

FixMatch: Simplifying Semi-Supervised Learning with Consistency and Confidence

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Abstract

Semi-supervised learning (SSL) provides an effective means of leveraging unlabeled data to improve a model's performance. In this paper, we demonstrate the power of a simple combination of two common SSL methods: consistency regularization and pseudo-labeling. Our algorithm, FixMatch, first generates pseudo-labels using the model's predictions on weakly-augmented unlabeled images. For a given image, the pseudo-label is only retained if the model produces a high-confidence prediction. The model is then trained to predict the pseudo-label when fed a strongly-augmented version of the same image. Despite its simplicity, we show that FixMatch achieves state-of-the-art performance across a variety of standard semi-supervised learning benchmarks, including 94.93% accuracy on CIFAR-10 with 250 labels and 88.61% accuracy with 40 – just 4 labels per class. Since FixMatch bears many similarities to existing SSL methods that achieve worse performance, we carry out an extensive ablation study to tease apart the experimental factors that are most important to FixMatch's success. We make our code available at <https://github.com/google-research/fixmatch>.

1. Introduction

Deep neural networks have become the de facto model for computer vision applications. Their success is partially attributable to their apparent *scalability*, i.e., the empirical observation that training them on larger datasets produces better performance [25, 17, 35, 46, 34, 18]. Deep networks often achieve their strong performance through supervised learning, which requires a labeled dataset. The performance benefit conferred by the use of a larger dataset can therefore come at a significant cost since labeling data often requires human labor. This cost can be particularly extreme when labeling must be done by an expert (for example, a doctor

in medical applications).

A powerful approach for training models on a large amount of data without requiring a large amount of labels is *semi-supervised learning* (SSL). SSL mitigates the requirement for labeled data by providing a means of leveraging unlabeled data. Since unlabeled data can often be obtained with minimal human labor, any performance boost conferred by SSL often comes with low cost. This has led to a plethora of SSL methods that are designed for deep networks [28, 39, 21, 43, 3, 45, 2, 22, 38].

A popular class of SSL methods can be roughly viewed as producing an artificial label for each unlabeled image and then training the model to predict the artificial label when fed the unlabeled image as input. For example, pseudo-labeling [22] (also called self-training [27, 46, 37, 40]) uses the model's class prediction as a label to train against. Similarly, consistency regularization [39, 21] obtains an artificial label using the model's predicted distribution after randomly modifying the input or model function.

In this work, we continue the trend of recent state-of-the-art methods that combine diverse mechanisms for producing artificial labels [3, 45, 2, 28]. We introduce FixMatch, which produces artificial labels using both consistency regularization and pseudo-labeling. Crucially, the artificial label is produced based on a *weakly*-augmented unlabeled image (e.g., using only flip-and-shift data augmentation) which is used as a target when the model is fed a *strongly*-augmented version of the same image. Inspired by UDA [45] and ReMixMatch [2], we leverage CutOut [13], CTAugment [2], and RandAugment [10] for strong augmentation, which all produce heavily distorted versions of a given image. Following the approach of pseudo-labeling [22], we only retain an artificial label if the model assigns a high probability to one of the possible classes. A diagram of FixMatch is shown in fig. 1.

While FixMatch comprises a simple combination of existing techniques, we nevertheless show that it obtains state-of-the-art performance on the most commonly-studied SSL benchmarks. For example, FixMatch achieves 94.93% ac-

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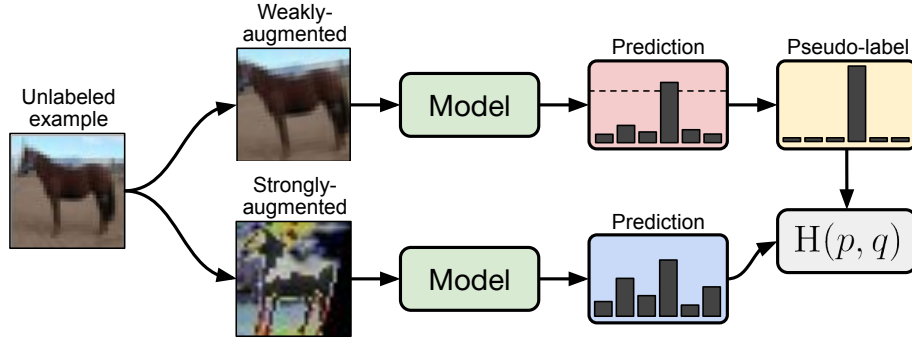


Figure 1: Diagram of FixMatch, our proposed semi-supervised learning algorithm. First, a weakly-augmented version of an unlabeled image (top) is fed into the model to obtain its predictions (red box). When the model assigns a probability to any class which is above a threshold (dotted line), the prediction is converted to a one-hot pseudo-label. Then, we compute the model’s prediction for a strongly augmented version of the same image (bottom). The model is trained to make its prediction on the strongly-augmented version match the pseudo-label via a standard cross-entropy loss.

accuracy on CIFAR-10 with 250 labeled examples compared to the previous state-of-the-art of 93.73% [2] in the standard experimental setting from [31]. We also explore the limits of our approach by applying it in the extremely-scarce-labels regime, obtaining 88.61% accuracy on CIFAR-10 with only 4 labels per class. Since FixMatch is similar to existing approaches but achieves substantially better performance, we include an extensive ablation study to determine which factors contribute the most to its success. Our ablation study also includes basic experimental choices that are often ignored or not reported when new SSL methods are proposed (such as the optimizer or learning rate schedule) because we found that they can have an outsized impact on performance.

In the following section, we introduce FixMatch and the ideas it builds upon. In section 3, we discuss how FixMatch relates to existing SSL algorithms. Section 4 and section 5 include our experimental results and ablation study, respectively. Finally, we conclude in section 6 with a summary and an outlook on future work.

2. FixMatch

Overall, the FixMatch algorithm is a simple combination of two common approaches to SSL: Consistency regularization and pseudo-labeling. Its main novelty comes from the combination of these two ingredients as well as the use of a separate weak and strong augmentation when performing consistency regularization. In this section, we first review consistency regularization and pseudo-labeling before describing the FixMatch algorithm in detail. We also describe the other factors, such as regularization, which contribute to FixMatch’s empirical success.

