Object Detection

Kuan-Wen Chen

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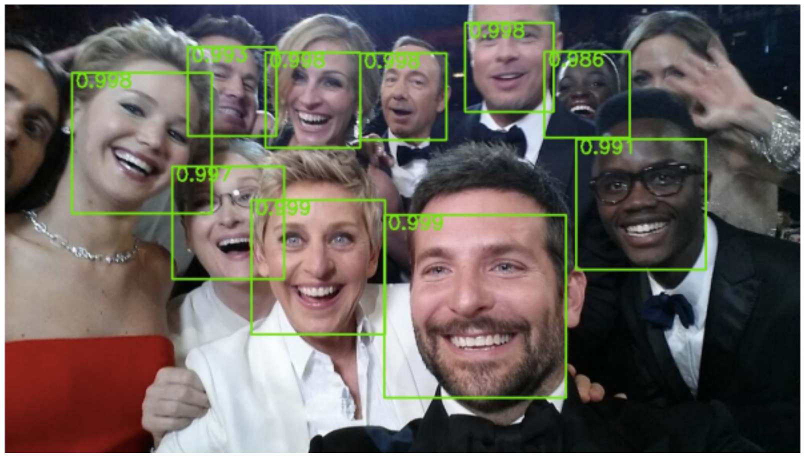
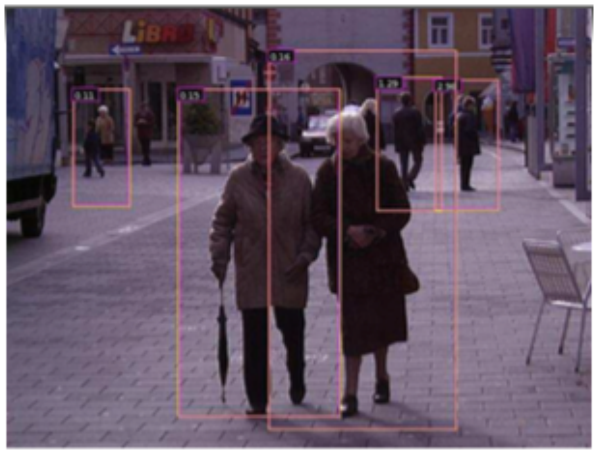
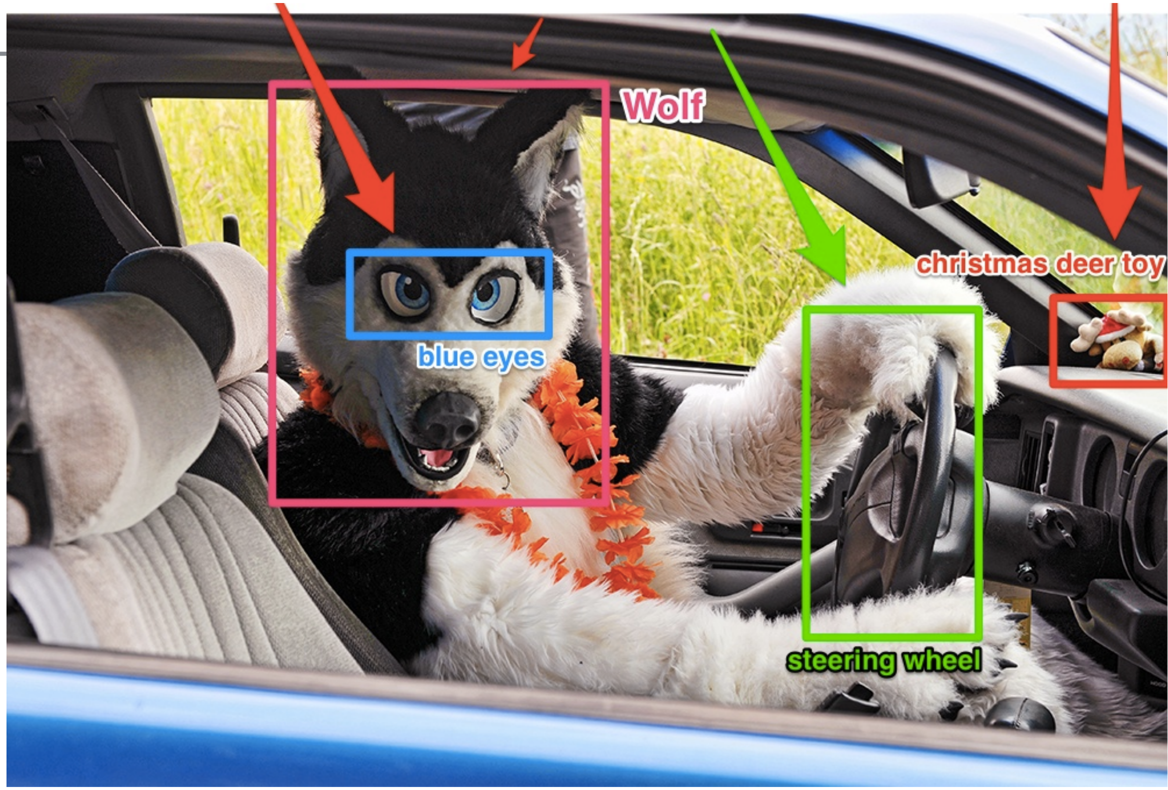




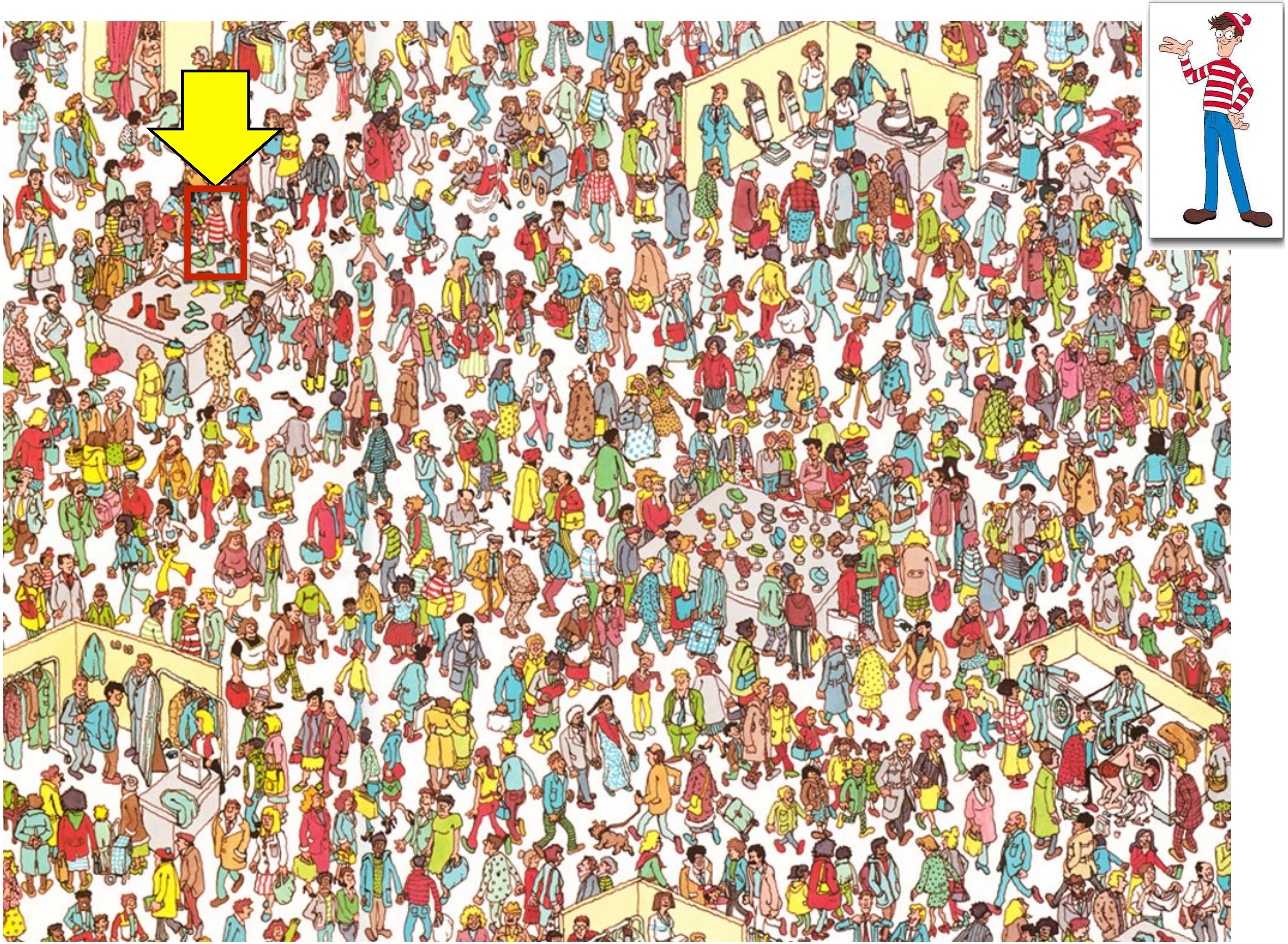
Object Detection

- Deal with detecting instances of semantic objects of a certain class (such as humans, buildings, or cars) in digital images and videos.
- In ITS, what we are interested in are car, scooter, pedestrian, lane, traffic sign, etc.



Object Detection

- Find the location of an object if it appear in an image
  - Does the object appear?
  - Where is it?



Object Detection

- A standard way is to

1. save a template or model for what you want to detect

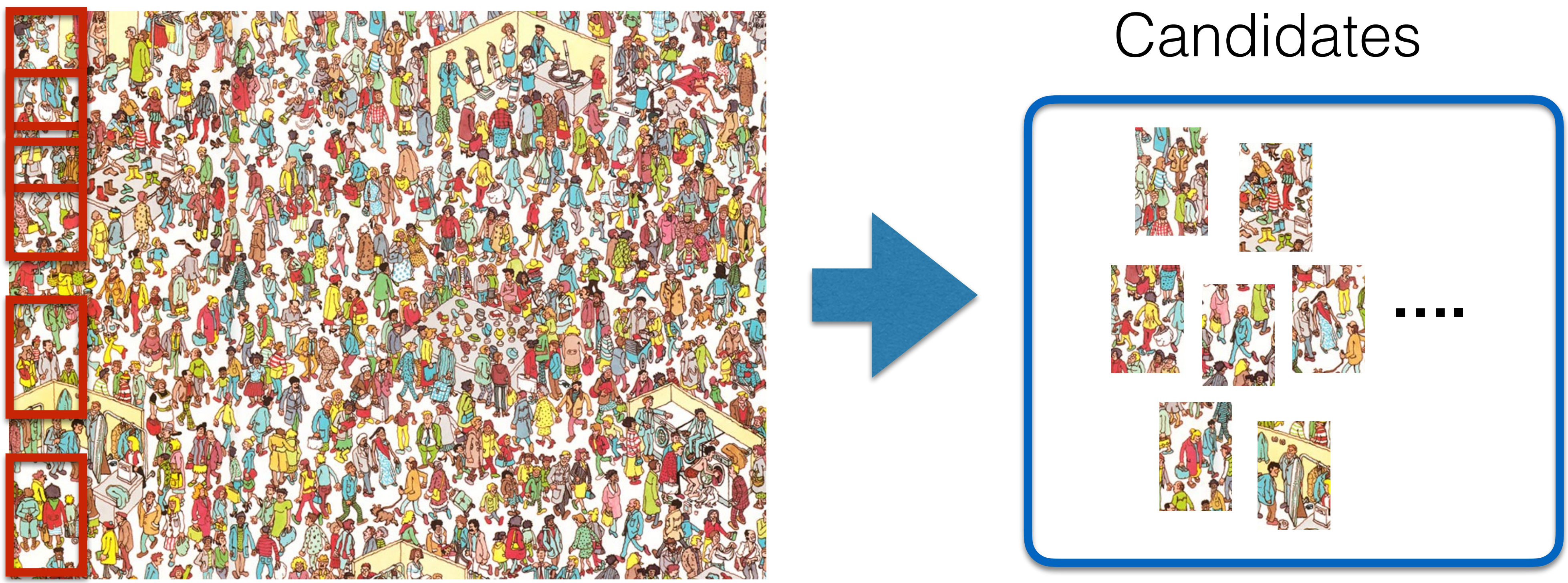
Training images

Template or Model

Object Detection

- A standard way is to

1. save a template or model for what you want to detect
2. use a sliding window search to generate candidates

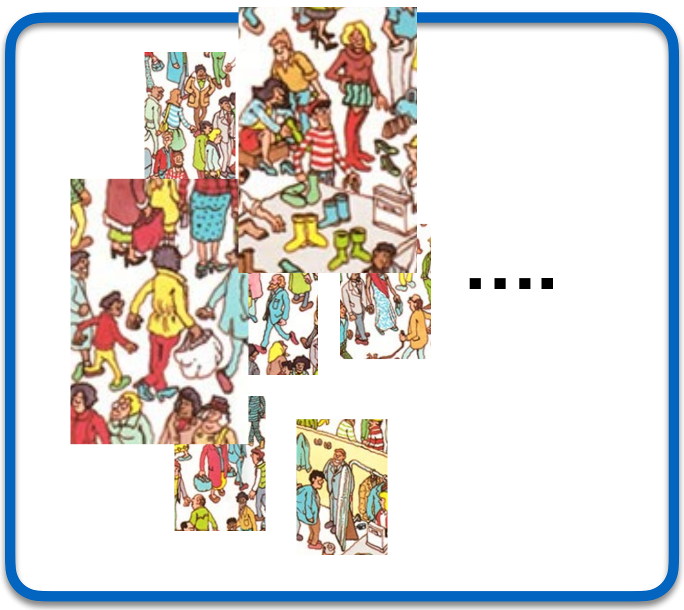


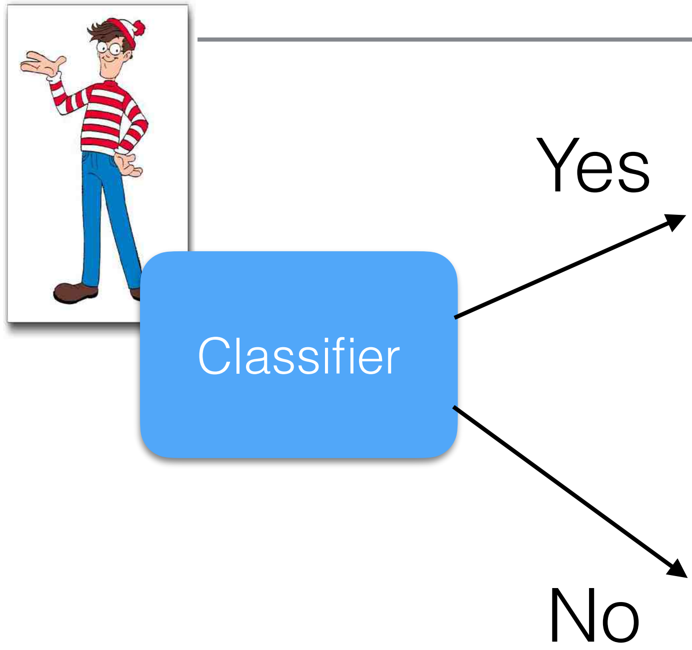
Object Detection

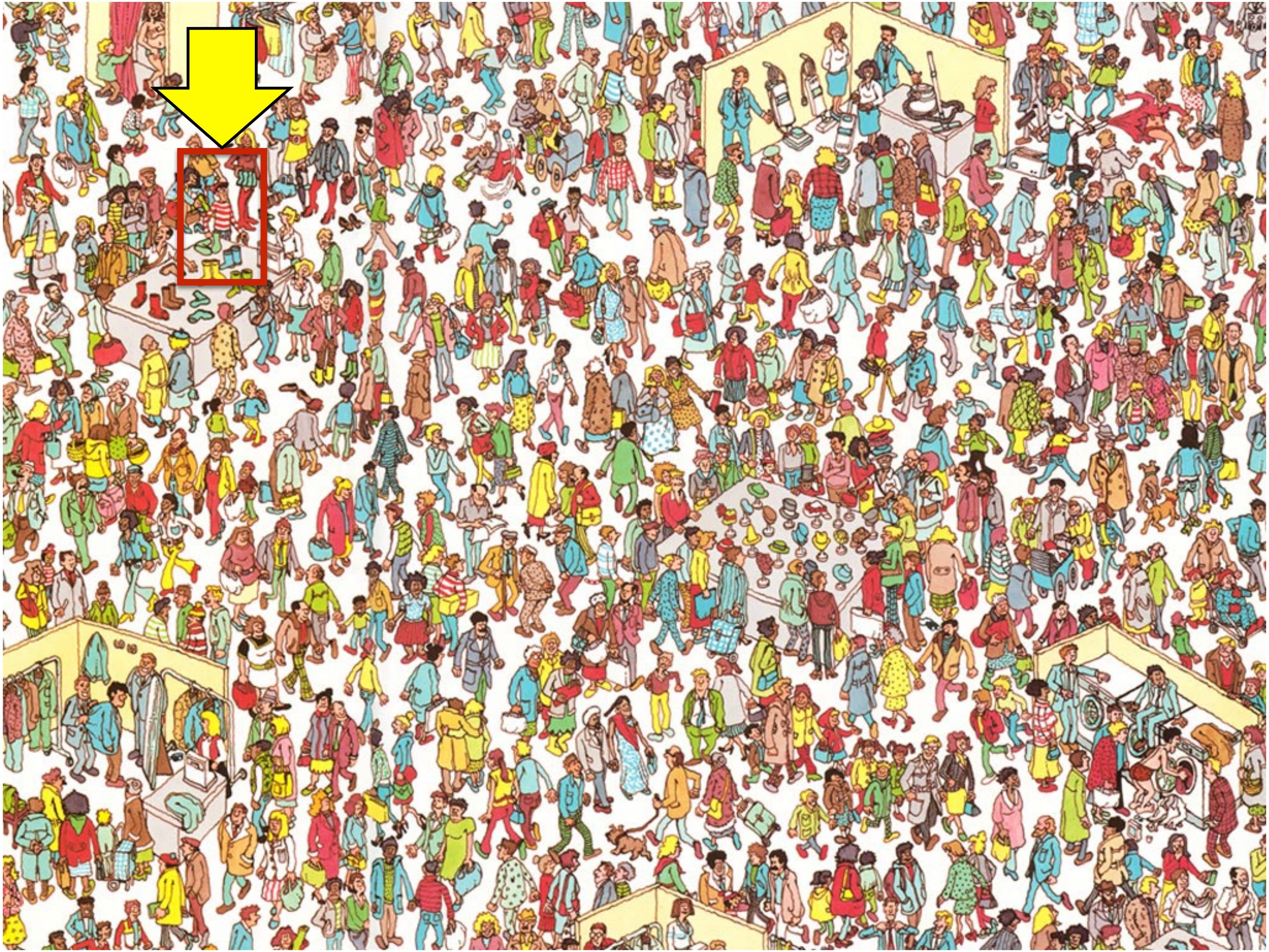
- A standard way is to

1. save a template or model for what you want to detect
2. use a sliding window search to generate candidates
3. classify the candidates: is it the object or not

Candidates







Object Detection

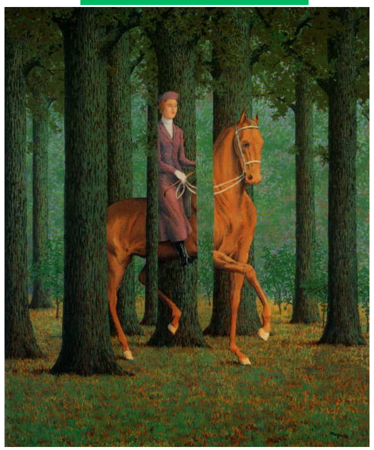
Challenges

view point variation

Michelangelo 1475-1564

illumination

occlusion



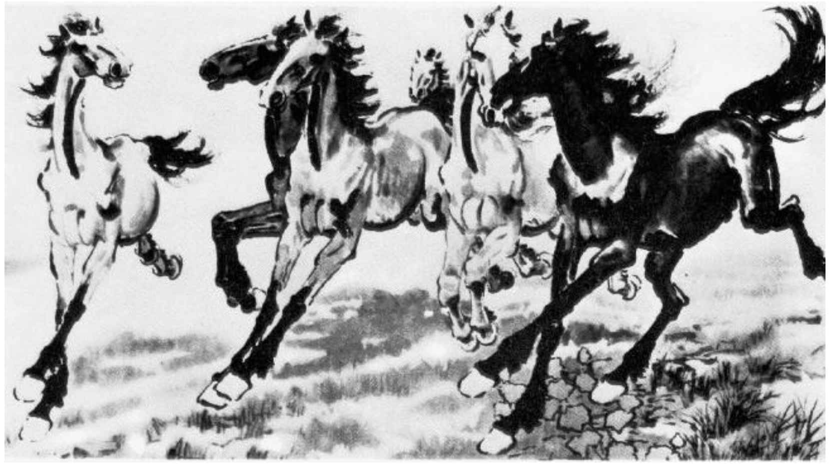
Magritte, 1957

scale

Slide credit: Fei-Fei Li

Challenges

deformation



Xu, Beihong 1943

background clutter

Klimt, 1913

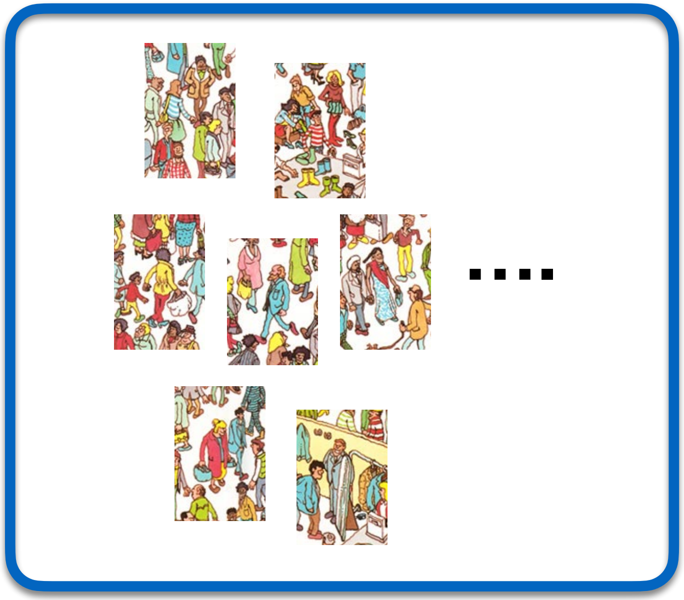
Slide credit: Fei-Fei Li

Object Detection

- A standard way is to

1. save a **template** or **model** for what you want to detect
2. use a sliding window search to generate candidates
3. **classify** the candidates: is it the object or not

Candidates

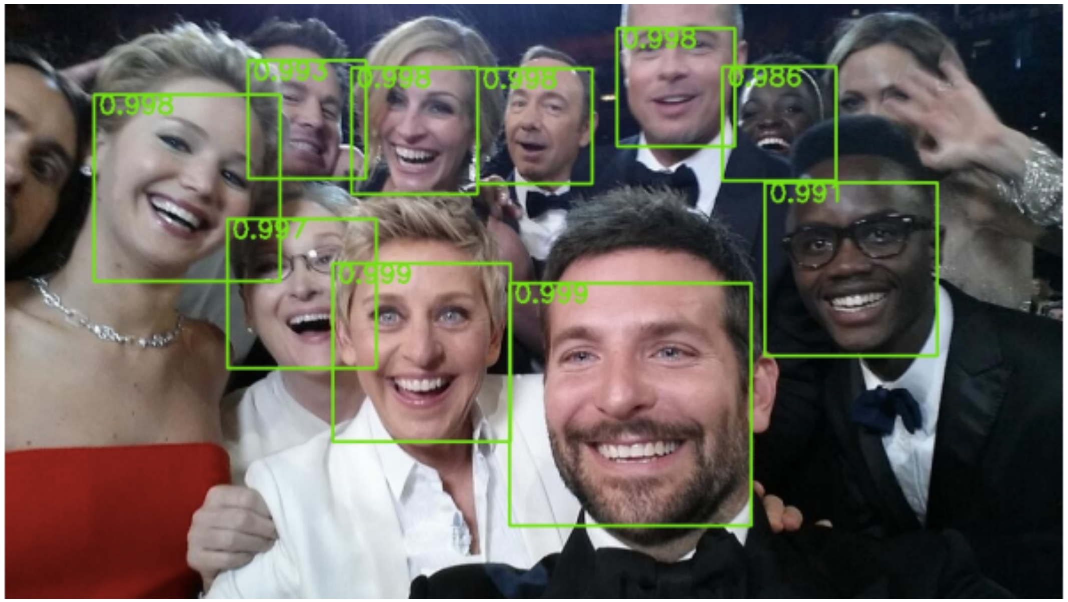


1. What's the model?
=> features

2. What's the classifier?
==> similarity metrics

3. Too many candidates
==> speed

Face Detection & Adaboost



Face detection before 2000

NIRMA
UNIVERSITY

KNOWLEDGE-BASED APPROACH

- It uses human-coded rules to model facial features, such as **two symmetric eyes,** a **nose in the middle** and a **mouth underneath the nose.**

Adaboost

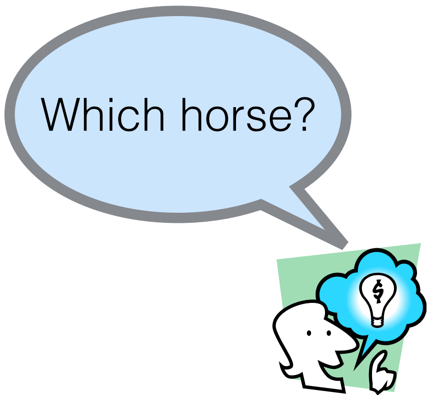
Y. Freund and R. E. Schapire, “A Short Introduction to Boosting,” *Journal of Japanese Society for Artificial Intelligence*, 1999.

$$\underbrace{\text{Ada}}_{\textbf{Adaptive}}\underbrace{\text{boost}}_{\textbf{Boosting}}$$

Y. Freund and R. E. Schapire, “A Short Introduction to Boosting,” *Journal of Japanese Society for Artificial Intelligence*, 1999.

Boosting

- The Horse-Racing Gambler Problem
  - Rules of thumb for a set of races
  - How should we choose the set of races in order to get the best rules of thumb?
  - How should the rules be combined into a single highly accurate prediction rule?

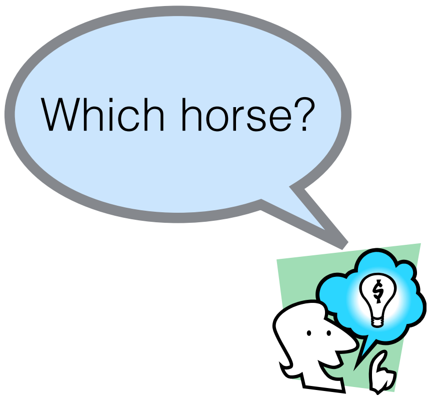


- race record
- current status
- horse owner
- ground type: firm, soft..
- …

Boosting!

Basic Idea of Boosting

- Hard to find single highly accurate classification (strong classifer) rule
- Finding many rough rules of thumb (weak classifier) can be a lot easier and more effective than finding a single, highly prediction rule.



- race record
- current status
- horse owner
- ground type: firm, soft..
- …

Basic Idea of Boosting

- Hard to find single highly accurate classification rule
- Finding many rough rules of thumb (weak classifier) can be a lot easier and more effective than finding a single, highly prediction rule.

Boosting

- boosting = general method of converting rough rules of thumb into highly accurate prediction rule
- technically:
  - assume given "weak" learning algorithm that can consistently find classifiers ("rules of thumb") at least slightly better than random, say, accuracy $\geq 55\%$ (in two-class setting)
  - given sufficient data, a boosting algorithm can provably construct single classifier with very high accuracy, say, 99%

Basic Boosting Algorithm

The Boosting Approach

- devise computer program for deriving rough rules of thumb
  Q1
- apply procedure to subset of examples
  Q2
- obtain rule of thumb
- apply to 2nd subset of examples
- obtain 2nd rule of thumb
- repeat T times
  Q3

Basic Boosting Algorithm

Challenges

Q1 how to choose rules of thumb?

