ABSTRACT
Unsupervised speech recognition has shown great potential to make Automatic Speech Recognition (ASR) systems accessible to every language. However, existing methods still heavily rely on hand-crafted pre-processing. Similar to the trend of making supervised speech recognition end-to-end, we introduce wav2vec-U 2.0 which does away with all audio-side pre-processing and improves accuracy through better architecture. In addition, we introduce an auxiliary self-supervised objective that ties model predictions back to the input. Experiments show that wav2vec-U 2.0 improves unsupervised recognition results across different languages while being conceptually simpler.

Index Terms— unsupervised learning, speech recognition

1. INTRODUCTION
State-of-the-art ASR models [1, 2] have greatly improved performance over the recent past. These models have been relying heavily on human supervision - requiring thousands of hours of transcribed speech. Consequently, the main limiting factor in building ASR systems for many more languages is the need for large amounts of labeled data, making it challenging or even impossible to build such supervised ASR systems for the vast majority of languages of the world [3].

Fortunately, recent advances [4, 5, 6] have shown that it is possible to train ASR systems in an unsupervised manner where speech annotation is no longer required. On a high level, these methods can be viewed as a two-step pipeline: a pre-processing step followed by the unsupervised training step, with the goal of transcribing speech into phoneme sequences.

The pre-processing step aims to transform input speech representations into features that are better aligned to the underlying phonetic content. This is done through speech segmentation and feature engineering. The goal of speech segmentation is to discover boundaries in the input sequence to mark the change from one phone to another. In practice, the boundaries can be determined through clustering representations [6] or other unsupervised methods [7, 8]. Besides speech segmentation, prior works also considered feature engineering a necessary step. From the input speech, they reduced the frequency by merging intra-segment features and the dimensionality through k-means clustering [4] or principal component analysis (PCA) [6].

While the motivation of the pre-processing step is clear, the disadvantages are also obvious. Prior work [9] discovered that the accuracy of segmentation can dramatically impact subsequent steps, yet unsupervised speech segmentation is usually far from perfect [10]. This results in cascading errors from segmentation and other feature engineering steps. To address these issues, we propose an end-to-end system, which, through a better architecture, is able to replace all audio-side pre-processing steps with a single speech-to-phoneme neural network.

In addition to relaxing the aforementioned limitation, we also improve the unsupervised ASR training step. The core idea of this step is to train a model which maps features extracted from a model pre-trained on unlabeled speech data into phoneme sequences by restricting the output vocabulary distribution and n-gram structures to be similar to real phoneme sequences. Existing solutions for imposing such restrictions include adversarial training [4] and empirical output distribution matching [5]. However, these methods do not ensure that the output is closely related to the spoken content. To make up for this deficiency, we propose a self-supervised auxiliary objective function that provides content-based guidance to the model by utilizing pseudo labels derived from the raw audio signal.

To summarize our work, we propose wav2vec-U 2.0 - an unsupervised ASR framework with an end-to-end style training and an improved objective function. In our experiments, we validate the effectiveness of the pipeline simplification and the proposed modification of the objective function. We show that wav2vec-U 2.0 performs better than the existing unsupervised frameworks across different languages from high-resource to low-resource. We also combine wav2vec-U 2.0 with self-training strategies [11, 6] to compare against prior works and supervised systems. The implementation is based on fairseq [12] and the code will be released soon.

2. BACKGROUND

2.1. Unsupervised ASR with Adversarial Training
Liu et al. [4] first achieved unsupervised phoneme recogni-
tion on TIMIT [13], a small and clean English dataset for proof-of-concept experiments. Their system takes MFCC representations of speech as the input and performs the pre-processing step combining speech segmentation with (a separately trained) segmental audio word2vec [7] and feature discretization with k-means clustering. Using the segmented discrete features, they train a phone-based ASR system through adversarial training inspired by Generative Adversarial Network (GAN) [14]. In the adversarial training framework, the ASR model serves as the generator which transcribes the discrete index sequence into phone sequence with a learnable embedding table followed by softmax activation. A 2-layer convolution-based discriminator is trained to distinguish the output of the generator and real phone sequences. The goal of the generator is to output phone sequences that cannot be distinguished by the discriminator. By iteratively training the two modules, the generator can learn to map the pre-processed feature sequences into phone sequences in an unsupervised manner.

