Milking CowMask for Semi-Supervised Image Classification

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Abstract
Consistency regularization is a technique for semi-supervised learning that has recently been shown to yield strong results for classification with few labeled data. The method works by perturbing input data using augmentation or adversarial examples, and encouraging the learned model to be robust to these perturbations on unlabeled data. Here, we evaluate the use of a recently proposed augmentation method, called CowMask (French et al., 2019), for this purpose. Using CowMask as the augmentation method in semi-supervised consistency regularization, we establish a new state-of-the-art result on Imagenet with 10% labeled data, with a top-5 error of 8.76% and top-1 error of 26.06%. Moreover, we do so with a method that is much simpler than alternative methods. We further investigate the behavior of CowMask for semi-supervised learning by running many smaller scale experiments on the small image benchmarks SVHN, CIFAR-10 and CIFAR-100, where we achieve results competitive with the state of the art, and where we find evidence that the CowMask perturbation is widely applicable. We open source our code at https://github.com/google-research/google-research/tree/master/milking_cowmask.

1. Introduction
Training accurate deep neural network based image classifiers requires large quantities of training data. While images are often readily available in many problem domains, producing ground truth annotations is usually a laborious and expensive task that can act as a bottleneck. Semi-supervised learning offers the tantalising possibility of reducing the amount of annotated data required by learning from a dataset that is only partially annotated.

Semi-supervised learning algorithms based on consistency regularization (Sajjadi et al., 2016a; Laine & Aila, 2017; Oliver et al., 2018) have proved to be simple while effective, yielding a number of state of the art results over the last few years. Consistency regularization is driven by encouraging consistent predictions for unsupervised samples under perturbation, frequently perturbing samples with data augmentation. Using CutOut (DeVries & Taylor, 2017) – in which part of an image is blanked to zero by modulating it with a rectangular mask – as the augmentation for semi-supervised learning has proved to be highly effective, making significant contributions to the effectiveness of rich augmentation strategies (Xie et al., 2019; Sohn et al., 2020).

In this paper, we use the CowMask (French et al., 2019) masking strategy, recently introduced for semi-supervised semantic segmentation, instead of rectangular masking, in semi-supervised image classification tasks. The successes of CowMask on semantic segmentation suggest that it may work better in settings with less clear class cluster boundaries, as we may expect to find in ImageNet. When used to erase parts of an image in a similar fashion to CutOut, CowMask outperforms rectangular masks in the majority of semi-supervised image classifications tasks that we tested.

Here’s how we applied mask-based mixing to semi-supervised learning: We extended the Interpolation Consistency Training (ICT) algorithm (Verma et al., 2019) to use mask-based mixing. We start from CutMix (Yun et al., 2019), where one copies a rectangular chunk from one image onto another as a form of regularization for supervised learning. We apply CutMix to unsupervised samples as well as supervised ones (mixing their imputed predictions). We then evaluate the same methodology with CowMask. Both CutMix and CowMask exhibit strong semi-supervised learning performance, with CowMask outperforming rectangular masks based mixing in the majority of cases. CowMask based mixing achieves a new state-of-the-art on semi-supervised Imagenet, and results comparable to state-of-the-art on multiple small image datasets, all without the need for previously proposed complex training procedures.

In Section 2 we discuss related work in the literature that form the basis of our approach, alongside other semi-supervised classification algorithms for comparison. We cover CowMask, the main ingredient to our approach, in

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Section 3. In Section 4 we describe how CowMask is used in our approach to semi-supervised learning. We present our experiments and results in Section 5. Finally we discuss our work and conclude in Section 6.

2. Background

2.1. Semi-supervised classification

A variety of semi-supervised deep neural network image classification approaches have been proposed over the last several years, including the use of auto-encoders (Wang et al., 2019; Rasmus et al., 2015), GANs (Salimans et al., 2016; Dai et al., 2017), curriculum learning (Cascante-Bonilla et al., 2020) and self-supervised learning (Zhai et al., 2019).

