Large-Scale Product Retrieval with Weakly Supervised Representation Learning

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Abstract

Large-scale weakly supervised product retrieval is a practically useful yet computationally challenging problem. This paper introduces a novel solution for the eBay Visual Search Challenge (eProduct) held at the Ninth Workshop on Fine-Grained Visual Categorisation workshop (FGVC9) of CVPR 2022. This competition presents two challenges: (a) E-commerce is a drastically fine-grained domain including many products with subtle visual differences; (b) A lack of target instance-level labels for model training, with only coarse category labels and product titles available. To overcome these obstacles, we formulate a strong solution by a set of dedicated designs: (a) Instead of using text training data directly, we mine thousands of pseudo-attributes from product titles and use them as the ground truths for multi-label classification. (b) We incorporate several strong backbones with advanced training recipes for more discriminative representation learning. (c) We further introduce a number of post-processing techniques including whitening, re-ranking and model ensemble for retrieval enhancement. By achieving 71.53% MAR, our solution Involution King achieves the second position on the leaderboard.

1. Introduction

The transition from offline to online shopping has been wide and deep across every aspect of our life. In 2020, retail e-commerce sales worldwide amounted to 4.28 trillion US dollars and are projected to grow to 5.4 trillion US dollars in 2022. Under this context, large-scale product identification becomes a major challenge for online service platforms. A powerful product search system can improve product discoverability and reachability, seller-buyer engagement and conversion rate in e-commerce [7, 30, 31].

To solve this grant challenge, eBay, a world-leading e-commerce company, introduced a million-scale benchmark, namely eProduct [31] to foster more advanced AI techniques. We participate in the eProduct competition in conjunction with the FGVC9 at CVPR 2022.

In this competition, we aim to develop an open-world retrieval system generalizable to daily added new products. We appreciate a couple of key characteristics. Firstly, product retrieval is essentially a super fine-grained task for reflecting individual user’s needs, e.g., a buyer needs to find a desired product among a large number of options without easily distinguishable nuances. Secondly, unlike many popular academic datasets [6, 17, 28], instance-level ground truth labels are much harder to acquire since sellers tend to upload their products independently. Further, sellers would most likely upload a product with some inaccurate short description and select a category for that item. As a result, coarse-grained class labels and text descriptions can be only considered as weak supervision.

There have been a recent surge in weakly supervised representation learning [1, 13, 22, 25, 32, 33]. Several works [1, 32] have empirically and theoretically demonstrated that optimizing the classification objective is the same or even better than optimizing pair-wise objectives for metric learning. This implies that a retrieval problem can be simplified into a classification problem by predicting coarse-grained class labels. A classification objective could be typically implemented with cross-entropy loss or supervised contrastive loss [13, 33]. Alternatively, cross-modal contrastive learning [22, 25] can also learn discriminative representations from different views (e.g., product image + product titles). However, we find that all these methods are not competent in the eProduct benchmark due to its aforementioned challenges (also see our evaluation in Section 3.3). We summarize the reasons as follows: (a) The model cannot learn instance-level discriminative features only with a typical classification loss using category-level labels; (b) The model cannot learn intra-modal discriminative features with the cross-modal contrastive loss only. This motivates us to formulate an intra-modal learning objective that maximizes the use of weakly-supervised information available.
Inspired by previous works [12, 19, 23], we introduce a novel pseudo multi-labeling strategy. Concretely, we extract pseudo-attributes from product titles and optimize a multi-label classification objective. This forms a weakly-supervised representation learning problem. The advantage of our formulation is two-folds: (a) Our pseudo-attributes instance-dependent and thus more fine-grained than category labels, despite being noisy by nature; (b) Our pseudo-attributes retain the majority of information from the text modality, whilst the visual feature learning is conducted in an intra-modal manner. This decoupling design well mitigates the challenges as discussed earlier. Further, we build a strong baseline model with ImageNet-pretrained backbones [16, 18], advanced training recipes (e.g., TrivialAugment [20] and random erasing [35]) and post-processing (feature whitening [11, 24], k-reciprocal reranking [34] and model ensemble). Empirically, we show that our method outperforms all competing methods by a large margin, getting hold of the second position out of about twenty teams on the leaderboard.

2. Methodology

In this section, we describe our solution for this challenge. In Sec 2.1, we describe our proposed label-smoothed multi-label classification objective based on pseudo attributes. In Sec 2.2, we discuss various training recipes that we have integrated to make our solution competitive. In Sec 2.3, the post-processing techniques are elaborated.

2.1. Optimization objectives

As described in Section 1, we empirically found that using the available weakly-supervised information is non-trivial for this task. This is due to the inherent challenge of this task: lack of instance-level fine-grained ground truth. To circumvent the absence of instance-level labels, we propose to mine pseudo-attributes from the product titles. Although some different products may share some overlapping pseudo-attributes, the set of attributes for each product is instance-dependent. Therefore, it is reasonable that the model can learn instance-wise discriminative features from these pseudo-attributes.

