UNISPEECH-SAT: UNIVERSAL SPEECH REPRESENTATION LEARNING WITH SPEAKER AWARE PRE-TRAINING

Sanyuan Chen\textsuperscript{1,2}, Yu Wu\textsuperscript{2}, Chengyi Wang\textsuperscript{2}, Zhengyang Chen\textsuperscript{2}, Zhuo Chen\textsuperscript{2}, Jinyu Li\textsuperscript{2}, Xiangzhan Yu\textsuperscript{1}

\textsuperscript{1}Harbin Institute of Technology, China, \textsuperscript{2}Microsoft Corporation

\section*{ABSTRACT}
Self-supervised learning (SSL) is a long-standing goal for speech processing, since it utilizes large-scale unlabeled data and avoids extensive human labeling. Recent years witness great successes in applying self-supervised learning in speech recognition, while limited exploration was attempted in applying SSL for modeling speaker characteristics. In this paper, we aim to improve the existing SSL framework for speaker representation learning. Two methods are introduced for enhancing the unsupervised speaker information extraction. First, we apply the multi-task learning to the current SSL framework, where we integrate the utterance-wise contrastive loss with the SSL objective function. Second, for better speaker discrimination, we propose an utterance mixing strategy for data augmentation, where additional overlapped utterances are created unsupervisely and incorporate during training. We integrate the proposed methods into the HuBERT framework. Experiment results on SUPERB benchmark show that the proposed system achieves state-of-the-art performance in universal representation learning, especially for speaker identification oriented tasks. An ablation study is performed verifying the efficacy of each proposed method. Finally, we scale up training dataset to 94 thousand hours public audio data and achieve further performance improvement in all SUPERB tasks.

\textbf{Index Terms—} Self-Supervised Learning, Pre-Training, Speaker

\section{1. INTRODUCTION}
Self-supervised learning has achieved great successes in natural language processing, which utilizes a large amount of unlabeled data to learn universal representation. The representation enjoys outstanding generalizability, re-usability, and effectiveness, thus brings significant performance improvements when employed by various downstream tasks. Motivated by this, a series of work in speech processing have been proposed to leverage unlabeled audio for representation learning.

Self-supervised learning methods are categorized into discriminative methods [1, 2, 3, 4, 5, 6, 7], generative methods [8, 9, 10, 11, 12, 13], and multi-task learning methods [14]. The typical generative method is Autoregressive Predictive Coding (APC) [8,9], where the model is similar to the autoencoder architectures except that the network is trained to predict features for future time steps. The discriminative methods usually employ contrastive learning [5] or classification on weak clustering label [6] to pre-train an encoder network with large-scale unsupervised data. Recently, the discriminative methods achieved great successes in automatic speech recognition (ASR), which outperforms the best system for Librispeech dataset in 2019 with significantly less supervised data. The improved performance on different speech tasks in SUPERB benchmark [15] also verifies the effectiveness of pre-training.

Although achieving numerous successes, most pretraining methods for speech application focus on the extraction of spoken content information, i.e. learning representation optimized for tasks such as speech recognition, keyword spotting, etc. Limited exploration was carried out on other speech characteristics. As speech signal contains multi-fold information, e.g. content, identity, presentation etc., optimization for one aspect might lead to sub-optimized representation for other tasks. Interestingly, even trained with ASR-oriented objective function, the representation learnt by unsupervised pre-training shows excellent performance in speaker identification related tasks, such as speaker verification, diarization etc., in SUPERB challenge. However, can the speaker tasks’ performance be further boosted, when provided embedding from matched pre-training, is still an open question.

