Buy Me That Look: An Approach for Recommending Similar Fashion Products

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ABSTRACT

The recent proliferation of numerous fashion e-commerce platforms has led to a surge in online shopping of fashion products. Fashion being the dominant aspect in online retail sales, demands for efficient and effective fashion products recommendation systems that could boost revenue, improve customer experience and engagement. In this paper, we focus on the problem of similar fashion item recommendation for multiple fashion items. Specifically, given a Product Display Page for a fashion item in an online e-commerce platform, we identify the images with a full-shot look, i.e., the one with a full human model wearing the fashion item. While the majority of existing works in this domain focus on retrieving similar products corresponding to a single item present in a query, we focus on the retrieval of multiple fashion items at once. This is an important problem because while a user might have searched for a particular primary article type (e.g., men’s shorts), the human model in the full-shot look image would usually be wearing secondary fashion items as well (e.g., t-shirts, shoes etc). Upon looking at the full-shot look image in the PDP, the user might also be interested in viewing similar items for the secondary article types. To address this need, we use human keypoint detection to first identify the fullshot images, from which we subsequently select the front facing ones. An article detection and localisation module pretrained on a large-dataset is then used to identify different articles in the image. The detected articles and the catalog database images are then represented in a common embedding space, for the purpose of similarity based retrieval. We make use of a triplet-based neural network to obtain the embeddings. Our embedding network by virtue of an active-learning component achieves further improvements in the retrieval performance. The efficacy and superiority of our framework is demonstrated both empirically and qualitatively over similar approaches.

CCS CONCEPTS
• Computing methodologies → Visual content-based indexing and retrieval; Image representations; Object detection.

KEYWORDS
Multimedia Content Retrieval, Customer Engagement, Image Similarity, Key-point Detection, Representation Learning

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1 INTRODUCTION

The proliferation of numerous online platforms (e.g., Zalando ¹, Ssense ², Myntra ³, Farfetch ⁴) dealing with fashion e-commerce has been witnessed lately. The prevalence of online shopping, added with the fact that fashion products top across all categories in online retail sales [9] necessitates the importance of fashion product recommendations.

However, contrary to traditional product recommendations, fashion product recommendation is challenging. For example, fashion products are often displayed under various settings (e.g., clean in-shop clothes, clothes worn by a model with studio/ street background etc) thus making it difficult to identify and extract the relevant product. Additionally, the enormous amount of variations present in fashion items by virtue of their color, texture, shapes, viewpoint, illumination and styles further add to the difficulty of efficient and effective fashion item recommendation.

In traditional query based product retrieval encountered in Content Based Item Recommendation (CBIR) systems of e-commerce platforms, they usually have only a single product to identify and retrieve. However, this is not the case in fashion products retrieval/recommendation. A noteworthy hurdle in fashion products recommendation is the fact that a typical Product Display Page (PDP) for a fashion item present in an online platform often displays the fashion product on a human model. The models can be seen wearing multiple fashion articles at the same time.

This poses an added difficulty in efficient recommendation. This is because, even though a user might have initially searched for men’s short as the primary product item, a PDP would retrieve an image with a model wearing additional items (t-shirt, shoes etc), apart from the men’s short being searched for (see Figure 1). Naturally, the user might be interested in viewing similar items corresponding to the additional articles present in the PDP.

Another realm where a similar problem is prevalent, is that of products recommendation in image based social media platforms (e.g., Instagram, Facebook). People often follow celebrities (or influencers), who regularly post images of themselves wearing fashion items. To mimic their favourite influencers, people would often want to view similar products that they could buy.

In this paper, we study an approach to address this problem of simultaneously recommending multiple similar fashion items as present in an image. It should be noted that in the recent years, a number of works in literature have addressed various problems encountered in fashion products recommendation [11, 12, 14, 20, 21]. However, the primary focus of majority of these approaches is the retrieval/recommendation of a single fashion item at a time. In contrast, we focus on detecting all the unique fashion items as present in an image, and recommending similar products corresponding to the detected ones. The major significance of our approach is that it not only promotes cross-sells to boost revenue, but also aims at improving customer experience, engagement, and hence, satisfaction. In practice, this is indicated by increases in metrics like Click Through Rate (CTR) or Add to Cart ratio.

