Computer Vision - Lecture 14

Part-based Models for Object Categorization

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Course Outline

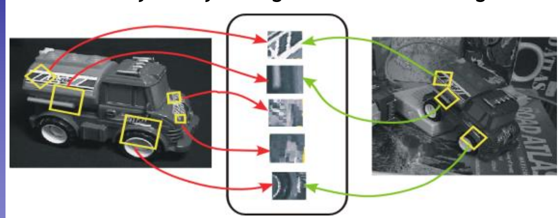
- Image Processing Basics
- Segmentation & Grouping
- Object Recognition
- Object Categorization I
  - Sliding Window based Object Detection
- Local Features & Matching
  - Local Features - Detection and Description
  - Recognition with Local Features
  - Indexing & Visual Vocabularies
- Object Categorization II
  - Bag-of-Words Approaches & Part-based Approaches
  - Deep Learning Methods
- 3D Reconstruction

Topics of This Lecture

- Recap: Specific Object Recognition with Local Features
  - Matching & Indexing
  - Geometric Verification
- Part-Based Models for Object Categorization
  - Structure representations
  - Different connectivity structures
- Bag-of-Words Model
  - Use for image classification
- Implicit Shape Model
  - Generalized Hough Transform for object category detection
- Deformable Part-based Model
  - Discriminative part-based detection

Recap: Recognition with Local Features

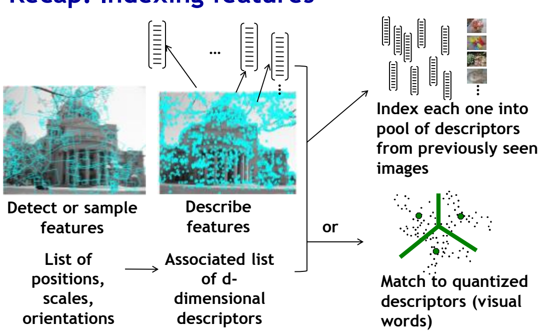
- Image content is transformed into local features that are invariant to translation, rotation, and scale
- Goal: Verify if they belong to a consistent configuration



Local Features,
e.g. SIFT

Slide credit: David Lowe

Recap: Indexing features



⇒ *Shortlist of possibly matching images + feature correspondences*

Slide credit: Kristen Grauman

Extension: *tf-idf* Weighting

- Term frequency - inverse document frequency
  - Describe frame by frequency of each word within it, downweight words that appear often in the database
  - (Standard weighting for text retrieval)

Number of occurrences of word i in document d

Total number of documents in database

$$t_i = \frac{n_{id}}{n_d} \log \frac{N}{n_i}$$

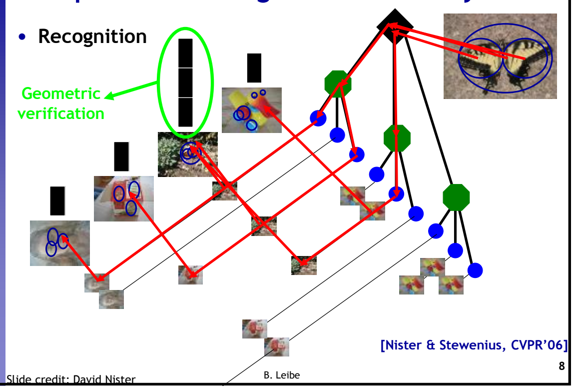
Number of words in document d

Number of occurrences of word i in whole database

Slide credit: Kristen Grauman

Recap: Fast Indexing with Vocabulary Trees

- Recognition



[Nister & Stewenius, CVPR'06]

Recap: Geometric Verification by Alignment

- Assumption
  - Known object, rigid transformation compared to model image
  - ⇒ *If we can find evidence for such a transformation, we have recognized the object.*
- You learned methods for
  - Fitting an ***affine transformation*** from ≥ 3 correspondences
  - Fitting a ***homography*** from ≥ 4 correspondences

