2nd Place Solution for ICCV2021 VIPriors Image Classification Challenge: An Attract-and-Repulse Learning Approach

Yilu Guo\textsuperscript{1*}, Shicai Yang\textsuperscript{1,2*}, Weijie Chen\textsuperscript{1,2}, Liang Ma\textsuperscript{1}, Di Xie\textsuperscript{1}, Shiliang Pu\textsuperscript{1†}

\textsuperscript{1}Hikvision Research Institute, Hangzhou, China
\textsuperscript{2}Zhejiang University, Hangzhou, China

\{guoyilu5, yangshicai, chenweijie5, maliang6, xiedi, pushiliang.hri\}@hikvision.com

Abstract

Convolutional neural networks (CNNs) have achieved significant success in image classification by utilizing large-scale datasets. However, it is still of great challenge to learn from scratch on small-scale datasets efficiently and effectively. With limited training datasets, the concepts of categories will be ambiguous since the over-parameterized CNNs tend to simply memorize the dataset, leading to poor generalization capacity. Therefore, it is crucial to study how to learn more discriminative representations while avoiding over-fitting. Since the concepts of categories tend to be ambiguous, it is important to catch more individual-wise information. Thus, we propose a new framework, termed Attract-and-Repulse, which consists of Contrastive Regularization (CR) to enrich the feature representations, Symmetric Cross Entropy (SCE) to balance the fitting for different classes and Mean Teacher to calibrate label information. Specifically, SCE and CR learn discriminative representations while alleviating over-fitting by the adaptive trade-off between the information of classes (attract) and instances (repulse). After that, Mean Teacher is used to further improve the performance via calibrating more accurate soft pseudo labels. Sufficient experiments validate the effectiveness of the Attract-and-Repulse framework. Together with other strategies, such as aggressive data augmentation, TenCrop inference, and models ensembling, we achieve the second place in ICCV 2021 VIPriors Image Classification Challenge.

Introduction

Convolutional neural networks (CNNs) have achieved tremendous success in image classification. However, it deeply depends on large-scale datasets, such as ImageNet (Deng et al. 2009) and OpenImage (Kuznetsova et al. 2018). Generally, CNNs learn to generalize well with massive data. When trained on a small-scale dataset, they are required to be pre-trained on a large-scale dataset in a supervised or unsupervised manner. Herein, we can’t help to ask, can we achieve comparable results on a small dataset by learning from scratch without any pre-training? This is an interesting and significant topic proposed in the VIPriors Image Classification Challenge (Bruintjes et al. 2021).

CNNs are data-hungry and they usually summarize different feature patterns by learning from large-scale dataset. While when the training data is limited, especially when the image amount of each category is quite small, the concept of category tends to be ambiguous. It is hard for CNNs to generalize the concept of category by merely exploiting a small amount of samples, but CNNs will still memorize the data resulting in over-fitting. Hence, it is a challenging problem to extract discriminative representations by learning from scratch on a very small-scale dataset. In addition, it is crucial to alleviate over-fitting since the models with a large network capacity are prone to memorize the dataset, leading to a poor generalization ability.

Recently, self-supervised learning has shown a great potential of learning discriminative representation from the training data without external label information. And the representations from self-supervised learning exhibit better generalizability than the counterparts from supervised learning (Tendle and Hasan 2021; Sariyildiz et al. 2021). In particular, the contrastive learning methods (Chen et al. 2020a; He et al. 2020) have demonstrated advantages over other self-supervised learning methods in learning better transferable representations for downstream tasks, like object detection and semantic segmentation. Contrastive learning is a remarkable self-supervised learning framework that learns invariant features by contrasting positive samples against negative ones without annotations. The representations learned by contrastive learning are individually discriminative and unbiased to the image labels, which can effectively prevent the model from over-fitting the classification patterns of any object category.

In this paper, we aim to explore the capability of contrastive learning under the data-deficient setting. We introduce contrastive learning into the class-probability space predicted by the model to strengthen the feature representations by individual discrimination and avoid over-fitting the ambiguous categories, which is termed as Contrastive Regularization (CR). And when the training data is deficient, the learning of different classes is prone to be unbalanced, we further use Symmetric Cross Entropy (SCE) (Wang et al. 2019) to balance the fitting of different classes. The SCE makes different classes to attract instances more evenly while the CR lets instances repulse with each other. The model can learn discriminative representations while alleviating over-fitting. Since the concepts of categories tend to be ambiguous, it is important to catch more individual-wise information. Thus, we propose a new framework, termed Attract-and-Repulse, which consists of Contrastive Regularization (CR) to enrich the feature representations, Symmetric Cross Entropy (SCE) to balance the fitting for different classes and Mean Teacher to calibrate label information. Specifically, SCE and CR learn discriminative representations while alleviating over-fitting by the adaptive trade-off between the information of classes (attract) and instances (repulse). After that, Mean Teacher is used to further improve the performance via calibrating more accurate soft pseudo labels. Sufficient experiments validate the effectiveness of the Attract-and-Repulse framework. Together with other strategies, such as aggressive data augmentation, TenCrop inference, and models ensembling, we achieve the second place in ICCV 2021 VIPriors Image Classification Challenge.
Figure 1: The pipeline of Attract-and-Repulse. The two views of images by different augmentation are packed and fed to both teacher and student models. For simplicity, $\delta$ is set 0 here. The views of the same images are regarded as positive pairs (green lines) while the negative ones (red lines) are formed by different images within a mini-batch in the Contrastive Regularization (CR). The yellow dotted box indicates the CR loss, the colored distributions indicate the outputs of models, and the distributions for the same image are denoted by the same color. The Symmetric Cross Entropy (SCE) can balance the fitting of different classes. After learning by CR and SCE, the exponential moving average (EMA) model (Mean Teacher) can produce a more accurate soft pseudo label for each augmented image to optimize the student model.

