FROST: Faster and more Robust One-shot Semi-supervised Training

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Abstract

Recent advances in one-shot semi-supervised learning have lowered the barrier for deep learning of new applications. However, the state-of-the-art for semi-supervised learning is slow to train and the performance is sensitive to the choices of the labeled data and hyper-parameter values. In this paper, we present a one-shot semi-supervised learning method that trains up to an order of magnitude faster and is more robust than state-of-the-art methods. Specifically, we show that by combining semi-supervised learning with a one-stage, single network version of self-training, our FROST methodology trains faster and is more robust to choices for the labeled samples and changes in hyper-parameters. Our experiments demonstrate FROST’s capability to perform well when the composition of the unlabeled data is unknown; that is, when the unlabeled data contain unequal numbers of each class and can contain out-of-distribution examples that don’t belong to any of the training classes. High performance, speed of training, and insensitivity to hyper-parameters make FROST the most practical method for one-shot semi-supervised training. Our code is available at https://github.com/HelenaELiu/FROST.

1. Introduction

Deep learning’s impressive performance on computer vision applications has made deep neural networks the standard for many tasks, such as image classification and object recognition. This impressive performance is often achieved by supervised learning, in which the model trains on large, balanced labeled datasets. Since studies have shown that more training data allows networks to reach higher accuracy and generalize better [42], these datasets typically contain thousands to millions of labeled images.

However, raw data is unlabeled in real world applications. Manually labeling the data can be impractical, as it is labor intensive to label huge amounts of data. Furthermore, in fields such as medicine, defense, and other scientific fields, images can often only be correctly classified by a limited number of people who are experts in the field. Therefore, a worthwhile goal is to achieve high performance without having to manually label massive amounts of data. In support of this goal, both unsupervised and semi-supervised learning have become popular techniques [40, 38, 2, 1, 32, 33, 4, 5].

In this paper, we demonstrate that combining semi-supervised learning with a specific form of one-stage self-training creates a more powerful method for semi-supervised learning that allows much faster and more robust training of neural networks. While any semi-supervised learning method could be used in our framework, in this work we use two previous state-of-the-art methods that have been successful for one-shot semi-supervised learning (i.e., BOSS [32] and FixMatch [33]) because none of the other semi-supervised methods (such as the π model, temporal ensembling [19], VAT [25], ICT [38], UDA [40], S4L [44], MixMatch [2], and Mean Teachers [35]) have demonstrated results with less than 25 labeled examples per class.

Figure 1 demonstrates that high performance with CIFAR-10 is possible with as little as one labeled sample per class and much fewer training epochs than FixMatch, BOSS, and
BOSS without handpicked prototypes (i.e., random samples) that we call BOSS-p. Specifically, Figure 1 shows that FROST achieves a 94% test accuracy during training within only 128 epochs, while the other methods achieve substantially less. In this paper, we also compare FROST on a number of other datasets, such as CIFAR-100, SVHN, and STL-10. In addition, FROST can be used in the more realistic scenario where the number of unlabeled samples in each class is not balanced and the unlabeled dataset might contain samples not belonging to any of the training classes.

A key element of our algorithm is a one-stage, single network form of self-training. The base model for self-training is commonly supervised and self-training is a multi-stage approach with training two networks [29]. Instead, our method uses a semi-supervised base and a one-stage, single network form of self-training. We call our proposed form of self-training “bootstrapping” in order to distinguish it from various other forms of self-training in the literature (this use of the term bootstrapping is along the lines of the idiomatic definition of the term rather than the statistical term).

In summary, our contributions in this paper are:

1. We present our novel methodology that combines semi-supervised learning and a single-stage form of self-training that we call bootstrapping.

2. We demonstrate this methodology achieves high performance, is much faster to train, and is more robust than previous methods on one-shot semi-supervised training.

3. Our experiments compare the FROST method over a range of datasets (CIFAR-10, CIFAR-100, SVHN, and STL-10) and when the unlabeled data is imbalanced or contains images that are not one of the training classes.

4. We demonstrate that our framework is versatile by comparing numerous combinations of our base model with consistency regularization, contrastive representation learning, class balancing, and class prototypes.

2. Related Work

Our methodology is built upon recent research advancements in semi-supervised learning. Semi-supervised learning is a combination of supervised and unsupervised learning that leverages the strengths of each. That is, semi-supervised learning uses a small amount of labeled data to define the desired task and uses a large amount of unlabeled data to avoid overfitting the labeled data. There is a vast amount of literature on semi-supervised, unsupervised, and self-supervised learning, with a number of surveys and books [46, 37, 3, 45] available for interested reader.

Our work builds on previous work in semi-supervised learning, especially the recent examples of one-shot semi-supervised learning in the FixMatch [33] and BOSS papers [32]. In addition, we compared the use of contrastive representation learning (CRL) [20, 16] to consistency training because CRL has been producing high performing networks by unsupervised transfer learning. In addition, consistency regularization and contrastive representation learning share some similarities. Consistency regularization utilizes unlabeled data by relying on the assumption that the model should output the same final predictions when fed perturbed versions as on the original image. In contrastive representation learning the assumption is that the model’s internal representations should be similar when fed perturbed versions as on the original image and these representations should be less similar than the representations of other images. The main difference between the two is where the comparisons are made: with the final predictions or for internal representations. However, most of the methods in the literature utilizing consistency regularization fall within semi-supervised learning and those utilizing contrastive representation learning are self-supervised or unsupervised learning. In this paper we explore applying both to semi-supervised learning.

