Computer Vision - Lecture 9

Sliding-Window based Object Detection II

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Course Outline

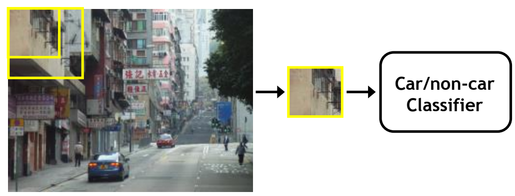
- Image Processing Basics
- Segmentation
  - Segmentation and Grouping
  - Segmentation as Energy Minimization
- Recognition & Categorization
  - Sliding-Window Object Detection
  - Image Classification
- Local Features & Matching
- 3D Reconstruction
- Motion and Tracking

Topics of This Lecture

- Recap: Classification with SVMs
  - Support Vector Machines
  - HOG Detector
- Classification with Boosting
  - AdaBoost
  - Viola-Jones Face Detection
- Discussion

Recap: Sliding-Window Object Detection

- If the object may be in a cluttered scene, slide a window around looking for it.



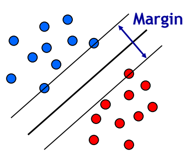
- Essentially, this is a brute-force approach with many local decisions.

Slide credit: Kristen Grauman

Recap: Support Vector Machine (SVM)

- Basic idea
  - The SVM tries to find a classifier which maximizes the margin between pos. and neg. data points.
  - Up to now: consider linear classifiers

$$\mathbf{w}^{\mathrm{T}}\mathbf{x} + b = 0$$



- Formulation as a convex optimization problem
  - Find the hyperplane satisfying

$$\arg\min_{\mathbf{w},b} \frac{1}{2}\|\mathbf{w}\|^2$$

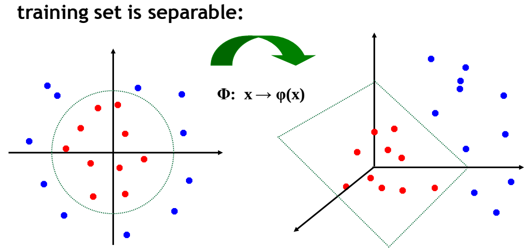
under the constraints

$$t_n(\mathbf{w}^{\mathrm{T}}\mathbf{x}_n + b) \geq 1 \quad \forall n$$

based on training data points $\mathbf{x}_n$ and target values $t_n \in \{-1, 1\}$.

Recap: Non-Linear SVMs

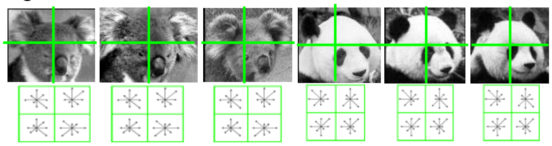
- General idea: The original input space can be mapped to some higher-dimensional feature space where the training set is separable:



Slide from Andrew Moore's tutorial: http://www.autonlab.org/tutorials/svm.html

Recap: Gradient-based Representations

- Consider edges, contours, and (oriented) intensity gradients



- Summarize local distribution of gradients with histogram
  - Locally orderless: offers invariance to small shifts and rotations
  - Contrast-normalization: try to correct for variable illumination

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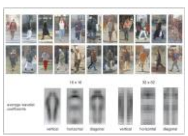
  - Support Vector Machines
  - HOG Detector
- Classification with Boosting
  - AdaBoost
  - Viola-Jones Face Detection
- Discussion

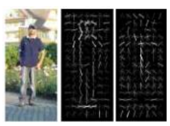
Pedestrian Detection

- Detecting upright, walking humans 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]

HOG Descriptor Processing Chain

Image Window

HOG Descriptor Processing Chain

- Optional: Gamma compression
  - Goal: Reduce effect of overly strong gradients
  - Replace each pixel color/intensity by its square-root

$$x \mapsto \sqrt{x}$$

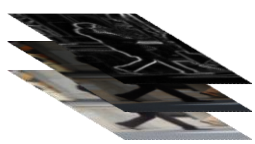
$\Rightarrow$ Small performance improvement

Gamma compression
↑
Image Window

HOG Descriptor Processing Chain

- Gradient computation
  - Compute gradients on all color channels and take strongest one
  - Simple finite difference filters work best (no Gaussian smoothing)