viating over-fitting by the adaptive trade-off between attraction and repulsion. After attracting and repulsing, instances can reach a suitable position among different classes, and Mean Teacher (Tarvainen and Valpola 2017) is used to improve the performance with the more accurate soft pseudo label. In conclusion, the Contrastive Regularization, Symmetric Cross Entropy, and Mean Teacher compose our proposed Attract-and-Repulse framework. Together with other strategies, such as aggressive data augmentation, TenCrop inference, and models ensembling, the proposed Attract-and-Repulse framework achieves a very competitive performance in the VIPriors Image Classification Challenge.\footnote{1We win the second place in ICCV 2021 VIPriors Image Classification Challenge. See Section 2.1.2 in the tech report (Lengyel et al. 2022).} It is worth emphasizing that we achieve 74.49% top-1 accuracy on ImageNet (Krizhevsky, Sutskever, and Hinton 2017) by using only about 8% training data, which surpasses the previous state-of-the-art approaches by a large margin.

To summarize, our main contributions are highlighted as:

- We propose Contrastive Regularization to strengthen the feature representations by individual discrimination and avoid over-fitting the ambiguous categories representations in the data-deficient setting.
- We propose Attract-and-Repulse, a novel framework to deal with data-deficient image classification, which learns discriminative representations while alleviating over-fitting by the adaptive trade-off between the information of classes (attract) and instances (repulse).
- Together with augmentation strategies and other strategies, Attract-and-Repulse achieves competitive performance in the VIPriors Image Classification Challenge.

Related Works

Contrastive Learning

Recently, contrastive learning approaches (Chen et al. 2020a; He et al. 2020; Grill et al. 2020) emerge as the mainstream paradigm in self-supervised learning which learns invariant features by contrasting positive samples against negative ones. A positive pair is usually formed with different augmented views of the same image, while negative ones are formed with different images. Particularly, SimCLR (Chen et al. 2020a) obtains positive and negative pairs within a mini-batch of training data and uses InfoNCE (van den Oord, Li, and Vinyals 2018) loss to learn the feature representations. It requires a large batch size to effectively balance the positive and negative ones. MoCo (He et al. 2020) builds a large and consistent feature queue to store negative samples using a slowly progressing momentum network...
which greatly reduces high memory cost. BYOL (Grill et al. 2020) and SimSiam (Chen and He 2021) challenge the indispensability of negative examples and achieve impressive performance by only using positive ones. Before BYOL and SiamSiam, UIC (Chen et al. 2020a) can be viewed as an earlier one which uses positive samples for contrastive learning without negative samples. SwAV (Caron et al. 2020) obtains a better performance by enforcing consistent cluster assignment prediction between multiple views of the same image. Supervised Contrastive Learning (SCL) (Khosla et al. 2020) adapts contrastive learning to the fully supervised setting to learn more informative representations by effectively leveraging label information. Furthermore, contrastive learning has promoted the performance of various tasks, including semi-supervised learning (Chen et al. 2020b; Li, Xiong, and Hoi 2020), learning with noisy label (Zheltonozhskii et al. 2021; Zhou, Ge, and Wu 2021) and so on.

Data Augmentation

Data augmentation is an effective way to improve CNNs’ generalization performance especially in the case of insufficient data. Mixup (Zhang et al. 2017) trains a model on elementwise convex combinations of pairs of examples and their labels together. Cutout (Devries and Taylor 2017) and random erasing (Zhong et al. 2020) randomly erase rectangle regions on input images during training. Rather than including a portion of an image, CutMix (Yun et al. 2019) replaces a patch of an image with a patch of a different image where the training labels are also mixed proportionally to the area of patches. Recently, with the emergence of AutoML, network learning strategies also can be searched from data. AutoAugmentation (Cubuk et al. 2019) originally uses reinforcement learning to choose a sequence of operations as well as their probability of application and magnitude. Since AutoAugmentation needs a huge space for searching. RandAugmentation (Cubuk et al. 2020) proposes a simplified search space that has less computational expense. TA³ (Li et al. 2022) utilizes RandAugmentation to enhance unsupervised domain adaptive object detection.

Method

Attract-and-Repulse is a new framework for data deficient learning, which consists of Contrastive Regularization, Symmetric Cross Entropy, and Mean Teacher. The entire pipeline is shown in Figure 1.

Preliminaries

Given a C-class dataset \( D = \{(x_i, y_i)\}_{i=1}^N \), with \( x \in \mathcal{X} \subset \mathbb{R}^d \) denoting a sample in the \( d \)-dimensional input space and \( y \in \mathcal{Y} = \{1, \cdots, C\} \) its associated label. In the data-deficient setting, the number of samples per class is quite small. For each sample \( x \), a classifier \( f(x) \) computes its probability of each label \( k \in \{1, \cdots, C\} : p(c|x) = \frac{e^{z_k c}}{\sum_{i=1}^C e^{z_i c}} \), where \( z_j \) are the logits. We denote the ground-truth distribution over labels for sample \( x \) by \( q(c|x) \), and \( \sum_{c=1}^K q(c|x) = 1 \). Consider the case of a single ground-truth label \( y \), then \( q(y|x) = 1 \) and \( q(c|x) = 0 \) for all \( c \neq y \).

