Hipster Wars: Discovering Elements of Fashion Styles

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Abstract. The clothing we wear and our identities are closely tied, revealing to the world clues about our wealth, occupation, and socio-identity. In this paper we examine questions related to what our clothing reveals about our personal style. We first design an online competitive Style Rating Game called *Hipster Wars* to crowd source reliable human judgments of style. We use this game to collect a new dataset of clothing outfits with associated style ratings for 5 style categories: hipster, bohemian, pinup, preppy, and goth. Next, we train models for between-class and within-class classification of styles. Finally, we explore methods to identify clothing elements that are generally discriminative for a style, and methods for identifying items in a particular outfit that may indicate a style.

1 Introduction

To me, clothing is a form of self-expression - there are hints about who you are in what you wear. – Marc Jacobs, fashion designer.

Clothing reveals information about its wearer's socio-identity, including hints about their wealth, occupation, religion, location, and social status. In this paper, we consider what clothing reveals about personal style, in particular focusing on recognizing styles of dress such as hipster, goth, or preppy. Personal style is closely tied to both how you perceive yourself, and how your identity is perceived by other people. At a broader level it even reflects and/or influences the people with whom you tend to interact and associate. We believe this makes it an important problem for consideration because it relates to improving our understanding and knowledge of human socio-identity. And, because clothing styles are generally composed of visual elements, computational vision techniques are the best avenue for automated exploration at a large scale.

Additionally, there are many potential research and commercial applications of style recognition. Imagine a billboard that could tailor which advertisements to show you as you walk by, based on what you're wearing. Another obvious application is personalized online shopping suggestions for clothing or other products. The annual revenue for online shopping alone totals over $200 Billion dollars annually [33], making this a growing industry for automatic applications of computer vision. At a higher level, recognizing aspects of identity could be used in recommendation systems for compatible matches on dating and other social networks.

Toward efforts on style recognition, we first collect a new style dataset. The dataset consists of 1893 images depicting five different fashion styles – bohemian, goth, hipster, pinup, and preppy. For each image we want to identify not only which style is reflected, but also how strongly the style is displayed, e.g. is this person an uber hipster or only somewhat hipster. Since direct rating based measures (e.g. asking a person to rate the style from 1 to 10) often produce unstable scores (see Fig. 4), we designed *Hipster Wars* (www.hipsterwars.com), a new tournament based rating game to crowd source reliable style ratings across a large number of people. Hipster Wars presents a user with two images and asks, for example, which image is more hipster? A ranking algorithm is used to progressively determine style ratings based on user clicks, and to match up images with similar ratings to produce more accurate and fine-detailed scores efficiently. Our game was released to great success, attracting over 1700 users who provided over 30,000 votes at the time of submission. The number of users is growing every day.

Next, we perform a number of experiments on our new dataset related to style recognition. The first set of experiments explore multi-class classification between styles, e.g. which style does an image depict, hipster, goth, pinup, preppy, or bohemian (Sec 5.1). Next we look at within class classification (Sec 5.2). Here we want to identify the degree to which a style is exhibited, the main motivation for collecting the pairwise comparisons using Hipster Wars.

We also attempt to automatically identify which elements of clothing are associated with each style (Sec 6). This goal involves both exploring methods to identify clothing elements that are generally discriminative for a style, and methods for identifying items in a particular outfit that may indicate a style.

Though an exciting problem, style recognition has not been explored much to date in the computer vision community. Problems related to style in general have been explored in recent work on recognizing distinctive visual elements of cities [7] or cars [20]. More closely related to this paper, some work attempts recognizing urban tribes in group photos of people at different social events [25, 17]. In that work, style recognition is treated as a multi-class classification problem where the goal is to predict which of k styles is depicted by a group of people. We take these efforts in a new direction by making use of state-of-the-art methods for clothing recognition to recognize style based only on the clothing that an individual person is wearing. Additionally, we examine two new problems: recognizing the strength of style depicted (e.g. how hipster is this person?), and recognizing which elements of clothing influence perception of style (e.g. which outfit items indicate that this person is a hipster?).

