Multi-resolution HuBERT

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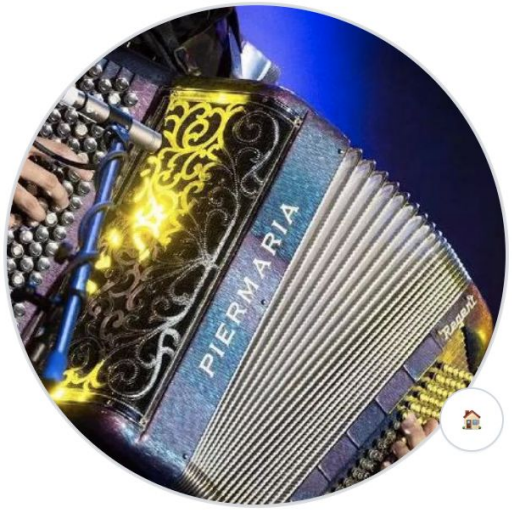
Self-intro

- 3rd Year Ph.D. Student
- Main research focus:
  - speech representation learning and its application
- Broad interests in many downstream tasks:
  - Typical speech tasks: ASR & TTS & ST & SLU
    - architectures
    - decoding
    - aspects in low-resource and multilingual
  - Related music tasks
    - singing voice synthesis
    - singing voice conversion
    - music generation



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Content

- Introduction: Does resolution matters?
- Multi-resolution HuBERT
  - Method
  - Design
- Experiments and Ablations
- Potential extensions and Future works

Speech and its Resolution

- Speech signal (single-channel):
  - a sequence samples in a **high** sampling rate (e.g., 16k, 24k, 48k)

- The local stability
  - Information of speech in **local sequences** of samples
  - Feature extractions happens to **downsample** speech into a sequence of vectors to represent locational information.
    - Conventional: Linear spectrogram, Mel spectrogram, Mel cepstral coefficients (10-30ms per frame)
    - Learnable filters: Convolutional networks, which can be applied in conventional speech downstream tasks or self-supervised models such as wav2vec2, HuBERT (20ms per frame)

Exploration on HuBERT with Multiple Resolutions

Jiatong Shi[1], *Yun Tang*[2], *Hirofumi Inaguma*[2], *Hongyu Gong*[2], *Juan Pino*[2], *Shinji Watanabe*[1]

[1]Language Technologies Institute, Carnegie Mellon University [2]Meta AI

Does resolution matters? (a pilot study in Interspeech 2023)

- Utilizing HuBERT with **different** resolutions

Table 1: *Configurations of the pre-trained HuBERT with multi-resolutions. The convolution (Conv.) module is represented in [(kernel-size, stride)* layer-number].*

ID	Res.(ms)	Param.	Conv. Module
A	20	94.7	(10,5)*1 + (3,2)*4 + (2,2)*2
B	40	95.2	(10,5)*1 + (3,2)*4 + (2,2)*3
C	100	97.3	(10,5)*2 + (3,2)*4 + (2,2)*2

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Does resolution matters? (a pilot study in Interspeech 2023)

- Utilizing HuBERT with **different** resolutions
- Use **simple** method to combine HuBERT features

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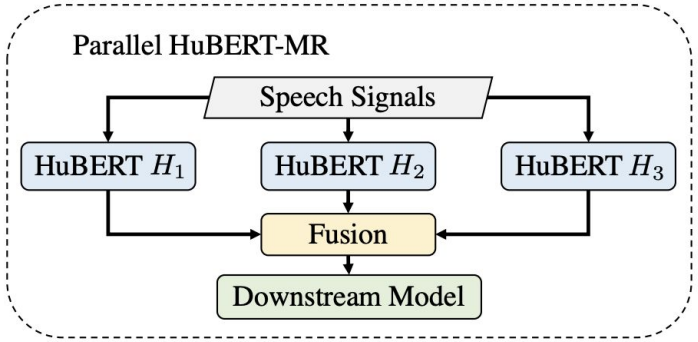

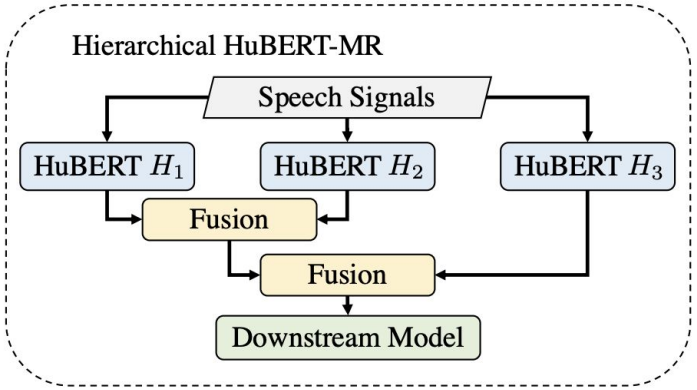

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Does resolution matters? (a pilot study in Interspeech 2023)

- Get **better performance over (7/9)** than HuBERT in frozen setting in SUPERB

Model	Res.(ms)	PR(↓)	ASR(↓)	ER(↑)	IC(↑)	SID(↑)	SD(↓)	SV(↓)	SE(↑)	ST(↑)
HuBERT	20	5.41	6.42	**64.92**	98.34	81.42	5.88	5.11	**2.58**	15.53
wav2vec2	20	5.74	6.43	63.43	92.35	75.18	6.08	6.02	2.55	14.81
HuBERT-MR-P	(100,40,20)	**4.83**	**5.48**	63.76	**98.51**	**83.23**	**5.75**	**5.10**	2.55	**16.18**

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Does resolution matters? (a pilot study in Interspeech 2023)

- With fine-tuning, still **better**

Model	Res.(ms)	WER(↓)
HuBERT	20	7.73(3.81)
HuBERT	40	12.38(4.90)
HuBERT	100	98.37(97.87)
HuBERT-MR-P	(100,20)	6.99(3.70)
HuBERT-MR-P	(40,20)	7.13(3.75)
HuBERT-MR-P	(100,40,20)	6.53(3.61)
HuBERT-MR-H	(100,20)	6.59(3.59)
HuBERT-MR-H	(40,20)	7.01(3.71)
HuBERT-MR-H	(100,40,20)	**6.11**(**3.31**)

Exploration on HuBERT with Multiple Resolutions

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Does resolution matters? (a pilot study in Interspeech 2023)

