Iterative Pseudo-Labeling for Speech Recognition

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Abstract
Pseudo-labeling has recently shown promise in end-to-end automatic speech recognition (ASR). We study Iterative Pseudo-Labeling (IPL), a semi-supervised algorithm which efficiently performs multiple iterations of pseudo-labeling on unlabeled data as the acoustic model evolves. In particular, IPL fine-tunes an existing model at each iteration using both labeled data and a subset of unlabeled data. We study the main components of IPL: decoding with a language model and data augmentation. We then demonstrate the effectiveness of IPL by achieving state-of-the-art word-error rate on the LibriSpeech test sets in both standard and low-resource setting. We also study the effect of language models trained on different corpora to show IPL can effectively utilize additional text. Finally, we release a new large in-domain text corpus which does not overlap with the LibriSpeech training transcriptions to foster research in low-resource, semi-supervised ASR.

Index Terms: speech recognition, language modeling, pseudo-labeling, semi-supervised learning, deep learning

1. Introduction
Recent advances in end-to-end speech recognition are largely due to acoustic model architecture improvements. Some of the most promising are from the Transformer family [1,2,3,4,5], which give state-of-the-art results on many ASR benchmarks and close the gap between end-to-end and hybrid systems. Given the performance gain from new architectures, research has shifted focus towards leveraging self and semi-supervised techniques to better-utilize unlabeled data. For example, pseudo-labeling successfully boosts the performance on LibriSpeech [6] baselines by a large margin [1]. Many algorithms exist which incorporate unlabelled data to improve ASR in the low-resource setting, including CPC [7,8], pseudo-labeling [9], local prior matching [10], pseudo-label augmentation [11], adversarial training [12] and back translation [13]. While many of these methods outperform a supervised baseline with limited resources, a large gap to fully-supervised training remains. Furthermore, not all approaches scale easily to large amounts of data, such as that recently used in the LibriLight benchmark [7].

In this work, we study iterative pseudo-labeling (IPL), a straightforward method that can easily scale to large unlabeled datasets and further boost the performance in both standard- and low-resource settings. IPL is motivated by the simplicity and effectiveness of pseudo-labeling (PL) [9,11]. A simple extension to [11] involves conducting more iterations of PL as the model trains so as to continuously refine and improve the quality of generated pseudo-labels. That said, training a model from scratch after each round of pseudo-labeling and relabeling a large collection of unlabeled data is expensive. IPL mitigates these challenges by 1) labeling only a subset of the unlabeled data in each iteration, and 2) fine tuning the existing model on this subset, rather than training from scratch. An intuitive motivation for this is shown in Figure 1 where the same acoustic model is trained to convergence with a fixed learning rate; both settings reach a similar WER. Training from scratch with PL is also shown to be roughly equivalent to iterating in a machine translation setting [14].

2. Method
In this section, we first introduce the iterative pseudo-labeling algorithm (IPL). We then give theoretical justifications for why IPL facilitates effective training. Finally, we perform analysis and experiments on a small-scale labeled dataset.

Algorithm 1: Iterative pseudo-labeling

| Data: Labeled data \( L = \{x_i, y_i\}_{i=1}^L \) | Unlabeled data \( U = \{x'_i\}_{i=1}^U \) |
|---|---|
| Result: Acoustic model \( p_0 \) | Initialize \( p_0 \) by training on only labeled data \( L \); |
| repeat | |
| | 1. Draw a subset of unpaired data \( \hat{U} \subseteq U \); |
| | 2. Apply \( p_0 \) and beam-search decoding with LM to the subset \( \hat{U} \) to generate \( \hat{U} = \{(x, \hat{y})| x \in \hat{U}\} \); |
| | 3. Fine tune \( p_0 \) on \( L \cup \hat{U} \) with data augmentation; |
| | until convergence or maximum iterations are reached; |

2.1. Iterative Pseudo-Labeling

As listed in Algorithm 1, IPL utilizes both labeled and unlabeled data as in the conventional semi-supervised learning. The
model minimizes the following loss function:

$$\mathcal{L} = \mathcal{L}_L + \lambda \mathcal{L}_U$$  \hspace{1cm} (1)

where \(\mathcal{L}_L\) and \(\mathcal{L}_U\) denote the parts of the loss function on labeled and unlabeled data accordingly:

$$\mathcal{L}_L = -\mathbb{E}_{x,y \sim p(x,y)} \log(p_\theta(y|x))$$  \hspace{1cm} (2)

$$\mathcal{L}_U = -\mathbb{E}_{x \sim p(x)} \mathbb{E}_{y \sim p(y|x)} \log(p_\theta(y|x)).$$  \hspace{1cm} (3)

