

MAESTRO-U: LEVERAGING JOINT SPEECH-TEXT REPRESENTATION LEARNING FOR ZERO SUPERVISED SPEECH ASR

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ABSTRACT

Training state-of-the-art Automated Speech Recognition (ASR) models typically requires a substantial amount of transcribed speech. In this work, we demonstrate that a modality-matched joint speech and text model introduced in [1] can be leveraged to train a massively multilingual ASR model without any supervised (manually transcribed) speech for some languages. This paper explores the use of jointly learnt speech and text representations in a massively multilingual, zero supervised speech, real-world setting to expand the set of languages covered by ASR with only unlabeled speech and text in the target languages. Using the FLEURS dataset, we define the task to cover 102 languages, where transcribed speech is available in 52 of these languages and can be used to improve end-to-end ASR quality on the remaining 50. First, we show that by combining speech representations with byte-level text representations and use of language embeddings, we can dramatically reduce the Character Error Rate (CER) on languages with no supervised speech from 64.8% to 30.8%, a relative reduction of 53%. Second, using a subset of South Asian languages we show that Maestro-U can promote knowledge transfer from languages with supervised speech even when there is limited to no graphemic overlap. Overall, Maestro-U closes the gap to oracle performance by 68.5% relative and reduces the CER of 19 languages below 15%.

Index Terms— Speech-text Representation learning, Zero Resource, Massively Multilingual zero-supervised-speech ASR

1. INTRODUCTION

The last few years have seen the emergence of two major directions of research towards improving low resource ASR quality. The first direction uses multilingual models to leverage the large amounts of supervised (manually transcribed) speech available for high resource languages to improve quality on low resource languages [2–5]. The second direction utilizes self-supervised pre-training on large amounts of unlabeled speech [6–9], unlabeled text [10, 11] or both [12–14] to complement the relatively small amounts of transcribed data available for these languages. An extreme example of the low-resource setting is learning ASR without

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the availability of any (in-language) transcribed resources (*zero-supervised-speech* ASR). In this work, we explore the possibility of using jointly learnt speech and text representations [13, 14] to expand ASR to languages lacking transcribed speech resources.

The zero-supervised-speech setting has previously been explored in several works [15–18]. However, most prior research on unsupervised ASR either learns models for phoneme recognition (implicitly assuming a model for phoneme to grapheme conversion), or assumes the availability of grapheme to phoneme (G2P) models for text augmentation. The construction of a G2P model requires at least as much expert human knowledge and effort as speech transcription. As such they are unavailable for many of the worlds’ languages. In many zero resources settings, lack of a lexicon can double the unit error rate [19]. In the ZeroSpeech2021 [20] challenge, researchers explored the ability of models to learn language models with raw speech and no textual resources. These models were evaluated on their ability to learn phonetics, lexicon, syntax and semantic structures in the language.

In this work, we define a practical setting in line with real world constraints, assuming the availability of unlabeled speech and text (graphemes) in all 102 languages under consideration, and the availability of supervised speech in 52 of these languages. Given these resources, we attempt to improve end-to-end ASR quality on the remaining 50 zero-supervised-speech languages. We establish that a joint speech-text representation learning model, Maestro [14] fails to perform well on this zero supervised speech task, reaching an average Character Error Rate (CER) of 54.2% averaged over 50 languages. To improve the joint speech and text representation learning for this setting we propose the following:

- Building on the FLEURS benchmark [21], we define a massively multilingual zero-supervised-speech ASR task motivated by real-world constraints, with the goal of expanding the set of languages covered by ASR models.
- We propose several improvements to the Maestro described in [1], namely, the use of language embeddings and adapters to learn better mappings (Section 3.2) across speech and text in languages sharing writing systems; and use of byte level text representations to enable better transfer to script-unique zero-supervised-speech languages (Section 3.3).
- We analyze and compare the role of different text injection strategies, including using phonemized text and byte-level text representations to understand the role of shared vocabularies in zero-supervised-speech ASR (Section 3.3)
- We conduct ablations of components used in representation learning to understand the role of our proposed techniques and those proposed in [14], including the importance of the learnt duration model and consistency losses.

