V^2L: Leveraging Vision and Vision-language Models into Large-scale Product Retrieval

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Abstract

Product retrieval is of great importance in the ecommerce domain. This paper introduces our 1st-place solution in eBay eProduct Visual Search Challenge (FGVC9), which is featured for an ensemble of about 20 models from vision models and vision-language models. While model ensemble is common, we show that combining the vision models and vision-language models brings particular benefits from their complementarity and is a key factor to our superiority. Specifically, for the vision models, we use a two-stage training pipeline which first learns from the coarse labels provided in the training set and then conducts fine-grained self-supervised training, yielding a coarse-to-fine metric learning manner. For the vision-language models, we use the textual description of the training image as the supervision signals for fine-tuning the image-encoder (feature extractor). With these designs, our solution achieves 0.7623 MAR@10, ranking the first place among all the competitors. The code is available at: V^2L.

1. Introduction

Given a query image, the goal of product retrieval is to determine whether there are the same product images from a reference dataset. It plays an important role in the e-commerce domain. There are two main challenges. First, because product retrieval is an instance of super fine-grained recognition, it is very difficult for algorithms to distinguish two products with subtle visual differences. Second, building large-scale product training datasets with fine-grained level labels is very time-consuming and expensive.

This paper tries to leverage Vision and Vision-Language models (V^2L) to compete for eBay eProduct Visual Search Challenge (FGVC9) [21] at CVPR’22. This competition builds a dataset with 2.5 million product images. Different from other similar datasets [1, 3], the dataset features: (1) It does not have fine-grained labels, i.e. it only provides categorical labels rather than product labels. In this way, we can build self-supervised learning algorithms on our previous winning solutions [17, 18]. (2) It provides text information (title) for each product image in the training set. In this way, we can explore multimodal learning methods. To explore the highest performance, we do not limit the amount of GPU and CPU resources. We use 6 standard Nvidia 8-A100 GPU servers and about 100 Intel 6240 CPUs (with 36 cores per CPU) in the competition.

The proposed approach consists of two parts, i.e. vision models, and vision-language models. For vision models, we perform a coarse-to-fine training strategy. First, backbones are trained with the provided 1,000 categories labels (without ImageNet pre-training). Then we adapt the strong self-supervised baseline in [18] to accommodate the product retrieval task. We choose many vision-language models, which are pre-trained and with suitable licenses (both code and the models themselves), and then finetune them using the product images and corresponding titles. That is how we perform multimodal learning. The final submission is obtained by ensembling different models’ results from two types of approaches. The illustration of the proposed V^2L is shown in Fig. 1. In summary, the main contributions of this paper are:
1. The paper demonstrates the effectiveness of vision-language models in product retrieval tasks for the first time.

2. We explore the performance threshold of current product retrieval tasks by using unimaginable resources.

3. The proposed V^2L approach ranks first in eBay eProduct Visual Search Challenge (FGVC9).

2. Proposed Method

In this section, we introduce each important component in the proposed V^2L. We will first introduce our vision models and then show the selected vision-language models. Finally, to promote reproducibility, all the used tricks are listed.

2.1. Vision Models

We basically follow the training process in the strong baseline from [18]. The changes are listed below.

2.1.1 Two-stage Training

We perform coarse-to-fine training. First, the randomly initialized backbones are trained using the 1, 000 coarse labels. Note that, we do NOT use the ImageNet-pre-trained backbones due to two issues: (1) The open-source codebases often do NOT include an explicit license for their released pre-trained models. We do NOT want to involve in the license issue in the final checking. (2) It seems that the scale of eBay training dataset is large enough for training from scratch. Then, using the strong baseline [18], the second stage training is performed. We use 8 and 4 Nvidia Tesla A100 GPUs for the two stages of training, respectively.