- application dependent - face, pedestrian, car…

Q2 how to choose examples on each round?

- concentrate on “hardest” examples (those most often misclassified by previous rules of thumb)

Q3 how to combine rules of thumb in to single classifier?

- take (weighted) majority vote of rules of thumb

Basic Boosting Algorithm

Challenges

Q1 how to choose rules of thumb?

- application dependent - face, pedestrian, car…

Q2 how to choose examples on each round?

- concentrate on “hardest” examples (those most often misclassified by previous rules of thumb)

→ **This is the main idea of AdaBoost**

Q3 how to combine rules of thumb in to single classifier?

- take (weighted) majority vote of rules of thumb

$\underbrace{\textbf{Ada}}_{\textbf{Adaptive}}\underbrace{\textbf{Boost}}_{\textbf{Boosting}}$

AdaBoost is adaptive in the sense that subsequent classifiers built are tweaked in favor of those instances misclassified by previous classifiers.

AdaBoost Concept

$$\left.\begin{aligned} h_1(x) &\in \{-1, +1\} \\ h_2(x) &\in \{-1, +1\} \\ &\vdots \\ h_T(x) &\in \{-1, +1\} \end{aligned}\right\} \quad H_T(x) = sign\left(\sum_{t=1}^{T} \alpha_t h_t(x)\right)$$

weak classifiers

strong classifier

slightly **better than random**

Weaker Classifiers

$$h_1(x) \in \{-1, +1\}$$
$$h_2(x) \in \{-1, +1\}$$
$$\vdots$$
$$h_T(x) \in \{-1, +1\}$$

weak classifiers

slightly **better than random**

- Each weak classifier learns by considering one simple feature
- T most beneficial features for classification should be selected
- How to
  - define features?
  - select beneficial features?
  - train weak classifiers?
  - manage (weight) training samples?
  - associate weight to each weak classifier?

A Formal Description of Boosting

- given training set $(x_1, y_1), \ldots, (x_m, y_m)$
- $y_i \in \{-1, +1\}$ correct label of instance $x_i \in X$
- for $t = 1, \ldots, T$:
  - construct distribution D_t on $\{1, \ldots, m\}$
  - find weak classifier ("rule of thumb")

    $$h_t : X \to \{-1, +1\}$$

    with small error ϵ_t on D_t:

    $$\epsilon_t = \Pr_{D_t}[h_t(x_i) \neq y_i]$$
- output final classifier H_{final}

AdaBoost Algorithm

- final classifier:
  - $H_{\text{final}}(x) = \text{sign}\left(\sum_t \alpha_t h_t(x)\right)$
- constructing D_t:
  - $D_1(i) = 1/m$

$D_t(i)$:probability distribution of x_i's at time t

- for $t = 1, \ldots, T$:
  - find weak classifier ("rule of thumb")

    $h_t : X \to \{-1, +1\}$

    with small error ϵ_t on D_t: $\varepsilon_j = \sum_{i=1}^{m} D_t(i)[y_i \neq h_j(x_i)]$

minimize weighted error

  - given D_t and h_t:

Give error classified patterns more chance for learning.

$$D_{t+1}(i) = \frac{D_t(i)}{Z_t} \times \begin{cases} e^{-\alpha_t} & \text{if } y_i = h_t(x_i) \\ e^{\alpha_t} & \text{if } y_i \neq h_t(x_i) \end{cases}$$

$$= \frac{D_t(i)}{Z_t} \exp(-\alpha_t \, y_i \, h_t(x_i))$$

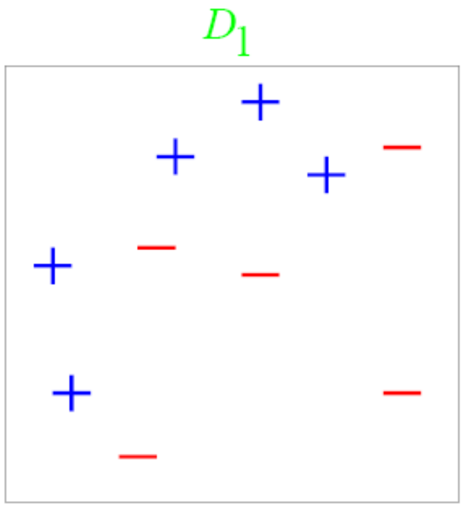
where Z_t = normalization constant

$$\alpha_t = \frac{1}{2} \ln\left(\frac{1 - \epsilon_t}{\epsilon_t}\right) > 0$$

Why? $\epsilon_t < 0.5$

Toy Examples

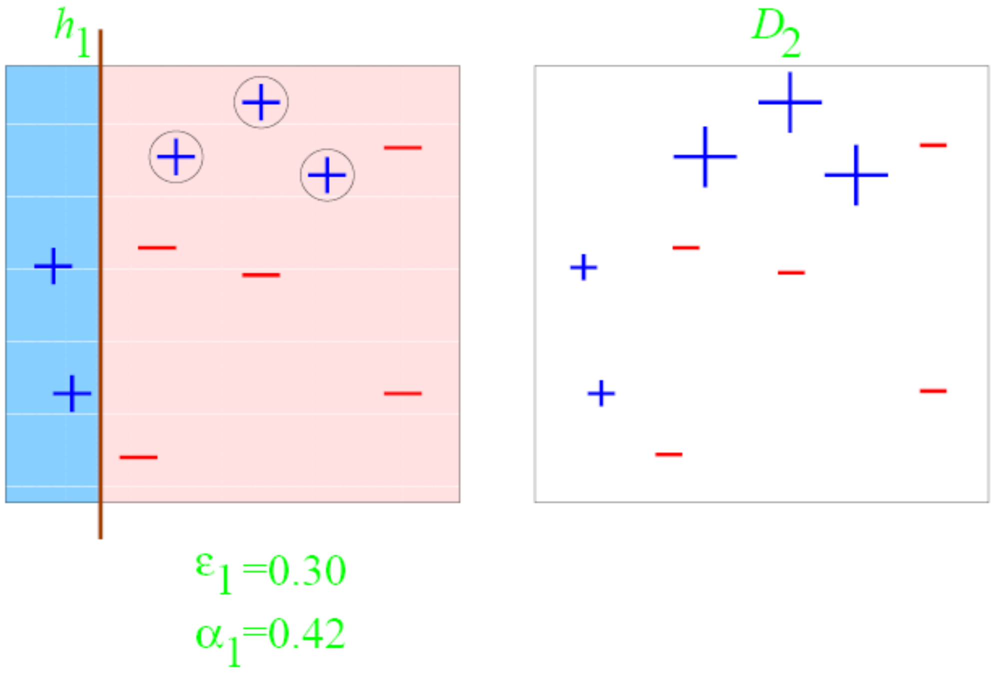
- constructing D_t:
  - $D_1(i) = 1/m$



weak classifiers = vertical or horizontal half-planes

Round 1

$$D_{t+1}(i) = \frac{D_t(i)}{Z_t} \times \begin{cases} e^{-\alpha_t} & \text{if } y_i = h_t(x_i) \\ e^{\alpha_t} & \text{if } y_i \neq h_t(x_i) \end{cases}$$
$$= \frac{D_t(i)}{Z_t} \exp(-\alpha_t \, y_i \, h_t(x_i))$$



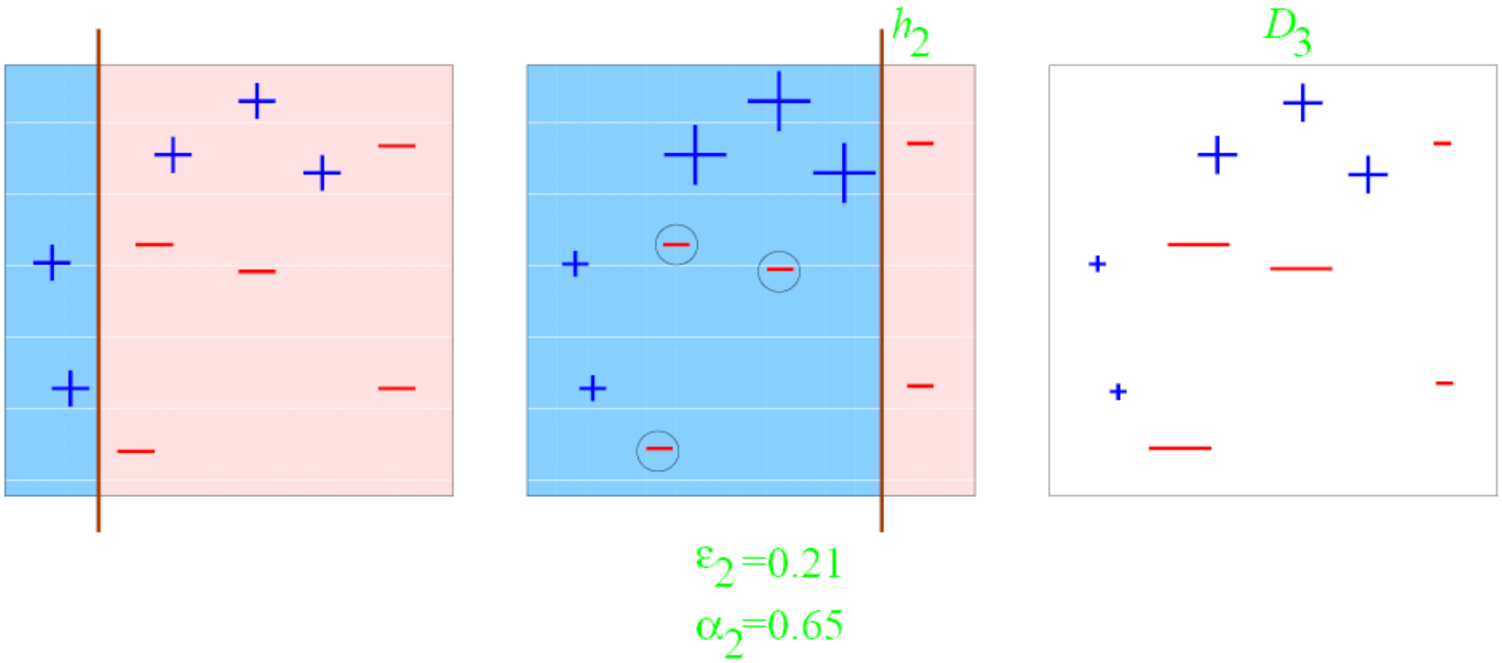
- for $t = 1, \ldots, T$:
  - find weak classifier ("rule of thumb")

    $h_t : X \to \{-1, +1\}$

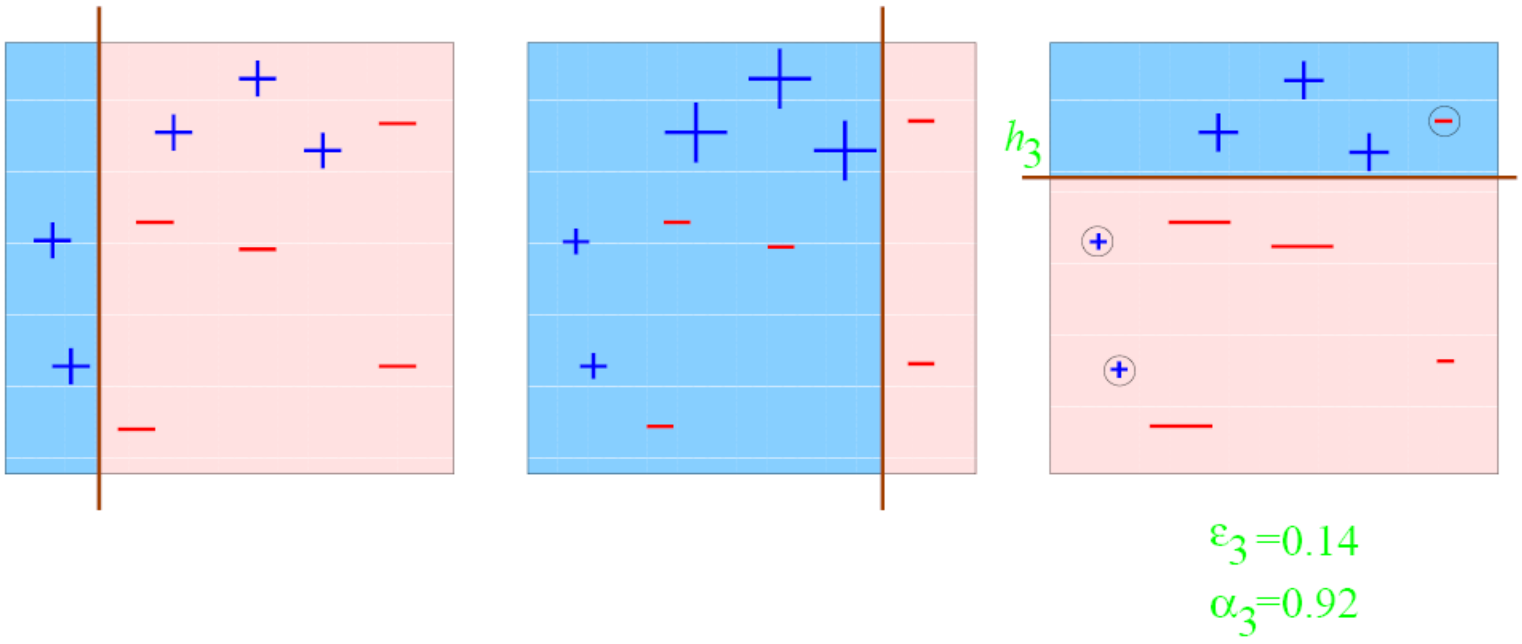
    with small error ϵ_t on D_t: $\varepsilon_j = \sum_{i=1}^{m} D_t(i)[y_i \neq h_j(x_i)]$

$$\alpha_t = \frac{1}{2} \ln\left(\frac{1-\epsilon_t}{\epsilon_t}\right) > 0$$

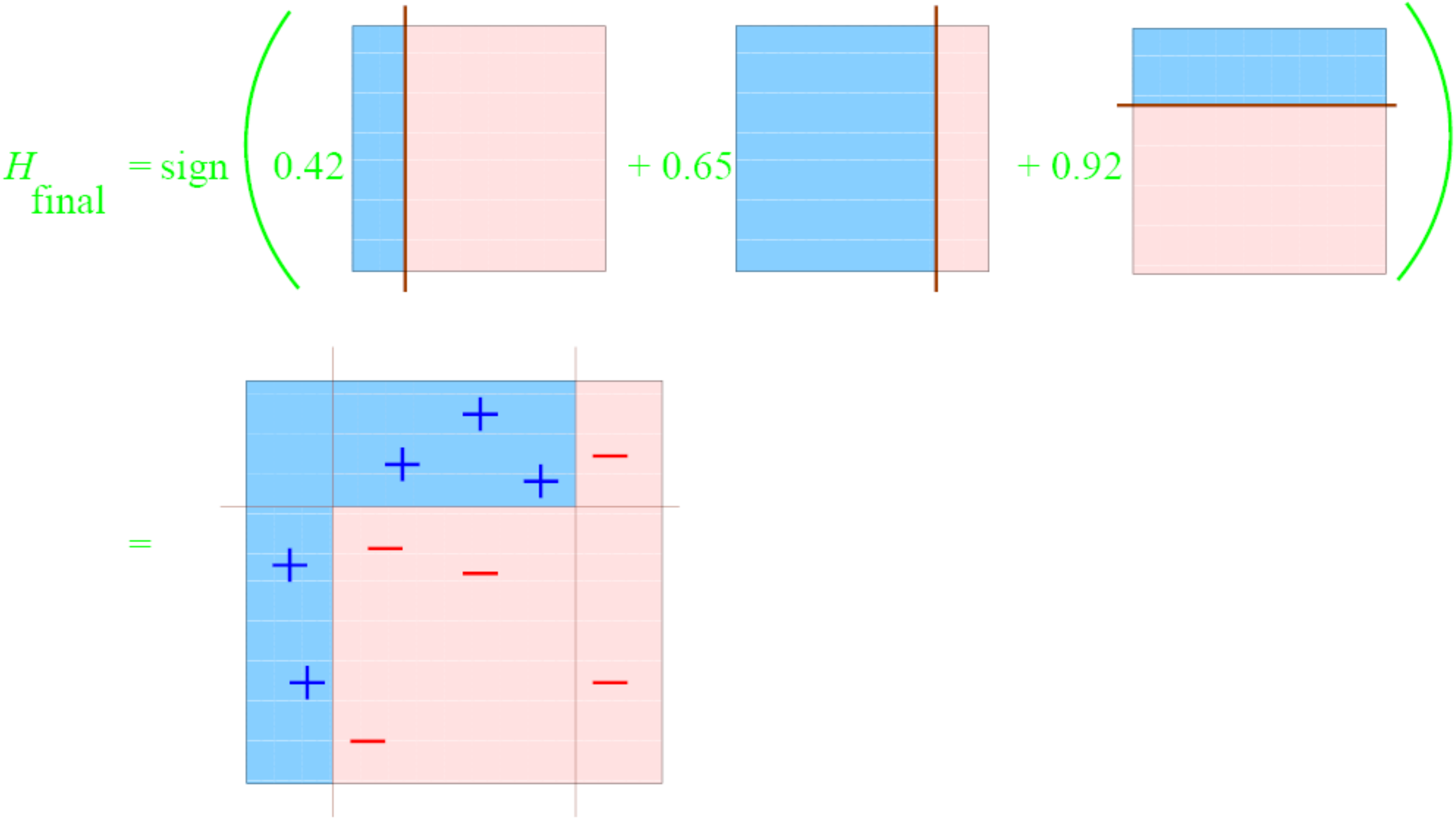
Round 2



Round 3



Final Classifier



Analysis of training error

- Theorem:
  - write ϵ_t as $1/2 - \gamma_t$
  - then

$$\begin{aligned} \text{training error}(H_{\text{final}}) &\leq \prod_t \left[2\sqrt{\epsilon_t(1-\epsilon_t)}\right] \\ &= \prod_t \sqrt{1-4\gamma_t^2} \\ &\leq \exp\left(-2\sum_t \gamma_t^2\right) \end{aligned}$$

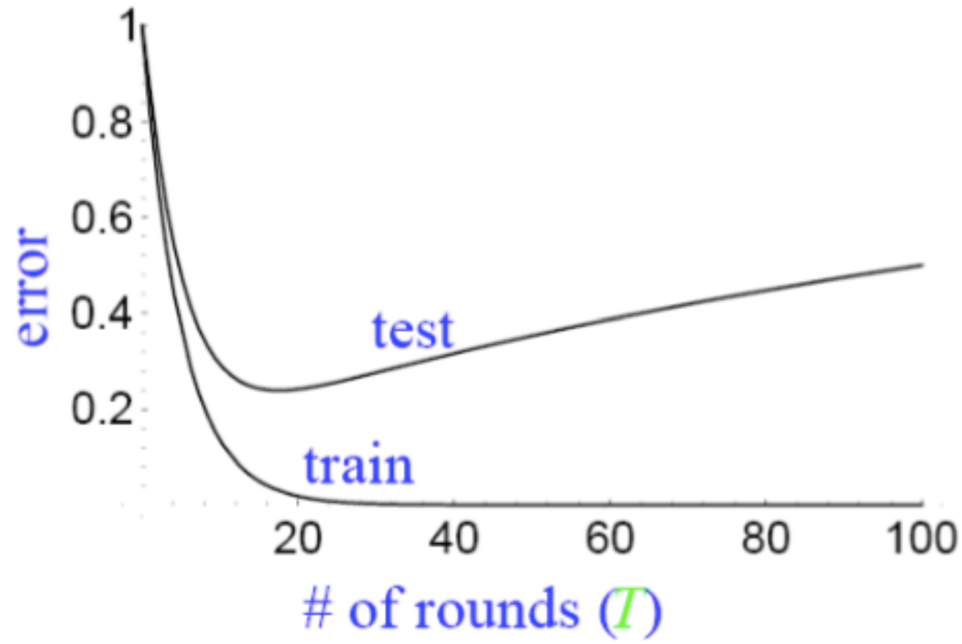
while T increases, the training error will become smaller and smaller

- so: if $\forall t: \ \gamma_t \geq \gamma > 0$
  then training error$(H_{\text{final}}) \leq e^{-2\gamma^2 T}$

< 0

γ **> 0**

How will test error behave? (A first guess)

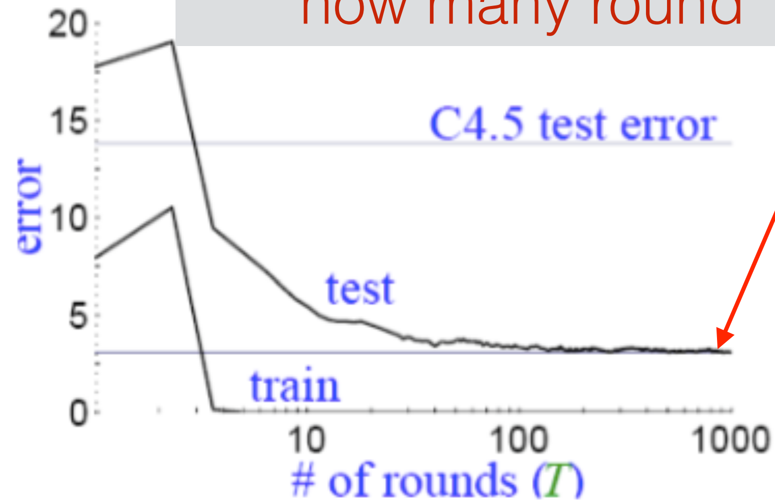


expect:

- training error to continue to drop (or reach zero)
- test error to increase when H_{final} becomes "too complex"
  - "Occam's razor"
  - overfitting
    - hard to know when to stop training

Actual Typical Run

there are still a limitation for testing error, and how many round T should we choose?



(boosting C4.5 on "letter" dataset)

- test error does not increase, even after 1000 rounds
    - (total size > 2,000,000 nodes)
- test error continues to drop even after training error is zero!

	# rounds		
	5	100	1000
train error	0.0	0.0	0.0
test error	8.4	3.3	3.1

$$H_T(x) = sign\left(\sum_{t=1}^{T} \alpha_t h_t(x)\right)$$

- Larger *T* ➔ More computation time

- The test error will not decrease while *T* is large enough

➔ Stop the loop!

- when the training error decrease to a preset value, ex. 5%
- when the training error decrease slowly
- …

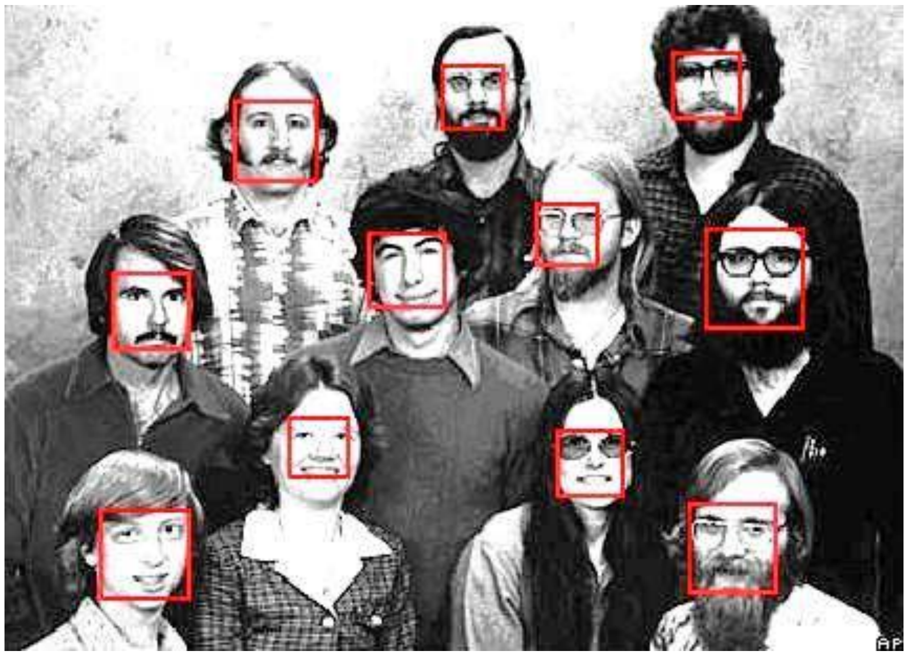
Face Detection

P. Viola and M. Jones, “Rapid Object Detection using a Boosted Cascade of Simple Features,” *CVPR*, 2001.
(cited number: 24645 from Google)

P. Viola and M. Jones, “Robust Real-Time Face Detection,” *International Journal of Computer Vision*, 2004.
(cited number: 21812 from Google)

Face Detection

- Detect and localize human faces in images
- Two issues are important
  - Accuracy
  - Efficiency



Basic Idea

- Slide a window across image and evaluate a face model at every location.

: Location & Scale

How many windows in one image?

Basic Idea

: Location & Scale

How many windows in one image?

500 x 500 image

shift window for every 2 pixels: **250 x 250 windows**

window size from 20 x 20, 22 x 22, …., to 200 x 200:
90 scales

total windows number is: **250 x 250 x 90 = about 5×10^6**

Challenges

- Slide a window across image and evaluate a face model at every location.
- Sliding window detector must evaluate tens of thousands of location/scale combinations.
- Faces are rare: 0–10 per image
  - For computational efficiency, we should try to spend as little time as possible on the non-face windows
  - A megapixel image has **$\sim 10^6$** pixels and a comparable number of candidate face locations
  - To avoid having a false positive in every image image, our false positive rate has to be less than **10^{-6}**

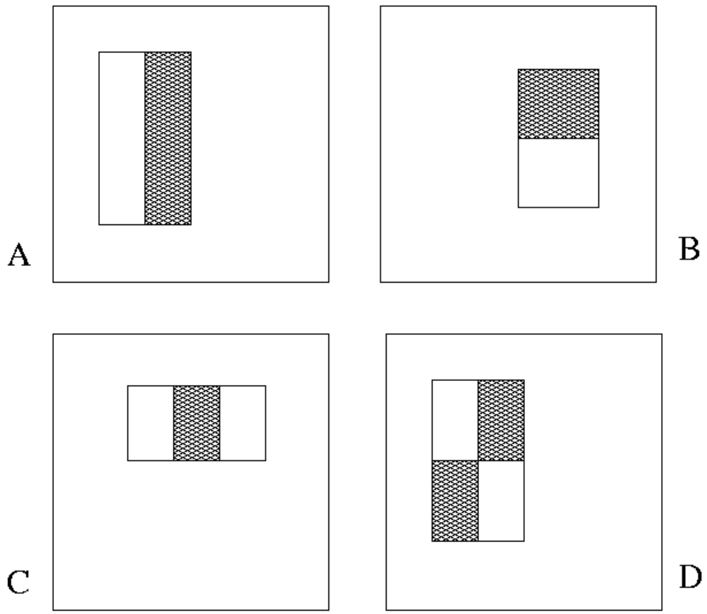
Viola & Jones Face Detector

- A seminal approach to **real-time** object detection
- Training is **slow**, but detection is very **fast**
- Key contribution
  - **Integral images** for fast feature evaluation
  - **AdaBoost algorithm** for feature selection and classification
  - **Cascade approach** for fast rejection of non-face windows

Haar Feature

- or **Haar-like features** owe their name to their intuitive similarity with Haar wavelets

- Four types of rectangular features:
    - *two-rectangle feature* type (horizontal/vertical)
    - three-rectangle feature type
    - four-rectangle feature type



$$\text{Feature Value} = \sum(\text{Pixel in white area}) - \sum(\text{Pixel in black area})$$

Capture the face symmetry

Haar Feature

- or **Haar-like features** owe their name to their intuitive similarity with Haar wavelets
- Four types of rectangular features:
  - *two-rectangle feature* type (horizontal/vertical)
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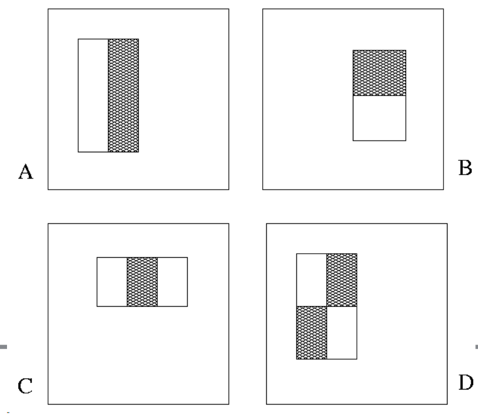
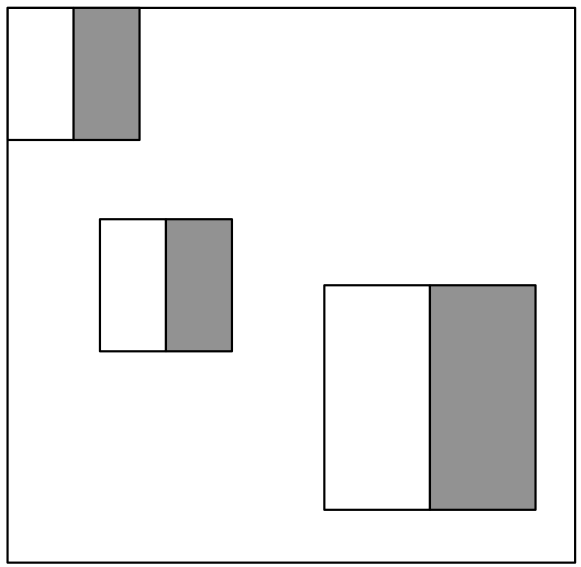


Type A



A 24x24 detection window

Can be extracted at **any location** with **any scale**!

