Attributes

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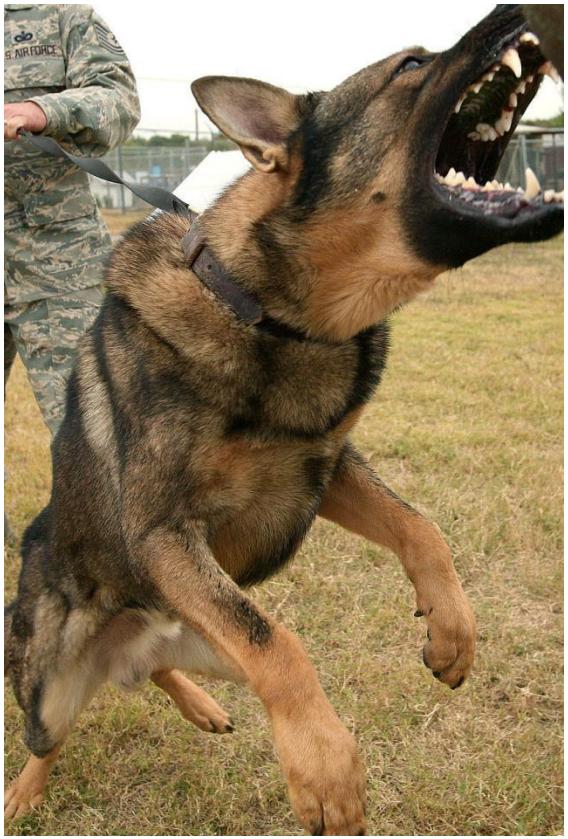
Describing Objects by Their Attributes

Based on Derek Hoiem's slide

Describe objects at a more abstract level



“Gradient changes from bottom to top. Especially, many corners at the top left region.”

vs.

“Large, angry animal with pointy teeth”

Why Infer Properties (if we can)

1. We want detailed information about objects
2. We want to be able to infer something about unfamiliar objects (name is *unknown*)
3. We want to make comparisons between objects or categories

Familiar Objects

Has Stripes
Has Ears
Has Eyes
….

Has Four Legs
Has Mane
Has Tail
Has Snout
….

Brown
Muscular
Has Snout
….

New Object

Has Stripes (like cat)
Has Mane and Tail (like horse)
Has Snout (like horse and dog)

Attributes (64)

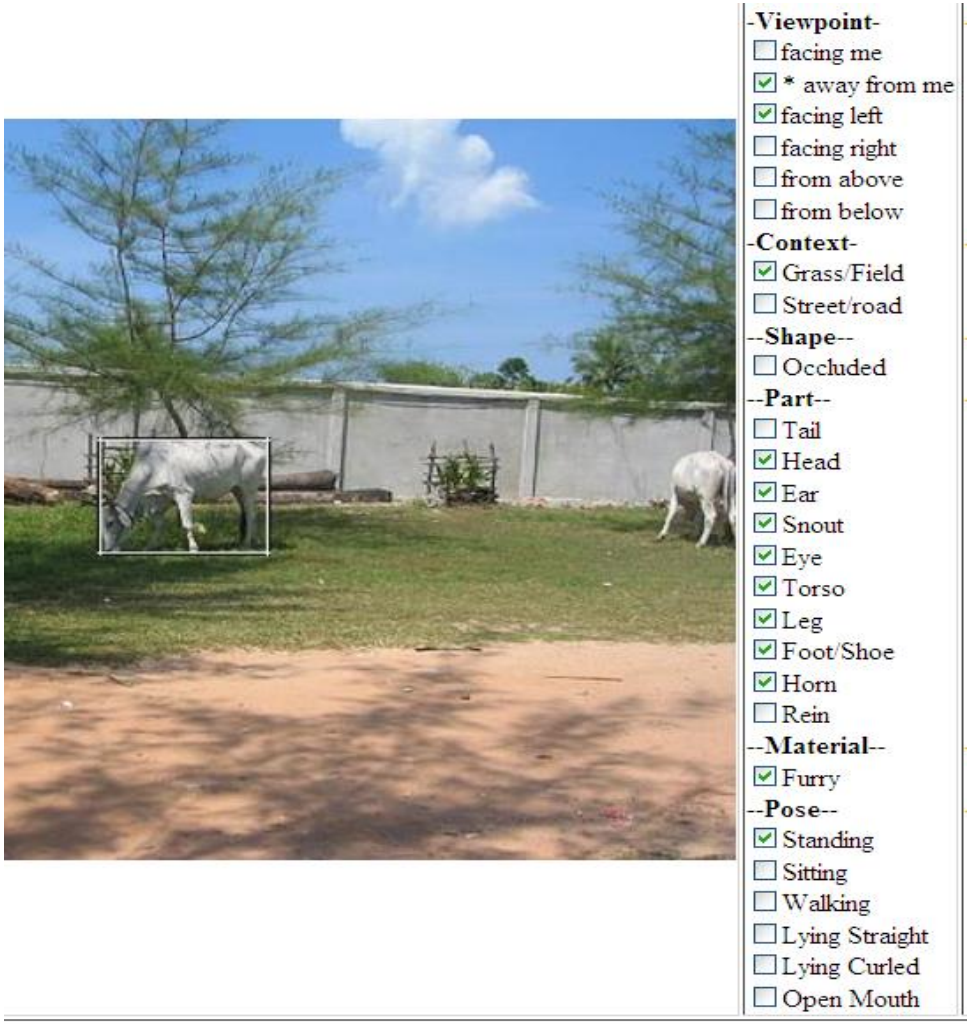
- *Visible parts*: “has wheels”, “has snout”, “has eyes”
- *Visible materials or material properties*: “made of metal”, “shiny”, “clear”, “made of plastic”
- *Shape*: “3D boxy”, “round”

Shape: Horizontal Cylinder
Part: Wing, Propeller, Window, *Wheel*
Material: *Metal*, Glass

Attribute dataset

- **a-Pascal**: 20 categories from PASCAL 2008 trainval dataset (10K object images)

