Align Yourself: Self-supervised Pre-training for Fine-grained Recognition via Saliency Alignment

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Abstract

Self-supervised contrastive learning has demonstrated great potential in learning visual representations. Despite their success on various downstream tasks such as image classification and object detection, self-supervised pre-training for fine-grained scenarios is not fully explored. In this paper, we first point out that current contrastive methods are prone to memorizing background/foreground texture and therefore have a limitation in localizing the foreground object. Analysis suggests that learning to extract discriminative texture information and localization are equally crucial for self-supervised pre-training in fine-grained scenarios. Based on our findings, we introduce cross-view saliency alignment (CVSA), a contrastive learning framework that first crops and swaps saliency regions of images as a novel view generation and then guides the model to localize on the foreground object via a cross-view alignment loss. Extensive experiments on four popular fine-grained classification benchmarks show that CVSA significantly improves the learned representation.

1 Introduction

Learning visual representations without supervision by leveraging pretext tasks has become increasingly popular. Various learning approaches such as colorization (Zhang, Isola, and Efros 2016), Rel-Loc (Noroozi and Favaro 2016), Rot-Pred (Gidaris, Singh, and Komodakis 2018) have been proposed to learn such representations. The objective of these pretext tasks is to capture invariant features through predicting transformations applied to the same image. More recently, self-supervised representation learning has witnessed significant progress by the use of contrastive loss (Hadsell, Chopra, and LeCun 2006; Logeswaran and Lee 2018; Hénaff et al. 2019; He et al. 2020; Chen et al. 2020a). Despite that contrastive-based methods have even outperformed supervised methods under some circumstances, their success has largely been confined to largescale general-purpose datasets (coarse-grained) such as ImageNet (Krizhevsky, Sutskever, and Hinton 2012). Little to no effort has been made to adapt representations learned on coarse-grained settings to fine-grained settings utilizing unlabeled fine-grained datasets during pre-training. We argue that current contrastive learning methods only work on coarse-grained iconic images with large foreground objects residing in the background with informative discriminative texture (e.g., ImageNet) but perform poorly when background texture provides little clue (e.g., CUB (Wah et al. 2011)) for fine-grained separation.

To bridge the substantial gap between self-supervised and supervised representation learning on fine-grained object recognition, we first analyze and compare knowledge learned by various self-supervised methods and supervised methods during pre-training. We find that current self-supervised contrastive learning methods tend to learn low-level texture information and lack the localization ability of the foreground object. In contrast, the supervised method shows better localization ability. Specifically, we show that the incompetence of localization of current contrastive learning is primarily due to the commonly adopted RandomResizedCrop (RRC) augmentation where a random size patch at a random location is cropped and resized to the original size. The model then might learn a semantic representation of the bird by contrasting the tree and the wing of the bird, as illustrated in Figure 5 in the appendix. This practice may be reasonable for coarse-grained recognition if background cues (e.g., p(bird|tree) > p(car|tree)). However, the background of the image being a tree is not as informative when distinguishing bird species. Consequently, the model learns by cheating on picking low-level texture information and lack the localization ability of the foreground object. In contrast, the supervised method shows better localization ability.
clues (usually from the background) instead of learning by localizing the foreground. This phenomenon is mutual for existing contrastive methods such as MoCo.v2 (Chen et al. 2020b), BYOL (Grill et al. 2020) and SimCLR (Chen et al. 2020a) despite different contrastive mechanisms.

The devil lies in semantically discriminative fine-grained feature extraction for a successful contrastive pre-training. To remedy the inadequacy of fine-grained feature capturing due to failure in localizing to discriminative regions, we propose to empower contrastive learning with localization ability by aligning fine-grained semantic features across augmented views, as shown in Figure 1. In particular, we come up with a pre-training framework called Cross-View Saliency Alignment (CVSA). CVSA consists of two algorithmic components: (a) A general plug-and-play data augmentation strategy called SaliencySwap, which swaps the saliency region of the reference image with the saliency region of a randomly selected background image. SaliencySwap ensures semantic consistency between augmented views while introducing background variation. A demonstration of SaliencySwap in comparison with RRC is shown in Figure 5 in the appendix. (b) An alignment loss that provides an explicit localization supervision signal by forcing the model to give the highest correspondence response intensity of the foreground object across views.

On top of the proposed CVSA, to further bridge the performance gap between self-supervised and supervised representation learning on the fine-grained recognition problem, we offer a dual-stage pre-training setting, which utilizes coarse-grained datasets for low-level feature extraction and fine-grained datasets for higher-level target discrimination and localization.

