What dress fits me best? Fashion Recommendation on the Clothing Style for Personal Body Shape

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ABSTRACT

Clothing is an integral part of life. Also, it is always an uneasy task for people to make decisions on what to wear. An essential style tip is to dress for the body shape, i.e., knowing one's own body shape (e.g., hourglass, rectangle, round and inverted triangle) and selecting the types of clothes that will accentuate the body's good features. In the literature, although various fashion recommendation systems for clothing items have been developed, none of them had explicitly taken the user's basic body shape into consideration. In this paper, therefore, we proposed a first framework for learning the compatibility of clothing styles and body shapes from social big data, with the goal to recommend a user about what to wear better in relation to his/her essential body attributes. The experimental results demonstrate the superiority of our proposed approach, leading to a new aspect for research into fashion recommendation.

CCS CONCEPTS

• **Information systems** → **Personalization**; **Recommender systems**; **Information extraction**;

KEYWORDS

Fashion analysis; recommender system; human body shape; clothing style; correlation

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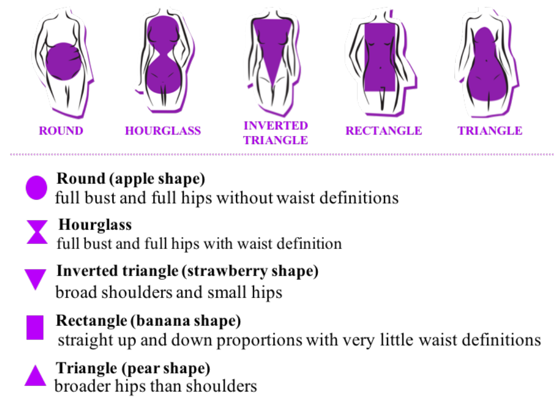


Figure 1: Visual illustration of five different body shapes. (Image courtesy of styleangel.com[1])

1 INTRODUCTION

"The dress must follow the body of a woman, not the body following the shape of the dress."

— Hubert de Givenchy, fashion designer

Nobody is perfect. Everyone has flaws and strengths, without exception to their body parts. Accordingly, everyone may have areas on their body they love to highlight and areas they feel like covering up [1]. By understanding the type of body shapes and what styles flatter and complement particular body shape, everyone surely can work with their body to give off amazing looks.

To the above challenge, body shape is the first thing to consider before choosing the perfect clothing styles. In particular, determining the type of body shape is all about the proportions between body measurements. There are several methods to determine body shapes, which are known as *body shape calculators*. They use different representations to describe the type of body shapes, such as in terms of alphabetical letters (e.g., the S-line for a body shape with ample breasts and buttocks when viewed from the side), fruit shapes (e.g., the apple for a body shape with a wide torso, broad shoulders, and a full bust, waist, and upper back), and geometric objects (e.g.,

[1] https://styleangel.com/discover-your-body-shape/

Figure 2: An example of guideline for choosing wedding dress. Finding the right wedding dress is probably one of the most crucial things for any bride to be. To find a gown with the perfect fit, it is essential to choose one which suits body shape and flatters the curves. (Image courtesy of viralyfeeds.com[2])

the top hourglass for a body shape with well defined waist and larger bust than hips). Most common are the five basic body shapes, as shown in Figure 1. The existing body shape calculators, however, are based on subjective measures, which are susceptible to multiple biases. To our best knowledge, there is no standardized method for determining the type of body shapes. Therefore, determining the type of body shapes is still a challenging analytical task.

After knowing the type of body shape, we can find out what kind of style fits best. The style of clothes affects appearance greatly as it would affect the look and tidiness. For example, as illustrated in Figure 2, the sheath dress, whose the style fits very closely to the contours of the body from head-to-toe, is best suited to those with an hourglass or rectangle body shape, but not good for other shapes since it will accentuate extra inches and can be unflattering. With so many rules, limitations and potential style disasters ahead, knowing how to best dress body shape and balance the physical characteristics can be tricky business.

Currently, intelligent fashion analysis has been conducted intensively due to the huge profit potential in the fashion industry. Though guide on how to dressing for body shapes is important in fashion styling and receiving much attention from fashionistas, this issue has been ignored in multimedia science. We, therefore, propose a novel intelligent fashion analysis framework to model the correlation between human body shapes and their most suitable clothing styles, which further can be applied to solve fashion recommendation tasks. In literature, there are two kinds of fashion recommendation studies. One is recommending outfits that users may be interested in [33, 44]. The other is recommending fashion items that suit to a user-provided fashion item (e.g., boots, cardigan, skirt) [15, 19]. Thus, our proposed work creates a new space in multimedia mining and recommendation.

There are three basic research problems studied with this framework – first, a dataset that can reflect the correlations underlying body shapes and clothing styles well; second, a learned model that can be used to determine the type of body shapes well; and third, a reasonable statistical model that can capture the correlations between body shapes and clothing styles well. Therefore, we exploit two kinds of data, i.e., human body measurements and clothing styles. In particular, following the styles of our favorite stylish people, regardless of whether they have the same body shape as ours, will cause a low chance of these styles to suit our body shape; while following the styles of people that we consider having similar body shapes to ours requires an understanding of whether their styles are fashionable or not. By incorporating both clothing style and body shape information, we mine the auxiliary clothing features to discover semantically important styles for each body shape. For this purpose, we construct graphs of images by visual and body shape information, respectively. Then, we automatically propagate the semantic and select the relevant styles across the visual and body shape graphs.

