Curriculum Labeling: Revisiting Pseudo-Labeling for Semi-Supervised Learning

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Abstract
In this paper we revisit the idea of pseudo-labeling in the context of semi-supervised learning where a learning algorithm has access to a small set of labeled samples and a large set of unlabeled samples. Pseudo-labeling works by applying pseudo-labels to samples in the unlabeled set by using a model trained on the combination of the labeled samples and any previously pseudo-labeled samples, and iteratively repeating this process in a self-training cycle. Current methods seem to have abandoned this approach in favor of consistency regularization methods that train models under a combination of different styles of self-supervised losses on the unlabeled samples and standard supervised losses on the labeled samples. We empirically demonstrate that pseudo-labeling can in fact be competitive with the state-of-the-art, while being more resilient to out-of-distribution samples in the unlabeled set. We identify two key factors that allow pseudo-labeling to achieve such remarkable results (1) applying curriculum learning principles and (2) avoiding concept drift by restarting model parameters before each self-training cycle. We obtain 94.91% accuracy on CIFAR-10 using only 4,000 labeled samples, and 68.87% top-1 accuracy on Imagenet-ILSVRC using only 10% of the labeled samples.

Introduction
Access to annotated examples has been critical in achieving significant improvements in a wide range of computer vision tasks (Halevy, Norvig, and Pereira 2009; Sun et al. 2017). However, annotated data is typically limited or expensive to obtain. Semi-supervised learning (SSL) methods promise 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 datasets while only relying on a small subset of the labeled data and using the rest as unlabeled data (Tarvainen and Valpola 2017; Miyato et al. 2018; Verma et al. 2019; Berthelot et al. 2019). These methods often optimize a combination of supervised and unsupervised objectives to leverage both labeled and unlabeled samples during training. Our work instead revisits the idea of pseudo-labeling where unlabeled samples are iteratively added into the training data by pseudo-labeling them with a weak model trained on a combination of labeled and pseudo-labeled samples. While pseudo-labeling has been proposed before (Lee 2013; Shi et al. 2018; Iscen et al. 2019; Arazo et al. 2020), we revise it by using a self-paced curriculum that we refer to as curriculum labeling, and restarting the model parameters before every iteration in the pseudo-labeling process. We empirically demonstrate through extensive experiments that an implementation of pseudo-labeling trained under curriculum labeling, achieves comparable performance against many other recent methods.

When training a classifier, a common assumption is that the decision boundary should lie in low-density regions in order to improve generalization (Chapelle and Zien 2005); therefore unlabeled samples that lie either near or far from labeled samples should be more informative for decision boundary estimation. Pseudo-labeling generally works by iteratively propagating labels from labeled samples to unlabeled samples using the current model to relabel the data (Scudder 1965; Fralick 1967; Agrawala 1970; Chapelle, Schlkopf, and Zien 2010). Typically, a classifier is first trained with a small amount of labeled data and then used to estimate the labels for all the unlabeled data. High confident predictions are then added as training samples for the next step. This procedure repeats for a specific number of steps or until the classifier cannot find more confident predictions on the unlabeled set. However, pseudo-labeling (Lee 2013; Iscen et al. 2019; Arazo et al. 2020) has been largely surpassed by recent methods (Xie et al. 2019; Berthelot et al. 2019, 2020), and there is little recent work on using this approach for this task.

Our work borrows ideas from curriculum learning (Bengio et al. 2009) where a model first uses samples that are easy and progressively moves toward hard samples. Prior work has shown that training with a curriculum improves performance in several machine learning tasks (Bengio et al. 2009; Hacohen and Weinson 2019). 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. In particular, we show in our experiments, vanilla handpicked thresholding, as used in previous pseudo-labeling approaches (Oliver et al. 2018), cannot guarantee success out of the box. Instead, we design a self-pacing strategy by analyzing the distribution of the predic-
Our work is most closely related to the general use of pseudo-labeling in semi-supervised learning (Lee 2013; Shi et al. 2018; Iscen et al. 2019; Arazo et al. 2020). Although these methods have been surpassed by consistency regularization methods, our work suggests that this is not a fundamental flaw of self-training algorithms and demonstrate that careful selection of thresholds and pacing of the pseudo-labeling of the unlabeled samples can lead to significant gains. Here (Lee 2013; Shi et al. 2018; Arazo et al. 2020) relied on a trained parametric model to pseudo-label unlabeled samples (e.g. by choosing the most confident class (Lee 2013; Shi et al. 2018), or using soft-labels (Arazo et al. 2020)), while (Iscen et al. 2019) proposed to propagate labels using a nearest-neighbors graph. Unlike these methods we adopt curriculum labeling which adds self-pacing to our training where we only add the most confident samples in the first few iterations and the threshold is chosen based on the distribution of scores on training samples.