In summary, the main contributions of our paper are:

1. An online competitive *Rating Game* to collectively compute style ratings based on human judgments.

2. A new style dataset depicting different fashion styles with associated crowd sourced style ratings.
3. Between-Class classification of styles, i.e. differentiating between the different style categories.
4. Within-Class classification of styles, i.e. differentiating between high and low ranked images within a style category.
5. Experiments to identify the outfit elements that are most predictive for each style (what makes a hipster hip) or within an image (what makes this particular person so hipster).

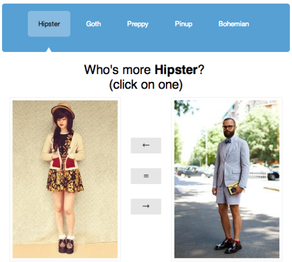
2 Related Work

Clothing Recognition: Identifying clothing in images has drawn recent attention in the computer vision community due to the vast potential for commercial applications such as context-aware advertisements and visual online shopping. Recent papers have looked at the problem of parsing clothing (predicting pixel-wise labelings of garment items) [35, 36] and clothing recognition for applications [22, 23, 11]. Parsing approaches take advantage of effective methods for human pose estimation [37]. Two different clothing parsing scenarios are examined, weakly supervised parsing where predictions are restricted to annotated garment item labels [35] and unrestricted parsing where the garment item labels are not provided [36]. The second scenario [36] is more appropriate for our task so we make use of this method here.

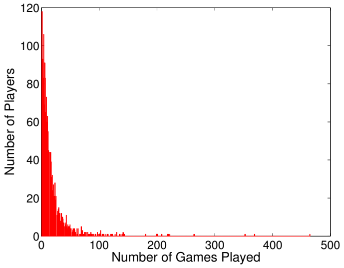
Attributes: Predicting useful mid-level semantic representations such as attributes have been well studied recently. Attribute methods have been applied to objects [16, 26, 14, 18, 9, 32], scenes [21, 34], and products [27, 13, 12]. Additionally attributes have been explored specifically in the context of clothing for describing attributes of upper body clothing [1] or for jointly estimating clothing attributes in a CRF based approach [4]. Work on attributes is related to our goal in that we also want to produce a mid-level representation. In our case we would like to predict the mid-level elements that are most indicative of a particular style of clothing. Currently we consider garments as our elements, but attributes would be a potential next step toward discovering distinctive predictors of a style.

Games for Image Annotation: Large-scale labeling of image data by people is becoming popular in the computer vision community, sometimes using domain experts for very specific labeling tasks [15], and alternatively addressing tasks requiring less specialized expertise or using a combination of human and computer feedback to allow non-experts to label imagery [13, 2, 3]. To more effectively leverage human labeling, some approaches make the labeling process into an entertaining game, as in the ESP Game [29] or [30]. More recently [6] uses a game setting to label important regions for fine-grained classification.

Recognizing Styles: Recently Doersch *et al* look at the problem of selecting discriminative patches that distinguish between the styles of different cities [7]. Lee *et al* use a related method to discover style elements connecting objects in



(a) Snapshot of the game



(b) Distribution of games played

Fig. 1: Left shows an example game for the hipster category on Hipster Wars. Users click on whichever image is more hipster or click "=" for a tie. Right shows the number of games played per player.

space and time. Most related to our work are methods to recognize social tribe of people in group photographs of events [25, 17]. We address a somewhat different problem, considering photos of individuals instead of groups and not making use of any features from the image backgrounds. In addition we analyze and predict the degree to which a style is exhibited. We also consider a new problem of predicting which outfit items most indicate styles in general, and which outfit elements indicate a specific person's style.

3 Hipster Wars: Style Dataset & Rating Game

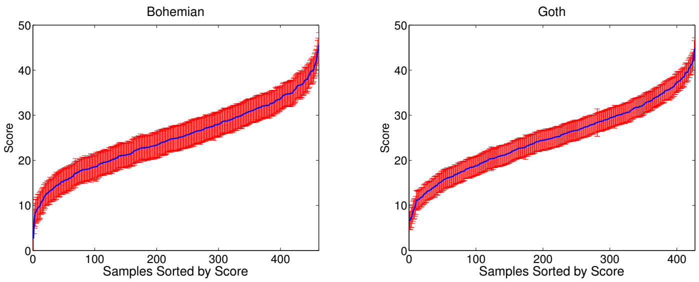
To study style prediction we first collect a new dataset depicting different fashion styles (Section 3.1). We then design a crowd-sourcing game called *Hipster Wars* to elicit style ratings for the images in our dataset (Section 3.2).

