The Ability of Self-Supervised Speech Models for Audio Representations

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Abstract

Self-supervised learning (SSL) speech models have achieved unprecedented success in speech representation learning, but some questions regarding their representation ability remain unanswered. This paper addresses two of them: (1) Can SSL speech models deal with non-speech audio?; (2) Would different SSL speech models have insights into diverse aspects of audio features? To answer the two questions, we conduct extensive experiments on abundant speech and non-speech audio datasets to evaluate the representation ability of currently state-of-the-art SSL speech models, which are wav2vec 2.0 and HuBERT in this paper. These experiments are carried out during NeurIPS 2021 HEAR Challenge as a standard evaluation pipeline provided by competition officials. Results show that (1) SSL speech models could extract meaningful features of a wide range of non-speech audio, while they may also fail on certain types of datasets; (2) different SSL speech models have insights into different aspects of audio features. The two conclusions provide a foundation for the ensemble of representation models. We further propose an ensemble framework to fuse speech representation models’ embeddings. Our framework outperforms state-of-the-art SSL speech/audio models and has generally superior performance on abundant datasets compared with other teams in HEAR Challenge. Our code is available at https://github.com/tony10101105/HEAR-2021-NeurIPS-Challenge—NTU-GURA.

Keywords: Self-Supervised Learning, Representation Learning, Ensemble Learning

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1. Introduction

Data representation is crucial to the performance of deep learning algorithms. A good representation catches the underlying patterns of the input data (Bengio et al., 2013) and can serve as effective inputs for neural networks, which usually reach better performance with a higher quality of inputs. The extraction of data can be done either in a hand-crafted way using heuristic methods or with the help of neural networks. For neural-network-based feature extractions, supervised and unsupervised learning are two techniques that have long been developed. The former utilizes labeled data and has a clearer training objective, while the scalability is also limited. The latter needs only unlabeled data but usually with inferior results.

In recent years, self-supervised learning (SSL) frameworks for speech representation, such as HuBERT (Hsu et al., 2021) and wav2vec 2.0 (Baevski et al., 2020), have proved their powerful abilities to extract useful speech audio features and deal with a wide range of downstream tasks, such as Speaker Identification (SID) and Automatic Speaker Verification (ASV). The achievements are mainly acquired by the use of various pre-training techniques with self-defined tasks on a huge amount of unlabeled corpus. For example, during the pre-training stage, HuBERT is required to predict the frame-level cluster assignments of the masked part of the input sequence. By solving self-defined tasks, SSL speech models are capable of capturing meaningful latent representations of given speech audio clips to help with diverse downstream tasks.

Intuitively, representations generated from SSL speech models probably contain different information about the data due to distinct training setups, including pre-training techniques, training corpus, and model architectures. However, few works have made attempts to demonstrate and clarify the differences. In addition, though SSL speech models have shown to be promising on a wide range of speech processing tasks, their representation ability for non-speech audio is still an unanswered question. Therefore, We further extend the question into the field of non-speech audio to investigate their potential and performance. Particularly, this work aims to clarify the capability of SSL speech models for both speech and non-speech applications. First, to examine whether different SSL speech models would pay attention to distinct aspects of the audio, tSNEs (Van der Maaten and Hinton, 2008) of feature embeddings produced by wav2vec 2.0 and HuBERT on three speech and non-speech datasets are displayed. Furthermore, a large number of datasets, including speech and non-speech, are adopted for the holistic evaluation of wav2vec 2.0 and HuBERT’s feature representation ability. Results show considerable performance gaps between the two SSL speech models on various speech and non-speech datasets. Specifically, wav2vec 2.0 may have high-quality feature presentations on certain datasets, where HuBERT cannot extract well, and vice versa. This implies their attention to various aspects of audio inputs. With the conclusion, we further propose a bagging-based ensemble learning schema, attempting to develop a general framework for generating comprehensive audio feature representation. Experimental results demonstrate its superior performances on various datasets compared with baselines, and the ablation studies again support our findings.

In summary, the contributions of this work is threefold:
1. Showing that SSL speech models may have promising performances on some non-speech audio datasets, while failure on certain types of audio datasets is also possible.

2. Showing that SSL speech models may focus on different aspects of audio features due to distinct pre-training techniques, even though they all have reached outstanding performances on benchmark datasets and have similar model architectures.