For an L -class classification problem, let us define $\mathcal{X} = \{(x_b, p_b) : b \in (1, \dots, B)\}$ a batch of B labeled examples,

where x_b are the training examples and p_b are one-hot labels. Let $\mathcal{U} = \{u_b : b \in (1, \dots, \mu B)\}$ be a batch of μB unlabeled examples where μ is a hyperparameter that determines the relative sizes of \mathcal{X} and \mathcal{U} . Let $p_m(y | x)$ be the predicted class distribution produced by the model for input x . We denote the cross-entropy between two probability distributions p and q as $H(p, q)$. We perform two types of augmentations as part of FixMatch: strong and weak, denoted by $\mathcal{A}(\cdot)$ and $\alpha(\cdot)$ respectively. We describe the form of augmentation we use for \mathcal{A} and α in section 2.3.

2.1. Background

Consistency regularization is an important component of many recent state-of-the-art SSL algorithms. **Consistency regularization** utilizes unlabeled data by relying on the assumption that the model should output similar predictions when fed perturbed versions of the same image. This idea was first proposed in [39, 21], where the model is trained both via a standard supervised classification loss and on unlabeled data via the loss function

$$\sum_{b=1}^{\mu B} \|p_m(y | \alpha(u_b)) - p_m(y | \alpha(u_b))\|_2^2 \quad (1)$$

Note that both α and p_m are stochastic functions, so the two terms in eq. (1) will indeed have different values. Extensions to this idea include using an adversarial transformation in place of α [28], using a running average or past model predictions for one invocation of p_m in eq. (1) [43, 21], using a cross-entropy loss in place of the squared ℓ^2 loss [28, 45, 2], using stronger forms of augmentation [45, 2], and using consistency regularization as a component in a larger SSL pipeline [3, 2].

Pseudo-labeling leverages the idea that we should use the model itself to obtain artificial labels for unlabeled data.

This idea was introduced decades ago [27, 40]. Pseudo-labeling specifically refers to the use of “hard” labels (i.e., the $\arg \max$ of the model’s output) and only retaining artificial labels whose largest class probability fall above a predefined threshold [22]. Letting $q_b = p_m(y|u_b)$, **pseudo-labeling uses the following loss function on unlabeled data:**

$$\frac{1}{\mu B} \sum_{b=1}^{\mu B} \mathbb{1}(\max(q_b) \geq \tau) H(\hat{q}_b, q_b) \quad (2)$$

where $\hat{q}_b = \arg \max(q_b)$ and τ is the threshold hyperparameter. Note that for simplicity we assume that $\arg \max$ applied to a probability distribution produces a valid “one-hot” probability distribution. The use of a hard label makes pseudo-labeling closely related to entropy minimization [16, 38], where the model’s predictions are encouraged to be low-entropy (i.e., high-confidence) on unlabeled data.

2.2. Our Algorithm: FixMatch

The loss function for FixMatch consists exclusively of two cross-entropy loss terms: a supervised loss ℓ_s applied to labeled data and an unsupervised loss ℓ_u . Specifically, ℓ_s is just the standard cross-entropy loss on weakly augmented labeled examples:

$$\ell_s = \frac{1}{B} \sum_{b=1}^B H(p_b, p_m(y | \alpha(x_b))) \quad (3)$$

For unlabeled data,¹ FixMatch computes an artificial label for each example which is then used in a standard cross-entropy loss. To obtain an artificial label, we first compute the model’s predicted class distribution given a *weakly*-augmented version of a given unlabeled image: $q_b = p_m(y | \alpha(u_b))$. Then, we use $\hat{q}_b = \arg \max(q_b)$ as a pseudo-label, except we enforce the cross-entropy loss against the model’s output for a *strongly*-augmented version of u_b :

$$\ell_u = \frac{1}{\mu B} \sum_{b=1}^{\mu B} \mathbb{1}(\max(q_b) \geq \tau) H(\hat{q}_b, p_m(y | \mathcal{A}(u_b))) \quad (4)$$

where τ is a scalar hyperparameter denoting the threshold above which we retain a pseudo-label. In sum, the loss minimized by FixMatch is simply $\ell_s + \lambda_u \ell_u$ where λ_u is a fixed scalar hyperparameter denoting the relative weight of the unlabeled loss. We present a complete algorithm for FixMatch in algorithm 1 of the supplementary material.

Note that eq. (4) is similar to the pseudo-labeling loss in eq. (2). The crucial difference is that the artificial label is computed based on a weakly-augmented image and the loss is enforced against the model’s output for a strongly-augmented image. This introduces a form of consistency

regularization which, as we will show in section 5, is crucial to FixMatch’s success. We also note that it is typical in modern SSL algorithms to increase the weight of the unlabeled loss term (λ_u) over the training [43, 21, 3, 2, 31]. We found that this was unnecessary for FixMatch, which may be due to the fact that $\max(q_b)$ is typically less than τ early in training. As training progresses, the model’s predictions become more confident and it is more frequently the case that $\max(q_b) > \tau$. This suggests that pseudo-labeling may produce a natural curriculum “for free”. Similar justifications have been used in the past for ignoring low-confidence predictions in visual domain adaptation [14].

2.3. Augmentation in FixMatch

FixMatch leverages two kinds of augmentations: “weak” and “strong”. In all of our experiments, weak augmentation is a standard flip-and-shift augmentation strategy. Specifically, we randomly flip images horizontally with a probability of 50% on all datasets except SVHN and we randomly translate images by up to 12.5% vertically and horizontally.

For “strong” augmentation, we experiment with two approaches which are based on AutoAugment [9]. AutoAugment learns an augmentation strategy based on transformations from the Python Imaging Library² using reinforcement learning. This requires labeled data to learn the augmentation pipeline, making it problematic to use in SSL settings where limited labeled data is available. As a result, variants of AutoAugment have been proposed which do not require the augmentation strategy to be learned ahead of time with labeled data. We experiment with two such variants: RandAugment [10] and CTAugment [2]. Note that, unless otherwise stated, we use Cutout [13] followed by either of these strategies.

Given a collection of transformations (e.g., color inversion, translation, contrast adjustment, etc.), RandAugment randomly selects transformations for each sample in a mini-batch. As originally proposed, RandAugment uses a single fixed global magnitude that controls the severity of all distortions [10]. The magnitude is a hyperparameter that must be optimized on a validation set e.g., using grid search. We found that sampling a random magnitude from a pre-defined range at each training step (instead of using a fixed global value) works better for semi-supervised training, similar to what is used in UDA [45].

Instead of setting the transformation magnitudes randomly, CTAugment [2] learns them online over the course of training. To do so, a wide range of transformation magnitude values is divided into bins (as in AutoAugment [9]) and a weight (initially set to 1) is assigned to each bin. All examples are augmented with a pipeline consisting of two transformations which are sampled uniformly at random. For a given transformation, a magnitude bin is sam-

¹In practice, we include all labeled examples as part of unlabeled data without using their labels when constructing \mathcal{U} .