- **Reduce** computation costs as well

Table 5: *Fine-tuning results on Librispeech-100h (comparison with other models). Results with language model rescoring are in brackets. * indicates the large model setting. The unlabeled column shows the number of hours used for SSL pre-training. HuBERT-MR-H is discussed in Sec 2.2. Noted that the HuBERT base model with 20ms is our baseline.*

Model	Res.(ms)	Unlabeled(h)	Param.(M)	MACs(G)	FLOPs(T)	WER(↓)
HuBERT	20	960	94.7	1669	3.34	7.73(3.81)
wav2vec2	20	960	95.0	1669	3.34	6.54(4.33)
wav2vec2*	20	60K	317.4	4326	8.66	5.90(3.45)
HuBERT*	20	60K	316.6	4324	8.66	**5.40(2.82)**
HuBERT-MR-H	(100,40,20)	960	298.4	3454	6.91	6.11(3.31)

Motivation of Multi-resolution HuBERT

- Data preparation challenge
- We found
  - HuBERT with multiple resolutions can have benefits to many of the tasks
  - However, pre-training multiple HuBERTs is time-consuming and cannot be applied to real-applications…

Motivation of Multi-resolution HuBERT

- We find some similar ideas of understanding sequencial information from different resolutions:
- Hourglass Transformer
  - https://arxiv.org/pdf/2110.13711.pdf
- Dynamic Token Poolking
  - https://arxiv.org/pdf/2211.09761.pdf

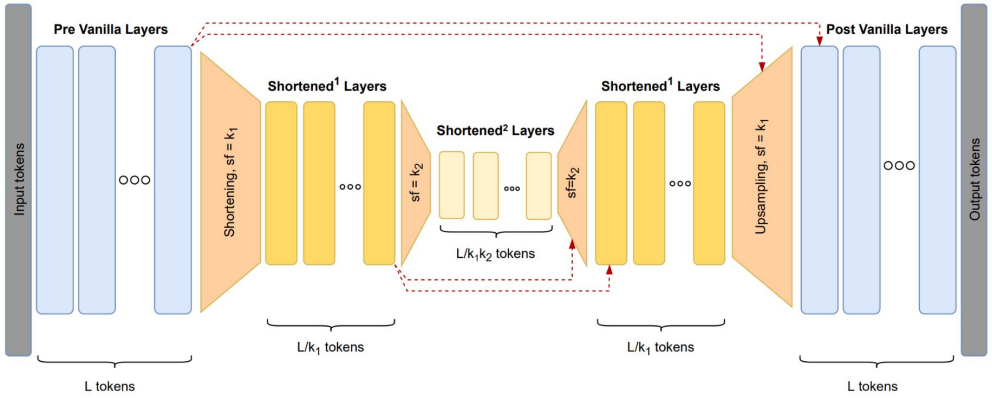
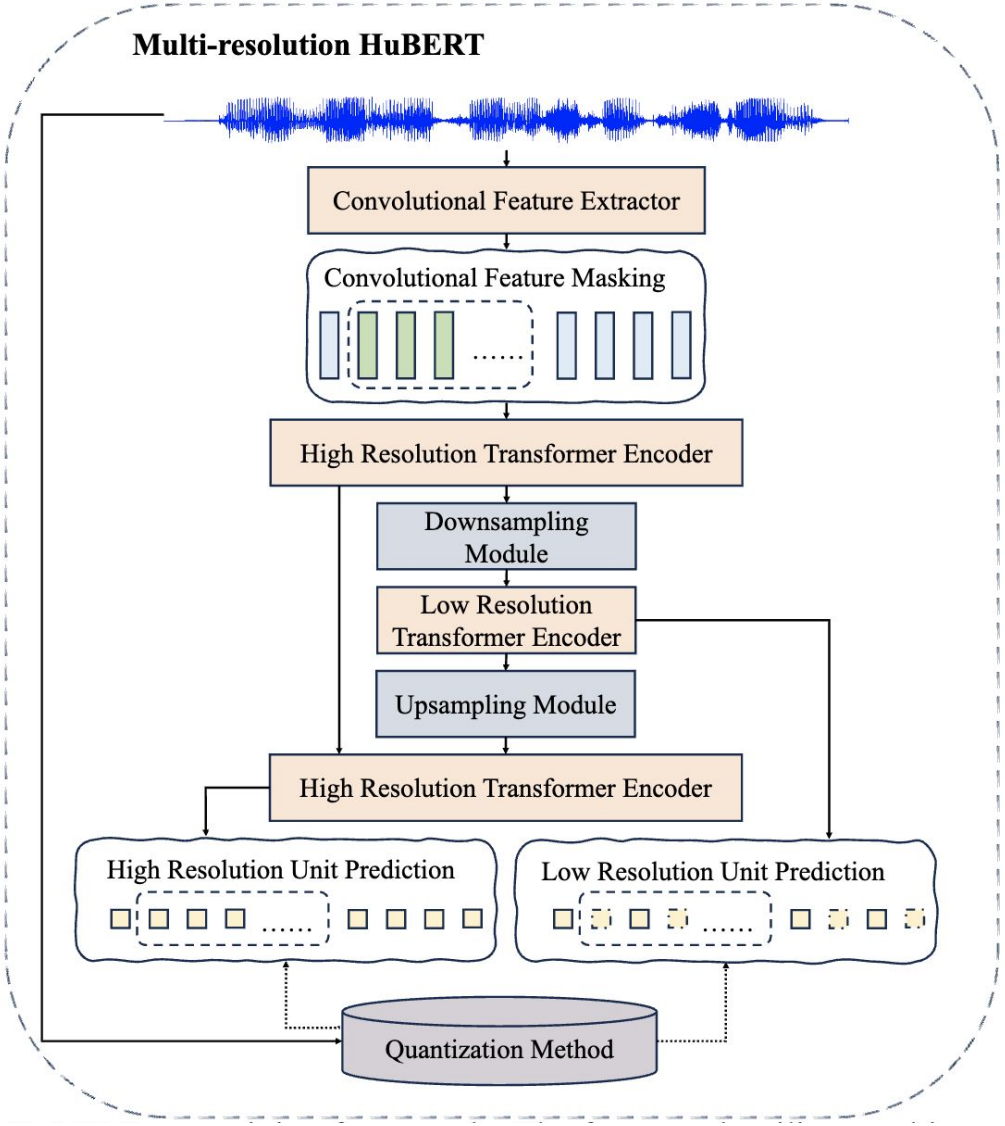


Figure 2: Hourglass - a high-level architecture overview. The arrows denote residual connections.