Affine: solve a system $At = b$ Homography: solve a system $Ah = 0$

- Correspondences may be noisy and may contain outliers
  - ⇒ Need to use robust methods that can filter out outliers
  - ⇒ Use RANSAC or the Generalized Hough Transform

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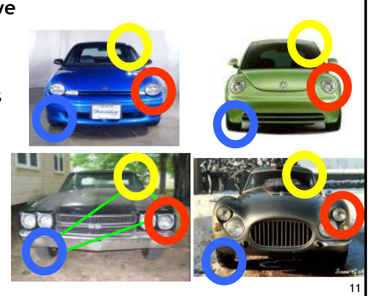
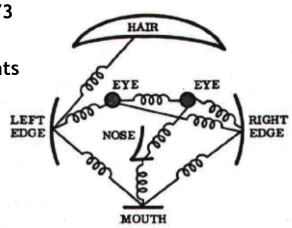
Recognition of Object Categories

- We no longer have exact correspondences…
- On a local level, we can still detect similar parts.
- Represent objects by their parts
  - ⇒ Bag-of-features
- How can we improve on this?
  - Encode structure

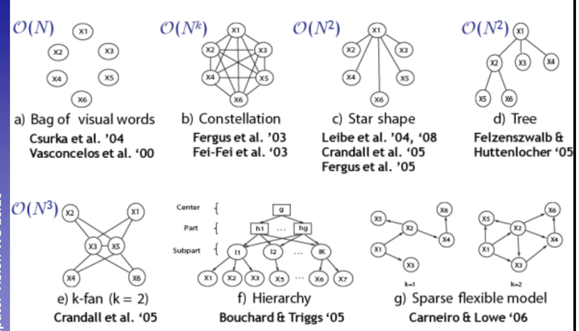


Part-Based Models

- Fischler & Elschlager 1973
- Model has two components
  - parts (2D image fragments)
  - structure (configuration of parts)



Different Connectivity Structures



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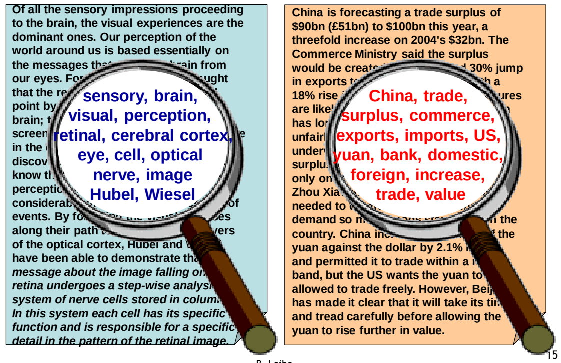
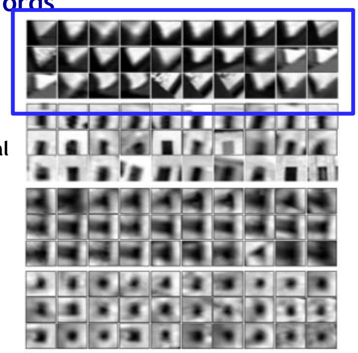
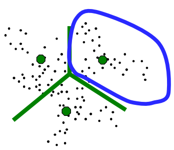
Recap: Analogy to Documents



Recap: Visual Words

- Quantize the feature space into "visual words"
- Perform matching only to those visual words.

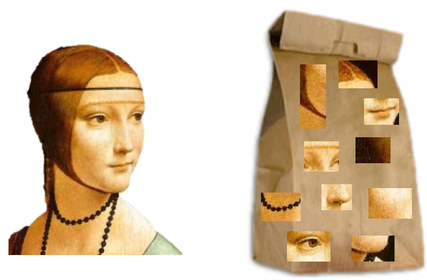




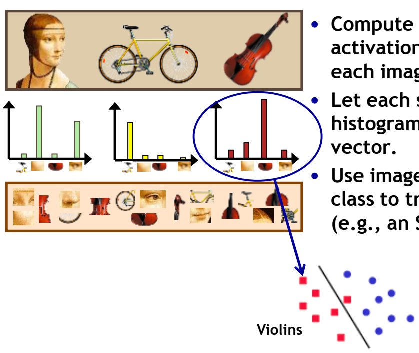
Exact feature matching → Match to same visual word