### 2.2. Wav2vec-U

Different from the prior work, Baevski et al. [6] proposed wav2vec-U (Fig. 2 in appendix) that first achieved unsupervised speech recognition on benchmark speech recognition datasets in many different languages. Wav2vec-U takes speech representations extracted from the wav2vec 2.0 model [15] as the input instead of human-defined features. Such representations can be obtained by self-supervised training on audio and have been proven to be much more effective than human-defined features for ASR.

For the pre-processing step, wav2vec-U applies a sequence of feature engineering on the speech representations: k-means clustering input frames, reducing the representation dimension with PCA, merging adjacent PCA features that share the same k-means cluster, and finally, mean pooling features from adjacent pairs of timesteps to better match the length of the phone sequences. To train the ASR model taking the pre-processed features as input, wav2vec-U followed the adversarial training approach with a single layer CNN generator and a two-layer discriminator.

Since the proposed wav2vec-U 2.0 model is closely related to wav2vec-U, we detail the prior work in Section 3.1 and highlight our contributions as follows: 1) we remove the need for the audio pre-processing step, and 2) we introduce an auxiliary objective that improves the segment transcriber.

### 3. METHODOLOGY

#### 3.1. Adversarial Training with wav2vec-U

To introduce the proposed wav2vec-U 2.0, we begin with the adversarial training defined in wav2vec-U [6]. Given X the sequence of pre-processed features (described in Section 2.2) and \(Y_u\) the phonemized unpaired text sequence, the goal of adversarial training is to train a Generator \(G\) which transcribes \(X\) into a phone sequence that cannot be distinguished from \(Y_u\) by a discriminator \(C\). The full objective function is defined as

\[
\min_G \max_C \mathbb{E}_{Y_u} [\log C(Y_u)] + \mathbb{E}_X [\log (1 - C(G(X)))] - \lambda L_{gp} + \gamma L_{sp} + \eta L_{pd} \tag{1}
\]

where the first two terms are the standard GAN objective [14]; the third term

\[
L_{gp} = \mathbb{E}_{X,Y_u,\alpha \sim U(0,1)} \left[ \left( \| \nabla C(\alpha \cdot G(X) + (1 - \alpha) \cdot Y_u) \| - 1 \right)^2 \right] \tag{2}
\]

is the gradient penalty on discriminator calculated with respect to a sample mixing real and fake input for better convergence [16] where \(\alpha\) is the mixing weight sampled from uniform distribution; the fourth term

\[
L_{sp} = \sum_{(p_t, p_{t+1}) \in G(X)} \| p_t - p_{t+1} \|^2 \tag{3}
\]

is the smoothness penalty to penalize locally inconsistent phone prediction from the generator where \(p_t\) is the unnormalized generator output at time \(t\); the fifth term

\[
L_{pd} = \frac{1}{|B|} \sum_{S \in B} -H_G(G(S)) \tag{4}
\]

is the phoneme diversity loss encouraging a diversified output over the phone set by maximizing entropy of the generator output distribution averaged over every frame in a mini-batch \(B\); and \(\lambda, \gamma, \eta\) are the weights for each term.

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![Fig. 1. Proposed wav2vec-U 2.0](image_url)
3.2. Removing Audio Pre-processing

As mentioned in Section 1, existing unsupervised ASR systems including wav2vec-U rely on hand-crafted pre-processing. Interestingly, we discovered that the pre-processing step in wav2vec-U is not necessary.

Without the need of speech segmentation, a generator taking raw speech representation sequence as the input itself can be sufficient for unsupervised ASR with proper output frequency (i.e. number of phones predicted per second). While there are various ways to control the output frequency of the generator, we found that simply changing the stride of the convolution neural network works well. With the input wav2vec 2.0 features sampled at 50 Hz, we found that outputting a phone candidate at around 16 Hz by using a stride of 3 worked consistently well across all 9 languages tested in this work. To further downsample the 16 Hz generator outputs to results closer to phone sequence, consecutive outputs sharing the identical most possible phone can be treated as a single output by random sampling as done in wav2vec-U. In addition, we found that PCA-based dimensionality reduction can be replaced by a simple batch normalization [17] along the time axis over the wav2vec 2.0 features.