In short, this paper makes the following contributions:

• We dive deep into the knowledge learned by various self-supervised methods compared to supervised methods during the fine-grained pre-training phase and point out the cause of limitations.

• We develop a novel contrastive learning framework for fine-grained recognition, which contains a data augmentation technique called SaliencySwap which guarantees semantic consistency between views and an alignment objective which enables the model to localize.

• We show our approach demonstrates consistent performance gain under various pre-training stage settings on fine-grained benchmarks via extensive experiments.

2 Related Work

Self-supervised methods have largely reduced the performance gap between supervised models on various downstream vision tasks. Most early methods design hand-crafted pretext tasks (Doersch, Gupta, and Efros 2015; Zhang, Isola, and Efros 2016; Gidaris, Singh, and Komodakis 2018). These pretext tasks rely on somewhat ad-hoc heuristics, which limits the generalization of learned representations. Another popular form is clustering-based methods (Caron et al. 2018; Zhan et al. 2020; Caron et al. 2020). Recently, contrastive learning (He et al. 2020; Chen et al. 2020a) achieved state-of-the-art performance, which learns instance-level discriminative representations by contrasting positive pairs against negative pairs. Various mechanisms (Chen and He 2021; Zbontar et al. 2021; Grill et al. 2020) are proposed to learn useful representations rather than trivial solutions in contrastive methods such as a constant representation. More recently, some research endeavors are made on top of contrastive methods to enhance pre-training quality for specific downstream tasks, such as object detection (Xie et al. 2021a). Most methods adopt detection or segmentation components to learn pixel-level contrastive representation (Yang et al. 2021; Gansbeke et al. 2021; Dai et al. 2021). LooC (Tete et al. 2021) proposed to construct separate embedding sub-spaces for each augmentation instead of a single embedding space. DiLo (Zhao et al. 2021a) proposed an augmentation approach that randomly pastes masked foreground onto a variety of backgrounds. However, existing methods are trained on general-purpose coarse-grained datasets while neglecting fine-grained scenarios. In this work, we propose a dual-stage pre-training pipeline that utilizes coarse- and fine-grained datasets for better fine-grained representation learning.

Current efforts (Xiao et al. 2015; Simon and Rodner 2015; Zheng et al. 2019; Huang and Li 2020; Ding et al. 2019; Zheng et al. 2021a) in fine-grained recognition are primarily dedicated to fine-tuning model pre-trained on supervised ImageNet either by localizing distinct parts or by learning fine-grained features. However, there exists little exploration in self-supervised pre-training for fine-grained categorization. In the paper, we attempt to bring the localization and fine-grained feature representation learning to the pre-training stage, using fine-grained datasets.

3 Fine-grained Pre-training Essentials

We evaluate the capabilities learned out of three classes of pre-training mechanisms, namely self-supervised contrastive, non-contrastive, and supervised methods. In particular, we focus on discriminative feature extraction and object localization ability. Without loss of generality, we select MoCo.v2, BYOL, Rot-Pred, and supervised classification for comparison. To explore the effects of object localization, we develop a simple binary classification as a pre-training task where the model is asked to classify images from CUB as foreground class and images from COCO as background class, (rather than design detection specific modules as InSLoc (Yang et al. 2021)).

3.1 Experimental Setup

Dataset. We evaluate the performance of baselines’ representation pre-trained on the training set of 100% IN (ImageNet), 10% IN, COCO, and CUB, details of datasets used are described in Sec. 5. We use the same fixed split for the 10% IN where we randomly sample 10% of the total training set size from each class.

Pre-training Details. To ensure impartial comparisons, we use the data augmentations adopted in MoCo.v2 for all self-supervised methods and follow the exact setup de-
Figure 2: (a) Performance analysis of RandomResizedCrop (RRC) and RandomCrop (RC) on STL-10. MoCo.v2 augmentations are used except for Only RRC. The horizontal axis on the top denotes the scale factor in RRC, while the bottom axis indicates various padding sizes for RC with reflect and constant padding modes. The Top-1 accuracy (in %) of fine-tune evaluation is reported. (b) Performance analysis of the binary classification task with various mixup methods. (c) Interpretation of existing contrastive methods vs. CVSA from a causal perspective, the direct link denotes the causality from the cause to the effect.

