

# ROBUST KNOWLEDGE DISTILLATION FROM RNN-T MODELS WITH NOISY TRAINING LABELS USING FULL-SUM LOSS

Mohammad Zeinelddeen<sup>1\*</sup>, Kartik Audhkhasi<sup>2</sup>, Murali Karthick Baskar<sup>2</sup>, Bhuvana Ramabhadran<sup>2</sup>

<sup>1</sup>Human Language Technology and Pattern Recognition, Computer Science Department,  
RWTH Aachen University, 52074 Aachen, Germany

<sup>2</sup>Google LLC, New York

## ABSTRACT

This work studies knowledge distillation (KD) and addresses its constraints for recurrent neural network transducer (RNN-T) models. In hard distillation, a teacher model transcribes large amounts of unlabelled speech to train a student model. Soft distillation is another popular KD method that distills the output logits of the teacher model. Due to the nature of RNN-T alignments, applying soft distillation between RNN-T architectures having different posterior distributions is challenging. In addition, bad teachers having high word-error-rate (WER) reduce the efficacy of KD. We investigate how to effectively distill knowledge from variable quality ASR teachers, which has not been studied before to the best of our knowledge. We show that a sequence-level KD, full-sum distillation, outperforms other distillation methods for RNN-T models, especially for bad teachers. We also propose a variant of full-sum distillation that distills the sequence discriminative knowledge of the teacher leading to further improvement in WER. We conduct experiments on public datasets namely SpeechStew and LibriSpeech, and on in-house production data.

**Index Terms**— Recurrent neural network transducer, knowledge distillation, semi-supervised learning

## 1. INTRODUCTION & RELATED WORK

Training high-performance end-to-end automatic speech recognition (ASR) systems such as recurrent neural network transducer (RNN-T) [1] heavily depends on the amount and the quality of the transcribed training data. It is usually difficult and very expensive to collect high-quality human transcription.

Knowledge distillation (KD) [2] is a method to transfer knowledge from a teacher model to a (smaller) student model. The teacher model generates pseudo labels using unsupervised data for training a student model. However, the quality of the pseudo labels depends on the quality of the teacher model where a bad teacher, i.e with a high word-error-rate (WER), can generate noisy pseudo labels which do not help in training good student models. To the best of our knowledge,

there has been no prior work that investigates the impact of bad teachers for KD in the context of ASR. [3] shows theoretically and empirically that distilling from a pool of bad teachers (randomly selected) helps to learn a better student model. [4, 5] proposes a simpler idea which is to add noise to the teacher’s logits to simulate the idea of training with multiple bad teachers. Both [3, 4] can be seen as regularization methods. There has also been related work in the context of adversarial label learning [6, 7] where students are trained to minimize the error caused by noisy labels generated by bad teachers. However, all these works use simple binary classifiers and focus more on theoretical analysis.

In addition, it is common to apply KD at the level of output logits [2]. Soft distillation can be used to distill the RNN-T alignments of the teacher model. However, this method is challenging when the teacher and student models have different alignments such as distilling knowledge from a non-causal teacher to a causal student. To fix this issue, [8, 9] shift the teacher alignments to the right when applying soft distillation since the causal student would emit labels later because of missing future context. However, it is a heuristic solution that requires finding the frame shift and increases the causal latency. In addition, when using soft distillation, the teacher and student models must have the same time dimension which limits the ability to train student models with higher time reduction for reducing recognition latency. [10] investigates different KD methods for connectionist temporal classification models [11] including sequence-level KD, which has not been studied for RNN-T models.

In this paper, we investigate how to effectively distill knowledge from varying quality RNN-T teachers including bad teachers which have not been studied before. We apply full-sum distillation, which is a sequence-level KD method that distills the sequence posterior probabilities, for the first time for RNN-T models using various loss functions. We also propose a variant of full-sum distillation which distills the sequence discriminative knowledge of the teacher model that leads to further improvements. We show that full-sum distillation is robust towards discrepancies of RNN-T alignments between the teacher and student models and that it

\*Work performed during an internship at Google.

scales when applied on our in-house data.

