Adversarial Contrastive Learning by Permuting Cluster Assignments

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Abstract

Contrastive learning has gained popularity as an effective self-supervised representation learning technique. Several research directions improve traditional contrastive approaches, e.g., prototypical contrastive methods better capture the semantic similarity among instances and reduce the computational burden by considering cluster prototypes or cluster assignments, while adversarial instance-wise contrastive methods improve robustness against a variety of attacks. To the best of our knowledge, no prior work jointly considers robustness, cluster-wise semantic similarity and computational efficiency. In this work, we propose SwARo, an adversarial contrastive framework that incorporates cluster assignment permutations to generate representative adversarial samples. We evaluate SwARo on multiple benchmark datasets and against various white-box and black-box attacks, obtaining consistent improvements over state-of-the-art baselines.

1 Introduction

Contrastive learning methods aim to learn representations without relying on semantic annotations of instances, by bringing closer augmented samples from the same instance (considered as a positive pair) and pushing further apart samples from other instances (treated as negative samples). Contrastive methods have gained popularity in recent literature as pretraining methods to improve label efficiency and model performance [Oord et al. 2018], [Hjelm et al. 2018], [He et al. 2020], [Chen et al. 2020c], [Caron et al. 2020], [Chuang et al. 2020], [Henaff 2020], [Tian et al. 2019], [Robinson et al. 2021].

A central step is the selection of positive and negative examples when computing the contrastive loss. In particular, prior works have shown that large batches of negative samples improve the learned representations [He et al. 2020], [Chen et al. 2020d]. Computing all pairwise comparisons or utilizing large memory banks of randomly selected negative examples are, however, impractical in realistic applications. Prior work also shows that instance-wise contrastive learning methods do not account for any global semantic similarities observed in data [Li et al. 2020]. To address these limitations, a few methods sample representative negative examples via clustering techniques, e.g., by contrasting prototypes of varying granularity [Li et al. 2020], predicting cluster labels with a swapped prediction mechanism [Caron et al. 2020], or sampling positive and negative pairs from weak cluster assignments [Sharma et al. 2020]. In general, clustering has been an effective way to capture semantic patterns in the data and has been used in several works, e.g., in semi-supervised learning [Zhang et al. 2009].
Nevertheless, most instance-wise and cluster-based methods presented lack robustness to adversarial examples. A few works target improving robustness in contrastive learning by devising adversarial perturbations of positive and negative examples [Kim et al. 2020, Jiang et al. 2020, McDermott et al. 2021, Bui et al. 2021]. These efforts try to design adversarially robust self-supervised learning frameworks by generating perturbations that maximize the contrastive loss of augmented instance-level samples, causing the model to make incorrect predictions. However, semantic cluster structures encoded in the data are rarely considered, and the designed perturbations may not generalize well in downstream tasks. Intuitively, and in the absence of label (class) information, the self-supervised gradient-based adversarial attacks imposed can be considered untargeted, as the gradient points towards a direction that maximizes the contrastive loss for same-class instances, without any target class in mind (see Figure 1 blue lines).

In this work, we introduce Swapping Assignments for Robust contrastive learning (SwARo), a simple and efficient alternative that leverages cluster-wise supervision to design semi-targeted adversarial attacks that missguide the contrastive loss towards true negatives, i.e., accounting for examples that have pseudo-label assignments different than the anchor class. Specifically, our method updates the gradient direction to obtain adversarial perturbations that maximize the loss for pairs with same pseudo-labels (Figure 1 blue lines), but also minimize the loss of negative pairs (Figure 1 red lines), leading to pseudo-targeted attacks.

Contributions The contributions of our work are summarized as follows:

(1) We introduce SwARo, a self-supervised contrastive learning method that jointly considers adversarial robustness and cluster-wise semantic information observed in the data.

(2) In contrast to prior work on adversarial contrastive learning, we utilize the pseudo-labels induced by clustering as targets to explicitly guide the gradient direction towards negatives.

(3) We verify the effectiveness of the proposed method and show that SwARo improves downstream performance (accuracy), robustness on unseen black-box and white-box attack types, and transfer learning performance.