Note that in ASR, instead of sampling from \(p_\theta(y|x)\), the transcriptions as well as the pseudo-labels are usually selected from the greedy path:

$$\hat{y} = \arg\max_y p_\theta(y|x).$$  \hspace{1cm} (4)

2.2. Avoidance of Local Minima

As discussed in [14], one bane of loss (1) optimization in fine-tuning is that it tends to get stuck at a local minima after each round of training with existing pseudo-labels; the conditional log likelihood (4) is already maximized when \(p_\theta(y|x)\) matches the underlying data distribution \(p_\theta(y|x)\), so that \(\nabla_{\theta} \mathcal{L}_{L|\theta=\theta^*} = 0\). The IPL algorithm has two distinct components: one with respect to the target \((y)\) and the other with respect to the data \((x)\), that we found to be effective to overcome this behaviour.

External Language Model (LM) In modern ASR systems, in addition to the acoustic model (AM) \(p_\theta\), a decoding procedure (typically either WFST-based [15] or beam-search-based (BS) [16, 17]) integrates an external language model (LM). With beam-search decoding, instead of using the greedy path (4) as transcriptions, we consider:

$$\hat{y}' = \arg\max_y \log p_\theta(y|x) + \alpha \log p_{LM}(y) + \beta |y|,$$  \hspace{1cm} (5)

where \(\alpha\) and \(\beta\) are hyper-parameters [11] usually optimized on validation set. This differs \(\hat{y}'\) from \(\hat{y}\) by introducing extra LM knowledge into transcriptions so that the learned weights \(\theta\) are no longer optimal given the new labels \(\hat{y}'\), and the model will keep training with \(\nabla_{\theta} \mathcal{L}_{L|\theta=\theta^*} \neq 0\). This is also observed in machine translation [14], where the gain from using greedy-path decoding is limited in self-training with PL.

Data Augmentation With respect to data, when data augmentation is introduced, the log likelihood the model optimizes also changes. We can rewrite (4) as

$$\mathcal{L}_U = -\mathbb{E}_{x \sim \hat{p}(x)} \mathbb{E}_{\hat{y} \sim \hat{p}(\hat{y}|x')} \log(p_\theta(y'|x')).$$  \hspace{1cm} (6)

where \(\hat{p}(\cdot)\) is the data augmentation function, which is SpecAugment [18] in our experiments. The model weights optimized before could be no longer optimal given the new augmented input; the model keeps updating with \(\nabla_{\theta} \mathcal{L}_{L|\theta=\theta^*} \neq 0\).

Empirical Study We use train-clean-100 and train-clean-360 in LibriSpeech as labeled and unlabeled training data and dev-other as a validation set. The AMs detailed in Section 3.3 are first trained on labeled data for 100 epochs (≈ 105 hours) and then continue with IPL. Pseudolabeling is performed every 10 epochs with all unlabeled data without down-sampling. The learning rate is fixed throughout training for a fair comparison. As shown in Figure 2 if both data augmentation and LM decoding are used, there is a dramatic WER drop when unlabeled data is first in use, and the

WER keeps decreasing as IPL progresses. If either data augmentation or LM decoding is removed, convergence degrades noticeably. Further, if both are removed, adding unlabeled data provides no benefit to IPL, which is consistent with hitting local minima. One should note that the model is not fully converged at epoch 100; the WER continues decreasing. The contribution of the beam search alone is also limited.

2.3. Dataset Distribution Approximation

Usually, unlabeled dataset \(U\) is much larger than the labeled one \(L\); it is very time-consuming to label the entire \(U\) in each round of PL. If only insufficient data is selected in each round, however, the \(p(x)\) in (3) will be poorly estimated, which will increase the chance of model overfitting. To balance the trade-off between the accuracy of \(p(x)\) approximation and the PL efficiency, with the same setup in [18] we conduct an empirical ablation where the PL is performed only on a randomly sampled subset of \(U\). Note that we treat samples from \(L\) and \(U\) equally following [11], so that the \(\lambda\) in (1) is implicitly set to \(|L|/|U|\), the ratio between the number of samples in the two sets.

As shown in Figure 3 even though there is an up to 5-time gap in \(\lambda\), using 20% to 40% of \(U\) can reach the same WER as using 100%. This motivates us to (1) pay less attention to \(\lambda\) tuning and (2) down sample \(U\) in PL, so as to perform more rounds of PL in total to better utilize large unlabeled set. On the
other hand, using only 10% from $U$ significantly hurts the convergence, which shows the importance of $p(x)$ approximation and sets up a lower bound of down-sample rate.

3. Experiments

3.1. Audio Data

Audio data for our experiments comes from two sources: LIBRISPEECH, containing 960h of audio and paired transcriptions, and audio from LIBRIVOX (54k hours of audio) extracted following [2]. Two setups of labeled data are used: either all of LIBRISPEECH or only its train-clean-100 subset. We use the standard development (for all hyper-parameters optimization) and test (for final evaluation only) sets from LIBRISPEECH.