Table 1: Comparison of pre-training methods. Top-1 fine-tune and linear accuracy (in %) and MaxBoxAcc are reported.

| Method            | 100% ImageNet | 10% ImageNet | COCO    | CUB    |
|-------------------|---------------|--------------|---------|--------|
| Supervised        | 79.25         | 67.64        | 51.68   |        |
| Rot-Pred          | 67.66         | 25.29        | 46.14   |        |
| MoCo.v2           | 69.99         | 33.33        | 47.52   |        |
| MoCo         | 72.61         | 27.17        | 49.23   |        |
| BYOL              | 70.42         | 20.38        | 46.52   | 70.09  |
| Fine-tune Linear  | 63.67         | 48.23        | 41.65   | 45.96  |
| MaxBoxAcc         | 14.50         | 15.03        | 33.36   |        |

Table 1: Comparison of pre-training methods. Top-1 fine-tune and linear accuracy (in %) and MaxBoxAcc are reported.

Evaluations. We evaluate the learned representation with a linear evaluation protocol, and a fully supervised fine-tune evaluation protocol. A detailed description of linear and fine-tune evaluation protocols and training details are given in Appendix A.1. The linear test accuracy of the pre-trained model is referred to as the model’s discriminative feature extraction ability. We refer to the fine-tune evaluation as the pre-training representation quality metric for fine-grained classification problems in a practical sense. For each method, we report mean top-1 accuracy on the test set over 3 trials. To evaluate the localization ability of different approaches, we use a class activation mapping (CAM) based metric called MaxBoxAcc described in (Choe et al. 2020). A larger MaxBoxAcc indicates better localization ability.

3.2 Essential Requirement and Formulation

Where does the gap lie between self-supervised and supervised pre-training? As shown in Table 1 when pre-trained on 100% IN and 10% IN, the supervised method consistently outperforms all self-supervised pre-training methods. Compared to supervised pre-training, all self-supervised approaches yield lower MaxBoxAcc, indicating a lack of localization ability. Self-supervised methods are task-agnostic and could only learn low-level features, i.e., gradient and direction-dependent features for rotation, invariant features across views to cluster different objects for contrastive methods. However, the supervised method discards task-irrelevant information and extracts related semantic features. Deep CNN, such as ResNet, has its natural ability in localization during the supervised pre-training process. However, such localization ability could hardly be acquired during self-supervised pre-training.

Why doesn’t the contrastive method look at the bird? We hypothesize that the lack of localization ability comes from the commonly adopted RandomResizedCrop (RRC) augmentation, where a random size patch at a random location is cut from the original image and then resized to the original size. When asked to pull together two patches cut from the same image, models often cheat by exploiting low-level texture features. As shown in Figure 2 (a), the performance of BYOL drops drastically as the cropped patch scale enlarges on STL-10 (Coates, Ng, and Lee 2011). The best accuracy is achieved with a scaling factor of 0.08, which is the default hyperparameter choice for current contrastive learning approaches. Contrasting overly small patches forces the model to extract local texture features and lack localization ability. Also, the hand-craft methods don’t rely on RRC, and this in turn explains their better performance than contrastive-based algorithms on CUB. We formulate current contrastive methods with a causal graph as illustrated in Figure 2 (c). Let X be images with content composed of background prior B and foreground target prior T, generated with style prior S as augmentations like color jittering. Latent representation Z is learned and used to infer
Is Localization All You Need? We report linear and fine-tune test accuracy as well as MaxBoxAcc of the binary classification on the CUB test set pre-training with various mixup augmentations [Zhang et al. 2017; Uddin et al. 2020; Liu et al. 2021; Yun et al. 2019] as well as image augmentations in Figure 2(b). It is observed that the fine-tuned model using binary classification as pre-training yields comparable MaxBoxAcc as supervised pre-training, which indicates that a simple binary classification supervision signal empowers the network with localization ability. Yet, there still exists a vast fine-tuned accuracy gap compared to supervised pre-training on IN. We assume that the gap mainly comes from an inferior feature extraction ability of the binary classification pre-training, as could be conducted from a much lower linear test accuracy. In other words, for better fine-grained recognition pre-training, discriminative feature extraction ability is as essential as localization ability.

Next, we investigate how different mixup augmentations affect the model’s localization ability. We notice a simple interpolation between images as done by Mixup brings a negative impact on model’s localization ability. This negative impact is largely due to the unnatural characteristics of the mixed images. Cutmix mixes samples by replacing the image region with a patch from another training image while SaliencyMix replaces the image region with the saliency region from another training image. We observe that both CutMix and SaliencyMix bring about better localization ability. However, directly applying these mixup-based augmentations to contrastive learning leads to degenerate solutions. Contrastive learning essentially expects positive pairs to share common semantic object while keeping negative pairs as much dissimilar as possible. Due to the randomness introduced by such mixup algorithms, augmented images may contain multiple semantic objects or contain no semantic object at all. Without proper supervision, this easily causes the learned representation space to collapse during self-supervised contrastive pre-training. We address this problem by proposing an image augmentation technique that swaps saliency regions of images which aims to introduce solely background variation.

