

Main Idea

• When people compare images, certain prominent differences stick out, are described first



Less comfortabl More rugged More shiny Less feminine More stylish More formal





Less feminine _ess colorful More rugged More stylish

Goal: Learn and use prominent differences



Important to our perception (ex. what stands out when comparing shopping items?)



Influences human input (ex. labeling, feedback to an nteractive system)

Relative Attributes

Express an image's attribute strength with respect to other images:



Learn more/less labels using a ranker

Ranker models used:



256 384 384 384 4096 4096

Ranking SVM [Parikh and Grauman 2011]

Learning Prominent Differences

Given pair y_{ij} , get relative attribute scores for each image:

$$x_i \to r_1^i, r_2^i, \dots, r_M^i, x_j \to r_1^j, r_2^j, \dots, r_M^j$$

Create symmetric representation $\phi(y_{ij})$ for pair using attribute scores

Train multiclass classifier on $\phi(y_{ii})$ using labeled prominence pairs

Given new image pair, predict prominent difference(s)

input:
$$y_{uv} = (x_u, x_v)$$



Compare and Contrast: Learning Prominent Visual Differences Steven Chen and Kristen Grauman University of Texas at Austin

Predicting Prominent Visual Differences

Datasets:

- UT-Zap50K Shoes [Yu and Grauman 2014]: 50,025 shoe images, 10 attributes (sporty, formal, etc.)
- LFW10 Faces [Sandeep et al. 2014]: 2,000 face images, 10 attributes (smiling, bald head, etc.)

Annotations:

- Collect 5,000 pairs / dataset, label prominent difference **Evaluation:**
- Benchmark accuracy compared to prior work [Turakhia and Parikh 2013 **] and baseline approaches



) colorful (>` sporty, comfortable



(i) **tall (<)** comfortable, sport

(j) masculine (>)

smiling, visible teeth



colorful, comfortable



comfortable, shiny





(k) bald head (<),

dark hair, visible teeth



(c) tall (<) colorful, sporty



o) visible teeth (>). mouth open, smiling



mouth open, smiling

(l) dark hair (<),



[Singh and Lee 2016]

Impact on Description Generation

Intuition: People describe images using prominent differences **Our Approach:** Name predicted prominent attributes first

Our descriptions contain more prominent differences than other approaches





1 2 3 4 Max # prominent in ground truth

LFW10 (CNN RA Scores)



T-	Ours:	69%	Baseline:	31%
ap50K	Ground Truth:	69%	Baseline:	31%
FW10	Ours:	61%	Baseline:	39%
	Ground Truth:	70%	Baseline:	30%



We outperform all baselines on both datasets and for both ranking algorithms



Ours: Left is more tall, less sporty, and less rugged than the right.

Baseline: Less colorful, more shiny, more feminine





Ours: Left has less dark hair, more bald, and more open mouth than right.

Baseline: More good looking, more mouth open, less young

Impact on Image Search

Apply prominence to WhittleSearch [Kovashka et al. 2012 ~], an interactive image search framework



Problem: Many images satisfy all feedback, and appear equally relevant to the system

Intuition: People choose prominent differences between images to tell the system **Our approach:** Order images by their prominence difference with user feedback



Our approach produces more relevant results, that are more similar to the user's target, yet requires no additional user feedback

Contributions

- Introduce prominent differences, a new functionality for understanding and expressing visual comparisons
- Model and predict prominent differences
- Demonstrate impact on visual search and natural language image description







More shiny

than this

User provides feedback: more formal / comfortable, etc. than this

System ranks images by feedback satisfied



www.stevenzc.com/ comparecontrast