More specifically, we propose a novel multi-stage automated framework leveraging computer vision based techniques. A high-level illustration of the pipeline of our framework can be seen in Figure 2. Usually, the images of the searched fashion product are present in different views (or looks/ shots) in the PDP (Figure 1). For example, the products may be shown in different views or angles, zoomed in, as a table-top image or in the full-shot look image on a human model. Of key interest among these images is the one in the full-shot (shown in pink in Figure 1-a), i.e., the one containing a human model wearing the article type. This is the image that consists of multiple fashion products.

Given a text or image query for a fashion product, we first retrieve all the images present in the PDP of the product. Among these, the full-shot look image is identified. This is done by extracting human key points in a PDP image. The presence of ankle and eyes keypoints indicate that an image is a full-shot image containing an entire human model. However, we further use a pose classification component to identify the frontal pose among all the full-shot images.

The obtained front-posing full-shot look image is used for further processing by an article detection and localisation module. This module is trained on a large collection of annotated images, thus helping in detection of different fashion items present in the image (e.g., men’s shorts, t-shirts, shoes etc). Having identified the different fashion articles, we train a model corresponding to each broader article type (bottom-wear, top-wear, outer-wear, footwear etc), to extract semantic embeddings that brings representations of similar fashion items together, while moving away dissimilar ones. In particular, we use a triplet network for obtaining the embeddings.

We train our triplet network on a standard dataset of images to obtain our initial triplets, and later fine-tune our embedding model by identifying harder negatives, i.e., the ones misclassified by our current model. Using the fine-tuned embedding network, we obtain representations of all articles present in the front-posing full-shot look image, and also the articles present in the database. The top items from the database, based on their similarities to the query articles with respect to the embeddings, are retrieved and recommended to the user.

It should be noted that while it is possible to manually identify full-shot images and pair them with secondary/complementary article types (or accessories) to be displayed in the PDP of the primary article type, it is a tedious task. This poses a limitation to the potential of efficient fashion item recommendation. Our proposed framework provides a solution to this issue by automatically detecting not only the key-points, but also the article types, in an end-to-end pipeline. Our approach being generic in nature, can also be utilized in other multimedia platforms like product recommendations in social media, apart from fashion e-commerce platforms.

Following are the major contributions of our work:

- We propose a multi-stage automated framework to address the problem of simultaneous, multiple similar fashion items recommendation.
- Additional contributions to our pipeline in the form of: i) Heuristics to identify a full-shot image from PDP images,
ii) An active learning based component in the object detection module of our pipeline, which further boosts the performance, and iii) Heuristics to place overlay icons on a detected object, to improve user experience.

- We thoroughly assess the effects, and justifications of different components of our method, both empirically, as well as qualitatively. We also demonstrate the superiority of our method in comparison to alternative approaches.

The rest of the paper is organized as follows: Section 2 discusses the related work. Section 3 introduces the proposed multi-stage framework, while also discussing the various underlying computer vision based components. Section 4 describes the experimental evaluation of our method. We conclude the paper in section 5, by summarizing our work and discussing its future scope.

2 RELATED WORK

The approaches available in literature with regard to fashion applications can be broadly categorized from three standpoints: 1. Retrieval of similar clothing items based on a query fashion item [1, 5, 2]. The extraction of attributes (e.g., texture, colour, pattern etc) from a given fashion item [3, 17, 18], and 3. Recommendation of complementary clothes, given a query fashion item [6, 15, 24, 28, 29].

Li et al.[14] recently proposed a fashion recommendation approach that models the compatibility among different fashion items. Their approach is based on a category-aware metric learning framework that embeds the fashion articles in such a way that the cross-category compatibility notions among the items are learned while preserving the intra-category diversity among them. Hadi et al.[5] proposed an approach to match a query item in a street image to one present in the online database. They posed the problem as a binary classification problem employing cross-entropy loss while constructing matching and non-matching pairs. Ak et al.[1] proposed an approach to fine-tune a query based search using extracted attribute representations (for e.g., based on collar-type, torso-color etc).

