KAIZEN: CONTINUOUSLY IMPROVING TEACHER USING EXPONENTIAL MOVING AVERAGE FOR SEMI-SUPERVISED SPEECH RECOGNITION

Vimal Manohar, Tatiana Likhomanenko, Qiantong Xu, Wei-Ning Hsu,
Ronan Collobert, Yatharth Saraf, Geoffrey Zweig, Abdelrahman Mohamed

Facebook AI

ABSTRACT

In this paper, we introduce the Kaizen framework that uses a continuously improving teacher to generate pseudo-labels for semi-supervised training. The proposed approach uses a teacher model which is updated as the exponential moving average of the student model parameters. This can be seen as a continuous version of the iterative pseudo-labeling approach for semi-supervised training. It is applicable for different training criteria, and in this paper we demonstrate it for frame-level hybrid hidden Markov model - deep neural network (HMM-DNN) models and sequence-level connectionist temporal classification (CTC) based models. The proposed approach shows more than 10% word error rate (WER) reduction over standard teacher-student training and more than 50% relative WER reduction over 10 hour supervised baseline when using large scale realistic unsupervised public videos in UK English and Italian languages.

Index Terms— speech recognition, semi-supervised training, pseudo-labeling, low-resource

1. INTRODUCTION

Self-training [1, 2, 3] is one of the most widely used approaches for semi-supervised training of automatic speech recognition (ASR) models. This approach uses an initial model that is called as "teacher" model or "seed" model to generate labels for the unsupervised data. The generated labels are called as pseudo-labels. The labeling can be done at the frame-level, which is usually in the form of soft targets or a distribution as in the case of knowledge distillation [4, 5, 6], or at sequence-level. While there are approaches to use a distribution over sequences [7, 8, 9] for sequence-level distillation, often only the best hypothesis sequence is used as pseudo-labels. The unsupervised data with the pseudo-labels is combined with the supervised data to train a new model. This approach is also known as "pseudo-labeling" and serves as the baseline for semi-supervised training. This process can be repeated for several "generations" to obtain better models in successive generations [10]. Strong data augmentation while training the student model is shown to improve self-training and helps to avoid local optima [11, 12, 13]. As opposed to changing the teacher model in discrete steps i.e. after each generation of pseudo-labeling, some recent works have explored updating the model continuously and using it to generate pseudo-labels [13, 12, 14]. In this class of approach, we propose a new pseudo-labeling framework named Kaizen. In Kaizen, we propose to use the Exponential Moving Average (EMA) of the student model as the teacher model. We show that this approach in combination with data augmentation stabilizes the training even when using large-scale realistic unsupervised dataset with only 1-10 hours of supervised data. The proposed approach shows more than 10% word error rate (WER) reduction over pseudo-labeling and more than 50% WER reduction over 10 hour supervised baseline when using large scale realistic unsupervised public videos in UK English and Italian languages.

In Section 2, we compare our proposed work to related works in the literature. In Section 3, we describe the proposed Kaizen framework and the training criteria used. In Section 4, we describe the experimental setup and discuss the results. In Section 5, we provide our conclusions and planned future work.

2. RELATED WORKS

Exponential Moving Average (EMA) has been used previously for semi/self-supervised training. Temporal Ensembling [15] uses EMA on network predictions while in this work we apply it on the network parameters. Mean Teacher [16] uses EMA on parameters and consistency cost for image recognition tasks. In this work, we generalize EMA teacher to use with sequence-level loss like CTC and on ASR tasks. BYOL [17] showed that EMA teacher can be used for self-supervised learning without using negative examples. Our work in this paper focuses on a semi-supervised learning setting. Multiple-iterations of pseudo-labeling along with strong data augmentation are shown to be superior to single generation of pseudo-labeling [11, 12]. In [13], Chen et al. extend this to continuously train a single model and using the latest model state to generate new pseudo-labels. This approach was found to be unstable due to model divergence in [14]. slimIPL [14] approach gets around this by using a dynamic cache containing pseudo-labels generated from an older model states. Our proposed Kaizen approach is an alternative way of stabilizing the training when using a continuously updating teacher by using exponential moving averaging with a sufficiently large discount factor.