²<https://www.pythonware.com/products/pil/>

pled randomly with a probability according to the (normalized) bin weights. To update the weights of the magnitude bins, a labeled example is augmented with two transformations whose magnitude bins are sampled uniformly at random. The magnitude bin weights are then updated according to how close the model’s prediction is to the true label. Further details on CTAugment can be found in [2].

2.4. Additional important factors

Semi-supervised performance can be substantially impacted by factors other than the SSL algorithm used because considerations like the amount of regularization can be particularly important in the low-label regime. This is compounded by the fact that the performance of deep networks trained for image classification can heavily depend on the architecture, optimizer, training schedule, etc. These factors are typically not emphasized when new SSL algorithms are introduced. Instead of minimizing the importance of these factors, we endeavor to quantify their importance and highlight which ones have a significant impact on performance. Most of this analysis is performed in section 5. In this section we identify a few key considerations.

First, as mentioned above, we find that regularization is particularly important. In all of our models and experiments, we use simple weight decay regularization. We also found that using the Adam optimizer [19] resulted in worse performance and instead use standard SGD with momentum [42, 33, 29]. We did not find a substantial difference between standard and Nesterov momentum. For a learning rate schedule, we use a cosine learning rate decay [23] which sets the learning rate to

$$\eta \cos\left(\frac{7\pi k}{16K}\right) \quad (5)$$

where η is the initial learning rate, k is the current training step, and K is the total number of training steps. Note that this schedule effectively decays the learning rate from η to close to 0 by following a cosine curve. Finally, we report final performance using an exponential moving average of model parameters.

3. Related work

Semi-supervised learning is a mature field with a huge diversity of approaches. In this review of related work, we focus only on methods closely related to FixMatch. Broader introductions to the field are provided in [51, 52, 5].

The idea behind pseudo-labeling or self-training has been around for decades [40, 27]. The generality of self-training (i.e., using a model’s predictions to obtain artificial labels for unlabeled data) has led it to be applied in a diversity of domains including NLP [26], object detection [37], image classification [22, 46], domain adaptation

[53], to name a few. Pseudo-labeling refers to a specific variant where model predictions are converted to hard labels and are only retained when the classifier is sufficiently confident [22]. Some studies have suggested that pseudo-labeling is not competitive against other modern SSL algorithms on its own [31]. However, recent SSL algorithms have used pseudo-labeling as a part of their pipeline to produce better results [1, 32]. Similarly, as mentioned above, pseudo-labeling results in a form of entropy minimization [16] which has been used as a component for many powerful SSL techniques [28].

Consistency regularization was first proposed as “Regularization With Stochastic Transformations and Perturbations for Deep Semi-Supervised Learning” (Transformation/Stability or TS for short) [39] or the “TI-Model” [36]. Early extensions included using an exponential moving average of model parameters [43] or using previous model checkpoints [21] when producing artificial labels. A variety of methods have been used to produce random perturbations including data augmentation [14], stochastic regularization (e.g. Dropout [41]) [39, 21], and adversarial perturbations [28]. More recently, it has been shown that using strong data augmentation can produce better results [45, 2]. These heavily-augmented examples are almost certainly outside of the data distribution, which has in fact been shown to be potentially beneficial for SSL [11].

Of the aforementioned work, FixMatch bears the closest resemblance to two recent algorithms: Unsupervised Data Augmentation (UDA) [45] and ReMixMatch [2]. UDA and ReMixMatch both use a weakly-augmented example to generate an artificial label and enforce consistency against strongly-augmented examples. Neither of them use pseudo-labeling, but both approaches “sharpen” the artificial label to encourage the model to produce high-confidence predictions. UDA in particular also enforces consistency when the highest probability in the predicted class distribution for the artificial label is above a threshold. The thresholded pseudo-labeling of FixMatch has a similar effect to sharpening. In addition, ReMixMatch anneals the weight of the unlabeled data loss, which we omit from FixMatch because **we posit that the thresholding used in pseudo-labeling has a similar effect (as mentioned in section 2.2).** These similarities suggest that FixMatch can be viewed as a substantially simplified version of UDA and ReMixMatch, where we have combined two common techniques (pseudo-labeling and consistency regularization) while removing many components (sharpening, training signal annealing from UDA, distribution alignment and the rotation loss from ReMixMatch, etc.).

Since the core approach of FixMatch is a simple combination of two existing techniques, it also bears substantial similarities to many previously-proposed SSL algorithms. We provide a concise comparison of each of these tech-

Table 1: Comparison of SSL algorithms which include a form of consistency regularization and which (optionally) apply some form of post-processing to the artificial labels. We only mention those components of the SSL algorithm relevant to producing the artificial labels (for example, Virtual Adversarial Training additionally uses entropy minimization [16], MixMatch and ReMixMatch also use MixUp [50], UDA includes additional techniques like training signal annealing, etc.).

Algorithm	Artificial label augmentation	Prediction augmentation	Artificial label post-processing	Notes
TS [39]/II-Model [36]	Weak	Weak	None	
Temporal Ensembling [21]	Weak	Weak	None	Uses model from earlier in training
Mean Teacher [43]	Weak	Weak	None	Uses an EMA of parameters
Virtual Adversarial Training [28]	None	Adversarial	None	
UDA [45]	Weak	Strong	Sharpening	Ignores low-confidence artificial labels
MixMatch [3]	Weak	Weak	Sharpening	Averages multiple artificial labels
ReMixMatch [2]	Weak	Strong	Sharpening	Sums losses for multiple predictions
FixMatch	Weak	Strong	Pseudo-labeling	

niques in table 1 where we list the augmentation used for the artificial label, the model’s prediction, and any post-processing applied to the artificial label. A more thorough empirical comparison of these different algorithms and their constituent approaches is provided in the following section.

4. Experiments

We evaluate the efficacy of FixMatch on several standard SSL image classification benchmarks. Specifically, we perform experiments with varying amounts of labeled data and augmentation strategies on CIFAR-10 [20], CIFAR-100 [20], SVHN [30], STL-10 [8], and ImageNet [12]. In many cases, we perform experiments with fewer labels than previously considered since FixMatch shows promise in extremely label-scarce settings. Note that we use an identical set of hyperparameters ($\lambda_u = 1$, $\eta = 0.03$, $\beta = 0.9$, $\tau = 0.95$, $\mu = 7$, $B = 64$, $K = 2^{20}$)³ across all amounts of labeled examples and all datasets with the exception of ImageNet. A complete list of hyperparameters is reported in the supplementary material. We include an extensive ablation study in section 5 to tease apart the importance of the different components and hyperparameters of FixMatch, including factors that are not explicitly part of the SSL algorithm such as the optimizer and learning rate.