3.2. Gutenberg Text Corpus

As discussed in [3], it is important to remove components of the LM training corpus that overlap with unlabeled audio to ensure the LM has no information about ground truth transcriptions from the unlabeled audio. We study the contribution of the LM to IPL and conduct rigorous experiments when a subset of LIBRISPEECH is used as unlabeled audio. For LM training, we prepare a larger in-domain text corpus using books from Project Gutenberg [19]. To prepare the corpus, we start with a large subset of English books from Project Gutenberg (which includes some of the 14.5k books present in the LIBRISPEECH LM corpus [6] with 0.8B words) and filter out all books present in LIBRIVOX audio data. We perform the same procedure as in [1] along with a manual matching step to find exact or similar titles (after normalization) in LIBRIVOX ($\alpha$, $\beta$ are the same as in [1]), filtering out the resulting books. Similarly, we remove from the corpus books present in the LIBRISPEECH validation and test sets. The resulting filtered corpus is normalized in the same way as in [1] which mimics the normalization in the LIBRISPEECH corpus, but has additional mappings of some abbreviations and does not split text mid-sentence. We denote this final corpus as $GB \setminus LV$ (2.16B words from 34k books). Further, with the same procedure, we filter out books containing LIBRISPEECH training transcriptions (960h) and form a new corpus denoted as $GB \setminus LV \setminus LS$ (2.11B words from 33.4k books).

3.3. Models

**Acoustic Model** We use the best-performing Transformer architecture on LIBRISPEECH and LIBRIVOX with 322M parameters from [1] in our experiments. In particular, there is a convolutional front-end containing 6 layers of 1-D convolutions with kernel-width 3 followed by 36 4-head Transformer blocks [20] with self-attention dimension $D_{tr} = 768$. The 2nd, 4th and the final convolutions in the front-end have stride 2, so the overall sub-sampling rate of the model is 8. The AMs take 80-channel log-mel filterbanks as input and are trained end-to-end with Connectionist Temporal Classification (CTC) loss [21].

**Language Model** For fair comparison with existing works, IPL experiments in Table1 use BS decoding with the 4-gram LM (200k vocabulary) used in [1], which is trained on the official LIBRISPEECHLM corpus with transcriptions in LIBRIVOX excluded, denoted as $LS \setminus LV$. Following [1] we train Transformer LM on the same corpus $LS \setminus LV$. As an ablation study, we train 5-gram LMs on $GB \setminus LV \setminus LS$ and $GB \setminus LV$ with top 200k words in each and without pruning using the KenLM toolkit [22]. The LMs perplexity is listed in Table2.

| Data       | $LS \setminus LV$ | $GB \setminus LV$ | $LS$ | $GB \setminus LV$ | Transf. |
|------------|-------------------|-------------------|------|-------------------|--------|
| dev-clean  | 161.7             | 101.6             | 99.7 | 48.2              |
| dev-other  | 152.5             | 112.9             | 110.5| 50.2              |

3.4. Model Training

We use word pieces (WP) [23] as modeling units in our experiments. Following [1], we use the same 10k WP estimated from the training transcriptions, if the whole LIBRISPEECH training set is used. If only train-clean-100 is in use, we switch to the 5k WP estimated on train-clean-100 transcriptions as in [10]. We use a lexicon, including words only in training.
4.14%, respectively. To achieve the same WER after round 3, Table 3: WER of greedy path on dev-other for IPL and training from scratch for multiple rounds. 4-gram LS \( \backslash \) LV LM is used for pseudo-labels generation.

| Data       | Labeled | Unlabeled | 0 | 1 | 2 | 3 | IPL          |
|------------|---------|-----------|---|---|---|---|--------------|
| LS-100     | 27.76   | 17.1      | 15.8 | 15.09 | 10.69 |   |              |
| LS-100     | 27.76   | 16.3      | 12.9 | 10.95 | 7.90  |   |              |
| LS-960     | 7.31    | 5.00      | 4.69 | 4.57  | 4.12  |   |              |

and validation sets, to limit the search space of the BS decoding in IPL. Dropout [24] and layer drop [25] are tuned and used to regularize each model. For models that are not trained on LIBRIVOX, we set both dropout and layer drop to 0.3; for models trained on LIBRIVOX, layer drop is set to 0.2 while dropout is 0.2 and 0.15 for models using 100 and 960 hours labeled data, respectively. All models are trained on 64 GPUs with a batch size of 4 per GPU if using LIBRIVOX and 6 otherwise. We use the Adagrad [26] optimizer; the learning rate is initialized to 0.03 and is never decreased for models trained on LIBRIVOX but is halved once at epoch 800 for LIBRISPEECH-only models.