3. Proposing a bagging-based ensemble framework for integrating SSL speech representation models. Experimental results on abundant audio datasets demonstrate its superiority over other state-of-the-art methods and ensemble learning’s potential in the field of speech representation learning.

2. Related Works

2.1. SSL speech and audio Models

The objective of SSL is to extract meaningful representations from the input data without any human annotations. It arranges auxiliary tasks with unlabeled data, driving models to learn the representative features by solving these tasks. Models pre-trained through SSL skills on diverse large corpus can be used as effective feature extractors afterward. As a whole, pre-training strategies for speech/audio models can be roughly categorized into three groups: generative, discriminative, and multi-task learning.

Generative training investigates the distribution of input data. Given a sequence of samples, models are asked to generate new samples to fit into the original distribution. APC (Chung et al., 2019) is pre-trained with a unidirectional RNN in an autoregressive manner to predict the information of future frames. VQ-APC (Chung et al., 2020) extends APC by applying Vector Quantized (VQ) layers to generate better quantized representation. Mockingjay (Liu et al., 2020) is pre-trained with Masked Language Model (MLM) to reconstruct the masked tokens in the time-axis. TERA (Liu et al., 2021) extends Mockingjay by using alteration to train the Transformer encoders. PANNs (Kong et al., 2020), which is an SSL audio model pre-trained on AudioSet (Gemmeke et al., 2017), proposes Wavegram-Logmel-CNN to concatenate both waveform and the log-mel spectrogram as input representations. PaSST (Koutini et al., 2021) presents the patchout method to optimize Transformers with audio spectrograms. Wav2CLIP (Wu et al., 2022) distills representations from CLIP (Radford et al., 2021) to produce general and robust audio representations.

Discriminative training aims to discriminate positive samples from negative samples in the embedding space. CPC (Oord et al., 2018) extracts features that maximally preserve the mutual information of the input sequence and the context latent representations over the time horizon. It makes use of a non-linear CNN-based encoder to embed the input sequence into latent representations and an autoregressive RNN-based network to generate the context latent representations by summarizing the encoder’s previous timesteps. Wav2vec (Schneider et al., 2019) improves CPC by adopting a CNN-based autoregressive network to parallelize the training process and thus enhance time efficiency. vq-wav2vec (Baevski et al., 2019) further boosts wav2vec by introducing VQ modules, such as Gumbel-Softmax (Jang et al., 2016) and online k-means clustering, to learn discrete speech representations. Wav2vec 2.0 refines the framework of vq-wav2vec by merging the two-stage pipeline to
perform end-to-end joint training. HuBERT is pre-trained on the task of predicting the k-means cluster of the masked tokens, currently achieving state-of-the-art performance on many speech tasks.

Multi-task learning solves multiple speech/audio tasks simultaneously to guide models to generate more comprehensive and robust representations. PASE (Pascual et al., 2019) utilizes regressors to predict training objectives, such as waveform, log power spectrum (LPS), mel-frequency cepstral coefficients (MFCC), and prosody features. Discriminators are also introduced into PASE, and strategies to sample positive and negative samples, such as local info max (LIM), global info max (GIM), and sequence predicting coding (SPC) are adopted. PASE+ (Ravanelli et al., 2020) improves PASE by applying online speech distortion modules to add several noises to input speech and using Quasi-RNN (QRNN) (Bradbury et al., 2016) to help the encoder learn the long-term dependencies.

2.2. Ensemble Learning

Ensemble learning is a machine learning technique that aggregates diverse base models to form an ensemble system with better robustness and performance. Generally, ensemble strategies can be categorized into boosting, bagging, and stacking (Ganaie et al., 2021).

Boosting strategy integrates weak models, converting them into a new learner with better generalization. Examples include but are not limited to linear combinations in regression problems and majority voting in classification tasks. AdaBoost (Freund et al., 1996) assembles weak classifiers into a stronger one by leveraging misclassified samples. During each training iteration, weights of correctly classified samples become lower, while those of misclassified ones increase. This pipeline propels classifiers in the next iteration to correctly classify samples misclassified previously. Gradient boosting (Friedman, 2001) works similarly to AdaBoost, while the shortcoming of the previous classifier is identified by gradient rather than the weights of data points. This method can be applied to any differentiable loss function. Variants of gradient boosting include XGBoost (Chen and Guestrin, 2016), a scalable end-to-end tree boosting system adopting a gradient boosting framework. XGBoost features parallel and distributed computing to speed up computation. For the optimization of memory efficiency, out-of-core computing and cache optimization are adopted.