2.1.2 Pseudo-label Generation

First, we randomly select 100, 000 training images from the training set. Through augmentation, each training image forms its only class. A model is trained on this 100, 000 classes. After training, features extracted by the model can be used for clustering. In this way, the training images are clustered. Note that, we only keep clusters with high confidence, i.e. each cluster only contains less than 10 images, and thus we only use about 1/5 training images in the second stage training. Specifically, after the clustering, we get 87, 125 classes. Then we randomly select $100K \times 87, 125 = 12, 875$ images from the training dataset. That means besides the 87, 125 clusters, we have 12, 875 extra classes (each class with one image). As a result, we have 246, 926 images from the 87, 125 clusters (2.8 images for each cluster on average). Then, the 12, 875 extra classes bring 12, 875 extra images. Therefore, finally we have $246, 926 + 12, 875 = 255, 801$ images.

2.1.3 Stronger Backbones

Instead of using the backbones in [18], in this competition, we use much stronger backbones with suitable licenses: ResNeSt [24] (license), ResNeXt [19] (license), CotNet [11] (license), HS-ResNet [22] (license), NAT [7] (license), ViT (from BEIT [2]) (license), and ViT (from SimMIM [20]) (license). The stronger backbones perform much better.

2.1.4 Simpler Augmentations

The augmentations used in [18] are designed for image copy detection, and thus they are too complexed. For product retrieval tasks, we only keep RandomResizedCrop, RandomRotation, RandomPerspectiveChange, RandomPadding, RandomImageUnderlay, RandomImageOverlay, RandomLightChange, RandomHorizontalFlip, RandomVerticalFlip, and GaussianBlur. For more details, please refer to the original paper [18].

2.1.5 Higher Resolution

In image copy detection, $256 \times 256$ resolution is the best. For the product retrieval task, we find that $512 \times 512$ resolution performs best. Though higher resolution brings performance improvement, it also brings much computational burden to the training and reference process.

2.1.6 Loss

To be computationally efficient, we replace the 8192-dim features [18] with commonly-used 2048-dim features. Moreover, instead of combining cross-entropy loss and triplet loss [8], we use a single CosFace [16].

2.1.7 Exponential Moving Average

Exponential Moving Average (EMA) is used to stabilize the training process of deep metric learning. It brings consistent performance improvement without increasing any burden.

2.2. Vision-language Models

In this section, we introduce the selected vision-language models and how we use that. Due to the license issue, we only choose BLIP [9] (license), ALBEF [10] (license), XVLM [23] (license), METER [6] (license), and SLIP [13] (license). We get the suitable licenses for both the code and the released models. We do NOT use the famous CLIP [15] because we cannot get the license for the pre-trained models.

The finetuning process is relatively easy. Because each algorithm takes the nature language and the image as input, we just use the product title as the description of one product.
image. After training, the image encoder is used to extract the features of query and reference images. Though the use of the vision-language models is easy, it provides a totally different prospective to the product retrieval task.

2.3. Ensemble Methods

2.3.1 Maximum Ensemble
The ensemble method in [17] is proved to be effective in the product retrieval task.

2.3.2 Voting Ensemble
Each model returns a ranking list, and we fetch the top-10 images. Many models vote for the final ranking list. It is similar (or same) with last year’s “Multiple networks rankings”.

2.4. Other Tricks

2.4.1 Global-local Matching
We split reference (index) images to match locally (The query images are kept). We name the used two strategies as Index5Crop and Index6Crop. They are illustrated in Fig. 2. Note that we only re-train 3 different methods to perform Index5Crop (2) and Index6Crop (1). The gained results are absorbed to final ranking by voting ensemble.

2.4.2 Re-ranking
The k-reciprocal re-ranking [25] is proved to be very useful for image retrieval tasks. However, it is not straightforward to apply it to millions of reference images. We distribute it with about 100 CPUs. The advantage is the speed is much faster, and the memory is enough. However, we cannot promise 100 CPUs work normally at the same time. Therefore, there may be some queries missing during the re-ranking process. We argue that because we ensemble a lot of models, some queries missing do not bring serious influence to the final result.

2.4.3 Multi-scale Testing
Because $512 \times 512$ resolution performs best, in the multi-scale testing, we use $400 \times 400$, $512 \times 512$, and $600 \times 600$ resolutions.

