

Relative Attributes

Devi Parikh, Kristen Grauman



(a) Smiling



(b) ?



(c) Not smiling



(d) Natural



(e) ?



(f) Manmade

Akanksha Saran
CS381V Paper Presentation

Outline

- Motivation
- Contributions
- Technical Details
- Experiments
- Discussion Points
- Extensions

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Slide Credit: Devi Parikh, Kristen Grauman

Donkey



Mule

Attributes

Is furry

Has four-legs

Legs shorter
than horses'

Tail longer
than donkeys'

Has tail

[Oliva 2001] [Ferrari 2007] [Lampert 2009] [Farhadi 2009] [Kumar 2009] [Wang 2009] [Wang 2010] [Berg 2010] [Branson 2010] [Parikh 2010] [ICCV 2011] ...

Mule ⁷

Binary

Is furry

Has four-legs

Legs shorter
than horses'

Tail longer
than donkeys'

Has tail

Mule ⁸

Binary

Is furry

Has four-legs

Legs shorter
than horses'

Tail longer
than donkeys'

Has tail

Mule ⁹

Relative

Is furry

Has four-legs

Legs shorter
than horses'

Tail longer
than donkeys'

Has tail

Image Search

“Downtown Chicago”



Slide Credit: Devi Parikh, Kristen Grauman



Relative Description

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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

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Learning Relative Attributes

For each attribute a_m , **open**

Supervision is

$$O_m: \left\{ \left(\left[\text{Cathedral} \right] \succ \left[\text{City} \right] \right), \dots \right\},$$

$$S_m: \left\{ \left\{ \left[\text{Beach} \right] \sim \left[\text{Field} \right] \right\}, \dots \right\}$$

Learning Relative Attributes

Learn a scoring function $r_m(\mathbf{x}_i) = \mathbf{w}_m^T \mathbf{x}_i$

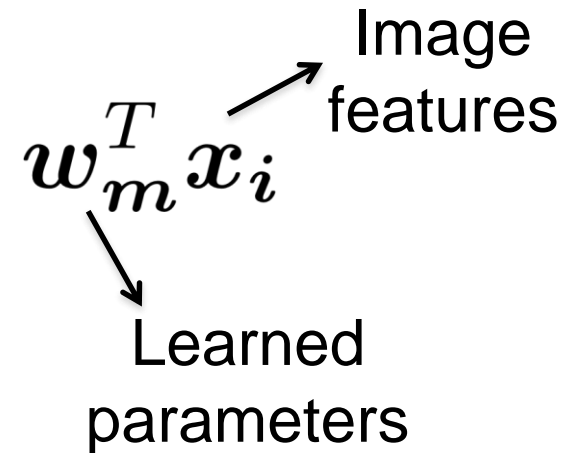


Image features

Learned parameters

that best satisfies constraints:

$$\forall (i, j) \in O_m : \mathbf{w}_m^T \mathbf{x}_i > \mathbf{w}_m^T \mathbf{x}_j$$

$$\forall (i, j) \in S_m : \mathbf{w}_m^T \mathbf{x}_i = \mathbf{w}_m^T \mathbf{x}_j$$

Learning Relative Attributes

Max-margin learning to rank formulation

$$\min \left(\frac{1}{2} \|\mathbf{w}_m^T\|_2^2 + C \left(\sum \xi_{ij}^2 + \sum \gamma_{ij}^2 \right) \right)$$

$$\text{s.t. } \mathbf{w}_m^T (\mathbf{x}_i - \mathbf{x}_j) \geq 1 - \xi_{ij}, \forall (i, j) \in O_m$$

$$|\mathbf{w}_m^T (\mathbf{x}_i - \mathbf{x}_j)| \leq \gamma_{ij}, \forall (i, j) \in S_m$$

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

Based on [Joachims 2002]