- **a-Yahoo**: 12 new categories from Yahoo image search



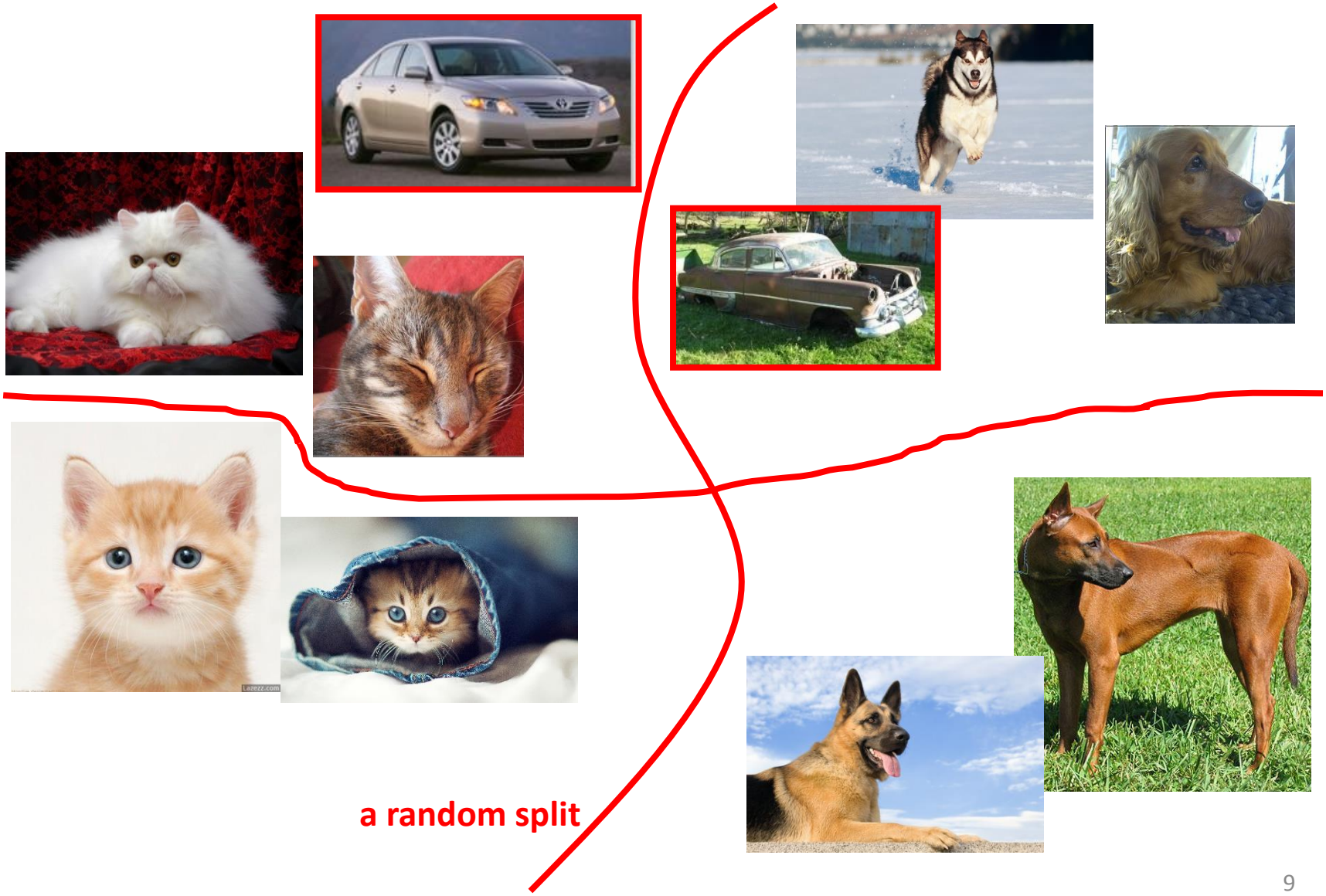
Attribute labels are somewhat ambiguous

- Agreement among “experts” (authors) 84.3
- Between experts and Turk labelers 81.4
- Among Turk labelers 84.1

Base features

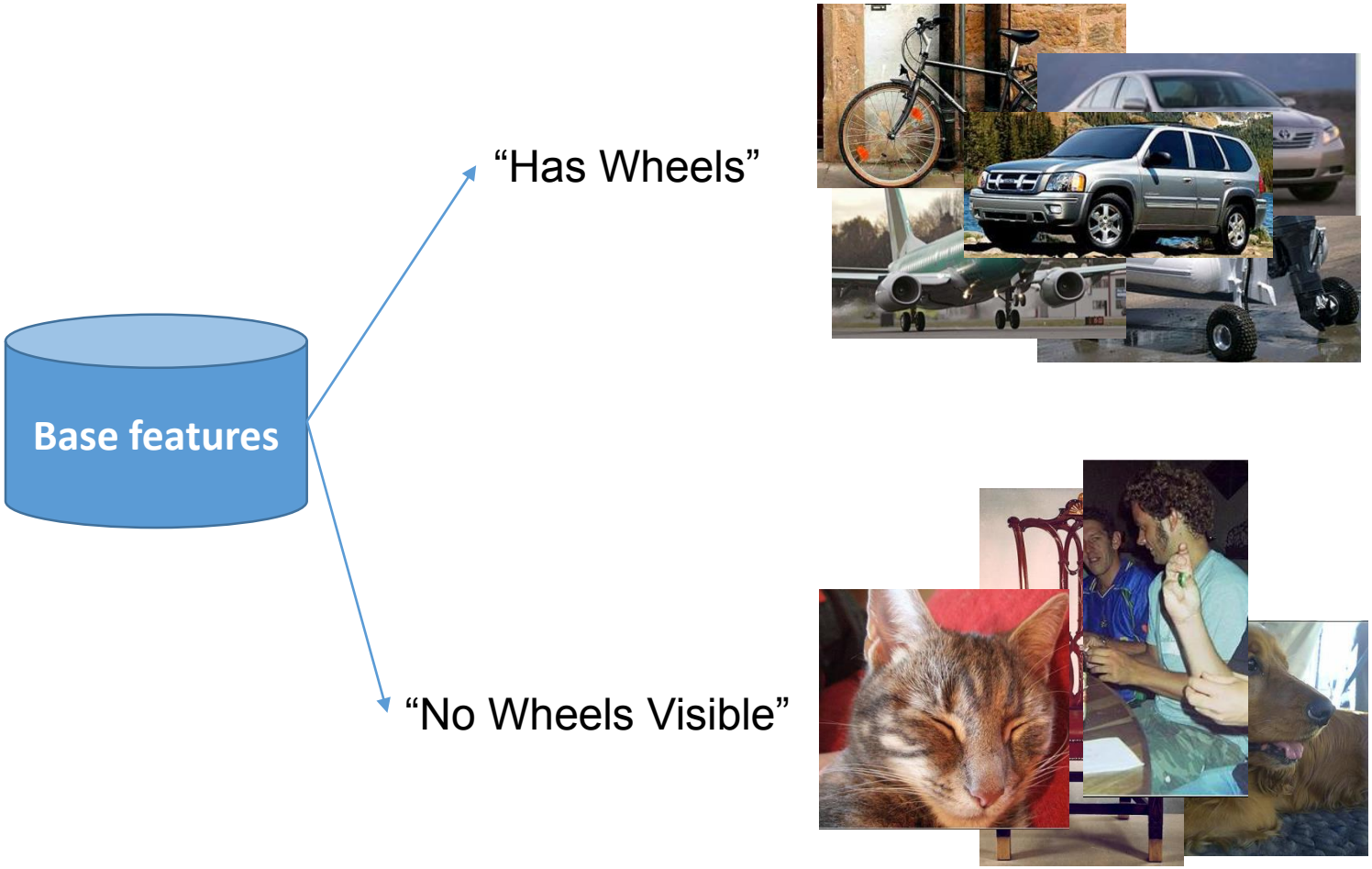
- Spatial pyramid histograms of quantized
  - Color and texture for **materials**
  - Histograms of gradients (HOG) for **parts**
  - Canny edges for **shape**

