Similarity Analysis of Self-Supervised Speech Representations

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Abstract

Self-supervised speech representation learning has recently been a prosperous research topic. Many algorithms have been proposed for learning useful representations from large-scale unlabeled data, and their applications to a wide range of speech tasks have also been investigated. However, there has been little research focusing on understanding the properties of existing approaches. In this work, we aim to provide a comparative study of some of the most representative self-supervised algorithms. Specifically, we quantify the similarities between different self-supervised representations using existing similarity measures. We also design probing tasks to study the correlation between the models’ pre-training loss and the amount of specific speech information contained in their learned representations. In addition to showing how various self-supervised models behave differently given the same input, our study also finds that the training objective has a higher impact on representation similarity than architectural choices such as building blocks (RNN/Transformer/CNN) and directionality (uni/bidirectional). Our results also suggest that there exists a strong correlation between pre-training loss and downstream performance for some self-supervised algorithms.

1 Introduction

Self-supervised learning is a form of unsupervised learning that treats the input or modifications of the input as learning targets. Thanks to this property, self-supervised learning can leverage very large-scale unlabeled data for training, and has enjoyed success in learning high-level representations of data from different modalities (Chen et al., 2020; Devlin et al., 2019; Baevski et al., 2020b). Recently, self-supervised approaches for learning speech representations have received great research attention. Methods like contrastive predictive coding (Oord et al., 2018), autoregressive predictive coding (Chung et al., 2019), masked predictive coding (Liu et al., 2020b; Wang et al., 2020; Jiang et al., 2019), and problem-agnostic speech encoder (Pascual et al., 2019) have been shown to be capable of learning representations that capture high-level properties of speech that are not easily accessible from surface features such as audio waveforms and spectrograms. These methods have been further extended or improved for tackling a wide range of speech applications, including speech recognition (Baevski et al., 2020a; Baevski and Mohamed, 2020; Chung and Glass, 2020a; Ling et al., 2020; Jiang et al., 2020; Song et al., 2020), speech translation (Nguyen et al., 2020; Wu et al., 2020a), speaker verification (Wu et al., 2020b; Ravi et al., 2020; Shani et al., 2020), unsupervised unit discovery (Peng and Scharenborg, 2020), and unsupervised phoneme segmentation (Kreuk et al., 2020), to name a few. There also exists a line of work that uses audio-visual or audio-textual input data for self-supervised speech representation learning (Harwath et al., 2020, 2016; Shukla et al., 2020; Chrupała et al., 2017; Khurana et al., 2020; Chung et al., 2020b; Chuang et al., 2020), while in this work we focus on the case where speech is the only source for learning representations.
Despite the recent progress in self-supervised speech representation learning, most of the effort is made to develop new algorithms or adapt existing methods to particular tasks, and only a few studies focus on reviewing existing approaches. In this work, we aim to provide a comparative study on some of the most representative self-supervised algorithms: contrastive predictive coding (CPC), autoregressive predictive coding (APC), and masked predictive coding (MPC). Our analysis focuses on the following two aspects. First, we hope to understand the similarity of representations learned by different self-supervised algorithms. To carry out this study, we adopt two similarity measures for quantifying the similarity of two given representations (to be more specific, two sequences of vectors). Although such a similarity analysis approach cannot discern absolute facts about the representations, it allows us to compare representations without subscribing to any specific type of information, and helps us answer questions like: Given the same input, how similar are different self-supervised representations? Which modeling choices, e.g., building blocks (RNN/Transformer/CNN) and directionality (uni/bidirectional), have a higher impact on representation similarity? How much does a model change when it is trained on more data?

Our second area of investigation examines, for each self-supervised algorithm, how well its pre-training loss correlates with downstream performance. Our approach is to use phonetic and speaker classification as probing tasks to measure the amount of phonetic and speaker information contained in the representations as a function of pre-training loss. This study could be useful for model selection if there exists a strong correlation between the pre-training loss and the probing task performance.

Only a few studies have focused on analyzing self-supervised models. [Chung et al. (2020a)] propose to incorporate vector quantization layers to restrict model capacity during pre-training so as to uncover a model’s preference in preserving speech information for achieving a maximal self-supervised objective. [Blandón and Räsänen (2020)] study the correlation between the self-supervised loss of APC and CPC and their performance on a phoneme discrimination task, which has the same goal as our second study. However, neither of these two works investigated the similarity between different self-supervised representations. For the correlation study, we also consider more self-supervised models with diverse modeling choices as compared to [Blandón and Räsänen (2020)].

