BLACK: Body Language Affect Classification Kernel

Undergrad-ient Descent Expedition
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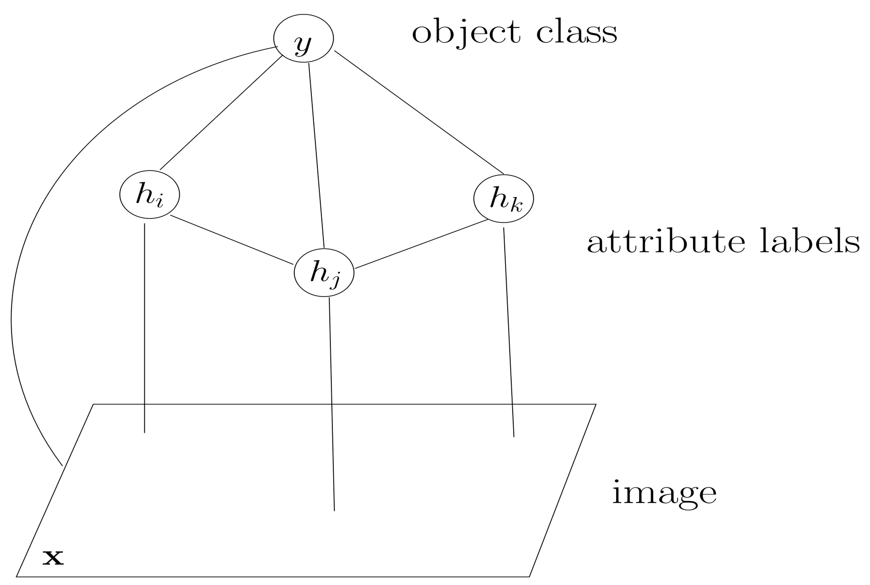
Overview

- Joint modeling of object classes and (correlated) attributes
- Demonstrating attributes can help object recognition
- A general learning framework for classification with auxiliary labels

Why attributes alone are not enough?

Model Formulation



Training data: $\{(\mathbf{x}^{(n)}, \mathbf{h}^{(n)}, y^{(n)})\}_{n=1}^{N}$

Scoring function: $f_{\mathbf{w}}(\mathbf{x}, y) = \max_{\mathbf{h}} \mathbf{w}^\top \Phi(\mathbf{x}, \mathbf{h}, y)$, where

$$
\begin{aligned}
\mathbf{w}^\top \Phi(\mathbf{x}, \mathbf{h}, y) = & \\
& \mathbf{w}_y^\top \phi(\mathbf{x}) \quad \text{object class model} \\
+ & \sum_{j \in \mathcal{V}} \mathbf{w}_{h_j}^\top \varphi(\mathbf{x}) \quad \text{global attribute model} \\
+ & \sum_{j \in \mathcal{V}} \mathbf{w}_{y,h_j}^\top \omega(\mathbf{x}) \quad \text{class-specific attribute model} \\
+ & \sum_{(j,k) \in \mathcal{E}} \mathbf{w}_{j,k}^\top \psi(h_j, h_k) \quad \text{attribute-attribute interaction} \\
+ & \sum_{j \in \mathcal{V}} v_{y,h_j} \quad \text{object-attribute interaction}
\end{aligned}
$$

Learning and Inference

Inference: tractable if attributes $\mathbf{h}$ have special structures (e.g. trees)

$$\mathbf{h}^* = \arg\max_{\mathbf{h}} \mathbf{w}^\top \Phi(\mathbf{x}, \mathbf{h}, y) \quad \forall y \in \mathcal{Y}$$

Learning with latent attributes:

$$
\begin{aligned}
& \min_{\mathbf{w}, \xi} \beta ||\mathbf{w}||^2 + \sum_{n=1}^{N} \xi^{(n)} \\
& \text{s.t.} \max_{\mathbf{h}} \mathbf{w}^\top \Phi(\mathbf{x}^{(n)}, \mathbf{h}, y^{(n)}) - \max_{\mathbf{h}} \mathbf{w}^\top \Phi(\mathbf{x}^{(n)}, \mathbf{h}, y) \\
& \quad \geq \Delta(y, y^{(n)}) - \xi^{(n)}, \forall n, \forall y
\end{aligned}
$$

Another choice is to use the ground-truth attribute labels $\mathbf{h}^n$ (i.e. learning with observed attributes).

Attribute Relation Graph

Running minimum spanning tree with $\mathrm{NormMI}(j, k)$ as the weight on the edge (j, k).

Other Loss Functions

A simple modification of Δ will optimize different (training) errors.