3.1 Data Collection

We collect a new dataset of images depicting five fashion styles, *Bohemian, Goth, Hipster, Pinup,* and *Preppy*. To construct our initial seed corpus, we query Google Image Search using each style name and download top ranked images. We then use Google's "Find Visually Similar Images" feature to retrieve thousands of additional visually similar images to our seed set and manually select images with good quality, full body outfit shots. We repeat this process with expanded search terms, e.g. "pinup clothing" or "pinup dress", to collect 1893 images in total. The images exhibit the styles to varying degrees.

3.2 Rating Game

We want to rate the images in each style category according to how strongly they depict the associated style. As we show in section 3.5, simply asking people to rate individual images directly can produce unstable results because each person may have a different internal scale for ratings. Therefore, we develop an online game to collectively crowd-source ratings for all images within each style category. A snapshot of the game is shown in Figure 1a.



(a) Bohemian

(b) Goth

Fig. 2: Style scores computed by our Style Rating Game, showing means and uncertainties for images sorted from smallest to largest mean.

Our game is designed as a tournament where a user is presented with a pair of images from one of the style categories and asked to click on whichever image more strongly depicts the solicited style, or to select "Tie" if the images equally depict the style. For example, for images in the hipster category the user would be asked "Who's more hipster?" After each pair of images, the user is provided with feedback related to the winning and losing statistics of the pair from previous rounds of the tournament.

Because we cannot afford to gather comparisons for all pairs of images in our dataset, we make use of the TrueSkill algorithm [10]. This algorithm iteratively determines which pair of images to compare in each tournament, and based on user input successively updates the ratings of images in our dataset. TrueSkill is a popular ranking system, originally developed to pair users in XBox Live. Though it was originally developed to pair players and determine their gaming skill levels, it is a general model that can be applied in any competitive game. Here we apply it to images.

There are several reasons we choose the TrueSkill algorithm. For each tournament the algorithm pairs up images with similar estimated ratings. Therefore over time we are able to focus on finer-grained distinctions between images and minimize the number of comparisons we need to make to estimate the true image ratings. Additionally, the algorithm is online (as opposed to batch). Users can upload their own photos and merge them seamlessly into the tournaments even after the game has started. The algorithm is also efficient, allowing us to update rankings in real-time after each tournament even when many users are playing at once. It also explicitly allows for ties and models uncertainty in ratings. Finally, TrueSkill converges quickly, reducing the number of games necessary to compute ratings for images.

3.3 Game Details

Each image is associated with a *skill* variable, s, representing how strongly the image represents the associated style. Our goal is to determine this skill level for each image in the dataset. An image's skill is modeled by a Gaussian distribution with mean, μ, and variance, σ^2, where $s \sim \mathcal{N}(s; \mu, \sigma^2)$. As different users play the tournaments there may be variations in how the styles are perceived, this is modeled with another variable, p, a Gaussian distribution around skill level, $p \sim \mathcal{N}(p; s, \beta^2)$.

Updating after Win/Loss: After each tournament is played, if the tournament does not result in a tie, we update the skill estimates for the winning player as:

$$\mu_{\text{winner}} \leftarrow \mu_{\text{winner}} + \frac{\sigma^2_{\text{winner}}}{c} . \mathbb{V}\left(\frac{(\mu_{\text{winner}} - \mu_{\text{loser}})}{c}, \frac{\epsilon}{c}\right) \tag{1}$$

$$\sigma^2_{\text{winner}} \leftarrow \sigma^2_{\text{winner}} \cdot \left(1 - \frac{\sigma^2_{\text{winner}}}{c^2} . \mathbb{W}\left(\frac{(\mu_{\text{winner}} - \mu_{\text{loser}})}{c}, \frac{\epsilon}{c}\right)\right) \tag{2}$$