Specifically, we extract all words with a simple blank-based tokenizer and only keep the words that appear more than 30 times to filter some noisy words, resulting in a list of 22,295 pseudo-attributes. We show the histogram of the top-100 pseudo-attributes in Figure 1. It is observed that all of them are truly highly-related to the product information but very noisy. To utilize these mined pseudo-attributes, we then perform multi-label classification for the weakly-supervised representation learning. A common trend to solve multi-label classification problem is to use sigmoid activation followed by logistic regression based loss terms. However, doing so may result in designing sophisticated label completion techniques and more hyper-parameter search which may reduce the efficacy of the solution. Following the works in [7, 9, 12, 19, 23], we use softmax activation coupled with cross-entropy loss as our optimization objective to overcome the above drawbacks. Formally, it is defined as follows:

$$\mathcal{L}_{CE} = -\frac{1}{N} \sum_{i}^{N} \sum_{t}^{T} Y^{(i)}_{t} \log P^{(i)}_{t},$$

where $N$ is the number of training data, $T$ is the number of pseudo classes, $Y^{(i)}_{t}$ is the target which is either $\frac{1}{K}$ or 0 at class $t$ depending on whether the corresponding pseudo-attribute is present or not. $K$ is the number of pseudo-attributes for $i$-th sample, and $P^{(i)}_{t}$ is the softmax probability of class $t$. Due to the long-tail nature of the dataset (ref to Fig. 1), generating pseudo-attributes may result in severe class-imbalance particularly for the tail attributes. To address this class-imbalance problem, we can apply either FocalLoss [15] or PolyLoss [14] as our training objective. For the simplicity in loss design, we chose PolyLoss as the objective function. It is defined as follows:

$$\mathcal{L}_{poly} = \mathcal{L}_{CE} + \frac{\epsilon}{N} \sum_{i}^{N} \sum_{t}^{T} (1 - Y^{(i)}_{t} P^{(i)}_{t}),$$

where $\epsilon$ is the scale of the regularization effect of the Poly-Loss. We train our model using Eq. 2 with $\epsilon = 0.5$.

2.2. Training recipes

We used the recently proposed CNN-based ConvNeXt [18] and Transformer-based Swin-L [16] as our model

| Training config | ConvNeXt-XL [18] / Swin-L [16] |
|-----------------|---------------------------------|
| training resolution | 224 / 384 |
| inference resolution | 316 & 384 / 384 |
| optimizer | AdamW |
| base learning rate | 1e-4 |
| weight decay | 1e-4 |
| poly loss $\epsilon$ [14] | 0.5 |
| optimizer momentum | $\beta_1, \beta_2 = 0.9, 0.999$ |
| batch size | $28 \times 8 / 14 \times 8$ |
| training epochs | 20 |
| learning rate schedule | cosine decay |
| warmup epochs | 5 |
| warmup schedule | linear |
| TrivialAugment [20] | $num_{magnitude\_bins} = 31$ |
| random erasing [35] | 0.25 |
| stochastic depth [10] | 0.4 |
| head init scale [26] | 0.01 |
| exp. mov. avg. (EMA) [21] | 0.9999 |
| reranking [34] | $K_1, K_2, \alpha = 8, 5, 0.5$ |

Table 1. All hyper-parameters used in our solution. Multiple hyper-parameters (e.g., 224 / 384 training resolution) are for each model (e.g., ConvNeXt-XL / Swin-L) respectively.
backbones followed by a linear projection and a softmax activation is added after the output from the backbone to compute the prediction probability $P$ in Eq. 2 respectively.

For all other training configurations, including tricks (e.g., TrivialAugment [20], and random erasing [35]) and hyper-parameters (e.g., batch size, learning rate, and learning scheduler), we have summarized them in Table 1.

### 2.3. Post-processing

**Inference resolution.** To extract features for retrieval, we compute using the image resolution of $316^2/384^2$ for ConvNeXt and $384^2$ for Swin-L. It is because larger image resolution can extract finer information from an image.

**Feature whitening.** To reduce correlation between dimensions of the features that could possibly improve the retrieval results [11, 24], we further apply feature whitening on both query and database features. The parameters used by feature whitening are computed using database features only. Finally, the whitened features are $l_2$ normalized.

**Ensemble models.** Ensembling can make better predictions and achieve better performance as it reduces the spread of the predictions (e.g., a single model might overfit or bias to some certain patterns, ensemble model can reduce the effect). We ensemble a ConvNeXt-XL model and three Swin-L models trained with different random seeds and slightly different learning rates. Note that feature whitening and $l_2$ normalization are applied for each model independently. All features are then concatenated at feature dimension.

**Distance metric.** During retrieval, we use cosine distance as the distance metric. We have also experimented with Euclidean distance, but we empirically found out that cosine distance has consistently 1-2% MAR@10 improvement.