Overall accuracy:

$$\Delta_{0/1}(y, y^{(n)}) = \begin{cases} 1 \text{ if } y \neq y^{(n)} \\ 0 \text{ otherwise} \end{cases}$$

Mean per-class accuracy:

$$\Delta_{\text{new}}(y, y^{(n)}) = \begin{cases} \frac{1}{m_p} \text{ if } y \neq y^{(n)} \text{ and } y^{(n)} = p \\ 0 \quad \text{otherwise} \end{cases}$$

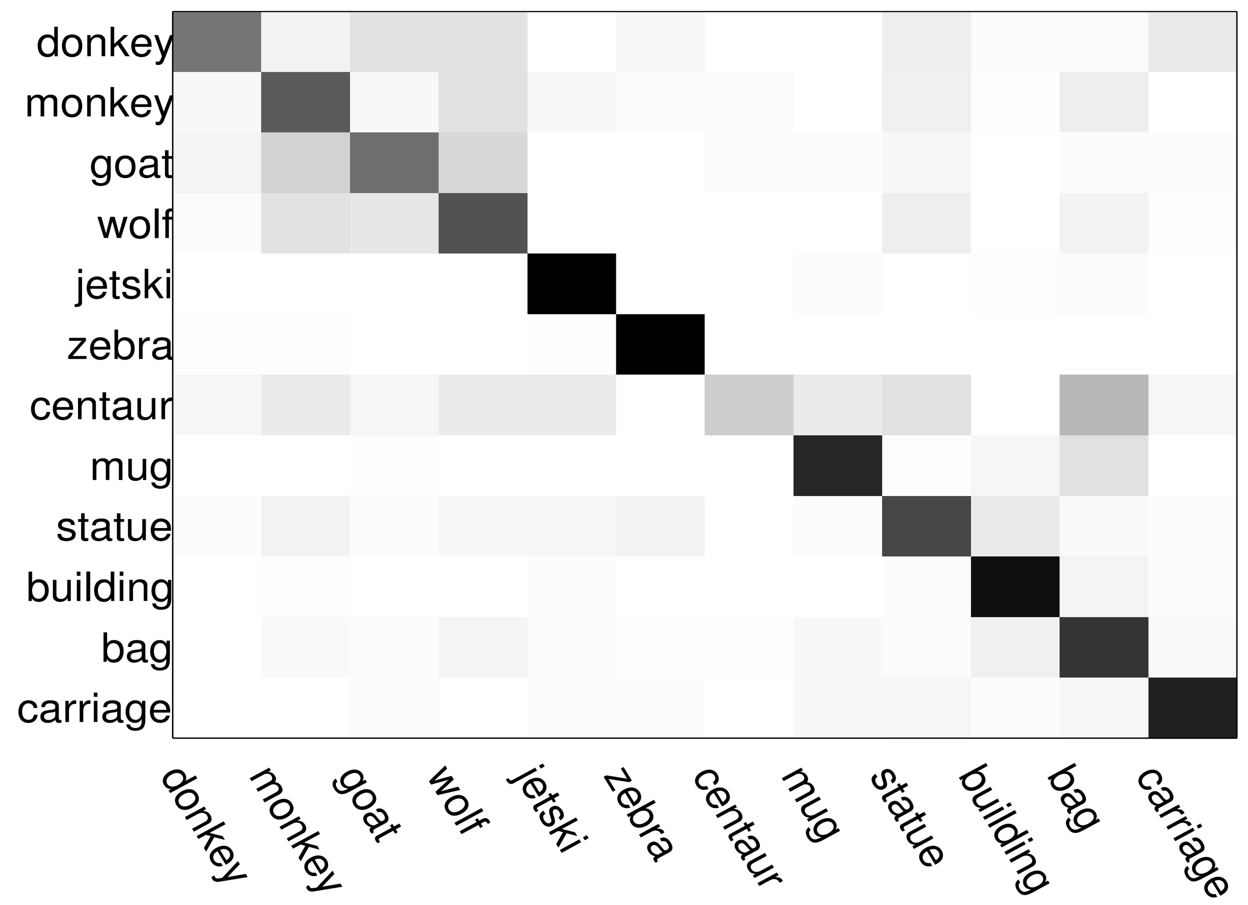
where m_p is the number of training examples with class p.

Experiments

a-Pascal dataset:

method	overall	mean per-class
Our approach with $\Delta_{0/1}$	**62.16**	**46.25**
Our approach with Δ_{new}	**59.15**	**50.84**
SVM with $\Delta_{0/1}$	58.77	38.52
SVM with Δ_{new}	53.74	44.04
Farhadi et al. CVPR09 (base features+SVM)	58.5	34.3
Farhadi et al. CVPR09 (best result)	59.4	37.7

a-Yahoo dataset:



method	overall	mean per-class
Our approach with $\Delta_{0/1}$	**78.67**	**71.45**
Our approach with Δ_{new}	**79.88**	**73.31**
SVM with $\Delta_{0/1}$	74.43	65.96
SVM with Δ_{new}	74.51	66.74