$$\tag{3}$$

Where:

$$\mathbb{V}(a, b) = \frac{\mathcal{G}_{0,1}(a - b)}{\Phi_{0,1}(a - b)} \tag{4}$$

$$\mathbb{W}(a, b) = \mathbb{V}(a, b) \cdot (\mathbb{V}(a, b) + a - b) \tag{5}$$

$$c^2 = 2\beta^2 + \sigma^2_{\text{winner}} + \sigma^2_{\text{loser}} \tag{6}$$

Where $\mathcal{G}_{0,1}$ and $\Phi_{0,1}$ are the PDF and CDF of normal distributions with zero mean and unit variance. The intuition behind these updates is that if the win was expected, i.e. the difference between skills of the winner image and the losing image was large relative to the total uncertainty, c, then the update on image skill estimates will be small. However, if the outcome of the tournament was surprising, the updates will be larger. Similar update rules are applied for the loser of the tournament.

Updating after Tie: If a tournament is tied, $\mathbb{V}$ and $\mathbb{W}$ are computed as:

$$\mathbb{V}(a, b) = \frac{\mathcal{G}_{0,1}(-b - a) - \mathcal{G}_{0,1}(b - a)}{\Phi_{0,1}(b - a) - \Phi_{0,1}(-b - a)} \tag{7}$$

$$\mathbb{W}(a, b) = \mathbb{V}^2(a, b) + \frac{(b - a) \cdot \mathcal{G}_{0,1}(b - a) + (a + b) \cdot \mathcal{G}_{0,1}(a + b)}{\Phi_{0,1}(b - a) - \Phi_{0,1}(-b - a)} \tag{8}$$

Similar intuition applies here. If both images already had similar skill levels there are not significant updates on beliefs for either image. If the result was more surprising, updates are more significant.

Selecting Pairs: For each tournament we must select a pair of images to play against each other. We would like to optimize two things: every image should be played enough times to reliably determine its rating, and we would like to pair up images with similar ratings estimates in order to produce fine-grained estimates of their ratings. Therefore, to select pairs we first choose the least played image from the dataset and then we choose as its pair, the image with highest probability of creating a draw with that image (to maximize the informativeness of each tournament) which following [10] is computed as:

$$q_{\text{draw}}(\beta^2, \mu_i, \mu_j, \sigma_i, \sigma_j) \equiv \sqrt{\frac{2\beta^2}{2\beta^2 + \sigma_i^2 + \sigma_j^2}} \cdot \exp\left(-\frac{(\mu_i - \mu_j)^2}{2(2\beta^2 + \sigma_i^2 + \sigma_j^2)}\right) \tag{9}$$

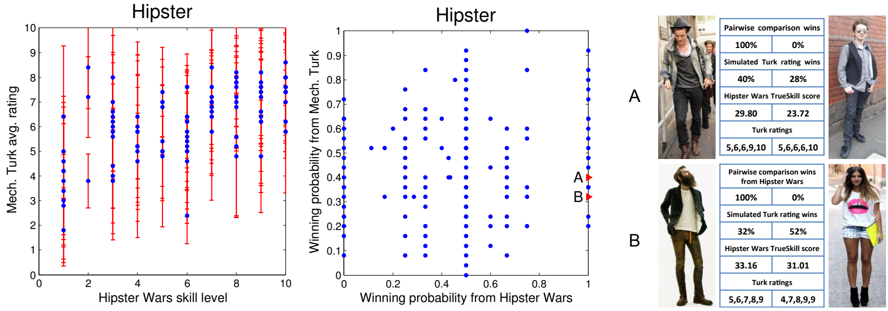
Fig. 3: Example results from our style rating game, *Hipster Wars*. Top and bottom rated for each style category.

Implementation details: We design our game such that image scores fall into the range $[0, 50]$. Our ranking system initializes ratings for all images with $\mu = 25$ and uncertainty $\sigma = \frac{25}{3}$. Value for ϵ, the draw margin, is calculated based on a 10% chance of draw assumed in every game and default value for β is set to $\frac{25}{6}$. Finally the 'true skill' of each image is given by $\mu - 3\sigma$, a conservative estimate which ensures images with high skill means and least uncertainties will be placed on the top.

