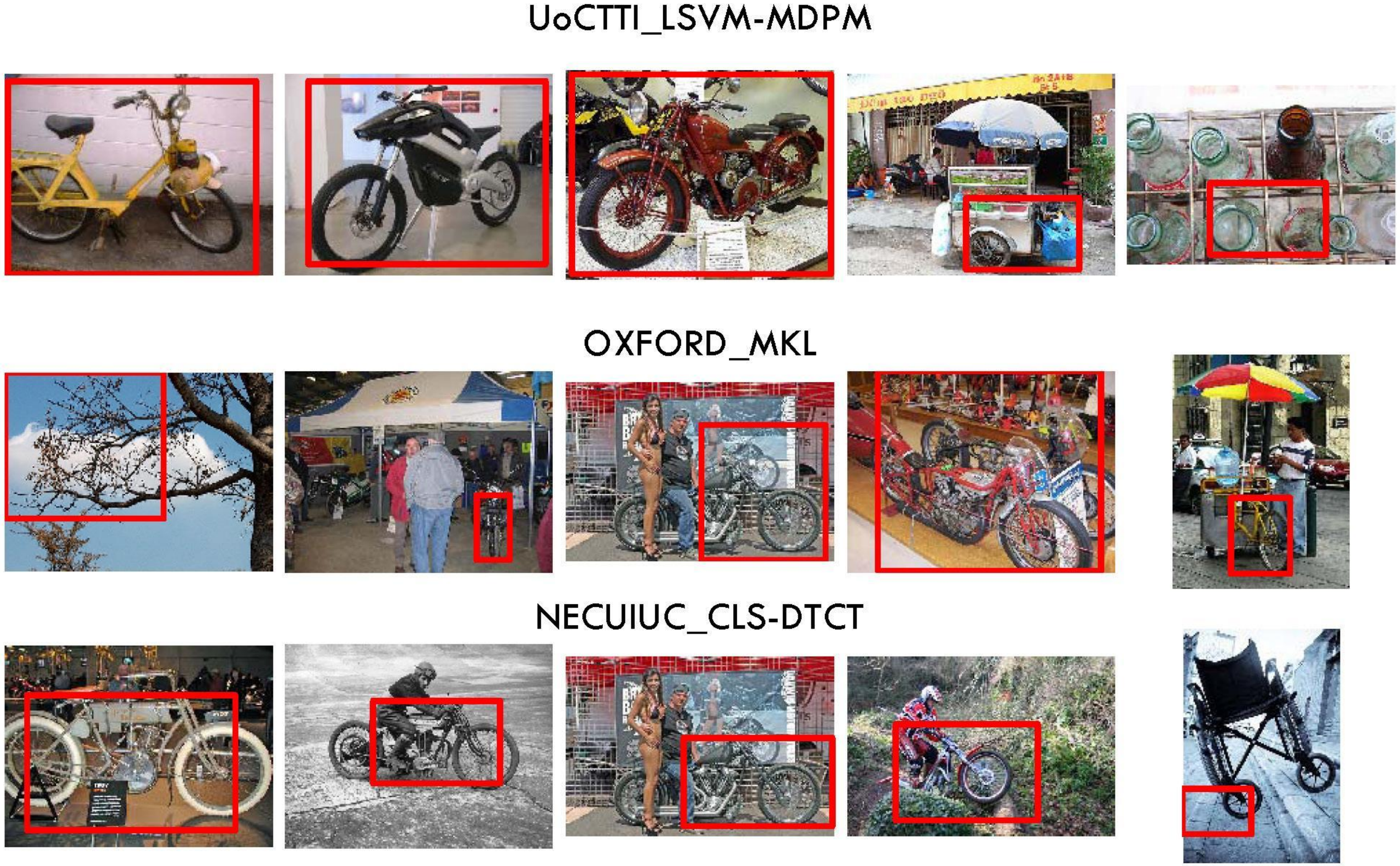
True positives - detecting bicycle

UoCTTI_LSVM-MDPM

OXFORD_MKL

NECUIUC_CLS-DTCT

False positives - detecting bicycle



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- Deformable parts model

Dalal-Triggs method

sliding window

At every patch as the window slides

1. Convert the image patch into your favorite feature representation
    a. For example:
        i. HoG,
        ii. HoG with PCA,
        iii. RGB with LDA,
        iv. Bag of words on RGB
        v. etc.
2. Use a trained classifier to determine if it is a specific class
    a. e.g. kNN classifier
3. Accumulate the predictions over all the patches

Sliding window + hog features

No person here

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

Sliding window + hog features

YES!! Person match found

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

Sliding window + hog features

No bus found

- But what if we were looking for buses?

Sliding window + hog features

No bus found

- But what if we were looking for buses?

Sliding window + hog features

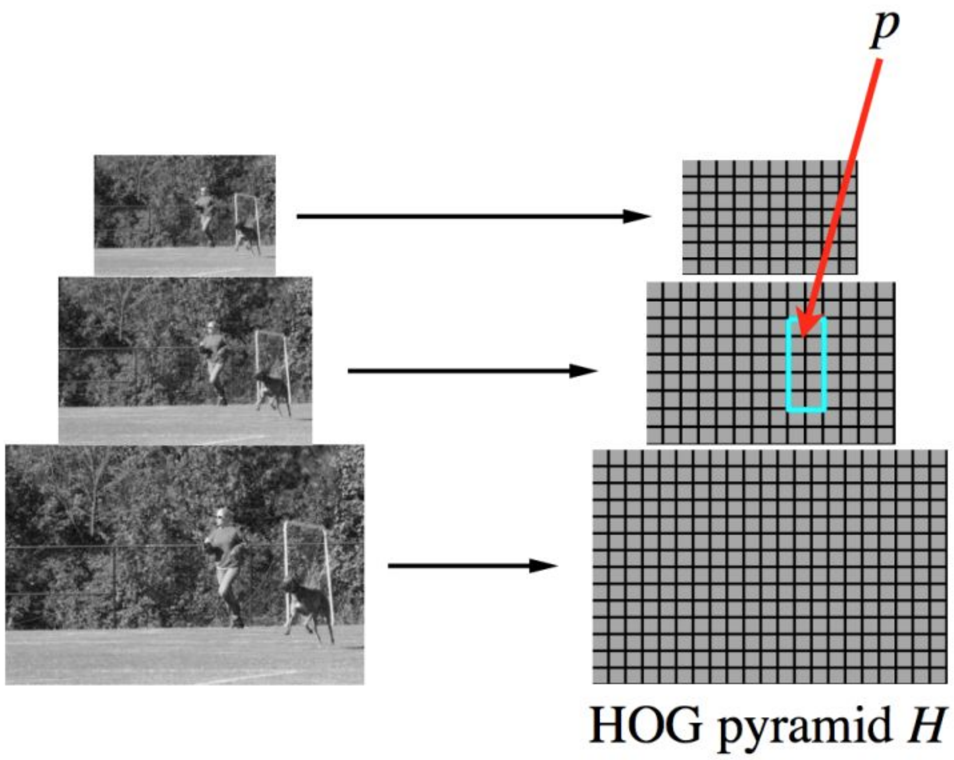
No bus found

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

Sliding window + hog features

- We need to do multi-scale sliding windows with pyramids

Computationally, we first resize the image to different sizes and then extract features at each size.



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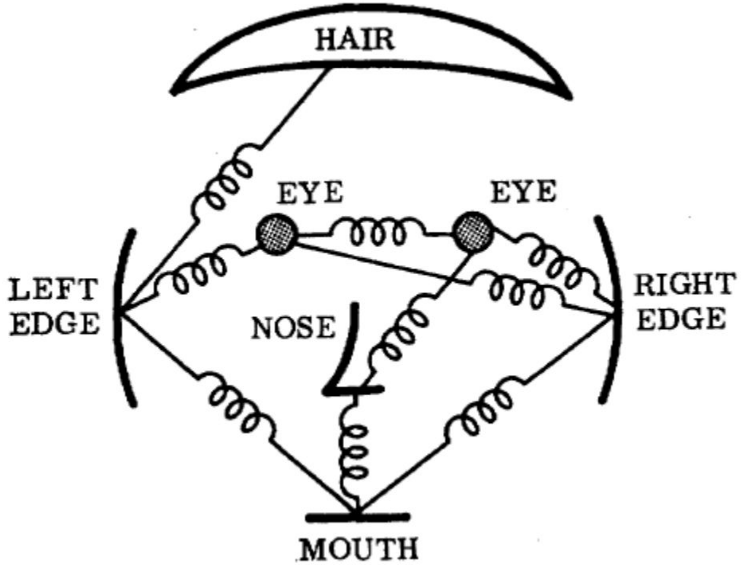
Recap – bag of words

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

- Can we use the location of these patches to find objects within those images?

Deformable Parts Model

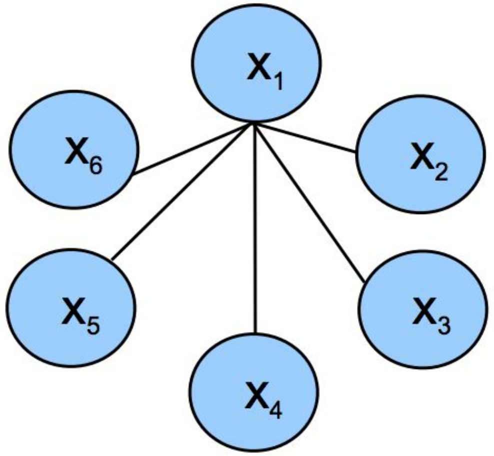
- Represents an object as a "collection of parts" arranged in a "deformable configuration"
- Each part represents local appearances
- Spring-like connections between certain pairs of parts

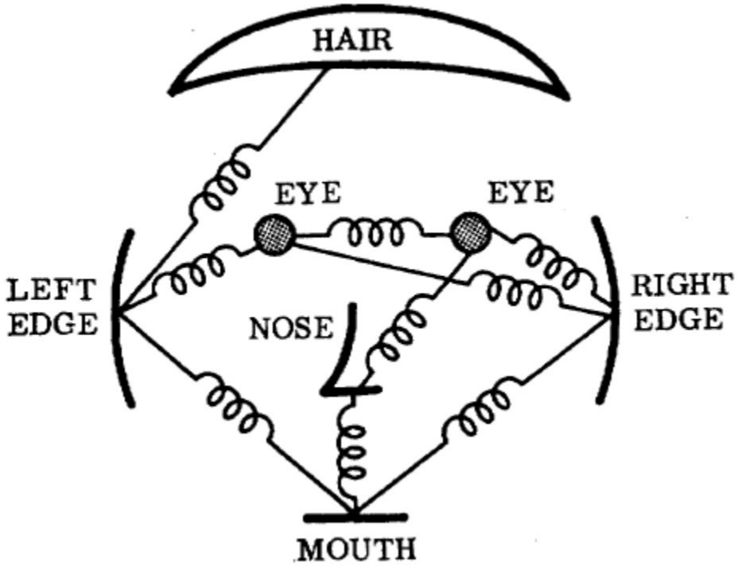


Fischler and Elschlager, Pictoral Structures, 1973

Deformable parts model

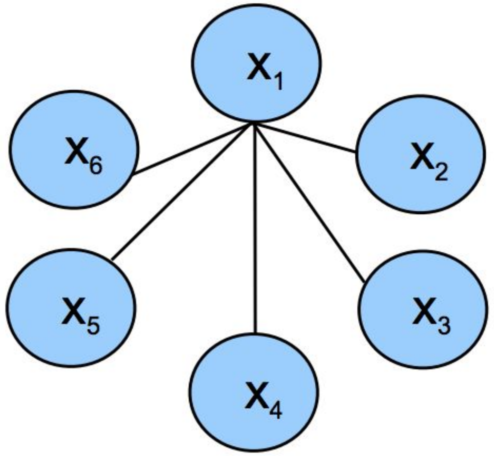
- The parts of an object form pairwise relationships.
- We can model this using a “star model”
  - where every part is defined relative to a root.





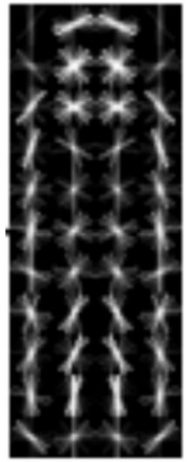
Detecting a person with their parts

- 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, which acts as the root.