Multi-resolution HuBERT

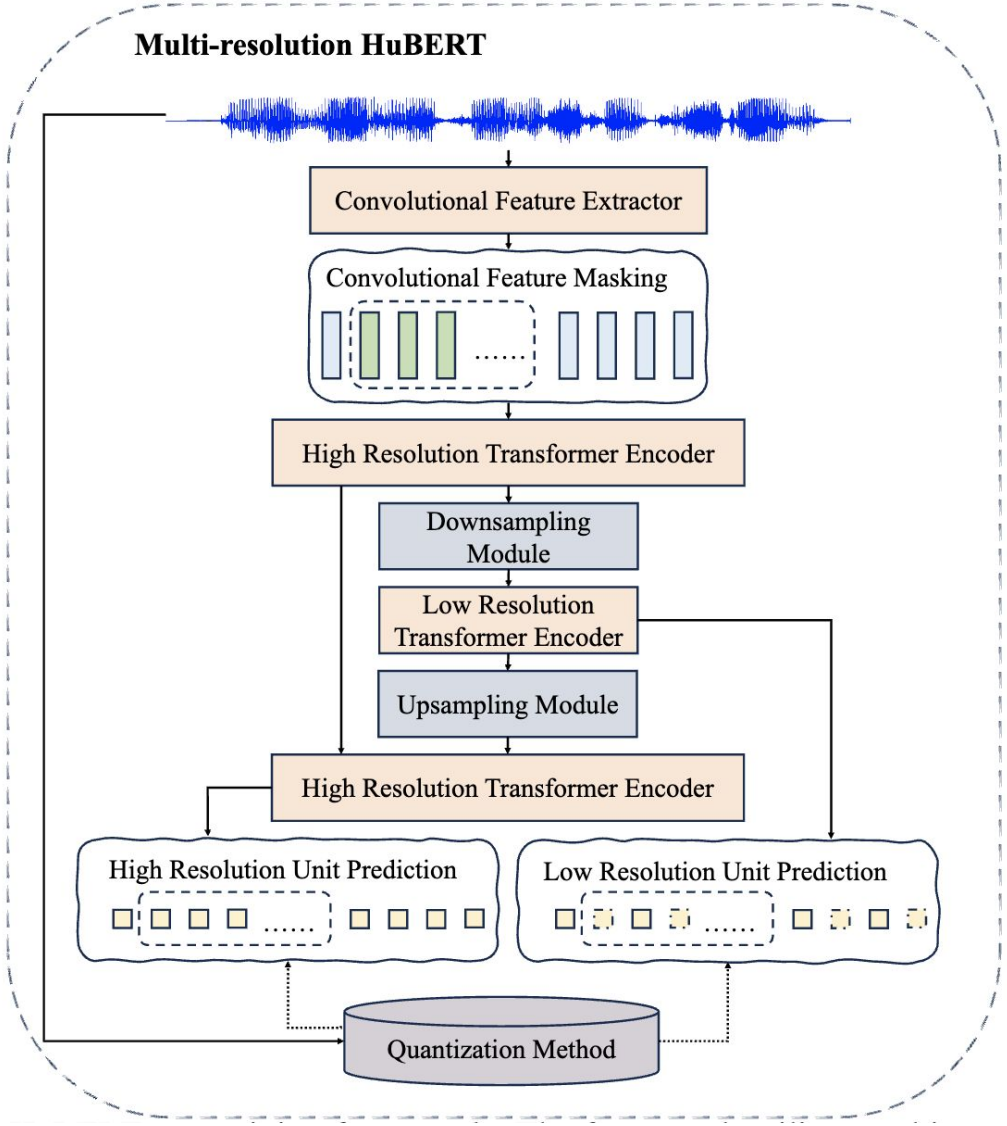
- By considering the motivations, we propose multi-resolution HuBERT
- Use the two-resolution case



Multi-resolution HuBERT

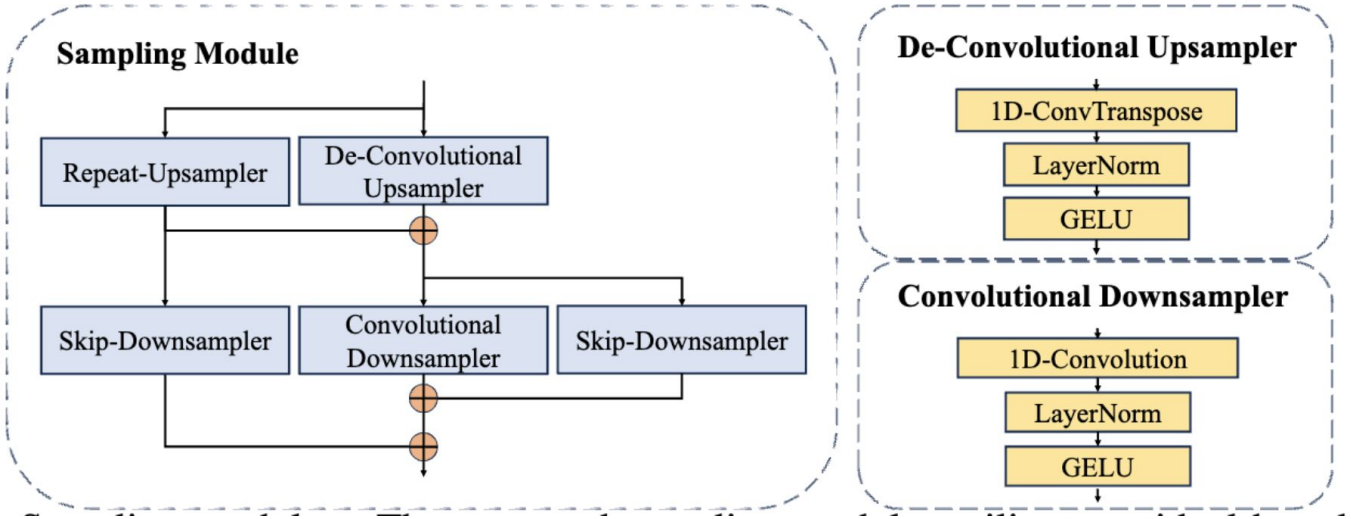
- By considering the motivations, we propose multi-resolution HuBERT