3. METHOD

3.1. Kaizen: Continuously improving teacher

The Kaizen framework consists of a pair of models – the teacher model and the student model – that are trained simultaneously. The student model is trained using standard gradient-based optimization. Let its parameters be θ_t after t updates. The teacher model parameters ξ_t are updated every Δ steps as the exponential moving average (EMA) of the student model parameters:

$$\xi_t = (1-\alpha)\xi_{t-\Delta} + \alpha\theta_{\lfloor \frac{t}{\Delta} \rfloor \Delta}, \quad (1)$$

where α is a discount factor. A higher α discounts the older student models' parameters and gives more weight to the more recent student models' parameters.

Kaizen can be described using a block diagram as in Figure 1. The audio features x from an utterance in the unsupervised dataset is fed through both teacher and student neural network models. For the student model, the data is augmented on-the-fly using data augmentation approaches like SpecAugment [18]. The student network hidden activations are also randomly dropped using dropout [19], while dropout is not applied on the teacher network. The resultant outputs from the teacher and student models, $\hat{y}$ and y respectively, are used to compute the loss $\mathcal{F}(\hat{y}, y)$. The gradients are backpropagated through the student network to update its parameters θ_t. The gradients are not backpropagated through the teacher model, which instead is updated as exponential moving average of the student model parameters as in (1).

3.2. Exponential Moving Average (EMA)

Exponential averaging is more commonly described by using a decay factor $\lambda = 1 - \alpha$. However, we find the discount factor α to be more intuitive to quantify the "distance" between the student model, which is also referred to as the online model, and its slow moving average (teacher model). The EMA model parameters can also be written as an infinite summation over student models after different number of updates as in (2). Each student model θ_i contributes with a weight w_i to the summation i.e.

$$\begin{aligned}\xi_t &= \sum_{i \le t} w_i \theta_i \\ &\triangleq \alpha\theta_t + (1-\alpha)\alpha\theta_{t-\Delta} + \dots + (1-\alpha)^n \alpha\theta_{t-n\Delta} + \dots\end{aligned} \quad (2)$$

α	Δ	λ	τ
0.01	1	0.99	69
0.001	1	0.999	693
0.0001	1	0.9999	6931
0.001	10	0.999	6928
0.0025	10	0.975	2769

Table 1. Half-lives for common values of α and Δ

Another useful quantity is the half-life τ which is defined as:

$$\begin{aligned}\tau &:= w_{t-\tau} = \frac{w_t}{2} \\ &= -\Delta \frac{\ln 2}{\ln(1-\alpha)}\end{aligned} \quad (3)$$

The half-lives from some values of α and Δ are shown in Table 1.

A larger α or equivalently a small half-life results in the teacher model being "too close" to the student model. This can encourage the model to produce targets that are easier for the model to predict, leading to "collapse" of the model so that the model starts predicting just silences or `<blank>`. This is consistent with the observations in [14] where the authors also observed divergence when not using dynamic cache, but is in contrast to the work in [13] where the authors were able to train the model successfully. However, our setup is significantly different from the setup in [13] because we only have 1-10hr of supervised data.

A smaller α gives smaller weight for the recent student model. This results in more stable training. However, the teacher model is more static and this can lead to worse performance. We find that for ideal performance and stable training, the half-life should be at least 1000 or higher.

In one extreme of $\alpha = 0$, the teacher model is not updated at all. This is equivalent to the single-stage pseudo-labeling a.k.a. teacher-student training. In the other extreme of $\alpha = 1$, the teacher model is replaced with the student model every Δ updates. This is equivalent to iterative pseudo-labeling (IPL). Our proposed Kaizen framework thus provides a generalized framework for semi-supervised training that encompasses both single-stage pseudo-labeling as well as IPL.