To answer this question, we investigate the unsupervised speaker pre-training methods that encourage the preservation of speaker identity. Specifically, we proposed two training methods: 1) We integrate the utterance-wise contrastive loss with the unsupervised representation learning, where the aggregated embedding from each utterance is employed for affinity computation, and a speaker-wise pseudo label is applied as reference. 2) We propose an utterance-mixing training strategy, where partially overlapped signal is constructed for each training sample, by mixing it with a randomly se-
collected speech piece, while the training objective remains the same. We integrate our proposed training method in the HuBERT framework [6], and conduct experiment on Speech processing Universal PERformance Benchmark (SUPERB) [15]. The experiment results show that our method significantly improves speaker identification, speaker verification, speaker diarization, and emotion recognition, while maintaining the same speech recognition performance. Finally, we extend our pre-training network to 94k hours of public English audio data, consisting of LibriVox [16], GigaSpeech [17], and VoxPopuli [18], which further increases performance on speaker tasks compared to previous work using 60k LibriVox data only.

The contribution of the paper is summarized into three-folds. 1) We propose a speaker aware pre-training method which is complementary to current ASR oriented pre-training. 2) We empirically evaluate the model performance on the SUPERB benchmark and achieve state-of-the-art performance in the overall evaluation. 3) We release our model at [https://github.com/microsoft/UniSpeech](https://github.com/microsoft/UniSpeech).

### 2. BACKGROUND

We first overview HuBERT [6] for universal speech representation learning, which serves as our baseline model. HuBERT has the state-of-the-art performance for several representation learning benchmarks [15]. The main idea of HuBERT is to learn the representation by iterative clustering. HuBERT firstly conducts an offline clustering step based on MFCC (Mel-Frequency Cepstrum Coefficient) of input signal, where the cluster center of each frame is indexed as the pseudo-label for later steps. Then, a Transformer model with an CNN as a feature extractor is trained on the MFCC and pseudo-labels for later steps. Then, a Transformer model with an CNN as a feature extractor is trained on the MFCC and pseudo-labels to form the representation for the first iteration. A mask pre-training is required to predict the pseudo-label of a masked region from the output of an intermediate Transformer encoder layer. Then we discretize the latent representation $L^b$ to a finite set of speech representations $Q^b = \{q^b_t\}_t=1$ with a quantization module [5].

Suppose the quantization module has $G$ codebooks with $V$ entries, we firstly linear transform each latent representation $l$ to $l' \in \mathbb{R}^{G \times V}$ and then use Gumbel softmax [19] to choose one discrete entry $e$ from each codebook. The probability for choosing the $v$-th entry from $g$-th codebook is

$$p_{g,v} = \frac{\exp(l'_v + n_u)}{\sum_{g'=1}^{G} \exp(l'_{g,v} + n_u)}$$

where $\tau$ is a non-negative temperature, $n_u = -\log(-\log(u))$, and $u$ is uniform sampled from $\mathcal{U}(0, 1)$. Then we concatenate the selected vectors as $[e_1, \ldots, e_G]$, and linear transform it to the quantized representation $q$.

For the latent representation $l^b_t$ centered over mask step $t$ in $b$-th utterance, the model is trained to identify the true quantized representations from the same utterance $Q^b = \{q^b_t | q^b_t \in Q^b, t \in M^b\}$ in a set of quantized candidate representations that uniformly sampled from all the masked time steps in all the utterances within the training batch $\mathcal{Q} = \bigcup_{b=1}^{B} Q^b$. The utterance-wise contrastive loss among $l^b_t$ and $Q^b$ is defined as:

$$L_{\text{Contrastive}} = \sum_{q^b_t \in Q^b} \log \frac{\exp(\text{sim}(l^b_t, q^b_t)/\kappa)}{\sum_{q^b_t \in Q^b} \exp(\text{sim}(l^b_t, q^b_t)/\kappa)} + \frac{1}{1 - q^b_t \in Q^b} \log \frac{\exp(\text{sim}(l^b_t, q^b_t)/\kappa + 1)}{\sum_{q^b_t \in Q^b} \exp(\text{sim}(l^b_t, q^b_t)/\kappa + 1)}$$

where $\text{sim}(a, b)$ denotes the cosine similarity between the latent representations and quantized representations $a^T b / ||a|| ||b||$. The utterance-wise contrastive loss is augmented by a codebook diversity loss to encourage the equal use of all the codebook entries $L_d = \frac{1}{dV} \sum_{g=1}^{G} \sum_{v=1}^{V} p_{g,v} \log p_{g,v}$, where $p_{g,v}$ is the average frequency of codebooks $g$ to be selected.