Figure 2: Diagram for the learning process using Cross Entropy (top) and Cross Entropy with Contrastive Regularization (bottom). The stars and the circles indicate the class centers and the instances respectively while the same class are denoted by the same color. The green lines and the red lines indicate the attraction and the repulsion, respectively. For simplicity, we don’t draw all red lines.

The cross entropy loss for sample \( x \) is (denote cross entropy as \( H(q, p) \)):

\[
L_{ce} = H(q, p) = - \sum_{c=1}^K q(c|x) \log p(c|x)
\]

Contrastive Regularization

When the data is deficient, the concepts of some categories will be more ambiguous. While the cross entropy loss attracts samples close to their own class centers, as shown on the top of Figure 2, the model will be easy to over-fit the ambiguous classes and resulting in weak generalization ability. Inspired by the appearance that the differences among the samples in an ambiguous class are larger than that in explicit one, we adapt contrastive learning to the model learning, which is called Contrastive Regularization. Contrastive Regularization makes the samples repulse with each other in the same classes and forms confrontation with the attraction of class centers, as shown on the bottom of Figure 2. The trade-off between attraction and repulsion prevents the model from over-fitting the ambiguous classes. What’s more, the repulsion among instances from the same class can make the instances disperse more uniformly around the class center, while the repulsion among instances from different classes can increase the distance between classes. And Contrastive Regularization also introduces more individual information into model learning, while catching more information is important in the data-deficient setting.

Supervised Contrastive Learning (SCL) (Khosla et al. 2020) adapts contrastive learning to the fully supervised setting to learn more informative representations by effectively leveraging label information. SCL is an excellent representation learning method, but the model learned by SCL usually needs to finetune on downstream tasks. Contrastive Regularization integrate SCL with the supervised target task by applying SCL on the final prediction of the model.
Within a multiview batch, let \( i \in I \equiv \{1, \ldots, 2N\} \) be the index of an arbitrary augmented sample, the original loss of SCL is as follow:

\[
L_{SCL} = \sum_{i \in I} \frac{-1}{K(i)} \sum_{k \in K(i)} \log \frac{\exp(z_i \cdot z_k / \tau)}{\sum_{a \in A(i)} \exp(z_i \cdot z_a / \tau)}
\]

Here, \( z_i \) is the normalized feature representation, \( \tau \) is a temperature hyper-parameter, \( A(i) \equiv I \setminus \{i\} \) and \( K(i) \equiv \{k \in A(i) : y_k = y_i\} \) is the set of indices of all positives in the multiviewed batch distinct from \( i \), and \( |K(i)| \) is its cardinality.

To make the confrontation between attraction and repulsion more direct, the proposed Contrastive Regularization changes the feature \( z_i \) to the probability distribution \( p_i \) of the model output:

\[
L_{CR} = \sum_{i \in I} \frac{-1}{K'(i)} \sum_{k \in K'(i)} \log \frac{\exp(p_i \cdot p_k / \tau)}{\sum_{a \in A(i)} \exp(p_i \cdot p_a / \tau)}
\]

Here, \( K'(i) \equiv \{k \in A(i) : \text{dis}(\tilde{y}_k, \tilde{y}_i) \leq \delta\} \). For alleviating the over-fitting problem, cutmix and mixup are usually used so that the hard-label are changed to soft-label and \( K'(i) \) is changed correspondingly. Kullback-Leibler divergence is usually used to measure the discrepancies between two distributions, while it is asymmetric. So we use Jensen-Shannon divergence, the symmetric variant of Kullback-Leibler divergence as \( \text{dis} \), and use \( \delta \) to adjust the attention level to individual-wise or class-wise contrasting. The \( \delta \) is smaller, the positive pairs need to have more similar soft-label distribution. Especially, when \( \delta = 0 \) the CR degrades to vanilla InfoNCE that only regards the two views of one image by different augmentation as positive pairs. A small \( \delta \) is used to strengthen the individual information to balance the fitting of the ambiguous classes.

### Symmetric Cross Entropy

Symmetric Cross Entropy (SCE) (Wang et al. 2019) is a simple yet effective loss for learning with noisy label. It aims to simultaneously address the hard class learning problem and the noisy label overfitting problem of Cross Entropy.

The label of ImageNet dataset is well-known to contain errors (Northcutt, Jiang, and Chuang 2021). And there are many similar category concepts that will be more ambiguous when the image amount of each category is limited. So, there may be some “noisy” labels that may have a correct label but also can be deemed to another class. Thus, we employ Symmetric Cross Entropy (Wang et al. 2019) to balance the fitting of different classes. The Symmetric Cross Entropy is easily constituted by standard cross entropy and reverse cross entropy.

\[
L_{SCE} = L_{CE} + \alpha L_{RCE} = H(p, q) + \alpha H(q, p)
\]

### Mean Teacher

Mean Teacher (Tarvainen and Valpola 2017) is proposed for semi-supervised learning. Here, we adapt it to provide stabilized and more accurate pseudo labels and stabilize model learning.

