PROBING ACOUSTIC REPRESENTATIONS FOR PHONETIC PROPERTIES

Danni Ma\textsuperscript{1}  Neville Ryan\textsuperscript{2}  Mark Liberman\textsuperscript{2}

\textsuperscript{1}Department of Computer and Information Science, University of Pennsylvania  
\textsuperscript{2}Linguistic Data Consortium, University of Pennsylvania

ABSTRACT

Pre-trained acoustic representations such as wav2vec and DeCoAR have attained impressive word error rates (WER) for speech recognition benchmarks, particularly when labeled data is limited. But little is known about what phonetic properties these various representations acquire, and how well they encode transferable features of speech. We compare features from two conventional and four pre-trained systems in some simple frame-level phonetic classification tasks, with classifiers trained on features from one version of the TIMIT dataset and tested on features from another. All contextualized representations offered some level of transferability across domains, and models pre-trained on more audio data give better results; but overall, DeCoAR, the system with the simplest architecture, performs best. This type of benchmarking analysis can thus uncover relative strengths of various proposed acoustic representations.

Index Terms— probing, pre-trained acoustic representations, phonetic knowledge, domain mismatch

1. INTRODUCTION

Inspired by the success of pre-trained word representations [1, 2], there has been increasing interest in unsupervised learning of distributed vector representations from acoustic data, which allows the representations to be pre-trained once and then used repeatedly for other tasks. These models [3, 4, 5, 6] aim to map acoustic sequences to a latent embedding space, in which vector distance provides estimates of phonetic similarities. Specifically, the audio segments that sound alike would have close vector representations in the embedding space.

More recent work has considered incorporating contextual information in the pre-training stage, and model the use of frames in context of the entire input sequence. The pre-training objectives, usually using self-supervised learning, include next step prediction [7, 8], masked acoustic modeling [9, 10, 11], and connectionist temporal classification [12]. Pre-trained contextualized acoustic representations appear to be extremely effective. For example, wav2vec 2.0 [13] and DeCoAR [14] have attained state-of-the-art results for speech recognition on corpora such as Wall Street Journal (WSJ; [15]) and LibriSpeech [16]. More impressively, they produce competitive results even when the amount of available labeled data is low – e.g., the wav2vec 2.0 LibriSpeech experiments use only 10 minutes of labeled data.

The gains in ASR performance show that pre-trained representations encode high-level abstractions of acoustic sequences. Some past work has studied the information encoded in different layers of acoustic models. Thus [17] probe a trained end-to-end ASR system, synthesizing speech from hidden layers of the ASR model to examine the information maintained in each layer. [18] and [19] take the complexity of speech signals into account when tackling the robust ASR problem, and try to decompose speech signals at many levels. But little has been done to study the exact phonetic information these representations are using to make predictions.

In this paper, we focus on the following questions:

(1) At what level of granularity can pre-trained representations capture phonetic knowledge?

(2) What are the advantages of pre-trained representations over conventional acoustic features (MFCCs, filter-banks) in acquiring phonetic information in speech data?

(3) How good are these representations when adapting to different domains?

Inspired by [20, 21], we address these questions via a series of probing experiments, which attempt to measure how
well information about phonetic structure can be extracted from representations. Each experiment has the same format: a simple classifier attempts to predict frame-wise labels using the last layer of a pre-trained encoder as features. Performance of these classifiers is taken as a proxy for how well the representation encodes the relevant phonetic differences; i.e., if a simple classifier is able to successfully perform phone classification using only the pre-trained encoder’s output as features, this is evidence that the encoder has learned relevant phonetic properties. For a visual depiction of this architecture, see Figure 1.

Using this paradigm, we produce a systematic comparison between several popular pre-trained acoustic representations. We analyze both their capacity for encoding phonetic information at different levels of granularity – speech, vowel, and phone – as well as their ability to generalize across domains. Our experimental results reveal the following findings:

1. All pre-trained representations outperform conventional acoustic features for these tasks.
2. For all representations, performance on the probing tasks drops as the granularity of the phonetic knowledge required grows finer. For example, classifiers perform best on speech activity detection, and worst for phone classification.
3. The different pre-trained representations differ dramatically in how well they perform, despite being conceptually similar and using the same pre-training data.
4. Pre-trained encoders appear to be more invariant to domain than conventional acoustic features. Across classification tasks, the drop in performance when there is a train/test domain differ is far lower for pre-trained encoders such as DeCoAR than for conventional acoustic features.

2. ACoustIC REPRESENTATION MODELS

For our probing experiments, we consider four pre-trained acoustic representations:

- **wav2vec** [8] is an extension of word2vec [1] to the audio domain. It consists of a multi-layer CNN operating on raw speech samples and optimized using a noise contrastive binary classification task. We use the wav2vec_large model distributed by fairseq [22].

- **vq-wav2vec** [23] is an extension of wav2vec that adds a self-supervised prediction task. In a first step, discrete labels are assigned to each frame by quantizing the dense outputs of a wav2vec encoder using either a Gumbel-Softmax or k-means clustering. This label sequence is then used as input to BERT pre-training [24] and the hidden activations of the resulting BERT model used as the acoustic representation. We use the bert_kmeans model distributed by fairseq.