2 Related Work

Adversarial Training There has been substantial research on increasing the robustness of deep neural networks against adversarial attacks. For example, [Goodfellow et al. 2014] propose the Fast Gradient Sign Method (FGSM), a white-box attack that generates adversarial perturbations by utilizing the model gradients to design small distortions, which when added to the original image will lead to maximizing the model loss. Training with such adversarial perturbations has been shown to improve model robustness. Subsequent work proposes iterative variants, e.g., extensions such as the Basic Iterative (BIM) [Kurakin et al. 2017] and Projected Gradient Descent (PGD) [Madry et al. 2018] methods. Besides the gradient-based cross-entropy attacks, TRADES [Zhang et al. 2019] empirically analyzes the trade-off between robustness and accuracy and introduces a defense mechanism that utilizes a KL-divergence loss between a clean example and its adversarial counterpart for learning a more robust latent feature space. [Ilyas et al. 2019] hypothesize that the adversarial vulnerability of neural networks is a direct result of their sensitivity to well-generalizing features
that are incomprehensible to humans. Schwinn et al. [2021] discover that cross-entropy attacks fail against models with large logits, and propose to add logit noise and enforce scale invariance on the loss to mitigate this limitation and encourage the model to design diverse attack targets. All above methods are originally designed for supervised learning tasks.

### Contrastive Learning

Instance-wise contrastive learning methods Ye et al. [2019], Chen et al. [2020c], Bachman et al. [2019], He et al. [2020], and supervised contrastive learning Khosla et al. [2020] methods have been proposed. For example, Li et al. [2020] utilize a cluster-based approach that brings contrastive representations closer to their assigned feature prototypes. Caron et al. [2020] propose SwAV, an image representation technique that instead of comparing representations of different image views, follows a swapped prediction strategy to predict the code of one view from another view of the same image by clustering image representations with a computationally efficient online clustering approach. Similar swapping strategies have been utilized in cross-modal retrieval Kim [2021]. SEER Goyal et al. [2021] is trained on large-scale unconstrained and uncurated image collections by improving the scalability of SwAV in terms of GPU memory consumption and training speed. Khosla et al. [2020] extend contrastive learning to a supervised setting that utilizes label information in positive-negative subset creation, i.e., images of the same class label are considered as positive examples. All aforementioned instance-wise and cluster-based contrastive learning techniques lack robustness against adversarial examples. Here, we briefly review works that aim to combine adversarial training with contrastive learning.

### Adversarial Contrastive Training

A number of works utilize adversarially constructed samples in contrastive learning to increase the robustness of the learned feature representations Bui et al. [2021], Kim et al. [2020], Jiang et al. [2020], Chen et al. [2020b], McDermott et al. [2021], Chen et al. [2020a]. RoCL Kim et al. [2020] introduces small perturbations to generate adversarial samples, leading to a more robust contrastive model. Jiang et al. [2020] experiment with different combinations of perturbations while generating positive and negative examples for calculating contrastive loss and found that using both standard data augmentations and adversarial samples increases robustness in a self-supervised pre-training procedure. Both works do not consider clustered prototypes during the contrastive loss computation or the adversarial sample generation process. Chen et al. [2020b] analyze robustness gains after applying adversarial training in both self-supervised pre-training and supervised fine-tuning, and find that adversarial pre-training contributes the most in robustness improvements. Bui et al. [2021] propose a minimax local-global algorithm to generate adversarial samples that improves the performance of SimCLR Chen et al. [2020c]. To the best of our knowledge, none of the previous works considered designing more targeted contrastive adversarial examples by leveraging useful cluster structures observed in the data.

### 3 Proposed Method

#### Problem Formulation

Given a set of unlabeled instances \( X = \{x_1, x_2, \ldots, x_n\} \), the goal is to learn a feature encoder \( f_\theta(\cdot) : X \rightarrow \mathbb{R}^d \) that maps data points to a \( d \)-dimensional embedding space and can later be used in downstream tasks. Contrastive learning methods learn such feature representations by minimizing the distance between similar data points (positive pairs) and maximizing the distance between dissimilar data points (negative pairs). The contrastive loss is typically calculated via a normalized temperature-scaled cross-entropy loss (NT-XENT) as shown in Eq. (1).

\[
L_{CL}(x_i, x_k) = -\log \frac{\exp \left( \frac{s(x_i, x_k)}{\tau} \right)}{\sum_{x_j \neq i \in X} \exp \left( \frac{s(x_i, x_j)}{\tau} \right)}, \tag{1}
\]
Also, depending on the choice of where \( x \) \( f \) where \( s \) \( \eta \) denotes the number of iterations, \( \eta \) is the step size, \( \text{sign}(\cdot) \) is the vector sign (direction), and \( \Pi \) denotes the norm-ball projection of interest, e.g., clipping \( \delta \) to lie within an \( \epsilon \)-range \( \Delta := \{ \delta : \| \delta \|_\infty \leq \epsilon \} \). Notice that the above formulation requires a class label \( y \) \( \mathcal{Y} \) to compute the supervised loss when crafting adversarial attacks and hence is inapplicable to self-supervised settings. Also, depending on the choice of \( y \), the attack can be untargeted or targeted. In targeted adversarial attacks the goal is to direct the perturbation towards a particular class of interest, other than the true class, e.g., confusing the model to misclassify a “cat” example as “dog”, by using as target the class label for “dog” instead of the model prediction.