Among a multiview batch, let \( i \in I \) be the index of an arbitrary augmented sample, the original loss of SCL is as follow:

\[
L_{SCL} = \sum_{i \in I} \frac{-1}{K(i)} \sum_{k \in K(i)} \frac{\exp(z_i \cdot z_k / \tau)}{\sum_{a \in A(i)} \exp(z_i \cdot z_a / \tau)}
\]

Here, \( z_i \) is the normalized feature representation, \( \tau \) is a temperature hyper-parameter, \( A(i) \equiv I \setminus \{i\} \) and \( K(i) \equiv \{k \in A(i) : y_k = y_i\} \) is the set of indices of all positives in the multiviewed batch distinct from \( i \), and \( |K(i)| \) is its cardinality.

To make the confrontation between attraction and repulsion more direct, the proposed Contrastive Regularization changes the feature \( z_i \) to the probability distribution \( p_i \) of the model output:

\[
L_{CR} = \sum_{i \in I} \frac{-1}{K'(i)} \sum_{k \in K'(i)} \frac{\exp(p_i \cdot p_k / \tau)}{\sum_{a \in A(i)} \exp(p_i \cdot p_a / \tau)}
\]

Here, \( K'(i) \equiv \{k \in A(i) : \text{dis}(\tilde{y}_k, \tilde{y}_i) \leq \delta\} \). For alleviating the over-fitting problem, cutmix and mixup are usually used so that the hard-label are changed to soft-label and \( K'(i) \) is changed correspondingly. Kullback-Leibler divergence is usually used to measure the discrepancies between two distributions, while it is asymmetric. So we use Jensen-Shannon divergence, the symmetric variant of Kullback-Leibler divergence as \( \text{dis} \), and use \( \delta \) to adjust the attention level to individual-wise or class-wise contrasting. The \( \delta \) is smaller, the positive pairs need to have more similar soft-label distribution. Especially, when \( \delta = 0 \) the CR degrades to vanilla InfoNCE that only regards the two views of one image by different augmentation as positive pairs. A small \( \delta \) is used to strengthen the individual information to balance the fitting of the ambiguous classes.

### Symmetric Cross Entropy

Symmetric Cross Entropy (SCE) (Wang et al. 2019) is a simple yet effective loss for learning with noisy label. It aims to simultaneously address the hard class learning problem and the noisy label overfitting problem of Cross Entropy.

The label of ImageNet dataset is well-known to contain errors (Northcutt, Jiang, and Chuang 2021). And there are many similar category concepts that will be more ambiguous when the image amount of each category is limited. So, there may be some “noisy” labels that may have a correct label but also can be deemed to another class. Thus, we employ Symmetric Cross Entropy (Wang et al. 2019) to balance the fitting of different classes. The Symmetric Cross Entropy is easily constituted by standard cross entropy and reverse cross entropy.

\[
L_{SCE} = L_{CE} + \alpha L_{RCE} = H(p, q) + \alpha H(q, p)
\]

### Mean Teacher

Mean Teacher (Tarvainen and Valpola 2017) is proposed for semi-supervised learning. Here, we adapt it to provide stabilized and more accurate pseudo labels and stabilize model learning.
pseudo labels. Thus, the model can avoid learning some inaccurate information via consistency loss and the learning process will be more robust.

**Attract-and-Repulse framework**

Finally, we reach a novel approach to deal with the data-deficient image classification, i.e., Attract-and-Repulse framework. It optimizes the Symmetric Cross Entropy loss with the Contrastive Regularization to catch and balance the information from instances and classes. And adopting Mean Teacher to use the more accurate pseudo labels. Algorithm 1 summarizes the proposed framework and the overall loss function of Attract-and-Repulse can be formulated as follows:

\[
L = L_{SCE} + \beta L_{CR} + \gamma L_{MT} \\
= L_{CE} + \alpha L_{RCE} + \beta L_{CR} + \gamma L_{MT}
\]

**Auxiliary Classifier** Supervisions to the intermediate output are usually used in deep learning to reduce the difficulty of optimizing the deep network (Szegedy et al. 2016; Zhao et al. 2017) or to enhance the information from different scales (Xie and Tu 2017). It is difficult to extract ample image information in the data-deficient setting, so we add an Auxiliary Classifier to the intermediate output of the model. And during inference, the prediction is computed by the weighted average of the intermediate output and the final output, which is termed as Auxiliary Fusion.

**Experiments**

**Dataset and Experimental Setting**

Visual Inductive Priors (VIPriors) Image Classification Challenge (Bruintjes et al. 2021) proposes the topic that how to learn from scratch in a data-deficient setting. The objective of VIPriors Image Classification Challenge is to increase the Top-1 Accuracy on ImageNet dataset (Deng et al. 2009) by only using a small subset of ImageNet dataset. The data is divided into three splits, including a training set, a validation set, and a testing set that is unavailable during the model optimization. The training and validation splits are two subsets of the original training split. The test set is taken from the original validation split directly. Each split includes 1,000 classes which are the same as the original ImageNet and 50 images per class, resulting in 50,000 images in total.

We train models on the subset of the ImageNet which was provided by the VIPrior Image Classification Challenge without any pre-trained models. In the following section of ablation study, we mainly train models on the training split (about 4% training data of the original ImageNet) and verify on the validation split. And in the section of comparison with other state-of-the-arts, we combine the training and validation splits for training (about 8% training data of the original ImageNet) and randomly split a few samples for validation.