### 3. UNISPEECH-SAT

We propose Universal Speech representation learning with Speaker Aware pre-Training (UniSpeech-SAT), which is shown in Figure 1 on top of HuBERT model, two approaches are proposed, namely the utterance-wise contrastive learning and the utterance mixing augmentation. The former is applied to enhance the single speaker information extraction to improve downstream tasks like speaker verification and speaker identification. The latter mainly benefits the multi-speaker tasks such as speech diarization problem.

#### 3.1. Utterance-wise Contrastive Learning

We combine the utterance-wise contrastive loss to enhance unsupervised speaker information modeling. Two assumptions are made for this integration: 1. Each training utterance contains one active speaker. 2. Each utterance in the training batch belongs to a different speaker, i.e., there is no speaker having two utterances in one batch. Given that the dataset is collected from various sources, we believe the two assumptions are mostly satisfied.

In proposed contrastive loss, embeddings within the utterance are considered as positive instances, while the negative instances consists of embedding from other utterances in the same batch. Suppose that the input feature sequence is $\{X^b\}_{b=1}$, where $B$ is the batch size. \forall $X^b$, we obtain the latent representation $L^b = \{l^b_t\}_{t=1}$ from the output of an intermediate Transformer encoder layer. Then we discretize the latent representation $L^b$ to a finite set of speech representations $Q^b = \{q^b_t\}_t=1$ with a quantization module [5].

Suppose the quantization module has $G$ codebooks with $V$ entries, we firstly linear transform each latent representation $l$ to logit $l' \in \mathbb{R}^{G \times V}$ and then use Gumbel softmax [19] to choose one discrete entry $e$ from each codebook. The probability for choosing the $v$-th entry from $g$-th codebook is

$$p_{g,v} = \frac{\exp(l'_v + n_u)}{\sum_{g'=1}^{G} \exp(l'_{g,v} + n_u)}$$

where $\tau$ is a non-negative temperature, $n_u = -\log(-\log(u))$, and $u$ is uniform sampled from $\mathcal{U}(0, 1)$. Then we concatenate the selected vectors as $[e_1, \ldots, e_G]$, and linear transform it to the quantized representation $q$.

For the latent representation $l^b_t$ centered over mask step $t$ in $b$-th utterance, the model is trained to identify the true quantized representations from the same utterance $Q^b = \{q^b_t | q^b_t \in Q^b, t \in M^b\}$ in a set of quantized candidate representations that uniformly sampled from all the masked time steps in all the utterances within the training batch $\mathcal{Q} = \bigcup_{b=1}^{B} Q^b$. The utterance-wise contrastive loss among $l^b_t$ and $Q^b$ is defined as:

$$L_{\text{Contrastive}} = \sum_{q^b_t \in Q^b} \log \frac{\exp(\text{sim}(l^b_t, q^b_t)/\kappa)}{\sum_{q^b_t \in Q^b} \exp(\text{sim}(l^b_t, q^b_t)/\kappa)} + \frac{1}{1 - q^b_t \in Q^b} \log \frac{\exp(\text{sim}(l^b_t, q^b_t)/\kappa + 1)}{\sum_{q^b_t \in Q^b} \exp(\text{sim}(l^b_t, q^b_t)/\kappa + 1)}$$

