MAGIC DUST FOR CROSS-LINGUAL ADAPTATION OF MONOLINGUAL WAVE2VEC-2.0

Sameer Khurana¹, Antoine Laurent², James Glass³

¹MIT Computer Science and Artificial Intelligence Laboratory, Cambridge, MA, USA
²LIM - Le Mans University, France

ABSTRACT

We propose a simple and effective cross-lingual transfer learning method to adapt monolingual wav2vec-2.0 models for Automatic Speech Recognition (ASR) in resource-scarce languages. We show that a monolingual wav2vec-2.0 is a good few-shot ASR learner in several languages. We improve its performance further via several iterations of Dropout Uncertainty-Driven Self-Training (DUST) by using a moderate-sized unlabeled speech dataset in the target language. A key finding of this work is that the adapted monolingual wav2vec-2.0 achieves similar performance as the toppling multilingual XLSR model, which is trained on fifty-three languages, on the target language ASR task.

Index Terms— Cross-lingual transfer learning, self training, self-supervised Learning, ASR, adaptation

1. INTRODUCTION

Few-shot learning, the ability to train a machine to exhibit intelligent behavior via a small amount of supervision has been a long-standing research goal in Artificial Intelligence. To build few-shot learners we turn to a class of transfer learning (TL) methods that extract knowledge from vast quantities of unlabeled data to make the task of learning from a few labeled examples easier. Recently, Self-Supervised Learning (SSL) has emerged as a promising TL approach of learning from unlabeled data [1,2].

SSL [3,4] refers to the process of Pre-Training (PT) a model on unlabeled data using an SSL task, such as masked self-prediction [2]. The Pre-Trained model is then Fine-Tuned (FT) on the target task via a few labeled examples. Hence, SSL forms the first stage of the PT then FT (PT → FT) sequential TL framework [5]. Recently, speech neural net encoders Pre-Trained using the wav2vec2 SSL framework have proven to be excellent few-shot learners for automatic speech recognition (ASR) across multiple languages [7,8]. However, wav2vec2 assumes access to massive amounts of unlabeled data for PT, which diminishes their usefulness to resource-scarce languages, where the massive unlabeled data assumption does not hold.

To remedy the above issue, [8] proposes x1sr, a cross-lingual sequential TL framework of the form mPT → FT, i.e., Multilingual Pre-Training of wav2vec2 followed by target language ASR fine-tuning on a few labeled examples. Indeed, Pre-Trained x1sr is an excellent few-shot learner for ASR in multiple languages. However, in this work, we show that x1sr’s ASR performance is quite poor if there is a domain mismatch between the target language speech and the speech data used to Pre-Train x1sr. Thus, to make x1sr a truly universal speech model, we would have to Pre-Train on speech from all languages in all possible speech domains, which is clearly an unscalable strategy. Instead, in this work, we propose a TL framework that could efficiently adapt any Pre-Trained wav2vec2 model, monolingual or multilingual, to make it a good few-shot ASR learner in any target language in any speech domain.

In this work, motivated by the SSL framework’s limitations when developing ASR for a resource-scarce language, we propose a simple yet effective cross-lingual TL framework (4) for wav2vec2 model adaptation to a target language. Our adaptation framework is a sequential TL framework consisting of three steps: First, we Pre-Train a wav2vec2 model on a high-resource language. Second, we perform supervised fine-tuning of the Pre-Trained wav2vec2 model on the target language ASR task using ten hours of labeled data. Finally, we perform Dropout Uncertainty-Driven Self-Training (DUST) [9] using a hundred hours of unlabeled speech data in the target language for adaptation of the Fine-Tuned wav2vec2 model.