To adapt adversarial training in self-supervised settings, recent work replaces the supervised loss with the contrastive NT-XENT loss in Eq. (1), i.e., generating adversarial views of an instance that confuse...
We utilize this indicator to better guide the sign with the contrastive NT-XENT loss computed as in Eq. (1). Figure 2 presents an overview and $\beta$ where

$$\text{assign pseudo-label for the two instances are similar (and hence the two examples are most likely to encode a positive pair) or not (and this can be indeed considered as a negative pair).}$$

Afterward, we calculate the contrastive loss and update the encoder model. Each step is discussed in detail.

**Cluster Assignments** We utilize clustering to obtain cluster centroids and assign a pseudo-label to each training sample. For simplicity, we apply k-means, however, we note that any clustering method can be used, including online clustering variants [Asano et al., 2019; Caron et al., 2018, 2020]. More formally, let $Z = \{z_1, z_2, \ldots, z_n\}$ be the intermediate latent representations obtained from feature encoder $f_B$ for unlabeled dataset $X$, and $K$ is the empirically-set number of clusters. A set of cluster centroids $C = \{c_j\}_{j=1}^K$ can be computed by applying k-means clustering on $Z$. Next, we assign pseudo-label $\hat{y}_x$ to each example $x_i \in X$ based on the distance from each cluster centroid, i.e.,

$$\hat{y}_x = \arg\min_j (z_i - c_j)^2.$$

**Adversarial Sample Generation** Let $X_B = \{x_i\}_{i=1}^B \subset X$ sampled batch of size $B$. To construct positive pairs, an example is augmented twice by applying two transformations $t_1, t_2 \in T$ that create two different views $\hat{x}_i^{(1)} = t_1(x_i)$ and $\hat{x}_i^{(2)} = t_2(x_i)$ of the same instance, producing a batch of positive pairs $\{(\hat{x}_i^{(1)}, \hat{x}_i^{(2)}), \ldots, (\hat{x}_i^{(1)}, \hat{x}_i^{(2)}), \ldots, (\hat{x}_B^{(1)}, \hat{x}_B^{(2)})\}$. Without loss of generality, a permutation induced from shuffling the second instance in each pair is denoted as:

$$\{(\hat{x}_i^{(1)}, \hat{x}_{\sigma(i)}^{(2)}), \ldots, (\hat{x}_i^{(1)}, \hat{x}_{\sigma(i)}^{(2)}), \ldots, (\hat{x}_B^{(1)}, \hat{x}_{\sigma(B)}^{(2)})\},$$

where $\sigma(\cdot): \{1, \ldots, B\} \rightarrow \{1, \ldots, B\}$ is a permutation. Based on the pseudo-labels created from clustering (Section 3.1), we can assign an indicator variable to each pair in the batch, according to whether both instances belong to the same cluster, i.e.,

$$I(\hat{x}_i^{(1)}, \hat{x}_{\sigma(i)}^{(2)}) = \left[\mathbb{1}\left(\hat{y}_{\hat{x}_i^{(1)}} = \hat{y}_{\hat{x}_i^{(2)}}\right) - \mathbb{1}\left(\hat{y}_{\hat{x}_i^{(1)}} \neq \hat{y}_{\hat{x}_i^{(2)}}\right)\right],$$

where $\hat{y}_{\hat{x}_i^{(1)}}$ and $\hat{y}_{\hat{x}_i^{(2)}}$ are pseudo-labels from clustering.