Many recent approaches are based on consistency regularization (Oliver et al., 2018), a simple approach exemplified by the $\pi$-model (Laine & Aila, 2017) and the Mean Teacher model (Tarvainen & Valpola, 2017). A typical consistency regularization based approach minimizes two loss terms; standard cross-entropy loss and consistency loss for supervised and unsupervised samples respectively. Consistency loss measures the difference between predictions resulting from differently perturbed variants of an unsupervised sample. The $\pi$-model perturbs samples twice using stochastic augmentation and minimises the squared difference between class probability predictions. The Mean Teacher model builds on the $\pi$-model by using two networks; a teacher and a student. The student is trained using gradient descent as normal while the weights of the teacher are an exponential moving average of those of the student. The consistency loss term measures the difference in predictions between the student and the teacher under different stochastic augmentation.

A variety of types of perturbation have been explored. Sajjadi et al. (2016b) employed richer data augmentation including affine transformations, while (Laine & Aila, 2017) and (Tarvainen & Valpola, 2017) used standard augmentation strategies such as random crop and noise for small image datasets. Virtual Adversarial Training (VAT) perturbs samples in an adversarial direction that maximises the difference in prediction of the classifier.

We describe all of the recent semi-supervised classification approaches with results on ImageNet in 1

2.2. Mixing regularization

Recent works have demonstrated that blending pairs of images and corresponding ground truths can act as an effective regularizer. MixUp (Zhang et al., 2018) draws a blending factor from the Beta distribution that is used to interpolate images and ground truth labels. Interpolation Consistency Training (ICT) (Verma et al., 2019) extends this approach to work in a semi-supervised setting by combining it with the Mean Teacher model. The teacher network is used to predict class probabilities for a pair of images $A$ and $B$ and MixUp is used to blend the images and the teachers’ predictions. The predictions of the student for the blended image are encouraged to be as close as possible to the blended teacher predictions.

MixMatch (Berthelot et al., 2019b) guesses labels for unsupervised samples by sharpening the averaged predictions from multiple rounds of standard augmentation and blends images and corresponding labels (ground truth for supervised samples, guesses for unsupervised) using MixUp (Zhang et al., 2018). The blended images and corresponding guessed labels are used to compute consistency loss.

2.3. Rich augmentation

AutoAugment (Cubuk et al., 2019a) and RandAugment (Cubuk et al., 2019b) are rich augmentation schemes that combine a number of image operations provided by the Pillow library (Lundh et al.). AutoAugment learns an augmentation policy for a specific dataset using reinforcement learning, requiring a large amount of computation to do so. RandAugment on the other hand has two hyper-parameters that are chosen via grid search; the number of operations to apply and a magnitude.

Unsupervised data augmentation (UDA) (Xie et al., 2019) employs a combination of CutOut (DeVries & Taylor, 2017) and RandAugment (Cubuk et al., 2019b) in a semi-supervised setting achieving state-of-the-art results in small image benchmarks such as CIFAR-10. Their approach encourages consistency between the predictions for the original un-modified image and the same image with RandAugment applied.

ReMixMatch (Berthelot et al., 2019a) builds on MixMatch by adding distribution alignment and rich data augmentation using CTAugment or RandAugment (depending on the dataset). CTAugment is a variant of AutoAugment that learns an augmentation policy during training, and RandAugment is a pre-defined set of 15 forms of augmentations with concrete scales. It is worth noting that ReMixMatch uses predictions from standard ‘weak’ augmentation as guessed target probabilities for unsupervised samples and encourages predictions arising from multiple applications of the richer CTAugment to be close to the guessed target probabilities. The authors found that using rich augmentation for guessing target probabilities (a la MixMatch) resulted in unstable training.

FixMatch (Sohn et al., 2020) is a simple semi-supervised learning approach that uses standard ‘weak’ augmentation to predict pseudo-labels for unsupervised samples. The same
samples are richly augmented using CTAugment and cross-entropy loss is computed using the pseudo-labels. Confidence thresholding (French et al., 2018) masks the unsupervised cross-entropy loss to zero for samples whose predicted confidence is below 95%.

2.4. Mask-based regularization

Erasing a rectangular region of an image by replacing it with zeros (DeVries & Taylor, 2017) or noise (Zhong et al., 2020) has proved to be an effective augmentation strategy that yields improvements in supervised image classification.

CutOut was found to act as an effective augmentation strategy for semi-supervised classification. The UDA authors (Xie et al., 2019) report impressive results, while the FixMatch authors (Sohn et al., 2020) report that CutOut alone is as effective as the combination of the other 14 image operations used in CTAugment.

