A Generalized Supervised Contrastive Learning Framework

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Abstract

Based on recent remarkable achievements of contrastive learning in self-supervised representation learning, supervised contrastive learning (SupCon) has successfully extended the batch contrastive approaches to the supervised context and outperformed cross-entropy on various datasets on ResNet. In this work, we present GenSCL: a generalized supervised contrastive learning framework that seamlessly adapts modern image-based regularizations (such as Mixup-Cutmix) and knowledge distillation (KD) to SupCon by our generalized supervised contrastive loss. Generalized supervised contrastive loss is a further extension of supervised contrastive loss measuring cross-entropy between the similarity of labels and that of latent features. Then a model can learn to what extent contrastives should be pulled closer to an anchor in the latent space. By explicitly and fully leveraging label information, GenSCL breaks the boundary between conventional positives and negatives, and any kind of pre-trained teacher classifier can be utilized. ResNet-50 trained in GenSCL with Mixup-Cutmix and KD achieves state-of-the-art accuracies of 97.6% and 84.7% on CIFAR10 and CIFAR100 without external data, which significantly improves the results reported in the original SupCon (1.6% and 8.2%, respectively). Pytorch implementation is available at [https://t.ly/yuUO](https://t.ly/yuUO).

1 Introduction

In computer vision, generative and discriminative approaches are dominant in self-supervised visual representation learning. While pixel-level generation in the input space [26, 14] is computationally expensive and not efficient for representation learning, discriminative approaches that learn from pseudo labels defined by pretext tasks have made great progress in self-supervised representation learning. Previously, such pretext tasks have relied on heuristics [11, 47, 32, 13], which could have limitations in generalization. Contrastive approaches have recently emerged and shown the great promise to address weaknesses of traditional heuristic discrimination approaches, achieving state-of-the-art performances even comparable to supervised learning [40, 4, 17, 5]. The basic idea of contrastive learning is the binary classification of positive/negative examples w.r.t. an anchor. In self-supervised context, where no label information is available, a data augmentation of an anchor is considered as a positive example. Supervised contrastive learning (SupCon [23]) has extended contrastive learning to the supervised context. By leveraging label information, all the same class examples from the minibatch are considered as positive examples. SupCon has outperformed cross-entropy loss on various datasets on ResNet [18], showing the great potential of contrastive learning in the supervised context.

Regularization tricks to improve generalization in deep neural nets have been continuously developed. Recently, [33] proposed the Unified Scheme for ImageNet (USI) to train top results on a wide variety of datasets.
of architectures on ImageNet [8], which mainly consists of RandAugment [7], Mixup [46] and CutMix [45], one-cycle learning rate scheduling [35], exponential-moving average of model weights [22] and knowledge distillation (KD [21]). While the importance of image-based regularizations (Mixup and Cutmix) and KD has been emphasized in the USI, an important commonality is that those regularization tricks change labels of images (i.e., one-hot to probability distribution). However, the commonality is an obstacle in the SupCon since label information is leveraged implicitly. Original supervised contrastive loss only consider the binary classification of the same class examples and cannot fully leverage the label information especially when it is in the form of probability distribution.

In this work, we present GenSCL: a generalized supervised contrastive learning framework that seamlessly adapts image-based regularizations and KD to SupCon. This adaption is available because of our proposed \textit{generalized supervised contrastive loss} that builds on supervised contrastive loss by \textit{fully} leveraging label information and adapting to modern regularization tricks. While original Supcon simply divides contrastive examples into positives and negatives according to the label and pulls all positives closer to an anchor evenly, our technical novelty is to consider pulling all contrasts in the minibatch to an anchor delicately according to the similarity of labels, which breaks the boundary between conventional positives and negatives. Our Generalized supervised contrastive loss is a generalization of self-supervised contrastive loss [17][4], MixCo loss [24] and supervised contrastive loss [23]. In GenSCL, comparisons between mixed examples and the information of
teacher’s label prediction are fully applicable as shown in Fig.1. Thus, GenSCL can be seen as the modification of USI in the contrastive learning paradigm.