- Notable architectural changes
  - Sampling Module
  - Multi-resolution Objectives



Sampling Module

- Residual module to maximize the information in other resolutions
- Combined upsample+ downsample to allow flexible resolution ratios (also better performances in large-scale modeling)



Experiments - Dataset

- Datasets (in hours)
  - Librispeech 960
    - mono-base -> compare to HuBERT-base
  - Librilight 60k
    - mono-large -> compare to HuBERT-large
  - Voxpopuli 100k
    - multi-base -> compare to mHuBERT-base / XLSR
    - multi-large (is released in the website, but not fully tested)

Experiments – Additional Baseline

- HuBERT-base+ -> a HuBERT-base use the same units as mono-base
- HuBERT-large* -> a HuBERT-large use the same units as mono-large
- mHuBERT-base* -> a HuBERT-base use the same units as multi-base

Experiments – ASR Fine-tuning

- Librispeech Fine-tuning experiments
  - 1h, 10h, 100h labeled Librispeech
  - Add a CTC layer for prediction
  - Greedy decoding / Beam search with LM shallow fusion

Experiments – ASR Fine-tuning

Model	Unlabeled Data (h)	dev-clean	dev-other	test-clean	test-other
		1-hour labeled			
HuBERT-base	960	20.17 (8.75)	28.11 (16.09)	20.64 (8.88)	28.87 (16.71)
HuBERT-base$^+$	960	19.64 (8.14)	25.08 (12.36)	20.15 (8.31)	25.63 (12.82)
HuBERT-large	60,000	14.42 (5.84)	18.80 (9.53)	14.40 (5.81)	19.29 (9.91)
HuBERT-large*	60,000	15.09 (4.30)	18.20 (**6.84**)	14.90 (4.30)	18.05 (**7.23**)
mono-base	960	18.78 (7.33)	23.72 (11.53)	19.26 (7.41)	24.46 (12.14)
mono-large	60,000	**6.44** (**3.64**)	**10.94** (6.85)	**6.37** (**3.75**)	**11.41** (**7.23**)
		10-hour labeled			
HuBERT-base	960	9.62 (4.88)	16.60 (8.51)	9.71 (4.97)	17.00 (9.15)
HuBERT-base$^+$	960	9.51 (4.85)	14.27 (8.37)	9.72 (4.88)	14.89 (8.94)
HuBERT-large	60,000	5.68 (3.27)	8.67 (5.51)	5.75 (3.50)	8.96 (5.93)
HuBERT-large*	60,000	5.61 (3.24)	8.68 (5.55)	5.57 (3.25)	9.02 (6.00)
mono-base	960	8.51 (4.80)	13.18 (8.29)	8.46 (4.91)	13.51 (8.33)
mono-large	60,000	**5.58** (**3.12**)	**8.57** (**5.44**)	**5.52** (**3.15**)	**8.74** (**5.86**)
		100-hour labeled			
HuBERT-base	960	5.76 (3.66)	12.90 (8.45)	5.81 (3.84)	12.76 (8.48)
HuBERT-base$^+$	960	5.71 (3.33)	10.66 (6.51)	5.97 (3.55)	10.87 (7.09)
HuBERT-large	60,000	3.11 (2.37)	**6.01** (**4.22**)	3.14 (2.48)	6.15 (4.67)
HuBERT-large*	60,000	**3.03** (2.44)	6.30 (4.61)	3.12 (2.62)	6.14 (4.69)
mono-base	960	4.89 (3.21)	9.04 (6.47)	4.92 (3.57)	9.17 (6.81)
mono-large	60,000	3.06 (**2.33**)	6.04 (4.54)	**3.01** (**2.44**)	**5.98** (**4.61**)

Beamsearch+LM-fusion results are in parenthesis.

- Notable finding:

In general, the multi-resolution HuBERT are **comparable or better** than HuBERT in **all the test scenarios.**

Shu-wen Yang[1], Po-Han Chi[1*], Yung-Sung Chuang[1*], Cheng-I Jeff Lai[2*], Kushal Lakhotia[3*], Yist Y. Lin[1*], Andy T. Liu[1*], Jiatong Shi[4*], Xuankai Chang[6], Guan-Ting Lin[1], Tzu-Hsien Huang[1], Wei-Cheng Tseng[1], Ko-tik Lee[1], Da-Rong Liu[1], Zili Huang[4], Shuyan Dong[5†], Shang-Wen Li[5†], Shinji Watanabe[6], Abdelrahman Mohamed[3], Hung-yi Lee[1]

Experiments – SUPERB Evaluation

- SUPERB evaluation
  - Phone recognition (PR) – Phone error rate (PER)
  - Speech Recognition (ASR) – Word error rate (WER)
  - Intent Classification (IC) – Accuracy (ACC)
  - Keyword spotting (KS) – Accuracy (ACC)
  - Slot-filling (SF) – F1 and Character error rate (CER)
  - Speech Translation (ST) – BLEU
  - Speech enhancement (SE) – STOI and PESQ
  - Speech Separation (SS) – Si-SNR

- Experimental settings
  - Frozen Representation + Shallow downstream models

Experiments – SUPERB Evaluation

Model	Understanding							Enhancement		
	PR(↓)	ASR(↓)	IC(↑)	KS(↑)	SF-F1(↑)	SF-CER(↓)	ST(↑)	SE-STOI(↑)	SE-PESQ(↑)	SS(↑)
HuBERT-base	5.40	6.42	98.34	96.30	88.53	25.20	15.53	**0.94**	2.58	9.36
HuBERT-base^{+}	4.56	6.34	98.39	96.46	89.12	23.10	16.33	0.93	2.55	9.72
HuBERT-large	3.54	3.62	98.76	95.29	89.81	21.76	20.01	**0.94**	2.64	10.45
HuBERT-large*	3.59	**3.53**	98.73	97.70	89.88	22.51	20.02	**0.94**	2.65	10.61
mono-base	4.16	5.76	98.68	96.49	88.96	23.59	16.94	**0.94**	2.55	9.92
mono-large	**3.15**	3.78	**98.76**	**97.76**	**90.57**	**20.60**	**21.05**	**0.94**	**2.67**	**10.97**

- The proposed multi-resolution HuBERT almost **excels over all the tasks except for ASR** (which might be because CTC cannot handle well the repeat upsampling for low-resolution for weighted sum.

