Curriculum Labeling: Self-paced Pseudo-Labeling for Semi-Supervised Learning

Paola Cascante-Bonilla  Fuwen Tan  Yanjun Qi  Vicente Ordonez
University of Virginia
{pc9za, fuwen.tan, yq2h, vicente}@virginia.edu

Abstract

Semi-supervised learning aims to take advantage of a large amount of unlabeled data to improve the accuracy of a model that only has access to a small number of labeled examples. We propose curriculum labeling, an approach that exploits pseudo-labeling for propagating labels to unlabeled samples in an iterative and self-paced fashion. This approach is surprisingly simple and effective and surpasses or is comparable with the best methods proposed in the recent literature across all the standard benchmarks for image classification. Notably, we obtain 94.91% accuracy on CIFAR-10 using only 4,000 labeled samples, and 88.56% top-5 accuracy on Imagenet-ILSVRC using 128,000 labeled samples. In contrast to prior works, our approach shows improvements even in a more realistic scenario that leverages out-of-distribution unlabeled data samples.

1. Introduction

Access to annotated examples has been critical in achieving significant improvements in diverse computer vision tasks [19, 49]. However, annotated data is typically limited or expensive to obtain. Semi-supervised learning (SSL) methods offer to leverage unlabeled samples in addition to labeled examples to obtain gains in performance. Recent SSL methods for image classification have achieved remarkable results on standard benchmarks for image classification. Notably, we obtain 94.91% accuracy on CIFAR-10 using only 4,000 labeled samples, and 88.56% top-5 accuracy on Imagenet-ILSVRC using 128,000 labeled samples. In contrast to prior works, our approach shows improvements even in a more realistic scenario that leverages out-of-distribution unlabeled data samples.

When training a classifier, a common assumption is that the decision boundary should lie in low-density regions in order to improve generalization [8]; therefore unlabeled samples that lie either near or far from labeled samples should be informative to estimate a decision boundary. Pseudo-labeling generally works by iteratively propagating labels from labeled samples to unlabeled samples using the current model to re-label the data [43, 16, 1, 7]. Typically, a classifier is first trained with a small amount of labeled data and then it is used to estimate the labels for all the unlabeled data, high confident predictions above some threshold are then added as training samples for the next iteration. This procedure repeats for a specific number of iterations or until the classifier cannot find more confident predictions on the unlabeled data-points. However, the success of pseudo-labeling depends on subtle choices such as the threshold or criteria used for adding training samples across iterations.

We borrow ideas from curriculum learning and propose curriculum labeling (CL) where the model first adds unlabeled samples that are easy to label and progressively moves toward hard samples. Prior work has shown that training with a curriculum improves the learning process and performance in several machine learning tasks [3, 18]. The main challenge in designing a curriculum is how to control the pace – going over the easy examples too fast may lead to more confusion than benefit while moving too slowly may lead to unproductive learning. We design a self-pacing strategy by analyzing the distribution of the confidence scores for the predictions on unlabeled samples and applying a criterion based on Extreme Value Theory (EVT) [11]. We empirically demonstrate that curriculum labeling can achieve state-of-the-art results matching the recently proposed UDA [53] on Imagenet and surpassing ICT [51] on CIFAR-10.

Current SSL benchmarks set aside a small part of the training data from regular image classification benchmarks as “labeled” and a large portion of the same training data split as “unlabeled”. This way of splitting the data leads to a scenario where all images in the unlabeled set have the implicit underlying guarantee to also belong to one of
the target classes of the image classifier [35]. As a result, current SSL methods relied heavily on the assumption that unlabeled samples are drawn from the same distribution as the labeled samples. This assumption was challenged and recognized as unrealistic by Oliver et al [35]. On the other hand, our curriculum labeling (CL) is surprisingly robust to out-of-distribution samples in the unlabeled set because it is not committed to using all the unlabeled samples on each round, so it is likely to discard samples that are out-of-distribution, especially during the crucial first few rounds.

We show in Figure 1 how curriculum labeling works on the synthetic two-moon dataset as it progressively labels the unlabeled data is progressively labeled, propagating labels from the most confident to the least confident samples.

Our contributions can be summarized as follows:

- We propose curriculum labeling (CL) which is based on a combination of pseudo-labeling and a careful curriculum choice of pacing criteria based on Extreme Value Theory (EVT).

- We demonstrate that this approach can deliver state-of-the-art results on the standard CIFAR-10 dataset, and near state-of-the-art results on Imagenet ILSVRC and SVHN – compared to very recently proposed methods.

