Hierarchical Learning for Object Detection

Long Zhu, Yuanhao Chen, William Freeman, Alan Yuille, Antonio Torralba

MIT and UCLA, 2010

Background I: Our prior work

- Our work for the Pascal Challenge is based on two recent publications from our group.
  - Latent Hierarchical Structural Learning for Object Detection. Long Zhu, Yuanhao Chen, Alan Yuille, William Freeman. CVPR 2010.
  - Active Mask Hierarchies for Object Detection. Yuanhao Chen, Long Zhu, Alan Yuille. ECCV 2010.

Background II: Related Work

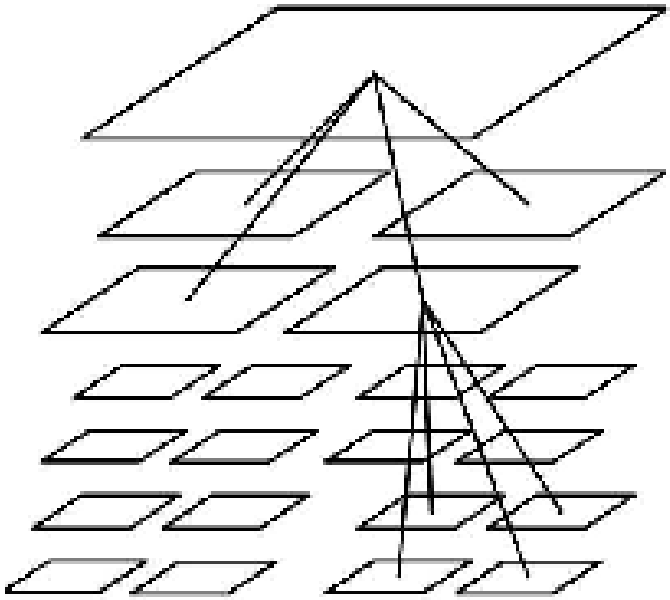
- We build on previous work:
- Learning part-based **structure** model
  - UoCTTI (Felzenszwalb PAMI2009), Berkeley (Bourdev ICCV2009), Caltech(ECCV 2008), Blaschko (ECCV2008)
- Learning **appearance** features
  - Oxford (Vedaldi ICCV2009, Bosch CIVR 007)
- Learning to include **contextual** information
  - UCI (Desai ICCV2009), MIT (Choi et al. 2010), INRIA (Harzallah et al. ICCV 2009).

Overview of our approach

1. **Hierarchical part-based models** with three layers. 4-6 models for each object to allow for pose.
2. **Energy potential terms:** (a) HOGs for edges, (b) Histogram of Words (HOWs) for regional appearance, (c) shape features.
3. **Detect objects** by scanning sub-windows using dynamic programming (to detect positions of the parts).
4. **Learn the parameters** of the models by machine learning: a variant (iCCCP) of Latent SVM.

Hierarchical Part-Based Models: (1)

- Each hierarchy is a 3-layer tree.
- Each node represents a part.
- Total of 46 nodes: (1+9+ 4 x 9)

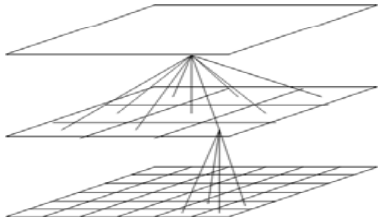


- Each node has a spatial position (parts can “move” or are “active”)
- Graph edges from parents to child – impose spatial constraints.

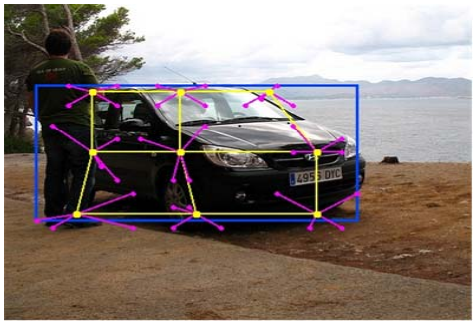
Hierarchical Part-Based Models: (2)

- The parts can move relative to each other. This allows the model to have spatial deformations.
- Constraints on these deformations are imposed by edges between parents and child (will be learnt)