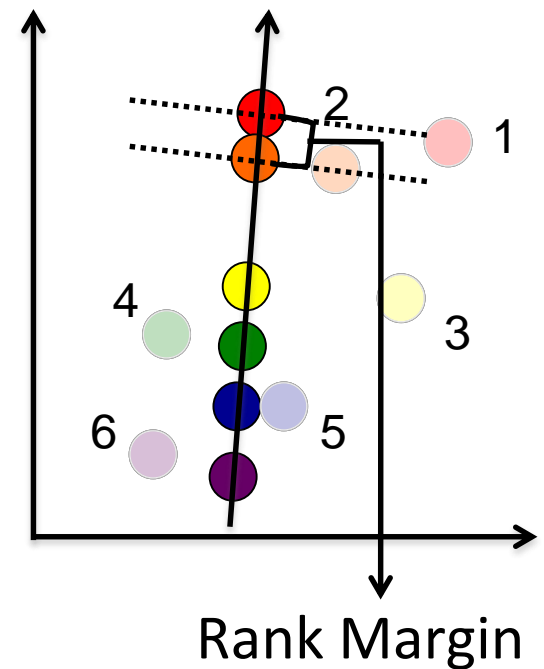


Image \rightarrow Relative Attribute Score

Relative Zero-shot Learning

Training: Images from **S seen** categories and

Descriptions of **U unseen** categories



Age: **Hugh** } **Clive** } **Scarlett**

Jared } **Miley**

Smiling:

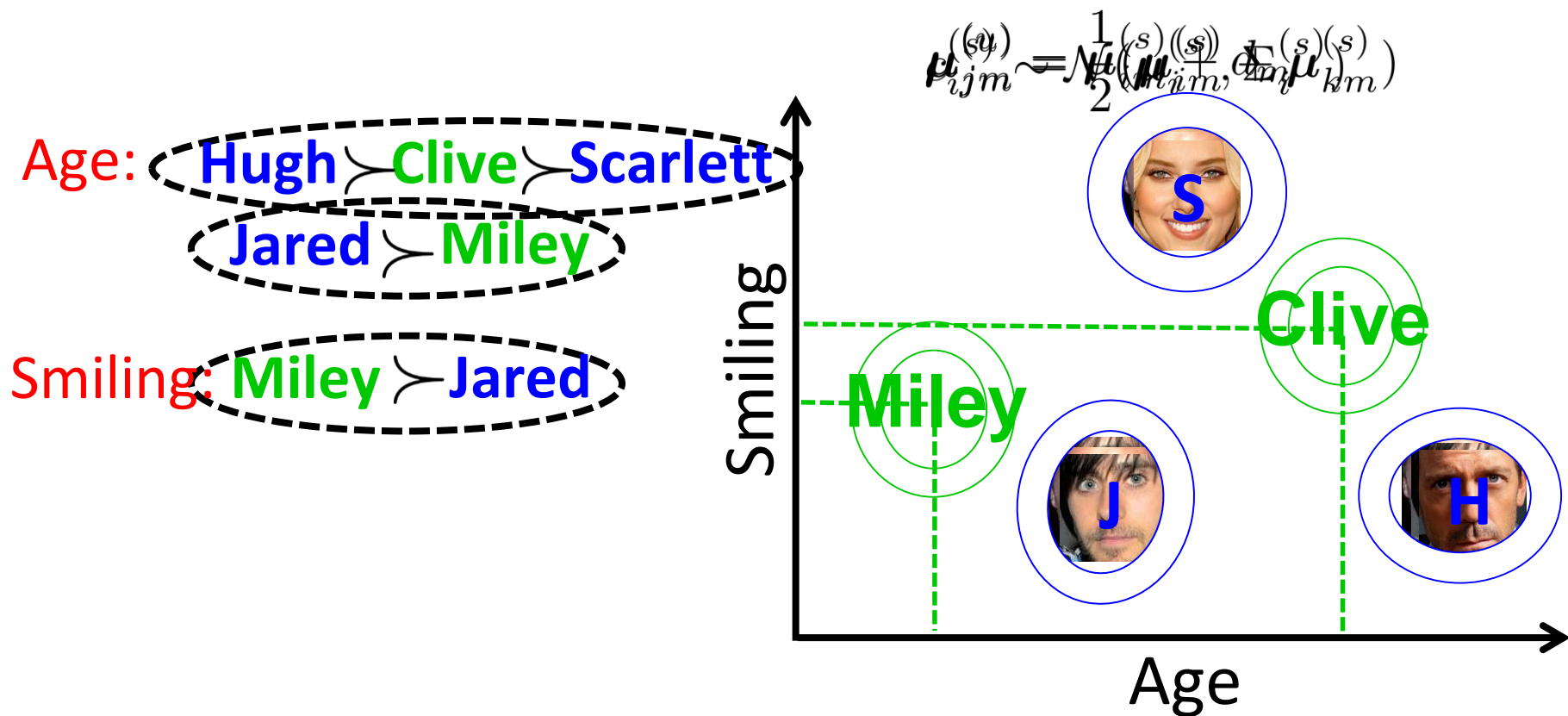
A stack of three images of Miley Cyrus's face, showing her with a neutral expression.