The bagging strategy works by training several weak models on datasets where each data point is randomly sampled from the original dataset. It aims to reduce model variance on the dataset. Bagging consists of three basic steps. The first step is bootstrapping, which resamples data points from the original dataset randomly with replacements to generate a new dataset. Secondly, it trains a set of base models parallelly. The last step is to aggregate the predictions of each model with averaging or majority voting. There are some variants of bagging with different sampling methods. For example, dagging randomly samples data without replacement to generate disjoint datasets, and wagging assigns weights to each data point under probability distributions like Gaussian distribution, Poisson distribution, etc. In particular, the Random Forest (Breiman, 2001) is an application of the bagging method. Fitting a set of decision trees with bootstrap samples, this method resolves the over-fitting issue of decision trees and adds flexibility to the model.

In some ensemble methods, such as majority voting or output averaging, each model contributes the same amount to the ensemble output, regardless of the model’s performance.
To address this issue, stacking strategy (Ganaie et al., 2021) takes predictions generated by each model as input, learning how to combine input predictions to achieve better performance. The base models are often referred to as level-0 models, and the models combining outputs from level-0 models are level-1 models, and so on. Stacking consists of two stages, where the first stage is to generate input data of level-1 models by k-fold cross-validation on level-0 models and the second stage is to train the level-1 models. A variant of stacking is blending, which implements a one-holdout set rather than k-fold cross-validation in the first stage.

3. Methods

We argue that speech models with different SSL techniques produce inhomogeneous feature representations given the same audio input. Hence, even though these cutting-edge models’ performances on various benchmark datasets are close, it could still be beneficial to merge their representations for climbing up to a higher performance. With this statement, we propose an ensemble framework that integrates the representations of speech models, which is further shown to be more holistic and contain more information compared with a single SSL speech/audio model.

The advocated ensemble method comprises three models and two techniques. The three models are wav2vec 2.0, HuBERT, and CREPE (Kim et al., 2018b). The two techniques are feature aggregation and feature concatenation, where the former is an intra-model operation that averages the output of a network’s different layers to form a single output feature and the latter is an inter-model operation that combines models’ output features as the final representation of input audio. The overview of the proposed framework is shown in Figure 1.

3.1. Models for Ensemble

Although the number of models for the bagging method is unlimited, three or five are often chosen in practice for balancing size and performance. Our method in HEAR adopts three models: wav2vec 2.0, HuBERT, and CREPE, which are trained on different datasets, paradigms, and techniques. Wav2vec 2.0 and HuBERT are both SSL speech models, while the former is pre-trained with masked vector quantization plus contrastive discrimination, and the latter is masked vector quantization plus token prediction/classification. Wav2vec 2.0 has Base and Large versions, and HuBERT has Base, Large, and Extra Large versions. The Base versions of both models are pre-trained on LibriSpeech 960 hr (Panayotov et al., 2015), while other versions are trained on Libri-Light 60k hr (Kahn et al., 2020). The model versions and even the models themselves used in the framework can be arbitrarily chosen. CREPE is a pitch estimation model pre-trained on music-based datasets. The adoption of CREPE is based on an observation that HuBERT and wav2vec 2.0 seem unable to handle pitch-related tasks well, which is further discussed in the experiment Section 5.

It should be emphasized that our framework does not limit the number and types of models to be assembled. It is completely plausible to replace wav2vec 2.0, HuBERT, and CREPE with other models, such as vq-wav2vec and TERA. While only the three models are studied during the challenge.
3.2. Feature Aggregation

Each layer of SSL Transformer-based speech models may have attention to a certain aspect of sequential input data. As a result, instead of merely using the last hidden state of the model, we take the average of all the hidden states, i.e., fuse the output of each transformer block plus the initial embedding outputs, to yield more comprehensive feature representations, as shown in Figure 1. There have been various layer aggregation methods (Yu et al., 2018) studied, while we simply utilize the most straightforward one for simplicity. In other words, though the choice and weight of hidden states are both optional, we sum up all the hidden states fairly. Our aggregation operation can be generally defined as:

\[ X = \frac{1}{L} \sum_{i=1}^{L} X_i, \]  

(1)

where \( L \) is the number of Transformer blocks and \( X_i \) is the \( i \)-th Transformer block’s output. Notice that the dimensions of different hidden states are all identical in both wav2vec 2.0 and HuBERT, so we can directly take the average, as shown in Equation (1).