2.1. Semi-supervised learning

2.1.1 Pseudo-labeling and Self-training.

Pseudo-labeling [21] defines a base model that is trained on labeled data and the model is used to predict labels for unlabeled data. Self-training [36] is a basic approach of pseudo-labeling where a classifier is trained with an initial small number of labeled examples, aiming to classify unlabeled points, and then it is retrained with its own most confident predictions, thus enlarging its labeled training set. Recent papers on self-training [41, 23] follow this process.

Our method differs from previous methods by utilizing a semi-supervised base learner in place of the supervised base learning. In addition, we use a single-stage, one network training method instead of the more common a multi-stage approach with training two networks [29]. We call this form of self-training “bootstrapping” in order to better distinguish it from various other forms of self-training in the literature.

2.1.2 Consistency Regularization

The early work for consistency regularization [28, 19], which is also called consistency training, applied it for semi-supervised learning and it has subsequently become popular in this domain. A partial list of methods that use consistency regularization includes the \( \pi \) model, temporal ensembling [19], VAT [25], ICT [38], UDA [40], S4L [44], MixMatch [2], ReMixMatch [1], and FixMatch [33]. In this paper we are focused on extending semi-supervised learning to labeling only one example per class (i.e., one-shot learning). FixMatch was the first paper to present results for one-shot semi-supervised learning, which was followed up by the BOSS method.
2.1.3 BOSS

The state-of-the-art for one-shot semi-supervised learning is the BOSS method [32]. The BOSS algorithm achieves high performance with one-shot semi-supervised learning by introducing three techniques: iconic prototype choice and refinement, class balancing, and self-training.

Prototype refining. Prototype refining starts with an expert manually sifting through some of their unlabeled dataset to find one iconic example of each class. After choosing these prototypes, the next step is to make a training run and examine the class accuracies. For any class with poor accuracy relative to the other classes, one picks a better prototype from the unlabeled data. Then the training is rerun and final class accuracies examined again. This iterative process ends when all the classes perform reasonably well.

Class balancing. BOSS borrowed techniques from the literature on training with imbalanced data [17, 39, 34] (i.e., some classes having many more training samples than other classes). An important difference of the semi-supervised from the data imbalanced domains is the lack of ground truth as to what are the majority and minority classes when applying these techniques to unlabeled data. The authors propose using the model’s pseudo-labels as a means to count each class and implicitly assumed that the unlabeled dataset is class balanced.

Class balancing methods are typically one of two types: data-level or algorithm-level. Data-level methods [39] oversample the minority classes and undersample the majority classes. Algorithm-level methods [34] ameliorate the imbalance by using larger weights in the loss function for training samples that belong to the minority classes, as well as smaller weights for the samples from the majority classes. Then the counts of the set of pseudo-labels were used to increase the numbers of minority class members by oversampling minority classes and reduce the impact of majority classes by decreasing their loss function weights. BOSS includes data-level, algorithmic-level, and hybrid methods.

2.1.4 Contrastive Representation Learning (CRL)

While the early work on contrastive loss [7] and the related triplet loss [30, 15] dates back to 2005 and 2014, respectively, recently there has been a number of CRL methods proposed in the literature for unsupervised pretraining in computer vision, including TNC [31], CPC [27], DIM [14], MoCo [6], SimCLR [4, 5], PCL [22], and BYOL [13]. In addition, a recent review paper [20] lists methods based on CRL with applications in language, computer vision, audio, and multimodal domains.

Contrastive representation learning calculates the distance or similarity between two feature vectors [11], also referred to as embedding spaces or representations. The SimCLR [4, 5] model creates two different augmentations of the same image, produces a feature vector from each, and tries to minimize the distance between their representations, while maximizing the distance between their representations and representations derived from other images.

3. FROST Methodology

In this work, we are solving an N-class classification problem. For an N-class classification problem, let us define $\chi = \{(x_b, y_b) : b \in \{1, ..., B\}\}$ as a batch of B labeled examples, where $x_b$ are the training examples and $y_b$ are its labels. We also define $U = \{u_b : b \in \{1, ..., \mu\}\}$ as a batch of $\mu$ unlabeled examples where $\mu = r_u B$ and $r_u$ is a hyper-parameter that determines the ratio of $U$ to $\chi$. When we compare contrastive representation learning to consistency regularization, we also define $\mu_c = r_c B$ where $r_c$ is another scalar hyper-parameter that determines the ratio of $U_c$ to $\chi$ that is analogous to what we used for consistency regularization.

