

# Image Ranking and Retrieval based on Multi-Attribute Queries

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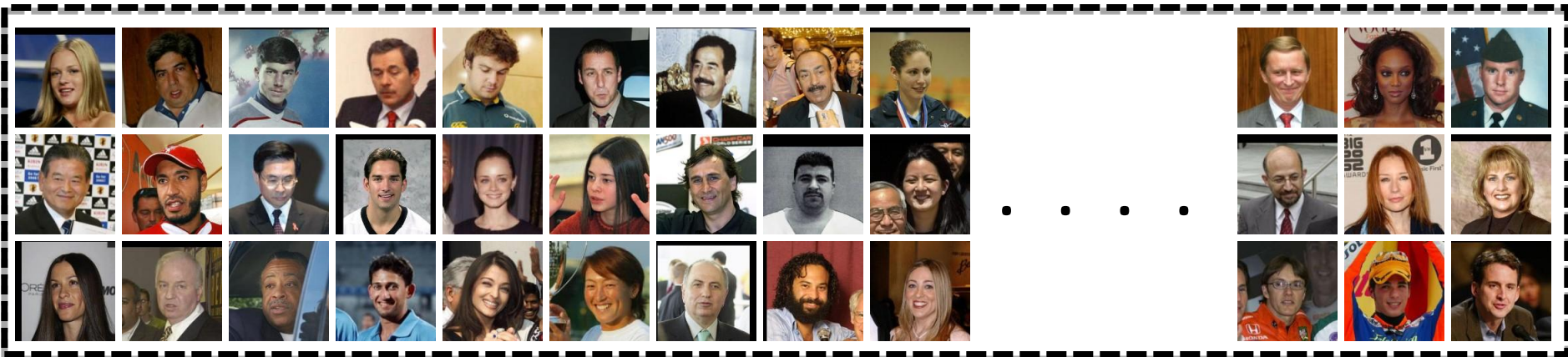
# Attribute based Image Retrieval

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“Young Asian woman wearing sunglasses”

# Attribute based Image Retrieval

“Young Asian woman wearing sunglasses”



# Attributes

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Physical traits or characteristics of a person



**Male**  
**Asian**  
**Middle-Aged**



**Female**  
**White**  
**Young**

# Attributes

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Physical traits or characteristics of a person



**Male**  
**Asian**  
**Middle-Aged**



**Female**  
**White**  
**Young**

**Object Properties**



**Round**  
**White**  
**Black**

# Attributes

---

Physical traits or characteristics of a person



Male  
Asian  
Middle-Aged



Female  
White  
Young

Object Properties



Round  
White  
Black

Object properties that span across object categories



Striped  
Four-legged  
Orange  
Black

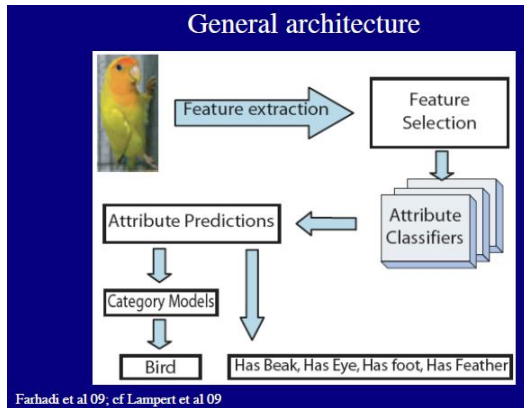


Striped  
Four-legged  
White  
Black

# Attribute based representation

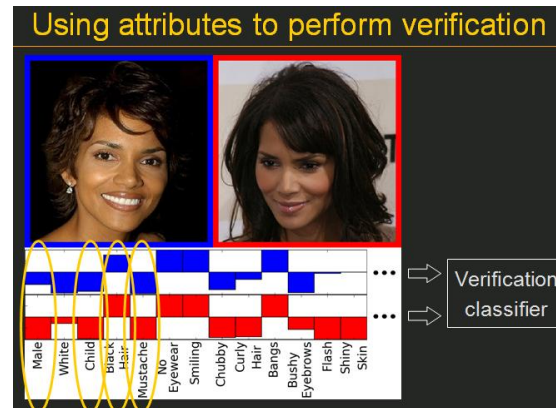
## Describing Images

Farhadi et al., CVPR 2009



## Face Verification

Kumar et al., ICCV 2009



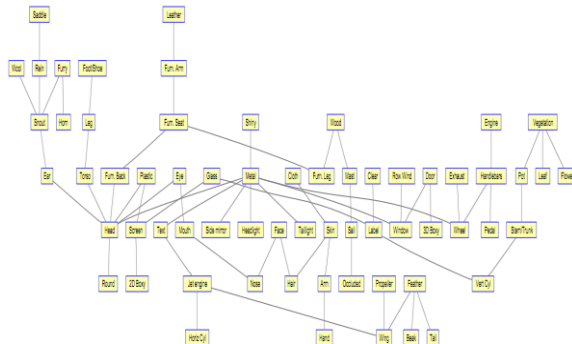
## Transfer Learning

Lampert et al., CVPR 2009

<u>otter</u>	black:	yes		
	white:	no		
	brown:	yes		
	stripes:	no		
	water:	yes		
	eats fish:	yes		
<u>polar bear</u>	black:	no		
	white:	yes		
	brown:	no		
	stripes:	no		
	water:	yes		
	eats fish:	yes		
<u>zebra</u>	black:	yes		
	white:	yes		
	brown:	no		
	stripes:	yes		
	water:	no		
	eats fish:	no		

## Object Recognition

Yang and Mori, ECCV 2010



## Identifying Outliers

Farhadi et al., CVPR 2009



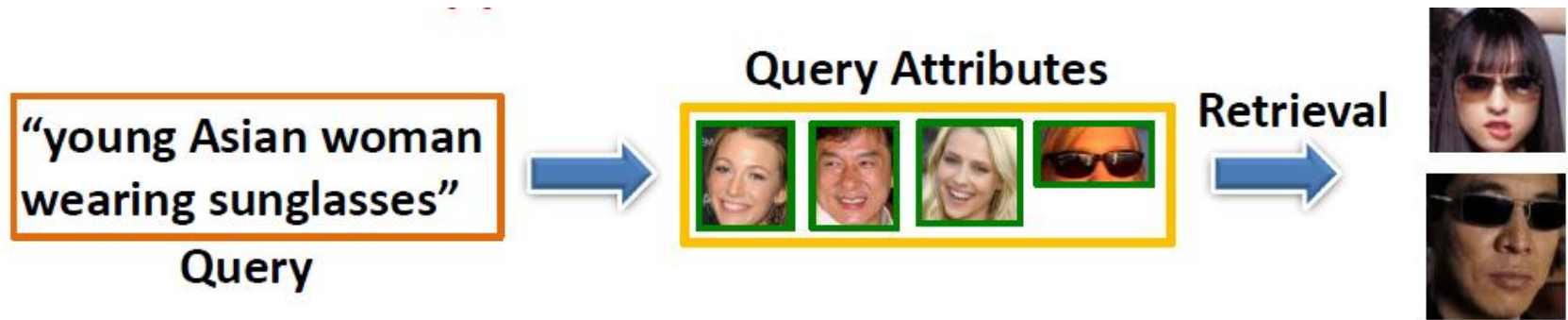
Unexpected attributes

Motorbike  
Has Cloth



# Multi-Attribute Image Retrieval

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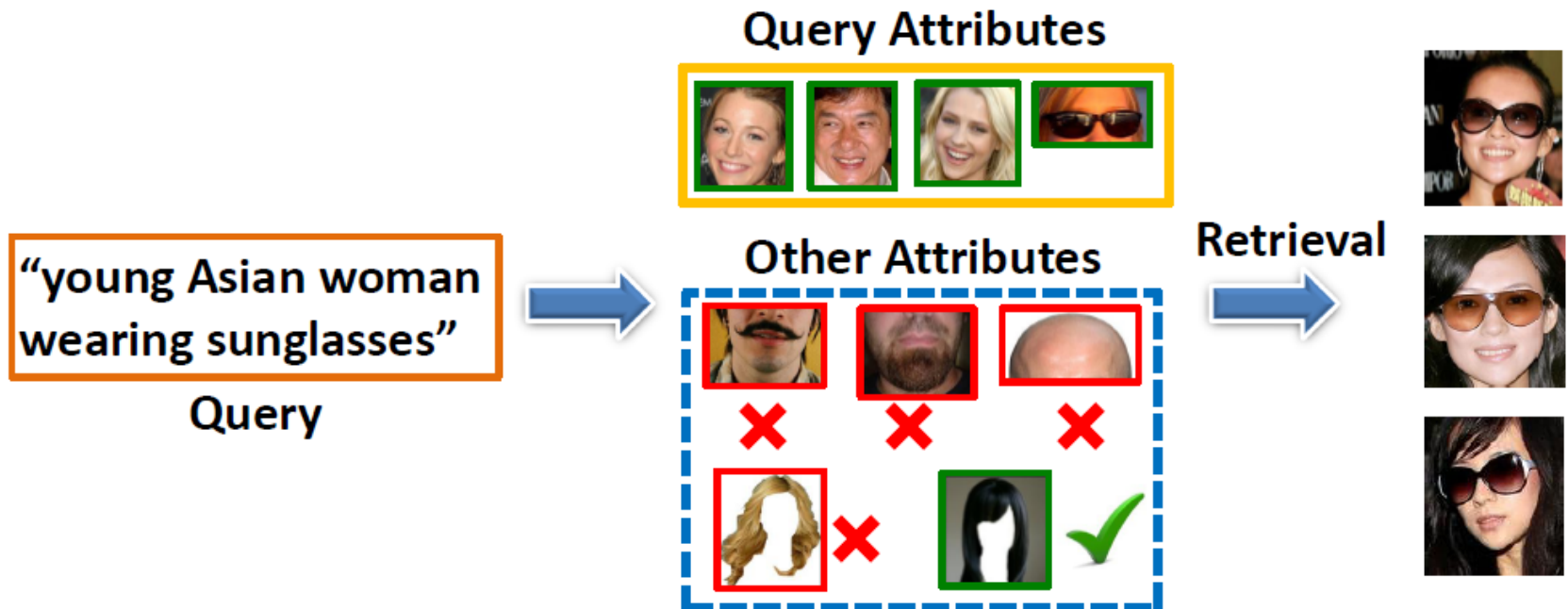
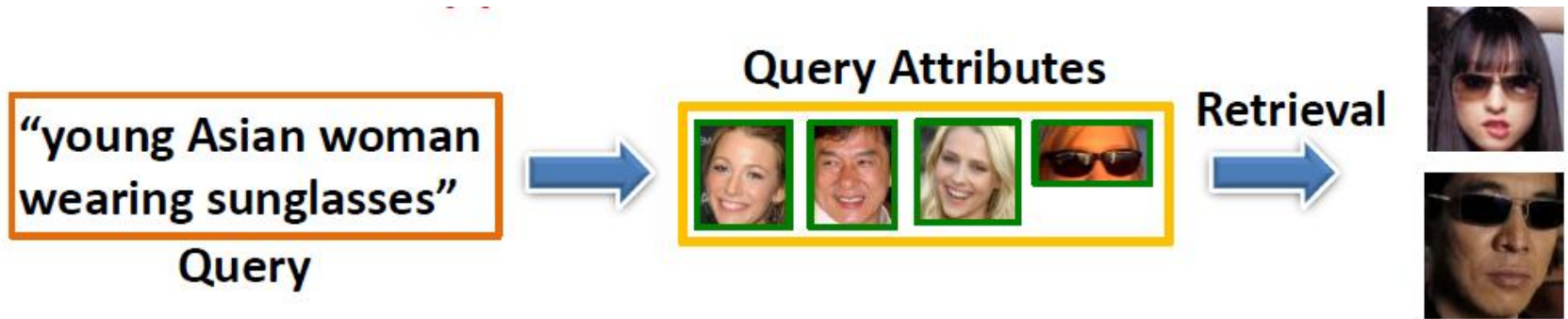
**Number of possible queries is exponential**

