VOGUE:
An Analysis of Vogue Fashion Photography’s Implications about the Female Face

By Christiana Wong
Advised by Prof. Holly Rushmeier
Seminar led by Prof. Andrew Barron
I. Introduction
Motivation

• Image analysis is increasingly popular area
• Access to restricted data set
• Long history and wide circulation of *Vogue*
• Strong interest in finding trends over 122 years in women’s fashion photography
• Interesting from academic and anthropological points of view
Abstract

- Study representation of women in *Vogue*
- Use Viola-Jones Algorithm for object detection
- Perform exploratory analysis for trends in:
  - Faceism
  - Position
  - Facial features
- Combine computational tools and traditional image analysis
Goals

• 1) Identify trends in facial features of cover models
  – → conveys beauty standards

• 2) Identify trends in faceism index
  – → more facial prominence suggests dominance, intelligence, ambition, attractiveness

• 3) Identify trends in location of face in fashion photography
Data

• High resolution scans of each page as ‘jpg’s
• Accompanying metadata in ‘xml’ files
• Included:
  – Date
  – Editor
  – Page number
  – Size of image
  – Company or industry or object depicted
  – Author
Processing

- CS senior David Li extracted each image at coordinates provided by meta data
- Processed 849,167 images ~9 days time
- 287,970 images returned faces detected
- Output the faces and information on faceism, facial features, and positions
- Merge image with metadata file
II. Methodology
Method: Viola Jones Algorithm
Improving Viola Jones Algorithm

- Trial and error in MATLAB
- Eliminate merge threshold
- Perform facial feature detector on all positive subwindows
- Eliminate any subwindows with less than 3 facial parts
- Coalesce and keep the rest
- Decreases number of false negatives and increases number of true positives
Conclusions about our implementation

• Algorithm is easy and fast to use
• Well documented and public information
• OpenCV and MATLAB implementations
• Convenient and fairly good/accurate (79% - could be higher with higher minimum face size threshold)
• Not great for profile faces, drawings, grainier photos, and also not the best facial feature finder
• Better algorithms out there such as Facebook’s algorithm
Face Detection Successes
Face Detection Failures
Facial Feature Detection Success?
Color Detection

• Implemented algorithm for color detection
• Found 605,469 B&W and 243,698 color
Facial Feature Detection

- Metrics:
  - Forehead
  - Eye girth
  - Nosebridge
  - Nose to mouth
  - Chin
  - Eye size
  - Nose size
  - Mouth size
  - Features size
Method: Faceism Calculation

- Area of face : area of image
Method: Position
III. Facial Features Results
Facial Feature Detection on Covers

- Detected covers with only 1 person = 1075 covers
- 296 grey scale and 779 color covers
- Standardized the ratios to the unit square
- Wrote program to detect median facial proportions/ratios and output actual image of model from the pool of covers
- No linear model fit well ($R^2 = 0.282$ at best)
- Suggests need for better facial parts algorithm
Facial Feature Detection on Covers

- Median Cover Per Year: forehead
- Median Cover Per Year: eyesight
- Median Cover Per Year: nosebridge
- Median Cover Per Year: nose to mouth
- Median Cover Per Year: chin
- Median Cover Per Year: eyesize
- Median Cover Per Year: nose size
- Median Cover Per Year: mouth size
- Median Cover Per Year: feature size
Output real faces per editor’s standards
Highest frequencies by yearly real face
IV. Faceism Results
Faceism genres

- All genres
- Only covers
- Only advertisements
- Only fashion spreads and articles
- Everything except covers
- Only covers, advertisements, and fashion shoots
5 variations

- All images in the group
- Only images that are a full page in size and only 1 face was detected
- Only images smaller than a full page and have more than 1 face detected
- Only black and white images that are a full page in size and have 1 face detected
- Only color images that are a full page in size and have 1 face detected
Add events

• Mark changes in:
  – Editorship
  – Economic conditions
  – Women’s rights movements
  – Changes in advertising industry
Faceism over time (R² = 69.6%)
Just Covers ($R^2 = 77.7\%$)
Correlates to what we expect

• Cause of shift is unclear, could be editor or women’s movements

• Pre-1960s 1960s – 1980s 1980s
Advertising ($R^2 = 61\%$)
Clinique Ads (p-val = 0.6 > 0.05)
Almay Ads (p-val = 0.405)
Estae Lauder (p-val = 0.004, $R^2 = 2.6\%$)
Cigarette Ads

- P-val > 0.05 but can see when cigarette advertising drops and explodes in volume
Watch Ads (significant, but $R^2 = 17.5\%$)
Color vs. B&W (h = 1)
Covers vs. Ads (h = 1)
Almay vs. Estae Lauder (h = 1)
V. Position Results

Same groups and variations of groups as for faceism
All faces’ locations
Covers
Ads
Position Over Time
Conclusion

1) Need to refine facial feature detector to see better trends in the data

2) Faceism does indeed grow linearly over time, which is a good thing for women

3) Position of the faces are quite stable over time and do not grow significantly linearly, but are clustered largely in upper middle area

Room for further research, particularly in detecting body orientation, studying the images without faces and comparing their purpose
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