Our analysis yields the following insights:

- The objective has a higher impact on representation similarity than model architecture.
- Under the same objective, a model’s directionality (uni/bidirectional) affects representation similarity more than its building blocks (RNN/Transformer/CNN).
- Both APC and MPC both have a stronger correlations between pre-training loss and phonetic and speaker classification performance than does CPC.
- While all models benefit from increasing the size of unlabeled training data, CPC is found to make use of these additional data more efficiently than APC and MPC.

The rest of the paper is organized as follows. We start with introducing our methods for studying the two aspects of our investigation in Section 2. Then, in Section 3, we describe our experimental setup, including the implementations of the considered self-supervised models, and datasets for pre-training and probing. Experimental results and analysis are presented in Section 4, followed by our conclusions in Section 5.

2 Analysis Methods

We are interested in two aspects of self-supervised speech representation learning: (1) the similarities between representations learned by various models, and (2) how well their self-supervised pre-training loss correlates with downstream performance. We describe our methods for analyzing these two aspects in Sections 2.1 and 2.2 respectively.

2.1 Approaches for measuring representation similarity

Consider a pre-trained self-supervised model $M$. For an acoustic feature sequence (in our case, a log Mel spectrogram) $x = (x_1, x_2, ..., x_T)$, where $x_t \in \mathbb{R}^{80}$, from a dataset $D$, the model $M$ transforms $x$ into a higher-level representation $M(x) = (m_1, m_2, ..., m_T)$, where $m_t \in \mathbb{R}^{512}$. Given two representations extracted by two self-supervised models $M^{(1)}$ and $M^{(2)}$, a similarity
measure outputs $\text{sim}(M^{(1)}(x), M^{(2)}(x)) \in \mathbb{R}$ that quantifies their similarity. Note that this approach does not require $D$ to be annotated.

Existing similarity measures are proposed to capture different similarity notions. Some focus on capturing the localization of information of two representations, which is usually done by comparing the behaviors of two individual elements $m^{(1)}_i$ and $m^{(2)}_j$ from $M^{(1)}(x)$ and $M^{(2)}(x)$, respectively (Bau et al., 2019). Other measures emphasize distributivity of information and find correlations between two representations $M^{(1)}(x)$ and $M^{(2)}(x)$ directly (Kriegeskorte et al., 2008; Kornblith et al., 2019; Raghu et al., 2017; Andrew et al., 2013): if two representations behave similarly over all of their elements, their similarity will be high even if no two individual elements have similar behaviors. In this work we focus on the latter case and adopt linear centered kernel alignment (lincka; Kornblith et al., 2019) and singular vector canonical correlation analysis (svcca; Raghu et al., 2017) as our similarity measures. We choose these two since they are found to be comparable or better than other measures in prior studies for analyzing contextual word representation models (Wu et al., 2020c).

2.2 Probing tasks for measuring phonetic and speaker information

We consider phonetic and speaker classification for measuring the amount of accessible phonetic and speaker content contained in a representation. Given a self-supervised model $M$ pre-trained on an unlabeled dataset $D_1$, we use $M$ to extract features $M(x) = (m_1, m_2, ..., m_T)$, where $m_t \in \mathbb{R}^{512}$ for another dataset $D_2$, and train a supervised linear classifier using the extracted features as input.

For phonetic classification, the goal is to correctly predict the phone identity of each frame in an input utterance. For speaker classification, the extracted features of the utterance are first averaged before being fed to the classifier, and the goal is to correctly predict the speaker identity of the utterance. The frame-level phone error rate and utterance-level speaker error rate on the test set of $D_2$ indicate the amount of phonetic and speaker content contained in the representation.

3 Experimental Setup

3.1 Self-supervised models

In this work we consider some of the most representative self-supervised models for comparison, including contrastive predictive coding (CPC) (Oord et al., 2018), autoregressive predictive coding (APC) (Chung et al., 2019), and masked predictive coding (MPC) (Liu et al., 2020b; Wang et al., 2020; Jiang et al., 2019).

