

# Relative Attributes

## **Team mob-psycho**

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# Introduction



# Introduction

When dealing with recognition tasks, human-nameable visual "attributes" can be beneficial, but:

- Sometimes it is hard to make a binary decision on whether an image satisfies an attribute.

- **Comparisons are easier.**



Natural



?



Not Natural



Smiling



?



Not Smiling

# Introduction

## Relative Attributes

- Great to describe and compare objects in the world.
- Indicate the strength of an attribute in an image with respect to other images.
- Allow relating images and categories to each other.



**A is more natural than B**  
**C is less natural than B**

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# Learning Relative Attributes

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# Learning Relative Attributes

**Model Relative Attributes:** Learn ranking function for each attribute

For each attribute  $a_m$ , **open**

Supervision is

**Set of ordered pair of images**  $\rightarrow$

$$O_m: \left\{ \left( \begin{array}{c} \text{Image 1} \\ \text{Image 2} \end{array} \succ, \dots \right) \right\},$$

**Set of unordered pair of images**  $\rightarrow$

$$S_m: \left\{ \left\{ \begin{array}{c} \text{Image 1} \\ \text{Image 2} \end{array} \right\} \sim, \dots \right\}$$

# Learning Relative Attributes

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

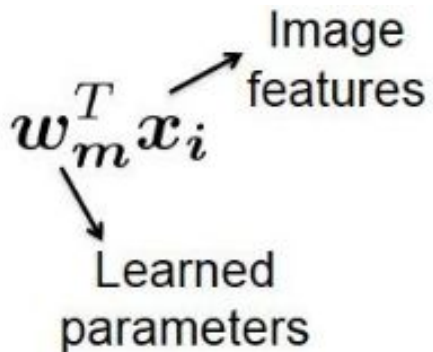


Image features

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]

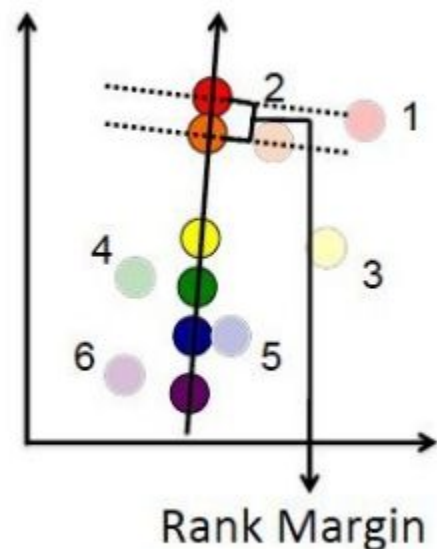
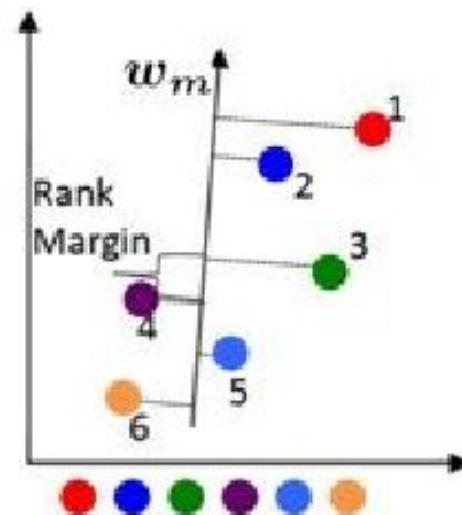
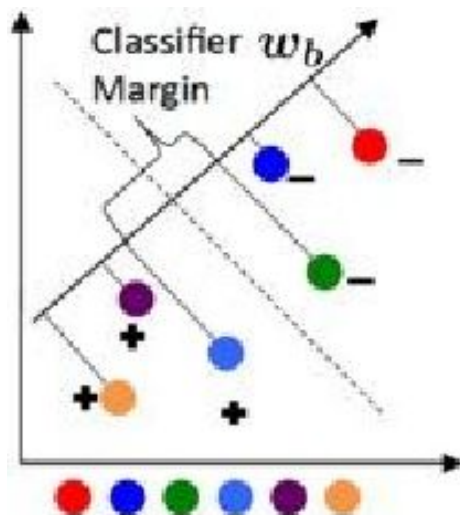


Image  $\rightarrow$  Relative Attribute Score



# Learning Relative Attributes

Wide-margin **binary classifier** VS Wide-margin **ranking function**



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# Applications

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# Applications

- **Zero Shot Learning:** Train a generative model (like GMM) to predict values for new class based on its relationship with current classes and no training images
- **Describing Images:** Automatically generating relative description of the images (like a particular image is more smiling and young than other image)

# 1. Zero Shot Learning

Divide Classes into 2 Categories:

## 1. Seen (S):

- Image set is available
- Relative description of attributes is present

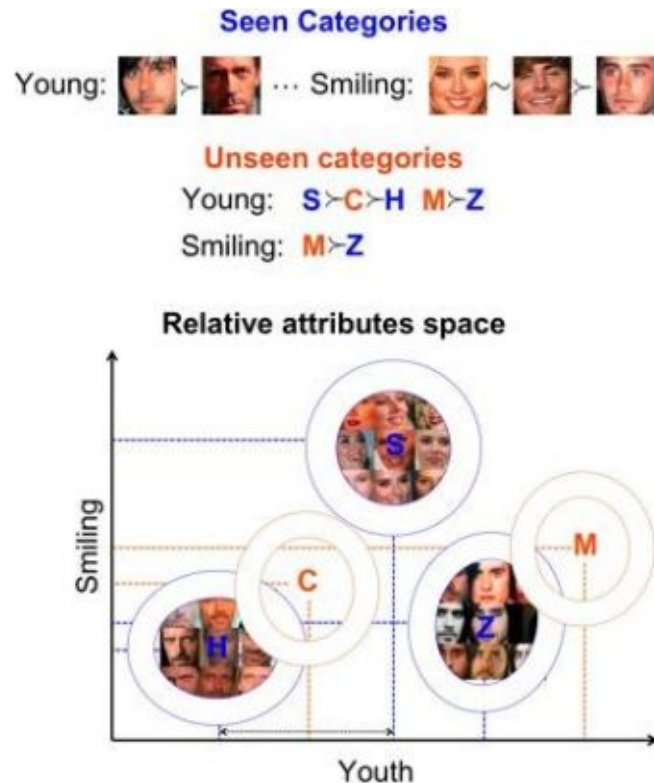
## 2. Unseen (U):

- No images available
- Some attributes described wrt seen categories

# 1. Zero Shot Learning

## Training

1. Train a set of relative attributes using  $S$  categories.
  - Learn all  $M$  relative attribute am.
  - Represent each image as  $m$ -vector
2. Build GMM for each  $S$  category using the responses of the relative attributes.
3. Infer the parameters of the generative models of  $U$  categories by using their relative descriptions.



# 1. Zero Shot Learning

Test (classify new images)

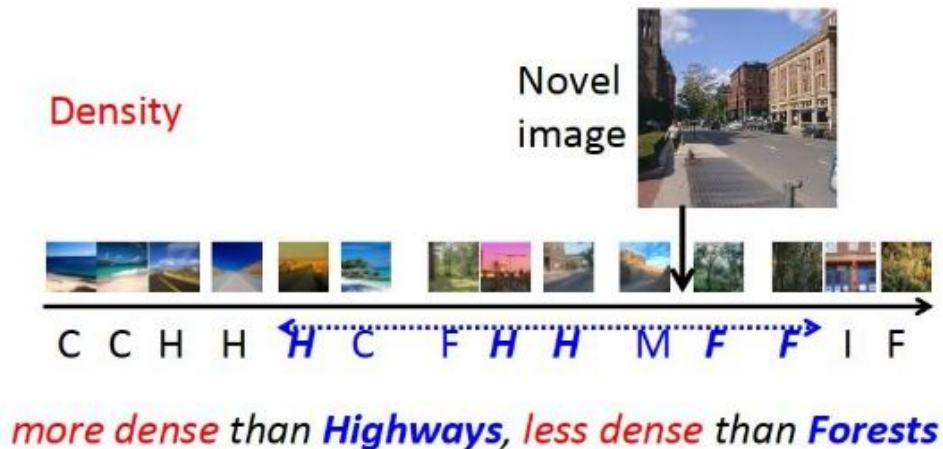
1. Compute  $x_i$  indicating its relative attribute ranking-scores for the image.
2. Assign it to the seen or unseen category that assigns it the highest likelihood:

$$c^* = \operatorname{argmax}_{j \in \{1, \dots, N\}} P(\tilde{x}_i \mid \mu_j, \Sigma_j).$$

## 2. Describing images

Given an image I to be described:

1. We evaluate all learnt ranking functions on I.
2. Identify 2 reference images from which image I will be described.
3. Can also describe an image relative to other categories.



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# Results Obtained

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# Results Obtained - Smiling Attribute

Attribute values for image 1 and 2 :

Value =[[0.12842465]]



Value =[[0.08821574]]