The overall loss is the weighted sum of the supervised loss and an unsupervised loss term for consistency regularization, which is $L = \lambda_s \ell_s + \lambda_u \ell_u$, and $\lambda_s$ and $\lambda_u$ are scalar hyperparameters. This controls the contribution of each part of the loss function to the total loss. When we compare contrastive representation learning (CRL), we add another term to the loss function:

$$L = \lambda_s \ell_s + \lambda_u \ell_u + \lambda_c \ell_c$$  \hspace{1cm} (1)$$

where $\lambda_c$ is an addition scalar hyper-parameters. Comparisons between consistency regularization and CRL can be easily performed by eliminating terms by setting the appropriate $\lambda$s to zero.

Let $p_m(y|x)$ be the predicted class distribution produced by the model for input $x_b$. We denote the cross-entropy between two probability distributions $p$ and $q$ as $H(p, q)$. The supervised loss $\ell_s$ is the cross-entropy loss on weakly augmented labeled examples:

$$\ell_s = \frac{1}{B} \sum_{b=1}^{B} H(y_b, p_m(y|\alpha(x_b)))$$  \hspace{1cm} (2)$$

where $\alpha(x_b)$ represent weak data augmentation on the unlabeled training samples, $x_b$.

3.1. Consistency regularization

For the unsupervised loss on unlabeled data, the algorithm computes the label based on weakly augmented versions of the image as $q_b = p_m(y|\alpha(u_b))$. The pseudo-label is computed as $\hat{q}_b = \arg\max(q_b)$ and the unlabeled loss is given as:

$$\ell_u = \frac{1}{\mu} \sum_{b=1}^{\mu} 1(\text{max}(q_b) \geq \tau) H(\hat{q}_b, p_m(y|A(u_b)))$$  \hspace{1cm} (3)$$
where $A(u_b)$ represents applying strong augmentation to sample $u_b$ and $\tau$ is a scalar confidence threshold. Only those terms with predictions above $\tau$ contribute to the loss in Equation 3.

Data augmentation. FROST uses the same data augmentations as in FixMatch; it defines both weak and strong augmentations, $\alpha(\cdot)$ and $A(\cdot)$, respectively. For weak augmentations images are randomly flipped horizontally with a probability of 50% and we randomly translate images by up to 12.5% vertically and horizontally.

Strong data augmentations include the use of Cutout [10] and transformations from the Python Imaging Library. It is also possible to use the methodologies of RandAugment [9] and CTAugment [1] but we found the impact of these methodologies on the performance to be minor so the default augmentation strategies were used (i.e., the augment hyper-parameter was set to “d.d.d” for all of our experiments). Further details on the methods for strong augmentations can be found in the FixMatch paper [33].

3.2. Contrastive representation learning

The FROST contrastive representation learning framework follows SimCLR [4]. A contrastive loss term, $\ell_c$, is defined for a contrastive representation learning. The contrastive loss is based on positive and negative samples, plus a pairwise similarity metric. Here, as in SimCLR, positive examples are two different transformations of the same image and comparisons of an image to transformations of all other images are considered negative examples.

Specifically, $\ell_c$ is a pairwise similarity between a pair of augmentations of the same image and we calculate $\ell_c$ for all samples. We define $Z = \{z_i, z_j : i, j \in \{1, ..., \mu_c\}\}$ and the similarity function is defined as:

$$sim(z_i, z_j) = \phi_{i, j} = z_i^T z_j / (\|z_i\| \|z_j\|).$$

(4)

The contrastive loss between two images is calculated in the formula below:

$$\ell_c = -\log \frac{\exp(\phi_{i,j}/T)}{\sum_{k=1}^{2\mu_c B} \mathbb{1}_{[k \neq i]} \exp(\phi_{i,k}/T)}$$

(5)

where the numerator consists of a positive pair (same image), and the denominator consists of a sum of all the negative pairs (different images), $\mathbb{1}$ is an indicator function evaluating to 1 if $k \neq i$, and $T$ denotes a temperature parameter. This loss has also been referred to in previous work as InfoNCE [27].

Two forms of data augmentation for contrastive representation learning were implemented in FROST. The first form leverages the weak and strong augmentations described in 3.1, where similarity of the representations is made between the weak and the strong augmentations of the same images. The second form follows SimCLR which only uses simple augmentations, such as random cropping, color distortions, and random Gaussian blur. Our experiments showed that using the weak and strong augmentations gave similar performance as using the augmentations used in SimCLR.

3.3. Bootstrapping

FROST uses a one-stage, single network self-training episodes by leveraging top ranked pseudo-labels from a semi-supervised base model as if they were ground-truth labels in the calculation of the supervised loss $\ell_s$. Please note that the use of a single network and self-training episodes takes advantage of transfer learning during training. That is, the weights of the partially trained network on the small labeled data are the initial values used when the training continues with a larger set of labeled data.

