HA NOI UNIVERSITY OF SCIENCE AND TECHNOLOGY
SCHOOL OF INFORMATION AND COMMUNICATION TECHNOLOGY

Computer Vision

Chapter 7 : Object detection (part 2)

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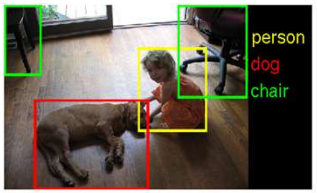
Chapter 7: Object detection (Part 2) Content

- Window-based generic object detection: Basic pipeline
- Boosting classifiers
- Face detection as case study
- SVM + HOG for human detection as case study
- Object proposals, Deformable Part Model (DPM)
- Evaluation

2

Object Detection

- **Problem**: Detecting and localizing generic objects from various categories, such as cars, people, etc.
- Challenges:
  - Illumination,
  - viewpoint,
  - deformations,
  - Intra-class variability



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Window-based generic object detection

Basic pipeline

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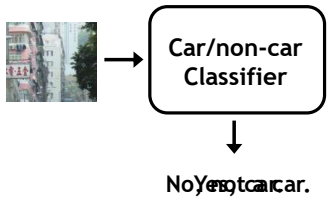
Generic category recognition: Basic framework

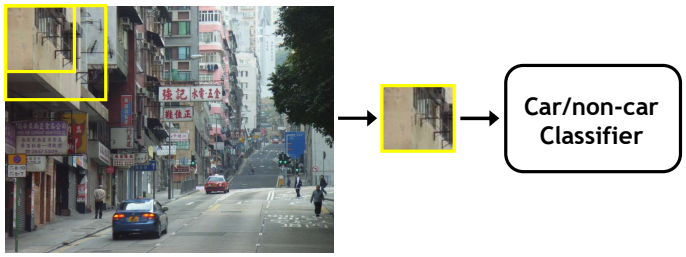
- Build/train object model
  - Choose a representation
  - Learn or fit parameters of model / classifier
- Generate candidates in new image
- Score the candidates

Window-based models Building an object model

Given the representation, train a binary classifier



Window-based models Generating and scoring candidates



Window-based models Generating and scoring candidates

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

YES!! Person match found

Window-based models
Generating and scoring candidates

- But what if we were looking for buses?

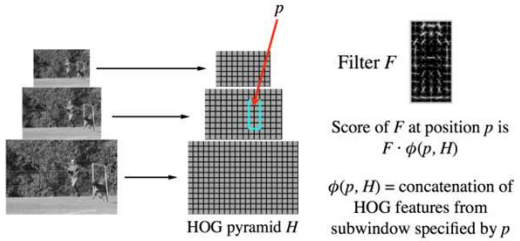
No bus found!

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

Bus found

Multi-scale sliding window

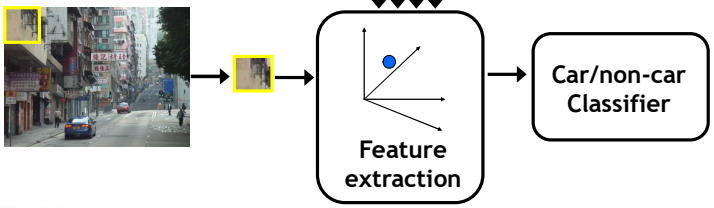
- Work with multiple size windows
- Create a feature pyramid



Window-based object detection: recap

Training:
1. Obtain training data
2. Define features
3. Define classifier

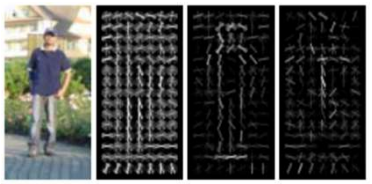
Given new image:
1. Slide window
2. Score by classifier



Slide: Kristen Grauman

Features

- HOG

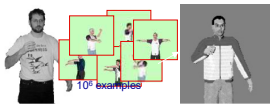


- Bags of visual words

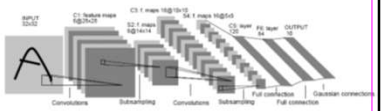
- Haar features, …

Discriminative classifier construction

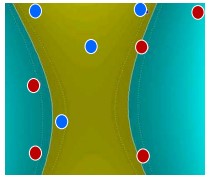
Nearest neighbor



Neural networks

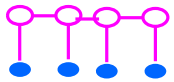


Support Vector Machines



Boosting

Conditional Random Fields



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Boosting classifiers

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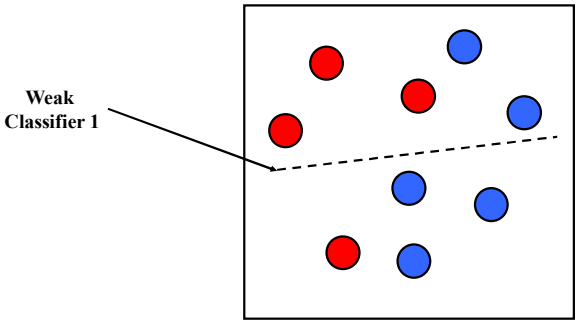
Boosting intuition



Slide credit: Paul Viola

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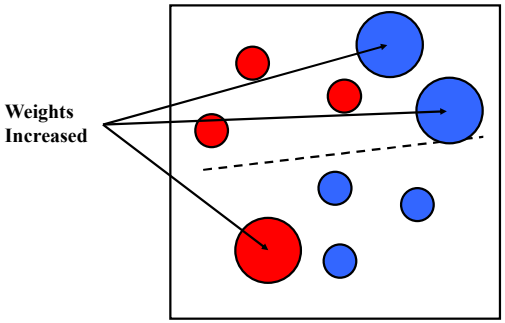
Boosting illustration



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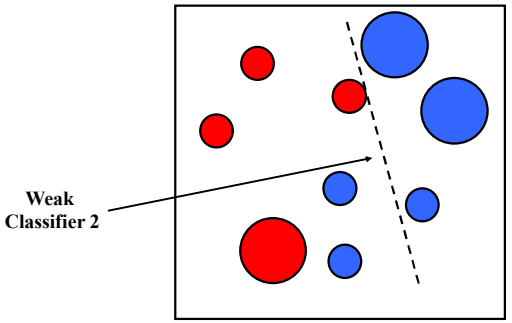
Boosting illustration