Experiments – SUPERB evaluation

Model	Understanding	Enhancement	General
HuBERT-base	861.2	98.20	670.4
HuBERT-base^{+}	876.9	150.2	695.2
HuBERT-large	932.6	456.0	813.4
HuBERT-large*	936.2	501.5	827.5
mono-base	885.8	195.0	708.7
mono-large	**949.7**	**609.5**	**864.6**

When, use SUPERB score, our proposed method has shown significant improvements in both understanding and enhancement tasks.

Experiments – SUPERB Evaluation

	PR	ASR	IC	KS	SF	ST	SE	SS
15	0.0773	0.0041	0.1588	0.0924	0.0051	0.0169	0.0384	0.0147
14	0.4173	0.0661	0.1228	0.0911	0.0191	0.2904	0.0335	0.0017
13	0.1124	0.3551	0.1085	0.0850	0.2418	0.2637	0.0296	0.0040
12	0.0490	0.0870	0.1039	0.0901	0.0489	0.0364	0.0372	0.0063
11	0.0040	0.0066	0.0796	0.0867	0.0061	0.0027	0.0435	0.0001
10	0.1806	0.0052	0.0613	0.0440	0.0070	0.1527	0.0123	0.0316
9	0.0592	0.2029	0.0928	0.0763	0.3045	0.0365	0.0210	0.0015
8	0.0024	0.2189	0.0760	0.0923	0.2165	0.0072	0.0196	0.0043
7	0.0019	0.0179	0.0415	0.0896	0.0159	0.0048	0.0240	0.0052
6	0.0001	0.0038	0.0278	0.0577	0.0050	0.0047	0.0338	0.0026
5	0.0414	0.0037	0.0245	0.0424	0.0088	0.0258	0.0111	0.0962
4	0.0251	0.0041	0.0246	0.0381	0.0106	0.0219	0.0270	0.0979
3	0.0096	0.0055	0.0260	0.0395	0.0175	0.0246	0.1269	0.1171
2	0.0066	0.0076	0.0257	0.0353	0.0323	0.0424	0.2116	0.1893
1	0.0130	0.0116	0.0262	0.0397	0.0611	0.0693	0.3304	0.4276

(a) **mono-base** (*base* MR-HuBERT)

	PR	ASR	IC	KS	SF	ST	SE	SS
13	0.0000	0.0007	0.0993	0.1359	0.0013	0.0073	0.0528	0.0001
12	0.4250	0.0194	0.1121	0.1057	0.0068	0.1503	0.0332	0.0270
11	0.3487	0.3853	0.1779	0.1343	0.2315	0.4271	0.0314	0.0095
10	0.1315	0.2937	0.2756	0.1542	0.3878	0.1887	0.0284	0.0058
9	0.0660	0.2001	0.1725	0.1181	0.1901	0.0460	0.0274	0.0066
8	0.0109	0.0645	0.0635	0.1091	0.0751	0.0096	0.0324	0.0190
7	0.0001	0.0044	0.0149	0.0391	0.0053	0.0071	0.0358	0.0375
6	0.0000	0.0011	0.0132	0.0309	0.0016	0.0089	0.0505	0.0728
5	0.0000	0.0011	0.0107	0.0336	0.0021	0.0121	0.0751	0.0776
4	0.0000	0.0025	0.0139	0.0276	0.0052	0.0146	0.1302	0.1308
3	0.0008	0.0044	0.0180	0.0381	0.0143	0.0183	0.1326	0.1003
2	0.0074	0.0087	0.0140	0.0253	0.0325	0.0349	0.1381	0.1505
1	0.0096	0.0141	0.0143	0.0481	0.0464	0.0750	0.2322	0.3624

(b) HuBERT-base

Mono-base (1-5 layer high resolution, 6-10 layer low resolution, 11-15 layer high resolution)

- Low resolution significantly contributes to PR, ASR, and SF
- Also there are some implications of inexplicit speech disentanglement in SE and SS (the low resolution layer weights are minimized)

Experiments – SUPERB Evaluation

	PR	ASR	IC	KS	SF	ST	SE	SS
27	0.0143	0.0187	0.1490	0.0402	0.0198	0.0099	0.0402	0.0038
26	0.0132	0.0203	0.0910	0.0477	0.0104	0.0008	0.0185	0.0000
25	0.0706	0.0184	0.0689	0.0463	0.0034	0.0224	0.0178	0.0000
24	0.0553	0.0525	0.0804	0.0441	0.0100	0.0480	0.0188	0.0000
23	0.0000	0.0447	0.0423	0.0406	0.0165	0.1074	0.0148	0.0000
22	0.0000	0.0723	0.0274	0.0360	0.0597	0.0167	0.0151	0.0000
21	0.0000	0.1221	0.0307	0.0345	0.0843	0.0047	0.0164	0.0000
20	0.0001	0.0425	0.0146	0.0328	0.0234	0.0019	0.0169	0.0000
19	0.0001	0.0175	0.0100	0.0324	0.0049	0.0037	0.0147	0.0000
18	0.4774	0.1652	0.0286	0.0348	0.1541	0.3636	0.0492	0.0405
17	0.0000	0.0186	0.1090	0.0471	0.0051	0.0038	0.0196	0.0000
16	0.0000	0.0325	0.0738	0.0441	0.0258	0.0104	0.0201	0.0000
15	0.0000	0.1085	0.0827	0.0424	0.1188	0.0008	0.0221	0.0000
14	0.0000	0.0888	0.0317	0.0399	0.0594	0.0004	0.0189	0.0000
13	0.0000	0.0007	0.0114	0.0341	0.0001	0.0003	0.0218	0.0000
12	0.0000	0.0003	0.0053	0.0305	0.0001	0.0004	0.0180	0.0000
11	0.0000	0.0007	0.0055	0.0294	0.0003	0.0007	0.0131	0.0000
10	0.0128	0.0574	0.0024	0.0304	0.0962	0.1766	0.0251	0.0724
9	0.3556	0.0912	0.0024	0.0307	0.2845	0.2194	0.0335	0.6435
8	0.0000	0.0015	0.0166	0.0438	0.0007	0.0003	0.0628	0.0000
7	0.0000	0.0016	0.0147	0.0391	0.0008	0.0004	0.0613	0.0000
6	0.0000	0.0011	0.0122	0.0350	0.0005	0.0005	0.0595	0.0117
5	0.0000	0.0012	0.0125	0.0338	0.0006	0.0005	0.0902	0.0400
4	0.0000	0.0022	0.0169	0.0337	0.0014	0.0007	0.0673	0.0161
3	0.0000	0.0035	0.0161	0.0332	0.0026	0.0009	0.0948	0.0923
2	0.0000	0.0068	0.0185	0.0320	0.0064	0.0015	0.0760	0.0515
1	0.0006	0.0094	0.0252	0.0316	0.0103	0.0033	0.0736	0.0281