Deformable parts model

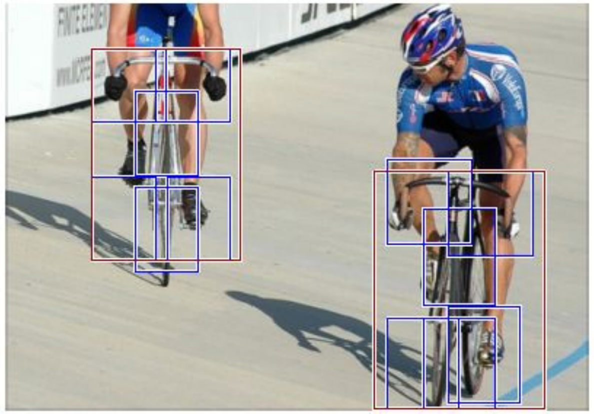
- Each model will have a global filter. And a set of part filters. Here is an example of a global person filter with it's 'head' part filter:

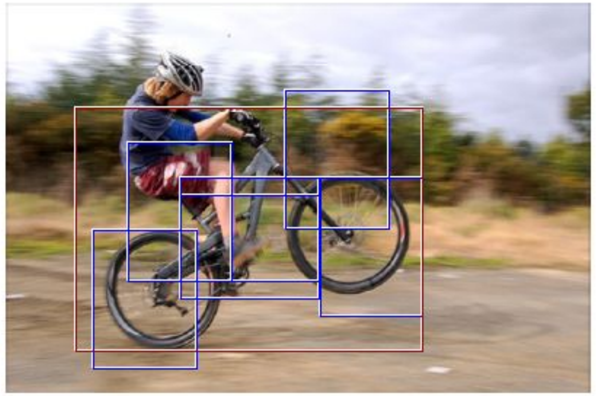


Global/root filter

Part filter

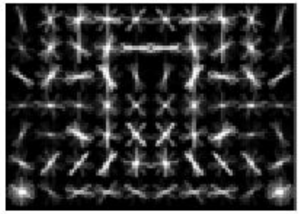
5-part bicycle model



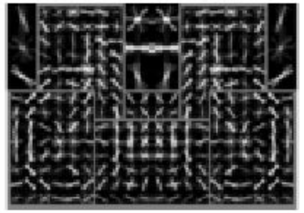


"side view" bike
model component

Root filter

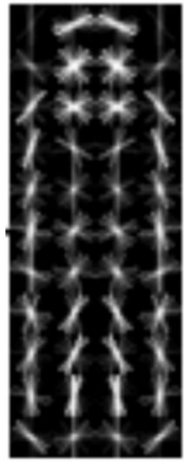


Part filters

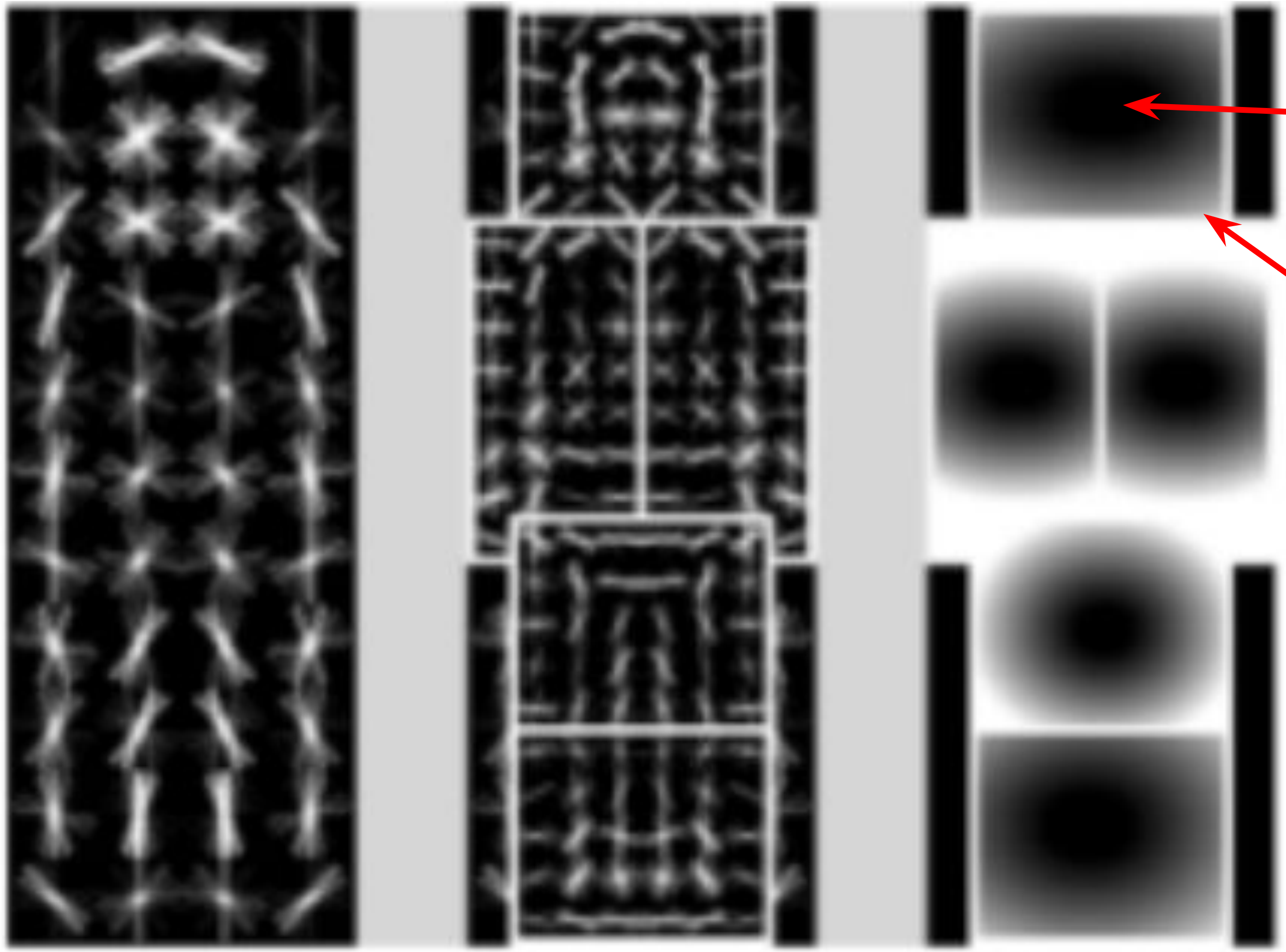


Deformable parts model

- Mixture of deformable part models
- Each component has global component + deformable parts
- Part filters have finer details