3. Ineffective Methods

We have tried a lot of methods in this competition, and only some of them work in the final ensemble period. The listed ineffective methods are representative and seem to work.

3.1. Title for Pseudo-labels
Last year’s winner finds using the product titles to create pseudo-labels useful. We find that, when the MAR@10 is
relatively low (less than 70), this approach is effective regardless of using a single model or ensemble. However, when the MAR@10 approaches 75, regardless of using BERT [5] or word2vec [12] to generate sentence embeddings, this approach cannot contribute to the final ensemble result.

3.2. Multiple Layers Features

It is reasonable that deep features of two images, which have subtle difference, may be indistinguishable. However, both training models with shallow features and directly combining shallow features with deep features do not work.

3.3. Multiple Augmented Queries

Performing test-time augmentation (TTA) is a common practice for image retrieval. However, we find performing TTA (e.g., center cropping, flipping) on query images do not bring performance improvement.

3.4. Query Expansion

The standard query expansion (QE) [4] and $\alpha$ query expansion ($\alpha$QE) [14] are widely used for image retrieval. However, both of them do not work in our approach.

3.5. Background Removal

We try to use a model to remove the background of all the query and index images. However, the performance decreases. It may because the background removal algorithm removes some discriminative matching information.

4. Experiments

To prove the superiority of the $V^2L$, we compare the proposed model with state-of-the-art methods from the leaderboard in the testing phase. The comparison results are shown in Table 1. We ranks first among all the competitors. We discover that (1) Our solution is much higher than other competitors’. (2) There is an obvious performance gap between top-3 and others’ scores. Also, we visualize some results of our final ranking list. They are shown in Fig. 3.

5. Conclusion

In this paper, we introduce our winning solution to the eBay eProduct Visual Search Challenge (FGVC9) at CVPR’22. The proposed $V^2L$ combines vision models and vision-language models. Experiments show that the combination and the ensemble are the key to our winning.
References

[1] Yalong Bai, Yuxiang Chen, Wei Yu, Linfang Wang, and Wei Zhang. Products-10k: A large-scale product recognition dataset. arXiv preprint arXiv:2008.10543, 2020.

[2] Hangbo Bao, Li Dong, and Furu Wei. Beit: Bert pre-training of image transformers. arXiv preprint arXiv:2106.08254, 2021.

[3] Lele Cheng, Xiangzeng Zhou, Liming Zhao, Dangwei Li, Hong Shang, Yun Zheng, Pan Pan, and Yinghui Xu. Weakly supervised learning with side information for noisy labeled images. In The European Conference on Computer Vision (ECCV), August 2020.

[4] Ondřej Chum, Andrej Mikulik, Michal Perdoch, and Jiří Matas. Total recall ii: Query expansion revisited. In CVPR 2011, pages 889–896. IEEE, 2011.

[5] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. Bert: Pre-training of deep bidirectional transformers for language understanding. arXiv preprint arXiv:1810.04805, 2018.

[6] Zi-Yi Dou, Yichong Xu, Zhe Gan, Jianfeng Wang, Shuohang Wang, Lijuan Wang, Chenguang Zhu, Pengchuan Zhang, Lu Yuan, Nanyun Peng, Zicheng Liu, and Michael Zeng. An empirical study of training end-to-end vision-and-language transformers. In Conference on Computer Vision and Pattern Recognition (CVPR), 2022.

[7] Ali Hassani, Steven Walton, Jiachen Li, Shen Li, and Humphrey Shi. Neighborhood attention transformer. 2022.

[8] Alexander Hermans, Lucas Beyer, and Bastian Leibe. In defense of the triplet loss for person re-identification. arXiv preprint arXiv:1703.07737, 2017.

[9] Jinnan Li, Dongxi Li, Caiming Xiong, and Steven Hoi. Blip: Bootstrapping language-image pre-training for unified vision-language understanding and generation. In ICML, 2022.