Kuang et al.[12] proposed an approach to match a query image to a gallery fashion item by using global as well as local representations in multiple scales. This is in contrast to other approaches that make use of a single global feature to represent an image thus submerging the local information, leading to sub optimal performance. Ibrahim et al.[8] explored the use of deep metric learning and ensemble models to address the cross-domain fashion object retrieval problem. While existing approaches focus on the retrieval of shop instances given a consumer instance, their focus was on bidirectional retrieval, while including the reverse direction as well.

Quintino et al.[21] proposed a model that employs convolutional neural networks to jointly learn fashion categories and attributes via an attention mechanism. Kinli et al.[11] explored the in-shop clothes retrieval problem by using Triplet-based Capsule Networks with Stacked Convolutional (SC) and Residual Connected (RC) blocks as input of the capsule layers. In addition, Park et al.[20] also studied different training strategies and combinations of loss functions (e.g., cross-entropy for classification and triplet-loss for similarity) for use in the fashion image retrieval problem. However, the focus of all the discussed approaches is to match a single detected fashion item. This is in contrast to our approach, that focuses on simultaneously retrieving similar image products corresponding to multiple fashion items present in an image.

Another noteworthy line of fashion recommendation based research was investigated by Tangseng et al.[25]. They proposed an approach where given a set of input images of different fashion items by a user (referred to as a fashion closet), the model predicts a score indicating the compatibility of the different input items to be worn together as a combined outfit.

3 PROPOSED FRAMEWORK

3.1 Front-facing Full-shot Image Detection

As displayed in Figure 1-a), a Product Display Page (PDP) contains the shots (or views) of the queried primary fashion article (men’s short in this case) from different angles and poses. The PDP also contains a full-shot look image where a full human model can be seen wearing the searched primary fashion product. However, in addition to the primary product, the model may also wear other secondary fashion items as well (e.g., t-shirts, shoes etc, in this case). This full-shot look image is the one that is of interest to us. To identify such a full-shot image among all the PDP images, we make use of a heuristic criterion along with estimation of human keypoints with a computer vision based human pose detection method [27].

Figure 2: An illustration of the pipeline of the proposed framework.
In particular, we made use of the state-of-the-art human pose estimation approach introduced by Xiao et al. [27]. The reason for choosing this method for the task of key-points detection is its surprisingly simple and effective nature. Remarkably, there are other methods for pose estimation as well, for instance, the Cascaded Pyramid Network (CPN) [4] and the Hourglass method [19]. The former is a dominant approach on the COCO 2017 key-point challenge, while the latter is dominant on the MPII benchmark. The method by Xiao et al. involves only a few deconvolutional layers added to the backbone ResNet network, and yet outperforms its sophisticated competitors CPN and Hourglass. Notably, on the COCO test-dev dataset, the method by Xiao et al. also outperforms the widely popular bottom-up approach CMU-Pose [2] that makes use of Part Affinity Fields (PAFs) to detect poses. However in practice, our method being generic in nature, could leverage any of these methods.

We now discuss our proposed heuristic criterion to identify a full-shot image, given the human keypoints. Specifically, we identify a given PDP image as a full-shot image, provided it has both the ankle and eyes keypoint in it. For a sample catalog image in Figure 3-a, the obtained keypoints are shown in Figure 3-b. We observe that the obtained keypoints are fairly accurate. It should be noted that being the first step of our pipeline, the keypoint detection is an important step. For this reason, we design the keypoint detection step as an individual component of our method using the state-of-the-art method by Xiao et al. This is despite the fact that our article detection and localisation module to be used next performs keypoint detection as well. Another reason for designing it as an individual component provides flexibility to replace it with any other off-the-shelf pose estimator.

Having identified the full-shot image, we provide another heuristic, viz, to use a front posing image for the subsequent pipeline. This is done mainly to ensure that the articles present in the full-shot image appear properly in the image, so as to improve the quality of embeddings to be learned later. To this end, we train a supervised pose classifier which would classify a full-shot image into one of the classes, viz, front, back, left, right or detailed shot. We obtain the annotated training data for this subtask by employing a team of in-house trained taggers. We employ a range of traditional, as well as deep learning based techniques to get the best pose classifier. The details of the same have been presented in the experiments section 4.1.