**k-reciprocal re-ranking.** After retrieving top-$N$ items from the index database, we then performed $k$-reciprocal re-ranking [34] among the top-$N$ items. We observed that re-ranking always boosted the MAR@10 for at least 4% in absolute performance.

**Algorithm.** We have summarized our retrieval pipeline with Pytorch-style pseudocode in Algorithm 1.

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**Algorithm 1 Pseudocode of our retrieval pipeline.**

```python
def compute_feats(model):
    q_feats = model(q_imgs) # (N, d)
    db_feats = model(db_imgs) # (M, d)
    db_mean, db_cov = compute_mean_cov(db_feats)
    q_feats = whitening(q_feats, db_mean, db_cov)
    db_feats = whitening(db_feats, db_mean, db_cov)

    return l2_norm(q_feats), l2_norm(db_feats)

def reranking(q_feats, db_feats):
    q_feats_ens = [compute_feats(model) for model in ensemble]
    db_feats_ens = []
    for q_feats, db_feats in zip(q_feats_ens, db_feats):
        db_feats_ens.append(db_feats)
    db_feats_ens = concat(db_feats_ens, dim=1)
    topn_db_ids = reranking(q_feats_ens, db_feats_ens)
    return topn_db_ids
```

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### 3. Experiments

#### 3.1. Implementation details

All of our experiments are performed using 8 NVIDIA GeForce RTX 3090 GPUs. We use the validation set for model evaluation and exclude the validation split images from training. All the hyper-parameters used in our training recipes are listed in Table 1. We use Pytorch Lightning [5] as our framework and use Hydra [29] as configuration system. We have used the ImageNet pre-trained ConvNext-XL and Swin-L models provided by timm [27].
3.2. Evaluation metric

For model evaluation, macro-average recall@k (i.e., MAR@k) metric is used. It is defined as the average of recall@k over all N queries: \( \text{MAR}@k = \frac{1}{N} \sum_{i=1}^{N} R_i \), where \( k \) is the number of top-k retrieved items, and \( R_i \) is the recall@k of i-th query. Quantitatively, if this metric is higher, it is better. Following the evaluation protocol of eProduct [31], we use MAR@10 as the evaluation metric, where \( k = 10 \) and \( N = 3000 \) for test phase.

3.3. Results

In this subsection, we show the effectiveness of our proposed learning objective and different modules mentioned in Section 2. Note that we can only report approximate numbers here, as we no longer have access to ground truth labels for accurate evaluation.

Comparison with competing methods. To demonstrate the superiority of our proposed multi-label classification optimization objective, we conducted several comparative experiments with other alternative methods based on ResNet50 [8]. We consider several methods including:

- Use the coarse-grained category labels as the targets and then optimize the model as single-label classification. Here, we consider two objectives: cross-entropy (X-Entropy) [1, 32] and supervised contrastive (SupCon) [13]. This method has been proved to be effective for coarse-grained image retrieval [1, 32].
- Use the product titles as the natural augmentation view of the product images and then optimize the model via cross-modal contrastive learning [25]. This method achieves great success in weakly-supervised cross-modal representation learning [22].
- Use off-the-shelf traditional clustering method (e.g., DBSCAN [4]) to assign pseudo instance labels for every image based on its feature and then use these pseudo labels as the ground truth. This method can be regarded as a special case of unsupervised cluster-based representation learning [2, 3].

We show the performance comparison in Table 2. It is obvious that our multi-label classification outperforms all other methods by a large margin. We conclude that this superiority can be attributed to two advantages of our learning objective: (a) the mined pseudo-attributes are instance-dependent and thus more fine-grained than category labels; (b) our learning process is intra-modal, thereby making the learned image features directly comparable to others. More interestingly, we observe that the clustering based single-label unsupervised contrastive learning approach outperforms all the other weakly-supervised methods except ours. This phenomenon reflects on the fact that it is non-trivial to use weakly-supervised information. Hence, if the learning objective is not designed properly, the model tends to overfit the coarse-grained information.

Ablation study of engineering tricks. We show the ablation study of different components of our proposed solution in Table 3. We empirically found that stochastic depth [10] can boost the performance a lot by alleviating the process of over-fitting. We also found that whitening [11, 24] and k-reciprocal re-ranking [34] are highly necessary for this open-world retrieval task.

4. Conclusion

In this challenge, we introduce a pseudo multi-labeling strategy. We mine pseudo-attributes from product titles for weakly supervised representation learning. Given many products with subtle visual differences, the mined pseudo-attributes act as an instance-level label for enabling instance-level discriminative feature learning. By applying strong backbones, advanced training recipes and post-processing techniques, our solution achieves 71.53% MAR@10 and ranks the second on the leaderboard of eBay Visual Search Challenge in FGVC9, CVPR 2022. Our take-home message is that, weakly supervised representation learning with instance-level pseudo-attributes is particularly powerful. We hope that this finding can foster more related research in academia and industry.

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