- We show how to effectively apply curriculum-labeling and run ablation studies analyzing its success. Moreover, we demonstrate that curriculum labeling (CL) leads to more consistent results in realistic evaluation settings as proposed by [35].

Our paper is organized as follows, we first introduce our curriculum labeling method and justify its self-pacing criteria (section 2), we then present connections to prior methods proposed for this problem (section 3), then we provide empirical evaluation of our work on standard benchmarks and detailed analysis of our method under various conditions (section 4), and finally we provide concluding remarks (section 5).

2. Our Method: Curriculum Labeling

In general, the goal of semi-supervised learning (SSL) is to achieve generalization by using unlabeled data. In this paper we tackle SSL in the multi-class classification setting where a dataset of training samples $D = \{x| x \in X\}$ is provided for which ground truth labels $Y$ are available only for a subset of samples $D_L = \{(x, y)| x \in X, y \in Y\}$ where $|D_L| \ll |D|$. Besides, a collection of unlabeled data points $D_{UL} = \{x| x \in X\}$ are given, and the goal is to use the predictions of $D_{UL}$ to augment the labeled set and find a better classifier.

Pseudo-Labeling Our approach builds upon the general idea of self-training [31], where a model goes through multiple rounds of training. At each round, the model uses the predictions from the previous round of training to re-label unlabeled samples. The method starts using only the fully labeled subset $D_L$ in the first round. In the last round, the model uses the entire training data ($D_L$ along with $D_{UL}$) and their corresponding predictions (pseudo-labels). Pseudo-labeling is a more recent self-training algorithm focusing on image classification. Pseudo-labeling trains using the labeled data simultaneously with all the unlabeled data. The corresponding predictions on unlabeled samples are also referred to as pseudo-labels [27]. In our case, we do not take into account all the unlabeled samples on each round, but instead propose a self-pacing curriculum based on EVT to gradually select a subset of unlabeled samples and their corresponding pseudo-labels.

We denote the training samples and the model in round $t$ as $(X_t, Y_t)$ and $P^t_\theta$. Here $t \in \{1, \cdots, T\}$. $\theta$ indicates the trainable parameters. $(X_1, Y_1)$ includes the labeled examples. After round $t$, unlabeled subset $X_t$ satisfying a predefined criterion is added into $X_{t+1} := X_t \cup \hat{X}_t$, and the new target set is defined as $Y_{t+1} := Y_t \cup \hat{Y}_t$. Here $\hat{Y}_t$ represents the pseudo labels of $\hat{X}_t$, predicted by model $P^t_\theta$.

In this sense, the labels are “propagated” to the unlabeled data points via $P^t_\theta$ at each round $t$. Note that, the unlabeled subset $\hat{X}_t$ is selected from the whole unlabeled set $D_{UL}$.
We can define the largest element observed in a cumulative distribution function $F$ as the Percentile $\text{Percentile} = \text{percentile of its highest confidence score over all categories}$. We prioritize data points to align well with the distribution learned by the model $P_\theta$.

**Extreme Value Theory (EVT)** is a statistical tool used to simulate extreme events in the tails of one-dimensional probability distributions [2] [10] [45], by assessing the probability of events that are more extreme. In practice, EVT is generally used when the observed data exhibits a long-tail distribution and the values at the extremes do not contain significant information [6] [39]. EVT has been used for novelty detection, where a large amount of data may be classified as normal or abnormal and a multi-class solution cannot be taken due to the nature of the data [11]: or in open set recognition, where there is no prior knowledge of all the possible classes of a set [24] [42]. Empirically, for this type of statistical distributions, the highly important events highly likely occur within the first 20% of items in the distribution. In our case, the distribution of the maximum probability predictions from all the unlabeled data (after the first iteration) follows this type of distribution, which is also called Pareto distribution. More formally speaking, EVT considers a set $X$ with $n$ independent and identically distributed random samples $X = \{x_1, x_2, ..., x_n\}$ drawn from a cumulative distribution function $F(x)$, and we can define the largest element observed in $X$ to be $x_{\text{max}} = \text{Percentile}(X, \mu_t)$. Relating to this paper’s setting, $X$ is the set of highest predictions for each unlabeled sample, and $\mu_t$ refers to the moving threshold. Once $x_{\text{max}}$ is set, we define the new distribution function for the extreme values to be $F_{\text{max}}(x) = F(x > x_{\text{max}})$. This setting allows us to follow the Pareto principle or principle of factor sparsity, which models events that are not equally distributed and states that 80% of the effects come from 20% of the causes (80/20 rule). We extend this idea to select the top confident predictions on the unlabeled data to obtain a significant improvement.