3.4 Game Results

Our style rating game was played by 1702 users for over 30,000 tournaments. On average users played about 18.5 tournaments, indicating reasonable engagement. Some users played hundreds of tournaments, with a max of 465. The distribution of number of games played per user is shown in Figure 1b. Scores sorted by their mean along with their uncertainty for two sample categories are shown in Figure 2.

This produces very reasonable ratings for each style category. Top and bottom rated images for each style are shown in Figure 3. Top rated images tend to depict very strong indications of the associated style while images rated toward the bottom of the set depict the style with much less strength.



(a) (b) (c)

Fig. 4: Hipster Wars Pairwise ratings vs. individual ratings from Amazon Mech. Turk.

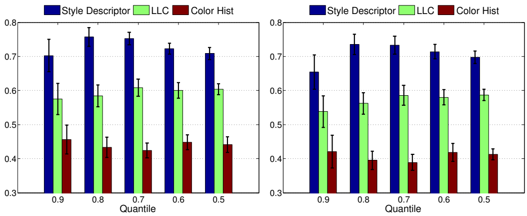
3.5 Pairwise vs. Individual Ratings

In order to evaluate the effectiveness of pairwise comparisons on Hipster Wars over a standard approach of rating style independently for each image, we used Amazon Mechanical Turk to conduct the following experiment. For each of the style categories, we divided the range of skills obtained from Hipster Wars into 10 equal size intervals which we call skill levels (1 :lowest, 10 :highest) and picked a subset of 100 images distributed uniformly over the intervals. For each of the images, we asked 5 individuals (on Mechanical Turk) to rate the degree of a particular style category. Example ratings from all skill levels were provided. Figure 4a shows a scatter plot of average ratings from Mechanical Turk vs the skill level estimated by Hipster Wars. Figure 4b shows the average ratings vs the actual win percentage of games on Hipster Wars. In general the ratings are much noisier than either the direct pairwise comparisons or the skill level estimated by Hipster Wars. Figure 4c shows example pairs where this discrepancy is very large. These results indicate that the pairwise comparison approach can provide more stable and useful ratings for subtle cues like style.

4 Style Representation

We represent the style of outfits using a number of visual descriptors found to be useful for clothing recognition tasks [36], including descriptors related to color, texture, and shape. In particular, we calculate a vector of the following features at each pixel within a patch centered around the pixel: a) RGB color value, b) Lab color value, c) MR8 texture response [28] (to encode local patterns) d) HOG descriptor [5] (to measure local object shape), e) Distance from image border, f) Probability of pixels belonging to skin and hair categories [36].

We form the Style Descriptor by accumulating these features following [36], but without dimensionality reduction to capture the details of clothing appearance. The exact procedure is the following: 1) We first estimate body pose [37]. 2) For each of the 24 estimated body part keypoints, we extract an image patch of size 32×32 pixels surrounding the keypoint. 3) We split each image patch into



(a) Accuracy (b) Average F-1

	Bohemian	Goth	Hipster	Pinup	Preppy
Bohemian	1904	99	135	73	99
Goth	83	1763	168	21	75
Hipster	188	303	1012	39	338
Pinup	137	59	27	668	47
Preppy	228	233	281	107	1313

(c) Confusion matrix of 5 way clothing style classification at $\delta = 0.5$

Fig. 5: Between-Class classification results showing accuracy and average f-1 scores for each style computed over random 100 folds for the classification of the top δ% rated images. Error bars are 95% confidence intervals from statistical bootstrapping.

4×4 cells and mean-std pooling of the features described above are computed. 4) We concatenate all pooled features over all 24 patches, for a total of $39,168$ dimensions.

We compared the classification performance of Style Descriptor against two other global visual descriptors computed on the detected bounding box by pose estimator: LLC encoding [31] of local SIFT [24] descriptors and color histogram. For LLC we extract SIFT features on a dense grid over the image and use LLC coding to transform each local descriptor into a sparse code and apply a multi-scale spatial pyramid (1×1, 2×2, 4×4) [19] max-pooling to obtain the final 43008-dimensional representation. Color histogram features were constructed by quantizing the R,G,B channels into 16 bins each, giving a final 4096-dimensional histogram for each image.