4.1. CIFAR-10, CIFAR-100, and SVHN

To begin with, we compare FixMatch to various existing methods on the standard CIFAR-10, CIFAR-100, and SVHN benchmarks. As recommended by [31], we reimplemented all existing baselines and performed all experiments using the same codebase. In particular, we use the same network architecture (a Wide ResNet-28-2 [47] with 1.5M parameters) and training protocol, including the optimizer, learning rate schedule, data preprocessing, across all SSL methods. For baselines, we mainly consider methods

that are similar to FixMatch and/or are state-of-the-art: II-Model [36], Mean Teacher [43], Pseudo-Label [22], MixMatch [3], UDA [45], and ReMixMatch [2]. With the exception of [2], previous work has not considered fewer than 25 labels per class on these benchmarks. We also consider the setting where only 4 labeled images are given for each class for each dataset. As far as we are aware, we are the first to run *any* experiments at 400 labeled examples on CIFAR-100.

We report the performance of all baselines along with FixMatch in table 2. We compute the mean and variance of accuracy when training on 5 different “folds” of labeled data. We omit results with 4 labels per class for II-Model, Mean Teacher, and Pseudo-Labeling since the performance was poor at 250 labels. MixMatch, ReMixMatch, and UDA all perform reasonably well with 40 and 250 labels, but we find that FixMatch substantially outperforms each of these methods while nevertheless being simpler. For example, FixMatch achieves an average error rate of 11.39% on CIFAR-10 with 4 labels per class. As a point of reference, among the methods studied in [31] (where the same network architecture was used), the lowest error rate achieved on CIFAR-10 with 400 labels per class was 13.13%. Our results also compare favorably to recent state-of-the-art results achieved by ReMixMatch [2], despite the fact that we omit various components such as the self-supervised loss.

Our results are state-of-the-art on all datasets except for CIFAR-100 where ReMixMatch is a bit superior. To understand why ReMixMatch performs better than FixMatch, we experimented with a few variants of FixMatch which copy various components of ReMixMatch into FixMatch. We find that the most important term is Distribution Alignment (DA), which encourages the model to emit all classes with equal probability. Combining FixMatch with DA reaches a 40.14% error rate with 400 labeled examples, which is substantially better than the 44.28% achieved by ReMixMatch.

We find that in most cases the performance of FixMatch

³ β refers to a momentum in SGD optimizer. The definition of other hyperparameters are found in section 2.

Table 2: Error rates for CIFAR-10, CIFAR-100 and SVHN on 5 different folds. FixMatch (RA) uses RandAugment [10] and FixMatch (CTA) uses CTAugment [2] for strong-augmentation. All baseline models (II-Model [36], Pseudo-Labeling [22], Mean Teacher [43], MixMatch [3], UDA [45], and ReMixMatch [2]) are tested using the same codebase.

Method	CIFAR-10			CIFAR-100			SVHN		
	40 labels	250 labels	4000 labels	400 labels	2500 labels	10000 labels	40 labels	250 labels	1000 labels
II-Model	-	54.26±3.97	14.01±0.38	-	57.25±0.48	37.88±0.11	-	18.96±1.92	7.54±0.36
Pseudo-Labeling	-	49.78±0.43	16.09±0.28	-	57.38±0.46	36.21±0.19	-	20.21±1.09	9.94±0.61
Mean Teacher	-	32.32±2.30	9.19±0.19	-	53.91±0.57	35.83±0.24	-	3.57±0.11	3.42±0.07
MixMatch	47.54±11.50	11.05±0.86	6.42±0.10	67.61±1.32	39.94±0.37	28.31±0.33	42.55±14.53	3.98±0.23	3.50±0.28
UDA	29.05±5.93	8.82±1.08	4.88±0.18	59.28±0.88	33.13±0.22	24.50±0.25	52.63±20.51	5.69±2.76	2.46 ±0.24
ReMixMatch	19.10 ±9.64	5.44 ±0.05	4.72±0.13	44.28 ±2.06	27.43 ±0.31	23.03 ±0.56	3.34 ±0.20	2.92 ±0.48	2.65±0.08
FixMatch (RA)	13.81 ±3.37	5.07 ±0.65	4.26 ±0.05	48.85±1.75	28.29±0.11	22.60 ±0.12	3.96 ±2.17	2.48 ±0.38	2.28 ±0.11
FixMatch (CTA)	11.39 ±3.35	5.07 ±0.33	4.31 ±0.15	49.95±3.01	28.64±0.24	23.18±0.11	7.65±7.65	2.64 ±0.64	2.36 ±0.19

Table 3: Error rates for STL-10 on 1000-label splits. All baseline models are tested using the same codebase.

Method	Error rate	Method	Error rate
II-Model	26.23±0.82	MixMatch	10.41±0.61
Pseudo-Labeling	27.99±0.80	UDA	7.66±0.56
Mean Teacher	21.43±2.39	ReMixMatch	5.23 ±0.45
FixMatch (RA)	7.98±1.50	FixMatch (CTA)	5.17 ±0.63

using CTAugment and RandAugment is similar, except in the settings where we have 4 labels per class. This may be explained by the fact that these results are particularly high-variance. For example, the variance over 5 different folds for CIFAR-10 with 4 labels per class is 3.35%, which is significantly higher than that with 25 labels per class (0.33%). The error rates are also affected significantly by the random seeds when the number of labeled examples per class is extremely small, as shown in table 4.

4.2. STL-10

The STL-10 dataset contains 5,000 labeled images of size 96×96 from 10 classes and 100,000 unlabeled images. There exist out-of-distribution images in the unlabeled set, making it a more realistic and challenging test of SSL performance. We test SSL algorithms on five of the predefined folds of 1,000 labeled images each. Following [3], we use a WRN-37-2 network (comprising 23.8M parameters). As in table 3, FixMatch achieves the state-of-the-art performance of ReMixMatch [2] despite being significantly simpler.

4.3. ImageNet

We also evaluate FixMatch on ImageNet to verify that it performs well on a larger and more complex dataset. Following [45], we use 10% of the training data as labeled examples and treat the rest as unlabeled samples. We also use a ResNet-50 network architecture and RandAugment [10] as strong augmentation for this experiment. We include additional implementation details in appendix C. FixMatch

Table 4: Error rates of FixMatch (CTA) on a single 40-label split of CIFAR-10 and SVHN with different random seeds.