## 2. RNN-T MODEL

In this work, we focus on the standard RNN-T model [1]. Let  $X$  denote the acoustic feature sequence of a speech utterance of length  $T$ . Let  $Y$  denote the output label sequence (e.g characters) of length  $U$ . Then, the sequence posterior probability is defined as:

$$P(Y|X) = \sum_{a \in \beta^{-1}(Y)} P(a|X) \quad (1)$$

where  $a$  belongs to the set of all possible alignments of  $Y$  consisting of output labels and a special blank label.  $\beta$  is a mapping function that maps an alignment sequence  $a$  to an output label sequence  $Y$  by removing blank labels. The RNN-T training loss is given by the negative log sequence posterior probability:  $\mathcal{L}_{\text{RNN-T}} = -\log P(Y|X)$ . This is also known as the full-sum (FS) loss. The probability  $P(Y|X)$  is computed over a lattice of dimension  $T \times U$ . At each position  $(t, u)$  in the lattice, features from the encoder and the prediction networks of the RNN-T model are fed to a joint network that computes a probability distribution  $P(k|t, u)$  for each output label  $k$  including the blank label. The RNN-T loss can be computed efficiently using forward-backward algorithm [1].

## 3. RNN-T DISTILLATION METHODS

The most common distillation methods are hard distillation and soft distillation [2]. Hard distillation uses the pseudo labels generated by a teacher model to train a student model. It is also possible to use a mix of pseudo labels and ground truth labels (supervised data). For RNN-T models, this means that the student model would learn the alignment by itself (i.e without any constraints) by minimizing the RNN-T loss. Soft distillation is applied by matching the posterior probability distributions for each output label  $k$  (including blank) of both teacher and student models over the lattice for each position  $(t, u)$  [12]. This can be achieved using Kullback-Leibler (KL) divergence loss as follows:

$$\mathcal{L}_{\text{Soft-Distill}} = \sum_{(t,u)} \sum_k \tilde{P}(k|t, u) \log \left[ \frac{\tilde{P}(k|t, u)}{P(k|t, u)} \right] \quad (2)$$

where  $\tilde{P}$  and  $P$  correspond to the teacher and student probability distributions respectively. [12] proposes an efficient method to apply soft distillation for RNN-T models by distilling only three posterior probabilities which are for target output label, blank label, and the rest labels. This reduces the memory complexity from  $O(T \times U \times K)$  to  $O(T \times U)$  where  $K$  is the vocabulary size. We use this efficient method for experiments with soft distillation.

## 4. FULL-SUM DISTILLATION METHOD

The main motivation behind this work is to utilize a simple yet effective KD method that is robust in case of noisy labels and when the architecture or design of the student and teacher models differs. Therefore, we use full-sum (FS) distillation, as a sequence-level KD method, that simply distills the FS

probabilities between the teacher and student model. The loss can be defined as:

$$\mathcal{L}_{\text{FS-Distill}} = \mathcal{F}(\tilde{P}(Y|X), P(Y|X)) \quad (3)$$

where  $\mathcal{F}$  denotes the loss function used to minimize the difference between both distributions. In this work,  $\mathcal{F}$  is defined as  $L_1$  loss or mean squared error (MSE) loss so that it is symmetric and is not impacted by any transformation of its two arguments. Therefore, we found that in practice using log-space probabilities makes training more stable. In addition, we can formulate the FS-Distill loss in terms of RNN-T loss as follows:

$$\mathcal{L}_{\text{FS-Distill}} = \mathcal{F}(-\log \tilde{P}(Y|X), -\log P(Y|X)) \quad (4)$$

Thus, we only need to compute the RNN-T losses of both teacher and student models to compute FS-Distill loss. Moreover, the FS-Distill loss can be formulated to distill the sequence discriminative knowledge of the teacher model to the student model. This can be done by distilling the approximated normalized sequence posterior probabilities using an N-best hypotheses list generated by the teacher model. This loss is called FS-Norm-Distill loss and can be written as follows:

$$\mathcal{F} \left( \log \frac{\tilde{P}(Y|X)}{\sum_{Y' \in \mathcal{B}_{\text{N-best}}} \tilde{P}(Y'|X)}, \log \frac{P(Y|X)}{\sum_{Y' \in \mathcal{B}_{\text{N-best}}} P(Y'|X)} \right) \quad (5)$$

where  $Y'$  belongs to the N-best hypotheses list denoted by  $\mathcal{B}_{\text{N-best}}$ .