CutMix (Yun et al., 2019) replaces the blending factor in MixUp with a rectangular mask and uses it to mix pairs of images, effectively cutting and pasting a rectangle from one image onto another. This yielded significant supervised classification performance gains.

CowMask is an alternative masking strategy that was successfully used by French et al. (2019) as part of a consistency regularization based semi-supervised semantic segmentation algorithm. In this paper we explore using CowMask for semi-supervised classification, and we briefly review CowMask in the next section.

They observed that semi-supervised semantic segmentation is particularly challenging as the data distribution does not exhibit low-density regions between classes. As a consequence the cluster assumption – identified in prior work (Miyato et al., 2017; Luo et al., 2018; Sajjadi et al., 2016a; Shu et al., 2018; Verma et al., 2019) as key to the success of consistency regularization based semi-supervised learning – does not apply. Concretely, two patches centred on immediately neighbouring pixels will have L2 pixel distances that exhibit little relation to whether the classes of the central pixels differ or not. Given that semantic segmentation models can be views as classifying the central pixels of sliding window patches, this implies that the data distribution cannot provide a useful training signal.

3. CowMask

CowMask (French et al., 2019) – so called due to the Friesian cow-like appearance of the masks as shown in Figure 1 – is a recently proposed mask generation strategy for generating flexibly shaped masks that was successfully used for semi-supervised semantic segmentation. We note that the concurrent work FMix (Harris et al., 2020) uses an inverse Fourier transform to generate masks with a similar
Algorithm 1 CowMask generation algorithm

Require: mask size $H \times W$

Require: scale range $(\sigma_{\min}, \sigma_{\max})$

Require: proportion range $(p_{\min}, p_{\max})$

Require: inverse error function $\text{erf}^{-1}$

\[
\sigma \sim \log U(\sigma_{\min}, \sigma_{\max}) \quad \{\text{Randomly choose sigma}\} \\
p \sim U(p_{\min}, p_{\max}) \quad \{\text{Randomly choose proportion}\} \\
\mathbf{x} \sim \mathcal{N}^{H \times W}(0, 1) \quad \{\text{Per-pixel Gaussian noise}\} \\
x_s = \text{gaussian\_filter\_2d}(\mathbf{x}, \sigma) \quad \{\text{Filter noise}\} \\
m = \text{mean}(x_s) \quad \{\text{Compute mean and std-dev}\} \\
s = \text{std\_dev}(x_s) \\
\tau = m + \frac{\sqrt{2}}{\tau} \cdot \text{erf}^{-1}(2p - 1) \cdot s \quad \{\text{Compute threshold } \tau\} \\
c = x_s > \tau \quad \{\text{Threshold filtered noise}\}
\]

Return $c$

Here, we explore using CowMask for semi-supervised classification. We discuss our approach in the next section.

4. Semi-Supervised Learning Method

Our proposed approach to semi-supervised learning consists in perturbing input images with the CowMask perturbation described in the previous section, and then applying a consistency loss to model predictions made on the perturbed images. We discussed the origin of this type of semi-supervised learning in Section 2.1.

Here, we study two different types of semi-supervised consistency regularization based on CowMask: mask-based erasure and mask-based mixing. In mask-based erasure we perturb our input data by erasing the part of the input image corresponding to a randomly sampled mask. In mask-based mixing we blend two input images together, with the blending weights given by the sampled mask. We show that CowMask is effective for both approaches. We follow French et al. (2019) when we use the term CowOut to refer to CowMask used for erasure and CowMix when used for mixing.

For both approaches, our training set consists of a set of supervised samples $S$ consisting of input images $s$ and corresponding target labels $t$, and a set of unsupervised samples $U$ consisting only of input images $u$. Given a labelled dataset we select the supervised subset randomly such that it maintains the class balance of the overall dataset¹ as is standard practice in the literature. All available samples are used as unsupervised samples. Our models $f_\theta$ are then trained to minimize a combined loss

\[L(\theta) = L_{\text{supervised}}(f_\theta(s), t) + \omega L_{\text{unsupervised}}(f_\theta(u)),\]

where we compute the unsupervised loss $L_{\text{unsupervised}}(f_\theta(u))$ using either Algorithm 2 or Algorithm 3, as further explained in the next sections.