In short, we assign $I(\hat{x}_i^{(1)}, \hat{x}_{\sigma(i)}^{(2)}) = 1$ to a pair if both of the examples in that pair belong to the same cluster (positive pair) and $I(\hat{x}_i^{(1)}, \hat{x}_{\sigma(i)}^{(2)}) = -1$ if they belong to different clusters (negative pair). We utilize this indicator to better guide the sign of the NT-XENT gradient w.r.t. the corresponding example pair. In essence, we maximize the contrastive loss w.r.t. positive pairs, and minimize the contrastive loss w.r.t. negative pairs, as shown in Eq. (6):

$$\delta^{t+1} := \Pi [\delta^t + \eta \beta_i \text{sign} \left(\nabla_{\delta_i} \mathcal{L}_{CCL} \left(f_B \left(x_i^{(1)} + \delta_i^{(1)}\right), f_B \left(x_i^{(2)}\right)\right)\right)],$$

where $\beta_i = I(\hat{x}_i^{(1)}, \hat{x}_{\sigma(i)}^{(2)})$ for brevity. Notice that $f_B \left(x_i^{(2)}\right)$, in combination with $\beta_i$, acts as a target for the adversarial attack. Applying these perturbations to each example in the batch creates adversarial examples $x_i^{adv} = \left(\hat{x}_i^{(1)} + \delta_i^{(1)}, \hat{x}_{\sigma(i)}^{(2)}\right)$ that aim to maximize the similarity when both examples in a pair belong to different clusters.

**Contrastive Training** Finally, pairs are reordered in their original configuration $X^{adv} = \{(\hat{x}_i^{(1)} + \delta_i^{(1)}, \hat{x}_{\sigma(i)}^{(2)})\}_{i=1}^B$, with one instance in each pair being adversarially attacked, and the model is trained with the contrastive NT-XENT loss computed as in Eq. (1). Figure 3 presents an overview and Algorithm 1 provides the pseudocode of the proposed method.
We evaluate SwARo with cross-entropy (we first train an unsupervised model and then train a linear layer to measure the accuracy. All reported results are averaged over multiple trials, and hyper-parameters are provided in the supplementary material. To ensure the efficacy of the clustering process, we rely on instance-wise adversarial attacks for the first 100 epochs and then utilize the proposed cluster-wise adversarial example generation.

Moreover, we compare SwARo classes and 600 [Krizhevsky et al., 2009] contains images similar to 10 originating from 10 classes, with 6,000 images per class. The training and test sets consist of 50,000 and 10,000 images, respectively.

Datasets & Baselines We conduct experiments on the following datasets:

CIFAR-10 [Krizhevsky et al., 2009]: The CIFAR-10 dataset includes 60,000 images of size 32×32, originating from 10 classes, with 6,000 images per class. The training and test sets consist of 50,000 and 10,000 images, respectively.

CIFAR-100 [Krizhevsky et al., 2009] contains images similar to CIFAR-10 but there exist 100 classes and 600 images per class. Train-to-test ratio remains the same as CIFAR-10.

Moreover, we compare SwARo against six types of baseline methods: (1) Supervised models trained with cross-entropy (CE), (2) traditional adversarial training methods such as AT [Madry et al., 2018] and TRADES [Zhang et al., 2019], (3) a vanilla contrastive learning method, SimCLR [Chen et al., 2020].

4 Experimental Results

We evaluate SwARo on two benchmark datasets comparing against existing self-supervised and supervised adversarial learning methods, and reporting results on black-box and white-box targeted and untargeted attacks. Similarly to [Kim et al., 2020], we consider a linear evaluation and a robust-linear evaluation (r-LLE) setting, where we compare the classification accuracy on clean and adversarial examples, respectively.

Experimental Setup For all experiments, we use a ResNet-18 [He et al., 2016] as the backbone encoder. All models, including baselines are trained with ℓ∞ Projected Gradient Descent (PGD) with ε = 8/255. As for the linear evaluation, we follow a similar setup as RoCL [Kim et al., 2020], where we first train an unsupervised model and then train a linear layer to measure the accuracy. All reported results are averaged over multiple trials, and hyper-parameters are provided in the supplementary material. To ensure the efficacy of the clustering process, we rely on instance-wise adversarial attacks for the first 100 epochs and then utilize the proposed cluster-wise adversarial example generation. This is to guarantee that the encoder has learned useful representations before initiating clustering.
Table 1: Comparison against PGD white-box attacks on CIFAR-10. Results marked with † are reported from [Kim et al. 2020]. CE is supervised cross-entropy. $A_{nat}$ denotes the accuracy of clean images. $\ell_\infty$ is the seen adversarial attack while $\ell_1$ and $\ell_2$ are unseen attacks. Colored fonts indicate best performance in each category: supervised (violet), self-supervised (teal), adversarial self-supervised on linear evaluation (black), and robust linear evaluation (purple).

