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

Computer Vision

Chapter (part 1): Object detection

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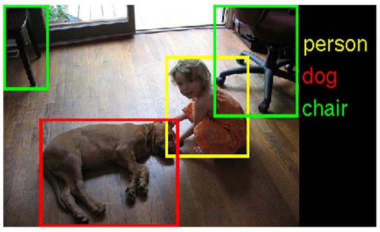
Contents

- Window-based generic object detection: basic pipeline
- Boosting classifiers
- Face detection as case study
- SVM + HOG for human detection as case study
- Object proposals
- [DPM]
- Evaluation

Object Detection

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

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



Window-based generic object detection

Basic pipeline

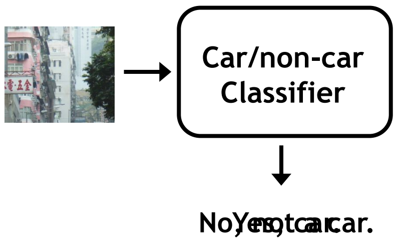
Generic category recognition: basic framework

- Build/train object model
  - Choose a representation
  - Learn or fit parameters of model / classifier

- Generate candidates in new image
- Score the candidates

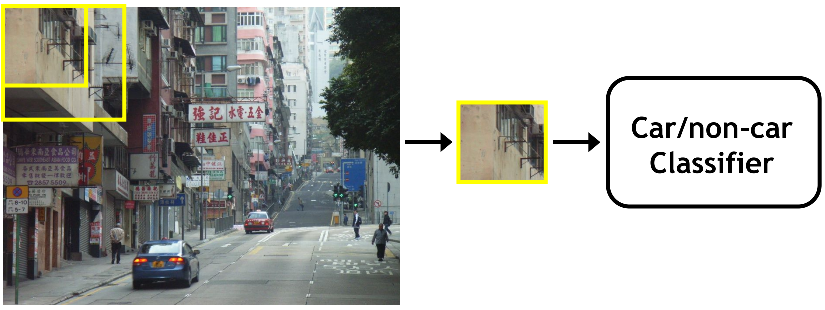
Window-based models
Building an object model

Given the representation, train a binary classifier



Slide: Kristen Grauman

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?

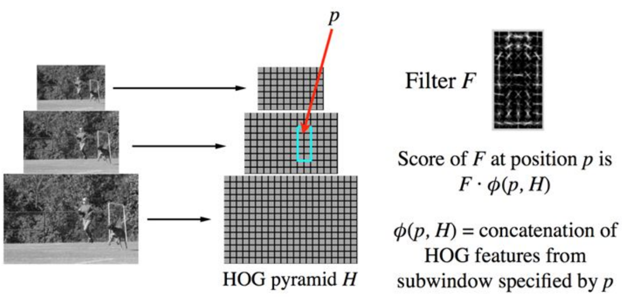
No bus found!

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

Bus found

Multi-scale sliding window

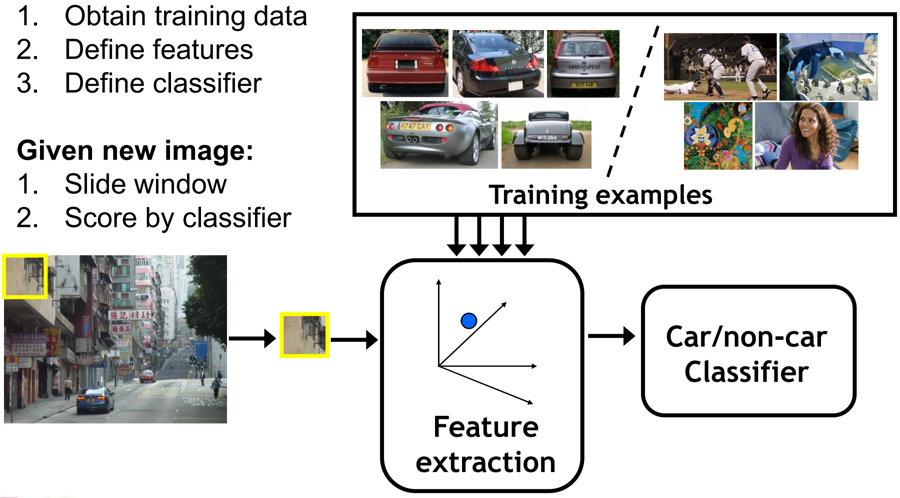
- Work with multiple size windows
- Create a feature pyramid



Window-based object detection: recap

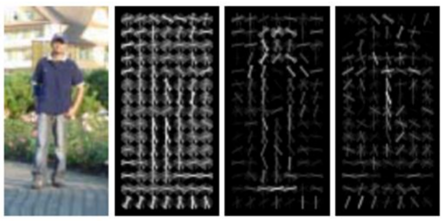
Training:
1. Obtain training data
2. Define features
3. Define classifier