4.1. Mask-based augmentation by erasure

When using masks to erase part of an image as an augmentation strategy we adopt the Mean Teacher (Tarvainen & Valpola, 2017) framework that uses two networks; the student $f_\theta(\cdot)$ and the teacher $g_\phi(\cdot)$, both of which generate class probability vectors. The student is trained by gradient descent as normal, while the weights of the teacher are an exponential moving average of those of the student. After every update to the student we update the teacher network using $\phi' = \phi + (1 - \alpha)\theta$, where $\theta$ is the parameters of the student and $\phi$ is the parameters of the teacher. The EMA momentum $\alpha$ controls the trade-off between the stability and the speed at which the teacher follows the student. Our approach is illustrated in Figure 2.

Prior work (Xie et al., 2019; Berthelot et al., 2019a; Sohn et al., 2020) used ‘weak’ standard augmentation schemes (e.g. crop and flip) for generating pseudo-targets that predictions resulting from the ‘strong’ augmentation schemes such as RandAugment should be encouraged to match. Using ‘strong’ augmentation to generate pseudo-targets too resulted in unstable training. Similarly, we found that mask erasure results in unstable training when applied to images passed to the teacher network for generating pseudo-targets. Therefore only standard augmentation is applied to images for the teacher network while the stronger masking augmentation is applied to the images passed to the student network.

¹ We use StratifiedShuffleSplit from Scikit-Learn (Buitinck et al., 2013)
4.1. CONFIDENCE THRESHOLDING

The τ-model (Laine & Aila, 2017) and the Mean Teacher model (Tarvainen & Valpola, 2017) both use a Gaussian ramp-up function to modulate the effect of consistency loss during the early stages of training. Reinforcing the random predictions of an untrained network was found to harm performance. In place of a ramp-up we opt to use confidence thresholding (French et al., 2018). Consistency loss is masked to zero for samples for which the teacher networks’ predictions are below a specified threshold. FixMatch (Sohn et al., 2020) uses confidence thresholding for similar reasons.

4.1.2. ALGORITHM

Our procedure for computing unsupervised consistency loss based on erasure is provided in Algorithm 2. During training we minimize the sum of standard cross-entropy loss for supervised samples and the unsupervised consistency loss, multiplied by consistency loss weight factor. For our small image experiments we found that the best value for this weight factor is 1.

Algorithm 2 CowOut erasure-based unsupervised loss

Require: unlabeled image \( x \), CowMask \( m \)

Require: teacher model \( f_{\text{teacher}} \) and student model \( f_{\text{student}} \)

Require: confidence threshold \( \psi \)

\( \hat{x} = \text{std}_\text{aug}(x) \) \{ standard augmentation \}

\( z = \text{stop}_\text{gradient}(f_{\text{teacher}}(\hat{x})) \) \{ teacher prediction \}

\( q = \max_i z[i] \geq \psi \) \{ confidence mask \}

\( \epsilon \sim N(0, I) \) \{ generate noise image \}

\( \hat{x}_m = \hat{x} \ast m + \epsilon \ast (1 - m) \) \{ apply mask \}

\( y_m = f_{\text{student}}(\hat{x}_m) \) \{ student prediction \}

\( d = q \ast ||y_m - z||^2 \) \{ confidence-masked cons. loss \}

Return \( d \)

4.2. Mask-based mixing

Alternatively, we can construct an unsupervised consistency loss by mask-based mixing of images in place of erasure. Our approach for mixing image pairs using masks is essentially that of interpolation consistency training (ICT) (Verma et al., 2019). ICT works by passing the original image pair to the teacher network, the blended image to the student, and encouraging the student networks’ prediction to match the blended teacher predictions. The blending factor used in ICT is a scalar sampled from a beta distribution that is used to blend both input images and teacher probability predictions. In contrast, we mix images using a mask, and mix probability predictions with the mean of that mask (the proportion of pixels with a value of 1). Our approach is illustrated in Figure 3.

Confidence thresholding required adaptation for use with mix-based regularization. Rather than applying confidence thresholding to the blended teacher probability predictions we opted to blend the confidence values before thresholding as this gave slightly better results. Further improvements resulted from modulating the consistency loss by the proportion of samples in the batch whose predictions cross the confidence threshold, rather masking the loss for each sample individually.