(a) **mono-large** (*large* MR-HuBERT)

	PR	ASR	IC	KS	SF	ST	SE	SS
25	0.9777	0.8306	0.0297	0.0466	0.7935	0.9266	0.0152	0.7418
24	0.0000	0.0035	0.0654	0.0966	0.0049	0.0003	0.0097	0.0000
23	0.0160	0.0110	0.0603	0.0617	0.0100	0.0030	0.0129	0.0000
22	0.0050	0.0193	0.0719	0.0632	0.0101	0.0275	0.0147	0.0000
21	0.0000	0.0144	0.0725	0.0561	0.0180	0.0283	0.0195	0.0000
20	0.0000	0.0070	0.0672	0.0445	0.0201	0.0035	0.0169	0.0000
19	0.0000	0.0101	0.0624	0.0361	0.0211	0.0011	0.0154	0.0000
18	0.0000	0.0275	0.0549	0.0305	0.0347	0.0003	0.0150	0.0000
17	0.0000	0.0206	0.0468	0.0281	0.0214	0.0002	0.0156	0.0000
16	0.0000	0.0040	0.0355	0.0303	0.0046	0.0002	0.0175	0.0000
15	0.0000	0.0016	0.0317	0.0327	0.0028	0.0002	0.0200	0.0000
14	0.0000	0.0339	0.0296	0.0324	0.0216	0.0002	0.0214	0.0000
13	0.0000	0.0029	0.0291	0.0357	0.0044	0.0002	0.0226	0.0000
12	0.0000	0.0004	0.0283	0.0388	0.0012	0.0002	0.0260	0.0000
11	0.0000	0.0001	0.0279	0.0376	0.0004	0.0002	0.0312	0.0002
10	0.0000	0.0000	0.0299	0.0344	0.0004	0.0002	0.0383	0.0042
9	0.0000	0.0000	0.0294	0.0284	0.0003	0.0003	0.0398	0.0080
8	0.0000	0.0001	0.0286	0.0281	0.0006	0.0003	0.0413	0.0095
7	0.0000	0.0001	0.0271	0.0295	0.0008	0.0003	0.0826	0.0250
6	0.0000	0.0002	0.0287	0.0333	0.0011	0.0004	0.1049	0.0141
5	0.0000	0.0005	0.0276	0.0318	0.0017	0.0004	0.0739	0.0312
4	0.0000	0.0008	0.0287	0.0358	0.0024	0.0006	0.0958	0.0196
3	0.0001	0.0015	0.0279	0.0327	0.0034	0.0007	0.0786	0.0594
2	0.0003	0.0035	0.0275	0.0321	0.0062	0.0015	0.0575	0.0524
1	0.0008	0.0062	0.0314	0.0431	0.0142	0.0035	0.1136	0.0346

(b) HuBERT-large

Mono-large (1-9 layer high resolution, 10-18 layer low resolution, 19-27 layer high resolution)

- Mono-large
  - High resolution emphasis: enhancement tasks SE, SS
  - Low resolution emphasis: understanding tasks PR, ASR, SF, and ST
  - Equitable emphasis: IC and KS for sentence classification

Experiments – SUPERB Evaluation

	PR	ASR	IC	KS	SF	ST	SE	SS
27	0.0143	0.0187	0.1490	0.0402	0.0198	0.0099	0.0402	0.0038
26	0.0132	0.0203	0.0910	0.0477	0.0104	0.0008	0.0185	0.0000
25	0.0706	0.0184	0.0689	0.0463	0.0034	0.0224	0.0178	0.0000
24	0.0553	0.0525	0.0804	0.0441	0.0100	0.0480	0.0188	0.0000
23	0.0000	0.0447	0.0423	0.0406	0.0165	0.1074	0.0148	0.0000
22	0.0000	0.0723	0.0274	0.0360	0.0597	0.0167	0.0151	0.0000
21	0.0000	0.1221	0.0307	0.0345	0.0843	0.0047	0.0164	0.0000
20	0.0001	0.0425	0.0146	0.0328	0.0234	0.0019	0.0169	0.0000
19	0.0001	0.0175	0.0100	0.0324	0.0049	0.0037	0.0147	0.0000
18	0.4774	0.1652	0.0286	0.0348	0.1541	0.3636	0.0492	0.0405
17	0.0000	0.0186	0.1090	0.0471	0.0051	0.0038	0.0196	0.0000
16	0.0000	0.0325	0.0738	0.0441	0.0258	0.0104	0.0201	0.0000
15	0.0000	0.1085	0.0827	0.0424	0.1188	0.0008	0.0221	0.0000
14	0.0000	0.0888	0.0317	0.0399	0.0594	0.0004	0.0189	0.0000
13	0.0000	0.0007	0.0114	0.0341	0.0001	0.0003	0.0218	0.0000
12	0.0000	0.0003	0.0053	0.0305	0.0001	0.0004	0.0180	0.0000
11	0.0000	0.0007	0.0055	0.0294	0.0003	0.0007	0.0131	0.0000
10	0.0128	0.0574	0.0024	0.0304	0.0962	0.1766	0.0251	0.0724
9	0.3556	0.0912	0.0024	0.0307	0.2845	0.2194	0.0335	0.6435
8	0.0000	0.0015	0.0166	0.0438	0.0007	0.0003	0.0628	0.0000
7	0.0000	0.0016	0.0147	0.0391	0.0008	0.0004	0.0613	0.0000
6	0.0000	0.0011	0.0122	0.0350	0.0005	0.0005	0.0595	0.0117
5	0.0000	0.0012	0.0125	0.0338	0.0006	0.0005	0.0902	0.0400
4	0.0000	0.0022	0.0169	0.0337	0.0014	0.0007	0.0673	0.0161
3	0.0000	0.0035	0.0161	0.0332	0.0026	0.0009	0.0948	0.0923
2	0.0000	0.0068	0.0185	0.0320	0.0064	0.0015	0.0760	0.0515
1	0.0006	0.0094	0.0252	0.0316	0.0103	0.0033	0.0736	0.0281