Most closely related to our approach is the concurrent work of Arazo et al (Arazo et al. 2020) where pseudo-labeling is adopted in combination with Mixup (Zhang et al. 2018) to prevent what is referred in that work as confirmation bias. Confirmation bias is related in this context to the phenomenon of concept drift where the properties of a target variable change over time. This deserves special attention in pseudo-labeling since the target variables are affected by the same model feeding onto itself. In our version of pseudo-labeling we alleviate this confirmation bias by re-initializing the model before every self-training iteration, and as such, pseudo-labels from past epochs do not have an outsized effect on the final model. While our results are comparable on CIFAR-10, the work of Arazo et al (Arazo et al. 2020) further solidifies our finding that pseudo-labeling has a lot more to offer than previously found.

Recent methods for semi-supervised learning rather use a consistency regularization approach. In these works (Sajjadi, Javanmardi, and Tasdizen 2016; Laine and Aila 2017; Tarvainen and Valpola 2017; Sohn et al. 2020), 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. Consistency losses generally encourage that in the absence of labels for a sample, its predictions should be consistent with the predictions for a perturbed version of the same sample. Various perturbation operations have been explored, including basic image processing operators (Xie et al. 2019), dedicated operators such as MixUp (Zhang et al. 2018; Berthelot et al. 2020), learned transformations (Cubuk et al. 2018), and ad-

Figure 1: Curriculum Labeling (CL) algorithm. The model is (1) trained on the labeled samples, then this model is used to (2) predict and assign pseudo-labels for the unlabeled samples. Then the distribution of the prediction scores is used to (3) select a subset of pseudo-labeled samples. Then a new model is (4) re-trained with the labeled and pseudo-labeled samples. This process is (5) repeated by re-labeling unlabeled samples using this new model. The process stops when all samples in the dataset have been used during training.
versarial perturbations (Miyato et al. 2018). While we optionally leverage data augmentation, our use of it is the same as in the standard supervised setting, and our method does not enforce any consistency for pairs of samples.

**Method: Pseudo-Labeling under Curriculum**

In semi-supervised learning (SSL), a dataset $D = \{x \mid x \in X\}$ is comprised of two disjoint subsets: a labeled set $D_L = \{(x, y) \mid x \in X, y \in Y\}$ and an unlabeled subset $D_{UL} = \{x \mid x \in X\}$, where $x$ and $y$ denote the input and the corresponding label. Typically $|D_L| \ll |D_{UL}|$.

Pseudo-labeling builds upon the general self-training framework (McLachlan 1975), where a model goes through multiple rounds of training by leveraging its own past predictions. In the first round, the model is trained on the labeled set $D_L$. In all subsequent rounds, the training data is the union of $D_L$ and a subset of $D_{UL}$ pseudo-labeled by the model in the previous round. In round $t$, let the training samples be denoted as $(X_t, Y_t)$ and the current model as $P_t^\theta$, where $\theta$ are the model parameters, and $t \in \{1, \cdots, T\}$. After round $t$, an unlabeled subset $X_t$ is added to $X_{t+1} := X_t \cup X_t$, and the new target set is defined as $Y_{t+1} := Y_t \cup Y_t$. Here $Y_t$ represents the pseudo labels of $X_t$, predicted by model $P_t^\theta$. In this sense, the labels are “propagated” to the unlabeled data points via $P_t^\theta$.

