## **MULTILINGUAL WORD ERROR RATE ESTIMATION: E-WER3**

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### ABSTRACT

The success of the multilingual automatic speech recognition systems empowered many voice-driven applications. However, measuring the performance of such systems remains a major challenge, due to its dependency on manually transcribed speech data in both mono- and multilingual scenarios. In this paper, we propose a novel multilingual framework – eWER3 – jointly trained on acoustic and lexical representation to estimate word error rate. We demonstrate the effectiveness of eWER3 to (*i*) predict WER without using any internal states from the ASR and (*ii*) use the multilingual shared latent space to push the performance of the close-related languages. We show our proposed multilingual model outperforms the previous monolingual word error rate estimation method (eWER2) by an absolute 9% increase in Pearson correlation coefficient (PCC), with better overall estimation between the predicted and reference WER.

Index Terms— Multilingual WER estimation, End-to-End systems

# 1. INTRODUCTION

Recent years have witnessed a surge in both mono- and multilingual speech recognition performances, with accuracy comparable or even outperforming the human performance on established benchmarks [1, 2]. With such success, automatic speech recognition (ASR) systems have been commoditized as speech processing pipelines in many voice-driven applications such as personal assistant devices and broadcast media monitoring among others. However, our means of evaluating the usefulness of the ASR output have remained largely unchanged.

Word error rate (WER) is the standard measure for evaluating the performance of ASR systems. To obtain a reliable estimation of the WER, a minimum of two hours of manually transcribed test data is typically required – a time-consuming and expensive process. Often voice-driven applications require quick quality estimation of the automated transcription, which is not feasible with such traditional reference-based measures. Moreover, even with offline applications, it is not always viable to obtain gold references (especially in multilingual scenarios) to evaluate the transcription quality. Thus, there is a need to develop techniques that can automatically estimate the quality of the ASR transcription without such manual effort [3, 4] and handle multilingualism.

Several studies have explored the automatic estimation of the WER. These studies included a large set of extracted features (with/without internal access to the ASR system) to train neural regression or classification models [5, 6, 7]. Some studies proposed a novel neural zero-inflated model [8], while others model uncertainty [9] in predictions to handle different challenges. However, all these studies are conducted with networks directly trained and tested in monolingual settings.

In this work, we design a single multilingual end-to-end model capable of estimating WER given the raw audio and the automatic transcription from different (mono- and multilingual) off-the-shelf ASR systems without having access to the ASR's internal feature representation (the concept is shown in Figure 1). For this, we entail the large self-supervised pretrained models as feature extractor and exploits the available multilingual corpora.

We evaluate our results using *Arabic*, *Italian*, *Spanish*, *English* and *Russian* – test sets. We train a monolingual estimator and compare it with our proposed multilingual model to show its efficacy for better performance. Our contributions are:

- Design the first multilingual WER estimation without using any internal features from the ASR (black-box);
- Compare our method with previous state-of-the-art results (e-wer [6] and e-wer2 [7]);
- Analyse the effect of imbalanced WER distribution on the estimator's performance and propose a new sampling technique.



Fig. 1: Overview of the study concept and proposed framework.

## 2. E2E MULTILINGUAL WER ESTIMATOR

Figure 2 shows an overview of the end-to-end system architecture designed to estimate speech recognition WER with no gold-standard reference transcription. As input to the estimator, we first pass raw audio along with its automatic transcription obtained from the speech recognition systems. We extract the speech and lexical representations and utilize these representations jointly to train the multilingual regression model.

Acoustic representation: We use XLSR-53 to extract phoneme aware speech representation. The XLSR-53 model is a multilingual variation of wav2vec 2.0 model fine-tuned on cross-lingual phoneme-recognition task [14, 15]. For our study, we remove the output (language model head) and use the representation only. We use XLSR-53 as a feature extractor, which includes a cascaded temporal convolutional network to map raw audio,  $X = \{x_1, x_2..., x_n\}$  to the latent speech representation  $Z = \{z_1, z_2..., z_t\}$ . This latent



Fig. 2: End-to-End Architecture used to estimate WER. A\* : acoustic representation from BLSTM and L: the lexical representation.

