Preface

In this independent report - fAshIon after fashion, we examine the development of fAshIon (artificial intelligence (AI) in fashion) and explore its potentiality to become a major disruptor of the fashion industry in the near future. To do this, we investigate AI technologies used in the fashion industry – through several lenses. We summarise fAshIon studies conducted over the past decade and categorise them into seven groups: Overview, Evaluation, Basic Tech, Selling, Styling, Design, and Buying. The datasets mentioned in fAshIon research have been consolidated on one GitHub page for ease of use. We analyse the authors’ backgrounds and the geographic regions treated in these studies to determine the landscape of fAshIon research. The results of our analysis are presented with an aim to provide researchers with a holistic view of research in fAshIon. As part of our primary research, we also review a wide range of cases of applied fAshIon in the fashion industry and analyse their impact on the industry, markets and individuals. We also identify the challenges presented by fAshIon and suggest that these may form the basis for future research. We finally exhibit that many potential opportunities exist for the use of AI in fashion which can transform the fashion industry embedded with AI technologies and boost profits.

In Brief

According to AI in Fashion Market Research Report 2021 [112], under the cumulative impact of COVID-19, global spending on AI in the fashion market is expected to grow from USD 229 million in 2019 to USD 1,260 million by 2024, at a Compound Annual Growth Rate (CAGR) of 40.8% during the forecast period. Global expenditure on AI in the fashion market is expected to grow from USD 352.58 million in 2020 to USD 825.19 million by the end of 2025.

In this report, we analyse the fAshIon research and their applications, explore the potential of fAshIon to transform the fashion industry and discuss the challenges and opportunities. Firstly, we investigate fAshIon research papers reported over the past decade. We search for papers focused on the applications of AI technologies in fashion involving the databases such as IEEE Xplore Digital Library, Google Scholar, and Arxiv. The earliest paper reviewed in this report was published on 31 March 2008 [42]; the most recent paper was published on 9 March 2021. Five hundred twenty-one papers are analysed, covering 1,465 authors affiliated with 383 different entities (different departments of the same university or company are not regarded as different affiliations; for example,
Figure 1: Global heatmap of fashion researchers’ regions based on the 521 papers investigated in this report. The data used to create this figure are derived from a tally of each author’s region of affiliation. We find that researchers came from 38 regions.

Amazon Lab126, Amazon Visual Search and AR Group are all counted as Amazon. As shown in Figure 1, China, the United States of America, Singapore, India, Japan, and Germany are identified as the hottest regions of fashion research. We present region information here to emphasise that fashion is extremely complicated which may be treated in different ways in different regions. Taking an example of the attribute datasets collected for fashion recognition, the data distribution is greatly different. ‘Paisley’, a specific type of ‘print’, which is a general attribute in the fashion datasets collected from India but may be a long-tailed attribute in the datasets collected from other regions. In the following, more detailed region information will be presented. This region information provides the interested parties in fashion with the hidden clues of the application popularity in different regions and the potential opportunities.

Unlike the general ‘Review Paper’, the methods and techniques of related fashion tasks using AI have not been presented in detail one by one. We organise fashion studies according to their applications in the fashion industry to clearly show the gap between existing research and practical requirements. Meanwhile, we point out the hottest topics according to the word cloud based on the titles of papers. Statistical results of these papers, including the authors, the author’s affiliations and their corresponding regions, the years of publication, most popular papers, most active researchers, etc., are presented to provide rich information of fashion for researchers. By presenting the analysis of fashion research, we hope to provide the information about 1. the gap between existing research and practical requirements; and 2. the hottest topics of each practical direction. As a result, researchers who have interests in this filed can quick start their fashion research by paying attention on the most active authors, reading the most popular papers, and utilizing the summary of published fashion datasets. Details can be found in Section 1.

Additionally, we also investigate related products and services provided by 126 companies and start-ups. A wide range of cases of applied fashion in the fashion industry are reviewed and analysed in terms of their impact on the industry, markets, and individuals. By presenting the analysis of fashion applications, we hope to present the following key information: 1. existence of current types of fashion applications; 2. many technologies not being converted to practical application; 3. existence of barriers between technical frameworks and business models. Details can be found in Section 2. Finally, we draw conclusions about the challenges and the opportunities that exist in fashion, which may form the basis for future research. This detailed analysis is described in Section 3 and in Section 4.

5https://github.com/AemikaChow/DATASOURCE
Figure 2: Distribution of published fashion papers by year. A search identified 521 papers published in the field. Apart from the 12 papers published in 2021 (which is not a final count) and the 76 papers published in 2020, we can see that the overall trend of these papers is growing.

Figure 3: Mind map of fashion research (some nodes are omitted in this graph for clarity).

1 fashion Research

To our knowledge, 521 papers related to fashion have been published in the last 13 years. Figure 2 indicates that the overall trend of fashion-related papers is one of growth. The first identified paper on fashion paper was published in 2008. Although there is no record of fashion papers published in 2009 or 2010, the number of papers has been increasing continuously since 2011. The year 2017 included a particularly conspicuous step in the growth of fashion research, which is consistent with the conclusion of the fashion market in [112]. During the years 2017, 2018, and 2019, 80, 130, and 135 papers on this topic were published, respectively. The number of papers published in 2020 is lower compared with those in 2019 and 2018 and almost equal to the number published in 2017. One possible reason for this is the influence of the COVID-19 pandemic, which swept the world in 2020.

Additionally, the gap between these research results and the market’s expectations also may have directly dampened the researchers’ enthusiasm to a certain extent. After carefully reading about these 521 papers, as shown in Figure 3, we categorised them into 7 groups, namely: Overview, Evaluation, Basic Tech, Selling, Styling, Design, and Buying. This taxonomy was inspired by [187], which divides fashion research into groups based on existing roles in the fashion industry, namely the fashion lover, the stylist, and the designer. We organise these papers in this taxonomy to better illustrate the relationship between computer vision problems and fashion tasks. As shown in Figure 3, fashion tasks are extremely complicated since they would be affected by many factors. For example, “compatibility learning” [44] which may help to reduce the workload of a stylist by generating the outfit composition automatically. Fitting a model to an outfit dataset is not difficult. The challenge is how to explain the generated results. Fashion is subjective. In most situations, a stylist needs a reasonable explanation to persuade customers to believe something or change their mind when they hold a different opinion. If no explanation to underpin the decision such as evaluation or recommendation, the decision is not convincing enough for the customers to accept. Naturally,
when tackling the compatibility learning task, how to give a concrete reason for the results needs to be taken into consideration. All in all, as the papers are categorised in this way, it is easier for identifying corresponding roles in the fashion industry and convenient for comparing existing research with practical requirements.

Based on this taxonomy, we further analyse the 521 papers. The distribution of published fAshlon papers by these 7 groups is shown in Figure 4. It can be found that most papers were focused on solving problems in the group of ‘Selling’. Based on the research interest, these groups sorted from high to low are ‘Selling’, ‘Design’, ‘Styling’, ‘Basic Tech’, ‘Buying’, ‘Overview’, and ‘Evaluation’. Furthermore, as shown on the right side of Figure 4, we can find more interesting information of fAshlon research. Papers in the group of ‘Overview’ were relatively evenly distributed by year. Very few researchers have focused on defining the evaluation standard for fashion tasks. Although solving the problems in the group of ‘Basic Tech’ is not so popular comparing with the other groups fAshlon research, it has still received attention every year. Additionally, we analyse the group of ‘Selling’, ‘Styling’, ‘Design’, and ‘Buying’ together since all these four groups are closely related to corresponding roles in the fashion industry. Researchers focused on solving the problems in ‘Selling’ at the earliest (in 2011) and gradually turned their attention to the research on ‘Styling’ (in 2012), ‘Design’ (in 2017), and ‘Buying’ (in 2017). ‘Selling’ is the most popular topic among these four groups before the year 2018. The sum of papers in these three groups, i.e. ‘Selling’, ‘Design’, and ‘Buying’, is 27 (i.e., $13 + 9 + 5 = 27$) in 2017. Meanwhile, 53 papers in total related to the tasks in the group of ‘Selling’ were published in 2017. In other words, in 2017, papers published in the ‘Selling’ group was over the total number of the ‘Styling’, ‘Design’, and ‘Buying’ group, i.e., $43$ versus $27$. In the following year 2018, the compared numbers are changed to $53$ versus $62$ (i.e. $25 + 35 + 2 = 62$). Even though the number of papers under ‘Selling’ group still accounted for the largest proportion of published papers among these four groups in 2018, the situation has started to change in 2019. The numbers of published papers in the ‘Selling’, ‘Styling’, and ‘Design’ group were very close and almost equal in 2019, which is $38$, $38$, and $39$, respectively. In other words, researchers turned their attention from solving problems in the ‘Selling’ group into tackling tasks related to ‘Styling’ and ‘Design’. ‘Design’ became the most popular topics among these four groups after 2019. In addition, it is worth mentioning that, although research in ‘Buying’ is relatively limited, it is important to the fashion industry as the same as ‘Selling’, ‘Styling’, and ‘Design’.

On the basis of the analysis above, we conclude that 1. the overall trend of the fAshlon papers is growing; 2. research on proposing the evaluation protocol for specific fashion tasks has not yet raised attention; 3. research on solving problems in the group of ‘Selling’ was popular before and slowly lost attention; 4. research on tackling tasks in the group of ‘Styling’ and ‘Design’ becomes increasingly hot in recent years; 5. research on problems related to ‘Buying’ was overall increased year by year. Papers in the group of ‘Buying’ are still relatively few which is not in directly proportional to its importance to the fashion industry. In the following sections, we present our detailed analysis according to each defined group. The definition of each group is given first, followed by a word cloud based on the titles of the papers in the group as appropriate. Then, we present the statistical analysis of papers organised by year of publication, authorial affiliations, the corresponding regions, and the authors. Although we do not introduce the methods proposed in these papers, the most active authors and the most popular papers (according to the number of citations) are listed as a reference for researchers.
1.1 Overview

The papers in this group are review papers [33, 65, 98, 11, 134] that summarise the developments in Fashion technology in different areas. Overview papers can help researchers to quickly understand the current situation of Fashion research and familiarise them with the corresponding methods, related datasets, baseline approaches, and evaluation protocols. For example, [65] presents a summary of the various retrieval techniques used in clothing retrieval, and [11] provides an analysis of the four main tasks in fashion: fashion detection, including landmark detection, fashion parsing, and item retrieval; fashion analysis, consisting of attribute recognition, style learning, and popularity prediction; fashion synthesis, which involves style transfer, pose transformation, and physical simulation; and fashion recommendation, which comprises fashion compatibility, outfit matching, and hairstyle suggestion. [11] also presents the benchmark datasets and the evaluation protocols of each task. [33] summarises the use of a recommendation system in situations using different methods such as End-to-End, Implicit Feedback-based, Weak Appearance Feature-based, Semantic Attribute Region-guided, and Using Adversarial Feature Transformer; then, the paper presents some approaches related to understanding aesthetics and realising personalisation in Fashion. The ratio of Overview papers to the total number of published Fashion papers is around 1.5%. As shown in Figure 5, 4 papers from China, 2 from India, 1 from Ireland, and 1 from Singapore are identified. These detailed numbers are derived from the regions of the first author’s affiliation rather than the nationality of the first author; for example, if the first author is affiliated with Amazon Lab126, the paper is counted as being from the United States. Although not takes a large proportion of the Fashion research, it still plays a role for researchers to quickly have a holistic view of Fashion from the perspective of technology.