## Existing Approaches

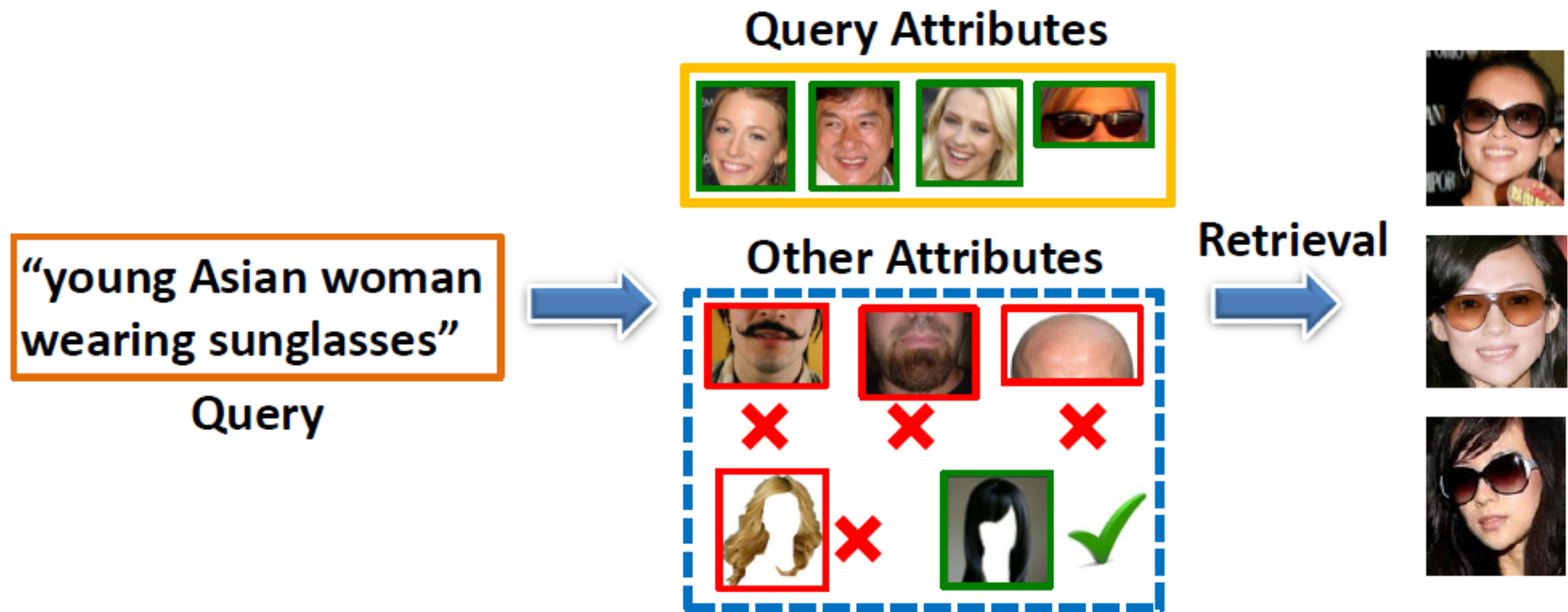
- Train independent classifiers for each attribute
- Sum up confidence scores



# Multi-Attribute Image Retrieval



# Multi-Attribute Image Retrieval



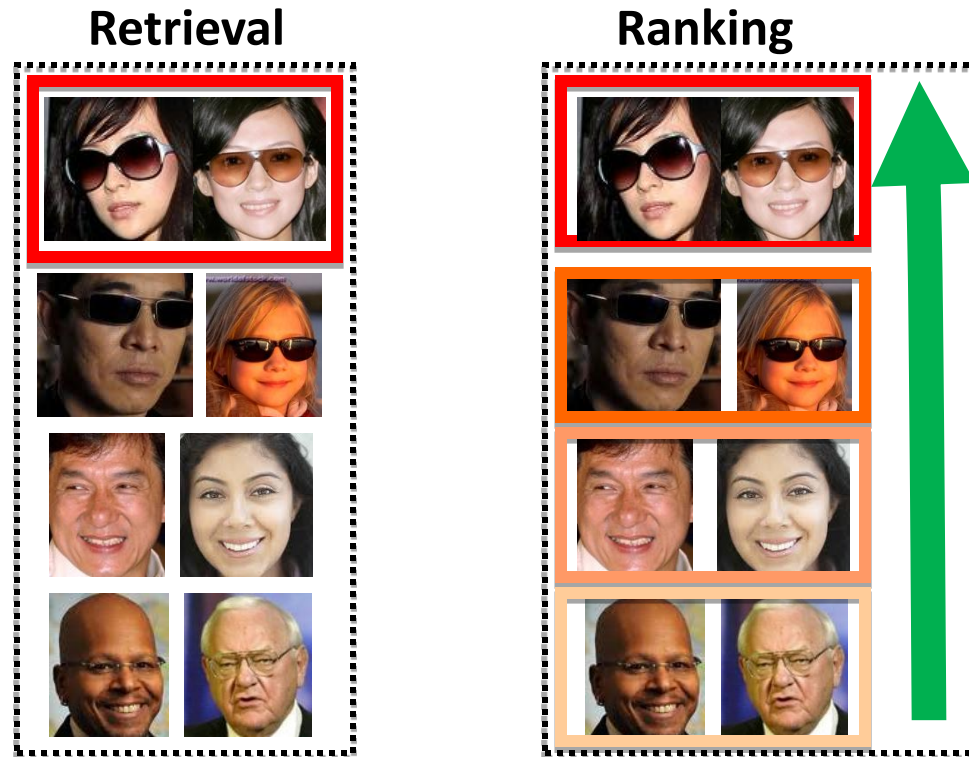
## Model Correlations between Attributes

- Explicitly utilize information from non-query attributes

# Multi-Attribute Image Retrieval

## Joint Ranking and Retrieval Framework

- Retrieval: Set of images
- Ranking: Ordered set of images



# Multi-Attribute Image Ranking/Retrieval

We are given:

- An attribute vocabulary

$$\mathcal{X} = \{x_1, x_2, \dots, x_K\}$$

- A set of training images

$$\mathcal{Y} = \{y_1, y_2, \dots, y_N\}$$

- Multi-label annotation for each image



**Hat**  
**Sunglasses**  
**Female**  
**Asian**  
**Young**



# Multi-Attribute Image Ranking/Retrieval

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Hat  
Sunglasses  
Female  
Asian  
Young



Our goal is:

- For a multi-label query  $Q$ , where  $Q \subset \mathcal{X}$

- Rank/Retrieve relevant images from a dataset



# Retrieval: Reverse Learning

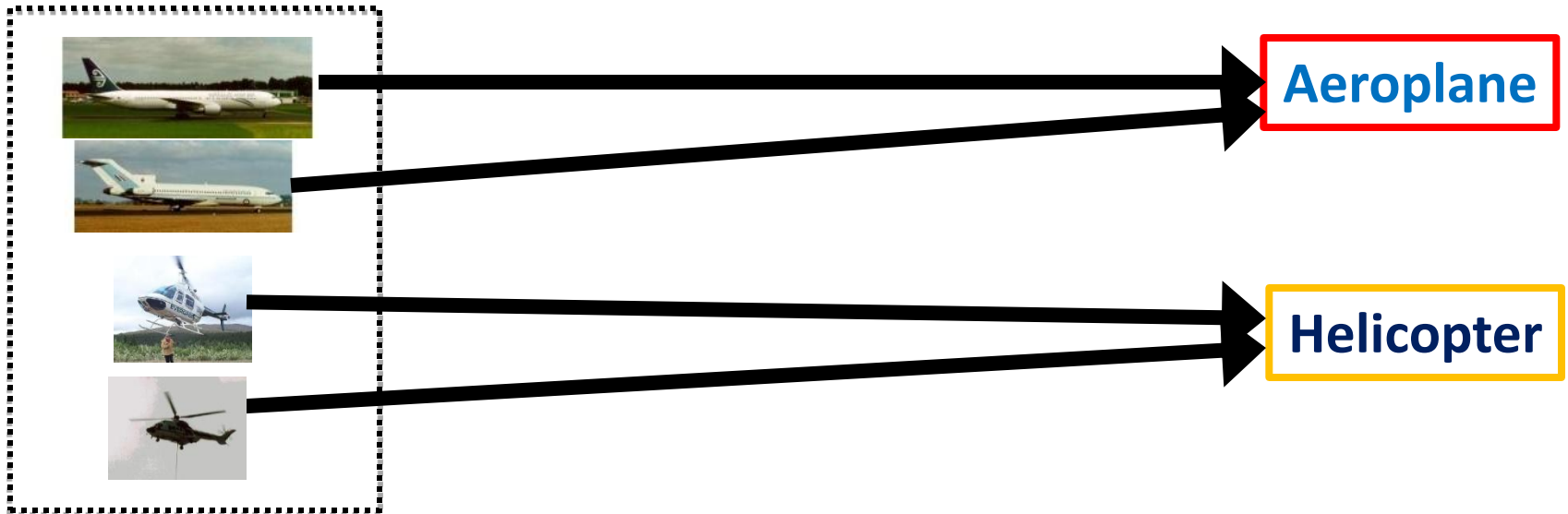
---

- Reverse Multi-label Learning, Petterson and Caetano, NIPS 2010
- Given a label  $x_i$  such that  $x_i \in \mathcal{X}$
- Predict the set of instances  $y(\subset \mathcal{Y})$  that containing the label  $x_i$