Lang	ASR Trained on	Architecture	ASR Type	Estimator Trained using	Estimator Tested on
English	LibriSpeech (960hours)	Conformer	Mono	LibriSpeech + TEDLIUM3 dev	TEDLIUM3 test
Spanish	CommonVoice (CV-ES) [10]	Conformer	Mono	CV-ES dev	CV-ES test
Italian	CommonVoice (CV-IT)	Conformer	Mono	CV-IT dev	CV-IT test
Russian	CommonVoice (CV-RU)	Conformer	Mono	CV-RU dev	CV-RU test
Arabic	QASR (Arabic) + LibriSpeech (English) (200hrs) [11]	Conformer	Multi	MGB2 [12] + QASR dev	SUMMA [13]

**Table 1**: Description of the ASR systems used to train and/or test the proposed estimator along with the Estimator training and test set. Lang. shows the language data used to train the estimator.

Train (Dev   Test)	<b>T.D</b> (hours)	A.D (secs)	A.U (words)	#
Arabic	10.36 (0.56   2.94)	6.14 (6.08   7.52)	12.66 (12.45   13.96)	6077 (332   1410)
English	3.72 (0.31   2.62)	5.83 (5.65   8.18)	16.68 (16.04   23.95)	2295 (196   1151)
Spanish	7.37 (0.84   17.31)	6.05 (6.11   6.12)	10.11 (10.17   9.84)	4384 (496   10179)
Italian	4.94 (0.53   12.26)	5.94 (5.91   6.13)	10.2 (10.13   9.74 )	2991 (322   7200)
Russian	1.73 (0.17   9.57)	5.94 (5.83   5.99)	9.86 (9.72   9.58)	1045 (102   5748)

**Table 2**: *Train, Dev and Test (Dev and Test in bracket seperated by |) Data Description. T.D: Total dataset duration in hours; A.D: Average utterance duration in seconds; A.U: Average utterance length in tokens; #:Total instances.* 

information is then passed through 24 Transformer [16] blocks with model dimension of 1,024 and 16 attention heads, to capture contextual representations,  $C(g: Z \mapsto C)$ . We then pass the frame-wise representation to a bi-directional LSTM and extracted the last step representations  $(\overrightarrow{A}, \overrightarrow{A})$ .

**Lexical representation:** Simultaneously, to extract the lexical embeddings, we pass the ASR transcription to the XLM-RoBERTa-Large model [17], pretrained using 100 different languages. The pretrained model follows the same architecture as BERT [16], with 24-layers of transformer modules – with 1, 024 hidden-state, and 16 attention heads. The model uses a byte-level BPE as a tokenizer and outputs the sequence of hidden-states for the whole input sentence. To obtain the final lexical representation (*L*), we averaged the embeddings over the sequences.

**Combining representations:** We concatenate the output representations from the acoustic and lexical module  $(\overleftarrow{A} + \overrightarrow{A} + L)$  and pass it through two fully-connected layers, before the output layer, for the regression task.

### 3. EXPERIMENTAL SETUP

### 3.1. Speech Recognition Systems

To train the estimator, we opt for the current state-of-the-art conformer [18] based end-to-end speech recognition systems (see Table 1).

For the Spanish, Italian, and Russian ASR systems, the models are trained using their respective CV train sets. The model has 12 encoder layers and 6 decoder layers each with 2,048 encoder/decoder units from FFN and 4 attention heads with 256 transformation dimensions and 15 CNN kernels.

As for the English ASR, we use a large conformer model with 12 encoder and 6 decoder layers containing 8 attention heads with 512 transformation dimensions and 31 CNN kernels. This large ASR is trained using the well-known 960 hours of librispeech data. We use similar architecture for multilingual Arabic ASR [19] trained with Arabic QASR [11] along with English librispeech data.

### 3.2. Data

**Data Preparation:** We train the multilingual estimator using the dataset mentioned in Table 1. The input audio to the estimator is first down-sampled to 16KHz to match the ASR input sample rate. For



Fig. 3: Data imbalance and missing target values.

training the model, we select audio instances with a duration of 10 seconds or less; this is based on the upper tail of overall duration distribution.