Formulation. From the previous analysis, given a fine-grained classification problem, similar to [Arora et al. 2019], we assume $\mathcal{X}$ to be a set of all samples with an underlying set of discrete latent classes $C$ that represent semantic content, we obtain the joint distribution between each sample $x$ and its class $c$:

$$p(c, x) = p(c|x_{fore}) \cdot p(x_{fore}|x),$$

(1)

where $x_{fore}$ stands for the foreground object. This factorization captures two important intuitions: (1) Given an image of a fine-grained object; the model should first localize the foreground object, namely, the localization ability of the model. (2) To further tell the species of the foreground object, discriminative texture features should be extracted, namely, the texture extraction ability of the model. Following this formulation, a dual-stage pre-training pipeline is naturally proposed for self-supervised fine-grained recognition. In particular, we refer to previous contrastive learning methods such as MoCo.v2 and BYOL on large datasets such as ImageNet or COCO as the first-stage and the proposed CVSA as the second-stage. The model’s discriminative texture extraction ability could be fulfilled by first-stage pre-training. In the first-stage, we regard the image content as a whole as the same assumption of current contrastive methods. For the second-stage pre-training, we propose a framework called cross-view saliency alignment (CVSA), attempting to break the causality between $B$ and $Y$ by enabling the model’s localization capability.

4 Cross-view Saliency Alignment

4.1 SaliencySwap

The purpose of SaliencySwap is to maximally utilize the saliency information for foreground semantic consistency across views while introducing background variation. Unlike RRC, our method guarantees that each view at least contains part of the foreground object and thus prevents the encoder from learning irrelevant feature representation through pure background information. Meanwhile, we swap the saliency region from the source image and the saliency region from another randomly selected image to avoid saliency ambiguity. After swapping, the encoder is thus forced to extract object-oriented semantic features from the common foreground instead of the random background.

Source Saliency Detection A saliency detection algorithm generates a saliency map which indicates the objects of interest (primarily foreground). Let $I \in \mathbb{R}^{W \times H \times C}$ be an image in the training set, define $\psi$ to be a saliency detection algorithm, then the output saliency map $S_{i,j} = \psi(I_{i,j}) \in \mathbb{R}^{W \times H}$ indicates the saliency intensity value at pixel $I_{i,j}$. The saliency information can be noisy. Therefore, we seek to find a bounding box $B = (l, t, W_b, H_b)$ of the foreground object with the highest averaged saliency information satisfying the following objective function:

$$\arg\max_{W_b, H_b, l, t} \sum_{i=l}^{i=l+W_b} \sum_{j=t}^{j=t+H_b} S_{i,j} \frac{W_b \times H_b}{W_b \times H_b}.$$  

(2)

A corresponding binary saliency mask $M \in \mathbb{R}^{W \times H}$ is defined by filling with 1 within the bounding box $B$, otherwise 0. Then we crop a random patch within the bounding box $B$. Similar to RRC, the size of the patch is determined based on an area ratio (to the area of the bounding box), which is sampled from a uniform distribution $U(\lambda, 1)$.

Foreground Background Fusion We then combine the cropped foreground patch from the source image (foreground image) with another randomly selected image (background image). To avoid saliency ambiguity where the augmented images are composed of multiple semantic objects, our approach restricts each augmented view to contain the saliency information only of one semantic object. Here we consider two ways of merging based on different choices
of the background dataset. (I) The background dataset is the same as the foreground dataset. The background image also contains a foreground object of the targeted fine-grained dataset. Therefore, the saliency information of the background needs to be eliminated. We first calculate the bounding box $B_f, B_b$ of the foreground and background images, respectively, using Eqn. 2. Then select a random patch from the foreground $B_f$ and resize it to the shape of $B_b$. Finally, we replace $B_b$ with the resized foreground patch. (II) The background dataset is different from the foreground dataset. To avoid the background from having an object of the same fine-grained class as the foreground, we wish the background dataset to be rich in different environments. Thus we choose dataset like COCO rather than the iconic dataset like ImageNet. Again, we first calculate the bounding box $B_f$ of the foreground and select a random patch. Then we resize the selected patch based on an area ratio (to the area of the background) which is sampled from a uniform distribution $(\beta, 1)$. Finally, we ‘paste’ the resized patch to a random location in the background.