Haar Feature

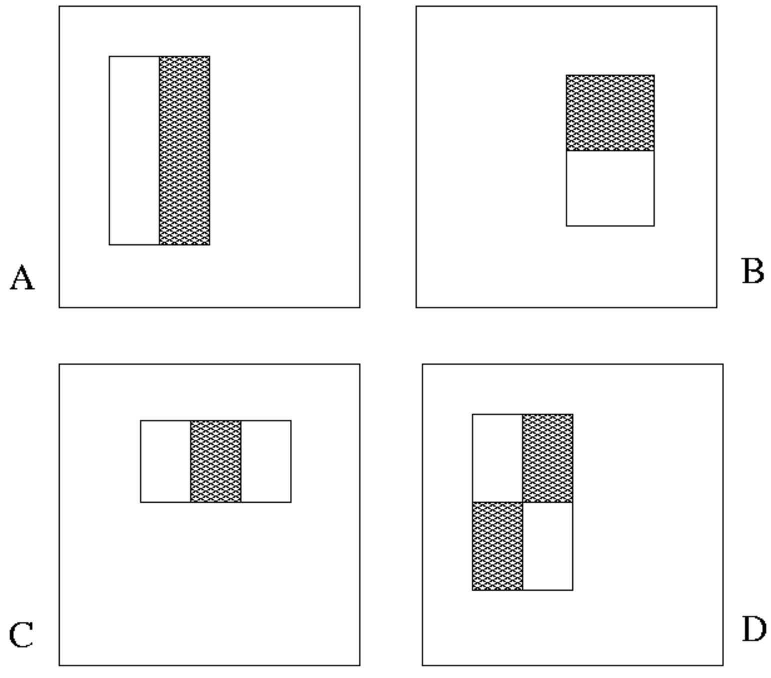
why 24x24?

- How many number of possible rectangle features for a 24x24 detection region?

The training data is 24x24

Haar Feature

- How many number of possible rectangle features for a 24x24 detection region?



A+B $2\sum_{w=2}^{12}\sum_{h=1}^{24}(24-2w+1)(24-h+1)+$

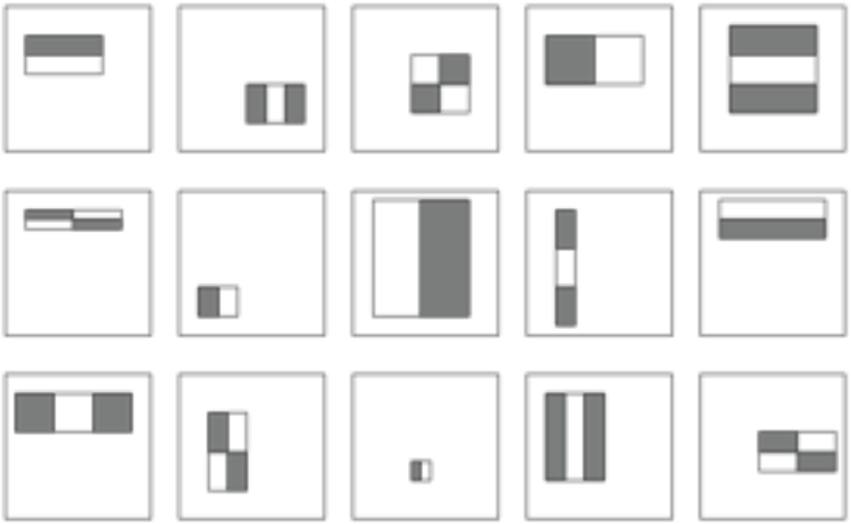
C $2\sum_{w=3}^{8}\sum_{h=1}^{24}(24-3w+1)(24-h+1)+$

D $\sum_{w=2}^{12}\sum_{h=2}^{12}(24-2w+1)(24-2h+1)$

$: 160{,}000$

Haar Feature

- How many number of possible rectangle features for a 24x24 detection region?



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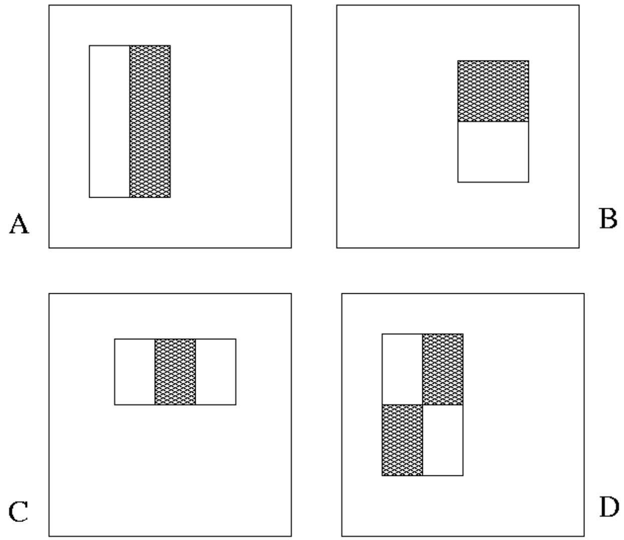
D $$\sum_{w=2}^{12}\sum_{h=2}^{12}(24-2w+1)(24-2h+1)$$

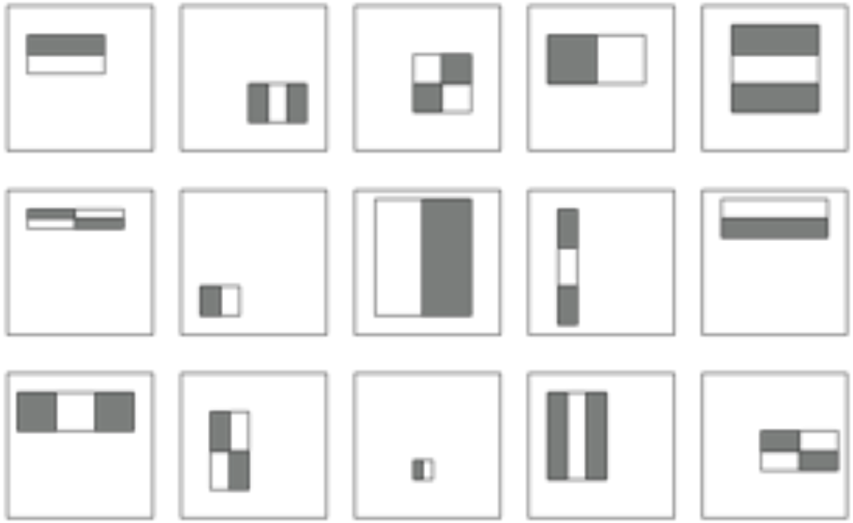
$$:\ 160,000$$

- What features are good for face detection?
- Can we create a good classifier using just **a small subset** of all possible features?
- **How** to select such a subset?

AdaBoost

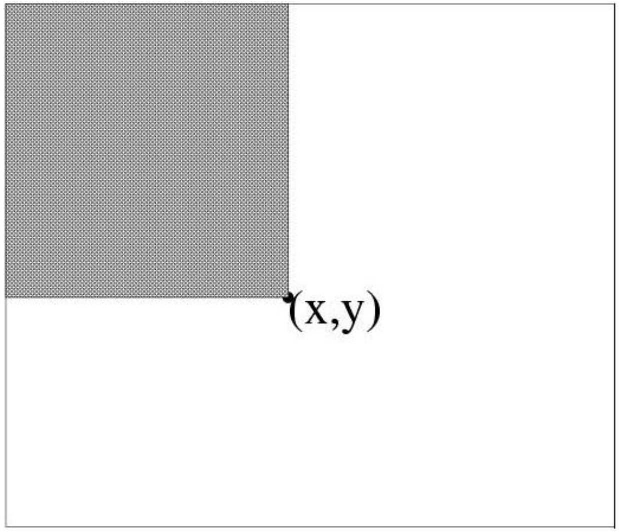
Haar Feature





The motivation behind using rectangular features, as opposed to more expressive steerable filters is due to their extreme computational efficiency

Integral Image



Definition: The *integral image* at location (x,y), is the sum of the pixel values above and to the left of (x,y), inclusive.

$$ii(x,y) = \sum_{x' \le x, y' \le y} i(x',y')$$

Example:

2	1	2	3	4	3
3	2	1	2	2	3
4	2	1	1	1	2

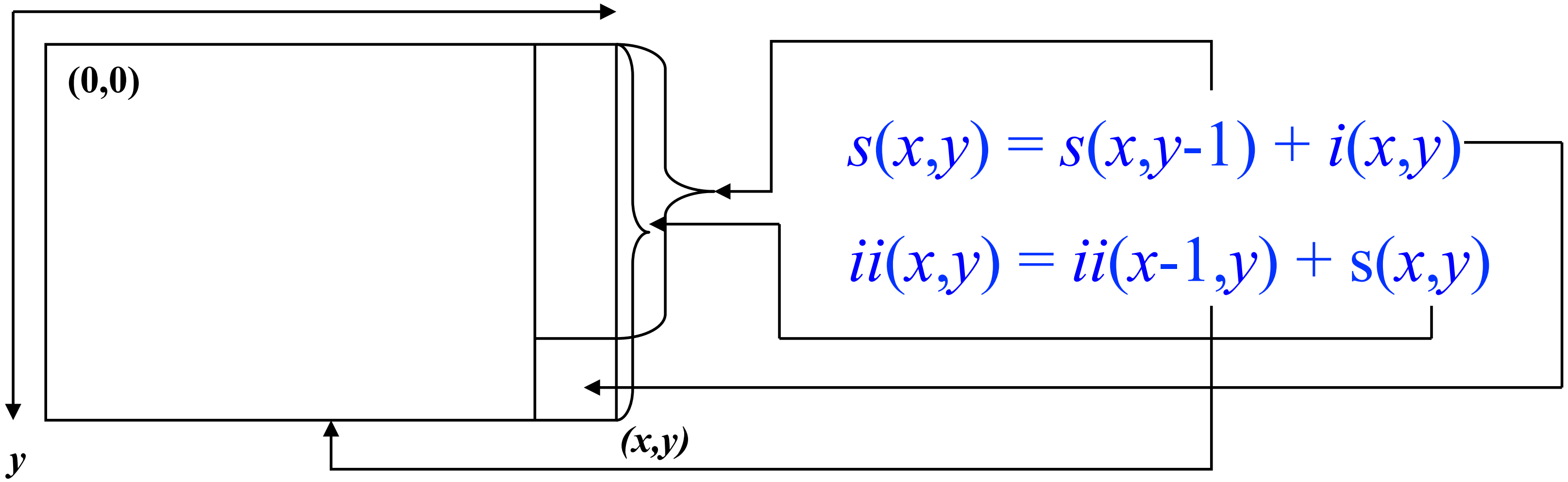
Image

2	3	5	8	12	15
5	8	11	16	22	28
9	14	18	24	31	39

Integral image

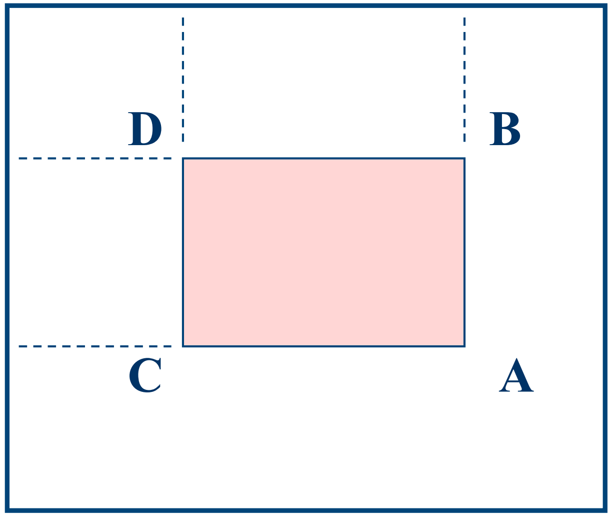
Integral Image

Using the following two recurrences, where *i*(*x*,*y*) is the pixel value of original image at the given location and *s*(*x*,*y*) is the cumulative column sum, we can calculate the integral image representation of the image in a single pass.



Rapid evaluation of rectangular features

Using the integral image representation one can compute the value of any rectangular sum in constant time.



$$sum = ii_A - ii_B - ii_C + ii_D$$

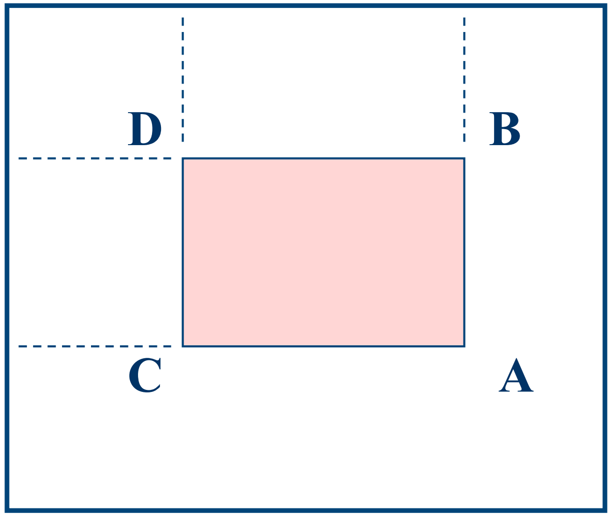
Only 3 additions are required for any size of rectangle!

As a result two-, three-, and four-rectangular features can be computed with 6, 8 and 9 array references, respectively.

Scaling

Using the integral image representation one can compute the value of any rectangular sum in constant time.

- Integral image enables us to evaluate all rectangle sizes in constant time.
- Therefore, no image scaling is necessary.
- Scale the rectangular features instead!



$$sum = ii_A - ii_B - ii_C + ii_D$$

Weak Classifiers for Face Detection

value of rectangle feature

threshold

$$h_t(x) = \begin{cases} 1 & \text{if } f_t(x) > \theta_t \\ 0 & \text{otherwise} \end{cases}$$

window

AdaBoost for face detection

- Given example images (x_1,y_1) , … , (x_n,y_n) where y_i = 0, 1 for negative and positive examples respectively.
- Initialize weights $w_{1,i} = 1/(2m)$, $1/(2l)$ for training example i, where m and l are the number of negatives and positives respectively.

For $t = 1 \dots T$

1) Normalize weights so that w_t is a distribution
2) For each feature j train a classifier h_j and evaluate its error ε_j with respect to w_t
3) Chose the classifier h_j with lowest error.
4) Update weights according to:

$$w_{t+1,i} = w_{t,i}\,\beta_t^{1-e_i}$$

where $e_i = 0$ is x_i is classified correctly, 1 otherwise, and

$$\beta_t = \frac{\varepsilon_t}{1-\varepsilon_t} < 1$$

- The final strong classifier is:

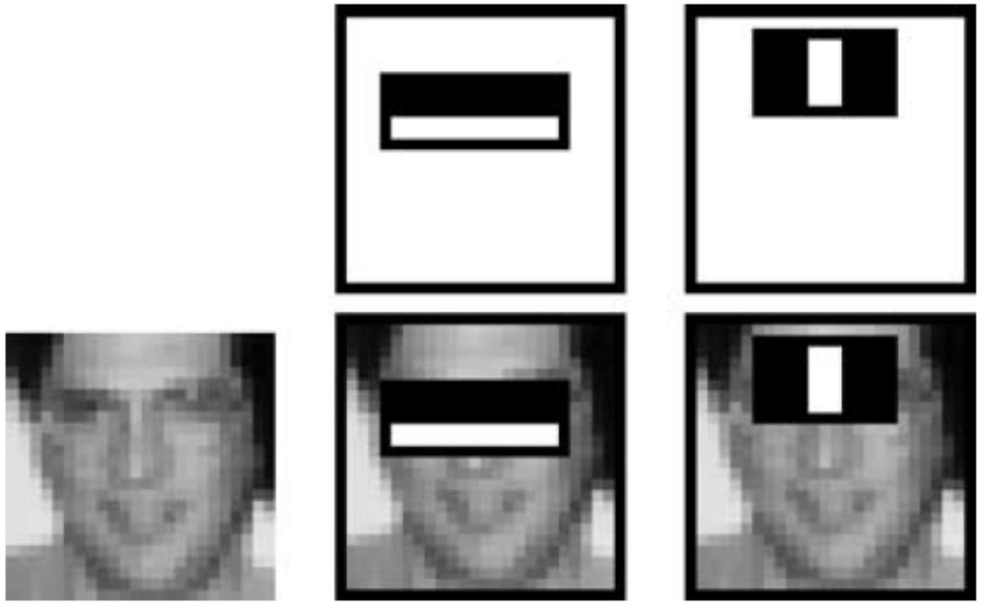
$$h(x) = \begin{cases} 1 & \sum_{t=1}^{T} \alpha_t h_t(x) \geq \frac{1}{2} \sum_{t=1}^{T} \alpha_t , \\ 0 & \textit{otherwise} \end{cases} \qquad \text{where} \qquad \alpha_t = \log\left(\frac{1}{\beta_t}\right)$$

AdaBoost for face detection

- Training set contains **face** and **non-face** examples
  - Initially, with equal weight
- For each round of boosting:
  - Evaluate each rectangle filter on each example
  - Select best threshold for each filter
  - Select best filter/threshold combination
  - Reweight examples

Features selected

- First two features selected by boosting:



- This feature combination can yield 100% detection rate and 50% false positive rate

AdaBoost for face detection

- Computational complexity of learning: $O(TNK)$
  - T rounds, N examples, K features

200 **10,000+** **160,000**

3,000,000+

How about testing?

$$O(TW)$$

T rounds (selected features), W window number

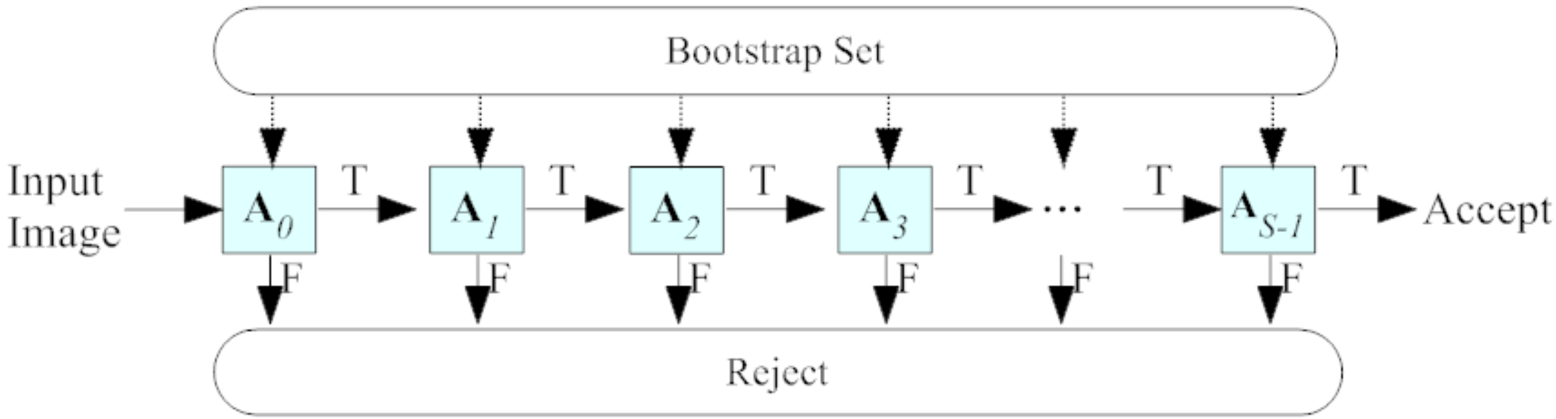
200 **10^6+**

- Faces are rare: 0–10 per image
- Number of windows: negative >> positive
  - Same decision time is paid for accepting or rejecting a window.

→ **Attentional Cascade**

Attentional Cascade

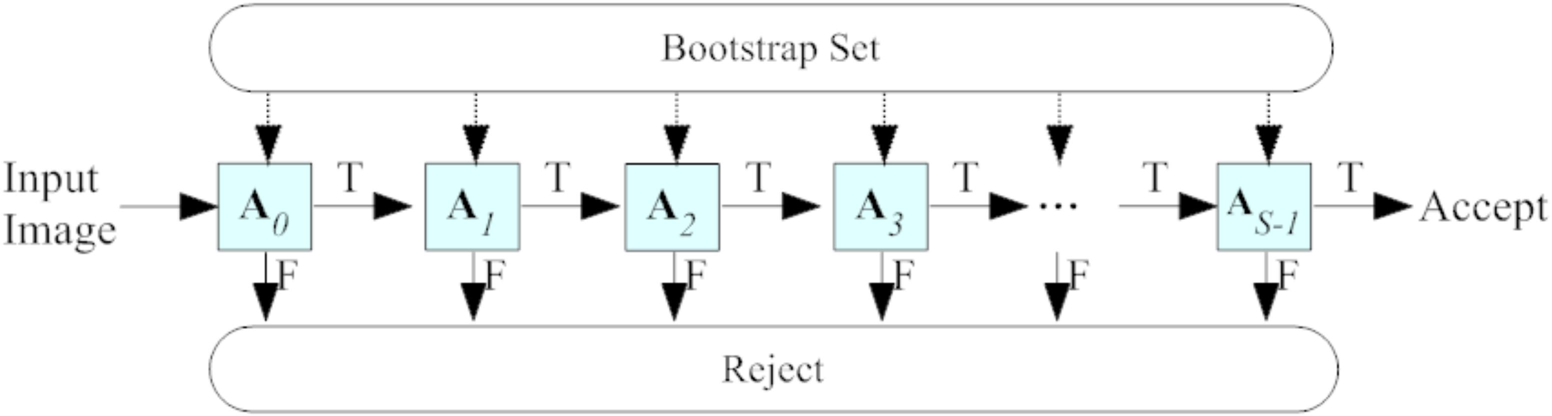
- Basic cascaded structure (S stages)



- Positive response from the first classifier triggers the evaluation of a second (more complex) classifier, and so on.
- A negative outcome at any point leads to the immediate rejection of the sub-window.

Attentional Cascade

- Basic cascaded structure (*S* stages)



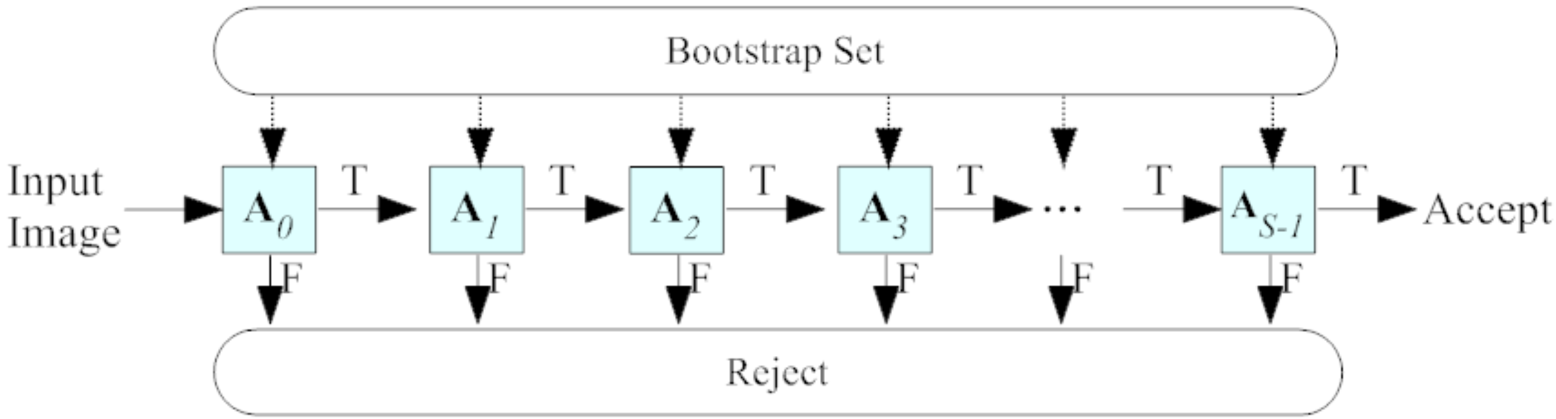
- Each stage has a very high detection rate (e.g. 99.95%) and a loose false positive rate (e.g. 50~90%).