It should be noticed that feature aggregation is not applied to CREPE since it is a relatively shallow vanilla CNN model with six convolutional layers. We only leverage the output of the fifth max-pooling layer as the feature embedding, following its official implementation*.

3.3. Feature Concatenation

Up/downsampling is required before feature concatenation since different models have an inconsistent time dimension. Specifically, models’ time dimensions are all resampled into 1024. After that, features are concatenated concerning the time dimension through an interpolation-like manner, rather than direct concatenation. For instance, assume output features of three models used for ensemble are \([x_1, x_2, ..., x_t]\), \([y_1, y_2, ..., y_t]\) and \([z_1, z_2, ..., z_t]\) respectively, the concatenated final output features will then be \([x_1, y_1, z_1, x_2, y_2, z_2, ..., x_t, y_t, z_t]\).

*https://github.com/marl/crepe
With this approach, the time information of the final output features is preserved, which is vital to certain downstream tasks such as sound event detection.

4. Experimental setup

Experiments are carried out during the NeurIPS 2021 HEAR Challenge, where sixteen benchmark or novel datasets are used for the holistic evaluation of audio representations. HEAR officials conduct the evaluation process, and the full results are displayed on its official website†.

4.1. HEAR evaluation pipeline

Our experiments follow HEAR’s evaluation pipeline, which adopts the evaluation principles of representation quality proposed by (Goyal et al., 2019). In this challenge, each team either utilizes existing pre-trained SSL models or trains their models for audio feature representations. The proposed upstream models are submitted to HEAR officials, and audio in the sixteen datasets is then fed into those models to produce feature embeddings, which further serve as inputs for the training of downstream shallow models. With downstream models’ architectures and hyperparameters fixed, their performances reflect the quality of given feature representations. Since HEAR’s philosophy is to foster the development of audio representation methods with strong generalizability, models are anticipated to have decent performances on all datasets, rather than excellent results on several datasets but poor on other tasks.

4.2. Datasets

HEAR has totally 16 tasks, each of which corresponds to a dataset. The datasets include Speech Commands (Warden, 2018), NSynth (Engel et al., 2017), DCASE 2016 Task 2 (Mesaros et al., 2017), Beehive States (Nolasco et al., 2019), Beijing Opera Percussion Instrument (Tian et al., 2014), CREMA-D (Cao et al., 2014), ESC-50 (Piczak, 2015), FSD50k (Fonseca et al., 2021), Gunshots recorded in an open field using iPod Touch devices (Gunshot Triangulation) (Cooper and Shaw), GTZAN Genre Collection (Tzanetakis and Cook, 2002), GTZAN Music/Speech (Tzanetakis, 1999), LibriCount (Stöter et al., 2018), MAESTRO (Hawthorne et al., 2018), Mridangam Stroke (Anantapadmanabhan et al., 2013), Vocal Imitation Set (Kim et al., 2018a) and VoxLingua107 (Valk and Alumäe, 2021).

Categories of these 16 datasets are presented in Table 1. Speech Command is a speech command classification dataset that contains 105829 utterances of 35 words, such as “Bed”, “Five”, “Wow”, etc. HEAR evaluates the whole dataset as well as a 5 hours version sub-dataset. NSynth is a pitch classification dataset having 305979 musical notes, each with a unique pitch, from 1006 instruments. Models have to classify the instrumental sounds into one of 88 pitches. HEAR assesses the 50 hours and 5 hours version sub-datasets. DCASE 2016 Task 2 is an office sound event detection dataset with 11 event categories, such as clearing throat and coughing, with 20 sound segments per event class for training. It should be noticed that HEAR uses a different way to split this dataset, so the evaluation result is not comparable to other work. Beehive States is a binary sound classification

†https://neuralaudio.ai/
Table 1: Categories of 16 datasets presented in HEAR Challenge’s evaluation process.