### 3.2 Fashion article Detection and Localisation

The output of the previous component of our pipeline is a front posing, full-shot look image, which is further passed to the fashion article detection module, as described next. Since a full-shot look image contains multiple articles and accessories as worn, or held by the human model, we need to identify each fashion article for which we want to recommend similar fashion products from the catalog database.

For this subtask of identifying different article types, we must crop or segment out the individual Regions Of Interests (ROIs) from the full-shot look image. However, mere segmentation of the fashion article might render out incomplete articles due to occlusion from other peripheral objects. Hence, we train the article type detection and localisation module using the bounding box tags for the fashion articles present in these images. Table 1 lists the targeted fashion articles present in our training images.

| Broad article category | Finer article types                  |
|------------------------|-------------------------------------|
| Topwear                | Women tops, Shirts, T-shirts        |
| Outerwear              | Sweaters, SweatShirts, Jackets, Blazers, Shrugs, NehruJackets |
| BottomWear             | Jeans, Trousers, Shirts, Track pants, Palazzos, Capris |
| Skirts                 | Shirts                              |
| Dresses                | Women dresses                       |
| Footwear               | Sports shoes, Casual shoes          |
| Bags                   | Hand bags                           |

#### 3.2.1 Bounding Box detection and classification.

Recently, darknet architecture based single-stage detectors like YOLO [22] have been the choice among researchers for the task of real-time object detection. However, our goal of object detection do not require real-time output, as this component of our pipeline can be done offline. Thus we would prefer to pick a model with a better mean Average Precision (mAP) score, while disregarding the run-time latency. The Mask RCNN [7] method has thus been picked for this purpose.

For the fashion article detection and localisation task, we train the Mask RCNN on a custom training dataset, which gives us the bounding box location, and classification for around 20 apparel types as mentioned in Table 1. Figure 3-c shows the detected article types for the full-shot look image in consideration.

We also incorporate active learning based feedback in this component. Essentially, we employ our in-house taggers to identify misclassified examples, and make use of them for re-training. This leads to further gains in performance metrics, as shown in the experiments.

### 3.3 Embedding generation for article types

Having extracted the relevant fashion articles from the full-shot look image, we now need to retrieve similar fashion products from the catalog database containing roughly 1 million images. For this, we seek to represent the extracted article types, and the products from the database, in a common embedding space, where similar articles are closer to each other, and dissimilar ones are far from one another. We make use of a triplet network to learn our embeddings, as illustrated in Figure 4.
A triplet network consists of three identical Convolutional Neural Networks (CNN) with shared weights. To train it, one requires triplets of examples, of the form \((x_a, x_p, x_n)\). Here, \(x_a\) is called a query or anchor image. The example \(x_p\) is called the positive image, that is semantically similar to the anchor. The example \(x_n\) is called the negative image, that is semantically dissimilar to the anchor and the positive. The objective for training the network is to bring the embeddings of \(x_a\) and \(x_p\) closer, while moving away \(x_n\).

To train the triplet network, we made use of a \textit{weighted triplet loss} defined as follows:

\[
L_{\text{total}} = L_{\text{triplet}} + \alpha L_{\text{embed}}
\]

Here, \(L_{\text{triplet}}\) is the \textit{triplet margin ranking loss} [23], defined as:

\[
L_{\text{triplet}} = \max(0, m + \delta^2(x_a, x_p) - \delta^2(x_a, x_n)),
\]

such that \(\delta^2(x_i, x_j) = \|x_i - x_j\|_2^2\) denotes the squared Euclidean distance between the pair of examples \(x_i\) and \(x_j\), with \(\|x_i\|_2\) being the squared \(L_2\) norm of \(x_i\). \(\alpha > 0\) is a trade-off hyper-parameter in (1). The objective of (2) is to constrain the squared Euclidean distance of the anchor-positive pair to be larger than the squared Euclidean distance of the anchor-negative pair by a margin \(m > 0\).