4.2.1. ALGORITHM

The procedure for computing unsupervised mix consistency loss is provided in Algorithm 3. As before, we minimize the sum of supervised cross-entropy loss and the mix consistency loss multiplied by a mix loss weight factor. We found that a higher weighting was appropriate for mix consistency; we used a value of 30 for our small image experiments.
We also obtained better results by computing separate batch statistics for all samples at once. We hypothesize that masking out regions of an image or mixing images changes the statistics of the feature representations within the network. As a consequence keeping original images, ‘erased’ images or mixed images in separate sub-batches results in batch statistics that are more representative of the samples being processed.

5. Experiments and results

We first evaluate CowMix for semi-supervised consistency regularization on the challenging ImageNet dataset, where we match the state of the art. Next, we examine CowMix and CowMask further and compare with previously proposed methods by trying multiple versions of our approach combined with multiple models on three small image datasets: CIFAR-10, CIFAR-100 and SVHN.

Our results are obtained by using the teacher network for evaluation. We report our results as error rates presented as the mean ± 1 standard deviation computed from the results of 5 runs, each of which uses a different subset of samples as the supervised set. Supervised sets are consistent for all experiments for a given dataset and number of supervised samples.

Our Python implementation uses Flax, a neural network library for Jax (Bradbury et al., 2018). It is open source and available at https://github.com/google-research/google-research/tree/master/milking_cowmask.
5.1. ImageNet 2012

We contrast the following scenarios: supervised training with 10% supervised examples only, semi-supervised training with 10% labelled examples and using CowMix consistency regularization on all unlabeled examples, and fully supervised training with all 100% labels. The training regimes used for both ImageNet and the small image datasets are sufficiently similar that we used the same codebase for all of our experiments.

5.1.1. Setup

We used the ResNet-152 architecture. We adopted a training regime as similar as possible to a standard ImageNet ResNet training protocol. We used SGD with Nesterov Momentum (Sutskever et al., 2013) with momentum set to 0.9 and weight decay (via L2 regularization) set to 0.00025. Our standard augmentation scheme consists of inception crop, random horizontal flip and colour jitter. We used a batch size of 1024. As in (Tarvainen & Valpola, 2017) we found that the standard learning rate of 0.1 resulted in unstable training. We stabilised training by reducing the learning rate to 0.04. We found that our semi-supervised learning approach benefits from training for longer than in supervised settings, so we doubled the number of training epochs to 180 and stretched the learning rate schedule by a factor of 2, reducing the learning rate at epochs 60, 120 and 160 and reduced it by a factor of 0.2 rather than 0.1. We used a teacher EMA momentum \( \alpha \) of 0.999.

We obtained our CowMix results using a mix loss weight of 100 and and a confidence threshold of 0.5. We drew the CowMask \( \sigma \) scale parameter from the range \((32, 128)\).

5.1.2. Results

Our ImageNet results are presented in Table 2. We match the state of the art \( S^3 L \) MOAM (Zhai et al., 2019) top-5 error result and beat their top-1 error result. By comparison the \( S^3 L \) MOAM result is obtained using a 3-stage training and fine-tuning procedure, whereas our approach trains in a single run using a comparatively simple approach.

| Approach      | Architecture | Top-5 err. | Top-1 err. |
|---------------|--------------|------------|------------|
| Our baselines |              |            |            |
| Sup 10%       | ResNet-152   | 22.12%     | 42.91%     |
| Sup 100%      | ResNet-152   | 5.67%      | 21.33%     |
| Other work    |              |            |            |
| MT            | ResNeXt-152  | 9.11% ± 0.12 | –         |
| UDA           | ResNet-50    | 11.2%      | 31.22%     |
| FixMatch      | ResNet-50    | 10.87 ± 0.28% | 28.54 ± 0.52% |
| \( S^3 L \) Full | ResNet-50 | \( 8.77\% \) | 26.79%     |
| (MOAM)        | (width \( \times 4 \)) |            |            |

\[ \text{Table 2. Results on ImageNet with 10\% labels. } \]

5.2. Small image experiments

Alongside CowOut and CowMix we implemented and evaluated Mean Teacher, Interpolation Consistency Training (ICT), CutOut/RandErase and CutMix, and we compare our method against these on small image datasets CIFAR-10, CIFAR-100, and SVHN.