5 Predicting Clothing Styles

We consider two different style recognition tasks: Between-class classification - Classifying outfits into one of the five fashion styles (Sec 5.1). Within-class classification - differentiating between high and low rated images for each style (Sec 5.2). For each of these tasks, we compare Style Descriptor versus the other global descriptors which we considered as baseline. In all classification experiments we use a linear kernel SVM using the liblinear package [8].

5.1 Between-class classification

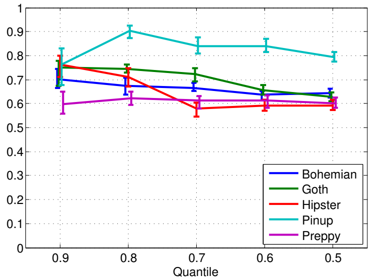
We consider classifying images as one of five styles. Results examine how performance varies for different splits of the data, defining a parameter δ which determines what percentage of the data is used in classification. We vary values of δ from 0.1 to 0.5 where $\delta = 0.1$ represents a classification task between the top rated 10% of images from each style (using the ratings computed in Sec 3.2). We use a $9:1$ train to test ratio, and repeat the train-test process 100 times. The results of our between-class classification are shown in Figure 5. Performance is good, varying slowly with δ, and the pattern of confusions is reasonable.

Fig. 6: Example results of within-classification task with $\delta = 0.5$. Top and bottom predictions for each style category are shown.

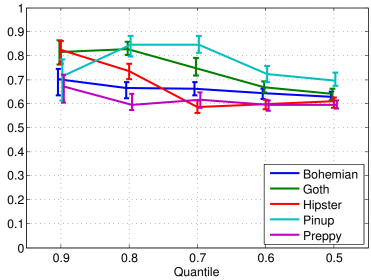
5.2 Within-class classification

Our next style recognition tasks considers classification between top rated and bottom rated examples for each style independently. Here we learn one linear SVM model for each style. The variable $\delta = 10\% \ldots 50\%$ determines the percentage of top and bottom ranked images considered. For example, $\delta = 0.1$ means the top rated 10% of images are used as positives and the bottom rated 10% of samples as negatives. We repeat the experiments for 100 random folds with a $9 : 1$ train to test ratio. In each experiment, C, is determined using 5 fold cross-validation.

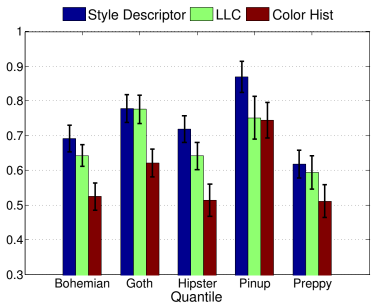
Results are reported in Figure 7. We observe that when δ is small we generally have better performance than for larger δ, probably because the classification task becomes more challenging as we add less extreme examples of each style. Additionally, we find best performance on the pinup category. Performance on the goth category comes in second. For the hipster category, we do quite well at differentiating between extremely strong or weak examples, but performance drops off quickly as δ increases. Example predictions for each style are shown in Figure 6.



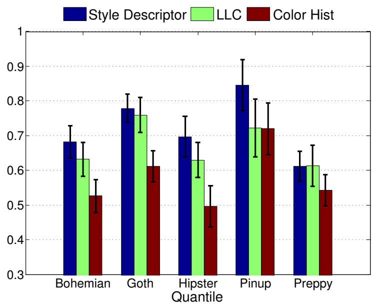
(a) Precision



(b) Recall



(c) Accuracy ($\delta = 0.2$)



(d) F-1 ($\delta = 0.2$)

Fig. 7: Within-Class classification results averaged for each style computed over random 100 folds balanced classification of the top and bottom δ% quartiles. Error bars are 95% confidence intervals from statistical bootstrapping.

6 Discovering the Elements of Styles

In this section, we are interested in two different questions: 1) what elements of style contribute to people in general being a hipster (or goth or preppy, etc), and 2) for a particular photo of a person, what elements of their outfit indicate that they are a hipster (or goth or preppy, etc)?