Miley } **Jared**

Need not use all attributes, or all seen categories

Testing: Categorize image into one of **S+U** categories

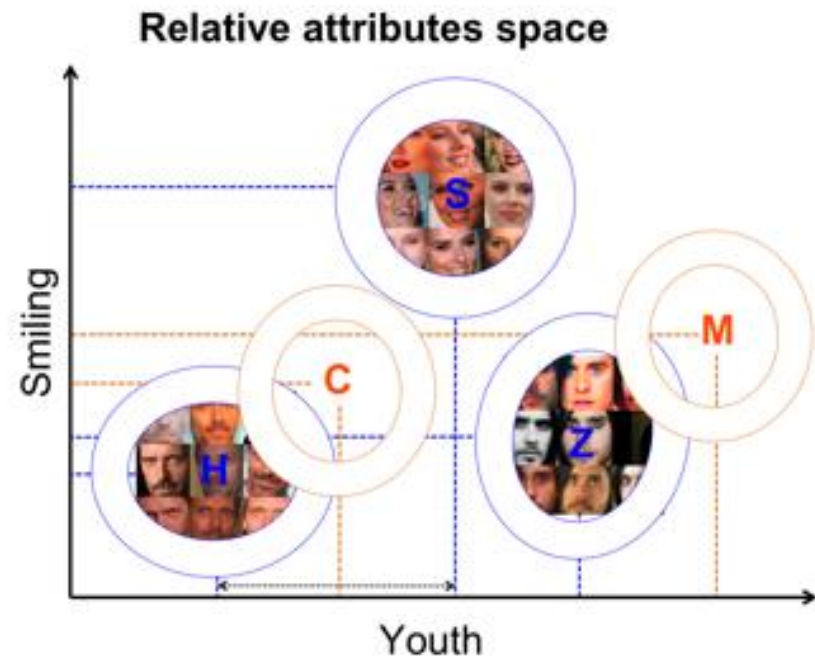
Relative Zero-shot Learning



Infer image category using max-likelihood

Relative zero-shot learning

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



Automatic Relative Image Description

Density



Novel image



Conventional binary description: *not dense*

Dense:



Not dense:



Automatic Relative Image Description

Density

Novel image



more dense than

less dense than



Automatic Relative Image Description

Density

Novel
image



C C H H **H** C F H H M F F I F

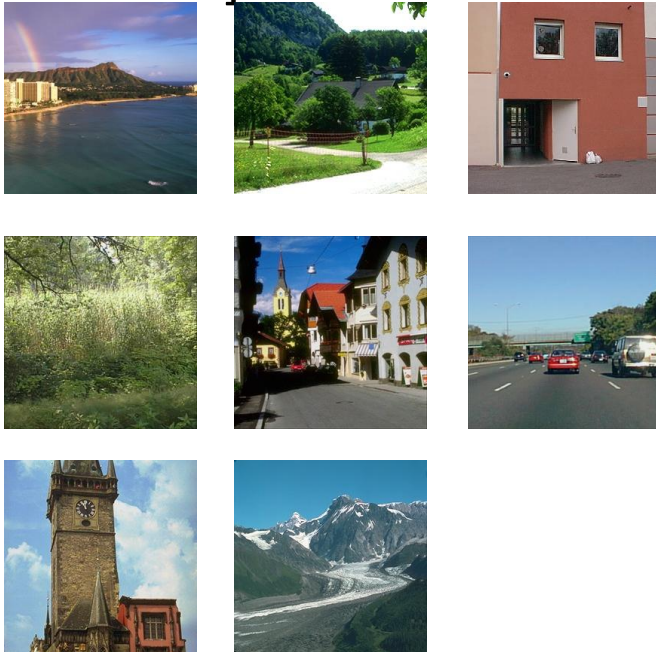
*more dense than **Highways**, less dense than **Forests***

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Datasets

Outdoor Scene Recognition (OSR)
[Oliva 2001]



8 classes, ~2700 images, Gist
6 attributes: open, natural, etc.

Public Figures Face (PubFig)
[Kumar 2009]

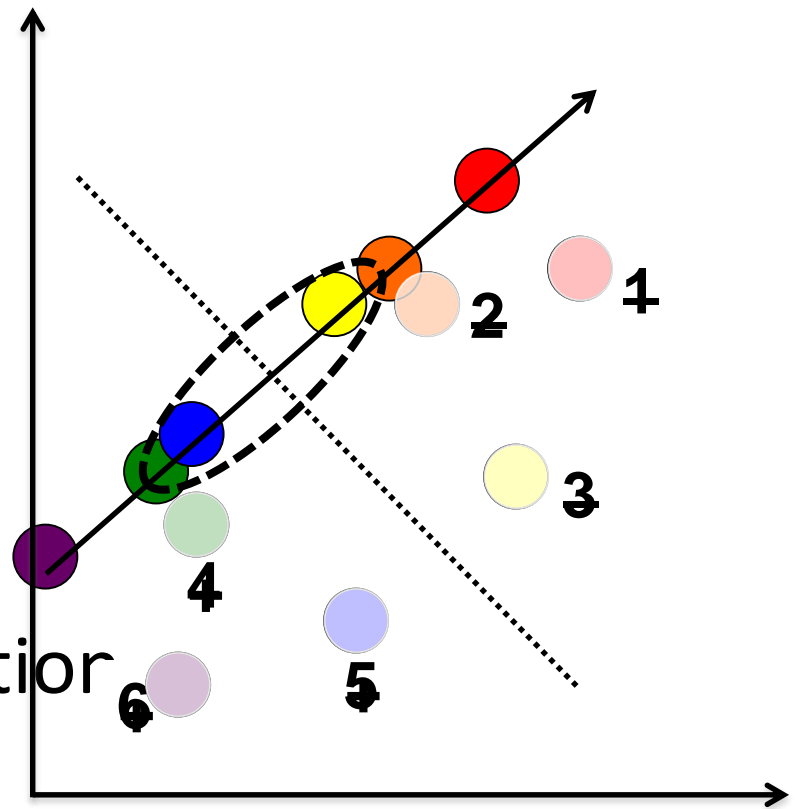


8 classes, ~800 images,
Gist+color
11 attributes: white, chubby, etc.