| Train type | Method | $A_{nat}$ | $\ell_\infty$ | $\ell_1$ | $\ell_2$ | $\ell_1$ | $\ell_2$ |
|------------|--------|-----------|---------------|-----------|-----------|-----------|-----------|
| CE⁴       | 92.82  | 0.00      | 0.00          | 20.77     | 12.96     | 28.47     | 15.56     |
| AT⁵       | Madry et al. 2018 | 81.63  | 44.50         | 14.47     | 72.26     | 59.26     | 66.74     | 55.74     |
| TRADES     | Zhang et al. 2019 | 77.03 | 48.01         | 22.55     | 68.07     | 57.93     | 62.93     | 53.79     |
| SCL⁴       | Khosla et al. 2020 | 94.05 | 0.08          | 0.00      | 22.17     | 10.29     | 38.87     | 22.58     |
| Self-Supervised | SimCLR⁴ Chen et al. 2020c | 91.25 | 0.63          | 0.08      | 15.3      | 2.08      | 41.49     | 25.76     |
| Adversarial | SwAV⁴ Caron et al. 2020 | 70.60 | 22.88         | 18.46     | 35.54     | 35.53     | 35.54     | 35.54     |
| Adversarial (Robust Eval.) | RoCL+rLE⁴ Kim et al. 2020 | 80.43 | 47.69         | 15.53     | 68.30     | 66.19     | 77.31     | 75.05     |
| Self-Supervised | SwARo (Ours) + rLE | 86.89 | 41.58         | 10.70     | 62.20     | 62.66     | 84.09     | 83.79     |

Table 2: Comparison against PGD white-box attacks on CIFAR-100. $A_{nat}$ denotes the accuracy of clean images. $\ell_\infty$ is the seen adversarial attack while $\ell_1$ and $\ell_2$ are unseen attacks.

| Method | $A_{nat}$ | $\ell_\infty$ | $\ell_1$ | $\ell_2$ | $\ell_1$ | $\ell_2$ |
|--------|-----------|---------------|-----------|-----------|-----------|-----------|
| ACL⁴  | Jiang et al. 2020 | 42.03 | 22.97        | 9.53      | 38.37     | 38.67     | 40.92     | 40.88     |
| RoCL⁴ | Kim et al. 2020 | 50.04 | 20.26        | 5.93      | 36.16     | 36.09     | 52.44     | 52.08     |
| SwARo (Ours) | 55.12 | 20.19 | 5.96       | 36.37     | 36.11     | 52.44     | 52.18     |

4.1 White Box Attacks

We first evaluate the robustness of the learned representations against seen and unseen attacks. In Table 1, we report results on CIFAR-10, comparing methods against Projected Gradient Descent (PGD) white-box attacks with linear evaluation and robust linear evaluation (rLE). Table 2 presents results for all adversarial self-supervised methods on CIFAR-100.

Traditional contrastive learning methods (SimCLR and SwAV) are vulnerable to adversarial attacks. Considering cluster information (SwAV) improves performance on seen $\ell_\infty$ attacks and unseen $\ell_2$ attacks but occurs considerable losses in accuracy on clean images $A_{nat}$. Among adversarial self-supervised approaches, SwARo achieves much higher clean accuracy, substantially higher robust accuracy against unseen $\ell_1$ target attacks, and comparable performance with RoCL on $\ell_\infty$ and $\ell_2$ attacks. ACL outperforms both on $\ell_\infty$ and $\ell_2$; this method benefits from additional batch normalization parameters and balancing two contrastive loss terms, a standard contrastive and an adversarial contrastive loss.

In addition to PGD, we also experiment with several additional state-of-the-art white-box attacks BIM Kurakin et al. [2017], FGSM Goodfellow et al. [2014], Jitter Schwinn et al. [2021]. SwARo outperforms baselines across all untargeted and targeted white-box attacks, showing consistent robust accuracy gains (Table 3). In particular, we observe approximately 3 – 4% relative gains on PGD variants such as BIM and FGSM w.r.t. the next best method. Additionally, we find that SwARo is performing 4 – 9% better compared to baselines on Jitter attacks, an adversarial attack method that incorporates scale invariance and encourages diverse attack targets with smaller perturbations Schwinn et al. [2021]. These results make SwARo more appealing in practice and suggest that our approach to
Table 3: Performance of SwARo against white-box attacks (BIM, FGSM, Jitter) on the CIFAR-10 dataset. Each column denotes the white-box attack used to generate adversarial samples with $\epsilon = 8/255$. Each row shows the performance of the target models against the white-box attacks.

