A Discriminatively Trained, Multiscale, Deformable Part Model

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Model overview

Model consists of root filter plus deformable parts

We have built & tested models for all 20 classes (no class tuning)
Image features - histograms of gradients

- Our implementation of DalalTriggs HOG features
  - Bin fine-scale gradients into 8x8 spatial neighborhoods and 9 orientation channels
- Normalize with respect to multiple local 16x16 regions
Multi-scale star model

root filter
8x8 resolution

discrete spatial model
Multi-scale star model

root filter
8x8 resolution

epart filters
4x4 resolution

discrete spatial model
Formal model

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

\( Z = \text{vector of part offsets} \)

\( \Phi(x, z) = \text{vector of HOG features (from root filter & appropriate part sub-windows) and part offsets} \)
Some stats

• We search over scales with an image pyramid (1.05 scaling)

• We search over 8-pixel strides for root filter, 4-pixel strides for part filter

• Training time: 3-4 hours per class using 1 cpu, including learning part models automatically

• Testing time: 2 seconds per image per model
Example models
Example models
Latent SVMs

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

Assume we are given positive and negative training windows \( \{x_i\} \)

\[ w^* = \arg \min_w \lambda \|w\|^2 + \ldots + \sum_{i \in \text{pos}} \max(0, 1 - f_w(x_i)) + \sum_{i \in \text{neg}} \max(0, 1 + f_w(x_i)) \]

If \( f() \) is linear classifier, this is a standard SVM (convex)
If \( f() \) is an arbitrary classifier, this (in general) is not convex
If \( f() \) is convex in \( w \), the training objective is ‘semi-convex’
(Instance of LeCun’s Energy Based Model)
Root filter initialization

• We select the aspect and size by a heuristic tuned on 2006 data (use most common aspect and smallest area > 80% of training bounding boxes)

• Train a root filter with SVM-light: use non-truncated positives (warped to fixed aspect & size) and random negatives
Part filter initialization

• Look for regions in root filter with lots of positive energy - part filter initialized to subwindow doubled in resolution

• Spatial model allows for a bounded offset from original anchor point - discrete deformation cost initialized to 0 everywhere
Model update

- Update positives
  - Apply current detector over all positions & scales
  - Find best-scoring $\Phi(x_i, z_i)$ that overlaps > 50% with ground truth positive bounding box
  - Allows for automatic adjustment of b. box

- Collect negative $\Phi(x_i, z_i)$'s by finding high-scoring detections, cycling through negative training images

- Use $\Phi(x_i, z_i)$'s to train a new detector (w) with SVM-light (Joachims)

- Repeat update 10 times
Ongoing work

Hierarchically learn parts
Ongoing work

Improves performance by 10% (AP of .29 vs .32)

Training & testing on Person2006
Conclusions

Deformable part model
Histograms-of-gradient features
Multi-scale / hierarchical
Discriminatively-trained