Dataset	Runs (ordered by accuracy)				
	1	2	3	4	5
CIFAR-10	5.46	6.17	9.37	10.85	13.32
SVHN	2.40	2.47	6.24	6.32	6.38

achieves a top-1 error rate of $28.54 \pm 0.52\%$, which is 2.68% better than UDA [45]. Our top-5 error rate is $10.87 \pm 0.28\%$. While S⁴L [48] holds state-of-the-art on semi-supervised ImageNet with a 26.79% error rate, it leverages 2 additional training phases (pseudo-label re-training and supervised fine-tuning) to significantly lower the error rate from 30.27% after the first phase. FixMatch outperforms S⁴L after their first phase, and it is possible that a similar performance gain could be achieved by incorporating these techniques into FixMatch.

4.4. Barely Supervised Learning

To test the limits of our proposed approach, we applied FixMatch to CIFAR-10 with **only one example per class**. We conduct two sets of experiments.

First, we create four datasets by randomly selecting one example per class. We train on each dataset four times and reach between 48.58% and 85.32% test accuracy with a median of 64.28%. The inter-dataset variance is much lower, however; for example, the four models trained on the first dataset all reach between 61% and 67% accuracy, and the second dataset reaches between 68% and 75%.

We hypothesize that this variability is caused by the quality of the labeled examples in a given dataset and that selecting low-quality examples might make it more difficult for the model to learn some particular class effectively. To test this, we construct eight new training datasets with examples ranging in “prototypicality” (i.e., representative of the underlying class). Specifically, we take the ordering of the CIFAR-10 training set from [4] that sorts examples from



Figure 2: FixMatch reaches 78% CIFAR-10 accuracy on this labeled training set—just 1 image per class (10 total).

those that are most representative to those that are least. This example ordering was determined after training many CIFAR-10 models with all labeled data. We thus do not envision this as a practical method for actually choosing examples for use in SSL, but rather to experimentally verify that examples that are more representative are better suited for low-label training. We divide this ordering evenly into eight buckets (so all of the most representative examples are in the first bucket, and all of the outliers in the last). We then create eight labeled training sets by randomly selecting one labeled example of each class from the same bucket.

Using the same hyperparameters, the model trained only on the most prototypical examples reaches a median of 78% accuracy (with a maximum of 84% accuracy); training on the middle of the distribution reaches 65% accuracy; and training on only the outliers fails to converge completely, with 10% accuracy. Figure 2 shows the full labeled training dataset for the split where FixMatch achieved a median accuracy of 78%. Further analysis is presented in Appendix B.3.

Table 5: Ablation study on optimizers. Error rates are reported on a single 250-label split from CIFAR-10.

Optimizer	Hyperparameters			Error
SGD	$\eta = 0.03$	$\beta = 0.90$	Nesterov	4.84
SGD	$\eta = 0.03$	$\beta = 0.90$		4.86
SGD	$\eta = 0.20$	$\beta = 0.0$	Nesterov	5.19
Adam	$\eta = 0.0003$	$\beta_1 = 0.9$	$\beta_2 = 0.999$	5.37

Table 6: Ablation study on learning rate decay schedules. Error rates are reported on a single 250-label split from CIFAR-10.

Decay Schedule	Error
Cosine (FixMatch)	4.84
Linear Decay (end 0.01)	4.95
Linear Decay (end 0.02)	5.55
No Decay	5.70

5. Ablation Study

Since FixMatch comprises a simple combination of two existing techniques, we perform an extensive ablation study to better understand why it is able to obtain state-of-the-art

Table 7: Ablation study on CutOut [13]. Error rates are reported on a single 250-label split from CIFAR-10.

Ablation	FixMatch	Only CutOut	No CutOut
Error	4.84	6.15	6.15

results. Recall that we report the mean and the standard deviation over 5 folds for each experimental protocol as our main results in table 2 and table 3. Due to the number of experiments in our ablation study, however, we focus on studying with a single 250 label split from CIFAR-10 and only report results using CTAugment. Note that FixMatch with default parameters achieves 4.84% error rate on this particular split. We present complete results in the supplementary material.

5.1. Sharpening and Thresholding

A “soft” version of pseudo-labeling can be designed by sharpening the predicted distribution instead of using one-hot labels. This formulation appears in UDA and is of general interest since other methods such as MixMatch and ReMixMatch also make use of sharpening (albeit without thresholding). Using sharpening instead of an arg max introduces a hyper-parameter: the temperature T [2, 45].

We study the interactions between the temperature T and the confidence threshold τ . Note that pseudo-labeling in FixMatch is recovered as $T \rightarrow 0$. The results are presented in fig. 3b and fig. 3c. The threshold value of 0.95 shows the lowest error rate, though increasing it to 0.97 or 0.99 did not hurt the performance. On the other hand, accuracy drops by more than 1.5% when using a small threshold value. Sharpening, on the other hand, did not show a significant difference in performance when a confidence threshold is used. In summary, we observe that swapping pseudo-labeling for sharpening and thresholding would introduce a new hyper-parameter while achieving no better performance.

5.2. Augmentation Strategy

We conduct an ablation study on different strong data augmentation policies as data augmentation plays a key role in FixMatch. Specifically, we chose RandAugment [10] and CTAugment [2], which have been used for state-of-the-art SSL algorithms such as UDA [45] and ReMixMatch [3] respectively. On CIFAR-10, CIFAR-100, and SVHN we observed highly comparable results between the two policies (table 2), whereas in table 3, we observe a significant gain by using CTAugment.

As mentioned in 2.3, CutOut [13] is used by default after strong augmentation in both RandAugment and CTAugment. We therefore measure the effect of CutOut in table 7. We find that both CutOut and CTAugment are required to obtain the best performance; removing either results in a

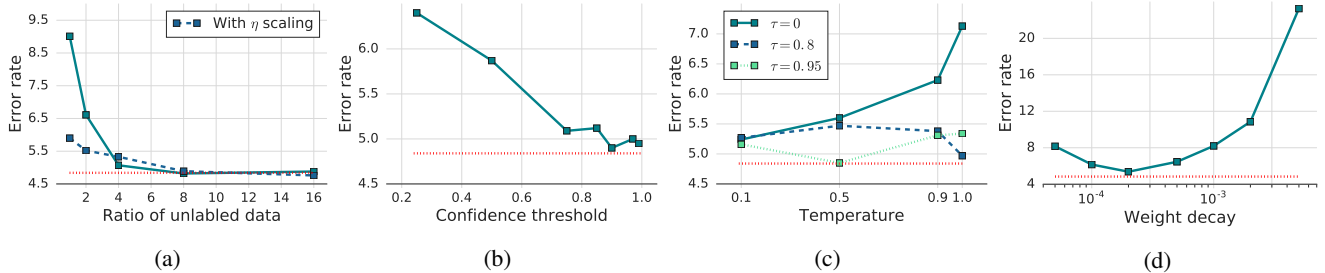


Figure 3: Plots of various ablation studies on FixMatch. (a) Varying the ratio of unlabeled data (μ) with different learning rate (η) scaling strategies. (b) Varying the confidence threshold for pseudo-labels. (c) Measuring the effect of “sharpening” the predicted label distribution while varying the confidence threshold (τ). (d) Varying the loss coefficient for weight decay. We include the error rate of FixMatch with the default hyperparameter setting in red dotted line for each plot.

comparable increase in error rate.