In GenSCL, SupCon with Mixup-Cutmix and KD achieves state-of-the-art accuracies of 97.6% and 84.7% on CIFAR10 and CIFAR100 [27] respectively on ResNet-50, which is 1.6% and 8.2% improvement over the results reported in original supervised contrastive learning. Our main contributions are summarized below:

- We propose a novel generalization of the supervised contrastive loss that fully and explicitly leverages label information, thus the boundary between conventional positives and negatives is eliminated.
- We adapt image-based regularizations (Mixup-Cutmix) to SupCon through our generalized supervised contrastive loss, and a complex comparison between mixed anchors and mixed contrasts is applicable.
- We propose a KD approach to applying any kind of pre-trained classifier (teacher) in SupCon through our generalized supervised contrastive loss.
- We present GenSCL that seamlessly adapts Mixup-Cutmix and KD to SupCon, which achieves state-of-the-art results in CIFAR.

2 Related Work

Contrastive visual representation learning  Recently, self-supervised representation learning approaches have shown astonishing results in natural language processing [30, 9, 1]. In computer vision, pretext tasks relied on heuristics [11, 47, 32, 13] have been developed to learn representations by predicting the context of images, which could have limitations in generalization. Inspired from noise contrastive estimation [15, 31] and N-pair losses [36], discriminative approaches from the paradigm of contrastive learning have recently been developed and showing state-of-the-art results [43, 20, 40, 4, 17, 5]. Here we focus on the most relevant papers. Batch contrastive approaches [17, 4, 5] that consider the data augmentation of an anchor as a positive and randomly chosen images from the minibatch as negatives are commonly used in self-supervised learning by the reason of their robust and efficient framework. In supervised context, cross-entropy is most widely used to train classifier networks, while several papers have studied the limitations of cross-entropy [48, 12, 3]. In supervised contrastive learning (SupCon [23]), which extends batch contrastive approaches to supervised context, supervised contrastive loss has been proposed as the alternative loss function of cross-entropy. The major difference is that SupCon considers many positives by matching the labels of contrasts with the label of an anchor. SupCon has successfully outperformed the state-of-the-art cross-entropy [28] on ResNet [18]. However, as the label information is leveraged implicitly in supervised contrastive loss (i.e. positives are obtained by binary classification with anchors), there is still a gap to adapt modern regularization tricks such as image-based regularizations [46, 45] and knowledge distillation [21] to SupCon.

Image-based regularizations  Data augmentation strategies are essential for generalization of deep neural nets, and stronger augmentations such as AutoAugment [6] and RandAugment [7] have shown improved performances. Especially, image-based regularizations such as Cutout [10], Mixup [46] and CutMix [45] have shown a quantum jump in performances, thus, image-based regularizations are widely used to achieving state-of-the-art results in cross-entropy. In [24], the convex combination of contrastive loss has been proposed to compare the mixed anchor with contrasts, which improves performances in self-supervised learning. A similar concept could be adapted to supervised contrastive loss, however, it is obvious that we cannot compare between mixed anchor and mixed contrasts under supervised contrastive loss. Thus, a generalized form of supervised contrastive loss is needed to fully adapt image-based regularizations.

Knowledge distillation  Knowledge distillation (KD [21]) has been proposed to use a pre-trained teacher network to guide the student network. In addition to cross-entropy, Kullback–Leibler divergence between student’s prediction and teacher’s prediction can boost the training of the student. A recent study [33] has shown that the training scheme based on modern tricks and knowledge distillation can stably achieve top results on cross-entropy. In contrastive learning paradigm, contrastive representation distillation [39] has shown that using teacher’s representations to guide teacher model
could outperform distilling knowledge about class probabilities. In original KD, randomly given a student network, any kind of pre-trained state-of-the-art classifier can be used as a teacher. However, the teacher network has to be tailored in the contrastive representation distillation.