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



Features

- HOG

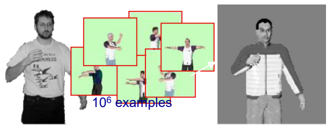


- Bags of visual words

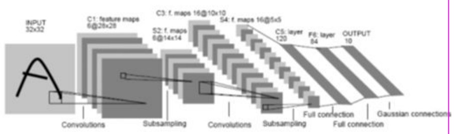
- Haar features, …

Discriminative classifier construction

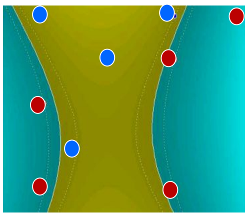
Nearest neighbor



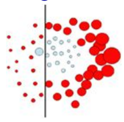
Neural networks



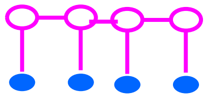
Support Vector Machines



Boosting

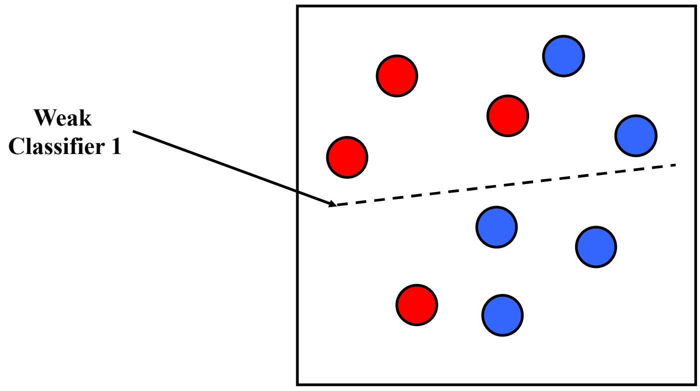


Conditional Random Fields



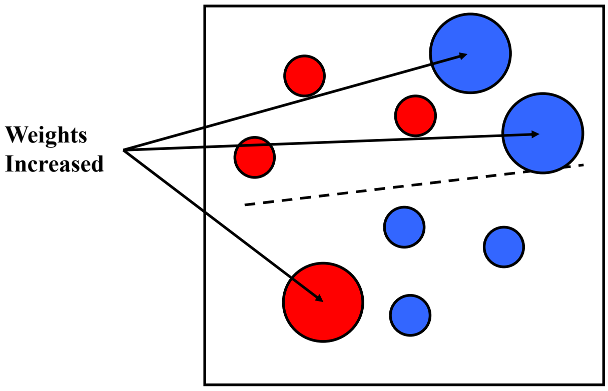
Boosting classifiers

Boosting intuition

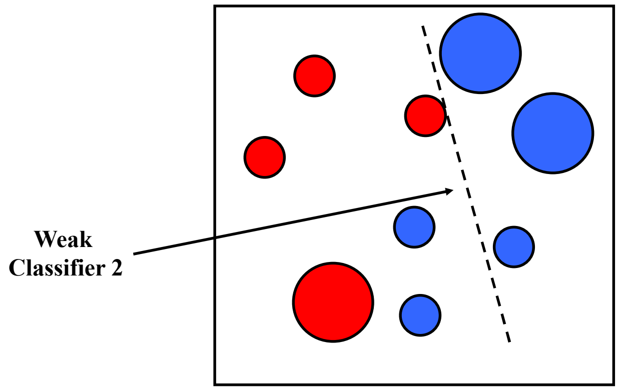


Slide credit: Paul Viola

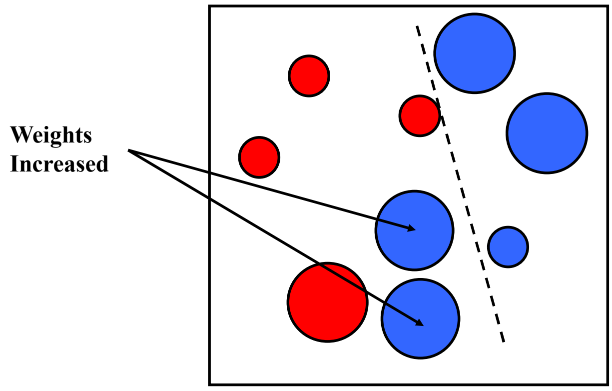
Boosting illustration



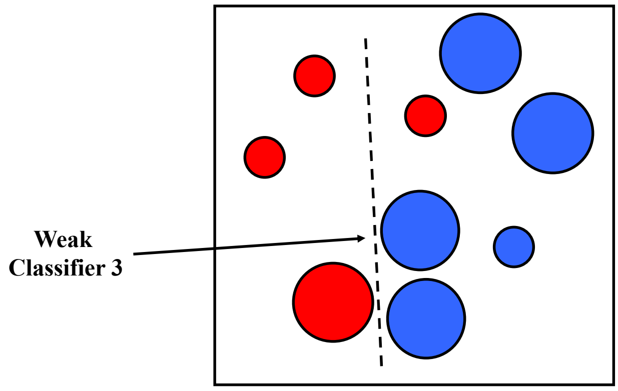
Boosting illustration



Boosting illustration

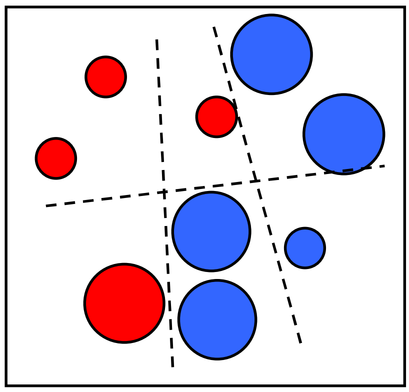


Boosting illustration



Boosting illustration

Final classifier is a combination of weak classifiers



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

Paul Viola
viola@merl.com
Mitsubishi Electric Research Labs
201 Broadway, 8th FL
Cambridge, MA 02139

Michael Jones
mjones@crl.dec.com
Compaq CRL
One Cambridge Center
Cambridge, MA 02142

Abstract

This paper describes a machine learning approach for vi-

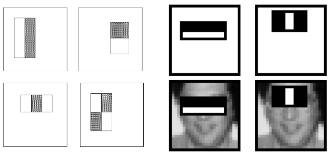
tected at 15 frames per second on a conventional 700 MHz Intel Pentium III. In other face detection systems, auxiliary information, such as image differences in video sequences,

Viola-Jones face detector

Main idea:

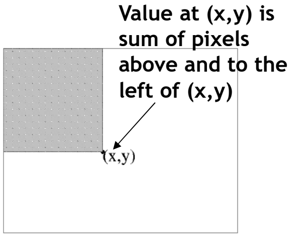
- Represent **local texture with efficiently computable “rectangular” features** within window of interest
- Select discriminative features to be weak classifiers
- Use boosted combination of them as final classifier
- Form a cascade of such classifiers, rejecting clear negatives quickly