# Retrieval: Conventional Learning

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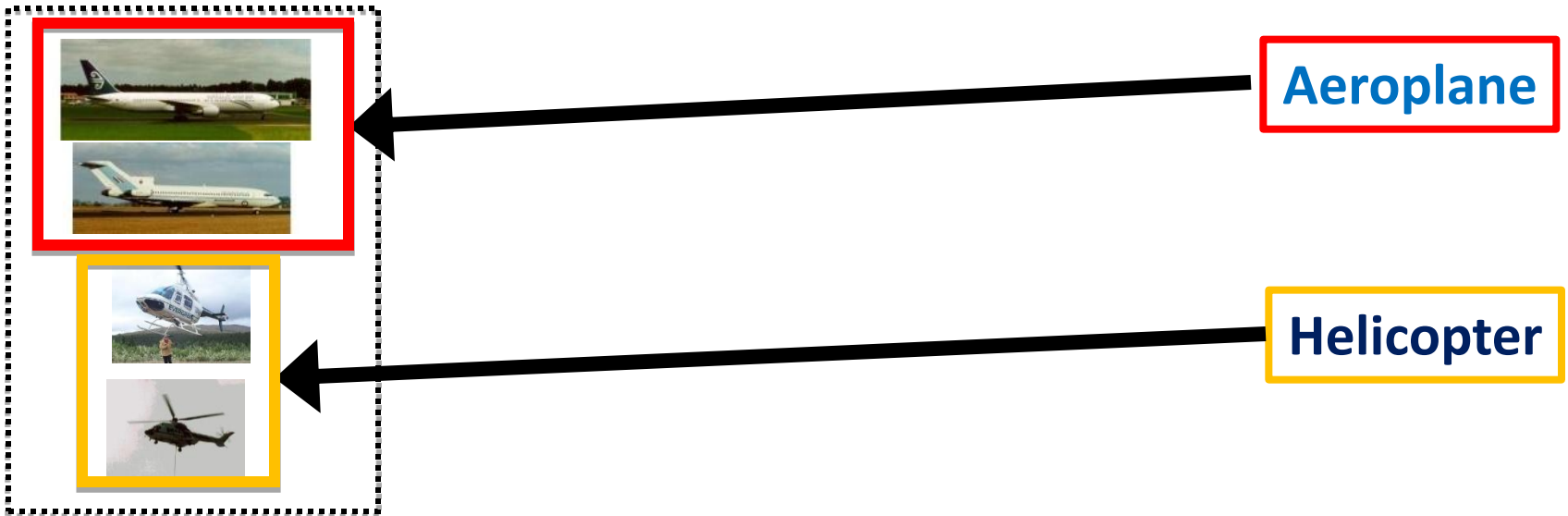
- Conventional Learning





# Retrieval: Reverse Learning

- Given a label  $x_i$  such that  $x_i \in \mathcal{X}$
- Predict the set of instances  $y(\subset \mathcal{Y})$  that containing the label  $x_i$



- Enables minimization of training loss based on a variety of metrics

# Retrieval: Formulation

---

Given multi-attribute query  $Q$ , output set of relevant images  $y$

Learn  $w$  such that  $y^* = \arg \max_{y \subset \mathcal{Y}} w^T \psi(Q, y)$

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Asian woman wearing Sunglasses

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Asian woman wearing Sunglasses



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Asian + woman + wearing Sunglasses

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Asian . Blonde hair

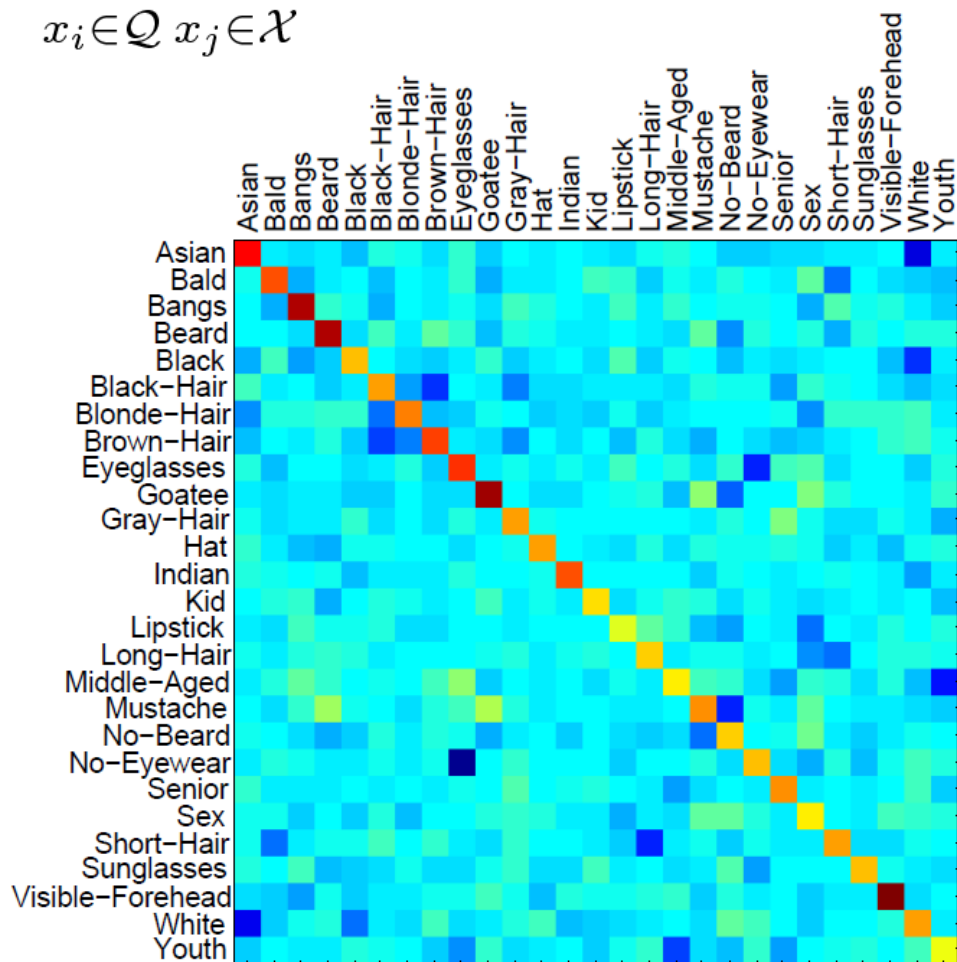
Asian . Gray hair

Asian . Black hair

# Retrieval: Formulation

## Weights Learnt

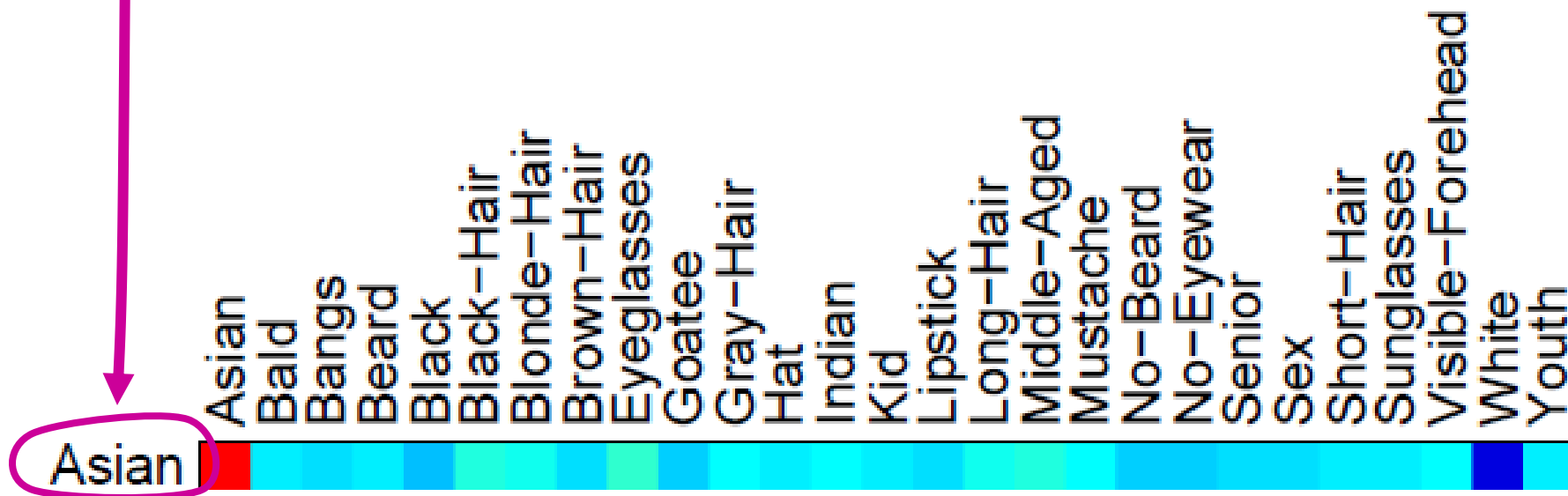
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# Retrieval: Formulation

