

Announcements

- A4 due today
- A5 out, due May 2
- Exam May 10, 2-5 pm

Last time

- Introduction to object categorization
- Window-based object detection
 - boosting classifiers
 - face detection as case study

Today

- Recap of boosting + face detection
- Pros/cons of window-based detectors
- Mosaic examples
- Support vector machines

See slides / handout from lecture 22	-	
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Boosting: pros and cons]	
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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

ual Object Recognition Tutoria

Slide: Kristen Grauman

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

ual Obj

Slide: Kristen Grauman

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)

• If considering windows in isolation, context is lost





Sliding window

Detector's view

Figure credit: Derek Hojem

Slide: Kristen Graumar

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





Image credit: Adam, Rivlin, & Shimshoni

Slide: Kristen Grauma

Summary so far

- Basic pipeline for window-based detection
 - Model/representation/classifier choice
 - Sliding window and classifier scoring
- · Boosting classifiers: general idea
- Viola-Jones face detector
 - Exemplar of basic paradigm
 - Plus key ideas: rectangular features, Adaboost for feature selection, cascade
- · Pros and cons of window-based detection

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









Color

contrast

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

Object proposals







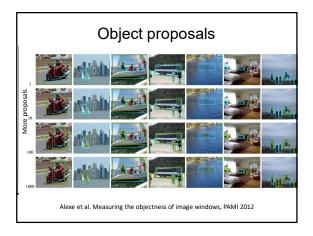






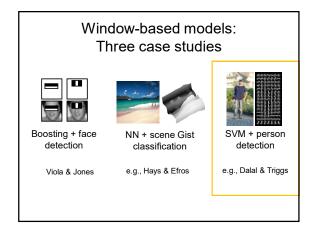


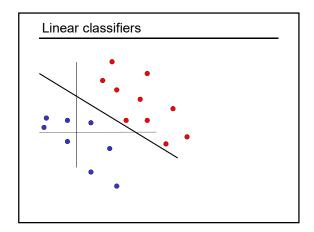
Alexe et al. Measuring the objectness of image windows, PAMI 2012

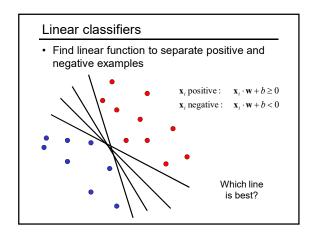


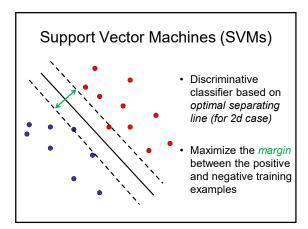
Region-based object proposals					
Parametric Min-Cuts Degree of foreground bias	Object Plausibility higher Ranking				
 J. Carreira and C. Sminchisescu. Cpmc: Automatic object segmentation using constrained parametric min-cuts. PAMI, 2012. 					

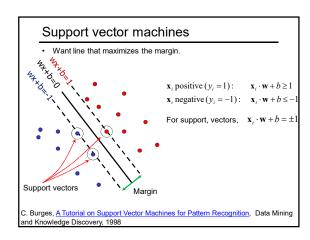
MOSAIC EXAMPLES

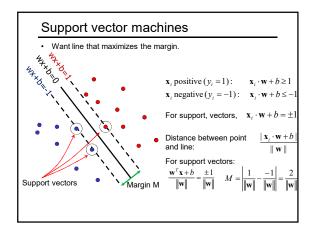












Support vectors

Support vector machines • Want line that maximizes the margin. \mathbf{x}_i positive $(y_i=1)$: $\mathbf{x}_i \cdot \mathbf{w} + b \ge 1$ \mathbf{x}_i negative $(y_i=-1)$: $\mathbf{x}_i \cdot \mathbf{w} + b \le -1$ For support, vectors, $\mathbf{x}_i \cdot \mathbf{w} + b = \pm 1$

Distance between point $|\mathbf{x}_i \cdot \mathbf{w} + b|$

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

Margin M

Finding the maximum margin line

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

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

Quadratic optimization problem:

Minimize $\frac{1}{2} \mathbf{w}^T \mathbf{w}$ Subject to $y_i(\mathbf{w} \cdot \mathbf{x}_i + b) \ge 1$

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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

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:

$$f(x) = \operatorname{sign}(\mathbf{w} \cdot \mathbf{x} + \mathbf{b})$$
$$= \operatorname{sign}(\sum_{i} \alpha_{i} y_{i} \mathbf{x}_{i} \cdot \mathbf{x} + \mathbf{b})$$

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

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



- 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/

Summary

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

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- What if the data are not linearly separable?
- What about the multi-class case?
- Nearest neighbors
- Convolutional neural networks

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