Recap: Bag-of-Word Representations (BoW)

Object → Bag of "words"



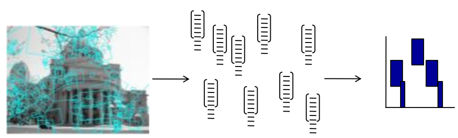
Recap: Categorization with Bags-of-Words



- Compute the word activation histogram for each image.
- Let each such BoW histogram be a feature vector.
- Use images from each class to train a classifier (e.g., an SVM).

Recap: Advantage of BoW Histograms

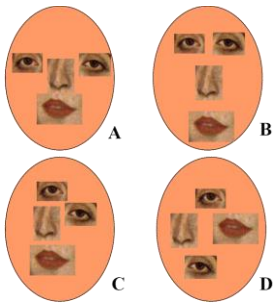
- Bag of words representations make it possible to describe the unordered point set with a single vector (of fixed dimension across image examples).



- Provides easy way to use distribution of feature types with various learning algorithms requiring vector input.

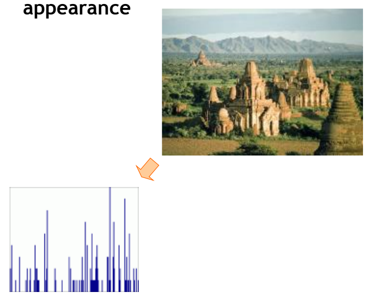
Limitations of BoW Representations

- The bag of words removes spatial layout.
- This is both a strength and a weakness.
- *Why a strength?*
- *Why a weakness?*



Spatial Pyramid Representation

- Representation in-between orderless BoW and global appearance



[Lazebnik, Schmid & Ponce, CVPR'06]

Spatial Pyramid Representation

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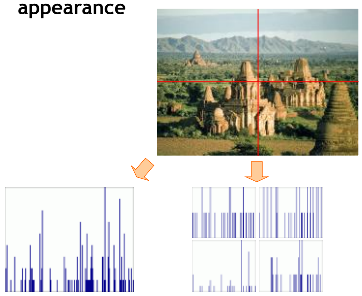

[Lazebnik, Schmid & Ponce, CVPR'06]

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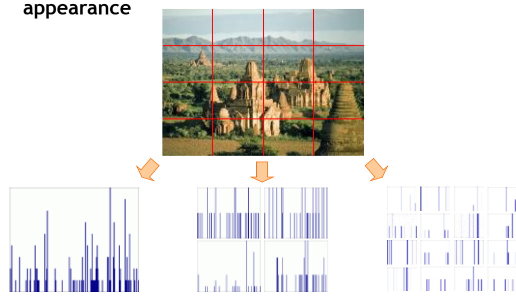

[Lazebnik, Schmid & Ponce, CVPR'06]

Summary: Bag-of-Words

- <u>Pros:</u>
  - Flexible to geometry / deformations / viewpoint
  - Compact summary of image content
  - Provides vector representation for sets
  - Empirically good recognition results in practice
- <u>Cons:</u>
  - Basic model ignores geometry - must verify afterwards, or encode via features.
  - Background and foreground mixed when bag covers whole image
  - When using interest points or sampling: no guarantee to capture object-level parts ⇒ Dense sampling is often better.