We summarize our main contributions as follows:

- To the best of our knowledge, this is the first study in learning the golden style rules to how to best flatter each body type by exploiting big social data.
- To obtain the relevant fashion knowledge rules, we present a mechanism of style propagation for discovering semantic relations between clothing styles by considering body figures of people wearing it.
- We construct a *body-style map* to model the correlation between clothing styles and body shapes. Based on the body-style map, we can describe which clothing styles that suit a particular body appearance, and vice versa, to provide a personalized style suggestion.
- We design a novel *body shape calculator* to determine female body figure. Empirical results demonstrate that our proposed method significantly outperforms existing methods.
- We construct a benchmark dataset for body shape style recommendations. This dataset contains body measurements of 3,150 female celebrities annotated with the corresponding types of body shapes and 349,298 images of 270 stylish celebrities annotated with the types of clothing items.

The rest of the paper is organized as follows. First, we discuss related work (Section 2). We then describe our new dataset in detail (Section 3), followed by the overview of our proposed framework (Section 4). Next, we explain our proposed approach in identifying human body shape (Section 5), modeling the correlation between fashion styles and human body shapes (Section 6), and selecting the representative styles that best suit body shape (Section 7). Finally, we provide experimental results (Section 8) and give conclusions and an outlook on further work (Section 9).

2 RELATED WORK

In this section, we review the related work in terms of (1) Fashion item analysis, (2) Fashion style understanding, and (3) Personalized style suggestions.

Fashion item analysis. Extensive previous research has been focused on object-based clothing image analysis, such as clothing recognition, annotation, segmentation, and retrieval [3]. In recent years, a number of models have been introduced to learn more discriminative representation in order to handle cross-scenario variations [8, 38]. Zhao *et al.* [45] proposed a novel memory-augmented

[2]https://viralyfeeds.com/wedding-dress-fit-body-type-best/

Attribute Manipulation Network which to manipulate image representation at the attribute level. For clothing annotation, Liu *et al.* [27] proposed a clothes dataset with comprehensive annotations and a new deep model which learns clothing features by jointly predicting clothing attributes and landmarks. Sun *et al.* [37] explored a part-based clothing image annotation approach which takes into account tag relevance and tag saliency. Both works of Zhao *et al.* [46] and Liu *et al.* [28] addressed the problem of clothing segmentation and clothing alignment. The result of their works can predict the positions of functional key points defined on the fashion items. The works [17, 19, 20] focused on clothing item retrieval research which can allow a user to upload a daily human photo captured in the general environment and find similar clothes in online shops.

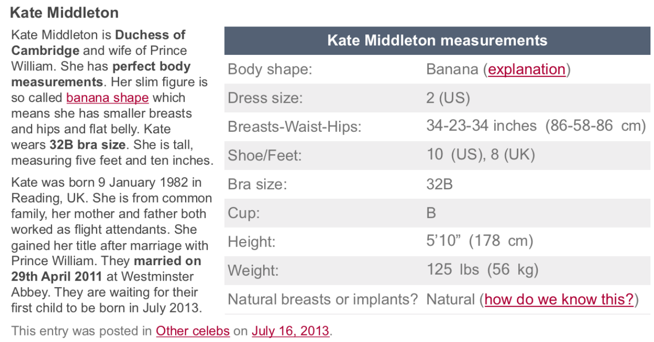
Fashion style understanding. In addition to some of the traditional problems, interest in high-level fashion understanding has been growing in the computer vision community recently. The works [12, 14, 20, 34] explored recognizing and estimating the degree of fashion styles. These methods allow learning features for more specific types of images that may be very costly and complicated to annotate. Moreover, clothing style understanding can benefit visual analytics of big social data. By modeling the appearance of human clothing and surrounding context, the occupation of the person can be predicted in [36]. Chang *et al.* [2] depict the street fashion of a city by discovering fashion items that are most iconic for the city. Attempting to directly predict more esoteric measurements, such as popularity [11, 41, 42] has also been recently studied. For style compatibility discovering, Han *et al.* [9] proposed to jointly learn a visual-semantic embedding and the compatibility relationships among fashion items in an end-to-end fashion.

Personalized style suggestions. User profiling helps personalization and has received much attention in the social multimedia research fields. Simo-Serral *et al.* [35] analyzed how fashionable a person looks at a photo whereby advising the user to improve the appeal. Wie *et al.* [40] intended to explore the inherent relationship between wearers' personality type and expressive wearing. Sanchez-Riera *et al.* [33] proposed a personalized clothing recommendation system through the analysis of user's personal images in his/her social networks to predict the most likable items. Liu *et al.* [26] developed an occasion oriented clothing recommendation and pairing system. The system automatically recommends the most suitable clothing by considering the wearing properly and wearing aesthetically principles. Though there are several works focus on clothing recommendation system, to the best of our knowledge, our work is the first work devoted to considering body measurement to build the personal clothing recommendation system.