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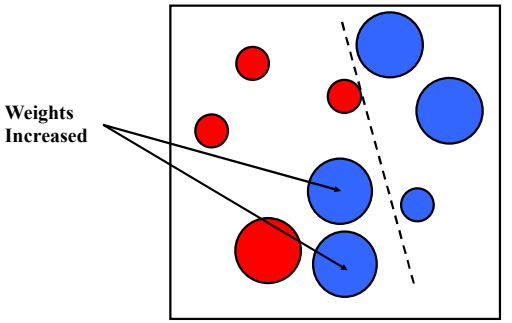
Boosting illustration



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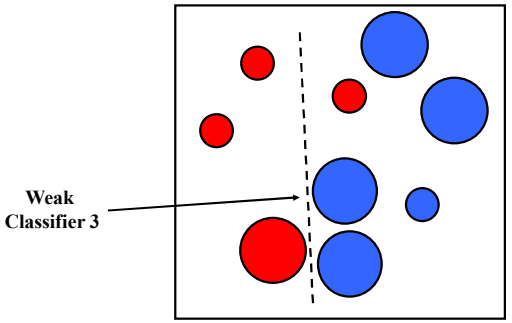
Boosting illustration



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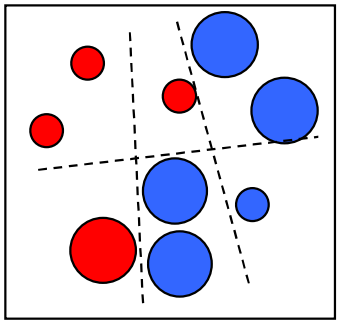
Boosting illustration

Final classifier is
a combination of weak
classifiers



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Boosting: training

- Initially, weight each training example equally
- In each boosting round:
  - Find the **weak learner** that achieves the lowest *weighted* training error
  - **Raise weights of training examples misclassified** by current weak learner
- Compute final classifier as linear combination of all weak learners
  - (weight of each learner is directly proportional to its accuracy)
- Exact formulas for re-weighting and combining weak learners **depend on the particular boosting scheme** (e.g., *AdaBoost*)

Slide credit: Lana Lazebnik

Face detection as case study

Viola-Jones face detector

ACCEPTED CONFERENCE ON COMPUTER VISION AND PATTERN RECOGNITION 2001

Rapid Object Detection using a Boosted Cascade of Simple Features

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Abstract

This paper describes a machine learning approach for vi-

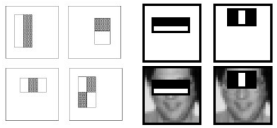
tected at 15 frames per second on a conventional 700 MHz Intel Pentium III. In other face detection systems, auxiliary information, such as image differences in video sequences,

Viola-Jones face detector

Main idea:

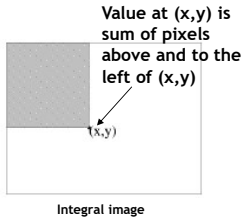
- Represent **local texture with efficiently computable "rectangular" features** within window of interest
- Select discriminative features to be weak classifiers
- Use boosted combination of them as final classifier
- Form a cascade of such classifiers, rejecting clear negatives quickly

Viola-Jones detector: features

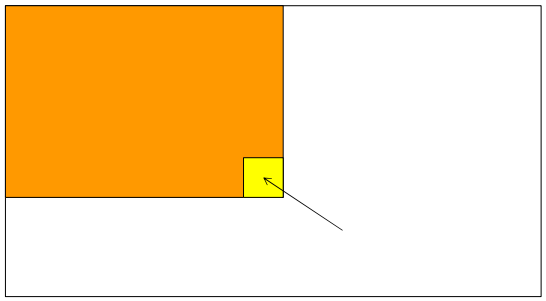


- **"Rectangular" filters**
  Feature output is difference between adjacent regions

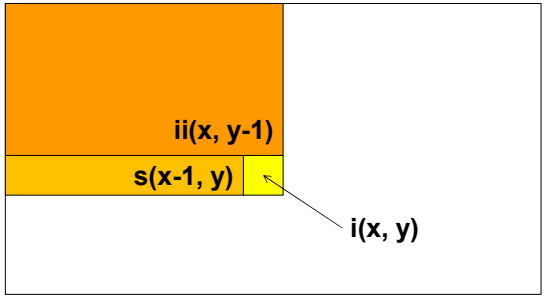
- Efficiently computable with **integral image**: any sum can be computed in constant time.



Computing the integral image



Computing the integral image



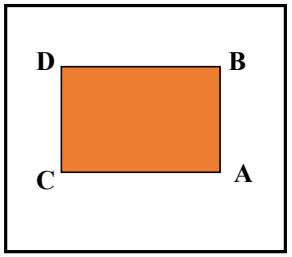
- Cumulative row sum: $s(x, y) = s(x–1, y) + i(x, y)$
- Integral image: $ii(x, y) = ii(x, y−1) + s(x, y)$

Computing sum within a rectangle

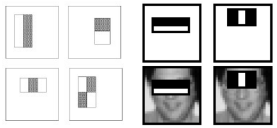
- Let A,B,C,D be the values of the integral image at the corners of a rectangle

- Then the sum of original image values within the rectangle can be computed as:
  sum = A – B – C + D

- Only 3 additions are required for any size of rectangle!



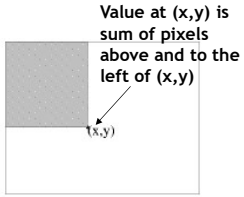
Viola-Jones detector: features



- **"Rectangular" filters**
  Feature output is difference between adjacent regions

- Efficiently computable with integral image: any sum can be computed in constant time

  Avoid scaling images → scale features directly for same cost



Integral image

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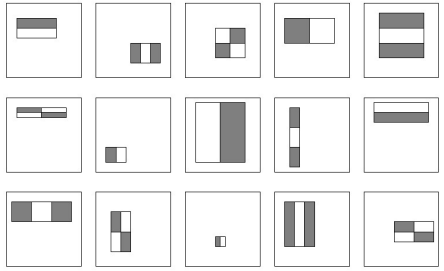
Viola-Jones detector: features



Considering all possible filter parameters: position, scale, and type:

180,000+ possible features associated with each 24 x 24 window

Which subset of these features should we use to determine if a window has a face?