In terms of IPL training, we implemented the automated pipeline in wav2letter++ [16]. We use random search with 256 jobs to optimize the hyper-parameters in BS decoding [17] with n-grams LM on dev-other and use the optimal values in the subsequent PL. As mentioned in Section 2.3, we only select 20% to 40% of the data in each round of PL if LIBRIVOX is the unlabeled dataset. Otherwise, if the rest of LIBRISPEECH is the unlabeled set, the entire unlabeled set is pseudo-labeled. Pseudo-labels are regenerated every 10 epochs.

3.5. Results and Analysis

In this section we compare our results with other recent work in semi-supervised learning. All results are listed in Table 1. Given train-clean-100 as labeled data, our method reaches 9.51% and 7.11% on test-other and test-clean with the rest of LIBRISPEECH and LIBRIVOX as unlabeled data, respectively. If all of LIBRISPEECH is used as labeled data, we achieve 4.01% on test-other. Our result achieves a clear state-of-the-art in all the three semi-supervised learning setups.

**Effectiveness** We conduct 3 rounds of pseudo labeling on the entire unlabeled set and retraining a new AM from scratch. As shown in Table 2, WER on dev-other decreases with better PL generated, but the marginal gain diminishes as iterations continue. IPL, however, clearly outperforms the 3 rounds PL baseline, indicating it is effective to accumulate gains through training with more (up to 80) rounds of PL updates.

**Efficiency** Given the same amount of time for 3 rounds of PL training in Table 2 to finish, which is 4, 11 and 17 days from top to bottom, IPL achieves WER 10.69%, 8.50% and 4.14%, respectively. To achieve the same WER after round 3, however, IPL takes only 0.7, 3.3 and 8 days. This efficiency derives directly from the two proposed changes in IPL: 1) fine-tuning the existing model with new labels to save computation in re-bootstrapping and 2) down sampling the unlabeled set to shorten the PL time, i.e. 20% down-sample rate leads to 5 time speed up in labeling.

**LM Study** Comparison of IPL with different LMs is shown in Table 4 with LMs perplexity in Table 2. Given a better LM, IPL better transfers LM knowledge into AM and achieves better performance. IPL can thus effectively leverage large amounts of unpaired text, in addition to unpaired audio. However, although the difference in perplexity between the GB \( \backslash \) LV and GB \( \backslash \) LV \( \backslash \) LS LMs is small, there is still a large gap in WER. This is because the LM implicitly leaks the labels of unlabeled audio. Fortunately, comparing WER between LS \( \backslash \) LV and GB \( \backslash \) LV \( \backslash \) LS, when the transcription leaking is completely removed, it is still possible to reach similar (or even better) WER by utilizing more in-domain text.

**Decoding Parameters Mismatch** As shown in Table 4, there is still an observable improvement in WER across greedy path and the BS decoding with n-grams LM. One inhibitor to transferring LM knowledge into the AM is a mismatch in decoding parameters: the parameters optimized on dev-other may not be optimal for decoding unlabeled audio. Thus, in the final stage of IPL training, the marginal WER improvement on dev-other is not reflected similarly on the one on unlabeled audio, so as to prevent the AM from improving.

4. Related Work

Semi-supervision in ASR is well-studied [27, 28, 29, 30, 31, 32]; our work builds primarily on recent work with end-to-end systems, especially PL [9, 1]. In [9], PL is shown to be effective with only 100h of labeled audio. The model uses a sequence-to-sequence loss, however and requires additional pseudo-label filtering to achieve best results. To mitigate the instability found in sequence-to-sequence decoding, as in [1] all pseudo-labels are generated with models trained with CTC. Our work extends [1] by conducting more rounds of PL and fine-tuning the existing model and demonstrates the effectiveness of the IPL approach in settings with both 960h and 100h of labeled audio. Still other work [8] learns discrete audio feature representations directly from the waveform and works quite well with limited data, even in settings with under 100h of labeled audio. In this setting, learned acoustic features are presumably more competitive than an AM trained end-to-end with MFCC or log-mel filterbank features. Other work including [10], those with CPC baseline [7], and those using adversarial training [12] and back-translation-style techniques [13] also provide promising end-to-end semi-supervised approaches, but results are not comparable as newer end-to-end approaches outperform these works’ baselines.
5. Conclusion

We have shown that iterative pseudo-labeling can give superior results in both standard and low-resource settings and provides an efficient algorithm with which to train compared to conventional pseudo-labeling approaches. Iterative pseudo-labeling benefits from beam search decoding with a language model and data augmentation along with dataset sub-sampling, which also improves efficiency. With our Transformer acoustic model, IPL achieves the state-of-the-art results on Librispeech test sets.

6. References

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