| Category          | Datasets                                                                                     |
|-------------------|----------------------------------------------------------------------------------------------|
| Speech            | Speech Commands (Warden, 2018)                                                               |
|                   | CREMA-D (Cao et al., 2014)                                                                    |
|                   | LibriCount (Stöter et al., 2018)                                                             |
|                   | Vocal Imitation Set (Kim et al., 2018a)                                                      |
|                   | VoxLingua107 (Valk and Alumae, 2021)                                                         |
| Instrument        | Nsynth (Engel et al., 2017)                                                                   |
|                   | Beijing Opera Percussion (Tian et al., 2014)                                                 |
|                   | Mridingham Stroke and Tonic (Anantapadmanabhan et al., 2013)                                 |
|                   | MAESTRO (Hawthorne et al., 2018)                                                              |
| Environmental sounds | DCASE 2016 Task 2 (Mesaros et al., 2017)                                                |
|                   | Beehive States (Nolasco et al., 2019)                                                        |
|                   | ESC-50 (Piczak, 2015)                                                                       |
|                   | Gunshot Triangulation (Cooper and Shaw)                                                     |
| General           | FSD50k (Fonseca et al., 2021)                                                                |
|                   | GTZAN Genre Collection (Tzanetakis and Cook, 2002)                                           |
|                   | GTZAN Music/Speech (Tzanetakis, 1999)                                                        |

dataset with 930 sound clips. The first class is normal beehives and the second class is the queen-less ones. Beijing Opera Percussion Instrument is a percussion instrument classification dataset with 236 clips from 6 percussion instruments, such as Ban and Gong, which are organized into four classes, such as Bangu and Daluo. CREMA-D is a 6-class audiovisual emotion recognition dataset. HEAR only adopts the audio recordings, with 7438 clips in total. ESC-50 is an environmental sounds classification dataset with 2000 sounds grouped into 50 classes. FSD50K is a human-labeled sound event classification dataset with 51197 Freesound (Fonseca et al., 2017) clips grouped into 200 classes drawn from AudioSet. Gunshot Triangulation is a distance classification dataset. A gun is placed at a fixed location and fires, with 4 iPod Touches located at different distances from the shooter. Models classify audio by the iPod Touch that records the shot. There are 7 different guns and 88 audio clips. GTZAN Genre Collection is a 10-class music genre classification dataset with 100 audio clips for each class. GTZAN Music/Speech is a binary classification dataset. Models are asked to distinguish between speech and music audio. The dataset has 120 samples (60 per class). LibriCount is a speaker count estimation dataset. Models have to identify the number of speakers in a simulated cocktail party audio recording. MAESTRO is a note onset detection dataset, which measures models’ ability to detect the occurrence of a note. HEAR evaluation adopts its 5 hours sub-dataset, with two measures note onset with and without offsets calculated. The Mridangam Stroke dataset contains 6977 audio examples of 10 different strokes played on Mridangams with 6 tonics. HEAR evaluation divides the dataset into two sub-tasks: stroke classification and tonic classification. The Vocal Imitation Set is a sound classification dataset. Models should predict which reference sound the audio is imitating. There are 5601 vocal imitations of 302 reference sounds curated on AudioSet. VoxLingua107 is a spoken-language classification dataset. HEAR evaluation adopts the 5-hours version sub-dataset with 972 audio clips, where only the 10 most frequent languages are involved.

For more information about these datasets and tasks, please refer to the official website of HEAR.
4.3. Our Method and Baselines

Our ensemble framework adopts pre-trained wav2vec 2.0, HuBERT, and CREPE without any fine-tuning. As a result, the utilized wav2vec 2.0 and HuBERT are both pure speech models pre-trained on LibriSpeech or Libri-Light, while CREPE is a pure music-based model pre-trained on several pitch-related datasets, such as RWC-Synth (Goto et al., 2002), MDB-STEM-Synth (Salamon et al., 2017) and NSynth.

Baselines include vanilla wav2vec 2.0, HuBERT, CREPE, and other teams’ methods. For vanilla wav2vec 2.0 and HuBERT, only the last hidden state is used as the input embedding. In terms of other teams in HEAR, we select five out of all teams’ submitted models: Wav2CLIP (Wu et al., 2022), PaSST (Koutini et al., 2021), PANNs (Kong et al., 2020), EfficientNet-B2 (Tan and Le, 2019) and BYOL-S (Scheidwasser-Clow et al., 2022). The first three are SSL speech and audio models, while EfficientNet is a series of CNN-based models whose architectures are determined by neural architecture search (NAS), denoted as EfficientNet-B0 to EfficientNet-B7. BYOL-S is proposed in SERAB (Scheidwasser-Clow et al., 2022) benchmark as a speech version of BYOL (Grill et al., 2020). BYOL is an image representation learning framework that comprises two networks with the same architectures, referred to as the online network and target network. By taking an image as the online network’s input and the augmented view as the target network’s input, BYOL aims to minimize the distance between the output embeddings of these two networks.