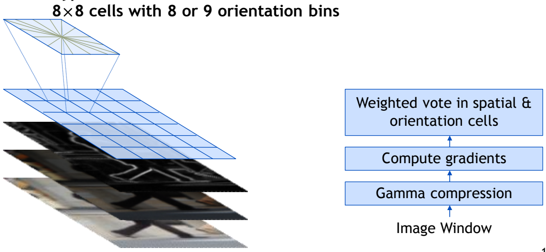
$$\begin{bmatrix}-1 & 0 & 1\end{bmatrix} \qquad \begin{bmatrix}-1 \\ 0 \\ 1\end{bmatrix}$$



Compute gradients
↑
Gamma compression
↑
Image Window

HOG Descriptor Processing Chain

- Spatial/Orientation binning
  - Compute localized histograms of oriented gradients
  - Typical subdivision: 8×8 cells with 8 or 9 orientation bins



Slide adapted from Navneet Dalal

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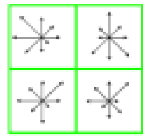
HOG Cell Computation Details

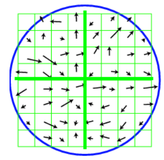
- Gradient orientation voting
  - Each pixel contributes to localized gradient orientation histogram(s)
  - Vote is weighted by the pixel's gradient magnitude



$$\theta = \tan^{-1}\left(\frac{\partial f}{\partial y} \Big/ \frac{\partial f}{\partial x}\right)$$

$$\|\nabla f\| = \sqrt{\left(\frac{\partial f}{\partial x}\right)^2 + \left(\frac{\partial f}{\partial y}\right)^2}$$

- Block-level Gaussian weighting
  - An additional Gaussian weight is applied to each 2×2 block of cells
  - Each cell is part of 4 such blocks, resulting in 4 versions of the histogram.



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HOG Cell Computation Details (2)

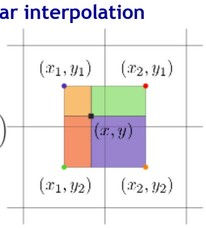
- Important for robustness: Tri-linear interpolation
  - Each pixel contributes to (up to) 4 neighboring cell histograms
  - Weights are obtained by bilinear interpolation in image space:

$$h(x_1,y_1) \leftarrow w \cdot \left(1-\frac{x-x_1}{x_2-x_1}\right)\left(1-\frac{y-y_1}{y_2-y_1}\right)$$

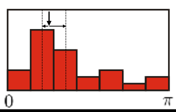
$$h(x_1,y_2) \leftarrow w \cdot \left(1-\frac{x-x_1}{x_2-x_1}\right)\left(\frac{y-y_1}{y_2-y_1}\right)$$

$$h(x_2,y_1) \leftarrow w \cdot \left(\frac{x-x_1}{x_2-x_1}\right)\left(1-\frac{y-y_1}{y_2-y_1}\right)$$

$$h(x_2,y_2) \leftarrow w \cdot \left(\frac{x-x_1}{x_2-x_1}\right)\left(\frac{y-y_1}{y_2-y_1}\right)$$



  - Contribution is further split over (up to) 2 neighboring orientation bins via linear interpolation over angles.



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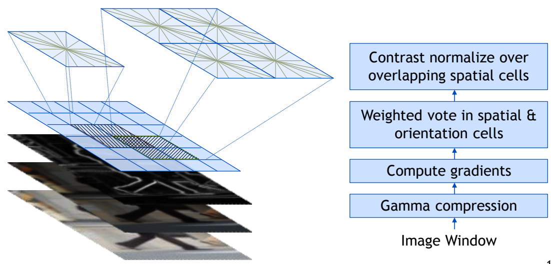
HOG Descriptor Processing Chain

- 2-Stage contrast normalization
  - L2 normalization, clipping, L2 normalization



Slide adapted from Navneet Dalal

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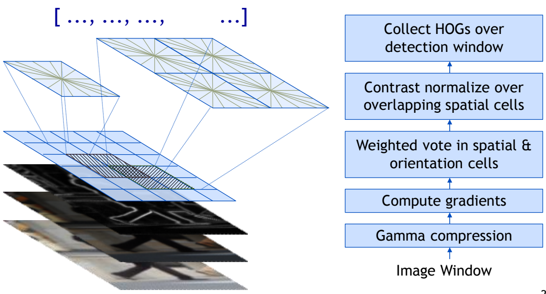
HOG Descriptor Processing Chain

- Feature vector construction
  - Collect HOG blocks into vector

[..., ..., ..., ...]