Use AdaBoost both to select the informative features and to form the classifier

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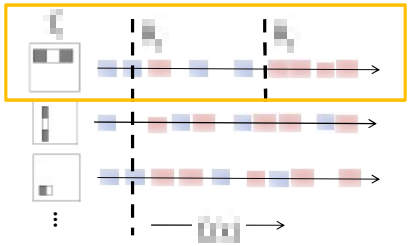
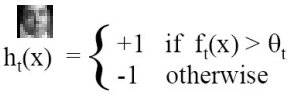
Viola-Jones detector: AdaBoost

- **Want to select the single rectangle feature and threshold that best separates positive (faces) and negative (non-faces) training examples, in terms of *weighted* error.**



Outputs of a possible rectangle feature on faces and non-faces.

Resulting weak classifier:



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

For next round, reweight the examples according to errors, choose another filter/threshold combo.

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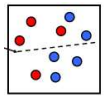
- Given example images $(x_1, y_1), \ldots, (x_n, y_n)$ where $y_i = 0, 1$ for negative and positive examples respectively.
- Initialize weights $w_{1,i} = \frac{1}{2m}, \frac{1}{2l}$ for $y_i = 0, 1$ respectively, where m and l are the number of negatives and positives respectively.
- For $t = 1, \ldots, T$:
  1. Normalize the weights,
     $$w_{t,i} \leftarrow \frac{w_{t,i}}{\sum_{j=1}^{n} w_{t,j}}$$
     so that w_t is a probability distribution.
  2. For each feature, j, train a classifier h_j which is restricted to using a single feature. The error is evaluated with respect to w_t, $\epsilon_j = \sum_i w_i |h_j(x_i) - y_i|$.
  3. Choose the classifier, h_t, with the lowest error ϵ_t.
  4. Update the weights:
     $$w_{t+1,i} = w_{t,i}\beta_t^{1-e_i}$$
     where $e_i = 0$ if example x_i is classified correctly, $e_i = 1$ otherwise, and $\beta_t = \frac{\epsilon_t}{1-\epsilon_t}$.
- The final strong classifier is:
  $$h(x) = \begin{cases} 1 & \sum_{t=1}^{T} \alpha_t h_t(x) \geq \frac{1}{2} \sum_{t=1}^{T} \alpha_t \\ 0 & \text{otherwise} \end{cases}$$
  where $\alpha_t = \log \frac{1}{\beta_t}$

Start with uniform weights on training examples

For T rounds



$\{x_1, \ldots x_n\}$

Evaluate *weighted* error for each feature, pick best.

Re-weight the examples:
Incorrectly classified -> more weight
Correctly classified -> less weight

Final classifier is combination of the weak ones, weighted according to error they had.

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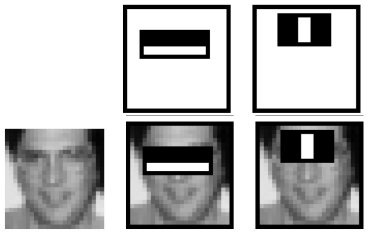
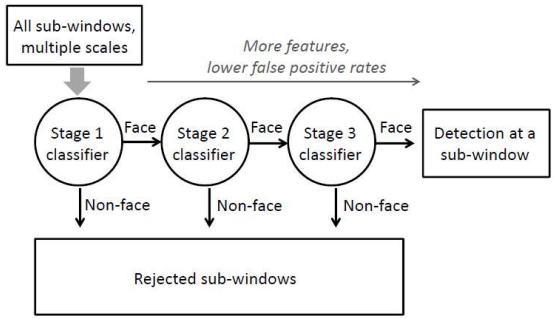
Viola-Jones Face Detector: Results



First two features selected

- Even if the filters are fast to compute, each new image has a lot of possible windows to search.
- How to make the detection more efficient?

Cascading classifiers for detection



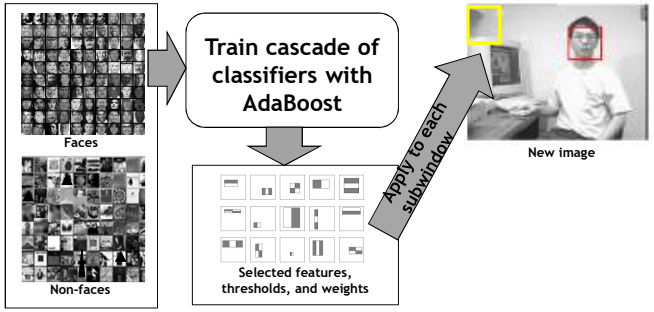
- Form a *cascade* with low false negative rates early on
- Apply less accurate but faster classifiers first **to immediately discard** windows that **clearly appear to be negative**

Slide: Kristen Grauman

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***

Viola-Jones detector: summary



- Train with 5K positives, 350M negatives
- Real-time detector using 38 layer cascade
- 6061 features in all layers

[Implementation available in OpenCV]

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Viola-Jones detector: summary

- A seminal approach to real-time object detection
  - 16,165 citations and counting
- Training is slow, but detection is very fast
- Key ideas
  - Integral images for fast feature evaluation
  - Boosting for feature selection
  - Attentional cascade of classifiers for fast rejection of non-face windows