Attributes labeled at category level

Baselines

- Zero-shot learning
 - Binary attributes:
Direct Attribute Prediction
[Lampert 2009]
 - Relative attributes via
classifier scores
- Automatic image-description
 - Binary attributes



Relative Zero-shot Learning

- Robustness:
 - Fewer comparisons to train relative attributes
 - More unseen (fewer seen) categories
- Flexibility in supervision:
 - ‘Looseness’ in description of unseen
 - Fewer attributes used to describe unseen

Relative Zero-shot Learning

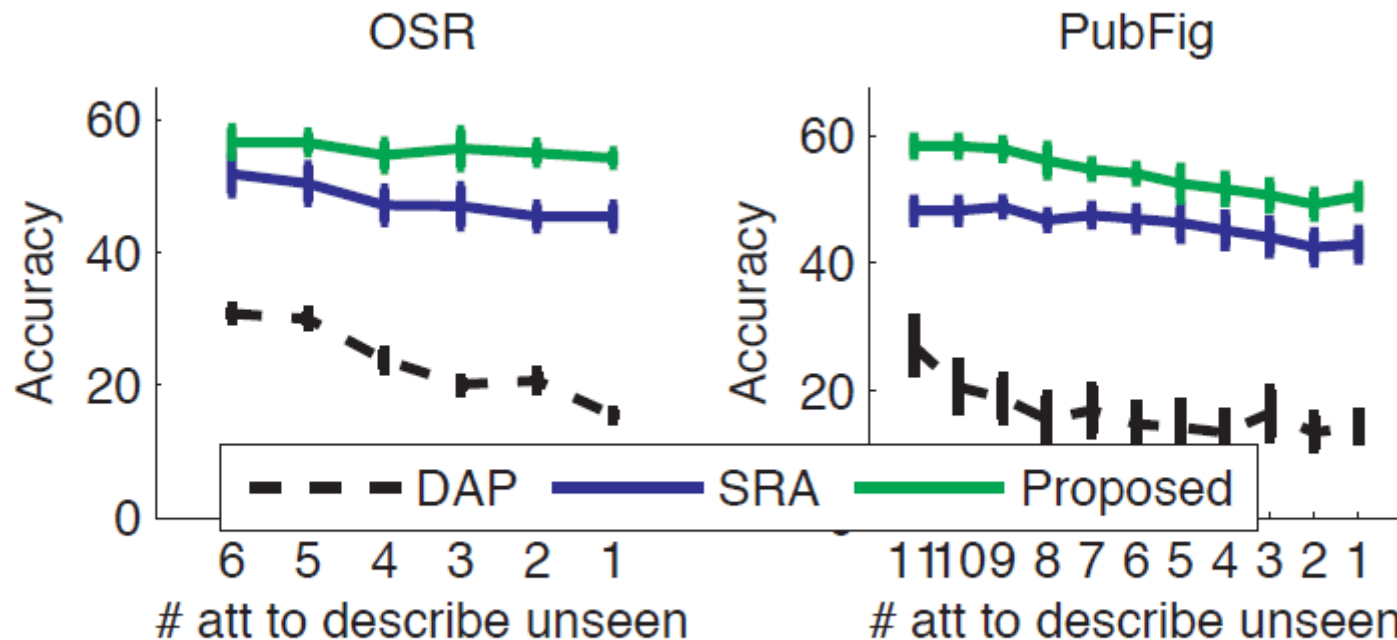


Figure 5. Zero-shot learning performance as fewer attributes are used to describe the unseen categories.

An attribute is more discriminative when used relatively

Automatic Relative Image Description

Binary (existing):

Not natural

Not open

Has perspective



Relative (proposed):

More natural than insidicity

Less natural than highway

More open than street

Less open than coast

Has more perspective than highway

Has less perspective than insidicity

Automatic Relative Image Description

Binary (existing):

Not natural

Not open

Has perspective



Relative (proposed):