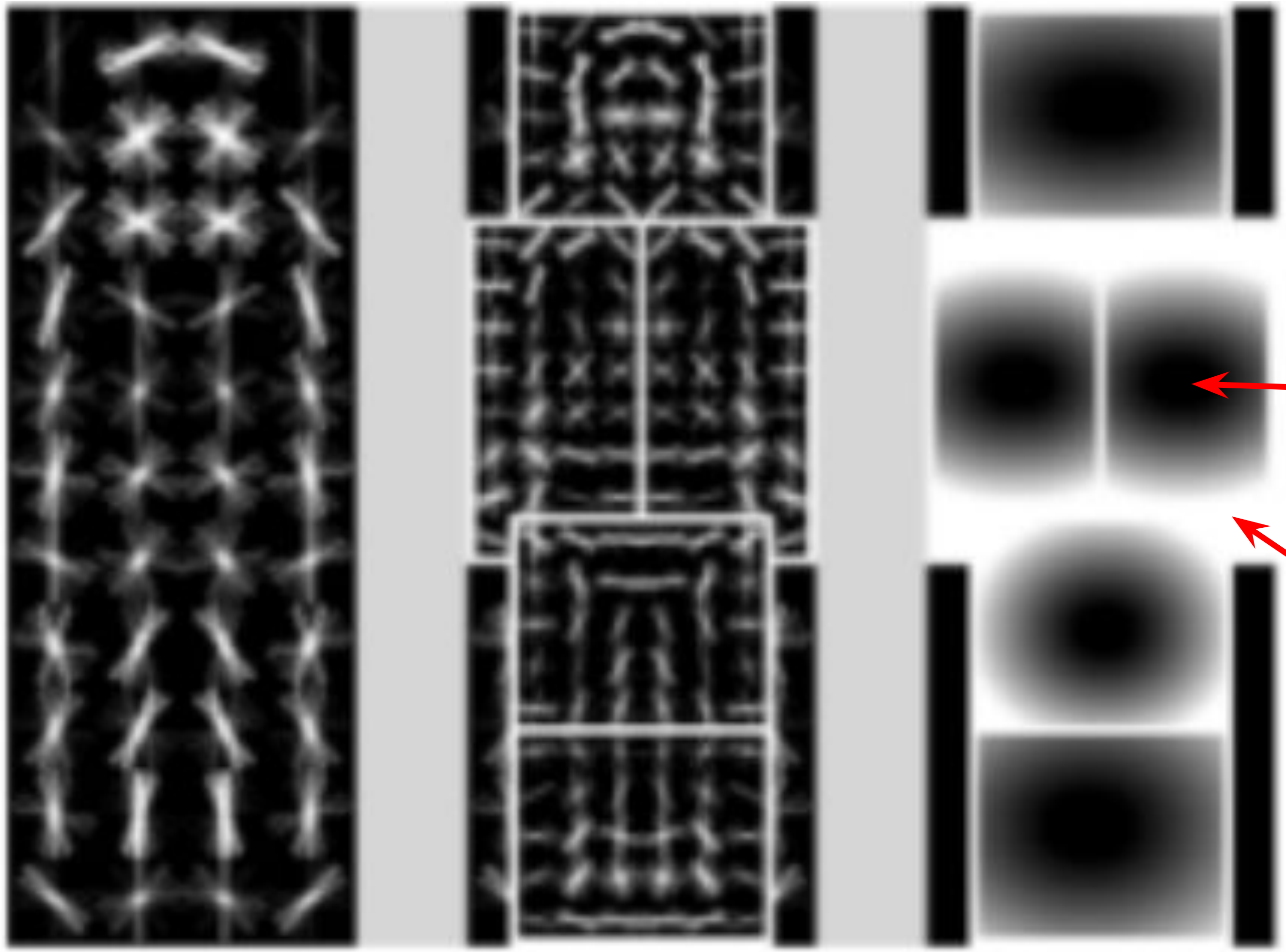
DPM for person model with 5 parts



If the head is here,
the penalty is low

If the head is here,
the penalty is high

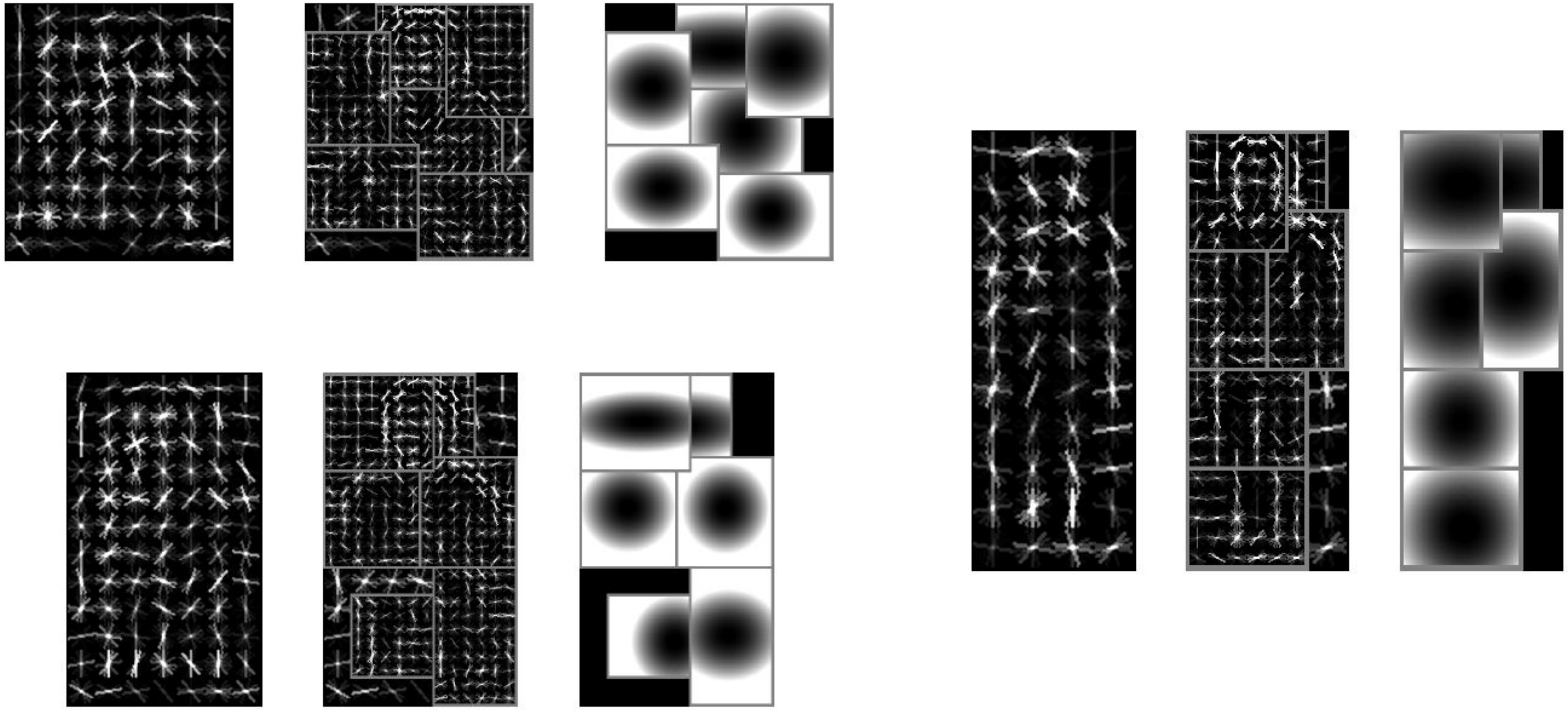
DPM for person model with 5 parts



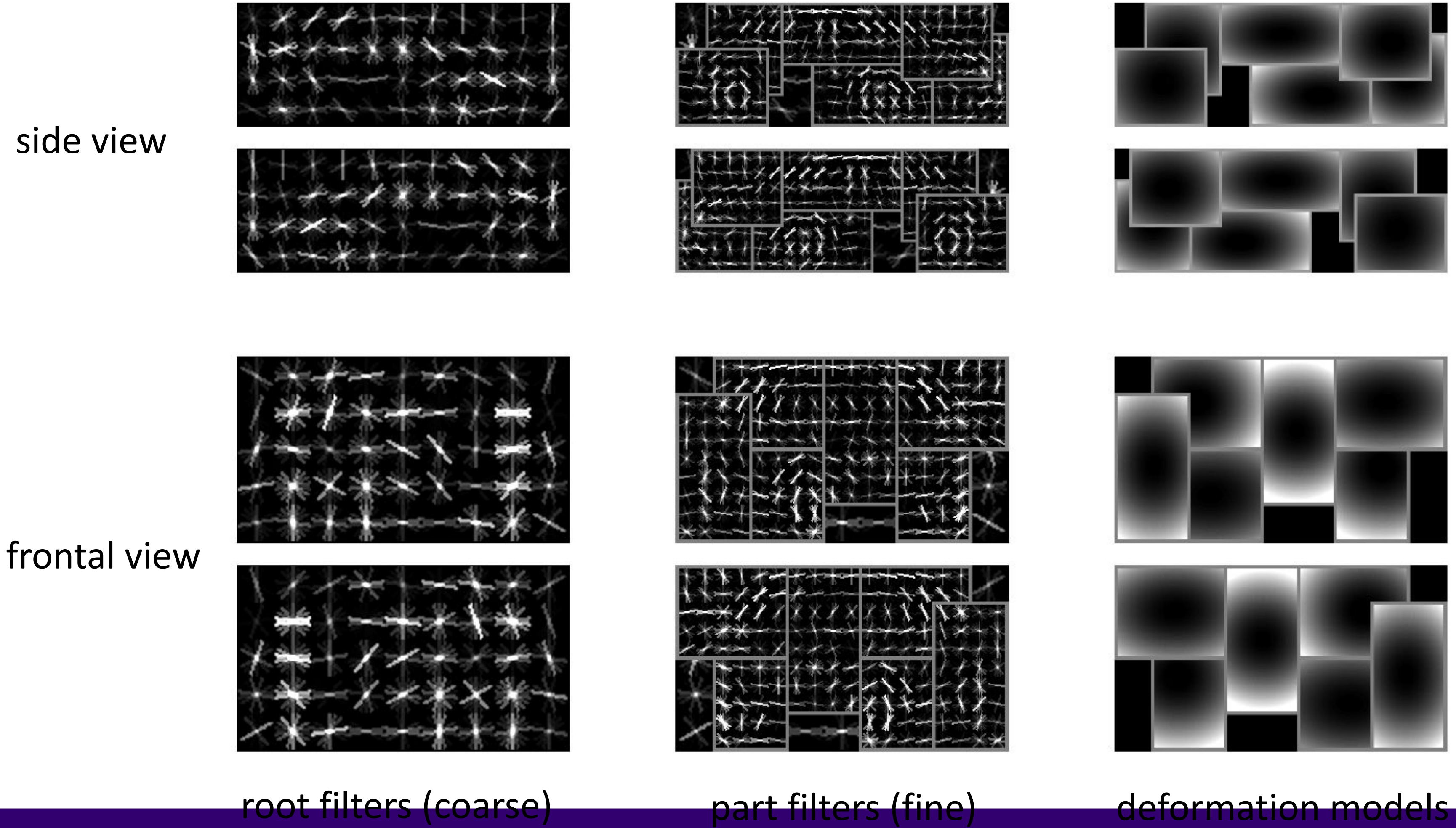
If the arm is here,
the penalty is low

If the arm is here,
the penalty is high

Multiple DPM for person model with 6 parts



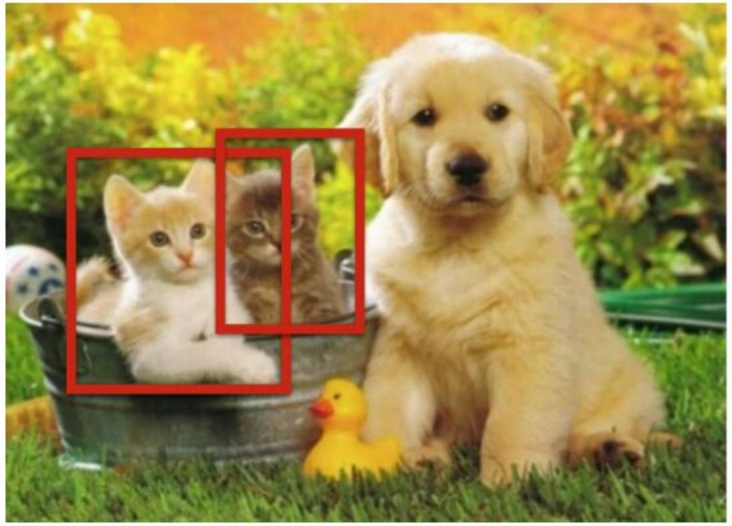
DPM for car with 6 parts



How do we use the parts to make a detection?

Intuition:

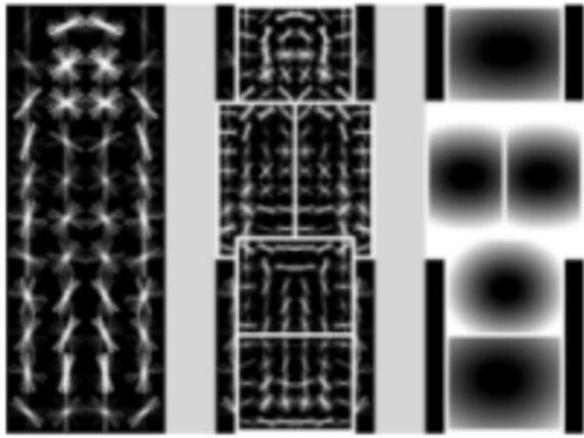
1. First, use the sliding windows at different pyramid scales to detect each part (and the root).
2. Each part gives you a score for where the person might be
3. Accumulate the global and part scores and penalize the deformation of the parts.