| Method   | Attack | Kurakin et al. [2017] | FGSM Goodfellow et al. [2014] | Jitter Schwinn et al. [2021] |
|----------|--------|-----------------------|-----------------------------|-----------------------------|
|          | Untargeted | Targeted | Untargeted | Targeted | Untargeted | Targeted |
| RoCL     | 37.07 | 62.92 | 57.27 | 67.06 | 45.41 | 63.67 |
| ACL      | 42.35 | 65.74 | 49.95 | 63.02 | 54.24 | 61.55 |
| SwARo (Ours) | 45.78 | 3.43 | 68.70 | 2.86 | 61.34 | 4.07 |
|          | 4.07 | 0.77 | 72.57 | 0.80 | 57.75 | 3.51 |

Table 4: Performance comparison against black-box attacks on the CIFAR-10 dataset. Columns denote black-box $\ell_1$ attacks and rows show model performance (models trained with $\ell_1$).

| Target Source | $\epsilon = 8/255$ | $\epsilon = 16/255$ |
|---------------|---------------------|---------------------|
| AT TRADES     | RoCL                | SwARo (Ours)        |
| Madry et al. [2018] | 41.67±0.06 | 43.06±0.08 | 43.53±0.05 | 36.97±0.08 | 40.81±0.14 | 41.89±0.06 |
| TRADES Zhang et al. [2019] | 82.29±0.04 | 74.41±0.04 | 73.31±0.10 | 80.10±0.09 | 55.88±0.11 | 55.55±0.07 |
| RoCL Kuznetsov et al. [2019] | 82.03±0.07 | 71.39±0.02 | 61.41±0.08 | 79.11±0.08 | 46.09±0.10 | 28.86±0.15 |
| ACL Jiang et al. [2020] | 80.28±0.05 | 69.62±0.04 | 63.53±0.04 | 63.06±0.10 | 77.95±0.13 | 34.56±0.03 |
| SwARo (Ours) | 84.99±0.12 | 74.35±0.08 | 64.27±0.12 | 81.80±0.23 | 45.40±0.09 | 25.61±0.15 |

Table 5: Comparison in a transfer learning setup across the CIFAR-10 and CIFAR-100 datasets with ResNet-18. Column “Source” corresponds to the dataset the encoder model is trained on, while “Target” presents the dataset used for evaluating the frozen encoder with an additional randomly-initialized finetuned linear layer (linear evaluation).

| Model          | Source | Target     | $A_{nat}$ | Source | Target    | $A_{nat}$ |
|----------------|--------|------------|-----------|--------|-----------|-----------|
| ACL Jiang et al. [2020] | CIFAR-100 | CIFAR-10 | 70.08 | CIFAR-100 | CIFAR-10 | 42.29 |
| RoCL Kim et al. [2020] | CIFAR-100 | CIFAR-10 | 73.93 | CIFAR-10 | CIFAR-100 | 45.84 |
| SwARo (Ours)  | CIFAR-100 | CIFAR-10 | 75.52 | CIFAR-100 | CIFAR-10 | 46.01 |

enforcing adversarial perturbations, that consider both positive and negative pairs as well as semantic cluster information, ensures robustness against a diverse set of attack types.

4.2 Black Box Attacks

We also verify the performance of SwARo against black-box attacks. We generate adversarial examples using black-box $\ell_1$ attacks such as AT Madry et al. [2018] and TRADES Zhang et al. [2019]. Table 4 shows that SwARo is able to better defend against TRADES and AT attacks. We additionally compare SwARo as a black-box adversarial attack on TRADES, AT, RoCL and ACL. Results show that SwARo attacks are stronger or comparable to baselines. An interesting observation is that as the perturbation radius $\epsilon$ becomes smaller, SwARo as an attack is stronger than RoCL, as SwARo’s performance on RoCL attacks is 64.27%, compared to RoCL’s performance on SwARo attacks that drops to 61.41%. Similarly, we also find that ACL and TRADES are better equipped against RoCL attacks than SwARo attacks.

4.3 Transfer Learning

We evaluate performance on a transfer learning setup and check whether the learned representations can be transferred across datasets. Specifically, we pretrain an encoder model on CIFAR-10 and then finetune a randomly-initialized linear classification layer on CIFAR-100, on top of the frozen encoder. We compare against adversarial self-supervised baselines, ACL Jiang et al. [2020] and ROCL Kim et al. [2020]. As shown in Table 5, SwARo achieves better accuracy across all cases.