3 Method

3.1 GenSCL: Generalized Contrastive Learning Framework

Inspired by USI [33], GenSCL successfully adapts image-based regularizations (Mixup [46] and CutMix [45], and knowledge-distillation (KD [21]) to supervised contrastive learning (SupCon [23]). As illustrated in Figure 2, our framework comprises the following main components:

- **Data Augmentation** module, \( \tilde{\text{Aug}}(\cdot) \): in addition to data augmentations \( \text{Aug}(\cdot) \) (such as SimAugment [4], AutoAugment [6] and RandAugment [7]), image-based regularizations \( \text{Mix}(\cdot) \) are also applied in our data augmentation module. For each input \( x \), we generate two different views of the data, \( \tilde{x} = \tilde{\text{Aug}}(x) = \text{Mix}(\text{Aug}(x)) \).

- **Encoder Network**, \( \text{Enc}(\cdot) \): a deep learning backbone for computer vision (ResNet-50 [18] in all our experiments) map \( x \) to latent features, \( r = \text{Enc}(x) \in \mathbb{R}^{D_E} \), which is also a student in our KD scheme. Each view of augmented data is input to the same encoder and \( D_E = 2048 \) is used in all our experiments, which is identical to [23].

- **Projection Network**, \( \text{Proj}(\cdot) \): a 2-layer MLP [16] with ReLU and normalization that maps latent features to the unit hypersphere where contrastive loss is measured, \( z = \text{Proj}(r) \in \mathbb{R}^{D_P} \) (\( D_P = 128 \)). \( \text{Proj}(\cdot) \) is discarded when we finish contrastive learning and replaced by a linear classifier when we trained the model for classification as in [4, 23].

- **Pre-trained Classifier**, \( \text{Cls}(\cdot) \): a pre-trained classifier (i.e. teacher in our KD scheme) with state-of-the-art performance outputs prediction label of augmented data, \( p^t = \text{Cls}(\tilde{x}) \in \mathbb{R}^{D_C} \) (\( D_C \) is equal to the number of classes), to guide the student encoder.

3.2 Contrastive Loss Functions

Given this framework, we will briefly review the supervised contrastive loss [23] and its limitation. Then we show that our generalized supervised contrastive loss is a generalization of it and analyze how GenSCL is valid under generalized supervised contrastive loss. For the remainder of this paper, we denote a set of \( N \) randomly sampled batch data/label pairs as \( \{x_k, y_k\}_{k=1,...,N} \) and corresponding multi-viewed batch as \( \{\tilde{x}_i, \tilde{y}_i\}_{i=1,...,2N} \), where \( \tilde{x}_{2k} \) and \( \tilde{x}_{2k-1} \) are two different views of \( x_k \) (\( k = 1,...,N \)). Within multi-viewed batch, let \( i \in I \equiv \{1,...,2N\} \) be the index of an anchor and \( A(i) \equiv I \setminus \{i\} \) is the set of contrasts w.r.t. an anchor \( i \).
3.2.1 Supervised Contrastive Loss

We denote superior supervised contrastive loss \( L_{\text{sup}} \) as \( L_{\text{sup}} \). For supervised contrastive loss, the label information is implicitly embedded in \( P(i) \equiv \{ p \in A(i) : y_p = y_i \} \). Same class positives are selected by comparing one-hot encoded labels with the anchor. As in Eq. 1, the symbol \( \cdot \) denotes the dot product, \( \tau \in \mathbb{R}^+ \) is a scalar temperature parameter, and \( |P(i)| \) is its cardinality.

\[
L_{\text{sup}} = \sum_{i \in I} L_{i}^{\text{sup}} = \sum_{i \in I} \frac{-1}{|P(i)|} \sum_{j \in P(i)} \log \frac{\exp(z_i \cdot z_j / \tau)}{\sum_{k \in A(i)} \exp(z_i \cdot z_k / \tau)}
\]

(1)

Here, \( z_i = \text{Proj}(E_{\text{enc}}(\bar{x}_i)) \in \mathbb{R}^{D_p} \), the symbol \( \cdot \) denotes the dot product, \( \tau \in \mathbb{R}^+ \) is a scalar temperature parameter, and \( |P(i)| \) is its cardinality.