## Weights Learnt

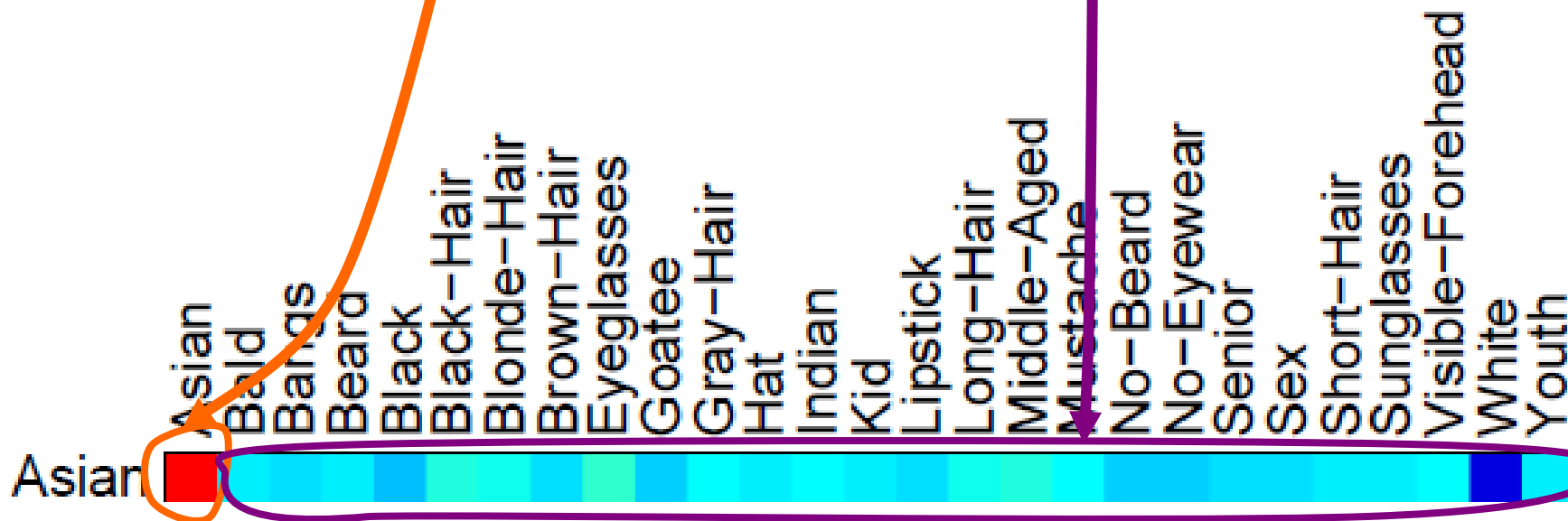
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# Retrieval: Formulation

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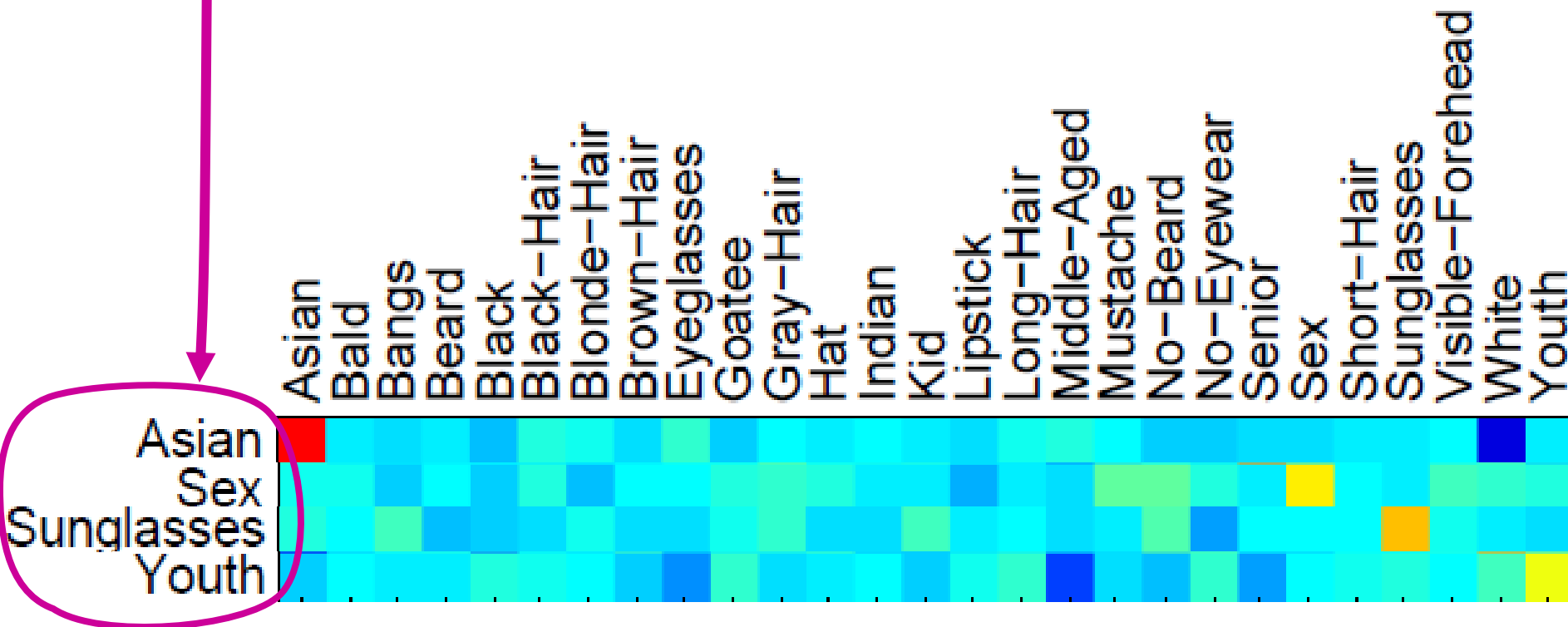
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# Retrieval: Formulation

## Weights Learnt

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# Retrieval: Training

---

Training

$$\arg \min_{w, \xi} \quad w^T w + C \sum_t \xi_t$$

$$\forall t \quad w^T \psi(Q_t, y_t^*) - w^T \psi(Q_t, y_t) \geq \Delta(y_t^*, y_t) - \xi_t$$

# Retrieval: Training

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loss function

$$\Delta(y^*, y) = \begin{cases} 1 - \frac{y \cap y^*}{y} & \text{precision} \\ 1 - \frac{y \cap y^*}{y^*} & \text{recall} \\ 1 - \frac{y \cap y^* + \bar{y} \cap \bar{y}^*}{\mathcal{Y}} & \text{hamming loss} \end{cases}$$

# Ranking

---

Given a query  $Q$ , rank documents in order of relevance

- Output is an ordered set (permutation)

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2010, San Francisco, CA, USA, 13-18 June 2010. IEEE 2010 ...

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# Ranking

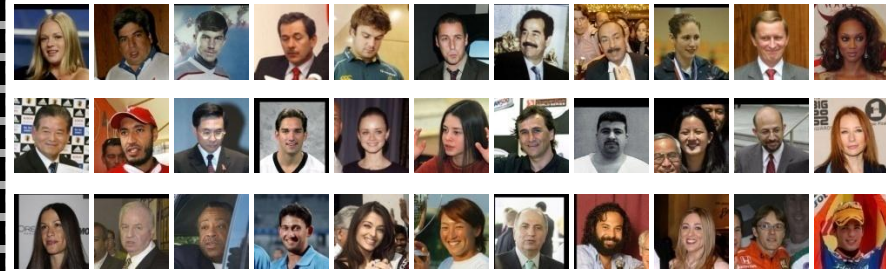
---

Given a query  $Q$ , rank documents in order of relevance

- Output is an ordered set (permutation)

Large Scale Datasets

- Ranking more important than retrieval



# Ranking: Formulation

---

Given a multi-attribute query  $\mathcal{Q}$ , generate permutation of images  $z$

Learn  $w$  such that  $z^* = \arg \max_{z \in \pi(\mathcal{Y})} w^T \psi(\mathcal{Q}, z)$

where  $w^T \psi(\mathcal{Q}, z) = \sum_{x_i \in \mathcal{Q}} w_i^a \hat{\Phi}_a(x_i, z) + \sum_{x_i \in \mathcal{Q}} \sum_{x_j \in \mathcal{X}} w_{ij}^p \hat{\Phi}_p(x_j, z)$

and 
$$\hat{\Phi}_a(x_i, z) = \sum_{z_k \in z} A(r(z_k)) \phi_a(x_i, z_k)$$
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# Ranking: Training

---

**Training**  $\arg \min_{w, \xi} w^T w + C \sum_t \xi_t$

$$\forall t \quad w^T \psi(Q_t, z_t^*) - w^T \psi(Q_t, z_t) \geq \Delta(z_t^*, z_t) - \xi_t$$



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**loss function**

$$\Delta(z^*, z) = 1 - \text{NDCG}_k(z^*, z)$$

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**where**

$$\text{NDCG}_k = \frac{1}{Z} \sum_{j=1}^k \frac{2^{\text{rel}(j)} - 1}{\log(1 + j)}$$

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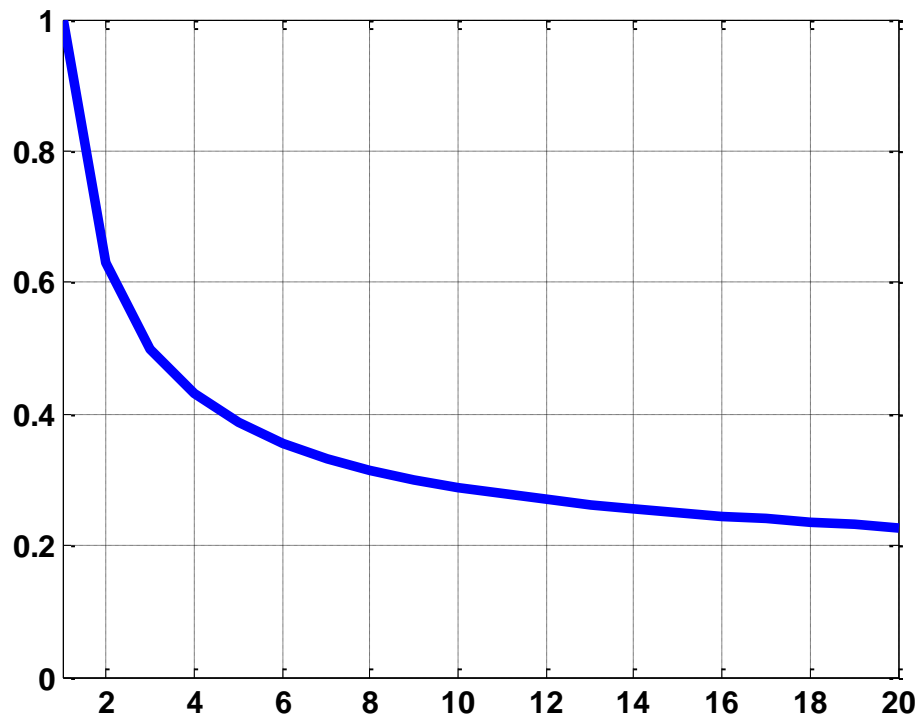
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**Asian + woman + wearing Sunglasses**

