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

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Code: https://github.com/microsoft/UniSpeech

Self-Supervised Learning

- **Self-supervised learning (SSL)** has achieved great successes in **NLP** and **CV**, especially for limited resource tasks.
  - SSL utilizes a large amount of unlabeled data to learn universal representation
  - The universal representation with outstanding generalizability, re-usability, and effectiveness can significantly benefit various downstream tasks
- Common practice:
  1. Optimize the pre-train model with SSL objective on the large-scale unlabeled data
  2. Optimize the downstream model on the various downstream annotated dataset, where the input feature is the universal representation extracted from the pre-trained model.
- SSL in **Speech**:
  - We have witnessed great success of SSL in **content related task.**
    - e.g. wav2vec 2.0/HuBERT SSL model in speech recognition task.
  - Can we also apply SSL in **speaker related task**?
    - e.g. speaker verification, diarization task

Speaker Aware Pre-Training

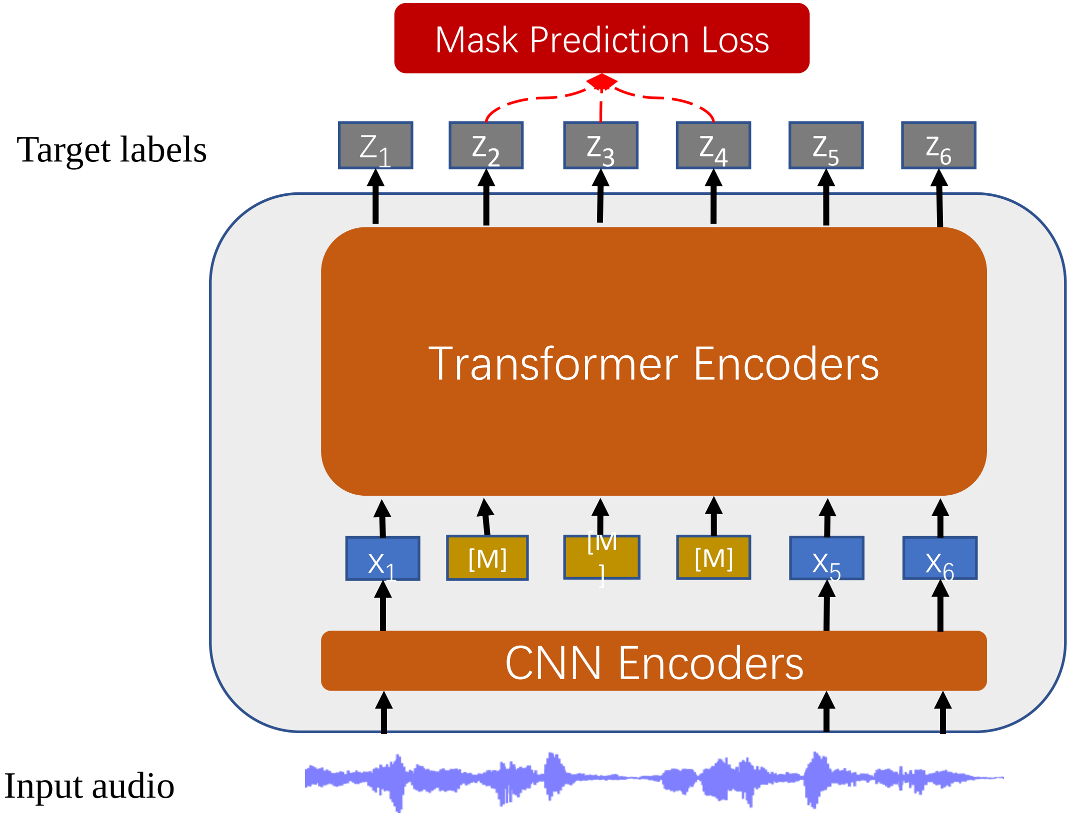
- Can we apply SSL in both **content related task** and **speaker related task**?
- **UniSpeech-SAT**
  - Universal Speech representation learning with Speaker Aware pre-Training
  - Aiming to improve existing SSL framework for speaker representation learning.
- **Methods:**
  - Mask prediction loss (from HuBERT) -> content representation learning
  - Utterance-wise contrastive loss -> single-speaker representation learning
  - Utterance mixing augmentation -> multi-speaker representation learning
  - Large and diverse pre-training data -> robust representation learning

Mask prediction loss (from HuBERT)

