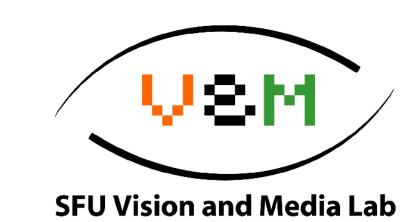




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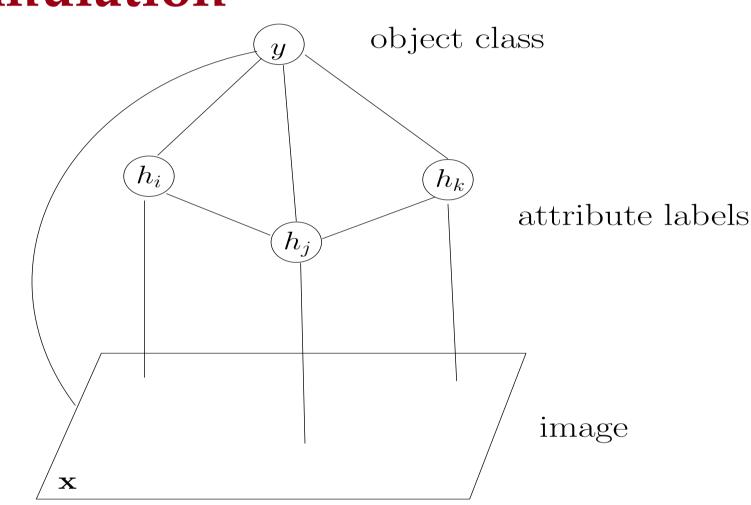


### Overview

- 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

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

## Learning and Inference

Inference: tractable if attributes 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:

$$\min_{\mathbf{w},\xi} \beta ||\mathbf{w}||^2 + \sum_{n=1}^{N} \xi^{(n)}$$
s.t.  $\max_{\mathbf{h}} \mathbf{w}^{\top} \Phi(\mathbf{x}^{(n)}, \mathbf{h}, y^{(n)}) - \max_{\mathbf{h}} \mathbf{w}^{\top} \Phi(\mathbf{x}^{(n)}, \mathbf{h}, y)$ 

$$\geq \Delta(y, y^{(n)}) - \xi^{(n)}, \forall n, \forall y$$

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 NormMI(j, k) as the weight on the edge (j, k).

## **Other Loss Functions**

A simple modification of  $\Delta$  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:

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

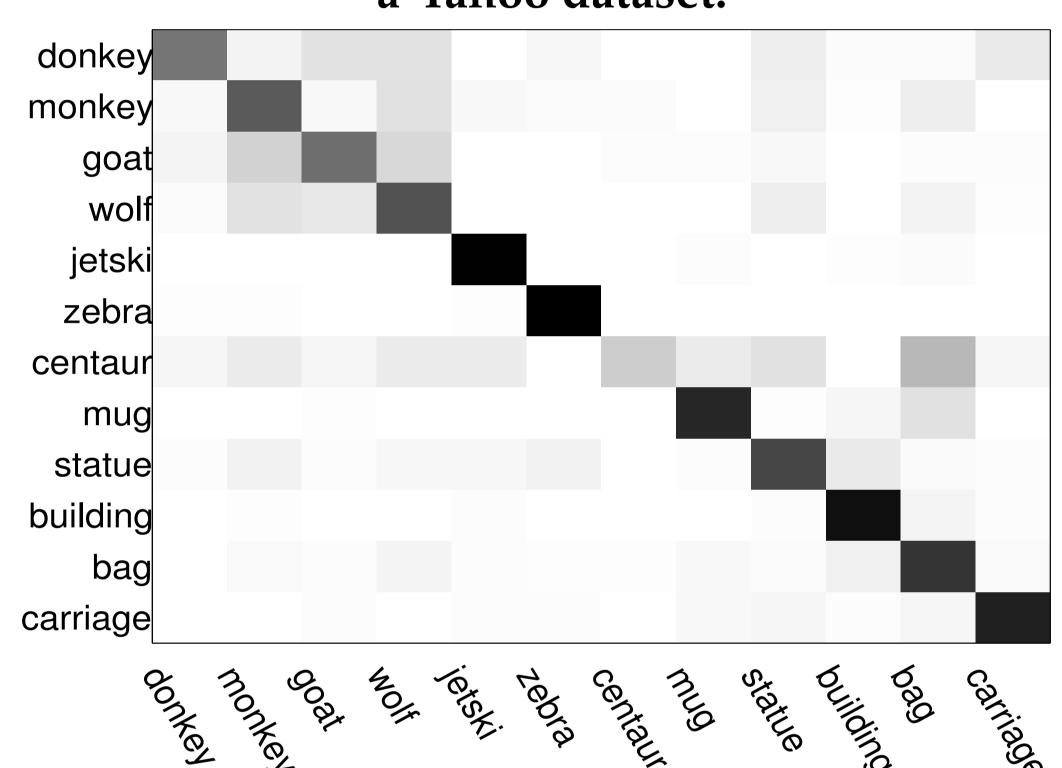
where  $m_p$  is the number of training examples with class p.

# Experiments

#### a-Pascal dataset:

method	overall	mean per-class
Our approach with $\Delta_{0/1}$	62.16	46.25
Our approach with $\Delta_{\mathrm{new}}$	59.15	50.84
SVM with $\Delta_{0/1}$	58.77	38.52
SVM with $\Delta_{ m new}$	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 $\Delta_{\mathrm{new}}$	79.88	73.31
SVM with $\Delta_{0/1}$	74.43	65.96
SVM with $\Delta_{ m new}$	74.51	66.74