These five teams (models) are officially considered to have the most competitive performances. For training setups, Wav2CLIP is pre-trained on VGG-Sound (Chen et al., 2020) for maximally 100 epochs with early stopping and 1e-3 learning rate. PaSST is pre-trained on AudioSet for maximally 130 epochs with 2e-5 initial learning rate plus learning rate decay. PANNs are pre-trained on AudioSet for 600k iterations with a 1e-3 learning rate. EfficientNet-B2 is pre-trained on ImageNet (Deng et al., 2009) for 218949 steps, with an initial learning rate of 0.256 plus learning rate decay. BYOL-S is pre-trained on speech samples in AudioSet for 100 epochs with a 3e-4 learning rate. For more information about the teams and codes that can be slightly different from the original paper of their methods, please refer to HEAR’s official website.

5. Results

5.1. Quantitative Results

Results of 15 out of 16 datasets are displayed in Table 2, and the missing one is the Beehive States dataset, which has a large input size, causing a big portion of teams’ models to run out of memory under the competition hardware setting and get no result. Mridingham is split into two subsets: Mridingham Tonic and Mridingham Stroke. The highest and second-highest scores in each dataset are marked in bold and underlined respectively. Our proposed framework is denoted as fusion-cat-xwc, which means HuBERT xLarge plus wav2vec 2.0 Large plus CREPE with intra-model feature aggregation and inter-model feature concatenation.

It is demonstrated that our framework possesses the best performances in general, with the finest or competitive results on a large portion of datasets presented in Table 1. Specifically, our method achieves top performances on Speech Commands, VoxLingua107, Vocal
I imitations, Beijing Opera Percussion, CREMA-D, and MAESTRO 5h, along with second places on DCASE 2016 Task 2, NSynth 50h, Gunshot Triangulation, Mridingham Tonic, Mridingham Stroke, and LibriCount. The datasets our method fails to conquer are GTZAN Genre, FSD50k, GTZAN Music/Speech, and ESC-50. Among the four failed datasets, it can be observed that our ensemble framework obtains relatively higher performances than those of HuBERT xLarge, wav2vec 2.0 Large, or CREPE alone on GTZAN Genre, FSD50k, and ESC-50 datasets. The only dataset our method does not show the superiority is GTZAN Music/Speech, while all methods get over 90% accuracy and are very close to each other. In addition, except for GTZAN Music/Speech, our ensemble method outperforms the state-of-the-art HuBERT xLarge and wav2vec 2.0 Large alone on all datasets, indicating that this technique can indeed stably increase a single model’s speech/audio representation ability.

On the other hand, other teams’ proposed methods also do not fall behind the HuBERT xLarge and wav2vec 2.0 Large. Specifically, PaSST base2levelmel owns the first place on 5 datasets and second place on 3 datasets, which is the second-best model in general. CREPE is exceptionally strong at the pitch- and note-related music tasks, such as NSynth 50h and MAESTRO 5h, which most current speech/audio SSL models fail to cope with. However, very poor performances on other datasets can also be found. As our framework incorporates CREPE as one of the assembled models in HEAR, it implies that this kind of feature ensemble can eliminate the shortcoming of each model since our framework still displays outstanding results on datasets CREPE cannot handle.

It is also noteworthy that, though AudioSet and VGG-Sound are two large-scale datasets containing both speech and non-speech audio clips, models pre-trained on them, such as PaSST, PANNs, and Wav2CLIP, do not remarkably surpass other models that are only pre-trained on speech audio, such as SERAB BYOL-S, HuBERT xLarge and wav2vec 2.0 Large, or even images, such as EfficientNet-B2. In addition, models pre-trained on the same corpus can still have great performance gaps on testing datasets. For instance, PaSST base2levelmel acquires 54.1 Pitch accuracy (Acc) and 56.6 Chroma Acc on NSynth 50h, while PANNs only get 30.1 and 32.3 respectively; wav2vec 2.0 Large has 65.3 Pitch accuracy (Acc) and 70.6 Chroma Acc on NSynth 50h, yet HuBERT xLarge only gets 42.0 and 45.8. This leads to a conclusion that, besides pre-training corpus, models’ attention to input audio can also be largely affected by a wide range of factors, such as model architectures.
Figure 2: tSNEs of embeddings of HuBERT xLarge fusion (left) and wav2vec 2.0 Large fusion (right) on 16 audio datasets. Each point is a sample in a dataset.

and pre-training objectives. Even though existing SSL speech models like wav2vec 2.0 and HuBERT normally have similar Transformer-based architectures, their abilities to extract speech and non-speech audio can still vary. This observation turns out to be the basis of the use of ensemble learning, and the promising performances of our proposed ensemble framework in turn validate this conclusion.