While there are additional models that have successfully been applied to speech applications, most of them are more or less an improvement or extension of the above models. For example, Rivière et al. (2020) improve CPC by modifying its batch normalization mechanism and replacing the linear prediction head with a 1-layer Transformer network. Kawakami et al. (2020) modify CPC to make it bidirectional. wav2vec (Schneider et al., 2019) is essentially CPC with a fully convolutional architecture and a proposal distribution dedicated for speech recognition. DeCoAR proposed by Ling et al. (2020) can be viewed as a bidirectional version of APC. Chung and Glass (2020b) propose an auxiliary loss serving as a regularizer to help APC generalize better. Liu et al. (2020a) apply SpecAugment (Park et al., 2019) to improve MPC’s masking techniques. Jiang et al. (2020) combine APC and MPC to form a unified pre-training objective. We leave the explorations of these extensions for future work. Below we briefly review the considered models: CPC, APC, and MPC.

CPC & APC Contrastive predictive coding (CPC) and autoregressive predictive coding (APC) share a similar methodology as both use an autoregressive model to learn representations through conditioning on the past context to make predictions of future information. Their main difference lies in the manner in which they optimize the autoregressive model: while APC attempts to predict a future frame via L1 regression, CPC incorporates a proposal distribution for drawing negative samples, and learns representations containing information that most discriminates the future frame.

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1 We adopt the setting where $D_1$ and $D_2$ have different distributions to simultaneously examine the richness and robustness against domain shift of a representation. We believe this is a more realistic setting than assuming $D_1$ and $D_2$ have the same distribution. Our setting is also closer to that in the literature of NLP pre-training models.
from the negative samples using a loss called InfoNCE, which is based on noise-contrastive estimation (Gutmann and Hyvärinen, 2010). We mainly follow the original papers (Oord et al., 2018; Chung et al., 2019) for implementing the models with small modifications described in Chung et al. (2019).

Since the objectives of APC and CPC are based on the notion of future prediction, bidirectional architectures are not applicable. A simple method for making these models have access to context from both directions is to separately train a forward and backward APC/CPC model and concatenate their output representations as the final representations (similar to how ELMo (Peters et al., 2018) is trained for learning contextualized word embeddings). This method has been explored for APC and CPC in Ling et al. (2020) and Kawakami et al. (2020), respectively.

Table 1: Information about various implementations of APC, MPC, and CPC to be compared in this work. All RNN and Transformer models have a hidden size of 512 (256 for forward and 256 for backward if bidirectional). For CPC, cpc-mixed_spk-rnn draws negative samples across speakers, while cpc-within_spk-rnn and cpc-within_spk-cnn draw negative samples from the same utterance.

| Notation            | Objective | Building block              | Directionality |
|---------------------|-----------|-----------------------------|----------------|
| apc-fw-rnn          | APC       | 3-layer GRU                 | Unidirectional |
| apc-fw+bw-rnn       | APC       | 3-layer GRU                 | Bidirectional  |
| apc-fw-trf          | APC       | 3-layer Transformer decoder | Unidirectional |
| apc-fw+bw-trf       | APC       | 3-layer Transformer decoder | Bidirectional  |
| mpc-birnn           | MPC       | 3-layer GRU                 | Bidirectional  |
| mpc-trf             | MPC       | 3-layer Transformer encoder | Bidirectional  |
| cpc-mixed_spk-rnn   | CPC       | 3-layer GRU                 | Unidirectional |
| cpc-within_spk-rnn  | CPC       | Same as Schneider et al. (2019) | - |
| cpc-within_spk-cnn  | CPC       | Same as Schneider et al. (2019) | - |

MPC  Inspired by the masked language modeling technique from BERT (Devlin et al., 2019), masked predictive coding (MPC) directly trains a bidirectional architecture by first masking parts of the input signals and then predicting them through conditioning on context from both directions. Similar to APC, MPC is optimized by minimizing the frame-wise L1 distance between the predicted output and the original input before masking. Transformer encoder (Liu et al., 2020b; Jiang et al., 2019) and bidirectional RNN (Wang et al., 2020) have both been used to implement MPC.

To account for multiple factors in model design (objective, RNN/Transformer/CNN, uni/bidirectional), we consider the implementations of APC, MPC, and CPC as listed in Table 1.