P. Viola and M. Jones. *Rapid object detection using a boosted cascade of simple features.* CVPR 2001.

P. Viola and M. Jones. *Robust real-time face detection.* IJCV 57(2), 2004.

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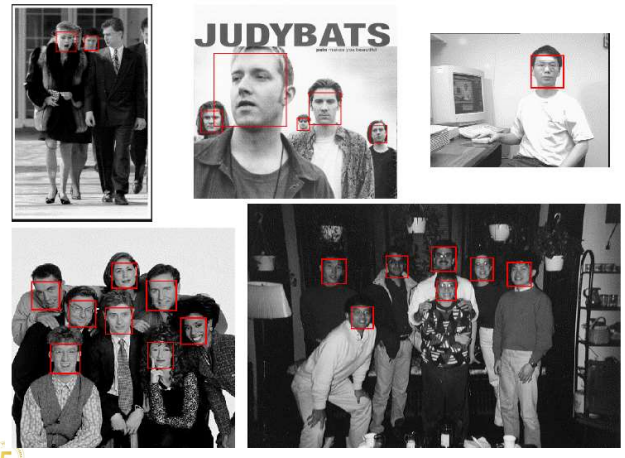
Viola-Jones Face Detector: Results



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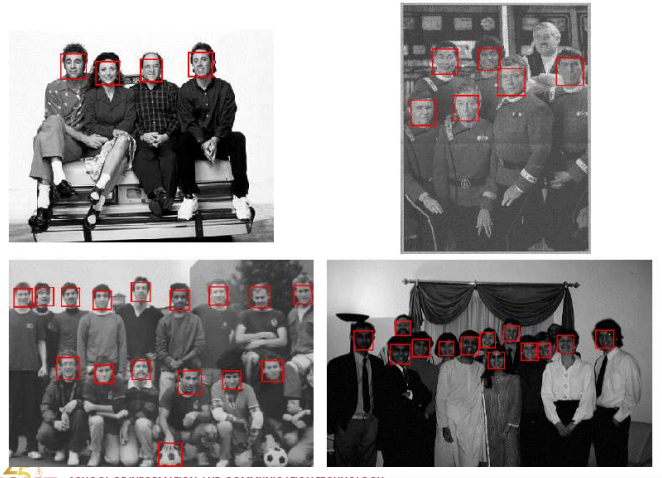
Viola-Jones Face Detector: Results



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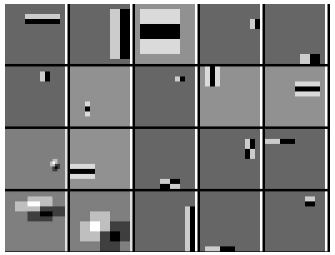
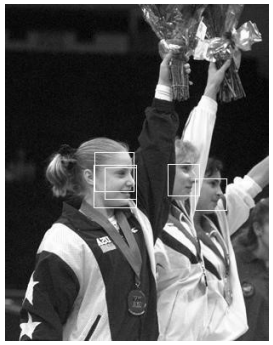
Viola-Jones Face Detector: Results

Detecting profile faces?

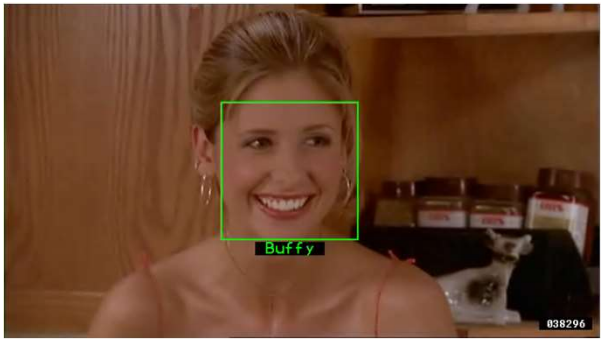
Can we use the same detector?



Viola-Jones Face Detector: Results

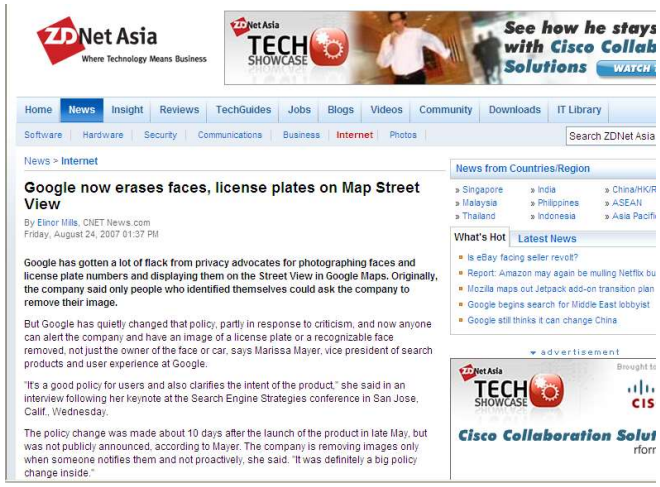


Example using Viola-Jones detector



Frontal faces detected and then tracked, character names inferred with alignment of script and subtitles.

Everingham, M., Sivic, J. and Zisserman, A.
"Hello! My name is... Buffy" - Automatic naming of characters in TV video,
BMVC 2006. http://www.robots.ox.ac.uk/~vgg/research/nface/index.html



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Consumer application: iPhoto

http://www.apple.com/ilife/iphoto/

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Consumer application: iPhoto

Things iPhoto thinks are faces

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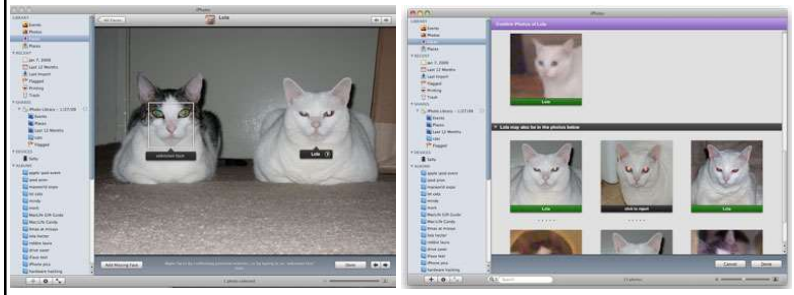
Consumer application: iPhoto

- Can be trained to recognize pets!