Slide adapted from Navneet Dalal

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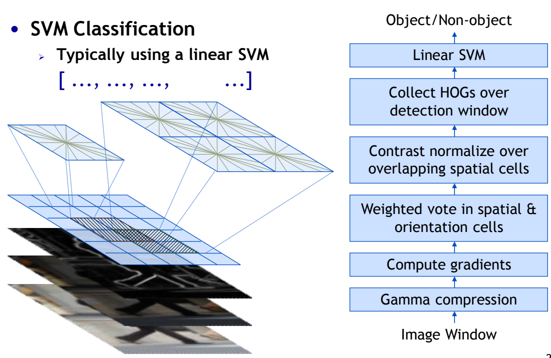
HOG Descriptor Processing Chain

- SVM Classification
  - Typically using a linear SVM

[..., ..., ..., ...]



Slide adapted from Navneet Dalal

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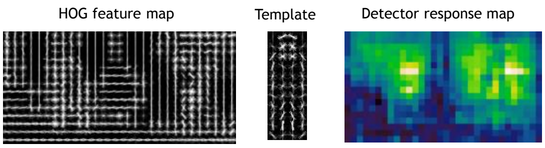
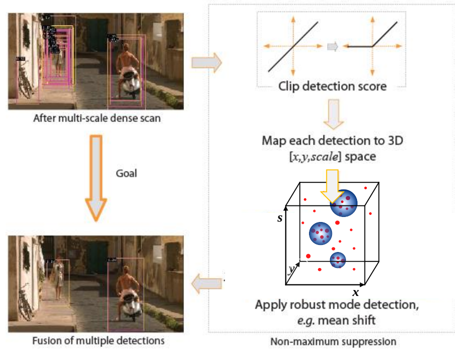
Pedestrian Detection with HOG

- Train a pedestrian template using a linear SVM
- At test time, convolve feature map with template



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

Non-Maximum Suppression



Pedestrian detection with HoGs & SVMs

- Navneet Dalal, Bill Triggs, Histograms of Oriented Gradients for Human Detection, CVPR 2005

Applications: Mobile Robot Navigation

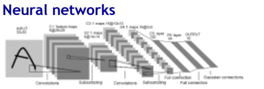
link to the video

Classifier Construction: Many Choices…

Nearest Neighbor

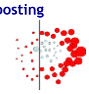
Shakhnarovich, Viola, Darrell 2003
Berg, Berg, Malik 2005,
Boiman, Shechtman, Irani 2008, …

Neural networks



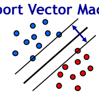
LeCun, Bottou, Bengio, Haffner 1998
Rowley, Baluja, Kanade 1998
…

Boosting



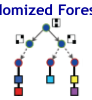
Viola, Jones 2001,
Torralba et al. 2004,
Opelt et al. 2006,
Benenson 2012, …

Support Vector Machines



Vapnik, Schölkopf 1995,
Papageorgiou, Poggio '01,
Dalal, Triggs 2005,
Vedaldi, Zisserman 2012

Randomized Forests



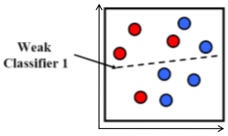
Amit, Geman 1997,
Breiman 2001,
Lepetit, Fua 2006,
Gall, Lempitsky 2009,…

Boosting

- Build a strong classifier H by combining a number of "weak classifiers" $h_1,\dots,h_M$, which need only be better than chance.
- Sequential learning process: at each iteration, add a weak classifier
- Flexible to choice of weak learner
  - including fast simple classifiers that alone may be inaccurate
- We'll look at Freund & Schapire's AdaBoost algorithm
  - Easy to implement
  - Base learning algorithm for Viola-Jones face detector

Y. Freund and R. Schapire, A short introduction to boosting, *Journal of Japanese Society for Artificial Intelligence*, 14(5):771-780, 1999.

AdaBoost: Intuition



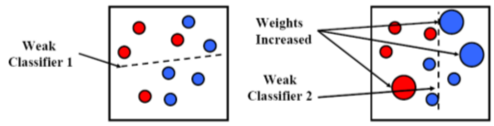
Consider a 2D feature space with positive and negative examples.

Each weak classifier splits the training examples with at least 50% accuracy.

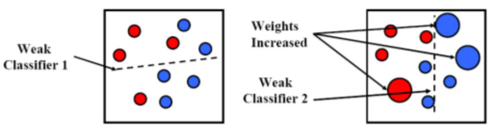
Examples misclassified by a previous weak learner are given more emphasis at future rounds.