Example for detecting people

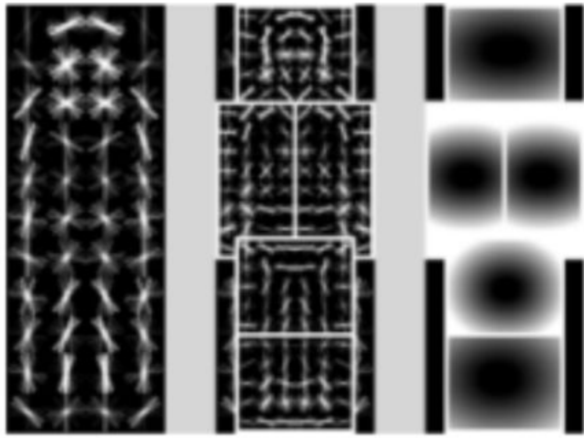
Image input

A feature template for person

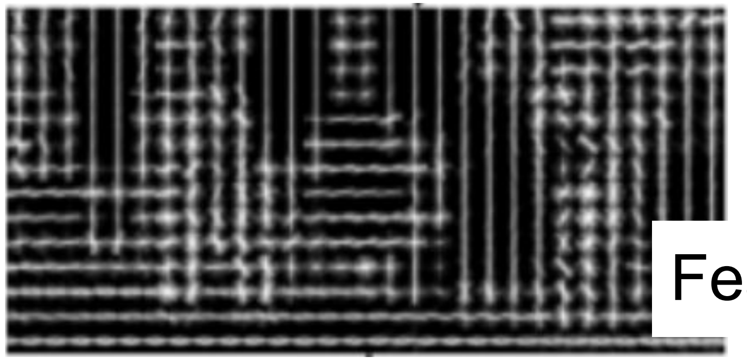


First extract features

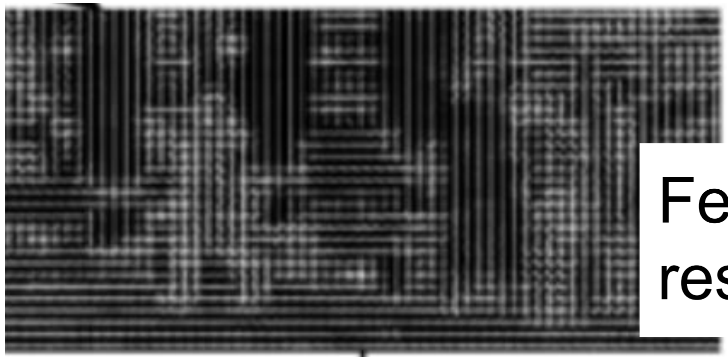
Image input



A feature template for person

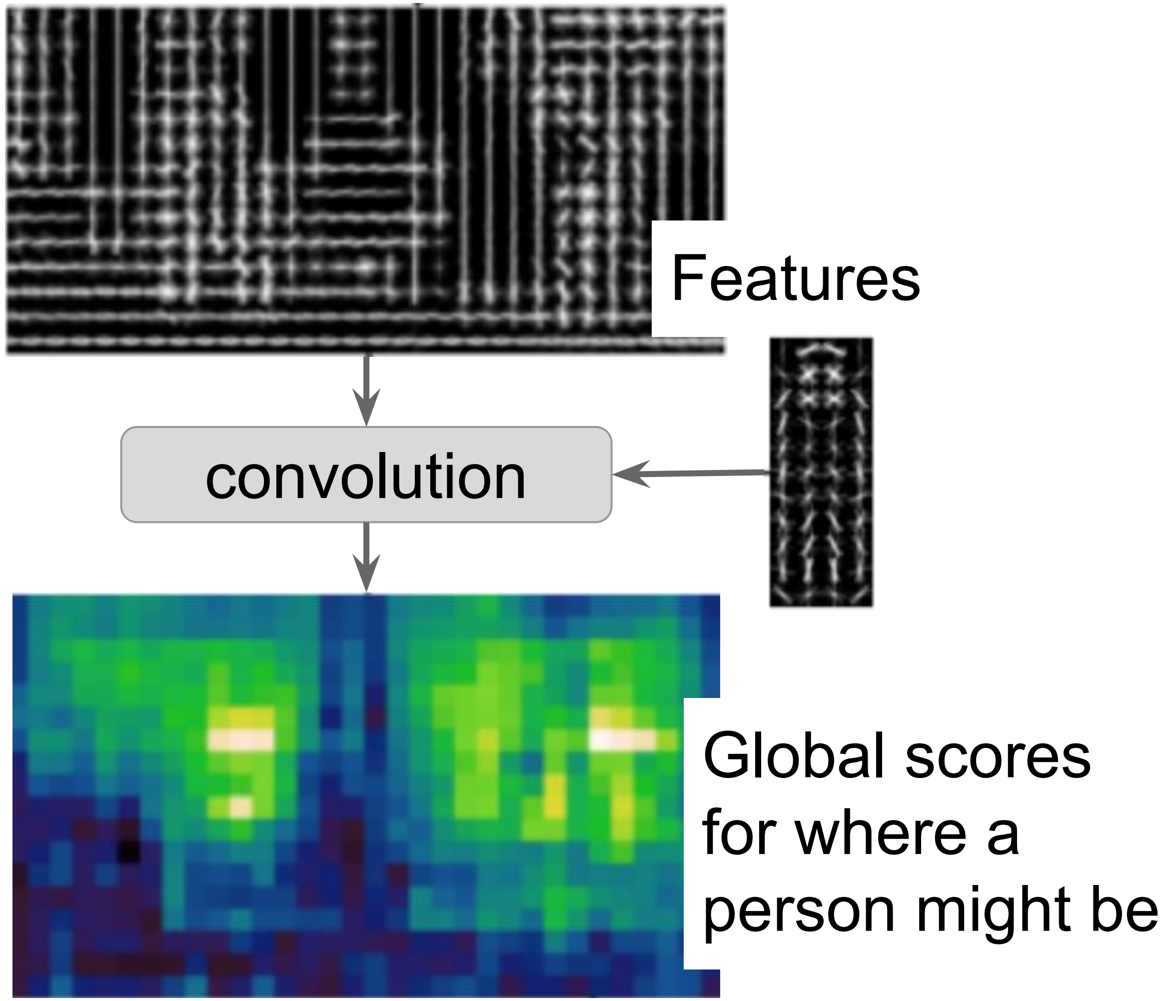


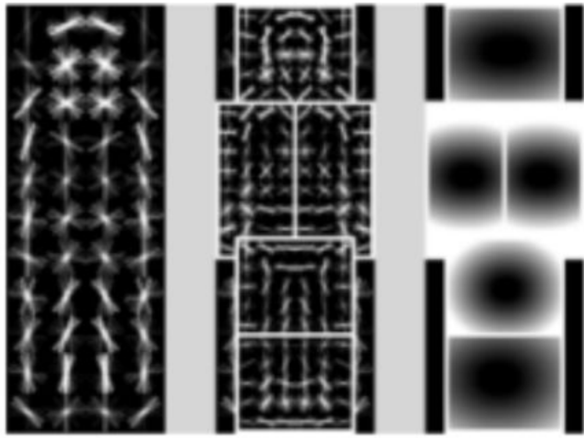
Features



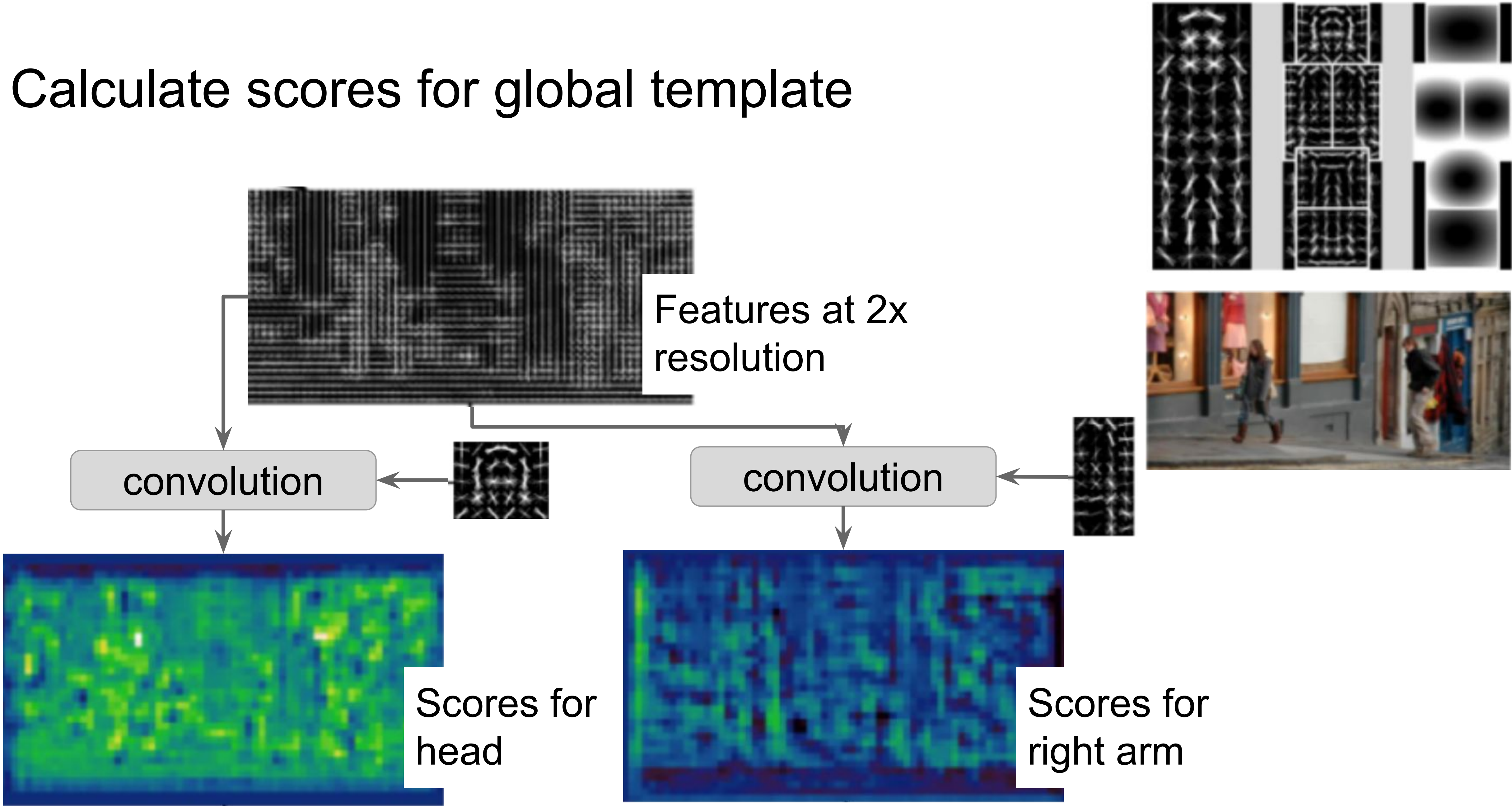
Features at 2x resolution

Calculate scores for part templates

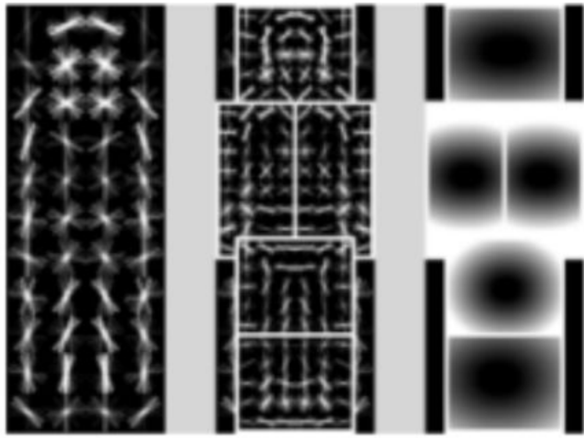




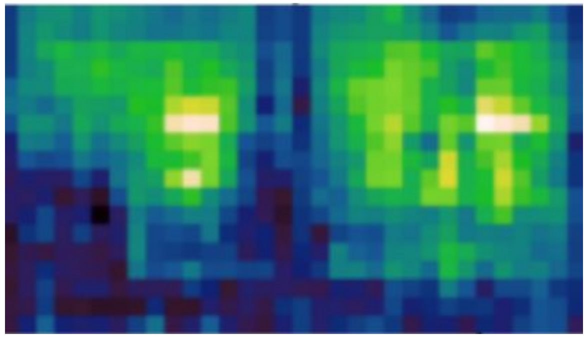
Calculate scores for global template



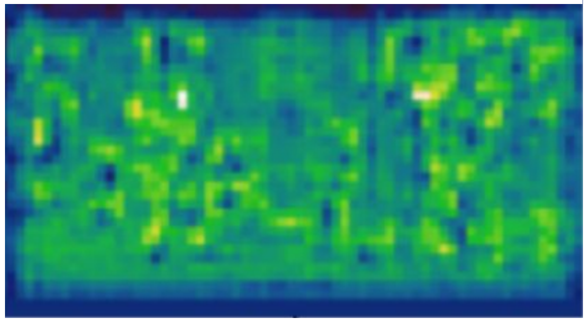
After step 1, we have scores for all parts and global template



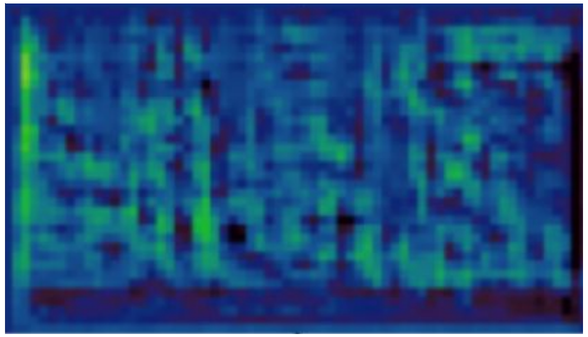
Global scores



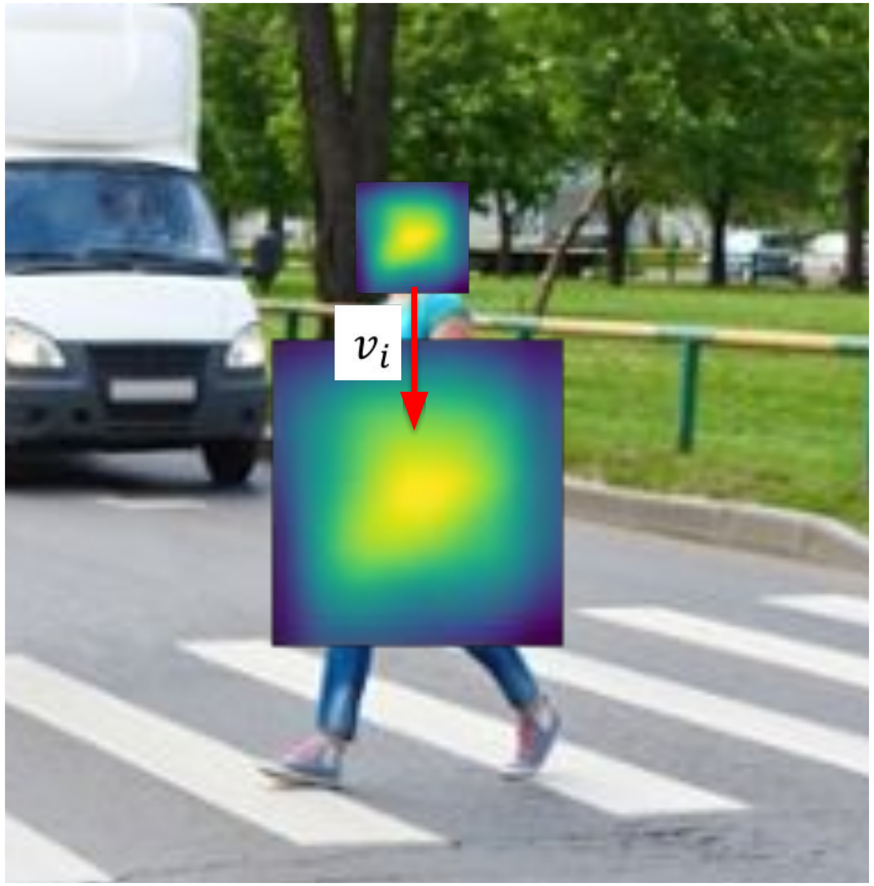
Scores for head



Scores for right arm

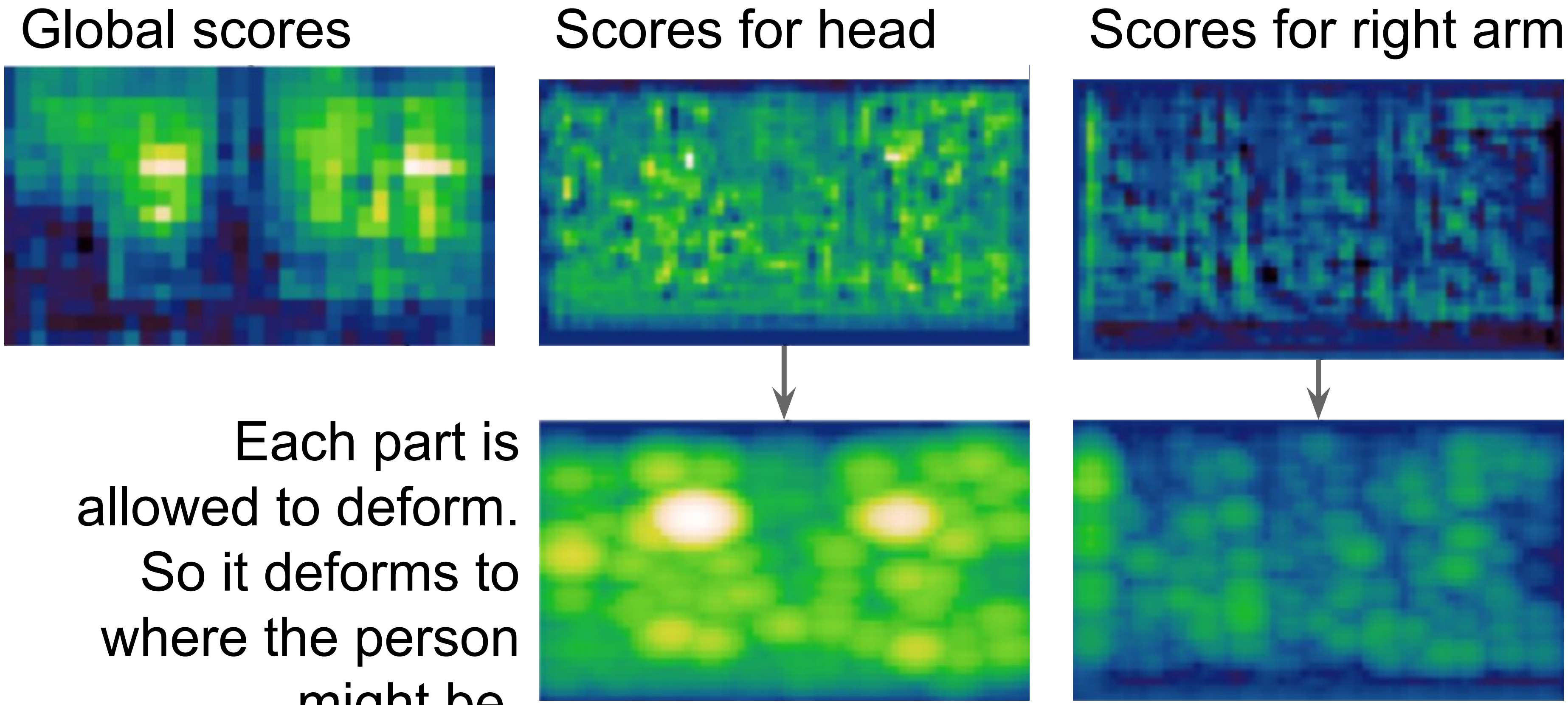


Allowing each part to deform and guess where the entire body is.