Our SSL algorithm needs to decide how many and which samples to incorporate into the training at each round. We choose to incorporate an unlabeled data point based on the percentile of its highest confidence score over all categories: $s_x = \max(P_\theta^t(x)), \bar{X}_t = \{x | s_x > \text{Percentile}(s_x, \mu_t)\}$. Here $\mu_t$ is a predefined percentile threshold for each step, and $\text{Percentile}$ is a function that computes the value below in which the $\mu_t$-th of the predictions may be found. In all our experiments we train the models for five rounds $(T = 5)$, and use the same set of percentile thresholds: $\mu_1 = 80\%, \mu_2 = 60\%, \mu_3 = 40\%, \mu_4 = 20\%, \mu_5 = 0\%$. Algorithm 1 shows the full pipeline of our model. The process ends when all the unlabeled set is pseudo-labeled and is used along with the labeled datapoints to train the final classifier $P_\theta^T(x)$.

### Algorithm 1 Our Method: Curriculum Labeling

1. **Require:** $D_L(x, y)$ \text{ set of labeled samples}
2. **Require:** $D_{UL}(x)$ \text{ set of unlabeled samples}
3. **Require:** $ST$ \text{ stepping threshold percent}
4. $t := 1$
5. $Tr := 100 - ST$
6. $P_\theta^t \leftarrow$ train classifier using $D_L(x, y)$ only
7. **while** $\text{True}$ **do**
8. $K := D_{UL}(x)$
9. $T := \text{Percentile}(max P(K), Tr)$
10. **for** $x \in K$ **do**
11. \hspace{1em} if $\text{max} P(x) > T$ **then**
12. \hspace{2em} $K := D_L \cup (x, p(x))$
13. \hspace{1em} $P_\theta^t \leftarrow$ train classifier using $K$
14. \hspace{1em} if $|K| = |D_L + D_{UL}|$ **then**
15. \hspace{2em} break
16. $t := t + 1$
17. $Tr := 100 - (ST \ast t)$
18. \textbf{end}

### 2.1. Self-Pacing Curriculum

The core idea of curriculum learning is to start with easier examples and gradually increase to more difficult examples. The motivation behind this idea comes from the observation that humans seem to learn better from a structured scheme, where the order of difficulty matters. In [4] the authors point out that difficult samples may confuse the model rather than help it establish the decision boundary. Easier samples can be inferred from the margin of the separating hyper-plane, where the closer to the boundary are also the more confident. Even though we do not train our model in a curriculum fashion, we use our model to annotate the data in a curriculum fashion: by first annotating the easiest samples and gradually increasing the annotated data with more difficult samples.

To do so, the model is first trained using only the labeled data. Then we get the probability distribution of the highest predictions for each unlabeled sample. We do so by obtaining the value at the the 80th percentile of the distribution...
allows the search space to be trained on the target task. We without a separate search phase on a proxy task, and instead mention [13], a technique that seeks data augmentation policies samples [56]. In [53], the authors take advantage of RandAug- plements [32], or by interpolating a random pair of image sam-


tates perturbations that take the form of adversarial exam-


dition techniques such as cropping, padding, whitening and horizontal flipping [38, 26, 50]. More recent work relies on heavy data augmentation policies that are learned au-


matically by using Reinforcement Learning [12] or den-


terial by using the new set, we reduce our threshold by obtaining the 60th percentile of the new probability distribution of the highest predictions for each unlabeled sample. We continue this process by decreasing the previous selected percentile by 20%. In this way, we take into account all the unlabeled data after 5 iterations.

We found that if we use a very large threshold on our first iteration, it is likely that most of the unlabeled set would be used on the next iterations, but since the network is fed with a huge amount of incorrect pseudo-labels, the incoming noise from those samples will be amplified and propagated. On the other hand, if we specify a more restrictive threshold, a small amount of high confident but less informative pseudo-annotations of the unlabeled set would be used. As a result, the model will suffer to generalize and will not achieve a significant progress on the next iterations.

Thus, when the model reaches the final iteration, it will be exposed to the most difficult samples. We found that our choice of thresholds as described in this section works well in all these scenarios. Figure 2 shows the data distribution of the maximum probability predictions of all the unlabeled data after the model is trained using only the available labeled data. Both show long-tailed distributions.

and use it as our initial threshold. After the model is trained using the new set, we reduce our threshold by obtaining the 60th percentile of the new probability distribution of the highest predictions for each unlabeled sample. We continue this process by decreasing the previous selected percentile by 20%. In this way, we take into account all the unlabeled data after 5 iterations.