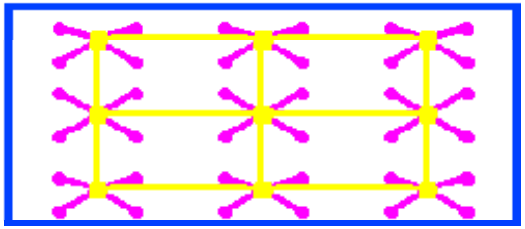
Parent-Child spatial constraints



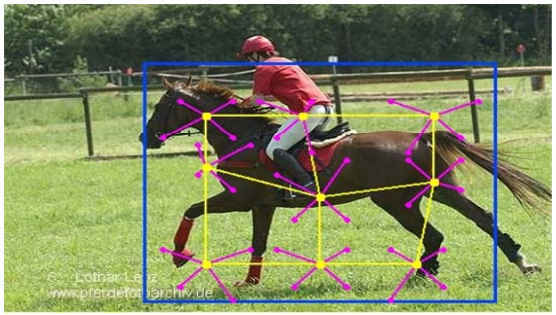
Deformations of the Car



Parts: blue (1), yellow (9), purple (36)

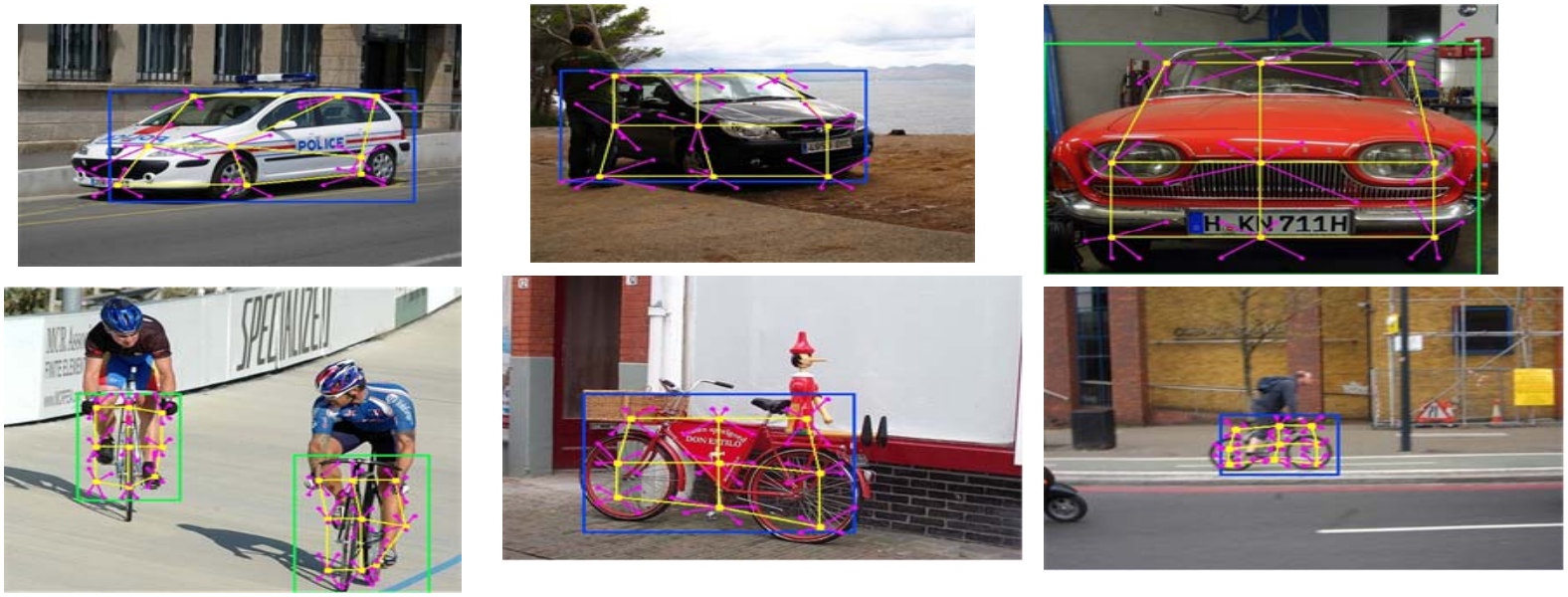


Deformations of the Horse



Hierarchical Part-Based Models: (3)

- Each object is represented by 4 or 6 hierarchical models (mixture of models).
- These mixture components account for pose/viewpoint changes.



Hierarchical Part-Based Models: (4)

- The object model has variables:

1. p – represents the position of the parts.
2. V – specifies which mixture component (e.g. pose).
3. y – specifies whether the object is present or not.
4. ω – model parameter (to be learnt).

- Note: during learning the part positions p and the pose V are unknown – so they are latent variables and will be expressed as $h = (V, p)$

Energy of the Model:

- The "energy" of the model is defined to be: $-\omega \cdot \Phi(x, y, h)$ where x is the image in the region.
- The object is detected by solving:

$$y^*, h^* = \arg\max \omega \cdot \Phi(x, y, h)$$

- If $y^* = +1$ then we have detected the object.
- If so, $h^* = (p^*, V^*)$ specifies the mixture component and the positions of the parts.