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**3**



**Asian + woman + wearing Sunglasses**

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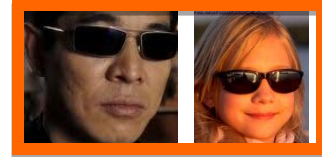
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3



2



**Asian + woman + wearing Sunglasses**

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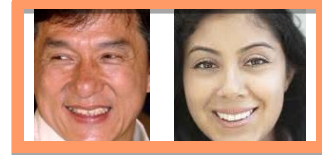
3



2



1



0



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**Asian + woman + wearing Sunglasses**

## **Strong Attributes**

- Race
- Age
- Gender

## **Weak Attributes**

- Hair Color
- Hair Style
- Facial Hair
- Eyewear



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**where**

$$\text{NDCG}_k = \frac{1}{Z} \sum_{j=1}^k \frac{2^{\text{rel}(j)} - 1}{\log(1 + j)}$$

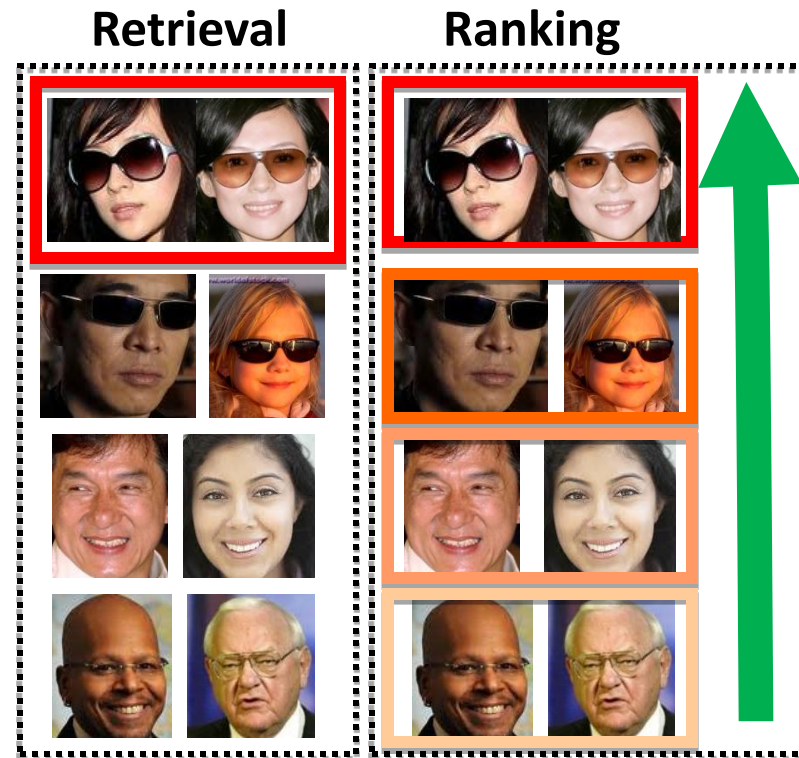
# Multi-Attribute Ranking and Retrieval

## Ranking and Retrieval

- Typically treated as separate problems


## Structured Formulation

- Optimize the same model according to different performance measures



# Labeled Faces in the Wild(LFW) Dataset

**Labeled Faces in the Wild**


















**Menu**

- LFW Home
- UMass Vision

**Database by name, all**

[A][Alf][Ang][B][Bin][C][Che][Col][D][Daw][Don][E][Eri][F][G][Goe][H][I][J][Jav][Jes][Joh][Jos][K][Kim][L][Li][M][Mark][Mel][Mik][N][O][P][Per][Q][R][Ric][Rog][S][Sha][Ste][T][Tim][U][V][W][X][Y][Z]

 Raaf Schefter (1)	 Raag Singhal (1)	 Rachel Corrie (1)	 Rachel Griffiths (3)	 Rachel Hunter (4)
 Rachel Kempson (1)	 Rachel Leigh Cook (1)	 Rachel Roy (1)	 Rachel Wadsworth (1)	 Rachel Wheatley (1)
 Radovan Karadzic (1)	 Raf Vallone (1)	 Rafael Bielsa (1)	 Rafael Ramirez (4)	 Rafael Vinoly (1)

## Attribute Annotation

- 9992 images
- 27 attributes

# LFW Dataset: Attributes

## Race

- Asian
- Black
- White
- Indian



## Age

- Kid
- Youth
- Middle-Aged
- Senior



## Gender

- Sex



## Other

- Hat
- Lipstick
- Visible Forehead

## Hair Color

- Black Hair
- Blonde Hair
- Brown Hair
- Gray Hair



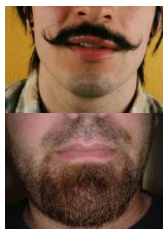
## Hairstyle

- Long Hair
- Short Hair
- Bangs
- Bald



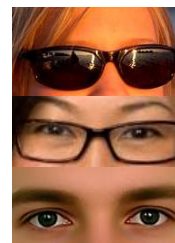
## Facial Hair

- Mustache
- Beard
- Goatee
- No Beard



## Eyewear

- Sunglasses
- Eyeglasses
- No Eyewear



# LFW Dataset: Feature Extraction

## Features

### Color

- Color Histograms
- Color Correlograms
- Color Moments
- Color Wavelet

### Texture

- Wavelet Texture
- LBP Histogram
- LBP PCA

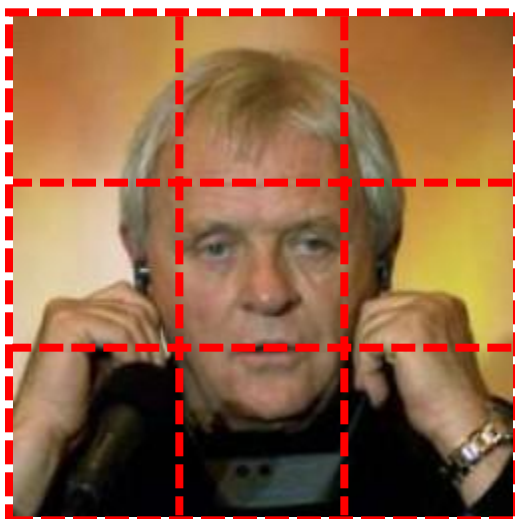
### Skin Information

- Skin Bitmap
- Skin Color
- Spatial Skin

### Shape

- Edge Histogram
- Shape Moments
- SIFTogram

## Features: Spatial Configurations



Center



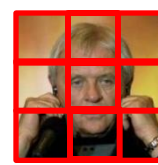
Global



Horizontal  
Parts

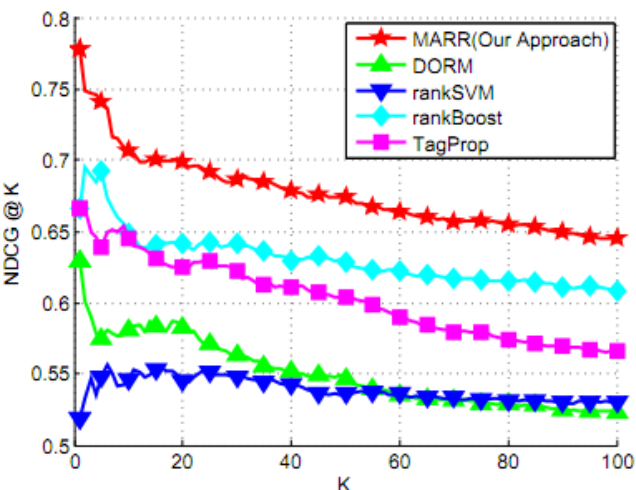


Vertical  
Parts

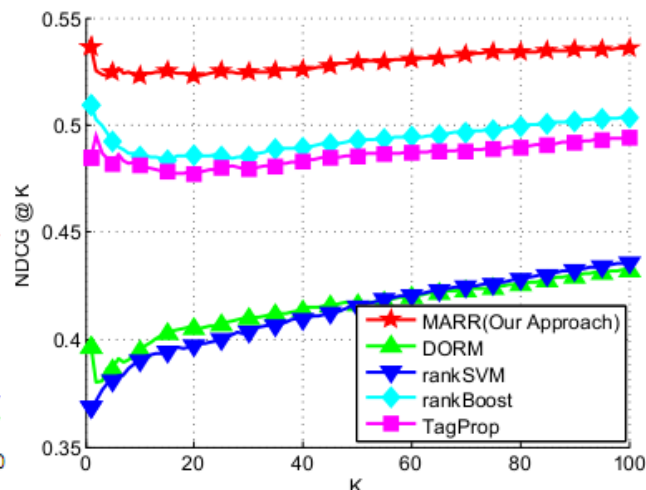


Layout

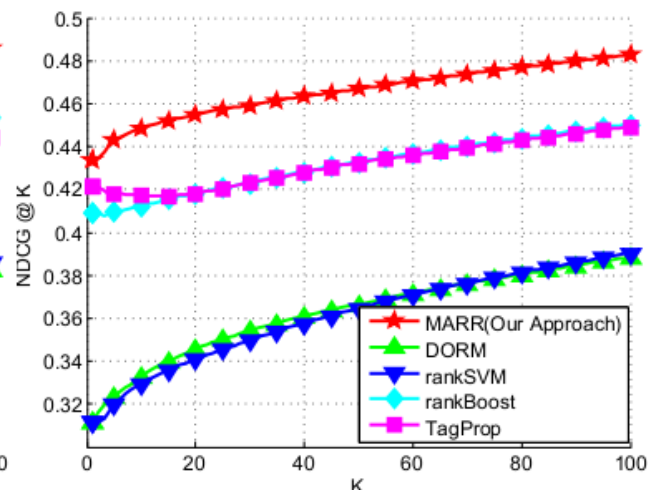
# LFW Dataset: Quantitative Results



(a) Single Attribute Queries



(b) Double Attribute Queries



(c) Triple Attribute Queries

## Ranking

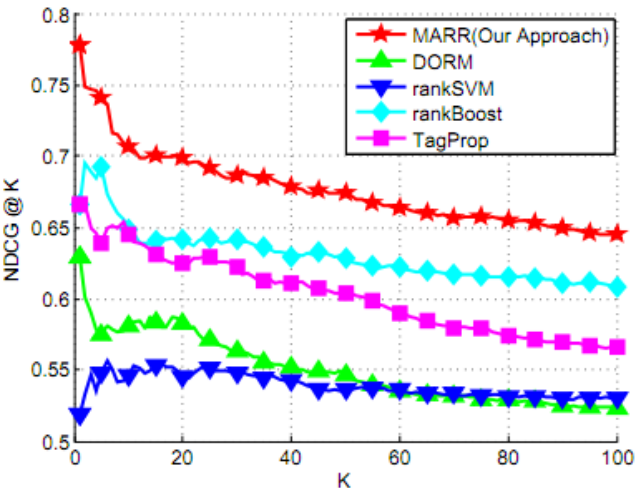
### ➤ Baselines

- RankSVM (T. Joachims, KDD 2002)
- RankBoost (Y. Freund, I. Iyer, R. Schapire, Y. Singer, JMLR 2003)
- DORM (Q. Li, A. Smola, NIPS workshop 2008)
- TagProp (M. Guillaumin, T. Mensink, J. Verbeek, C. Schmid, ICCV 2009)