Discriminative Attributes



Learning (semantic) attributes

Simplest approach: Train classifier using all features for each attribute independently



Correlated attributes

Big Problem: Many attributes are strongly correlated through the object category



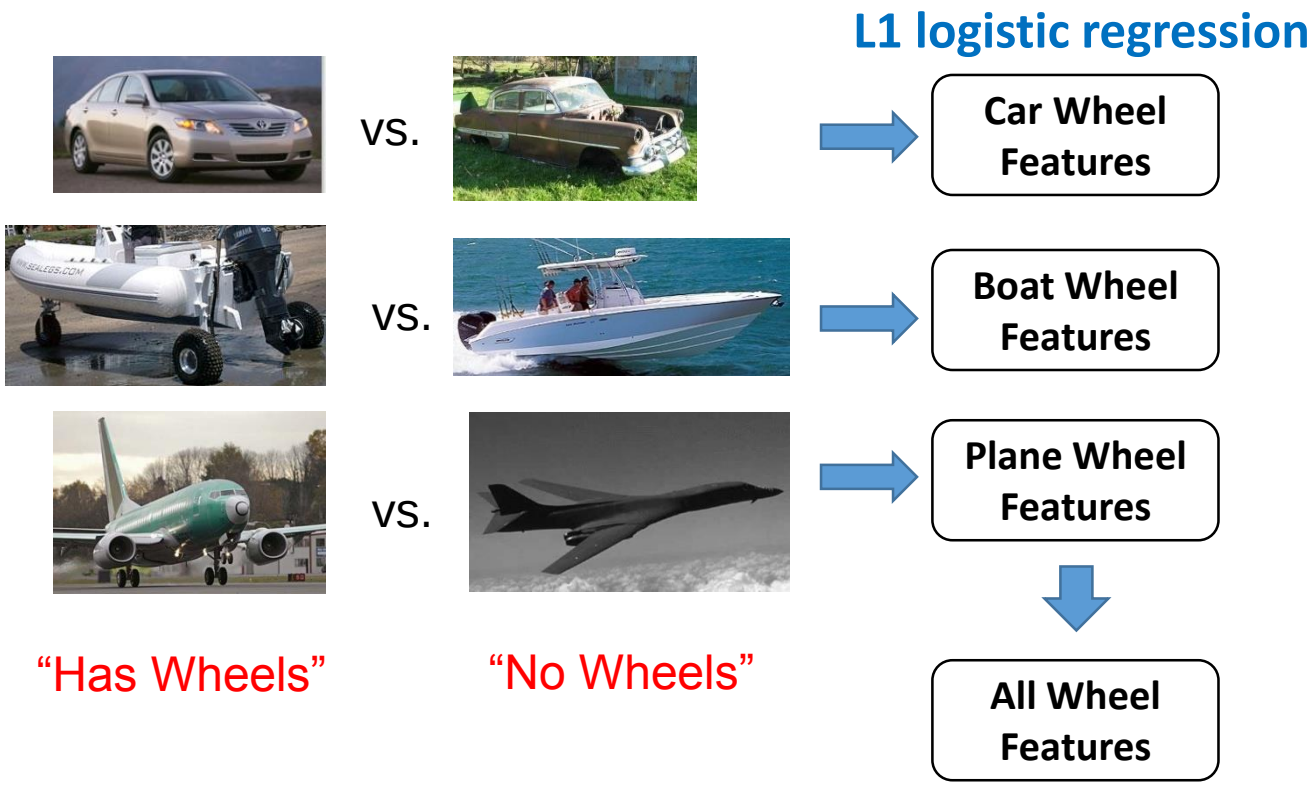
Most things that “have wheels” are “made of metal”

When we try to learn “has wheels”, we may accidentally learn “made of metal”

Has Wheels, Made of Metal?