2.2. Data Augmentation

Data augmentation has shown to be extremely efficient in order to improve image classification methods [47, 36, 46] [15]. Previous work on SSL only use basic augmentation techniques such as cropping, padding, whitening and horizontal flipping [38, 26, 50]. More recent work relies on heavy data augmentation policies that are learned automatically by using Reinforcement Learning [12] or density matching [28]. Other augmentation techniques generates perturbations that take the form of adversarial examples [22], or by interpolating a random pair of image samples [56]. In [53], the authors take advantage of RandAug ment [13], a technique that seeks data augmentation policies without a separate search phase on a proxy task, and instead allows the search space to be trained on the target task. We explore both moderate and heavy data augmentation tech-

niques that do not require to learn or search any policy, but instead apply transformations in an entirely random fashion. We show that using arbitrary transformations on the training set yields positive results. We refer to this technique as Random Augmentation (RA) in our experiments.

3. Connections to Prior Work

Our work is most closely related to the pseudo-labeling approach [27] which was proposed before for semi-supervised learning but has been shown to be surpassed by most recent methods. We argue that this is not a fundamental flaw of self-training algorithms but demonstrate that careful selection of thresholds and pacing of the pseudo-labeling of the unlabeled samples can lead to state-of-the-art accuracy. Another difference lies on the fact that this prior pseudo-labeling approach [27] relied on a combination of labeled and unlabeled samples on each batch, and seemed to over-emphasize the importance of labeled samples over the much larger set of unlabeled samples. In our curriculum labeling method, we do not insist on balancing the amount of labeled and pseudo-labeled samples on each batch but treat all samples equally after the first round. We explore more deeply connections to these methods and other types of methods in the following subsections.

3.1. Entropy Regularization

Pseudo-labeling has been previously analyzed as an equivalent to Entropy Regularization [34, 27]. The conditional entropy of the class probabilities can be used for a measure of class overlap: by minimizing the entropy for unlabeled data, the overlap of class probability distribution can be reduced. This regularization scheme aids the low density separation by minimizing the conditional entropy of class probabilities when dealing with unlabeled data [27, 17].

Following this idea, in the work of [27] the authors propose a method that selects the class which has the maximum predicted probability every weights update for each unlabeled sample. By doing this, they avoid to re-train the model for a specific number of iterations. As their implementation always takes into account the maximum predicted probability, they incorporate a balance coefficient into the overall loss function to alleviate the discrepancy between the number of labeled and unlabeled data. However, this setting is prone to add a significant amount of noisy data-points to the labeled set, biasing the classification of unlabeled data to incorrect classes, making the algorithm unable to correct its own mistakes in the next updates. If the algorithm’s predictions on unlabelled data are confident but wrong, the erroneous data is incorporated into the training process and the errors will be amplified.
3.2. Consistency Regularization

Consistency regularization is another well known technique, where a network is trained to make consistent predictions in response to perturbation of unlabeled samples, by combining the standard cross-entropy loss with a consistency loss term. The idea is to minimize the distance between the prediction function’s outputs, leveraging the unlabeled data for a classifier to effectively separate each class cluster, by forcing the samples to be all close together. Formally, the loss function measures the distance between the predictions resulting from an unsupervised sample and a perturbed version of the same sample.

Data augmentation is a common consistency regularization technique, which applies input transformations to the data and leverages the idea that a classifier should output the same class distribution for an unlabeled example even after it has been augmented. In [5], the authors exploit the consistency regularization approach by passing each unlabeled sample through a classifier using stochastic augmentation, dropout and Gaussian noise. Their temporal model maintains a per-sample moving average of historical predictions and encourages subsequent predictions to be consistent with the average. Following this idea, [50] encourages consistency between predictions from two neural networks: a student and a teacher network. The idea is to use a prediction function parametrized by an exponentially accumulated average of θ over training, the mean squared error is added as a regularization term with a weighting hyperparameter, and the weights of the teacher are an exponential moving average of those of the student.

In [32], the algorithm generates perturbations that take the form of adversarial examples, by maximizing the change in class prediction by computing the gradient of the prediction change with respect to the input image pixels. In [51] the idea is to interpolate a random pair of training samples (Mixup) [56]; [51] uses the mean teacher model [50] and applies MixUp to unsupervised samples, combining input images along with teacher class predictions to produce a blended input and target to train the student. On the other hand, [5] apply stochastic augments multiple times and averages the predictions to produce unsupervised targets. More recently, [53] enforce the predictions to be similar for an unlabeled example and the augmented unlabeled example, employing random data augmentations. By computing a consistency loss between the unlabeled example and its augmented counterpart, a final loss is minimized by jointly optimizing both the supervised loss from the labeled data and the unsupervised consistency loss from the unlabeled data. This allows the labeled information to propagate from labeled to unlabeled examples. In [57], the authors use the supervised performance on the labeled part as a lower bound and then perform knowledge distillation by ensuring that each training minibatch contains a mixture of manually labeled data and pseudo-labeled data. In [55] the authors unify self-supervised visual representation learning approaches with semi-supervised image classification methods and achieve state-of-the-art results on ImageNet (ILSVRC-2012) when using only 10% of the dataset as the labeled set.