- State-of-the-art SSL method for content representation learning
- **Main idea**: conduct iterative offline clustering to provide target labels and perform BERT-like mask prediction loss.
- **Steps**:
  1. Conduct **k-means clustering** on the MFCC feature of input signals
  2. Set the **clustering center** of each input frame as the **pseudo target label**
  3. Train a Transformer-based model with the **mask prediction loss**, where the Transformer encoders are fed with the masked input features $\tilde{X}$, and predict the pseudo target label z_t in the masked region M

$$\mathcal{L}_{\text{Content}} = -\sum_{t \in M} \log f(z_t | \tilde{X}, t)$$

  4. Given the pre-trained model, we conduct **k-means clustering** on the **latent representations** generated by the pre-trained model, and start a new iteration from step 2



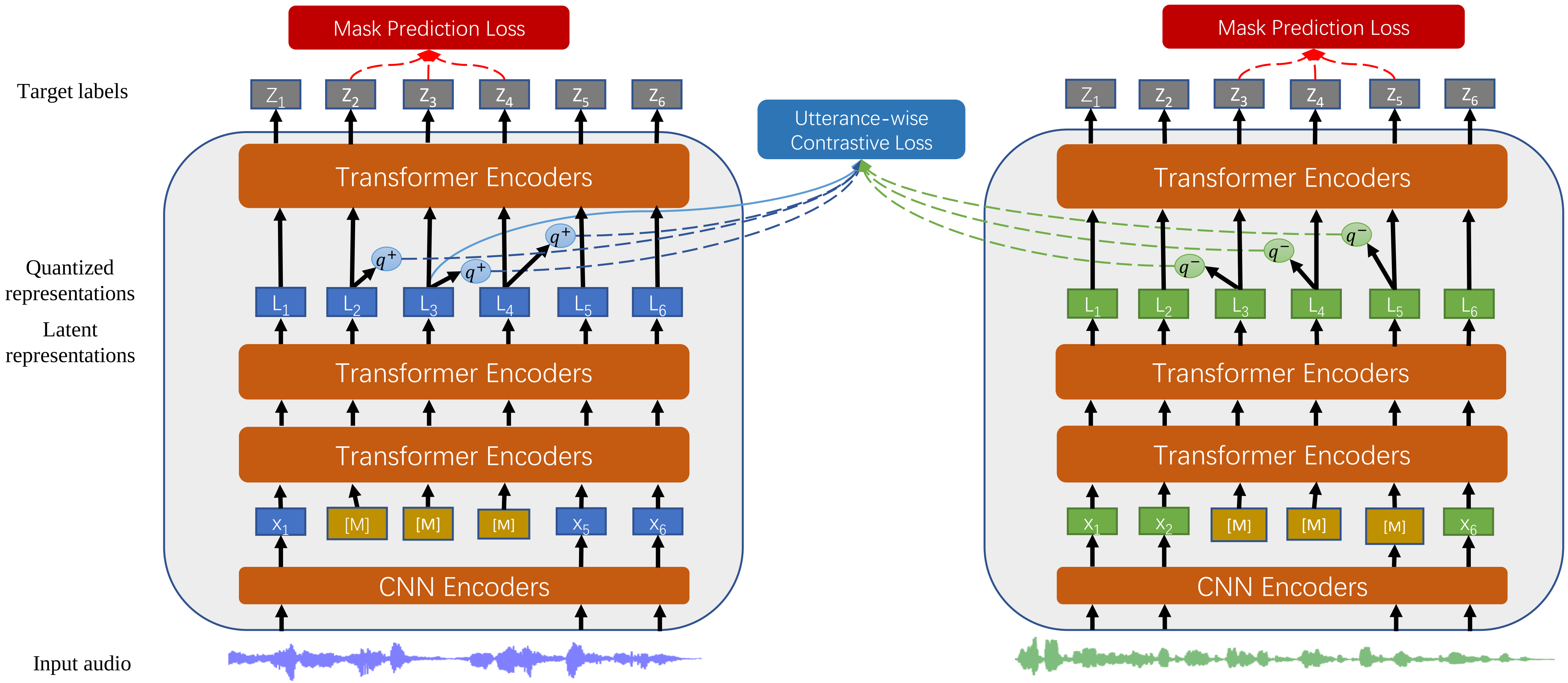
Utterance-wise contrastive loss

$$\mathcal{L}_{\text{Contrastive}} = -\left(\sum_{q_t^b \in \hat{Q}^b} \log \frac{\exp(\text{sim}(l_t^b, q_t^b)/\kappa)}{\exp(\text{sim}(l_t^b, q_t^b)/\kappa)+1} - \sum_{q_t^b \sim \hat{Q} \setminus \hat{Q}^b} \log \frac{1}{\exp(\text{sim}(l_t^b, q_t^b)/\kappa)+1}\right)$$