**Implementation Details**

We use the RMSprop (Dauphin et al. 2015) optimizer with alpha set to 0.9 and momentum set to 0.9. Models are trained with 8 GPUs and 64 samples per GPU. Our learning rates are adjusted according to a cosine decaying policy (Goyal et al. 2017) and the initial learning rate is set to 0.005. The warm-up (Goyal et al. 2017) strategy is applied over the first 3 epochs, gradually increasing the learning rate linearly from 1e-6 to the initial value for the cosine schedule. The weight decay is set to 1e-5. The default image resolution is 320x320 during the training.

**Ablation Study**

**Model Architectures and Capacity** We simply compare the models with different architectures and capacities. We train some models with different architectures and capacities on the training split with some basic regularizations like dropout (Srivastava et al. 2014). Table 1 shows the performances. We can see that the larger models perform the better, like most other deep learning tasks. And EfficientNet (Tan and Le 2019) surpasses ResNet (He et al. 2016) in the data-deficient setting. While Swin Transformer (Liu et al. 2021) behaves badly. When the data is limited, the...
Attract-and-Repulse framework without postprocess like Auxiliary accuracy from 58.77% to 61.71%. Attract-and-Repulse framework improving the top-1 accuracy. Classifier also have a slight refinement. As a result, the Mean Teacher further enhance the performance and Auxiliary promotion by introducing the individual information. The Table 3 shows, the SCE balance the learning of different classes to make the baseline better and the CR makes the biggest enhancement. For the Mean Teacher, the influence of $\gamma$ is larger, many class-wise contrasts. While when $\delta$ is larger, many noisy samples are introduced into the contrasts resulting in the degradation. For the Mean Teacher, the influence of $\gamma$ is shown in Figure 4(c). The performance achieves the optimal when the weights for ground-truth and pseudo labels are balanced.

**Attract-and-Repulse Framework** In this section, we perform ablation studies to demonstrate the effectiveness of the proposed Attract-and-Repulse framework over the VIPriors ImageNet training split with EfficientNet-b2. As Table 3 shows, the SCE balance the learning of different classes to make the baseline better and the CR makes the biggest promotion by introducing the individual information. The Mean Teacher further enhance the performance and Auxiliary Classifier also have a slight refinement. As a result, the Attract-and-Repulse framework improving the top-1 accuracy from 58.77% to 61.71%.

We further analyze the main components of the Attract-and-Repulse framework without postprocess like Auxiliary Fusion. Figure 4(a) shows the influence of the weight ($\alpha$) for RCE in the SCE. It reaches a good performance when $\alpha = 0.01$, while the performance decreases if keep increasing the $\alpha$. The effect of the weight ($\beta$) for CR is presented in Figure 4(b). The improving performance as $\beta$ increases demonstrates the CR is beneficial to the data-deficient learning. When $\beta$ is too large, the repulsion among instances suppresses the attraction of classes resulting in the degradation of performance. We also compare the CR with usual contrastive learning by features that add a projector after the backbone, results from Figure 4(b) show the performance of “feature” is much worse than CR. We further analyze the effect of $\delta$ in the CR. When $\delta = 0$, the CR degrades to vanilla InfoNCE that only regards the two different views of the same images as positive pairs. As shown in Figure 4(d), we can see $\delta = 0.005$ is optimal but the performance is changed slightly by $\delta$. Due to the large computing resource consumption, we only use a small batch size of 64 per GPU, so there are only a few sample pairs with a distance smaller than $\delta$. So the CR with small $\delta$ is similar because there are not many class-wise contrasts. While when $\delta$ is larger, many noisy samples are introduced into the contrasts resulting in the degradation. For the Mean Teacher, the influence of $\gamma$ is shown in Figure 4(c). The performance achieves the optimal when the weights for ground-truth and pseudo labels produced by the EMA model are balanceable.

**Visualization** Figure 5 provides a t-SNE visualization (van der Maaten and Hinton 2008) of the learned features for baseline (left) and Attract-and-Repulse (right). The figure illustrates how Attract-and-Repulse works. Due to the repulsion among individuals from different classes, the classes are more dispersed leading to a better generalization and performance. Although there also are repulsion among individuals in the same class, the features for the same class can still form cluster due to the attraction from the CE loss.
Comparison with Other State-of-The-Arts

For better performance in the VIPrior competition, we combine the train and val split to train the model and randomly split a few samples for validation. And several other strategies and stronger backbone models are used for better performance (smaller batch sizes are used due to the larger computing resource consumption of stronger backbone).

We find that a larger resolution (448x448) can further boost the performance both on the training and the inference. And during the inference, TenCrop is utilized. After using these, we get an excellent performance (top-1 accuracy of 72.14%) by a single model (EfficientNet-b7). Table 4 shows the comparison with other competing methods by using single model. Our framework is competitive and shows comparable results to current state-of-the-art methods.

Furthermore, experimental evidence shows that the ensemble method is usually much more accurate than a single model. We average the predictions of above methods in total of 16 models including EfficientNet-b5 (Tan and Le 2019), EfficientNet-b6, EfficientNet-b7, DSK-ResNeXt101 (Sun et al. 2020), ResNet-152 (He et al. 2016), SEResNet-152 (Hu et al. 2018). Finally, we got the top-1 accuracy of 74.49% on the testing set. We also compare with other state-of-the-art approaches by using model ensembling as shown in Table 5 which demonstrates that our framework can surpass the previous state-of-the-art methods by up to 1.41%, a significant improvement in the benchmark of ImageNet with only 8% images.