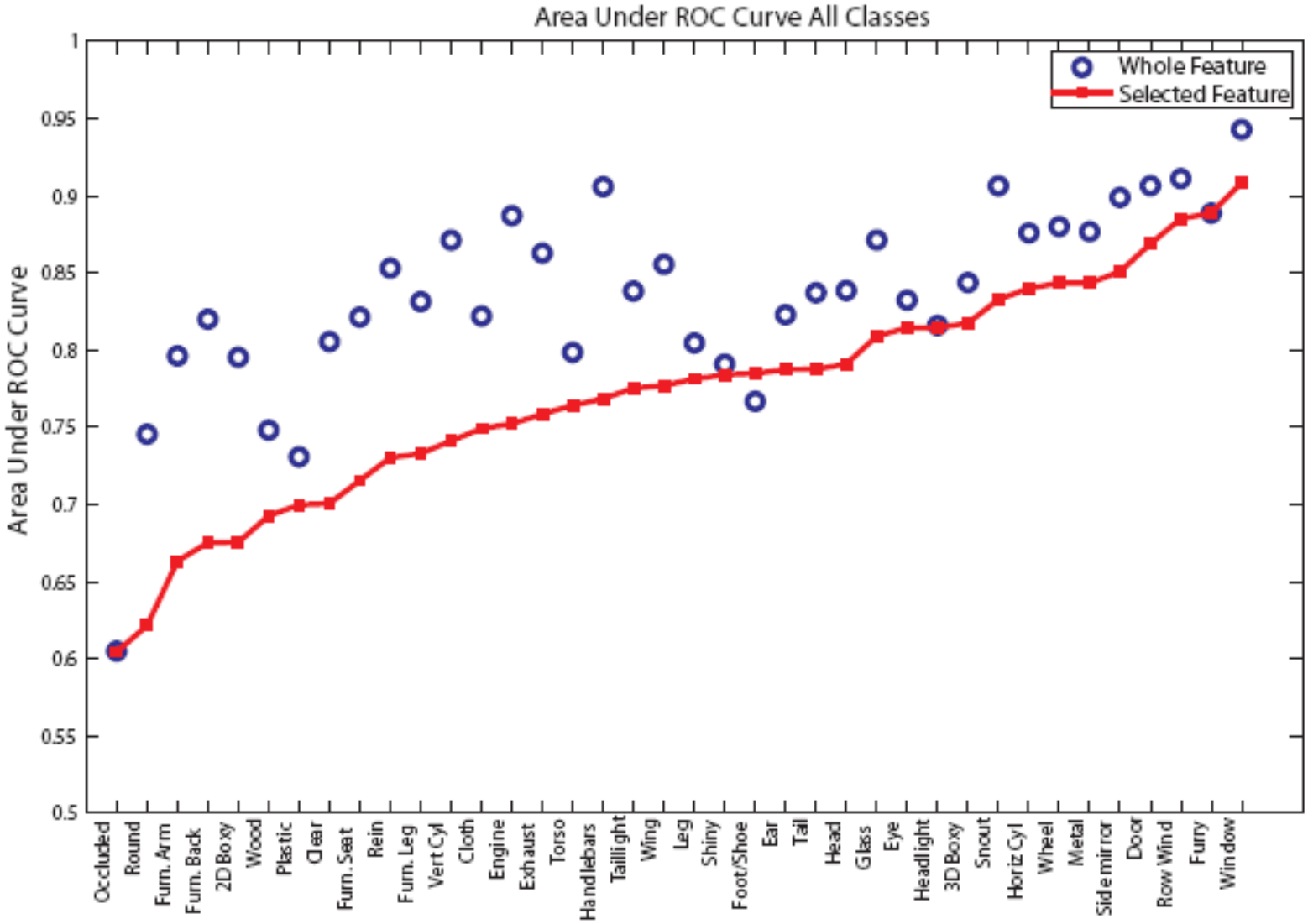
Feature selection

- Select features that can distinguish between two classes
  - Things that have the attribute (e.g., wheels)
  - Things that do not, but have similar attributes to those that do