3 DATASET CONSTRUCTION

We collected a novel dataset, the Style4BodyShape Dataset[3], to enable personalized style suggestion applications that make use of celebrities' style as the knowledge resource. This dataset contains three types of data: (1) a list of the most stylish female celebrities, who are known for their sophisticated sense of style, (2) body measurements of female celebrities, and (3) stylish celebrities photos. In the following subsections, we describe our dataset in detail.

[3] http://bit.ly/Style4BodyShape.


Kate Middleton

Kate Middleton is **Duchess of Cambridge** and wife of Prince William. She has **perfect body measurements**. Her slim figure is so called banana shape which means she has smaller breasts and hips and flat belly. Kate wears **32B bra size**. She is tall, measuring five feet and ten inches.

Kate was born 9 January 1982 in Reading, UK. She is from common family, her mother and father both worked as flight attendants. She gained her title after marriage with Prince William. They **married on 29th April 2011** at Westminster Abbey. They are waiting for their first child to be born in July 2013.

Kate Middleton measurements	
Body shape:	Banana (explanation)
Dress size:	2 (US)
Breasts-Waist-Hips:	34-23-34 inches (86-58-86 cm)
Shoe/Feet:	10 (US), 8 (UK)
Bra size:	32B
Cup:	B
Height:	5'10" (178 cm)
Weight:	125 lbs (56 kg)
Natural breasts or implants?	Natural (how do we know this?)

This entry was posted in Other celebs on July 16, 2013.

Figure 3: Example of a celebrity profile page.

3.1 A List of Stylish Celebrity Collection

In particular, the celebrities' styles are usually regarded as fashion references as they hire fashion stylist(s) to help them get dressed to visually alter their actual body figure. In this work, we therefore propose to exploit the style of stylish female celebrities to learning the compatibility of clothing styles and body shapes. We collected a list of the top stylish female celebrities from a popular crowdsourced polling website, i.e., Ranker[4], and six popular fashion magazine websites, i.e., Vogue[5], Harper's Bazaar[6], Marie Claire[7], Glamour[8], and PopSugar[9]. The top stylish celebrities listed on Ranker are based on polling of more than 6,300 voters, while the top stylish celebrities listed on fashion magazines are selected by fashion editors who have expert knowledge in fashion domain. By utilizing these websites as a source of information, we can provide an in-depth understanding of the concept of correlation between body shapes and clothing styles from the perspective of society as well as fashion experts. We then recorded all of the names of stylish celebrities listed on these websites and eliminated the duplicate ones. Finally, we obtained 270 names as the top stylish female celebrities for our experiment.

3.2 Body Measurement Collection

We crawled a collection of human body measurements from a celebrity measurements website, http://www.bodymeasurements.org. We obtained body measurements of 3,150 female celebrities, including actress, singers, models, politicians, etc. Each record consists of the following attributes: name, short bio, type of body shape (i.e., hourglass, rectangle, round, triangle, or inverted triangle), dress size, bust circumstance, waist circumstance, hip circumstance, shoe size, bra size, cup size, height, weight, and information about breasts (natural breasts or implants). Note that body shape information provided on this website is merely based on visual judgment. Figure 3 shows the profile of one of the celebrities on the website as an example. We further discarded the data about bio and breasts information, as they are not meant to characterize features for determining the type of body shape.

[4] https://www.ranker.com/crowdranked-list/most-stylish-female-celebrities
[5] https://www.vogue.com/tag/franchise/10-best-dressed
[6] https://www.harpersbazaar.com/celebrity/red-carpet-dresses/g8366/female-fashion-icons/
[7] http://www.marieclaire.co.uk/fashion/best-dressed-2016-457756
[8] http://www.glamourmagazine.co.uk/gallery/best-dressed-women-2017
[9] https://www.popsugar.com/fashion/Most-Stylish-Celebrities-2017-44071762

Table 1: List of clothing items considered in this work.

Category	Items
Dress	Dress
Outerwear	Blazer, cape, cardigan, coat, jacket, vest
Pants	Jeans, legging, pants, shorts, stockings, tights
Skirt	Skirt
Top	Blouse, shirt, sweater, sweatshirt, T-shirt, top

Table 2: Statistics of stylish celebrity image dataset.

	Total	Minimum[a]	Maximum[b]	Average[c]
Dress	67,617	204	278	249.43
Outerwear	66,452	95	277	245.12
Pants	69,178	205	295	255.21
Skirt	66,962	218	291	256.51
Top	79,089	249	322	291.92

[a] Minimum means the minimum number of images per celebrity.
[b] Maximum means the maximum number of images per celebrity.
[c] Average means the average number of images per celebrity.

3.3 Stylish Celebrity Image Collection

We crawled a large collection of images of stylish female celebrities via Google search engine, by issuing each stylish celebrity name combined with clothing category to be collected as a search query. In particular, we used a list of stylish female celebrities retrieved in Section 3.1 and a list of clothing categories presented in Table 1 to generate queries. For example, the keyword "Gigi Hadid skirt" is used to retrieve images of a stylish celebrity named Gigi Hadid wearing a skirt. For each query, we downloaded the first 300 returned images. After removing duplicate images, a total of 347,948 images of stylish female celebrities were collected. Table 2 shows the statistics of our collected images.

4 FRAMEWORK

Knowing the type of body shape is the foundation for determining clothing styles that flatter silhouette. Therefore, in this work we first build a body shape model using our collected body measurements data and then use this model to classify the type of body shape for a given body measurements data (cf. Section 5).