3.2 Pre-training datasets

We use the LibriSpeech corpus (Panayotov et al., 2015), which contains 960 hours of read speech produced by 2,338 speakers, for pre-training all considered self-supervised models. We also use the unlabeled subset from the Libri-Light corpus (Kahn et al., 2020), which contains about 6k hours of speech audio produced by 1,742 speakers, for additional experiments in Section 4.3. We use 80-dimensional log Mel spectrograms as input acoustic features, i.e., \( \mathbf{x}_t \in \mathbb{R}^{80} \). All models are trained for 10 epochs using Adam with a batch size of 32 and an initial learning rate of \( 10^{-3} \). During pre-training, only the speech portion from the dataset is used.

3.3 Probing datasets

Representation similarity measures  For calculating representation similarity with lincka and svcca (described in Section 2.1), we use the si284 subset from the Wall Street Journal corpus (WSJ) (Paul and Baker, 1992) and the train set from the TIMIT corpus (Garofolo et al., 1993).

Phonetic and speaker classification  We carry out both classification tasks on WSJ. For phonetic classification, there are a total of 42 phone categories, and we follow the standard split of WSJ, using 90% of si284 for training, 10% for validation, and reporting frame-level phone error rate on dev93. The phone alignments are generated with a speaker adapted GMM-HMM model. For speaker
classification, we follow Chung and Glass (2020a) and consider a 259-class classification task where each class corresponds to a unique speaker, using 80% of si284 for training, the other 10% for validation, and reporting utterance-level speaker error rate on the rest 10%. We note that speaker classification is not a typical task for WSJ, and only serves as a sanity check for the presence of speaker information. For both tasks, the classifier is a linear logistic regression trained for 10 epochs using SGD with a batch size of 32 and a fixed learning rate of $10^{-4}$. All reported error rates are an average of 5 runs, of which variances are negligibly small and not included.

4 Results and Analysis

4.1 Similarity of different self-supervised representations

Figures 1 and 3 (in appendix A) show heatmaps of similarities between representations learned by various self-supervised models according to similarity measures $\text{lincka}$ and $\text{svcca}$ on two probing datasets WSJ and TIMIT. Brighter colors indicate higher similarity between two representations. We find all heatmaps exhibiting consistent patterns regardless of the probing dataset and similarity measure, and all self-supervised representations are very different from the surface feature (in our case, the log Mel spectrogram). The heatmaps reveal the following insights.

Objective affects similarity more than architecture. The most evident pattern from the heatmaps is that there is always a greater similarity within an objective than across objectives, indicated by the bright block diagonal. For example, $\text{apc-fw-rnn}$ is always more similar to $\text{apc-fw+bw-rnn}$, $\text{apc-fw-trf}$, and $\text{apc-fw+bw-trf}$ than to any MPC and CPC variants, even when $\text{apc-fw-rnn}$ and $\text{cpc-mixed_spk-rnn}$/$\text{cpc-within_spk-rnn}$ share the same building block and directionality. This conclusion also holds for the MPC- and CPC-family. Representations learned by generative-based objectives, i.e., variants of APC and MPC, are also more similar to one other than to the CPC variants.

Directionality affects similarity more than building block. When the objective is the same, we find that model’s directionality (uni/bidirectional) has a higher impact on representation similarity than its building block (RNN/Transformer/CNN). For instance, the similarity between $\text{apc-fw-rnn}$...
Figure 2: Scatter plots of various self-supervised representations’ performance on phonetic and speaker classification as a function of their pre-training loss. For each figure, the x-axis is the pre-training loss, and the y-axis on the left is the corresponding phone error rate and on the right the speaker error rate.

and apc-fw-trf, which are both unidirectional while the former uses RNNs and the latter uses Transformers, is higher than that between apc-fw-rnn and apc-fw+bw-rnn, which both use RNNs while the former is unidirectional and the latter is bidirectional. Furthermore, as may be expected, making APC bidirectional reduces its difference with MPC, which is indicated by the fact that mpc-birnn is more similar to apc-fw+bw-rnn than to apc-fw-rnn, and mpc-trf is more similar to apc-fw+bw-trf than to apc-fw-trf. Source of negative samples affects similarity more than architecture. When focusing on the CPC-family, we find that proposal distribution where the negative samples are drawn—which could also be regarded as the objective—is more impactful on representation similarity than building block. This is indicated by the fact that cpc-within_spk-rnn is more similar to cpc-within_spk-cnn than to cpc-mixed_spk-rnn, where the two models in the former case share the same proposal distribution but use different building blocks, and the two models in the latter case share the same building block but incorporate different proposal distributions.