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- **Implicit Shape Model**
  - Generalized Hough Transform for object category detection
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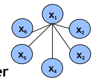
Implicit Shape Model (ISM)

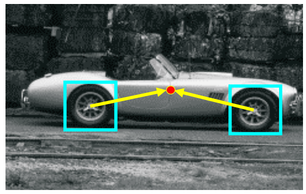
- Basic ideas
  - Learn an appearance codebook
  - Learn a star-topology structural model
    - Features are considered independent given obj. center



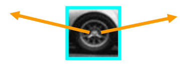
- Algorithm: probabilistic Gen. Hough Transform
  - Exact correspondences → Prob. match to object part
  - NN matching → Soft matching
  - Feature location on obj. → Part location distribution
  - Uniform votes → Probabilistic vote weighting
  - Quantized Hough array → Continuous Hough space

Implicit Shape Model: Basic Idea

- Visual vocabulary is used to index votes for object position [a visual word = "part"].



Training image

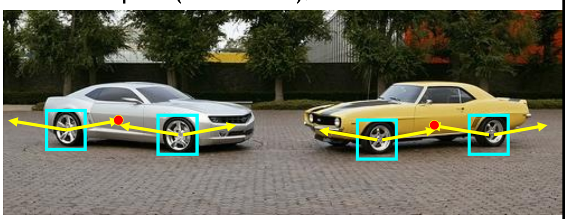


Visual codeword with displacement vectors

B. Leibe, A. Leonardis, and B. Schiele, Robust Object Detection with Interleaved Categorization and Segmentation, International Journal of Computer Vision, Vol. 77(1-3), 2008.

Implicit Shape Model: Basic Idea

- Objects are detected as consistent configurations of the observed parts (visual words).

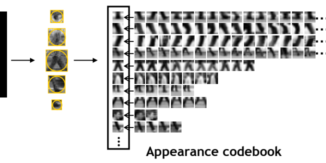


Test image

B. Leibe, A. Leonardis, and B. Schiele, Robust Object Detection with Interleaved Categorization and Segmentation, International Journal of Computer Vision, Vol. 77(1-3), 2008.

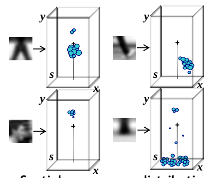
Implicit Shape Model - Representation

Training images (+reference segmentation)



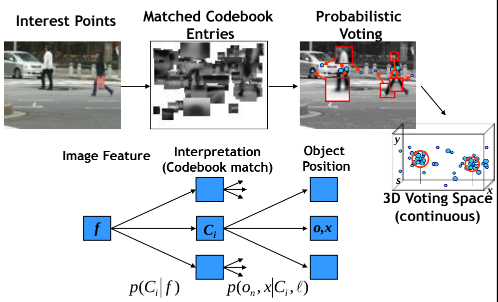
Appearance codebook

- Learn appearance codebook
  - Extract local features at interest points
  - Agglomerative clustering ⇒ codebook
- Learn spatial distributions
  - Match codebook to training images
  - Record matching positions on object



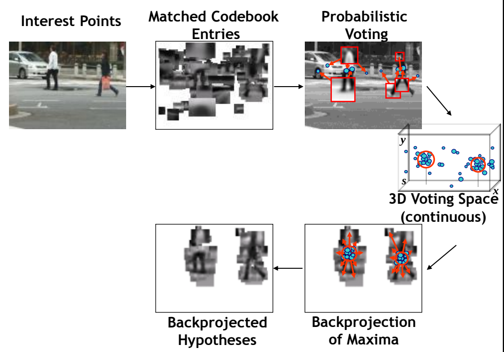
Spatial occurrence distributions

Implicit Shape Model - Recognition



Probabilistic vote weighting

Implicit Shape Model - Recognition



Example: Results on Cows

Original image

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Example: Results on Cows

Interest points

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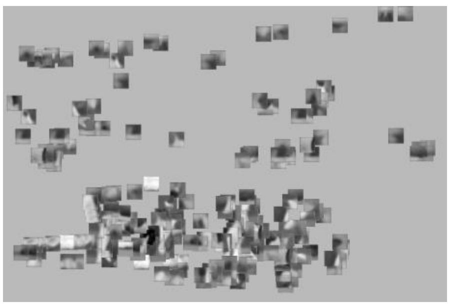
Example: Results on Cows