**Imbalanced Distribution:** Given the remarkable performance of the current end-to-end ASR models, the WER often exhibits imbalanced distributions, where certain target values have significantly fewer observations than others. In this case, the majority of the training set has a WER of '0', making the training data highly skewed (see Figure 3). Moreover, the dataset shows a tendency of missing data for certain target values, thus making the task more challenging. In order to handle the abundance of '0' WER scores in the training set, we sampled n instances from each language with WER = 0. We determine the value n based on the sum of instances falls under the next two most frequent score groups.

**Data Split:** For our dev set, we divide the training dataset into 10 bins of target WER, with equal intervals such as [0, 10),  $[10, 20) \cdots$  [90, 100]. From each bin, we then randomly sample  $\approx 10\%$  of the instances to create the validation set. The details of the resultant (balanced) split are shown in Table 2.

**Estimator Output:** As the output score of the estimator, it is worth noting that we bound the target value (WER) of the estimator to a range of [0,1] (i.e. 0 - 100%).<sup>1</sup>

## 3.3. WER Estimator Design

**Model Parameters**: We train the end-to-end WER estimator using a an Adam optimizer for 20 epochs with a learning rate of 1e - 3and a dropout-rate of 0.1, and freeze the parameters of the pretrained self-supervised models. In the acoustic pipeline, we use one layer of BiLSTM model and for the joint training, we opt for two fullyconnected layers (600, 32 neurons) with ReLU activation function. As for the loss function, we use mean squared error. Same architecture and hyperparameters are used to train mono- and multilingual models with balanced and natural distribution data.

### 3.4. Evaluation Measures

Given the uneven scores distribution (towards small WER value), we use Pearson correlation coefficient (PCC) as our main evaluation metric. However, we also report root mean square error (RMSE) to compare with previous studies [6, 7]. Moreover, to effectively estimate the eWER3 for the complete test set, we report weighted WER:  $(eWER3 = \frac{\sum WER_{utt}*Dur(utt)}{\sum^n Dur})$  using the utterance level estimated WER ( $WER_{utt}$ ) and the corresponding duration (Dur(utt)).

## 4. RESULTS AND DISCUSSION

#### 4.1. Monolingual Comparison

We benchmark the proposed framework eWER3 in a monolingual setting (Arabic) and compare it with the previous estimation models – eWER and eWER2. The results, reported in Table 3, show that our model outperforms both eWER and eWER2 with an absolute increase of 3% and 9% in PCC, and a decrease of 21% and 6% in RMSE respectively. Such improvement indicates the estimation power of our architecture without using any additional feature from the ASR decoder.

Moreover, when the monolingual models (for both Arabic and English – in Table 4) were tested in the cross-lingual Italian dataset, both models' performance (both in correlation coefficient and RMSE) decrease drastically. Yet, it is observed that the Italian test set benefits more from the English monolingual model with RMSE: 0.19 compared to RMSE:0.32 in the Arabic model. Thus indicating the potential advantage of having shared latent space for close languages in multilingual settings.



**Fig. 4**: Cumulative WER over time with all sentences for (a) Arabic SUMMA test set. X-axis is the number of instances and Y-axis is Aggregated WER in %.

#### 4.2. Multilingual E2E Estimator Performance

Table 4 shows that the multilingual model gives a comparable correlation and RMSE compared to the monolingual models. We notice the 4% performance increase in PCC for English test set when in multilingual setting, showing the added advantage of such a multilingual estimator. Furthermore, for all the language test sets (Arabic, English, Italian, Spanish, Russian), in addition to a smaller RMSE and significant correlation – per utterance, the overall predicted WER is also within a close range (0 – 5 points) of the actual WER.

For brevity, we present the Arabic Summa test set's cumulative WER aggregated over the sentences in Figure 4 and the corresponding scatter plot for the Arabic (best PCC obtained) and Russian (lowest performing PCC) test sets in Figure 5.