Viola-Jones detector: features



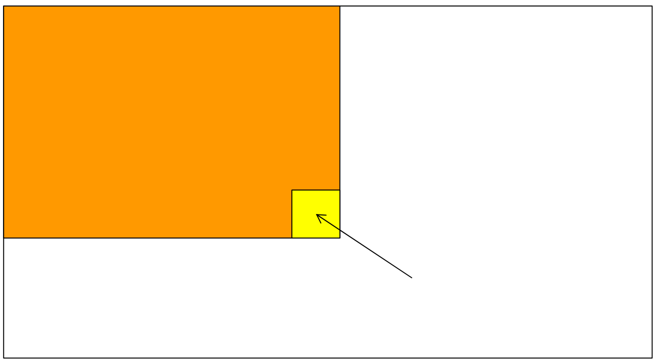
- **"Rectangular" filters**
  Feature output is difference between adjacent regions

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

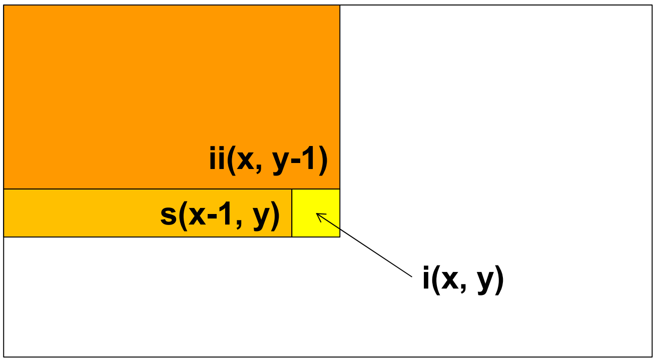


Integral image

Computing the integral image



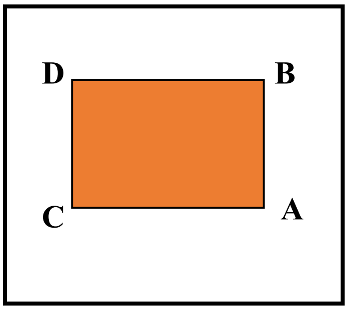
Computing the integral image



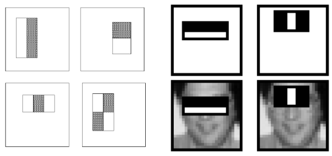
- Cumulative row sum: s(x, y) = s(x–1, y) + i(x, y)
- Integral image: ii(x, y) = ii(x, y−1) + s(x, y)

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



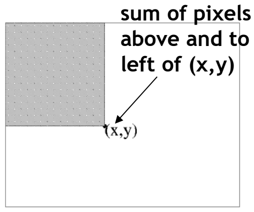
- **“Rectangular” filters**

  Feature output is difference between adjacent regions

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

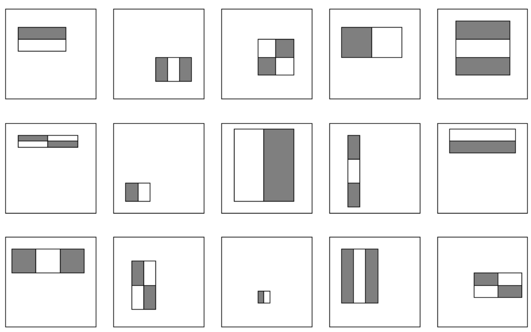
  Avoid scaling images → scale features directly for same cost

Value at (x,y) is sum of pixels above and to the left of (x,y)



Integral image

Viola-Jones detector: features



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

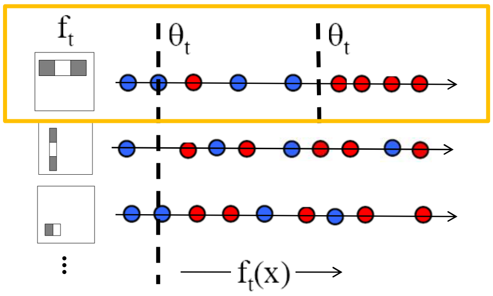
180,000+ possible features associated with each 24 x 24 window

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

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:

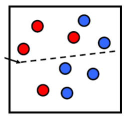
$$h_t(x) = \begin{cases} +1 & \text{if } f_t(x) > \theta_t \\ -1 & \text{otherwise} \end{cases}$$

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

Slide: Kristen Grauman

- 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



$\{x_1, \ldots x_n\}$

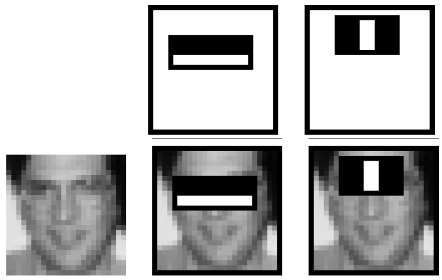
For T rounds

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.

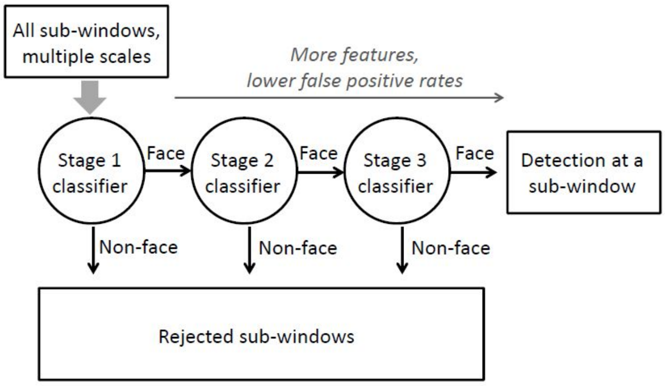
Viola-Jones Face Detector: Results



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



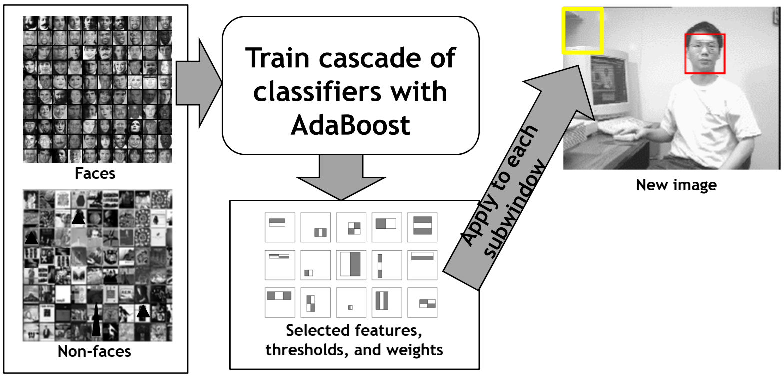
- Form a *cascade* with low false negative rates early on
- Apply less accurate but faster classifiers first **to immediately discard** windows that **clearly appear to be negative**