Through this work, we make the following contributions: 1) We analyze the cross-lingual transferability of several Pre-Trained English wav2vec2 models (Table 1) across eight target languages. We show that by simply fine-tuning English wav2vec2 on ten hours of labeled data in target languages, we can recover on average up to 86% of the performance of the fine-tuned multilingual x1sr topline. Still, there is a considerable gap in performance between wav2vec2 and x1sr on target languages that are considered in-domain for x1sr, but the gap is much smaller on a more challenging out-of-domain Arabic target language. Another interesting finding is that ASR Fine-Tuning of the Pre-Trained wav2vec2 models on labeled data in the source language (English) before Fine-Tuning on the target languages hurts cross-lingual transfer. 2) We adopt an English wav2vec2 model to two target languages, French and Arabic, under the constraint that in each target language we have ten hours of labeled data for ASR training and a hundred hours of unlabeled data for adaptation. For French, we show that by starting with a Pre-Trained English wav2vec2 model and applying the proposed adaptation procedure (4), we can reach similar ASR performance as the x1sr topline. For Arabic, both the x1sr and English wav2vec2 perform poorly and hence, we apply the adaptation procedure to both the models and improve the ASR performance considerably. A key finding of this study is that it is possible to adapt a monolingual wav2vec2 model Pre-Trained on a high-resource language using moderately-sized unlabeled data and small-sized labeled data in the target language to achieve similar performance as the multilingual wav2vec2 model Pre-Trained on multiple languages. Although the amount of unlabeled data that we use for adaptation is orders of magnitude smaller than the data used to Pre-Train wav2vec2 models, a moderate-sized unlabeled dataset might not be available for extremely resource-scarce and endangered languages. This scenario is out of scope for this paper.

This work uses HPC resources of IDRIS under the allocation AD011012527 made by GENCI.
2. METHOD

Self-Training  Self-Training (ST) [10] is a Teacher/Student (T/S) TL framework that leverages unlabeled data by pseudo-labeling it. ST proceeds by building a base model, known as teacher, using the labeled data. The teacher is used to predict (pseudo-)labels for the unlabeled data points. Then, a new model, known as student, is trained on the combined labeled and pseudo-labeled data points. Due to having access to more supervision, the student is expected to generalize better than the teacher on the task at hand. ST is an iterative process, where the student from a previous round becomes the teacher for the next round of ST. Recently, ST has shown excellent results in neural sequence generation tasks such as ASR [9][11][12] and Machine Translation [13]

Transfer Learning Algorithm  The overall transfer learning process is described in Algorithm 1. We assume access to a set \( \mathcal{L}_T \) of labeled examples and a set \( \mathcal{U}_T \) of unlabeled speech utterances in the target language. Also, we are given a set \( \mathcal{U}_S \) of unlabeled speech utterances in the source language. The transfer learning process proceeds by Pre-training a neural network \( f_{0,p} \) on unlabeled source language set \( \mathcal{U}_S \) with dropout layers, using a dropout probability \( p \in [0,1] \). The Pre-training process leads to the initial model \( f_{0,p} \), which is Fine-Tuned on the target language labeled set \( \mathcal{L}_T \) to give the first-generation teacher model \( f_{\phi_1,p} \) for Dropout-Uncertainty driven Self-Training (DUST). Next, the base teacher model \( f_{\phi_1,p} \) is used to provide predictions on the target language unlabeled set \( \mathcal{U}_T \) to provide pseudo-parallel data of which a subset \( \mathcal{P} \) is chosen based on the model’s uncertainty about its predictions on each unlabeled data point \( x_u \in \mathcal{U}_T \). Finally, a student model, is trained on the combined labeled \( \mathcal{L}_T \) and pseudo-labeled set \( \mathcal{P} \). We perform \( N \) iterations of the Teacher/Student training, where the student \( f_{\phi_n,p} \) from the \( n^{th} \) iteration becomes teacher for the \((n+1)^{th}\) iteration. Usually, in each iteration of DUST, a randomly initialized neural network is used as the student model, but, in our adaptation framework, the Pre-Trained source language SSL model \( f_{\phi_0,p} \) is used as the student in each DUST iteration.