A naïve way to figure out what to wear for a body shape is to consider the outfits of stylish celebrities having the same body shape as the given query. However, the simple method may not capture the important features that make up a suitable style. With a large amount of the collection of styles, it could be a bit overwhelming at times and hard to know the right things to do when there is so much information. Therefore, analysis of the data yields valuable information that deepens understanding of styling tips.

Having body shape information and image collections of stylish celebrities, we propose a data mining mechanism that leverages both clothing styles and body shape of celebrities wearing them to approximate the semantic representations of the two modalities (cf. Section 6). In particular, we augment each clothing image in the image collections with relevant semantic features. We construct graphs of images by the visual appearance of clothing styles and body shape information, respectively. Then, we automatically propagate and select the informative semantic features across the graphs by exploiting an Auxiliary Visual Words Discovery technique [24]. The discovered semantic features reveal visual features of clothing styles that are correlated with specific body shapes. Afterward, we utilize the discovered semantic features to select the representative clothing styles for each body shape by adopting the concept of *stylistic coherence and uniqueness* (cf. Section 7). We illustrate the proposed framework in Figure 4.

5 BODY SHAPE CALCULATOR

As mentioned previously, determining body shape is the first step in learning how to dress in a way that makes a body look its best. However, existing body shape calculators are very subjective which means influenced by personal feelings. One promising idea for determining the type of body shape is to use unsupervised learning algorithms to discover the "natural" grouping(s) of a set of body measurements. We see that clustering can be thought of as a viable option to solve this problem.

Formally, given a collection of body shapes each of which is described by a set of body measurement attributes, clustering aims to derive a useful division of the n body shapes into a number of types. Although there are a large number of methods available to perform clustering, determining different types of body shapes is related to the need of a clustering method that does not require to select the number of clusters. Thus, Affinity Propagation [7], a clustering algorithm based on the concept of "message passing" between data points, is suitable for our intended purpose.

Let $V = \{v_1, v_2, ..., v_N\}$ be a set of data points representing body measurement features, and also let $\sigma(v_i)$ be the index of the nearest community center associated to v_i. Affinity Propagation aims to find the mapping σ by minimizing the cost function defined as:

$$E[\sigma] = \sum_{i=1}^{N} s(v_i, v_{\sigma(v_i)}), \tag{1}$$

where $s(v_i, v_j)$ is the similarity between the pairs v_i and v_j. In this work, we set $s(v_i, v_j)$ to be the negative squared error (Euclidean distance) between v_i and v_j. The initialized values of $s(v_i, v_i)$ is set equally each other as the median of the input similarities.

In particular, we take advantage of parameters introduced by existing body shape calculators to construct features for body shape classification task. These parameters are: (1) body height; (2) body mass; (3) bra size; (4) cup size; (5) bust circumference; (6) waist circumference; (7) hip circumference; (8) the ratio between bust and hip circumferences; (9) the ratio between waist and hip circumferences; (10) the ratio between bust and waist circumferences; (11) the difference between bust and hip circumferences; (12) the difference between waist and hip circumferences; (13) the difference between bust and waist circumferences; (14) body mass index, which is defined as the body mass divided by the square of the body height; and (15) body shape index, which is calculated by dividing waist circumference by its estimate obtained from allometric regression of body mass and height. Body mass is in kilograms; body height, bust, waist, and hip circumferences are in meters; and bra size and cup size are in US bra sizing. Since bra size and cup size are categorical data, we then convert them into numerical data using one-hot encoding scheme. As a result, body measurements of each person is represented by 1×77 dimensional feature vectors.

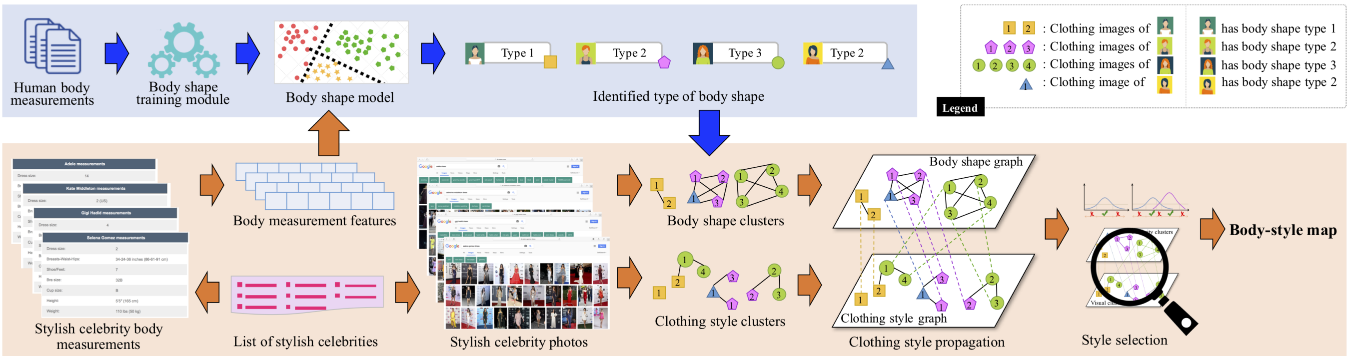


Figure 4: An overview of the proposed framework for generating the proposed body-style map. For simplicity in this illustration, we assume that there are four stylish celebrities and a total of ten clothing items in the same category.