3.3. Training criteria

The Kaizen framework can be used with different training criteria and modeling paradigms. In this paper, we investigate two modeling paradigms:

- Hybrid HMM-DNN: This is the simplest paradigm where the neural network model predicts context-dependent character (chenone) units [20] at the frame-level. In the Kaizen framework, we train the student network to minimize the Kullbeck-Leiber divergence [21] between the teacher network's chenone posterior

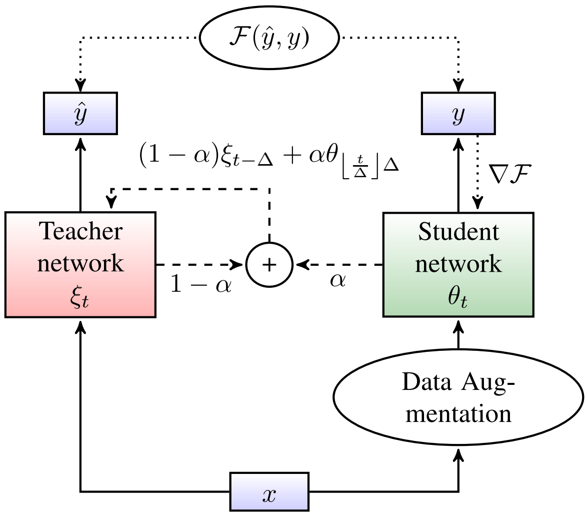

Fig. 1. Block diagram of the Kaizen framework

distribution $\hat{y}$ and student network's chenone posterior distribution y. This is similar to the case of standard teacher-student training. In our work, we take the top K posteriors from the teacher network to get at least 0.99 probability mass as done in [22].

$$\mathcal{F}(\hat{y}, y; x) = \mathcal{D}(\hat{y} \mid\mid y) \tag{4}$$

- CTC: In this paradigm, the neural network model is trained with the sequence-level criterion of connectionist temporal classification (CTC) [23]. In the Kaizen framework, we train the student network using the CTC loss (5) of minimizing the conditional probability of the token sequence $\hat{y}$ predicted by the teacher network. In this work, we use greedy decoding as in [13, 14] where the sequence $\hat{y}$ is obtained by de-duplicating the output label sequence of the teacher model and removing the `<blank>` labels.

$$\mathcal{F}(\hat{y}, y; x) = -\log p_\theta(\hat{y} \mid x) \tag{5}$$

Alternatively, a beam-search decoding can be used to obtain $\hat{y}$. However, this is computationally more expensive and we did not try this here.

3.4. Half-precision floating-point (fp16) training

When the models are in full-precision floating point (fp32) representation, the Kaizen approach is straightforward. However, when the models use half-precision floating point (fp16), we found that it is critical that the EMA parameters are accumulated in fp32. This results in an extra copy of EMA parameters in fp32. Without this additional copy of EMA parameters in fp32, there is significant degradation relative to fp32 training and for some parameter settings, it does no better than single generation of pseudo-labeling. This shows that high precision is essential to capture the small changes in the EMA model.

Note that the additional fp32 copy is only used for the EMA update step. After the update step of EMA parameters, it can be casted to fp16 so that the forward pass through the teacher network is in fp16. This allows using 1.5 times larger batch size compared to fp32 without any loss in accuracy.

4. EXPERIMENTS

4.1. Data

For training data, we use de-identified public videos with no personally identifiable information (PII) in UK English and Italian languages. In this paper, we simulate a low-resource scenario by limiting to a subset of 10 hours of supervised data, and a more extreme scenario with just 1 hour of supervised data in UK English. For both these languages, we use a much larger amount of unsupervised data consisting – 75000 hours for UK English and 50000 hours for Italian. As an upper-bound experiment, we compare with a supervised-only setting where we have 650 hours for UK English and 3700 hours for Italian. The supervised data is augmented 3x with speed perturbation [24]. For evaluation, we use a 14 hour test set for UK English and a 20 hour test set for Italian. We use a separate development set of the same size for hyper-parameter tuning.

For UK English language, we use transcripts corresponding 650 hours plus an additional 13000 hours of generic English video transcripts for language model (LM) training. For Italian language, we use the transcripts from the same 3700 hours for LM training.

We used a hybrid flatstart lattice-free maximum mutual information (LFMMI) [25] trained time-delay neural network - bi-directional long short-term memory (TDNN-BLSTM) [26, 27] model for data preparation. We refer to this as the alignment model. This was used to align and segment the data into 10s segments for training. The unsupervised data was pre-processed using a proprietary voice activity detection (VAD) model to select only speech segments of maximum duration of 45s. These segments were then decoded using the alignment model to produce machine generated transcription which is used as reference for the data preparation stage (aligning and segmentation into 10s).