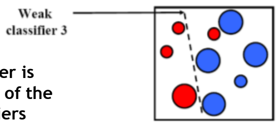
Figure adapted from Freund and Schapire

AdaBoost: Intuition



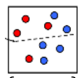
AdaBoost: Intuition



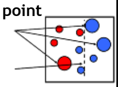


Final classifier is combination of the weak classifiers

AdaBoost - Formalization

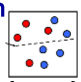


- 2-class classification problem
  - Given: training set $\mathbf{X} = \{\mathbf{x}_1, \ldots, \mathbf{x}_N\}$ with target values $\mathbf{T} = \{t_1, \ldots, t_N\}$, $t_n \in \{-1,1\}$.
  - Associated weights $\mathbf{W}=\{w_1, \ldots, w_N\}$ for each training point.
- Basic steps
  - In each iteration, AdaBoost trains a new weak classifier $h_m(\mathbf{x})$ based on the current weighting coefficients $\mathbf{W}^{(m)}$.
  - We then adapt the weighting coefficients for each point
    - Increase w_n if $\mathbf{x}_n$ was misclassified by $h_m(\mathbf{x})$.
    - Decrease w_n if $\mathbf{x}_n$ was classified correctly by $h_m(\mathbf{x})$.
  - Make predictions using the final combined model



$$H(\mathbf{x}) = sign\left(\sum_{m=1}^{M} \alpha_m h_m(\mathbf{x})\right)$$

AdaBoost: Detailed Training Algorithm



1. Initialization: Set $w_n^{(1)} = \frac{1}{N}$ for $n = 1,\ldots,N$.
2. For $m = 1,\ldots,M$ iterations
   a) Train a new weak classifier $h_m(\mathbf{x})$ using the current weighting coefficients $\mathbf{W}^{(m)}$ by minimizing the weighted error function

   $$J_m = \sum_{n=1}^{N} w_n^{(m)} I(h_m(\mathbf{x}_n) \neq t_n) \qquad I(A) = \begin{cases} 1, & \text{if } A \text{ is true} \\ 0, & \text{else} \end{cases}$$

   b) Estimate the weighted error of this classifier on $\mathbf{X}$:

   $$\epsilon_m = \frac{\sum_{n=1}^{N} w_n^{(m)} I(h_m(\mathbf{x}_n) \neq t_n)}{\sum_{n=1}^{N} w_n^{(m)}}$$

   c) Calculate a weighting coefficient for $h_m(\mathbf{x})$:

   $$\alpha_m = \ln\left\{\frac{1-\epsilon_m}{\epsilon_m}\right\}$$

   d) Update the weighting coefficients:

   $$w_n^{(m+1)} = w_n^{(m)} \exp\{\alpha_m I(h_m(\mathbf{x}_n) \neq t_n)\}$$

AdaBoost: Recognition

- Evaluate all selected weak classifiers on test data.

$$h_1(\mathbf{x}), \ldots, h_m(\mathbf{x})$$

- Final classifier is weighted combination of selected weak classifiers:

$$H(\mathbf{x}) = sign\left(\sum_{m=1}^{M} \alpha_m h_m(\mathbf{x})\right)$$

- Very simple procedure!
  - Less than 10 lines in Matlab!
  - But works extremely well in practice...

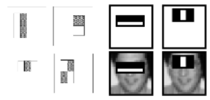
Example: Face Detection

- Frontal faces are a good example of a class where global appearance models + a sliding window detection approach fit well:
  - Regular 2D structure
  - Center of face almost shaped like a “patch”/window

- Now we’ll take AdaBoost and see how the Viola-Jones face detector works

Feature extraction

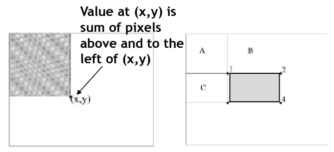
“Rectangular” filters



Feature output is difference between adjacent regions

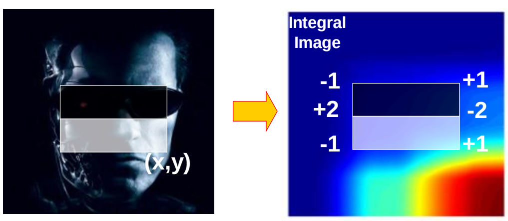
Efficiently computable with integral image: any sum can be computed in constant time

Avoid scaling images → scale features directly for same cost

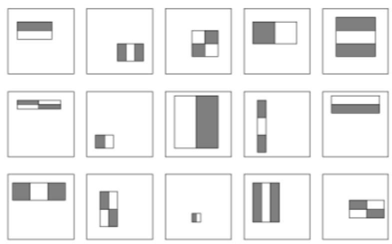


$$D = 1 + 4 - (2 + 3)$$
$$= A + (A + B + C + D) - (A + C + A + B)$$
$$= D$$

Example



Large Library of Filters



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

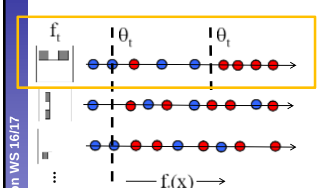
180,000+ possible features associated with each 24 x 24 window

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

Weak classifier: filter output > θ?