Matched patches

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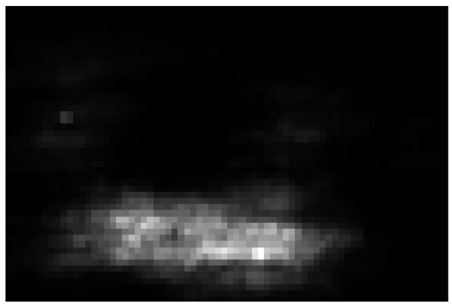
Example: Results on Cows



Prob. Votes

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Example: Results on Cows

1st hypothesis

K. Grauman, B. Leibe

Computer Vision WS 15/16

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Example: Results on Cows

2nd hypothesis

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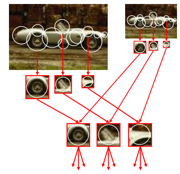
Example: Results on Cows

3[rd] hypothesis

Scale Invariant Voting

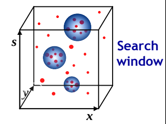
- Scale-invariant feature selection
  - Scale-invariant interest regions
  - Extract scale-invariant descriptors
  - Match to appearance codebook



- Generate scale votes
  - Scale as 3[rd] dimension in voting space

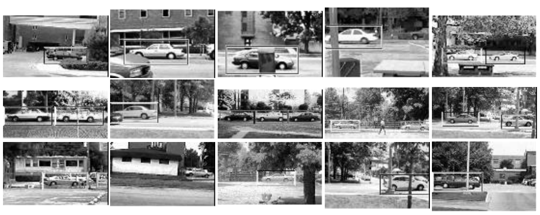
$$\begin{aligned} x_{vote} &= x_{img} - x_{occ}(s_{img}/s_{occ}) \\ y_{vote} &= y_{img} - y_{occ}(s_{img}/s_{occ}) \\ s_{vote} &= (s_{img}/s_{occ}). \end{aligned}$$

  - Search for maxima in 3D voting space

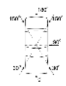


Detection Results

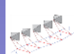
- Qualitative Performance
  - Recognizes different kinds of objects
  - Robust to clutter, occlusion, noise, low contrast



Detections Using Ground Plane Constraints



Battery of 5 ISM detectors for different car views

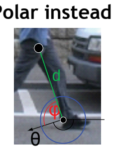


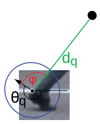
left camera
1175 frames

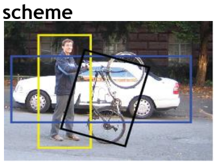
[Leibe, Cornelis, Cornelis, Van Gool, CVPR'07]

Extension: Rotation-Invariant Detection

- Polar instead of Cartesian voting scheme







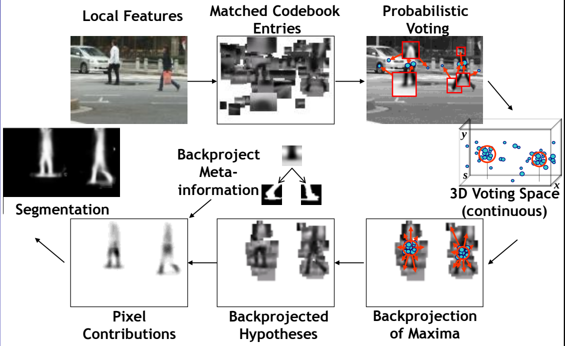
- Benefits:
  - Recognize objects under image-plane rotations
  - Possibility to share parts between articulations.
- Caveats:
  - Rotation invariance should only be used when it's really needed. (Also increases false positive detections)

[Mikolajczyk, Leibe, Schiele, CVPR'06]