4.2. Model details

The hybrid TDNN-BLSTM LFMMI alignment model has 2 BLSTM [28] layers with 640 hidden units in each recurrence direction and 3 TDNN layers [29, 30] with 640 hidden units interleaved between input and first BLSTM layer, and between the 2 BLSTM layers. The modeling units for this is context-dependent bi-character units, each modeled with a 1-state HMM topology with state-tying done using context-dependency tree built using purely the text transcripts (no alignments) and silence inserted randomly between words as done in [31].

We investigate the Kaizen approach with two modeling paradigms – hybrid HMM-DNN and CTC. For hybrid HMM-DNN paradigm, the modeling units are context-dependent tri-character units, each modeled with a 1-state HMM topology with state-tying done using a context-dependency tree build using statistics from the frame-level character alignments produced by the alignment model. For CTC paradigm, we use sentence-piece [32] units. For both these paradigms, we use a neural network model with a 2 VGG layers [33] followed by 12 transformer blocks (768 hidden units, 8 heads) [34] following [35]. Each VGG layer sub-samples by 2 in the time-axes using max-pooling [36], resulting in the model that outputs at a rate of 25Hz (40ms time step).

The input features to all the models are 80 dimensional Mel-scale log filterbank coefficients computed every 10ms over 25ms windows. Spectral masking is applied on-the-fly using SpecAugment except for the teacher model in Kaizen approach.

4.3. Training details

For 10 hour or 1 hour of data, the hybrid TDNN-BLSTM LFMMI trained alignment model has lower WER than the 12-layer transformer model trained using either cross-entropy (CE) loss or CTC loss. For e.g., the dev results in Table 2 for 10 hour supervised with CTC paradigm is significantly worse than the hybrid model. Thus the alignment model also serves as the supervised baseline.

For the semi-supervised experiments, we have a “pre-training” stage where we train only on unsupervised data for 150k or 200k updates. For Kaizen approach, first 25k updates we use the labels produced by the baseline model (just like in regular pseudo-labeling). The EMA model is started to be accumulated after 15k updates. There is a “burn-in” period for EMA model from 15k updates to 25k updates where the EMA model is being updated, but the student model is still being trained using labels from the baseline model. After 25k updates, we switch to using pseudo-labels from continuously updated teacher model. We follow the pre-training stage with a fine-tuning stage where the model is fine-tuned on the supervised data.

We use the Adam [37] optimizer with mixed-precision [38] training and gradient norm clipping at 10. For the supervised LFMMI baseline, we use a learning rate that rises from 1.25e-6 to 1.25e-4 in 500 updates and then reduces by a factor of 0.5 when the valid loss improvement is less than 1e-4 relative. We use distributed data-parallel training (DDP) with batch of 40 min of audio distributed across 4 GPUs. For the pre-training stage of semi-supervised experiments, we use a learning rate schedule that rises linearly for 7.5k updates to 1.5e-4 and decreases linearly to 0 after 200k updates of training. We use DDP with batch of 17.1 hours of audio distributed across 64 GPUs. For fine-tuning, we use a learning rate schedule that rises linearly for 500 updates and decreases linearly until 10k updates. We use DDP with batch of 40min of audio distributed across 4 GPUs.

Model	Paradigm	dev	test	WERR
10hr sup	Hybrid	53.9	51.1	
10hr sup	CTC	74.4	-	
650 hr ub	Hybrid	23.3	22.4	56.3
PL	Hybrid	30.2	29.8	41.7
Kaizen	Hybrid	27.3	26.8	47.6
PL	CTC	26.2	25.5	50.2
Kaizen	CTC	23.2	22.7	**55.5**
IPL	CTC	23.9	23.4	54.2