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]

Slide: Kristen Grauman

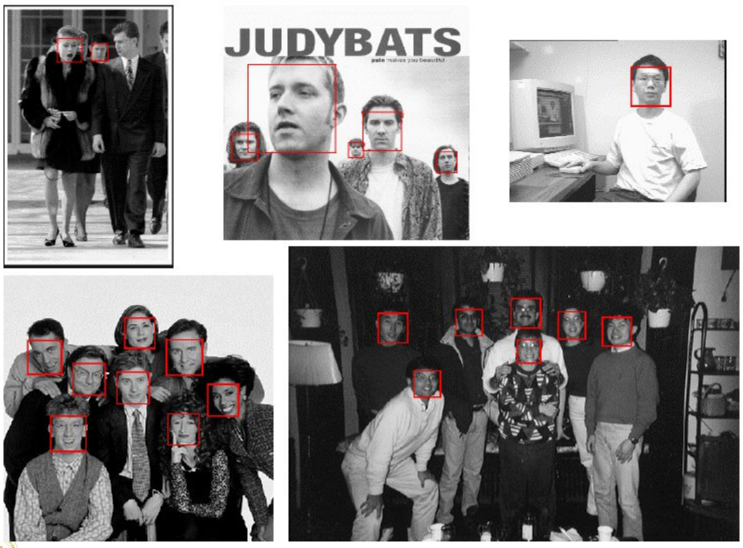
Viola-Jones detector: summary

- 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

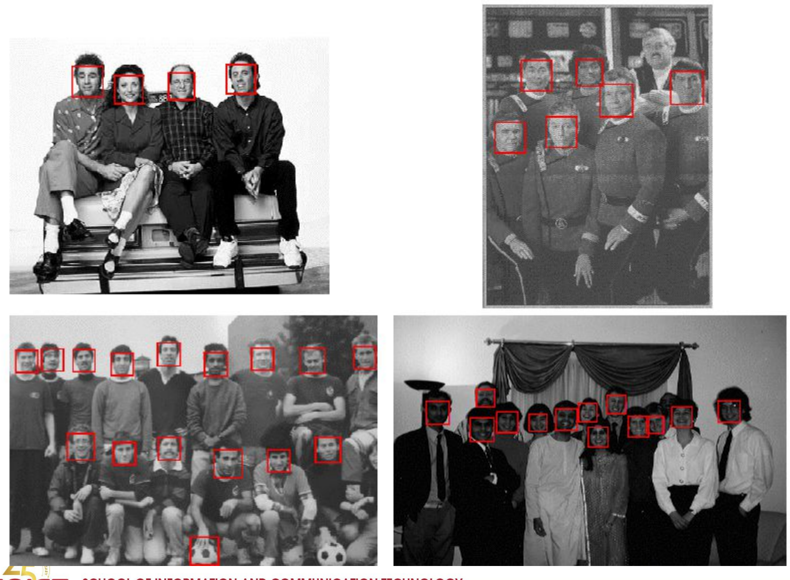
P. Viola and M. Jones. *Rapid object detection using a boosted cascade of simple features.* CVPR 2001.

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

Viola-Jones Face Detector: Results



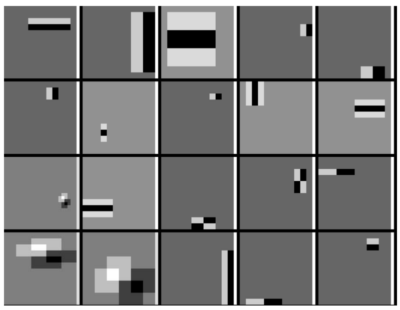
Viola-Jones Face Detector: Results



Viola-Jones Face Detector: Results

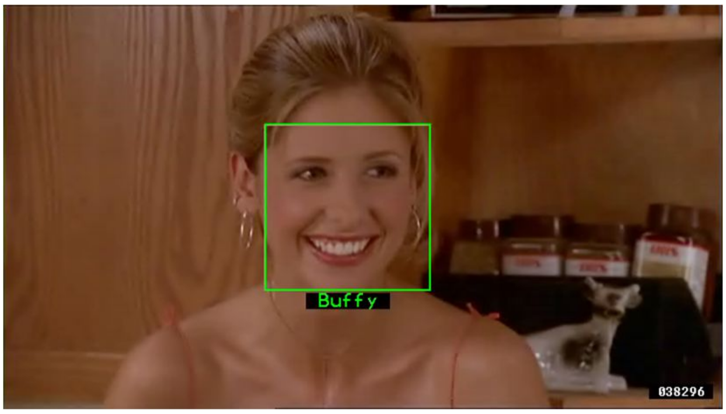
Detecting profile faces?

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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Google now erases faces, license plates on Map Street View

By Elinor Mills, CNET News.com
Friday, August 24, 2007 01:37 PM

Google has gotten a lot of flack from privacy advocates for photographing faces and license plate numbers and displaying them on the Street View in Google Maps. Originally, the company said only people who identified themselves could ask the company to remove their image.

But Google has quietly changed that policy, partly in response to criticism, and now anyone can alert the company and have an image of a license plate or a recognizable face removed, not just the owner of the face or car, says Marissa Mayer, vice president of search products and user experience at Google.

"It's a good policy for users and also clarifies the intent of the product," she said in an interview following her keynote at the Search Engine Strategies conference in San Jose, Calif., Wednesday.

The policy change was made about 10 days after the launch of the product in late May, but was not publicly announced, according to Mayer. The company is removing images only when someone notifies them and not proactively, she said. "It was definitely a big policy change inside."