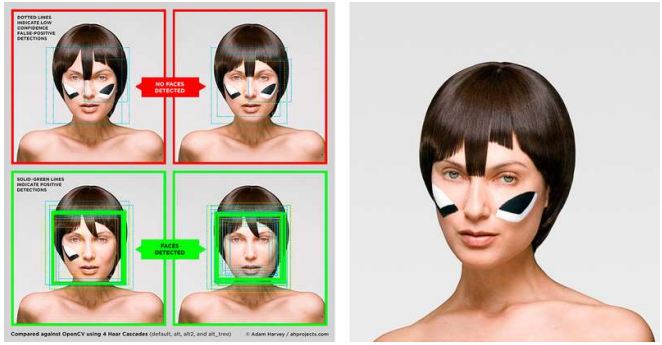


http://www.maclife.com/article/news/iphotos_faces_recognizes_cats

Slide credit: Lana Lazebnik

Privacy Gift Shop – CV Dazzle

- http://www.wired.com/2015/06/facebook-can-recognize-even-dont-show-face/
- Wired, June 15, 2015



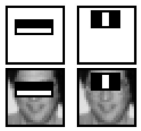
Slide: Kristen Grauman

Boosting: pros and cons

- Advantages of boosting
  - Integrates classification with feature selection
  - Complexity of training is linear in the number of training examples
  - Flexibility in the choice of weak learners, boosting scheme
  - Testing is fast
  - Easy to implement
- Disadvantages
  - Needs many training examples
  - Other discriminative models may outperform in practice (SVMs, CNNs,…)
    - especially for many-class problems

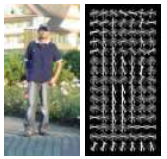
Slide credit: Lana Lazebnik

Window-based models: Two case studies



Boosting + face detection

Viola & Jones



SVM + person detection

e.g., Dalal & Triggs

SVM + HOG for human detection as case study

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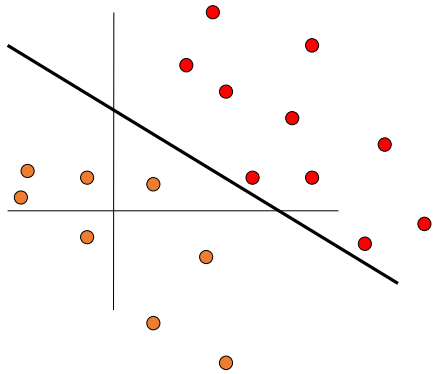
Linear classifiers



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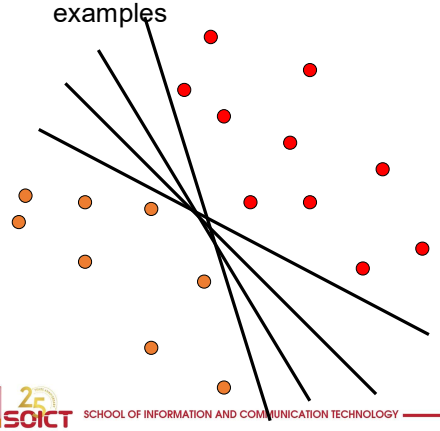
Linear classifiers

- Find linear function to separate positive and negative examples



$\mathbf{x}_i$ positive : $\mathbf{x}_i \cdot \mathbf{w} + b \geq 0$

$\mathbf{x}_i$ negative : $\mathbf{x}_i \cdot \mathbf{w} + b < 0$

Which line is best?

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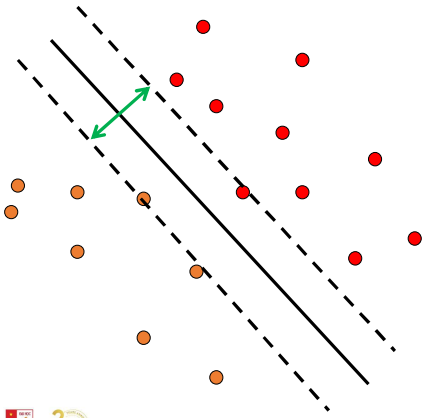
Support Vector Machines (SVMs)



- Discriminative classifier based on *optimal separating line (for 2d case)*
- Maximize the *margin* between the positive and negative training examples

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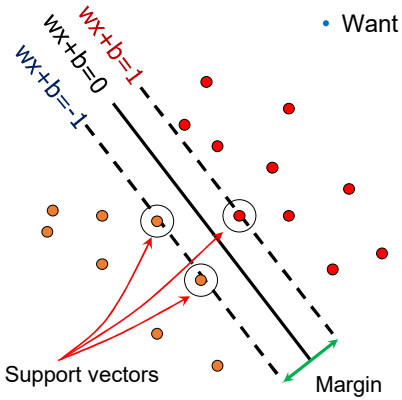
Support vector machines



- Want line that maximizes the margin

$\mathbf{x}_i$ positive $(y_i = 1)$: $\mathbf{x}_i \cdot \mathbf{w} + b \geq 1$
$\mathbf{x}_i$ negative $(y_i = -1)$: $\mathbf{x}_i \cdot \mathbf{w} + b \leq -1$

For support, vectors, $\mathbf{x}_i \cdot \mathbf{w} + b = \pm 1$

C. Burges, A Tutorial on Support Vector Machines for Pattern Recognition, Data Mining and Knowledge Discovery, 1998

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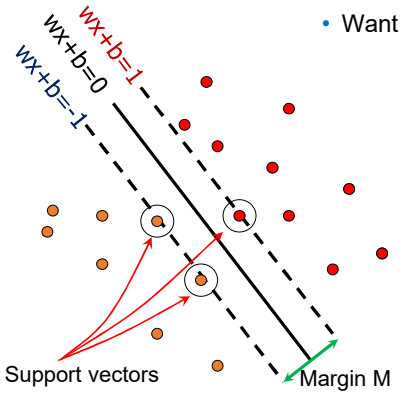
Support vector machines



- Want line that maximizes the margin

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$\mathbf{x}_i$ negative $(y_i = -1)$: $\mathbf{x}_i \cdot \mathbf{w} + b \leq -1$

For support vectors, $\mathbf{x}_i \cdot \mathbf{w} + b = \pm 1$

Distance between point and line: $\frac{|\mathbf{x}_i \cdot \mathbf{w} + b|}{\|\mathbf{w}\|}$