Layer number	1	2	3 to 5	6 and 7	8 to 12	13 to 32
Number of feautures	2	5	20	50	100	200
Detection rate	100%	100%	-	-	-	-
Rejection rate	60%	80%	-	-	-	-

more than 60% windows can be eliminated by using only 2 features

Training the cascade

- Set target detection and false positive rates for each stage
- Keep adding features to the current stage until its target rates have been met
  - Need to lower AdaBoost threshold to maximize detection (as opposed to minimizing total classification error)
  - Test on a validation set
- If the overall false positive rate is not low enough, then add another stage
- Use false positives from current stage as the negative training examples for the next stage



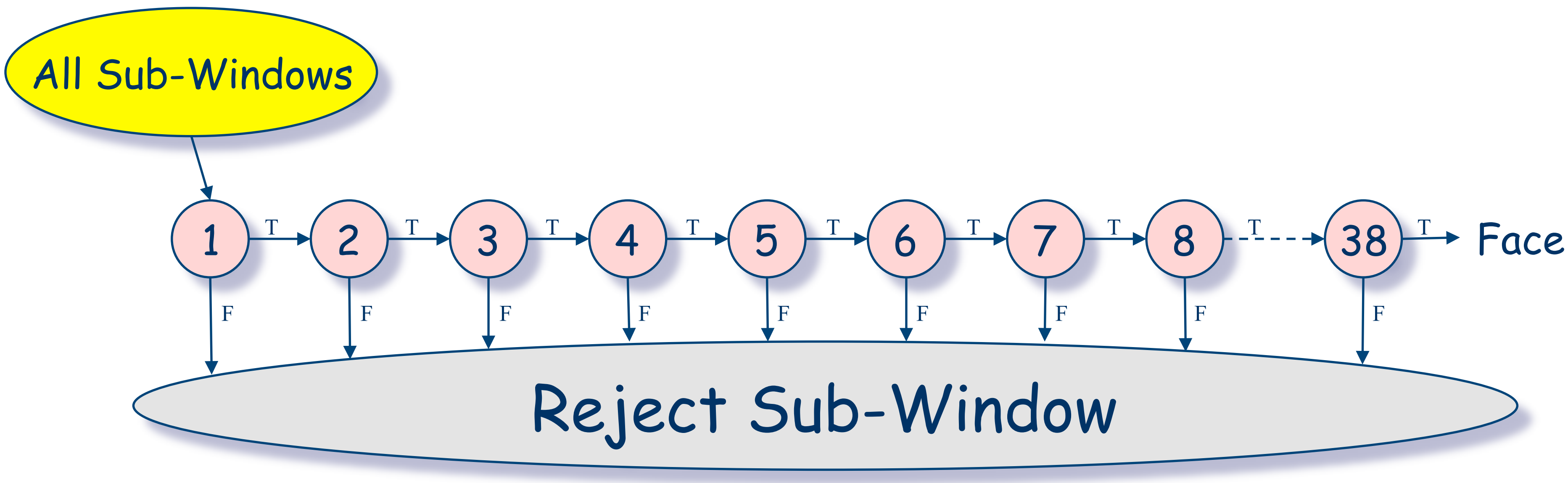
Experiments - Dataset for training

- 4916 positive training example were hand picked aligned, normalized, and scaled to a base resolution of 24x24

- 3,000,000+ negative examples were selected by randomly picking sub-windows from 9500 images which did not contain faces

Experiments
- structure of the detector cascade

- The final detector had **38** layers and **6061** features in total



Experiments
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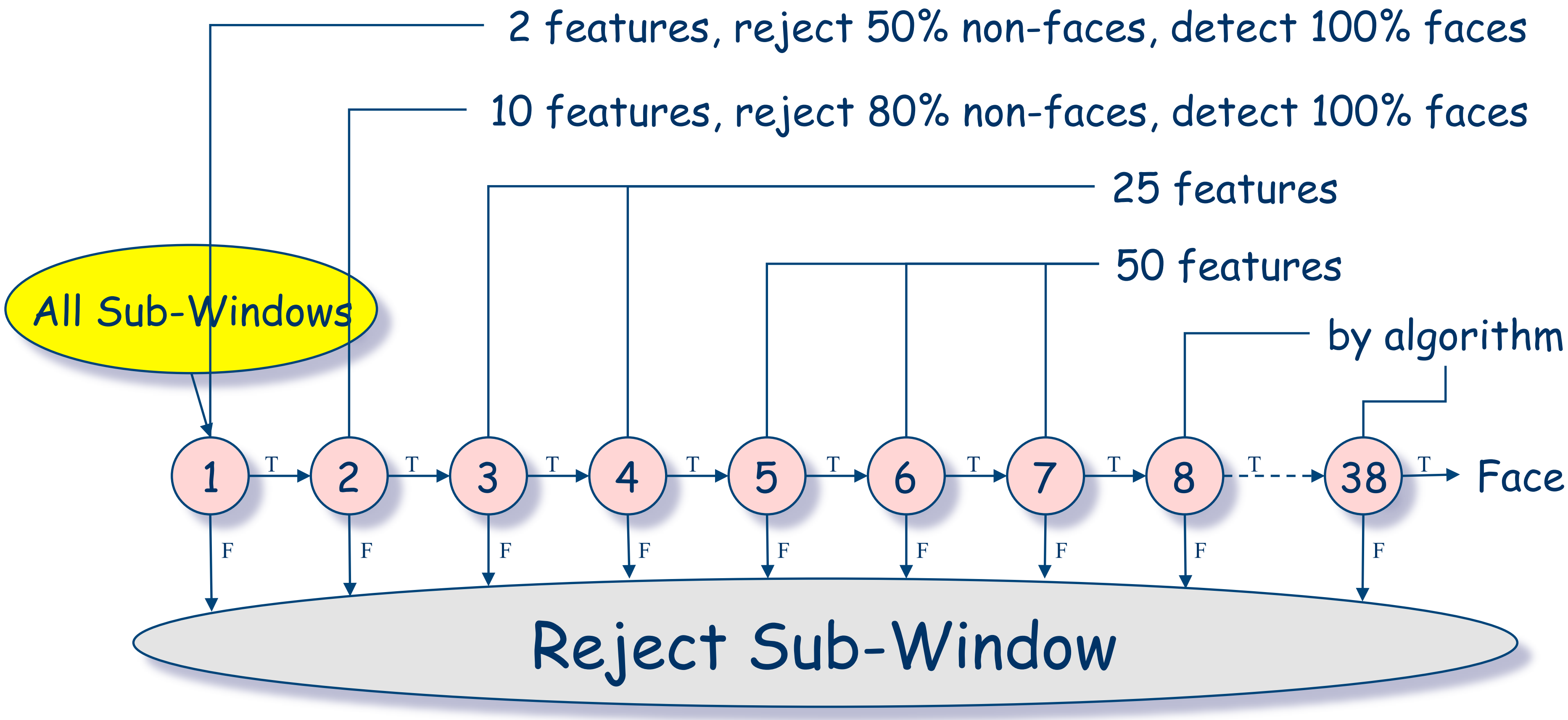


Experiments
- Speed of the Final Detector

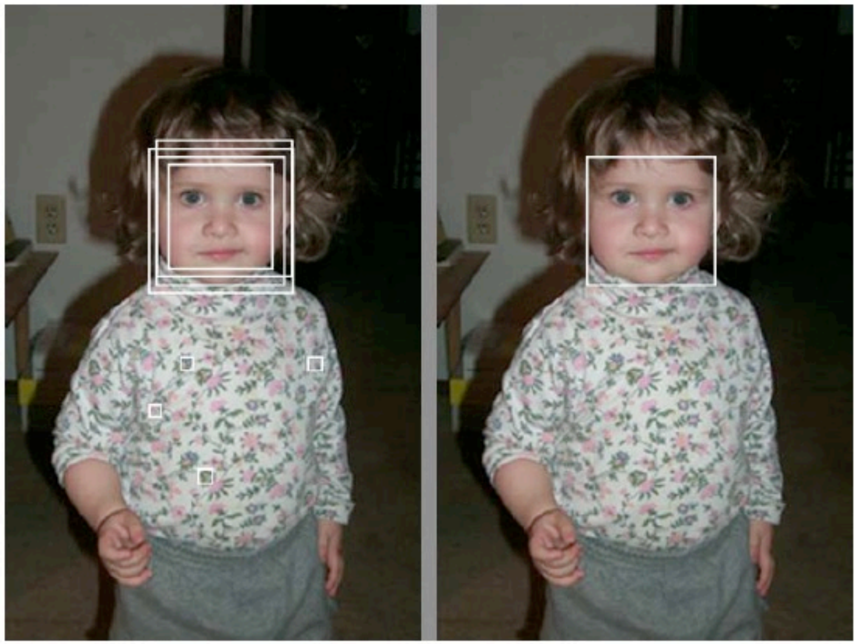
- Speed of the detector ~ total number of features evaluated
- On the MIT-CMU test set the average number of features evaluated is 8 (out of 6061).

- The processing time of a 384 by 288 pixel image on a conventional personal computer (700 MHz Intel P-III) about 0.067 seconds (15 fps).
- Processing time should linearly scale with image size, hence processing of a 3.1 mega pixel images taken from a digital camera should approximately take 2 seconds.

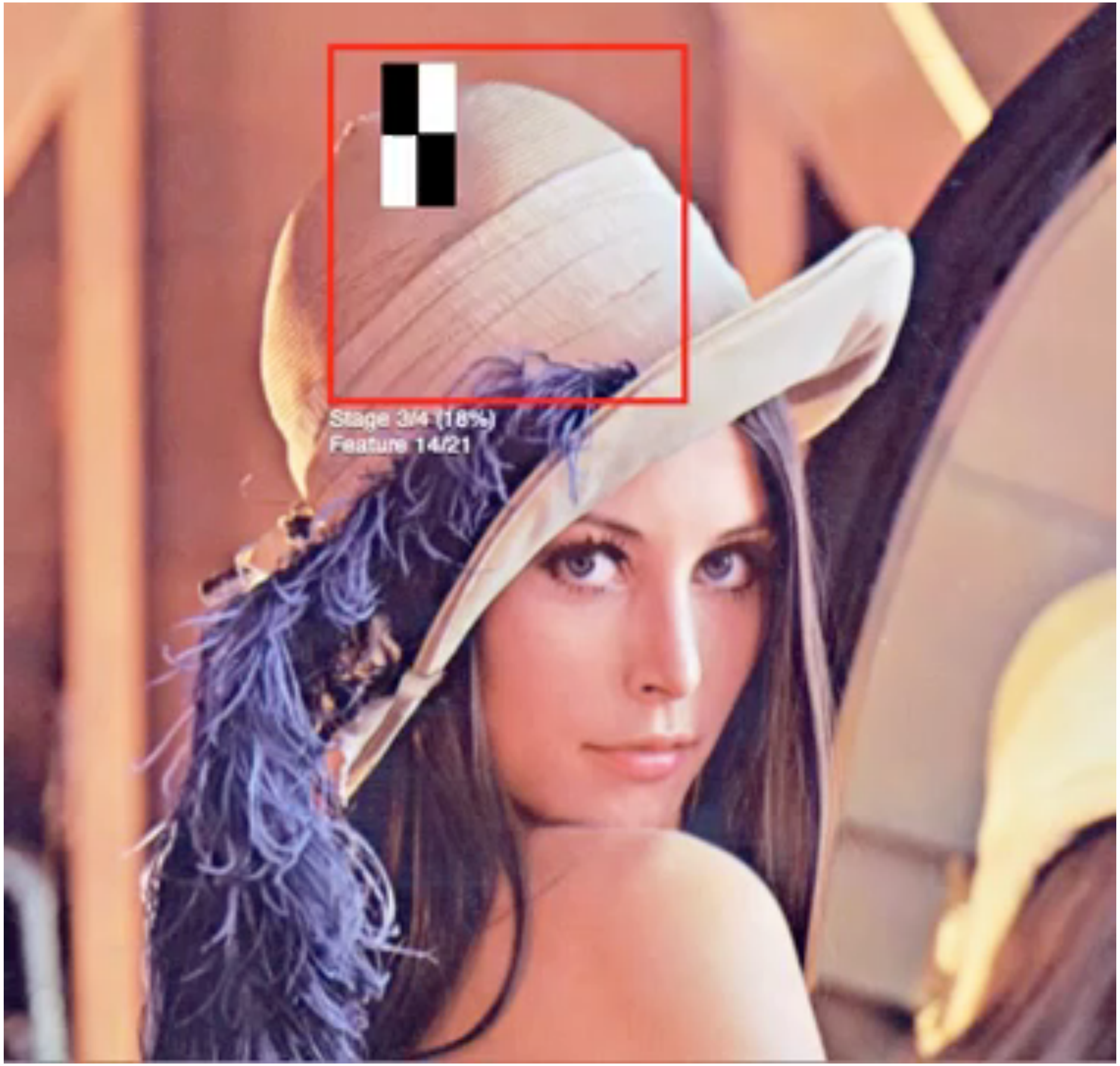
Operation of the face detector

- Since training examples were normalized, image sub-windows needed to be normalized also. This **normalization** of images can be efficiently done using two integral images (regular / squared).
- **Detection at multiple scales** is achieved by scaling the image
- The amount of **shift** between subsequent sub-windows is determined by some constant number of pixels and the current scale.

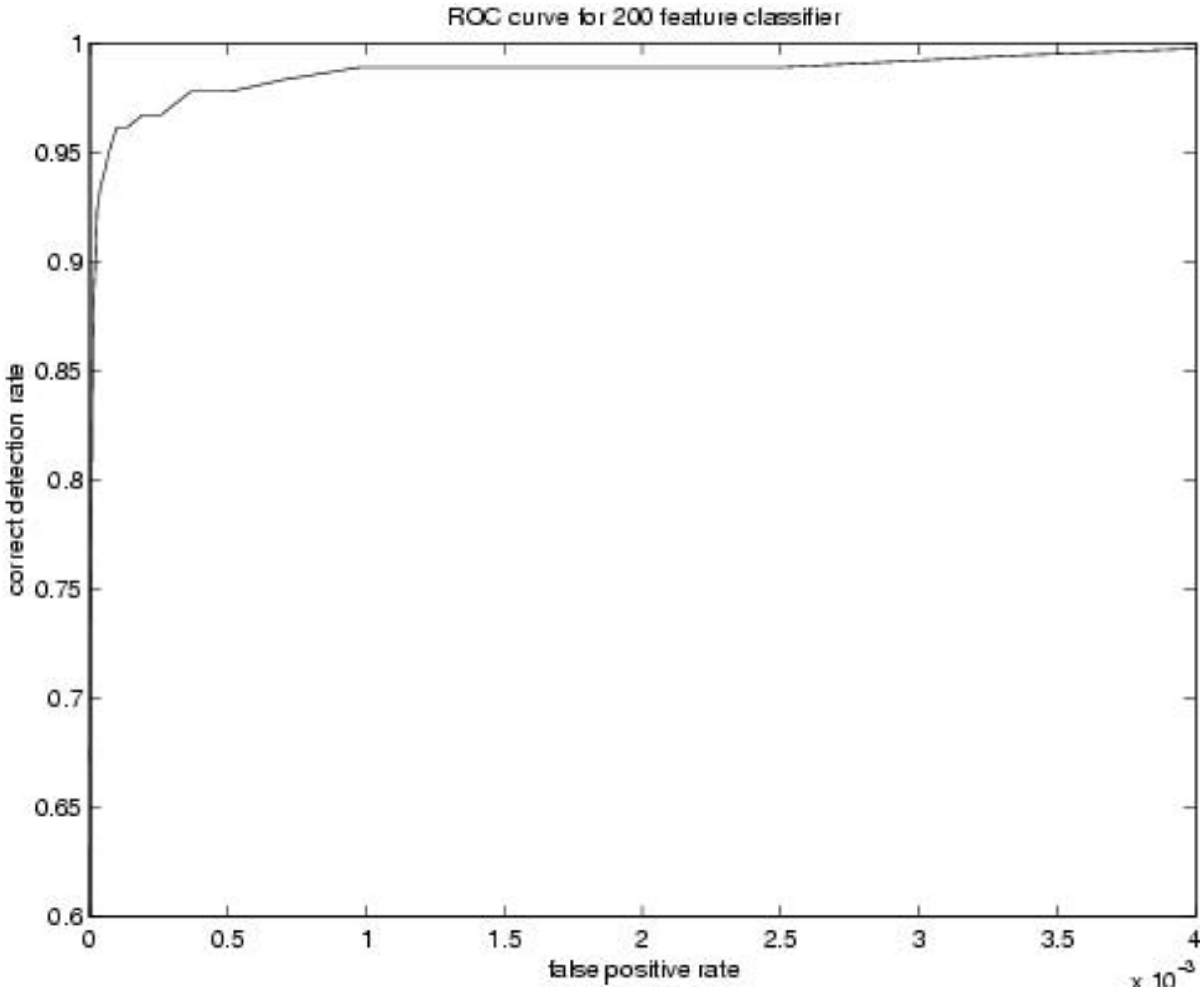
- **Multiple detections** of a face, due to the insensitivity to small changes in the image of the final detector were, were combined based on overlapping bounding region.



Haar Cascade Visualization

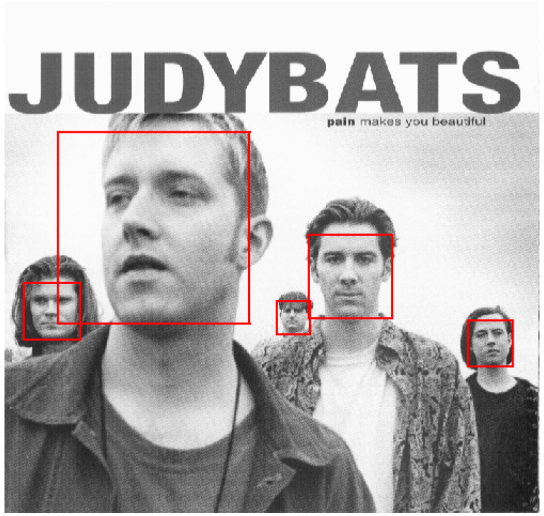


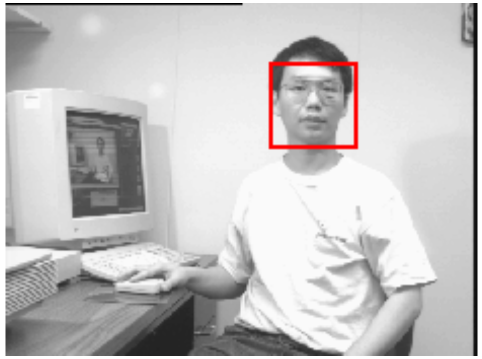
Performance

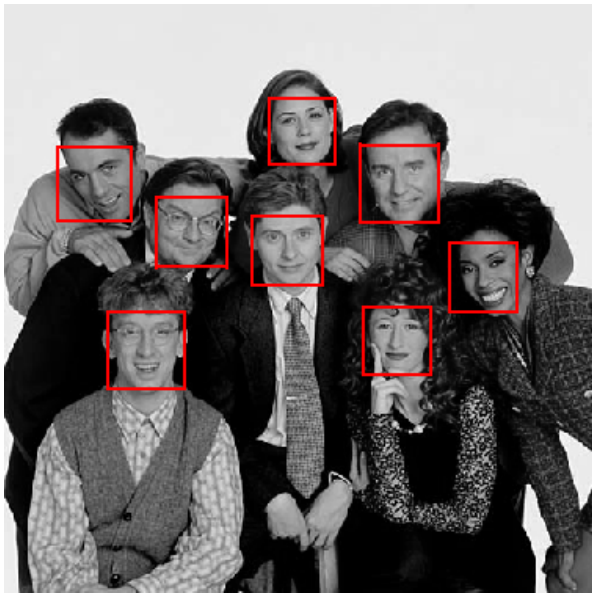


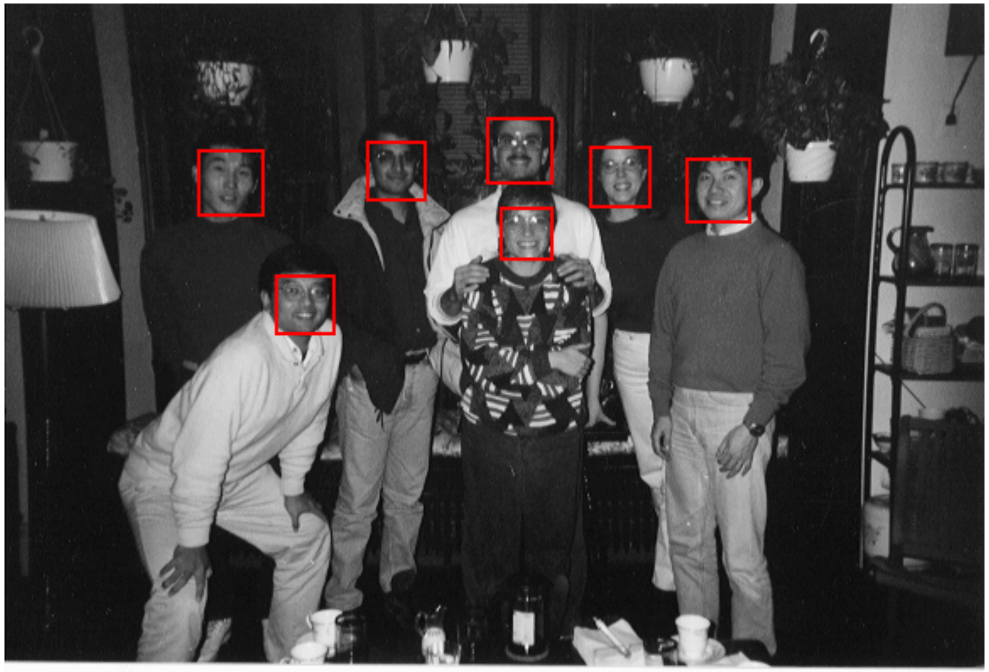
First two features selected

Results



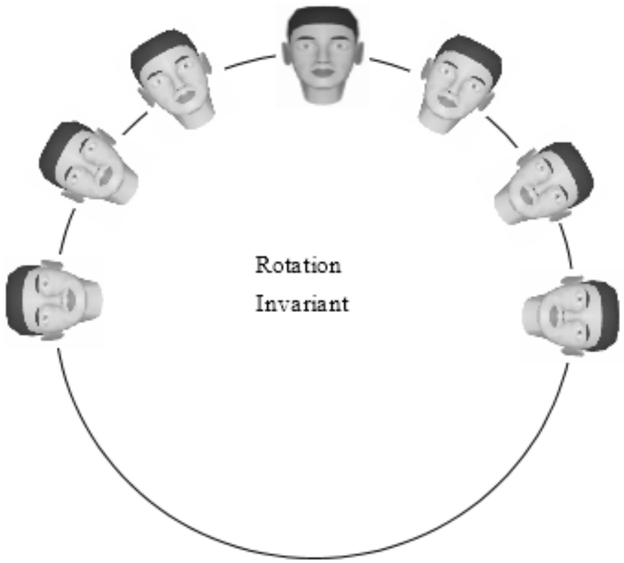




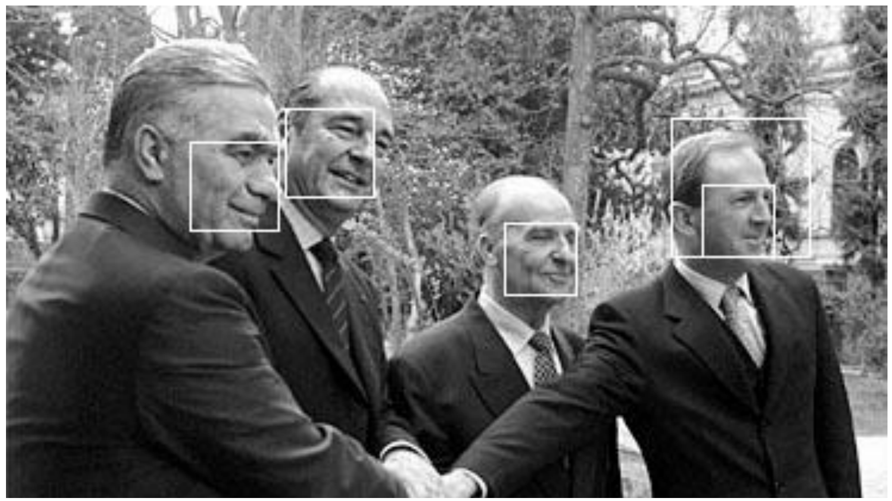


Rotation of face

In-Plane Rotation

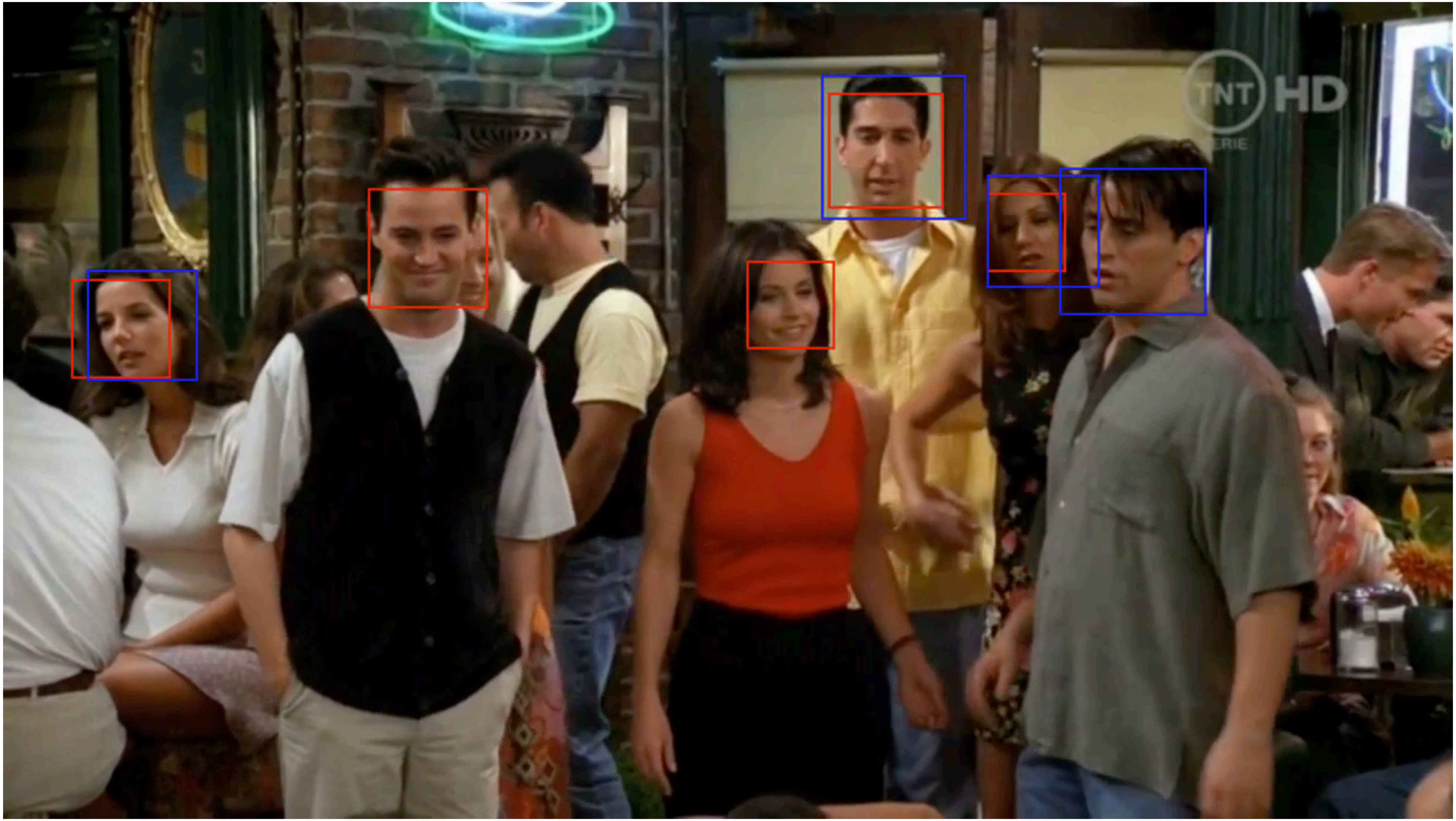


Out-Plane Rotation

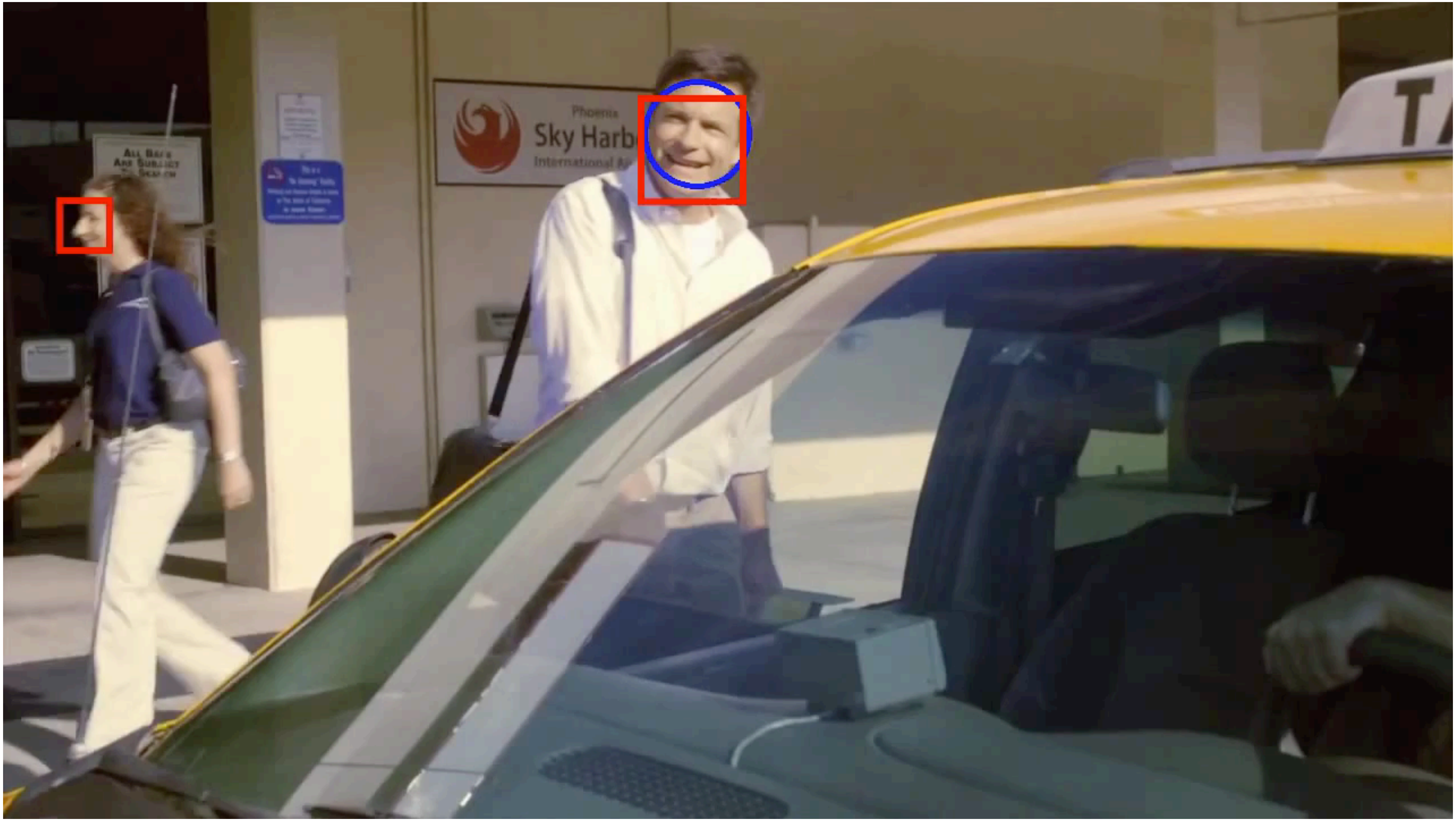


Profile face detection

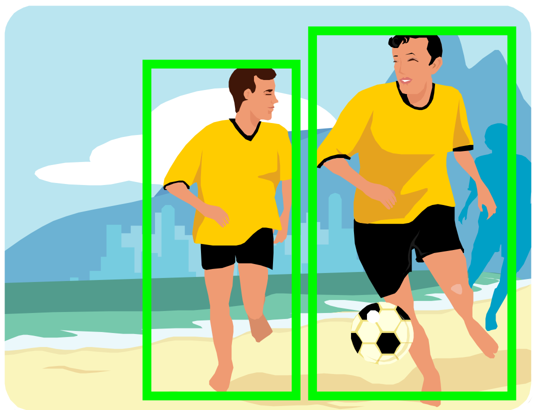
Frontal and Profile Face Detection - OpenCV