where $\text{sim}(a, b)$ denotes the cosine similarity between the latent representations and quantized representations $a^T b / ||a|| ||b||$. The utterance-wise contrastive loss is augmented by a codebook diversity loss to encourage the equal use of all the codebook entries $L_d = \frac{1}{dV} \sum_{g=1}^{G} \sum_{v=1}^{V} p_{g,v} \log p_{g,v}$, where $p_{g,v}$ is the average frequency of codebooks $g$ to be selected.
and content loss by term. Our model will learn the combination of speaker loss $L_{\text{Speaker}}$ from the batch. Then for each utterance with batch size $B$, randomly choose $S$ utterances $\{u^i\}_{i=1}^B$ from the batch. For each utterance $u$, we randomly choose an utterance from the batch $u^b \in U$, crop a chunk of random length from $u^b$, and mix it with $u$ in a random region. With the utterance mixing method, the model is trained to extract the information of the main speaker from the mixed audio with the single-speaker information modeling loss (Section 3.1), and predict the content information corresponding to the main speaker with the content information modeling loss (Section 2). Note that we constrain the mixing portion in each utterance to be less than 50%, avoiding potential label permutation problem.

### 3.2. Utterance Mixing Augmentation

We introduce utterance mixing strategy to further boost speaker information modeling in pre-training, especially for multi-speaker tasks such as speaker diarization etc. The utterance mixing method aims to simulate the multi-speaker information modeling in pre-training, especially for large and diverse pre-training data.

![Algorithm 1 Utterance Mixing](image)

**Algorithm 1 Utterance Mixing**

1. *given* a batch of speech utterances $U = \{u^i\}_{i=1}^B$ with batch size $B$ and length $L$, mixing probability $\alpha$ 
2. Choose $S$ utterances $U^S \subset U$ by Bernoulli sampling with probability $\alpha$
3. for $u$ in $U^S$ do
4. Sample a utterance $u^b$ from discrete uniform distribution with probability $P(u^b = x) = \frac{1}{B}$, $x \in U$ 
5. Sample the mix length $l$ from discrete uniform distribution with probability $P(l = x) = \frac{1}{L}$, $x \in \{1, \ldots, \frac{L}{2}\}$ 
6. Sample a start position $s$ of $u$ from discrete uniform distribution with probability $P(s = x) = \frac{1}{L}$, $x \in \{1, \ldots, L - l\}$ 
7. Sample a start position $s^b$ of $u^b$ from discrete uniform distribution with probability $P(s^b = x) = \frac{1}{L}$, $x \in \{1, \ldots, L - l\}$
8. $u[s : s + l] \leftarrow \text{mixing}(u[s : s + l], u^b[s^b : s^b + l])$
9. return $U$

covering both read and spontaneous speaking styles, and a variety of topics, such as arts, science, sports, etc. (2) 24K hours VoxPopuli data [18], which from European Parliament (EP) event recordings including plenary sessions, committee meetings and other events. Finally, we have 94k hours data, including LibriVox, VoxPopuli, and Gigaspeech. We believe the diverse dataset can improve model performance on all tasks, because it contains diverse audio background, more speakers, and different contents of speech.

### 4. EXPERIMENT

#### 4.1. Implementation Details

We implement and pretrain our UniSpeech-SAT model following previous work [6]. We pretrain the UniSpeech-SAT Base model for 400k steps on LibriSpeech 960 hours audio [20] using the label generated by clustering the 6-th transformer layer output of the first iteration model of HuBERT Base model. The UniSpeech-SAT Base+ and UniSpeech-SAT Large model is pretrained for 400k steps on 94K large-scale diverse data (Section 3.3) using the label generated by clus-

![Fig. 1: An illustration of our method. We conduct contrastive loss in the intermediate layer, and use mixed utterance as input.](image)
Table 1: Universal speech representation evaluation on SUPERB benchmark. The overall score is computed by ourselves: we multiply the QbE score with 100, replace each error rate score with (1 - error rate), and average the scores of all tasks.