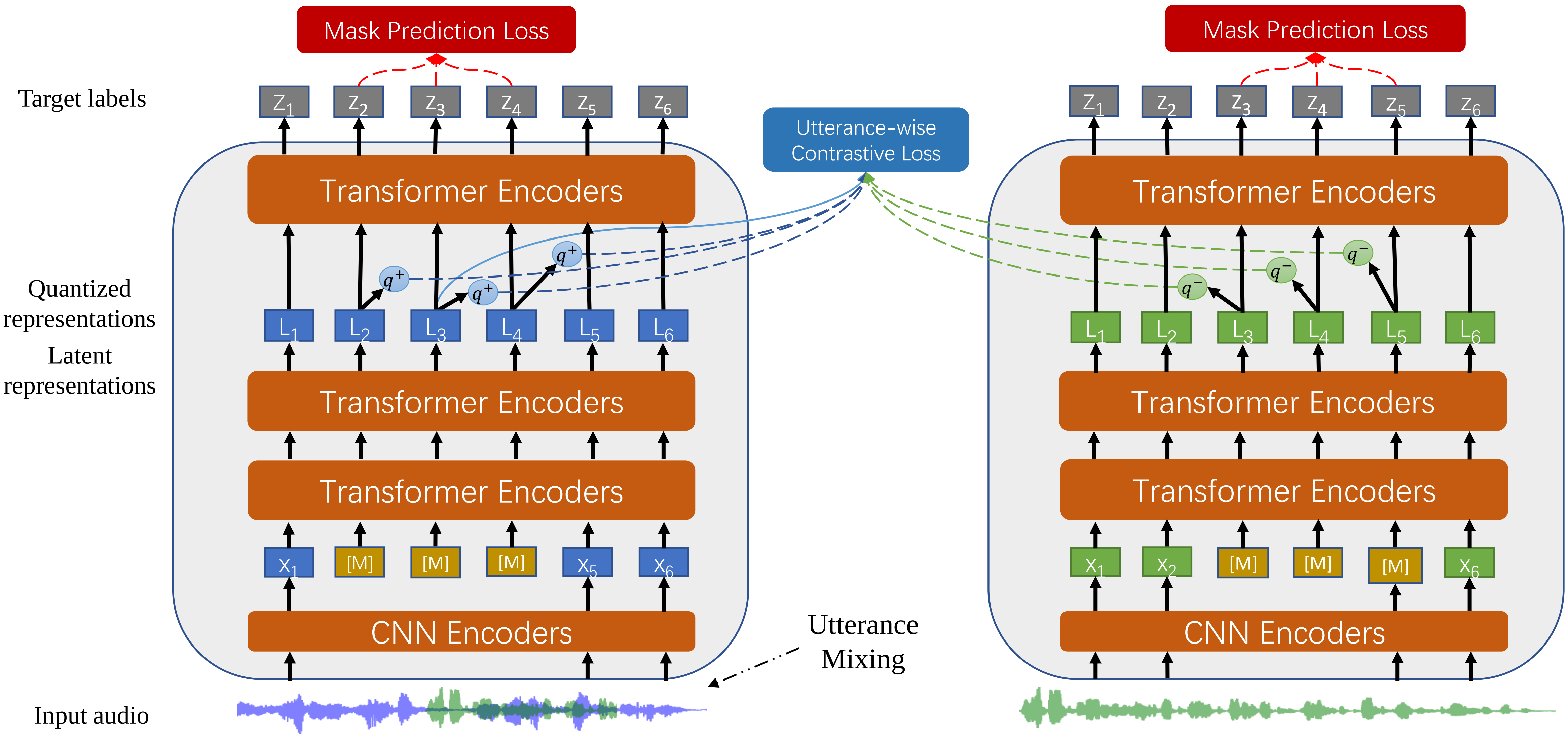
$$\mathcal{L}_{\text{diversity}} = \frac{1}{GV} \sum_{g=1}^{G} \sum_{v=1}^{V} \bar{p}_{g,v} \log \bar{p}_{g,v}$$

$$\mathcal{L}_{\text{Speaker}} = \mathcal{L}_{\text{Contrastive}} + \alpha \mathcal{L}_{\text{diversity}}$$

$$\mathcal{L}_{\text{UniSpeech-SAT}} = \mathcal{L}_{\text{Speaker}} + \beta \mathcal{L}_{\text{Content}}$$