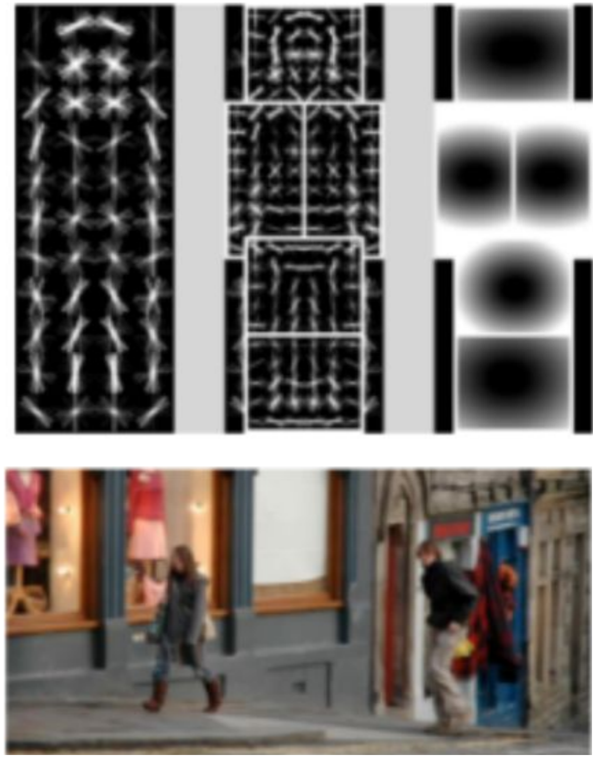


- Given the location for the detected head, we can guess where the body should be.
- The body should be in the direction (v_i) predefined in the model
- Bodies can be of different sizes and shapes. So we allow it to deform by some variable d_i
- This deformation spreads the scores to potential locations of the body

Step 2: each part gives you a score for where the person might be

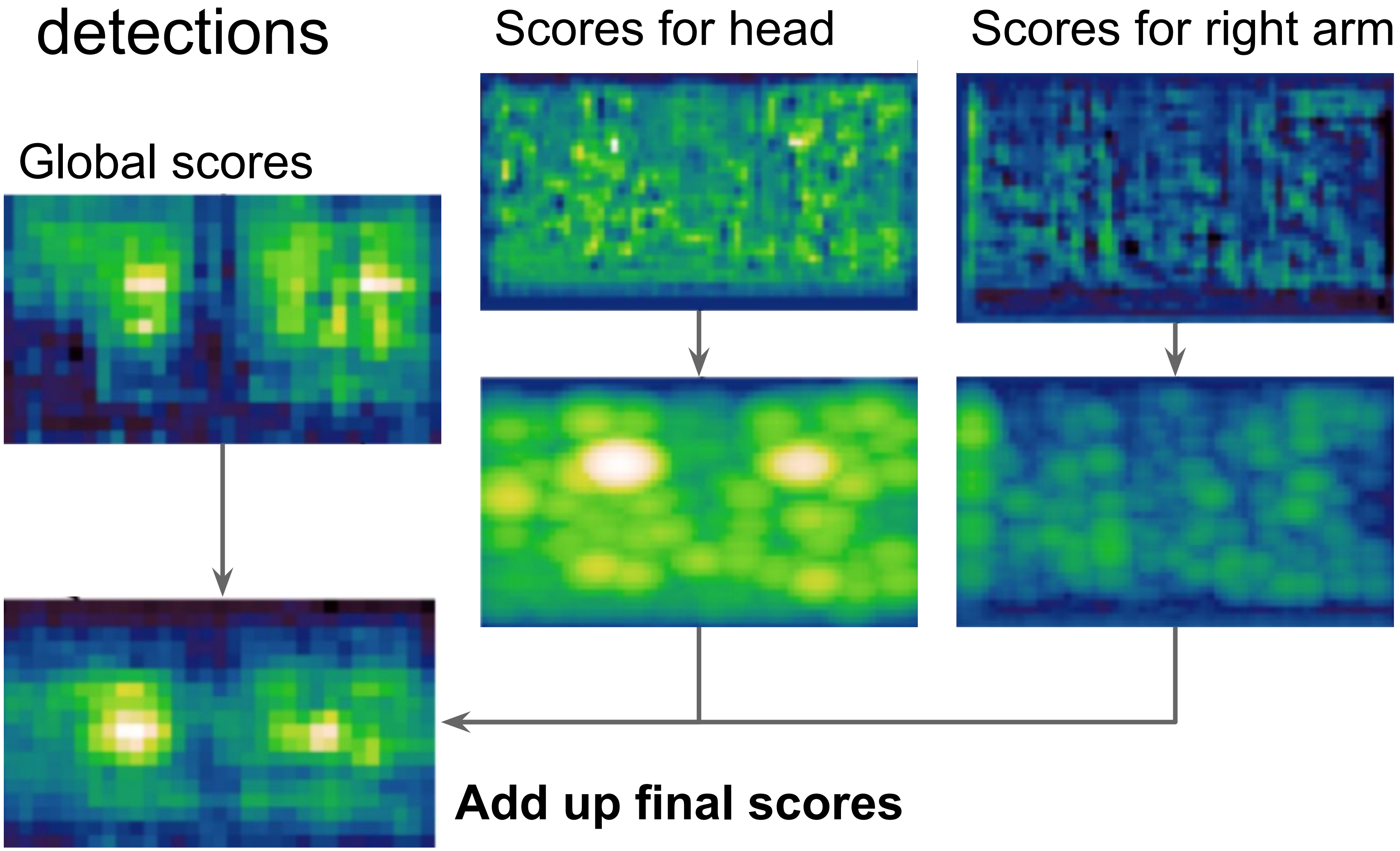


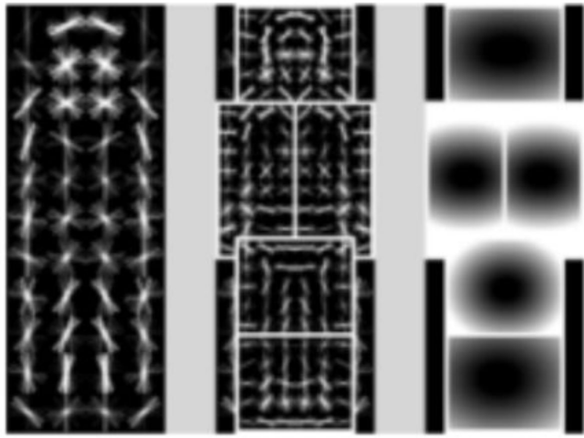
Each part is allowed to deform. So it deforms to where the person might be.



Intuition: If the head is here, where is the whole person likely to be?

Step 3: Add up the scores for the final detections





Formally, DPM is defined as:

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

$$(\underbrace{F_0}_{\text{Root filter}}, \underbrace{P_1}_{\text{Model for 1st part}}, \cdots, P_n, \underbrace{b}_{\text{Bias term}})$$

- Each part-based model defined as:

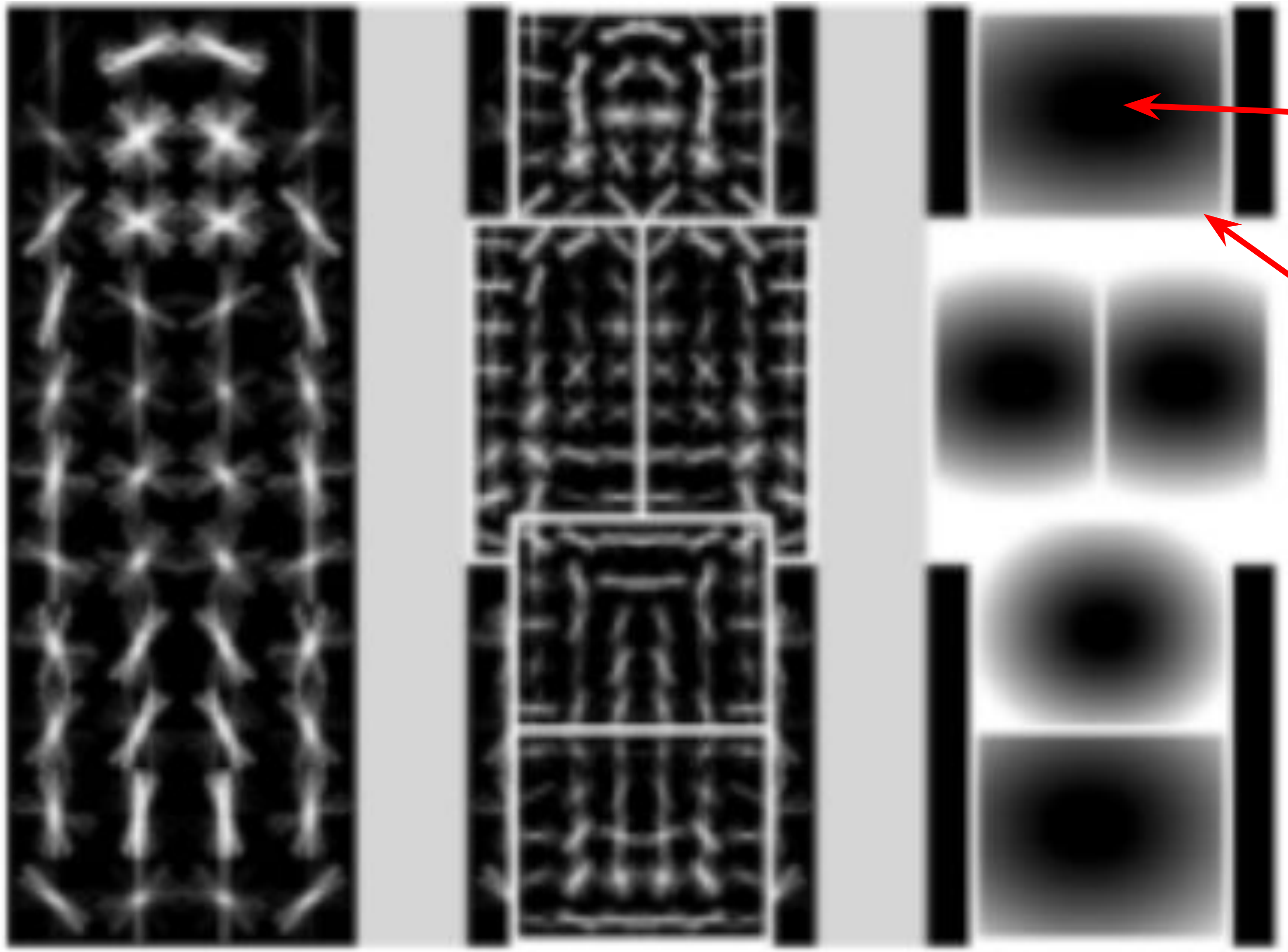
$$(F_i, v_i, d_i)$$

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

d_i can be defined in many ways. We will use a Gaussian filter to define it.



If the head is here, the penalty is low

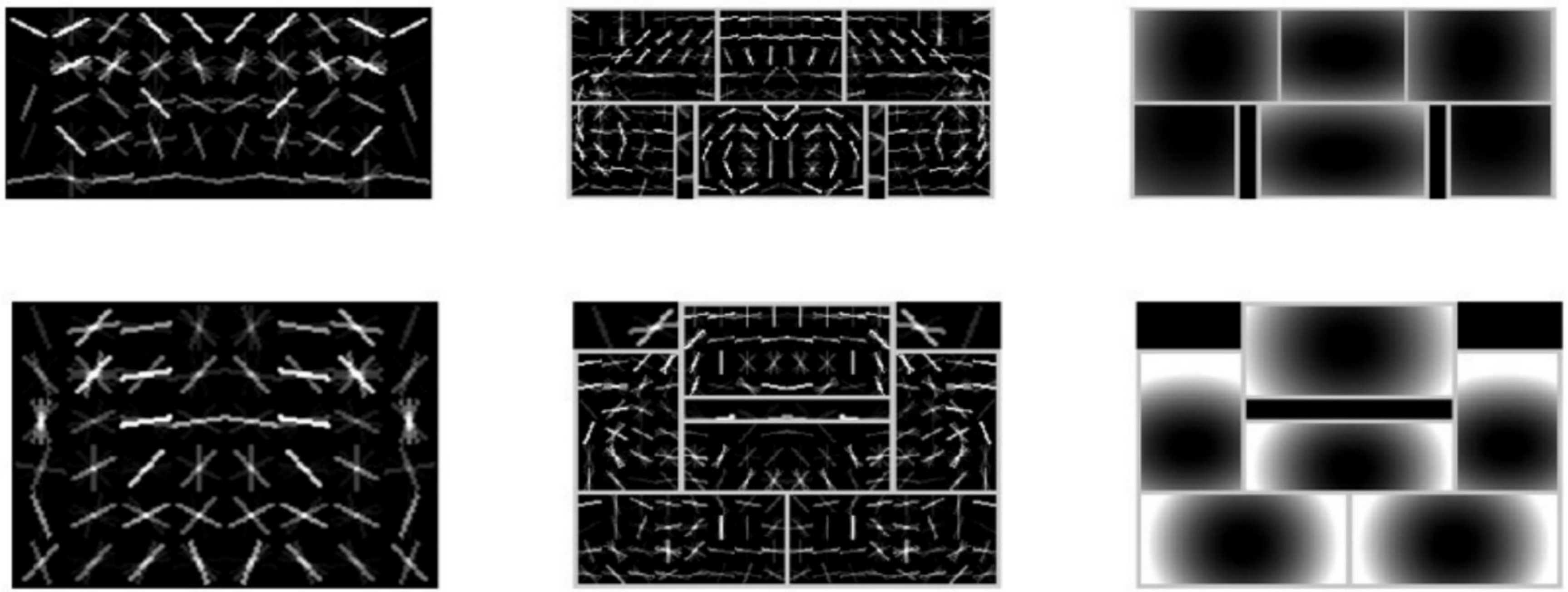
If the head is here, the penalty is high

Calculating the score for a detection

The score for a detection is defined as the sum of scores for the global and part detectors *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.