| Method                  | #Params | Corpus     | SID Acc | ASV EER | SD DER | PR PER | ASR (WER) % | KS M1 WVV | QbE F1 | IC Acc | SF | ER CER | Overall Score |
|-------------------------|---------|------------|---------|---------|--------|--------|-------------|----------|-------|-------|-----|-------|---------------|
| UniSpeech-SAT Base      | 94.68M  | 960 hr     | 96.97   | 4.35    | 5.18   | 4.36   | 70.99       | 87.59    | 98.34 | 0.0866 | 99.34 | 92.13 | 18.01 | 70.68 | 85.6 |
| UniSpeech-SAT Large     | 316.61M | 94k hr     | 95.16   | 3.84    | 3.85   | 3.38   | 66.32       | 93.28    | 93.28 | 0.0200 | 65.64 | 82.1  |        |       |    |
| Mockingjay [12]         | 58.42M  | 960 hr     | 57.57   | 9.89    | 5.41   | 41.98  | 38.80       | 10.29    | 93.38 | 0.0699 | 74.48 | 68.53 | 53.58 | 65.97 | 82.7 |
| TERA [13]               | 21.35M  | 360 hr     | 55.92   | 9.40    | 20.20  | 15.48  | 32.29       | 61.66    | 93.38 | 0.0835 | 74.48 | 68.53 | 53.58 | 65.97 | 82.7 |
| NPC [11]                | 19.38M  | 360 hr     | 55.92   | 9.40    | 20.20  | 15.48  | 32.29       | 61.66    | 93.38 | 0.0835 | 74.48 | 68.53 | 53.58 | 65.97 | 82.7 |
| VQ-APC [10]             | 4.63M   | 360 hr     | 60.15   | 8.72    | 41.08  | 21.20  | 57.57       | 87.59    | 98.34 | 0.0866 | 99.34 | 92.13 | 18.01 | 70.68 | 85.6 |
| APC [9]                 | 4.11M   | 360 hr     | 60.15   | 8.72    | 41.08  | 21.20  | 57.57       | 87.59    | 98.34 | 0.0866 | 99.34 | 92.13 | 18.01 | 70.68 | 85.6 |
| wav2vec [3]             | 32.54M  | 960 hr     | 56.56   | 7.99    | 31.58  | 15.86  | 32.29       | 61.66    | 93.38 | 0.0835 | 74.48 | 68.53 | 53.58 | 65.97 | 82.7 |
| vq-wav2vec [4]          | 23.45M  | 960 hr     | 56.56   | 7.99    | 31.58  | 15.86  | 32.29       | 61.66    | 93.38 | 0.0835 | 74.48 | 68.53 | 53.58 | 65.97 | 82.7 |
| wav2vec 2.0 Base [5]    | 95.04M  | 960 hr     | 75.18   | 5.74    | 6.08   | 6.43   | 47.99       | 96.23    | 0.0233 | 93.25 | 88.30 | 24.77 | 63.43 | 80.3 |
| HuBERT Base [6]         | 94.68M  | 960 hr     | 85.76   | 4.31    | 5.40   | 6.75   | 86.75       | 97.95    | 0.0927 | 98.58 | 88.98 | 23.56 | 66.04 | 83.0 |
| Utterance mixing        | 94.68M  | 960 hr     | 84.74   | 4.61    | 5.22   | 6.80   | 51.77       | 96.79    | 0.0956 | 98.31 | 88.56 | 24.00 | 65.60 | 82.8 |
| Tables 1 shows the evaluation results. There is a significant improvement on speaker diarization task in both base and large setting, where the diarization error rate (DER) is reduced by over 25%. The results demonstrate that the proposed utterance mixing method is very effective for the multitalker task. Moreover, positive results are observed in speaker identification and speaker verification, which is attributed to the utterance contrastive loss. Surprisingly, our model also obtains substantial gain on emotion recognition. One possible explanation is that the task also requires utterance level information rather than content information. However, we model a degradation on ASR without LM. The word error rate of our large model is 9% worse than the baseline, while the gap becomes less than 2% in the base setting. Our explanation is speaker information and content information orthorectic, and the content information is sacrificed given that the model capacity is limited.