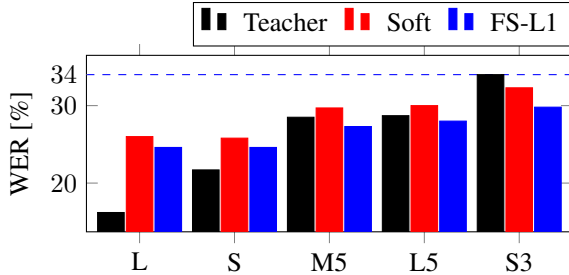
Note also that FS distillation method does not depend on time dimension as compared to soft distillation which means that the teacher and student models can have different time subsampling rates.

## 5. EXPERIMENTS

In this section, we present results on different public corpora, namely, SpeechStew [13] (Section 5.1) and LibriSpeech [14] (Section 5.2). For distillation experiments, no dropout or data augmentation is applied to the speech input of the teacher model since it was observed that this leads to better performance [8]. In addition to that, training batches are constructed by sampling 10% from the supervised data and 90% from the unsupervised data. We use a beam size of 8 to generate hypotheses for unsupervised data and then select the top-1 hypothesis as the target label sequence. All student models are trained from scratch. All models use 80-dimensional Log-Mel filterbank features as input and 1024 wordpieces as output labels. No language model is used for recognition.

### 5.1. SpeechStew Setup

We train varying quality teacher models using SpeechStew dataset [13] to better understand the effect of each distillation method depending on the teacher's quality. SpeechStew consists of 5K hours and it is a mix of common speech public corpora. We split the dataset into 2 parts: supervised data consisting of 250 hours (5%) and unsupervised data consisting of 4.75K hours (95%). We use ConformerL, ConformerM, and ConformerS RNN-T architectures [15] to train teacher



**Fig. 1:** Comparison between soft and full-sum distillation using varying quality teachers. The horizontal dashed line is the WER of the student model. WERs are computed as the average WER on IHM and SDM1 dev sets of AMI dataset.

| Model       | Teacher | IHM  |      | SDM  |      |
|-------------|---------|------|------|------|------|
|             |         | dev  | eval | dev  | eval |
| Student     | -       | 23.3 | 24.5 | 44.7 | 48.6 |
| Hard        | L       | 24.4 | 24.1 | 38.4 | 40.9 |
| Hard + Soft |         | 17.9 | 17.9 | 35.3 | 38.4 |
| Soft        |         | 17.2 | 17.1 | 34.8 | 38.1 |
| Hard        | S3      | 27.6 | 28.2 | 42.9 | 45.9 |
| Hard + Soft |         | 22.3 | 23.1 | 42.3 | 46.1 |
| Soft        |         | 22.1 | 22.9 | 42.4 | 46.3 |

**Table 1:** Comparison between soft and hard distillation.

models having a different number of parameters. In addition, we train on subsets of the supervised training data to increase the WER variance between different teacher models. We train 5 different teacher models named as L, S, M5, L5, and S3 where the letter corresponds to which conformer architecture is used and the number represents the percentage of supervised training data (e.g M5 is ConformerM trained on all supervised data). Teachers L and S are trained using all SpeechStew data. The student model follows ConformerS architecture and it is trained using the supervised data.