Table 2. WERs on 10hr UK English setup with 75k hours of unsupervised data

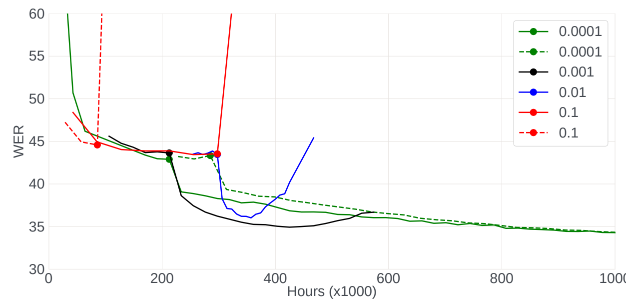

Fig. 2. Effect of EMA discount factor α

4.4. Results

4.4.1. Public videos

Tables 2, 3 and 4 show WER results comparing standard pseudo-labeling (PL), Kaizen and IPL on 10hr UK English, 10hr Italian and 1hr UK English public video setups. We also use a hybrid model trained on 10hr or 1hr of supervised data as the baseline. The WER reductions (WERR) are reported

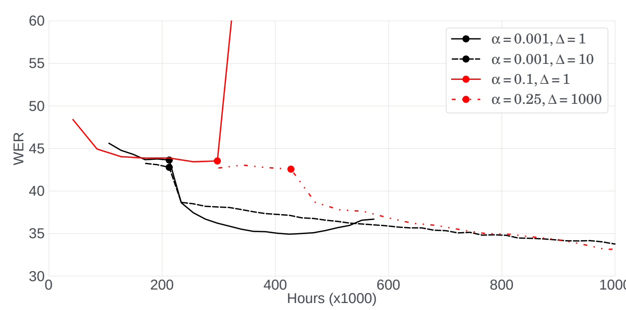

Fig. 3. Effect of EMA update frequency Δ

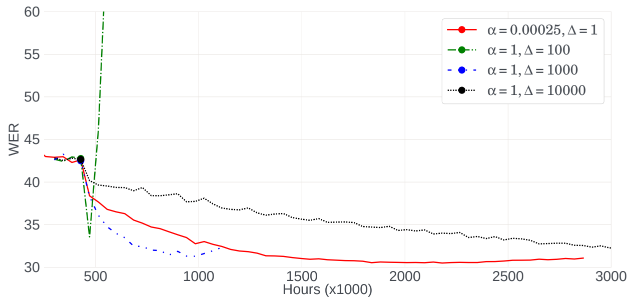

Fig. 4. Comparing IPL and Kaizen

Model	Paradigm	clean	noisy	extreme	WERR
10hr sup	Hybrid	39.7	43.9	60.4	
2.7khrs ub	CTC	9.3	11.8	17.2	73.8
PL	CTC	13.2	17.2	26.3	61.4
Kaizen	CTC	11.5	14.6	21.8	67.2
IPL	CTC	11.5	14.6	21.8	67.2

Table 3. WERs on 10hr Italian setup with 50k hours of unsupervised data

relative to this baseline for all the models. We also report performance of an upper-bound (ub) model that is trained on all the supervised data that we have access to i.e. 650 hours on UK English and 2.7k hours on Italian. On UK English setups, we show WERs on dev and test sets. On Italian setup, we show WER on 3 test sets – clean, noisy and extreme.

We can see from the results that Kaizen out-performs PL by more than 10% relative on all the setups and both hybrid HMM-DNN and CTC paradigms. Kaizen is also similar to or slightly better than IPL on all the setups. On both UK English and Italian languages, we close the gap to the upper-bound ASR system that uses 650hr or 2.7khrs respectively using just 10 hours of supervised data and a large amount of unsupervised data.

Model	Paradigm	dev	test	WERR
1hr sup	Hybrid	81.1	79.9	
650 hr ub	Hybrid	23.3	22.4	72.0
PL	Hybrid	64.6	62.3	22.0
Kaizen	Hybrid	53.4	53.0	33.7
PL	CTC	55.3	54.8	31.4
Kaizen	CTC	37.2	35.3	55.8
IPL	CTC	37.9	36.7	54.1

Table 4. WERs on 1hr UK English setup with 75k hours of unsupervised data

4.4.2. *Effect of EMA parameters*

In this section, we study the effect of two EMA parameters – the decay factor α and update frequency Δ. We do this investigation on the UK English videos dataset in the hybrid HMM-DNN paradigm. The stability of training depends on the distance between teacher and student models, which for Kaizen is quantified using half-life 3.

The plots in Figures 2, 3 and 4 show the WER on UK English 10 hours supervised setup during the "pre-training" stage as a function of number of hours of training for various training runs. For each training run, the point where the model switches to using the continuously generated pseudo-labels is marked with a solid circle.

