How To Extract Fashion Trends From Social Media?
A Robust Object Detector With Support For Unsupervised Learning

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ABSTRACT

With the proliferation of social media, fashion inspired from celebrities, reputed designers as well as fashion influencers has shortened the cycle of fashion design and manufacturing. However, with the explosion of fashion related content and large number of user-generated fashion photos, it is an arduous task for fashion designers to wade through social media photos and create a digest of trending fashion. Designers do not just wish to have fashion related photos at one place but seek search functionalities that can let them search photos with natural language queries such as ‘red dress’, ‘vintage handbags’, etc in order to spot the trends. This necessitates deep parsing of fashion photos on social media to localize and classify multiple fashion items from a given fashion photo. While object detection competitions such as MSCOCO have thousands of samples for each of the object categories, it is quite difficult to get large labeled datasets for fast fashion items. Moreover, state-of-the-art object detectors [2, 7, 9] do not have any functionality to ingest large amount of unlabeled data available on social media in order to fine tune object detectors with labeled datasets. In this work, we show application of a generic object detector [11], that can be pretrained in an unsupervised manner, on 24 categories from recently released Open Images V4 dataset. We first train the base architecture of the object detector using unsupervised learning on 60K unlabeled photos from 24 categories gathered from social media, and then subsequently fine tune it on 8.2K labeled photos from Open Images V4 dataset. On 300 × 300 image inputs, we achieve 72.7% mAP on a test dataset of 2.4K photos while performing 11% to 17% better as compared to the state-of-the-art object detectors. We show that this improvement is due to our choice of architecture that lets us do unsupervised learning and that performs significantly better in identifying small objects. ¹

KEYWORDS

Social Media Fashion, Fashion Object Detection, Unsupervised Learning

¹We are in the process of open sourcing details of labeled datasets chosen, links to unlabeled datasets, and trained fashion detection models.

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1 INTRODUCTION

Fashion designers today actively seek inspirations from social media photos to formulate innovative designs before they are put into production. In last several years, social media is flooded with fashion inspirations from celebrities, reputed designers as well as fashion influencers. However, it has only made the task of manually parsing and extracting intelligence from these photos arduous for fashion designer. Fashion designers today wish to have an easy to use tool with several search functionalities that can let them search photos with natural language queries such as ‘red dress’, ‘flora handbags’, ‘vintage tees’, etc. The main bottleneck in creating this digest is the identification of fashion photos and fashion items inside these photos. This necessitates deep parsing of fashion photos on social media to localize and classify multiple fashion items from a given fashion photo.

Image object detection involves identifying bounding boxes encapsulating objects and classifying each bounding box to recognize the underlying object category. Recently there has been mounting interest in the research community to detect multiple objects in an image using Single Shot Detection techniques [7, 9]. These techniques effectively combine region proposal and classification into a single step by foregoing the candidate box proposal (or region proposal) module employed by several two-step detection techniques [1, 3, 4, 6, 10].

While these techniques have made some progress, they fundamentally lack two key features to solve problems such as detecting fashion objects from fashion photos in the wild: (1) ability to ingest large amount of unlabeled dataset and (2) ability to maintain detection accuracy in the absence of large labeled datasets for small and big object alike. These two problems are especially relevant to parse fashion photos on social media since social media has large amount of unlabeled fashion photos, i.e., fashion photos for which classes and boxes are absent. Moreover, there are no labeled datasets that have several thousands of labeled photos for each of several tens of fashion categories. It is not easy to get such large dataset labeled owing expertise, cost, and timing constraints.

In this work, we apply a convolution-deconvolution based object detector to extract fashion objects from fashion photos. Specifically,

- We apply an end-to-end trainable convolution-deconvolution based single shot detection framework
Our detection framework enables us to pretrain the model on 60K fashion photos in the wild. Subsequently, we train our technique on 8.2K photos from Open Images V4 dataset and test it on 2.4K photos.

We compare our object detector with state-of-the-art object detectors. We take object detection models pretrained on PASCAL VOC dataset and then fine tune them on fashion datasets. We show that our model performs 11% to 17% better.
2 CDSSD ARCHITECTURE

We apply the technique proposed in CDSSD [11] to detect fashion objects from fashion photos. In this section, we first give a primer on SSD architecture that is popularly used for object detection. We then explain why this architecture is inadequate for us to process social media fashion photos. We then briefly explain how CDSSD architecture extends SSD and discuss how we benefit by applying CDSSD architecture to extract fashion objects from fashion photos in the wild.