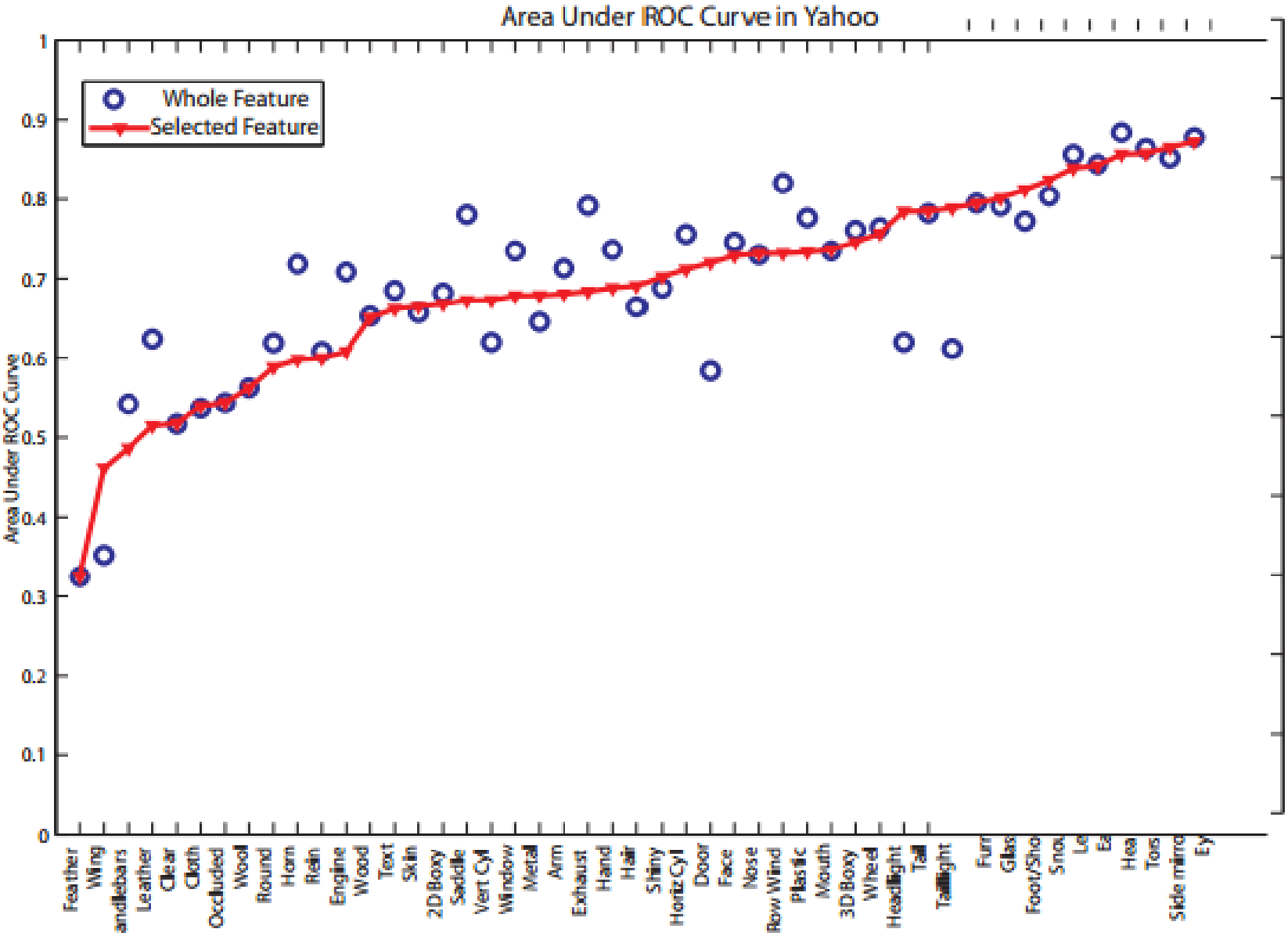
Assigning attributes

Train and Test on Same Classes from PASCAL (*)



Assigning attributes

Train on 20 PASCAL classes + Test on 12 different Yahoo classes



Naming familiar objects

- Use attribute predictions as features

- Train linear SVM to categorize objects

PASCAL 2008	Base Features	Semantic Attributes	All Attributes
Classification Accuracy	58.5%	54.6%	**59.4%**
Class-normalized Accuracy	35.5%	28.4%	**37.7%**

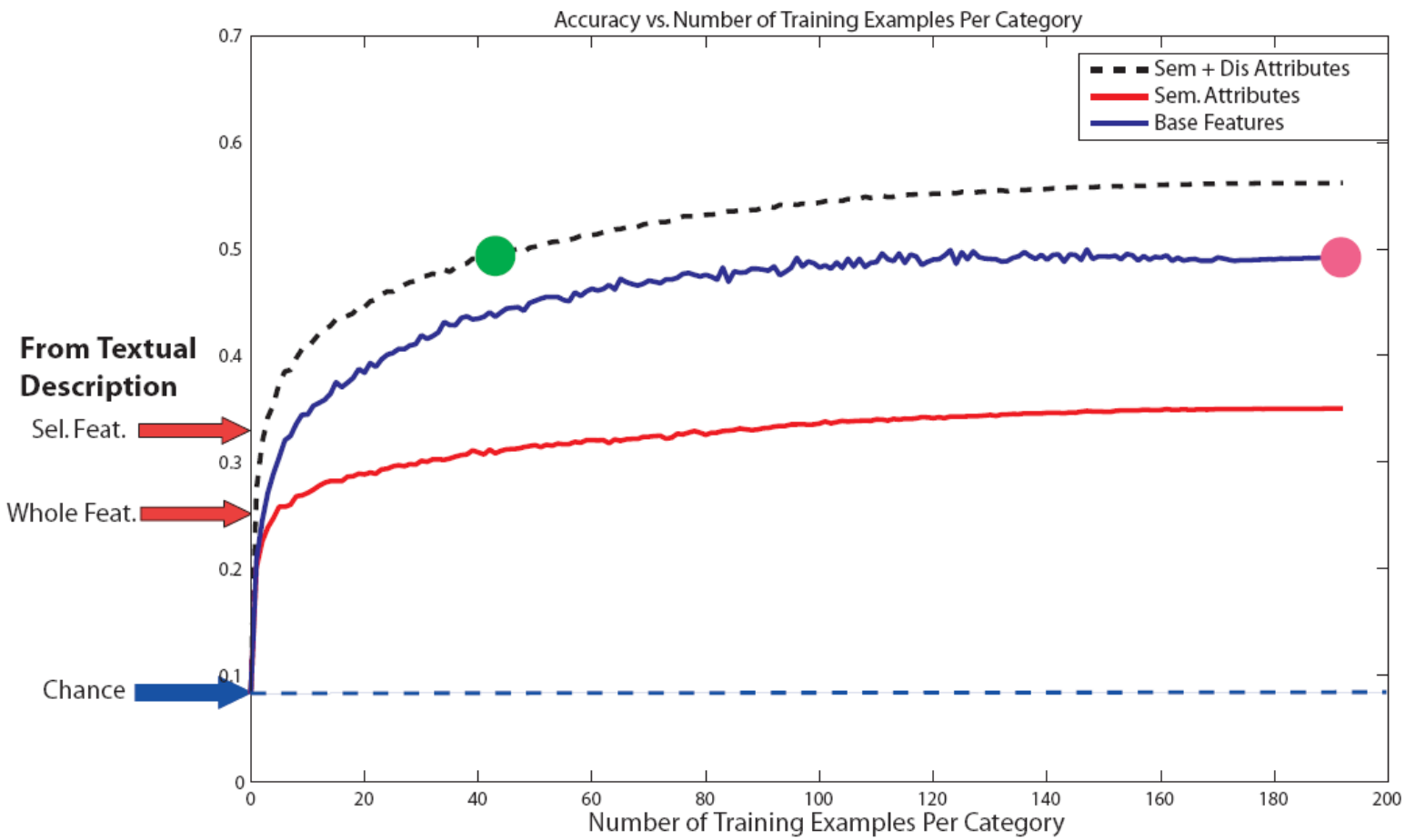
Attributes not big help when sufficient data

Unusual attributes

752 reports

68% are correct

Learning to identify new objects



Textual only = 100 examples in sematic attribute space
= 8 examples in base features space
= 3 examples in semantic & discriminative attribute space

Take away points

- Semantic attributes are helpful for certain tasks:
  - Learning from textual description only
  - Describe unknown objects
  - Identify unusual attributes
- And it is ***feasible*** to learn semantic attributes from base features and sufficient datasets.
- Its shortcomings?

Relative attributes
(> absolute attributes?)