Furthermore, the loss term \(L_{\text{embed}}\) in (1) denotes the embedding loss, and is defined as follows:

\[
L_{\text{embed}} = \tau(\|x_a\|_2^2 + \|x_p\|_2^2 + \|x_n\|_2^2).
\]

Here, \(\tau = \frac{1}{3\sqrt{d}}\), such that \(x_a, x_p, x_n \in \mathbb{R}^d\), i.e., \(d\) is the embedding size. Essentially, \(L_{\text{embed}}\) performs a normalization of the representations of the examples in the triplet to ensure that the image embeddings remain within the radius range of the margin value. It should be noted that for inference one only needs to take a single branch (commonly, the top one for the anchor). This is possible because the branches share the weights among them.

### 3.4 Deciding the coordinates of clickable overlay icons

To present our recommended fashion items to an user, we incorporate overlay clickable points over the detected fashion items in an input image, which can be clicked to view the recommendations for the article on which the icon is placed. Existing solutions offered by image search engines (e.g., Bing) place the clickable points on the centroids of the bounding boxes for the detected articles. However, for bottomwear article types such as trousers, shorts etc, it is not a good practice because the clickable points may lie outside the cloth perimeter. Hence, for bottomwears we suggest a heuristic of placing the clickable icons at the 25\textsuperscript{th} quartile point on a line-segment starting from the detected knee keypoint and ending at the hip keypoint. Figure 5 illustrates an example of overlay icons obtained using the two strategies, viz, centroid-based, and our heuristic. Our heuristic is clearly better than the centroid based method. For topwears, we can use the centroid of an apparel as usual.

![Figure 4: An illustration of the triplet network used in our approach for obtaining embeddings to compute image similarity. We made use of ResNets as our backbone CNN, while employing a weighted triplet embedding loss.](image-url)

![Figure 5: An overlay icon obtained using a) centroid of the article bounding-box, and b) our heuristic.](image-url)

### 4 EXPERIMENTATION AND RESULTS

#### 4.1 Front-facing full-shot image identification

As our initial experiment, we study the first stage of our framework as discussed in subsection 3.1, viz, the identification of the front-facing full-shot image from the PDP. As discussed, the presence of ankle and eyes keypoints indicate a full-shot image. For identifying a front-facing image among the full-shot ones, we separately train a supervised classifier to detect the pose of an image. We make use of our own catalog images, which are manually annotated by our in-house taggers to one of the classes: front, back, left, right, and detail shot. Please note that we use our own real-world catalog images instead of benchmarks like DeepFashion to satisfy the business use cases specific to our own organization. We fix the ResNet18 model as the \textit{pose classifier}. Figure 6 shows the confusion matrices for two article types, using the ResNet model. The perfectly block-diagonal nature of the matrices indicates the reliability and efficacy
of our pose classifier. This is particularly noteworthy because of its position as the first stage of the overall pipeline.

Figure 6: Confusion matrices corresponding to two broad article types, obtained by the pose classifier.

4.2 Detecting fashion articles
We now perform experiments to study our fashion article detection module as discussed in subsection 3.2. We apply the Mask RCNN [7] method on the obtained front-facing full-shot images to detect and localise the fashion articles. We train the Mask RCNN on a custom training dataset to provide us the bounding box location and classification from across the 20 apparel types, as mentioned in Table 1. The training dataset for the Mask RCNN is obtained from catalog images from various fashion e-commerce platforms including ours, and annotated by our in-house taggers. It consists of roughly 7-9k training images and around 800 test images for each fashion article type, resulting in a total of roughly 150k training images. We obtain an average mAP of 78% for all the classes, while reaching as high as 92% for some of the topwear classes (shirts and t-shirts). These values are inline with this model’s performance on the MS COCO data set, which is around 60.3% at IOU 0.5. This is justified because the COCO dataset has more number of classes with natural real world images, whereas images in our case are from 20 odd article categories. A sample object detection is shown in Figure 3-c.