DUST performs pseudo-label filtering by measuring the model’s confidence about its predictions on the unlabeled points \( x_u \in \mathcal{U}_T \). The filtering process for a particular unlabeled example \( x_u \) consists of the following steps: 1) First, we generate a reference hypothesis \( \hat{y}_{n}^{ref} \) for the unlabeled instance \( x_u \) using beam search. During inference, the model’s dropout layers are deactivated and hence, this step imitates the usual ASR inference process. 2) Second, we sample \( R \) hypotheses \( (\hat{y}_{u}^{n})_{r=1}^{R} \) from the model by running beam search \( R \) times with a different random seed \( r \in R \) each time. During inference, the dropout layers are active, hence each beam search iteration would lead to a slightly different hypothesis. This is akin to getting predictions from different models. 3) Finally, we compute the Levenshtein edit distance [14] normalized by the length of the reference hypothesis between each of the \( R \) stochastically sampled hypothesis and the one reference hypothesis, which gives us a set \( \mathcal{E} \) of \( R \) edit distances. If all the edit-distances in \( \mathcal{E} \) are less than the threshold ratio \( \tau \) of the length \( |\hat{y}_{u}^{ref}| \) of the reference hypothesis, then we add the pseudo-labeled data points \( \{(x_u, \hat{y}_{u}^{ref}), (x_u, \hat{y}_{u}^{0}), \ldots, (x_u, \hat{y}_{u}^{R})\} \) to \( \mathcal{P} \), otherwise we reject it. In practice, we set \( R = 3 \) and hence, we have a total of four hypotheses per utterance. Unlike the original DUST that adds only the reference pseudo-label hypothesis for \( x_u \) to the set \( \mathcal{P} \), we also add the sampled hypotheses. Adding multiple pseudo-labels corresponding to an unlabeled instance \( x_u \) for student model training could increase model’s robustness to noise in pseudo-labels. This idea is also explored in [15].

Algorithm 1 Transfer Learning Algorithm

1: Given labeled data \( \mathcal{L}_L \) and unlabeled data \( \mathcal{U}_L \) in the source language
2: Given labeled data \( \mathcal{L}_T \) and unlabeled data \( \mathcal{U}_T \) in the target language
3: Given \( R \) natural numbers
4: Pre-Train \( f_{\phi,p} \) on \( \mathcal{U}_S \) to get \( f_{\phi_0,p} \)
5: Fine-Tune \( f_{\phi_0,p} \) on \( \mathcal{L}_T \) to get \( f_{\phi_1,p} \)
6: for \( n=1 \) to \( N \) do
7: \( f_{\phi_{n+1},p} = \text{DUST}(f_{\phi_{n},p}, f_{\phi_1,p}, \mathcal{L}_T, \mathcal{U}_T) \)
8: end for
9: function \( \text{DUST}(f_{\phi_0,p}, f_{\psi,p}, \mathcal{L}_T, \mathcal{U}_T) \)
10: \( \mathcal{P} \) be the set of selected pseudo-labeled data points
11: \( \mathcal{E} \) be a set of edit distances
12: Initialize \( \mathcal{P} \) and \( \mathcal{E} \) as empty sets
13: for all \( x_u \in \mathcal{U}_T \) do
14: Compute deterministic forward pass \( g_{\phi_0}^{\text{Teacher}}(x_u) \)
15: \( \hat{y}_{u}^{\text{ref}} = \text{beam_search}(g_{\phi_0}^{\text{Teacher}}(x_u)) \)
16: for all \( r \in R \) do
17: Set random seed to \( r \)
18: Compute stochastic forward pass \( g_{\phi_0}^{\text{Teacher}}(x_u) \)
19: \( \hat{y}_{u}^{r} = \text{beam_search}(g_{\phi_0}^{\text{Teacher}}(x_u)) \)
20: \( e = \text{edit_distance}(\hat{y}_{u}^{\text{ref}}, \hat{y}_{u}^{r}) \)
21: Add \( e \) to the set \( \mathcal{E} \)
22: end for
23: if \( \max(\mathcal{E}) < \tau |\hat{y}_{u}^{\text{ref}}| \) (with \( \tau \) a filtering threshold) then
24: Add \( \{(x_u, \hat{y}_{u}^{\text{ref}}), (x_u, \hat{y}_{u}^{0}), \ldots, (x_u, \hat{y}_{u}^{R})\} \) to \( \mathcal{P} \)
25: end if
26: end for
27: Fine-Tune \( f_{\psi}^{\text{Student}} \) on \( A = \mathcal{L} \cup \mathcal{P} \)
28: return \( f_{\psi}^{\text{Student}} \)
29: end function

Pre-Training  In our work, we explore the following Pre-Trained wav2vec2 SSL models that provide the initial model \( f_{\phi_0,p} \) (Algorithm 1) for transfer learning.