6.1 General Style Indicators

We would like to determine which garment items are most indicative of each style in general. For this, we compute clothing segmentation on all images of each style, and obtain the percentage of each predicted garment item present. Figure 8 shows the percentage of pixels occupied by each garment item across images of each style. Based on this automatic analysis, we can make some interesting observations using our clothing recognition predictions. For example, we find that pinups and bohemians tend to wear dresses whereas hipsters and preppies do not. Goths fall somewhere in between. Pinups also tend to display a lot of skin while this is less true for goths. Hipsters and preppies wear the most jeans and pants. Preppies tend to wear more blazers while goths and hipsters wear the most boots.

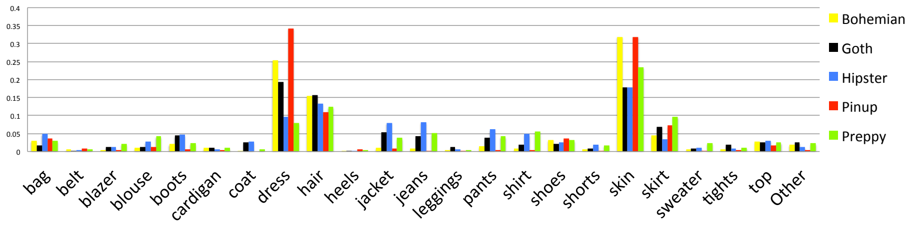


Fig. 8: Clothing items across styles.

6.2 Style Indicators for Individuals

Our second approach is a bit more complex. In this model we make use of our models trained on Style Descriptors. We essentially transfer predictions from the Style Descriptor to the underlying parse while making use of computed priors on which garment items are most likely for each style.

Discriminative part discovery: Suppose we have a set of image features $\mathbf{x}_i$ from each part i that we locate from a pose estimator. Then our style prediction model can be described by a linear model:

$$y = \sum_{i \in \text{parts}} \mathbf{w}_i^{\mathrm{T}} \mathbf{x}_i + b, \tag{10}$$

where y is a decision value of the prediction, $\mathbf{w}_i$ is model parameters corresponding to part i, and b is a bias parameter.

In this paper, we specifically view the individual term $\mathbf{w}_i \mathbf{x}_i$ as a distance from the decision boundary for part i in the classification, and utilize the weights to *localize* where discriminative parts are located in the input image. This interpretation is possible when the input to the linear model is uniformly interpretable, i.e., same feature from different locations. Also to guarantee the equivalence of parts interpretation, we normalize the part features $\mathbf{x}_i$ to have zero-mean and uniform standard deviation in training data.

To calculate the score of the part i, we apply a sigmoid function on the decision value and get probabilities of a style given a single part:

$$p_i \equiv \frac{1}{1 + \exp\left(-\mathbf{w}_i^{\mathrm{T}} \mathbf{x}_i\right)}. \tag{11}$$

Learning is done in the same manner as within-class style classification, using L2-regularized logistic regression.

From parts to items: Part scores tell us which locations in the outfit are affecting style prediction. However, to convert these to an interpretable prediction, we map predicted garments back to garments predicted in the original parse. This produces a more semantic output, e.g. “She looks like a hipster because of her hat.” To map parts to garments in the parse, we first compute a *saliency map* of parts; At each keypoint, we project the part score $p(\mathbf{x}_i)$ to all pixels in the patch

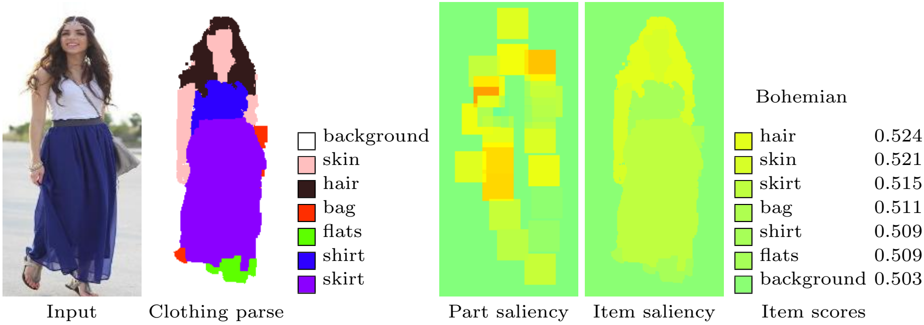


Fig. 9: From parts to items. We compute contributions of each part, and project them in image coordinates (Part saliency). Then, using clothing parse, we compute the scores of items. When the score is above 0.5, the associated item indicates a positive influence on the queried style. Note that the scores only show the relative strength of style-indication among items in the picture.