We also study different combinations of weak and strong augmentations for pseudo-label generation and prediction (i.e., the upper and lower paths in fig. 1). When we replaced the weak augmentation for label guessing with strong augmentation, we found that the model diverged early in training. This suggests that the pseudo-label needs to be generated using weakly augmented data. Using weak augmentation in place of strong augmentation to generate the model’s prediction for training peaked at 45% accuracy but was not stable and progressively collapsed to 12%, suggesting the importance of strong data augmentation for model prediction at training. This observation is well-aligned with those from supervised learning [9].

5.3. Ratio of Unlabeled Data

In fig. 3a we plot the error rates of FixMatch with different ratios of unlabeled data (μ). We observe a significant decrease in error rates by using a large amount of unlabeled data, which is consistent with the finding in UDA [45]. In addition, scaling the learning rate η linearly with the batch size (a technique for large-batch supervised training [15]) was effective for FixMatch, especially when μ is small.

5.4. Optimizer and Learning Rate Schedule

While the study of different optimizers and their hyperparameters is seldom done in previous SSL works, we found that they can have a strong effect on performance. As shown in table 5, SGD with momentum of 0.9 works the best. Without momentum, the best error rate we could reach is 5.19%, compared to 4.84 with momentum. We found that the Nesterov variant of momentum [42] is not required for achieving an error below 5%. For Adam [19], none of the combinations of parameters for η, β_1, β_2 that we explored appeared competitive with momentum. We refer table 9 in the supplementary material for more details.

It is a popular choice in recent works [23] to use a cosine learning rate decay. In our experiments, a linear learning

rate decay performed nearly as well. Note that, as for the cosine learning rate decay, picking a proper decaying rate is important. Finally, using no decay results in worse accuracy (a 0.86% degradation).

5.5. Weight Decay

We find that tuning the weight decay is exceptionally important for low-label regimes: choosing a value that is just one order of magnitude larger or smaller than optimal can cost ten percentage points or more, as shown in fig. 3d.

6. Conclusion

There has been rapid recent progress in semi-supervised learning. Unfortunately, much of this progress comes at the cost of increasingly complicated learning algorithms with sophisticated loss terms and numerous difficult-to-tune hyper-parameters. We introduce FixMatch, a simpler semi-supervised learning algorithm that achieves state-of-the-art results across many datasets. We also show how FixMatch can begin to bridge the gap between low-label semi-supervised learning and few-shot learning—or even clustering: we obtain surprisingly-high accuracy with just one label per class. Using only standard cross-entropy losses on both labeled and unlabeled data, FixMatch’s training objective can be written in just a few lines of code.

Because of this simplicity, we are able to investigate nearly all aspects of the algorithm to understand why it works. We find that to obtain strong results, especially in the limited-label regime, certain design choices are often underemphasized – most importantly, weight decay and the choice of optimizer. The importance of these factors means that even when controlling for model architecture as is recommended in [31], the same technique can not always be directly compared across different implementations.

On the whole, we believe that the existence of such simple but performant semi-supervised machine learning algorithms will help to allow machine learning to be deployed

in increasingly many practical domains where labels are expensive or difficult to obtain.

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A. Algorithm

We present the complete algorithm for FixMatch in algorithm 1.

B. Comprehensive Experimental Results

B.1. Hyperparameters

As mentioned in section 4, we used almost identical hyperparameters of FixMatch on CIFAR-10, CIFAR-100, SVHN and STL-10. Note that we used similar network architectures for these datasets, except that more convolution filters were used for CIFAR-100 to handle larger label space and more convolutions were used for STL-10 to deal with larger input image size. Here, we provide a complete list of hyperparameters in table 8. Note that we did ablation study for most of these hyperparameters in section 5 (τ in section 5.1, μ in section 5.3, lr and β (momentum) in section 5.4, and weight decay in section 5.5).

Table 8: Complete list of hyperparameters of FixMatch for CIFAR-10, CIFAR-100, SVHN and STL-10.

	CIFAR-10	CIFAR-100	SVHN	STL-10
τ		0.95		
λ_u		1		
μ		7		
B		64		
lr		0.03		
β		0.9		
Nesterov		True		
weight decay	0.0005	0.001	0.0005	0.0005

B.2. Full Ablation Results on Optimizers

We present full ablation results on optimizers in table 9. First, we studied the effect of momentum (β) for SGD optimizer. We found that the performance is somewhat sensitive to β and the model did not converge when β is set too large. On the other hand, small values of β still worked fine. When β is small, increasing the learning rate improved the performance, though they are not as good as the best performance obtained with $\beta = 0.9$. Nesterov momentum resulted in a slightly lower error rate than that of standard momentum SGD, but the difference was not significant.

As studied in [44, 24], we did not find Adam performing better than momentum SGD. While the best error rate of the model trained with Adam is only 0.53% larger than that of momentum SGD, we found that the performance was much more sensitive to the change of learning rate (e.g., increase in error rate by more than 8% when increasing the learning rate to 0.002) than momentum SGD. Additional exploration along this direction to make Adam more competitive includes the use of weight decay [24, 49] instead of

Table 9: Ablation study on optimizers. Error rates are reported on a single 250-label split from CIFAR-10.