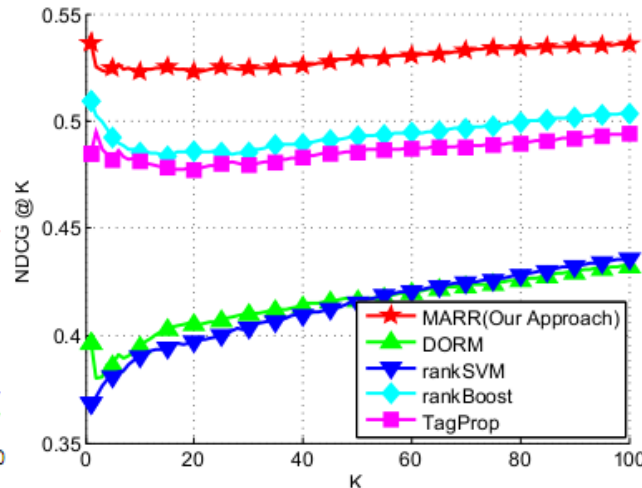
### ➤ NDCG@K



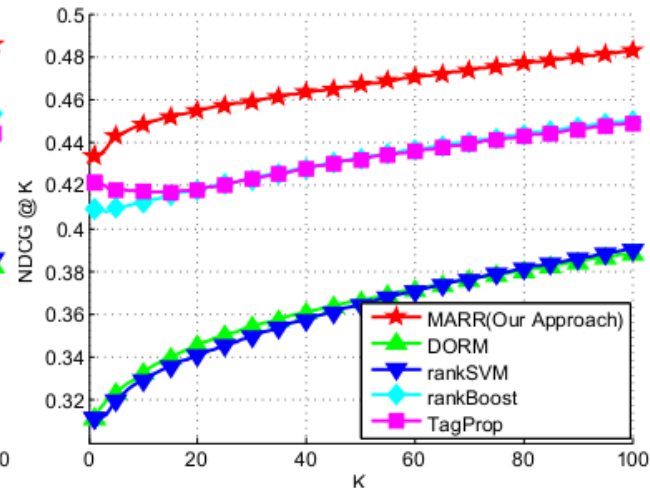
# LFW Dataset: Quantitative Results



(a) Single Attribute Queries



(b) Double Attribute Queries



(c) Triple Attribute Queries

## Results

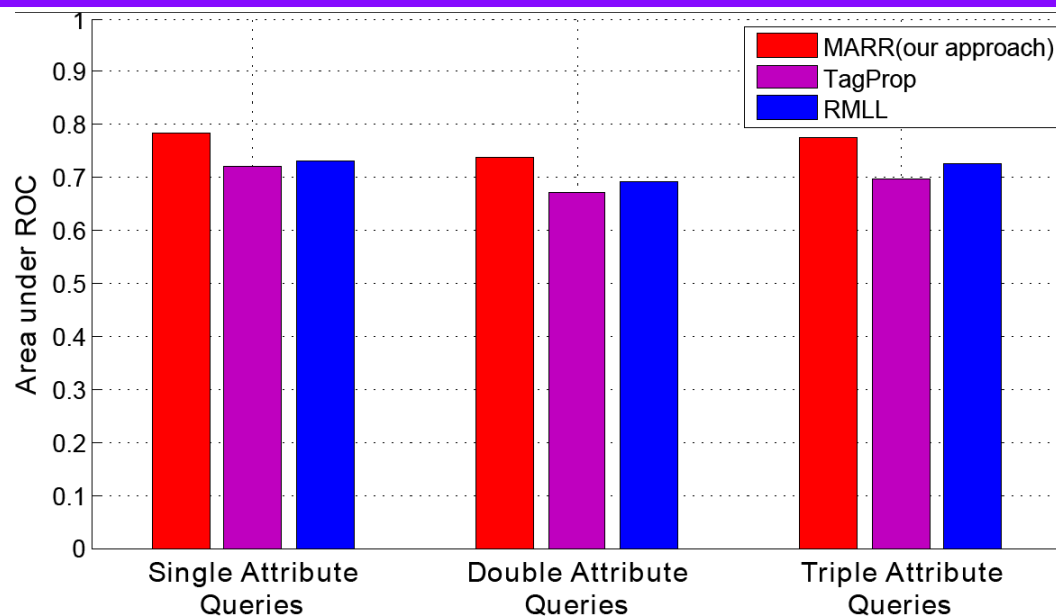
➤ rankBoost is the 2<sup>nd</sup> best

➤ Performance gain

- Single Attribute Queries: 8.9% improvement in NDCG@10
- Double Attribute Queries: 7.7% improvement in NDCG@10
- Triple Attribute Queries: 8.8% improvement in NDCG@10



# LFW Dataset: Quantitative Results



## Retrieval

### ➤ Baselines

- Reverse Multi-Label Learning, (J. Petterson and T. Caetano, NIPS 2010)
- TagProp, (M. Guillaumin, T. Mensink, J. Verbeek, C. Schmid, ICCV 2009)