AdaBoost for Feature+Classifier Selection

- 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.

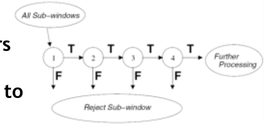
AdaBoost for Efficient Feature Selection

- Image features = weak classifiers
- For each round of boosting:
  - Evaluate each rectangle filter on each example
  - Sort examples by filter values
  - Select best threshold for each filter (min error)
    - Sorted list can be quickly scanned for the optimal threshold
  - Select best filter/threshold combination
  - Weight on this features is a simple function of error rate
  - Reweight examples

P. Viola, M. Jones, Robust Real-Time Face Detection, IJCV, Vol. 57(2), 2004. (first version appeared at CVPR 2001)

Cascading Classifiers for Detection

- Even if the filters are fast to compute, each new image has a lot of possible windows to search.
- For efficiency, apply less accurate but faster classifiers first to immediately discard windows that clearly appear to be negative; e.g.,
  - Filter for promising regions with an initial inexpensive classifier
  - Build a chain of classifiers, choosing cheap ones with low false negative rates early in the chain

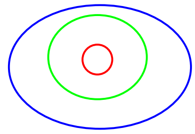


[Fleuret & Geman, IJCV 2001]
[Rowley et al., PAMI 1998]
[Viola & Jones, CVPR 2001]

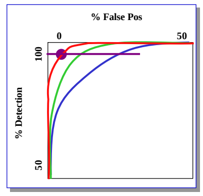
Slide credit: Kristen Grauman
B. Leibe
Figure from Viola & Jones CVPR 2001

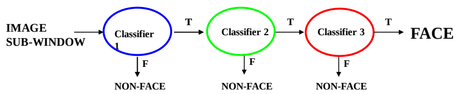
Cascading Classifiers

- Chain classifiers that are progressively more complex and have lower false positive rates:



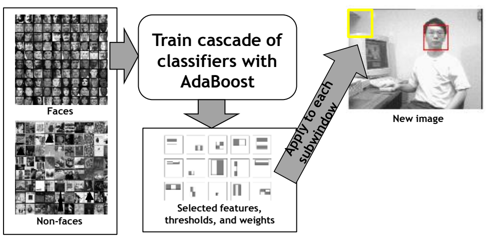
Receiver operating characteristic





Slide credit: Svetlana Lazebnik

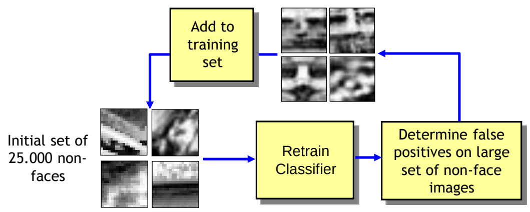
Viola-Jones Face Detector: Summary



- Train with 5K positives, 350M negatives
- Real-time detector using 38 layer cascade
- 6061 features in final layer
- [Implementation available in OpenCV: http://sourceforge.net/projects/opencvlibrary/]

Slide credit: Kristen Grauman
B. Leibe

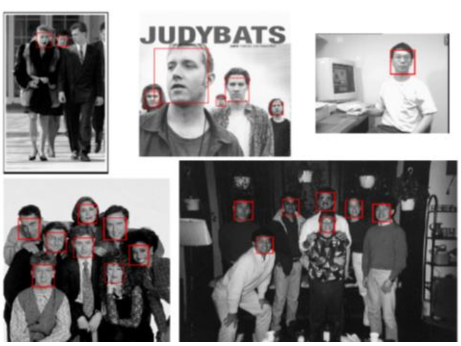
Practical Issue: Bootstrapping



- Problem: 1 face in 116'440 examined windows
  - Can easily find negative examples, but which ones are useful?
  - Apply iterative training approach
  - False positives on negative validation images are included in training set as "hard negatives"

