The Design of High-Level Features for Photo Quality Assesment

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…or how to shoot stock photos

- High-level feature set describing photo ‘quality’
- Distinguish between pro-photos and snapshots
- 72% accurate on their metrics

What makes a high-quality photo?

- Simplicity
  - Bokeh
  - Contrast
- Realism (snapshots real, pros surreal)
  - Color palette
  - Camera settings
  - Subject Matter

Feature Set

- Spatial Distribution of Edges
- Color Distribution
- Hue Count
- Blur
- Contrast Quality
- Brightness Level

First the pros

stock images from corbis


corbis


corbis

then the good

the best from dpchallenge.com


2"

..and now the bad

the worst from dpchallenge.com


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Spatial Distribution of Edges

1. Apply 3x3 Laplacian, to filter for edges
2. Resize image to 100x100 an norm img sum to 1
3. Take the mean of each pixel value for all images in each set Mp and Ms
4. Compare test image edge differences to each Mp and Ms at each pixel
5. Take L1 distance off all pixels for each Mp and Ms set, subtract and get a metric ql

Alternate Edge Distribution

1. Project Laplacian image onto x,y axes
2. Calculate bounding box of 96.04% of all edge energy
3. Metric is 1 minus area of bounding box

Color Distributions

1. Quantize image into 16x16x16 color levels, and calculate densities of each color
2. kNN algorithm, k=5, for query image in training set
3. Metric is qcd = np – ns within a distance of k=5 in 4096 color space histogram

Hue Count

1. Convert to HSV (hue, saturation, intensity value)
2. Limit to S>0.2, and 0.15>V>0.95
3. Place H values in 20-bin histogram
4. Compute max value *m* of histogram
5. N is the set of bins with value greater than αm
6. Metric is 20 – N

Blur

1. Take FFT of image
2. Allow frequencies greater than 5
3. Metric is ratio of high frequencies to size of image

Lower-level features

- Contrast
  - Width of 98% of composite RGB histogram
- Brightness
  - Average brightness

Classification

- Since metrics are non-linear, naïve Bayes classifier used.

$$\begin{aligned} q_{all} &= \frac{P(Prof \mid q_1 \ldots q_n)}{P(Snap \mid q_1 \ldots q_n)} \\ &= \frac{P(q_1 \ldots q_n \mid Prof)P(Prof)}{P(q_1 \ldots q_n \mid Snap)P(Snap)}, \end{aligned}$$

$$q_{all} = \frac{P(q_1 \mid Prof) \ldots P(q_n \mid Prof)P(Prof)}{P(q_1 \mid Snap) \ldots P(q_n \mid Snap)P(Snap)}.$$