Energy of the Model:

- There are three types of potential terms $\Phi(x, y, h)$

  (1) Spatial terms $\Phi_{shape}(y, h)$ which specify the distribution on the positions of the parts.

  (2) Data terms for the edges of the object

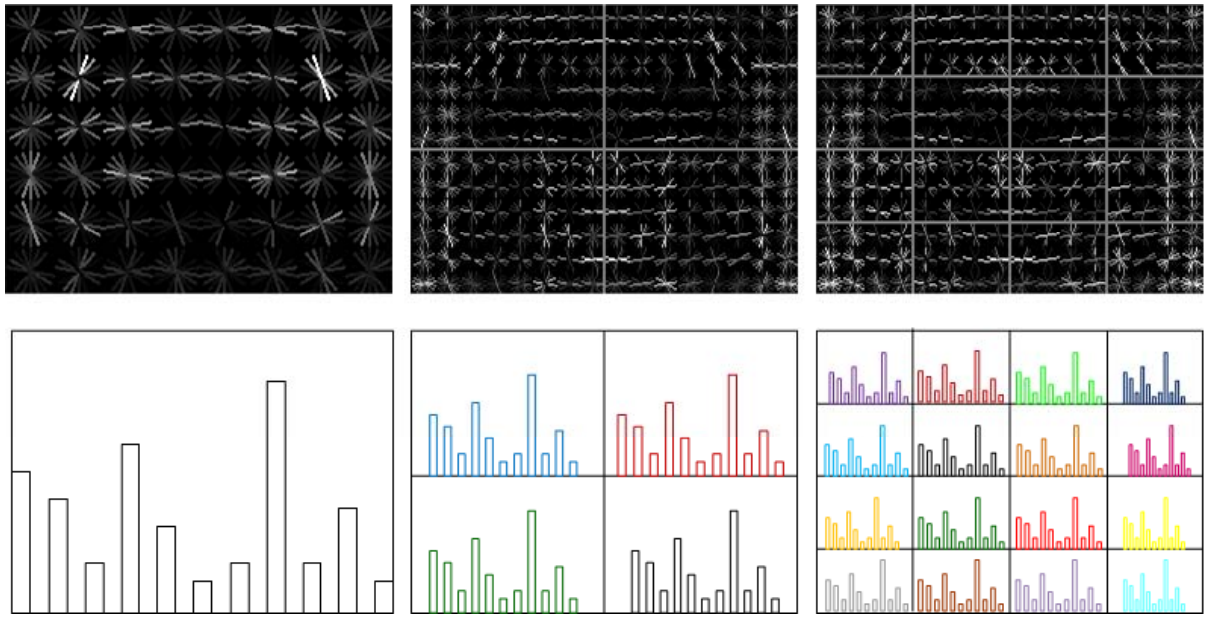
  $\Phi_{HOG}(x, y, h)$ defined using HOG features.

  (3) Regional appearance data terms

  $\Phi_{HOW}(x, y, h)$ defined by histograms of words (HOWs – using grey SIFT features and K-means).

Energy of the Model: HOGs and HOWs

- Edge-like: Histogram of Oriented Gradients (Upper row)
- Regional: Histogram Of Words (Bottom row)
- Dense sampling: 13950 HOGs + 27600 HOWs



Object Detection

- To detect an object requiring solving:

$$y^*, h^* = \arg\max \omega \cdot \Phi(x, y, h)$$

  for each image region.

- We solve this by scanning over the subwindows of the image, use dynamic programming to estimate the part positions p and do exhaustive search over the y & V

Learning by Latent SVM

- The input to learning is a set of labeled image regions. $\{(x\_i, y\_i) : i = 1, \ldots, N\}$

- Learning require us to estimate the parameters ω
- While simultaneously estimating the hidden variables $h = (p, V)$

Latent SVM Learning

- We use Yu and Joachim's (2009) formulation of latent SVM.
- This specifies a non-convex criterion to be minimized. This can be re-expressed in terms of a convex plus a concave part.

$$\min_w \frac{1}{2}\| w \|^2 + C\sum_{i=1}^{N}\left[\max_{y,h}[w\cdot\Phi(x_i,y,h)+L(y_i,y,h)] - \max_h[w\cdot\Phi(x_i,y_i,h)]\right]$$

$$\Rightarrow \quad \min_w\left[\frac{1}{2}\| w \|^2 + C\sum_{i=1}^{N}\max_{y,h}[w\cdot\Phi(x_i,y,h)+L(y_i,y,h)]\right] - \left[C\sum_{i=1}^{N}\max_h[w\cdot\Phi(x_i,y_i,h)]\right]$$

Latent SVM Learning

- Yu and Joachims (2009) propose the CCCP algorithm (Yuille and Rangarajan 2001) to minimize this criterion.
- This iterates between estimating the hidden variables and the parameters (like the EM algorithm).
- We propose a variant – incremental CCCP – which is faster.
- Result: our method works well for learning the parameters *without* complex initialization.