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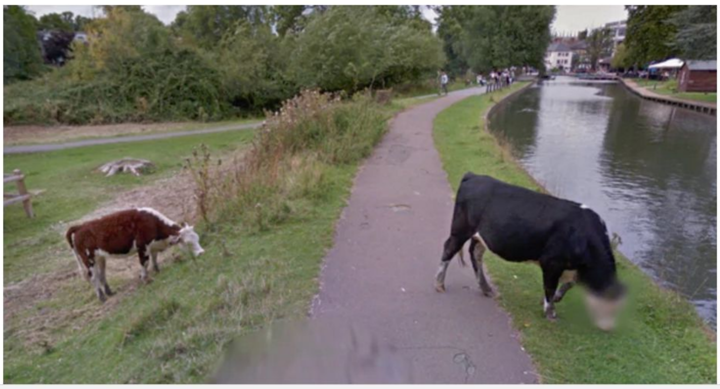
- Google begins search for Middle East lobbyist
- Google still thinks it can change China

Technology

Google street view blurs face of cow to protect its identity

share



Slide: Kristen Grauman

Consumer application: iPhoto

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

Slide credit: Lana Lazebnik

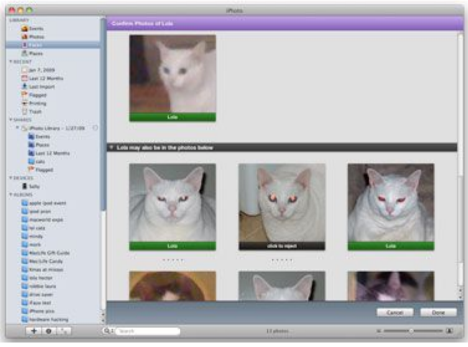
Consumer application: iPhoto

Things iPhoto thinks are faces

Slide credit: Lana Lazebnik

Consumer application: iPhoto

- Can be trained to recognize pets!

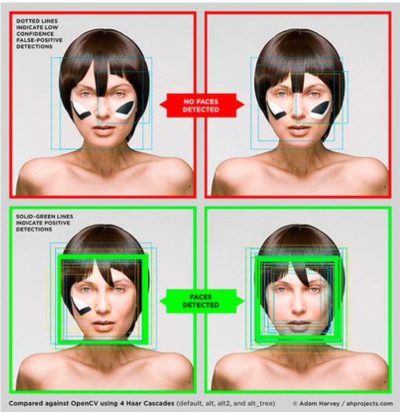


http://www.maclife.com/article/news/iphotos_faces_recognizes_cats

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



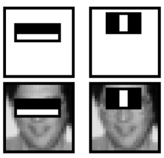
Slide: Kristen Grauman

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

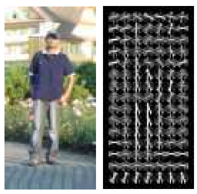
Slide credit: Lana Lazebnik

Window-based models: Two case studies



Boosting + face detection

Viola & Jones

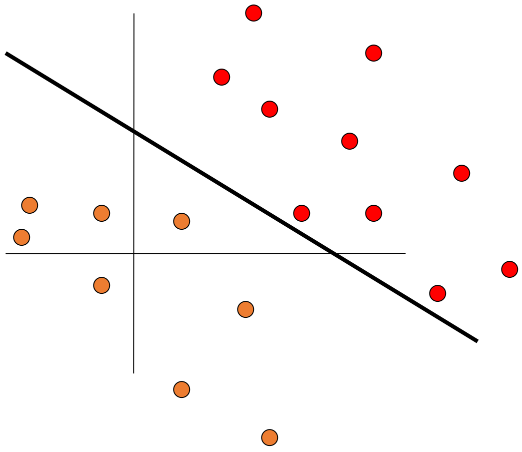


SVM + person detection

e.g., Dalal & Triggs

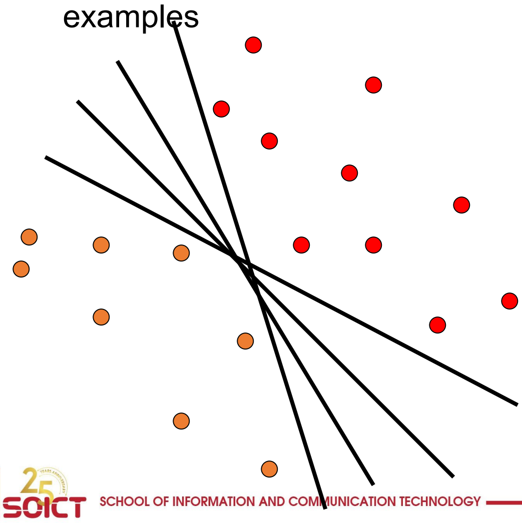
SVM + HOG for human detection as case study

Linear classifiers



Linear classifiers

- Find linear function to separate positive and negative examples

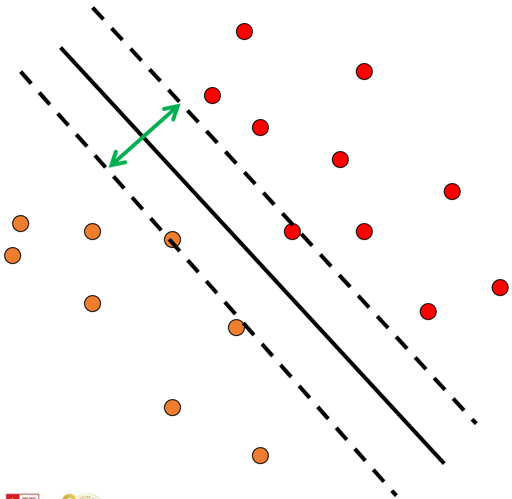


$\mathbf{x}_i$ positive: $\quad \mathbf{x}_i \cdot \mathbf{w} + b \geq 0$

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

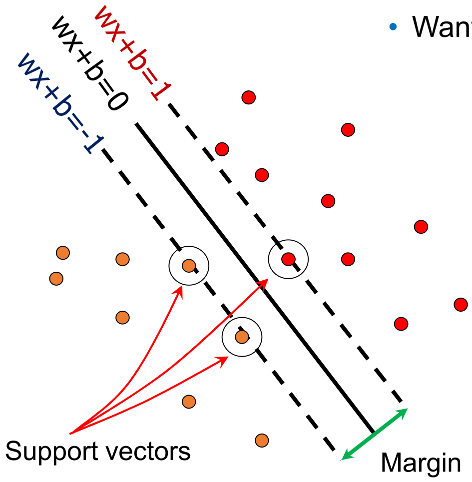
Which line is best?