We use the 'ResNet-101-FPN' variant for training, on a Tesla v100-PCIE-16GB GPU, with an image batch size of 16. It converges around 200k iterations. The standard hyper-parameters are taken from the paper (weight decay of 0.0001 and momentum of 0.9). The bounding-box (b-box) detection is taken as positive, only on a correct classification of bounding box for a IOU of 0.5 and above with ground truth b-box. The learning rate was initially kept at 0.03 with natural real world images, whereas images in our case are

Table 2: Class wise AP improvement after employing active learning strategies for some broad fashion categories.

| Broad Category | AP (mAP) without active learning | AP (mAP) with active learning |
|----------------|----------------------------------|-----------------------------|
| topwear        | 82.65                            | 87.69                       |
| bottomwear     | 87.11                            | 96.25                       |
| outerwear      | 81.35                            | 83.98                       |
| dress          | 89.26                            | 85.51                       |
| skirts         | 71.42                            | 69.09                       |
| footewear      | 87.32                            | 88.47                       |
| bags           | 69.71                            | 78.37                       |

article type in Table 1. To form triplets, we first use the street2shop dataset [5] which contains pairs of images where the first image contains a garment item worn by a person in an uncontrolled setting (e.g., streets, complex backgrounds). The second image contains the same garment object in a controlled online-shop setting (e.g., mannequins, cleaner backgrounds). The pairs obtained in this manner help us in forming hard anchor-positive pairs that are semantically similar, but have huge variations among them. A negative can be randomly sampled, containing an image from a different garment for same article type. Using such triplets in our method makes it robust to variations in the query image, and also lets us perform similar products recommendations from images in the wild, as shown later. We further perform semi-hard triplet mining [25], and retrain our model.

We use ADAM optimizer with learning rate of $5 \times 10^{-5}$ and batch size of 32 on a Tesla v100-PCIE-16GB GPU. The value of $\alpha$ in equation 1 was fixed at $5 \times 10^{-5}$ following Veit et al.[26]. The training accuracies range from 92% for bottomwear, to 98% for topwear articles. The Precision (P) and Recall (R) values at different K values were used as the metric to evaluate our method quantitatively.

Figure 7 shows results of ablation studies by changing various hyperparameters in the triplet network of our method. With respect to P@14 and R@14 metrics, we observed that the optimal set of hyperparameters for our method are: margin $m = 0.2$ in (2) and embedding size $d = 2048$ in (3). We also evaluated our method with different variants of the ResNet architecture, and observed a consistently better performance with ResNet50. For inference, we used the cosine similarity among embeddings.

4.4 Comparison with baseline approaches
Despite the presence of many works in literature performing image based fashion product retrieval, there is a lot of variation in their settings. Majority of them focus on the retrieval based on a single product, while we seek to retrieve products for multiple articles. Hence a direct comparison among them would be unfair. The approach by Lasserre et al.[13] made an attempt to simultaneously retrieve similar products for multiple fashion objects in a query. As mentioned in their paper, the fDNA feature representation used by them was trained on thousands of articles, details of which are internal to their organization. As a direct replication of it is not possible, we do not compare our method against theirs. However, a crucial point to note is that their method deals with the studio-to-shop setting where the query images mainly have plain backgrounds. As shown in Figure 8, our method is inherently capable of detecting objects in the wild, with complex backgrounds, thus making it fundamentally superior.
Another noteworthy method by Kalantidis et al.[10] also attempted at retrieving multiple fashion items in an image. They made use of a clustering based object detection technique, which still fails to detect objects in certain images [10]. In Figure 8, we show two images from their paper, which they have presented as failure cases, and report our object detection performance. While the baseline approach incorrectly predicts article types (e.g., leggings) which are absent in the image, our method correctly detects the objects despite the complex backgrounds.

To make further justifications for the choice of our bbox based object detection, we also compare the results of object detection using a state-of-the-art approach [16] that performs segmentation to parse images, and detect objects using a pretrained model. Figure 9 shows that compared to the segmentation based detection, our bbox based component performs better. In Figure 10, we present the qualitative results of our end-to-end pipeline, on the two images used in Figure 8. We observe that our method is capable of recommending similar products fairly well. Retrieval results on a catalog image is also shown in Figure 1. We also compare the end-to-end retrieval performance of our method against the following end-to-end baseline alternative approaches:
• Xiao et al.[27] + Mask RCNN [7] + SIFT: The approach by Kalantidis et al.[10] makes use of clustering based object detection, followed by handcrafted features for similarity embeddings. In figure 8, we have already shown that our object detection component outperforms their object detection component. To ensure a fair comparison, we make use of the same keypoint detection [27] and object detection component [7] as ours, and make use of SIFT based image embeddings to mimic the approach by Kalantidis et al.