The criterion used to decide which subset of samples in $D_{UL}$ to incorporate into the training in each round is key to our method. Different uncertainty metrics have been explored in the previous literature, including choosing the samples with the highest-confidence (Zhu 2005), or retrieving unlabeled data points via the nearest samples in feature space (Shi et al. 2018; Iscen et al. 2019; Luo et al. 2017). We draw insights from Extreme Value Theory (EVT) which is often used to simulate extreme events in the tails of one-dimensional probability distributions by assessing the probability of events that are more extreme (Broadwater and Chellappa 2010; Rudd et al. 2018; Al-Behadili, Grumpe, and Wöhler 2015; Clifton et al. 2008; Shi et al. 2008). In our problem, we observed that the distribution of the maximum probability predictions for pseudo-labeled data follows this type of Pareto distribution. So instead of using fixed thresholds or tuning thresholds manually, we use percentile scores to decide which samples to add. Algorithm 1 shows the full pipeline of our model, where $\text{Percentile}(X, T_r)$ returns the value of the $r$-th percentile. We use values of $r$ from $0\%$ to $100\%$ in increments of $20\%$.

Note that, in Algorithm 1 $X_t$ is selected from the whole unlabeled set $D_{UL}$, enabling previous pseudo-annotated samples to enter or to leave the new training set. This is used to discourage concept drift or confirmation bias, as it can prevent erroneous labels predicted by an undertrained network during the early stages of training to be accumulated. To further alleviate the problem, we also reinitialize the model parameters $\theta$ randomly after each round, and empirically observe that, as opposed to fine-tuning, our reinitialization strategy leads to better performance.

Our data consists of $N$ labeled samples $(X_i, Y_i)$ and $M$ unlabeled samples $X_j$. Let $\mathcal{H}$ be a set of hypotheses $h_\theta$ where $h_\theta \in \mathcal{H}$ and each of them denotes a function mapping $X$ to $Y$. Let $L_\theta(X_i)$ denote the loss for a given example $X_i$. To choose the best predictor with the lowest possible error, our formulation can be explained with a regularized Empirical Risk Minimization (ERM) framework. Below, we define $\mathcal{L}(\theta)$ as the pseudo-labeling regularized empirical loss as:

$$\mathcal{L}(\theta) = \frac{1}{N} \sum_{i=1}^{N} L_\theta(X_i) + \frac{1}{M} \sum_{j=1}^{M} L_\theta(X_j)$$

$$\hat{\theta} = \arg \min_{\theta} \mathcal{L}(\theta)$$

Here $\text{CEE}$ indicates cross entropy. Following (Hacohen and Weinshall 2019) this can be rewritten as follows:

$$\hat{\theta} = \arg \min_{\theta} \mathcal{L}(\theta) = \arg \max_{\theta} \exp(-\mathcal{L}(\theta))$$

Now to simplify the notions, we reformulate the objective as to maximize a so-called Utility objective, where $\delta$ is an indicator function:

$$U_\delta(X) = e^{-\delta(X \in X_L) L_\theta(X) - \delta(X \in X \cup X_L) L'_\theta(X)}$$

$$U(\theta) = \frac{1}{N} \sum_{i=1}^{N} U_\delta(X_i) + \frac{1}{M} \sum_{i=1}^{M} U'_\delta(X_j)$$

The pacing function in our pseudo curriculum labeling effectively provides a Bayesian prior for sampling unlabeled samples. This can be formalized as in Eq 4:

$$U_\delta(\theta) = \frac{1}{N} \sum_{i=1}^{N} U_\delta(X_i) + \frac{M}{\sum_{j=1}^{M} U'_\delta(X_j) p_j}$$

$$\hat{\theta} = \arg \max_{\theta} U_\delta(\theta)$$

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**Theoretical Analysis**

Al-Behadili, Grumpe, and Wöhler 2015; Clifton et al. 2008; extreme (Broadwater and Chellappa 2010; Rudd et al. 2018; Clifton et al. 2008; Shich i et al. 2008). In our problem, we observed that the distri-