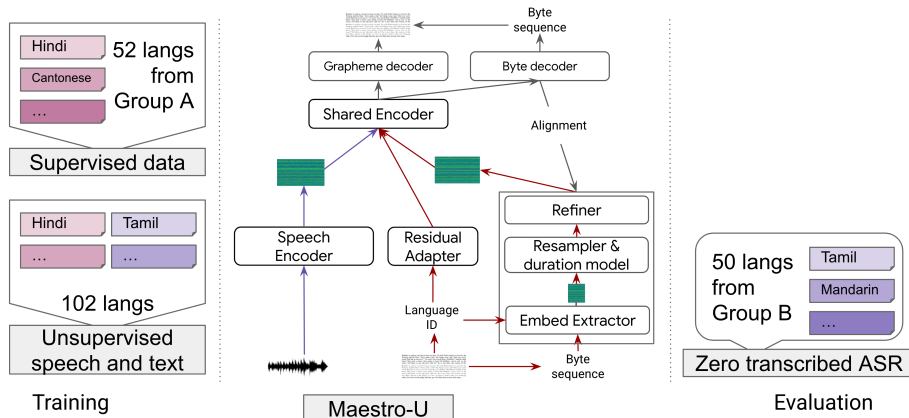


Fig. 1. Maestro-U Training for Zero Supervised Speech ASR. The zero supervised speech ASR is defined in Section 2. Speech, shared and text encoders are described in Section 3.1. The use of bytes, language ID and residual adapter are described in Section 3.2 and 3.3.

The proposed work in this paper results in a final zero supervised speech average CER of 30.8%, a relative reduction of 43% relative over Maestro [1]. To the best of our knowledge, we believe this is the first demonstration that competitive ASR performance can be achieved for an unseen language using no language resources other than unspoken text and untranscribed speech.

2. FLEURS ZERO SUPERVISED SPEECH ASR

We define our massively multilingual zero supervised speech ASR task building on the FLEURS benchmark [21]. FLEURS is a publicly available, multi-way parallel dataset of just 10 hours of read speech in each of the 102 languages spanning 7 geo-groups, which can be used as a benchmark task for ASR. Of the 102 languages present in the FLEURS benchmark, we choose 52 to serve as our supervised languages (*Group A*) while the remaining 50 will be utilized in a zero-supervised-speech setting (*Group B*). In order to understand zero supervised speech performance across all geo-groups, we balance the number of languages in Groups A and B from each geo-group as shown in Table 1.

In addition to FLEURS, following [13, 14], we also include supervised speech and unlabeled speech from the MLS [4], VoxPopuli [22], CommonVoice [23] and Babel [24] datasets when available. While mC4 [25] is a good text resource for injection, it contains noisy data that can hurt ASR quality [26]. Therefore, we cleaned this text further using the language-id and wordlist-based approaches described in [27].

To understand graphemic overlap between the supervised languages $L^{(A)}$ and zero supervised speech languages $L^{(B)}$ and its effect on the ASR performance, we define the unseen grapheme ratio $\gamma(l)$ of language l in group B w.r.t. group A languages in Equation 1,

$$\gamma(l) = 1 - \frac{\left| \bigcup_{k=1}^n (V(l) \cap V(L_k^{(A)})) \right|}{|V(l)|}, \quad l \in L^{(B)} \quad (1)$$

where $V(l)$ denotes the grapheme vocabulary of the language l , which can be obtained from any text resource for l . In this work, we obtain $V(l)$ from the FLEURS release in [21].