For support vectors:

$$\frac{\mathbf{w}^T\mathbf{x} + b}{\|\mathbf{w}\|} = \frac{\pm 1}{\|\mathbf{w}\|} \qquad M = \left|\frac{1}{\|\mathbf{w}\|} - \frac{-1}{\|\mathbf{w}\|}\right| = \frac{2}{\|\mathbf{w}\|}$$

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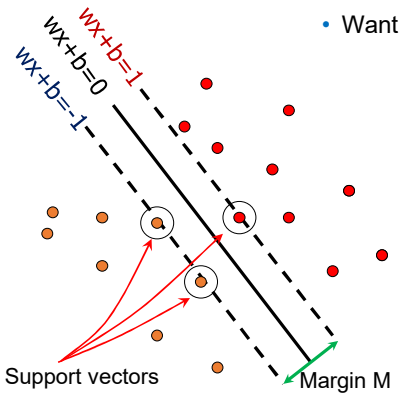
Support vector machines



- Want line that maximizes the margin

$\mathbf{x}_i$ positive $(y_i = 1)$: $\mathbf{x}_i \cdot \mathbf{w} + b \geq 1$
$\mathbf{x}_i$ negative $(y_i = -1)$: $\mathbf{x}_i \cdot \mathbf{w} + b \leq -1$

For support vectors, $\mathbf{x}_i \cdot \mathbf{w} + b = \pm 1$

Distance between point and line: $\frac{|\mathbf{x}_i \cdot \mathbf{w} + b|}{\|\mathbf{w}\|}$

Therefore, the margin is $2 / \|\mathbf{w}\|$

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Finding the maximum margin line

1. Maximize margin $2/\|\mathbf{w}\|$
2. Correctly classify all training data points:

$\mathbf{x}_i$ positive $(y_i = 1)$: $\mathbf{x}_i \cdot \mathbf{w} + b \geq 1$

$\mathbf{x}_i$ negative $(y_i = -1)$: $\mathbf{x}_i \cdot \mathbf{w} + b \leq -1$

Quadratic optimization problem:

Minimize $\frac{1}{2}\mathbf{w}^T\mathbf{w}$

Subject to $y_i(\mathbf{w} \cdot \mathbf{x}_i + b) \geq 1$

C. Burges, A Tutorial on Support Vector Machines for Pattern Recognition, Data Mining and Knowledge Discovery, 1998

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Finding the maximum margin line

- Solution: $\mathbf{w} = \sum_i \alpha_i y_i \mathbf{x}_i$

learned weight

Support vector

C. Burges, A Tutorial on Support Vector Machines for Pattern Recognition, Data Mining and Knowledge Discovery, 1998

Finding the maximum margin line

- Solution: $\mathbf{w} = \sum_i \alpha_i y_i \mathbf{x}_i$

  $b = y_i - \mathbf{w} \cdot \mathbf{x}_i$ (for any support vector)

  $\mathbf{w} \cdot \mathbf{x} + b = \sum_i \alpha_i y_i \mathbf{x}_i \cdot \mathbf{x} + b$

- Classification function:

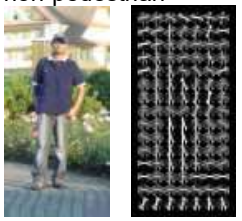
$$f(x) = \text{sign}(\mathbf{w} \cdot \mathbf{x} + b)$$
$$= \text{sign}\left(\sum_i \alpha_i y_i \mathbf{x}_i \cdot \mathbf{x} + b\right)$$

If f(x) < 0, classify as negative,
if f(x) > 0, classify as positive

C. Burges, A Tutorial on Support Vector Machines for Pattern Recognition, Data Mining and Knowledge Discovery, 1998

Person detection with HoG's & linear SVM's

- Histogram of oriented gradients (HoG):
  - Map each grid cell in the input window to a histogram counting the gradients per orientation.
- Train a linear SVM
  - using training set of pedestrian vs. non-pedestrian windows.



Dalal & Triggs, CVPR 2005

Person detection with HoGs & linear SVMs

- For more detail about HoG:
  - Histograms of Oriented Gradients for Human Detection, Navneet Dalal, Bill Triggs, International Conference on Computer Vision & Pattern Recognition - June 2005
  - http://lear.inrialpes.fr/pubs/2005/DT05/

Window-based detection: strengths

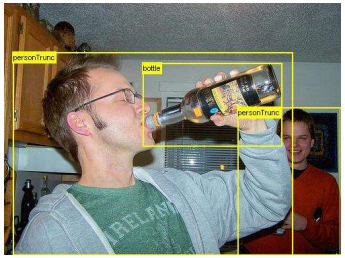
- Sliding window detection and global appearance descriptors:
  - Simple detection protocol to implement
  - Good feature choices critical
  - Past successes for certain classes

Window-based detection: Limitations

- High computational complexity
  - For example: 250,000 locations x 30 orientations x 4 scales = 30,000,000 evaluations!
  - If training binary detectors independently, means cost increases linearly with number of classes
- With so many windows, false positive rate better be low

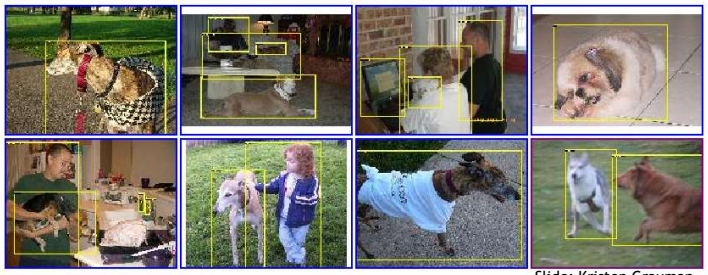
Limitations (continued)

- Not all objects are “box” shaped

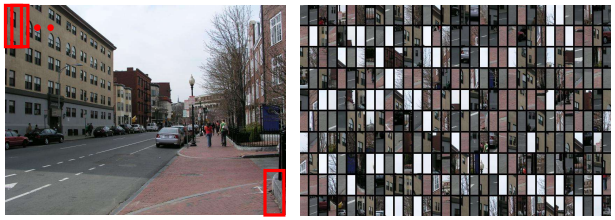



Limitations (continued)