4.2 Correlation between self-supervised loss and phonetic & speaker classification performance

Experiments so far have only revealed the similarities between different self-supervised representations. In this study, we further uncover the correlation between self-supervised loss during pre-training and the amount of phonetic and speaker information contained in the representations, measured by their performance on phonetic and speaker classification defined in Section 2.2. We only consider apc-fw-rnn, mpc-birnn, cpc-mixed_spk-rnn, and cpc-within_spk-rnn in this experiment for
Table 2: Pearson correlation coefficients between the self-supervised loss and the phone and speaker error rates. * denotes statistical significance at $\rho < 0.05$.

| Model                | Phone   | Speaker |
|----------------------|---------|---------|
| apc-fw-rnn           | 0.989*  | 0.950*  |
| mpc-birnn            | 0.885*  | 0.847*  |
| cpc-mixed_spk-rnn    | 0.643*  | 0.762*  |
| cpc-within_spk-rnn   | 0.675*  | -0.071  |

a comparison only in terms of their objectives (except mpc-birnn, which has to be bidirectional). Figure 2 displays the scatter plots of phone and speaker error rates as a function of self-supervised loss for the four considered models.

For each model, we only consider loss after 10k steps until the end of training (10 epochs, which is about 88k steps). Within this interval, we take 15 data points—each corresponding to a model checkpoint—with equally-sized chunk, and sort them with ascending order according to their loss values. Next, for each of these 15 checkpoints, we run the probing tasks and report the corresponding phone and speaker error rates. We also calculate the Pearson correlation coefficients $r$ between loss value and both phone and speaker error rates, as listed in Table 2.

Overall, generative-based objectives (APC and MPC) are found to have a stronger positive correlation between the self-supervised loss and both their phonetic and speaker classification performance than contrastive-based objectives. In particular, apc-fw-rnn features the strongest correlation among the four considered self-supervised models. Our finding aligns with [Blandón and Räsänen (2020)], where the autoregressive loss of APC is found to be more correlated with the ABX-score of a phone discrimination task than the InfoNCE loss of CPC.

It is noteworthy that the loss of cpc-within_spk-rnn has almost no correlation with speaker classification performance. This result seems natural since the model always draws negative samples from the same utterance as the positive sample, so speaker information is never found to be useful for distinguishing them and thus not learned by the representation. On the other hand, the proposal distribution of cpc-mixed_spk-rnn allows the model to learn from negative samples coming from both the same and different utterances as the positive sample, meaning that both phonetic and speaker information could be relevant for discriminating them. Therefore, we find the loss of cpc-mixed_spk-rnn is still correlated with the speaker error rate to some degree.

We emphasize that our findings here are not meant to claim any self-supervised approach to be the best, but aim to provide some results for other researchers for future reference. For example, APC and MPC’s strong correlation between their self-supervised loss and phonetic and speaker classification performance could be useful for model selection even during the pre-training stage, since a lower pre-training loss would indicate a richer phonetic and speaker representation. CPC, though exhibiting a smaller correlation between its self-supervised loss and phonetic and speaker classification performance, could still be extremely powerful when the downstream task is known and thus the pre-training proposal distribution can be determined beforehand, as shown by its recent impressive performance on semi-supervised speech recognition ([Baevski et al. (2020b)].

4.3 Effect of increasing unlabeled data for self-supervised pre-training

One of the biggest advantages of self-supervised learning is its capability to leverage very large-scale unlabeled data for representation learning. Here we train apc-fw-rnn, mpc-birnn, cpc-mixed_spk-rnn, and cpc-within_spk-rnn on 2k, 4k, and 6k hours of speech audio, all sampled from the unlabeled subset of the Libri-Light corpus, and calculate the similarities between each of these variants and their counterpart trained on the original 960 hours LibriSpeech audio according to lincka. Results are shown in Table 3.