8% (X) vs. 100% (X) vs. 10% (X)+90% (U) ImageNet

In this section, we compare the proposed Attract-and-Repulse framework using about 8% labeled training data (“X”) with the popular fully-supervised methods using the entire ImageNet (100% labeled training data, “X”), as well as the popular semi-supervised methods using 10% labeled training data (“X”) and 90% unlabeled training data (“U”). Although there is a huge disparity of about 13% top-1 accuracy between Attract-and-Repulse and the state-of-the-art fully-supervised methods, it needs to be mentioned that we merely use a tenth of ImageNet, and our result is approaching ResNet-50 with fully supervision. As for the semi-supervised with 10% ImageNet, they use a bit more amount of labeled data and much more unlabeled data. It is very delightful that there is only a small gap with the SOTA results, and Attract-and-Repulse even surpasses some methods. We also train the NFNet-F6 and EfficientNet-B7 in the training setting of our Strong Baseline with 8% ImageNet. Surprisingly, under the same condition, our Attract-and-Repulse surpasses them by a large margin higher than 2.72%. (NFNet-F6 performs worse than EfficientNet-B7 perhaps because it is difficult to optimize the extremely large model with a small dataset.)

Although these performance comparisons with fully-supervised with 100% ImageNet or semi-supervised with 10% ImageNet are somewhat “unfair”, it can reflect the performance of our framework to some extent. Also, we can see that the improvement of the generalization algorithm still can not replace the role of tremendous training data.

Conclusions

It is of great challenge to learn from scratch on small-scale datasets efficiently since the model is difficult to learn the ambiguous concepts of categories or the model is easy to over-fit the data. We propose the Attract-and-Repulse framework to deal with the data-deficient image classification which consists of Contrastive Regularization, Symmetric Cross Entropy, and Mean Teacher. The Attract-and-Repulse mainly depends on the trade-off between the learning of instance-wise information and class-wise information, which can prevent the model from over-fitting the ambiguous classes. Ablation studies demonstrate that our framework is effective in data deficient learning. And together with other strategies, we achieve competitive performance in the VIPriors Image Classification Challenge and
surpass the previous state-of-the-art approaches. It is very delightful that Attract-and-Repulse achieves a competitive performance compared with the fully-supervised methods using the entire ImageNet and the semi-supervised methods with 10% ImageNet. We hope the research direction of data deficient learning can take us close to the core of representation learning, and we hope our work can bring new inspirations to the community of representation learning.

Table 6: Performance comparison with fully-supervised learning and semi-supervised learning on ImageNet. “X” and “U” denote labeled and unlabeled data, respectively.

| Method                              | top-1 Acc. (%) |
|-------------------------------------|----------------|
| supervised with 100%(X)             |                |
| VOLO-D5 [Yuan et al. 2021]          | 87.1           |
| NFNNet-F6 [Brock et al. 2021]       | 86.5           |
| SWIN-B [Liu et al. 2021]            | 84.5           |
| EfficientNet-B7 [Tan and Le 2019]  | 84.3           |
| SENet [Hu et al. 2018]              | 82.7           |
| ResNet-101 [Xie et al. 2017]        | 80.9           |
| DenseNet-264 [Huang et al. 2017]    | 77.9           |
| ResNet-152 [He et al. 2016]         | 77.8           |
| FENet 1.375x + SE V2 [Chen et al. 2019] | 76.5           |
| ResNet-50 [He et al. 2016]          | 76.0           |
| semi-supervised with 10%(X)+90%(U)  |                |
| SimCLRv2 [Chen et al. 2020b]        | 80.9           |
| TWIST [Wang et al. 2021]            | 75.3           |
| CoMatch [Li, Xiong, and Hou 2020]   | 73.7           |
| FixMatch [Sohn et al. 2020]         | 71.5           |
| supervised with 8%(X)               |                |
| Strong Baseline (NNet-F6)           | 66.89          |
| Strong Baseline (EfficientNet-B7)   | 69.42          |
| Attract-and-Repulse (EfficientNet-B7) | **72.14**     |
| Attract-and-Repulse (Ensemble)       | **74.49**      |

References

Brock, A.; De, S.; Smith, S.; and Simonyan, K. 2021. High-Performance Large-Scale Image Recognition Without Normalization. In ICML 2021: 38th International Conference on Machine Learning, 1059–1071.

Bruintjes, R.-J. 2021. VIPriors Image Classification Challenge. https://github.com/VIPriors/vipriors-challenges-toolkit/blob/master/image-classification/readme.md.

Bruintjes, R.-J.; Lengyel, A.; Baptista-Rios, M.; Kayhan, O. S.; and van Gemert, J. 2021. VIPriors I: Visual Inductive Priors for Data-Efficient Deep Learning Challenges. arXiv preprint arXiv:2103.03768.

Caron, M.; Misra, I.; Mairal, J.; Goyal, P.; Bojanowski, P.; and Joulin, A. 2020. Unsupervised Learning of Visual Features by Contrasting Cluster Assignments. In 34th Conference on Neural Information Processing Systems, NeurIPS’20, volume 33, 9912–9924.

Chen, T.; Kornblith, S.; Norouzi, M.; and Hinton, G. 2020a. A Simple Framework for Contrastive Learning of Visual Representations. In ICML 2020: 37th International Conference on Machine Learning, volume 1, 1597–1607.