6 STYLE AND BODY SHAPE CORRELATION MODELING

In this section, we focus on modeling the correlations between body shapes and clothing styles. We formulate this problem as follows. Each image sample is represented by $(b, c, \boldsymbol{x})$, where b is the type of body shape, $c = (c_1, c_2, ..., c_5)$ denotes the clothing categories, and $\boldsymbol{x} = (\boldsymbol{x}_1, \boldsymbol{x}_2, ..., \boldsymbol{x}_5)$ denotes the features describing the visual appearance of clothing styles.

Definition 1. Body shape type b. Each image sample contains a stylish female celebrity having specific body measurements. Thus, b is the body shape type associated with body measurements.

Definition 2. Clothing categories $c = (c_1, c_2, ..., c_5)$. c with $|c| = 5$ is the clothing category vector, whose each dimension represents the presence or absence of a specific clothing category in the image. The details of clothing categories are summarized in Table 1.

Definition 3. Features describing visual appearances of clothing styles $\boldsymbol{x} = (\boldsymbol{x}_1, \boldsymbol{x}_2, ..., \boldsymbol{x}_5)$. Each dimension of $\boldsymbol{x}$ is associated to a specific clothing category in c; that is, $\boldsymbol{x}_i$ is the visual features of clothing item(s) in category c_i.

Mining Task. We aim to augment each clothing image with relevant semantic features in order to capture the intrinsic correlations between body shapes and clothing styles. Note that this task is performed on each clothing category separately.

In the following subsections, we provide a detailed description of the methods we employ to model the correlations between body shapes and clothing styles.

6.1 Representation of Clothing Items

According to [32], there are hundreds of different types of clothing items can be categorized into seven basic categories: shirt, outerwear, skirt, dress, pants, underwear, and swimsuit. In this work, we only focus on investigating shirt, outerwear, skirt, dress, pants. We neglect on analyzing swimsuit and underwear due to privacy issues of some celebrities.

In [43], Yamaguchi et al. suggested there are 56 basic components that compose a fashion photograph. Of these 56 components, 53 of them are fashion items. We further adopt 20 fashion items defined in their work since these items are in the taxonomy of clothing categories being analyzed in this study. A list of our adopted fashion items and associated categories is presented in Table 1.

Let f represent the outfit of a person in image sample. We define f as a collection of T random variables $\{f_1, ..., f_T\}$ representing the adopted 20 fashion items ($T = 20$). If the t-th item is not included in the outfit, then $f_n = \emptyset$. To localize the region of a specific clothing category c_i, we combine the pixels of its corresponding fashion items. After that, we adopt HSV color histogram [29] and Bag-of-Visual-Word (BoVW) histogram [31] to extract the visual features. We use these low-level image features since we observed that both the color and local structures are important. We then concatenate both a color histogram $histColor_i$ and a BoVW histogram $histStructure_i$ into a single feature vector to form $\boldsymbol{x}_i$

$$\boldsymbol{x}_i \equiv (histColor_i, histStructure_i). \qquad (2)$$

6.2 Style Feature Propagation

In order to obtain more semantically relevant style features for each clothing image, we propose to augment each clothing image with additional features propagated from the body shape and clothing style clusters based on an Auxiliary Visual Words Discovery technique [24]. Such auxiliary features can enrich the style description of the clothing images. For example, it is promising to derive more semantic features for a clothing style by simply exchanging the features among images of the same body shape cluster. We will further remove irrelevant or noisy features and preserve representative ones by selection operation (described later in Section 6.3).

Assume there are N clothing images denotes as $\{I_1, I_2, ..., I_N\}$ in a category C. Each image I_n is represented by $1 \times D$ visual feature vector as we defined in Equation (2). For mining the auxiliary features, we start by constructing body shape graph and clothing style graph with N nodes each. The body shape graph consists of body shape clusters that group clothing images of top stylish celebrities with the same body shape in the same cluster, while the clothing style graph consists of clothing style clusters that group visually similar clothing images in the same cluster. We apply affinity propagation (AP) [7] to cluster images on the clothing style graph, making it unnecessary to determine the number of clusters.

Next, we augment each image with additional auxiliary features propagated from the body shape and clothing style clusters. This propagation is conducted on each *extended clothing style cluster*, containing the images in a clothing style cluster and those additional ones co-occurring with these images in specific body shape clusters.

Let the matrix $\boldsymbol{X} \in \mathbb{R}^{Z \times D}$ represent the features of Z images in the extended clothing style cluster, and each row represent feature vector of each image. Assume M among Z images are from the same clothing style cluster. The style feature propagation is conducted by the propagation matrix $\boldsymbol{P} \in \mathbb{R}^{M \times Z}$, which controls the contributions from different images in the extended clothing style cluster. We then define the auxiliary style feature $\boldsymbol{X}_{aux}$ as

$$\boldsymbol{X}_{aux} \equiv \boldsymbol{P}\boldsymbol{X}. \tag{3}$$

Given the initial propagation matrix $\boldsymbol{P}_0$ (i.e., $\boldsymbol{P}_0(i,j)$ is the similarity score between image i and image j), the operation to find a better propagation matrix $\boldsymbol{P}$ is formulated as