Based on Devi Parikh's slides

Using attributes describe a MULE

Comparison is helpful

Has tail

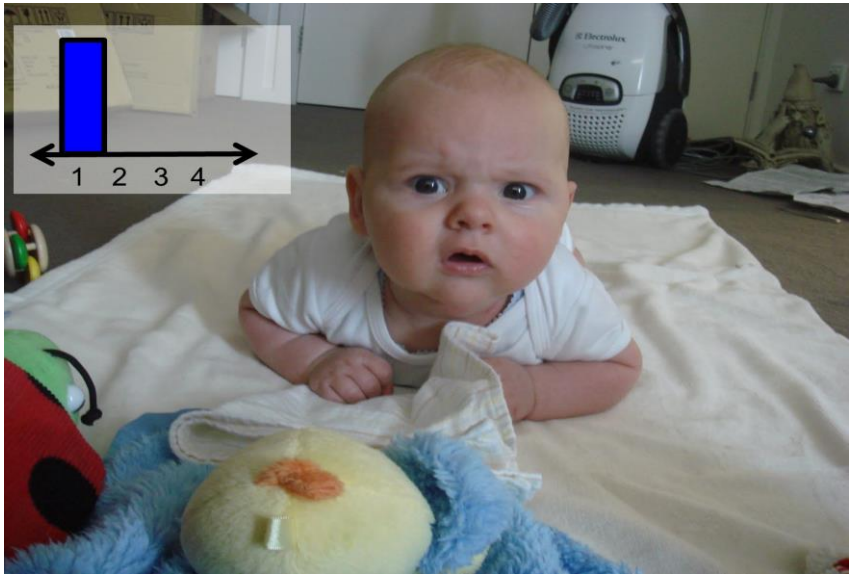
Is furry

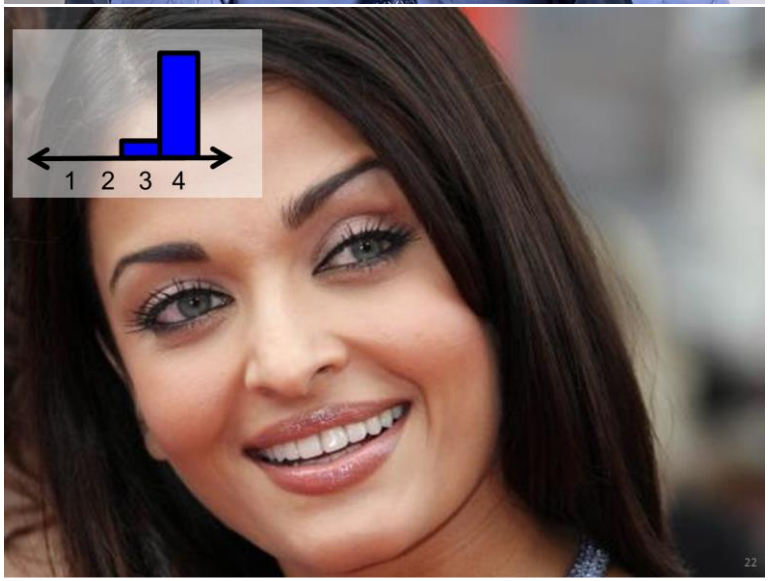
Has four-legs

Legs shorter than horses’

Tail longer than donkeys’

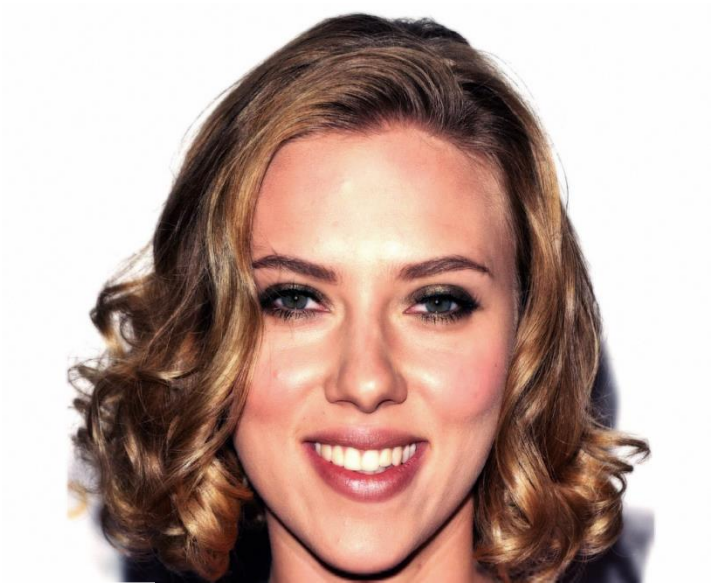
Absolute comparison (smiling)

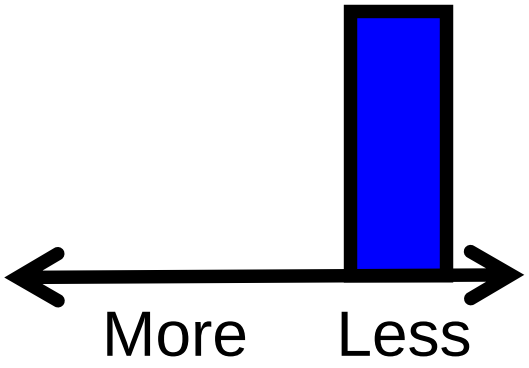




Relative comparison (smiling)

vs





Relative attributes

- Enhanced human-machine communication
- More informative
- Natural for humans

Contributions

- Relative attributes
  - Allow relating images and categories to each other
  - Learn ranking function for each attribute
- Novel applications
  - Zero-shot learning from attribute comparisons
  - Automatically generating relative image descriptions

Learning Relative Attributes

For each attribute a_m, open

Supervision is

O_m: {( $\succ$ ), ...},

S_m: {{  $\sim$  }, ...}

Learning Relative Attributes

Learn a scoring function $r_m(\boldsymbol{x_i}) = \boldsymbol{w_m^T x_i}$

Image features

Learned parameters

that best satisfies constraints:

$\{($  $\succ$  $), \ldots\}$ $\forall (i,j) \in O_m : \boldsymbol{w_m^T x_i} > \boldsymbol{w_m^T x_j}$

$\{\{$  $\sim$  $\}, \ldots\}$ $\forall (i,j) \in S_m : \boldsymbol{w_m^T x_i} = \boldsymbol{w_m^T x_j}$