We note the following differences between our implementation and those of CutOut and CutMix: 1. Our boxes are chosen so that they entirely fit within the bounds of the mask, whereas CutOut and CutMix use a fixed or random size respectively and centre the box anywhere within the mask, with some of the box potentially being outside the bounds of the mask. 2. CutOut uses a fixed size box, CutMix randomly chooses an area but constrains the aspect ratio to be that of the mask, we choose both randomly.

5.2.1. Setup

For the small image experiments we use a 27M parameter Wide ResNet 26-96x2d with shake-shake regularization (Gastaldi, 2017). We note that as a result of a mistake in our implementation we used a \( 3 \times 3 \) convolution rather than a \( 1 \times 1 \) in the residual shortcut connections that either downsample or change filter counts, resulting in a slightly higher parameter count.

The standard Wide ResNet training regime (Zagoruyko & Komodakis, 2016) is very similar to that used for ImageNet. We used the same SGD with momentum optimizer, set weight decay to 0.0005 and used a batch size of 256. As before, the standard learning rate of 0.1 had to be reduced to ensure stability, this time to 0.05. The small image experiments also benefit from training for longer; 300 epochs instead of the standard 200 used in supervised settings. The adaptations made to the Wide ResNet learning rate schedule were nearly identical to those made to the ImageNet schedule. We doubled its length and reduced the learning rate by a factor of 0.2 rather than 0.1. We did however remove the last step; the learning rate is reduced at epochs 120 and 240 rather than epochs 60, 120 and 160 as used in supervised settings. For erasure experiments we used a teacher EMA momentum \( \alpha \) of 0.99 and for mixing experiments we used 0.97.

When using CowOut and CowMix we obtained the best results when the CowMask scale parameter \( \sigma \) is drawn from the range \((4, 16)\). We note that this corresponds to a range of \((\frac{1}{3}, \frac{1}{2})\) relative to the \(32 \times 32\) image size and that the \( \sigma \) range used in our ImageNet experiments bears a nearly identical relationship to the \(224 \times 224\) image size used there.
For erasure experiments using CowOut we obtained the best results when drawing $p$, the proportion of pixels that are retained from the range $(0.25, 1)$. Intuitively it makes sense to retain at least 25% of the image pixels as encouraging the network to predict the same result for an image and a blank space is unlikely to be useful. For mixing experiments using CowMix we obtained the best results when drawing $p$ from the range $(0.2, 0.8)$.

We performed hyper-parameter tuning on the CIFAR-10 dataset using 1,000 supervised samples and evaluating on 5,000 training samples held out as a validation set. The best hyper-parameters found were used as-is for CIFAR-100 and SVHN.

5.2.2. Results

Our results for CIFAR-10, SVHN, and CIFAR-100 datasets are presented in Tables 3, 4, and the supplementary material respectively. Considering the the techniques we explore we find that mix-based regularization outperforms erasure based regularization, irrespective of the mask generation method used.

We would like to note that our 27M parameter model is larger than the 1.5M parameter models used for the majority of results in other works, so we cannot make an apples-to-apples comparison in these cases. Our CIFAR-10 results are competitive with recent work, except in small data regimes of less than 500 samples where EnAET (Wang et al., 2019) and FixMatch (Sohn et al., 2020) outperform CowMix. Our CIFAR-100 and SVHN results are competitive with recent approaches but are not state of the art. We note that we did not tune our hyper-parameters for these datasets.

6. Conclusions

We evaluated the CowMask perturbation for use in semi-supervised consistency regularization, achieving a new state of the art on semi-supervised ImageNet, with a much simpler method than in previously proposed approaches. We examined both erasure-based and mixing-based perturbations using CowMask, and find that the mixing-based perturbation, which we call CowMix, is particularly effective for semi-supervised learning. Further experiments on small image data sets SVHN, CIFAR-10, and CIFAR-100 demonstrate that CowMask is universally useful.

Research on semi-supervised learning is moving fast, and many new approaches have been proposed over the last year alone that use mask-based perturbation. In future work we would like to further explore the use of CowMask in combination with these other recently proposed methods.