Learning Algorithm: Incremental CCCP

- Iterative Algorithm:
  - Step 1: fill in the latent positions with best score(DP)
  - Step 2: solve the structural SVM problem using partial negative training set (incrementally enlarge).
- Initialization:
  - No pretraining (no clustering).
  - No displacement of all nodes (no deformation).
  - Pose assignment: maximum overlapping
- Simultaneous multi-layer learning

Kernels

- We use a quasi-linear kernel for the HOW features, linear kernels of the HOGs and for the spatial terms.
- We use:

  (i) equal weights for HOGs and HOWs

  (ii) equal weights for all nodes at all layers

  (iii) same weights for all object categories.
- Note: tuning the weights for different categories may improve the performance.

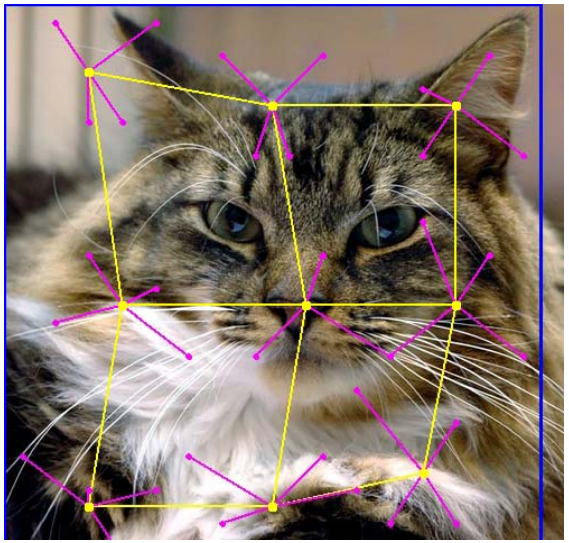
Post-processing: Context Modeling

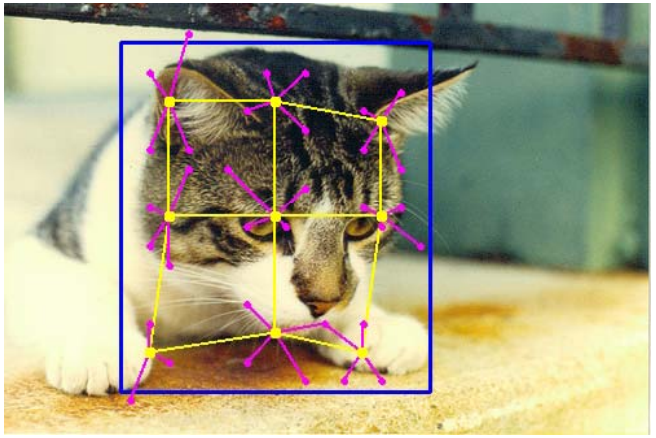
- Post-processing:
  - Rescoring the detection results
- Context modeling: SVM+ contextual features
  - best detection scores of 20 classes, locations, recognition scores of 20 classes
- Recognition scores (Lazebnik CVPR06, Van de Sande PAMI 2010, Bosch CIVR07)
  - SVM + spatial pyramid + HOWs (no latent position variable)