As may be expected, for all self-supervised models, their representations become more dissimilar when more unlabeled data are used for training. Interestingly, we find that CPC’s representations change more than those of APC and MPC when increasing the data size. For instance, the similarity “only” drops from 0.957 to 0.923 for apc-fw-rnn when increasing the data size from 2k hours to 6k hours, while for cpc-mixed_spk-rnn, the similarity drops from 0.911 to 0.837.
Table 3: Representation similarity between self-supervised models pre-trained on \( \sim 1k \) hours of audio and their counterparts pre-trained on increasing amounts of audio according to Lincka.

| Model                  | Hours of pre-training audio |
|------------------------|----------------------------|
|                        | \( \sim 2k \) | \( \sim 4k \) | \( \sim 6k \) |
| apc-fw-rnn             | 0.957 | 0.935 | 0.923 |
| mpc-birnn              | 0.940 | 0.939 | 0.925 |
| cpc-mixed_spk-rnn      | 0.911 | 0.883 | 0.837 |
| cpc-within_spk-rnn     | 0.920 | 0.896 | 0.861 |

Changes in representation similarity can be attributed to encoding details of speech other than phonetic and speaker information that might be unnecessary, such as background noises. To confirm whether such changes in representation similarity correspond to an actual richer phonetic and speaker representation, we again use phonetic and speaker classification performance to quantify the amount of phonetic and speaker information contained in the representation. Results are reported in Table 4.

Table 4: Phonetic and speaker classification results of self-supervised models pre-trained on different amounts of unlabeled data (in hours). Phone and speaker error rates are reported.

| Model                  | Phone error rate | Speaker error rate |
|------------------------|------------------|-------------------|
|                        | \( \sim 1k \) | \( \sim 2k \) | \( \sim 4k \) | \( \sim 6k \) | \( \sim 1k \) | \( \sim 2k \) | \( \sim 4k \) | \( \sim 6k \) |
| apc-fw-rnn             | 33.2 | 32.5 | 32.3 | 31.9 | 8.6 | 8.4 | 8.2 | 8.1 |
| mpc-birnn              | 33.0 | 32.2 | 32.1 | 31.8 | 8.9 | 8.1 | 8.0 | 7.8 |
| cpc-mixed_spk-rnn      | 34.9 | 33.7 | 33.2 | 33.0 | 8.6 | 7.9 | 7.5 | 6.8 |
| cpc-within_spk-rnn     | 32.8 | 29.8 | 28.5 | 28.1 | 40.6 | 38.7 | 42.2 | 40.5 |

Encouragingly (and probably unsurprisingly), we observe that most self-supervised models’ performance on both tasks are improved when being trained on more data. The only exception is cpc-within_spk-rnn on speaker classification, which is expected as speaker information is never found relevant for discriminating positive and negative samples during its training. However, its performance on phonetic classification obtains the largest gain among all considered self-supervised models, with phone error rate decreasing from 32.8 to 28.1. Concerning cpc-mixed_spk-rnn, in addition to showing improvement on both tasks, the drop of its speaker error rate from 8.6 to 6.8 is also the largest among all models. Intuitively, having more data means that CPC models are provided with more comparisons of negative and positive samples to learn from, and our results seem to suggest that this is a more effective way for learning representations when large amounts of unlabeled data are available, as opposed to attempting to reconstruct details of the speech signals as APC and MPC models do. That being said, both generative- and contrastive-based objectives also benefit from having more unlabeled training data.

5 Conclusions

We have analyzed representations learned by contrastive predictive coding (CPC), autoregressive predictive coding (APC), and masked predictive coding (MPC) through the lens of similarity analysis. Extensive experiments have been conducted to study the impact of different modeling choices for training self-supervised models, the effect of the size of unlabeled training data, and how well the self-supervised loss correlates with phonetic and speaker classification performance. We have found that the self-supervised objective has a much higher impact on representation similarity than architectural choices such as building blocks (RNN/Transformer/CNN) and directionality (uni/bidirectional). We have also observed that APC has the strongest correlation between its self-supervised loss and phonetic and speaker classification performance, which is useful for model selection. Finally, while all self-supervised models benefit from having more training data, CPC is found to learn from the additional data more efficiently than APC and MPC.
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Appendices