1.2 Evaluation

Evaluation protocols are important for research. Unlike the studies of art, which are extremely subjective, science is quantifiable. From a research perspective, science undoubtedly needs objective indicators to demonstrate the advantage of one approach to accomplish a specific task. It is unfair to evaluate a paper as better than another based on subjective criteria. For example, ‘accuracy’ is one of the criteria used to evaluate whether a recognition model is good. Demonstrating the advantage of one model based solely on the retrieved results is not possible. However, there is a huge contradiction here. As has been mentioned, fashion is closer to art than science. The consideration of how to design an evaluation protocol for Fashion research with a high degree of subjectivity has become challenging. Very few research have specifically investigated the evaluation protocols in Fashion research. The most mainstream evaluation indicators have been adopted directly from corresponding computer science tasks, such as accuracy for fashion recognition (image recognition tasks) or inception score [7] for fashion generation (image generation tasks). To our knowledge, [128] is the only paper that describes the process of conducting research from the perspective of evaluation protocol. (Note: the use of ‘only’ does not mean that no other Fashion evaluation indicators have been introduced in other papers. Fill-in-the-blank accuracy and compatibility prediction AUC [152, 14, 156] are two evaluation indicators that have been introduced for the assessment of fashion compatibility. The papers in which they are introduced have adopted unique Fashion indicators, but this is not the main...
1.3 Basic Tech

The third fAshlon research group is Basic Tech. Papers in this group are mainly focused on the basic technology used to process fashion images [49, 89, 186, 6, 52, 60, 173, 81, 87, 77, 159, 147, 100, 166, 85, 158, 104, 25, 99, 163, 97, 163, 162, 155]. It is also a foundation of all computer vision tasks. To provide a snapshot of the research in this group, we present a word cloud based on these research titles. Words such as ‘the’, ‘a’, and ‘toward’ were manually deleted, while some words with similar meanings, e.g., ‘clothing’ and ‘clothings’ or ‘model’ and ‘models’, were grouped together. It can be seen in Figure 6 that the keywords in this group are Parsing, Fashion, Clothing, Human, Segmentation, and Landmark. We conclude that the research in Basic Tech focus on image-level processing, e.g., clothing parsing, landmark detection, key point, and apparel detection. The ratio of Basic Tech papers to all fAshlon papers is around 13.2%.

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6https://www.truefit.com/en/Home
Table 1: List of the top 4 authors who have published papers in the Basic Tech group, sorted from high to low and the most relevant papers according to their citations.

| Researchers       | No. of papers | (citations | year) | (citations | year) | (citations | year) |
|-------------------|---------------|-----------|--------|-----------|--------|-----------|--------|
| Xiaodan Liang     | 6             | 86 | 2016 | 210 | 2015 | 191 | 2015 |
| Si Liu            | 5             | 97 | 2013 | 59 | 2015 | 54 | 2011 |
| Jian Dong         | 3             | 24 | 2013 | 84 | 2014 | 25 | 2011 |
| Kota Yamaguchi    | 3             | 162 | 2012 | 272 | 2013 | 164 | 2014 |

As shown in Figure[7], this group comprises 69 papers, including 34 from China, 13 from the USA, and 6 from Singapore. The hottest topic in this group is clothing parsing with regard to clothing segmentation in semantic-level [85, 100, 77, 87, 26, 99, 163, 97, 162, etc]. We list the authors who have published papers in this group, sorted from high to low. Here, we emphasise the top 4 authors (taking only the first author into consideration): Xiaodan Liang[7] from the School of Intelligent Systems Engineering, Sun Yat-sen University; Si Liu[8] from the Institute of Information Engineering, Chinese Academy of Sciences; Jian Dong[9] from the Department of Electrical and Computer Engineering, National University of Singapore; and Kota Yamaguchi[10] from CyberAgent, Inc., previously from Tohoku University.

In Table[1] aside from the numbers of papers published by these authors in this group, we also present the top 3 related papers according to the number of citations. ‘[86]: 236 | 2016’ refers to the paper ‘Semantic Object Parsing with Graph LSTM’, which was published in 2016 and has been cited 236 times so far. ‘[162]: 468 | 2012’ refers to the paper ‘Parsing Clothing in Fashion Photographs’, which was published in 2012 and has been cited 468 times. ‘[163]: 272 | 2013’ refers to the paper ‘Paper Doll Parsing: Retrieving Similar Styles to Parse Clothing Items’, which was published in 2013 and has been cited 272 times.

Many other authors have also contributed excellent works to this field. Overall, 227 authors worldwide have been identified; among these, 52 authors have been identified. The top 12 listed authors with their number of publications (in bracket) are Shicheng Yan (13), Liang Lin (12), Xiaodan Liang (11), Xiaohui Shen (8), Si Liu (7), Jiashi Feng (6), Ping Luo (5), Jianchao Yang (5), Ke Gong (4), Jian Dong (4), Kota Yamaguchi (4), and M. Hadi Kiapour (4). These works form the foundation of fAshIon research, especially in the application of functions to complicated images such as crowd images or images from social media.

These first three groups, Overview, Evaluation, and Basic Tech, are more general and not so closely related to roles in the fashion industry. Next, we will introduce the tasks involved with similar duties of certain roles in fashion.

1.4 Selling

In this section, we introduce the tasks involved with similar duties of certain areas in fashion, namely Selling, Styling, Design, and Buying. The seller takes a main role in the fashion retail sector to sell products. A good seller in fashion needs to recommend accurate products to his or her customers. Their aim is to increase sales as much as possible. The basic requirements for the seller are therefore:

- That he or she can recognise the detailed attributes of fashion products and know how to find similar items according to a general description using simple words provided by his or her customers.
- That he or she can accurately recommend fashion products according to observations on both his or her customers and of trends.
- That he or she can reply quickly to his or her customers about whether a particular item or size is available or out of stock.

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[7] https://lemondan.github.io/
[8] https://sites.google.com/site/siliuhome/
[9] https://sites.google.com/site/homejiandong/
[10] https://sites.google.com/view/kyamagu
Figure 8: Word cloud based on the titles of papers in the Selling group. The keywords are Fashion, System, Clothing, Retrieval, Image, Attributes, and Recommendation.

Figure 9: Distribution of Selling papers. This group includes 53 papers from China, 41 from the USA, 21 from India, 16 from Singapore, 10 from Japan, 9 from Korea, 9 from Germany, 9 from the UK, 3 from Poland, 3 from Canada, 3 from the Netherlands, 2 from France, 2 from the Philippines, 2 from Portugal, 2 from Sweden, 2 from Brazil, 2 from Vietnam, 2 from Belgium, 1 from Malaysia, 1 from Turkey, 1 from Spain, 1 from Austria, 1 from Switzerland, 1 from Australia, and 1 from Italy.

According to these requirements, we identify many research papers that aim to provide methods to create online virtual sellers. These papers are then categorised into the Selling group [4, 18, 115, 59, 170, 105, 68, 131, 61, 161, 88, 165, 154, 103, 113, 143, 43, 58, 74, 35, 12, 36, 111, 40, 71, 188, 39, 9]. It can be seen in Figure 8 that the keywords of this group are Fashion, Clothing, System, Attributes, Image, Retrieval, Recommendation, and Classification. We conclude that the research in Selling has been focused on marketing fashion products like a seller, e.g., by using fashion item recognition, recommendation, and retrieval. The ratio of Selling papers to the total number of papers is around 37.8%; accounting for the largest proportion of research among all of the seven groups identified in the current papers.

This group includes 197 papers. As shown in Figure 9, these include 53 papers from China, 41 from the USA, 21 from India, 16 from Singapore, 10 from Japan, 9 from Korea, 9 from Germany, and 9 from the UK. China, the USA, and India are therefore identified as the hottest regions for this type of research. Large bodies of research were published in 2017, 2018, and 2019. Attribute recognition and image retrieval are identified as the hottest topics in this group.
Table 2: List of the top 3 authors who have published papers in the Selling group, sorted from high to low and the most relevant papers according to their citations.

| Researchers       | No. of papers | (citations | year) | (citations | year) | (citations | year) | (citations | year) |
|-------------------|---------------|-----------|--------|-----------|--------|-----------|--------|-----------|--------|
| Huijing Zhan      | 11            | [177]: 10 | 2019   | [175]: 6  | 2017   | [176]: 4   | 2017   |
| M. Hadi Kiapour   | 3             | [41]: 365 | 2015   | [68]: 219 | 2014   | [40]: 3    | 2018   |
| Qi Dong           | 3             | [29]: 134 | 2018   | [27]: 83  | 2017   | [28]: 60   | 2017   |

We list the authors who have published papers in this group, sorted from high to low. Here, we emphasise the top 3 authors (taking only the first author into consideration): Huijing Zhan from DL2.0 of the Institute for Infocomm Research (I2R); M. Hadi Kiapour from Dawnlight, previously from eBay Inc.; and Qi Dong from the Recognition and Video team at AWS, Amazon (previously from Queen Mary University of London).

In Table 2, in addition to the numbers of papers published by the authors in this group, we also present the top 3 related papers according to the number of citations. Particularly, we emphasise some papers that have received much attention. ‘Image-based Recommendations on Styles and Substitutes [114]’ was published in 2015 and has been cited 1,089 times. ‘DeepFashion: Powering Robust Clothes Recognition and Retrieval with Rich Annotations [103]’ was published in 2016 and has been cited 857 times. ‘Describing Clothing by Semantic Attributes [8]’ was published in 2012 and has been cited 412 times. ‘Street-to-shop: Cross-scenario Clothing Retrieval via Parts Alignment and Auxiliary Set [96]’ was published in 2012 and has been cited 370 times. ‘Where to Buy it: Matching Street Clothing Photos in Online Shops [41]’ was published in 2015 and has been cited 361 times. ‘Whittlesearch: Image search with Relative Attribute Feedback [70]’ was published in 2012 and has been cited 336 times. ‘Fine-grained visual comparisons with local learning [171]’ was published in 2014 and has been cited 304 times.

Many other authors have also contributed excellent works to this field. Overall, 574 authors are identified worldwide, including 151 first authors. The top 16 listed authors are Huijing Zhan (11), M. Hadi Kiapour (3), Qi Dong (3), Shuohao Li (2), Sanyi Zhang (2), Dipu Manandhar (2), Ruifan Li (2), Zhi-Qi Cheng (2), Kenan E. Ak (2), Roshanank Zakizadeh (2), Julia Lasserre (2), Shuhui Jiang (2), Kaori Abe (2), Xiaoling Gu (2), Sirion Vittayakon (2), and Junshi Huang (2). Their works have focused on the most general fashion scenarios with regard to selling products.

This body of work aims to provide a better shopping experience to online shoppers, thus improving the performance of sales. In addition, this kind of research provides a foundation for higher-level tasks. The ability to execute fine-grained fashion attributes recognition comprises the basic knowledge needed to deal with higher-level tasks such as mixing and matching.

1.5 Styling

Generally speaking, a stylist who provides styling advice to customers should have good beauty sense and an ability to provide personal styling services to individual customers. They should be able to recognise fashion attributes. The basic requirements for a stylist are:

- That he or she has a good sense of clothing aesthetics, such as a sense of colour, a sense of texture, and a sense of silhouette, and can easily create a well-composed outfit. (Understand Clothing Aesthetic)
- That he or she knows how to make an outfit attain visual balance for a given customer and mix and match according to different situations, such as for an occasion, the seasons, or body figure. (Do Personal Styling)
- That he or she understands what beauty is and can convincingly explain his or her selections, enabling him or her to persuade the customer and provide satisfactory service. (Good Story Teller)

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11 https://zhanhuijing.github.io/
12 http://www.cs.unc.edu/~hadi/
13 https://www.aminer.cn/profile/qi-dong/53f42d48dabfaeb1a7b89950
That he or she always stays aware of fashion trends and can apply these trends to his or her work.