[10] Jinnan Li, Ramprasaath R. Selvaraju, Akhilesh Deepak Gomare, Shafiq Joty, Caiming Xiong, and Steven Hoi. Align before fuse: Vision and language representation learning with momentum distillation. In NeurIPS, 2021.

[11] Yehao Li, Ting Yao, Yingwei Pan, and Tao Mei. Contextual transformer networks for visual recognition. arXiv preprint arXiv:2107.12292, 2021.

[12] Tomas Mikolov, Kai Chen, Greg Corrado, and Jeffrey Dean. Efficient estimation of word representations in vector space. arXiv preprint arXiv:1301.3781, 2013.

[13] Norman Mu, Alexander Kirillov, David Wagner, and Saining Xie. Slip: Self-supervision meets language-image pre-training. arXiv preprint arXiv:2112.12750, 2021.

[14] Filip Radenović, Giorgos Tolias, and Ondřej Chum. Fine-tuning cnn image retrieval with no human annotation. IEEE transactions on pattern analysis and machine intelligence, 41(7):1655–1668, 2018.

[15] Alec Radford, Jong Wook Kim, Chris Hallacy, Aditya Ramesh, Gabriel Goh, Sandhini Agarwal, Girish Sastry, Amanda Askell, Pamela Mishkin, Jack Clark, Gretchen Krueger, and Ilya Sutskever. Learning transferable visual models from natural language supervision. In Marina Meila and Tong Zhang, editors, Proceedings of the 38th International Conference on Machine Learning, volume 139 of Proceedings of Machine Learning Research, pages 8748–8763. PMLR, 18–24 Jul 2021.

[16] Hao Wang, Yitong Wang, Zheng Zhou, Xing Ji, Dihong Gong, Jingchao Zhou, Zhifeng Li, and Wei Liu. Cosface: Large margin cosine loss for deep face recognition. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 5265–5274, 2018.

[17] Wenhao Wang, Yifan Sun, Weipu Zhang, and Yi Yang. D2tv: A data-driven and local-verification approach for image copy detection. arXiv preprint arXiv:2111.07090, 2021.

[18] Wenhao Wang, Weipu Zhang, Yifan Sun, and Yi Yang. Bag of tricks and a strong baseline for image copy detection. arXiv preprint arXiv:2111.08004, 2021.

[19] Saining Xie, Ross Girshick, Piotr Dollár, Zhuowen Tu, and Kaiming He. Aggregated residual transformations for deep neural networks. arXiv preprint arXiv:1611.05431, 2016.

[20] Zhenda Xie, Zheng Zhang, Yue Cao, Yutong Lin, Jianmin Bao, Zhuliang Yao, Qi Dai, and Han Hu. Simmim: A simple framework for masked image modeling. arXiv preprint arXiv:2111.09886, 2021.

[21] Jiangbo Yuan, An-Ti Chiang, Wen Tang, and Antonio Haro. eproduct: A million-scale visual search benchmark to address product recognition challenges. arXiv preprint arXiv:2107.05856, 2021.

[22] Pengcheng Yuan, Shufei Lin, Cheng Cui, Yuning Guo, Dongliang He, Errui Ding, and Shumin Han. Hsresnet: Hierarchical-split block on convolutional neural network. arXiv preprint arXiv:2010.07621, 2020.

[23] Yan Zeng, Xinsong Zhang, and Hang Li. Multi-grained vision language pre-training: Aligning texts with visual concepts. arXiv preprint arXiv:2111.08276, 2021.

[24] Hang Zhang, Chongrui Wu, Zhongyue Zhang, Yi Zhu, Zhi Zhang, Haibin Lin, Yue Sun, Tong He, Jonas Muller, R. Mannmatha, Mu Li, and Alexander Smola. Resnest: Split-attention networks. arXiv preprint arXiv:2004.08955, 2020.

[25] Zhuo Zhong, Liang Zheng, Donglin Cao, and Shaozi Li. Re-ranking person re-identification with k-reciprocal encoding. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 1318–1327, 2017.