HUBERT-TR: REVIVING TURKISH AUTOMATIC SPEECH RECOGNITION WITH SELF-SUPERVISED SPEECH REPRESENTATION LEARNING

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ABSTRACT

While the Turkish language is listed among low-resource languages, literature on Turkish automatic speech recognition (ASR) is relatively old. In this paper, we present HUBERT-TR, a speech representation model for Turkish, based on HUBERT. HUBERT-TR achieves state-of-the-art results on several Turkish ASR datasets. We investigate pre-training HUBERT for Turkish with large-scale data curated from online resources. We pre-train HUBERT-TR using over 6,500 hours of speech data curated from YouTube that includes extensive variability in terms of quality and genre. We show that language-specific models are superior to other pre-trained models, where our Turkish model HUBERT-TR-BASE performs better than the x10 times larger state-of-the-art multilingual XLS-R-1B model in low-resource settings. Moreover, we study the effect of scaling on ASR performance by scaling our models up to 1B parameters. Our best model yields a state-of-the-art word error rate of 4.97% on the Turkish Broadcast News dataset. Models are available at https://huggingface.co/asafaya

Index Terms— Self-supervised Learning, Speech representation, Turkish, Automatic Speech Recognition

1. INTRODUCTION

As the demand for expanding speech processing models to a broader mass of languages grows, labeled-data scarcity is becoming a fundamental problem for low-resource languages. unsupervised learning approaches, which require much less labeled data, have become the way to solve this problem.

This effect can be seen in Natural Language Processing (NLP) using unsupervised language modeling (ELMO, BERT) [1][2]. Likewise, speech representation learning models have been developed for speech tasks. For instance, WAV2VEC and WAV2VEC 2.0, are ones of the early approaches to speech representation learning using contrastive learning [3][4]. Following methods such as Discrete-BERT, Hidden-unit BERT (HUBERT), and WAVLM utilize BERT-style Masked Hidden Unit Prediction as an objective for self-supervised training [5][6][7]. These models and their derivatives showed significant improvements over supervised methods on speech tasks such as Automatic Speech Recognition (ASR) and other tasks by utilizing unlabeled large-scale data [5][6][4].

Unfortunately, large-scale data such as LibriSpeech [8], LibriLight [9] are mainly available for the English language. Due to this, most speech representation models were initially pre-trained for English, which puts English at a big advantage compared to other languages.

More recently, speech models were extended to multilingual settings, as in CPC-8K and XLS-R [10][11]. However, these models do not cover all languages equally in their pre-training data. For instance, the Turkish subset of XLS-R pre-training data contained only 70hrs of audio. This compares the effectiveness of these multilingual models against monolingual models with small data.

In this work, we present HUBERT-TR, a monolingual speech model for Turkish based on HUBERT [6]. Unlike previous work, we effectively utilize user-generated, publicly available speech data, which we curate only from YouTube for the pre-training process. We deliver state-of-the-art results on several Turkish ASR datasets. Moreover, comparing our models with the English HUBERT-EN and the multilingual XLS-R, we show that language-specific pre-trained models are less data-hungry than other models.

We review related work on Turkish ASR in Section 2. Afterward, we describe our strategy of collecting pre-training data and pre-training HUBERT for the Turkish language in Section 3. Subsequently, in Section 4, we present the results of fine-tuning our models on ASR.

2. TURKISH AUTOMATIC SPEECH RECOGNITION

Turkish ASR still has room for improvement and has yet to catch up to English ASR performance. Previous work on Turkish ASR has been limited due to a lack of resource variability [12]. Early work on Turkish ASR utilizes Hidden Markov Models (HMMs) and Gaussian Mixture Models (GMMs) [12]. For instance, a GMM-based system achieved a word error rate of 27.70% on the Turkish Broadcast News (TBN) dataset [13].

With the rise of neural networks, acoustic neural methods such as DeepSpeech2 [14] introduced notable improvements to Turkish ASR [15][13]. Another recent study examined neural network-based acoustic and language models for the Turkish ASR [16]. They utilized time-delay neural networks (TDNNs) for the acoustic model, using both cross-entropy and sequence discriminative objective functions. By incorporating an LSTM-based language model, they attained a 9.83% word error rate on the TBN dataset, which is approximately halved compared to earlier HMM/GMM-based models.

Attempts to deal with limited data problems include utilizing language models in variant ways [17][13] and applying data augmentation [15] to improve ASR performance.