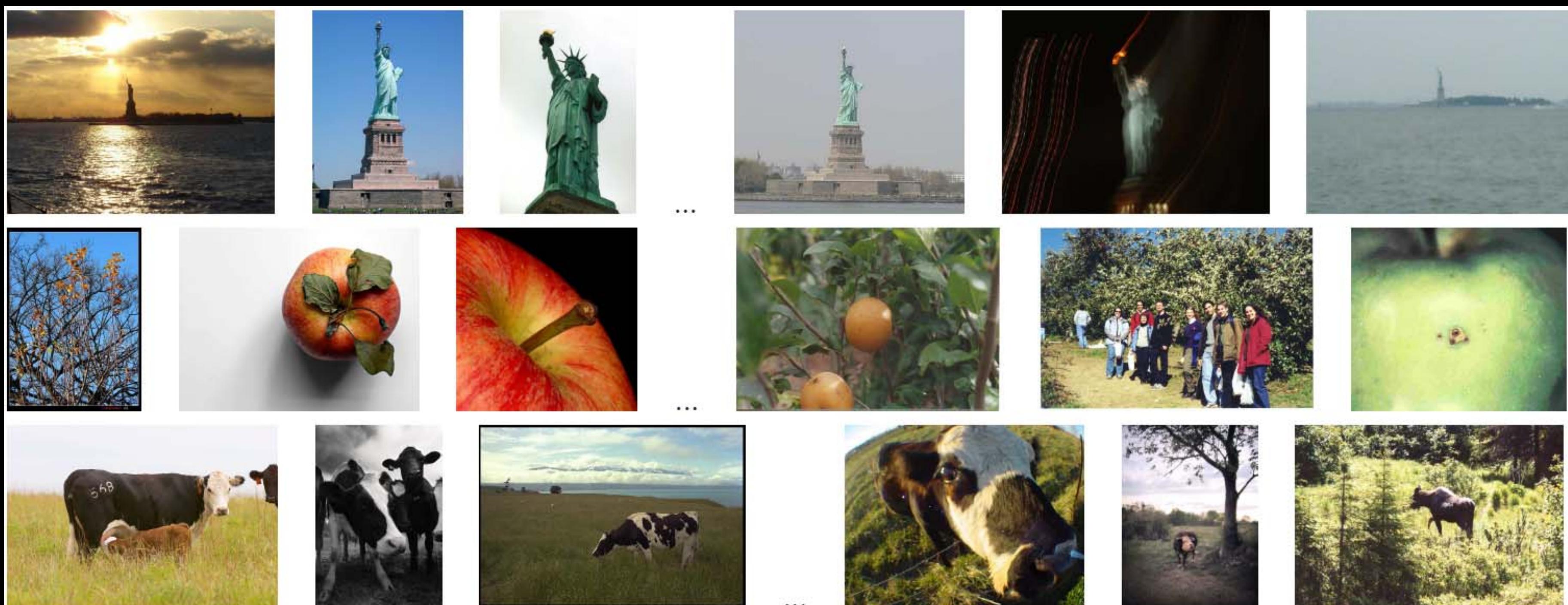
Dataset

- Images from DPChallenge.com, user graded from 1 to 10
- 60,000 photos from 40,000 photographers
- Each photo rated by at least 100 users
- Top and bottom 10% extracted and assigned as high and low quality
- Half of photos used as training set
- Borders removed

Results

- 28% error rate in identification with Bayes classifier
- 24% error rate using Real-AdaBoost
- Error rate reduced with more differentiated dataset

	Testing on top and bottom n%				
	10%	8%	6%	4%	2%
Error rate	28%	26%	24%	23%	19%



Some other features to consider

- Composition
- Juxtaposition
- Depth
- Gaze
- Texture
- Color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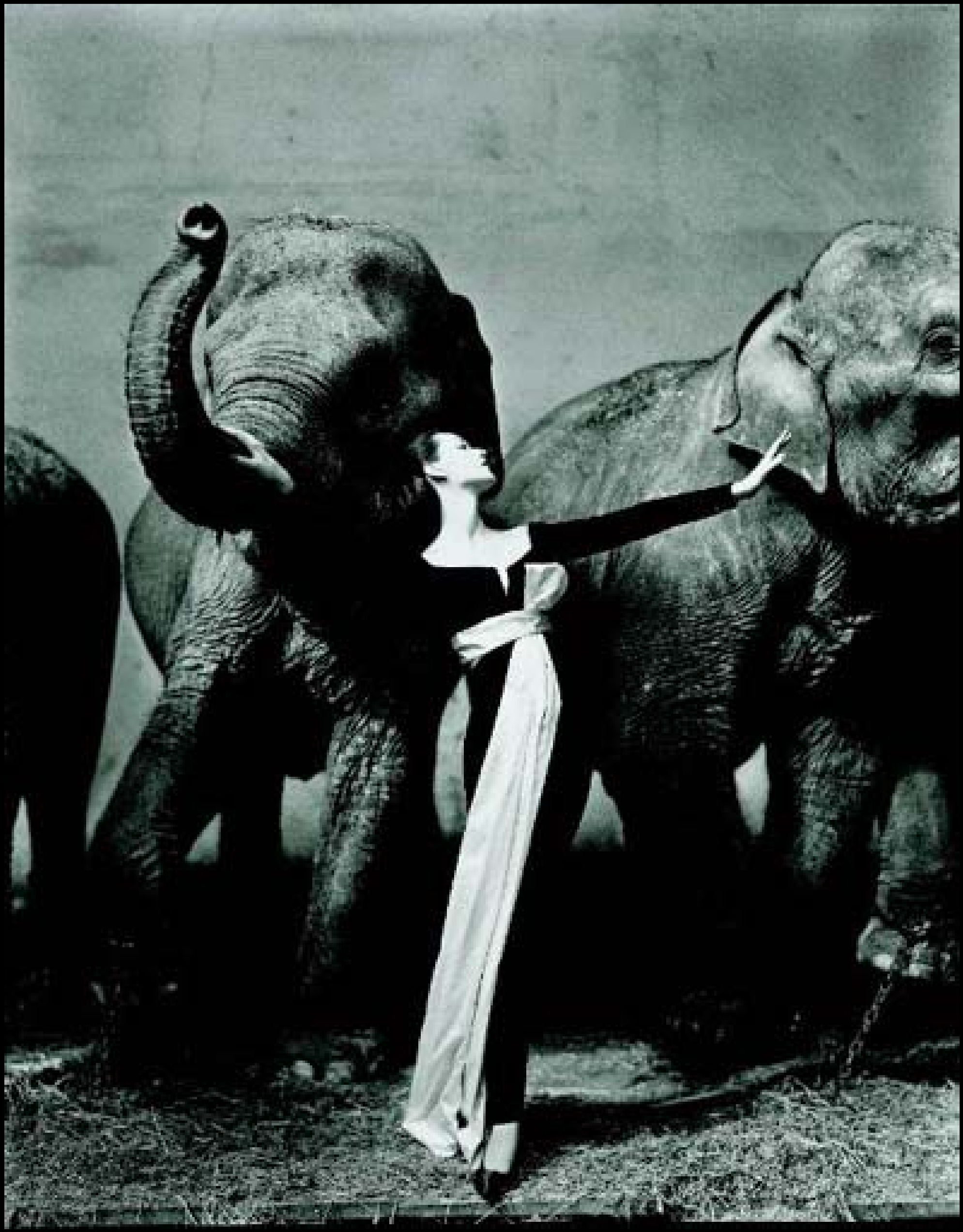

retinal contrast adaptation