$\text{Algorithm 1 Pseudo-Labeling under Curriculum Labeling}$

1: Require: $D_L \triangleright$ set of labeled samples
2: Require: $D_{UL} \triangleright$ set of unlabeled samples
3: Require: $\Delta := 20$ \triangleright $\Delta$ is the stepping threshold percent
4: $P_0^\theta \leftarrow$ train classifier using $D_L$ only
5: $t := 1$
6: $T_r := 100 - \Delta$
7: do
8: $T := \text{Percentile}(P_t^\theta(D_{UL}), T_r)$
9: $X_t := D_L$
10: for $x \in D_{UL}$ do
11: if $P_t^\theta(x) > T$ then
12: $X_t := X_t \cup \{x \text{, pseudo-label}(P_t^\theta, x)\}$
13: $P_t^\theta \leftarrow$ train classifier from scratch using $X_t$
14: $t := t + 1$
15: $T_r := T_r - \Delta$
16: while $|X_t| \neq |D_L + D_{UL}|$
17: end

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Here \( p_j = p(X_j) \) denotes the induced prior probability we use to decide how to sample the unlabeled samples and is determined by the pacing function of curriculum labeling algorithm, thus, \( p(X_j) \) works like an indicator function where \( 1/M \) are the unlabeled samples whose scores are in the top \( \mu \) percentile, and 0 otherwise.

We can then rewrite part of Eq (4) as follows:

\[
\begin{align*}
U_p(\theta) &= \frac{1}{N} \sum_{i=1}^{N} U_\theta(X_i) + \sum_{j=1}^{M} (U'_\theta(X_j) - \bar{E}[U'_\theta])(p_j - \bar{E}[p]) \\
&\quad + M * \bar{E}[U'_\theta]\bar{E}[p] \\
&= \frac{1}{N} \sum_{i=1}^{N} U_\theta(X_i) + \text{Cov}[U'_\theta, p] + M * \bar{E}[U'_\theta]\bar{E}[p] \\
&= U(\theta) + \text{Cov}[U'_\theta, p]
\end{align*}
\]

Eq (5) tells that when we sample the unlabeled data points according to a probability that positively correlates with the confidence of the predictions of \( X_j \) (negative correlating with the loss \( L'(X_j) \)), we are improving the utility of the estimated \( \theta \). Under such a pacing curriculum, we are minimizing the overall loss \( L \). The smaller the \( L'(X_j) \) (the larger the utility of an unlabeled point \( X_j \)), the more likely we sample \( X_j \). This proves that we want to sample more those unlabeled points that are predicted with more confidence.

**Experiments**

We first discuss our experiment settings in detail, then we compare against previous methods using the standard semi-supervised learning practice of setting aside a portion of the training data as labeled, and the rest as unlabeled, then we test in the more realistic scenario where unlabeled training samples do not follow the same distribution as labeled training samples, finally we conduct extensive evaluation justifying why our version of pseudo-labeling and specifically curriculum labeling enables superior results compared to prior efforts on pseudo-labeling.

**Experimental Settings**

**Datasets:** We evaluate the proposed approach on three image classification datasets: CIFAR-10 (Krizhevsky 2012), Street View House Numbers (SVHN) (Netzer et al. 2011), and ImageNet ILSVRC (Russakovsky et al. 2015; Deng et al. 2009). With CIFAR-10 we use 4,000 labeled samples and 46,000 unlabeled samples for training and validation, and evaluate on 10,000 test samples. We also report results when the training set is restricted to 500, 1,000, and 2,000 labeled samples. With SVHN we use 1,000 labeled samples and 71,257 unlabeled samples for training, 1,000 samples for validation, which is significantly lower than the conventional 7,325 samples generally used, and evaluate on 26,032 test samples. With ImageNet we use \( \sim 10\% \) of the dataset as labeled samples (102,000 for training and 26,000 for validation), 1,253,167 unlabeled samples and 50,000 test samples.

**Model Details:** We use CNN-13 (Springenberg et al. 2014) and WideResNet-28 (Zagoruyko and Komodakis 2016) (depth 28, width 2) for CIFAR-10 and SVHN, and ResNet-50 (He et al. 2015) for ImageNet. The networks are optimized using Stochastic Gradient Descent with nesterov momentum. We use weight decay regularization of 0.0005, momentum factor of 0.9, and an initial learning rate of 0.1 which is then updated by cosine annealing (Loshchilov and Hutter 2016). Note that we use the same hyper-parameter setting for all of our experiments, except the batch size when applying moderate and heavy data augmentation. We empirically observe that small batches (i.e. 64-100) work better for moderate data augmentation (random cropping, padding, whitening and horizontal flipping), while large batches (i.e. 512-1024) work better for heavy data augmentation. For CIFAR-10 and SVHN, we train the models for 750 epochs. Starting from the 500th epoch, we also apply stochastic weight averaging (SWA) (Izmailov et al. 2018) every 5 epochs. For ImageNet, we train the network for 220 epochs and apply SWA, starting from the 100th epoch.