3. PROPOSED METHOD: MAESTRO-U

In this work, we pursue the idea of expanding an ASR model to new languages while requiring zero supervised speech, using only text and untranscribed speech. This is done by text injection with the previously proposed Maestro [14] with a series of innovations to handle unseen scripts and promote multilingual knowledge transfer. Figure 1 summarizes the Maestro-U training process.

3.1. Text injection using Maestro

Zero- or few-shot approaches require training models that can map one sequence to another implicitly. This has been achieved for several text style transfer and MT tasks via training cross-lingual models with GANs [28], self-supervised pre-training and for ASR for mapping audio to phonemes with GANs [18]. Recent work on speech-text pre-training, like mSLAM [13] and Maestro [14], have demonstrated that it is possible to learn shared representations of speech and text in the same model.

Maestro was proposed in [14] to address the speech-text representation learning problem by first aligning text to speech using an RNN-T decoder and then training a *Text Encoder*. The resultant text encoder can be used to map unspoken text to this aligned shared space and learn from it. When learning from untranscribed speech data, we use contrastive loss on the speech encoder outputs and a masked language model (MLM) loss on the shared encoder output similar to W2v-BERT [29]. When learning from paired speech and text, the text encoder uses this RNN-T model to generate alignments between the text targets and the speech encoder output. The *Resampler* and *Refiner* layers replicate the initially learned text embeddings to match the duration of the speech embedding using this alignment information and a Mean-Squared Error (MSE) training objective is used to enforce consistency between the resultant speech and text representations.

When learning from unspoken text, speech-text alignment information is unavailable. Therefore, Maestro uses durations predicted from a duration prediction model in a fashion similar to speech synthesis [30]. This model is trained to predict the duration of each token. The predicted duration on unspoken text is subsequently used to upsample the learned text embeddings to match the speech frame-rate. RNN-T loss is applied over the resultant upsampled text

Table 1. Languages in Group A and Group B from the Fleurs benchmark.

Group A
Central Asian, Middle-East and North Africa (CMN): Azerbaijani (az), Kazakh (kk) Kyrgyz (ky), Mongolian (mn), Pashto (ps), Persian (fa) CJK: Cantonese (yue), Korean (ko) Eastern European (EE): Belarusian (be), Estonian (et), Georgian (ka), Latvian (lv), Macedonian (mk), Polish (pl), Slovak (sk), Serbian (sr) South Asia (SA): Bengali (bn), Hindi (hi), Malayalam (ml), Nepali (ne), Punjabi (pa), Urdu (ur), Telugu (te) South-east Asia (SEA): Cebuano (ceb), Indonesian (id), Khmer (km), Malay (ms), Thai (th), Vietnamese (vi) Sub-Saharan Africa (SSA): Amharic (am), Hausa (ha), Kamba (kam), Lingala (ln), Northern-Sotho (nso), Oromo (om), Somali (so) Swahili (sw), Wolof (wo), Yoruba (yo) Western European (WE): American English (en), Bosnian (bs), Croatian (hr), Finnish (fi), French (fr), German (de), Greek (el), Irish (ga) Italian (it), Kabuverdianu (kea), Maltese (mt), Occitan (oc), Welsh (cy)
Group B
CMN: Arabic (ar), Hebrew (he), Sorani-Kurdish (ckb), Tajik (tg), Turkish (tr), Uzbek (uz) CJK: Japanese (ja), Mandarin (cmn) EE: Armenian (hy), Bulgarian (bg), Czech (cs), Lithuanian (lt), Romanian (ro), Russian (ru), Slovenian (sl), Ukrainian (uk) SA: Assamese (as), Gujarati (gu), Kannada (kn), Marathi (mr), Oriya (or), Sindhi (sd), Tamil (ta) SEA: Burmese (my), Filipino (fil), Javanese (jv), Lao (lo), Maori (mi) SSA: Afrikaans (af), Fula (ff), Ganda (lg), Igbo (ig), Luo (luo), Nyanja (ny), Shona (sn), Umbundu (umb), Xhosa (xh), Zulu (zu) WE: Asturian (ast), Catalan (ca), Danish (da), Dutch (nl), Galician (gl), Hungarian (hu), Icelandic (is), Latin American Spanish (es) Luxembourgish (lb), Norwegian (nb), Portuguese (pt), Swedish (sv)

embeddings with masking in frequency and time domain similar to SpecAugment [31]. This allows for the use of the same RNN-T objective on both speech embeddings or text embeddings.