Deformable Parts Model (DPM) - bicycle

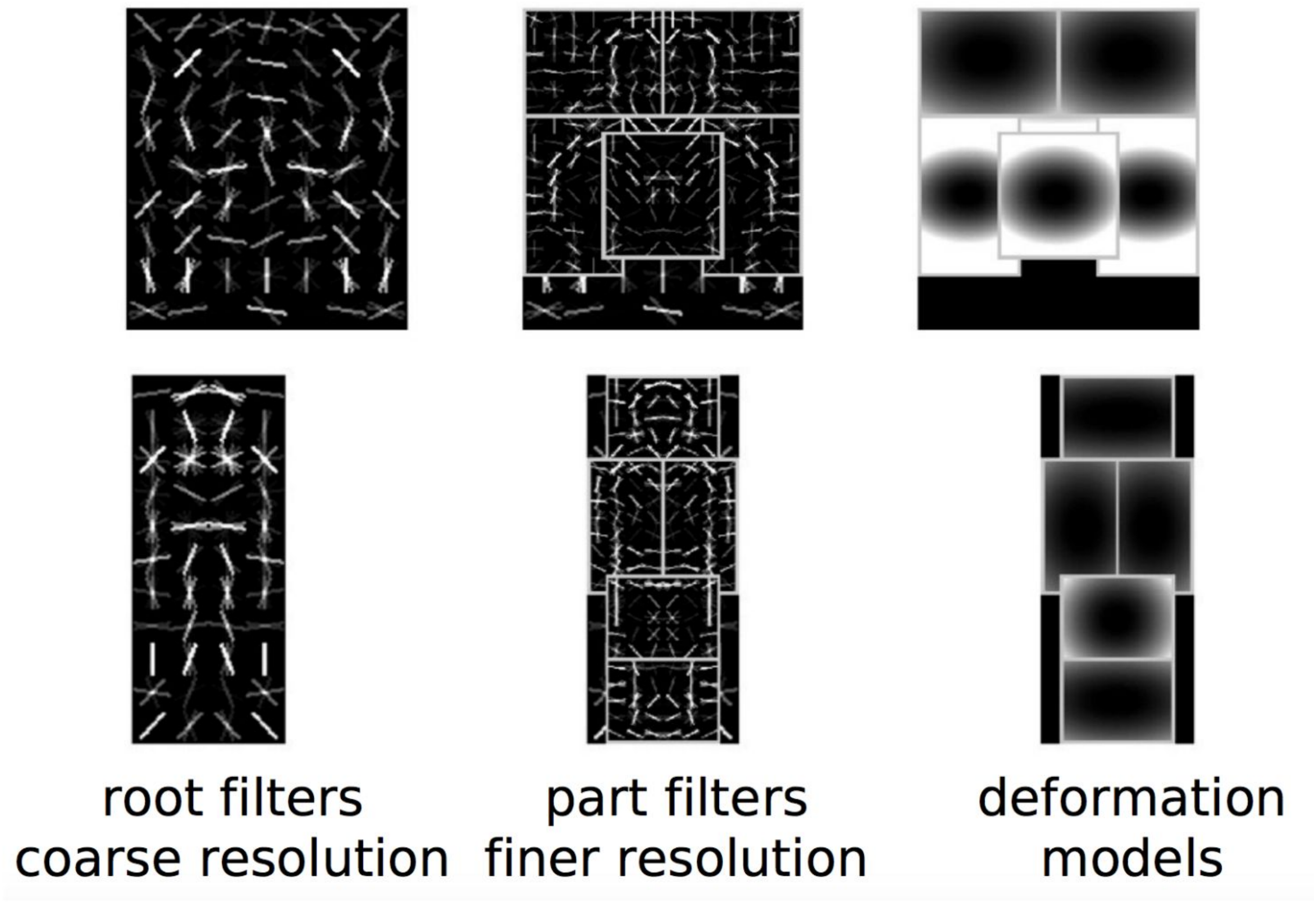


root filters
coarse resolution

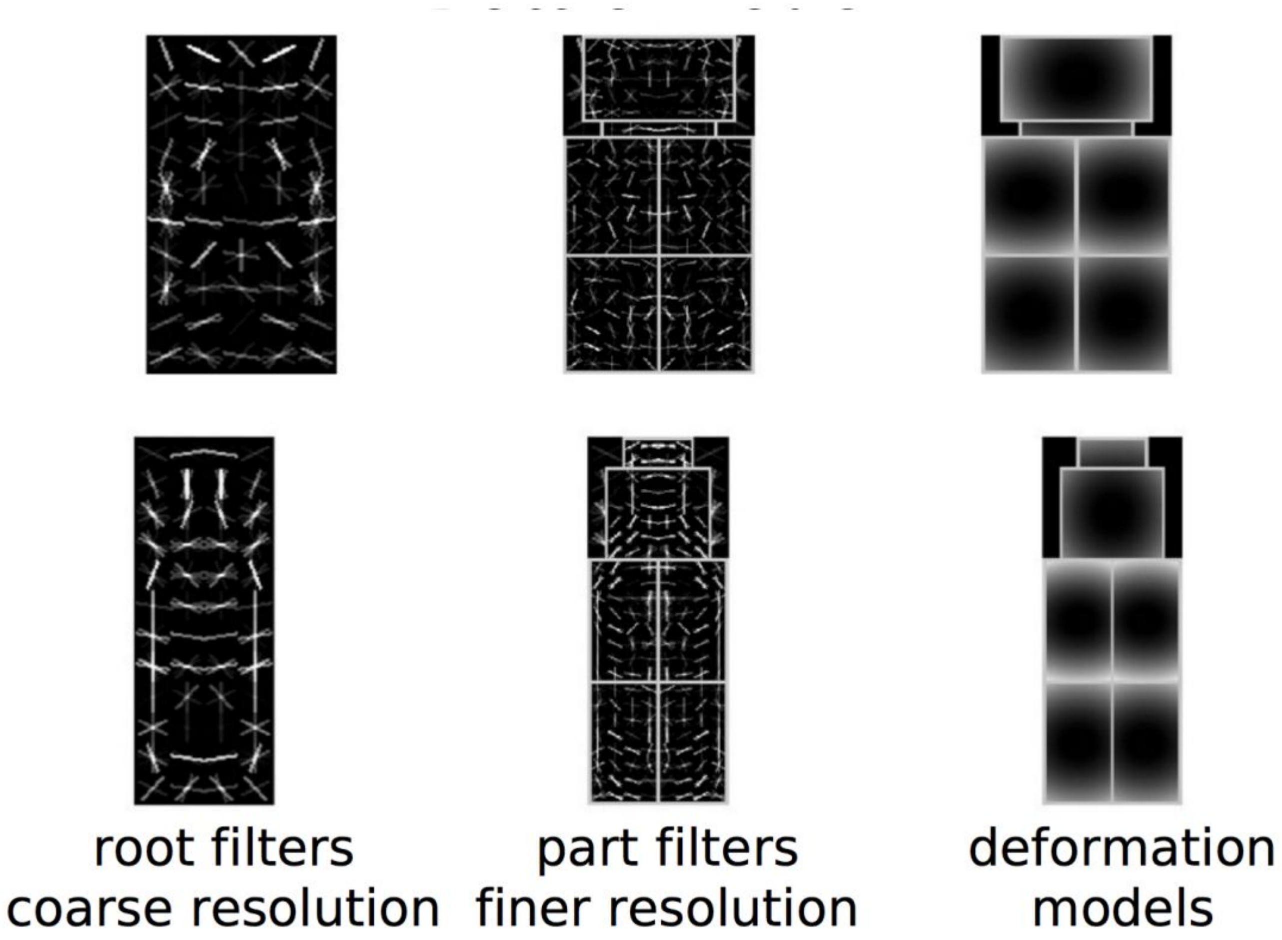
part filters
finer resolution

deformation
models

DPM with HoG features - person



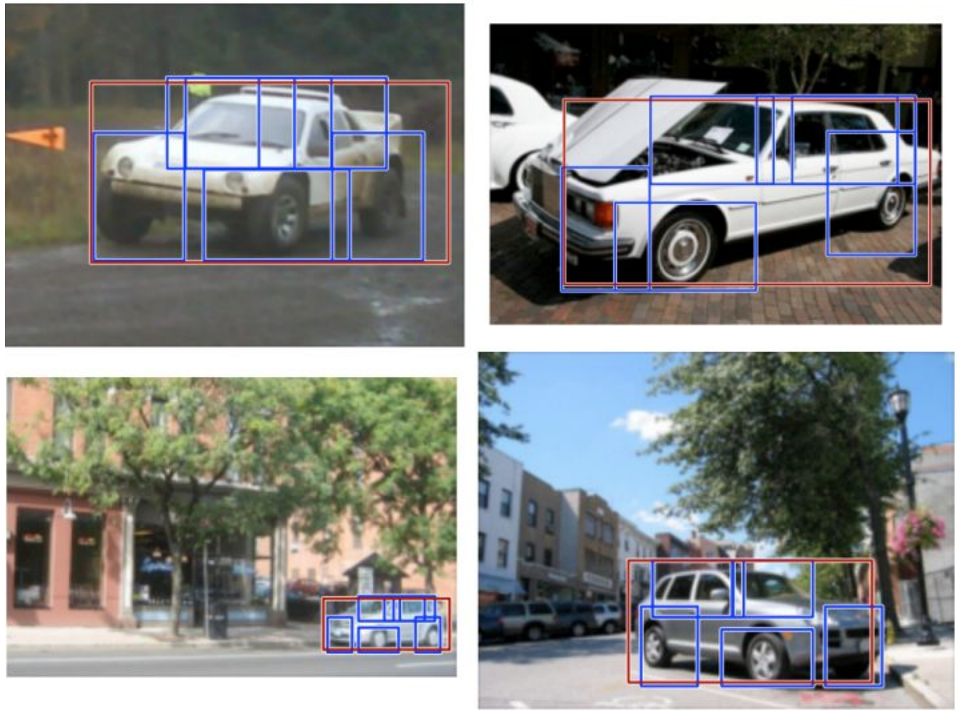
DPM - bottle



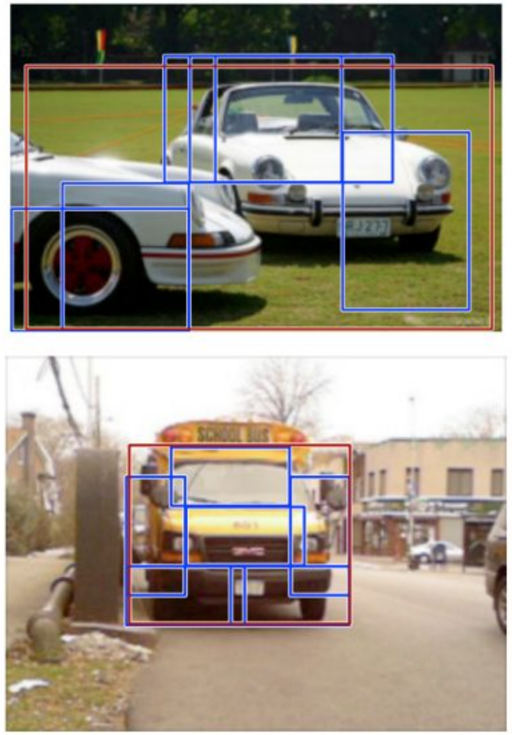
root filters
coarse resolution
part filters
finer resolution
deformation
models