**Data Augmentation:** While data augmentation has become a common practice in supervised learning especially when the training data is scarce (Simard, Steinkraus, and Platt 2003; Perez and Wang 2017; Shorten and Khoshgoftaar 2019; Devries and Taylor 2017), previous work on SSL typically use basic augmentation operations such as cropping, padding, whitening and horizontal flipping (Rasmus et al. 2015; Laine and Aila 2017; Tarvainen and Valpola 2017). More recent work relies on heavy data augmentation policies that are learned automatically by Reinforcement Learning (Cubuk et al. 2018) or density matching (Lim et al. 2019). Other augmentation techniques generate perturbations that take the form of adversarial examples (Miyato et al. 2018), or by interpolations between a random pair of image samples (Zhang et al. 2018). We explore both moderate and heavy data augmentation techniques 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. However, we also report results without the use of data augmentation.

**Comparisons with the State-of-the-Art**

**CIFAR-10/SVHN:** In Table 1 and 2, we compare different versions of our method with state-of-the-art approaches using the WideResnet-28/CNN-13 architectures on CIFAR-10 and SVHN. Our method surprisingly surpasses previous pseudo-labeling based methods (Lee 2013; Shi et al. 2018; Iscen et al. 2019; Arazo et al. 2020) and consistency-regularization methods (Xie et al. 2019; Berthelot et al. 2019, 2020) on CIFAR-10. In SVHN we obtain competitive test error when compared with all previous methods that rely on moderate augmentation (Lee 2013; Rasmus et al. 2015; Laine and Aila 2017; Tarvainen and Valpola 2017; Luo et al. 2017), moderate-to-high data augmentation (Miyato et al. 2018; Jackson and Schulman 2019; Verma et al. 2019; Berthelot et al. 2019), and heavy data augmentation (Xie et al. 2019).

A common practice to test SSL algorithms, is to vary the size of the labeled data using 50, 100 and 200 samples per
Table 1: Test error rate on CIFAR-10 and SVHN using WideResNet-28. We show that our CL method can achieve comparable results to the state-of-the-art. "Supervised" refers to using only 4,000/1,000 labeled samples from CIFAR-10/SVHN without relying on any unlabeled data.

| Approach          | Method                  | CIFAR-10 N_l = 4000 | SVHN N_l = 1000 |
|-------------------|-------------------------|----------------------|------------------|
|                   |                         | 2013                 | 2018             |
|                   | Supervised              | 20.26 ± 0.38         | 12.83 ± 0.47     |
| **Pseudo Labeling** | PL (Lee 2013)           | 17.78 ± 0.57         | 7.62 ± 0.29      |
|                   | PL-CB (Arazo et al. 2020) | 6.28 ± 0.3       | -                |
| **Consistency Regularization** | II Model (Laine and Aila 2017) | 16.37 ± 0.63       | 7.19 ± 0.27      |
|                   | Mean Teacher (Tarvainen and Valpola 2017) | 15.87 ± 0.28       | 5.65 ± 0.47      |
|                   | VAT (Miyato et al. 2018) | 13.86 ± 0.27       | 5.63 ± 0.20      |
|                   | VAT + EntMin (Miyato et al. 2018) | 13.13 ± 0.39       | 5.35 ± 0.19      |
|                   | LGA + VAT (Jackson and Schulman 2019) | 12.06 ± 0.19       | 6.58 ± 0.36      |
|                   | ICT (Verma et al. 2019) | 7.66 ± 0.17         | 5.35 ± 0.07      |
|                   | MixMatch (Berthelot et al. 2019) | 6.24 ± 0.06         | 3.27 ± 0.31      |
|                   | UDA (Xie et al. 2019) | 5.29 ± 0.25         | 2.46 ± 0.17      |
|                   | ReMixMatch (Berthelot et al. 2020) | 5.14 ± 0.04       | 2.42 ± 0.09      |
|                   | FixMatch (Sohn et al. 2020) | 4.26 ± 0.05       | 2.28 ± 0.11      |
| **Pseudo Labeling** | CL                      | 2020                 | 5.65 ± 0.11      |
|                   | CL+FA (Lim et al. 2019) | 5.51 ± 0.14         | 2.90 ± 0.19      |
|                   | CL+FA (Lim et al. 2019)+Mixup(Zhang et al. 2018) | 5.09 ± 0.18       | 2.75 ± 0.15      |
|                   | CL+RA+Mixup(Zhang et al. 2018) | 5.27 ± 0.16       | 2.80 ± 0.18      |