location. Articulated parts get the average score from all parts. Areas outside of any patch are set to 1/2 (i.e., decision boundary). Using the computed clothing segmentation [36], we compute the average score of each garment item from the *saliency map*. This produces, for each item k in the clothing parse of an image, a score p_k that we can use to predict items that strongly indicate a style. Figure 9 depicts this process.

Prior filtering: The result of part-based factorization can still look noisy due to errors in pose estimation and clothing parsing. Therefore, we smooth our predictions with a prior on which garment items we expect to be associated with each style.

Our prior is constructed by building a linear classifier based on the area of each clothing item that we obtain from the clothing segmentation [36]. Denoting the log pixel-count of item k by x_k, we express the prior model by a linear function: $y = \sum_k w_k x_k + b$, where y is the decision value of style classification, and w_k and b are model parameters. Using the same idea from the previous subsections, we compute the score of each item by: $q_k \equiv \frac{1}{1+\exp(-w_k x_k)}$.

Once we compute the part-based score p_k and the prior score q_k, we merge them into the final indicator score r_k for garment-item k:

$$r_k \equiv \lambda_1 p_k + \lambda_2 \left[\frac{\sigma_p}{\sigma_q} \left(q_k - \frac{1}{2} \right) + \frac{1}{2} \right], \tag{12}$$

where λ_1 and λ_2, are weights given to each score, σ_p and σ_q are standard deviations of p_k and q_k at each image. The intuition here is that we assume both p_k and q_k follow a normal distribution with mean at 0.5. We adjust the shape of q_k distribution to that of p_k in the second term. Then, we use λ's to mix two scores and produce the final result. We set λ's to cross-validation accuracies of classification during training normalized to sum to a unit, so that the resulting score reflects the accuracy of style prediction.

Fig. 10: Example predicted style indicators for individuals.

Method	Bohemian	Goth	Hipster	Pinup	Preppy
Random	0.357	0.258	0.171	0.427	0.232
Our method	0.379	0.282	0.154	0.454	0.241

Table 1: Ratio of images that include the top choice from crowds in the first 5 elements of our discovery method.

6.3 Analysis of Style Indicator for Individuals

Figure 10 shows examples of discovered style indicators for individuals. Predicted elements for each outfit are ordered by indicator scores. We find that our method captures the most important garment-items well such as shirt for preppy styles, graphic t-shirts for hipsters, or dresses for pinups.

We also attempted to quantitatively verify the results using crowdsourcing. We obtained the "ground truth" by asking workers to vote on which element they think is making a certain style. However, the naive application of this approach resulted in a number of problems; 1) workers tend to just vote on all visible items in the picture, 2) small items are ignored, 3) workers mark different items with a different name (e.g., shoes vs. flats) and 4) different workers are not consistent due to the great subjectivity in the question. We show in Table 1 the ratio of images from our discovery that included the worker's top choice. Our method achieved slightly better result than the random ordering. However, we note that the "ground truth" in this evaluation does not necessarily constitute a good measurement for benchmarking, leaving open the question of how to "ground truth" annotation for such subtle socially-defined signals.

7 Conclusions

We have designed a new game for gathering human judgments of style ratings and have used this game to collect a new dataset of rated style images. We have explored recognizing and estimating the degree of fashion styles. We have also begun efforts to recognize which elements of outfits indicate styles generally and which items in a particular outfit indicate a style. Results indicate that it is possible to determine whether you are a hipster and that it may even be possible to determine why you are a hipster! (We gratefully acknowledge NSF Award# 1444234, and Google Faculty Award, "Seeing Social".)

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