As illustrated in Fig. 1, wav2vec-U 2.0 simply takes the raw representations extracted from wav2vec 2.0 model as input $X$ instead of pre-processed features as is done in wav2vec-U (Fig. 2 in appendix). These modifications allow wav2vec-U 2.0 to be trained without the need of a complicated pre-processing pipeline. More importantly, learning the mapping from speech representations to phone sequences in an end-to-end style avoids the defects brought by hand-crafted pre-processing and performs better as demonstrated in Section 4.2.

3.3. Auxiliary Self-supervised Objective

Since speech transcriptions are not available in the unsupervised setting, the generator relies only on adversarial training to learn the mapping between speech representations and phone units. The generator can possibly learn to satisfy the adversarial criterion without learning the correct mapping - for example, by consistently producing the most common n-grams regardless of the input speech.

To address this issue, we introduce an auxiliary objective function that aids self-supervised learning by reconstructing a pseudo label sequence $Z = (z_1, z_2, \ldots, z_T)$ derived from the input audio. We use pseudo-labels generated by k-means clustering on Mel-frequency cepstral coefficient (MFCC) features with 64 clusters. We found that this choice of pseudo labels works consistently well across different languages, and we show the effect of different choices of pseudo labels in appendix Section A.2. The auxiliary self-supervised objective for the generator is defined as

$$L_{ss} = - \sum_t \log P_{G}(z_t|X)$$

where $P_{G}(z_t|X)$, the probability of predicting the pseudo label $z_t$ at time $t$, is obtained by an additional linear transformation with the softmax function from the intermediate layer of the generator as illustrated in Fig. 1. The complete objective function of wav2vec-U 2.0 can be obtained by adding the auxiliary objective to Eq. 1 with a weight $\delta$:

$$\min_{\psi} \max_{\mathcal{C}} \mathbb{E}_{Y} \left[ \log \mathcal{C}(Y_u) \right] - \mathbb{E}_{X} \left[ \log (1 - \mathcal{G}(X)) \right] - \lambda L_{gp} + \gamma L_{sp} + \eta L_{pd} + \delta L_{ss}$$

The benefit of introducing the auxiliary loss is two-fold: a) it provides a content-based regularization to ensure the output of the generator is closely related to the input speech and b) it guides the generator with a more explicit signal by approximating the underlying phone sequence with pseudo labels derived from speech.

4. EXPERIMENTS

4.1. Setup

We follow Baevski et al. [6] and perform experiments on 9 different languages from LibriSpeech [27], Multi-Lingual LibriSpeech [26], and CommonVoice [28]. Unpaired text data is phonemized with an off-the-shelf phonemizer for English [29] and other languages with silence token padded on both sides of each sentence and inserted at word boundaries with a probability of 0.5. LJSpeech [30] is also considered for preliminary experiments on end-to-end models outputting characters. We summarize each dataset below and refer readers to prior work for more details on the dataset pre-processing.

LibriSpeech & Libri-Light. 960 hours of English speech from LibriSpeech, discarding the transcriptions, is used for adversarial training. In addition, 53.2k hours of speech from Libri-Light is used for self-training. For the unpaired text used to train wav2vec-U 2.0 and language model, we used the official text corpus provided by LibriSpeech excluding the transcriptions of the speech data [22]. Evaluation is done on the standard dev/test sets.

Multi-Lingual LibriSpeech. For each of the 6 languages (Dutch, French, German, Italian, Portuguese, and Spanish) selected from Multilingual LibriSpeech, 100 hours of speech is used for adversarial training and the official text corpus is used as unpaired text. Evaluation is done on the standard test set.