Specifically, FROST defines a bootstrapping schedule as a hyper-parameter that indicates at what fractions of the training epochs to perform bootstrapping episode; that is, to use the model on the unlabeled samples to predict pseudo-labels and their associated confidence levels. These samples are sorted from high confidence down for each class. The bootstrapping factor, $f_b$, is a scalar hyper-parameter that multiplies by the current number of labeled examples to define the number of highest confidence pseudo-labeled examples per class to be used going forward in the training. For example, if the schedule indicates bootstrapping twice and the initial training is with only one training example per class, the first bootstrap episode will increase the number of “labeled” samples to $f_b$ number per class and the second episode will increase them to $f_b^2$. In Section 4.6, we compare the results of setting $f_b$ to 2, 4, 8, 12, and 16. Intuitively, it makes sense that the larger values of $f_b$, the better the final performance. Since the original labeled images are randomly selected and hence might not be the most representative of its class, FROST replaces the previous labeled set with the top ranked pseudo-labeled set as the new labeled set.

The bootstrapping schedule indicates one or multiple times during training to perform a bootstrapping episode. In Section 4.6, we compare the results for three potential schedules:

1. $\frac{1}{4}, \frac{3}{4}$ (Halfway during training and again at three-quarters).
2. $\frac{1}{3}, \frac{2}{3}$ (One third the way during training and again at two thirds).
3. $\frac{1}{4}, \frac{1}{2}, \frac{3}{4}$ (One quarter the way during training, halfway, and again at three-quarters).

Intuitively one wants to train long enough that the model can accurately classify $f_b$ number of training samples for every class. This can depend on the size of the unlabeled dataset, the quality of the samples, the optimization algorithms, and numerous other factors. However, our experience is that the
model trains surprisingly quickly to reasonable accuracies of the top few examples to label and Section 4.6 indicates that the final performance is robust to any of these choices for the schedule.

In summary, the introduction of both hyper-parameters is not too burdensome since there are only a few discrete and intuitive choices.

4. Experiments

In this Section we demonstrate that FROST can attain high test accuracies with one-shot semi-supervised learning when training on a fraction of the number of epochs used to train previous state-of-the-art methods such as BOSS [32] and FixMatch [33]. Unlike the BOSS method, FROST attains reasonably low variances even though the choices for labeled training samples is random. Although we implemented FROST in both TensorFlow and PyTorch, our TensorFlow implementation executed much more quickly and gave slightly better results so our experiments were all with the TensorFlow version, unless specifically stated otherwise.

We made our code available at https://github.com/HelenaELiu/FROST to facilitate replication and for use with future real-world applications. Our baseline implementation started with the BOSS code base\(^1\) and utilized code from SimCLR to implement contrastive representation learning\(^2\).

4.1. Setup

Datasets. The datasets that we used for training and testing were CIFAR-10 and CIFAR-100 [18], SVHN [26], and STL-10 [8]. These are standard benchmark datasets that are commonly used for semi-supervised learning. Unlike the other datasets, CIFAR-100 has 10 times the number of classes of the other datasets. In addition, we created a data imbalanced version of CIFAR-10 to use in our experiments on imbalanced unlabeled training data\(^3\).

The STL-10 dataset contains 5,000 labeled images of size 96x96 from 10 classes and 100,000 unlabeled images. In addition, there is a large set of unlabeled examples in which there exist out-of-distribution images (i.e., images that do not belong to one of the training classes) in the unlabeled set, making it a more realistic and challenging test of semi-supervised learning performance.

Model and hyper-parameters. Our experiments used a Wide ResNet-28-2 [45] that matches the BOSS reported model and the same cosine learning rate schedule described by FixMatch [33], where the learning rate schedule adapts to the number of epochs used for training. The values of the hyper-parameters used are discussed in the Appendix. In addition, we repeated our experiments with a ShakeNet model [12] and obtained similar results that lead to the same insights and conclusions. The ShakeNet model results are in the Appendix.

Baselines. To the best of our knowledge, only FixMatch and BOSS have presented performance results for one-shot semi-supervised learning. In this Section we use these methods for our semi-supervised base and we compare FROST to these two prior methods. In addition, we expect analogous results when using other semi-supervised methods for our base, such as the \(\pi\) model, temporal ensembling [19], VAT [25], ICT [38], UDA [40], S4L [44], MixMatch [2], and Mean Teachers [35], even though none of these other methods have previously been shown results with less than 25 labeled examples per class for CIFAR-10 and SVHN or less than 100 examples per class for CIFAR-100 and STL-10. Unless specified otherwise, we report the mean and standard deviation of test accuracy from four training runs. Also, all of our results for FixMatch and BOSS reported in this paper were obtained using our own implementations and experiments.

4.2. Faster: reduced number of epochs

The code for FixMatch indicates that the model was trained for 1024 epochs and, similarly, the BOSS code indicates it is run for two stages of self-training and each stage were trained for 512 epochs each, for a total of 1024 epochs. Here we present the results for training one-shot semi-supervised learning for much fewer epochs.

| Method   | 64   | 128  | 192  | 256  |
|----------|------|------|------|------|
| FixMatch | 34±5 | 42±10| 54±8 | 63±6 |
| BOSS     | 40±5 | 74±8 | 77±13| 82±6 |
| BOSS-p   | 39±7 | 40±5 | 57±16| 51±9 |
| FROST    | 92.4±0.3 | 94.1±0.1 | 94.4±0.2 | 94.8±0.1 |
| Supervised | 93.8±0.2 | 94.2±1 | 94.6±1 | 94.7±2 |

Table 1: CIFAR-10. Average test accuracies and standard deviations over 4 runs of training for a limited number of epochs using the TensorFlow version of FROST. The BOSS method includes manually chosen prototypes (1 per class) and the BOSS-p are the results with a random selection for the labeled data.