Chen, T.; Kornblith, S.; Swersky, K.; Norouzi, M.; and Hinton, G. E. 2020b. Big Self-Supervised Models are Strong Semi-Supervised Learners. In Advances in Neural Information Processing Systems, volume 33, 22243–22255.

Chen, W.; Pu, S.; Xie, D.; Yang, S.; Guo, Y.; and Lin, L. 2020c. Unsupervised Image Classification for Deep Representation Learning. In ECCV workshop, 430–446.

Chen, W.; Xie, D.; Zhang, Y.; and Pu, S. 2019. All you need is a few shifts: Designing efficient convolutional neural networks for image classification. In CVPR.

Chen, X.; and He, K. 2021. Exploring Simple Siamese Representation Learning. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 15750–15758.

Cubuk, E. D.; Zoph, B.; Mane, D.; Vasudevan, V.; and Le, Q. V. 2019. AutoAugment: Learning Augmentation Strategies From Data. In 2019 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), 113–123.

Cubuk, E. D.; Zoph, B.; Shlens, J.; and Le, Q. 2020. RandAugment: Practical Automated Data Augmentation with a Reduced Search Space. In Advances in Neural Information Processing Systems, volume 33, 18613–18624.

Dauphin, Y. N.; de Vries, H.; Chung, J.; and Bengio, Y. 2015. RMSProp and equilibrated adaptive learning rates for non-convex optimization. arXiv: Learning.

Deng, J.; Dong, W.; Socher, R.; Li, L.-J.; Li, K.; and Fei-Fei, L. 2009. ImageNet: A large-scale hierarchical image database. In 2009 IEEE Conference on Computer Vision and Pattern Recognition, 248–255.

Devries, T.; and Taylor, G. W. 2017. Improved Regularization of Convolutional Neural Networks with Cutout. arXiv preprint arXiv:1708.04552.

Dosovitskiy, A.; Beyer, L.; Kolesnikov, A.; Weissenborn, D.; Zhai, X.; Unterthiner, T.; Dehghani, M.; Minderer, M.; Heigold, G.; Gelly, S.; Uszkoreit, J.; and Houlsby, N. 2021. An Image is Worth 16x16 Words: Transformers for Image Recognition at Scale. In ICLR 2021: The Ninth International Conference on Learning Representations.

Goyal, P.; Dollár, P.; Girshick, R. B.; Noordhuis, P.; Wesolowski, L.; Kyrola, A.; Tulloch, A.; Jia, Y.; and He, K. 2017. Accurate, Large MiniBatch SGD: Training ImageNet in 1 Hour. arXiv preprint arXiv:1706.02677.

Grill, J.-B.; Strub, F.; Altché, F.; Tallec, C.; Richemond, P. H.; Buchatskaya, E.; Doersch, C.; Pires, B. A.; Guo, Z. D.; Azar, M. G.; Piot, B.; Kavukcuoglu, K.; Munos, R.; and Valko, M. 2020. Bootstrap Your Own Latent: A New Approach to Self-Supervised Learning. In Advances in Neural Information Processing Systems, volume 33, 21271–21284.

He, K.; Fan, H.; Wu, Y.; Xie, S.; and Girshick, R. 2020. Momentum Contrast for Unsupervised Visual Representation Learning. In 2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), 9729–9738.

He, K.; Zhang, X.; Ren, S.; and Sun, J. 2016. Deep Residual Learning for Image Recognition. In 2016 IEEE Conference...
on Computer Vision and Pattern Recognition (CVPR), 770–778.

Hu, J.; Shen, L.; Albanie, S.; Sun, G.; and Wu, E. 2018. Squeeze-and-Excitation Networks. In 2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition, volume 42, 2011–2023.

Huang, G.; Liu, Z.; van der Maaten, L.; and Weinberger, K. Q. 2017. Densely Connected Convolutional Networks. In 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2261–2269.

Khosla, P.; Teterwak, P.; Wang, C.; Sarna, A.; Tian, Y.; Isola, P.; Maschinot, A.; Liu, C.; and Krishnan, D. 2020. Supervised Contrastive Learning. In Advances in Neural Information Processing Systems, volume 33, 18661–18673.

Krizhevsky, A.; Sutskever, I.; and Hinton, G. E. 2017. ImageNet classification with deep convolutional neural networks. Communications of The ACM, 60(6): 84–90.

Kuznietsova, A.; Rom, H.; Alldrin, N.; Uijlings, J.; Krasin, I.; Pont-Tuset, J.; Kamali, S.; Popov, S.; Malloci, M.; Kolesnikov, A.; Duerig, T.; and Ferrari, V. 2018. The Open Images Dataset V4: Unified image classification, object detection, and visual relationship detection at scale. arXiv preprint arXiv:1811.00902.

Lengyel, A.; Bruintjes, R.; Baptista-Rios, M.; Kayhan, O.S.; Zambrano, D.; Tomen, N.; and van Gemert, J. 2022. VIPriors 2: Visual Inductive Priors for Data-Efficient Deep Learning Challenges. CoRR, abs/2201.08625.

Li, J.; Xiong, C.; and Hoi, S. C. H. 2020. CoMatch: Semi-supervised Learning with Contrastive Graph Regularization. arXiv preprint arXiv:2011.11183.

Li, Z.; Zhao, L.; Chen, W.; Yang, S.; Xie, D.; and Pu, S. 2022. Target-Aware Auto-Augmentation for Unsupervised Domain Adaptive Object Detection. In ICASSP.

