Object detection with deformable part-based models

Many slides based on P. Felzenszwalb
Challenge: Generic object detection
Histograms of oriented gradients (HOG)

- Partition image into blocks and compute histogram of gradient orientations in each block

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

Image credit: N. Snavely
Pedestrian detection with HOG

• Train a pedestrian template using a linear support vector machine

positive training examples

negative training examples

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

- Train a pedestrian template using a linear support vector machine
- At test time, convolve feature map with template
- Find local maxima of response
- For multi-scale detection, repeat over multiple levels of a HOG pyramid

Example detections

[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
Discriminative part-based models

P. Felzenszwalb, R. Girshick, D. McAllester, D. Ramanan, 
Object Detection with Discriminatively Trained Part Based Models, PAMI 32(9), 2010
Discriminative part-based models

Multiple components

P. Felzenszwalb, R. Girshick, D. McAllester, D. Ramanan, 
Object Detection with Discriminatively Trained Part Based Models, PAMI 32(9), 2010
Discriminative part-based models

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Object Detection with Discriminatively Trained Part Based Models, PAMI 32(9), 2010
Object hypothesis

- Multiscale model: the resolution of part filters is twice the resolution of the root.
Scoring an object hypothesis

- The score of a hypothesis is the sum of filter scores minus the sum of deformation costs

\[
score(p_0, ..., p_n) = \sum_{i=0}^{n} F_i \cdot H(p_i) - \sum_{i=1}^{n} D_i \cdot (dx_i, dy_i, dx_i^2, dy_i^2)
\]

Filters  Deformation weights
Scoring an object hypothesis

- The score of a hypothesis is the sum of filter scores minus the sum of deformation costs

\[
\text{score}\left(p_0, \ldots, p_n\right) = \sum_{i=0}^{n} F_i \cdot H(p_i) - \sum_{i=1}^{n} D_i \cdot (dx_i, dy_i, dx_i^2, dy_i^2)
\]

\[
\text{score}(z) = w \cdot H(z)
\]
Detection

- Define the score of each root filter location as the score given the best part placements:

\[
score(p_0) = \max_{p_1, \ldots, p_n} score(p_0, \ldots, p_n)
\]
Detection

- Define the score of each root filter location as the score given the best part placements:

\[
\text{score}(p_0) = \max_{p_1, \ldots, p_n} \text{score}(p_0, \ldots, p_n)
\]

- Efficient computation: \textit{generalized distance transforms}

- For each “default” part location, find the score of the “best” displacement

\[
R_i(x, y) = \max_{dx, dy} \left( F_i \cdot H(x + dx, y + dy) - D_i \cdot (dx, dy, dx^2, dy^2) \right)
\]

Head filter

Deformation cost
Detection

- Define the score of each root filter location as the score given the best part placements:

\[
score(p_0) = \max_{p_1, \ldots, p_n} score(p_0, \ldots, p_n)
\]

- Efficient computation: *generalized distance transforms*
  - For each “default” part location, find the score of the “best” displacement

\[
R_i(x, y) = \max_{dx, dy} \left( F_i \cdot H(x + dx, y + dy) - D_i \cdot (dx, dy, dx^2, dy^2) \right)
\]

Head filter
Distance transform
Detection

feature map
feature map at twice the resolution
model

response of root filter
response of part filters
transformed responses
color encoding of filter response values
combined score of root locations
Detection result
Training

- Training data consists of images with labeled bounding boxes
- Need to learn the filters and deformation parameters
Training

• Our classifier has the form

\[ f(x) = \max_z w \cdot H(x, z) \]

• \( w \) are model parameters, \( z \) are \textit{latent} hypotheses

• \textbf{Latent SVM} training:
  • Initialize \( w \) and iterate:
    • Fix \( w \) and find the best \( z \) for each training example (detection)
    • Fix \( z \) and solve for \( w \) (standard SVM training)

• Issue: too many negative examples
  • Do “data mining” to find “hard” negatives
Car model

Component 1

Component 2
Car detections

high scoring true positives

high scoring false positives
Person model
Person detections

high scoring true positives

high scoring false positives
(not enough overlap)
Cat model
Cat detections

high scoring true positives

high scoring false positives (not enough overlap)
Bottle model
More detections

horse

sofa

bottle
PASCAL VOC Challenge (2005-2012)

http://host.robots.ox.ac.uk/pascal/VOC/

- Challenge classes:
  Person: person
  Animal: bird, cat, cow, dog, horse, sheep
  Vehicle: aeroplane, bicycle, boat, bus, car, motorbike, train
  Indoor: bottle, chair, dining table, potted plant, sofa, tv/monitor

- Dataset size (by 2012):
  11.5K training/validation images, 27K bounding boxes, 7K segmentations
Quantitative results (PASCAL 2008)

- 7 systems competed in the 2008 challenge
- Out of 20 classes, first place in 7 classes and second place in 8 classes
Object detection progress

PASCAL VOC

Before deep convnets

Using deep convnets
Detection with deep networks

**R-CNN: Regions with CNN features**

1. Input image
2. Extract region proposals (~2k)
3. Compute CNN features
4. Classify regions

**Object detection system overview.** Our system (1) takes an input image, (2) extracts around 2000 bottom-up region proposals, (3) computes features for each proposal using a large convolutional neural network (CNN), and then (4) classifies each region using class-specific linear SVMs. **R-CNN achieves a mean average precision (mAP) of 53.7% on PASCAL VOC 2010.** For comparison, Uijlings et al. (2013) report 35.1% mAP using the same region proposals, but with a spatial pyramid and bag-of-visual-words approach. The popular deformable part models perform at 33.4%.