In Table 1 we compare FixMatch, BOSS and FROST test accuracies on CIFAR-10 for training with 64, 128, 192, and 256 epochs. Due to the much short training epochs, the results for BOSS are without self-training. We also present results for BOSS without handpicked prototypes (i.e., using...
a random choice for the one sample per class) and we call this BOSS-p.

Table 1 shows a reduction in performance for FixMatch with a drop in the number of training epochs. The FixMatch paper [33] reports test accuracies between 48.58% and 85.32% with a drop in the number of training epochs. The BOSS performance is higher than FixMatch but it can be seen from this table that much of this improvement comes from the handpicked prototypes because the BOSS-p test performance is much closer to the FixMatch results. On the other hand, FROST reaches test accuracies of 92.4% with as few as 64 epochs and over 94% when trained for 128 or more epochs.

For reference, Table 1 shows the performance of supervised training on the full dataset and the FROST performance is close to supervised training for the same number of epochs.

### 4.3. More robust

One disadvantage of the BOSS method for one-shot semi-supervised learning is that this method is highly sensitive to the choices for the handpicked prototypes, the hyper-parameters, and the implementation [32]. Hence, BOSS requires manual prototype refining and iterations of hyper-parameter fine-tuning that can be time-consuming. In addition, the BOSS paper showed that the performance differed somewhat between their TensorFlow and PyTorch versions. In this Section, we demonstrate that FROST is more stable to the prototypes (i.e., can be picked randomly), hyper-parameter settings, and implementation.

| Method | Number of Epochs Trained |
|--------|--------------------------|
| FixMatch | 64 | 128 | 192 | 256 |
| BOSS-p | 36±7 | 42±10 | 44±6 | 44±6 |
| FROST | 89.9±0.3 | 92.6±0.4 | 93.1±0.3 | 93.7±0.1 |

Table 3: PyTorch version. Average test accuracies and standard deviations over 4 runs for training with CIFAR-10 for a limited number of epochs using the PyTorch version of FROST.

Table 3 illustrates the comparisons for PyTorch implementations of FixMatch, BOSS, BOSS-p, and FROST. While there are quantitative differences between the TensorFlow and PyTorch versions, the qualitative differences are similar and the conclusions are the same. That is, FROST provides a more stable and higher performing test accuracies for one-shot semi-supervised learning in much fewer training epochs than the other semi-supervised learning methods.

### 4.4. CIFAR-100, SVHN, and STL-10

Generalization of semi-supervised learning methodology over a variety of datasets is crucial for successful algorithms. This Section demonstrates that FROST provides improvement in speed and performance for training CIFAR-100, SVHN, and STL-10. The STL-10 dataset contains larger images (i.e., 96x96 instead of 32x32) and the unlabeled set contains examples that are not of the same classes as the labeled image classes (i.e., there exist out-of-distribution images).

Table 4 presents the comparisons of FixMatch, BOSS-p, and FROST for CIFAR-100 and SVHN. These results are analogous to the results shown in Table 1 for CIFAR-10 but with perhaps a larger gap in performance between FROST versus FixMatch and BOSS-p. The results from supervised training with the full labeled dataset is provided for reference and the FROST results are close to the supervised results.

| Method | Number of Epochs Trained |
|--------|--------------------------|
| FixMatch | 64 | 128 | 192 |
| BOSS-p | 27±3 | 32±4 | 35±5 |
| FROST | 89±0.6 | 92.0±0.2 | 93.1±0.1 |

Table 5: STL-10. Average test accuracies and standard deviations over 4 runs of training for a limited number of epochs.
Table 4: CIFAR-100 and SVHN. Average test accuracies and standard deviations over 4 runs of training for a limited number of epochs.

| Method      | CIFAR-100       | SVHN     |
|-------------|-----------------|----------|
|             | 64   128 192 256 | 64   128 192 256 |
| FixMatch    | 6.5 ± 1.1 12 ± 1 17 ± 1 21 ± 1 | 13 ± 2 14 ± 3 32 ± 12 38 ± 5 |
| BOSS-p      | 12 ± 2 19 ± 2 22 ± 1 24 ± 1 | 31 ± 6 53 ± 3 58 ± 8 64 ± 4 |
| FROST       | 69.7 ± 0.3 72.7 ± 0.3 74.0 ± 0.3 74.6 ± 0.2 | 97.5 ± 0.04 97.7 ± 0.04 97.8 ± 0.04 97.8 ± 0.04 |
| Supervised  | 74.8 ± 0.06 75.1 ± 0.3 75.3 ± 0.2 75.5 ± 0.5 | 97.9 ± 0.06 98.0 ± 0.03 98.2 ± 0.05 98.2 ± 0.01 |

Table 5 contains the results for training on the STL-10 dataset for 64, 128, and 192 epochs. Here too FROST provides substantially better performance, even though the unlabeled dataset contains out-of-distribution examples.