Support Vector Machines (SVMs)



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

Support vector machines



- Want line that maximizes the margin

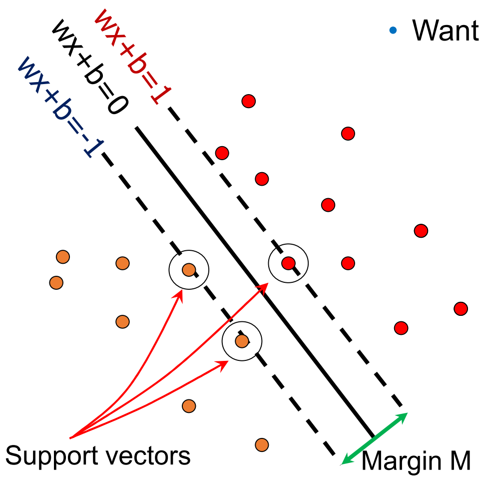
$\mathbf{x}_i$ positive $(y_i = 1)$: $\quad \mathbf{x}_i \cdot \mathbf{w} + b \geq 1$

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

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

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

Support vector machines



- Want line that maximizes the margin

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

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

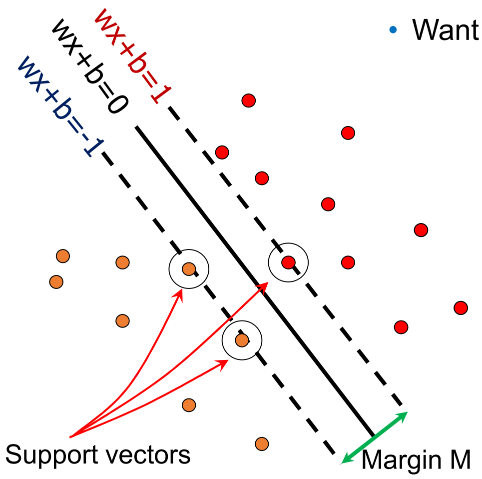
For support vectors, $\quad \mathbf{x}_i \cdot \mathbf{w} + b = \pm 1$

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

For support vectors:

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

Support vector machines



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

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

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

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

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

Finding the maximum margin line

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

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

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

Quadratic optimization problem:

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

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

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

Finding the maximum margin line

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

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:

$$f(x) = \text{sign}\,(\mathbf{w} \cdot \mathbf{x} + \text{b})$$

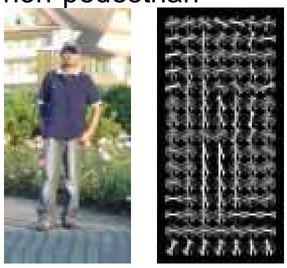
$$= \text{sign}\left(\sum_i \alpha_i y_i \boxed{\mathbf{x}_i \cdot \mathbf{x}} + b\right)$$

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

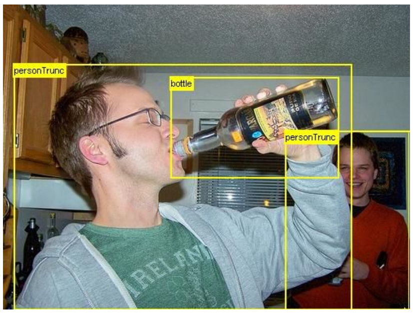
- Sliding window detection and global appearance descriptors:
  - Simple detection protocol to implement
  - Good feature choices critical
  - Past successes for certain classes

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)

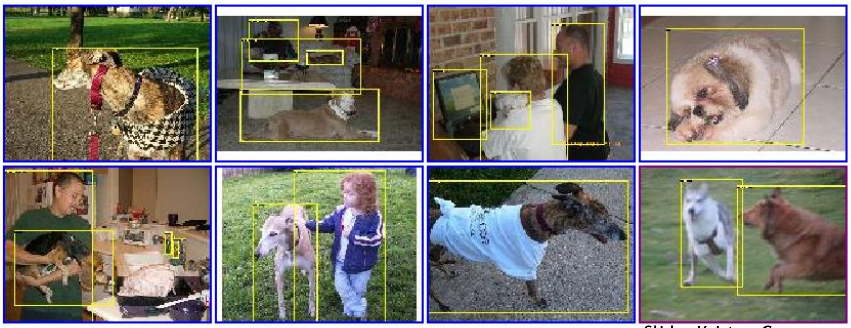
- Not all objects are “box” shaped



Slide: Kristen Grauman

Limitations (continued)

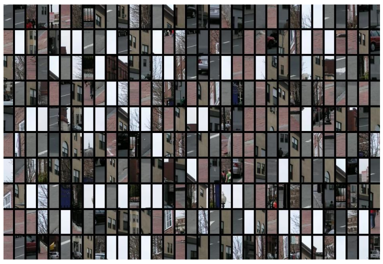
- Non-rigid, deformable objects not captured well with representations assuming a fixed 2d structure; or must assume fixed viewpoint
- Objects with less-regular textures not captured well with holistic appearance-based descriptions



Slide: Kristen Grauman

Limitations (continued)

Sliding window



Detector's view

If considering windows in isolation,
context is lost

Figure credit: Derek Hoiem
Slide: Kristen Grauman

Limitations (continued)