According to these requirements, we identify many research papers that aim to provide online styling services. We then categorise these papers into the Styling group [49, 153, 52, 2, 121, 101, 180, 69, 122, 90, 79, 183, 133, 73, 139, 76, 64, 16, 3, 90, 119, 141, 91, 156, 138, 10, 179, 44, 189]. It can be seen in Figure 10 that the keywords of this group are Fashion, Clothing, System, Image, Attributes, Retrieval, Recommendation, and Classification. We conclude that the research in Styling has been focused on providing online styling services, e.g., by using fashion compatibility learning, outfit creation, and recommendation. The ratio of Styling papers to the total number of papers is around 20.7%.

As shown in Figure 11 this group comprises 108 papers, including 37 papers from China, 36 from the USA, 9 from Singapore, 6 from India, and 5 from Japan. China, the USA, and Singapore are identified as the hottest regions for this type of research. Large bodies of research were published in 2017, 2018, and 2019. Compatibility learning and outfit recommendation are identified as the hottest topics in this group.
Table 3: List of the top 3 authors who have published papers in the Styling group, sorted from high to low and the most relevant papers according to their citations.

| Researchers              | No. of papers | (citations | year) | (citations | year) | (citations | year) |
|--------------------------|---------------|-----------|--------|-----------|--------|-----------|--------|
| Xuemeng Song             | 6             | 135: 99 | 2017  | 136: 70 | 2018   | 137: 71 | 2019   |
| Xun Yang                 | 3             | 167: 22 | 2019  | 168: 13 | 2019   | 169: -1 | 2020   |
| Wang-Cheng Kang          | 2             | 63: 113 | 2017  | 64: 25  | 2019   | -        |        |
| Ruining He               | 2             | 50: 894 | 2016  | 51: 60  | 2016   | -        |        |
| Pongsate Tangseng        | 2             | 148: 29 | 2017  | 149: 6  | 2020   | -        |        |

We also list the authors who have published papers in this group, sorted from high to low. Here, we emphasise the top 5 authors (taking only the first author into consideration): Xuemeng Song from Shandong University, Xun Yang from the National University of Singapore, Wang-Cheng Kang from Google Research (Brain team), Ruining He from Google Research, and Pongsate Tangseng from the Graduate School of Information Sciences, Tohoku University.

In Table 3, aside from the number of papers published by these authors in this group, we also present the top 3 related papers according to the number of citations. Particularly, we emphasise a paper which has received much attention: ‘Ups and downs: Modeling the Visual Evolution of Fashion Trends with One-Class Collaborative Filtering’ was published in 2016 and has been cited 894 times. ‘Hi, Magic Closet, Tell me What to Wear!’ was published in 2012 and has been cited 272 times. ‘Neuroaesthetics in Fashion: Modeling the Perception of Fashionability’ was published in 2015 and has been cited 196 times. ‘Learning Fashion Compatibility with Bidirectional LSTMs’ was published in 2017 and has been cited 175 times. ‘Large Scale Visual Recommendations from Street Fashion Images’ was published in 2014 and has been cited 119 times.

Many other authors have also contributed excellent works to this field. Overall, this group includes 454 authors worldwide, including 120 first authors. The top 9 authors in this group are Julian McAuley (7), Tat-Seng Chua (5), Xun Yang (4), Yunshan Ma (4), Xuemeng Song (4), Xingnan He (4), Reza Shirvany (4), Urs Bergmann (4), and Jun Ma (4). Works in this group focus on duties, such as those of a stylist in the fashion industry.

The works aim to provide personalised online styling services that can cross-sell to increase the exposure rate of products (outfit recommendation) and to create new business models that offer either an online mix-and-match service or complete outfit boxes based on the personal preference of the customer (do personal styling).

1.6 Design

In the fashion industry, a good design depends on the abilities of a fashion designer. Generally speaking, the designer is most closely related to the stylist and needs to have similar aesthetic abilities to those of the stylist. More importantly, a designer should know not only what beauty is but also how to create it. The unique requirements for a designer are:

- That he or she has the ability to transform highly abstract concepts or stories into fashion items (e.g., garments, accessories, bags, shoes, etc.) through the language of clothing.
- That he or she has the ability to transfer images or feelings from his or her brain to papers via his or her hand drawing or computer software.
- That he or she has the ability to create new designs based on a theme or conditioned by different constraints, such as the seasons, the trends, or the DNA of the brand (Brand DNA is the essence of your identity as a business).
- That he or she always remains aware of fashion trends and can apply these trends to his or her work.
According to these requirements, we identify many research papers that aim to help fashion designers, which we categorise into the Design group. The keywords of this group are Fashion, GAN, Cloths, Design, Image, Generative, Adversarial, Try-On, and Synthesis. We conclude that the research in Design focus on fashion generation, virtual try-on, clothing synthesis. The ratio of Design papers to the total number of papers is around 21.3%.

As shown in Figure 13, this group comprises 111 papers, including 37 from the USA, 32 from China, 7 from Germany, 5 from the UK, 5 from Japan, 5 from Switzerland, 5 from France, 3 from India, 2 from Singapore, 2 from Turkey, 2 from Korea, 2 from Russia, 2 from Spain, 1 from the Netherlands, 1 from Poland, 1 from Italy, and 1 from Sweden. Large bodies of research were published in 2018, 2019, and 2020. Virtual Try-On (VITON), Neural Style Transfer, Image Synthesis, and 3D Clothing Generation are identified as the hottest topics in this group. Moreover, we list the authors who have published papers in this group, sorted from high to low. Here, we emphasise the top 4 authors (taking only the first author into consideration): Haoye Dong from https://www.scholat.com/donghaoye
Table 4: List of the top 3 authors who have published papers in the Design group, sorted from high to low and the most relevant papers according to their citations.

| Researchers          | No. of papers | (citations | year) | (citations | year) | (citations | year) |
|----------------------|---------------|------------|--------|------------|--------|------------|--------|
| Haoye Dong           | 7             | 19: 75 | 2018   | 20: 50 | 2019   | 55: 47 | 2018   |
| Xintong Han          | 3             | 45: 177 | 2018   | 47: 27 | 2019   | 46: 27 | 2019   |
| Erhan Gundogdu       | 2             | 37: 39 | 2019   | 38: 11 | 2020   | -       |         |
| Natsumi Kato         | 2             | 60: 12 | 2018   | 67: 6  | 2019   | -       |         |

Sun Yat-sen University; Xintong Han\(^{20}\) from Huya Inc., previously from the University of Maryland; Erhan Gundogdu\(^{21}\) from Amazon Berlin; and Natsumi Kato\(^{22}\) from the University of Tsukuba.

In Table 4, aside from the number of papers published by these top authors in the group, we also present the top 3 related papers according to the number of citations. Particularly, we emphasise a paper that has received much attention: ‘Disentangled Person Image Generation [107]’ was published in 2018 and has been cited 267 times. ‘Deformable GANs for Pose-based Human Image Generation [130]’ was published in 2018 and has been cited 211 times. ‘A Variational U-Net for Conditional Appearance and Shape Generation [31]’ has published in 2018 and has been cited 207 times. ‘VITON: An Image-based Virtual Try-on Network [45]’ was published in 2018 and has been cited 177 times. ‘BodyNet: Volumetric Inference of 3D Human Body Shapes [150]’ was published in 2018 and has been cited 174 times. ‘Be Your Own Prada: Fashion Synthesis with Structural Coherence [185]’ was published in 2017 and has been cited 166 times.

Many other authors have also contributed excellent works to this field. Overall, this group includes 427 authors worldwide, of which 99 are first authors. The top 10 listed authors are Xiaodan Liang (7), Haoye Dong (7), Gerard Pons-Moll (5), Jian Yin (4), Zeng Huang (3), Xintong Han (3), Duygu Ceylan (3), Tony Tung (3), Hao Li (3), and Christian Theobalt (3). These works have focused on helping the fashion designer, particularly via image generation, style transfer, and 3D garment generation.

Most of current works focus on helping designers or online retailers to visually demonstrate their ideas, e.g., attribute editing [23, 140, 54], 3D garment generation [118, 5, 169, 150, 37, 38], virtual try-on [125, 21, 72, 20, 13, 45], etc. These methods can speed up the process of design in terms of time saving on design detail modification to a certain extent. Furthermore, material waste can be reduced since making up a physical sample for each design is not necessary. In addition, marketing materials such as videos, brochures, flyers, etc. for promoting fashion products of retailers can be generated by using GAN models and thus marketing costs involved in shooting, promotional material design, etc. can be reduced. Certainly, with a holistic view of the ‘Design’ research, there are many interesting but challenging tasks remain. Can AI models create new designs based on a theme or subject to different predetermined constraints, such as seasons, trends, brand images, etc.? Can AI models transform highly abstract concepts or themes into fashion items, such as garments, accessories, bags, shoes, etc.?

1.7 Buying

The last group is Buying. In the fashion industry, a buyer performs the action of buying the right products for fashion brands and retailers in the retail sector. Unlike a stylist or a designer, a buyer’s work depends on making the decision to buy the right products in the right quantities. The unique requirements for a buyer are:

- That he or she can draw conclusions from the records of previous sales.
- That he or she has great insight into the market and the ability to make predictions.
- That he or she is very experienced in fashion retail and fully knows the market trends.

\(^{20}\)http://users.umiacs.umd.edu/ xintong/
\(^{21}\)https://egundogdu.github.io/
\(^{22}\)https://digitalnature.slis.tsukuba.ac.jp/2017/04/natsumi-kato/
According to these requirements, we identify many research papers on the subject of Buying [53, 110, 144, 124, 109, 151, 142, 132]. It can be seen in Figure 14 that the keywords of this group are Fashion, Trends, Discovering, Visualisation, Prediction, and Social Media. We conclude that the research in Buying focus on trend prediction and culture discovering. The ratio of Design papers to the total number of papers is around 5.2%.

As shown in Figure 15, 27 papers are categorised in this group, including 8 papers from India, 7 from the USA, and 3 from Japan. India, USA, and Japan are identified as the hottest regions for this group. A large body of studies was published in 2020. Trend forecasting is identified as the hottest topic in this group.

Moreover, we present a list of authors who have published papers in this group, sorted from high to low. This group comprises 81 authors worldwide, including 17 first authors. The top 4 listed authors are Ziad Al-Halah (3), Utkarsh Mall (2), Sajan Kedia (2), and Shin Woong Sung (2). The research in this group aim to mimic the duties of a fashion buyer. Utilising the power of data-driven techniques to speed up information filtering and the sorting and analysis of big data can greatly benefit fashion retailers, including commercial fashion brands. Most research in this area has been focused on fashion forecasting, prediction, and selling.
In addition to our research on Fashion, we also focus on related companies and start-ups. Based on our investigation, 126 companies and start-ups that offer Fashion-related services, applications, or technology support have emerged in recent years. For example, Echo Look by Amazon (Figure 16) provides customers with a special online service that compares two uploaded outfits and selects the better outfit using AI. Thus, the user can determine the best look for the day. The technology used in this application belongs to the previously described Styling group. Other products and functions, such as Fashion Box provided by STITCH FIX\textsuperscript{23} utilise similar technologies. After completing a style quiz, the customer receives a box of clothing items recommended for them, providing a different shopping experience from before. Some companies, such as Alibaba, focus on outfit generation and recommendation, presenting outfit compositions on the checkout page for cross-selling. In this section, we introduce the opportunities for Fashion based on an analysis of the products or services provided by the investigated companies. Existing applications or products in the industry are presented briefly. Detailed information can be found on their official websites. We do not present the statistical results for these investigated companies because these numbers are largely inconsequential and because the website links of some of the investigated companies are now invalid, such as that of Glitch\textsuperscript{24}, an AI clothing brand founded by computer scientists turned fashion designers at MIT. We review a wide range of cases of applied Fashion in the fashion industry and categorized them according to their corresponding technologies (i.e., Selling, Styling, Design, Buying). We summarise the current situations in Fashion and analyse its impact on the industry, markets and individuals in the end of this section.