CommonVoice. We follow Baevski et al. [6] to select 2 (Kyrrgyz and Tatar) out of 38 languages from CommonVoice using 1.8 and 4.6 hours of unpaired speech respectively. For the unpaired text of both languages, we use a mixed text corpus following Baevski et al. [6]. Evaluation is done on the dev/test set following Riviere et al. [31].

https://github.com/bootphon/phonemizer
Table 1. Interpolation from wav2vec-U (Fig. 2 in appendix) to wav2vec-U 2.0 (Fig. 1). Phone Error Rate (PER) computed with greedy decoding on LibriSpeech dev-other set averaged over 8 runs. \textit{Freq.} refers to the frequency of sequence, i.e. number of tokens per second.

| Pre-processing | Generator configuration | Result |
|----------------|-------------------------|--------|
| Adjacent pooling | Cluster pooling | PCA reduction | Batch norm. | Linear proj. | Auxiliary loss | Stride | Freq. (Hz) | Average PER |
| wav2vec-U | ✓ | ✓ | ✓ | - | - | - | 1 | 14 | 18.8 ± 0.9 |
| step (i) | - | ✓ | ✓ | - | - | - | 1 | 28 | > 100 |
| step (ii) | - | - | ✓ | - | - | - | 2 | 14 | 18.5 ± 0.6 |
| step (iii) | - | - | - | - | - | - | 2 | 25 | > 100 |
| step (iv) | - | - | - | - | - | - | 3 | 16 | 19.0 ± 0.9 |
| step (v) | - | - | - | - | - | - | 3 | 16 | > 100 |
| step (vi) | - | - | - | ✓ | - | - | 3 | 16 | 16.4 ± 0.7 |
| step (vii) | - | - | - | ✓ | ✓ | ✓ | 3 | 16 | 15.9 ± 1.1 |
| wav2vec-U 2.0 | - | - | - | ✓ | ✓ | ✓ | 3 | 16 | 13.6 ± 0.9 |

input wav2vec 2.0 feature
ground truth phone sequence

50
~10

LJSpeech. This is a single-speaker corpus containing 24 hours of English speech. Following prior works [32, 33] on weakly-supervised speech recognition, we randomly select 300 utterances for validation and testing each and used the rest as unpaired speech for training. For the unpaired text, we used the same data as the LibriSpeech setup.

Implementation Details For English speech from LibriSpeech, the input features are extracted from the 15th layer of a pre-trained wav2vec2.0 Large model [15] encoded from the audio of which silences have been removed using an unsupervised voice activity detection tool [34]. For non-English speech, features are extracted from the XLSR-53 [35] model, a multi-lingual version of wav2vec 2.0.

As illustrated in Fig. 1, the generator is a 2-layer CNN with batch normalization over the input features. We found that initializing the scaling factor of batch normalization to 30 for wav2vec 2.0 Large and 35 for XLSR-53 features is critical for convergence. During adversarial training, when obtaining the output probability distribution from the generator, consecutive frames that share the same most probable phoneme are merged into one by random selection.

The discriminator is a 2-layer CNN that uses the output of the generator or a one-hot representation of the real phone sequence as input. A single scalar indicating whether the probability of the input sequence is real or not is obtained by taking the average over output sequence followed by the sigmoid activation.

The generator and discriminator are trained for 100k steps in total interleaving the updates of each (50k updates for each) with a fixed learning rate of 5e-5 and 3e-4 respectively. Each batch contains 160 audio samples and 160 randomly selected text samples. With the choice of weights in Eq. 6 being 1.0 / 1.5, 1.5 / 2.5, 0 / 3, 0.3 / 0.5 for \( \lambda, \gamma, \eta, \delta \) respectively, we run each model with 4 different random seeds and we observe that over 80% of the models will converge during training.

Models are selected with the Unsupervised Cross-Validation Metric proposed by Baevski et al. [6]. Pykaldi [36] is used to decode the phone-based ASR outputs into words. While the generator must be trained with a stride of 3, we found decoding using a language model with a stride of 2 (higher output frequency) leads to a more accurate output.

4.2. Comparison to wav2vec-U

We first compare wav2vec-U 2.0 with the closely related prior work wav2vec-U [6] to show the benefit of removing pre-processing steps and introducing the auxiliary objective.