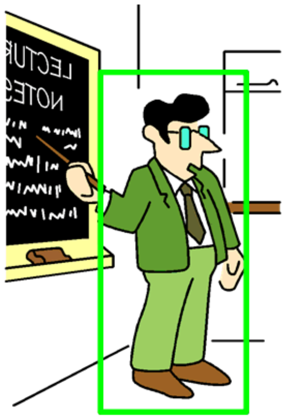


Dlib vs OpenCV face detection



Pedestrian Detection



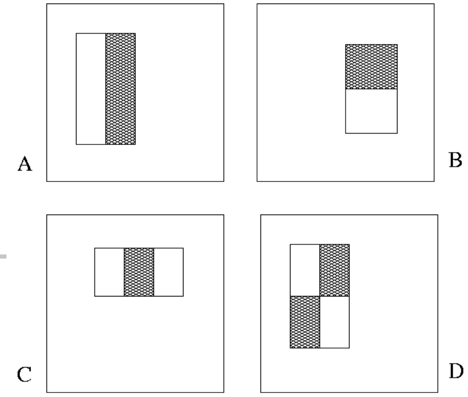


Pedestrian Detection

- Detect and localize human/pedestrian in images
- Similar to face detection, but with more deformation and occlusion challenges



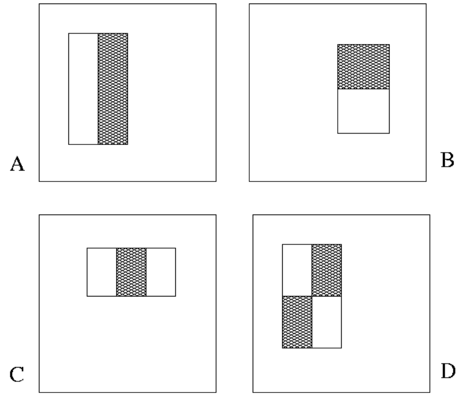
Pedestrian Detection



- Detect and localize human/pedestrian in images

Are Haar features suitable for pedestrian detection?

Pedestrian Detection



- Detect and localize human/pedestrian in images

Are Haar features suitable for pedestrian detection?

Pedestrian Detection

- **Challenges**:
  - Wide variety of articulated poses
  - Variable appearance/clothing
  - Complex backgrounds
  - Unconstrained illumination
  - Occlusions
  - Different Scales

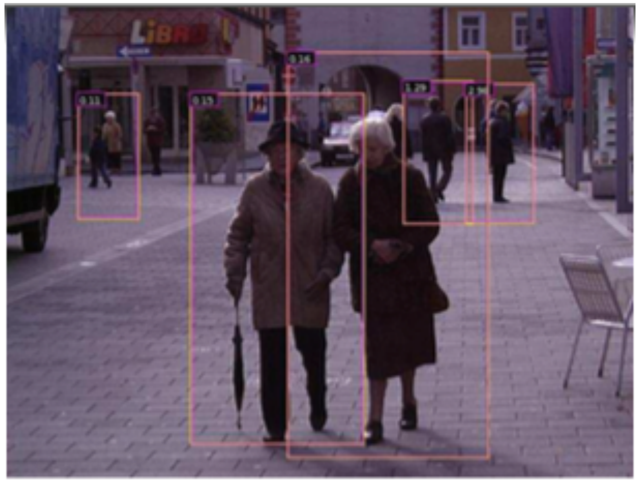
Are any other features more suitable for pedestrian detection?

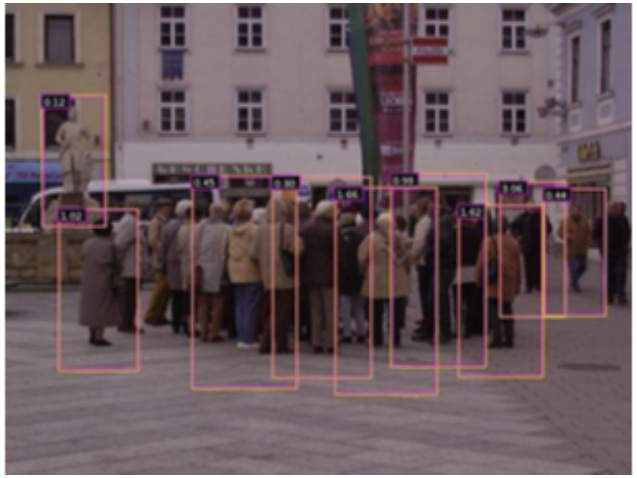
Histograms of Oriented Gradients (HOG)

N. Dalal and B. Triggs, “Histograms of Oriented Gradients for Human Detection,” *CVPR*, 2005.
(cited number: 39101 from Google)

Contributions

- Focus on building **robust feature sets (HOG)**
  - Classifier is just linear SVM on normalised image windows
- A human data set (**INRIA Person dataset**)
  - http://pascal.inrialpes.fr/data/human/





INRIA Person dataset

- A human data set (**INRIA Person dataset**)
  - http://pascal.inrialpes.fr/data/human/

Data Set

Train	*Test*
614 positive images	288 positive images
1218 negative images	453 negative images
1208 positive windows	566 positive windows
Overall 1774 human annotations + reflections	

- Well-designed dataset.
- Humans are standing in different positions with different orientations and poses.
- Image resolution is 64 x 128

Human

Non-Human

INRIA Person dataset

- A human data set (**INRIA Person dataset**)
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Data Set	*Train*	*Test*
	614 positive images	288 positive images
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	1208 positive windows	566 positive windows
	Overall 1774 human annotations + reflections	

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Positive images:

INRIA Person dataset

- A human data set (**INRIA Person dataset**)
  - http://pascal.inrialpes.fr/data/human/

Data Set	Train	Test
	614 positive images	288 positive images
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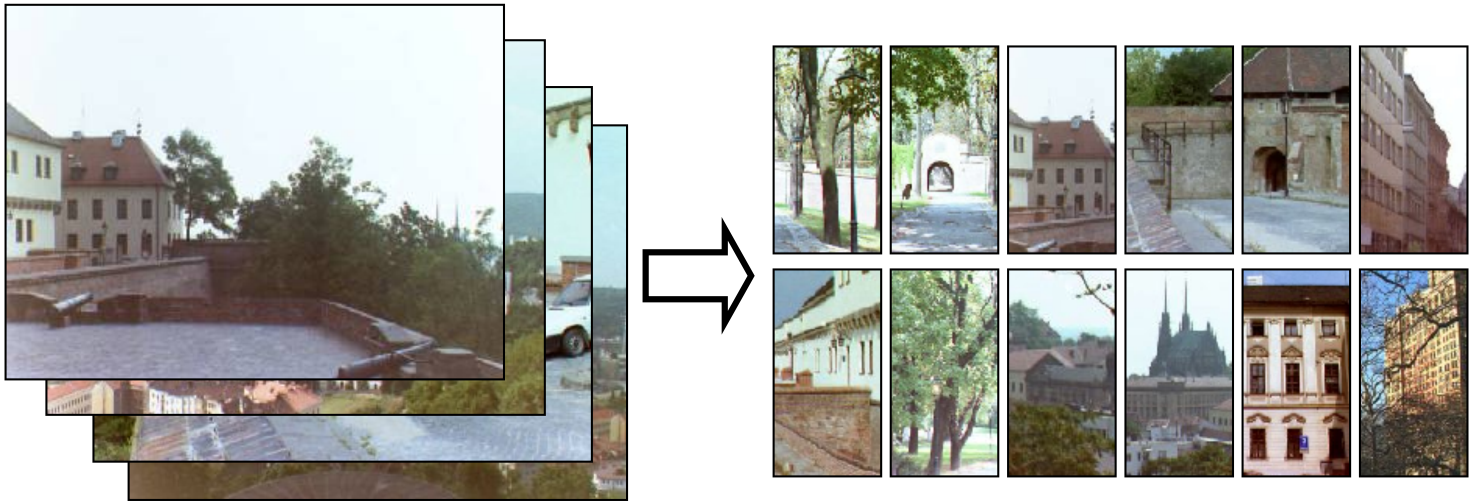
	Overall 1774 human annotations + reflections	

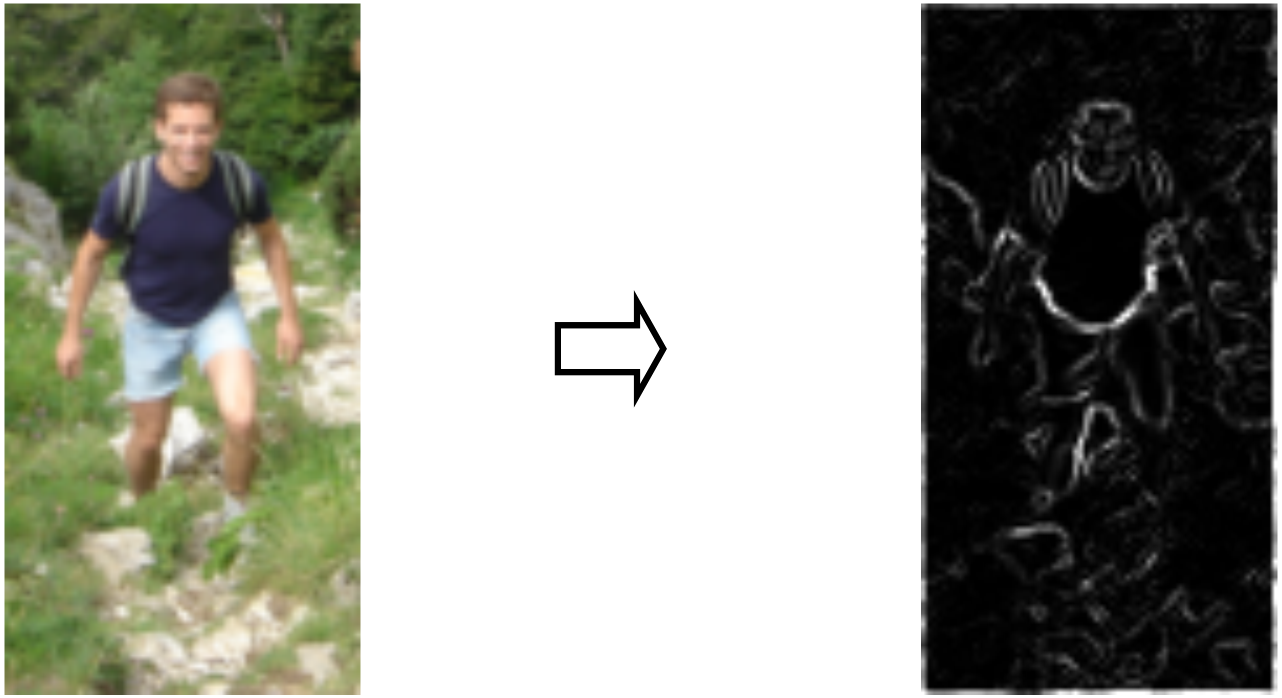
- Well-designed dataset.
- Humans are standing in different positions with different orientations and poses.
- Image resolution is 64 x 128

Negative images:



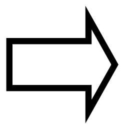
HOG Feature

- HOG (Histogram of Oriented Gradients)
    - For each training image (64 x128), the pixel gradient magnitude and gradient orientation are calculated



HOG Feature

- HOG (Histogram of Oriented Gradients)
  - For each training image (64 x128), the pixel gradient magnitude and gradient orientation are calculated
  - Each training image (64 x128) is divided into non-overlapped **cells** (8 x 8)
    - There are 8 x 16 cells.



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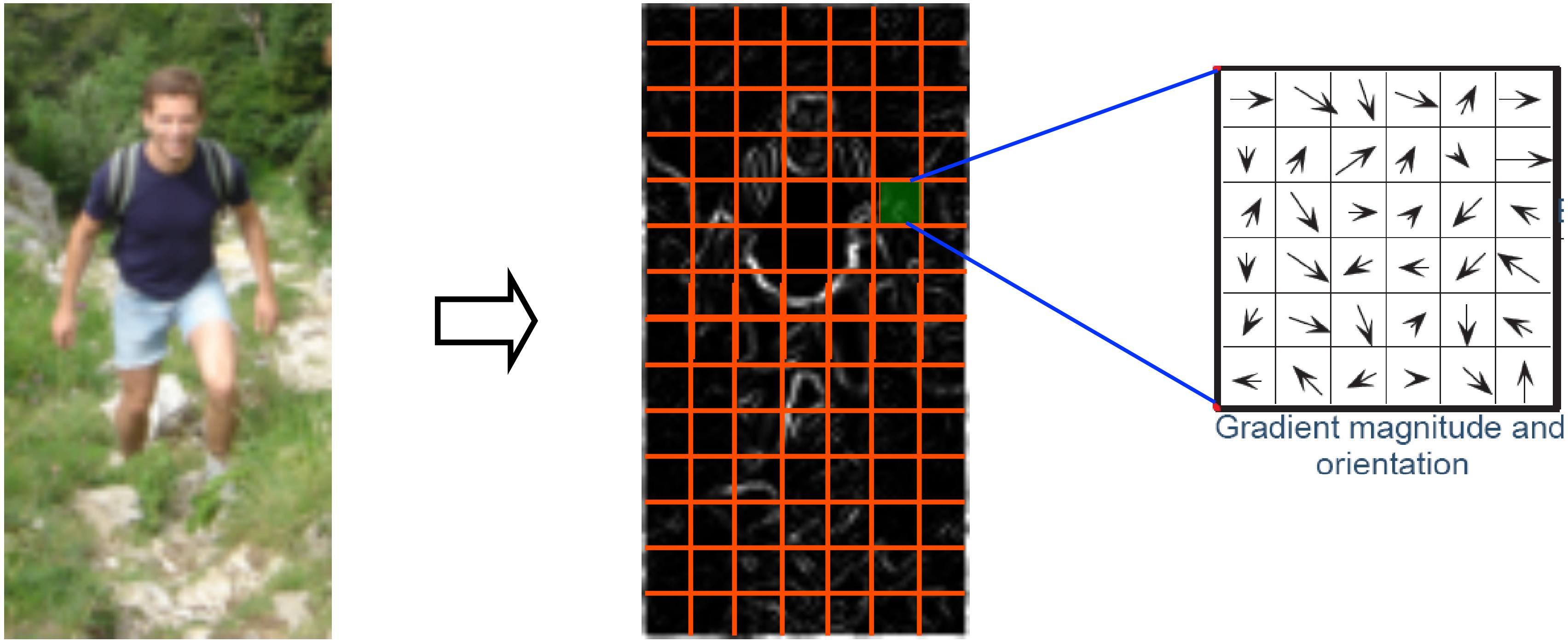
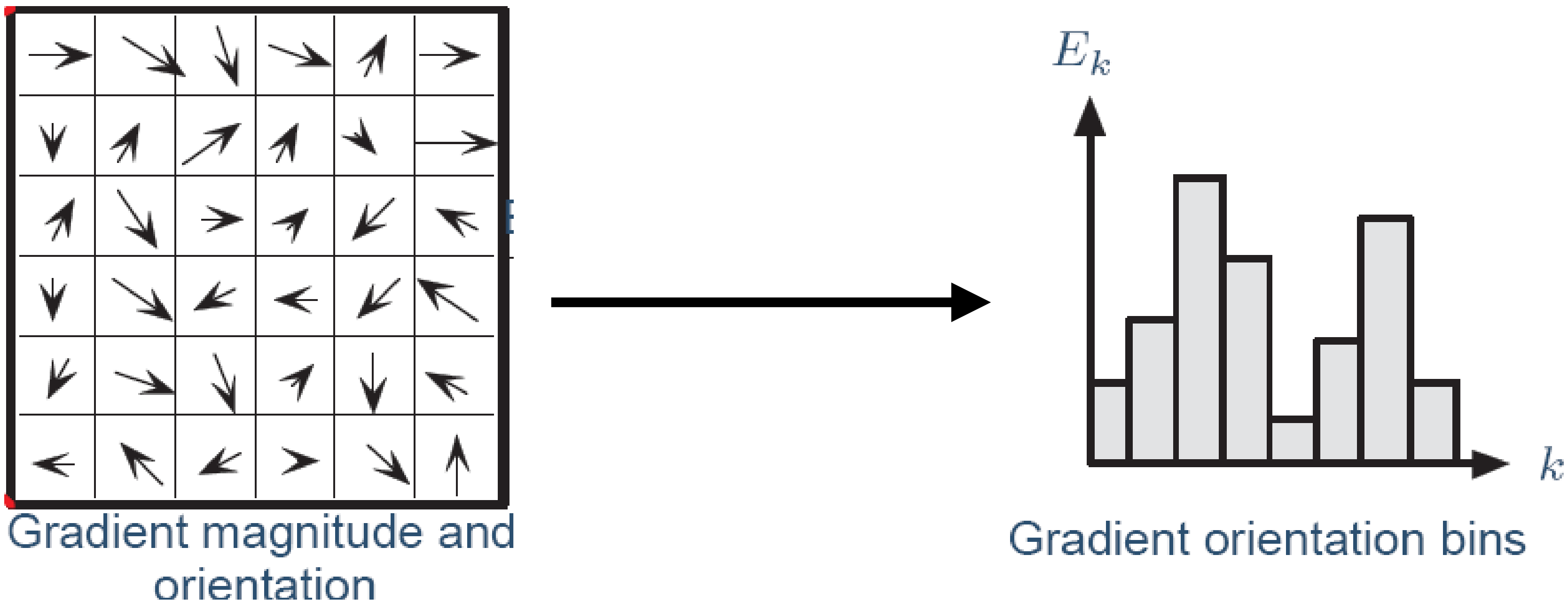


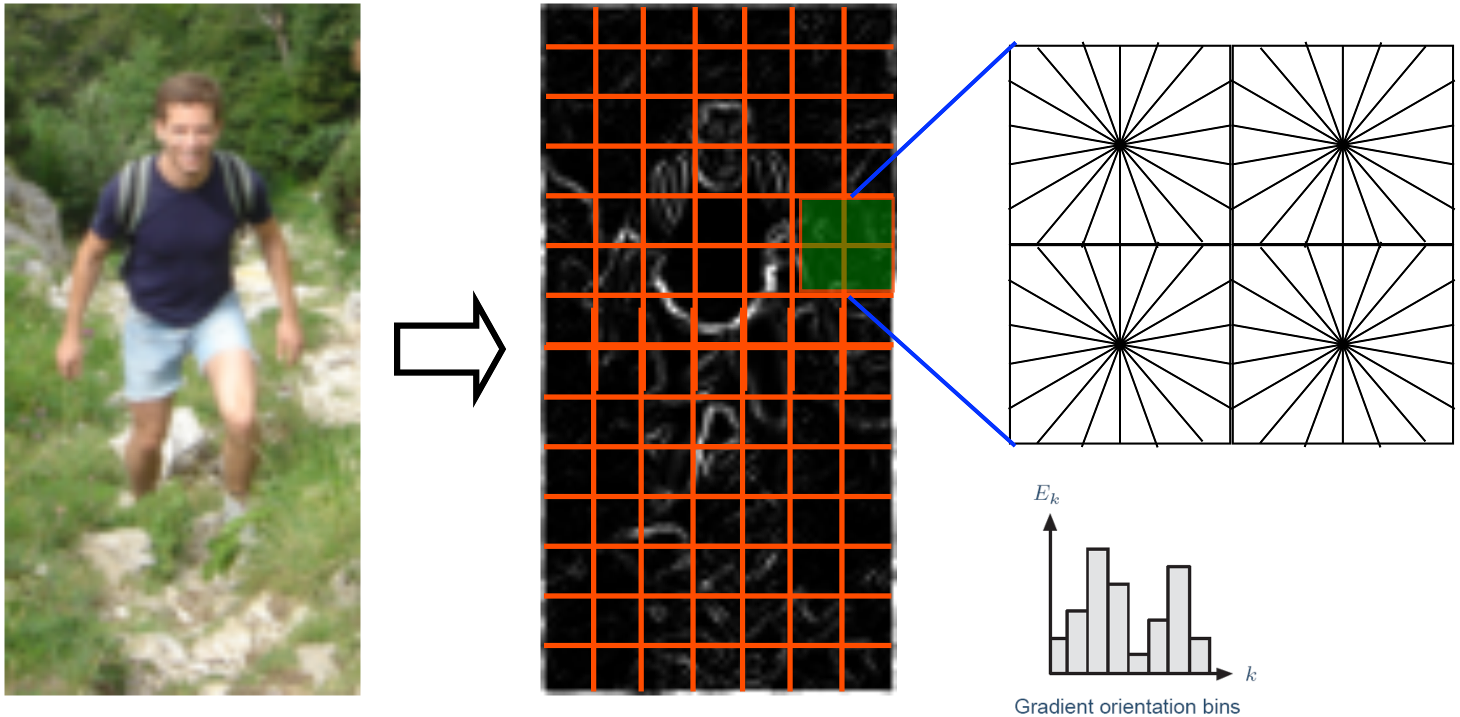
HOG Feature

- HOG (Histogram of Oriented Gradients)
  - For each cell, the gradient orientation histogram E (with K bins over 0^{o}~180^{o}) is measured.
    - ex. K = 9



HOG Feature

- HOG (Histogram of Oriented Gradients)
  - A **block** (16 x16) is composed by four connected cells.
    - A block use 36 dimensional feature vector to capture local gradient orientation.
    - This feature vector is normalized to a unit vector.
  - Different blocks can be overlapped.
    - There are 7 x 15 blocks.



$\in R^{36}$

HOG Feature

- HOG (Histogram of Oriented Gradients)

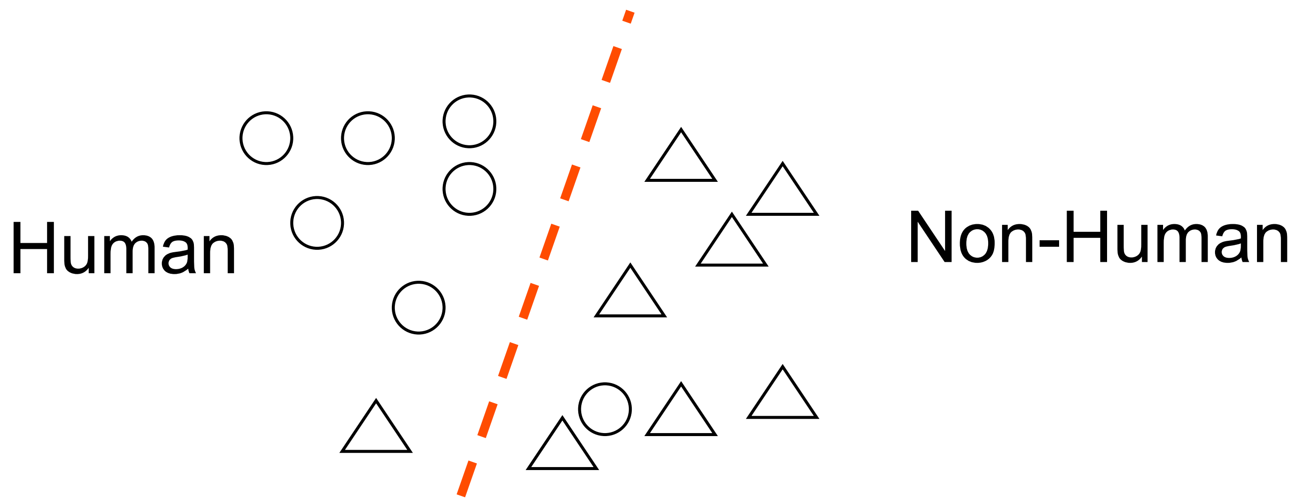
  - Feature vectors of all blocks are combined as a super vector to capture global gradient orientation.
    - The super vector is a 3780 (7 x 15 x 36) dimensional vector.

  - In summary:
    - Each training data (a 64 x 128 image) is characterized by a 3780 dimensional vector.
    - This vector capture local and global gradient orientation information.

  - Drawback:
    - High dimensional feature vector ⇒ High computation Cost!

Classifier

Linear Support Vector Machine (LSVM)



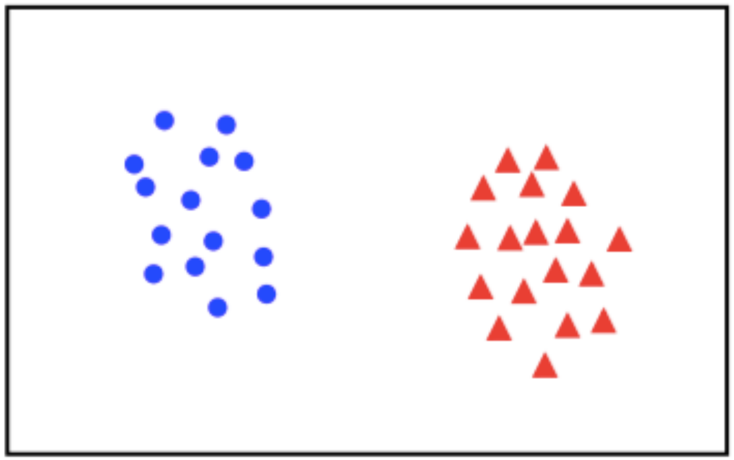
Linear SVM

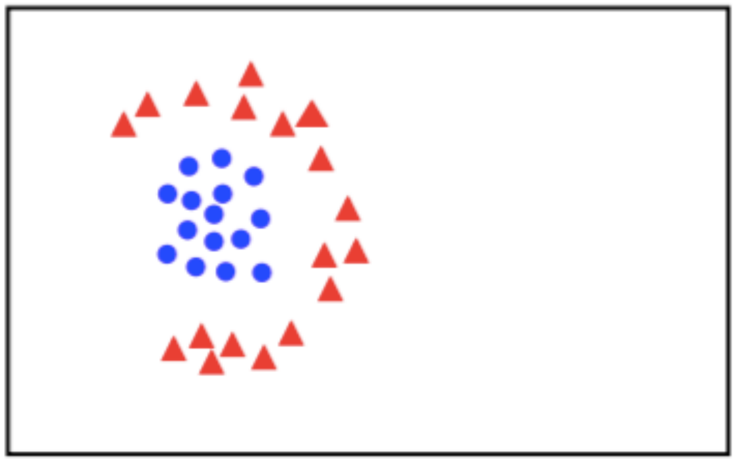
Binary Classification

Given training data $(\mathbf{x}_i, y_i)$ for $i = 1 \ldots N$, with $\mathbf{x}_i \in \mathbb{R}^d$ and $y_i \in \{-1, 1\}$, learn a classifier $f(\mathbf{x})$ such that

$$f(\mathbf{x}_i) \begin{cases} \geq 0 & y_i = +1 \\ < 0 & y_i = -1 \end{cases}$$

i.e. $y_i f(\mathbf{x}_i) > 0$ for a correct classification.