### 4.2 Cross-view Saliency Alignment

Given two views $I_q$ and $I_k$ of Image $I$ augmented by a pipeline containing SaliencySwap and other augmentation operations such as random flipping and color jittering. Define $M_k$ and $M_q$ to be their saliency masks, respectively. Let $z^l_q \in \mathbb{R}^{W^l \times H^l \times C^l}$ and $z^l_k \in \mathbb{R}^{W^l \times H^l \times C^l}$ be the $C^l$ dimensional $H^l \times W^l$ feature maps encoded by an encoder network $z = f(I)$ (e.g., ResNet) truncated at stage $l$. We adopt two types of non-linear projector necks $g(\cdot)$ on top of the encoder to form a $d$-dim projection. The two-layer MLP projector generates the following projection $h_{mlp} = g_{mlp}(z)$ as proposed by SimCLR. Similarly, a convolutional projection $h_{conv}$ is given by a convolution projector $g_{conv}$ which consists of two $1 \times 1$ convolution layers with a batch normalization layer and a ReLU layer in between. Following BYOL, two predictor heads $p_{mlp}(\cdot)$ and $p_{conv}(\cdot)$, which have the same network structures as the two projectors except for different input dimensions, are adopted to match the output of one view to the other. Specially, $p_{conv}(\cdot)$ is proposed for saliency alignment. The overall framework is shown in Figure 3(a).

**Cross-view Attention.** We seek to capitalize on the pixel-level foreground semantic interactions between the feature maps of two different augmented views. We first build a cross-view attention map:

$$A^l_{q,k} = p_{conv}(h^l_{q,conv}) \odot h^l_{k,conv}^T,$$  \hspace{1cm} (3)

where $A^l_{q,k}$ denotes the attention map of view $k$ w.r.t. view $q$, $T$ denotes matrix transposition, and $\odot$ denotes matrix multiplication. The location-aware attention map $A^l \in \mathbb{R}^{W^l \times H^l \times H^l \times W^l}$ then indicates a pair-wise spatial correspondence between any pixel from $p_{conv}(h^l_{q,conv})$ and any pixel from $h^l_{k,conv}$. Symetrically, we get the attention map $A^l_{k,q}$ of view $q$ w.r.t. view $k$ by interchanging $q$ and $k$ of Eqn. 3.

**Joint Saliency Alignment.** The SaliencySwap ensures that the feature map of each view contains semantic consistent features. To further enhance the encoder’s ability to identify the location of the foreground object, we propose to align the saliency mask with a correspondence intensity matrix that captures the pixel-level correlation from the feature map of one view to the other, as shown in Figure 3(b). The correspondence intensity matrix $C$ is formulated as follows:

$$C^l_{q,k} = \max(Sigmoid(A^l_{q,k})).$$  \hspace{1cm} (4)

Note that the shape of $C^l_{q,k}$ is $W^l \times H^l$ and the $\max(\cdot)$ operation is performed over the second axis of $A^l_{q,k}$. We then define a symmetrized alignment loss between the saliency mask $M$ and the correspondence intensity matrix $C$:

$$\mathcal{L}_{align} = \|\delta(M_q) - C^l_{q,k}\|^2 + \|\delta(M_k) - C^l_{k,q}\|^2,$$  \hspace{1cm} (5)

![Figure 3: Conceptual illustration of learning paradigm of Cross-view Saliency Alignment.](image)
where $\delta(\cdot) : \mathbb{R}^{W \times H} \rightarrow \mathbb{R}^{W' \times H'}$ denotes the bilinear downsampling operation. The proposed alignment loss restricts the most cross-view correlated pixels to the saliency region and thus gives the model localization ability. In addition, leveraging cross-layer semantics also enhances the representation of multi-scale learning.

**Joint Objective.** Following [Chen and He 2021], we define a contrastive loss $\mathcal{L}_{\text{cont}}$ with the prediction vector $p_{q,\text{mlp}} = p_{\text{mlp}}(h_{q,\text{mlp}})$ and the projection vector $h_{k,\text{mlp}}$ using symmetrized negative cosine similarity $\langle \cdot, \cdot \rangle$ as:

$$
\mathcal{L}_{\text{cont}} = \frac{1}{2} D(p_{q,\text{mlp}}, h_{k,\text{mlp}}) + \frac{1}{2} D(p_{k,\text{mlp}}, h_{q,\text{mlp}}),
$$

where $D(p, h) = -\frac{p}{\|p\|_2} \cdot \frac{h}{\|h\|_2}$. The joint objective for the second-stage pretext task is defined as:

$$
\mathcal{L}_{\text{CV-SA}} = \mathcal{L}_{\text{cont}} + \mathcal{L}_{\text{align}}.
$$

