Generic Object-Face detection

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Many slides adapted from P. Viola, K. Grauman, S. Lazebnik and many others
Today

- Window-based generic object detection
  - basic pipeline
  - boosting classifiers
  - face detection as case study
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

Yes, car.
No, not a car.
Discriminative classifier construction

- Nearest neighbor
  - $10^6$ examples
  - Shakhnarovich, Viola, Darrell 2003
  - Berg, Berg, Malik 2005...

- Neural networks
  - LeCun, Bottou, Bengio, Haffner 1998
  - Rowley, Baluja, Kanade 1998
  - ...

- Support Vector Machines
  - Guyon, Vapnik
  - Heisele, Serre, Poggio, 2001,...

- Boosting
  - Viola, Jones 2001, Torralba et al.
  - 2004, Opelt et al. 2006,...

- Conditional Random Fields
  - McCallum, Freitag, Pereira 2000; Kumar, Hebert 2003
  - ...

Slide adapted from Antonio Torralba
Window-based models
Generating and scoring candidates

Car/non-car Classifier
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

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Face detection
Face detection

- Basic idea: slide a window across image and evaluate a face model at every location
Face detection

Behold a state-of-the-art face detector!
(Courtesy Boris Babenko)
Consumer application: Apple iPhoto

http://www.apple.com/ilife/iphoto/
Consumer application: Apple iPhoto

- Can be trained to recognize pets!

Consumer application: Apple iPhoto

This iPhoto thinks one of your cookies is a face.
Funny Nikon ads

"The Nikon S60 detects up to 12 faces."
Funny Nikon ads

"The Nikon S60 detects up to 12 faces."
Challenges of face detection

- 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, our false positive rate has to be less than $10^{-6}$
The Viola/Jones Face Detector

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

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
Idea: Using Many Simple Features

- Viola Jones / Haar Features

(Generalized) Haar Features:

- rectangular blocks, white or black
- 3 types of features:
  - two rectangles: horizontal/vertical
  - three rectangles
  - four rectangles
- in 24x24 window: 180,000 possible features
Example
Def: The *integral image* at location \((x,y)\), is the sum of the pixel values above and to the left of \((x,y)\), inclusive. We can calculate the integral image representation of the image in a single pass.

\[
\begin{align*}
\text{ii}(x,y) & \quad \text{– value of the integral image – sum of all pixels above and left of } (x,y) \\
\text{s}(x,y) & \quad \text{– cumulative row sum}
\end{align*}
\]
Efficient Computation of Rectangle Value

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

Example: Rectangle D

\[ ii(4) + ii(1) - ii(2) - ii(3) \]

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

Idea: Compute lot of simple features – outputs of convolution with the box like filters

Object detection: classification problem
Feature selection

- For a 24x24 detection region, the number of possible rectangle features is \( \sim 160,000 \)!
Feature selection

- For a 24x24 detection region, the number of possible rectangle features is ~160,000!
- At test time, it is impractical to evaluate the entire feature set
- Can we create a good classifier using just a small subset of all possible features?
- How to select such a subset?
Boosting for face detection

- Define weak learners based on rectangle features

\[
\text{window} \rightarrow \text{value of rectangle feature} \rightarrow \text{parity} \rightarrow \text{threshold}
\]
Boosting

- Boosting is a classification scheme that works by combining *weak learners* into a more accurate ensemble classifier
  - A weak learner need only do better than chance
- Training consists of multiple *boosting rounds*
  - During each boosting round, we select a weak learner that does well on examples that were hard for the previous weak learners
  - “Hardness” is captured by weights attached to training examples

AdaBoost Idea (in Viola/Jones):

- Given set of “weak” classifiers:
  - Pick best one
  - Reweight training examples, so that misclassified images have larger weight
  - Reiterate; then linearly combine resulting classifiers

Weak classifiers: Haar features
Boosting illustration

- Weak classifier is a hyperplane
Boosting illustration

Weights Increased
Boosting illustration
Boosting illustration

Weights Increased
Boosting illustration

Weak Classifier 3
Final classifier is a combination of weak classifiers
Boosting vs. SVM

- Advantages of boosting
  - Integrates classification with feature selection
  - Complexity of training is linear instead of quadratic 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
  - Often doesn’t work as well as SVM (especially for many-class problems)
AdaBoost learning algorithm

Discrete AdaBoost (Freund & Schapire 1996b)

1. Start with weights $w_i = 1/N$, $i = 1, \ldots, N$.

2. Repeat for $m = 1, 2, \ldots, M$:
   
   (a) Fit the classifier $f_m(x) \in \{-1, 1\}$ using weights $w_i$ on the training data.
   (b) Compute $\text{err}_m = E_w[1_{(y \neq f_m(x))}]$, $c_m = \log((1 - \text{err}_m)/\text{err}_m)$.
   (c) Set $w_i \leftarrow w_i \exp[c_m \cdot 1_{(y \neq f_m(x))}]$, $i = 1, 2, \ldots N$, and renormalize so that $\sum_i w_i = 1$.