Figure 2 shows various training runs with $\alpha \in \{0.1, 0.01, 0.001, 0.0001\}$ and $\Delta = 1$. We see that the model diverges very quickly when $\alpha = 0.1$, which corresponds to a half-life $\tau = 7$. The model training gets more stable progressively as we increase the α value towards the most stable 0.0001, which corresponds to half-life $\tau = 6931$.

Figure 3 demonstrates the effect of EMA update frequency Δ. For $\alpha = 0.001$, there is divergence with $\Delta = 1$ ($\tau = 693$), but the training is stable and WER improves continuously with $\Delta = 10$ ($\tau = 6928$). For higher value of α like 0.1 or 0.25 where half-life is less than 10 if $\Delta = 1$, the training diverges almost immediately as seen for $\alpha = 0.1, \Delta = 1$. But even with such α, the training is stable if Δ is increased to 1000 as seen for $\alpha = 0.25, \Delta = 1000$ ($\tau = 2409$).

Figure 4 compares the basic Kaizen case of $\alpha = 0.00025, \Delta = 1$ with IPL ($\alpha = 1, \Delta \in \{100, 1000, 10000\}$). We see that with $\Delta = 100$, IPL diverges very soon after switching to using continuously generated pseudo-labels. Increasing Δ stabilizes it as seen with $\Delta = 1000$ where the divergence happens only after training on 1M hours. Using a much larger Δ value of 10000 (For batch size of 17.1 hours and dataset of 75k hours, this is 171k hours = 2.8 epochs), the model trains stably but improves more slowly. Using typical Kaizen parameters of $\alpha = 0.00025, \Delta = 1$ corresponding to half-life of 2772, the training is stable while also showing better WER after 2M hours.

These results show that the model training is not stable unless the distance between teacher and student models is sufficiently large (half-life of more than 2000). Smaller distances i.e. smaller half-lives lead to "collapse" and WER degrades rapidly. In particular, we find that for updating the model continuously $\Delta = 1$ as in [13] requires a small EMA discount factor to discount most recent student models. We also tried to mix-in some supervised data such that 10% of data in each epoch is supervised. This did not help stability. We hypothesize that this is partly due to our supervised dataset being very small in the order of 1-10hr. Further experiments with larger datasets are needed in the future to investigate this.

5. CONCLUSIONS AND FUTURE WORK

We introduce the Kaizen framework for semi-supervised training that uses a continuously improving teacher model to generate pseudo-labels. The teacher model is updated as the exponential moving average of the student model. The proposed framework is shown as a generalization of pseudo-labeling and IPL. We analyzed the effect of the EMA parameters and showed that the distance between the teacher and student models is the key for effective and stable training. A small EMA half-life leads to collapse of the model and poor performance, while too large a half-life leads to slow improvement. We showed that the proposed approach gives more than 10% WERR over standard teacher-student training and performs comparatively to IPL on public videos dataset in UK English and Italian languages.

5.1. Future Work

This work has explored Kaizen for Hybrid HMM-DNN and CTC based models, and we plan to explore this further for sequence-to-sequence models like RNN-T. Preliminary experiments show that scheduling EMA parameters is promising. Using larger discount factor in the beginning of training allows the teacher to forget the history and benefit from the fast improving student in the beginning. The discount factor can be later reduced to make the training more stable. While current work as shown applicability in low-resource scenario, we plan to further expand it to higher resource settings that have 100s to 1000s of hours of supervised data. The proposed approach naturally fits into online training of ASR models.

6. REFERENCES

[1] George Zavaliagkos and Thomas Colthurst, "Utilizing untranscribed training data to improve performance," in *DARPA Broadcast News Transcription and Understanding Workshop*, 1998.

[2] Samuel Thomas, Michael L. Seltzer, Kenneth Church, and Hynek Hermansky, "Deep neural network features and semi-supervised training for low resource speech recognition," in *2013 IEEE International Conference on Acoustics, Speech and Signal Processing*, 2013, pp. 6704–6708.

[3] Jacob Kahn, Ann Lee, and Awni Hannun, "Self-training for end-to-end speech recognition," *arXiv preprint arXiv:1909.09116*, 2019.