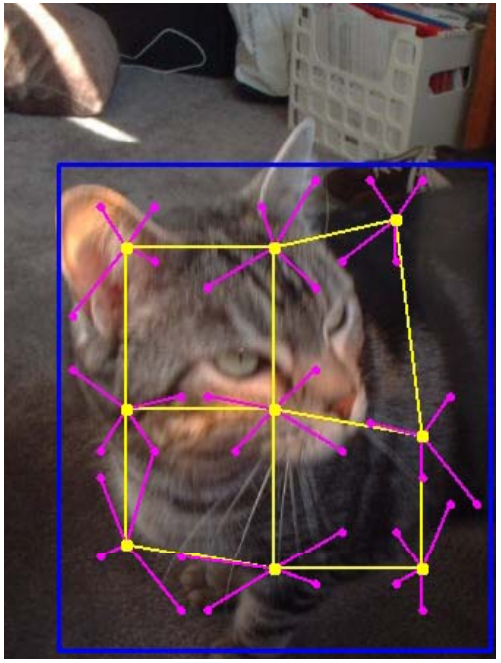
Experiments on Pascal 2010

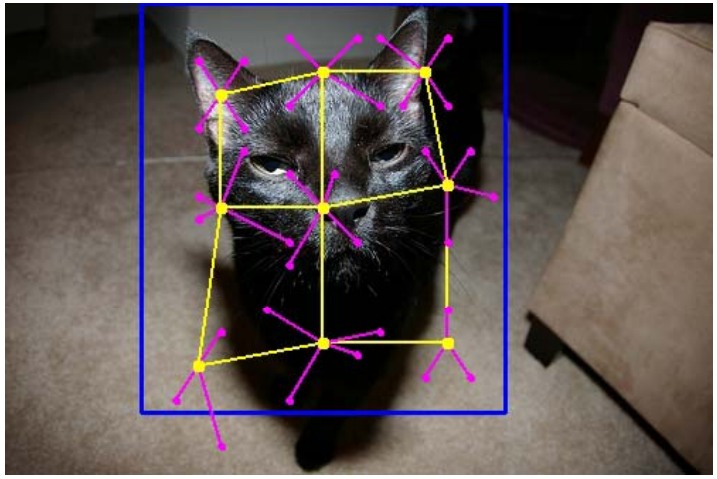
- 4 or 6 mixture components/poses.
- All other parameter settings (C, the relative weights of appearance features, the number of visual words, etc.) are identical for all categories.
- 300 visual words: one round of K-means.