# Results Obtained - Big Lips Attribute

Value =  $[-0.18477103]$



Value =  $[-1.07309342]$



# Results Obtained - Chubby Attribute

Value =  $\begin{bmatrix} -0.20013611 \end{bmatrix}$

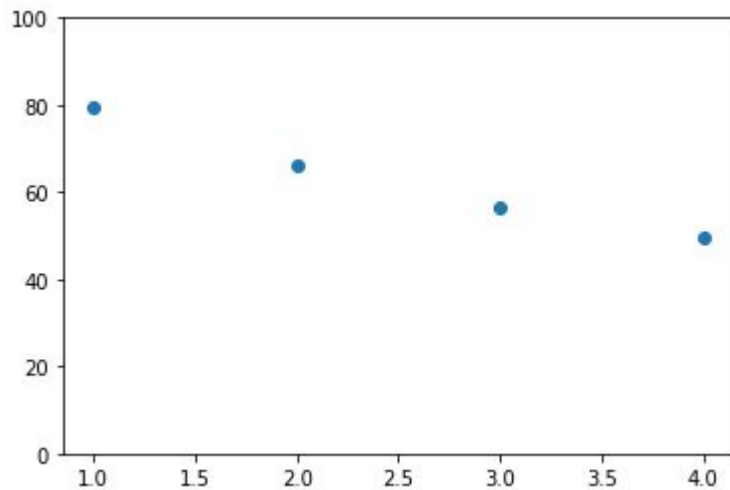


Value =  $\begin{bmatrix} -1.43647949 \end{bmatrix}$



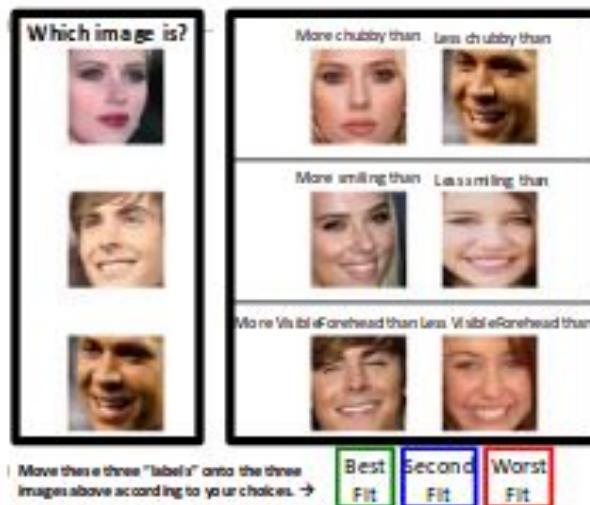
# Results Obtained - Zero Shot Learning

Number of Unseen Classes	Accuracy
1	79.583 %
2	66.204 %
3	56.592 %
4	49.481 %

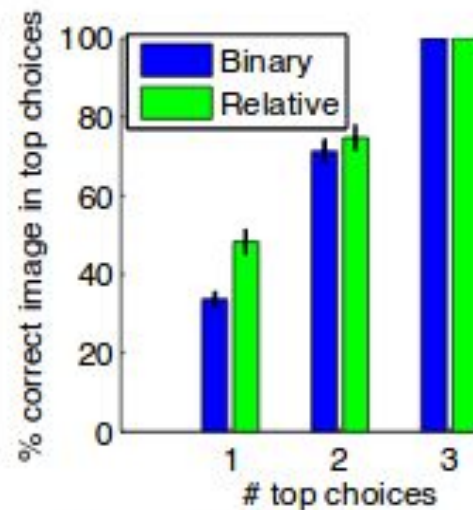


# Results Obtained - Describing Images

Analysis conducted by Authors



(a) Human Study Interface



(b) Results (both datasets)

# Results Obtained - Describing Images

**Attribute = Smiling**

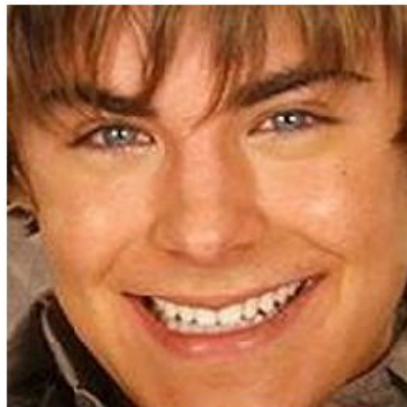
Value = -0.298639147492



Value = [[0.12842465]]



Value = 0.601809617635



# Results Obtained - Describing Images

**Attribute = Big Lips**

Value = -0.755304992066



Value = [-0.25540029]



Value = 0.664094646003

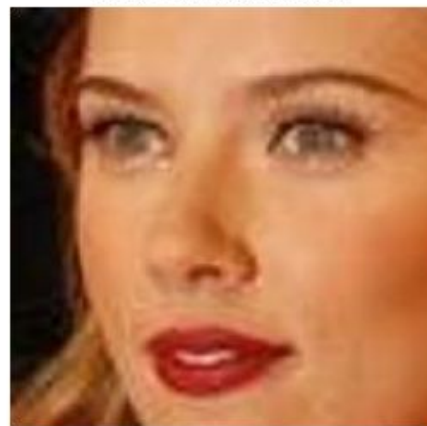


Image is more BigLips than ScarlettJohansson\_100.jpg and less BigLips than CliveOwen\_89.jpg



# Results Obtained - Describing Images

**Attribute = Male**

Value = -0.482523724035



Value = [-0.02635795]



Value = 0.541561750807



Image is more Male than CliveOwen\_119.jpg and less Male than ViggoMortensen\_146.jpg



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**Thank  
You**

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