(a) **mono-large** (*large* MR-HuBERT)

	PR	ASR	IC	KS	SF	ST	SE	SS
25	0.9777	0.8306	0.0297	0.0466	0.7935	0.9266	0.0152	0.7418
24	0.0000	0.0035	0.0654	0.0966	0.0049	0.0003	0.0097	0.0000
23	0.0160	0.0110	0.0603	0.0617	0.0100	0.0030	0.0129	0.0000
22	0.0050	0.0193	0.0719	0.0632	0.0101	0.0275	0.0147	0.0000
21	0.0000	0.0144	0.0725	0.0561	0.0180	0.0283	0.0195	0.0000
20	0.0000	0.0070	0.0672	0.0445	0.0201	0.0035	0.0169	0.0000
19	0.0000	0.0101	0.0624	0.0361	0.0211	0.0011	0.0154	0.0000
18	0.0000	0.0275	0.0549	0.0305	0.0347	0.0003	0.0150	0.0000
17	0.0000	0.0206	0.0468	0.0281	0.0214	0.0002	0.0156	0.0000
16	0.0000	0.0040	0.0355	0.0303	0.0046	0.0002	0.0175	0.0000
15	0.0000	0.0016	0.0317	0.0327	0.0028	0.0002	0.0200	0.0000
14	0.0000	0.0339	0.0296	0.0324	0.0216	0.0002	0.0214	0.0000
13	0.0000	0.0029	0.0291	0.0357	0.0044	0.0002	0.0226	0.0000
12	0.0000	0.0004	0.0283	0.0388	0.0012	0.0002	0.0260	0.0000
11	0.0000	0.0001	0.0279	0.0376	0.0004	0.0002	0.0312	0.0002
10	0.0000	0.0000	0.0299	0.0344	0.0004	0.0002	0.0383	0.0042
9	0.0000	0.0000	0.0294	0.0284	0.0003	0.0003	0.0398	0.0080
8	0.0000	0.0001	0.0286	0.0281	0.0006	0.0003	0.0413	0.0095
7	0.0000	0.0001	0.0271	0.0295	0.0008	0.0003	0.0826	0.0250
6	0.0000	0.0002	0.0287	0.0333	0.0011	0.0004	0.1049	0.0141
5	0.0000	0.0005	0.0276	0.0318	0.0017	0.0004	0.0739	0.0312
4	0.0000	0.0008	0.0287	0.0358	0.0024	0.0006	0.0958	0.0196
3	0.0001	0.0015	0.0279	0.0327	0.0034	0.0007	0.0786	0.0594
2	0.0003	0.0035	0.0275	0.0321	0.0062	0.0015	0.0575	0.0524
1	0.0008	0.0062	0.0314	0.0431	0.0142	0.0035	0.1136	0.0346

(b) `HuBERT-large`

- While the layer weight distribution presents a quite good alignment with the tasks, it also indicated the implicit speech disentanglement (or focus differences in the multi-resolution HuBERT)
  - This model might be able to extend to be a interpretable framework for understanding self-supervised learning in speech

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Experiments – ML-SUPERB

- ML-SUPERB
- A multilingual speech benchmark with 143 languages covered in a balanced setting (10min or 1hour for each language as training set)
- Frozen representation + shallow downstream (2-layer transformer + CTC)
- Four tasks
  - Monolingual ASR - test on 9 languages by training monolingual ASR on each
  - Multilingual ASR - test on 123 languages with full set and 20 languages as few shot (only 5 utterances)
  - Language Identification (LID) - test on 123 languages with full set
  - Multilingual ASR + LID - test on joint multilingual ASR + LID

Experiments – ML-SUPERB

SSL	Monolingual ASR	Multilingual ASR		LID	Multilingual ASR + LID			SUPERB$_s$(↑)
		Normal	Few-shot	Normal	Normal		Few-shot	
	CER/PER(↓)	CER(↓)	CER(↓)	ACC(↑)	ACC(↑)	CER(↓)	CER(↓)	
HuBERT-base	42.8 / 35.3	39.8 / 31.4	44.5 / 42.7	61.2 / 86.1	**71.5** / 86.0	39.2 / 30.9	43.8 / 41.8	831.9 / 884.9
HuBERT-base$^+$	42.9 / 35.3	41.5 / 31.2	45.8 / 42.8	63.8 / 81.9	70.1 / 85.8	39.6 / 31.3	44.6 / 40.7	819.1 / 875.8
HuBERT-large	**38.2** / 32.2	44.4 / 37.7	48.2 / 43.5	46.5 / 64.1	55.4 / 77.7	45.6 / 35.1	49.3 / 42.2	678.7 / 783.6
HuBERT-large*	41.2 / 32.6	42.8 / 32.8	45.6 / 42.5	42.3 / 58.9	59.2 / 84.7	42.3 / 29.8	44.1 / 41.4	704.5 / 817.6
mHuBERT-base	41.0 / 33.0	40.5 / 33.4	45.6 / 43.6	52.4 / 72.5	46.6 / 70.9	36.8 / 29.7	44.2 / 43.1	746.2 / 812.7
mHuBERT-base*	40.1 / 32.3	36.3 / **27.3**	**38.6** / 39.0	**64.0** / 82.0	70.4 / 84.6	35.4 / **27.1**	**39.0** / 37.0	950.8 / 964.5
mono-base	42.8 / 34.6	40.2 / 30.6	45.0 / 42.2	67.2 / **86.3**	68.7 / **86.9**	40.3 / 30.6	44.1 / 41.6	843.5 / 899.9
mono-large	40.5 / 32.0	38.9 / 29.4	42.7 / 40.5	45.1 / 75.4	67.6 / 85.9	39.0 / 29.7	43.8 / 40.8	785.2 / 905.4
multi-base	38.3 / **30.6**	**34.1** / 27.5	39.6 / **38.9**	**64.0** / 85.1	69.9 / 84.4	**34.4** / 28.0	40.9 / **36.6**	**957.2 / 986.8**

For monolingual models, mono-base and mono-large excels much over their counterparts.
For multilingual models, multi-base get comparable or better results than mHuBERT-base* and a much better overall scores