[4] Cristian Buciluundefined, Rich Caruana, and Alexandru Niculescu-Mizil, "Model compression," in *Proceedings of the 12th ACM SIGKDD*, 2006.

[5] Lei Jimmy Ba and Rich Caruana, "Do deep nets really need to be deep?," in *NIPS*, Cambridge, MA, USA, 2014, MIT Press.

[6] Geoffrey Hinton, Oriol Vinyals, and Jeffrey Dean, "Distilling the knowledge in a neural network," in *NIPS Deep Learning and Representation Learning Workshop*, 2015.

[7] Jeremy HM Wong and Mark Gales, "Sequence student-teacher training of deep neural networks," in *Interspeech*, 2016.

[8] V. Manohar, H. Hadian, D. Povey, and S. Khudanpur, "Semi-supervised training of acoustic models using Lattice-Free MMI," in *ICASSP*, 2018.

[9] Wei-Ning Hsu, Ann Lee, Gabriel Synnaeve, and Awni Hannun, "Semi-supervised speech recognition via local prior matching," *arXiv preprint arXiv:2002.10336*, 2020.

[10] F. Wessel and H. Ney, "Unsupervised training of acoustic models for large vocabulary continuous speech recognition," *IEEE Transactions on Speech and Audio Processing*, vol. 13, 2005.

[11] Daniel S Park, Yu Zhang, Ye Jia, Wei Han, Chung-Cheng Chiu, Bo Li, Yonghui Wu, and Quoc V Le, "Improved noisy student training for automatic speech recognition," *arXiv preprint arXiv:2005.09629*, 2020.

[12] Qiantong Xu, Tatiana Likhomanenko, Jacob Kahn, Awni Hannun, Gabriel Synnaeve, and Ronan Collobert, "Iterative pseudo-labeling for speech recognition," *arXiv preprint arXiv:2005.09267*, 2020.

[13] Yang Chen, Weiran Wang, and Chao Wang, "Semi-supervised ASR by End-to-end Self-training," in *Interspeech*, 2020.

[14] Tatiana Likhomanenko, Qiantong Xu, Jacob Kahn, Gabriel Synnaeve, and Ronan Collobert, "slimipl: Language-model-free iterative pseudo-labeling," *arXiv preprint arXiv:2010.11524*, 2020.

[15] Samuli Laine and Timo Aila, "Temporal ensembling for semi-supervised learning," *arXiv preprint arXiv:1610.02242*, 2016.

[16] Antti Tarvainen and Harri Valpola, "Mean teachers are better role models: Weight-averaged consistency targets improve semi-supervised deep learning results," *arXiv preprint arXiv:1703.01780*, 2017.

[17] Jean-Bastien Grill, Florian Strub, Florent Altché, Corentin Tallec, Pierre H Richemond, Elena Buchatskaya, Carl Doersch, Bernardo Avila Pires,

Zhaohan Daniel Guo, Mohammad Gheshlaghi Azar, et al., "Bootstrap your own latent: A new approach to self-supervised learning," *arXiv preprint arXiv:2006.07733*, 2020.

[18] Daniel S Park, William Chan, Yu Zhang, Chung-Cheng Chiu, Barret Zoph, Ekin D Cubuk, and Quoc V Le, "Specaugment: A simple data augmentation method for automatic speech recognition," *arXiv preprint arXiv:1904.08779*, 2019.

[19] Nitish Srivastava, Geoffrey Hinton, Alex Krizhevsky, Ilya Sutskever, and Ruslan Salakhutdinov, "Dropout: a simple way to prevent neural networks from overfitting," *The journal of machine learning research*, vol. 15, no. 1, pp. 1929–1958, 2014.

[20] Duc Le, Xiaohui Zhang, Weiyi Zheng, Christian Fügen, Geoffrey Zweig, and Michael L Seltzer, "From senones to chenones: Tied context-dependent graphemes for hybrid speech recognition," *ASRU*, 2019.

[21] Solomon Kullback and Richard A Leibler, "On information and sufficiency," *The annals of mathematical statistics*, vol. 22, no. 1, pp. 79–86, 1951.