4.5. Imbalanced unlabeled training data

In real-world unlabeled datasets the number of examples for each class is typically unknown. For a semi-supervised algorithm to be practical, it must work when the number of examples of each class varies substantially.

To test this situation, we created a modified version of the CIFAR-10 dataset where the number of training examples of each class were allowed to vary by as much as an order of magnitude. Specifically, the number of unlabeled training examples for classes 1 to 10 were: 5000, 5000, 2487, 1651, 1228, 980, 810, 694, 606, 532, respectively.

Table 6 shows the results for FixMatch, BOSS-p and FROST. The test accuracies with the FROST method are within 2% of the accuracies when trained with supervised learning on a balanced dataset and far exceed the results from FixMatch or BOSS-p. This and the results on STL-10 demonstrate that it is unnecessary to know the composition of the unlabeled dataset.

| Method   | Number of Epochs Trained |
|----------|--------------------------|
|          | 64   128 192 256         |
| FixMatch | 24 ± 3 32 ± 4 33 ± 2 30 ± 2 |
| BOSS-p   | 28 ± 3 42 ± 6 46 ± 12 46 ± 9 |
| FROST    | 91.1 ± 0.3 92.4 ± 0.2 92.8 ± 0.1 92.8 ± 0.0 |

Table 6: Imbalanced unlabeled training data. Average test accuracies and standard deviations over 4 runs for training with an unbalanced unlabeled version of CIFAR-10 for a limited number of epochs. The number of unlabeled training examples per class varies from 500 to 5,000.

These results are particularly interesting as a potential solution to the data imbalance and long tailed dataset problem. That is, if one’s dataset is imbalanced, one can label a balanced number of samples for each class and leave the remaining imbalanced samples as unlabeled. Then a network trained with the FROST methodology might perform as well as state-of-the-art methods for imbalanced datasets.

4.6. Bootstrap hyper-parameters

Bootstrapping introduces two new hyper-parameters: bootstrapping factor $f_b$ and the bootstrapping schedule. Fortunately, both hyper-parameters are intuitive and have a limited number of discrete choices that simplify choosing reasonable values.

Figure 2: Bootstrap Factor. Test accuracies during training with the CIFAR-10 dataset for $f_b = 2, 4, 8, 12, 16$ using schedule 2.

The bootstrapping factor, $f_b$, is a scalar hyper-parameter that multiplies by the current number of labeled examples to define the number of labeled examples to be used going forward in the training. Intuitively one would expect that larger factors would lead to better accuracies because more labeled data will be utilized during training. Figure 2 confirms one’s intuition that larger factors lead to better final performance but with diminishing returns as the factor increases. This Figure shows the results for the CIFAR-10 dataset and $f_b = 2, 4, 8, 12, 16$ using bootstrap schedule 2. Since larger factors improve performance, a factor of 16 was used by default for the our experiments, unless noted otherwise.

The bootstrap schedule indicates one or multiple times during training to perform a bootstrapping episode.
compare the results for three schedules: 1) Halfway during training and again at three-quarters, 2) One third the way during training and again at two thirds, and 3) one quarter the way during training, halfway, and again at three-quarters. Figure 3 shows test accuracies for these three schedules during training with CIFAR-10. These experiments demonstrate that the schedule has only a small impact on the trained network’s final performance. By comparing the third schedule with $f_b = 4$ versus with $f_b = 8$, one can see that the bootstrap factor makes a more substantial difference. By default, we used the second schedule in our experiments, unless specified otherwise.

4.7. Add-ons and ablations

FROST is a simple method primarily composed of consistency regularization and bootstrapping. One might think that it could benefit from some of the many additional methods from the semi-supervised and self-supervised literature. We explore this by comparing the results from adding a contrastive loss function, class balancing, and the use of prototypes in place of random class samples but found little benefit from adding more components.

Figure 4 plots the test accuracies during training for a number of variations of the FROST methodology. We use the following notation to distinguish between algorithms: -CR = without consistency regularization; +CRL = with contrastive loss term; +p = with handpicked prototypes for the initial one-shot learning; +b = adding a class balancing method; and +BS = adding bootstrapping. The reader might note that FixMatch+BS = FROST and BOSS+BS = FROST+p+b.

Figure 4 also shows one ablation experiment: replacing consistency regularization with contrastive representation learning (CRL) via a loss term. CRL has been receiving a substantial amount of attention for unsupervised representation learning followed by transfer learning and fine tuning on a final task [20]. We investigated how well CRL works in replacing consistency regularization in the semi-supervised domain and discovered that CRL is a poor substitute for consistency regularization. In addition, we found little benefit to using both consistency regularization with contrastive representation learning in our model.

5. Conclusion

Our work highlights how far one-shot semi-supervised learning has come. Most previous work on semi-supervised learning have been demonstrated with 25 or more labeled training samples per class, with the exception of only BOSS, FixMatch, and ReMixMatch (i.e., 4 samples/class). Here we showed that when large amounts of unlabeled data is available, semi-supervised learning can achieve comparable performance as supervised learning. A next step is to replace supervised models with semi-supervised learning in new applications.