3. Output the classifier $\text{sign}[\sum_{m=1}^{M} c_m f_m(x)]$
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)
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
  - Often found not to work as well as an alternative discriminative classifier, support vector machine (SVM)
    - especially for many-class problems
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
Boosting for face detection

- Define weak learners based on rectangle features

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

- For each round of boosting:
  Evaluate each rectangle filter on each example
  Select best filter/threshold combination based on weighted training error reweight examples
Boosting for face detection

- Define weak learners based on rectangle features
- 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
- Computational complexity of learning: $O(MNK)$
  - $M$ rounds, $N$ examples, $K$ features
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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AdaBoost Algorithm

Start with uniform weights on training examples

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.

- 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 \(w_t\), \(e_j = \sum_i w_i |h_j(x_i) - y_i|\).
  3. Choose the classifier, \(h_t\), with the lowest error \(e_t\).
  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 \(\beta_t = \frac{e_t}{1-e_t}\).

- 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 \(\alpha_t = \log \frac{1}{\beta_t}\).
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?
Boosting for face detection

- First two features selected by boosting:

![Face Detection Features](image)
Example Classifier for Face Detection

A classifier with 200 rectangle features was learned using AdaBoost.

95% correct detection on test set with 1 in 14084 false positives.

Slide credit: Frank Dellaert, Paul Viola, Foryth&Ponce
Classifier are Efficient

- Given a nested set of classifier hypothesis classes

Slide credit: Frank Dellaert, Paul Viola, Forsyth&Ponce
Cascaded Classifier

- A 1 feature classifier achieves 100% detection rate and about 50% false positive rate.
- A 5 feature classifier achieves 100% detection rate and 40% false positive rate (20% cumulative)
  - using data from previous stage.
- A 20 feature classifier achieve 100% detection rate with 10% false positive rate (2% cumulative)

Slide credit: Frank Dellaert, Paul Viola, Foryth&Ponce
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: http://www.intel.com/technology/computing/opencv/]

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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

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Solving other “Face” Tasks

Facial Feature Localization

Profile Detection

Demographic Analysis

Slide credit: Frank Dellaert, Paul Viola, Forsyth&Ponce
Face Localization Features

- Learned features reflect the task

Slide credit: Frank Dellaert, Paul Viola, Forsyth&Ponce
Face Profile Detection

Slide credit: Frank Dellaert, Paul Viola, Foryth&Ponce
Face Profile Features
What other categories are amenable to \textit{window-based representation}?
Pedestrian detection

- Detecting upright, walking humans also possible using sliding window’s appearance/texture; e.g.,

  SVM with Haar wavelets [Papageorgiou & Poggio, IJCV 2000]

  Space-time rectangle features [Viola, Jones & Snow, ICCV 2003]

  SVM with HoGs [Dalal & Triggs, CVPR 2005]
Finding Cars (DARPA Urban Challenge)

- Hand-labeled images of generic car rear-ends
- Training time: ~5 hours, offline

Credit: Hendrik Dahlkamp
Generating even more examples

- Generic classifier finds all cars in recorded video.
- Compute offline and store in database

Credit: Hendrik Dahlkamp
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

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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)

- If considering windows in isolation, context is lost

Figure credit: Derek Hoiem
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
Summary

- 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
Summary Viola-Jones

- Rectangle features
- Integral images for fast computation
- Boosting for feature selection
- Attentional cascade for fast rejection of negative windows

- Many simple features
  - Generalized Haar features (multi-rectangles)
  - Easy and efficient to compute
- Discriminative Learning:
  - finds a small subset for object recognition
  - Uses AdaBoost
- Result: Feature Cascade
  - 15fps on 700Mhz Laptop (=fast!)

- Applications, Face detection, Car detection, Many others