When applied in the zero supervised speech ASR, the text duration model used to upsample the text representation to the shared speech-text space is trained on only those languages where transcribed speech is available. This duration model is used to upsample the text representation of every language whether or not paired data is available. This approach allows us to use this upsampled text representation to train an ASR model purely on unspoken text from an unseen language.

3.2. Promote multilingual knowledge transfer

We found that Maestro works reasonably well for several languages (Section 5.1), but sometimes recognizes audio from zero resource languages with graphemes from supervised languages. This phenomenon is common in many multilingual ASR systems [32]. To encourage the model to generate text in the correct language, we modify Maestro to utilize language-id signals and language-specific parameters in several ways.

Given that new languages and their scripts are learned only through text data, we inject a learned language embedding in the input of the RNN-T decoder to bias the output script. Additionally, language information can be missing when using a common text representation across languages (e.g. phonemes) (Section 3.3). Thus, we add the language information back to the text encoder with a similar learned language embedding. The shared encoder of the Maestro model is the backbone to learn joint speech-text representations. To introduce language dependent parameters there, we use language id conditioned residual adapter layers [33] to condition the shared encoder. Residual adapters are small feed forward networks typically two layers with a bottleneck dimension (though other structures are possible) whose inputs are the inputs to a conformer block and whose outputs are added to the output of the same block. Language-id conditioned residual adapters are applied to all conformer blocks in the shared encoder.

The Maestro model in [14] relies on the supervised fine-tuning after the Maestro training process to get the best performance. In zero supervised speech ASR, there is no supervised data in the target language for fine-tuning. We will show in Section 5.1 that supervised fine-tuning on Group A languages can hurt the zero-transcribed performance on Group B. In this zero supervised speech setting, we empirically found two additional techniques to improve performance of languages in Group B: i) upscaling unspoken text loss weight to 12.0; ii) loss tapering of the W2v-BERT loss in the last 50k steps of the training. These two modifications focus the training on text sources. An ablation study describes the value of these modifications in Section 5.3.

3.3. Handling unseen writing systems (scripts)

Our preliminary text injection experiment shows that performance of this approach substantially suffers when the target Group B language (being trained without any transcribed speech) has a textual form (script) (for example Brahmic), that has no overlap with any language in Group A, where transcribed speech is available. When the text encoder, trained on Group A, has never observed a script, the reliability of the alignments and thus the shared representation predictions suffer. The central problem we need to solve here is how to share information across scripts. We do this by converting input graphemes (text) into a common representation that is shared across all languages.

We explore different text representations for the input to the Maestro text encoder to enable more overlap across languages. Notably, while deriving these varieties of intermediate representations, the output targets (a.k.a. RNN-T decoder output) of the Maestro model is always the same native script grapheme units.

Assuming no extra human knowledge, we look at whether the model can learn script clustering implicitly. Since we assume that the text is machine readable, there is necessarily a digital representation of the text. We use the UTF-8 byte coding of the input text to establish a shared text representation of 256 encoding vocabulary size for the text encoder.