Sometimes, Rotation Invariance Is Needed…

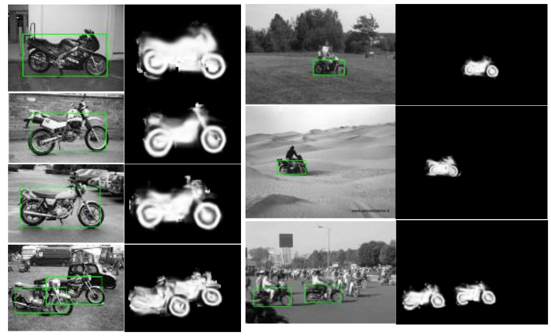
Figure from [Mikolajczyk et al., CVPR'06]

Implicit Shape Model - Segmentation



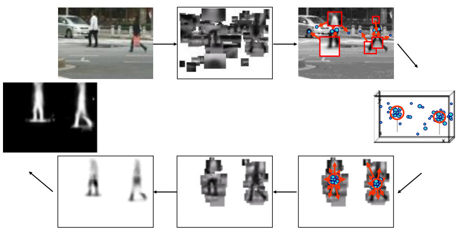
[Leibe, Leonardis, Schiele, DAGM'04; IJCV'08]

Example Results: Motorbikes



[Leibe, Leonardis, Schiele, SLCV'04; IJCV'08]

You Can Try It At Home…



- Linux source code & binaries available
  - Including datasets & several pre-trained detectors
  - http://www.vision.rwth-aachen.de/software

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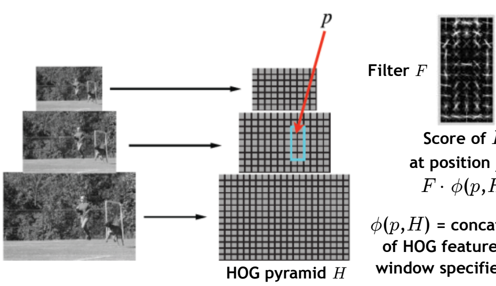
Starting Point: HOG Sliding-Window Detector

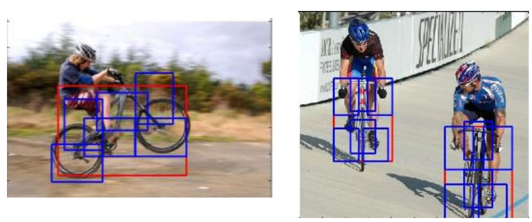


Score of F at position p is $F \cdot \phi(p, H)$

$\phi(p, H)$ = concatenation of HOG features from window specified by p.

- Array of weights for features in window of HOG pyramid
- Score is dot product of filter and vector

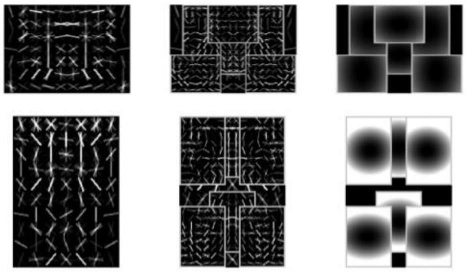
Deformable Part-based Models



- Mixture of deformable part models (pictorial structures)
- Each component has global template + deformable parts
- Fully trained from bounding boxes alone

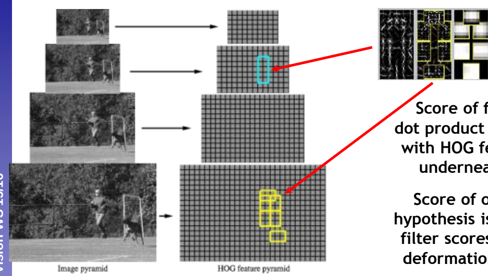
Slide credit: Pedro Felzenszwalb

2-Component Bicycle Model



Root filters coarse resolution | Part filters finer resolution | Deformation models

Object Hypothesis



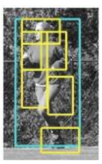
Score of filter: dot product of filter with HOG features underneath it