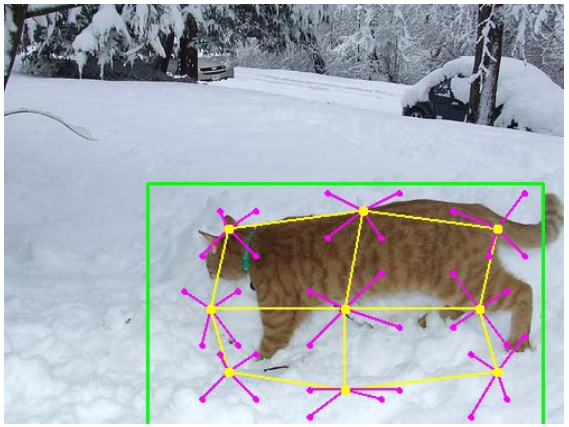
Detection Results on PASCAL 2010: Cat



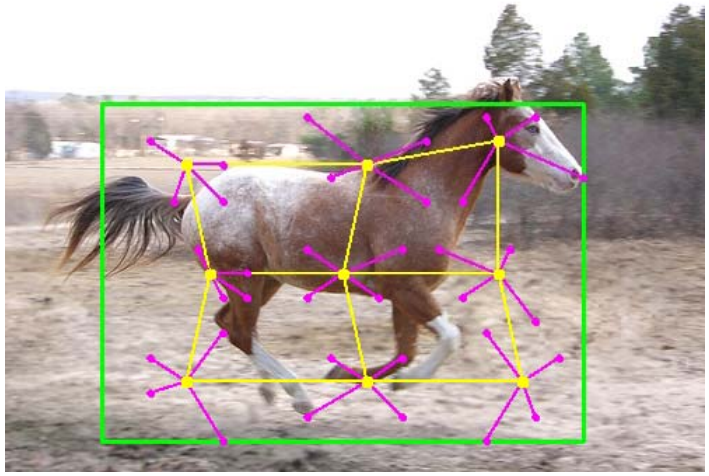


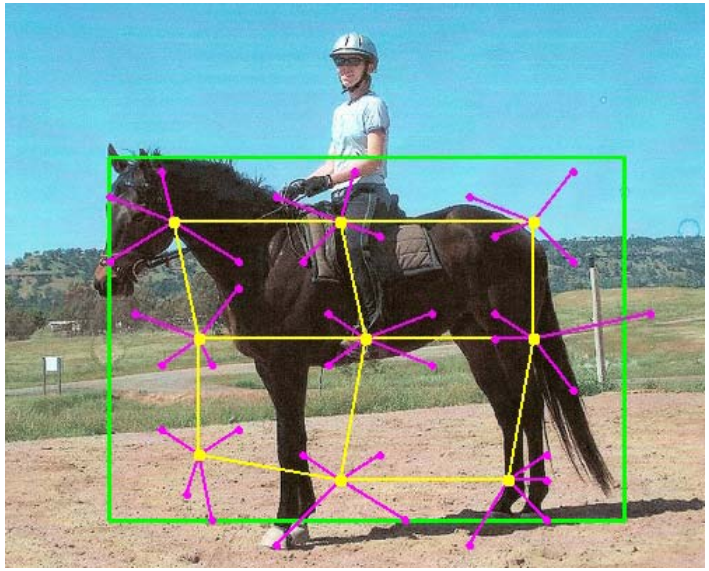


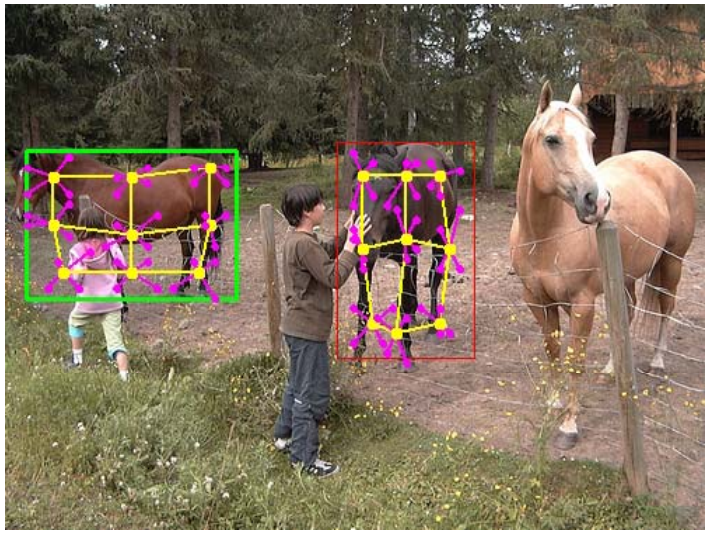


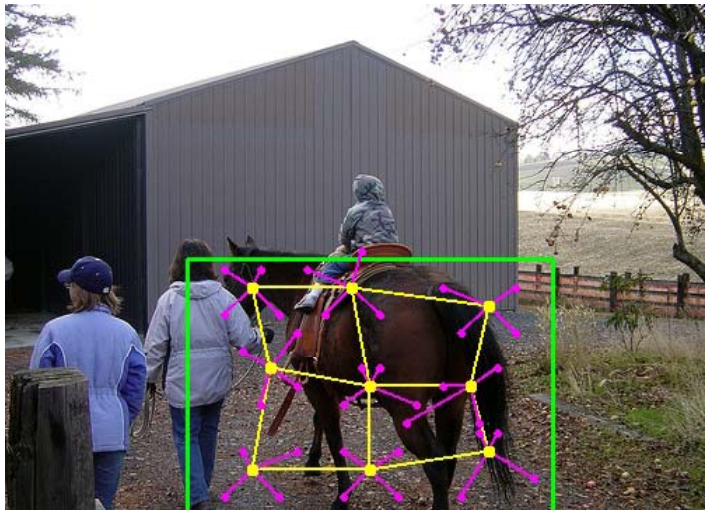


Horse

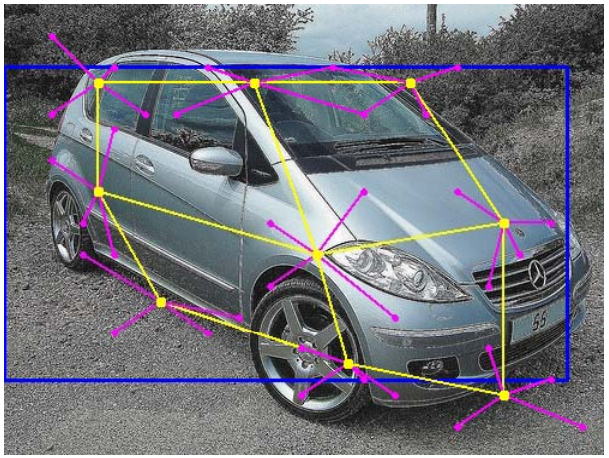


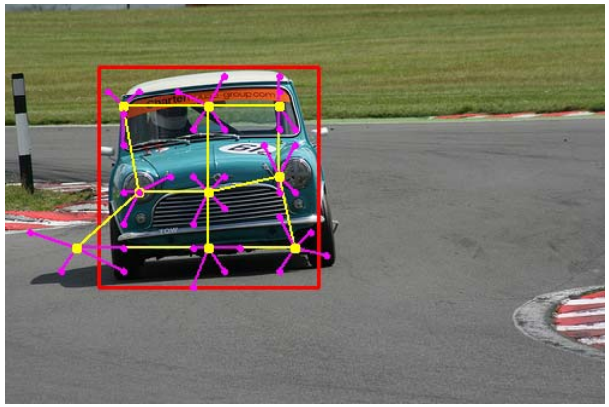


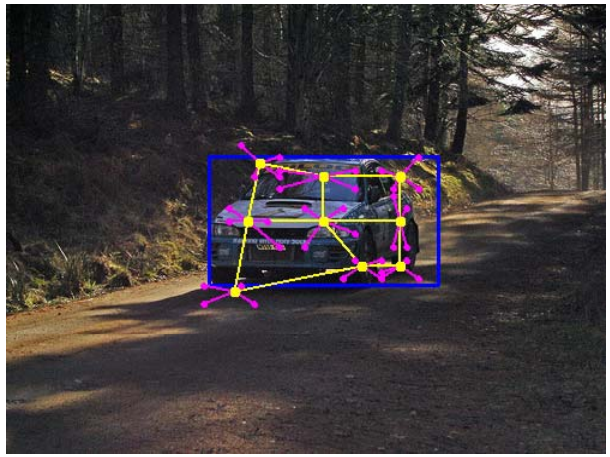


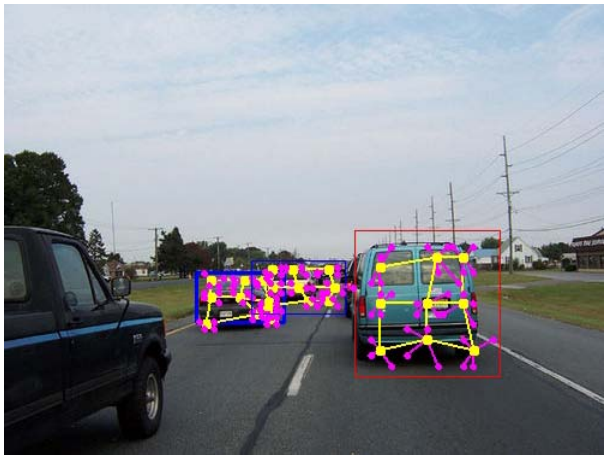


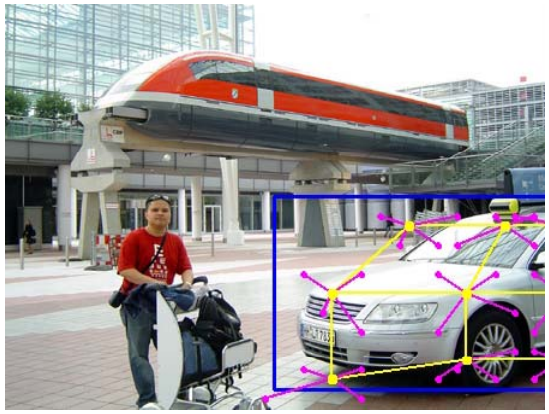