Table 2. Overall performance of Maestro-U: Models trained in the *supervised* setting include the available supervised training data (10 hours per language), while models trained in the *zero supervised training data* setting do not include any supervised data from the 50 languages in group **B**.

method	Paired	Text	Speech	Finetune	CER		
<i>Supervised setting on languages in Group A and B</i>					A+B	A	B
W2v-BERT	A+B	N	Y	Y	12.3	11.8	12.8
Maestro-U (proposed)	A+B	Y	Y	Y	8.7	7.8	9.7
<i>Zero supervised resource setting on languages in Group B</i>					A+B	A	B
W2v-BERT	A	N	Y	Y	41.3	17.4	66.2
Joint W2v-BERT	A	N	Y	N	46.5	29.0	64.8
Standard Maestro	A	Y	Y	N	39.6	25.5	54.2
Maestro-U (proposed)	A	Y	Y	N	21.1	11.8	30.8

Another approach is to use a pronunciation model that can map input text to phoneme (IPA, X-SAMPA) sequences, thereby modeling phonetic representations in the text encoder. These phonetic representations describe speech sounds in a language agnostic inventory. In this way, the duration and text representation prediction can be shared and implicitly clustered across different language scripts. However, high quality pronunciation models are expensive, and not readily available for all of the world’s languages, which limits the utility of this method.

A third approach to this problem might be to transliterate the text into a different script [34]. However, it is not clear that transliteration is a simpler problem to solve than pronunciation modeling. Transliteration models as they can be as error prone as pronunciation models. While we consider transliteration a reasonable approach to address the problem of unseen scripts, we leave this direction to future work.

We include these intermediate representations in a manner similar to [14]. We include two RNN-T decoders to model bytes and graphemes respectively. The byte RNN-T is then used to obtain the alignment for the text encoder when learning with bytes as input. With this design, the unspoken text is first converted to byte encodings and then extracted and upsampled by the text encoder. The text representations are then fed to the shared encoder. Both byte and grapheme decoders are used to enforce unspoken text learning through RNN-T losses. The final ASR hypothesis is produced by the target grapheme RNN-T decoder.

4. ARCHITECTURE DETAILS

Standard Maestro We follow the architecture in [14] as the standard Maestro model for aligned speech-text representation learning.

Speech encoder and shared encoder : The speech and shared encoders are a stack of “Conformer blocks”. We use the Conformer XL architecture described in [35] with 24 layers of full-context Conformer blocks (600M parameters) where the speech encoder comprises of the lower 6 layers and the upper 18 layers form the shared component, encoding both speech and text.

Text encoder : The text embedding extractor includes 512 dimensional input embedding lookup layer, 3 convolutional layers of 512 filters with kernel size (5, 1), followed by a 6-layer Transformer with positional embedding. Durations for the injected text are modeled by repeating the original text embedding to the target length of specified duration. The Refiner includes 2 layers of 8-headed self-attention blocks with 17×1 lightweight convolutions [36]. The du-

ration model includes four blocks of 3×1 lightweight convolutions transforming the original text embedding to predict the duration.

RNN-T decoder : We use a 2-layer, 1280-dim LSTM with a joint network of 640 dims as the RNN-T decoder. By default we use grapheme as the target with the vocabulary size of 6100 [21]. When using phoneme or byte as the target, we include an additional RNN-T decoder to predict to these and the original grapheme target independently.

Additions in Maestro-U The language embedding in the input of the RNN-T decoder has 1024 dimensions and it is added to the original shared encoder output embedding. The language embedding in the text encoder has 16 dimensions and it is concatenated with the text embedding extractor output. The language id based residual adapter [33] projects to a 32-dimensional bottleneck, passes through a ReLU non-linearity, then projects back up to the original size. They are added after each of the conformer block in the shared encoder.

We explore different text encoder inputs to handle the unseen scripts while the grapheme RNN-T decoder is always used to produce ASR hypotheses. We use UTF-8 bytes [37] as the text encoder input in the byte based experiments. X-SAMPA is used in the phoneme experiment.

Training hyper-parameters We include untranscribed speech, unspoken text, transcribed speech in each batch with fixed batch sizes, (1024, 8192, 512) respectively. To follow the pretrain setup in [14] where exponential-moving-averaged (EMA) with decay rate 0.9999 is used. A curriculum learning schedule starts from untranscribed speech-only training, includes transcribed speech after 500k steps and unspoken text after another 15k steps. The joint training of three types of data lasts for another 300k steps with a learning rate schedule and optimizer given in [38].