### 5.1.1. Distillation Results

As our aim is to improve knowledge distillation when using bad or high-WER teacher models, we report results on the AMI dataset [16] since it is noisy and considered a difficult task. Table 1 shows the results of applying hard distillation using the strongest teacher L and the weakest teacher S3. We can observe that even with teacher L, hard distillation is much worse than using soft distillation. In addition, WER increases when using the weakest teacher S3. The reason behind this is that the pseudo labels generated by such teacher models are very noisy, especially on AMI which requires utilizing other distillation methods. Figure 1 shows a comparison between soft distillation and FS distillation when using varying quality teachers. We use L1 loss for FS distillation. First, we can observe that the quality of the teacher model has a significant effect on improving the WER of the student model. FS distillation outperforms soft distillation for all teachers. The student model outperforms the teacher models M5, L5, and S3 when using FS distillation whereas with soft distillation it

| $\mathcal{F}$ | Norm | IHM         |             | SDM         |             |
|---------------|------|-------------|-------------|-------------|-------------|
|               |      | dev         | eval        | dev         | eval        |
| MSE           | No   | 17.7        | 17.5        | 34.4        | 37.6        |
|               | Yes  | 16.7        | 16.5        | 33.5        | 36.8        |
| L1            | No   | 16.1        | 16.4        | 33.1        | 36.2        |
|               | Yes  | <b>15.8</b> | <b>15.7</b> | <b>32.3</b> | <b>35.5</b> |

**Table 2:** Comparison between using L1 and MSE loss functions for FS and FS-Norm distillation for teacher L.

only outperforms S3. This shows the robustness of FS distillation method.

### 5.1.2. Comparison between L1 and MSE loss for Full-sum Distillation

We investigate using two different losses for FS distillation: L1 loss and MSE loss. We select the strongest teacher L and the weakest teacher S3 for distillation experiments and present the results in Table 2. We can observe that using L1 loss gives much better performance in terms of WER compared to MSE loss. We argue that the training convergence is affected by outliers when using MSE loss. To analyze this, we plot the distillation loss value using 100 segments from AMI dataset. For the case of MSE, there are many outliers, and the distillation loss value is quite large while this is not the case when using L1. In addition, if we apply approximated normalization as described in Equation (5), then we do not observe outliers anymore which could explain also why using FS-Norm variant helps (more details in Section 5.1.3).

### 5.1.3. Full-sum Norm Distillation

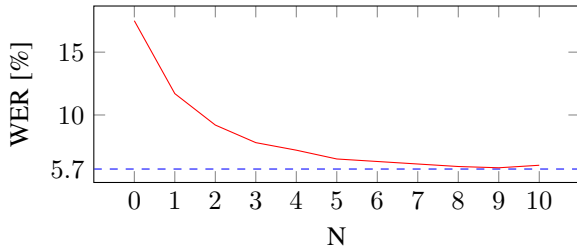
Furthermore, we conduct experiments using FS-Norm variant (Equation (5)) and the results are shown in Table 2. We use the strongest teacher L for distillation. Applying normalization further improves the WER of the student model especially when using MSE loss since it reduces outliers.

## 5.2. LibriSpeech Setup

We conduct experiments on LibriSpeech (LS) 960 hours [14] and LibriLight (LL) 60k hours [17]. LL consists of unlabeled data which is the main target data for distillation. The teacher model is a non-causal w2v-BERT XL Conformer model following this setup [8]. It has 600M parameters. It is pre-trained using w2v-BERT [18] on LL dataset and then iterative training is applied using offline pseudo labels to further improve the performance. The pseudo labels used were generated by a w2v-BERT XXL model [18] having 1B parameters. The WERs [%] of w2v-BERT XL and w2v-BERT XXL teacher models are 1.3/2.5/1.4/2.6 and 1.4/2.4/1.4/2.5 on dev-clean, dev-other, test-clean, and test-other respectively. The non-causal student model is based on the ConformerL architecture [15]. It has 120M parameters. The causal student model uses the same architecture but with causal conformer blocks where 65 frames are used as past context for self-attention modules and no future context. SpecAugment [19] is applied for data augmentation using the same hyperparameters as [8].