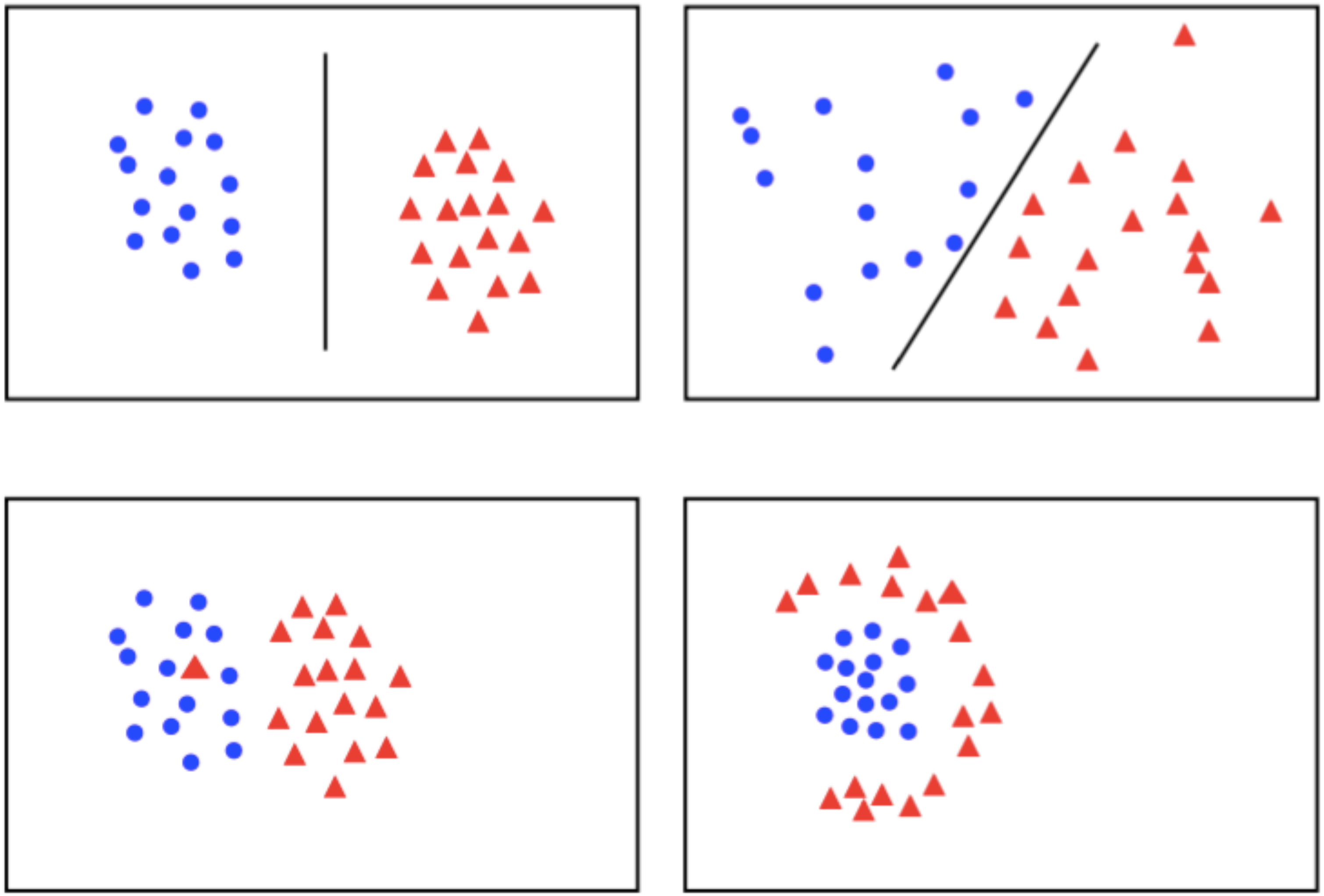


Linear SVM

Linear separability

linearly separable

not linearly separable

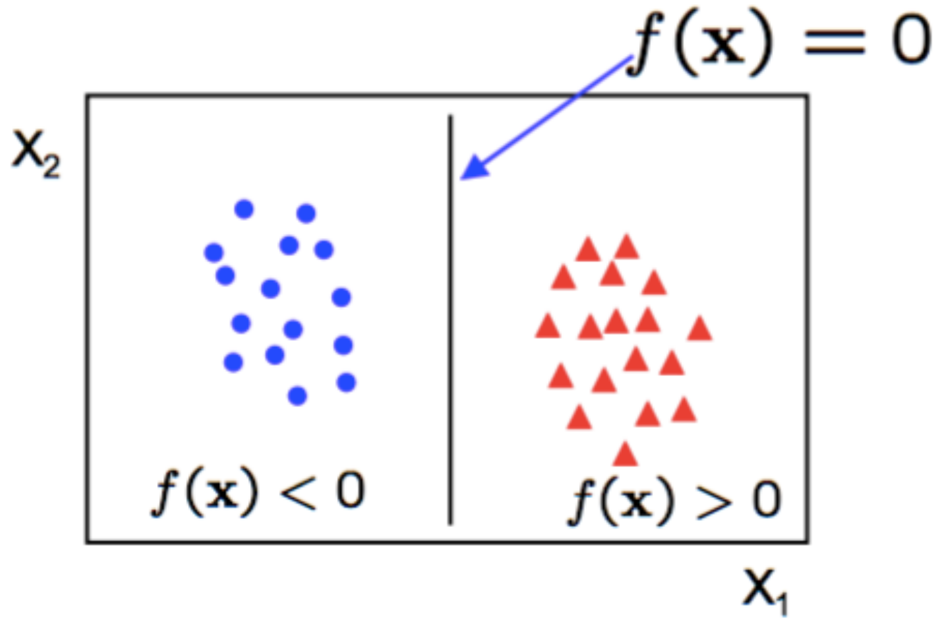


Linear SVM

Linear classifiers

A linear classifier has the form

$$f(\mathbf{x}) = \mathbf{w}^\top \mathbf{x} + b$$



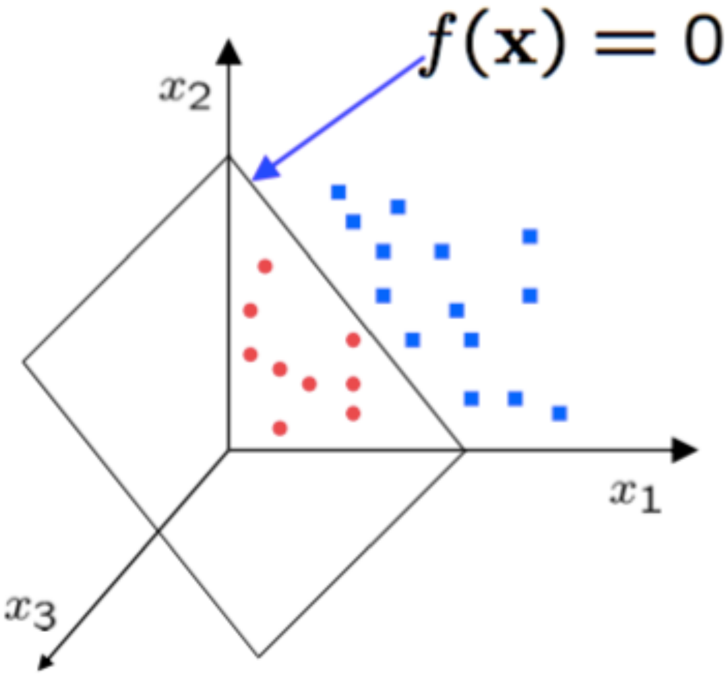
- in 2D the discriminant is a line
- $\mathbf{w}$ is the normal to the line, and b the bias
- $\mathbf{w}$ is known as the weight vector

Linear SVM

Linear classifiers

A linear classifier has the form

$$f(\mathbf{x}) = \mathbf{w}^\top \mathbf{x} + b$$



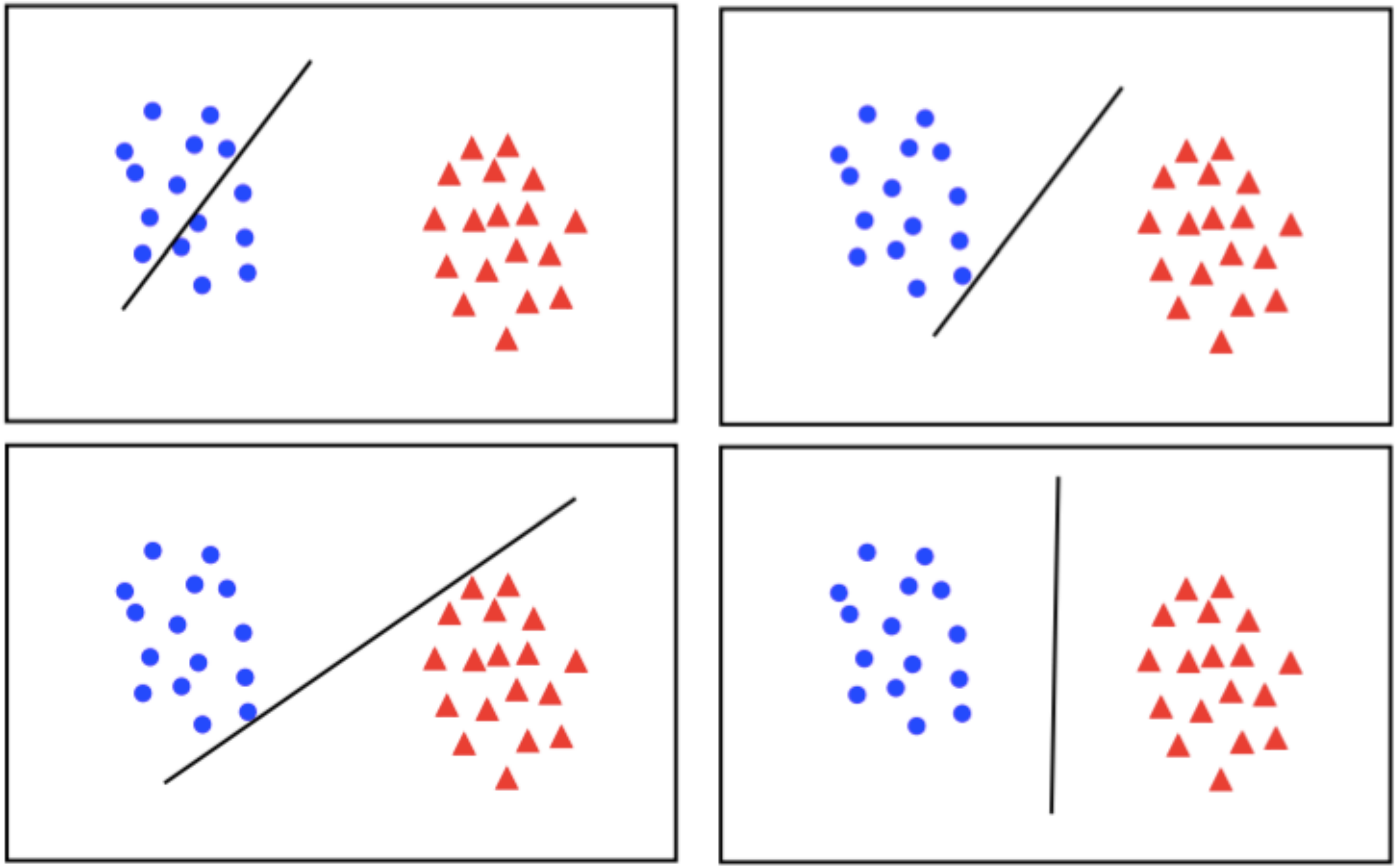
- in 3D the discriminant is a plane, and in nD it is a hyperplane

For a linear classifier, the training data is used to learn **w** and then discarded

Only **w** is needed for classifying new data

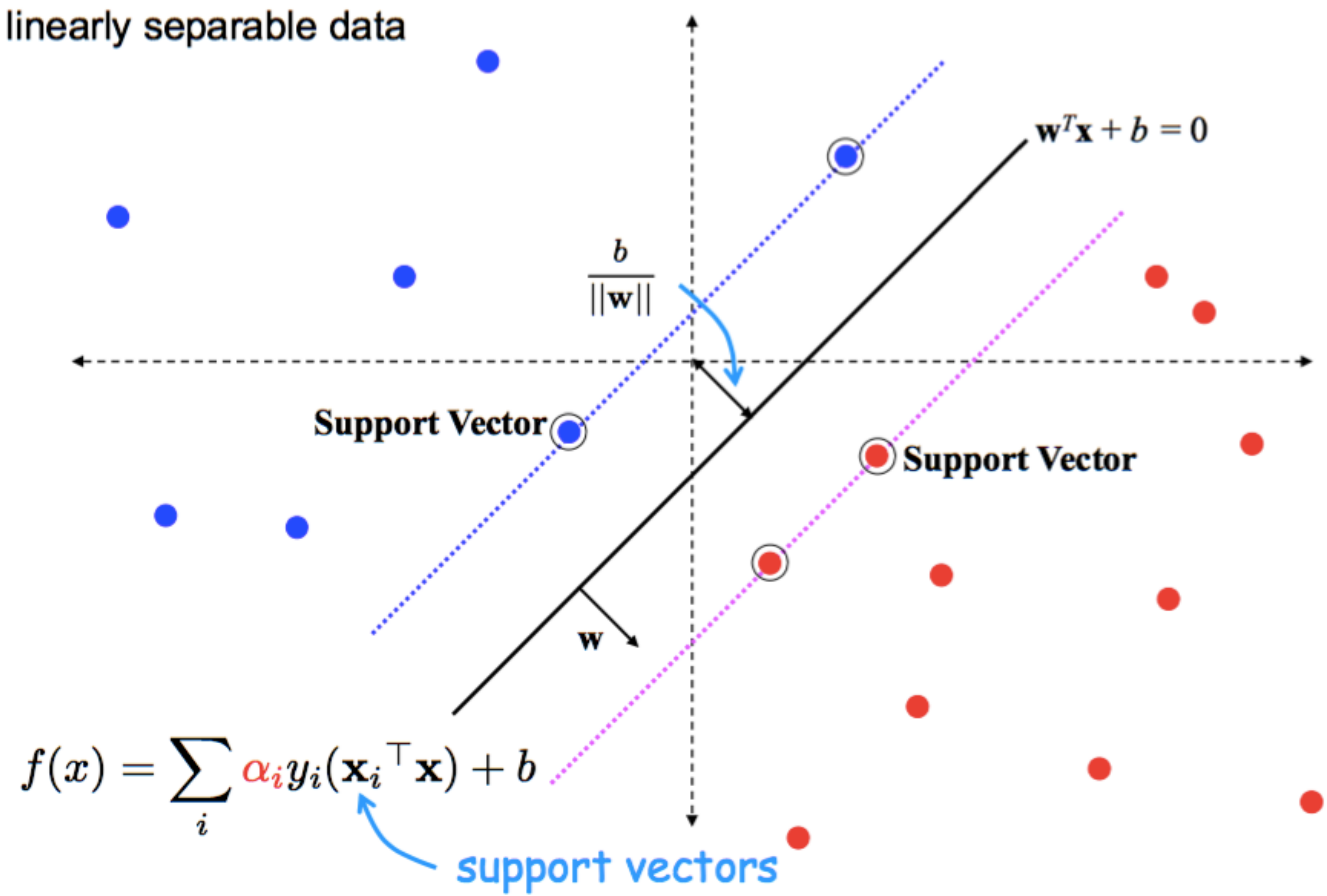
Linear SVM

What is the best w?



- maximum margin solution: most stable under perturbations of the inputs

Linear SVM



$$f(x) = \sum_i \alpha_i y_i (\mathbf{x}_i{}^\top \mathbf{x}) + b$$

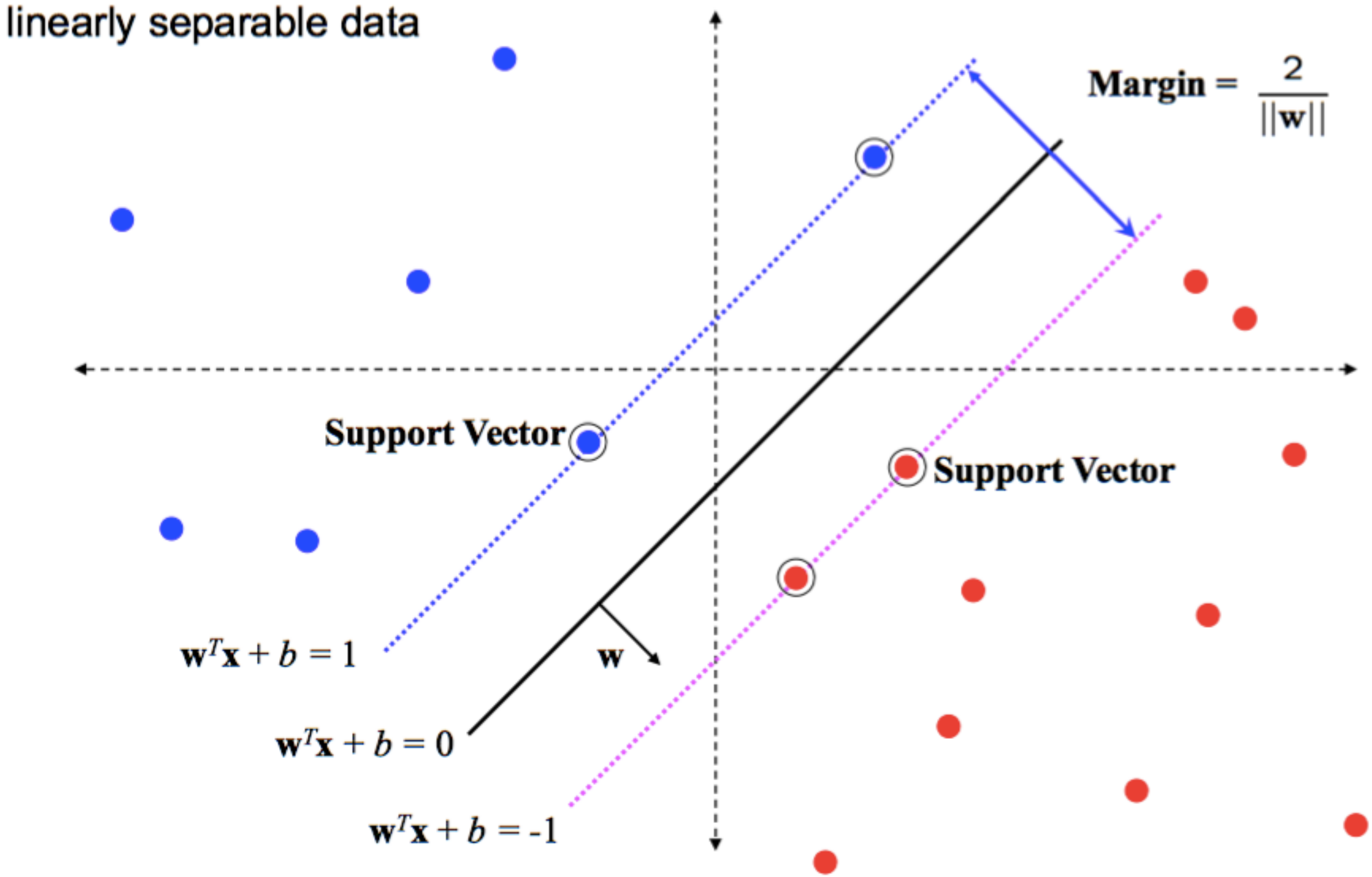
Linear SVM

SVM – sketch derivation

- Since $\mathbf{w}^\top \mathbf{x} + b = 0$ and $c(\mathbf{w}^\top \mathbf{x} + b) = 0$ define the same plane, we have the freedom to choose the normalization of $\mathbf{w}$
- Choose normalization such that $\mathbf{w}^\top \mathbf{x}_+ + b = +1$ and $\mathbf{w}^\top \mathbf{x}_- + b = -1$ for the positive and negative support vectors respectively
- Then the margin is given by

$$\frac{\mathbf{w}}{||\mathbf{w}||} \cdot \left(\mathbf{x}_+ - \mathbf{x}_-\right) = \frac{\mathbf{w}^\top \left(\mathbf{x}_+ - \mathbf{x}_-\right)}{||\mathbf{w}||} = \frac{2}{||\mathbf{w}||}$$

Linear SVM


linearly separable data
Margin = $\frac{2}{||\mathbf{w}||}$
Support Vector
Support Vector
$\mathbf{w}^T\mathbf{x} + b = 1$
$\mathbf{w}$
$\mathbf{w}^T\mathbf{x} + b = 0$
$\mathbf{w}^T\mathbf{x} + b = -1$

Linear SVM

SVM – Optimization

- Learning the SVM can be formulated as an optimization:

$$\max_{\mathbf{w}} \frac{2}{||\mathbf{w}||} \text{ subject to } \mathbf{w}^\top \mathbf{x}_i + b \begin{array}{ll} \geq 1 & \text{if } y_i = +1 \\ \leq -1 & \text{if } y_i = -1 \end{array} \text{ for } i = 1 \dots N$$

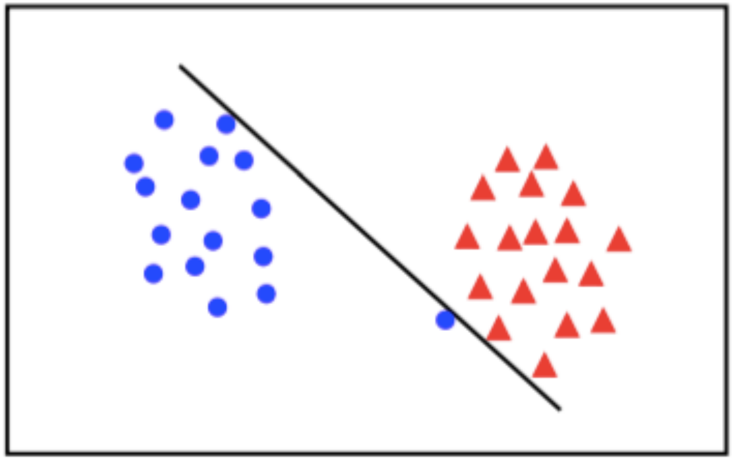
- Or equivalently

$$\min_{\mathbf{w}} ||\mathbf{w}||^2 \text{ subject to } y_i \left(\mathbf{w}^\top \mathbf{x}_i + b\right) \geq 1 \text{ for } i = 1 \dots N$$

- This is a quadratic optimization problem subject to linear constraints and there is a unique minimum

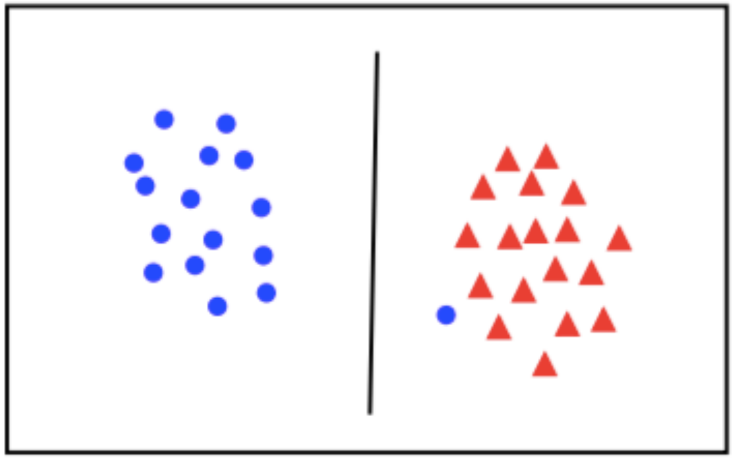
Linear SVM

Linear separability again: What is the best w?



hard-margin

- the points can be linearly separated but there is a very narrow margin



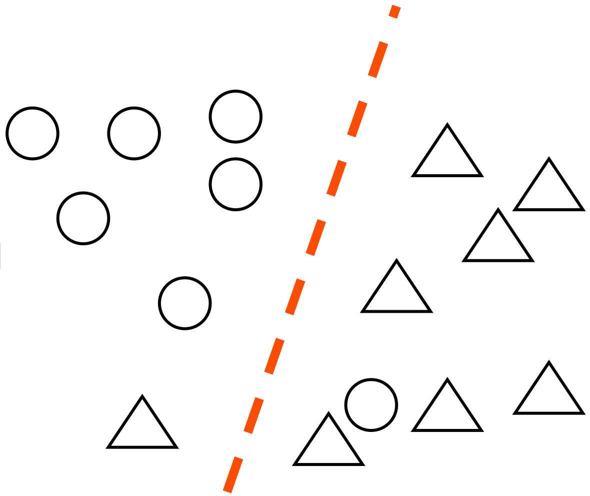
soft-margin

- but possibly the large margin solution is better, even though one constraint is violated

In general there is a trade off between the margin and the number of mistakes on the training data