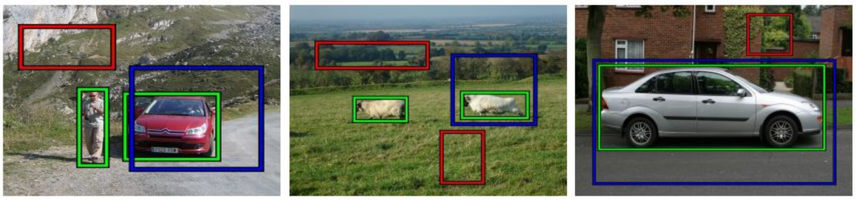
- In practice, often entails large, cropped training set (expensive)
- Requiring good match to a global appearance description can lead to sensitivity to partial occlusions

Slide: Kristen Grauman

Object proposals

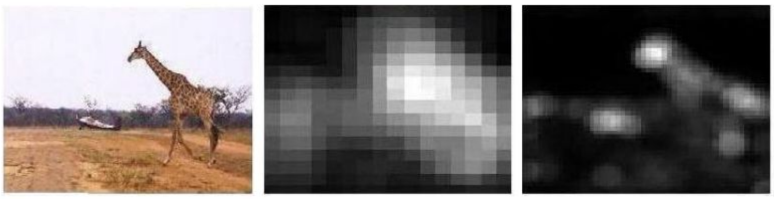
Object proposals

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



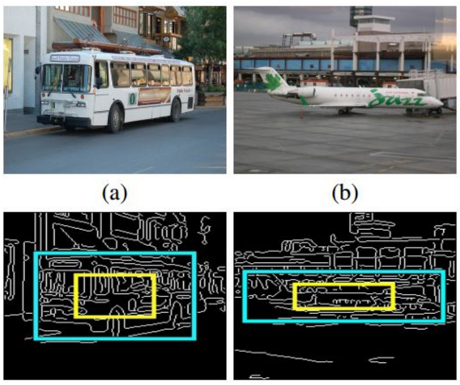
Multi-scale saliency

Color contrast

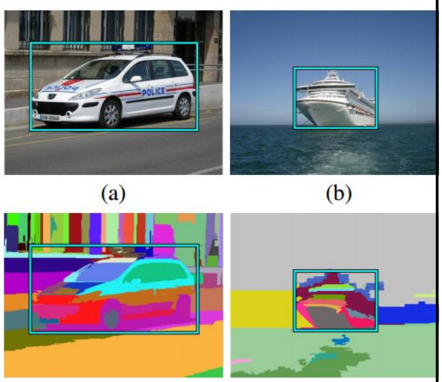
Alexe et al. Measuring the objectness of image windows, PAMI 2012

Object proposals

Edge density



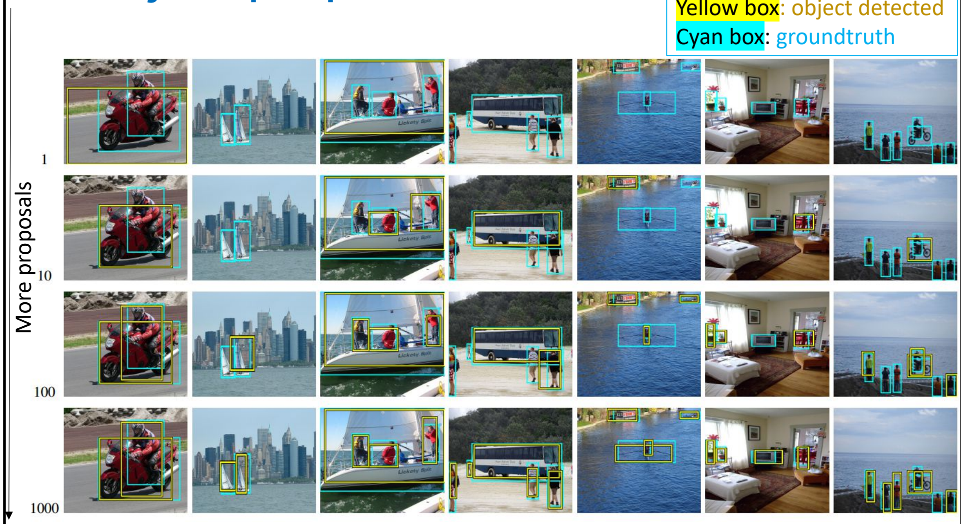
Superpipxel straddling



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

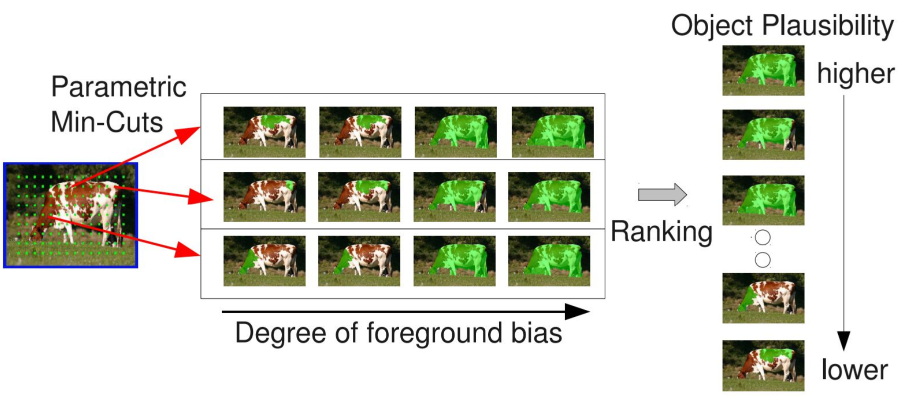
Object proposals

Yellow box: object detected
Cyan box: groundtruth



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

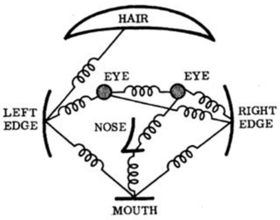
Region-based object proposals



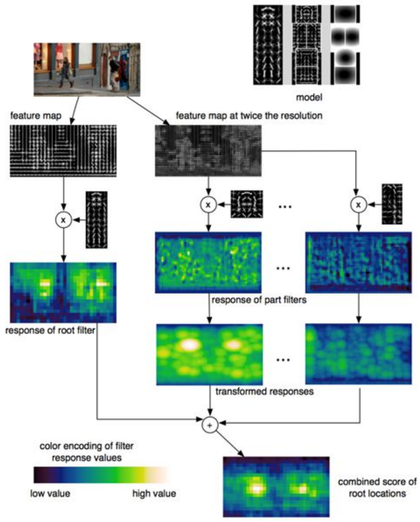
- J. Carreira and C. Sminchisescu. Cpmc: Automatic object segmentation using constrained parametric min-cuts. PAMI, 2012.