Results – car detection

high scoring true positives



high scoring false positives

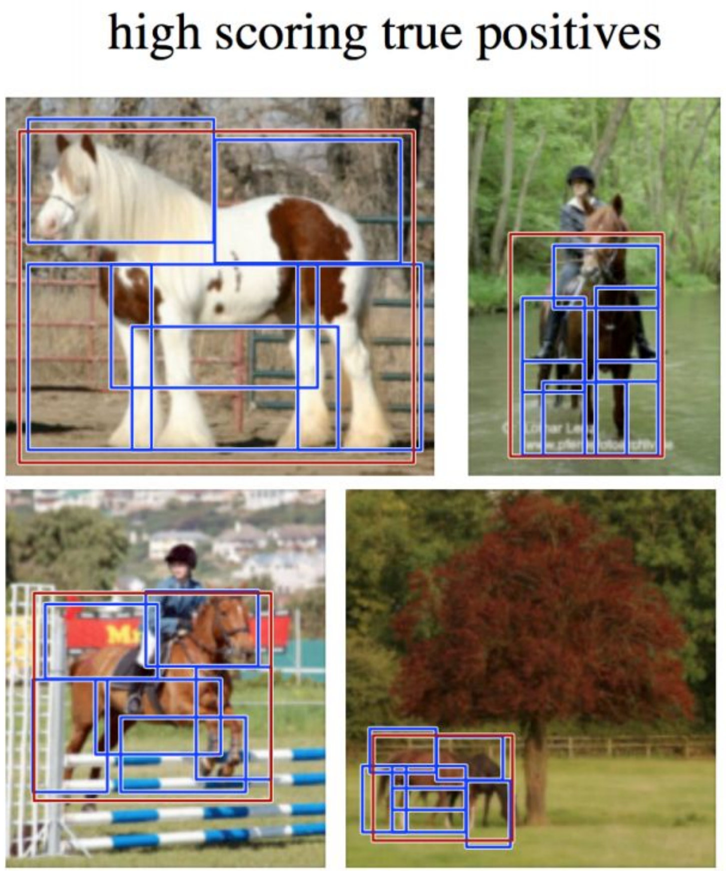


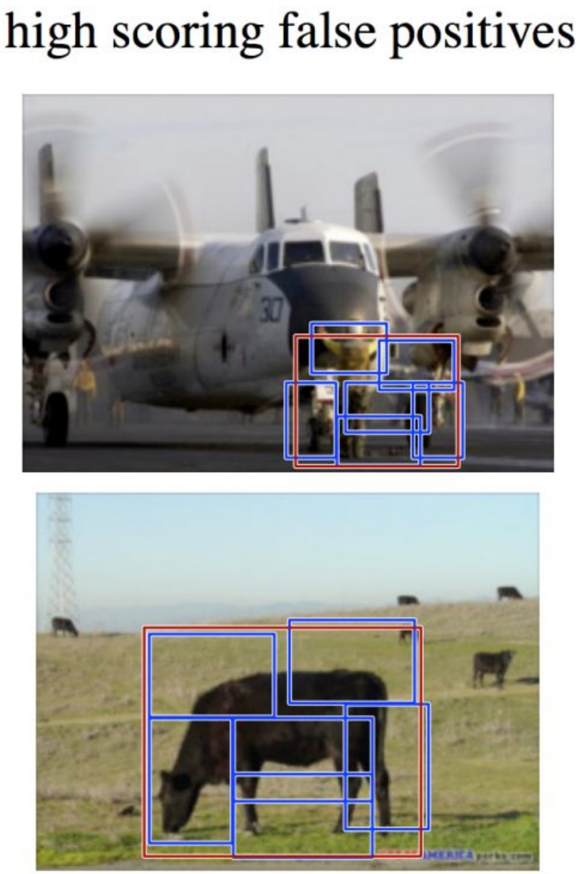
Results – Person detection

high scoring true positives

high scoring false positives
(not enough overlap)

Results – horse detection



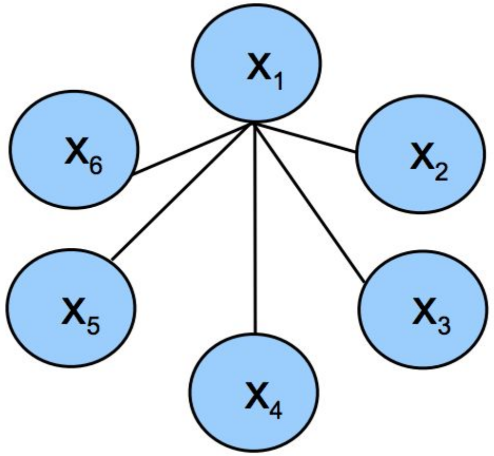


DPM - discussion

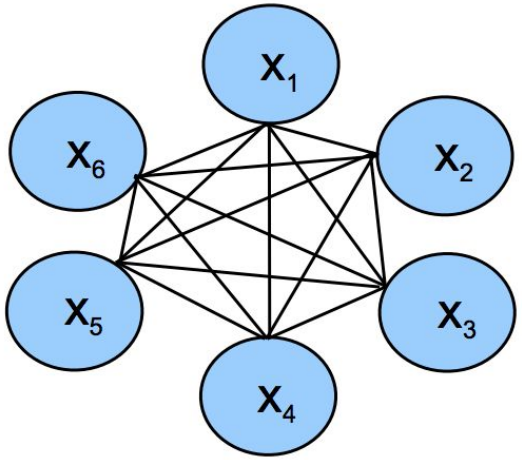
- **Approach**
  - Manually selected set of parts - Specific detector trained for each part
  - Spatial model trained on part activations
  - Evaluate joint likelihood of part activations
- **Pros**
  - Parts have intuitive meaning.
  - Standard detection approaches can be used for each part.
  - Works well for specific categories.
- **Disadvantages**
  - Parts need to be selected manually
  - Some parts don’t have a simple appearance
  - No guarantee that some important part hasn’t been missed
  - When adding a new category, it takes a lot of manual effort

Extensions - From star shaped model to constellation model

“Star” shape model



Fully connected shape model



Today's agenda

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

Next lecture

Motion and Tracking

Calculating the score for a detection

The score for a detection is defined as the sum of scores for the global and part detectors *minus* the sum of deformation costs for each part.

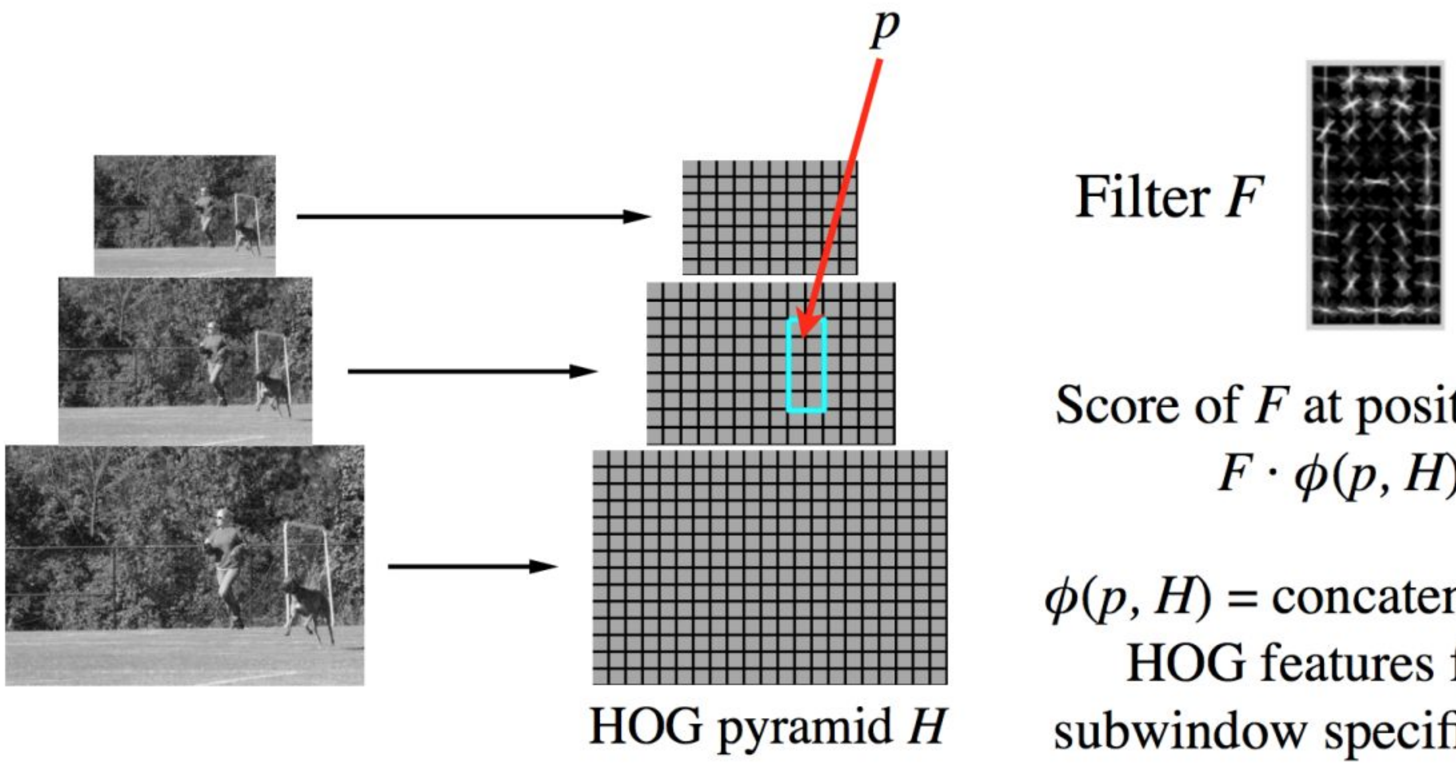
$$detection\ score = \sum_{i=0}^{n} F_i\, \phi(p_i, H) - \sum_{i=1}^{n} d_i\left(\Delta x_i, \Delta y_i, \Delta x_i^2, \Delta y_i^2\right)$$

Calculating the score for a detection

$$detection\ score = \sum_{i=0}^{n} F_i\,\phi(p_i, H) - \sum_{i=1}^{n} d_i(\Delta x_i, \Delta y_i, \Delta x_i^2, \Delta y_i^2)$$

Scores for each part filter + global filter (similar to Dalal and Triggs).

