Extracting Brand Perceptions from Consumer Created Images: A Machine Learning Approach

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2016 Stanford GSB Digital Marketing Conference
Visual Content on the Rise

“3.8 trillion photos were taken in all of human history until mid-2011, but 1 trillion photos were taken in 2015 alone…” (Kane & Pear, 2016)

New successful social media platforms emphasize visual content

![Social Media Logos](https://www.instagram.com/press/)

1. e.g., Instagram users add an average of 95M photos/videos daily

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Brands Embrace Visual Marketing

Companies develop visual stimuli to shape customers’ perceptions of brands

- One-third of total annual marketing budgets was earmarked for creating, producing, and promoting visual content in 2016 (Gujral, 2015).
Consumer-Created Brand Images (i.e., #brand)

- Consumers post millions of photos online to share their experiences and communicate their feelings, thoughts, and attitudes.
- They often hashtag brands and depict their interactions with brands
  - 49,580,574 posts on Instagram with #nike (retrieved Nov. 2016)

#eddiebauer  #prada
Do consumer-created brand images reflect their brand perceptions?

#eddiebauer
rugged

#prada
glamorous
Do consumer-created brand images reflect their brand perceptions?

Propose a method for extracting brand perceptions from images

Apply it to consumer-created images, and demonstrate that these images reflect consumers’ brand perceptions.
Related Literature

Visual Design: color, shape, texture as fundamental elements of design (Hashimoto & Clayton, 2009; Dondis, 1974; Arnheim, 1954)

Computer Vision: extract quantifiable features (Shapiro & Stockman, 2001)

Visual Marketing: visual stimuli impact consumer behavior and perceptions (see Wedel & Pieters, 2007) for a review)
Outline of the Talk

- **Methodology: Perceptual attributes image classification**
  1. Collect images labeled with perceptual attributes
  2. Extract visual features
  3. Train classifiers

- **Application on Consumer-Created Images**
  - Compare consumer and firm-created images to consumer brand perceptions measured in survey

- **Summary**
Outline of the Talk

- **Methodology:** Perceptual attributes image classification
  1. Collect images labeled with perceptual attributes
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- **Application on Consumer-Created Images**
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- **Summary**
1. Collect Images Labeled with Perceptual Attributes

Brand perceptual attributes:
- \{glamorous, rugged, fun, healthy, reliable, trustworthy\}

Query Flickr: search for perceptual attributes and antonyms
(Karayev et al., 2013; Zhang, Korayem, Crandall, & LeBuhn, 2012; Dhar, Ordonez, & Berg, 2011; McAuley & Leskovec, 2012)
About 4,000 images per perceptual attribute and 23,404 in total

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Brand Perception
2016 Stanford
glamorous    drab    rugged    gentle
About 4,000 images per perceptual attribute and 23,404 in total
2. Extract Visual Features

**Color**
e.g., hue, saturation, brightness

**Shape**
e.g., line, corner, edge/gradient direction

**Texture**
e.g., local binary pattern, gabor filter

![Hue Changes](image)
![Saturation Changes](image)
![Brightness Changes](image)

![Images of color changes](image)

![Images of shape changes](image)

![Images of texture changes](image)
# List of Features by Feature Type

<table>
<thead>
<tr>
<th>Feature Type</th>
<th>Feature</th>
</tr>
</thead>
</table>
| **Color**    | RGB color histogram  
|              | HSV color histogram  
|              | L*a*b color histogram |
| **Shape**    | Line: number of straight lines  
|              | Line: percentage of parallel lines  
|              | Line: histogram of line orientations & distances  
|              | Line: histogram of line orientations  
|              | Corner: percentage of global corners  
|              | Corner: percentage of local corners  
|              | Edge Orientation Histogram  
|              | Histogram of Oriented Gradients (HOG)  
| **Texture** | Local Binary Pattern (LBP)  
|              | Gabor |
3. Train Classifiers

- **Input**: \( \{(x_i, y_i), i = 1, \ldots, N_p\} \)

- **Classification function**: 
  \[
  f_p(x_i; w_p, b_p) = w_p^T x_i + b_p
  \]
  s.t. \( y_i f(x_i; w_p, b_p) > 0, i = 1, \ldots, N_p \) \hspace{1cm} (1)

**Support Vector Machine (SVM)**

\[
\min_{w_p, b_p} \frac{1}{2} w_p^T w_p + C \sum_{i=1}^{N_p} \xi_i
\]
  s.t. \( y_i(w_p^T x_i + b_p) \geq 1 - \xi_i, \xi_i \geq 0, i = 1, \ldots, N_p \) \hspace{1cm} (2)

- \( p \): perceptual attribute
- \( x_i \): D-dimensional visual feature vector for image \( i \)
- \( y_i \in \{-1, +1\} \): class labels
- \( \xi_i \): slack variables
Feature Selection

- Train SVM with single type of feature and feature combinations
- 80% train and 20% test
## Classification Performance