5 Experiments

5.1 Experimental settings

**Implementation details.** We use ResNet as the encoder $f$ followed by two projectors and two predictor sub-networks. During the *first-stage* pre-training, we follow the exact experimental setup in BYOL. For the *second-stage* in dual-stage pre-training, the model is initialized with the pretrained weight from the *first-stage* and the first two stages of the ResNet backbone are frozen. We use a learning rate of $lr \times \text{BatchSize}/256$ with $\text{BatchSize} = 1024$ and a base $lr$ selected from $\{0.3, 0.6, 0.9, 1.2\}$. The embedding dimension is set to $d = 256$ as BYOL. As for image augmentations, we follow the settings in MoCo.v2 for all contrastive learning methods. We replace RandomResizedCrop (RRC) with the proposed SaliencySwap and adopt all other augmentations in MoCo.v2. We grid search cropping scale ratio of SaliencySwap $\lambda \in \{0.08, 0.2, 0.5, 0.8\}$. For simplicity, we use the ground truth bounding box of fine-grained datasets due to most saliency detectors are trained in a supervised manner. An ablation study of the performance using different detection algorithms is given in appendix A.2.

We use the same setup as in Sec.5 for other unstated setups.

**Dataset.** We assess the performance of the representation pre-trained using dual-stage, first-stage only and second-stage only on four fine-grained benchmarks: 1) CUB-200-2011 [Wah et al. 2011] (CUB) contains 11,788 images from 200 wild bird species, 2) Stanford-Cars [Krause et al. 2013] (Cars) contains 16,185 images of 196 car subcategories, 3) FGVC-Aircraft [Maji et al. 2013] (Aircrafts) contains 10k images of 100 classes of aircrafts and 4) NA-birds [Van Horn et al. 2013] (NAbirds) is a large dataset with 48,562 images for over 555 bird classes. We follow the standard dataset partition in the original works. For the *first-stage* pre-training, we adopt two popular datasets: 1) ImageNet contains 1.28 million of training images. 2) COCO contains 118k images with more complex scenes of many objects.

### Table 2: Comparison of using second-stage only settings on fine-grained benchmarks.

| Methods | Stage 2 | CUB | NAbirds | Aircrafts | Cars |
|---------|---------|-----|---------|-----------|------|
| BYOL+DiLo | ✓ | 66.16 (±1.31) | 73.42 (±0.88) | 73.75 (±1.15) | 76.74 (±0.87) |
| BYOL+CVSA | ✓ | 66.88 (±0.20) | 73.75 (±1.21) | 74.55 (±1.95) | 77.45 (±1.58) |

### Table 3: Comparison of using dual-stage settings on COCO and fine-grained benchmarks.

| Methods | Stage 2 | CUB | NAbirds | Aircrafts | Cars |
|---------|---------|-----|---------|-----------|------|
| BYOL+CVSA | ✓ | 69.14 (±0.59) | 77.57 (±1.26) | 82.77 (±1.84) | 87.13 (±0.77) |

### Table 4: Comparison of using dual-stage settings on ImageNet and fine-grained benchmarks.

| Methods | Stage 2 | CUB | NAbirds | Aircrafts | Cars |
|---------|---------|-----|---------|-----------|------|
| BYOL+CVSA | ✓ | 76.91 (±0.28) | 79.40 (±0.61) | 87.27 (±0.88) | 89.63 (±0.64) |

5.2 Comparison with State-of-the-art

We perform 800 epochs pre-training with ResNet-50 encoder using different pre-training stage settings on four fine-grained datasets and report the top-1 classification accuracy under the fine-tune protocol. We choose two hand-crafted methods (Rel-Loc and Rot-Pred), three commonly used contrastive learning methods (SimCLR, MoCo.v2, and BYOL), and three extension methods (Looc*, DiLo, and InsLoc) for comparison. Note that DiLo and InsLoc are reproduced using official code, with other methods reproduced using OpenSelfSup. Looc* denotes its rotation version reproduced by us. Since our approach extends BYOL, we choose BYOL as baseline. As shown in Table 2 when performing the *second-stage only* setting, namely pre-training
with the training set of fine-grained datasets from scratch, our proposed CVSA outperforms BYOL by a large margin on all benchmarks. When applying the dual-stage setting using COCO for the first-stage, as shown in Table 3, CVSA shows a consistent improvement on representations learned during the first-stage while most comparing methods yield worse performance than the first-stage pre-trained BYOL baseline. However, when using ImageNet for the first-stage pre-training, as shown in Table 4, the improvement of CVSA in the dual-stage setting is not as significant on Aircraft and Cars. We hypothesize that this is due to the iconic nature of these two datasets. We find that most images of these two datasets are of similar and straightforward background, restricting our proposed SaliencySwap. Besides, comparison of Table 2 with Table 3 and 4 suggests that the performance gain from the first stage is higher than the second stage for all methods. This is consistent with our formulation in Sec. 3 that discriminative feature extraction relies on the size of the pre-training dataset, and localization ability alone is not enough for fine-grained recognition. In conclusion, our proposed CVSA and pre-training pipeline improve learned representation for fine-grained classification.