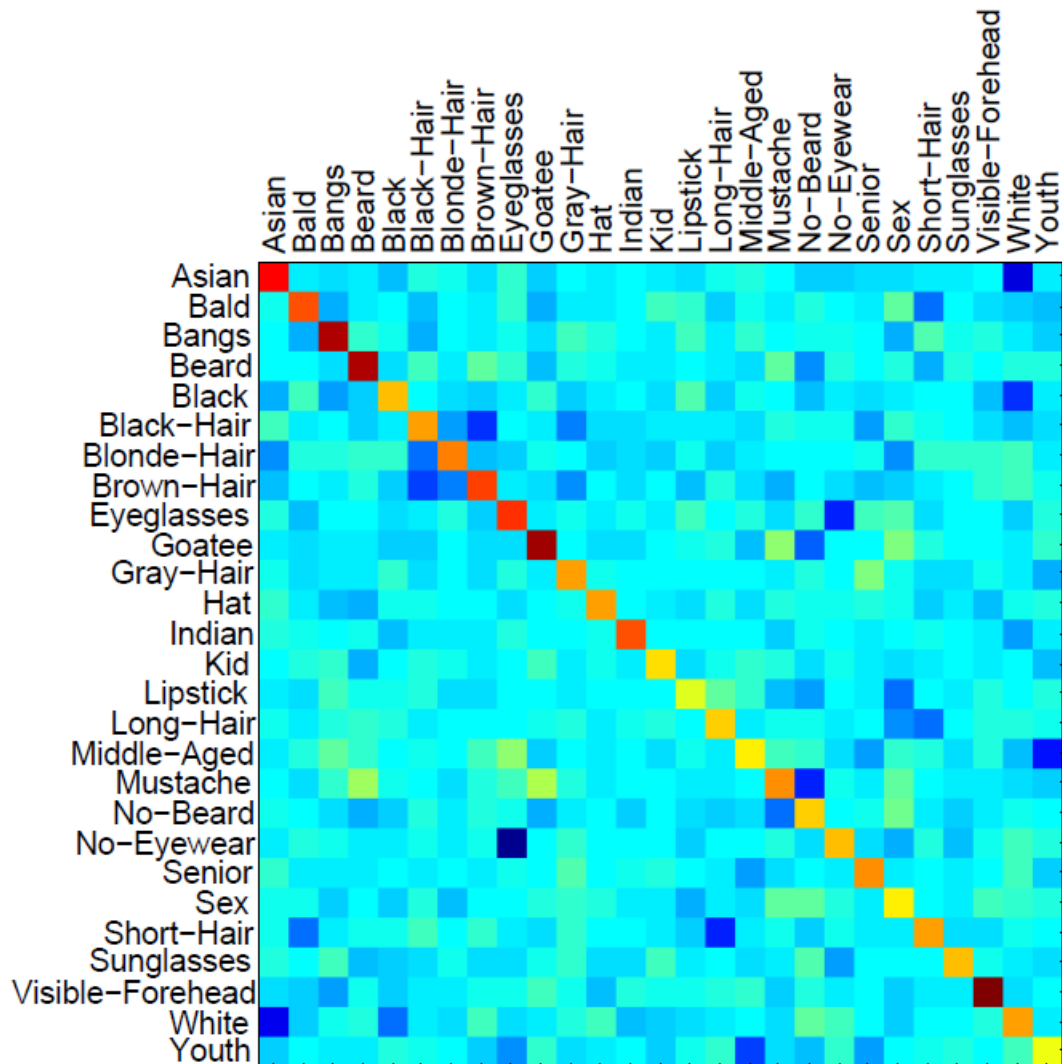
### ➤ mean Area under ROC

### ➤ Performance gain

- ~5% w.r.t. RMLL
- ~7% w.r.t. TagProp

# LFW Dataset: Analysis

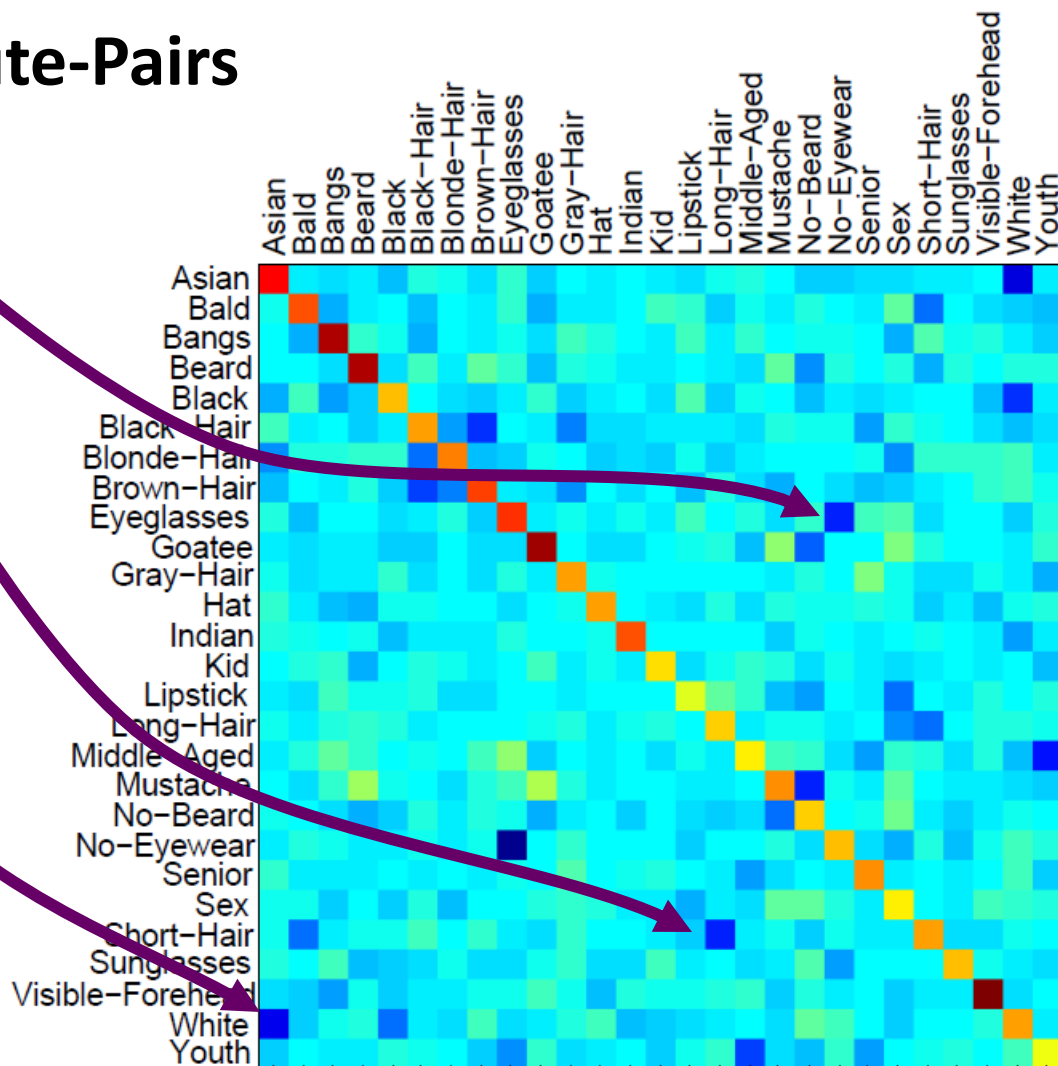
## Weights Learnt



# LFW Dataset: Analysis

## Mutually Exclusive Attribute-Pairs

- (White, Asian)
- (Eyeglasses, No-Eyewear)
- (Short-Hair, Long-Hair)