Score of object hypothesis is sum of filter scores minus deformation costs

- Multiscale model captures features at two resolutions

Score of a Hypothesis

$$\mathrm{score}(p_0,\dots,p_n) = \underbrace{\sum_{i=0}^{n} \underbrace{F_i}_{\text{filters}} \cdot \phi(H,p_i)}_{\text{"data term"}} - \underbrace{\sum_{i=1}^{n} \underbrace{d_i}_{\text{deformation parameters}} \cdot \underbrace{(dx_i^2, dy_i^2)}_{\text{displacements}}}_{\text{"spatial prior"}}$$



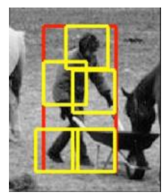
$$\mathrm{score}(z) = \beta \cdot \Psi(H,z)$$

β: concatenation filters and deformation parameters

$\Psi(H,z)$: concatenation of HOG features and part displacement features

Recognition Model

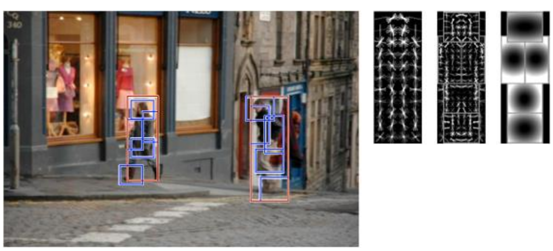
$f_w(x) = w \cdot \Phi(x)$



$f_w(x) = \max_z w \cdot \Phi(x,z)$

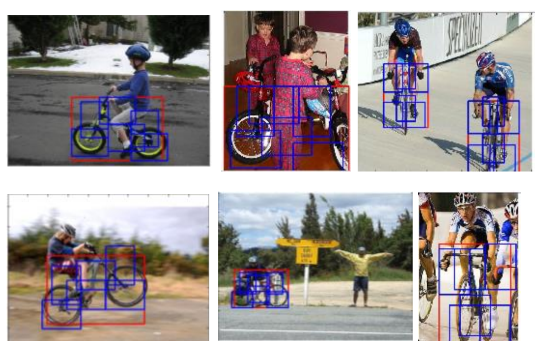
- z : vector of part offsets
- $\Phi(x,z)$: vector of HOG features (from root filter & appropriate part sub-windows) and part offsets

Results: Persons



- Results (after non-maximum suppression)
  - ~1s to search all scales

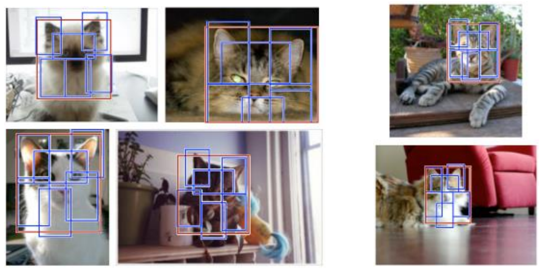
Results: Bicycles



False Positives

- Bicycles

Results: Cats



High-scoring true positives

High-scoring false positives (not enough overlap)

Slide credit: Pedro Felzenszwalb

You Can Try It At Home…

- Deformable part-based models have been very successful at several recent evaluations.

⇒ State-of-the-art approach in object detection for several years

- Source code and models trained on PASCAL 2006, 2007, and 2008 data are available here:

  http://www.cs.uchicago.edu/~pff/latent

References and Further Reading

- Details about the ISM approach can be found in
  - *B. Leibe, A. Leonardis, and B. Schiele,* Robust Object Detection with Interleaved Categorization and Segmentation, International Journal of Computer Vision, Vol. 77(1-3), 2008.
- Details about the DPMs can be found in
  - *P. Felzenszwalb, R. Girshick, D. McAllester, D. Ramanan,* Object Detection with Discriminatively Trained Part Based Models, IEEE Trans. PAMI, Vol. 32(9), 2010.
- Try the ISM Linux binaries
  - http://www.vision.ee.ethz.ch/bleibe/code
- Try the Deformable Part-based Models
  - http://www.cs.uchicago.edu/~pff/latent