• Xiao et al.[27] + Mask RCNN [7] + Euclidean: This baseline uses the same components as our method, except that it uses the Euclidean distance during inference.

• Xiao et al.[27] + Mask RCNN [7] + Cosine + Euclidean: This baseline uses the same components as our method, except that it uses the combination of cosine similarity and Euclidean distance during inference.

In Table 3, we show that our method outperforms all the baselines. This justifies the choices made in our end-to-end pipeline. To further investigate the performance of the SIFT based baseline, we qualitatively examine a sample query image and a retrieved catalog image (see Figure 11). We found that the SIFT based features match query images to database images having completely different fashion articles. This explains the severe drop in precision and recall metrics.

Table 3: Quantitative comparison of our end-to-end approach against a few alternative end-to-end baseline approaches.

| Method                                | P@1  | R@1  | P@5  | R@5  | P@10 | R@10 | P@14 | R@14 |
|---------------------------------------|------|------|------|------|------|------|------|------|
| Xiao et al.[27] + Mask RCNN [7] + SIFT | 0.009| 0.009| 0.007| 0.007| 0.005| 0.012| 0.004| 0.012|
| Xiao et al.[27] + Mask RCNN [7] + Euclidean | 0.240| 0.130| 0.193| 0.204| 0.125| 0.297| 0.100| 0.350|
| Xiao et al.[27] + Mask RCNN [7] + Cosine + Euclidean | 0.283| 0.199| 0.210| 0.225| 0.155| 0.322| 0.110| 0.379|
| Ours                                  | 0.284| 0.153| 0.246| 0.261| 0.158| 0.374| 0.122| 0.417|

Figure 11: The SIFT based features match query images to database images having completely different fashion articles. This leads to the severe drop in precision and recall metrics.

4.5 Other discussions and results

4.5.1 Inference time of different components. Table 4 reports the average inference times of different components of our method on a Tesla v100-PCIE-16GB GPU.

| Model                                | Inference time on GPU |
|---------------------------------------|-----------------------|
| Human pose                            | ~200ms                |
| Bounding Box                          | ~400ms                |
| Image Similarity                      | ~100ms                |
| Similarity Retrieval                  | ~5ms                  |

4.5.2 Results of A/B testing and future improvement scope. Despite the qualitative and quantitative improvements observed in our experiments, we wanted to evaluate our method by employing an online A/B experiment for our recommendation framework. Notably, we observed an increase in Click Through Rate (CTR) by 25%, and add to cart ratio by 4%. Furthermore, we also observed an increase in overall user session time, which depicts an improved customer engagement.

To give a better perspective, we divide the set of users in two halves: The first set for which we do not provide recommendations, and the second set, where we make recommendations based on our approach. We then compute specific metrics for each set of users. On average, we observed better metrics for the subset of users for which we make recommendations using our method. For example, we observed better add-to-cart numbers, and an increase in the quantity of products selected.

Additionally, we employed a team of catalog experts to provide feedback on our retrieval results. Out of 500 randomly drawn similar products recommendation results, 477 were marked as visually relevant and correct (around 95%). The experts provided us further feedback that we should take the following into account for a future version of our model: i) the occasion of an apparel/accessory (e.g., workout, formal, party etc), and ii) the finer attributes (e.g., neck type, sleeve length etc). Incorporation of these additional features in our model would further enhance the performance of our model. However, doing so is beyond the scope of this paper, and hence left as a future work.

5 CONCLUSION

This paper proposed a convenient and efficient method for automatic product searches, facilitating users to easily look for similar products as displayed on a product display page. We introduced a method that includes identifying the full-shot look of a product among the set of product display images, followed by identification of human key-points, detection of broad fashion objects, and identification of similar products for each of the detected fashion articles by leveraging a triplet based embedding network. In the future, we would like to incorporate article attributes and occasion based filtering to facilitate better and robust product search.

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