More natural than tallbuilding

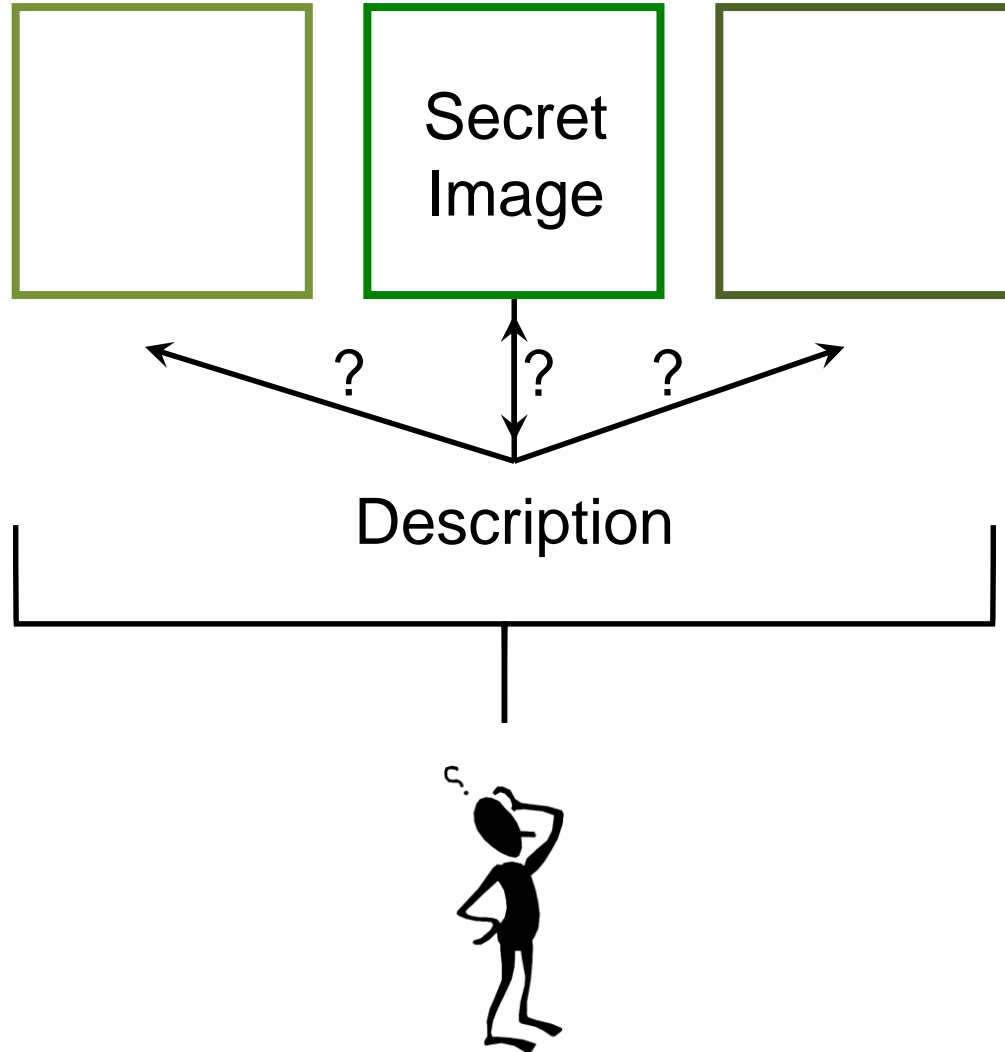
Less natural than forest

More open than tallbuilding

Less open than coast

Has more perspective than tallbuilding

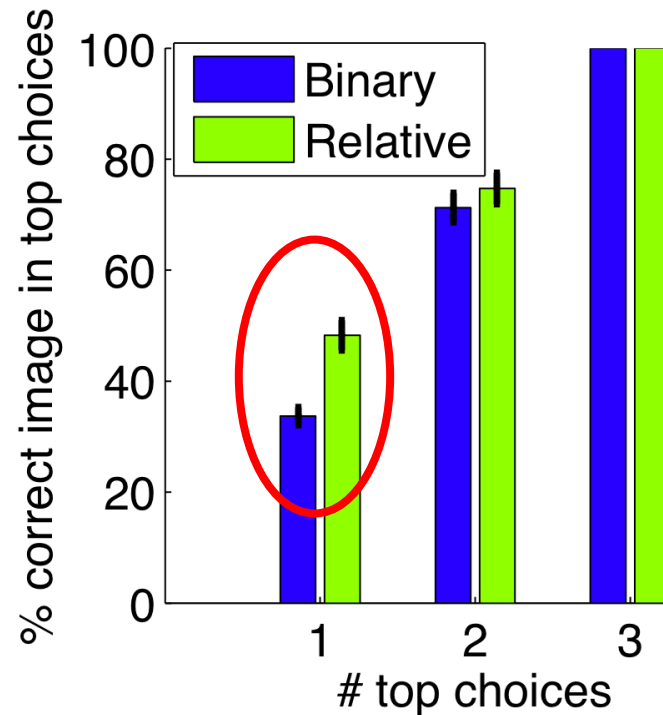
Human Studies: Which Image is Being Described?



Automatic Relative Image Description

18 subjects

Test cases:
10OSR, 20 PubFig



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Advantages

- Natural Descriptions: Leverages a natural mode of description
- Flexibility: Allows use of as many attributes for defining relations among as many classes

Image based based Attribute Ranking

Relative ordering for attributes are transferred to all images in a category

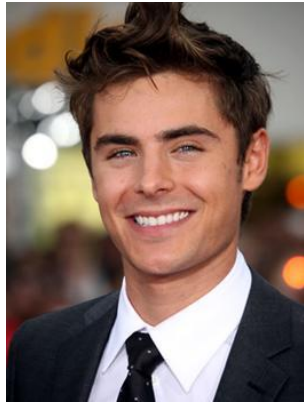


Image based based Attribute Ranking

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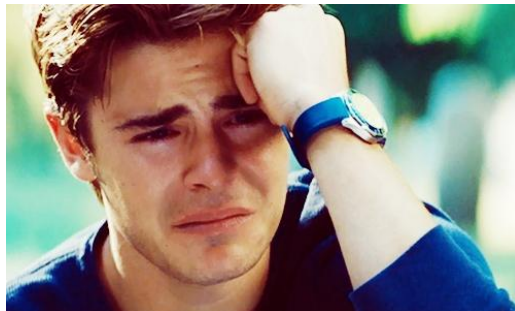
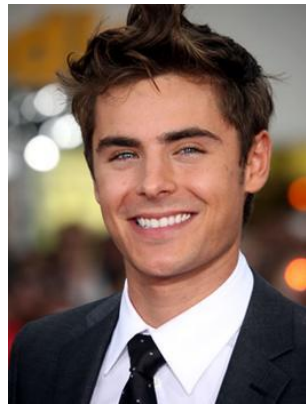


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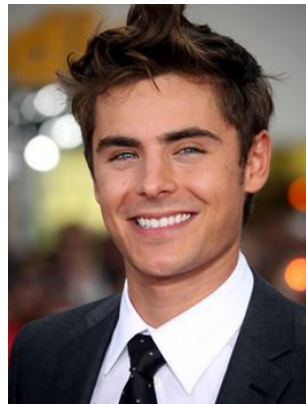


Image Search



Gaussian distribution in joint attribute space

- Underlying distributions may be multi-modal



Fine-grained differences?

Can retaining the ranks for two very similar images/categories help identify them ?

male russet sparrow



male spanish sparrow



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- Strengths and Weaknesses
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Extensions

- **Relative attributes learned per image**
“Image Search with Interactive Feedback: Whittle Search”, A. Kovashka, D. Parikh, K. Grauman
- **Active Learning of Discriminative Classifiers through feedback from users**
“Simultaneous Active Learning of Classifiers & Attributes via Relative Feedback”, A. Biswas, D. Parikh
- **Use of binary and relative attributes together**
' A horse has 4 legs'
- **More expressive features instead of global features**
To discriminate a large set of image categories
“Discovering Spatial Extent of Relative Attributes”, F. Xiao, Y.J. Lee
- **Scalability to more categories and attribute labels**

Thank you!