- **Mockingjay** [10] is a direct adaptation of BERT to the acoustic domain. A transformer is trained to reconstruct masked filterbank outputs using an L1 loss function. We use the implementation from the S3PRL toolkit [25] and the LinearLarge-libri checkpoint.

- **DeCoAR** [14] is inspired by ELMo [26]. Like Mockingjay, it is a bidirectional encoder trained under a reconstruction loss, though it uses a bidirectional LSTM instead of a transformer as its encoder. Conceptually, it is the simplest of the pre-trained representations. We use the implementation from Amazon’s speech-representations GitHub repo with the decoar-encoder-29b8e2ac checkpoint.

Basic information about these four representations, including output dimensionality and pre-training corpus, are available in Table 1.

In addition, we consider two non-pretrained acoustic representations:

- **MFCC** – 40-D Mel frequency cepstral coefficients (MFCCs)
- **fbank** – 40-D Mel scale filterbank outputs

The MFCC and filterbank features are extracted using librosa [27] with a 10 ms step size and a 35 ms analysis window. For both feature types, we concatenate an 11-frame context (5-1-5), yielding a final feature dimension of 440.

| Model     | Dimensionality | Encoder | Unlabeled data |
|-----------|----------------|---------|----------------|
| wav2vec   | 512            | CNN     | 960h Libri.    |
| vq-wav2vec| 768            | CNN     | 960h Libri.    |
| Mockingjay| 768            | Transformer | 360 Libri.    |
| DeCoAR    | 2048           | Bi-LSTM | 960h Libri.    |

Table 1. Basic information about pre-trained acoustic representation models used in this paper. *Encoder*: the pre-trained encoder; *Unlabeled data*: the amount of unlabeled data used for pre-training; *Libri.*: LibriSpeech.

3. PROBING SET-UP

3.1. The prediction tasks

For our probing tasks, we select five frame-level prediction tasks: speech activity detection (SAD), sonorant detection,
vowel detection, fricative detection and phoneme classification. The first four tasks are binary classification tasks, which require determining whether or not a frame belongs to a chosen phonetic class (e.g., speech vs non-speech, sonorant vs non-sonorant, etc). The last task, phone classification, is a multi-way classification task that requires determining which of 39 phones a frame belongs to. Together, these tasks cover a range of phonetic phenomena differing greatly in their granularity, ranging from the superficial (distinguishing speech from non-speech) to very fine-grained (distinguishing between individual phonemes).

Frame labels are assigned using the manual phone-level segmentation distributed with TIMIT. For the binary classification tasks, the target classes are defined as follows:

- **fricative**: ch, dh, f, hh, jh, s, sh, th, v, z, zh
- **vowel**: aa, ae, ah, ao, aw, ax, ax-h, axr, ay, eh, el, en, eng, er, ey, ih, ix, iy, ow, oy, uh, uw, ux
- **sonorant**: aa, ae, ah, ao, aw, ax, ax-h, axr, ay, eh, el, en, eng, er, ey, ih, ix, iy, i, m, n, ng, nx, ow, oy, r, uh, uw, ux, w, y
- **speech**: aa, ae, ah, ao, aw, ax, ax-h, axr, ay, b, bcl, ch, d, dcl, dh, dx, eh, el, em, en, eng, er, ey, f, g, gcl, hh, hv, ih, ix, iy, jh, k, kcl, l, m, n, ng, nx, ow, oy, p, pcl, q, r, s, sh, t, tcl, th, uh, uw, ux, v, w, y, z, zh

For the phone classification task, we train using the full 61 phone set, then map to the standard 39 phone set used for TIMIT phone classification experiments [28].

### 3.2. Datasets

For our probing experiments, we utilize the standard TIMIT [29] plus five TIMIT derivatives:

- **NTIMIT** [30] – derived by retransmitting the original TIMIT utterances over a telephone handset and the NYNEX telephone network; each utterance was transmitted on a separate call, so there is large variation in channel conditions.
- **CTIMIT** [31] – generated by transmitting TIMIT over cellular telephone handsets; the transmitting handset was located inside an acoustically isolated cage mounted inside a van driving around New England and the corpus exhibits many transmission related artifacts such as crosstalk, dropout, and low SNR.
- **FFMTIMIT** [32] – alternate free-field microphone recordings from the original TIMIT recording sessions.
- **STC-TIMIT** [33] – similar to NTIMIT, but all recordings sent through the same telephone channel.
- **WTIMIT** [34] – retransmission of the TIMIT files over a 3G AMR-WB mobile network using Nokia 6220 handsets; much higher quality than CTIMIT.

NTIMIT and STC-TIMIT are narrowband speech, while the remaining variants are wideband. All experimental results are reported using the full test set.

### 3.3. Probing classifiers

We consider three simple probing classifiers:

- **LR** – logistic regression as implemented by sklearn’s LogisticRegression class.
- **SVM** – a max-margin classifier fit using sklearn’s SGDClassifier class.
- **NN** – a simple feedforward neural network consisting of two fully-connected layers of 128 ReLUs. The network was trained for 50 epochs with early stopping using skorch [36].