3.2.2 Generalized Supervised Contrastive Loss

We propose a generalized supervised contrastive loss to overcome the aforementioned limitations in supervised contrastive loss. As in Eq. 2, generalized supervised contrastive can be formulated as cross-entropy between similarities of labels and that of latent features. Especially, since there are just contrasts in our loss and we pulled contrasts closer to the anchor according to their label similarities, the boundary between positives and negatives in previous contrastive learning \([41, 35, 4, 23]\) is eliminated in our loss.

\[
L_{\text{gen}} = \sum_{i \in I} L_{i}^{\text{gen}} = \sum_{i \in I} \frac{1}{|A(i)|} \text{CE}(Y(i), Z(i)) = \sum_{i \in I} \frac{-1}{|A(i)|} \sum_{j \in A(i)} \text{sim}(y_i, y_j) \log \frac{\exp(z_i \cdot z_j / \tau)}{\sum_{k \in A(i)} \exp(z_i \cdot z_k / \tau)}
\]

(2)

Here, \( \text{sim}(u, v) = u^T v / \|u\| \|v\| \) (i.e. cosine similarity), \( Y(i) \equiv \{ \text{sim}(y_i, y_{i''}) \}_{i'' \in A(i)} \), \( Z(i) \equiv \{ \exp(z_i \cdot z_j / \tau) / \sum_{k \in A(i)} \exp(z_i \cdot z_k / \tau) \} \), and CE denotes cross-entropy.

When image-based regularizations meet our generalized supervised contrastive loss, the following three scenarios can be embraced by our loss:

- naïve anchor vs. naïve contrasts: the setting in original supervised contrastive learning, which is the special case in our loss when \( \text{sim}(y_i, y_p) = 1 \).
- mixed anchor vs. naïve contrasts: it can be represented by convex combination of supervised contrastive loss similar to \([24]\).
- mixed anchor vs. mixed contrasts: supervised contrastive loss is not available to cover this scenario.

3.3 Knowledge Distillation

We first review conventional KD applied for classification. Then we will discuss how to seamlessly adapt KD to GenSCL.

3.3.1 Knowledge Distillation for Classification

Given an image, a classifier outputs a logit \( z = \{ z_i \}_{i=1...C} \), where \( C \) is the number of classes. With label-smoothing regularization \([37]\), the softened prediction \( \hat{p}(\tilde{\tau}) = \{ p_i \}_{i=1...C} \), where

\[
p_i(\tilde{\tau}) = \frac{\exp(z_i / \tilde{\tau})}{\sum_{j=1}^{C} \exp(z_j / \tilde{\tau})}
\]

(3)
Table 1: Classification Accuracy (%) on CIFAR10 and CIFAR100 [27] on ResNet-50 [18]. We compare unsupervised contrastive learning (SimCLR [4]), cross-entropy (CE), supervised contrastive learning (SupCon [23]) and SupCon with knowledge distillation (KD [21]) and Mixup-Cutmix (M-C [46, 45]) in our generalized supervised contrastive learning framework (GenSCL). The numbers in SimCLR and SupCon are the published results in [23]. Note that GenSCL significantly improves the performances on CIFAR.