- Wav2Vec2.0 Base (wav2v_base) [7]: consists of 0.1 billion parameters and is Pre-Trained on the Librispeech 960 hours (LS960) [16] English speech dataset in the read speech domain.
- Wav2Vec2.0 Large (wav2v_large) [7]: consists of 0.3 billion parameters and is Pre-Trained on either LS960 or Libri-Light 60k (LL60k) hours [17] English read speech dataset.
- Wav2Vec2.0 Robust (wav2v_rob) [18]: consists of the same architecture as the large model but, is trained on three speech datasets namely Switchboard (SWBD), English part of CommonVoice (CV-En) and LL60k. We refer to the combination of these three datasets as LL60k+. We use the publicly available Pre-Trained wav2vec2 model checkpoints from fairseq toolkit [19].
Table 1: Cross-Lingual Transferability of Pre-Trained wav2vec2 model on eight target languages. Seven languages are from the MLS dataset of read audiobooks, while Arabic is from the MGB broadcast news dataset.

| Target Lang Model | MLS/en | MLS/fr | MLS/de | MLS/it | MLS/pl | MLS/pt | MLS/nl | MGB/ar | WER / CER [%] | WERR / CERR |
|-------------------|--------|--------|--------|--------|--------|--------|--------|--------|--------------|-------------|
| **Baseline**      | 119.1  | 58.5   | 114.2  | 51.6   | 106.0  | 41.5   | 99.5   | 35.0   | 111.9/44.7   | 107.0/45.3  |
| **w2v_base**      | 23.4   | 8.1    | 44.0   | 14.5   | 28.6   | 6.9    | 34.1   | 7.3    | 35.6/6.9     | 37.2/8.6    |
| **w2v_large**     | 17.1   | 5.8    | 40.9   | 13.3   | 28.3   | 6.8    | 33.3   | 6.9    | 32.0/6.2     | 23.6/5.6    |
| **w2v_large**     | 12.3   | 4.0    | 39.9   | 12.7   | 26.7   | 6.4    | 31.8   | 6.7    | 32.8/6.4     | 21.9/5.1    |
| **w2v_sup**       | 12.8   | 4.2    | 38.3   | 12.3   | 26.7   | 6.4    | 30.3   | 6.2    | 34.2/6.6     | 22.9/5.3    |
| **w2v_large_sup** | 7.6    | 2.5    | 44.2   | 14.2   | 31.1   | 7.2    | 37.7   | 7.8    | 46.5/9.0     | 28.1/6.4    |
| **Topline (x1lr)**| 17.6   | 6.3    | 19.7   | 6.5    | 11.1   | 3.1    | 17.1   | 3.6    | 16.4/3.3     | 7.9/2.1     |

Table 2: Transfer of Pre-Trained w2v_rob to the target French language in the MLS dataset.

| Method          | | WER [%] | WERR [%] |
|-----------------|-----------------|---------|---------|
| Baseline (w2v_rob) | 38.3             | 19.7    |
| DUST1           | 20.2             | 13.1    |
| DUST2           | 24.3             | 17.4    |
| DUST3           | 20.0             | 14.2    |
| DUST4           | 19.2             | 23.5    |
| **DUST5**       | **18.7**         | **22.3**|
| **Topline (x1lr)** | **19.7**        | **100** |

Hyperparameters For ASR Fine-Tuning  ASR Fine-Tuning of the Pre-Trained SSL models is performed on the ten hours labeled data of the target language. The model is trained using the Connectionist Temporal Classification (CTC) [21] loss. For optimization, we use the Adam optimizer with a learning rate schedule given by the following equation:

$$lr = \text{max}._{lr} \times \text{warmup steps}^{0.5} \times \min(\text{step}^{-0.5}, \text{step} \times \text{warmup steps}^{-1.5})$$

where, max._{lr} is the maximum learning rate, and warmup steps are the number of training iterations before the maximum learning rate is achieved and step refers to the current training iteration. We use a relatively small value of 1e-4 for max._{lr} and the first 8k training iterations for warmup. The model is trained for a total of 300 epochs. For the first 4k training iterations, we only train the linear projection layer until convergence.

Decoding  We use beam search decoding without a language model (LM) with a beam size of 10. We do not use an LM because, in this work we are solely concerned about the acoustic model adaptation. Also, in a resource-scarce ASR scenario, we might not have text data to train a LM.