A Additional similarity heatmaps

(a) svcca on WSJ

|                | apc-fw-mm | apc-fw+bw-mm | apc-fw-trf | apc-fw+bw-trf | mpc-birnn | mpc-trf | cpc-mixed_spk-mm | cpc-within_spk-mm | cpc-within_cpk-cnn | log Mel |
|----------------|-----------|--------------|------------|--------------|-----------|--------|------------------|------------------|-------------------|---------|
| apc-fw-mm      | 1         | 0.78         | 0.83       | 0.73         | 0.49      | 0.4    | 0.29             | 0.26             | 0.24              | 0.1     |
| apc-fw+bw-mm   | 0.78      | 1            | 0.74       | 0.84         | 0.53      | 0.49   | 0.23             | 0.18             | 0.16              | 0.054   |
| apc-fw-trf     | 0.83      | 0.74         | 1          | 0.77         | 0.41      | 0.46   | 0.28             | 0.24             | 0.21              | 0.164   |
| apc-fw+bw-trf  | 0.73      | 0.84         | 0.77       | 1            | 0.48      | 0.54   | 0.21             | 0.16             | 0.15              | 0.11    |
| mpc-birnn      | 0.49      | 0.53         | 0.41       | 0.48         | 1         | 0.74   | 0.22             | 0.17             | 0.16              | 0.073   |
| mpc-trf        | 0.4       | 0.49         | 0.46       | 0.54         | 0.74      | 1      | 0.18             | 0.13             | 0.12              | 0.069   |
| cpc-mixed_spk-mm| 0.28      | 0.23         | 0.28       | 0.21         | 0.22      | 0.18   | 1                | 0.71             | 0.68              | 0.088   |
| cpc-within_spk-mm| 0.26     | 0.18         | 0.24       | 0.16         | 0.17      | 0.13   | 0.71             | 1                | 0.76              | 0.053   |
| cpc-within_cpk-cnn| 0.24   | 0.16         | 0.21       | 0.15         | 0.16      | 0.12   | 0.65             | 0.76             | 1                 | 0.098   |
| log Mel        | 0.1       | 0.054        | 0.064      | 0.11         | 0.073     | 0.089  | 0.088            | 0.088            | 0.053             | 0.098   |

(b) lincka on TIMIT

|                | apc-fw-mm | apc-fw+bw-mm | apc-fw-trf | apc-fw+bw-trf | mpc-birnn | mpc-trf | cpc-mixed_spk-mm | cpc-within_spk-mm | cpc-within_cpk-cnn | log Mel |
|----------------|-----------|--------------|------------|--------------|-----------|--------|------------------|------------------|-------------------|---------|
| apc-fw-mm      | 1         | 0.89         | 0.95       | 0.86         | 0.86      | 0.86   | 0.45             | 0.43             | 0.42              | 0.16    |
| apc-fw+bw-mm   | 0.89      | 1            | 0.86       | 0.94         | 0.71      | 0.67   | 0.4              | 0.36             | 0.33              | 0.11    |
| apc-fw-trf     | 0.95      | 0.86         | 1          | 0.86         | 0.59      | 0.65   | 0.43             | 0.42             | 0.38              | 0.12    |
| apc-fw+bw-trf  | 0.95      | 0.94         | 0.85       | 1            | 0.66      | 0.72   | 0.39             | 0.34             | 0.32              | 0.17    |
| mpc-birnn      | 0.68      | 0.71         | 0.59       | 0.66         | 1         | 0.85   | 0.4              | 0.34             | 0.33              | 0.13    |
| mpc-trf        | 0.58      | 0.67         | 0.65       | 0.72         | 0.85      | 1      | 0.35             | 0.3              | 0.3               | 0.12    |
| cpc-mixed_spk-mm| 0.45      | 0.4          | 0.43       | 0.39         | 0.4       | 0.35   | 1                | 0.83             | 0.76              | 0.14    |
| cpc-within_spk-mm| 0.43     | 0.36         | 0.42       | 0.34         | 0.34      | 0.3   | 0.83             | 1                | 0.67              | 0.1     |
| cpc-within_cpk-cnn| 0.42   | 0.33         | 0.38       | 0.32         | 0.33      | 0.3   | 0.76             | 0.87             | 1                 | 0.16    |
| log Mel        | 0.16      | 0.11         | 0.12       | 0.17         | 0.13      | 0.12   | 0.14             | 0.1              | 0.16              | 1      |
Figure 3: Similarity heatmaps of various self-supervised representations on different probing datasets with different similarity measures.

(c) avcca on TIMIT