**Table 3:** Comparing distillation methods from non-causal w2v-BERT XL teacher model to causal/non-causal student model on LibriSpeech dataset. WERs [%] are reported on dev-other and test-other sets.

| Model       | Non-causal |            | Causal     |            |
|-------------|------------|------------|------------|------------|
|             | dev        | test       | dev        | test       |
| Student     | 4.4        | 4.6        | 10.4       | 9.5        |
| Hard        | 3.6        | 3.6        | 9.4        | 8.6        |
| Soft        | 3.7        | 3.8        | 8.4        | 7.9        |
| Hard + Soft | 3.7        | 3.8        | 8.6        | 8.2        |
| Full-sum    | <b>3.2</b> | <b>3.3</b> | <b>8.3</b> | <b>7.7</b> |



**Fig. 2:** WERs[%] using soft distillation from non-causal teacher to a causal student. The alignment of the teacher model is shifted by  $N$  frames to the right. The horizontal dashed line corresponds to the WER of FS distill without any shifting. The WERs are computed by averaging over all dev and test sets of LibriSpeech.

### 5.2.1. Distillation Results

Experiments for comparing different KD methods for LS task using non-causal and causal student models are shown in Table 3. In both cases, we can observe that FS distillation outperforms other distillation methods. For non-causal student experiments, FS distillation achieves 27% and 28% relative improvement in terms of WER on dev-other and test-other sets respectively compared to the student baseline model. Moreover, FS distillation achieves 11% and 8.3% relative improvement compared to hard distillation on dev-other and test-other sets respectively. When using a causal student model, the RNN-T alignments of the student model do not match the ones of the teacher model due to the lack of future context that will delay the emission of output labels. Thus, we can observe that soft distillation only works well when we shift the alignments of the teacher to the right by  $N$  frames. Figure 2 shows that we need to shift by 9 frames to achieve good performance. It also requires finding the correct frames shift. FS distillation is robust towards mismatch of alignments and can already achieve better results without any shifting. Overall, we achieve 20% and 18.9% relative improvement in terms of WER on dev-other and test-other sets respectively compared to the causal student model.

## 6. LARGE SCALE DISTILLATION

In this section, we demonstrate the robustness and scalability of full-sum distillation to models trained with several thousands of hours of labeled and unlabeled data in two In-

**Table 4:** Comparing distillation methods from 120M teacher (causal and non-causal) model to 120M causal student model.

| Model    | Bengali     |             | Malayalam   |             |
|----------|-------------|-------------|-------------|-------------|
|          | Causal      | Non-causal  | Causal      | Non-causal  |
| Teacher  | 16.4        | 13.3        | <b>33.4</b> | 32.5        |
| Hard     | 15.4        | 15.1        | 37.5        | 35.2        |
| Soft     | 15.6        | 15.4        | 35.4        | 33.6        |
| Full-sum | <b>15.0</b> | <b>14.9</b> | 33.9        | <b>33.3</b> |

dic languages, Bengali and Malayalam. The in-house ASR training data comprises of short voice search utterances that are anonymized and hand-transcribed, and representative of Google’s voice search traffic. The supervised training data for Bengali and Malayalam contains 7.5M and 2.6M transcribed utterances which approximately corresponds to 9.4K and 4.7K hours respectively. This data is further augmented with various noise styles [20], time and frequency masking-based augmentation [19] and simulated multi-microphone utterances [21]. The unsupervised training data consists of 59.8M utterances for Bengali and 23.5M utterances for Malayalam which approximately corresponds to 75K and 42.5K hours respectively. The development set is a small fraction of the training set held out for validation. The test set comprises of anonymous, transcribed utterances from the voice-search task (3.7k utterances for Bengali, 9.2k utterances for Malayalam). We report error rates using the transliteration-optimized WER metric described in [22] to accommodate mixed writing scripts frequently seen in Indic.