$$f_{\boldsymbol{P}} = \min_{\boldsymbol{P}} \alpha \frac{\| \boldsymbol{P}\boldsymbol{X} \|_F^2}{\| \boldsymbol{P}_0\boldsymbol{X} \|_F^2} + (1-\alpha) \frac{\| \boldsymbol{P} - \boldsymbol{P}_0 \|_F^2}{\| \boldsymbol{P}_0 \|_F^2}, \tag{4}$$

where $\| \cdot \|_F$ stands for the Frobenius norm, and α stands for the influence between the first and the second terms. The objective of the first term is to prevent from propagating too many features (i.e., propagating conservatively). The second term is to maintain the similarity to the original propagation matrix $\boldsymbol{P}_0$. In [24], Kuo *et al.* has a proof that Equation (4) is a strictly convex, unconstrained quadratic optimization problem. Analytic solver, a quadratic programming solver, thus can be used to find the optimal solution. By adopting analytic solver, the final propagation matrix $\boldsymbol{P}$ can be derived as

$$P = \alpha_2 \boldsymbol{P}_0 \left(\alpha_1 \boldsymbol{X}\boldsymbol{X}^T + \alpha_2 I_M \right)^{-1}, \tag{5}$$

where $\alpha_1 = (\alpha)/(\| \boldsymbol{P}_0\boldsymbol{X} \|_F^2)$, $\alpha_2 = (1-\alpha)/(\| \boldsymbol{P}_0 \|_F^2)$, and I_M is an identity matrix of size M. In our experiment, we set $\alpha = 0.5$. Having the propagation matrix $\boldsymbol{P}$, we can thus obtain the auxiliary style feature $\boldsymbol{X}_{aux}$ by Equation (3).

6.3 Common Style Feature Selection

After the previous style feature propagation step, each image can obtain more different features. However, it is possible to obtain some less representative ones that may decrease the precision. Thus, in order to preserve important (representative) features and suppress the irrelevant ones, we propose representative style feature selection. We select representative features in each clothing style cluster since clothing images in the same clothing style cluster are visually similar to each other.

Given the initial selection matrix $\boldsymbol{S}_0$ (i.e., $\boldsymbol{S}_0$ is a matrix of ones, which means we select all the dimensions), the operation to find a better selection matrix $\boldsymbol{S}$ is formulated as

$$f_S = \min_S \beta \frac{\| \boldsymbol{X}\boldsymbol{S}_0 - \boldsymbol{X}\boldsymbol{S} \|_F^2}{\| \boldsymbol{X}\boldsymbol{S}_0 \|_F^2} + (1-\beta) \frac{\| \boldsymbol{S} \|_F^2}{\| \boldsymbol{S}_0 \|_F^2}, \tag{6}$$

where β modulates the importance between the first and the second terms, and $\boldsymbol{S}_0$ and $\boldsymbol{S}$ indicate the weight on each dimension before and after selection process, respectively. In particular, the objective of the first term is to avoid excessive distortions, while the second term is to reduce the number of the selected features in the clothing style clusters. Previous work [24] proves that this equation is a strictly convex, unconstrained quadratic problem. Thus, by using analytic solver, the final selection matrix $\boldsymbol{S}$ can be derived as

$$\boldsymbol{S} = \beta_1 \boldsymbol{X}^T \left(\beta_1 \boldsymbol{X}\boldsymbol{X}^T + \beta_2 I_Z \right)^{-1} \boldsymbol{X}\boldsymbol{S}_0, \tag{7}$$

where $\beta_1 = (\beta)/(\| \boldsymbol{X}\boldsymbol{S}_0 \|_F^2)$, $\beta_2 = (1-\beta)/(\| \boldsymbol{S}_0 \|_F^2)$, and I_Z is an identity matrix of size Z. In our experiment, we set $\beta = 0.5$. After we solve the selection matrix $\boldsymbol{S}$, the total number of features retained after the selection operation can be calculated as

$$\boldsymbol{S}_{sel} \equiv \boldsymbol{X}\boldsymbol{S}. \tag{8}$$

7 REPRESENTATIVE STYLES SELECTION

In this section, we focus on identifying the most representative clothing styles that are suitable for a specific body type. As we mentioned previously, all body shapes are unique. There are best features that need to draw attention, as well as less positive features that need to play down. Given the representative of the most suitable clothing styles for each body shape, we can understand the characteristics of clothing styles that flatter a specific body shape.

Let $\hat{\boldsymbol{X}} = \{\hat{\boldsymbol{x}}_1, \hat{\boldsymbol{x}}_2, ..., \hat{\boldsymbol{x}}_N\}$ be the auxiliary features of N clothing images in category C obtained from Section 6, and let y_j denote a type of body shape. To find clothing images portraying the representative styles for a specific body shape, we adopt the concept of *stylistic coherence and uniqueness* of fashion items [13]. Specifically, clothing styles are considered as the representative styles for a certain body shape if they are both coherent (frequently worn by people with a body shape) and unique (worn much more often by people with a body shape than with other body shapes).