Optimizer	Hyperparameters			Error
SGD	$\eta = 0.03$	$\beta = 0.90$	Nesterov	4.84
SGD	$\eta = 0.03$	$\beta = 0.999$	Nesterov	84.33
SGD	$\eta = 0.03$	$\beta = 0.99$	Nesterov	21.97
SGD	$\eta = 0.03$	$\beta = 0.50$	Nesterov	5.79
SGD	$\eta = 0.03$	$\beta = 0.25$	Nesterov	6.42
SGD	$\eta = 0.03$	$\beta = 0$	Nesterov	6.76
SGD	$\eta = 0.05$	$\beta = 0$	Nesterov	6.06
SGD	$\eta = 0.10$	$\beta = 0$	Nesterov	5.27
SGD	$\eta = 0.20$	$\beta = 0$	Nesterov	5.19
SGD	$\eta = 0.50$	$\beta = 0$	Nesterov	5.74
SGD	$\eta = 0.03$	$\beta = 0.90$		4.86
Adam	$\eta = 0.002$	$\beta_1 = 0.9$	$\beta_2 = 0.00$	29.42
Adam	$\eta = 0.002$	$\beta_1 = 0.9$	$\beta_2 = 0.90$	14.42
Adam	$\eta = 0.002$	$\beta_1 = 0.9$	$\beta_2 = 0.99$	15.44
Adam	$\eta = 0.002$	$\beta_1 = 0.9$	$\beta_2 = 0.999$	13.93
Adam	$\eta = 0.0008$	$\beta_1 = 0.9$	$\beta_2 = 0.999$	7.35
Adam	$\eta = 0.0006$	$\beta_1 = 0.9$	$\beta_2 = 0.999$	6.12
Adam	$\eta = 0.0005$	$\beta_1 = 0.9$	$\beta_2 = 0.999$	5.95
Adam	$\eta = 0.0004$	$\beta_1 = 0.9$	$\beta_2 = 0.999$	5.44
Adam	$\eta = 0.0003$	$\beta_1 = 0.9$	$\beta_2 = 0.999$	5.37
Adam	$\eta = 0.0002$	$\beta_1 = 0.9$	$\beta_2 = 0.999$	5.57
Adam	$\eta = 0.0001$	$\beta_1 = 0.9$	$\beta_2 = 0.999$	7.90

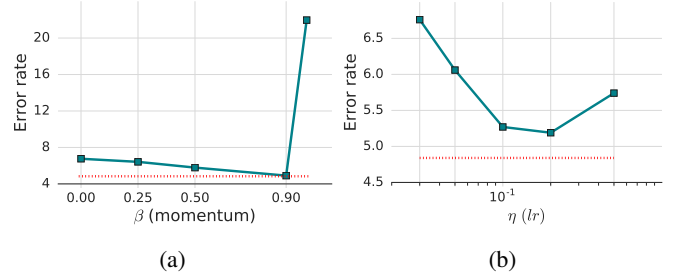


Figure 4: Plots of ablation studies on optimizers. (a) Varying β . (b) Varying η with $\beta = 0$.

L2 weight regularization and a better exploration of hyperparameters [6, 7].

B.3. Labeled Data for Barely Supervised Learning

In addition to fig. 2, we visualize the full labeled training images obtained by ordering mechanism [4] used for barely supervised learning in fig. 5. Each row contains 10 images from 10 different classes of CIFAR-10 and is used as the complete labeled training dataset for one run of FixMatch. The first row contains the most prototypical images of each class, while the bottom row contains the least prototypical images. We train two models for each dataset and compute the mean accuracy between the two and plot this in fig. 6. Observe that we obtain over 80% accuracy when training on the best examples.

Algorithm 1 FixMatch algorithm.

```

1: Input: Labeled batch  $\mathcal{X} = \{(x_b, p_b) : b \in (1, \dots, B)\}$ , unlabeled batch  $\mathcal{U} = \{u_b : b \in (1, \dots, \mu B)\}$ , confidence threshold  $\tau$ , unlabeled data ratio  $\mu$ , unlabeled loss weight  $\lambda_u$ .
2:  $\ell_s = \frac{1}{B} \sum_{b=1}^B H(p_b, \alpha(x_b))$  // Cross-entropy loss for labeled data
3: for  $b = 1$  to  $\mu B$  do
4:    $\tilde{u}_b = \mathcal{A}(u_b)$  // Apply strong data augmentation to  $u_b$ 
5:    $q_b = p_m(y | \alpha(u_b); \theta)$  // Compute prediction after applying weak data augmentation of  $u_b$ 
6: end for
7:  $\ell_u = \frac{1}{\mu B} \sum_{b=1}^{\mu B} \mathbb{1}\{\max(q_b) > \tau\} H(\arg \max(q_b), \tilde{u}_b)$  // Cross-entropy loss with pseudo-label and confidence for unlabeled data
8: return  $\ell_s + \lambda_u \ell_u$ 

```

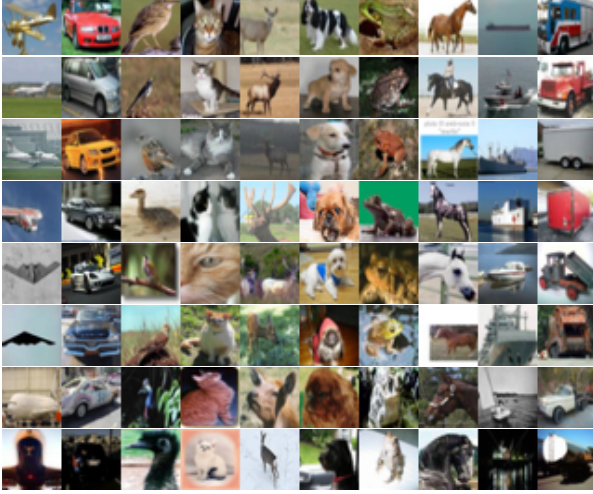


Figure 5: Labeled training data for the 1-label-per-class semi-supervised experiment. Each row corresponds to the complete labeled training set for one run of our algorithm, sorted from the most prototypical dataset (first row) to least prototypical dataset (last row).

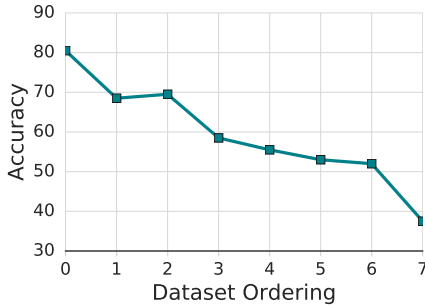


Figure 6: Accuracy of the model when trained on the 1-label-per-class datasets from Figure 5, ordered from most prototypical (top row) to least (bottom row).

B.4. Comparison to Supervised Baselines

In table 10 and table 11, we present the performance of models trained only with the labeled data using strong data augmentations to highlight the effectiveness of using unlabeled data in FixMatch.

beled data in FixMatch.