5.2. Representation Visualization

Figure 2 plots the tSNEs (perplexity fixed at 50) of embeddings of wav2vec 2.0 Large and HuBERT xLarge with intra-model feature fusion on all datasets appeared in Table 1 except for Beehive States dataset. It can be observed that, though the two models are trained with different SSL techniques, their embeddings both follow the rule: far from each other for two inhomogeneous datasets, and close or overlapping with each other for two similar corpora. For example, tSNEs of Mridingham Stroke and Mridingham Tonic overlap since they are both musical instrument datasets. This holds for either HuBERT xLarge or wav2vec 2.0 Large. In addition, the embeddings of FSD50k are relatively sparse, scattering across the figure and overlapping some other datasets. This is because FSD50k is a large-scale sound event dataset with clips categorized into 200 classes. Thus, some clips in it may have acoustic features similar to audio in other corpora.

5.3. Ablation Study

Ablation studies are conducted to verify the contributions of operations and components in our ensemble framework. Results are shown in Tables 3, 4, 5 and 6.

We first look into the use of intra-model feature aggregation. As displayed in Table 3, the direct fusion of all hidden states increases HuBERT xLarge’s and wav2vec 2.0 Large’s performances on most datasets. For instance, for DCASE 2016 Task 2, the event onset
Table 3: Performance of HuBERT xLarge and wav2vec 2.0 Large w/ and w/o feature fusion.

| Methods                  | DCASE 2020 Task 2 | Speech Commands | Segment Error Rate | Segment Error Rate | Pitch Acc | Chroma Acc | Chord Acc | Note Onset FMS | Note Onset w/ Offset FMS | Acc | mAP |
|--------------------------|-------------------|-----------------|--------------------|--------------------|-----------|-------------|-----------|----------------|--------------------------|-----|-----|
| wav2vec 2.0 Large        | 82.8              | 58.0            | 65.1               | 58.0               | 78.7      | 83.7        | 78.2      | 83.7           | 15.5                      | 68.2| 31.1|
| Fusion HuBERT xLarge     | 82.0              | 52.7            | 70.3               | 54.7               | 72.2      | 82.2        | 74.8      | 80.1           | 11.4                      | 37.3| 25.8|

Table 4: Performance of feature averaging versus feature concatenation of wav2vec 2.0 Large plus HuBERT Large.

| Methods                  | DCASE 2020 Task 2 | Speech Commands | Segment Error Rate | Segment Error Rate | Pitch Acc | Chroma Acc | Chord Acc | Note Onset FMS | Note Onset w/ Offset FMS | Acc | mAP |
|--------------------------|-------------------|-----------------|--------------------|--------------------|-----------|-------------|-----------|----------------|--------------------------|-----|-----|
| wav2vec 2.0 Large        | 82.8              | 58.0            | 65.1               | 58.0               | 78.7      | 83.7        | 78.2      | 83.7           | 15.5                      | 68.2| 31.1|
| Fusion HuBERT xLarge     | 82.0              | 52.7            | 70.3               | 54.7               | 72.2      | 82.2        | 74.8      | 80.1           | 11.4                      | 37.3| 25.8|

Table 5: Performance of HuBERT xLarge w/ and w/o CREPE.

| Methods                  | DCASE 2020 Task 2 | Speech Commands | Segment Error Rate | Segment Error Rate | Pitch Acc | Chroma Acc | Chord Acc | Note Onset FMS | Note Onset w/ Offset FMS | Acc | mAP |
|--------------------------|-------------------|-----------------|--------------------|--------------------|-----------|-------------|-----------|----------------|--------------------------|-----|-----|
| wav2vec 2.0 Large        | 82.8              | 58.0            | 65.1               | 58.0               | 78.7      | 83.7        | 78.2      | 83.7           | 15.5                      | 68.2| 31.1|
| Fusion HuBERT xLarge     | 82.0              | 52.7            | 70.3               | 54.7               | 72.2      | 82.2        | 74.8      | 80.1           | 11.4                      | 37.3| 25.8|