Table 1 shows our proposed changes to wav2vec-U (Fig. 2 in appendix vs. Fig.1) where changes are applied gradually from step (i) to step (vii).

Note, steps (i)-(iv) use pooling mechanisms to control the output frequency of the model. Removing these steps results in higher frequency and the model fails to converge to a reasonable accuracy. However, accuracy can be recovered by adjusting the output frequency by changing the stride of the generator (step (ii) & (iv)). The fact that models with higher output frequency (step (i) & (iii)) failed to converge shows that having output frequency close to ground truth (around 10 Hz) is important.

We also observe a similar performance to the original framework after completely removing all pre-processing (step (iv)) and conclude that pre-processing speech representations in order to segment them into phone-like units are not necessary to obtain a working unsupervised ASR system, which can benefit from learning in an end-to-end fashion.

Comparing steps (iv) and (v), we see that some feature engineering in form of PCA dimensionality reduction is indeed important for adversarial training to work, but it can be replaced with a simple batch normalization layer as in step (vi).
Finally, looking at steps (vii) and the final step (viii), we see that introducing the auxiliary self-supervised objective improves PER significantly.

4.3. Results on LibriSpeech

In Table 2, we compare wav2vec-U 2.0 with supervised, semi-supervised, and unsupervised prior work on the well-studied English benchmark dataset LibriSpeech. Without self-training, wav2vec-U 2.0 performs reducing word error rate (WER) by 2% to 4% compared to wav2vec-U. This shows that removing the pre-processing steps and introducing the self-supervised auxiliary objective can lead to improved performance on speech recognition. Next, we combine our method with the 3-stage self-training pipeline described in Section A.1. Results show that WER can be significantly reduced with self-training, reaching below 3.7% WER on the clean data and 6.3% on the noisy data.

On the other hand, we observe the gap between wav2vec-U and wav2vec-U 2.0 is much smaller after applying the self-training strategy. This suggested that unsupervised ASR on LibriSpeech might be bottle-necked by the self-training pipeline. Improving the self-training approach can likely further improve the performance of unsupervised ASR.

4.4. Results on Multi-lingual LibriSpeech

We have also tested our approach on a number of European languages from Multi-lingual LibriSpeech and show the results in Table 3.

We observe that wav2vec-U 2.0 also outperforms wav2vec-U in this setup, especially on the languages with higher error rate. Overall, the proposed framework is able to improve the average WER on MLS by 8% absolute without self-training. This further demonstrates the benefit of having an end-to-end learning framework with self-supervision.

The results show that wav2vec-U 2.0 consistently improves over wav2vec-U with self-training. Average WER improves to 15.3% compared to 18.6% for wav2vec-U. This is a significant improvement since the supervised topline is 10% WER. On Portuguese, the WER is only 1.2% worse than the supervised topline.

4.5. Results on CommonVoice

Other than English and European languages, we experiment on two low-resource Turkic languages in CommonVoice and the results are shown in Table 4. Since we only measure the phone error rate, we only use the HMM stage of the self-training pipeline.

Compared to the supervised topline using 17 hours of labeled speech, wav2vec-U 2.0 is able to achieve 10.1% / 15.2% PER on Tatar / Kyrgyz using just 4.6 / 1.8 hours of speech. This once again shows the value of developing unsupervised ASR for low-resource languages.
Table 3. Word Error Rate (WER) on the Multilingual Librispeech (MLS) for German (de), Dutch (nl), French (fr), Spanish (es), Italian (it) and Portuguese (pt).

| Model | Labeled data used | LM | de | nl | fr | es | it | pt | Avg. |
|-------|-------------------|----|----|----|----|----|----|----|------|
|       |                   |    | 2k | 1.6k | 1.1k | 918 | 247 | 161 |      |

**Supervised learning**

| Pratap et al. [26] full | 5-gram | 6.49 | 12.02 | 5.58 | 6.07 | 10.54 | 19.49 | 10.0 |