Both non-causal and causal models are chosen to act as teacher, while the student is kept as causal model. All the student models used in this experiment are initialized with the causal teacher model. Table 4 shows that the full-sum (L1 with norm) provides consistent gains across both Bengali and Malayalam for both causal and non-causal teacher models. We observed that the production data contains several outliers, as corroborated by a high WER of 16.6% obtained using the full-sum MSE loss on Bengali with non-causal teacher.

## 7. CONCLUSIONS

We investigated using sequence-level knowledge distillation (KD) methods, namely full-sum (FS) distillation, for recurrent neural network transducer (RNN-T) models for the first time. We showed how to effectively distill knowledge from bad teacher models that can generate noisy pseudo labels for training student models. We also showed that FS distillation is robust towards discrepancies of RNN-T alignments between teacher and student models. We applied FS distillation on public data and large scale in-house production data, where it outperformed other KD methods.

## 8. ACKNOWLEDGEMENT

We thank Dongseong Hwang, Gary Wang, Zhong Meng, Zhe-huai Chen, Isabel Leal, Oscar Chang for useful discussions.

## 9. REFERENCES

- [1] Alex Graves, “Sequence transduction with recurrent neural networks,” *CoRR*, vol. abs/1211.3711, 2012.
- [2] Geoffrey E. Hinton, Oriol Vinyals, and Jeffrey Dean, “Distilling the knowledge in a neural network,” *CoRR*, vol. abs/1503.02531, 2015.
- [3] Gal Kaplun, Eran Malach, Preetum Nakkiran, and Shai Shalev-Shwartz, “Knowledge distillation: Bad models can be good role models,” *CoRR*, vol. abs/2203.14649, 2022.
- [4] Bharat Bhushan Sau and Vineeth N. Balasubramanian, “Deep model compression: Distilling knowledge from noisy teachers,” *CoRR*, vol. abs/1610.09650, 2016.
- [5] Michal Lukasik, Srinadh Bhojanapalli, Aditya Krishna Menon, and Sanjiv Kumar, “Does label smoothing mitigate label noise?,” in *ICML*. 2020, vol. 119 of *Proceedings of Machine Learning Research*, pp. 6448–6458, PMLR.
- [6] Chidubem Arachie and Bert Huang, “Adversarial label learning,” in *The Thirty-Third AAAI Conference on Artificial Intelligence, AAAI 2019, The Thirty-First Innovative Applications of Artificial Intelligence Conference, IAAI 2019, The Ninth AAAI Symposium on Educational Advances in Artificial Intelligence, EAAI 2019, Honolulu, Hawaii, USA, January 27 - February 1, 2019*. 2019, pp. 3183–3190, AAAI Press.
- [7] Chidubem Arachie and Bert Huang, “A general framework for adversarial label learning,” *J. Mach. Learn. Res.*, vol. 22, pp. 118:1–118:33, 2021.
- [8] Dongseong Hwang, Khe Chai Sim, Yu Zhang, and Trevor Strohman, “Comparison of soft and hard target rnn-t distillation for large-scale asr,” 2022.
- [9] Xiaoyu Yang, Qiujia Li, and Philip C. Woodland, “Knowledge distillation for neural transducers from large self-supervised pre-trained models,” in *IEEE International Conference on Acoustics, Speech and Signal Processing, ICASSP 2022, Virtual and Singapore, 23-27 May 2022*. 2022, pp. 8527–8531, IEEE.
- [10] Ryoichi Takashima, Sheng Li, and Hisashi Kawai, “An investigation of a knowledge distillation method for CTC acoustic models,” in *ICASSP*. 2018, pp. 5809–5813, IEEE.