4.4 Ablation Studies

We study the trade-off between robustness and accuracy. In particular, we design an ablation study among our proposed SwARo and a stochastic variant that selects between the targeted attacks and the traditional adversarial contrastive learning that maximizes the loss between positive pairs. Since
Figure 3: t-SNE visualization of the three contrastive pretraining methods ACL [Jiang et al. 2020], RoCL [Kim et al. 2020] and SwARo (Ours) on the CIFAR-10 dataset. The 10 classes are represented with different colors, and the legend shows label information. SwARo produces well-separated clusters compared to the rest of the baselines.

Table 6: Performance of SwARo, varying the probability of selection $p$ for the proposed adversarial example generation or reverting to the traditional contrastive adversarial example generation [Kim et al. 2020]. Results reported on the CIFAR-10 dataset.

| $p$ | $A_{nat}$ | $\ell_{\infty}$ | $\ell_2$ | $\ell_1$ |
|-----|---------|----------------|---------|---------|
| 0.10 | 84.11 | 39.58 | 10.68 | 73.80 | 72.51 | 82.31 | 82.25 |
| 0.25 | 84.11 | 37.93 | 9.26 | 73.09 | 70.36 | 82.04 | 81.92 |
| 0.50 | 85.78 | 38.37 | 10.10 | 68.78 | 67.76 | 82.70 | 82.70 |
| 0.75 | 87.38 | 37.33 | 9.13 | 59.69 | 59.10 | 84.06 | 83.69 |
| 0.90 | 89.13 | 35.95 | 9.68 | 42.02 | 47.86 | 84.98 | 84.36 |

our method improves accuracy on clean images and on unseen $\ell_1$ attacks, we hope that this stochastic selection will be able to balance between this improvement and robustness to seen attacks. In Table 6, the first column $p$ presents the probability of selecting an adversarial generation strategy. For example, $p = 0.90$ denotes applying the proposed SwARo adversarial contrastive method to 90% of the batches during training, while applying RoCL to 10% of the batches. Results show that smaller $p$ values result in improvements on seen $\ell_\infty$ attacks and unseen $\ell_2$ attacks, while the performance on clean images and unseen $\ell_1$ attacks improves as $p$ increases. We leave further exploration with other stochastic variants and extensive hyper-parameter tuning to future work. We perform additional ablation studies to test the effect of clustering and the variability on performance as training progresses. Results can be found in the supplementary material.

4.5 Qualitative Analysis

We present qualitative results on the learned representations. We create t-SNE visualizations [Van der Maaten and Hinton 2008] for RoCL, ACL and our method SwARo. Each semantic class on the CIFAR-10 dataset is assigned a different color, and the legend presents the object category. Figure 3 shows that representations obtained from SwARo produce well-separated clusters compared to the baselines. Overall our results indicate that SwARo results in better representation learning performance and improved robustness to unseen attacks.

5 Conclusion

In this work, we present SwARo, an adversarial contrastive learning method that learns robust self-supervised representations. Our approach is able to better guide the adversarial perturbation process. More specifically, by permuting pseudo-labels our method is able to create targeted attacks that maximize the loss for positive pairs and minimize the loss for negative pairs, leading to improvements
in clean accuracy and unseen attacks. Through experimental analysis on black-box and white-box attacks, with two benchmark datasets and comparing against a variety of baselines, ranging from vanilla self-supervised methods to previously proposed adversarial contrastive learning approaches, we showcase that our proposed approach, SwARo, outperforms baselines that only consider positive pairs when creating adversarial examples. Additional experiments on a diverse set of white-box attacks show that SwARo is robust on realistic adversarial scenarios against a diverse set of attack types. Qualitative analysis shows that incorporating pseudo-label information produces well-separated clusters, leading to better learned robust representations. In the future, we hope to evaluate our method on additional datasets with more complex model architectures. Future directions could include extensions to multi-modal data and structured tasks, as well as improving robustness on hierarchical fine-grained representation learning settings.

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A Appendix

A.1 Training Progress

In addition, we present the learning progress as the number of epochs increases. Table 7 reports results on CIFAR-10, on both clean accuracy and robust accuracy on seen and unseen attacks.