4.2. Universal Representation Evaluation

We evaluate our models on SUPERB, which is designed to provide a standard and comprehensive testbed for pretrained models on various speech tasks. It covers ten tasks, including Speaker Identification (SID), Automatic Speaker Verification (ASV), Speaker Diarization (SD), Phoneme Recognition (PR), Automatic Speech Recognition (ASR), Keyword Spotting (KS), Query by Example Spoken Term Detection (QbE), Intent Classification (IC), Slot Filling (SF), Emotion Recognition (ER). The tasks can be grouped into four aspects of speech: speaker, content, semantics, and paralinguistics. We follow the policies created by SUPERB. 1) The design of task specific layers follows the rules of SUPERB. 2) Transformer model is frozen to limit the space of fine-tuning hyperparameter search. We perform the policies created by SUPERB. 3) The task specific layer uses the weighted sum results of hidden states from different layers. Table 2 shows the evaluation results. There is a significant improvement on speaker diarization task in both base and large setting, where the diarization error rate (DER) is reduced by over 25%. The results demonstrate that the proposed utterance mixing method is very effective for the multitalker task. Moreover, positive results are observed in speaker identification and speaker verification, which is attributed to the utterance contrastive loss. Surprisingly, our model also obtains substantial gain on emotion recognition. One possible explanation is that the task also requires utterance level information rather than content information. However, our model shows a degradation on ASR without LM. The word error rate of our large model is 9% worse than the baseline, while the gap becomes less than 2% in the base setting. Our explanation is speaker information and content information orthorectic, and the content information is sacrificed given that the model capacity is limited.

5. CONCLUSION

In this work, we integrate contrastive loss and utterance mixing to existing framework for unsupervised speech representation learning, aiming at improving the speaker discrimination in learnt embedding. The evaluation on the SUPERB benchmark shows our model achieves the state-of-the-art performance and outperforms other baselines by a large margin.
6. REFERENCES

[1] Aäron van den Oord, Yazhe Li, and Oriol Vinyals, “Representation learning with contrastive predictive coding,” *CoRR*, vol. abs/1807.03748, 2018.

[2] Morgane Rivière, Armand Joulin, Pierre-Emmanuel Mazaré, and Emmanuel Dupoux, “Unsupervised pre-training transfers well across languages,” in *ICASSP*, 2020, pp. 7414–7418.

[3] Steffen Schneider, Alexei Baevski, Ronan Collobert, and Michael Auli, “wav2vec: Unsupervised pre-training for speech recognition.” in *Interspeech*, 2019.

[4] Alexei Baevski, Steffen Schneider, and Michael Auli, “vq-wav2vec: Self-supervised learning of discrete speech representations,” in *ICLR*, 2020.

[5] Alexei Baevski, Yuhao Zhou, Abdelrahman Mohamed, and Michael Auli, “wav2vec 2.0: A framework for self-supervised learning of speech representations,” in *NeurIPS*, 2020.

[6] Wei-Ning Hsu, Benjamin Bolte, Yao-Hung Hubert Tsai, Kushal Lakhotia, Ruslan Salakhutdinov, and Abdelrahman Mohamed, “Hubert: Self-supervised speech representation learning by masked prediction of hidden units,” *arXiv preprint arXiv:2106.07447*, 2021.

[7] Yu Zhang, Daniel S Park, Wei Han, James Qin, Anmol Gulati, Joel Shor, Aren Jansen, Yuanzhong Xu, Yanping Huang, Shibo Wang, et al., “Bigssl: Exploring the frontier of large-scale semi-supervised learning for automatic speech recognition,” *arXiv preprint arXiv:2109.13226*, 2021.