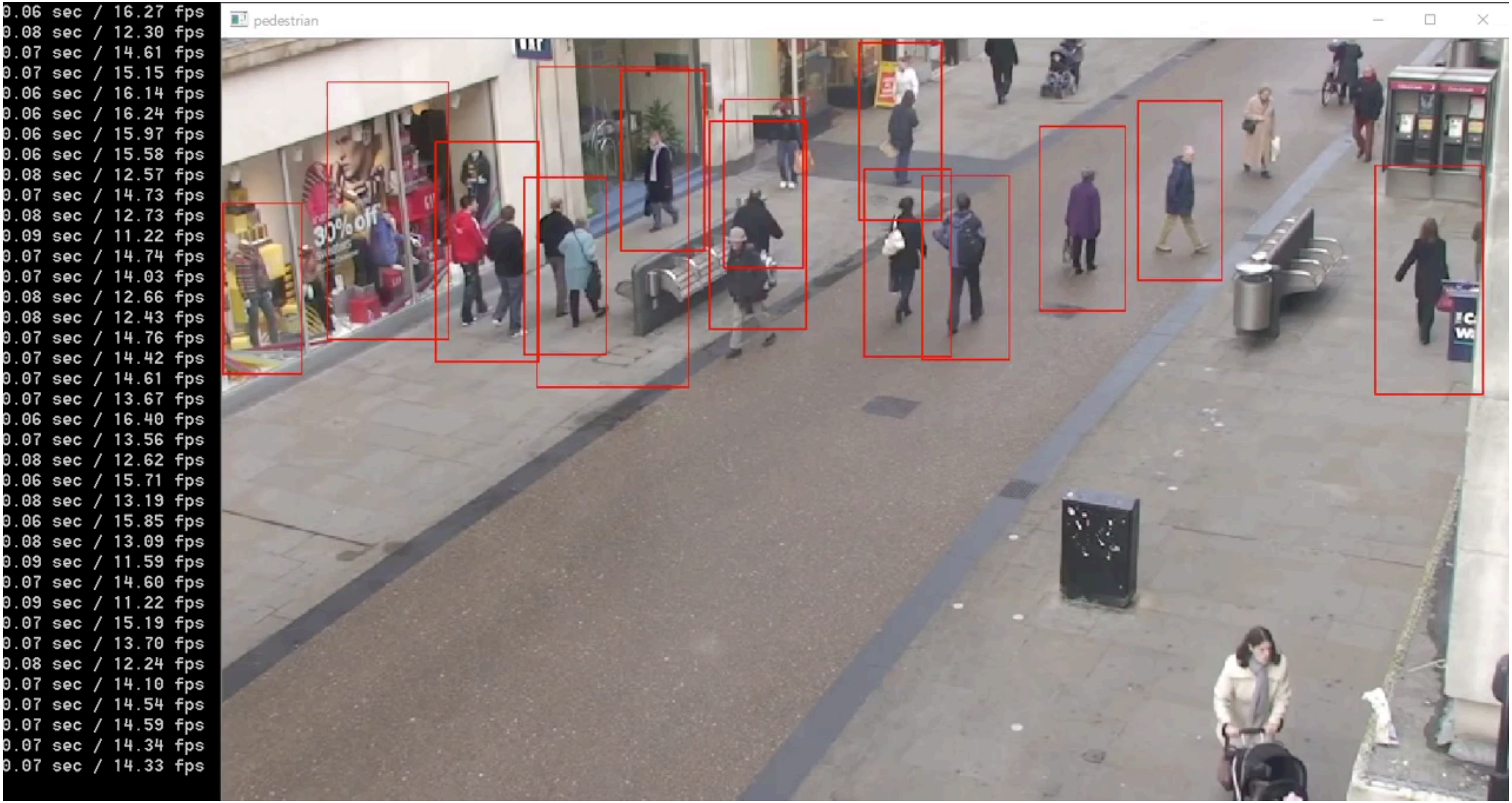
Classifier

Linear Support Vector Machine (LSVM)

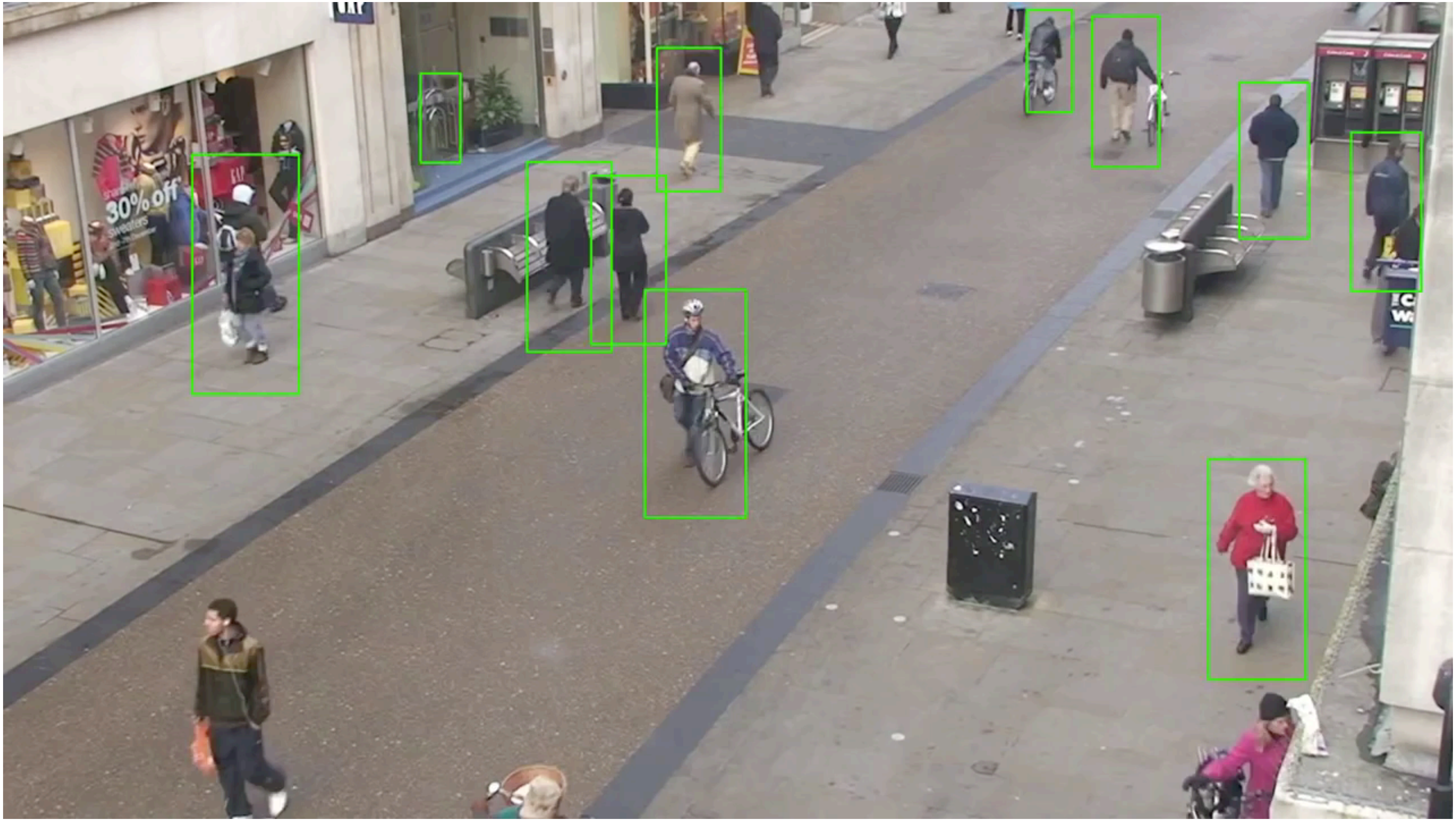


Results

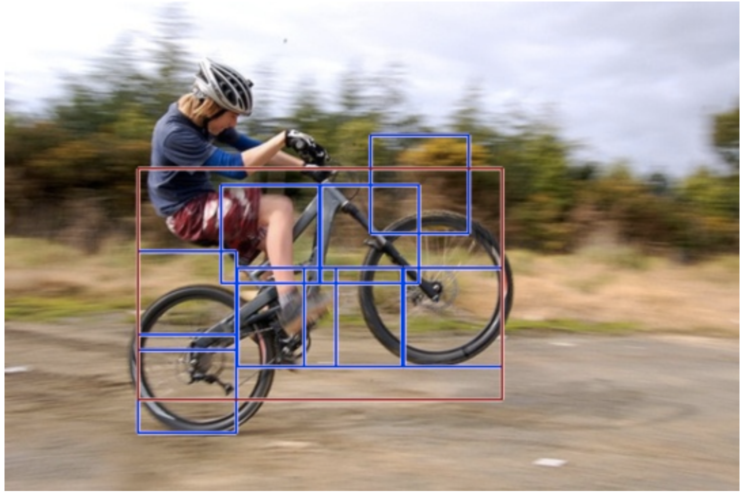
Pedestrian detection using hog+svm (OpenCV)



Pedestrian detection using hog+svm (OpenCV)



Deformable Part Models



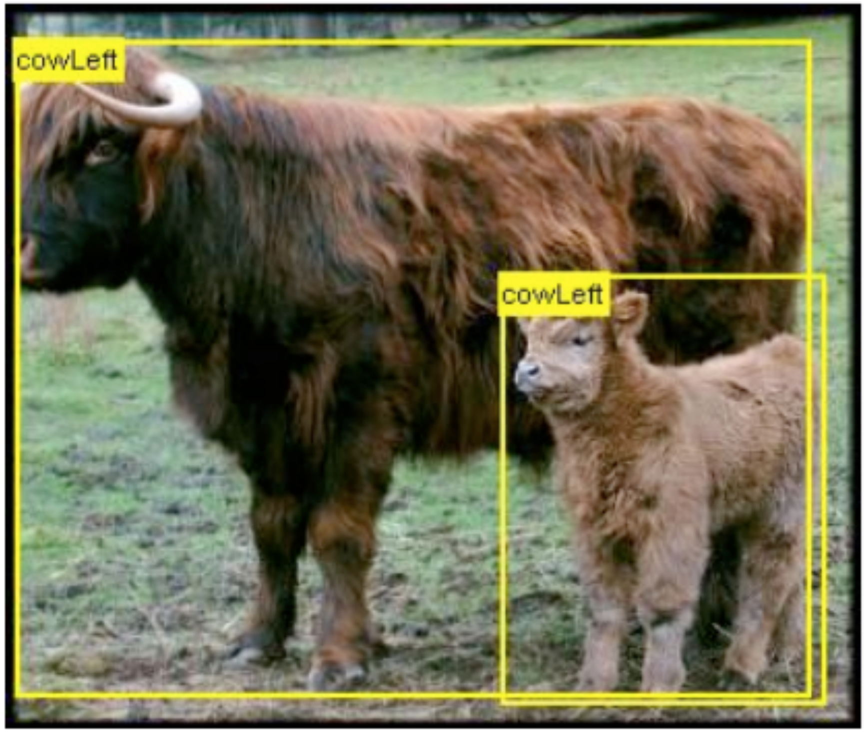
P. Felzenszwalb, D. McAllester, and D. Ramanan, "A Discriminatively Trained, Multiscale, Deformable Part Model," *CVPR*, 2008.
(cited number: 3324 from Google)

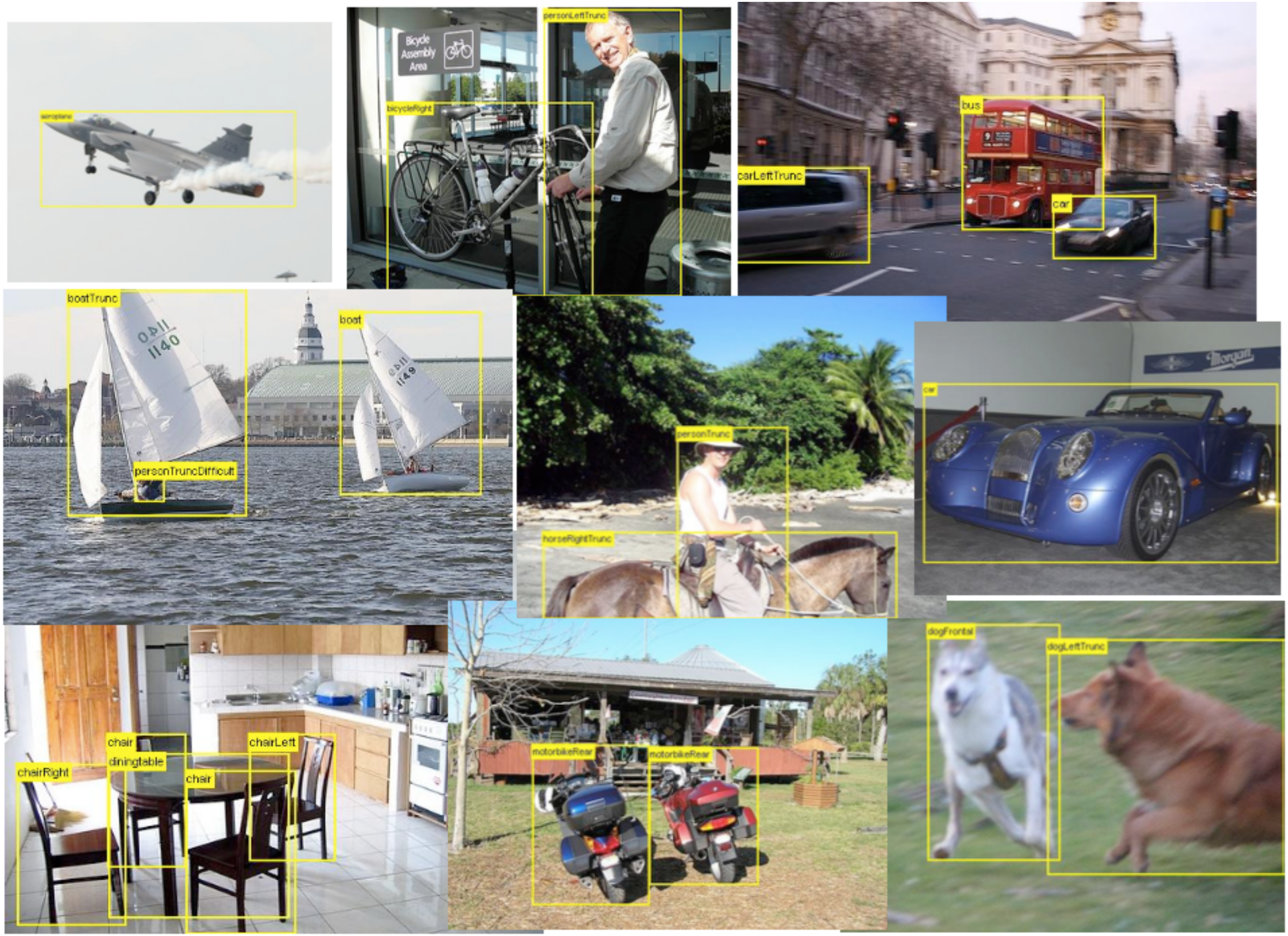
P. Felzenszwalb, R. Girshick, D. McAllester, and D. Ramanan, "Object Detection with Discriminatively Trained Part Based Models," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 2010.
(cited number: 11393 from Google)

http://www.rossgirshick.info/latent/

PASCAL Challenge

- ~10,000 images, with ~25,000 target objects
  - Objects from 20 categories (person, car, bicycle, cow, table...)
  - Objects are annotated with labeled bounding boxes





aeroplane
Bicycle
Assembly
Area
personLeftTrunc
bicycleRight
bus
carLeftTrunc
car
boatTrunc
1140
boat
1149
personTruncDifficult
personTrunc
horseRightTrunc
Morgan
car
chair
diningtable
chairLeft
chairRight
chair
motorbikeRear
motorbikeRear
dogFrontal
dogLeftTrunc

Why is it hard?

- Object in rich categories exhibit significant variability

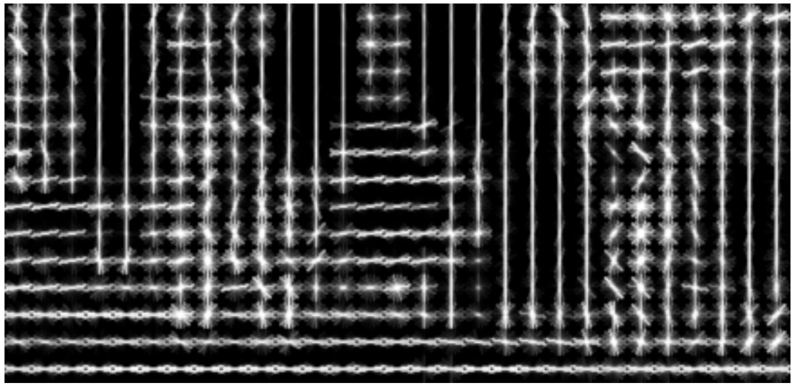
  - Photometric variation
  - Viewpoint variation
  - Intra-class variability
    - Cars come in a variety of shapes (sedan, minivan, etc)
    - People wear different clothes and take different poses

We need rich object models
But this leads to difficult matching and training problems

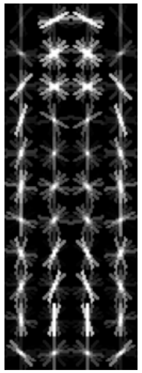
Pedestrian detection with HOG

- Train a pedestrian template using a linear support vector machine
- At test time, convolve feature map with template
- Find local maxima of response
- For multi-scale detection, repeat over multiple levels of a HOG *pyramid*

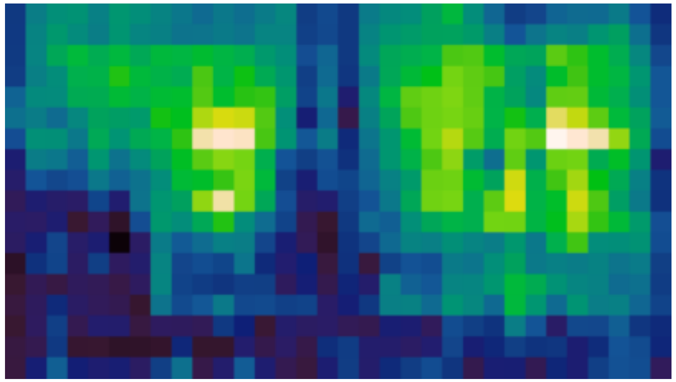
HOG feature map



Template



Detector response map



N. Dalal and B. Triggs, [Histograms of Oriented Gradients for Human Detection](), CVPR 2005

Challenges

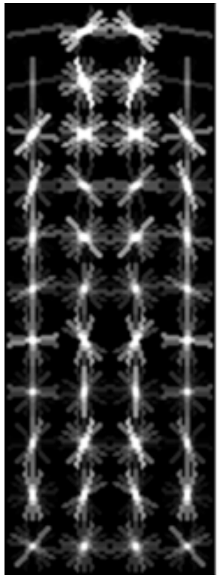
- Single rigid template usually not enough to represent a category
  - Many objects (e.g. humans) are articulated, or have parts that can vary in configuration

  - Many object categories look very different from different viewpoints, or from instance to instance

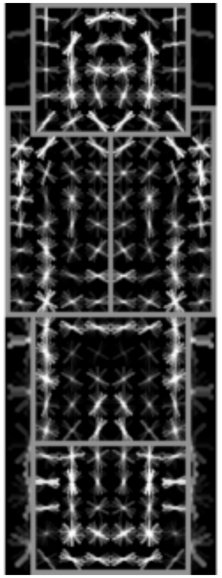
Slide by N. Snavely

Deformable part models

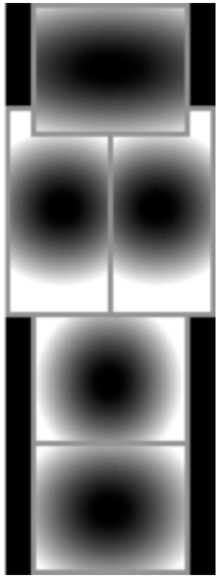
Root filter

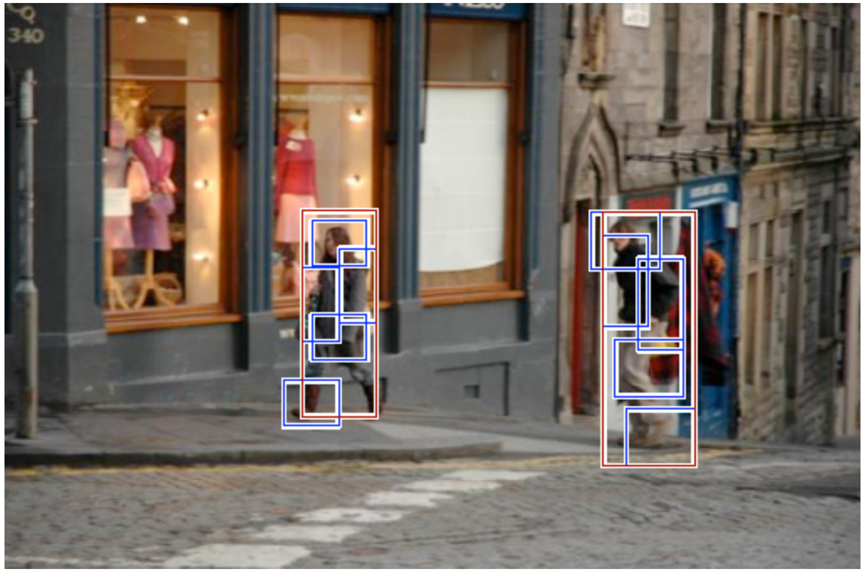


Part filters



Deformation weights

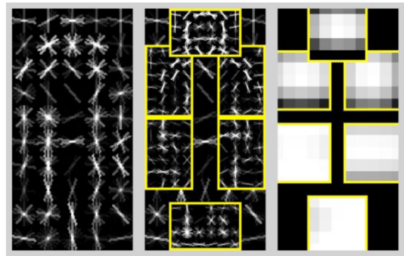


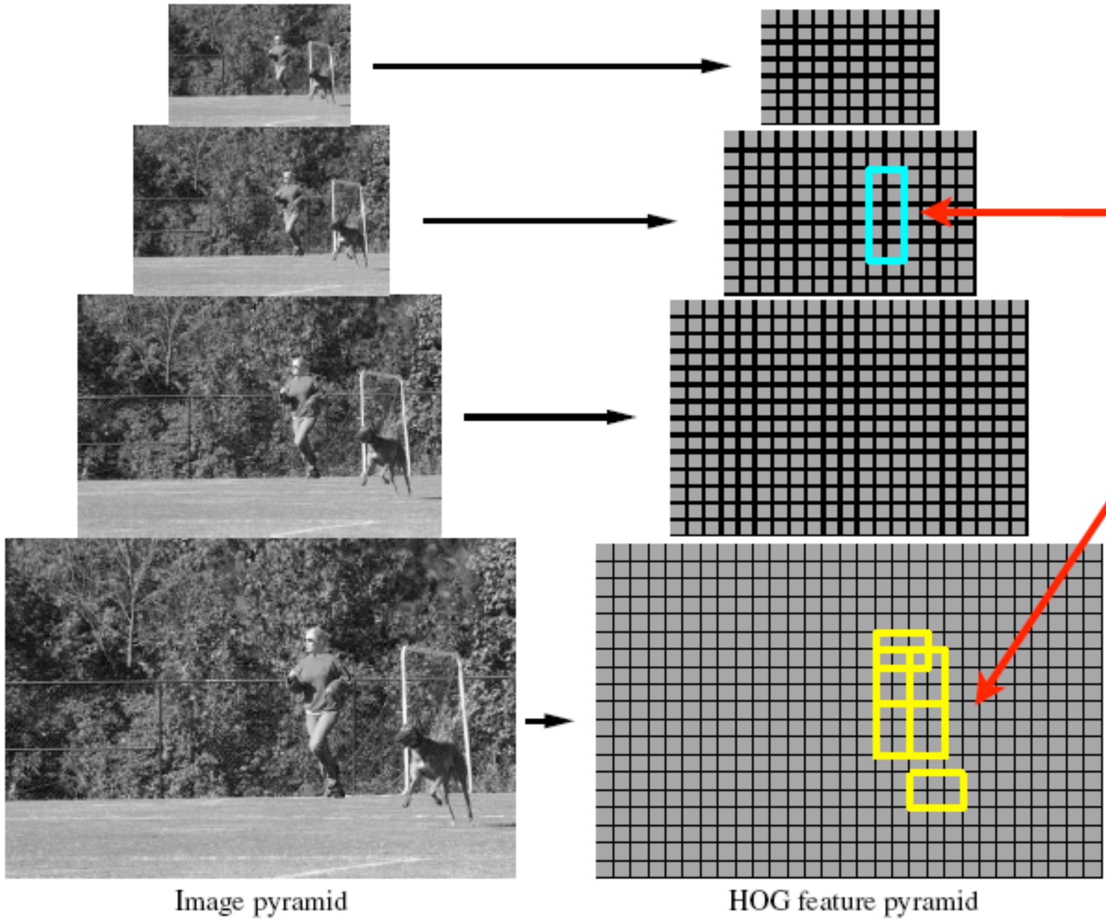


- Mixture of deformable part models
- Each component has global template + deformable parts
- Fully trained from bounding boxes alone

Object hypothesis

- Multiscale model: the resolution of part filters is twice the resolution of the root





$z = (p_0, \ldots, p_n)$

p_0 : location of root

$p_1, \ldots, p_n$: location of parts

Score is sum of filter scores minus deformation costs

Scoring an object hypothesis

- The score of a hypothesis is the sum of filter scores minus the sum of deformation costs

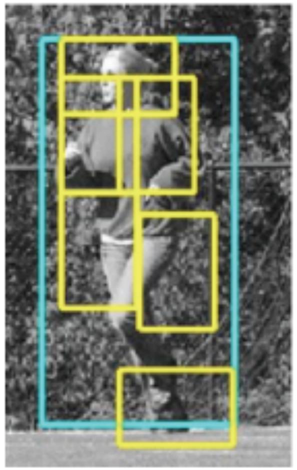
Subwindow features

Displacements

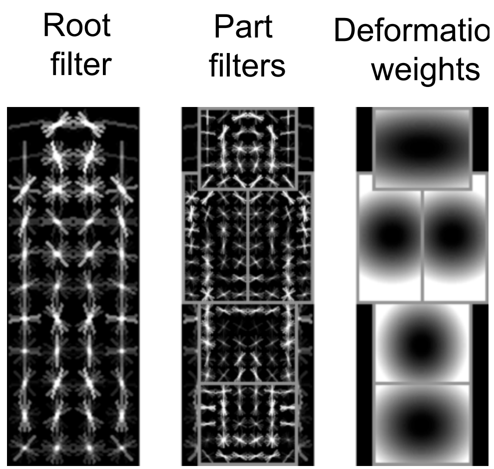
$$score(\mathbf{p}_0,\ldots,\mathbf{p}_n) = \sum_{i=0}^{n} \mathbf{F}_i \cdot \mathbf{H}(\mathbf{p}_i) - \sum_{i=1}^{n} \mathbf{D}_i \cdot (dx_i, dy_i, dx_i^2, dy_i^2)$$

Filters

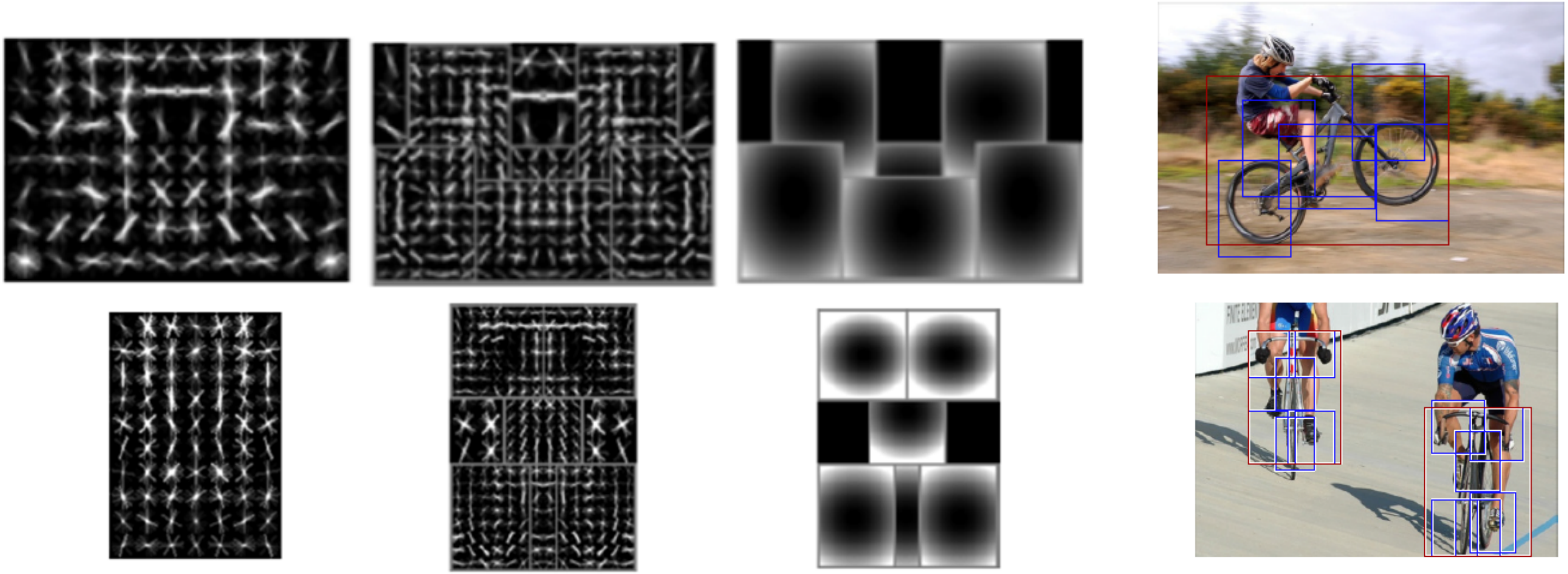
Deformation weights



Score = (filter scores) – (deformation costs)