Here, $\tilde{\tau} \in \mathbb{R}^+ \forall \mathbb{R}$ is a scalar temperature parameter for softmax activation function. For convenience, $\tilde{\tau} = 1$ is used in this paper, then $p(\tilde{\tau})$ is simply denoted as $p$. The objective function for training the student classifier is a combination of cross-entropy (CE) and Kullback-Leibler (KL),

$$L = L_{CE}(p^s, y) + \alpha_{kd}L_{KL}(p^s, p^t)$$

where $p^s$ and $p^t$ is the prediction of student and teacher classifier respectively, $y$ is ground-truth label, and $\alpha_{kd}$ is a hyper-parameter for adjusting the weight of KD loss.

### 3.3.2 Knowledge Distillation for Supervised Contrastive Learning

In contrastive representation distillation [39], maximizations of a lower-bound to the mutual information between the teacher and student representations outperform distilling knowledge about class probabilities. However, in our study, we present an approach to adapt KD about class probabilities to SupCon so that any kind of state-of-the-art pre-trained classifier can be a teacher in supervised contrastive learning. With generalized supervised contrastive loss, the objective function Eq. 5 is the combination of cross-entropy between similarities of ground-truth labels and that of latent features, and weighted cross-entropy between similarities of teacher’s prediction and similarities of latent features:

$$L = \frac{1}{|A(i)|} \{CE(Y(i), Z(i)) + \alpha_{kd}CE(P^t(i), Z(i))\}$$

$$= \frac{-1}{|A(i)|} \sum_{j \in A(i)} \left(\text{sim}(y_i, y_j) + \alpha_{kd}\text{sim}(p^t_i, p^t_j)\right) \log \frac{\exp(z_i \cdot z_j / \tau)}{\sum_{k \in A(i)} \exp(z_i \cdot z_k / \tau)}$$

Here, $P^t(i) \equiv \{\text{sim}(p^t_l, p^t_j)\}_{l \in A(i)}$.

### 4 Experiments

In this section, we first evaluate our generalized supervised contrastive learning framework by measuring classification accuracy on common benchmarks - CIFAR10 and CIFAR100 [27] (Sec. 4.1). For a fair comparison with original supervised contrastive learning, we use ResNet-50 [18] as the encoder architectures in all experiments and the same hyper-parameter settings with [23]. Then we show image-based regularizations (Sec. 4.2) and knowledge-distillation (Sec. 4.3) can significantly improve classification accuracies in generalized supervised contrastive learning framework. ImageNet-1K [8] pretrained EfficientNetV2-M [38] is used as teacher classifier in all experiments (respect accuracies of 95.8% and 83.9% on CIFAR10 and CIFAR100). Lastly, the training details are provided in Sec. 4.4.

#### 4.1 Classification Accuracy

Table 1 shows that GenSCL significantly improves the generalizations on CIFAR10 and CIFAR100. While both knowledge distillation and Mixup-Cutmix can outperform original SupCon, we find
Table 2: Classification accuracy (%) for different image-based regularizations on CIFAR10 and CIFAR100 on ResNet-50. Every regularization is applied to both contrasts and anchors after SimAugment (Sim [4]). Here, Mixup-Cutmix denotes randomly applied Mixup or Cutmix with the same probabilities. Note that Mixup-Cutmix outperforms single Mixup or Cutmix.

| Regularization Type | CIFAR10 | CIFAR100 |
|---------------------|---------|----------|
| Sim                 | 95.7 (+0.0) | 76.5 (+0.0) |
| w/ Cutout [10]      | 96.8 (+1.1) | 77.3 (+0.8) |
| w/ Mixup [46]       | 96.7 (+1.0) | 80.6 (+4.1) |
| w/ Cutmix [45]      | 97.1 (+1.4) | 81.7 (+5.2) |
| w/ Mixup-Cutmix     | 97.3 (+1.6) | 82.8 (+6.3) |

Table 3: Classification Accuracy (%) for different knowledge distillation (KD [21]) relative weights on CIFAR10 and CIFAR100 on ResNet-50. Here, KD is applied after SimAugment (Sim [4]).