C. Implementation Details for Section 4.3

For our ImageNet experiments we use standard ResNet50 pre-activation model trained in a distributed way on a TPU device with 32 cores.⁴ We report results over five random folds of labeled data. We use following set of hyperparameters for our ImageNet model:

- **Batch size.** On each step our batch contains 1024 labeled examples and 5120 unlabeled examples.
- **Training time.** We train our model for 300 epochs of unlabeled examples.
- **Learning rate schedule.** We utilize linear learning rate warmup for the first 5 epochs until it reaches an initial value of 0.4. Then we decay learning rate at epochs 60, 120, 160, and 200 epoch by multiplying it by 0.1.
- **Optimizer.** We use Nesterov Momentum optimizer with momentum 0.9.
- **Exponential moving average (EMA).** We utilize EMA technique with decay 0.999.
- **FixMatch loss.** We use unlabeled loss weight $\lambda_u = 10$ and confidence threshold $\tau = 0.7$ in FixMatch loss.
- **Weight decay.** Our weight decay coefficient is 0.0001. Similarly to other datasets we perform weight decay by adding L2 penalty of all weights to model loss.
- **Augmentation of unlabeled images.** For strong augmentation we use RandAugment with random magnitude [10]. For weak augmentation we use a random horizontal flip.
- **ImageNet preprocessing.** We randomly crop and rescale to 224×224 size all labeled and unlabeled training images prior to performing augmentation. This is considered a standard ImageNet preprocessing technique.

⁴<https://github.com/tensorflow/tpu/tree/master/models/official/resnet>

Table 10: Error rates for CIFAR-10, CIFAR-100 and SVHN on 5 different folds. Models with (RA) uses RandAugment [10] and the ones with (CTA) uses CTAugment [2] for strong-augmentation. All models are tested using the same codebase.

Method	CIFAR-10			CIFAR-100			SVHN		
	40 labels	250 labels	4000 labels	400 labels	2500 labels	10000 labels	40 labels	250 labels	1000 labels
Supervised (RA)	64.01±0.76	39.12±0.77	12.74±0.29	79.47±0.18	52.88±0.51	32.55±0.21	52.68±2.29	22.48±0.55	10.89±0.12
Supervised (CTA)	64.53±0.83	41.92±1.17	13.64±0.12	79.79±0.59	54.23±0.48	35.30±0.19	43.05±2.34	15.06±1.02	7.69±0.27
FixMatch (RA)	13.81±3.37	5.07±0.65	4.26±0.05	48.85±1.75	28.29±0.11	22.60±0.12	3.96±2.17	2.48±0.38	2.28±0.11
FixMatch (CTA)	11.39±3.35	5.07±0.33	4.31±0.15	49.95±3.01	28.64±0.24	23.18±0.11	7.65±7.65	2.64±0.64	2.36±0.19

Table 11: Error rates for STL-10 on 1000-label splits. All models are tested using the same codebase.

Method	Error rate	Method	Error rate
Supervised (RA)	20.66±0.83	FixMatch (RA)	7.98±1.50
Supervised (CTA)	19.86±0.66	FixMatch (CTA)	5.17±0.63

D. List of Data Transformations

We used the same sets of image transformations used in RandAugment [10] and CTAugment [2]. For completeness, we listed all transformation operations for these augmentation strategies in table 12 and table 13.

Table 12: List of transformations used in RandAugment [10].

Transformation	Description	Parameter	Range
Autocontrast	Maximizes the image contrast by setting the darkest (lightest) pixel to black (white).		
Brightness	Adjusts the brightness of the image. $B = 0$ returns a black image, $B = 1$ returns the original image.	B	[0.05, 0.95]
Color	Adjusts the color balance of the image like in a TV. $C = 0$ returns a black & white image, $C = 1$ returns the original image.	C	[0.05, 0.95]
Contrast	Controls the contrast of the image. A $C = 0$ returns a gray image, $C = 1$ returns the original image.	C	[0.05, 0.95]
Equalize	Equalizes the image histogram.		
Identity	Returns the original image.		
Posterize	Reduces each pixel to B bits.	B	[4, 8]
Rotate	Rotates the image by θ degrees.	θ	[-30, 30]
Sharpness	Adjusts the sharpness of the image, where $S = 0$ returns a blurred image, and $S = 1$ returns the original image.	S	[0.05, 0.95]
Shear_x	Shears the image along the horizontal axis with rate R .	R	[-0.3, 0.3]
Shear_y	Shears the image along the vertical axis with rate R .	R	[-0.3, 0.3]
Solarize	Inverts all pixels above a threshold value of T .	T	[0, 1]
Translate_x	Translates the image horizontally by $(\lambda \times \text{image width})$ pixels.	λ	[-0.3, 0.3]
Translate_y	Translates the image vertically by $(\lambda \times \text{image height})$ pixels.	λ	[-0.3, 0.3]

Table 13: List of transformations used in CTAugment [2]. The ranges for the listed parameters are discretized into 17 equal bins, except for the M parameter of the Rescale transformation, which takes one of the following six options: anti-alias, bicubic, bilinear, box, hamming, and nearest.

Transformation	Description	Parameter	Range
Autocontrast	Maximizes the image contrast by setting the darkest (lightest) pixel to black (white), and then blends with the original image with blending ratio λ .	λ	[0, 1]
Brightness	Adjusts the brightness of the image. $B = 0$ returns a black image, $B = 1$ returns the original image.	B	[0, 1]
Color	Adjusts the color balance of the image like in a TV. $C = 0$ returns a black & white image, $C = 1$ returns the original image.	C	[0, 1]
Contrast	Controls the contrast of the image. A $C = 0$ returns a gray image, $C = 1$ returns the original image.	C	[0, 1]
Cutout	Sets a random square patch of side-length $(L \times \text{image width})$ pixels to gray.	L	[0, 0.5]
Equalize	Equalizes the image histogram, and then blends with the original image with blending ratio λ .	λ	[0, 1]
Invert	Inverts the pixels of the image, and then blends with the original image with blending ratio λ .	λ	[0, 1]
Identity	Returns the original image.		
Posterize	Reduces each pixel to B bits.	B	[1, 8]
Rescale	Takes a center crop that is of side-length $(L \times \text{image width})$, and rescales to the original image size using method M .	L	[0.5, 1.0]
		M	see caption
Rotate	Rotates the image by θ degrees.	θ	[-45, 45]
Sharpness	Adjusts the sharpness of the image, where $S = 0$ returns a blurred image, and $S = 1$ returns the original image.	S	[0, 1]
Shear_x	Shears the image along the horizontal axis with rate R .	R	[-0.3, 0.3]
Shear_y	Shears the image along the vertical axis with rate R .	R	[-0.3, 0.3]
Smooth	Adjusts the smoothness of the image, where $S = 0$ returns a maximally smooth image, and $S = 1$ returns the original image.	S	[0, 1]
Solarize	Inverts all pixels above a threshold value of T .	T	[0, 1]
Translate_x	Translates the image horizontally by $(\lambda \times \text{image width})$ pixels.	λ	[-0.3, 0.3]
Translate_y	Translates the image vertically by $(\lambda \times \text{image height})$ pixels.	λ	[-0.3, 0.3]