Slide adapted from Bernd Heisele

Viola-Jones Face Detector: Results



Slide credit: Kristen Grauman
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Viola-Jones Face Detector: Results

Slide credit: Kristen Grauman
B. Leibe

Viola-Jones Face Detector: Results

You Can Try It At Home…

- The Viola & Jones detector was a huge success
  - First real-time face detector available
  - Many derivative works and improvements
- C++ implementation available in OpenCV [Lienhart, 2002]
  - http://sourceforge.net/projects/opencvlibrary/
- Matlab wrappers for OpenCV code available, e.g. here
  - http://www.mathworks.com/matlabcentral/fileexchange/19912

P. Viola, M. Jones, Robust Real-Time Face Detection, IJCV, Vol. 57(2), 2004

Example Application

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

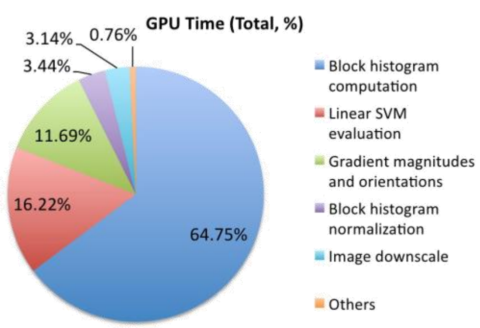
Summary: Sliding-Windows

- Pros
  - Simple detection protocol to implement
  - Good feature choices critical
  - Past successes for certain classes
  - Good detectors available (Viola & Jones, HOG, etc.)
- Cons/Limitations
  - High computational complexity
    - For example: 250,000 locations x 30 orientations x 4 scales = 30,000,000 evaluations!
    - This puts tight constraints on the classifiers we can use.
    - If training binary detectors independently, this means cost increases linearly with number of classes.
  - With so many windows, false positive rate better be low

Feature Computation Trade-Off

- Linear SVM Detectors
  - Same computations performed for each image window
  - It pays off to precompute the features once
  - Complex features can be used
- AdaBoost Cascaded Detectors
  - Potentially different computations for each window location
  - May be more efficient to evaluate the features on-the-fly for each image window
  - If cascading shall be used, simple features are preferable

What Slows Down HOG (CUDA Implem.)



- Results from fastHOG (10fps) [Prisacariu & Reid 2009]

Limitations: Low Training Resolutions

- Many (older) S/W detectors operate on tiny images
  - Viola&Jones: 24×24 pixels
  - Torralba et al.: 32×32 pixels
  - Dalal&Triggs: 64×96 pixels (notable exception)
- Main reasons
  - Training efficiency (exhaustive feature selection in AdaBoost)
  - Evaluation speed
  - Want to recognize objects at small scales
- But…
  - Limited information content available at those resolutions
  - Not enough support to compensate for occlusions!

Limitations: Changing Aspect Ratios

- Sliding window requires fixed window size
  - Basis for learning efficient cascade classifier
- How to deal with changing aspect ratios?
  - Fixed window size

  ⇒ Wastes training dimensions

  - Adapted window size

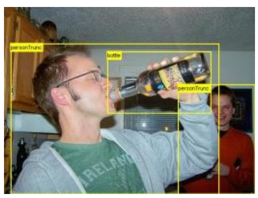
  ⇒ Difficult to share features

  - “Squashed” views [Dalal&Triggs]

  ⇒ Need to squash test image, too

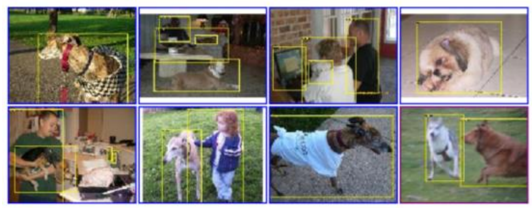
Limitations (continued)

- 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

Sliding window

Detector’s view

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

References and Further Reading

- Read the Viola-Jones paper
  - P. Viola, M. Jones,
    Robust Real-Time Face Detection,
    IJCV, Vol. 57(2), 2004.
    (first version appeared at CVPR 2001)

- Viola-Jones Face Detector
  - C++ implementation available in OpenCV [Lienhart, 2002]
    - http://sourceforge.net/projects/opencvlibrary/
  - Matlab wrappers for OpenCV code available, e.g. here
    - http://www.mathworks.com/matlabcentral/fileexchange/19912

- HOG Detector
  - Code available: http://pascal.inrialpes.fr/soft/olt/