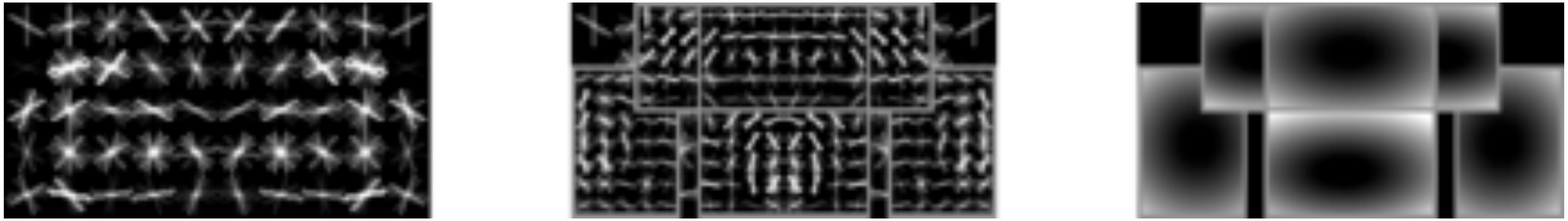


Bicycle model

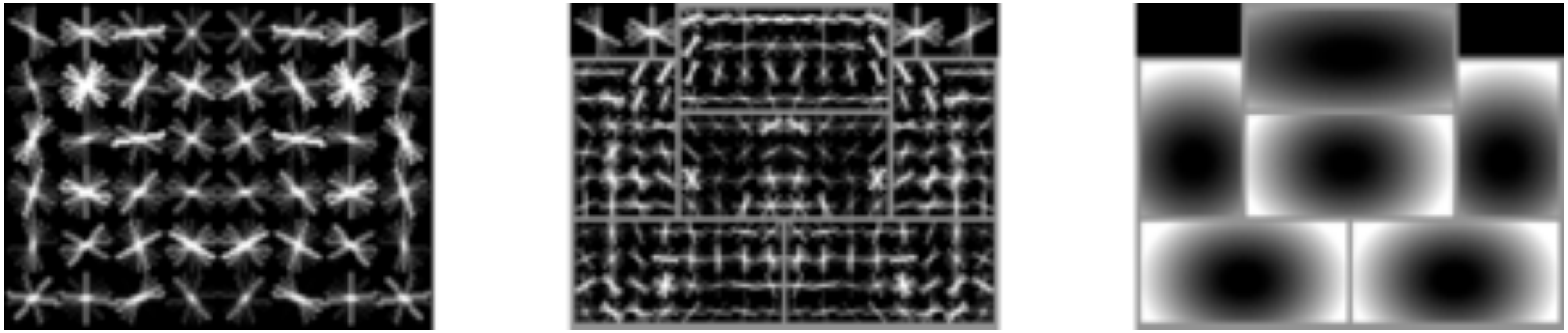


Car model

Component 1

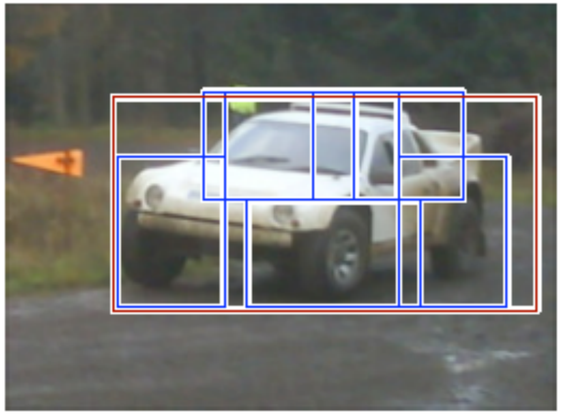


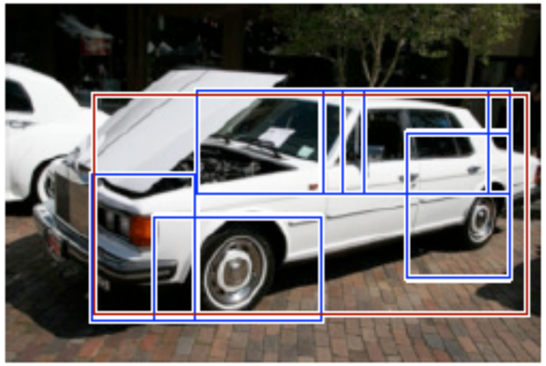
Component 2

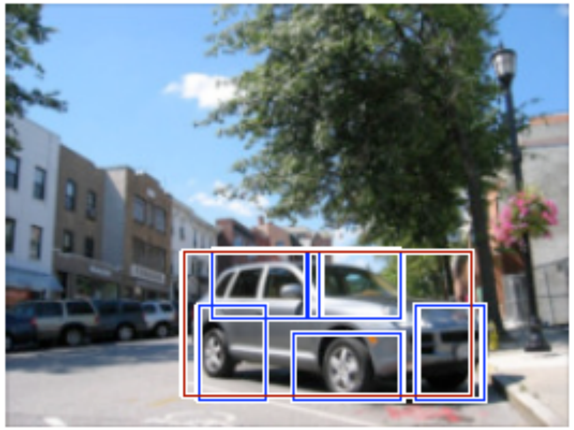


Car detection

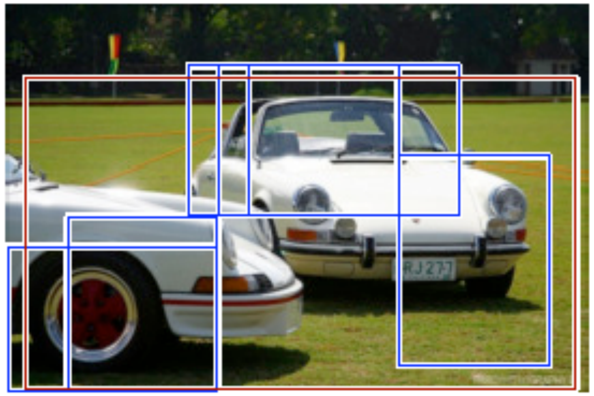
high scoring true positives

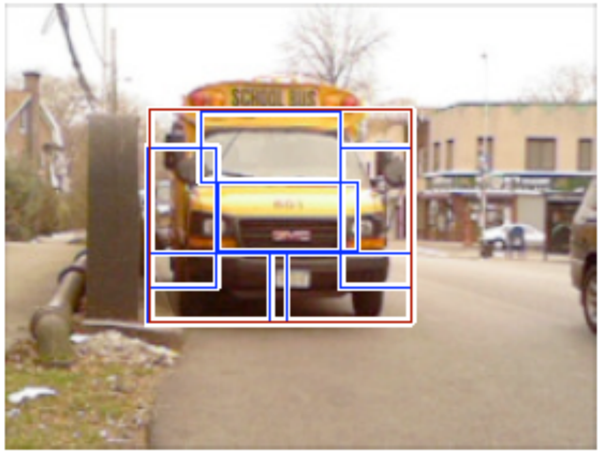




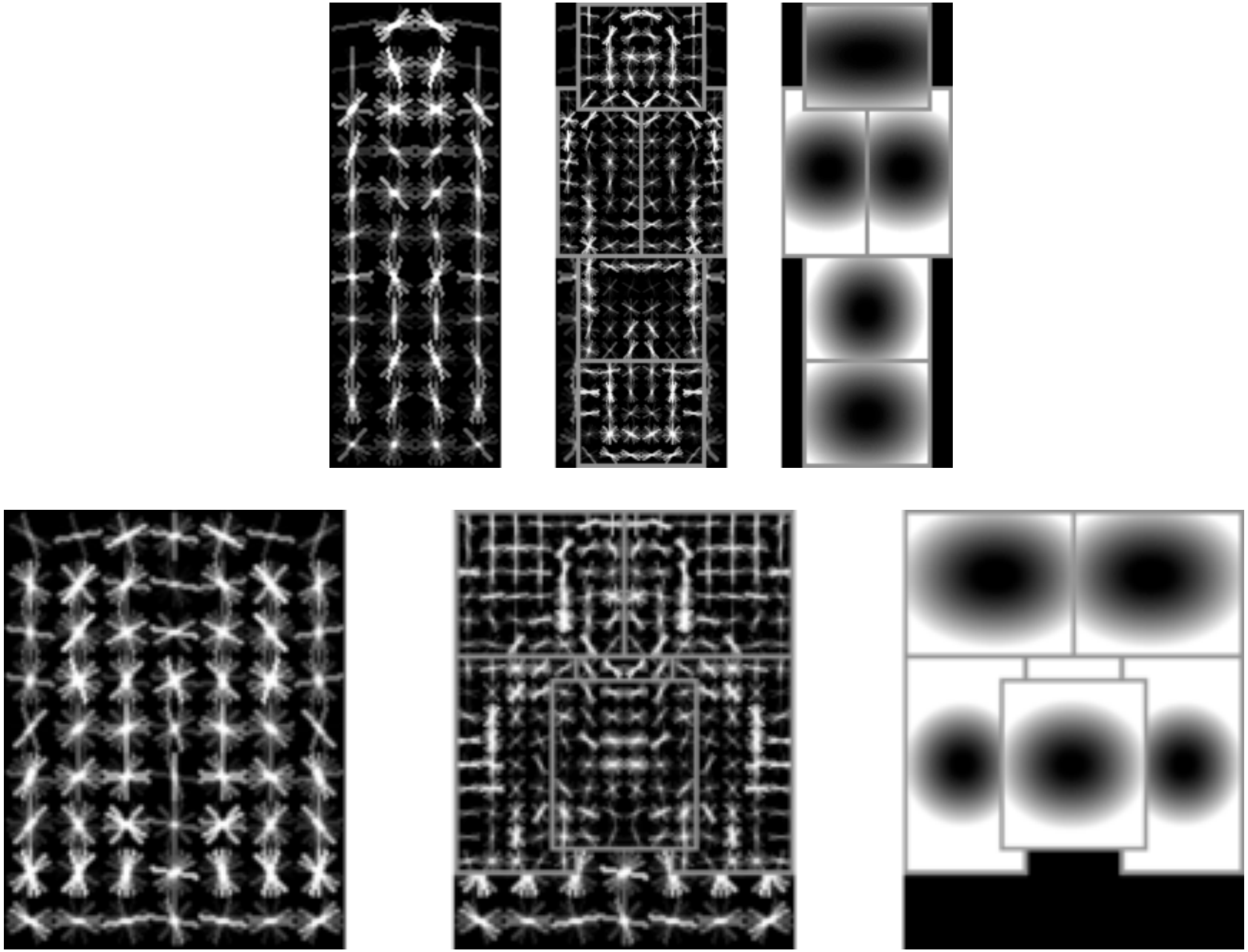


high scoring false positives



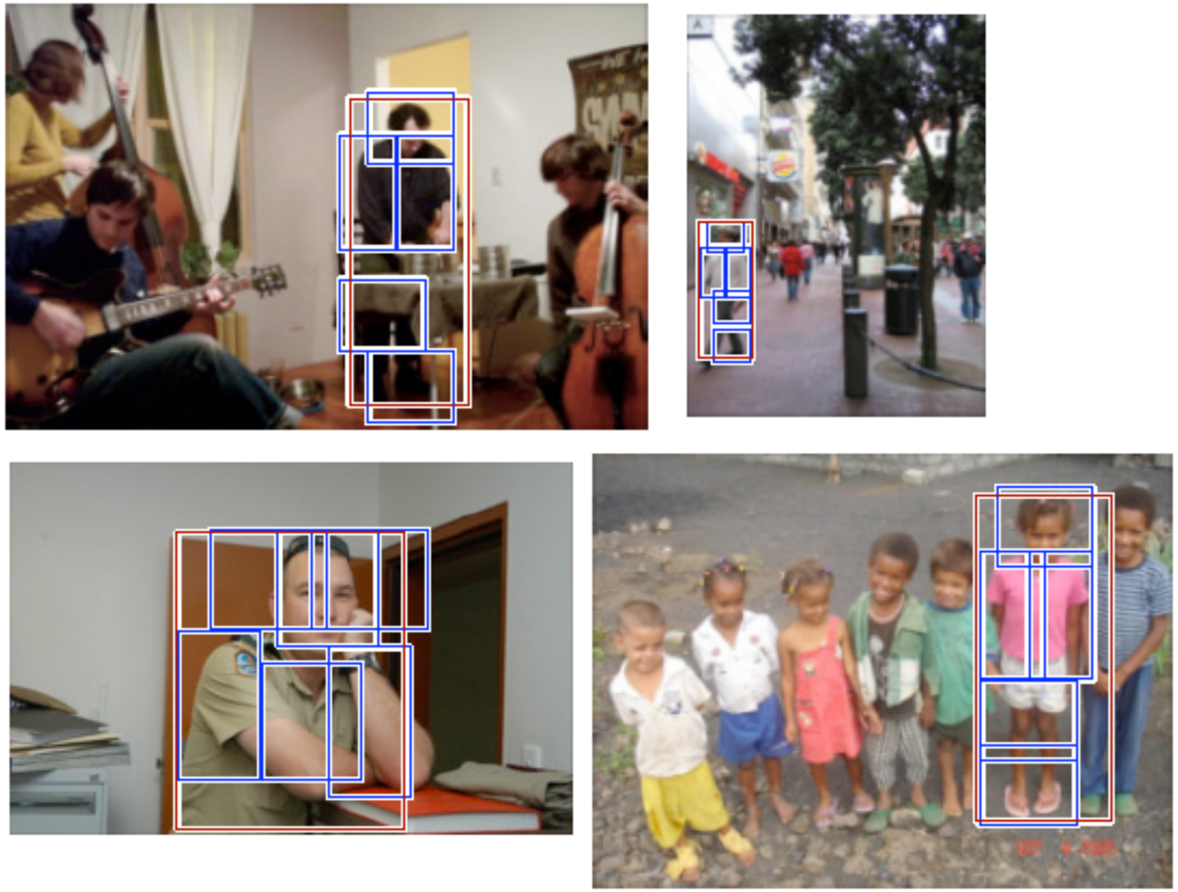


Person model

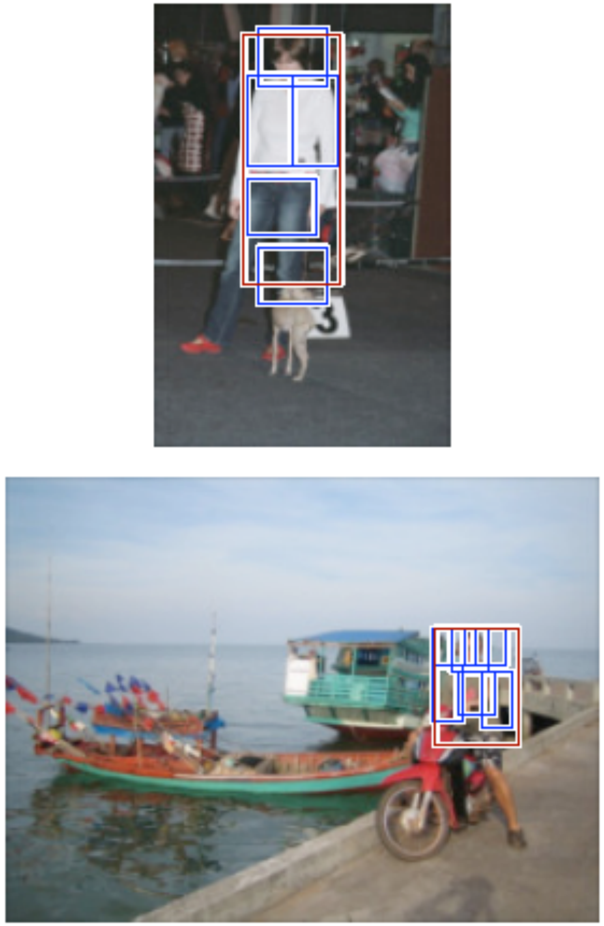


Person detection

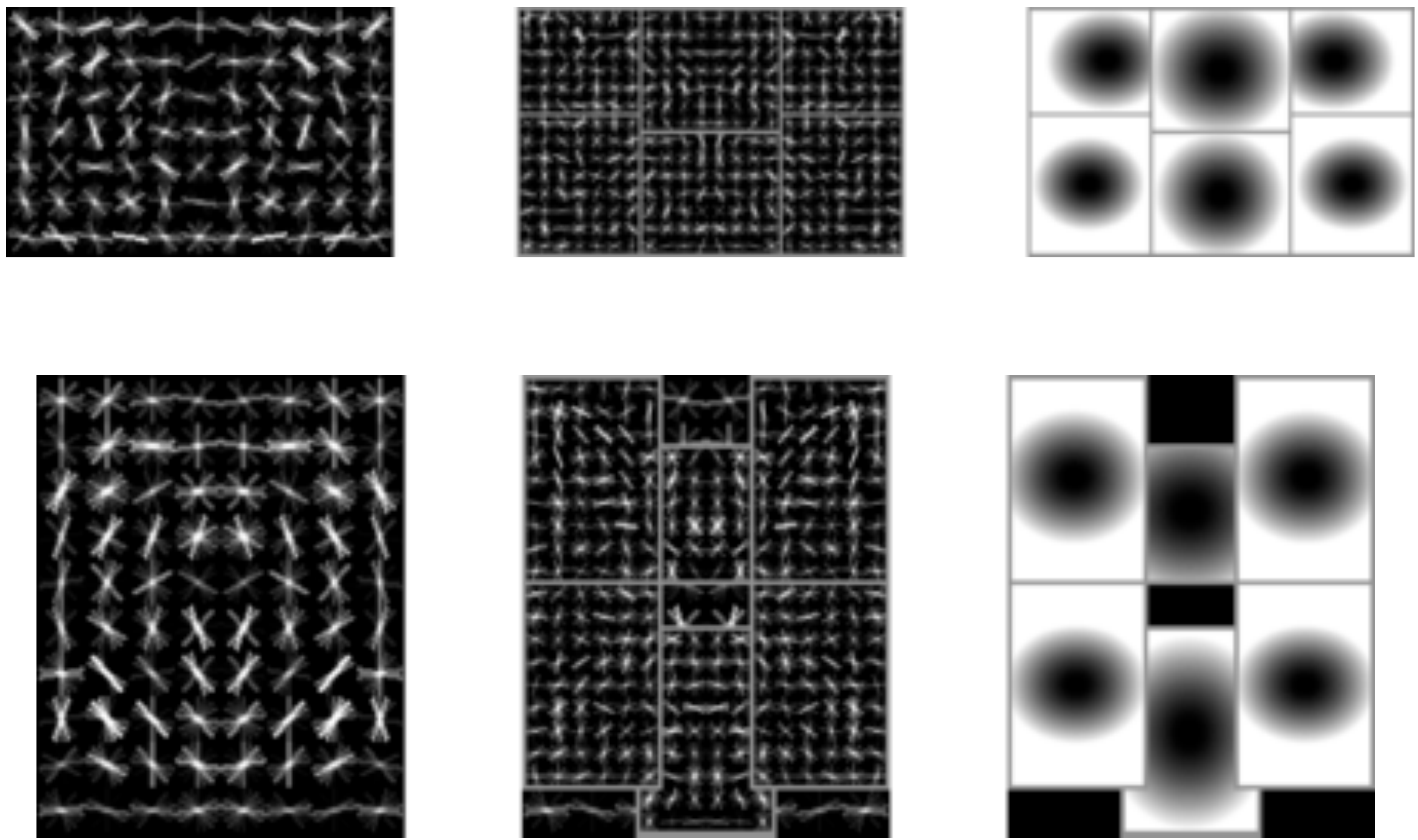
high scoring true positives



high scoring false positives
(not enough overlap)

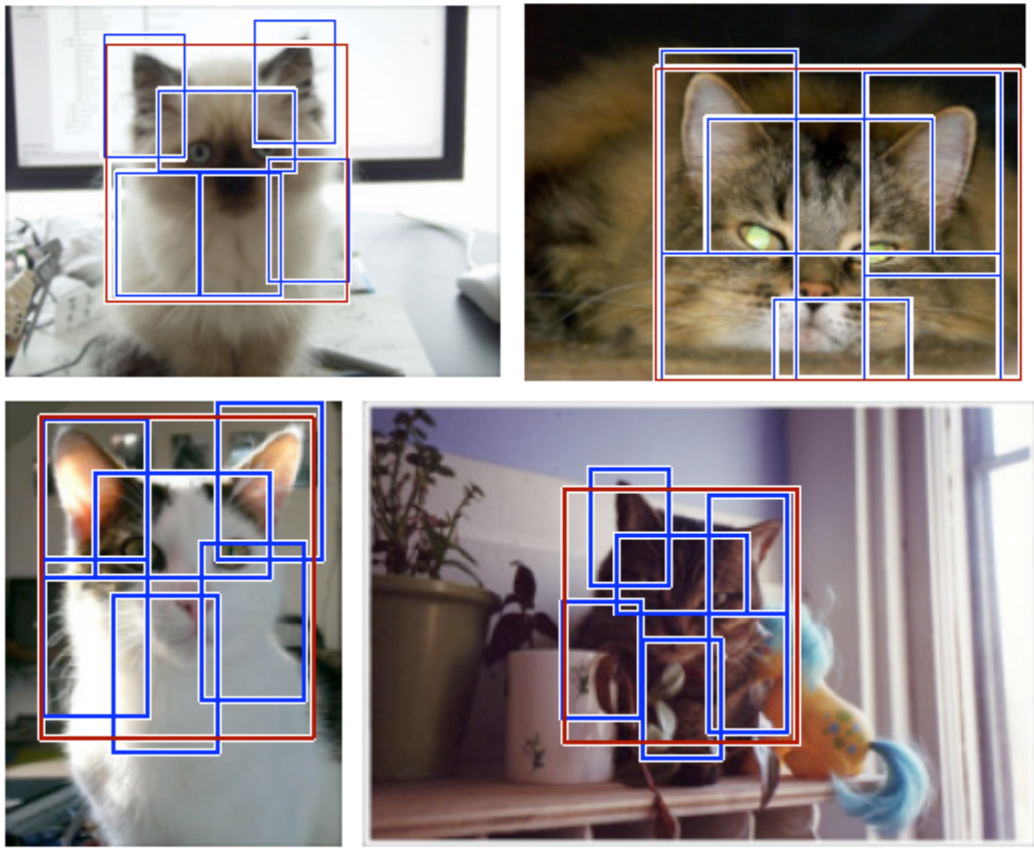


Cat model

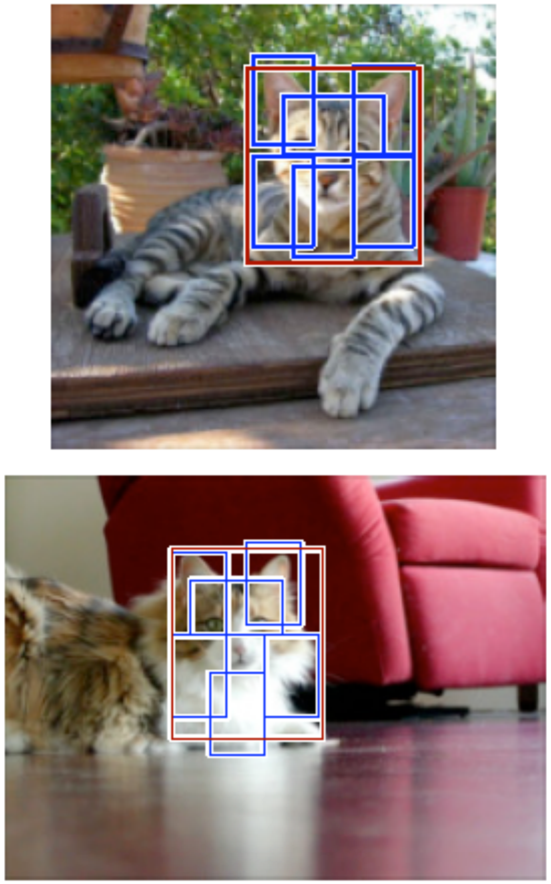


Cat detection

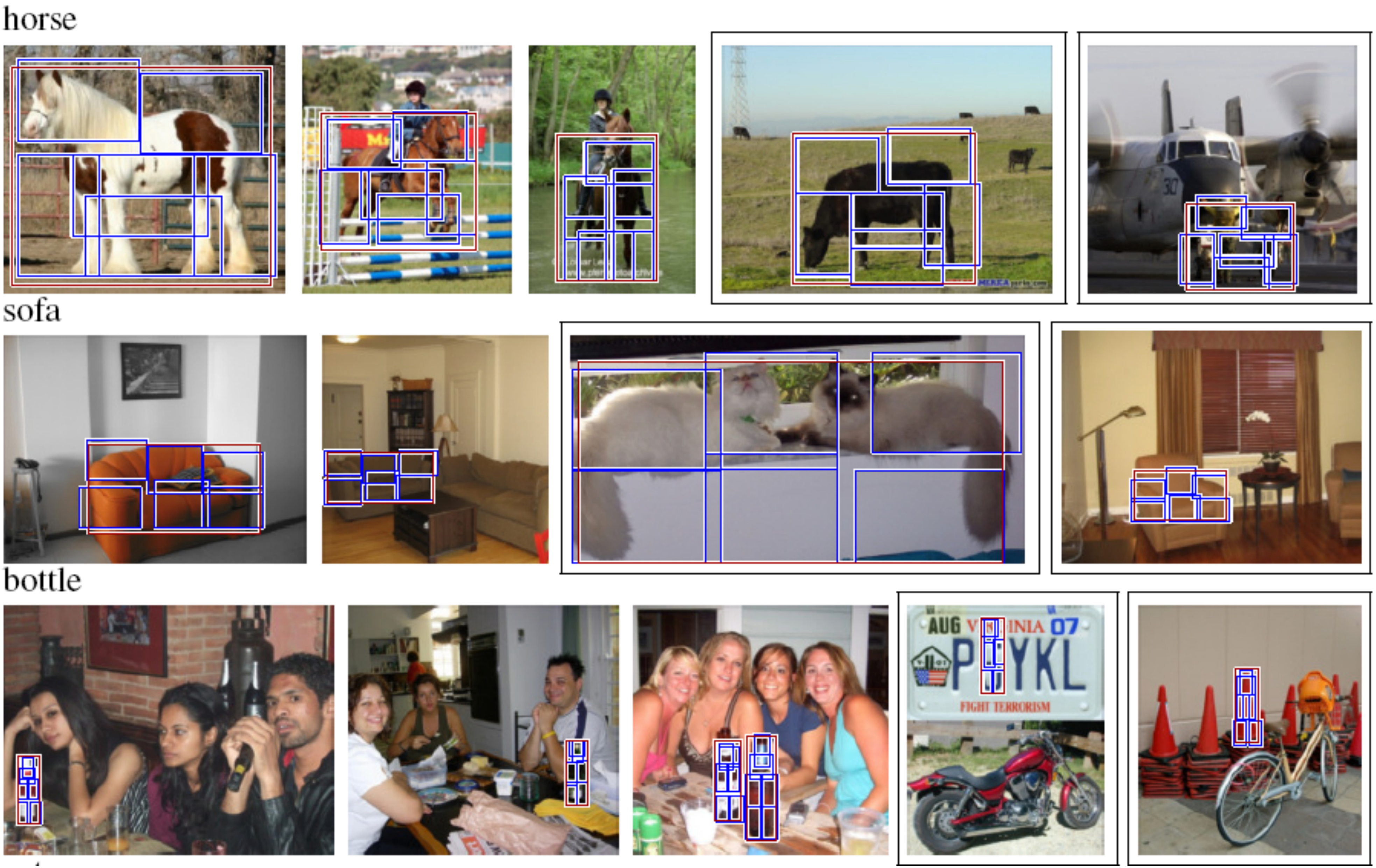
high scoring true positives



high scoring false positives
(not enough overlap)



More detections



More detections

Object Detection

Kuan-Wen Chen
2022/4/21