Remember from Dalal and Triggs

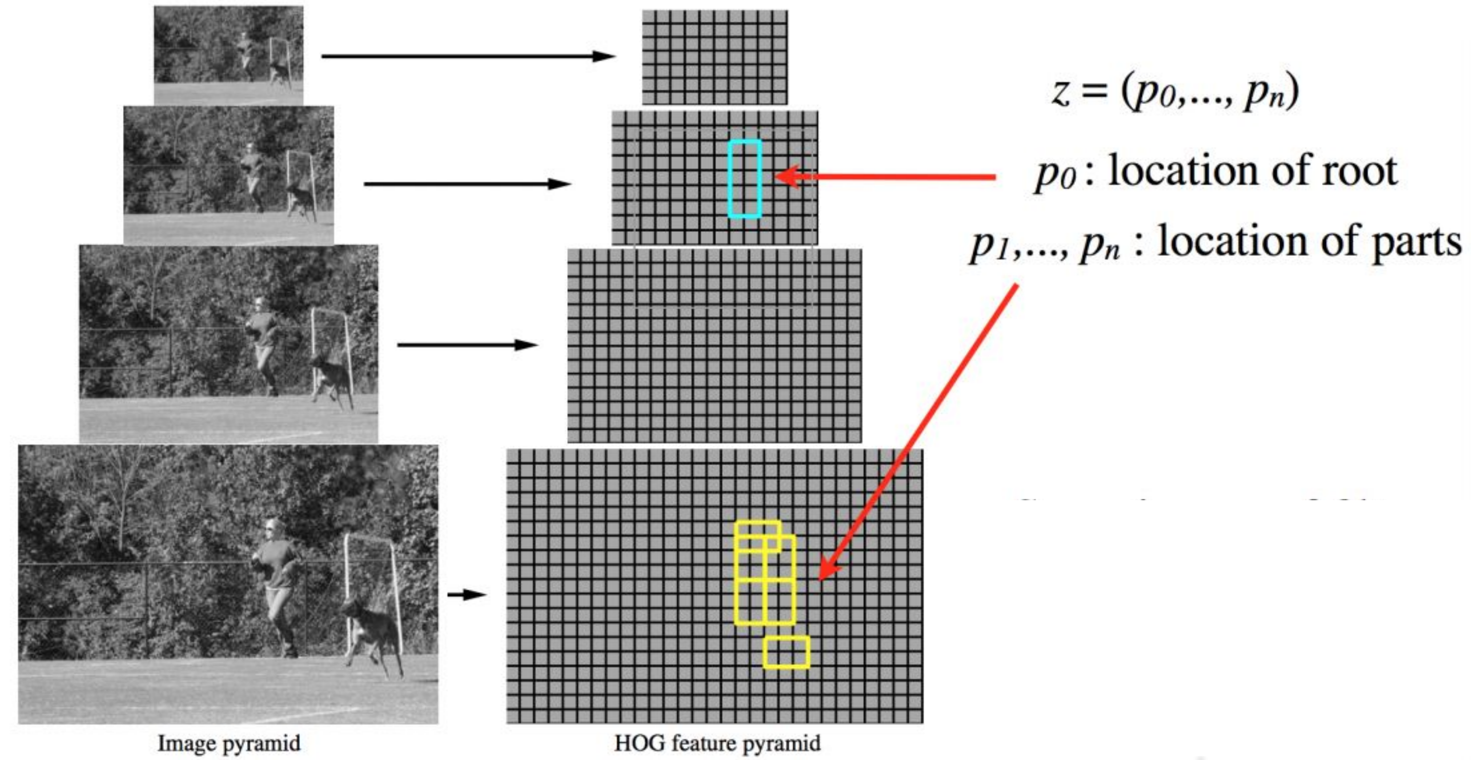


Score of F at position p is
$F \cdot \phi(p, H)$

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

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

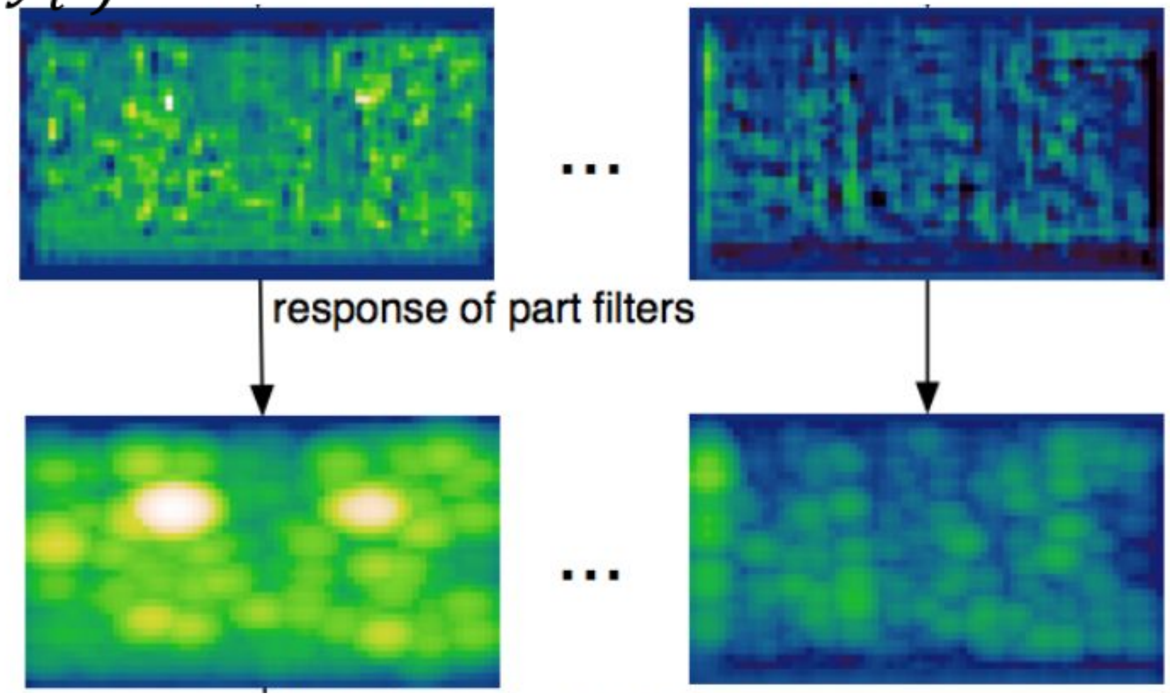
$p_i = (x_i, y_i, l_i)$ specifies the level and position of the i-th filter



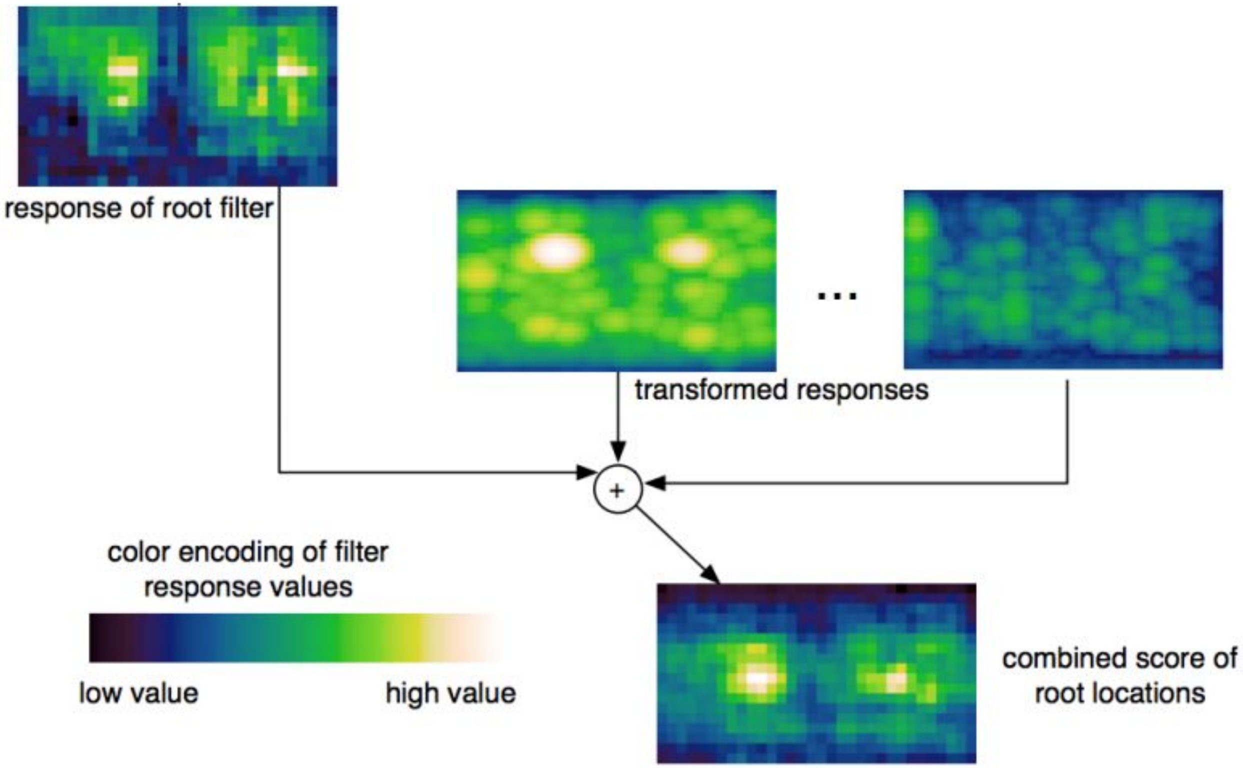
Detection pipeline

Now apply the spatial costs for each part:

$$detection\ score$$
$$= F_i\,\phi(p_i, H) - d_i(\Delta x_i, \Delta y_i, \Delta x_i^2, \Delta y_i^2)$$



Detection pipeline



Now add the global filter:

$$detection\ score = F_0 \phi(p_i, H) + \sum_{i=1}^{n} F_i\, \phi(p_i, H) - \sum_{i=1}^{n} d_i\big(\Delta x_i, \Delta y_i, \Delta x_i^2, \Delta y_i^2\big)$$

Calculating the score for a detection

$$detection\ score = \sum_{i=0}^{n} F_i\, \phi(p_i, H) - \sum_{i=1}^{n} d_i(\Delta x_i, \Delta y_i, \Delta x_i^2, \Delta y_i^2)$$

The deformation costs for each part.

Δx_i measures the distance in the x-direction from where part i should be.

Δy_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

$$detection\ score = \sum_{i=0}^{n} F_i\, \phi(p_i, H) - \sum_{i=1}^{n} d_i(\Delta x_i, \Delta y_i, \Delta x_i^2, \Delta y_i^2)$$

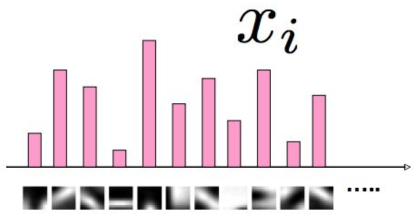
If d_i = (0, 0, 1, 0). What does this mean?

What we will learn today

- Naïve Bayes

Naïve Bayes

- Classify image using histograms of occurrences on visual words:

$\mathbf{x} =$ 

- where:
  - x_i is the event of visual word v_i appearing in the image,
  - $N(i)$ the number of times word v_i occurs in the image,
  - m is the number of words in our vocabulary.

Csurka Bray, Dance & Fan, 2004

Naïve Bayes - classification

- Our goal is to classify that the image represented by $\boldsymbol{x}$ is belongs class that has the highest *posterior* probability:

$$c^* = arg \max_c P(c \mid \boldsymbol{x})$$

Naïve Bayes – conditional independence

- Naïve Bayes classifier assumes that visual words are conditionally independent given object class.
- Therefore, we can multiply the probability of each visual word to obtain the joint probability.
- Model for image x under object class c:

$$P(x\,|c) = \prod_{i=1}^{m} P(x_i\,|\,c)$$

- How do we compute $P(x_i\,|\,c)$?

Csurka Bray, Dance & Fan, 2004

Naïve Bayes – prior

- Class priors $P(c)$ encode how likely we are to see one class versus others.
- Note that:

$$\sum_{c} P(c) = 1$$

Csurka Bray, Dance & Fan, 2004

Naïve Bayes - posterior

- With the equations from the previous slides, we can now calculate the probability that an image represented by $\boldsymbol{x}$ belongs to class category c.

$$P(c \mid \boldsymbol{x}) = \frac{P(c)\, P(\boldsymbol{x} \mid c)}{\sum_{c'} P(c')\, P(\boldsymbol{x} \mid c')}$$

Bayes Theorem

Naïve Bayes – posterior

- With the equations from the previous slides, we can now calculate the probability that an image represented by $\boldsymbol{x}$ belongs to class category c.

$$P(c \mid \boldsymbol{x}) = \frac{P(c)\, P(\boldsymbol{x} \mid c)}{\sum_{c'} P(c')\, P(\boldsymbol{x} \mid c')}$$

$$P(c \mid \boldsymbol{x}) = \frac{P(c) \prod_{i=1}^{m} P(x_i \mid c)}{\sum_{c'} P(c') \prod_{i=1}^{m} P(x_i \mid c')}$$

Let's break down the posterior

The probability that $\boldsymbol{x}$ belongs to class c_1:

$$P(c_1 \mid \boldsymbol{x}) = \frac{P(c_1)\prod_{i=1}^{m} P(x_i \mid c_1)}{\sum_{c'} P(c')\prod_{i=1}^{m} P(x_i \mid c')}$$

And the probability that $\boldsymbol{x}$ belongs to class c_2:

$$P(c_2 \mid \boldsymbol{x}) = \frac{P(c_2)\prod_{i=1}^{m} P(x_i \mid c_2)}{\sum_{c'} P(c')\prod_{i=1}^{m} P(x_i \mid c')}$$

Both their denominators are the same

The probability that $\boldsymbol{x}$ belongs to class c_1:

$$P(c_1 \mid \boldsymbol{x}) = \frac{P(c_1) \prod_{i=1}^{m} P(x_i \mid c_1)}{\sum_{c'} P(c') \prod_{i=1}^{m} P(x_i \mid c')}$$

And the probability that $\boldsymbol{x}$ belongs to class c_2:

$$P(c_2 \mid \boldsymbol{x}) = \frac{P(c_2) \prod_{i=1}^{m} P(x_i \mid c_2)}{\sum_{c'} P(c') \prod_{i=1}^{m} P(x_i \mid c')}$$

Both their denominators are the same

- Since we only want the max, we can ignore the denominator:

$$P(c_1 \mid \boldsymbol{x}) \propto P(c_1) \prod_{i=1}^{m} P(x_i \mid c_1)$$

$$P(c_2 \mid \boldsymbol{x}) \propto P(c_2) \prod_{i=1}^{m} P(x_i \mid c_2)$$

For the general class c,

$$P(c \mid \boldsymbol{x}) \propto P(c) \prod_{i=1}^{m} P(x_i \mid c)$$

For the general class c,

$$P(c \mid \boldsymbol{x}) \propto P(c) \prod_{i=1}^{m} P(x_i \mid c)$$

We can take the log:

$$\log P(c \mid \boldsymbol{x}) \propto logP(c) + \sum_{i=1}^{m} logP(x_i \mid c)$$

Naïve Bayes - classification

- We can now classify that the image represented by $\boldsymbol{x}$ is belongs class that has the highest probability:

$$c^{*} = arg\max_{c} P(c \mid \boldsymbol{x})$$

$$c^{*} = arg\max_{c} \log P(c \mid \boldsymbol{x})$$

Naïve Bayes - classification

- So, the following classification becomes:

$$c^* = arg \max_c P(c \mid \boldsymbol{x})$$

$$c^* = arg \max_c \log P(c \mid \boldsymbol{x})$$

$$c^* = arg \max_c logP(c) + \sum_{i=1}^{m} logP(x_i \mid c)$$