In this work, we approach Turkish ASR by taking advantage of self-supervised learning. We pre-train a set of three models on 6.5K hours of unlabeled audio. We compare our models to the multilingual pre-trained XLS-R model [11]. We report state-of-the-art results on three Turkish ASR datasets, with the best word error rate of 4.97% on the Turkish Broadcast News dataset.

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3. PRE-TRAINING HUBERT-TR

HUBERT is a self-supervised speech representation model, that is pre-trained on predicting pseudo-labels of masked audio segments. These pseudo-labels are automatically generated using audio features, such as MFCCs or by clustering hidden representations [6]. In this section, we explain the process of pre-training HUBERT-TR. This procedure consists of four stages: configuring the model, preparing the pre-training data, producing pseudo-labels for the training set, and pre-training the model.

3.1. Model

Following the original HUBERT paper [6], we pre-train a set of three models BASE/LARGE/XLARGE (details are given in Table 1), which allows us to examine the scaling effect on downstream tasks.

HUBERT encodes speech using two components: the feature extractor and the feature encoder. The feature extractor is composed of a set of consecutive Convolutional blocks. This feature extractor takes in raw speech signal with a sample-rate of 16,000 Hz, and encodes it as a sequence of hidden vectors. Each hidden vector encodes 20ms of audio. Afterward, the extracted hidden vectors are passed into the feature encoder, which is a Transformer encoder [19].

We employ seven consecutive Convolutional blocks in the feature extractor. Convolutional blocks consist of a one-dimensional convolution layer of 512 channels, with five strides in the first block and two in the rest. A Layer Normalization [20] and GELU [21] activation follow the convolution layer. This configuration is the same for all model sizes. We configure the feature encoder’s architecture depending on the model’s size. We present configurations in Table 1.

3.2. Data

English speech models were pre-trained using relatively big speech datasets, such as LibriSpeech (960 hours) [8], Librilight (60K hours) [9]. On the other hand, multilingual models such as XLS-R were pre-trained on a collection of small datasets to cover as many languages as possible. This collection includes BABEL, MLS, VoxPopuli, and CommonVoice [11]. Even though the overall size of the pre-training corpora is around 436K hours, it does not cover all languages equally, and the Turkish portion of this multilingual set is only 70 hours. This resource difference keeps the English language far ahead and creates wide performance gaps between languages [11].

We curate a new pre-training set from YouTube videos to solve the scarcity of Turkish speech data. We describe the process of collecting this pre-training set as follows.

3.2.1. Content

We manually pick up to a hundred YouTube channels. We only choose popular YouTube channels with a high watching rate. Moreover, these channels are chosen based on their content’s genre. We mainly pick content from four different genres, as shown in Figure 1. We predominantly pick news channels due to their topics and speakers’ observed representativeness and diversity.

![Figure 1. Genre distribution of pre-training speech data, as estimated based on the genre of each YouTube channel](image)

Moreover, we filter out videos shorter than 5 minutes as a naive heuristic to avoid redundant content such as video clips and duplicated content. Overall, we download the audio of 13,372 videos with a mean length of 29 minutes and a total length of 6,500 hours. We download the highest available quality for each video, and we resample the audio later to 16,000 Hz.

3.2.2. Pre-processing

After resampling audio files into a 16,000 Hz mono-channel, we chunk all of the audio sequences into a maximum length of 30 minutes to be able to process them easily. Next, we pass audio segments through a Voice-Activity Detection (VAD) pipeline to eliminate empty audio segments. We use speechbrain’s pre-trained VAD model [22], which is composed of convolutional, recurrent, and fully-connected networks. Based on the VAD predictions, we segment the audio sequences into segments with a minimum length of 28 seconds and a maximum length of 32 seconds. We combine short consecutive active audio segments until we reach at least the desired length.

This process resulted in 541K audio samples, with a total length of 4.5K hours. We allocate approximately 10 hours of audio for validation and use the rest for training.

3.3. Pseudo-labeling

HUBERT pre-training process employs iterative pseudo-labeling. A teacher model does pseudo-labeling after each iteration to train the student model in the next iteration. In the original work, the initial iteration labels were generated as 100-clusters using KMeans clustering on 39-dimensional MFCC features on the training set. In the following iterations, the MFCC features are replaced by the hidden features from the ninth layer of the feature encoder [6].

We extract hidden features of size of 1024 from the 20th layer of hubert-large-ll60k model [6]. Next, we apply KMeans clustering with 500 clusters on approximately 2% of the training set (due to memory limitations). Afterward, we conclude the pseudo-labeling process by labeling all audio frames of the extracted hidden features from the training and validation sets by mapping them into their corresponding clusters. Labeling every 20ms audio frame in the training set into its corresponding cluster resulted in 800M labels.