4. RESULTS

In Table 1 we show the cross-lingual transferability of different Pre-Trained wav2vec2 models on eight target languages. The goal is to...
analyze how much of the multilingual \( \text{x1sr} \) topline’s performance can be recovered by simply Fine-Tuning the English \( \text{wav2vec2} \) models on ten hours of labeled data in target languages. We Fine-Tune a randomly initialized transformer encoder which consists of the same architecture as \( \text{wav2vec2} \) on ten hours of labeled data in each language to use as a baseline. We perform ASR Fine-Tuning of several Pre-Trained English \( \text{wav2vec2} \) models on ten hours of labeled data in target languages and compare their ASR performance against the Fine-Tuned \( \text{x1sr} \) model topline. We make the following conclusions: 1) \textbf{Pre-Training Matters}: ASR Fine-Tuning of Pre-Trained English \( \text{wav2vec2} \) models lead to significant improvements in WERs on target languages over the baseline. Through the simple PT \( \rightarrow \) FT process, we are able to recover on average 79% to 86% of the WER and 88% to 93% of the CER of the \( \text{x1sr} \) topline. 2) \textbf{Big SSL models provide better transfer}: By Fine-Tuning \( \text{w2v}_{\text{large}} \) that is Pre-Trained on the LS960 dataset, we are able to recover on average 83% of the topline WER compared to 79% achieved by Fine-Tuning \( \text{w2v}_{\text{base}} \) that is also Pre-Trained on LS960. 3) \textbf{Pre-training dataset size matters up to a point}: Fine-Tuned \( \text{w2v}_{\text{large}} \) that is Pre-Trained on LL60k recovers on average 86% of the topline WER compared to 84% recovered by Fine-Tuning \( \text{w2v}_{\text{large}} \) that is Pre-Trained on LS960. But the gap in average Word Error Rate Recovery (WERR) between \( \text{w2v}_{\text{rob}} \) that is Pre-Trained on the combined CV, SWBD and LL60k datasets, and \( \text{w2v}_{\text{large}} \) that is Pre-Trained only on LL60k is less than one percentage point (pp). 4) \textbf{ASR Fine-Tuning of SSL models on source language hurts transfer}: The average WERR on target languages of \( \text{w2v}_{\text{large sup}} \) model which is Pre-Trained on LL60k followed by its ASR Fine-Tuning on labeled LS960 is worse than directly Fine-Tuning the Pre-Trained \( \text{wav2vec2} \) models on the target languages. The WERR for \( \text{w2v}_{\text{large sup}} \) is about 8pp worse than \( \text{w2v}_{\text{rob}} \) that is directly Fine-Tuned on target languages. 5) \textbf{About the out-of-domain Arabic Target Language}: We see that on the seven in-domain languages (MLS/x, where x is the target language) \( \text{x1sr} \) achieves an average WER of 16.5% compared to 29.8% achieved by the ASR Fine-Tuning of \( \text{w2v}_{\text{rob}} \), the best of the English \( \text{wav2vec2} \) models, giving a performance gap of about 14pp between the two. However, on the out-of-domain Arabic target language (MGB/ar), the gap is less than 4pp. Next, we perform cross-lingual adaptation of Pre-Trained \( \text{wav2vec2} \) models using DUST. We choose French and Arabic as the target languages for transfer learning and \( \text{w2v}_{\text{rob}} \) and \( \text{x1sr} \) as the target models for adaptation.

In Table 2 we use DUST to perform cross-lingual adaptation of Pre-Trained \( \text{w2v}_{\text{rob}} \) to French (MLS/fr). DUST proceeds as follows: 1) First, we perform the ASR Fine-Tuning of the initial \( \text{w2v}_{\text{rob}} \) (\( f_{\phi_0,p} \)) model using the standard nine hours labeled split provided by MLS/fr dataset to get the first-generation teacher \( f_{\phi_0,p} \) (\( \phi_0 \)). 2) Second, \( f_{\phi_0,p} \) is used to generate pseudo-labels on the random 100 hours unlabeled split from MLS/fr, which amounts to about 30k utterances, using the pseudo-label generation process explained in \( \phi_1 \) to give a set \( \mathcal{P} \) of pseudo-parallel data. We use 0.2 as the value of the DUST filtering threshold \( \tau \). We choose \( \tau \) blindly without tuning it on a labeled validation set. 3) Lastly, we Fine-Tune \( \text{w2v}_{\text{rob}} \) (student), \( f_{\phi_0,p} \), on the combined labeled and pseudo-labeled data \( \mathcal{P} \) to get \( f_{\phi_2,p} \), which is used as the teacher for the next iteration of DUST. We perform a total of five DUST iterations. The final student model \( f_{\phi_5,p} \) achieves a WER of 22.3% which is 16pp lower than the WER of 38.3% achieved by the first generation teacher model \( f_{\phi_0,p} \). Furthermore, \( f_{\phi_5,p} \) is able to recover 86% of the \( \text{w2v} \) topline’s WER. Additionally, we make the following observations: 1) Unsurprisingly, the size of the filtered pseudo-label set \( \mathcal{P} \) (denoted as \( |\mathcal{P}| \) in Table 2) is larger in later DUST iterations due to the continual improvement in the quality of the student (see WER [%] in Table 2), which leads to an improved teacher for subsequent DUST iterations: an improved teacher leads to cleaner pseudo-labels and hence less rejected unlabeled data points during the pseudo-label filtering process. 2) Also, in the later DUST iterations the quality of the pseudo-labels improve, which is implied by the lower WER on pseudo-label set \( \mathcal{P} \) during the later iterations. Next, we consider Arabic (MGB/ar) as the target language for transfer learning, a more challenging transfer learning scenario.