Car

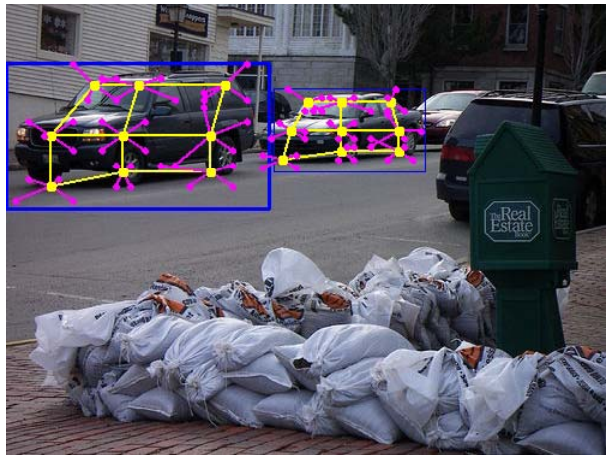




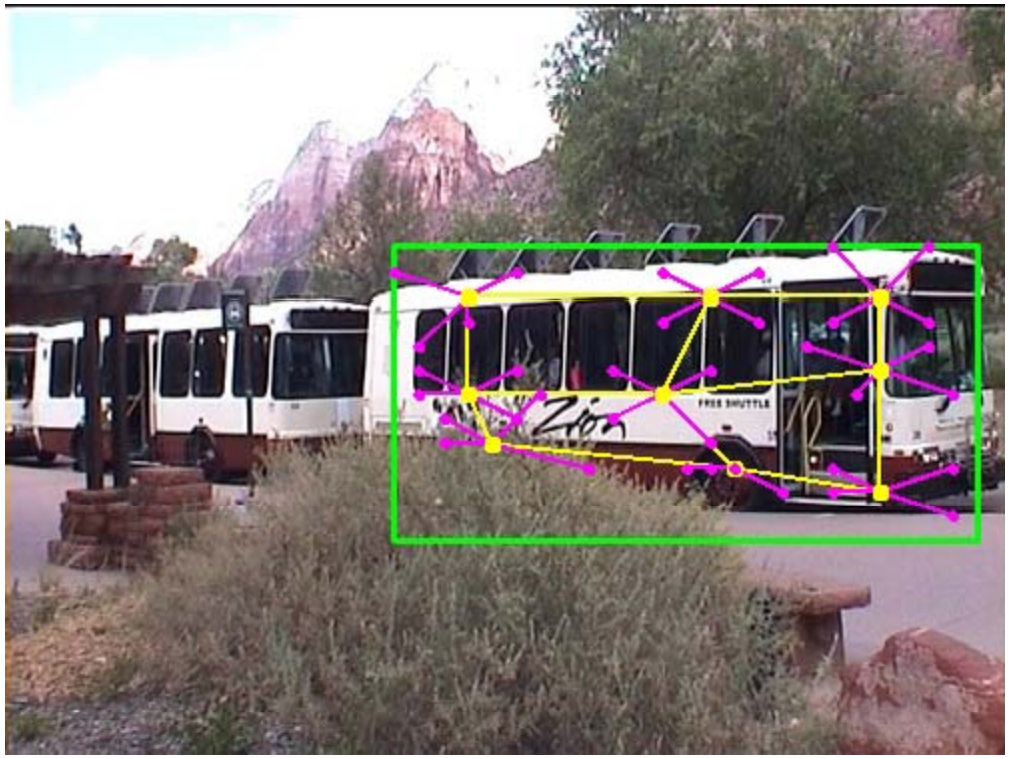


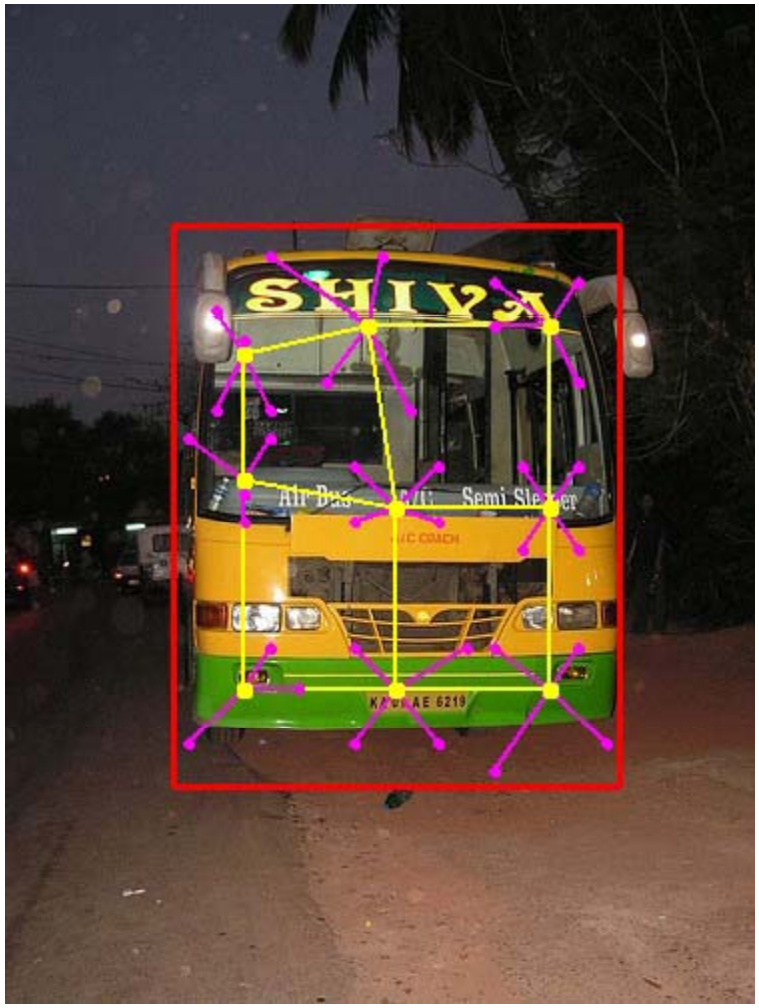






Bus





Comparisons on PASCAL 2010

- Mean Average Precision (mAP) is reported.
- Note: the calculations of AP used in 2010 and 2009 are different.

Methods (trained on 2010)	MIT-UCLA	NLPR	NUS	UoCTTI	UVA	UCI incomplete
Test on 2010	35.99	36.79	34.18	33.75	32.87	32.52
Test on 2009	36.72	37.65	35.53	34.57	34.47	33.63

Conclusion

- Objects are represented by mixture of Hierarchical Models of parts.
- The energy for the model contains spatial terms, edge-like terms (HOGs), and regional appearance terms (HOWs).
- We learn the model parameter by a variant of latent SVM -- incremental CCCP – which only requires simple initialization.
- The code will be available soon.
- Current and future work
  - Increase the number of components/poses
  - Part sharing