# CS4670 / 5670: Computer Vision

**Noah Snavely** 

#### Lecture 31: Modern recognition



Visual Object Classes Challenge 2009 (VOC2009)





# Object detection: where are we?

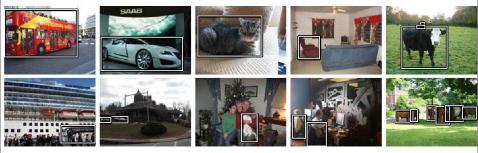


Credit: Flickr user neilalderney123

- Incredible progress in the last ten years
- Better features, better models, better learning methods, better datasets
- Combination of science and hacks

#### **Vision Contests**

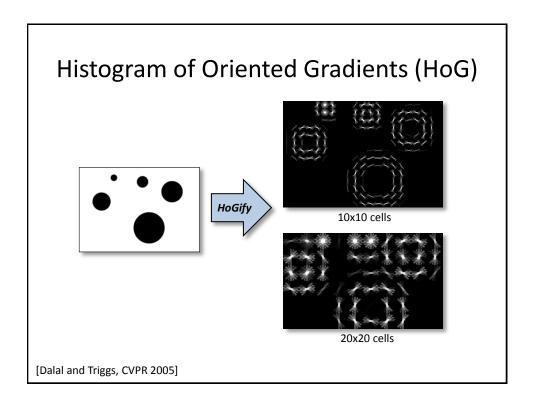
PASCAL VOC Challenge



- 20 categories
- Annual classification, detection, segmentation, ... challenges

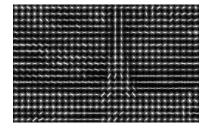
## Machine learning for object detection

- What features do we use?
  - intensity, color, gradient information, ...
- Which machine learning methods?
  - generative vs. discriminative
  - k-nearest neighbors, boosting, SVMs, ...
- What hacks do we need to get things working?



## Histogram of Oriented Gradients (HoG)





### Histogram of Oriented Gradients (HoG)

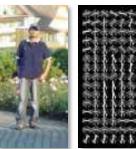


- Like SIFT (Scale Invariant Feature Transform), but...
  - Sampled on a dense, regular grid
  - Gradients are contrast normalized in overlapping blocks

[Dalal and Triggs, CVPR 2005]

#### Histogram of Oriented Gradients (HoG)

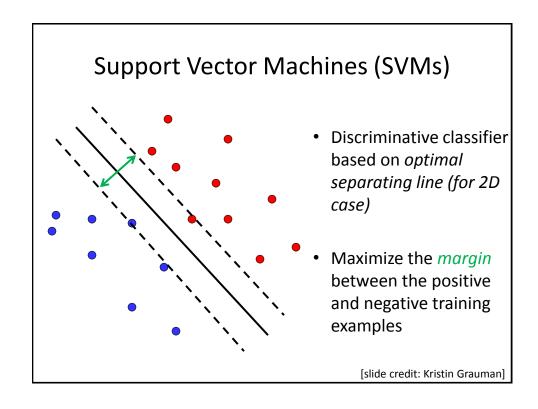
- First used for application of person detection [Dalal and Triggs, CVPR 2005]
- Cited since in thousands of computer vision papers



# • Find linear function to separate positive and negative examples $\mathbf{x}_i \text{ positive:} \quad \mathbf{x}_i \cdot \mathbf{w} + b \geq 0$ $\mathbf{x}_i \text{ negative:} \quad \mathbf{x}_i \cdot \mathbf{w} + b < 0$

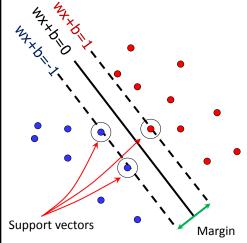
Which line is best?

[slide credit: Kristin Grauman]



## 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,  $\mathbf{x}_i \cdot \mathbf{w} + b = \pm 1$ 

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

[slide credit: Kristin Grauman]

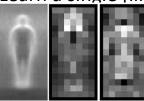
### Person detection, ca. 2005

1. Represent each example with a single, fixed HoG template

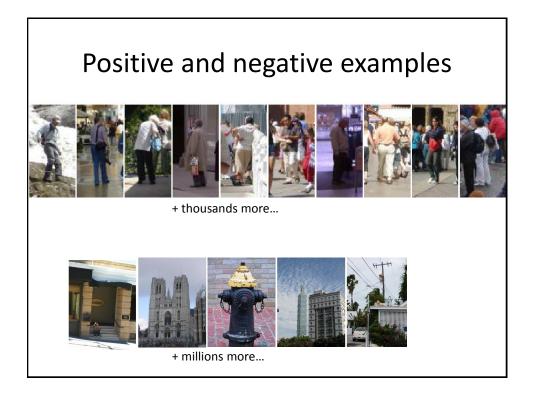


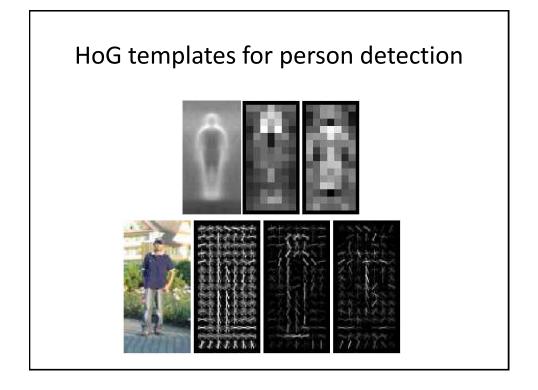


2. Learn a single [linear] SVM as a detector



(average gradient image, max positive weight, max negative weight)





### Detection

- Run detector as a sliding window over an image, at a range of different scales
- Non-maxima suppression

#### Person detection with HoG & linear SVM



[Dalal and Triggs, CVPR 2005]

#### Are we done?

 Single, rigid template usually not enough to represent a category

 Many objects (e.g. humans) are articulated, or have parts that can vary in configuration



 Many object categories look very different from different viewpoints, or from instance to instance





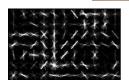
#### Difficulty of representing positive instances

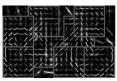
- Discriminative methods have proven very powerful
- But linear SVM on HoG templates not sufficient?
- Alternatives:
  - Parts-based models [Felzenszwalb et al. CVPR 2008]
  - Latent SVMs [Felzenszwalb et al. CVPR 2008]

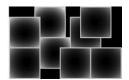
#### Parts-based models



Our first innovation involves enriching the Dalal-Triggs model using a star-structured part-based model defined by a "root" filter (analogous to the Dalal-Triggs filter) plus a set of parts filters and associated deformation models.







Felzenszwalb, et al., Discriminatively Trained Deformable Part Models, <a href="http://people.cs.uchicago.edu/~pff/latent/">http://people.cs.uchicago.edu/~pff/latent/</a>

#### Latent SVMs

- Rather than training a single linear SVM separating positive examples...
- ... cluster positive examples into "components" and train a classifier for each (using all negative examples)

# Two-component bicycle model





"side" component







"frontal" component

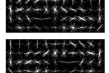




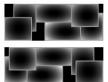


# Six-component car model

side view

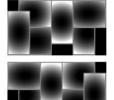






frontal view





root filters (coarse)

part filters (fine)

deformation models