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Table 3. Results on CIFAR-10 test set, error rates as mean ± std − dev of 5 independent runs.

| Labeled samples | 50 | 100 | 250 | 500 | 1000 | 2000 | 4000 | ALL |
|-----------------|----|-----|-----|-----|------|------|------|-----|
| Other work: uses smaller Wide ResNet 26-2 model with 1.5M parameters |
| EnAE T           | 16.45% | 9.35% | 7.6% ± 0.04 | 7.27% | 6.95% | 6.0% | 5.35% |
| UDA             | 8.76% ± 0.90 | 6.68% ± 0.24 | 5.87% ± 0.13 | 5.51% ± 0.21 | 5.29% ± 0.25 |
| MixMatch        | 11.08% ± 0.87 | 9.65% ± 0.97 | 7.75% ± 0.52 | 7.03% ± 0.15 | 6.24% ± 0.06 |
| ReMixMatch      | 6.27% ± 0.34 | 5.73% ± 0.16 | 5.14% ± 0.04 | 4.26% ± 0.05 |
| FixMatch (RA)   | 5.07% ± 0.68 | 4.26% ± 0.05 | 3.95% ± 0.76 | 3.72% ± 0.60 | 3.13% ± 0.11 | 2.90% ± 0.19 | 2.18% ± 0.06 |

Our results: uses 27M parameter Wide ResNet 26-96x2d with shake-shake

| Labeled samples | 100 | 250 | 500 | 1000 | 2000 | 4000 | ALL |
|-----------------|-----|-----|-----|------|------|------|-----|
| Other work: uses smaller Wide ResNet 26-2 model with 1.5M parameters |
| EnAE T           | 16.92% | 3.21% ± 0.21 | 3.05% | 2.92% | 2.84% | 2.69% |
| UDA             | 2.55% ± 0.99 | 3.78% ± 0.26 | 3.64% ± 0.46 | 3.27% ± 0.31 | 3.04% ± 0.13 | 2.89% ± 0.06 |
| MixMatch        | 3.10% ± 0.50 | 2.83% ± 0.30 | 2.48% ± 0.38 | 2.28% ± 0.11 | 2.42% ± 0.09 |
| ReMixMatch      | 2.48% ± 0.11 | 2.48% ± 0.38 | 3.05% ± 0.46 | 3.27% ± 0.31 | 3.04% ± 0.13 | 2.89% ± 0.06 |
| FixMatch (RA)   | 2.48% ± 0.11 | 2.48% ± 0.38 | 3.05% ± 0.46 | 3.27% ± 0.31 | 3.04% ± 0.13 | 2.89% ± 0.06 |

Table 4. Results on SVHN test set, error rates as mean ± stdev of 5 independent runs.

| Labeled samples | 100 | 250 | 500 | 1000 | 2000 | 4000 | ALL |
|-----------------|-----|-----|-----|------|------|------|-----|
| Other work: uses smaller Wide ResNet 26-2 model with 1.5M parameters |
| EnAE T           | 71.24% ± 5.40 | 37.02% ± 6.15 | 18.85% ± 1.49 | 11.71% ± 0.55 | 8.23% ± 0.38 | 6.01% ± 0.46 | 2.82% ± 0.08 |
| UDA             | 62.16% ± 10.92 | 8.23% ± 4.62 | 3.84% ± 0.15 | 3.75% ± 0.10 | 3.61% ± 0.15 | 3.47% ± 0.12 | 2.73% ± 0.04 |
| MixMatch        | 52.55% ± 7.03 | 7.61% ± 1.71 | 6.17% ± 1.25 | 4.81% ± 0.46 | 3.66% ± 0.15 | 3.21% ± 0.22 | 2.36% ± 0.04 |
| ReMixMatch      | 66.66% ± 19.71 | 12.11% ± 1.82 | 5.94% ± 0.38 | 4.36% ± 0.29 | 3.59% ± 0.25 | 3.04% ± 0.04 | 2.42% ± 0.09 |
| FixMatch (RA)   | 9.54% ± 2.53 | 9.73% ± 4.01 | 3.59% ± 0.30 | 3.80% ± 0.60 | 3.72% ± 0.60 | 3.13% ± 0.11 | 2.90% ± 0.19 | 2.18% ± 0.06 |

Our results: uses 27M parameter Wide ResNet 26-96x2d with shake-shake
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