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

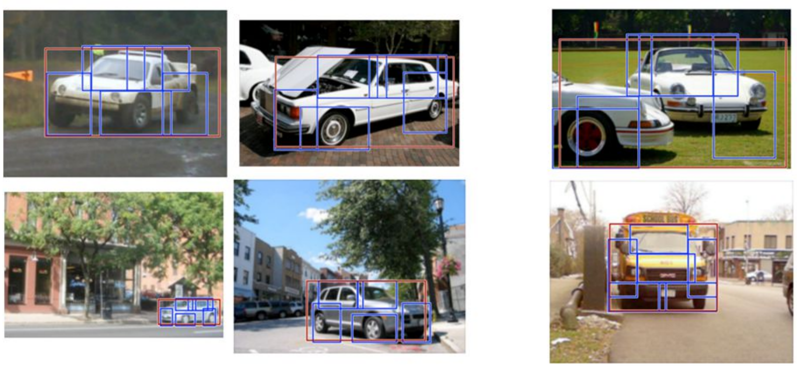


Felzenszwalb et al. , PAMI 2010

Deformable Part Model (DPM)

high scoring true positives

high scoring false positives



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

Object detection: Evaluation

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**?

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

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

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

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

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

How do we evaluate object detection?

predictions
ground truth

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

So what is the
- precision?
- recall?

Precision versus recall

- Precision:
  – how many of the object detections are correct?
- Recall:
  – how many of the ground truth objects can the model detect?
  – True Positive Rate (TPR)

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

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

- 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!

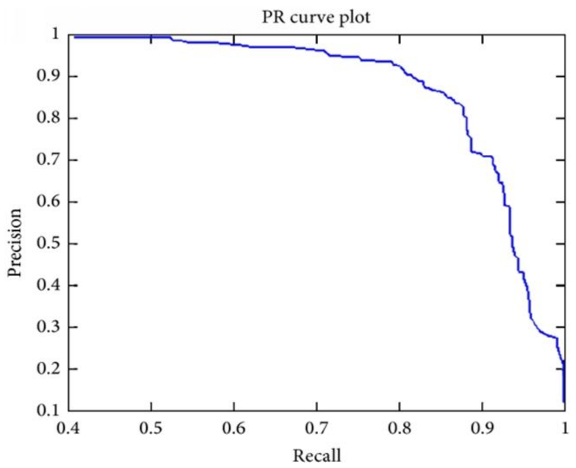
How do we evaluate object detection?

predictions
ground truth

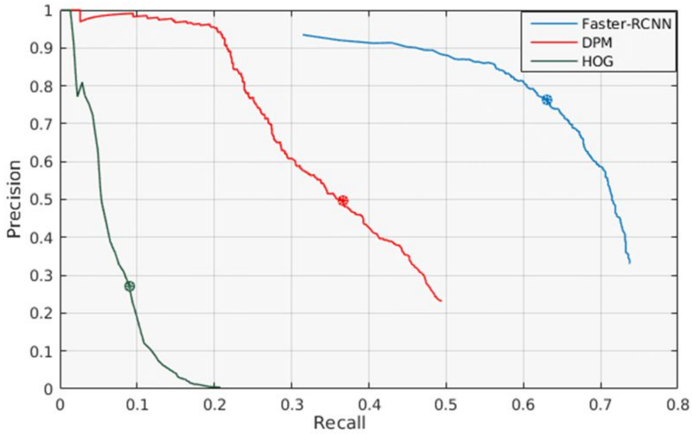
Here are all the boxes that are predicted with score > 0.5

We are setting a threshold of 0.5

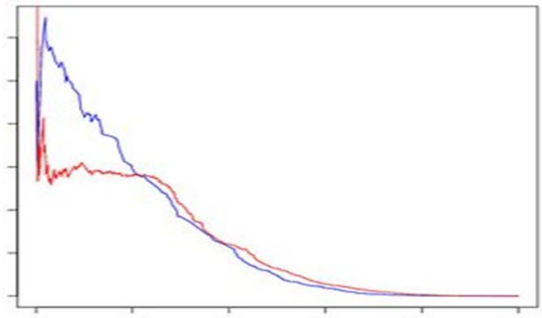
Precision – recall curve (PR curve)



Which model is the best?

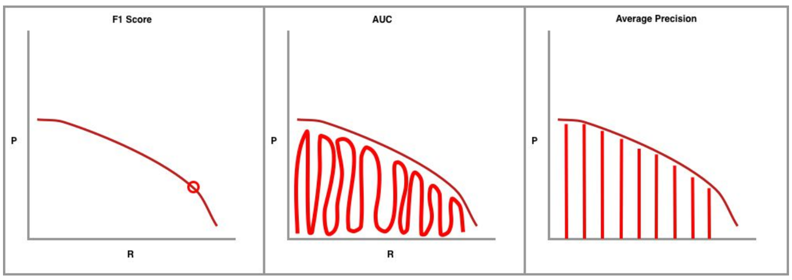


Which model is the best?



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

Which model is the best?



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

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

mAP: the average of AP

$$= \frac{1}{11}(1 + 1 + 1 + 1 + 0.67 + 0.67 + 0.67 + 0.5 + 0.5 + 0.5 + 0.5)$$

$$\approx 0.728$$

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:

1. Kristen Grauman (CS 376: Computer Vision, Spring 2018, The University of Texas at Austin)

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Thank you!