**Unsupervised learning**

| wav2vec-U 0h 4-gram | 32.5 | 40.2 | 39.8 | 33.3 | 58.1 | 59.8 | 43.9 |
| wav2vec-U 2.0 0h 4-gram | 23.5 | 35.1 | 35.7 | 25.8 | 46.9 | 48.5 | 35.9 |

**Unsupervised learning + Self-training** (described in appendix Section A.1)

| wav2vec-U 0h 4-gram | 11.8 | 21.4 | 14.7 | 11.3 | 26.3 | 26.3 | 18.6 |
| wav2vec-U 2.0 0h 4-gram | 11.5 | 17.6 | 12.8 | 10.9 | 18.6 | 20.6 | 15.3 |

Table 4. Phone Error Rate (PER) on CommonVoice.

| Model | tt | ky |
|-------|----|----|
| **Supervised learning** |
| Fer et al. [37] | 42.5 | 38.7 |
| m-CPC [31] | 42.0 | 41.2 |
| XLSR-53 [35] | 5.1 | 6.1 |
| **Unsupervised learning** |
| wav2vec-U | 25.7 | 24.1 |
| wav2vec-U 2.0 | 22.5 | 24.3 |
| **Unsupervised learning + HMM training** |
| wav2vec-U | 13.7 | 14.9 |
| wav2vec-U 2.0 | 10.1 | 15.2 |

Table 5. Recognition Error Rate on LJSpeech. Unit error rate refers to the greedy decoding phone error rate for phone-based models or character error rate for letter-based model. Word error rate is obtained through phone-to-word or letter-to-word decoding.

| Model | Labeled data used | Phone-based (lexicon required) | Unit error rate | Word error rate |
|-------|-------------------|------------------------------|----------------|----------------|
|       |                   |                              |                |                |
| **Semi-supervised learning** |
| Ren et al. [32] 20min | ✓ | 11.7 | - |
| Liu et al. [33] 10min | ✓ | 64.2 | - |
| **Unsupervised learning** |
| wav2vec-U 2.0 0min | ✓ | 16.0 | 14.4 |
| wav2vec-U 2.0 letter-based 0min | X | 34.6 | 64.0 |

4.6. End-to-end Attempt on LJSpeech

While wav2vec-U 2.0 removed the need for human-engineered pre-processing steps and pipeline design, it is still not fully end-to-end. Like conventional supervised ASRs and existing unsupervised ASRs, wav2vec-U 2.0 relied on a lexicon which is an expert-defined word-to-phone mapping. Since the phoneme inventory is defined by a set of distinctive sounds, learning a speech-to-phoneme transformation is naturally easier for the model than a speech-to-grapheme mapping or a speech-to-word mapping. However, collecting a lexicon for every language can be difficult in practice as it requires expertise in both linguistics and phonetics.

We, therefore, evaluate wav2vec-U 2.0 without relying on lexicon by replacing all phones (for both adversarial training and language modeling) with letters that can be directly inferred from the text data. Results on LJSpeech with the end-to-end version of wav2vec-U 2.0 are presented in Table 5. We first show that wav2vec-U 2.0, using no labeled data at all, is already outperforming previous works on semi-supervised ASR [32, 33] which use small amounts of human-labeled data.

When switching to an entirely letter-based system without a lexicon, the unit error rate increases substantially. Such degradation is reasonable as the former needs to learn to spell alongside the mapping between acoustic and writing units. Unfortunately, we also discover that the word error rate of the letter-based model is significantly higher than the phone-based model. These results suggest that end-to-end unsupervised ASR could be possible but further research and development are necessary.

5. CONCLUSION

An end-to-end approach for unsupervised ASR is key to increasing applicability to low-resource languages. In this work, we move towards this goal by removing the need for human-engineered pre-processing and by improving accuracy. While wav2vec-U 2.0 is simpler and more accurate, additional work is required to enable a fully end-to-end approach. Future work includes simplifying the self-training pipeline and removing the need for a phonemizer. Possible solutions for the latter are incorporating unsupervised lexicon discovery [38] or training unsupervised ASR with graphemic text units such as letters directly as for supervised systems.
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