Because the input representations vary greatly in their dimensionality (ranging from 440 to 2,048), the input features are reduced to 400 dimensions prior to fitting to eliminate this potential confound. Dimensionality reduction is performed by applying singular value decomposition to the features and selecting the top 400 singular vectors.
4. EXPERIMENTAL RESULTS

Table 2 compares different representations and baselines on prediction tasks. It is evident that performance varies greatly as a function of both representation and task, which we will touch on in the subsequent sections. However, we see little variation in performance of the three classifiers. Thus, to simplify exposition, we present only results from logistic regression in the remainder of the paper.

4.1. Comparison of representations

All the contextualized representations encode some amount of phonetic information, but DeCoAR performs best across all the tasks, and shows strong generalization ability.

While all pre-trained representations outperform the baselines for SAD, we note that a consistent pattern emerges for other tasks. As the tasks require finer-grained phonetic knowledge, they become harder with performance decreasing for all combinations of representation and classifier. Moreover, we see increasing variance in the performance with increasing task difficulty.

Specifically, DeCoAR and wav2vec have encoded rich phonetic knowledge during the pre-training phase, and their performances do not drop much when the probing task becomes more difficult. On the contrary, vq-wav2vec is seriously underperforming, yielding even worse results compared to MFCC/filterbank. We take phone classification task and neural network classifier for example, DeCoAR has achieved an F1 score of 67.23, while vq-wav2vec only achieves 14.25 under the same setting.

| Task     | fricative | vowel | sonorant | SAD |
|----------|-----------|-------|----------|-----|
| Conditional entropy | 0.9449    | 0.8615 | 0.8350   | 0.5835 |

Table 3. In-domain conditional entropy (CE) in bits for binary classification tasks on CTIMIT using vq-wav2vec. Maximum possible CE: 1.

4.2. Task difficulty

If a task is too easy, it provides little information about the relative strengths of different representations. For example, Table 2 demonstrates that every representation performs well on SAD. Even the majority baseline can achieve an F1 score over 90. Therefore, SAD is not a good probing task to distinguish among representations. In this section, we investigate task difficulty quantitatively.

We calculate the conditional entropy (CE) for each binary prediction task using vq-wav2vec, and rank the difficulty of tasks by CE. Table 3 shows the ranking. Fricative detection proved to be the most difficult task, while SAD is the most straightforward task.

4.3. Domain mismatch

All the previous discussion is focusing on in-domain performance. We have not yet considered what the results look like when the probing classifier is tested in a different dataset. In this section, we analyze domain mismatch in different TIMIT variants. We will experiment on phone classification task, because it is difficult and representations show great differences. In general, the most extreme combinations of task and domain
mismatch will tell the most about how good a representation model is.

Figure 2(a) illustrates the in-domain and cross-domain performance of all the representations. DeCoAR again exhibits very strong transferability, while vq-wav2vec behaves poorly, similar to its performance in the in-domain setting. We also notice a significant performance drop in MFCC and filterbank when switching to cross-domain. Although they both incorporate information from neighboring frames, this ad-hoc “contexualization” is not comparable to pre-trained features which encode general phonetic patterns. Therefore, pre-training improves both the generalization ability and domain invariability of a representation. We are also interested in which dataset is the most difficult. Figure 2(b) presents the results of each combination of training and test set among six TIMITs. There is obvious decline of performance when the model is tested on CTIMIT, making it the hardest dataset. As described in [31], CTIMIT contains lots of background noise from traffic, and has the most severe recording environment.

To better understand how difficult CTIMIT is, we take DeCoAR as an example, measure the conditional entropy and visualize predictions and true labels in Figure 3(a). The confusion matrix indicates that most errors come from misclassifying labels to “sil” and “ah”. “sil” is the most frequent phone in all TIMITs, and it becomes the last resort when a classifier fails to distinguish features. But why there are so many false positives for “ah” remains to be investigated.

In conclusion, out-of-domain generalization is still difficult for all the representations, including those with extensive pre-training. We find an average of 54.65% performance drop when a classifier is tested in noisier domains in phone classification task. Suggestively, one future direction for improving pre-trained acoustic representations is to increase their robustness and transferability.

5. CONCLUSION

We compared the performance of various acoustic representations on various phonetic classification tasks. These tasks are of different difficulty, and require different granularity levels of phonetic information. We find that probing tasks requiring finer-grained phonetic knowledge are more challenging, and that pre-training enhances generalization ability and cross-domain performance. In addition, we observe a significant performance drop when testing in a noisy target domain, indicating that this is still a major challenge.

We hope that our analysis will motivate more research on the interpretability of acoustic representations. There are many fascinating directions for future work. First, it is in-
teresting that the system with the simplest architecture, DeCoAR, performs best overall. Given also that wav2vec and vq-wav2vec are pre-trained with similar tasks on the same data, but achieve very different performance, broader probes of encoder architecture are warranted. Second, it is worth investigating how pre-training methods affect the generalization ability of representations. Lastly, we hope to see improvement on robustness in new pre-trained representations.

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