Utterance mixing augmentation



Large and diverse pre-training data

- **Previous works** only use the audiobook speech for pre-training, which limits the generalizability of the pre-trained speech representation in diverse scenarios.
- Towards robust speech representation learning, we scale up unlabeled pre-training data to 94k hours of public audios from diverse domains
  - 10K hours **Gigaspeech** data, from audiobooks, podcasts and YouTube.
  - 24K hours **VoxPopuli** data, from European Parliament (EP) event recordings.
  - 60k hours **LibriVox** data, from audiobooks

Experiments

- Universal Representation Evaluation with **SUPERB**
- **Ten speech tasks**
  - Speaker related tasks:
    - Speaker Identification (SID), Automatic Speaker Verification (ASV), Speaker Diarization (SD)
  - Content related tasks:
    - Phoneme Recognition (PR), Automatic Speech Recognition (ASR), Keyword Spotting (KS) Query by Example Spoken Term Detection (QbE)
  - Semantic related tasks:
    - Intent Classification (IC), Slot Filling (SF)
  - Paralinguistics related tasks
    - Emotion Recognition (ER)

Experiments

- Universal Representation Evaluation with **SUPERB**
- **Policies**
  - The design of task specific layers follows the SUPERB official implementations for each downstream task.
  - Pre-trained models are frozen to limit the space of the fine-tuning hyperparameter search
  - The task specific layers consume the weighted sum results of the hidden states extracted from each layer of the pre-trained model

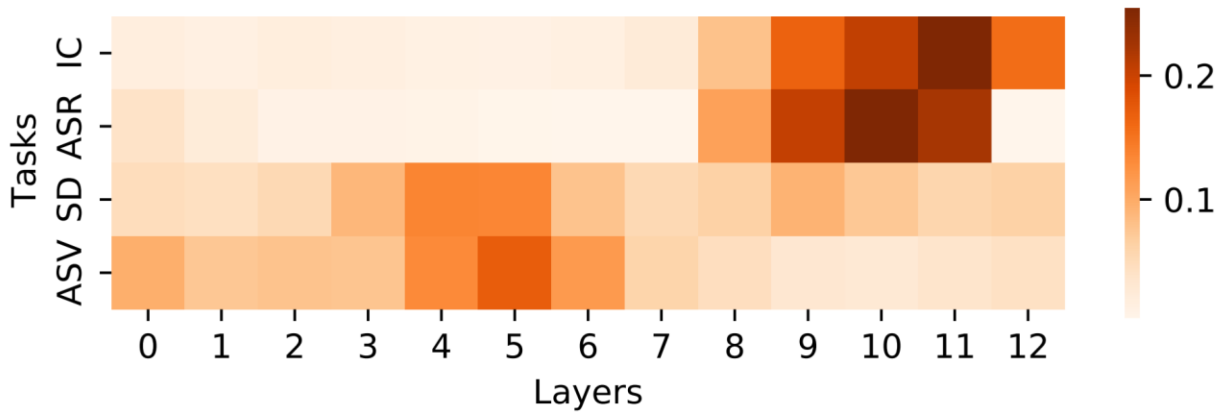
Universal Representation Evaluation Results