Table 7: Ablation study on the number of epochs. Results reported on the CIFAR-10 dataset.

| Number of Epochs | seen | unseen | \(\ell_{\infty}\) | \(\ell_{2}\) | \(\ell_{1}\) |
|------------------|------|--------|-----------------|-----------------|-----------------|
|                  | \(A_{nat}\) | \(8/255\) | 16/255 | 0.25 | 0.5 | 7.84 | 12 |
| 200              | 78.03 | 27.73 | 6.44 | 51.96 | 51.66 | 78.14 | 77.64 |
| 400              | 81.97 | 23.90 | 4.69 | 51.87 | 50.90 | 73.46 | 72.99 |
| 600              | 83.32 | 29.79 | 6.31 | 54.82 | 53.20 | 79.85 | 79.34 |
| 800              | 85.63 | 32.04 | 6.51 | 59.78 | 58.90 | 81.67 | 81.25 |
| 1000             | 84.43 | 33.03 | 7.52 | 57.65 | 57.20 | 82.52 | 81.99 |
| 1200             | 86.55 | 33.91 | 7.92 | 61.13 | 59.92 | 83.44 | 82.98 |
| 1400             | 87.05 | 36.53 | 9.13 | 59.38 | 59.35 | 83.97 | 83.57 |
| 1600             | 87.21 | 36.32 | 8.62 | 60.66 | 60.50 | 84.23 | 83.82 |
| 1800             | 87.35 | 36.94 | 8.80 | 58.81 | 59.21 | 84.09 | 83.69 |
| 2000             | 87.38 | 37.33 | 9.13 | 59.69 | 59.10 | 84.06 | 83.69 |

A.2 Number of Clusters

Table 8 presents results with varying the number of clusters \(K\). In general, there are marginal performance differences across clean and robust accuracy, and seen and unseen attacks, showing that SwARo remains robust to the choice of this hyper-parameter.

Table 8: Ablation study on the number of clusters. Results reported on the CIFAR-10 dataset.

| #K Clusters | seen | unseen | \(\ell_{\infty}\) | \(\ell_{2}\) | \(\ell_{1}\) |
|-------------|------|--------|-----------------|-----------------|-----------------|
|             | \(A_{nat}\) | \(8/255\) | 16/255 | 0.25 | 0.5 | 7.84 | 12 |
| 25          | 87.61 | 37.34 | 9.49 | 59.07 | 59.91 | 84.36 | 84.10 |
| 50          | 87.12 | 37.86 | 9.48 | 57.98 | 60.72 | 84.60 | 84.21 |
| 100         | 87.42 | 37.36 | 9.61 | 58.91 | 59.41 | 84.21 | 83.79 |
| 250         | 87.79 | 37.72 | 9.17 | 59.22 | 61.21 | 85.26 | 84.84 |
| 500         | 87.42 | 36.98 | 9.26 | 59.12 | 59.44 | 84.37 | 83.81 |
| 1000        | 87.38 | 37.33 | 9.13 | 59.69 | 59.10 | 84.06 | 83.69 |
| 2500        | 87.38 | 37.83 | 9.96 | 58.68 | 59.90 | 84.57 | 84.08 |
| 5000        | 87.34 | 37.35 | 9.67 | 59.26 | 59.41 | 84.44 | 83.95 |
| 10000       | 87.48 | 38.17 | 9.01 | 59.46 | 59.91 | 84.37 | 83.70 |

A.3 Hyper-parameter Details

For all models, we adopt the training setup of RoCL [Kim et al.] [2020]. For completeness, in this supplementary material we report important hyper-parameters, as well as newly introduced hyper-parameters. We use a 0.01 learning rate for linear evaluation and 0.02 for robust linear evaluation. We utilize a ResNet-18 as a base encoder for all models. In the training phase, we use a two-layered projection layer as the projection head. The embedding dimension of the projection head is 128. For the adversarial attacks in the training phase, we set \(\epsilon = 8/255\) and \(\eta = 1/255\), and \(t = 7\). Here \(\epsilon\) is the perturbation radius, \(\eta\) is the step size, and \(t\) is the number of PGD iterations. Unless otherwise specified, we use \(K = 1000\) for CIFAR-10 and \(K = 5000\) for CIFAR-100, where \(K\) is the number of
clusters. We set \( p = 0.75 \), which is the probability of applying SwARo to a batch. We train all our models for 2000 epochs. We use a batch size of 256 for running all our training. For the rest, we follow a similar optimization setup and data augmentation as RoCL [Kim et al., 2020]. Training time for SwARo is approximately 5 hours and 20 minutes per 100 epochs with two NVIDIA V100 GPUs with 16GB memory.