Liu, Z.; Lin, Y.; Cao, Y.; Hu, H.; Wei, Y.; Zhang, Z.; Lin, S.; and Guo, B. 2021. Swin Transformer: Hierarchical Vision Transformer using Shifted Windows. arXiv preprint arXiv:2103.14030.

Luo, Z.; Li, G.; and Zhang, Z. 2020. A Technical Report for VIPriors Image Classification Challenge. arXiv: Computer Vision and Pattern Recognition.

Northcutt, C. G.; Athalye, A.; and Mueller, J. 2021. Pervasive Label Errors in Test Sets Destabilize Machine Learning Benchmarks. In Thirty-fifth Conference on Neural Information Processing Systems Datasets and Benchmarks Track (Round 1).

Northcutt, C. G.; Jiang, L.; and Chuang, I. L. 2021. Confident Learning: Estimating Uncertainty in Dataset Labels. Journal of Artificial Intelligence Research, 70: 1373–1411.

Sariyildiz, M. B.; Kalandidis, Y.; Larlus, D.; and Alahari, K. 2021. Concept Generalization in Visual Representation Learning. In Proceedings of the IEEE/CVF International Conference on Computer Vision, 9629–9639.

Sohn, K.; Berthelot, D.; Li, C.-L.; Zhang, Z.; Carlini, N.; Cubuk, E. D.; Kurakin, A.; Zhang, H.; and Raffel, C. 2020. FixMatch: Simplifying Semi-Supervised Learning with Consistency and Confidence. In Advances in Neural Information Processing Systems, volume 33, 596–608.

Srivastava, N.; Hinton, G.; Krizhevsky, A.; Sutskever, I.; and Salakhutdinov, R. 2014. Dropout: a simple way to prevent neural networks from overfitting. Journal of Machine Learning Research, 15(1): 1929–1958.

Sun, P.; Jin, X.; Su, W.; He, Y.; Xue, H.; and Lu, Q. 2020. A Visual Inductive Priors Framework for Data-Efficient Image Classification. In European Conference on Computer Vision, 511–520.

Szegedy, C.; Vanhoucke, V.; Ioffe, S.; Shlens, J.; and Wojna, Z. 2016. Rethinking the Inception Architecture for Computer Vision. In 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2818–2826.

Tan, M.; and Le, Q. V. 2019. EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks. In International Conference on Machine Learning, 6105–6114.

Tarvainen, A.; and Valpola, H. 2017. Mean teachers are better role models: Weight-averaged consistency targets improve semi-supervised deep learning results. In ICLR (Workshop).

Tendle, A.; and Hasan, M. R. 2021. A study of the generalizability of self-supervised representations. Machine Learning with Applications, 6: 100124.

van den Oord, A.; Li, Y.; and Vinyals, O. 2018. Representation Learning with Contrastive Predictive Coding. arXiv preprint arXiv:1807.03748.

van der Maaten, L.; and Hinton, G. 2008. Visualizing Data using t-SNE. Journal of Machine Learning Research, 9(86): 2579–2605.

Wang, F.; Kong, T.; Zhang, R.; Liu, H.; and Li, H. 2021. Self-Supervised Learning by Estimating Twin Class Distributions. arXiv preprint arXiv:2110.07402.

Wang, Y.; Ma, X.; Chen, Z.; Luo, Y.; Yi, J.; and Bailey, J. 2019. Symmetric Cross Entropy for Robust Learning With Noisy Labels. In 2019 IEEE/CVF International Conference on Computer Vision (ICCV), 322–330.

Xie, S.; Girshick, R.; Dollar, P.; Tu, Z.; and He, K. 2017. Aggregated Residual Transformations for Deep Neural Networks. In 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 5987–5995.

Xie, S.; and Tu, Z. 2017. Holistically-Nested Edge Detection. International Journal of Computer Vision, 125(1): 3–18.

Yuan, L.; Hou, Q.; Jiang, Z.; Feng, J.; and Yan, S. 2021. VOLO: Vision Outlooker for Visual Recognition. arXiv preprint arXiv:2106.13112.

Yun, S.; Han, D.; Chun, S.; Oh, S. J.; Yoo, Y.; and Choe, J. 2019. CutMix: Regularization Strategy to Train Strong Classifiers With Localizable Features. In 2019 IEEE/CVF International Conference on Computer Vision (ICCV), 6022–6031.

Zhang, H.; Cisse, M.; Dauphin, Y. N.; and Lopez-Paz, D. 2017. mixup: Beyond Empirical Risk Minimization. In International Conference on Learning Representations.

Zhao, B.; and Wen, X. 2020. Distilling Visual Priors from Self-Supervised Learning. In European Conference on Computer Vision, 422–429.
Zhao, H.; Shi, J.; Qi, X.; Wang, X.; and Jia, J. 2017. Pyramid Scene Parsing Network. In 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 6230–6239.

Zheltonozhskii, E.; Baskin, C.; Mendelson, A.; Bronstein, A. M.; and Litany, O. 2021. Contrast to Divide: self-supervised pre-training for learning with noisy labels. In arXiv e-prints.

Zhong, Z.; Zheng, L.; Kang, G.; Li, S.; and Yang, Y. 2020. Random Erasing Data Augmentation. In Proceedings of the AAAI Conference on Artificial Intelligence, volume 34, 13001–13008.

Zhou, Y.; Ge, Y.; and Wu, J. 2021. Friends and Foes in Learning from Noisy Labels. CoRR, abs/2103.15055.