Fashion Searching and Complete the Look - ‘Selling’: Technology can help customers to search for fashion items immediately conditioned on uploaded images. Utilising the recognition model to perform attributes tagging can also speed up the process of launching new products. Additionally, algorithms can make fashionable recommendations for achieving a complete look, a feature that may be widely applicable in cross-selling. A case study of Fashion Searching and Complete the Look by MACTY (Figure 17) reveals that the platform can enable one-click searching to obtain a full outfit. This technology can help to inspire users who are considering what to wear and how to combine pieces by automatically creating the perfect look.

\textsuperscript{23}https://www.stitchfix.com/
\textsuperscript{24}https://glitch-ai.com/
Figure 17: Case study of Fashion Searching and Complete the Look by MACTY. Such platforms enable one-click searches to obtain a full outfit and can also learn customer preferences, promote bundle up and sell up, and improve the searching experience. This technology can help to inspire users who are considering what to wear and how to combine pieces by automatically creating the perfect look.

Figure 18: Case Study of a Stylist Service provided by DAILYLOOK. Technology can help users to find their perfect fit and achieve a one-of-a-kind style by selecting from among exclusive brands hand-selected by an expert stylist.

More information can be found at catchoom; chicengine; intelistyle; MACTY; Markable AI; OMNIOUS; SNAPVISION; Streamoid; syte; Truefit; VISENZE; WIDE EYES; ximilar.

Stylist Service - ‘Styling’: As shown in Figure 18, technology can help users to find their perfect fit and achieve one-of-a-kind style by selecting items from the exclusive brands that are hand-selected by an expert stylist.

25https://catchoom.com/
26http://www.chicengine.com/
27https://www.intelistyle.com/
28https://macty.eu/index.html
29https://markable.ai/
30https://www.omnious.com/
31https://www.snap.vision/
32https://www.streamoid.com/
33https://www.syte.ai/
34https://www.truefit.com/en/Home
35https://www.visenze.com/
36https://wideeyes.ai/
37https://www.ximilar.com/
Figure 19: Case study of Virtual Fitting by DATAGRID. Here, AI is used to generate non-existent photorealistic digital humans, and the company aims to utilise it as a new interface for machines in a future society. This type of work can also be used as an advertising model for apparel e-commerce.

More information can be found at COUCHFASHION[^38] STITCH FIX[^39] TRUNK CLUB[^40] Vue.ai[^41] DAILYLOOK[^42] frockbox[^43] MODABOX[^44]

**Virtual Fitting - ‘Design’**: Technology can improve customers’ online shopping experiences by allowing them to virtually visualise the apparel. Fashion brands and retailers can also use this technology to generate sale or advertising images for their new products without taking new photographs. Virtual Fitting by DATAGRID (Figure 19) uses AI to generate non-existent, photorealistic digital humans. This technology may be utilised as a new interface for machines in a future society where AI has permeated everything. Such work can also be used as an advertising model for apparel e-commerce. Moreover, technology forms an important part of the ‘Virtual Retail’ business model, which can accelerate the transformation of the fashion industry from selling Products into selling Service. Notably, 2D and 3D versions of this technology have now been developed. Certainly, there are some attempts of utilising neural networks to create virtual fashions which will be transformed into real clothing; e.g., ‘Project Muse[^45]’ designed by Google in partnership with Zalando in 2016.

More information can be found at ARMOI[^46] DATAGRID[^47] ELSE Corp[^48] secret sauce[^49] 3DLOOK[^50] BIGTHINX[^51] BOLD METRICS[^52] TOZI[^53] VIRTUSIZE[^54]

**Business Strategy - ‘Buying’**: Technology can help businesses to make predictions by using consumer data from various sources and adjusting businesses’ selling strategies to drive revenue while maintaining profitability. Retail buyers, planners, and merchandisers can use this type of technology to react faster to market trends, obtain competitive assortment benchmarking, and optimise prices. Technology can analyse data to understand the emotional context behind shoppers’ purchases; businesses can then deliver the most relevant, personalised experiences to their consumers. Automatically generating the fashion trending report will be one of the most useful tools.

[^38]: https://deck.couchfashion.com/
[^39]: https://www.stitchfix.com/
[^40]: https://www.trunkclub.com/
[^41]: https://vue.ai/
[^42]: https://www.dailylook.com/
[^43]: https://www.frockbox.ca/
[^44]: https://moda-box.com/
[^45]: https://techcrunch.com/2016/09/02/googles-new-project-muse-proves-machines-arent-that-great-at-fashion-design/
[^46]: https://www.armoi.com
[^47]: https://datagrid.co.jp/en/
[^48]: https://www.else-corp.com/
[^49]: https://secretsaucepartners.com/
[^50]: https://3dlook.me/
[^51]: https://bigthinx.com/
[^52]: https://www.boldmetrics.com/
[^53]: https://www.emtailor.com/
[^54]: http://www.virtusize.com/site/
From the above summary, we can see that AI has already been applied for practical use and some conventional fashion business models have been changed. One of the most typical cases is ‘fashion searching’. Based on the technology in the group of ‘Selling’, online retailers or online shopping platforms can provide their customers with ‘intelligent sales person’. Comparing with the basic requirements for the seller, the AI model can recognise the attributes of fashion products and retrieve the related results. This technology undoubtedly affects the business model of online selling. Meanwhile, it is apparent that there is still big room for us to put efforts for improvement, e.g., recommendation of fashion products based on the fashion trends and observations on the customers. Additionally, many technologies have not been applied; e.g., attributes editing in the group of ‘Design’. Especially the COVID-19 has changed the conventional practice of the industry. During the global pandemic, many large-scale activities were forced to cancel. Many design houses debuted their new collections via digitalised ways like films or games. For example, as shown in Figure 20, Balenciaga debuted its fall 2021 collection through the ‘record-breaking video game,’ which is titled, ‘Afterworld: The Age of Tomorrow’. Demna Gvasalia (creative director of Balenciaga) depicted the world of 2031 in this game. The concept of ‘parallel world’ is utilised to catch a glimpse of the near future based on our understanding about the middle Ages.

*Art at its most significant is a Distant Early Warning System that can always be relied on to tell the old culture what is beginning to happen to it. – Marshall McLuhan*
3 Challenges

Fashion is a challenging field for computer vision. In addition to the most basic function of clothing, i.e., covering the body, well dress-up can bring the feeling of beauty to us. Fashion is an art form, just like music, painting, poetry, etc. Although creating AI models to assist with the different types of works done by fashion practitioners, including sellers, stylists, designers, and buyers can empower the current industry by upgrading its structure while elevating the economy, to teach an AI model to understand fashion is not an easy thing. The first question that should be answered is: ‘What is beauty and how to evaluate it?’ Philosophers have been discussing this issue for millennia. Different perspectives, such as those of the materialist and the idealist, are juxtaposed and have shaped the meaning of aesthetics. It is generally recognised that beauty produces a feeling that is similar to happiness. The beauty or deformity of an object is caused by its gene. Generally, to perceive beauty, one must perceive the essence that beauty from both internal and external perspectives. Internal meaning differs from external meaning. The external senses may detect traits that do not rely on any priori perception. In other words, if you do not perceive or at least grasp the object, its beauty cannot be perceived. Perception is a major keyword in aesthetics [120].

Haute Couture gowns possess the unique individuality of an object d’art. They are among the last items made by hand, the human hand, whose value is irreplaceable, because it gives its creations that which no machine can ever give: poetry and life. – Christian Dior, 1957

We agree with Dior. No matter how far technology advances, the creative capacity of humans is irreplaceable. In terms of computers, strong AI technology remains a controversial topic, and most mainstream viewpoints oppose conducting related research. Unlike humans, computers cannot express themselves in an emotional context. Creating beautiful and valuable artwork is a complicated challenge for a computer because it has no ability to express emotions. Fortunately, perceiving an object’s nature or its structure differs from perceiving its beauty [127]. Therefore, if we only focus on the essential concept, i.e., beauty is balance or harmony among the fundamental elements of fashion in an item of apparel or an outfit, fashion tasks can be completed to a certain extent by a computer. Naturally, the basic knowledge learning serves as the foundation of all higher-order fashion tasks.

However, even though we do not take ‘perception’ into consideration, only visually understanding fashion still remains many challenges. Specifically, it is difficult to obtain a clear definition of what constitutes the basic knowledge in fashion; e.g., ‘attributes’, ‘styles’, ‘trends’, and ‘design themes’. Here, we will present some easily comprehensible examples as a simple demonstration. The 7 shirt dresses shown in Figure 21 are obviously very different. The attributes that are most immediately obvious are the differences in their colours, branding, and prices. Furthermore, some of the dresses have different prints; the first shirt dress is colour-blocked, whereas the second and the last dresses are striped and the others are solid colours. Moreover, the materials used to make these shirt dresses are also different: the second dress is made of cotton, and the fourth is made of satin. Their silhouettes also differ: the fourth dress is H-line and the sixth is A-line. Thus far, we have only considered the...
main differences. If we investigate in further detail, we find that the waists of these 7 dresses are all
different from each other. The design of the pockets and the opening designs are also different. There
are many aspects that make these shirt dresses different from each other. We have only described a
few such aspects here. If we imagine these design attributes as letters in an alphabet, then the garment
is a word made up of these letters. Then, an outfit is like a sentence composed of many words, all
obeying a fixed grammar. Many outfits gather together to express a certain theme, such as a collection
in a fashion show, tell a story composed of many sentences. Now, we ask two questions:

- Is the love of Romeo and Juliet related to the 26 letters of the Roman alphabet?
- Is *Hamlet* only defined as a tragedy because of some of the words or sentences used in the
  play?

Here, we use the show *S. W. A. L. K. II* to explore similar concepts. The link below presents the
related media and information that can be easily find, such as a paragraph describing this show:

*The connectivity of interdependence becomes revalued in times of separation. The reliance of one
person upon another is a vital pas de deux activated by instinct and trust. For the Co-Ed Collection
Spring-Summer 2021, Maison Margiela interprets this concord through the tango. Vigorous and
intense, the dance is cathartic: releasing the spirit of the old, it inspires the lust to move on. It
compels acceptance; it heralds new beginnings; it beckons change.*

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65 https://en.wikipedia.org/wiki/Hamlet
66 https://www.maisonmargiela.com/us

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Figure 22: *S. W. A. L. K. II* (Sealed With A Loving Kiss, Maison Margiela Co-Ed SS21 by John
Galliano). Group picture. Standing, from left to right: Look 39, Look 37, Look 35, Look 30, Look
31, Look 33. Sitting, from left to right: Look 36A, Look 36B, Look 29, Look 32, Look 34.
We present some of the looks in this series in Figure 22. How did the designer use tulle, velvet, worn, silk, chiffon, leather, and other materials to express the theme of this show, as mentioned above?

- Are the feelings or emotions evoked by this collection closely related to the attributes of fashion that have been adopted?
- Can the theme expressed by this fashion show be understood by considering only Look 29 (a white stretch-tulle circular cut dress with farmed plumed trims worn over a white muslin, circular cut long-sleeved dress with white chiffon ghillies and white painted leather Tango pumps) or Look 30 (an ecru wool, double-breasted tuxedo with silk duchesse lapels worn over a white tuxedo shirt with white painted leather Hyperion ankle-strap shoes)?