In Table 3 we perform adaptation of \( \text{w2v}_{\text{rob}} \) and \( \text{x1sr} \) to the MGB/ar dataset. Here, the results are achieved by following the same adaptation process detailed above for experiments in Table 2. After five DUST iterations, we achieve the final WER of 20.8% when starting with a Fine-Tuned \( \text{x1sr} \) model as the first generation teacher \( f_{\phi_0,p} \). This result is about 17pp better than the WER of 37.4% with \( f_{\phi_0,p} \). Similar improvements are achieved when using the Fine-Tuned \( \text{w2v}_{\text{rob}} \) as \( f_{\phi_0,p} \) for DUST iterations.

5. CONCLUSIONS

We conclude by summarizing the key findings of the paper. We show (Table 1) that the monolingual Pre-Trained \( \text{wav2vec2} \) models transfer well across multiple languages. In particular, we show that by performing ASR Fine-Tuning of \( \text{wav2vec2} \) on ten hours of labeled data in a target language we are able to recover on average 86% of the performance of the topline multilingual \( \text{x1sr} \) model that is Pre-Trained on 53 languages and Fine-Tuned on the same amount of labeled target language data. This finding concurs with similar findings of \( \phi_1 \) on cross-lingual transfer of monolingual Pre-Trained SSL models to different target languages for the task of phoneme recognition. Our work goes a step further and proposes a simple yet effective cross-lingual transfer learning algorithm (\( \phi_2 \)) for adaptation of monolingual \( \text{wav2vec2} \) models via Dropout Uncertainty-Driven Self-Training (DUST) by leveraging hundred hours of unlabeled speech data from the target language. We show (Table 2) that DUST improves over the baseline model that is Fine-Tuned only on labeled target language data, and is able to recover 86% of the WER of the topline \( \text{x1sr} \) model when adapting to French. We show similar results (Table 3) when considering Arabic as the target language. Future work should explore combining our method with the adapter framework for cross-lingual transfer learning (\( \phi_3 \) to \( \phi_7 \)).
6. REFERENCES

[1] T. Chen, S. Kornblith, M. Norouzi, and G. Hinton, “A simple framework for contrastive learning of visual representations,” 2020.

[2] J. Devlin, M.-W. Chang, K. Lee, and K. Toutanova, “Bert: Pre-training of deep bidirectional transformers for language understanding,” 2019.

[3] A. van den Oord, Y. Li, and O. Vinyals, “Representation learning with contrastive predictive coding,” 2019.

[4] V. R. DeSa, “Learning classification with unlabeled data,” in Proceedings of the 6th International Conference on Neural Information Processing Systems, ser. NIPS’93. San Francisco, CA, USA: Morgan Kaufmann Publishers Inc., 1993, p. 112–119.

[5] J. Schmidhuber, “Making the world differentiable: On using self-supervised fully recurrent neural networks for dynamic reinforcement learning and planning in non-stationary environments,” Tech. Rep., 1990.

[6] D. Wang and T. F. Zheng, “Transfer learning for speech and language processing,” 2015.

[7] A. Baevski, H. Zhou, A. Mohamed, and M. Auli, “wav2vec 2.0: A framework for self-supervised learning of speech representations,” arXiv preprint arXiv:2006.11477, 2020.

[8] A. Conneau, A. Baevski, R. Collobert, A. Mohamed, and M. Auli, “Unsupervised cross-lingual representation learning for speech recognition,” 2020.