Max-margin learning to rank formulation

$$\min \quad \left(\frac{1}{2}||\boldsymbol{w}_{\boldsymbol{m}}^T||_2^2 + C\left(\sum \xi_{ij}^2 + \sum \gamma_{ij}^2\right)\right)$$

$$\text{s.t} \quad \boldsymbol{w}_{\boldsymbol{m}}^T(\boldsymbol{x}_{\boldsymbol{i}} - \boldsymbol{x}_{\boldsymbol{j}}) \geq 1 - \xi_{ij}, \forall (i,j) \in O_m$$

$$|\boldsymbol{w}_{\boldsymbol{m}}^T(\boldsymbol{x}_{\boldsymbol{i}} - \boldsymbol{x}_{\boldsymbol{j}})| \leq \gamma_{ij}, \forall (i,j) \in S_m$$

$$\xi_{ij} \geq 0; \gamma_{ij} \geq 0$$

Based on [Joachims 2002]

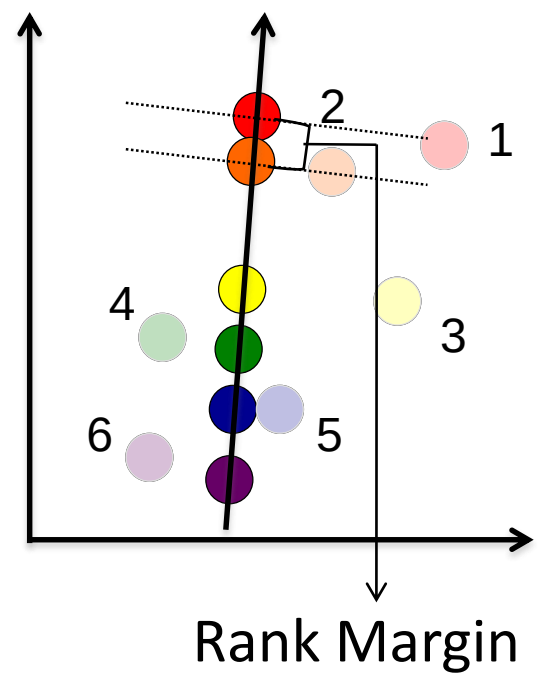


Image $\rightarrow$ Relative Attribute Score

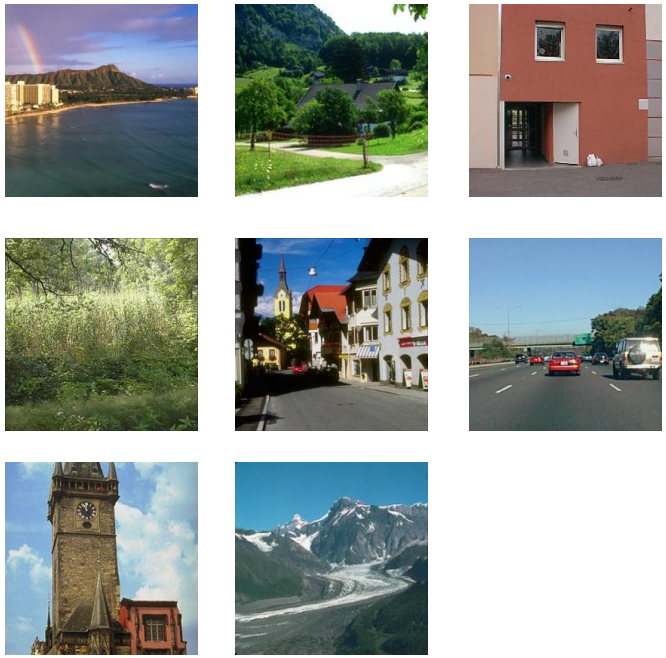
Features

- Gist descriptor
- Lab color histogram

Datasets

Outdoor Scene Recognition (OSR)

[Oliva 2001]



8 classes, ~2700 images, Gist

6 attributes: open, natural, etc.

Public Figures Face (PubFig)

[Kumar 2009]

8 classes, ~800 images, Gist+color

11 attributes: white, chubby, etc.

Relative zero-shot learning ($R^n \rightarrow R^m$)

Can predict new classes based on their relationships to existing classes – without training images

$c_i^{(s)} \sim \mathcal{N}(\boldsymbol{\mu}_i^{(s)}, \Sigma_i^{(s)})$ **(S,J,H)**

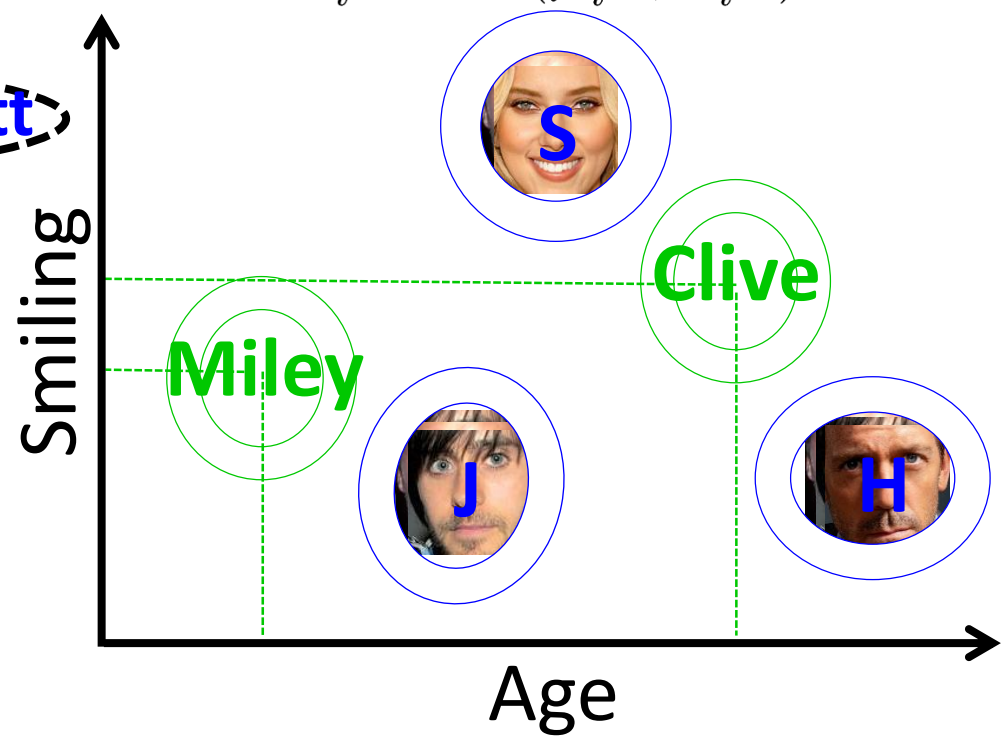
Age: **Hugh** $\succ$ **Clive** $\succ$ **Scarlett**