In this work, we propose to model the aforementioned concept as a class-conditional-probability density [5]. Assume the elements in $\hat{\boldsymbol{X}}$ are mutually independent and obey the Gaussian distribution. Then, for each body shape y_j, the class-conditional-probability density for a clothing image having auxiliary feature $\hat{\boldsymbol{x}}_n$ can be formulated as

$$P(\hat{\boldsymbol{x}}_n|y_j) = \frac{1}{\sqrt{(2\pi)^D |\Sigma_j|}} \exp\left[-\frac{1}{2} \left(\hat{\boldsymbol{x}}_n - \mu_j \right)^T \Sigma_j^{-1} \left(\hat{\boldsymbol{x}}_n - \mu_j \right) \right], \tag{9}$$

where π_j and Σ_j are computed using maximum similarity estimation. Thus, the probability of clothing image $\hat{\boldsymbol{x}}_n$ portraying representative style of body shape y_j can be obtained by

$$P(y_j|\hat{\boldsymbol{x}}_n) = \frac{P(\hat{\boldsymbol{x}}_n|y_j)P(y_j)}{P(\hat{\boldsymbol{x}}_n)}. \tag{10}$$

Clothing image $\hat{\boldsymbol{x}}_n$ is considered as a representative style of body shape y_j if it satisfies two criteria: (1) if $P(y_j|\hat{\boldsymbol{x}}_n)$ is higher than a threshold $\mathcal{T}_1$, which means this style is frequently worn by top stylish celebrities with body shape y_j; and (2) if the difference between the probability of clothing image $\hat{\boldsymbol{x}}_n$ to class y_j and class y_k is higher than a threshold $\mathcal{T}_2$, which means this style is worn much more often by top stylish celebrities with body shape y_j than with other body shapes. In our experiments, $\mathcal{T}_1$ and $\mathcal{T}_2$ are set 50% and 15%, respectively.

8 EXPERIMENTS

To evaluate the efficacy and performance of our proposed method, we conduct extensive experiments and compare the performance with some baseline methods – body shape classification (Section 8.1), body-shape-based style ranking (Section 8.2), and style-based body shape ranking (Section 8.3). Next, we provide examples of clothing items depicting suitable styles for specific body shape in Section 8.4. Finally, in Section 8.5, the subjective evaluation results are reported.

Table 3: Body shape classification accuracy (in percentage).

Existing body shape calculators							Ours
[6]	[18]	[4]	[21]	[22]	[25]	[30]	
31.84	5.97	37.87	16.41	1.59	28.63	20.38	76.83

8.1 Body Shape Classification

In this section, we investigate the effectiveness of existing body shape calculators. Seven different methods widely used to determine the type of body shapes are compared. For this evaluation, we used our collected body measurements (cf. Section 3.2) and performed five-fold cross-validation. We report the accuracy of recognizing body shapes using existing methods in the first seven columns of Table 3. From these results, we can see that existing body shape calculators do not perform well. The highest accuracy rate is achieved when using the method implemented in [4][10].

Inspired by the huge success of convolutional neural networks (CNNs) in the tasks of classification [23], we adopted a CNN-based method to perform body shape classification task. Specifically, we used CNN architecture based on Dense Convolutional Network (DenseNet) [16], which uses a densely connected path to concatenate the input features with the output features, enabling each micro-block to receive raw information from all previous micro-blocks. The body shape features described in Section 5 are employed. Before feeding the CNN, we reshaped the normalized body shape features into a square matrix of size 77×77 by filling the missing entries in rows with zeroes. By transforming our data into an image-like structure, the height of feature matrix won't reduce too quick after multiple downsampling of pooling process.

We report the performance of our proposed body shape calculator obtained from 5-fold cross-validation in the last column of Table 3. We can see that our proposed body shape calculator outperforms existing methods. These experiments further confirm the contribution of the proposed method in determining body shapes using the existing definition of body shape types.

However, since body shape calculator plays an important role in the decision on what to wear, the performance of our body shape calculator still does not meet the desired accuracy target. The problem can be due to confusing definition of body shape types. Therefore, we propose to discover the different types of body shapes in an unsupervised manner, as described in Section 5. Seven types of body shapes are identified using this approach.

8.2 Body-shape-based Style Recommendation

The purpose of this experiment is to evaluate the overall correlation between body shapes and clothing styles as described in Section 6. In this task, we seek suitable clothing style for the given body shape. We cinducted this evaluation on stylish celebrity images from our collection database. For each stylish celebrity, 80% of images (samples) are used for training, 10% for validation, and 10% for testing, in 9-fold cross-validation.

We measure performance using the average precision, a performance metric commonly used to evaluate the ranked retrieval results. For a single query, the average precision approximates the area under the uninterpolated precision-recall curve. Therefore, we also compute the mean average precision over a set of queries to evaluate the overall system performance. Intuitively, a higher average precision indicates a higher quality.

[10]Note that the cited references here are representative of several body shape calculators that use the same methods.

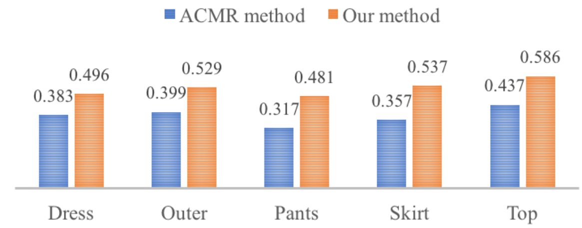


Figure 5: Comparison of Average Precision for clothing style recommendation by body shape.