Table 2: Test error rate on CIFAR-10 and SVHN using CNN-13. N_l is the number of labeled samples in the training set.

| Approach          | Method                  | CIFAR-10 N_l = 4000 | SVHN N_l = 1000 |
|-------------------|-------------------------|----------------------|------------------|
| **Pseudo Labeling** | TSSDL-MT (Shi et al. 2018) | 9.30 ± 0.55         | 3.35 ± 0.27      |
|                   | LP-MT (Iscen et al. 2019) | 10.61 ± 0.28       | -                |
| **Consistency Regularization** | Ladder net (Rasmus et al. 2015) | 12.36 ± 0.31       | -                |
|                   | MeanTeacher (Tarvainen and Valpola 2017) | 12.31 ± 0.24       | 3.95 ± 0.19      |
|                   | Temporal ensembling (Laine and Aila 2017) | 12.16 ± 0.24       | 4.42 ± 0.16      |
|                   | VAT (Miyato et al. 2018) | 11.36 ± 0.34       | 5.42             |
|                   | VAT+EntMin (Miyato et al. 2018) | 10.55 ± 0.05       | 3.86             |
|                   | SNTG (Luo et al. 2017) | 10.93 ± 0.14       | 3.86 ± 0.27      |
|                   | ICT (Verma et al. 2019) | 7.29 ± 0.02        | **2.89 ± 0.04**  |
| **Pseudo Labeling** | CL                      | 2020                 | 4.75 ± 0.28      |
|                   | CL+RA                   | **5.92 ± 0.07**     | 3.96 ± 0.10      |

In Figure 2, we also evaluate our method using this setting on WideResNet for CIFAR-10. We use the standard validation set size of 5,000 to make our method comparable with previous work. Decreasing the size of the available labeled samples recreates a more realistic scenario where there is less labeled data available. We keep the same hyperparameters we use when training on 4,000 labeled samples, which shows that our model does not drastically degrade when used with smaller labeled sets. We show the lines for the mean and shaded regions for the standard deviation across five independent runs, and our results are closer to the current best method under this benchmark.

**ImageNet:** We further evaluate our method on the large-scale ImageNet dataset (ILSVRC). Following prior works (Verma et al. 2019; Xie et al. 2019; Berthelot et al. 2019), we use 10%/90% of the training split as labeled/unlabeled data. Table 3 shows that we achieve competitive results with the state-of-the-art with scores very close to the current top performing method, UDA (Xie et al. 2019) on both top-1 and top-5 accuracies.

Realistic Evaluation with Out-of-Distribution Unlabeled Samples

In a more realistic SSL setting (Oliver et al. 2018), the unlabeled data may not share the same class set as the labeled data. We test our method under a scenario 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 (Oliver et al. 2018). We reproduce the experiment by synthetically varying the class overlap on CIFAR-10, choosing only the animal classes to reproduce the experiment by synthetically varying the class distribution, but the unlabeled data contains classes not present in the labeled data as proposed by (Oliver et al. 2018). We also include the results of (Verma et al. 2019; Xie et al. 2019) obtained by running their released source code. Figure 3 shows that our method is robust to out-of-distribution classes, while the performance
Table 3: Top-1 and top-5 accuracies on ImageNet with 10% of the labeled set. Here UDA and CL are trained using ResNet-50. Previous methods (Lee 2013; Miyato et al. 2018; Zhai et al. 2019) use ResNet-50v2 to report their results.