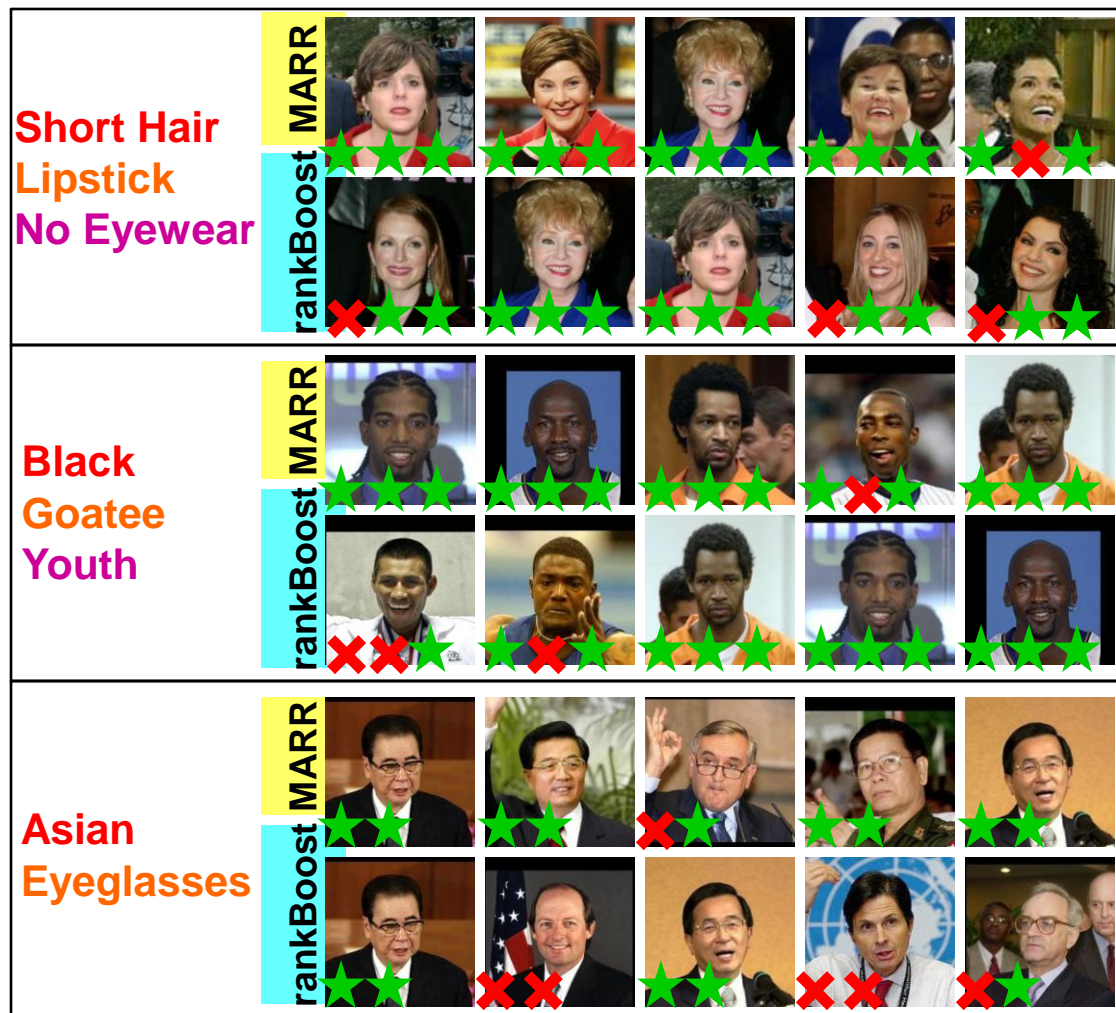






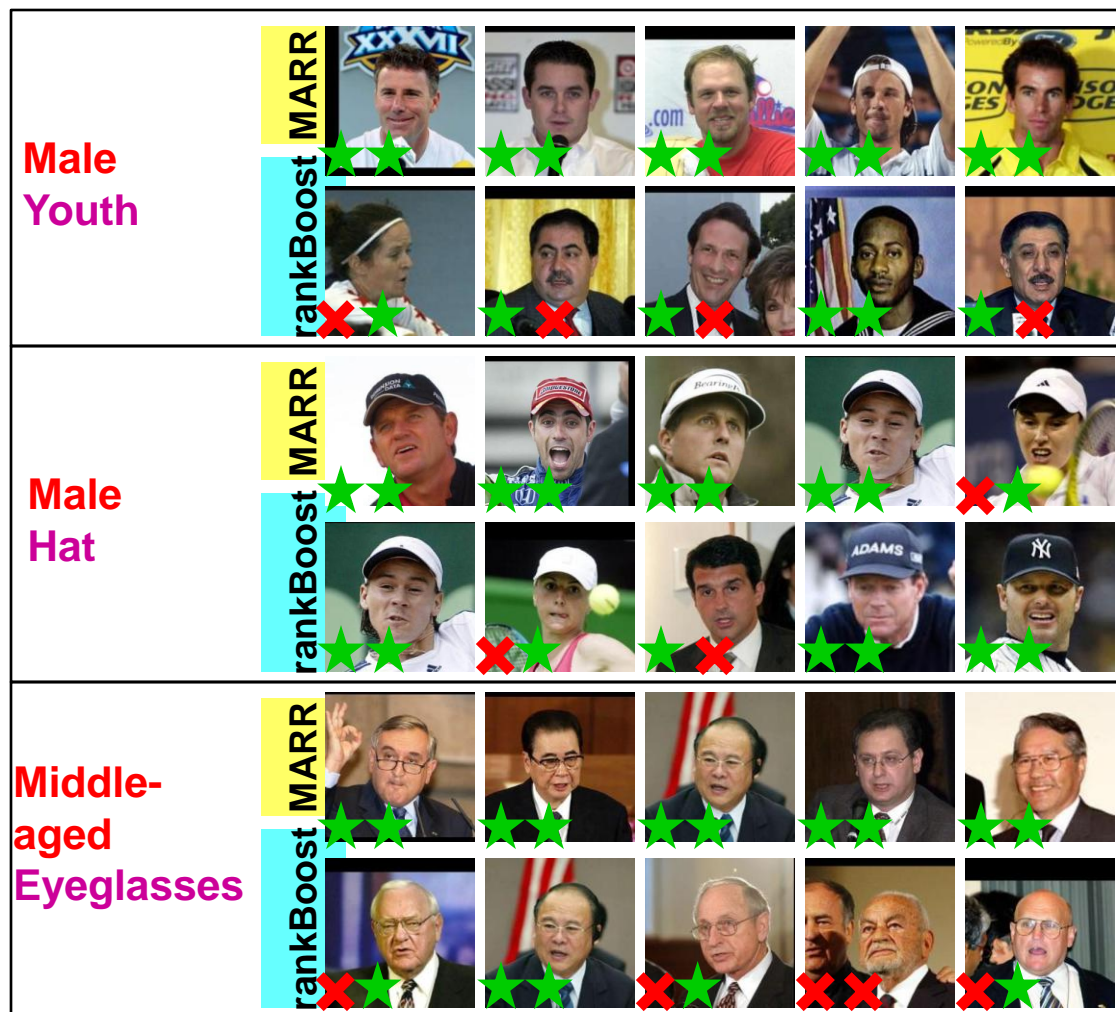


# LFW Dataset: Qualitative Results





# LFW Dataset: Qualitative Results





# FaceTracer Dataset

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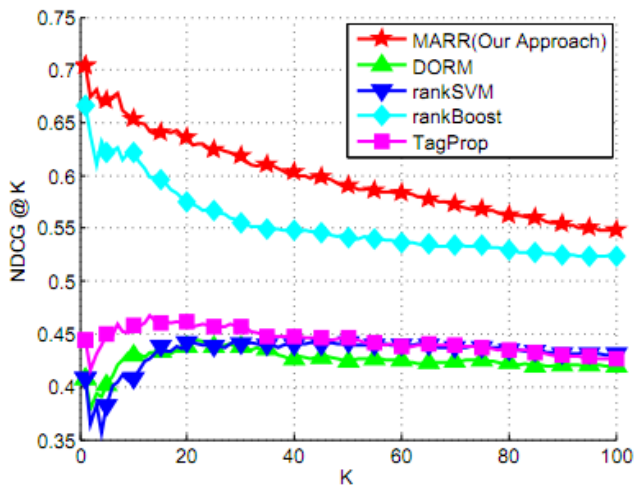


(Kumar et. al, ECCV 2008)

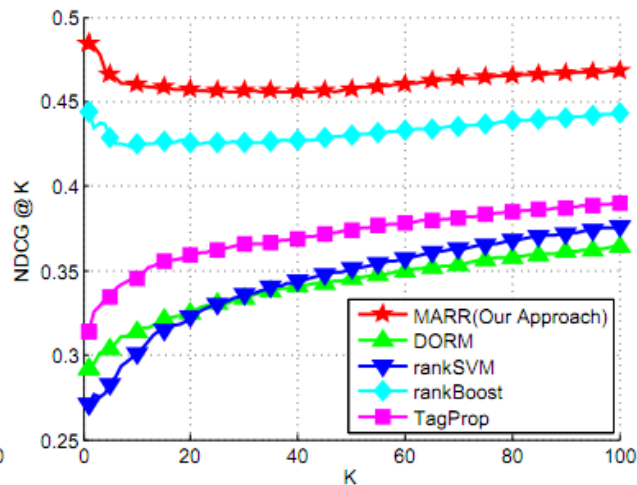
## Attribute Annotation

- 3000 images
- 27 attributes

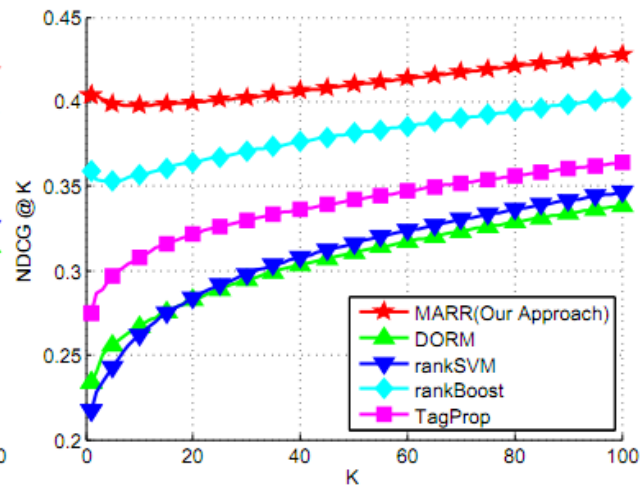
# FaceTracer Dataset: Quantitative Results



(a) Single Attribute Queries



(b) Double Attribute Queries



(c) Triple Attribute Queries

## Results

➤ rankBoost is the 2<sup>nd</sup> best

➤ Performance gain

- Single Attribute Queries: 5.0% improvement in NDCG@10
- Double Attribute Queries: 8.1% improvement in NDCG@10
- Triple Attribute Queries: 11.6% improvement in NDCG@10

# Pascal Dataset

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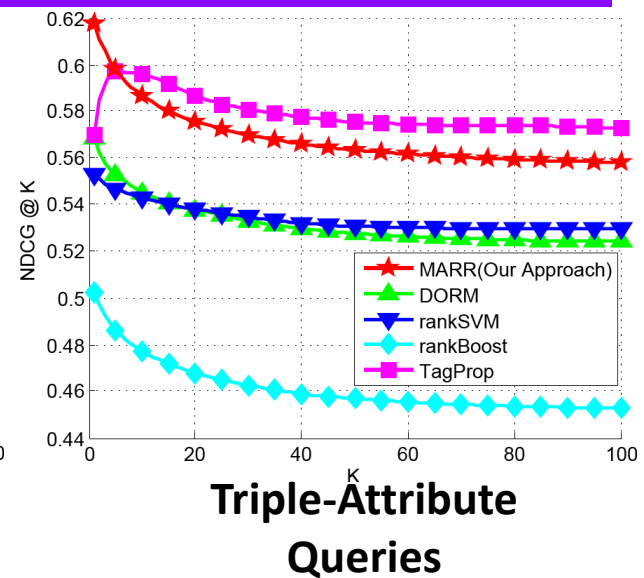
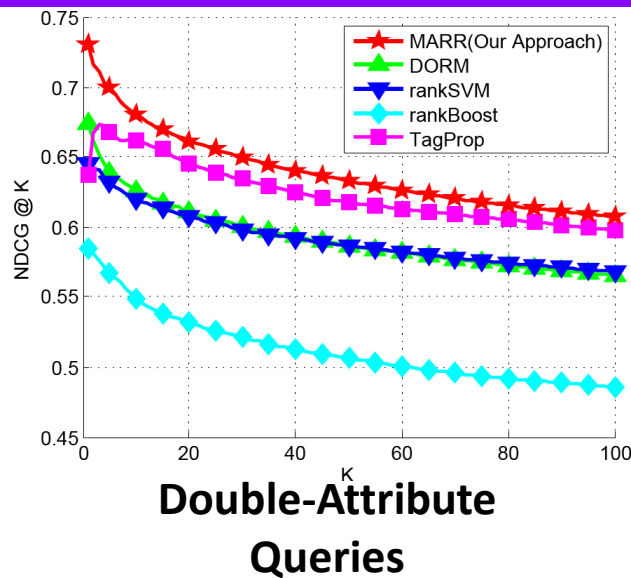
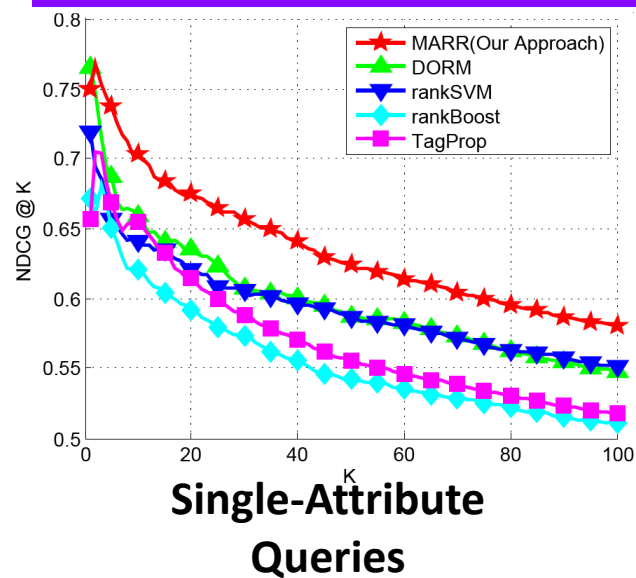


## Visual Object Classes Challenge 2008 (VOC2008)

### Dataset Statistics

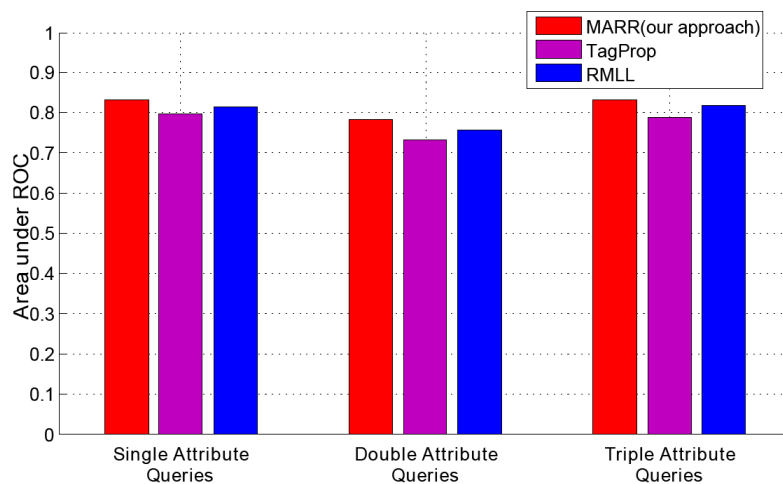
- 12695 images (6340 train, 6355 test)
- 20 classes
  - Airplane, bicycle, bus, horse, person, ...
- 64 Attributes and Parts
  - Attributes: 2D Boxy, Round, Vertical Cylinder, Horizontal Cylinder, ...
  - Parts: Window, Headlight, Text, Leg, ...

# Pascal Dataset: Quantitative Results



## Ranking

## Retrieval

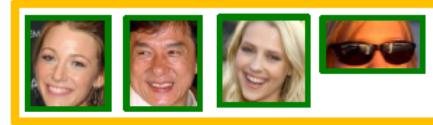


# Image Ranking and Retrieval based on Multi-Attribute Queries

“young Asian woman wearing sunglasses”

Query

Query Attributes



Other Attributes



Retrieval



Retrieval

Ranking



# Questions?

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**Asian  
Eyeglasses**



**Male  
Hat**