As described in the summary of the hierarchy of visual understanding, the first, or lowest, level in the hierarchy is data (discrete elements), the second level is information (linked elements), the third level is knowledge (organised information), and the highest level is wisdom (applied knowledge). The challenges increase progressively at higher levels of visual understanding, and may include:

- Recognising data (visual recognition of fashion images).
- Turning data into effective information (obtaining fashion-related information from the recognised attributes, e.g., recognising a style or evaluating an outfit and knowing the behind reason for this evaluation judgement).
- Translating information into knowledge based on understanding (understanding clothing aesthetics, knowing how to predict trends and why trends occur).
- Applying information freely and forming insights (knowing how to create beauty and lead trends).

4 Opportunities

FASHION is a fresh field that full of opportunities. As summarised in the last Section, there has long way to go, even if only visually understand fashion. Undoubtedly, large amount of problems remain for researchers to tackle. In addition, under the impact of the epidemic, embracing technology becoming the new trend in fashion. The whole industry will be unavoidably be reshaped in the Post-COVID-19 Era. Addition to the Balenciage Fall 2021, many other designers also expressed their own thinkings to the FASHION in the near future; e.g., after Prada 2021 SS, there has ‘a conversation’ in which Miuccia talked her ideas about the relationship between humans and machines. We do not forecast the future of FASHION in the industry due to our limited abilities. Here we would like to use what Demna Gvasalia said to represent our viewpoints: ‘I believe in a future that is spiritual. Loading a forgotten past.’ In the following, we conduct a focused analysis of opportunities for research and summarise the possible directions:

Opportunities in ‘Evaluation’: ‘In God we trust; all others must bring data.’ As mentioned before, very few research have focused on the evaluation protocols in FASHION. In addition to the requirements for the algorithms proposed for a specific task to be compared fairly, a company also needs clear criteria to evaluate whether a model is qualified to be embedded in their online products or whether the modelled numbers or predictions can be trusted.

Opportunities in ‘Basic Tech’: Even though the research in the group of ‘Basic Tech’ are not directly related to a role in fashion, it is the foundation for computer to understand fashion images. As mentioned before, most studies targeted on clothing parsing [86, 83, 84, 26, 99, 163, 25, 94, 162, 158, 85, 100, 77, 87, 23, 42, 97, 24]. However, in terms of clothing parsing, none of them paid attention to the segmentation between the front piece and the back piece of a given single clothing item in a fashion image. Meanwhile, when several garments are dressed by a person at the same time, it arises a occlusion problem. In addition, it is great help if the model can segment the garment according to its design regions; e.g., neck region, sleeve region, body region, cuff region, shoulder region, chest region, waist region etc.

67 https://informationisbeautiful.net/2010/data-information-knowledge-wisdom/
68 https://www.vogue.com/fashion-shows/spring-2021-ready-to-wear/prada
69 W. Edwards Deming
Opportunities in ‘Selling’: From Figure 22, it is easy to see that there are many attributes of fashion that should be recognised. This is a multi-label classification task. We roughly estimate that the number of classification labels is over 250 [188]. Moreover, there is no existing open-access datasets of comprehensive and well-annotated fashion attributes. Thus, the efforts to train an AI model using current data will face challenges such as weakly labelled data and noises. The diverse format of fashion image data, including fashion show images, product images, model images, street photos, and social media images, also increases the difficulty of recognition. Here we would like to recall the basic requirements for the seller: 1. can recognise the detailed attributes of fashion products and know how to find similar items according to a general description using simple words provided by his or her customers; 2. can accurately recommend fashion products according to observations on both his or her customers and of trends; 3. can reply quickly to his or her customers about whether a particular item or size is available or out of stock. Therefore, the conclude the possible future directions including: 1. multi-label classification in weakly supervised manner; 2. fine-grained attributes recognition in webly data or videos; 3. image retrieval in massive data.

Opportunities in ‘Styling’: Current research in the group of ‘Styling’ are mainly focused on creating outfit composition for online recommendation. The basic requirements for a stylist are: 1. has a good sense of clothing aesthetics, such as a sense of colour, a sense of texture, and a sense of silhouette, and can easily create a well-composed outfit; 2. knows how to make an outfit attain visual balance for a given customer and mix and match according to different situations, such as for an occasion, the seasons, or body figure; 3. understands what beauty is and can convincingly explain his or her selections, enabling him or her to persuade the customers and provide satisfactory service; 4. always stays aware of fashion trends and can apply these trends to his or her work. Therefore, we conclude the possible future directions including: 1. evaluating an outfit is good or not with convincing explanation; 2. understanding about the basic ‘principles’ of mix and match and behind logic; 3. recommending personalised styling advice and catching up the trend in time.

Opportunities in ‘Design’: Most of current works focus on helping designers or online retailers to visually demonstrate their ideas, e.g., attribute editing [23,140,54], 3D garment generation [118,5,150,37,38], virtual try-on [125,21,72,20,13,45], etc. Certainly, with a holistic view of the ‘Design’ research, there remain many interesting but challenging tasks. Can AI models create new designs based on a theme with different predetermined constraints, such as seasons, trends, brand image, etc.? Thus, we conclude the possible future directions including: 1. utilising generation methods in virtual marketing; 2. applying generation methods in the process of fashion design; 3. expressing a concept or idea using fashion language.

Opportunities in ‘Buying’: Most research in this area focus on fashion forecasting, prediction, and selling [53,110,1144,124,109,151,142,132]. As a good buyer, he or she should: 1. can draw conclusions from records of previous sales; 2. have great insight into the market and the ability to make predictions; 3. very experienced in fashion retail and fully knows the market trends. Therefore, we conclude the possible future directions including: 1. predicting the market trends based on the analysis of massive data; 2. understanding the culture and inferring the effect of an event on fashion which can lead the trend of fashion.

‘Big data can tell us what is wrong, not what is right’[70]. Therefore, we should be very sceptical of any ‘big data analyst’ or ‘data scientist’ who claims to be able to explain a system in a particular domain without the requisite domain expertise or intimate knowledge of the underlying system under consideration[71]. To really help the industry, it is better to design tasks and solutions based on the domain knowledge.

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[70]N. Taleb
[71]https://medium.com/@adambreckler/in-god-we-trust-all-others-bring-data-96784d01e9be

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References

[1] Ziad Al-Halah and Kristen Grauman. Modeling fashion influence from photos. *IEEE Transactions on Multimedia*, 2020.

[2] Ziad Al-Halah and Kristen Grauman. From paris to berlin: Discovering fashion style influences around the world. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 10136–10145, 2020.

[3] Elaine M Bettaney, Stephen R Hardwick, Odysseas Zisimopoulos, and Benjamin Paul Chamberlain. Fashion outfit generation for e-commerce. *arXiv preprint arXiv:1904.00741*, 2019.

[4] Lukas Bossard, Matthias Dantone, Christian Leistner, Christian Wengert, Till Quack, and Luc Van Gool. Apparel classification with style. In *Asian conference on computer vision*, pages 321–335. Springer, 2012.

[5] Akin Caliskan, Armin Mustafa, Evren Imre, and Adrian Hilton. Multi-view consistency loss for improved single-image 3d reconstruction of clothed people. In *Proceedings of the Asian Conference on Computer Vision*, 2020.

[6] Hassler Castro and Mariana Ramirez. Segmentation task for fashion and apparel. *arXiv preprint arXiv:2006.11375*, 2020.

[7] Tong Che, Yanran Li, Athul Paul Jacob, Yoshua Bengio, and Wenjie Li. Mode regularized generative adversarial networks. *arXiv preprint arXiv:1612.02136*, 2016.

[8] Huizhong Chen, Andrew Gallagher, and Bernd Girod. Describing clothing by semantic attributes. In *European conference on computer vision*, pages 609–623. Springer, 2012.

[9] Lele Chen, Justin Tian, Guo Li, Cheng-Haw Wu, Erh-Kan King, Kuan-Ting Chen, Shao-Hang Hsieh, and Chenliang Xu. Tailorgan: Making user-defined fashion designs. In *Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision*, pages 3241–3250, 2020.

[10] Wen Chen, Pipei Huang, Jiaming Xu, Xin Guo, Cheng Guo, Fei Sun, Chao Li, Andreas Pfadler, Huan Zhao, and Bingqiang Zhao. Pog: personalized outfit generation for fashion recommendation at alibaba ifashion. In *Proceedings of the 25th ACM SIGKDD international conference on knowledge discovery & data mining*, pages 2662–2670, 2019.

[11] Wen-Huang Cheng, Sijie Song, Chieh-Yun Chen, Shintami Chusnul Hidayati, and Jiaying Liu. Fashion meets computer vision: A survey. *arXiv preprint arXiv:2003.13988*, 2020.

[12] Zhi-Qi Cheng, Xiao Wu, Yang Liu, and Xian-Sheng Hua. Video2shop: Exact matching clothes in videos to online shopping images. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 4048–4056, 2017.

[13] Chao-Te Chou, Cheng-Han Lee, Kaipeng Zhang, Hu-Cheng Lee, and Winston H Hsu. Pivtons: Pose invariant virtual try-on shoe with conditional image completion. In *Asian Conference on Computer Vision*, pages 654–668. Springer, 2018.

[14] Guillem Cucurull, Perouz Taslakian, and David Vazquez. Context-aware visual compatibility prediction. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 12617–12626, 2019.

[15] Yi Rui Cui, Qi Liu, Cheng Ying Gao, and Zhongbo Su. Fashiongan: Display your fashion design using conditional generative adversarial nets. In *Computer Graphics Forum*, volume 37, pages 109–119. Wiley Online Library, 2018.

[16] Zeyu Cui, Zukun Li, Shu Wu, Xiao-Yu Zhang, and Liang Wang. Dressing as a whole: Outfit compatibility learning based on node-wise graph neural networks. In *The World Wide Web Conference*, pages 307–317, 2019.

[17] Prutha Date, Ashwinkumar Ganesan, and Tim Oates. Fashioning with networks: neural style transfer to design clothes. In *KDD ML4Fashion workshop*, 2017.

[18] Wei Di, Catherine Wah, Anurag Bhardwaj, Robinson Piramuthu, and Neel Sundaresan. Style finder: Fine-grained clothing style detection and retrieval. In *Proceedings of the IEEE Conference on computer vision and pattern recognition workshops*, pages 8–13, 2013.

[19] Haoye Dong, Xiaodan Liang, Ke Gong, Hanjiang Lai, Jia Zhu, and Jian Yin. Soft-gated warping-gan for pose-guided person image synthesis. *arXiv preprint arXiv:1810.11610*, 2018.
[20] Haoye Dong, Xiaodan Liang, Xiaohui Shen, Bochao Wang, Hanjiang Lai, Jia Zhu, Zhiting Hu, and Jian Yin. Towards multi-pose guided virtual try-on network. In Proceedings of the IEEE/CVF International Conference on Computer Vision, pages 9026–9035, 2019.

[21] Haoye Dong, Xiaodan Liang, Xiaohui Shen, Bowen Wu, Bing-Cheng Chen, and Jian Yin. Fw-gan: Flow-navigated warping gan for video virtual try-on. In Proceedings of the IEEE/CVF International Conference on Computer Vision, pages 1161–1170, 2019.

[22] Haoye Dong, Xiaodan Liang, Xuyuan Zhang, Xujie Zhang, Zhenyu Xie, Bowen Wu, Ziqi Zhang, Xiaohui Shen, and Jian Yin. Fashion editing with multi-scale attention normalization. CoRR, abs/1906.00884, 2019.

[23] Haoye Dong, Xiaodan Liang, Yixuan Zhang, Xujie Zhang, Xiaohui Shen, Zhenyu Xie, Bowen Wu, and Jian Yin. Fashion editing with adversarial parsing learning. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 8120–8128, 2020.