3.4. Pre-training

HUBERT is pre-trained using a self-supervised method inspired by the masked language modeling approach used in BERT. Instead of...
predicting the masked token as in BERT, HUBERT is pre-trained to predict the hidden-units of the masked audio frames.

We start pre-training by randomly picking \( p = 8\% \) of the input frames as masked-span starting points, and we mask corresponding spans with a length of \( l = 10 \). Next, we pre-train HUBERT-TR on predicting the hidden-units of audio frames (The labels extracted as explained in Subsection 3.3). The loss function is a combination of two losses: \( L_m \), which is cross-entropy loss over predicting masked frames hidden-units, and \( L_u \), which is the same loss for predicting the non-masked frames hidden units. The combined loss function is defined as:

\[
L = \alpha L_m + (1 - \alpha) L_u
\]

where the \( \alpha \) value determines the weight of \( L_m \) and \( L_u \) in the total loss. However, setting \( \alpha = 1.0 \) is demonstrated to yield better results [6].

We pre-train our models using one computation node with 8 NVIDIA A100-SXM-80GB GPUs. We use the same effective batch size for all model sizes, equivalent to 512 seconds per GPU. We accumulate gradients to keep the batch size consistent for 2/4/5 steps for BASE/LARGE/XLARGE models, giving an effective batch size of 1.14 hours. The overall pre-training resulted in 10 epochs over the pre-training data. We follow [6] in using Adam optimizer [23], and we employ learning-rate polynomial decay with 5000 warm-up steps and a peak learning rate of \( 1e-3 \). Figure 2 shows the convergence difference between the models.

### 4. FINETUNING AND ASR

To assess the quality of the learned speech representations, we fine-tune HUBERT-TR, HUBERT-EN and XLS-R on three different Turkish ASR datasets. We show that language-specific speech representations of HUBERT-TR are far superior to the other models. We describe the datasets, fine-tuning setup, and results in this section.

#### 4.1. Turkish ASR datasets

We use three Turkish ASR datasets of different sizes and genres. We provide statistics on these datasets in Table 2.

Middle East Technical University Turkish Microphone Speech Corpus v1.0 (METU-TMS) [24], is a collection of carefully selected 5K sentences. These sentences were voiced by 120 speakers (40 sentences per speaker), with native speakers of Turkish speakers with an age range from 19 to 50 years. This dataset is relatively small compared to the other two datasets we use. A training set of only 4.1 hours makes a good evaluation for low-resource settings.

Common Voice is an open-source project based on crowdsourcing for collecting ASR data for over 30 languages [25]. We only use the Turkish subset of CommonVoice v8.0. We note that CommonVoice is a crowd-sourced dataset; hence it has a lower annotation/audio quality than the other two datasets.

The Turkish Broadcast News Speech and Transcripts (TBN) dataset [26] is the last dataset we use for fine-tuning. It contains 130 hours of Voice of America Turkish radio broadcasts and transcripts. Using the dataset’s segmentation labels, we eliminate non-speech segments, which leaves us 94.54 hours. Moreover, the dataset does not offer any splits. Therefore, we create splits, which we share with the preprocessing script.

#### 4.2. Tokenization

Due to the agglutinative nature of the Turkish language, vocabulary is unlimited, rendering word-based tokenization impractical, and leaving us with two options: subwords and characters. However, it is shown that subword tokenization outperforms character-based ASR and yields better generalization on the Turkish language [27].

We utilize subword tokenization by training a unigram model with a vocabulary size of 256 for each dataset using the transcripts of its training set.

#### 4.3. Automatic Speech Recognition

Since we focus on studying the effect of speech representations, we do not employ any language model or use any additional decoders. We leave experimentation with language models and advanced decoding to future research.

We fine-tune our models with Connectionist Temporal Classification (CTC) loss [28]. We employ an MLP of three sequential layers on top of the pre-trained models and fine-tune them together on the ASR task. Each layer has a hidden size of 1024 and is followed by a GELU activation function and a dropout with \( p = 0.2 \) to prevent overfitting. Finally, a CTC Linear layer is added to the end of the MLP to map the features from the hidden space (1024) to the output tokens (256).

We fine-tune model components using two different optimizers. We utilize Adam optimizer [23] to train the backbone pre-trained model, and Adadelta optimizer [29] to train both the MLP on top and the CTC layer. For the HUBERT-(TR/EN)-XLARGE and XLS-R-(1/2B) models, we use learning rates of \( 1e-5, 5e-1 \) for Adam and Adadelta respectively, and \( 5e-5, 9e-1 \) for the rest.