[22] Kritika Singh, Vimal Manohar, Alex Xiao, Sergey Edunov, Ross Girshick, Vitaliy Liptchinsky, Christian Fuegen, Yatharth Saraf, Geoffrey Zweig, and Abdelrahman Mohamed, "Large scale weakly and semi-supervised learning for low-resource video asr," *arXiv preprint arXiv:2005.07850*, 2020.

[23] Alex Graves, Santiago Fernández, and Faustino Gomez, "Connectionist temporal classification: Labelling unsegmented sequence data with recurrent neural networks," in *ICML 2006*.

[24] Tom Ko, Vijayaditya Peddinti, Daniel Povey, and Sanjeev Khudanpur, "Audio augmentation for speech recognition.," in *INTERSPEECH*, 2015.

[25] Daniel Povey, Vijayaditya Peddinti, Daniel Galvez, Pegah Ghahremani, Vimal Manohar, Xingyu Na, Yiming Wang, and Sanjeev Khudanpur, "Purely sequence-trained neural networks for asr based on lattice-free mmi," in *Interspeech*, 2016.

[26] Gaofeng Cheng, Vijayaditya Peddinti, Daniel Povey, Vimal Manohar, Sanjeev Khudanpur, and Yonghong Yan, "An exploration of dropout with lstms.," in *Interspeech*, 2017, pp. 1586–1590.

[27] Vijayaditya Peddinti et al., *Low latency modeling of temporal contexts for speech recognition*, Ph.D. thesis, Johns Hopkins University, 2017.

[28] Sepp Hochreiter and Jürgen Schmidhuber, "Long short-term memory," *Neural computation*, vol. 9, no. 8, pp. 1735–1780, 1997.

[29] Kevin J Lang, Alex H Waibel, and Geoffrey E Hinton, "A time-delay neural network architecture for isolated word recognition," *Neural networks*, vol. 3, no. 1, pp. 23–43, 1990.

[30] Vijayaditya Peddinti, Daniel Povey, and Sanjeev Khudanpur, "A time delay neural network architecture for efficient modeling of long temporal contexts," in *Sixteenth Annual Conference of the International Speech Communication Association*, 2015.

[31] Hossein Hadian, Hossein Sameti, Daniel Povey, and Sanjeev Khudanpur, "End-to-end Speech Recognition Using Lattice-free MMI," in *Interspeech*, 2018, pp. 12–16.

[32] Taku Kudo and John Richardson, "SentencePiece: A simple and language independent subword tokenizer and detokenizer for neural text processing," in *EMNLP*, 2018.

[33] Karen Simonyan and Andrew Zisserman, "Very deep convolutional networks for large-scale image recognition," *arXiv preprint arXiv:1409.1556*, 2014.

[34] Ashish Vaswani et.al., "Attention is all you need," in *NeurIPS 2017*.

[35] Yongqiang Wang, Abdelrahman Mohamed, Duc Le, Chunxi Liu, Alex Xiao, et al., "Transformer-based acoustic modeling for hybrid speech recognition," in *ICASSP*, 2020.

[36] Kouichi Yamaguchi, Kenji Sakamoto, Toshio Akabane, and Yoshiji Fujimoto, "A neural network for speaker-independent isolated word recognition," in *First International Conference on Spoken Language Processing*, 1990.

[37] Diederik Kingma and Jimmy Ba, "Adam: A method for stochastic optimization," *ICLR*, 2014.

[38] Sharan Narang, Gregory Diamos, Erich Elsen, Paulius Micikevicius, Jonah Alben, David Garcia, Boris Ginsburg, Michael Houston, Oleksii Kuchaiev, Ganesh Venkatesh, et al., "Mixed precision training," in *Int. Conf. on Learning Representation*, 2017.

↑ TOP of text, page 2 and following pages, aligned to line ↑

↑ TOP of title, centered and aligned to line — page 1 ↑

↑ Author(s) name(s), centered and aligned to line — page 1 ↑

Author affiliation(s), email address(es) centered below names

[Abstract in area between dashed lines — page 1]
[leave two blank lines (12mm) between last line of Abstract and first line of text.]

Keep all text and graphics within the column margins.

↓ Last line of text must not extend below this line. ↓

[Begin 2nd column of text here — page 1 only]

Keep all text and graphics within the column margins.

↓ Last line of text must not extend below this line. ↓