[24] Jian Dong, Qiang Chen, Wei Xia, Zhongyang Huang, and Shuicheng Yan. A deformable mixture parsing model with parselets. In Proceedings of the IEEE International Conference on Computer Vision, pages 3408–3415, 2013.

[25] Jian Dong, Qiang Chen, Xiaohui Shen, Jianchao Yang, and Shuicheng Yan. Towards unified human parsing and pose estimation. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 843–850, 2014.

[26] Jian Dong, Qiang Chen, Zhongyang Huang, Jianchao Yang, and Shuicheng Yan. Parsing based on parselets: A unified deformable mixture model for human parsing. IEEE transactions on pattern analysis and machine intelligence, 38(1):88–101, 2015.

[27] Qi Dong, Shaogang Gong, and Xiatian Zhu. Class rectification hard mining for imbalanced deep learning. In Proceedings of the IEEE International Conference on Computer Vision, pages 1851–1860, 2017.

[28] Qi Dong, Shaogang Gong, and Xiatian Zhu. Multi-task curriculum transfer deep learning of clothing attributes. In 2017 IEEE Winter Conference on Applications of Computer Vision (WACV), pages 520–529. IEEE, 2017.

[29] Qi Dong, Shaogang Gong, and Xiatian Zhu. Imbalanced deep learning by minority class incremental rectification. IEEE transactions on pattern analysis and machine intelligence, 41(6):1367–1381, 2018.

[30] Alpana Dubey, Nitish Bhardwaj, Kumar Abhinav, Suma Mani Kuriakose, Sakshi Jain, and Veenu Arora. A p assisted apparel design. arXiv preprint arXiv:2007.04950, 2020.

[31] Patrick Esser, Ekaterina Sutter, and Björn Ommer. A variational u-net for conditional appearance and shape generation. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 8857–8866, 2018.

[32] Yuying Ge, Ruimao Zhang, Xiaogang Wang, Xiaoou Tang, and Ping Luo. Deepfashion2: A versatile benchmark for detection, pose estimation, segmentation and re-identification of clothing images. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 5337–5345, 2019.

[33] Wei Gong and Laila Khalid. Aesthetics, personalization and recommendation: A survey on deep learning in fashion. arXiv preprint arXiv:2101.08301, 2021.

[34] Qiao Gu, Guanzhi Wang, Mang Tik Chiu, Yu-Wing Tai, and Chi-Keung Tang. Ladn: Local adversarial disentangling network for facial makeup and de-makeup. In Proceedings of the IEEE/CVF International Conference on Computer Vision, pages 10481–10490, 2019.

[35] Xiaoling Gu, Yongkang Wong, Pai Peng, Lidan Shou, Gang Chen, and Mohan S Kankanhalli. Understanding fashion trends from street photos via neighbor-constrained embedding learning. In Proceedings of the 25th ACM international conference on Multimedia, pages 190–198, 2017.

[36] Xiaoling Gu, Yongkang Wong, Lidan Shou, Pai Peng, Gang Chen, and Mohan S Kankanhalli. Multimodal and multi-domain embedding learning for fashion retrieval and analysis. IEEE Transactions on Multimedia, 21(6):1524–1537, 2018.

[37] Erhan Gundogdu, Victor Constantin, Amrollah Seifoddini, Minh Dang, Mathieu Salzmann, and Pascal Fua. Garnet: A two-stream network for fast and accurate 3d cloth draping. In Proceedings of the IEEE/CVF International Conference on Computer Vision, pages 8739–8748, 2019.
[38] Erhan Gundogdu, Victor Constantin, Shaifali Parashar, Amrollah Seifoddini Banadkooki, Minh Dang, Mathieu Salzmann, and Pascal Fua. Garnet++: Improving fast and accurate static 3d cloth draping by curvature loss. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 2020.

[39] Sheng Guo, Weilin Huang, Xiao Zhang, Prasanna Srikhanta, Yin Cui, Yuan Li, Hartwig Adam, Matthew R Scott, and Serge Belongie. The imaterialist fashion attribute dataset. In *Proceedings of the IEEE International Conference on Computer Vision Workshops*, pages 0–0, 2019.

[40] M Hadi Kiapour and Robinson Piramuthu. Brand> logo: Visual analysis of fashion brands. In *Proceedings of the European Conference on Computer Vision (ECCV)*, pages 0–0, 2018.

[41] M Hadi Kiapour, Xufeng Han, Svetlana Lazebnik, Alexander C Berg, and Tamara L Berg. Where to buy it: Matching street clothing photos in online shops. In *Proceedings of the IEEE international conference on computer vision*, pages 3343–3351, 2015.

[42] Feng Han and Song-Chun Zhu. Bottom-up/top-down image parsing with attribute grammar. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 31(1):59–73, 2008.

[43] Xintong Han, Zuxuan Wu, Phoenix X. Huang, Xiao Zhang, Menglong Zhu, Yuan Li, Yang Zhao, and Larry S. Davis. Automatic spatially-aware fashion concept discovery. In *IJCC*, 2017.

[44] Xintong Han, Zuxuan Wu, Yu-Gang Jiang, and Larry S Davis. Learning fashion compatibility with bidirectional lstms. In *Proceedings of the 25th ACM international conference on Multimedia*, pages 1078–1086, 2017.

[45] Xintong Han, Zuxuan Wu, Zhe Wu, Ruichi Yu, and Larry S Davis. Viton: An image-based virtual try-on network. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 7543–7552, 2018.

[46] Xintong Han, Xiaojun Hu, Weilin Huang, and Matthew R Scott. Clothflow: A flow-based model for clothed person generation. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 10471–10480, 2019.

[47] Xintong Han, Zuxuan Wu, Weilin Huang, Matthew R Scott, and Larry S Davis. Finet: Compatible and diverse fashion image inpainting. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 4481–4491, 2019.

[48] Yu Han, Shuai Yang, Wenjing Wang, and Jiaying Liu. From design draft to real attire: Unaligned fashion image translation. In *Proceedings of the 28th ACM International Conference on Multimedia*, pages 1533–1541, 2020.

[49] Rajdeep Hazra Banerjee, Abhinav Ravi, and Ujjal K Dutta. Attr2style: A transfer learning approach for inferring fashion styles via apparel attributes. *arXiv e-prints*, pages arXiv–2008, 2020.

[50] Ruining He and Julian McAuley. Ups and downs: Modeling the visual evolution of fashion trends with one-class collaborative filtering. In *Proceedings of the 25th international conference on world wide web*, pages 507–517, 2016.

[51] Ruining He, Charles Packer, and Julian McAuley. Learning compatibility across categories for heterogeneous item recommendation. In *2016 IEEE 16th International Conference on Data Mining (ICDM)*, pages 937–942. IEEE, 2016.

[52] Shintami Chusnul Hidayati, Ting Wei Goh, Ji-Sheng Gary Chan, Cheng-Chun Hsu, John See, Wong Lai Kuan, Kai-Lung Hua, Yu Tsao, and Wen-Huang Cheng. Dress with style: Learning style from joint deep embedding of clothing styles and body shapes. *IEEE Transactions on Multimedia*, 2020.

[53] Wei-Lin Hsiao and Kristen Grauman. From culture to clothing: Discovering the world events behind a century of fashion images. *arXiv preprint arXiv:2102.01690*, 2021.

[54] Wei-Lin Hsiao, Isay Katsman, Chao-Yuan Wu, Devi Parikh, and Kristen Grauman. Fashion++: Minimal edits for outfit improvement. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 5047–5056, 2019.

[55] Zhiting Hu, Zichao Yang, Ruslan Salakhutdinov, Xiaodan Liang, Lianhui Qin, Haoye Dong, and Eric Xing. Deep generative models with learnable knowledge constraints. *arXiv preprint arXiv:1806.09764*, 2018.

[56] Junshi Huang, Rogerio S Feris, Qiang Chen, and Shuicheng Yan. Cross-domain image retrieval with a dual attribute-aware ranking network. In *Proceedings of the IEEE international conference on computer vision*, pages 1062–1070, 2015.
[57] Zeng Huang, Yuanlu Xu, Christoph Lassner, Hao Li, and Tony Tung. Arch: Animatable reconstruction of clothed humans. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 3093–3102, 2020.

[58] Naoto Inoue, Edgar Simo-Serra, Toshihiko Yamasaki, and Hiroshi Ishikawa. Multi-Label Fashion Image Classification with Minimal Human Supervision. In Proceedings of the International Conference on Computer Vision Workshops (ICCVW), 2017.

[59] Vignesh Jagadeesh, Robinson Piramuthu, Anurag Bhardwaj, Wei Di, and Neel Sundaresan. Large scale visual recommendations from street fashion images. In Proceedings of the 20th ACM SIGKDD international conference on Knowledge discovery and data mining, pages 1925–1934, 2014.

[60] Menglin Jia, Mengyun Shi, Mikhail Sirotenko, Yin Cui, Bharath Hariharan, Claire Cardie, and Serge Belongie. The fashionpedia ontology and fashion segmentation dataset. Cornell University, 2019.

[61] Boyi Jiang, Juyong Zhang, Yang Hong, Jinhao Luo, Ligang Liu, and Hujun Bao. Benet: Learning body and cloth shape from a single image. In European Conference on Computer Vision, pages 18–35. Springer, 2020.

[62] Shuhui Jiang and Yun Fu. Fashion style generator. In Proceedings of the 26th International Joint Conference on Artificial Intelligence, pages 3721–3727, 2017.

[63] Wang-Cheng Kang, Chen Fang, Zhaowen Wang, and Julian McAuley. Visually-aware fashion recommendation and design with generative image models. In 2017 IEEE International Conference on Image Mining (ICDM), pages 207–216. IEEE, 2017.

[64] Wang-Cheng Kang, Eric Kim, Jure Leskovec, Charles Rosenberg, and Julian McAuley. Complete the look: Scene-based complementary product recommendation. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 10532–10541, 2019.

[65] Divva Kashilani, Lalit B Damahhe, and Nileshsingh V Thakur. An overview of image recognition and retrieval of clothing items. In 2018 International Conference on Research in Intelligent and Computing in Engineering (RICE), pages 1–6. IEEE, 2018.

[66] Natsumi Kato, Hiroyuki Osone, Daitsu Sato, Naoya Muramatsu, and Yoichi Ochiai. Deepwear: a case study of collaborative design between human and artificial intelligence. In Proceedings of the Twelfth International Conference on Tangible, Embedded, and Embodied Interaction, pages 529–536, 2018.

[67] Natsumi Kato, Hiroyuki Osone, Kotaro Oomori, Chun Wei Ooi, and Yoichi Ochiai. Gans-based clothes design: Pattern maker is all you need to design clothing. In Proceedings of the 10th Augmented Human International Conference 2019, pages 1–7, 2019.

[68] M Hadi Kiapour, Kota Yamaguchi, Alexander C Berg, and Tamara L Berg. Hipster wars: Discovering elements of fashion styles. In European conference on computer vision, pages 472–488. Springer, 2014.

[69] Donghyun Kim, Kuniaki Saito, Kate Saenko, Stan Sclaroff, and Bryan A Plummer. Self-supervised visual attribute learning for fashion compatibility. arXiv preprint arXiv:2008.00348, 2020.

[70] Adriana Kovashka, Devi Parikh, and Kristen Grauman. Whittlesearch: Image search with relative attribute feedback. In 2012 IEEE Conference on Computer Vision and Pattern Recognition, pages 2973–2980. IEEE, 2012.

[71] Zhenzhong Kuang, Jun Yu, Zhou Yu, and Jianping Fan. Ontology-driven hierarchical deep learning for fashion recognition. In 2018 IEEE Conference on Multimedia Information Processing and Retrieval (MIPR), pages 19–24. IEEE, 2018.