### Out of sample classification accuracy

<table>
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<th>Best Classifier</th>
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<th>Texture</th>
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<tr>
<td>glamorous</td>
<td>74.1%</td>
<td>69.5%</td>
<td>70.0%</td>
<td>70.9%</td>
</tr>
<tr>
<td>rugged</td>
<td>73.3%</td>
<td>65.6%</td>
<td>70.0%</td>
<td>67.2%</td>
</tr>
<tr>
<td>trustworthy</td>
<td>70.2%</td>
<td>70.2%</td>
<td>67.8%</td>
<td>65.2%</td>
</tr>
<tr>
<td>fun</td>
<td>65.3%</td>
<td>60.4%</td>
<td>57.3%</td>
<td>55.6%</td>
</tr>
<tr>
<td>healthy</td>
<td>63.4%</td>
<td>63.4%</td>
<td>56.0%</td>
<td>51.4%</td>
</tr>
<tr>
<td>reliable</td>
<td>57.4%</td>
<td>56.2%</td>
<td>56.7%</td>
<td>53.0%</td>
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### Feature composition

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<tbody>
<tr>
<td>glamorous</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>rugged</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>trustworthy</td>
<td>1</td>
<td>0</td>
<td>0</td>
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1 = feature included in best classifier, 0 = feature not included in best classifier
Outline of the Talk

- Methodology
  - Collect training data
  - Extract image features
  - Train and validate classifier out-of-sample

- Application
  - Compare consumer and firm-created images to consumer brand perceptions measured in survey

- Summary
Consumer-Created and Firm-Created Brand Images

- Consumers: photos on Instagram (#brand)
- Firms: photos on official accounts on Instagram
- 56 brands from Apparel and Beverages
  - About 2,000 consumer hashtagged photos per brand and 114,367 photos in total
  - 72,089 photos in total from brands' official accounts.
Images of brand $j$: $I^j = \{I^j_1, \ldots, I^j_{N_j}\}$

Classifier of perceptual attribute $p$: $f_p(x; w_p, b_p)$

Compute the ratio of brand $j$ images that express the perceptual attribute

$$F\{j, p\} = \frac{\sum_{i=1}^{N_j} \mathbb{1}(f_p(x_i; w_p, b_p) > 0)}{N_j},$$

where $N_j$ is number of photos of brand $j$, $x_i$ is the visual feature vector extracted from the $i^{th}$ image.
Example: Percentage of Images Expressing Perceptual Attribute

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Prada</th>
<th>Eddie Bauer</th>
</tr>
</thead>
<tbody>
<tr>
<td>glamorous</td>
<td>60.7%</td>
<td>47.1%</td>
</tr>
<tr>
<td>rugged</td>
<td>34.3%</td>
<td>40.6%</td>
</tr>
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P-value < 0.0001
Compare Consumer and Firm Images to Brand Perception Survey

Young and Rubicams Brand Asset Valuator (BAV) (Lovett, Peres, & Shachar, 2014)
Pearson’s Correlation: Consumer vs. BAV, Consumer vs. Firm, Firm vs. BAV

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<tr>
<th>Product Category</th>
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<th>Consumer Image vs. BAV</th>
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<tbody>
<tr>
<td>Apparel (N = 29)</td>
<td>rugged</td>
<td>0.400* (p=0.0157)</td>
<td>0.708** (p=9e-6)</td>
<td>0.430** (p=0.0099)</td>
</tr>
<tr>
<td></td>
<td>glamorous</td>
<td>0.491** (p=0.0034)</td>
<td>0.820** (p=3e-8)</td>
<td>0.581** (p=0.0005)</td>
</tr>
<tr>
<td>Beverages (N = 27)</td>
<td>rugged</td>
<td>0.400* (p=0.0195)</td>
<td>0.440* (p=0.0156)</td>
<td>0.388* (p=0.0304)</td>
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<tr>
<td></td>
<td>healthy</td>
<td>0.451** (p=0.0091)</td>
<td>0.332 (p=0.0566)</td>
<td>0.314 (p=0.0673)</td>
</tr>
<tr>
<td></td>
<td>fun</td>
<td>0.346* (p=0.0387)</td>
<td>0.611** (p=0.0008)</td>
<td>0.228 (p=0.1422)</td>
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<td></td>
<td>glamorous</td>
<td>0.198 (p=0.1608)</td>
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(*p < 0.05, **p < 0.01)

2 N=24 for when comparing firm images. 3 beverage firms don’t have official accounts on Instagram.
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Summary

- Photos consumers share on social media contain valuable brand information
- Extracting this information requires new tools
- Develop methodology for extracting brand perceptions from images, and demonstrate that some brand perceptual attributes can be represented with basic elements of visual design
- Demonstrate that for some perceptual attributes, photos consumers post online represent their perception of the brand
Thank you

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Daria Dzyabura (ddzyabur@stern.nyu.edu)
Natalie Mizik (nmizik@uw.edu)


References II


Color histogram (RGB) computed from top 25 images that are most representative of each perceptual attribute and its antonym
Recognizing Image Style (Karayev et al., 2013)

- Classification task: image style (e.g., Minimal, Vintage)
- Data: Flickr
- Classifier: Deep Convolutional Neural Network
- Average per-class accuracy: 78%