- Non-rigid, deformable objects not captured well with representations assuming a fixed 2d structure; or must assume fixed viewpoint
- Objects with less-regular textures not captured well with holistic appearance-based descriptions



Limitations (continued)



Sliding window

Detector's view

If considering windows in isolation, context is lost

Figure credit: Derek Hoiem
Slide: Kristen Grauman

Limitations (continued)

- In practice, often entails large, cropped training set (expensive)
- Requiring good match to a global appearance description can lead to sensitivity to partial occlusions

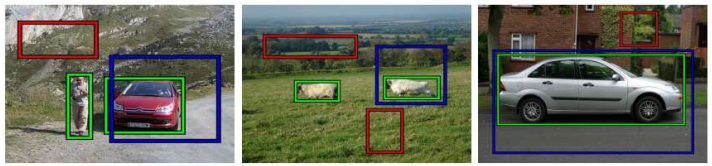
Slide: Kristen Grauman

Object proposals

Object proposals

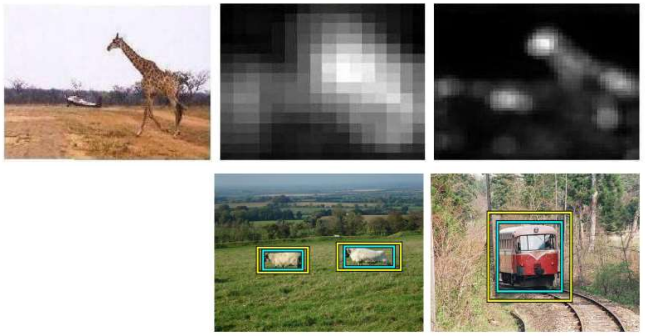
Main idea:

- Learn to generate category-independent regions/boxes that have **object-like** properties.
- Let object detector **search over "proposals"**, not exhaustive sliding windows



Alexe et al. Measuring the objectness of image windows, PAMI 2012

Object proposals



Multi-scale saliency

Color contrast

Alexe et al. Measuring the objectness of image windows, PAMI 2012

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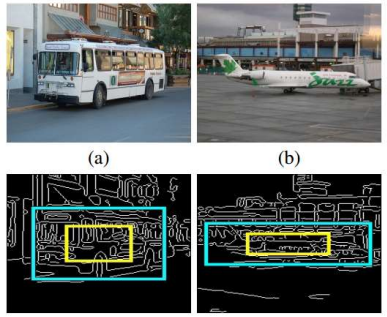
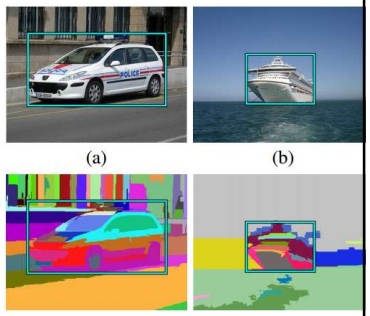
Object proposals

Edge density



(a) (b)

Superpipxel straddling



(a) (b)

Alexe et al. Measuring the objectness of image windows, PAMI 2012

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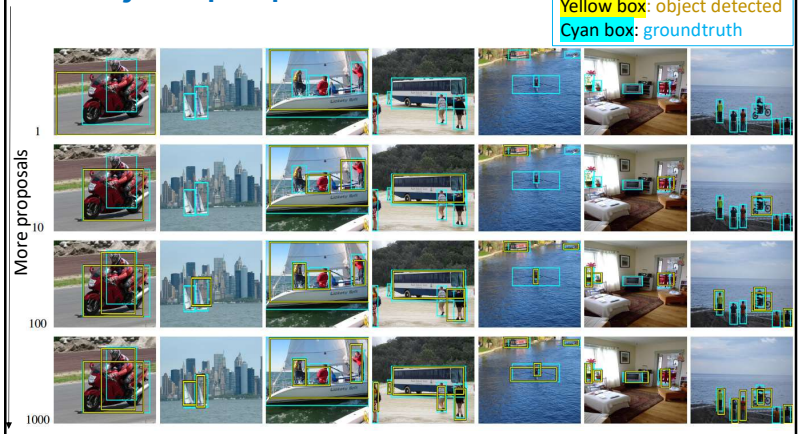
Object proposals

Yellow box: object detected
Cyan box: groundtruth



Alexe et al. Measuring the objectness of image windows, PAMI 2012

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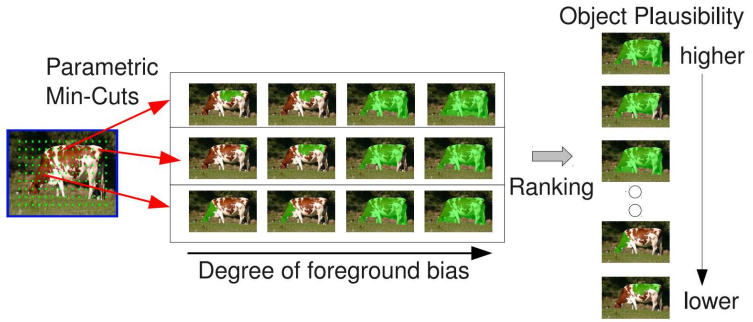
Region-based object proposals



- J. Carreira and C. Sminchisescu. Cpmc: Automatic object segmentation using constrained parametric min-cuts. PAMI, 2012.