[72] Gaurav Kuppa, Andrew Jong, Xin Liu, Ziwei Liu, and Teng-Sheng Moh. Shineon: Illuminating design choices for practical video-based virtual clothing try-on. In Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision, pages 191–200, 2020.

[73] Katrien Laenen and Marie-Francine Moens. Attention-based fusion for outfit recommendation. In Fashion Recommender Systems, pages 69–86. Springer, 2020.

[74] Katrien Laenen, Susana Zoghbi, and Marie-Francine Moens. Cross-modal search for fashion attributes. In Proceedings of the KDD 2017 Workshop on Machine Learning Meets Fashion, volume 2017, pages 1–10. ACM, 2017.

[75] Sumin Lee, Sungchan Oh, Chanho Jung, and Changick Kim. A global-local embedding module for fashion landmark detection. In Proceedings of the IEEE/CVF International Conference on Computer Vision Workshops, pages 0–0, 2019.

26
[76] Kedan Li, Chen Liu, and David Forsyth. Coherent and controllable outfit generation. *arXiv preprint arXiv:1906.07273*, 2019.

[77] Qizhu Li, Anurag Arnab, and Philip HS Torr. Holistic, instance-level human parsing. *arXiv preprint arXiv:1709.03612*, 2017.

[78] Tingting Li, Ruihe Qian, Chao Dong, Si Liu, Qiong Yan, Wenwu Zhu, and Liang Lin. Beautygan: Instance-level facial makeup transfer with deep generative adversarial network. In *Proceedings of the 26th ACM international conference on Multimedia*, pages 645–653, 2018.

[79] Xingchen Li, Xiang Wang, Xiangnan He, Long Chen, Jun Xiao, and Tat-Seng Chua. Hierarchical fashion graph network for personalized outfit recommendation. In *Proceedings of the 43rd International ACM SIGIR Conference on Research and Development in Information Retrieval*, pages 159–168, 2020.

[80] Yao Li, Xianggang Han, Nianjuan Jiang, Kui Jia, and Jiangbo Lu. A deep learning based interactive sketching system for fashion images design. *arXiv preprint arXiv:2010.04413*, 2020.

[81] Yixin Li, Shengqin Tang, Yun Ye, and Jinwen Ma. Spatial-aware non-local attention for fashion landmark detection. In *2019 IEEE International Conference on Multimedia and Expo (ICME)*, pages 820–825. IEEE, 2019.

[82] Yue Li, Marc Habermann, Bernhard Thomaszewski, Stelian Coros, Thabo Beeler, and Christian Theobalt. Deep physics-aware inference of cloth deformation for monocular human performance capture. *arXiv preprint arXiv:2011.12866*, 2020.

[83] Xiaodan Liang, Si Liu, Xiaohui Shen, Jianchao Yang, Luoqi Liu, Jian Dong, Liang Lin, and Shuicheng Yan. Deep human parsing with active template regression. *IEEE transactions on pattern analysis and machine intelligence*, 37(12):2402–2414, 2015.

[84] Xiaodan Liang, Chunyan Xu, Xiaohui Shen, Jianchao Yang, Si Liu, Jinhui Tang, Liang Lin, and Shuicheng Yan. Human parsing with contextualized convolutional neural network. In *Proceedings of the IEEE international conference on computer vision*, pages 1386–1394, 2015.

[85] Xiaodan Liang, Liang Lin, Wei Yang, Ping Luo, Junshi Huang, and Shuicheng Yan. Clothes co-parsing via joint image segmentation and labeling with application to clothing retrieval. *IEEE Transactions on Multimedia*, 18(6):1175–1186, 2016.

[86] Xiaodan Liang, Xiaohui Shen, Jiashi Feng, Liang Lin, and Shuicheng Yan. Semantic object parsing with graph lstm. In *European Conference on Computer Vision*, pages 125–143. Springer, 2016.

[87] Xiaodan Liang, Xiaohui Shen, Jianchao Yang, Si Liu, Jinhui Tang, Liang Lin, and Shuicheng Yan. Deep human parsing with active template regression. *IEEE transactions on pattern analysis and machine intelligence*, 41(4):871–885, 2018.

[88] Kevin Lin, Huei-Fang Yang, Kuan-Hsien Liu, Jen-Hao Hsiao, and Chu-Song Chen. Rapid clothing retrieval via deep learning of binary codes and hierarchical search. In *Proceedings of the 5th ACM on International Conference on Multimedia Retrieval*, pages 499–502, 2015.

[89] Tzu-Heng Lin. Aggregation and finetuning for clothes landmark detection. *arXiv preprint arXiv:2005.00419*, 2020.

[90] Yen-Liang Lin, Son Tran, and Larry S Davis. Fashion outfit complementary item retrieval. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 3311–3319, 2020.

[91] Yusan Lin, Maryam Moosaei, and Hao Yang. Learning personal tastes in choosing fashion outfits. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops*, pages 0–0, 2019.

[92] Kuan-Hsien Liu, Ting-Yen Chen, and Chu-Song Chen.Mvc: A dataset for view-invariant clothing retrieval and attribute prediction. In *Proceedings of the 2016 ACM on International Conference on Multimedia Retrieval*, pages 313–316, 2016.

[93] Linlin Liu, Haijun Zhang, Yuzhu Ji, and QM Jonathan Wu. Toward ai fashion design: An attribute-gan model for clothing match. *Neurocomputing*, 341:156–167, 2019.

[94] Si Liu, Shuicheng Yan, Tianzhu Zhang, Changsheng Xu, Jing Liu, and Hanqing Lu. Weakly supervised graph propagation towards collective image parsing. *IEEE Transactions on Multimedia*, 14(2):361–373, 2011.
[115] Shinya Miura, Toshihiko Yamasaki, and Kiyoharu Aizawa. Snapper: fashion coordinate image retrieval system. In 2013 International Conference on Signal-Image Technology & Internet-Based Systems, pages 784–789. IEEE, 2013.

[116] Ryota Natsume, Shunsuke Saito, Zeng Huang, Weikai Chen, Chongyang Ma, Hao Li, and Shigeo Morishima. Siclope: Silhouette-based clothed people. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 4480–4490, 2019.

[117] Nilesh Pandey and Andreas Savakis. Poly-gan: Multi-conditioned gan for fashion synthesis. Neurocomputing, 414:356–364, 2020.

[118] Chaitanya Patel, Zhouyingcheng Liao, and Gerard Pons-Moll. Tailornet: Predicting clothing in 3d as a function of human pose, shape and garment style. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 7365–7375, 2020.

[119] Luisa F Polanía and Satyajit Gupte. Learning fashion compatibility across apparel categories for outfit recommendation. In 2019 IEEE International Conference on Image Processing (ICIP), pages 4489–4493. IEEE, 2019.

[120] Thomas Reid. Essays on the intellectual powers of man. Number 66. J. Bartlett, 1850.

[121] Himani Sachdeva and Shreelekha Pandey. Interactive systems for fashion clothing recommendation. In Emerging Technology in Modelling and Graphics, pages 287–294. Springer, 2020.

[122] Dikshant Sagar, Jatin Garg, Prarthana Kansal, Sejal Bhalla, Rajiv Ratn Shah, and Yi Yu. Pai-bpr: Personalized outfit recommendation scheme with attribute-wise interpretability. In 2020 IEEE Sixth International Conference on Multimedia Big Data (BigMM), pages 221–230. IEEE, 2020.

[123] Shunsuke Saito, Zeng Huang, Ryota Natsume, Shigeo Morishima, Angjoo Kanazawa, and Hao Li. Pifu: Pixel-aligned implicit function for high-resolution clothed human digitization. In Proceedings of the IEEE/CVF International Conference on Computer Vision, pages 2304–2314, 2019.

[124] Shravan Sajja, Nupur Aggarwal, Sumanta Mukherjee, Kushagra Manglik, Satyam Dwivedi, and Vikas Raykar. Explainable ai based interventions for pre-season decision making in fashion retail. In 8th ACM IKDD CODS and 26th COMAD, pages 281–289. 2021.

[125] Igor Santesteban, Miguel A Otaduy, and Dan Casas. Learning-based animation of clothing for virtual try-on. In Computer Graphics Forum, volume 38, pages 355–366. Wiley Online Library, 2019.

[126] Ohman Shai, Mohamed Elhoseiny, Antoine Bordes, Yann LeCun, and Camille Couprie. Design: Design inspiration from generative networks. In Proceedings of the European Conference on Computer Vision (ECCV) Workshops, pages 0–0, 2018.

[127] James Shelley. The concept of the aesthetic. 2017.

[128] Jake Sherman, Chinmay Shukla, Rhonda Textor, Su Zhang, and Amy A Winecoff. Assessing fashion recommendations: A multifaceted offline evaluation approach. arXiv preprint arXiv:1909.04496, 2019.

[129] Wu Shi, Tak-Wai Hui, Ziwei Liu, Dahua Lin, and Chen Change Loy. Learning to synthesize fashion textures. arXiv preprint arXiv:1911.07472, 2019.

[130] Aliaksandr Siarohin, Enver Sangineto, Stéphane Lathuiliere, and Nicu Sebe. Deformable gans for pose-based human image generation. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 3408–3416, 2018.

[131] Edgar Simo-Serra, Sanja Fidler, Francesc Moreno-Noguer, and Raquel Urtasun. Neuroaesthetics in Fashion: Modeling the Perception of Fashionability. In Proceedings of the Conference on Computer Vision and Pattern Recognition (CVPR), 2015.

[132] Pawan Kumar Singh, Yadunath Gupta, Nilpa Jha, and Aruna Rajan. Fashion retail: Forecasting demand for new items. arXiv preprint arXiv:1907.01960, 2019.

[133] Anirudh Singhal, Ayush Chopra, Kumar Ayush, Utkarsh Patel Govind, and Balaji Krishnamurthy. Towards a unified framework for visual compatibility prediction. In Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision, pages 3607–3616, 2020.

[134] Sijie Song and Tao Mei. When multimedia meets fashion. IEEE MultiMedia, 25(3):102–108, 2018.
[135] Xuemeng Song, Fuli Feng, Jinhuan Liu, Zeikun Li, Liqiang Nie, and Jun Ma. Neurostylist: Neural compatibility modeling for clothing matching. In Proceedings of the 25th ACM international conference on Multimedia, pages 753–761, 2017.

[136] Xuemeng Song, Fuli Feng, Xianjing Han, Xin Yang, Wei Liu, and Liqiang Nie. Neural compatibility modeling with attentive knowledge distillation. In The 41st International ACM SIGIR Conference on Research & Development in Information Retrieval, pages 5–14, 2018.

[137] Xuemeng Song, Xianjing Han, Yunkai Li, Jingyuan Chen, Xin-Shun Xu, and Liqiang Nie. Gp-bpr: Personalized compatibility modeling for clothing matching. In Proceedings of the 27th ACM International Conference on Multimedia, pages 320–328, 2019.

[138] Omprakash Sonie, Muthusamy Chelliah, and Shamik Sural. Personalised fashion recommendation using deep learning. In Proceedings of the ACM India Joint International Conference on Data Science and Management of Data, pages 368–368, 2019.

[139] Maria Anastassia Stefanis, Vassilios Stefanis, and John Garofalakis. Crfs: A trends-driven collaborative fashion recommendation system. In 2019 10th International Conference on Information, Intelligence, Systems and Applications (IISA), pages 1–4. IEEE, 2019.

[140] Zhaoqi Su, Tao Yu, Yangang Wang, Yipeng Li, and Yebin Liu. Deepcloth: Neural garment representation for shape and style editing. arXiv preprint arXiv:2011.14619, 2020.