![Figure 4: Ablation of hyperparameters. (a) shows effect of different scaling factors of SS during second-stage. (b) demonstrates effect of freezing different ResNet stages during second-stage. The dotted grey line indicates the performance of BYOL pre-trained on COCO during first-stage.](image)

### 5.3 Ablation Study

We perform 400 epochs pre-training with ResNet-18 encoder and report the top-1 accuracy under the fine-tune evaluation on CUB dataset during ablation studies.

**Module Effectiveness Ablation.** We demonstrate the effectiveness of our CVSA by adding modules one by one onto the baseline. We first validate our proposed augmentation SaliencySwap (SS). We compare the performance of MoCo.v2 and BYOL using SS against RandomResizedCrop (RRC) while keeping all other augmentations unchanged. As shown in Figure 4, SS outperforms RRC both for MoCo.v2 and BYOL. We then add the saliency alignment loss (Align) onto BYOL using SS. We observe a further performance improvement. Now, we have shown that both SS and Align contribute to higher performance.

**Hyperparameter Ablation.** We then analyze the performance of SS using different crop scaling factors, specifically $\lambda \in \{0.08, 0.2, 0.3, 0.4, 0.5, 0.8\}$ in Figure 2. From Figure 2 (b), the performance of BYOL fluctuates drastically under the different scaling factors of RRC with the best result achieved with a scaling factor being 0.08. However, BYOL yields similar performance under different choices of $\lambda$ of SS. We argue that SS, together with Align, helps the model to localize on the foreground object, and thus local texture is no longer the only clue for contrastive pre-training to learn representation. Then, we study the effect when freezing various stages of ResNet-18 in the second-stage. We initialize the model of all methods in the second-stage with the weights of BYOL baseline pre-trained on COCO in the first-stage. As shown in Figure 4, the horizontal axis indicates freezing up to different stages of ResNet-18. The highest accuracy is achieved when freezing up to the second-stage of ResNet for all methods. Early stages of ResNet mostly extract low-level texture information, and the later stages for higher-level features such as localization. Intuitively, we wish to enhance the model’s localization ability without jeopardizing the texture extraction ability acquired during the first-stage. This explains the reason for freezing the first two stages during the second-stage, which is a common practice in object detection [Ren et al., 2015].

| Background | BYOL+DiLo | BYOL+SS | BYOL+SS+Align |
|------------|-----------|---------|---------------|
| CUB        | 64.14 (+0.00) | 64.35 (+0.00) | 65.02 (+0.00) |
| COCO       | 60.07 (+0.07) | 60.42 (-3.93) | 61.23 (-3.79) |
| NAbirds    | 62.51 (+1.81) | 63.06 (-1.29) | 64.80 (-0.22) |
| CUB+COCO   | 61.26 (+2.88) | 61.49 (+2.86) | 62.01 (+3.01) |
| CUB+NAbirds| 64.38 (+0.24) | 63.98 (-0.37) | 65.50 (+0.48) |

Table 5: Evaluation of background datasets extension for second-stage pre-training. We study the effect of fusing different background datasets based on CUB dataset.

**Background Dataset Ablation.** Lastly, we compare different foreground-background fusion methods (SS and DiLo) based on CUB dataset using second-stage only settings. As shown in Table 5, replacing the background with other datasets usually results in performance degradation, while fusing with complex backgrounds might improve the performance. We hypothesize that exploring the task-specific backgrounds is more critical in fine-grained scenarios. Meanwhile, it indicates that the proposed CVSA (SS+Align) can well explore the background of CUB.

### 6 Conclusion

We first investigate the cause of the performance gap between supervised and contrastive based pre-training for fine-grained scenarios. We point out that the model abilities of localization and discriminative feature extraction are equally important. Under this formulation, we propose a dual-stage pre-training pipeline with the first-stage to train feature extraction and the second-stage to train localization. To empower the model with localization abilities in the second-stage, we propose cross-view saliency alignment, a new unsupervised contrastive learning framework. Extensive experiments on fine-grained benchmarks demonstrate the effectiveness of our contributions in learning better fine-grained representations. Future work includes investigating combining the dual-stage pipeline to a single-stage framework.
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A Appendix

We first describe the evaluation protocols in Sec. A.1. Then we introduce additional implementation details in Sec. A.2. Finally, we provide more ablation studies of our approach in Sec. A.3 for a clearer insight into our method.