Using the same settings for HUBERT-(TR/EN) and XLS-R, we fine-tune all model sizes on each dataset separately, ending up with eight models per dataset. We train the models for 50 epochs on the relevant training sets and save the best-performing checkpoint on the validation set for the final evaluation on the test set.

### Table 2. Dataset size (hours) of the Turkish ASR datasets

| Dataset       | METU-TMS | COMMONVOICE | TBN   |
|---------------|----------|-------------|-------|
| Training      | 4.1      | 16.26       | 86.09 |
| Validation    | 0.49     | 8.28        | 3.76  |
| Test          | 0.96     | 9.62        | 4.69  |
| Total         | 5.55     | 34.16       | 94.54 |

- **Fig. 2.** The masked unit loss convergence throughout the pre-training process.
Table 3. Word error rates (validation/test) of the fine-tuned models on Turkish ASR datasets: The margin in performance of HUBERT-TR can be seen clearly, as it achieves the best results on all datasets.

|               | METU-TMS | COMMONVOICE | TBN          |
|---------------|----------|-------------|--------------|
| DNN [13]      | - / 64.55| -           | - / 22.63    |
| TDNN w/LSTM LM [16] | -        | - | 8.86 / 9.83 |
| TDNN w/Subwords [27] | -        | - | - / 7.92    |
| HUBERT-EN     |          |             |              |
| LARGE (0.3B)  | 49.22 / 48.52 | 37.36 / 50.01 | 14.23 / 12.83 |
| XLARGE (1B)   | 45.53 / 43.41 | 44.92 / 56.85 | 13.92 / 12.69 |
| XLS-R 0.3B    | 29.76 / 27.08 | 26.31 / 37.24 | 9.50 / 8.18  |
| 1B             | 17.88 / 15.34 | 16.97 / 25.68 | 8.52 / 7.04  |
| 2B             | 14.20 / 11.63 | 15.12 / 23.41 | 8.42 / 6.77  |
| HUBERT-TR     |          |             |              |
| BASE (0.1B)   | 15.43 / 13.36 | 17.47 / 24.40 | 8.95 / 7.77  |
| LARGE (0.3B)  | 12.25 / 11.65 | 10.93 / 15.59 | 7.37 / 5.75  |
| XLARGE (1B)   | 9.90 / 8.26  | 8.59 / 12.72 | 6.60 / 4.97  |

4.4. Word Error Rates

We evaluate the models on the corresponding test sets and report the word error rate values for each of them in Table 3. Additionally, we include word error rates reported in previous work. However, these results are incomplete and are not available for all of the datasets we use.

We find that HUBERT-TR yields the best results on the studied datasets, surpassing the English HUBERT-EN model and the multilingual XLS-R model. Furthermore, even though it has 0.3B parameters, HUBERT-TR LARGE surpasses the performance of the largest XLS-R model with 2B parameters. Additionally, it can be noticed from the results that, monolingual or not, pre-trained speech models are superior to their non-pre-trained counterparts.

We explore the ASR errors and find that most of these errors can be avoided via language model-based decoding. We include example errors from models’ outputs on a test sample taken from COMMONVOICE dataset in Table 4.

4.4.1. Low resource setting

METU-TMS and COMMONVOICE datasets can be considered low-resource datasets due to their small training sets’ size (4 hours, 16 hours respectively). Looking at Table 3, the gap in performance between the models and the gain of language-specific pre-training in HUBERT-TR can be observed clearly. This is especially important for developing ASR systems in low-resource settings.

5. CONCLUSION AND FUTURE WORK

In this paper, we approached Turkish ASR by utilizing self-supervised speech representations, achieving state-of-the-art ASR results on three datasets. We presented HUBERT-TR, a pre-trained speech representation model specific to the Turkish language. We described the process of curating the pre-training data from online resources and provided details about the pre-training process. Moreover, we conducted experiments to compare the effectiveness of multilingual models with monolingual models by fine-tuning HUBERT-TR, HUBERT-EN and XLS-R on Turkish ASR datasets. We found that language-specific pre-trained models are far superior to other models. The difference is more notable in low-resource settings, where HUBERT-TR BASE performs better than the x10 times larger XLS-R 1B model. Nevertheless, pre-trained speech models are more effective than their non-pre-trained counterparts. Hence, we still encourage utilizing multilingual models in case of the absence of monolingual models. Additionally, although we focus on improving Turkish language ASR performance, we believe that other low-resource languages can benefit from the same strategy.

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