3.3. Other related approaches

Active Learning (AL) is another case study, where the aim is to develop learning frameworks to build competitive image classifiers by incrementally selecting and annotating the most informative unlabeled samples. AL has been widely studied and applied to several vision, text classification, and retrieval tasks.

In [52], the authors propose a cost-effective AL framework, which is enabled to fine-tune the model by automatically selecting and pseudo-annotating unlabeled samples. They progressively feed the samples from the unlabeled dataset into the model, and select samples for fine-tuning according to the output of models classifiers. In [9] the authors integrate the active learning framework into the label spreading algorithm which is a graph-based SSL approach for better data selection. In [52] the authors use Generative Adversarial Networks to synthesize training instances for querying to increase the learning speed.

4. Experiments

Datasets: We evaluate our framework on three standard image classification datasets: CIFAR-10 [25], Street View House Numbers (SVHN) [33], and ImageNet ILSVRC [40] [14]. In each dataset we used small portions of the training set as the labeled images, leaving the rest unlabeled. We evaluate the performance on the independent test set.

With CIFAR-10 we use 4,000 labeled samples for training and validation, 46,000 unlabeled samples, and the 10,000 test samples to report our results. We also include results using 500 labeled samples, 1000 labeled samples and 2000 labeled samples in section 4.4. With SVHN we use 1,000 labeled samples, 71,257 unlabeled samples, 1,000 samples for validation (which is significantly lower than the conventional 7,325 samples generally used), and the 26,032 test samples to report our results. With ImageNet we use ~10% of the dataset as labeled samples (102,000 for training and 26,000 for validation), 1,253,167 unlabeled samples and the 50,000 test samples to report our results.

Implementation details: We test our framework using CNN-13 [43] and a Wide ResNet [54] with depth 28 and width 2 for CIFAR-10 and SVHN datasets, and ResNet-50 [20] for ImageNet. We use Stochastic Gradient Descent with nesterov momentum optimizer, L2 regularization of 0.0005, momentum factor of 0.9, and an initial learning rate of 0.1 which is then annealed using the cosine annealing technique [29] in all of our experiments. We did not...
run hyperparameter search, and kept the same configuration settings for all of our experiments, except for the batch size when using moderate and heavy data augmentation. We found that small batches (i.e. 64-100) work better for moderate data augmentation (random cropping, padding, whitening and horizontal flipping), but large batches (i.e. 512-1024) work better for heavy data augmentation. An analysis of this setting is discussed in section 4.5.

We run our experiments for 750 epochs and apply stochastic weight averaging (SWA) [22] from the 500th epoch every 5 epochs on each iteration using CIFAR-10 and SVHN. We report the mean and standard deviation across five independent runs. We use an Nvidia Titan X GPU and 12 CPU threads to report the performance on all of our experiments. For ImageNet we run the experiment for 220 epochs and apply stochastic weight averaging from the 100th epoch on each iteration. We randomly initialize the model on each iteration. We also report the results when the model is randomly initialized on each iteration and when it is fine-tuned (these results are shown in the supplementary material). Since the random initialization yield better results, we isolate each experiment on a virtual machine on Google Cloud and compare the time-cost against previous methods. We refer to time-cost efficiency and scalability in section 4.2.

4.1. Performance Comparison

Table 1 shows our results for CIFAR-10 and SVHN datasets using WideResNet architecture with depth 28 and width 2. We compare our method against previous and more recent consistency-enforcing approaches, along with the pseudo-labeling framework proposed in [27]. We show that our approach improves the test error by 6.95% on CIFAR-10 and matches the test error on SVHN when compared with all previous methods that rely on moderate augmentation [27, 26, 50]. For the methods that rely on moderate-to-high data augmentation [32, 23, 51, 5], and heavy data augmentation [53], our approach improves the test error by 0.02% when applying heavy random data augmentation and 0.2% when using the augmentation policy found in [28] (FA) on CIFAR-10.