<sup>&</sup>lt;sup>1</sup>If WER > 100%, the value is scaled down to 100.

Ar:SUMMA	PCC	RMSE	Input to the Estimator
eWER	0.66	0.35	Lexical + Grapheme + Decoder + Numerical [6]
eWER2	0.72	0.20	MFCC+ Lexical + Phonetic [7]
eWER3 mono	0.75	0.14	Raw Audio, Lexical Transcription

 Table 3: Monolingual (Arabic) transcription quality estimator results on Ar:SUMMA test set.

Sets	PCC	RMSE	eWER3	WER	#		
Monolingual Estimator Model - Arabic							
Ar:SUMMA	0.75	0.14	16.0%	18.0%	1410		
It:CV	0.45	0.32	41.0%	17.0%	7200		
Monolingual Estimator Model - English							
En:TedL	0.62	0.14	7.0%	12.0%	1151		
It:CV	0.49	0.19	10.0%	17.0%	7200		
Multilingual Estimator Model							
Ar:SUMMA	0.74	0.15	15.0%	18.0%	1410		
It:CV	0.60	0.17	14.0%	17.0%	7200		
Es:CV	0.53	0.14	13.0%	11.0%	10179		
En:TedL	0.66	0.14	8.0%	12.0%	1151		
Ru:CV	0.51	0.12	6.0%	7.0%	5748		

 Table 4: Reported performance of monolingual and multilingual

 WER estimator on Arabic (Ar), English (En), Italian (It), Spanish (Es)

 and Russian (Ru) test sets.



**Fig. 5**: Scatter Plot for test sets with highest PCC 0.74 – Arabic (a); and the lowest PCC 0.51 – Russian.

#### 4.3. Effects of Imbalanced Data and Sampling

We analyse the effect of training the model with sampled data (Model Sampled:  $\psi$ ) instead of natural distribution (Model Natural: $\varphi$ ). With respect to the  $\psi$ , we noticed  $\varphi$  has a slightly better correlation coeffi-

cient, yet has higher RMSE-values and large difference in aggregated estimated eWER3 than the Oracle WER. For example, for ES:CV test set,  $\varphi(PCC) = 0.58$ ,  $\varphi(RMSE) = 0.15$ ,  $\varphi(eWER3) = 7.0\%$ , whereas,  $\psi(PCC) = 0.53$ ,  $\psi(RMSE) = 0.14$ ,  $\psi(eWER3) = 13.0\%^2$ .

The density curve, from  $\varphi$  and  $\psi$  model predictions (Figure 6), indicates that with natural distribution the model ( $\varphi$ ) learns to predict lower WER better than the  $\psi$ . However, the prediction is scaled down to a lower range (see the shift in the peak of both the curves) thus increasing RMSE and the difference between the overall predicted eWER3 and Oracle WER. This is a potential limitation of the current study and a future endeavor for experimenting with zero-inflated output layers [20] for such a multilingual network.



**Fig. 6**: Density curves using estimated WER for the multilingual model trained using sampled distribution (blue line) and natural distribution (orange) train set, showing the effect of imbalanced data labels. x-axis represents WER. The prediction is from aggregated in-language test sets.

### 5. CONCLUSION

In this study, we propose a novel framework, for estimating multilingual WER without the need of manual transcription. Our proposed framework is a joint acoustic-lexical model exploiting the selfsupervised learning paradigm. Using a small subset of languages, our results suggest the efficacy of such model to predict utterance-level and overall WER for the test sets. When compared with monolingual models, the multilingual framework performs comparably for the distant languages (e.g., Arabic) while boosting the performance of the close languages (e.g.,  $En_{mono}$ : 0.62 PCC vs  $En_{multi}$ : 0.66 PCC). The current study can be used as a proof of concept to utilize the representation models to design such a predictor for an ASR. We exploit pretrained models as a feature-extractor for computational feasibility. In the future, we will focus on improving the performance by handling the imbalanced target distribution, with improved neural architecture and cover more languages.

<sup>&</sup>lt;sup>2</sup>A higher RMSE and overall WER difference is seen for other datasets while using natural distribution.

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