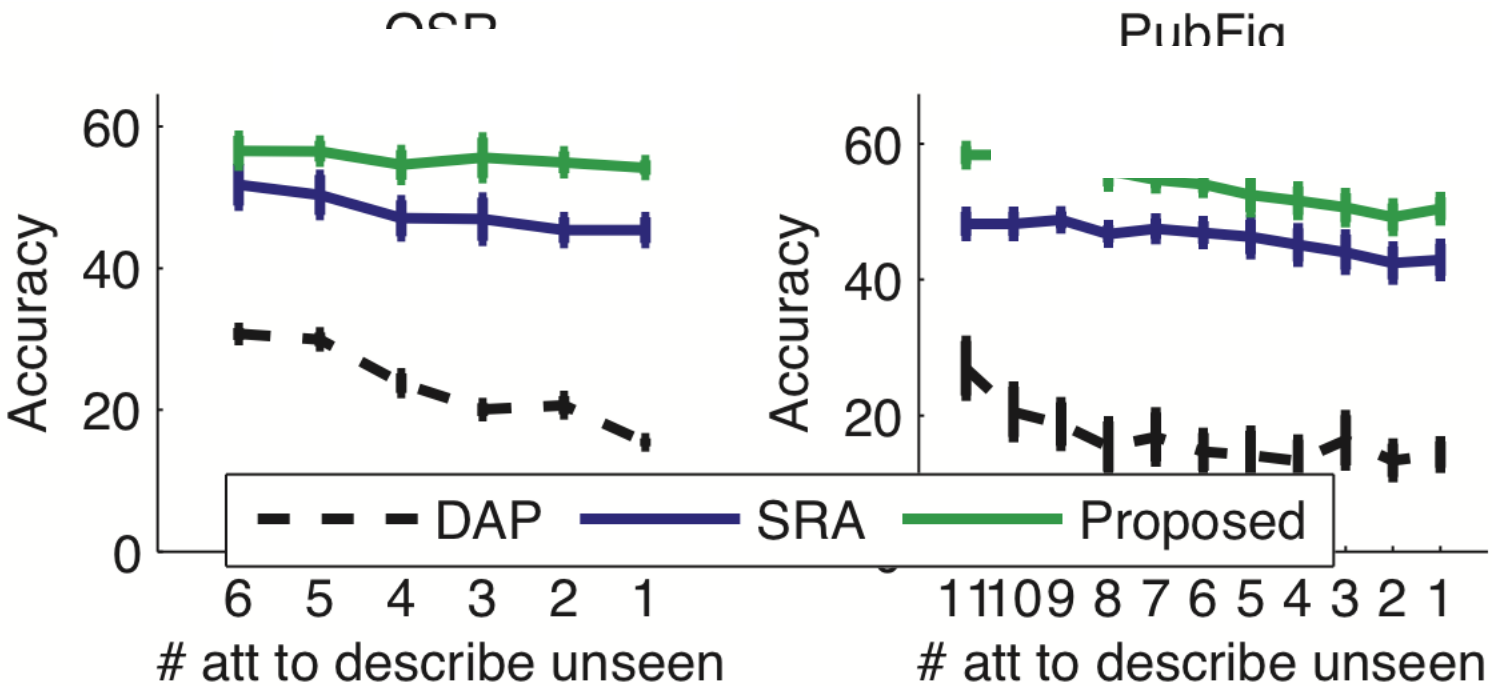
Jared $\succ$ **Miley**

$$\boldsymbol{\mu}_{jm}^{(u)} = \frac{1}{2}(\boldsymbol{\mu}_{im}^{(s)} + \boldsymbol{\mu}_{km}^{(s)})$$

Smiling: **Miley** $\succ$ **Jared**

$$\boldsymbol{\mu}_{jm}^{(u)} = \boldsymbol{\mu}_{im}^{(s)} + d_m$$





DAP: binary attr
SRA: rel attr (classifier score)
Proposed: rel attr (ranked score)

An attribute is more discriminative when used relatively

Describe image results

Density

Novel image

Conventional binary description: *not dense*

Dense:

Not dense:

Density

Novel image

more dense than

less dense than

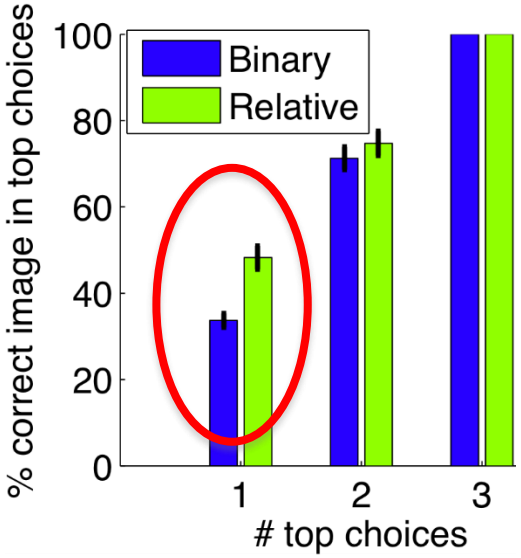
Human Studies: Which Image is Being Described?

Binary (existing):
Not natural
Not open
Has perspective

Relative (ours):
More natural than insidecity
Less natural than highway
More open than street
Less open than coast
Has more perspective than highway
Has less perspective than insidecity

18 subjects

Test cases:
10 OSR, 20 PubFig



Take away points

Relative attributes learnt as ranking functions

- Natural and accurate zero-shot learning of novel concepts by relating them to existing concepts
- Precise image descriptions for human interpretation
- The approach has been explored by many research projects after that.

Questions