[8] Yu-An Chung, Wei-Ning Hsu, Hao Tang, and James Glass, “An Unsupervised Autoregressive Model for Speech Representation Learning,” in *Interspeech*, 2019, pp. 146–150.

[9] Y. Chung and J. Glass, “Generative pre-training for speech with autoregressive predictive coding,” in *ICASSP 2020 - 2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, 2020, pp. 3497–3501.

[10] Yu-An Chung, Hao Tang, and James Glass, “Vector-quantized autoregressive predictive coding,” in *Interspeech*, 2020, pp. 3760–3764.

[11] Alexander H Liu, Yu-An Chung, and James Glass, “Non-autoregressive predictive coding for learning speech representations from local dependencies,” *arXiv preprint arXiv:2110.00406*, 2020.

[12] Andy T. Liu, Shu-wen Yang, Po-Han Chi, Po-chun Hsu, and Hung-yi Lee, “Mockingjay: Unsupervised speech representation learning with deep bidirectional transformer encoders,” *ICASSP*, 2020.

[13] Andy T Liu, Shang-Wen Li, and Hung-yi Lee, “Tera: Self-supervised learning of transformer encoder representation for speech,” *arXiv preprint arXiv:2007.06028*, 2020.

[14] Mirco Ravanelli, Jianyuan Zhong, Santiago Pascual, Pawel Swietojanski, Joao Monteiro, Jan Trmal, and Yoshua Bengio, “Multi-task self-supervised learning for robust speech recognition,” in *ICASSP*, 2020, pp. 6989–6993.

[15] Shu wen Yang, Po-Han Chi, Yung-Sung Chuang, Cheng-I Jeff Lai, Kushal Lakhotia, Yist Y. Lin, Andy T. Liu, Jiatong Shi, Xuankai Chang, Guan-Ting Lin, Tsu-Hsien Huang, Wei-Cheng Tseng, Ko tik Lee, Da-Rong Liu, Zili Huang, Shuyan Dong, Shang-Wen Li, Shinji Watanabe, Abdelrahman Mohamed, and Hung yi Lee, “SUPERB: Speech Processing Universal PERformance Benchmark,” in *Proc. Interspeech 2021*, 2021, pp. 1194–1198.

[16] Jacob Kahn, Morgane Rivière, Weiyi Zheng, Evgeny Kharitonov, Qiantong Xu, Pierre-Emmanuel Mazaré, Julien Karadayi, Vitaliy Liptchinsky, Ronan Collobert, Christian Fuegen, et al., “Libri-light: A benchmark for asr with limited or no supervision,” in *ICASSP 2020-2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP).* IEEE, 2020, pp. 7669–7673.

[17] Guoguo Chen, Shuzhou Chai, Guanbo Wang, Jiayu Du, Wei-Qiang Zhang, Chao Wang, Dan Su, Daniel Povey, Jan Trmal, Junbo Zhang, et al., “Gigaspeech: An evolving, multi-domain asr corpus with 10,000 hours of transcribed audio,” in *Proc. Interspeech 2021*, 2021.

[18] Changhan Wang, Morgane Rivi`ere, Ann Lee, Anne Wu, Chaitanya Talnikar, Daniel Haziza, Mary Williamson, Juan Pino, and Emmanuel Dupoux, “Voxpopuli: A large-scale multilingual speech corpus for representation learning, semi-supervised learning and interpretation,” *arXiv preprint arXiv:2101.00390*, 2021.

[19] Eric Jang, Shixiang Gu, and Ben Poole, “Categorical reparameterization with gumbel-softmax,” *arXiv preprint arXiv:1611.01144*, 2016.

[20] V. Panayotov, G. Chen, D. Povey, and S. Khudanpur, “Librispeech: An ASR corpus based on public domain audio books,” in *ICASSP*, 2015, pp. 5206–5210.