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	Speaker			Content					Semantics			ParaL	Overall
			SID	ASV	SD	PR	ASR (WER)		KS	QbE	IC	SF		ER	
			Acc ↑	EER ↓	DER ↓	PER ↓	w/o ↓	w/ LM ↓	Acc ↑	MTWV ↑	Acc ↑	F1 ↑	CER ↓	Acc ↑	Score ↑
FBANK	-	-	8.5E-4	9.56	10.05	82.01	23.18	15.21	8.63	0.0058	9.10	69.64	52.94	35.39	44.2
PASE+ [14]	7.83M	LS 50 hr	37.99	11.61	8.68	58.87	25.11	16.62	82.54	0.0072	29.82	62.14	60.17	57.86	57.5
APC [8]	4.11M	LS 360 hr	60.42	8.56	10.53	41.98	21.28	14.74	91.01	0.0310	74.69	70.46	50.89	59.33	67.6
VQ-APC [10]	4.63M	LS 360 hr	60.15	8.72	10.45	41.08	21.20	15.21	91.11	0.0251	74.48	68.53	52.91	59.66	67.2
NPC [11]	19.38M	LS 360 hr	55.92	9.40	9.34	43.81	20.20	13.91	88.96	0.0246	69.44	72.79	48.44	59.08	67.0
Mockingjay [12]	85.12M	LS 360 hr	32.29	11.66	10.54	70.19	22.82	15.48	83.67	6.6E-04	34.33	61.59	58.89	50.28	56.1
TERA [13]	21.33M	LS 360 hr	57.57	15.89	9.96	49.17	18.17	12.16	89.48	0.0013	58.42	67.50	54.17	56.27	64.2
modified CPC [2]	1.84M	LL 60k hr	39.63	12.86	10.38	42.54	20.18	13.53	91.88	0.0326	64.09	71.19	49.91	60.96	65.1
wav2vec [3]	32.54M	LS 960 hr	56.56	7.99	9.90	31.58	15.86	11.00	95.59	0.0485	84.92	76.37	43.71	59.79	71.5
vq-wav2vec [4]	34.15M	LS 960 hr	38.80	10.38	9.93	33.48	17.71	12.80	93.38	0.0410	85.68	77.68	41.54	58.24	69.3
wav2vec 2.0 Base [5]	95.04M	LS 960 hr	75.18	5.74	6.02	6.08	6.43	4.79	96.23	0.0233	92.35	88.30	24.77	63.43	80.3
HuBERT Base [6]	94.68M	LS 960 hr	81.42	5.11	5.88	5.41	**6.42**	**4.79**	96.30	0.0736	98.34	88.53	25.20	64.92	82.0
UniSpeech-SAT Base	94.68M	LS 960 hr	85.76	**4.31**	4.41	5.40	6.75	4.86	96.75	0.0927	98.58	88.98	23.56	66.04	83.0
– contrastive loss	94.68M	LS 960 hr	84.74	4.61	4.72	5.22	6.80	5.17	96.79	0.0956	98.31	88.56	24.00	65.60	82.8
– utterance mixing	94.68M	LS 960 hr	85.97	4.35	5.87	5.06	7.04	5.05	96.88	0.0866	98.10	88.50	24.52	65.97	82.7
UniSpeech-SAT Base+	94.68M	CD 94k hr	**87.59**	4.36	**3.80**	**4.44**	6.44	4.88	**97.40**	**0.1125**	**98.84**	**89.76**	**21.75**	**68.48**	**84.0**
wav2vec 2.0 Large [5]	317.38M	LL 60k hr	86.14	5.65	5.62	4.75	3.75	3.10	96.6	0.0489	95.28	87.11	27.31	65.64	82.1
HuBERT Large [6]	316.61M	LL 60k hr	90.33	5.98	5.75	3.53	**3.62**	**2.94**	95.29	0.0353	98.76	89.81	21.76	67.62	83.5
UniSpeech-SAT Large	316.61M	CD 94k hr	**95.16**	**3.84**	**3.85**	**3.38**	3.99	3.19	**97.89**	**0.0836**	**99.34**	**92.13**	**18.01**	**70.68**	**85.6**

Analysis

- Layer contribution to different tasks
  - Shallow layers contribute more to the speaker related tasks
  - Top layers contribute more to the content and semantic related tasks



Analysis

- Affect of different ratios of mixing utterances
  - Utterance mixing is still effective for 94k hours setting
  - Speaker related task benefit from larger mixing ratio
  - Content related task benefit from smaller mixing ratio

Table 2: Results of UniSpeech-SAT Base+ with various mixing ratios on 94k hours training data.

Method	Ratio	Speaker	Content		Semantics	ParaL
		SD	ASR (WER)		IC	ER
		DER ↓	w/o ↓	w/ LM ↓	Acc ↑	Acc ↑
HuBERT Base [6]	-	5.88	6.42	4.79	98.34	64.92
UniSpeech-SAT Base+	0.0	5.04	**6.39**	**4.76**	99.24	66.32
	0.2	3.80	6.44	4.88	98.84	**68.48**
	0.5	**3.73**	6.65	5.18	**99.29**	67.36

Conclusion

- In this work, we propose a **speaker aware pre-training method** which is complementary to current ASR oriented pre-training.
- The evaluation on the SUPERB benchmark shows our universal speech representation achieves **state-of-the-art overall performance** and outperforms other baselines by a large margin.

- This work is extended to a journal paper **WavLM**
  - SOTA results on all the 10 tasks of SUPREB.
  - SOTA results on 4 typical speech tasks from different speech aspects
    - speaker verification, speech separation, speaker diarization and speech recognition
  - Paper: https://arxiv.org/pdf/2110.13900.pdf
  - Code: https://aka.ms/wavlm

Thanks!