Experiments - ML-SUPERB Full Benchmark

SSL	Monolingual ASR	Multilingual ASR		LID	Multilingual ASR + LID			SUPERB$_s$
		Normal	Few-shot	Normal	Normal		Few-shot	
	CER/PER	CER	CER	ACC	ACC	CER	CER	
ML-SUPERB Benchmark (Shi et al., 2023a)								
FBank	72.1 / 63.7	62.4 / 59.3	58.3 / 57.4	11.1 / 9.3	35.9 / 43.5	62.0 / 58.6	58.9 / 58.1	0 / 0
wav2vec2-base	44.2 / 35.9	43.0 / 35.5	45.7 / 44.3	54.4 / 80.8	66.9 / 83.6	40.6 / 32.1	44.2 / 42.6	755.2 / 827.2
wav2vec2-large	42.0 / 35.4	42.6 / 35.7	45.8 / 43.9	30.9 / 8.0	54.6 / 78.2	45.5 / 34.7	50.3 / 42.2	598.3 / 586.9
robust-wav2vec2-large	44.4 / 35.7	40.1 / 31.1	45.4 / 42.2	50.8 / 72.1	33.1 / 62.9	38.6 / 33.7	44.9 / 46.0	680.3 / 768.6
wav2vec2-base-23	49.2 / 35.1	37.7 / 32.0	43.4 / 42.2	58.7 / 71.9	45.1 / 66.3	37.2 / 30.9	44.3 / 43.0	735.7 / 798.0
wav2vec2-large-23	42.0 / 34.2	42.1 / 35.3	44.3 / 42.4	1.1 / 64.2	21.8 / 49.7	43.4 / 35.2	46.1 / 43.1	433.8 / 724.9
XLSR-53	49.5 / 34.9	33.9 / 26.9	43.6 / 40.6	6.6 / 87.1	45.6 / 76.9	33.4 / 28.6	43.2 / 44.6	528.8 / 894.0
XLSR-128	39.7 / **30.6**	**29.2** / **22.0**	40.9 / 39.3	**66.9** / **87.9**	55.6 / 85.6	**28.4** / **22.9**	42.1 / 42.4	947.5 / **996.0**
HuBERT-base	42.8 / 35.3	39.8 / 31.4	44.5 / 42.7	61.2 / 86.1	71.5 / 86.0	39.2 / 30.9	43.8 / 41.8	831.9 / 884.9
HuBERT-large	**38.2** / 32.2	44.4 / 37.7	48.2 / 43.5	46.5 / 64.1	55.4 / 77.7	45.6 / 35.1	49.3 / 42.2	678.7 / 783.6
HuBERT-base-cmn	43.1 / 35.3	40.8 / 31.4	45.4 / 42.7	49.3 / 86.1	**75.1** / **86.1**	37.7 / 30.9	43.5 / 41.8	779.0 / 810.2
HuBERT-large-cmn	39.4 / 32.2	42.6 / 37.7	45.8 / 43.5	39.5 / 64.1	66.4 / 77.7	41.9 / 35.1	45.2 / 42.2	715.4 / 783.6
mHuBERT-base	41.0 / 33.0	40.5 / 33.4	45.6 / 43.6	52.4 / 72.5	46.6 / 70.9	36.8 / 29.7	44.2 / 43.1	746.2 / 812.7
Additional Baseline (Section 4.1)								
HuBERT-base$^+$	42.9 / 35.3	41.5 / 31.2	45.8 / 42.8	63.8 / 81.9	70.1 / 85.8	39.6 / 31.3	44.6 / 40.7	819.1 / 875.8
HuBERT-large*	41.2 / 32.6	42.8 / 32.8	45.6 / 42.5	42.3 / 58.9	59.2 / 84.7	42.3 / 29.8	44.1 / 41.4	704.5 / 817.6
mHuBERT-base*	40.1 / 32.3	36.3 / 27.3	**38.6** / 39.0	64.0 / 82.0	70.4 / 84.6	35.4 / 27.1	**39.0** / 37.0	950.8 / 964.5
Proposed Method (Section 4.1)								
mono-base	42.8 / 34.6	40.2 / 30.6	45.0 / 42.2	67.2 / 86.3	68.7 / 86.9	40.3 / 30.6	44.1 / 41.6	843.5 / 899.9
mono-large	40.5 / 32.0	38.9 / 29.4	42.7 / 40.5	45.1 / 75.4	67.6 / 85.9	39.0 / 29.7	43.8 / 40.8	785.2 / 905.4
multi-base	38.3 / **30.6**	34.1 / 27.5	39.6 / **38.9**	64.0 / 85.1	69.9 / 84.4	34.4 / 28.0	40.9 / **36.6**	**957.2** / 986.8

Compared to XLSR-128, multi-base can reach comparable performance (slightly better in 10min, slightly worse in 1h), with

- ⅓ model size
- ¼ pre-trained data
- ⅕ language coverage

More in https://arxiv.org/abs/2310.02720

Experiments – Ablation Studies

- Layer size for each encoder (high-resolution encoder1, low-resolution encoder, high-resolution encoder2)
  - Mono-base (4,4,4)
    - (2, 4, 6): slight better in semantics
    - (5, 2, 5): best in ASR
    - (6, 4, 2): better in spk tasks (not in paper)
- Multi-resolution analysis (introducing three resolutions)
  - More resolutions helps with the **speed up** (inference MACs)
  - **Similar or worse performance** (however, the results might change when extend to larger-scale)
- Simple Downsampling
  - Do not use the proposed one, but only half (downsample or upsample) module
  - Similar performance on ASR and understanding tasks, but worse in enhancement tasks
- Single prediction target
  - Always worse

More in https://arxiv.org/abs/2310.02720

Experiments – Ablation Studies

- Single resolution (same architecture but with single resolution)
  - Similar or worse performance in ASR experiments
  - Worse in both understanding and enhancement tasks
- Compact model
  - With only ¾ parameters, the model can perform similar performance as the original HuBERT on ASR
- Large-scale experiments
  - Using HuBERT-large to extract units can get better results
  - Audio normalization should not be used in large models
  - Batch size matters
  - Simplified sampling is not recommended

Potential Directions

- Integration with other SSL frameworks (e.g., wav2vec2, w2v-bert, data2vec)
- Diverse Resolution (More resolution and more diverse resolution)
- Richer Representation (Speech generation perspective)
- Speech Disentanglement (Insights from the layer weight analysis)

MULTI-RESOLUTION HUBERT: MULTI-RESOLUTION SPEECH SELF-SUPERVISED LEARNING WITH MASKED UNIT PREDICTION

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