| Method                                      | Approach          | Top-1  | Top-5  |
|---------------------------------------------|-------------------|--------|--------|
| Supervised Baseline (Zhai et al. 2019)      | –                 | –      | 80.43  |
| Pseudo-Label (Lee 2013)                     | Pseudo Labeling   | –      | 82.41  |
| VAT (Miyato et al. 2018)                    | Consist. Reg.     | –      | 82.78  |
| VAT + EntMin (Miyato et al. 2018)           | Consist. Reg.     | –      | 83.39  |
| $S^4$ L-Rotation (Zhai et al. 2019)         | Self-Supervision  | –      | 83.82  |
| $S^4$ L-Exemplar (Zhai et al. 2019)         | Self-Supervision  | –      | 83.72  |
| UDA Supervised (Xie et al. 2019)            | –                 | 55.09  | 77.26  |
| UDA Supervised (w. Aug) (Xie et al. 2019)   | –                 | 58.84  | 80.56  |
| UDA (w. Aug) (Xie et al. 2019)              | Consist. Reg.     | 68.78  | 88.80  |
| FixMatch (Sohn et al. 2020)                 | Consist. Reg. + PL| 71.46  | 89.13  |
| CL Supervised (w. Aug)                      | –                 | 55.75  | 79.67  |
| CL (w. Aug)                                 | Pseudo Labeling   | 68.87  | 88.56  |

Figure 2: Comparison of test error rate using WideResNet 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.

Ablation Studies

Here we justify the effectiveness of the two main design differences in our version of pseudo-labeling with respect to previous attempts. We first demonstrate that the choice of thresholds using percentiles as in curriculum labeling, has a large effect on the results compared to fixed thresholds, then we show that training the model parameters from scratch in each round of self-training is more beneficial than fine-tuning over previous versions of the model.

Effectiveness of Curriculum Labeling

We first show results when applying vanilla pseudo-labeling with no curriculum, and without a specific threshold (i.e. 0.0). Table 4 shows the effect when applying different data augmentation techniques (Random Augmentation, Mixup and SWA). We show that only when heavy data augmentation is used, this approach is able to match our curriculum design without any data augmentation. This vanilla pseudo-labeling approach is similar to the one reported in previous literature (Lee 2013), and is not able to outperform recent work based on consistency regularization techniques. We also report experiments applying smaller thresholds in each iteration, and show our results in table 5. Our curriculum design is able to yield a significant gain over the pseudo-labeling approach that uses a fixed threshold even when heavy data augmentation is applied. This shows that our curriculum approach is able to alleviate the concept drift and confirmation bias.

Then we compare our self-pacing curriculum labeling with handpicked thresholding mimicking the experiments presented in Oliver et al (Oliver et al. 2018) and report more detailed results per iteration. As performed in this earlier work, we re-label only the most confident samples; in our experiments we fixed the thresholds to 0.9 and 0.9995. We test on CIFAR-10 with 4000 labeled samples, and use...
| Data Augmentation | Mixup | SWA | Top-1 Error |
|-------------------|-------|-----|-------------|
| None              | X     | X   | 38.47       |
| None              | ✓     | X   | 34.03       |
| None              | ✓     | ✓   | 37.35       |
| None              | ✓     | ✓   | 32.85       |
| Moderate          | X     | X   | 22.8        |
| Moderate          | ✓     | ✓   | 16.11       |
| Moderate          | ✓     | ✓   | 21.63       |
| Moderate          | ✓     | ✓   | 15.83       |
| Heavy (RA)        | X     | X   | 11.38       |
| Heavy (RA)        | ✓     | ✓   | 8.88        |
| Heavy (RA)        | ✓     | ✓   | 11.32       |
| Heavy (RA)        | ✓     | ✓   | 8.59        |

Table 4: Test errors when using pseudo-labeling without a curriculum (the threshold is set to 0.0). We use WideResnet-28 as the base network. Additionally, we report which data augmentation technique was applied.