- [11] Alex Graves, Santiago Fernández, Faustino J. Gomez, and Jürgen Schmidhuber, “Connectionist temporal classification: labelling unsegmented sequence data with recurrent neural networks,” in *ICML*, William W. Cohen and Andrew W. Moore, Eds. 2006, vol. 148 of *ACM International Conference Proceeding Series*, pp. 369–376, ACM.
- [12] Sankaran Panchapagesan, Daniel S. Park, Chung-Cheng Chiu, Yuan Shangquan, Qiao Liang, and Alexander Gruenstein, “Efficient knowledge distillation for rnn-transducer models,” in *IEEE International Conference on Acoustics, Speech and Signal Processing, ICASSP 2021, Toronto, ON, Canada, June 6-11, 2021*. 2021, pp. 5639–5643, IEEE.
- [13] William Chan, Daniel S. Park, Chris A. Lee, Yu Zhang, Quoc V. Le, and Mohammad Norouzi, “Speechstew: Sim- ply mix all available speech recognition data to train one large neural network,” *CoRR*, vol. abs/2104.02133, 2021.
- [14] Vassil Panayotov, Guoguo Chen, Daniel Povey, and Sanjeev Khudanpur, “Librispeech: An asr corpus based on public domain audio books,” in *2015 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, 2015, pp. 5206–5210.
- [15] Anmol Gulati, James Qin, Chung-Cheng Chiu, Niki Parmar, Yu Zhang, Jiahui Yu, Wei Han, Shibo Wang, Zhengdong Zhang, Yonghui Wu, and Ruoming Pang, “Conformer: Convolution-augmented transformer for speech recognition,” in *INTERSPEECH*. 2020, pp. 5036–5040, ISCA.
- [16] Jean Carletta, Simone Ashby, Sebastien Bourban, Mike Flynn, Maël Guillemot, Thomas Hain, Jaroslav Kadlec, Vasilis Karaiskos, Wessel Kraaij, Melissa Kronenthal, Guillaume Lathoud, Mike Lincoln, Agnes Lisowska, Iain McCowan, Wilfried Post, Dennis Reidsma, and Pierre Wellner, “The AMI meeting corpus: A pre-announcement,” in *MLMI 2005, Edinburgh, UK, July 11-13, 2005, Revised Selected Papers*, Steve Renals and Samy Bengio, Eds. 2005, vol. 3869 of *Lecture Notes in Computer Science*, pp. 28–39, Springer.
- [17] J. Kahn, M. Rivière, W. Zheng, E. Kharitonov, Q. Xu, P. E. Mazaré, J. Karadayi, V. Liptchinsky, R. Collobert, C. Fuegen, T. Likhomanenko, G. Synnaeve, A. Joulin, A. Mohamed, and E. Dupoux, “Libri-light: A benchmark for asr with limited or no supervision,” in *ICASSP*, 2020, pp. 7669–7673.
- [18] Yu-An Chung, Yu Zhang, Wei Han, Chung-Cheng Chiu, James Qin, Ruoming Pang, and Yonghui Wu, “w2v-bert: Combining contrastive learning and masked language modeling for self-supervised speech pre-training,” in *IEEE Automatic Speech Recognition and Understanding Workshop, ASRU 2021, Cartagena, Colombia, December 13-17, 2021*. 2021, pp. 244–250, IEEE.
- [19] 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,” in *Interspeech 2019, 20th Annual Conference of the International Speech Communication Association, Graz, Austria, 15-19 September 2019*, Gernot Kubin and Zdravko Kacic, Eds. 2019, pp. 2613–2617, ISCA.
- [20] Chanwoo Kim, Ananya Misra, Kean Chin, Thad Hughes, Arun Narayanan, Tara Sainath, and Michiel Bacchiani, “Generation of large-scale simulated utterances in virtual rooms to train deep-neural networks for far-field speech recognition in Google Home,” in *INTERSPEECH*, 2017.
- [21] Chanwoo Kim, Ananya Misra, Kean K. Chin, Thad Hughes, Arun Narayanan, Tara N. Sainath, and Michiel Bacchiani, “Generation of large-scale simulated utterances in virtual rooms to train deep-neural networks for far-field speech recognition in google home,” in *INTERSPEECH*, 2017.
- [22] Jesse Emond, Bhuvana Ramabhadran, Brian Roark, Pedro Moreno, and Min Ma, “Transliteration based approaches to improve code-switched speech recognition performance,” in *SLT*. IEEE, 2018, pp. 448–455.