A.1 Evaluation Protocols

Linear Evaluation. The linear evaluation is a commonly adopted protocol detailed in [Chen et al. 2020b, He et al. 2020], i.e., train a linear classifier on top of the frozen representation on the full training set with labels. We use a SGD optimizer with a cosine learning rate scheduler. The SGD momentum is 0.9, and the weight decay is 0. Based on supervised fine-grained classification settings, the batch size is 16, and the total training epoch is 50. To avoid evaluation deviations caused by the learning rate, we report the best test performance achieving among the initial learning rate $lr \in \{0.1, 0.01, 0.001\}$ for each comparing method.

Fine-tune Evaluation. We perform a fully supervised fine-tune evaluation protocol proposed in [Zhai et al. 2019, Chen et al. 2020b], i.e., fine-tune the entire network on the training set with labels. Since the original protocols are designed for coarse-grained datasets such as ImageNet, we adopt special training settings for fine-grained datasets. We use the SGD optimizer with a cosine learning rate schedule, and the SGD momentum is 0.9. We set the batch size to 16 and train 50 epochs. To avoid evaluation deviations caused by training settings, we sweep over the initial learning rate $lr \in \{0.1, 0.05, 0.01, 0.005, 0.001\}$ and weight decay $wd \in \{0.0005, 0.0001\}$ and select the hyperparameters achieving the best performance on the validation set.

A.2 More Implementation Details

Data Augmentation. In contrastive learning pre-training, the input resolution is $224 \times 224$ and the data augmentation strategy follows MoCo.v2 [Chen et al. 2020] as following: Geometric augmentation is RandomResizedCrop with the scale in $[0.2, 1.0]$ and RandomHorizontalFlip. Color augmentation is ColorJitter with $\{\text{brightness, contrast, saturation, hue}\}$ strength of $0.4, 0.4, 0.4, 0.1$ with an applying probability of 0.8, and RandomGrayscale with an applying probability of 0.2. Blurring augmentation is using square Gaussian kernel of size $23 \times 23$ with a standard deviation uniformly sampled in $[0.1, 2.0]$. During evaluation, images are resized to 256 pixels along the shorter side and is center cropped to $224 \times 224$ similar to SimCLR [Chen et al. 2020].

Hyperparameters for CVSA. We search the optimal hyperparameters for our proposed CVSA on the validation set of fine-grained datasets using ResNet-18 as the encoder. We set the batch size to 1024 and follow other training settings of BYOL (Grill et al. 2020). The base learning rate is set to 0.3 for the Cars dataset and 0.6 for the other three datasets. The cropping scale ratio of SaliencySwap is $\lambda = 0.5$ by default. As for the stage $l$ in CVSA, we analyze the performance and the computational cost of using $l \in \{3, 4\}$ since the first two stages are frozen in the dual-stage. And we find that using $l = 4$ achieves a balance between the performance and the computation cost.

A.3 More Ablation Studies of SaliencySwap

Method Comparison and Discussion. As we discussed in Sec. 5.1, the proposed SaliencySwap keeps semantic consistency of foreground targets and introduces background variation, as shown in Figure 5. Compared to SaliencyMix (Uddin et al. 2020) and DiLo (Zhao et al. 2021a), our SaliencySwap swaps the saliency region in the randomly selected background image and the source image and regards the augmented view as a positive sample. DiLo randomly places the masked foreground objects to raw background images such as texture backgrounds. The proposed SaliencySwap and SaliencyMix only require coarse saliency information described by bounding boxes, while DiLo uses pixel-wise saliency masks.

### Table 6: Evaluation of different saliency detection methods for second-stage only pre-training

| Method             | VSFs | GS  | RBD  | BSANet | Groundtruth |
|--------------------|------|-----|------|--------|-------------|
| BYOL+SS            | 64.27| 64.32| 64.34| 64.33  | 64.35       |
| BYOL+SS+Align      | 64.89| 64.94| 64.97| 65.04  | 65.02       |

Ablation of Saliency Detection. We further study the impact of using saliency information provided by different saliency detection methods based on experiment settings in Sec. 5.3. We compare four well-recognized saliency detection methods (VSFs [Montabone and Soto 2010], GS [Wei et al. 2012], RBD [Zhu et al. 2014] and BSANet [Qin et al. 2019]) and the ground truth bounding box on CUB. As shown in Table 6, the proposed SaliencySwap and alignment loss are robust to the quality of saliency bounding boxes because our approach helps the network to localize the object roughly and extract fine-grained semantic features. It is no need to provide accurate segmentation masks of the foreground objects as in downstream tasks like object detection and segmentation (Gansbeke et al. 2021).