Table 6: Performance of wav2vec 2.0 Large plus CREPE with feature concatenation w/ and w/o HuBERT xLarge.

| Methods                  | DCASE 2020 Task 2 | Speech Commands | Segment Error Rate | Segment Error Rate | Pitch Acc | Chroma Acc | Chord Acc | Note Onset FMS | Note Onset w/ Offset FMS | Acc | mAP |
|--------------------------|-------------------|-----------------|--------------------|--------------------|-----------|-------------|-----------|----------------|--------------------------|-----|-----|
| wav2vec 2.0 Large        | 82.8              | 58.0            | 65.1               | 58.0               | 78.7      | 83.7        | 78.2      | 83.7           | 15.5                      | 68.2| 31.1|
| Fusion HuBERT xLarge     | 82.0              | 52.7            | 70.3               | 54.7               | 72.2      | 82.2        | 74.8      | 80.1           | 11.4                      | 37.3| 25.8|
f-measure (FMS) of wav2vec 2.0 Large increases from 66.3 to 79.8 with fusion strategy, and the segment error rate also decreases by 10.3. HuBERT xLarge follows the same trend but with more significant improvements, with event onset FMS rocketing to 82.6 and segment error rate dropping to 15.0. However, feature aggregation does not always produce better results. For example, wav2vec 2.0 Large’s classification accuracy on LibriCount drops from 69.2 to 65.3 after applying the feature fusion. Nevertheless, this technique still generally possesses a positive effect on models’ representation ability.

Table 4 displays the comparison between inter-model feature concatenation and simple feature averaging. Cat xw and avg xw denote the concatenation and the average of HuBERT Large and wav2vec 2.0 Large, respectively. Results show that the cat xw has better performances on ten datasets and avg xw wins five. For FSD50k, the cat xw achieves higher mAP, while d’ value is higher on avg xw. With the abundant results shown on 16 datasets, we conclude that, by and large, feature concatenation brings more benefits than feature averaging, and the former is subsequently adopted in our framework.

Table 5 illustrates the effects of adding CREPE. Avg xc means HuBERT Large plus CREPE with simple feature averaging. With CREPE, HuBERT xLarge’s performances on DCASE 2016 Task 2, NSynth 50h, GTZAN Music/Speech, and MAESTRO 5h rise, especially significantly in NSynth 50h and MAESTRO 5h. It should be noticed that NSynth 50h, GTZAN Music/Speech, and MAESTRO 5h are all music-related. Besides, DCASE 2016 Task 2 and MAESTRO 5h are event onset detection datasets. It can be derived that, SSL speech models may still have blind spots on music-related contents, and their abilities on event detection datasets are also not as strong as in other kinds of tasks such as classification/identification. However, Combining CREPE also leads to drops in other tasks by a considerable margin. For instance, its performance on Speech Commands decreases from 95.4 Acc to 73.7 after combining CREPE. The reason is that, given that embeddings on Speech Command produced by CREPE contain very little content information, it will further jeopardize the information in embeddings generated by HuBERT Large if we take the average of these two vectors. The solution is to use feature concatenation rather than averaging, and our concatenation-based final framework indeed achieves 96.8 Acc on Speech Command even with CREPE being inside.

Finally, the contribution of HuBERT xLarge among all three models is examined in Table 6. The ablation study is conducted to see if HuBERT xLarge can provide extra information that is not given by wav2vec 2.0 Large and CREPE. Cat wc denotes the ensemble of wav2vec 2.0 Large plus CREPE with feature concatenation, while cat xwc means the same schema but with the join of HuBERT xLarge. Table 6 shows that HuBERT xLarge helps cat xwc attain higher results on nearly all tasks. For example, the event onset FMS rises from 58.5 to 66.1 in DCASE 2016 Task 2 and the segment error rate is decreased by 10.5.

6. Conclusion

This work first examines the representation ability of SSL speech models on diverse speech and audio datasets provided in the NeurIPS 2021 HEAR Challenge. Results show their potential to deal with non-speech scenarios, while failure on certain types of audio can also be observed. In addition, different SSL speech models might have insights into different aspects of audio features. Based on these observations, we further propose an ensemble
framework for integrating models’ audio representations. As a whole, our method achieves superior performances compared with single state-of-the-art SSL speech models and other teams’ methods in HEAR, demonstrating the strength and potential of ensemble learning in the field of speech representation learning.

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