We compared our proposed method with Adversarial Cross-Modal Retrieval (ACMR) method [10, 39], a cross-media retrieval method built around the concept of adversarial learning. This method involves two processes, i.e., a feature projector and a modality classifier, conducted as a minimax game. A feature projector generating modality-invariant and discriminative representations and aiming to confuse the modality classifier, while a modality classifier distinguishing the items in terms of their modalities.

On average, our proposed method outperformed ACMR method by over 11.26-17.96% in terms of mAP when evaluating style recommendations by body shape. We show a comparison of our proposed method with ACMR method for each of the five clothing categories in Figure 5. Different from ACMR method, our method approximate the semantic representations of two modalities, namely by leveraging both the clothing style and associated body shape information. Therefore, it can retrieve more semantically related results and, thus, it achieves higher accuracy.

8.3 Style-based Body Shape Recommendation

To provide another view for evaluating the overall correlation between body shapes and clothing styles constructed using our proposed framework, we conduct body shape recommendations by clothing style. Different from the previous evaluation that seeks suitable clothing styles for a given body shape query, in this evaluation we seek body shape that is best-suited for a given clothing image query. For this purpose, we used the same training and testing data as in experiment described in Section 8.2. We also compared our results with ACMR method, and evaluated their performances in terms of the average precision.

Figure 6 shows comparisons of our proposed method with ACMR method for each of the seven types of body shapes. On average, our proposed method outperformed ACMR method by over 3.84-34.74%. Thus, based on the results of our evaluations, we confirm that there are strong correlations between body shape and clothing style, and our proposed framework can model this correlation better than ACMR method, a state-of-the-art cross-media retrieval method.

8.4 Exemplar Results

In this section, we present some examples of clothing styles for certain body shapes obtained using the method described in Section 7. As shown in Figure 7, each body shape has unique clothing styles.

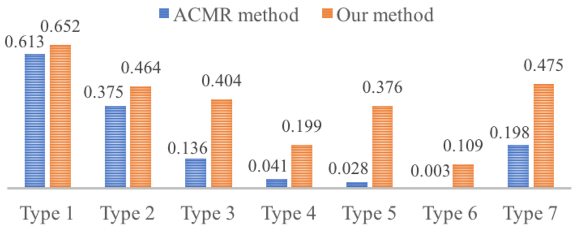


Figure 6: Comparison of Average Precision for body shape recommendation by clothing style shape.

Figure 7: Representative clothing styles for three different body shapes.

For example, the celebrity who has body shape type 1 tends to use a belt to emphasize her waistline, while the celebrity who has body shape type 7 tends to wear a strapless dress that shows off the bare shoulders.

8.5 User Study Evaluation

We conducted a user study to measure users' preference towards recommended styles generated by the proposed and comparison methods. After finding the recommended styles of each body shapes, we recruited twenty female students from our campus as the participants. The study process is divided into two phases: pre-study phase and on-study phase.

The main objective of pre-study phase is to give the participants some general idea of the correlation between fashion styles and body shapes. We firstly collected a number of online fashion tips on dressing to flatter body shapes (e.g., https://blog.stitchfix.com/fashion-tips/ and https://www.wikihow.com/Dress-for-Your-Body-Type), and then showed them to the participants. Each participant was allowed to freely explore the web pages with no time limit. After that, the participants started to perform the next phase.

In the on-study phase, we use body measurements of each participant as query to retrieve the top five most suitable clothing styles generated by our proposed method and the comparison method. Since we focus on five clothing items, a total of 50 images were shown to each participant. The generating method of each image was blind to the participants and the display order was randomly determined. We further asked the participants to give a rating from 1 to 5 to indicate how suitable each recommended style for their body shape, with 5 being the highest suitability.

Table 4: User evaluation results.

Method	Satisfaction score		Preference
	Average	Standard deviation	
ACMR [39]	2.878	1.240	25.00%
Ours	3.574	1.154	54.60%

We report the user evaluation results in Table 4. It shows that the proposed method achieved the highest average satisfaction score of more than 3. Most users prefer the styles recommended by our proposed method. Thus, it verifies that our proposed recommendation framework can help people find the best clothing styles for their body shape.

9 CONCLUSIONS AND FUTURE WORK

A visual summary of clothing designs is essential to gain a deeper understanding of fashion style rules. In this paper, we built scalable models to capture the semantic correlation between fashion styles and body appearances. Based on the created models of data analysis, two questions related to fashion styling tips can be addressed: (1) what are the most suitable clothing styles for a given human body measurement? and (2) which human body shape is best-suited to a given clothing item? To the best of our knowledge, this is the first work devoted to investigating the semantics concepts of fashion designs through the visual analytics of big data. Moreover, we showed how the rich amount of stylish celebrities data available online can be exploited, modeled, and analyzed to provide fashion styling tips.

Several research topics are open for future investigation. Since our final goal is to help users find the most suitable clothing which can perfectly flatter their figure and make them look gorgeous, investigating multiple personal factors will be helpful for enhancing the recommendation system performance. Currently, our analysis focuses on the body measurements, the incorporation of other contextual factors, such as age or skin color might be useful to improve the system. Creative applications like personal recommendation can be realized. The user can provide more personal data for the system to recommend the most trendy and well fitted daily outfit. Besides, we can also use our recommendation result as the reference to realize online product retrieval, which can greatly enhance customers' shopping experience.

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