[141] Guang-Lu Sun, Jun-Yan He, Xiao Wu, Bo Zhao, and Qiang Peng. Learning fashion compatibility across categories with deep multimodal neural networks. Neurocomputing, 395:237–246, 2020.

[142] Shin Woong Sung, Hyunsuk Baek, Hyeonjun Sim, Eun Hie Kim, Hyunwoo Hwangbo, and Young Jae Jang. Breaking moravec’s paradox: Visual-based distribution in smart fashion retail. arXiv preprint arXiv:2007.09102, 2020.

[143] Moeko Takagi, Edgar Simo-Serra, Satoshi lizuka, and Hiroshi Ishikawa. What makes a style: Experimental analysis of fashion prediction. In Proceedings of the IEEE International Conference on Computer Vision Workshops, pages 2247–2253, 2017.

[144] Satoshi Takahashi, Keiko Yamaguchi, and Asuka Watanabe. Cat street: Chronicle archive of tokyo street-fashion. arXiv preprint arXiv:2009.13395, 2020.

[145] Koya Tango, Marie Katsurai, Hayato Maki, and Ryosuke Goto. Anime-to-real clothing: Cosplay costume generation via image-to-image translation. arXiv preprint arXiv:2008.11479, 2020.

[146] Pongsatie Tangseng and Takayuki Okatani. Toward explainable fashion recommendation. In Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision, pages 2153–2162, 2020.

[147] Pongsatie Tangseng, Zhipeng Wu, and Kota Yamaguchi. Looking at outfit to parse clothing. arXiv preprint arXiv:1703.01386, 2017.

[148] Pongsatie Tangseng, Kota Yamaguchi, and Takayuki Okatani. Recommending outfits from personal closet. In Proceedings of the IEEE International Conference on Computer Vision Workshops, pages 2275–2279, 2017.

[149] Qing Tian, Sampath Chanda, KC Kumar, and Douglas Gray. Improving apparel detection with category grouping and multi-grained branches. arXiv preprint arXiv:2101.06770, 2021.

[150] Gul Varol, Duygu Ceylan, Bryan Russell, Jimei Yang, Ersin Yumer, Ivan Laptev, and Cordelia Schmid. Bodynet: Volumetric inference of 3d human body shapes. In Proceedings of the European Conference on Computer Vision (ECCV), pages 20–36, 2018.

[151] Rajesh Kumar Vashisth, Vibhuti Burman, Rajan Kumar, Srividhya Sethuraman, Abhinay R Sekar, and Sharadha Ramanan. Product age based demand forecast model for fashion retail. arXiv preprint arXiv:2007.05278, 2020.

[152] Mariya I. Vasileva, Bryan A. Plummer, Krishna Dusad, Shreya Rajpal, Ranjitha Kumar, and David Forsyth. Learning type-aware embeddings for fashion compatibility. In ECCV, 2018.

[153] Dhruv Verma, Kshitij Gulati, and Rajiv Ratan Shah. Addressing the cold-start problem in outfit recommendation using visual preference modelling. In 2020 IEEE Sixth International Conference on Multimedia Big Data (BigMM), pages 251–256. IEEE, 2020.
[154] Sirion Vittayakorn, Takayuki Umeda, Kazuhiko Murasaki, Kyoko Sudo, Takayuki Okatani, and Kota Yamaguchi. Automatic attribute discovery with neural activations. In European Conference on Computer Vision, pages 252–268. Springer, 2016.

[155] Nan Wang and Haizhou Ai. Who blocks who: Simultaneous clothing segmentation for grouping images. In 2011 International Conference on Computer Vision, pages 1535–1542. IEEE, 2011.

[156] Xin Wang, Bo Wu, and Yueqi Zhong. Outfit compatibility prediction and diagnosis with multi-layered comparison network. In Proceedings of the 27th ACM International Conference on Multimedia, pages 329–337, 2019.

[157] Nannan Wu, Qianwen Chao, Yanzhen Chen, Weiwei Xu, Chen Liu, Dinesh Manocha, Wenxin Sun, Yi Han, Xinran Yao, and Xiaogang Jin. Example-based real-time clothing synthesis for virtual agents. arXiv preprint arXiv:2101.03088, 2021.

[158] Qiong Wu and Pierre Boulanger. Enhanced reweighted mrfs for efficient fashion image parsing. ACM Transactions on Multimedia Computing, Communications, and Applications (TOMM), 12(3):1–16, 2016.

[159] Fangting Xia, Peng Wang, Xianjie Chen, and Alan L Yuille. Joint multi-person pose estimation and semantic part segmentation. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 6769–6778, 2017.

[160] Wenqi Xian, Patsorn Sangkloy, Varun Agrawal, Amit Raj, Jingwan Lu, Chen Fang, Fisher Yu, and James Hays. Texturegan: Controlling deep image synthesis with texture patches. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 8456–8465, 2018.

[161] Tong Xiao, Tian Xia, Yi Yang, Chang Huang, and Xiaogang Wang. Learning from massive noisy labeled data for image classification. In CVPR, 2015.

[162] Kota Yamaguchi, M Hadi Kiapour, Luis E Ortiz, and Tamara L Berg. Parsing clothing in fashion photographs. In 2012 IEEE Conference on Computer vision and pattern recognition, pages 3570–3577. IEEE, 2012.

[163] Kota Yamaguchi, M Hadi Kiapour, and Tamara L Berg. Paper doll parsing: Retrieving similar styles to parse clothing items. In Proceedings of the IEEE international conference on computer vision, pages 3519–3526, 2013.

[164] Kota Yamaguchi, M Hadi Kiapour, Luis E Ortiz, and Tamara L Berg. Retrieving similar styles to parse clothing. IEEE transactions on pattern analysis and machine intelligence, 37(5):1028–1040, 2014.

[165] Kota Yamaguchi, Takayuki Okatani, Kyoko Sudo, Kazuhiko Murasaki, and Yukinobu Taniguchi. Mix and match: Joint model for clothing and attribute recognition. In BMVC, volume 1, page 4, 2015.

[166] Sijie Yan, Ziwei Liu, Ping Luo, Shi Qiu, Xiaogang Wang, and Xiaou Tang. Unconstrained fashion landmark detection via hierarchical recurrent transformer networks. In Proceedings of the 25th ACM international conference on Multimedia, pages 172–180, 2017.

[167] Xun Yang, Xiangnan He, Xiang Wang, Yunshan Ma, Fuli Feng, Meng Wang, and Tat-Seng Chua. Interpretable fashion matching with rich attributes. In Proceedings of the 42nd International ACM SIGIR Conference on Research and Development in Information Retrieval, pages 775–784, 2019.

[168] Xun Yang, Xiaoyu Du, and Meng Wang. Learning to match on graph for fashion compatibility modeling. In Proceedings of the AAAI Conference on Artificial Intelligence, volume 34, pages 287–294, 2020.

[169] Jae Shin Yoon, Kihwan Kim, Jan Kautz, and Hyun Soo Park. Neural 3d clothes retargeting from a single image. arXiv preprint arXiv:2102.00062, 2021.

[170] A. Yu and K. Grauman. Fine-grained visual comparisons with local learning. In Computer Vision and Pattern Recognition (CVPR), Jun 2014.

[171] Aron Yu and Kristen Grauman. Fine-grained visual comparisons with local learning. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 192–199, 2014.

[172] Cong Yu, Yang Hu, Yan Chen, and Bing Zeng. Personalized fashion design. In Proceedings of the IEEE/CVF International Conference on Computer Vision, pages 9046–9055, 2019.

[173] Weijiang Yu, Xiaodan Liang, Ke Gong, Chenhan Jiang, Nong Xiao, and Liang Lin. Layout-graph reasoning for fashion landmark detection. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 2937–2945, 2019.
[174] Chenxi Yuan and Mohsen Moghaddam. Garment design with generative adversarial networks. *arXiv preprint arXiv:2007.10947*, 2020.

[175] Huijing Zhan, Boxin Shi, and Alex C Kot. Cross-domain shoe retrieval with a semantic hierarchy of attribute classification network. *IEEE Transactions on Image Processing*, 26(12):5867–5881, 2017.

[176] Huijing Zhan, Boxin Shi, and Alex C Kot. Street-to-shop shoe retrieval with multi-scale viewpoint invariant triplet network. In *2017 IEEE Conference on Image Processing (ICIP)*, pages 1102–1106. IEEE, 2017.

[177] Huijing Zhan, Boxin Shi, Ling-Yu Duan, and Alex C Kot. Deepshoe: An improved multi-task viewpoint-invariant cnn for street-to-shop shoe retrieval. *Computer Vision And Image Understanding*, 180:23–33, 2019.

[178] Huijing Zhan, Chenyu Yi, Boxin Shi, Jie Lin, Ling-Yu Duan, and Alex C Kot. Pose-normalized and appearance-preserved street-to-shop clothing image generation and feature learning. *IEEE Transactions on Multimedia*, 23:133–144, 2020.

[179] Haijun Zhang, Wang Huang, Linlin Liu, and Xiaofei Xu. Clothes collocation recommendations by compatibility learning. In *2018 IEEE International Conference on Web Services (ICWS)*, pages 179–186. IEEE, 2018.

[180] Heming Zhang, Xuewen Yang, Jianchao Tan, Chi-Hao Wu, Jie Wang, and C-C Jay Kuo. Learning color compatibility in fashion outfits. *arXiv preprint arXiv:2007.02388*, 2020.

[181] Meng Zhang, Tuanfeng Wang, Duygu Ceylan, and Niloy J Mitra. Deep detail enhancement for any garment. *arXiv e-prints*, pages arXiv–2008, 2020.

[182] Zhenjie Zhao and Xiaofei Xu. A compensation method of two-stage image generation for human-ai collaborated in-situ fashion design in augmented reality environment. In *2018 IEEE International Conference on Artificial Intelligence and Virtual Reality (AVIR)*, pages 76–83. IEEE, 2018.

[183] Haitian Zheng, Kefei Wu, Jong-Hwi Park, Wei Zhu, and Jiebo Luo. Personalized fashion recommendation from personal social media data: An item-to-set metric learning approach. *arXiv preprint arXiv:2005.12439*, 2020.

[184] Xingran Zhou, Siyu Huang, Bin Li, Yingming Li, Jiachen Li, and Zhongfei Zhang. Text guided person image synthesis. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 3663–3672, 2019.

[185] Shizhan Zhu, Raquel Urtasun, Sanja Fidler, Dahua Lin, and Chen-Change Loy. Be your own prada: Fashion synthesis with structural coherence. In *Proceedings of the IEEE international conference on computer vision*, pages 1680–1688, 2017.

[186] Thomas Ziegler, Judith Butepage, Michael C Welle, Anastasiia Varava, Tonci Novkovic, and Danica Krugic. Fashion landmark detection and category classification for robotics. In *2020 IEEE International Conference on Autonomous Robot Systems and Competitions (ICARSC)*, pages 81–88. IEEE, 2020.

[187] Xingxing Zou, Wai Keung Wong, and Dongmei Mo. Fashion meets ai technology. In *International Conference on Artificial Intelligence on Textile and Apparel*, pages 255–267. Springer, 2018.

[188] Xingxing Zou, Xiangheng Kong, Waikeung Wong, Congde Wang, Yuguang Liu, and Yang Cao. Fashionai: A hierarchical dataset for fashion understanding. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops*, pages 0–0, 2019.

[189] Xingxing Zou, Zhizhong Li, Ke Bai, Dahua Lin, and Waikeung Wong. Regularizing reasons for outfit evaluation with gradient penalty. *arXiv preprint arXiv:2002.00460*, 2020.