| Method                  | CIFAR-10 $N_l = 4000$ | SVHN $N_l = 1000$ |
|-------------------------|-----------------------|--------------------|
| Supervised              | 20.26 ± 0.38          | 12.83 ± 0.47       |
| Pseudo-Label            | 17.78 ± 0.57          | 7.62 ± 0.29        |
| II Model [26]           | 16.37 ± 0.63          | 7.19 ± 0.27        |
| Mean Teacher [50]       | 15.87 ± 0.28          | 5.65 ± 0.47        |
| VAT [32]                | 13.86 ± 0.27          | 5.63 ± 0.20        |
| VAT + EntMin [32]       | 13.13 ± 0.39          | 5.35 ± 0.19        |
| LGA + VAT [23]          | 12.06 ± 0.19          | 6.58 ± 0.36        |
| ICT [51]                | 7.66 ± 0.17           | 3.53 ± 0.07        |
| MixMatch [5]            | 6.24 ± 0.06           | 3.27 ± 0.31        |
| UDA [53]                | 5.29 ± 0.25           | 2.46 ± 0.17        |
| CL                      | 8.92 ± 0.03           | 5.65 ± 0.11        |
| CL+FA [28]              | 5.51 ± 0.14           | 2.90 ± 0.19        |
| CL+FA+Mixup [56]        | 5.09 ± 0.18           | 2.75 ± 0.15        |
| CL+RA+Mixup [56]        | 5.27 ± 0.16           | 2.80 ± 0.18        |

Table 1: Test error rate of semi-supervised learning methods on CIFAR-10 and SVHN using WideResNet architecture. "Supervised" refers to using only 4,000 and 1,000 labeled datapoints from CIFAR-10 and SVHN respectively without any unlabeled data.

We also show our results for CIFAR-10 and SVHN datasets using CNN-13 architecture in Table 2. We show that our approach improves the test error by 2.85% on CIFAR-10 and matches the test error on SVHN when compared with all previous methods that rely on moderate aug-
For the methods that rely on moderate-to-high data augmentation [32, 51], our method improves the test error by 1.34% when applying heavy random data augmentation on CIFAR-10.

| Method                  | CIFAR-10       | SVHN           |
|-------------------------|----------------|----------------|
| Ladder net [38]         | 12.36 ± 0.31   | --             |
| MeanTeacher [50]        | 12.31 ± 0.24   | 3.95 ± 0.19    |
| Temporal ensembling [26]| 12.16 ± 0.24   | 4.42 ± 0.16    |
| VAT [32]                | 11.36 ± 0.34   | 5.42           |
| VAT + EntMin [32]       | 10.55 ± 0.05   | 3.86           |
| S4 L-Rotation [55]      | 10.93 ± 0.14   | 3.86 ± 0.27    |
| S4 L-Exemplar [55]      | 7.29 ± 0.02    | **2.89 ± 0.04**|
| CL                      | 9.81 ± 0.22    | 4.75 ± 0.28    |
| CL + RA                 | **5.92 ± 0.07**| 3.96 ± 0.10    |

Table 2: Test error rate of semi-supervised learning methods on CIFAR-10 and SVHN using the CNN-13 architecture. The value $N_l$ stands for the number of labeled examples in the training set.

### 4.2. Scalability and Computational Cost

In figure 4, we compare the time consumption versus the test accuracy on Wide ResNet for CIFAR-10 using 4,000 labeled samples. To report this results we perform our experiments on an isolated virtual machine on Google Cloud with 16 vCPUs and 1 Nvidia Tesla K80 GPU, and run each experiment separately. When considering both test accuracy and time cost, our approach shows strong advantages over other baselines.

![Figure 4: Comparison of time consumption and test accuracy on CIFAR-10 using 4,000 labeled samples.](image)

### 4.3. Analysis: Mismatch Between Labeled & Unlabeled Categories

We test our method on the case where the labeled and unlabeled data come from the same underlying distribution, but the unlabeled data contains classes not present in the labeled data as proposed by [35]. We reproduce the experiment by synthetically varying the class overlap on CIFAR-10 choosing only the animal classes to perform the classification (bird, cat, deer, dog, frog, horse). In this setting, the unlabeled data comes from four classes. The idea is to vary how many of those classes are among the six animal classes to modulate class distribution mismatch. We report the results on [27, 32] and modified the available code for [51, 53] to compare our results. Our method is not hurt by adding unlabeled data from a mismatched set of classes, but the performance of previous methods significantly drops. We show our results in figure 5.