[9] S. Khurana, N. Moritz, T. Hori, and J. L. Roux, “Unsupervised domain adaptation for speech recognition via uncertainty driven self-training,” Proc. ICASSP, 2021.

[10] H. Scudder, “Probability of error of some adaptive pattern-recognition machines,” IEEE Trans. Inf. Theory, vol. 11, no. 3, pp. 363–371, 1965.

[11] J. Kahn, A. Lee, and A. Hannun, “Self-training for end-to-end speech recognition,” ICASSP 2020 - 2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), May 2020. [Online]. Available: http://dx.doi.org/10.1109/ICASSP40776.2020.9054295

[12] Q. Xu, T. Likhomanenko, J. Kahn, A. Hannun, G. Synnaeve, and R. Collobert, “Iterative pseudo-labeling for speech recognition,” arXiv preprint arXiv:2005.09267, 2020.

[13] J. He, J. Gu, J. Shen, and M. Ranzato, “Revisiting self-training for neural sequence generation,” arXiv preprint arXiv:1909.13788, 2019.

[14] V. I. Levenshtein, “Binary Codes Capable of Correcting Deletions, Insertions and Reversals,” Soviet Physics Doklady, vol. 10, p. 707, Feb. 1966.

[15] S. Dey, P. Motlicek, T. Bui, and F. Demoncour, “Exploiting semi-supervised training through a dropout regularization in end-to-end speech recognition,” arXiv preprint arXiv:1908.05227, 2019.

[16] V. Panayotov, G. Chen, D. Povey, and S. Khudanpur, “LibriSpeech: An ASR corpus based on public domain audio books,” in Proc. ICASSP, Apr. 2015.

[17] J. Kahn, M. Rivière, W. Zheng, E. Kharitonov, Q. Xu, P. E. Mazaré, J. Karadayi, V. Liptchinsky, R. Collobert, C. Fugen, T. Likhomanenko, G. Synnaeve, A. Joulin, A. Mohamed, and E. Dupoux, “Libri-light: A benchmark for asr with limited or no supervision,” in ICASSP 2020 - 2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), 2020, pp. 7669–7673, https://github.com/facebookresearch/libri-light.

[18] W.-N. Hsu, A. Sriram, A. Baevski, T. Likhomanenko, Q. Xu, V. Pratap, J. Kahn, A. Lee, R. Collobert, G. Synnaeve, and M. Auli, “Robust wav2vec 2.0: Analyzing domain shift in self-supervised pre-training,” 2021.

[19] M. Ott, S. Edunov, A. Baevski, A. Fan, S. Gross, N. Ng, D. Grangier, and M. Auli, “Fairseq: A fast, extensible toolkit for sequence modeling,” 2019.

[20] A. Ali, P. Bell, J. Glass, Y. Messaoui, H. Mubarak, S. Renals, and Y. Zhang, “The mgb-2 challenge: Arabic multi-lingual broadcast media recognition,” 2019.

[21] A. Graves, “Sequence transduction with recurrent neural networks,” arXiv preprint arXiv:abs/1211.3711, 2012.

[22] S. Watanabe, F. Boyer, X. Chang, P. Guo, T. Hayashi, Y. Higuchi, T. Hori, W.-C. Huang, H. Inaguma, N. Kamo, S. Karita, C. Li, J. Shi, A. S. Subramanian, and W. Zhang, “The 2020 espnet update: new features, broadened applications, performance improvements, and future plans,” 2020.

[23] M. Rivière, A. Joulin, P.-E. Mazaré, and E. Dupoux, “Unsupervised pretraining transfers well across languages,” 2020.

[24] J. Pfeiffer, I. Vulić, I. Gurevych, and S. Rudr, “Mad-x: An adapter-based framework for multi-task cross-lingual transfer,” 2020.

[25] A. Kannan, A. Datta, T. N. Sainath, E. Weinstein, B. Ramabhadran, Y. Wu, A. Bapna, Z. Chen, and S. Lee, “Large-scale multilingual speech recognition with a streaming end-to-end model,” 2019.

[26] S. Kessler, B. Thomas, and S. Karout, “Continual-wav2vec2: an application of continual learning for self-supervised automatic speech recognition,” 2021.

[27] W. Hou, H. Zhu, Y. Wang, J. Wang, T. Qin, R. Xu, and T. Shinnozaki, “Exploiting adapters for cross-lingual low-resource speech recognition,” 2021.