| Threshold | Moderate Aug | Heavy (RA) |
|-----------|--------------|-------------|
| 0.1       | 21.12        | 7.87        |
| 0.2       | 21.12        | 8.57        |
| 0.3       | 20.59        | 7.90        |
| 0.4       | 22.11        | 8.15        |
| 0.5       | 19.98        | 7.46        |
| 0.6       | 19.51        | 6.88        |
| 0.7       | 19.35        | 6.65        |
| 0.8       | 18.08        | 6.29        |
| 0.9       | 17.11        | 6.21        |
| CL        | 8.92         | 5.27        |

Table 5: Test errors when using pseudo-labeling with several fixed thresholds and different data augmentation techniques. We use WideResnet-28 as the base network. The Heavy Augmentation applies Random Augmentation, Mixup and SWA. Last row shows results of our approach.

| Confidence | #       | Reinitializing | Fine Tuning |
|------------|---------|----------------|-------------|
| Fully Supervised | -       | -              | 15.42       |
| 1st Iteration          | 80%     | 8k             | 10.04       |
| 2nd Iteration          | 60%     | 16k            | 8.56        |
| 3rd Iteration          | 40%     | 24k            | 7.03        |
| 4th Iteration          | 20%     | 32k            | 6.22        |
| 5th Iteration          | 0%      | 41k            | 5.41        |

Table 6: Test errors when using two static thresholds (0.9 and 0.9995) and our self-pacing training. We use WideResnet-28(WRN) as the base network. Fully Supervised refers to using only 4,000 labeled datapoints from CIFAR-10 without any unlabeled data. The # columns show the average numbers of images automatically selected for each iteration during training. We used ZCA preprocessing and moderate data augmentation on these experiments.

| Fully Supervised | 0.9     | WRN2 | 0.9995 | WRN2 | Self-pacing | WRN2 | Self-pacing |
|------------------|---------|------|--------|------|-------------|------|-------------|
| 1st Iteration    | ~35k    | 15.25| ~13k   | 17.18| 8k          | 15.41|
| 2nd Iteration    | ~41k    | 14.53| ~14k   | 15.2 | 16k         | 11.55|
| 3rd Iteration    | ~43k    | 13.91| ~14k   | 14.64| 24k         | 10.83|
| 4th Iteration    | ~44k    | 14.01| ~17k   | 14.84| 32k         | 9.54 |
| 5th Iteration    | ~44k    | 12.92| ~15k   | 15.29| 41k         | 8.92 |

Table 7: Comparison of model reinitialization and finetuning, in each iteration of training. We observe that reinitializing the model performs consistently better in each iteration.

WideResnet-28 as the base network with moderate data augmentation. As shown in Table 6, using handpicked thresholds is sub-optimal. Especially when only the most confident samples are re-labeled as in (Lee 2013). Particularly, there is little to no improvement after the first iteration. Our self-pacing model significantly outperforms fixed thresholding and continues making progress in different iterations.

**Effectiveness of Reinitializing vs Finetuning.** Due to confirmation bias and concept drift, errors caused by high confident mislabeling in early iterations may accumulate during multiple rounds of training. Although our self-pacing sample selection encourages excluding incorrectly labeled samples in early iterations, this might still be an issue. As such, we reinitialize the model after each iteration, instead of finetuning the previous model. Reinitializing the model yields at least 1% improvement and does not add a significant overhead to our self-paced approach, which is significantly faster than recent methods (additional experiments in the Appendix). In Table 7, we compare the performance of model reinitializing and finetuning on CIFAR-10 on the 4,000 labeled training samples regime. We use WideResnet-28 as the base network and apply data augmentation during training. It shows that reinitializing the model, as opposed to finetuning, indeed improves the accuracy significantly, demonstrating an alternative and perhaps simpler solution to alleviate the issue of confirmation bias (Arazo et al. 2020).

**Conclusion**

In this paper, we revisit pseudo-labeling in the context of semi-supervised learning and demonstrate comparable results with the current state-of-the-art that mostly relies on enforcing consistency on the predictions for unlabeled samples. As part of our version of pseudo-labeling, we propose curriculum labeling where unlabeled samples are chosen by using a threshold that accounts for the skew in the distribution of the prediction scores on the unlabeled samples. We additionally show that concept drift and confirmation bias can be mitigating by discarding the current model parameters before each epoch in the self-training loop of pseudo-labeling. We demonstrate our findings with strong empirical results on CIFAR-10, SVHN, and ImageNet ILSVRC.

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