2.1 SSD

The SSD network is a convolutional architecture that utilizes different layers to predict presence of multiple objects in an image. To recognize objects at different scales, SSD utilizes predictions on different feature maps, each from a different layer, of a single network. Instead of processing the image at different scales, these feature maps are processed by a fixed-size collection of bounding boxes customized for each layer. The boxes are applied on each feature map. Each default box is then evaluated for the presence of object class instances. For feature map \( f \) of size \( m \times n \) with \( p \) channels, \( K \) default-sized bounding boxes are applied on each of \( m \times n \) cells. Subsequently, \( C \) filters of size \( 3 \times 3 \times p \) are applied for each cell and for a given bounding box to produce individual scores to predict each of \( C \) classes, and \( 4 \) additional filters are applied to produce offsets (center coordinate, height, width) to position the box on the underlying cell in order to encapsulate the object (as shown in Fig. 2(c)). Note that, for a given feature map \( f \), the default boxes are scaled with a scaling factor \( f^{scale} \) with respect \( m \) and \( n \) and they are customized to have different aspect ratios. Hence, bounding boxes on initial stage feature maps cover a smaller receptive field to identify objects at a smaller size, whereas bounding boxes on later stage feature maps cover larger receptive fields to identify objects with larger scale. By utilizing predictions for all the default boxes with different scales and aspect ratios from all locations of many feature maps, SSD attempts a diverse set of predictions, covering various input object sizes and shapes.

While SSD technique is useful to detect fashion objects from fashion photos, it has two main limitations.

- It does not have any provision to input unlabeled fashion photos, and train the feature maps in an unsupervised fashion. Thus, although social media has several hundreds of thousands of fashion photos, these photos cannot be directly applied unless they are labeled with classes and bounding boxes.
- It is known to perform poorly to identify small-sized objects. This is especially a concern for fashion photos since object categories such as earrings or clutches are small in size and appear in all sorts of sizes and shapes. Furthermore, since tops and tees or such fashion pairs look quite similar, extracting fashion objects from photos in the wild is necessarily a harder problem than extracting objects such as planes vs people that are relatively easy to distinguish.

2.2 CDSSD Architecture

As mentioned in [11], CDSSD facilitates unsupervised training of the underlying network architecture. For the purpose of this work, we use ResNet 101 architecture [5] and construct a convolution-deconvolution based auto-encoder (shown in Fig. 2(a)). The convolution block produces an image of the same dimension as input. We use an input image of \( 300 \times 300 \times 3 \), with 7 meta-layers of convolution and pooling and 7 meta-layers of deconvolution with learned upsampling. Given an image dataset, we first pretrain the architecture several thousands of fashion photos in the wild. After pretraining, we fine tune the same network by applying supervised object detection.

It is well-known that feature maps in different layers of a network have different receptive fields and hence they learn different sets of features; initial layers especially learn generic features whereas final layers learn semantically rich features. [8, 13] observe that the initial layers of a deep network lack strong semantic information and respond to only high-level features of an image. Furthermore, the improvement in acquiring semantic information across consecutive feature maps is only marginal, especially in initial layers of a network. CDSSD exploits these observations and fuses generic and semantic features to enrich feature maps. Furthermore, CDSSD combines all the four feature maps of a given meta-layer as shown in Fig. 2(a). Similar to SSD, CDSS then applies a set of \( K \) default-boxes and \( (C + 4) \times m \times n \times K \) filters on the resulting feature map to predict detection of objects. Note that, since 6th and 7th meta-layers have higher reception field and contain richer semantic information, they are quite capable of detecting bigger size and scale objects [2].

This feature especially helps us to locate and classify small size objects such as earrings, sandals, hats, boots, wrist-watches, sunglasses from photos in the wild. Similar to CDSSD, to compute different aspect ratios for each cell, we take a statistical approach and compute a cumulative distribution of aspect ratios of the ground truth boxes in a given dataset. We then divide the distribution into \( B \) bins and pick the average value of a bin as one of the aspect ratio, thus resulting in \( B \) aspect ratios. For each \( b_i \in B \), for a feature map with size \( m \times n \) and scale of \( f^{scale} \), we then set height to be \( m \times b_i \times f^{scale} \) and width to be \( n \times b_i \times f^{scale} \). With optimized aspect ratios that fit the underlying dataset and different scales for different layers, we apply appropriate default boxes at box-pooled locations in each feature map, covering different object sizes and shapes.

We trained CDSSD architecture on 60K social media photos in an unsupervised fashion, and 8.2 photos in a supervised photos. After training, we applied the model on 2.4K photos for evaluation. Furthermore, we applied the model to more than 500K fashion photos, and extracted fashion objects and monthwise trends of different fashion styles.

3 RESULTS

Our experiments are governed to answer the following key question: can we achieve better results in identifying fashion items from photos in the wild by employing unsupervised learning and confluence of feature maps from convolution and deconvolution blocks? Towards answering this question, we compare our approach with prior work on two state-of-the-art techniques: SSD [7] and YOLO [9]. Note that, SSD and YOLO do not employ unsupervised learning and do not consider confluence contextual and semantic features from convolution and deconvolution blocks. We take object detection
models for each of these techniques, pretrained on PASCAL VOC dataset, and then fine tune them on 8.2K labeled photos from 24 categories.

### 3.1 Dataset

We consider recently released Open Images V4 dataset that has photos and bounding boxes for the following object categories.

**Object Categories:** sandal, high-heels, boot, jeans, shorts, swimwear, brassiere, shirt, coat, suit, miniskirt, jacket, dress, sunhat, cowboy-hat, umbrella, glasses, belt, earrings, handbag, watch, backpack, suitcase, briefcase.