| KD relative weight, $\alpha_{kd}$ | CIFAR10 | CIFAR100 |
|-----------------------------------|---------|----------|
| Sim w/ Mixup-Cutmix              |         |          |
| 0 (no KD)                         | 95.7 (+0.0) | 76.5 (+0.0) |
| 1                                 | 96.3 (+0.6) | 79.6 (+3.1) |
| 5                                 | 97.1 (+1.4) | 82.5 (+6.0) |
| $\infty$ (only KD)               | 95.0 (-0.7) | 81.9 (+5.4) |

4.2 Cutout vs. Mixup vs. Cutmix

Image-based regularizations such as Cutout [10], Mixup and Cutmix are important strategies to achieve state-of-the-art results in computer vision. Table 2 shows that Mixup-Cutmix (randomly applying Mixup or Cutmix with the same probabilities) outperforms applying Mixup or Cutmix alone, and improves generalization on CIFAR best. Mixup and Cutmix can be applied to both contrasts and anchors because of generalized supervised contrastive loss, which gives stronger regularization than just applying to anchors [24].

Following the results in [10], we use patch lengths of 16 and 8 for Cutout respectively on CIFAR10 and CIFAR100. The combination ratio $\lambda$ is sampled from beta distribution Beta($\alpha, \alpha$) [46, 45], and $\alpha = 1.0$ is used for both Cutmix and Mixup in our experiments.

4.3 KD Teacher Relative Weight

In Table 3 we investigate the impact of KD relative weight, $\alpha_{kd}$ in Eq. 5 on the generalization. As can be seen, KD with proper $\alpha_{kd}$ can improve the generalization of SupCon (i.e. $\alpha_{kd} = 0$) and achieve state-of-the-art results when utilizing with Mixup-Cutmix in GenSCL, which even outperforms the teacher classifier (97.6% vs. 95.8% and 84.7% vs. 83.9%, respectively on CIFAR10 and CIFAR100). Different from the result that using only teacher’s prediction (i.e. $\alpha_{kd} = \infty$) can achieve top results [33], ground-truth is still needed in GenSCL. A teacher classifier with better performances could potentially improve results better.
4.4 Training Details

**Supervised Contrastive Learning** To evaluate the performance of GenSCL, we employed two-stage training \[4, 23\]: contrastive learning and linear evaluation. At both stages, we used almost the same hyper-parameter setting as \[23\] on CIFAR. At contrastive learning stage, we trained models (ResNet-50) for 500 epochs with batch size of 1024. SGD (learning rate=0.5) with momentum (=0.9) and weight decay (=10\(^{-4}\)) was used with learning rate warmup and cosine learning rate decay \[19\]. Temperature of \(\tau = 0.1\) was used in all our results. At linear evaluation stage, we followed linear evaluation protocol that freezes the encoder and trains a single-layer classifier.

**Teacher model** ImageNet1K pre-trained EfficientNetV2-M \[38\] provided on timm \[42\] was used as teacher classifier in all experiments. We finetuned the teacher for 100 epochs with the batch size of 512 with Adam \[25\]. We used several regularization tricks including drop-path \[2\], label-smoothing \[37\], exponential-moving average of model weights \[22\], cutout, erasing \[49\] and Mixup-Cutmix. Reference code is released at [https://t.ly/yuU0](https://t.ly/yuU0).

5 Conclusion

In this study, we propose generalized supervised contrastive loss that measures cross-entropy between the similarity of labels and that of latent features, which generalizes supervised contrastive loss and fully leverages label information. Based on our proposed loss, we introduce a novel generalized supervised contrastive learning framework, called GenSCL. GenSCL adapted Mixup-Cutmix and knowledge distillation to supervised contrastive learning seamlessly and enables to significantly outperform naïve supervised contrastive learning on classification accuracies on CIFAR. Our approach shows great potential to utilize modern training tricks developed in cross-entropy to the supervised contrastive learning paradigm.

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