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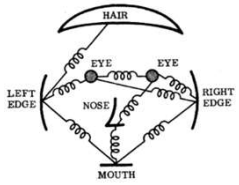
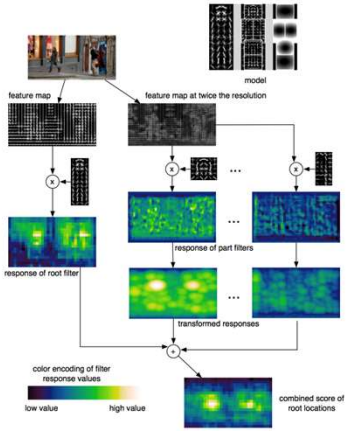
Deformable Part Model (DPM)

- 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



Felzenszwalb et al. , PAMI 2010

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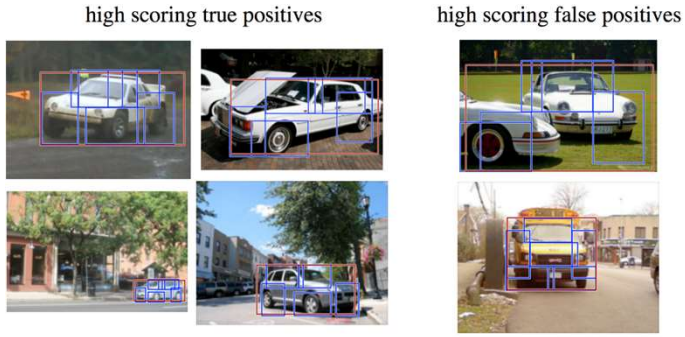
Deformable Part Model (DPM)



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Deformable Part Model (DPM)

- References
  - Pedro F. Felzenszwalb & Daniel P. Huttenlocher, Pictorial Structures for Object Recognition, IJCV 2005
    - https://www.cs.cornell.edu/~dph/papers/pict-struct-ijcv.pdf
  - P. F. Felzenszwalb, R. B. Girshick, D. McAllester, and D. Ramanan. Object detection with discriminatively trained part based models. IEEE Transactions on Pattern Analysis and Machine Intelligence, 32(9):1627–1645, 2010

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Object detection: Evaluation

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Object Detection Benchmarks

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

- Common Objects in Context (COCO)
  - 80 Object categories

How do we evaluate object detection?

predictions

ground truth

True positive:
- The overlap of the prediction with the ground truth is MORE than a threshold value (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 a threshold value (0.5)

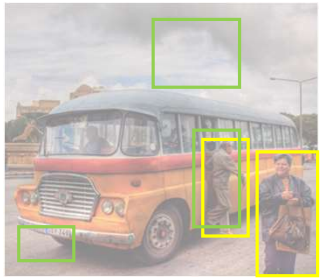
How do we evaluate object detection?

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**?

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	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

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

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

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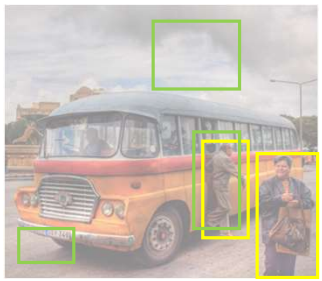
How do we evaluate object detection?



predictions

ground truth

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

So what is the
- precision?
- recall?

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Precision versus recall

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

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

- Recall:
  - how many of the ground truth objects can the model detect?
  - True Positive Rate (TPR)

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

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- 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!

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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

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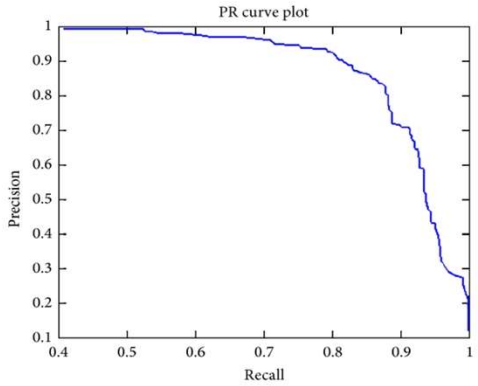
Precision – recall curve (PR curve)



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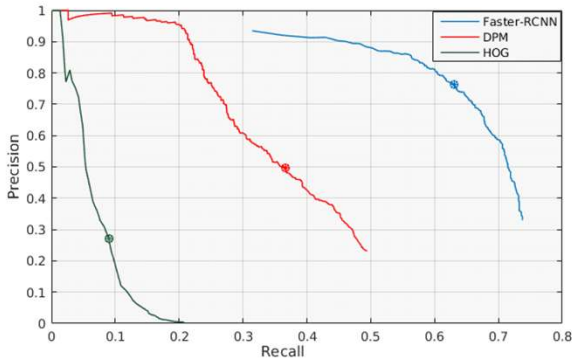
Which model is the best?



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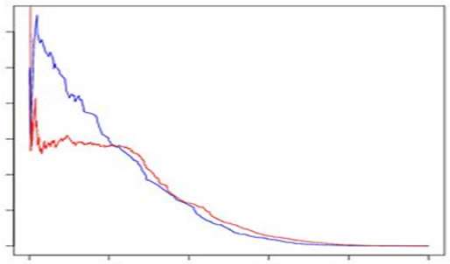
Which model is the best?



- **Area under curve (AUC), average precision (AP)**
- **F1-score** (highest value at optimal confidential score)

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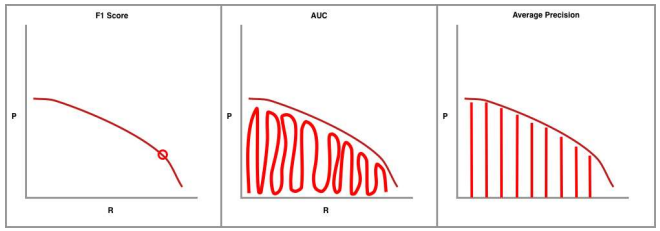
Which model is the best?



AP: The metric calculates the average precision (AP) for each class individually across all of the IoU thresholds

$$AP = \frac{1}{11} \sum_{r \in \{0, 0.1, 0..., 0.9, 1\}} p_{interp}(r)$$

mAP: the average of AP $= \frac{1}{11}(1 + 1 + 1 + 1 + 0.67 + 0.67 + 0.67 + 0.5 + 0.5 + 0.5 + 0.5)$

≈ 0.728

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Summary

Summary

- Object recognition as classification task
  - Boosting (face detection ex)
  - Support vector machines and HOG (human detection ex)
  - Sliding window search paradigm
    - Pros and cons
    - Speed up with attentional cascade
    - Object proposals, proposal regions as alternative

References:

Most of these slides were adapted from:
Kristen Grauman (CS 376: Computer Vision, Spring 2018, The University of Texas at Austin)

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SCHOOL OF INFORMATION AND COMMUNICATION TECHNOLOGY

Thank you!

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