We totally consider 8.2K photos with on an average 600 instances for each object category. In Addition, we consider an unlabeled dataset of 60K photos collected from public APIs of social media networks, Facebook and Instagram. These photos contain even distribution of the above categories.

### 3.2 Training

The configuration of our network architecture is shown in Fig. 2. We keep the dropout layers during unsupervised training and remove them while training for object detection. We train our models on Azure GPU instances that have NVIDIA K80 GPUs with 12GB of memory. We use batch size of 16, momentum as 0.9 and weight decay 0.0005. Similar to SSD [7], we match a default box to target ground truth boxes, if Jaccard overlap is larger than a threshold (e.g. 0.5). We compute the target ground truth box for each layer of the

\[ \sigma(w_1 \cdot f_1 + w_2 \cdot f_2) \]

**Figure 2:** CDSSD combines information from convolution and deconvolution feature maps

**Table 1:** Comparison of single-shot detection techniques on 2.4K fashion photos, trained on 8.2K fashion photos

| method          | network  | mAP | number of default boxes | fps  | lib   |
|-----------------|----------|-----|-------------------------|------|-------|
| YOLOv2_352 [9]  | DarkNet-19 | 56.7| 98                      | 81   | DarkNet   |
| DSSD321 [2]     | ResNet-101 | 63.6| 43688                   | 9.5  | Caffe    |
| Stairnet [12]   | VGGNet   | 64.8| 8732                    | 30   | PyTorch  |
| CDSSD300        | ResNet-101 | 72.7| 1182                    | 51   | TF      |
network by scaling it with respect to the feature map and original image sizes. We minimize the joint localization loss (i.e., smooth L1) and confidence loss (i.e., softmax-cross-entropy). Note that after the matching step, most of the default boxes are negatives. Hence, to avoid the imbalance between the positive and negative training examples, we sort the negative boxes using the joint loss for each default box and then pick the top ones to maintain a 2:1 negative to positive ratio. We found 2:1 ratio leads to faster optimization as compared to the ratio of 3:1 as mentioned in the original SSD paper.

We further make the model robust to different input object sizes and shapes by invoking extensive augmentation. Specifically, we sample a patch from a ground truth box so that the minimum Jaccard overlap with the objects is 0.5, 0.7, or 0.9. Furthermore, we randomly sample a patch between [0.5, 1] of the original image size, and the aspect ratio is between [1, 2]. Also, we randomly flip each patch horizontally with probability of 0.5, apply different transformations such as gaussian blur, emboss, edge prominence, random black-out of 20% of pixels, and color (hue, saturation, contrast) distortions. We apply $3 \times 3$ box pooling for layer 3 and 4, $2 \times 2$ box pooling for layer 5, and no box pooling for layer 6 and 7. We apply non-maximum suppression (NMS) to post-process the predictions to get final detection results.

We train the entire network with learning rate at $10^{-3}$ for 25K batches, and then with learning rate of $10^{-4}$ for 60K batches to execute unsupervised pretraining on the underlying train dataset. During object detection training, we again fine-tune the entire network with learning rate of $2 \times 10^{-3}$ for 30K iterations, and 60K iterations with learning rate of $10^{-4}$.

### 3.3 Results

Comparison of mAP for different models on the test fashion set are shown in Tab. 1. Although 2.4K is a smaller dataset for MAP evaluation, we clearly get an indication that CDSSD performs better due to the facility of pretraining using unsupervised learning. Note that the same 8.2K labeled dataset is used to fine-tune all the networks. Per category results are shown in Tab. 2. These results corroborate that by adding unsupervised pretraining and confluence of feature maps, CDSSD consistently outperforms YOLO and SSD by 11% to 17% points for several object categories. CDSSD especially shows significant improvement for small objects such as boots, high-heels, hand-bags. CDSSD detects majority objects with high confidence with less localization error and less confusion for similar object categories. Finally, CDSSD achieves high-precision at high-recall range and outperforms YOLO and SSD (Tab. 3).

### 3.4 Fashion Trends

Using the object detection technique, we could identify several fashion trends on social media platform. We mainly did analysis of Indian social media trends. We could predict the use of palazzos in 2015 before they became famous in India in 2016. By parsing celebrity photos, we could predict plum as the dominant color for hands-bags for 2018. Parsing photos published by fashion weeks and fashion shows, we could identify light gray color as the dominant color for long dresses. Furthermore, we could identify plums as the complementary color for tops that are paired with black jeans. This level of trend analysis would not have been possible without deeply parsing photos and extracting each fashion object along with its class and bounding box.

### 4 Conclusion

We design an end-to-end framework using convolution-deconvolution deep networks to improve the state-of-the-art of single shot object detection techniques. Using a combination of unsupervised learning and confluence of feature maps with different receptive fields, we demonstrate substantial improvement in mAP for different objects in PASCAL VOC and MS COCO datasets while reducing the bounding box requirement by 8 times, thus improving inference time by 10%. We believe that our work will inspire extensions to region proposal based detection techniques as well as other genres of objection detection towards
finding more effective and efficient ways to combine feature maps of convolution and deconvolution blocks.

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