The effectiveness of bootstrapping is perhaps surprising and the deep learning research community should take note. Bootstrapping makes semi-supervised learning practical in domains with large unlabeled datasets but few labeled examples. This work paves the way for similar advances in related
fields, such as long-tailed training, continuous learning and data efficient deep reinforcement learning.

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6. Appendix

6.1. Hyper-parameters

The hyper-parameters we used for FixMatch [33] and BOSS [32] are the values stated in their respective papers. For FROST, we used the same hyper-parameters for CIFAR-10, CIFAR-100, SVHN and STL-10. The default hyper-parameters are listed in Table 7. For all the experiments in Section 4, any hyper-parameters that are different from the default values are clearly indicated.

| Hyper-parameter                  | Symbol | Default |
|---------------------------------|--------|---------|
| batch size, labeled             | $B$    | 32      |
| batch size factor, CR           | $\mu$  | 7       |
| batch size factor, CRL          | $\mu_c$| 7       |
| coefficient of supervised loss  | $\lambda_s$ | 1     |
| coefficient of unlabeled (CR) loss | $\lambda_u$ | 2    |
| coefficient of contrastive loss | $\lambda_c$ | 0     |
| learning rate                   | $lr$   | 0.03    |
| momentum                        | $\beta$| 0.9     |
| pseudo label threshold          | $\theta$| 0.95  |
| temperature                     | $\tau$ | 0.5     |
| weight decay                    | $wd$   | 0.0005  |
| bootstrapping factor            | $f_b$  | 16      |
| bootstrapping schedule          | bootschedule | 1 |
| type of data augmentation       | augment | ‘d.d.d’ |
| class balance method            | balance| 0       |
| class balance threshold delta    | $\delta$| 0.2    |

Table 7: Default values of hyper-parameters of FROST. The same values for these hyper-parameters were used for all the datasets, CIFAR-10, CIFAR-100, SVHN and STL-10.

6.2. Why is contrastive loss less effective than consistency regularization?

Due to the popularity of contrastive representation learning, we initially expected contrastive representation learning performance in semi-supervised learning to be similar to that of consistency regularization. We were surprised both that replacing consistency regularization with contrastive representation learning led to worse performance and that combining contrastive representation learning with consistency regularization provided no benefit. We believe the reason lies in the differences in evaluation of learned representations in unsupervised learning and evaluation for semi-supervised learning.

To evaluate the learned representations, SimCLR used a linear evaluation protocol, where a linear classifier is trained on top of the frozen base network, and test accuracy is used as a proxy for representation quality. SimCLR used this so it could be compared against the state-of-the-art on semi-supervised and transfer learning.

However, linear evaluation is in essence a supervised method that uses the entire labeled dataset. As such, SimCLR is not comparable to FROST since semi-supervised learning only uses the labeled samples and not the additional labeled samples in the dataset.

6.3. Additional results

Here we present some additional results that did not fit within the body of the main paper. Specifically, we present comparisons of FROST with the ShakeNet model and additional comparisons for the two bootstrap hyper-parameters (i.e., the bootstrap factor $f_b$ and the bootstrap schedule) at a range of training epochs.

| Method       | Number of Epochs Trained |
|--------------|--------------------------|
|              | 64 | 128 | 192 | 256 |
| FixMatch     | 32 ± 6 | 48 ± 7 | 52 ± 12 | 64 ± 7 |
| BOSS         | 35 ± 8 | 64 ± 10 | 62 ± 8 | 68 ± 9 |
| BOSS-p       | 38 ± 10 | 43 ± 10 | 37 ± 9 | 52 ± 12 |
| **FROST**    | **92.5 ± 0.1** | **94.2 ± 0.1** | **94.7 ± 0.1** | **94.9 ± 0.1** |
| Supervised   | 94.1±0.05 | 94.4±0.1 | 94.5±0.05 | 94.8±0.2 |

Table 8: ShakeNet on CIFAR-10. Over 4 runs for training with CIFAR-10 for a limited number of epochs.

6.3.1 Other architectures

One might wonder if the FROST methodology is impacted by the model architecture used for the experiments in the main paper. Here we replicate some of the experiments in the main paper using a ShakeNet model [12] instead of a Wide ResNet-28-2.

Table 8 contains a comparison of FROST to FixMatch, BOSS, and supervised training for CIFAR-10. There are only small differences between these results then those in the main paper, and these small difference do not impact the insights and conclusions of our research. In addition, Table 9 contains a comparison of FROST to FixMatch, BOSS, and supervised training for the CIFAR-100 and SVHN datasets. One can again see that there are only minor differences between these results and those in the main paper, which implies that the insights and conclusions of the main paper carry over to other architectures.