![Figure 5: Comparison of time consumption and test accuracy on CIFAR-10 using 4,000 labeled samples.](image)
### Table 5: Comparison of test error rate descent with our iterative method using two different network baselines with moderate and heavy data augmentation. Fully Supervised refers to using only 4,000 labeled datapoints from CIFAR-10 without any unlabeled data. Top Confidence, refers to the threshold applied in each Iteration, and # of Pseudo-Labeled Samples is the average number of images automatically selected for each iteration when training.

| Iteration | Top Confidence | # of Pseudo-Labeled Samples | Without Augmentation | With Augmentation |
|-----------|----------------|-----------------------------|----------------------|-------------------|
|           |                | WRN-28-2 | CNN-13 | WRN-28-2 | CNN-13 |
| Fully Supervised | - | - | 18.25 ± 0.29 | 19.55 ± 0.17 | 13.73 ± 0.12 | 15.40 ± 0.15 |
| 1 Iteration | 80% | 8k | 15.41 ± 0.06 | 16.65 ± 0.17 | 8.82 ± 0.36 | 12.44 ± 0.18 |
| 2 Iteration | 60% | 16k | 11.55 ± 0.16 | 13.56 ± 0.13 | 7.05 ± 0.25 | 9.20 ± 0.09 |
| 3 Iteration | 40% | 24k | 10.83 ± 0.15 | 11.49 ± 0.05 | 6.01 ± 0.18 | 8.23 ± 0.20 |
| 4 Iteration | 20% | 32k | 9.54 ± 0.03 | 10.22 ± 0.02 | 5.45 ± 0.15 | 7.23 ± 0.12 |
| 5 Iteration | 0% | 41k | 8.92 ± 0.03 | 9.81 ± 0.22 | 5.27 ± 0.16 | 5.92 ± 0.07 |

Figure 5: Comparison of test error on CIFAR-10 (six animal classes) with varying overlap between classes. For example, in 50%, two of the four classes in the unlabeled data are not present in the labeled data. Supervised refers to using only the 2,400 labeled images.

### 4.4. Analysis under Varying Training Size

A common practice to test SSL algorithms, is to vary the size of the labeled data using 50, 100 and 200 samples per class. In figure 6 we compare the test error using this setting on Wide ResNet for CIFAR-10. We use the standard validation set size of 5,000 to make our method comparable with previous work.

We find that combining multiple data augmentation techniques significantly improves the overall accuracy of the learned model. In particular, we perform experiments without using any augmentation policy, but instead, perform random transformations agnostic to the data and the model. We also used mixup [56] and compare our results with an augmentation policy deliberately learned for a specific dataset [28]. We perform empirical studies using different batch sizes and found that bigger batches perform better when applying heavy random transformations. This results are shown in the supplementary material.

### 4.5. Impact of Data Augmentation

Table 7 shows results on CNN-13 and WideResNet architectures using the same hyperparameters and threshold selection criteria after each iteration. We compare the moderate and heavy data augmentation methods we apply in our experiments. We use CIFAR-10 with 4000 labeled samples, 41000 unlabeled samples, 5000 samples for validation, and the 10000 test samples to report our results.

Figure 6: Comparison of test error rate using Wide ResNet varying the size of the labeled samples on CIFAR-10. We use the standard validation set size of 5,000 to make our method comparable with previous work.

In table 6 we show the test error rate in Wide ResNet using two static thresholds. We selected two handpicked threshold mimicking the pseudo-labeling approach [35], one of 0.9 and a very restrictive threshold of 0.9995. We show that after the first iteration, there is little to no im-

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**Note:** The table and figure images are placeholders and should be replaced with actual content from the source document. The text represents the natural reading of the document, excluding any images or tables that are present in the source.
provement. We use CIFAR-10 with 4000 labeled samples, 41000 unlabeled samples, 5000 samples for validation, and use the 10000 test samples.

| Iteration | Fully Supervised | WRN | #1 | WRN1 | #2 | WRN2 |
|-----------|------------------|-----|----|------|----|------|
| 1 Iteration | - | 18.25 | - | 18.25 | - | 18.25 |
| 2 Iteration | ~35k | 15.25 | ~13k | 17.18 | ~14k | 15.2 |
| 3 Iteration | ~41k | 14.53 | ~14k | 15.2 | ~14k | 14.64 |
| 4 Iteration | ~43k | 13.91 | ~14k | 14.64 | 14.01 | 14.84 |
| 5 Iteration | ~44k | 12.92 | ~15k | 15.29 | ~15k | 15.29 |

Table 6: Comparison of test error rate in Wide ResNet using two static thresholds (0.91 and 0.9995).