6.3.2 Bootstrap factor and schedule

Table 10 shows the results for the CIFAR-10 dataset with $f_b = 2, 4, 8, 12, 16$ and for training over 64, 128, 192, and 256 epochs and using the bootstrap schedule 2. For all four training times, a larger factor leads to higher final accuracy but with diminishing returns as $f_b$ and the training times increase. Furthermore, we observed an anomaly for $f_b = 2$ and training for 256 epochs that we are not able to explain.

Table 11 shows the results with the CIFAR-10 dataset for three different schedules for training over 64, 128, 192,
with CIFAR-100 and SVHN datasets for a limited number of epochs using the ShakeNet architecture. The BOSS-p are the results with random selection for the 1 sample per class.

Table 9: ShakeNet on CIFAR-100 and SVHN. Average test accuracies and standard deviations (over 4 runs) for training with CIFAR-100 and SVHN datasets for a limited number of epochs using the ShakeNet architecture. The BOSS-p are the results with random selection for the 1 sample per class.

| Method   | CIFAR-100 | SVHN |
|----------|-----------|------|
|          | 64 | 128 | 192 | 256 | 64 | 128 | 192 | 256 |
| FixMatch | 6.8 ± 0.3 | 8.3 ± 0.8 | 11.7 ± 1.1 | 15.9 ± 1.3 | 36 ± 5 | 43 ± 2 | 54 ± 8 | 52 ± 8 |
| BOSS-p   | 10 ± 2 | 16.6 ± 1.2 | 17 ± 2 | 20.3 ± 1.4 | 32 ± 13 | 49 ± 5 | 60 ± 3 | 55 ± 8 |
| FROST    | 70.0 ± 0.4 | 73.6 ± 0.3 | 74.5 ± 0.1 | 75.5 ± 0.2 | 97.65 ± .05 | 97.8 ± .04 | 97.8 ± .07 | 97.9 ± .08 |
| Supervised | 75.1 ± 0.4 | 75.8 ± 0.2 | 75.8 ± 0.2 | 76.0 ± 0.4 | 98.0 ± 0.03 | 98.1 ± 0.06 | 98.3 ± 0.04 | 98.2 ± 0.03 |

Table 10: Bootstrap Factor. Average test accuracies and standard deviations over 4 runs for training with CIFAR-10 dataset. A default bootstrap factor = 16 was used in our experiments.

| Factor | Number of Epochs Trained | 64 | 128 | 192 | 256 |
|--------|--------------------------|----|-----|-----|-----|
| 2      | 75 ± 4 | 89 ± 2 | 90 ± 1 | 82 ± 4 |
| 4      | 87.9 ± .5 | 91.7 ± .5 | 92.1 ± .3 | 92.6 ± .7 |
| 8      | 90.7 ± .5 | 93.0 ± .5 | 93.8 ± 1 | 94.1 ± 2 |
| 12     | 91.9 ± +2 | 93.7 ± 1 | 94.2 ± 2 | 94.5 ± 1 |
| 16     | 92.4±0.3 | 94.1±0.1 | 94.4±0.2 | 94.8±0.1 |

Table 11: Bootstrap Schedules. Average test accuracies and standard deviations over 4 runs for training with varying the bootstrap schedules, which are described in the main text. The training was with the CIFAR-10 dataset. A bootstrap schedule = 2 was used in our experiments.

| Schedules | Number of Epochs Trained | 64 | 128 | 192 | 256 |
|-----------|--------------------------|----|-----|-----|-----|
| 1         | 91.8 ± .4 | 93.8 ± .1 | 93.8 ± .3 | 94.6 ± .1 |
| 2         | 92.4±0.3 | 94.1±0.1 | 94.4±0.2 | 94.8±0.1 |
| 3 (fb = 4) | 90.9 ± .9 | 93.3 ± .1 | 93.8 ± .3 | 94.2 ± .04 |
| 3 (fb = 8) | 93.0 ± .2 | 94.4 ± .2 | 94.8 ± .1 | 95.0 ± .04 |

6.4. Limitations (i.e., a FROST warning)

Any scientific paper is limited by the scope of the work. Our paper and experiments were limited to the computer vision domain. While there are not any reasons to believe that these ideas won’t carry over to other domains and modalities, this was considered beyond the scope of this work.

Furthermore, our experiments with the two bootstrapping hyper-parameters were limited to CIFAR-10. As noted in the main body of the paper, these hyper-parameters can be a function of the size of the unlabeled dataset, the quality of the samples, the optimization algorithms, and numerous other factors but a global characterization of them was beyond the scope of this work.

In addition, it was demonstrated that bootstrapping provides much of the boost in performance. Since an objective of this paper was to demonstrate the potential for relatively fast training, it is likely that longer training might improve the performance but with diminishing returns.

A self-training loop where the pseudo-labeled examples are used to train a fresh network with random weights was not tested and while it might produce a better performing network, it would be at the expense of much longer training times. Bootstrapping can be seen as a combination of self-training with transfer learning, since each iteration with an additional larger set of labeled data continues to train the same network weights. This significantly reduces the training time but it is unknown if this transfer learning limits the final performance of the network relative to what is possible if instead the labels were used to train another network with randomly initialized weights. So the question remains for future investigation if the early semi-supervised training causes the network to find a sub-optimal local minimum.