5. Conclusion

In this paper, we propose curriculum labeling, which combines an early idea of semi-supervised learning, pseudo-labeling, with curriculum learning. Curriculum labeling is surprisingly simple and effective. Our empirical results show strong state-of-the-art results on the standard CIFAR-10 dataset, and near state-of-the-art results on ImageNet ILSVRC and SVHN. We demonstrate that a naive application of pseudo-labeling is not effective and justify our approach with rigorous analysis on several benchmarks and under various testing conditions.

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Batch Size and Fine-tuning

In table 7, we show the performance of our method when using data augmentation and we vary the batch size. We also show results after fine-tuning on each iteration. We keep the same hyperparameters across all experiments to ensure a fair comparison with the results obtained when training our method with a batch size of 512. We use CIFAR-10 with 4,000 labeled samples, using the rest of the training set as unlabeled samples, and report our results using the 10,000 test samples.

Table 7: Comparison of test error rate descent with our iterative method using two different batch sizes when using heavy data augmentation. Fully Supervised refers to using only 4,000 labeled datapoints from CIFAR-10 without any unlabeled data. Top Confidence, refers to the threshold applied in each Iteration, and # of Pseudo-Labeled Samples is the average number of images automatically selected for each iteration when training.

| Fully Supervised | Top Confidence | # of Pseudo-Labeled Samples | Varying Batch Size | When Fine-tuning |
|------------------|---------------|----------------------------|-------------------|-----------------|
| 1 Iteration      | 80%           | 8k                         | 12.76             | 15.42           | 15.3            |
| 2 Iteration      | 60%           | 16k                        | 10.19             | 10.04           | 9.85            |
| 3 Iteration      | 40%           | 24k                        | 9.32              | 8.56            | 7.99            |
| 4 Iteration      | 20%           | 32k                        | 8.49              | 7.03            | 7.20            |
| 5 Iteration      | 0%            | 41k                        | 7.34              | 6.22            | 6.55            |

Random Data Augmentations

Functions randomly applied to the input images:

- Cutout
- Contrast
- Color
- Rotate
- Invert

- Brightness
- Posterize
- Translate X
- Translate Y
- Sharpness

- Solarize
- Equalize
- Shear X
- Shear Y
- Auto Contrast

ImageNet Results

In table 8, we show our results using 10% of ImageNet as our labeled data. In table 9, we show the test error after each iteration. We use 128,000 labeled samples for training, and perform random data augmentation. TC refers to the threshold applied in each Iteration, and # is the average number of images automatically selected on each iteration.
Table 8: Top-1 and top-5 accuracy on ImageNet with 10% of the labeled set using ResNet50.

| Method                  | Top-1 | Top-5 |
|-------------------------|-------|-------|
| CL Supervised (w. Aug)  | 55.75 | 79.67 |
| CL (w. Aug)             | 68.86 | 88.56 |

Table 9: Comparison of test error rate descent on ImageNet with our iterative method using ResNet50. Top Confidence refers to the threshold applied in each Iteration, and # is the average number of images automatically selected for each iteration when training used as pseudo-labeled samples.

| Top Confidence | # of Pseudo-Labeled Samples | Top-1 | Top-5 |
|----------------|-----------------------------|-------|-------|
| Fully Supervised | -                          | -    | 55.75 | 79.67 |
| 1 Iteration    | 80%                         | ~230k | 62.24 | 84.08 |
| 2 Iteration    | 60%                         | ~461k | 66.09 | 86.54 |
| 3 Iteration    | 40%                         | ~692k | 67.86 | 87.86 |
| 4 Iteration    | 20%                         | ~922k | 68.61 | 88.22 |
| 5 Iteration    | 0%                          | ~1153k| 68.87 | 88.56 |

ImageNet Samples

In figure 7, we show some samples when using different augmentations on ImageNet. The first row show samples with moderate data augmentation (horizontal flipping and random crops after zero-padding by 2 pixels on each side). The second row show samples with random data augmentation (functions mentioned in section 5). The third row show samples with random data augmentation and mixup [53].

Figure 7: ImageNet samples reprocessed for training. Each row shows a different data augmentation technique – from moderate to heavy.

Pseudo-Labeled Samples

We show pseudo-labeled samples annotated by our method on CIFAR-10 (figure 8), and ImageNet (figure 9). We show correct and incorrect samples for 10 categories with their corresponding scores after the last iteration. We show the highest scores for each class in each column. Under the incorrectly pseudo-labeled column we also show the ground truth category for the image annotated by the model.
Figure 8: CIFAR-10 pseudo-labeled samples annotated by our method. We show correct and incorrect samples for the 10 categories with their corresponding scores after the last iteration.
Figure 9: ImageNet pseudo-labeled samples annotated by our method. We show correct and incorrect samples for 10 chosen categories with their corresponding scores after the last iteration.