Optional supervised finetuning In zero supervised speech ASR, we directly evaluate Maestro using its RNN-T decoder output as no fine-tuning is possible. For the other settings, we use the available transcribed data to conduct supervised multilingual fine-tuning. All fine-tuning parameters follow [14]. Since Maestro training incorporates both an encoder and decoder, in fine tuning experiments, both components are pretrained.

5. EXPERIMENTS AND RESULTS

5.1. Overall Performance

The experiments in this paper fall under two scenarios: with supervised training data (manually labeled) and with zero supervised

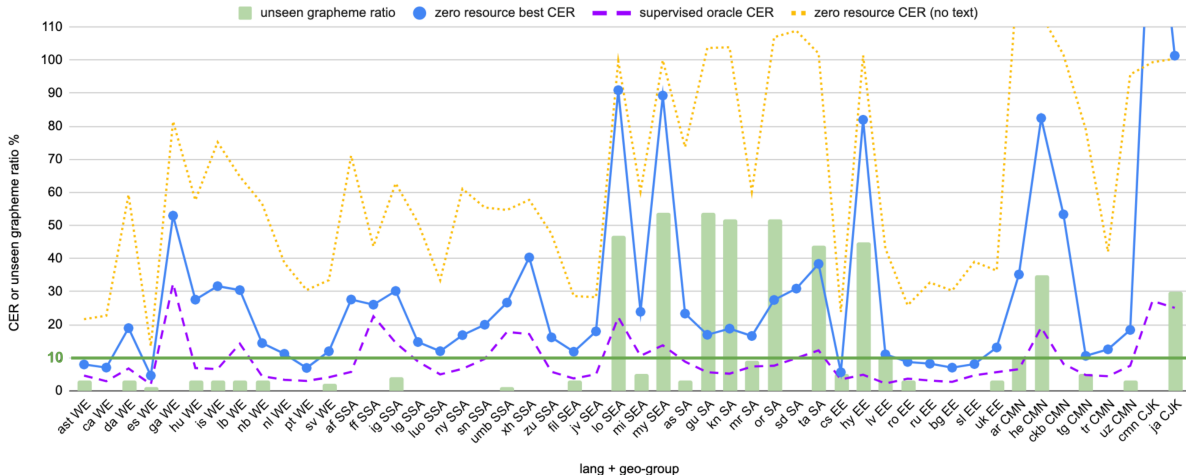


Fig. 2. Per-language breakdown of CER reduction with Maestro-U

speech. Both scenarios include any available untranscribed speech and unspoken text in all the languages. Table 2 summarizes the results under these two scenarios. In the *Supervised Setting* section of the table, the models are trained using all available supervised and unsupervised speech and unspoken text data from all the 102 languages, thus serving as our *oracle*. Column *A+B* presents the average performance of various models on all the 102 languages in the FLEURS corpus, while columns *A* and *B* denote performance on languages in group *A* and *B* respectively. We evaluate performance using Character Error Rate (CER) as proposed in [21]. We use a *W2V-BERT* model trained with untranscribed speech and fine-tuned with transcribed speech as the baseline for all experiments with no other text injection.

Our first observation is when supervised data is available, the proposed method (Section 3.2) is able to reduce the average CER for all language groups, showing an overall relative improvements of 29.2% for all 102 languages. A breakdown of the gains across language groups shows a relative win of 33.9% and 24% for languages in the groups *A* and *B* respectively.

The second half of Table 2 summarizes the performance of various models when zero supervised speech training material is available. The goal of this work is to bring the performance on the 50 languages in Group B as close as possible to Row 2 when supervised training data is available. We observe that the *W2V-BERT* model’s performance worsens across all datasets when the supervised material from Group B languages is no longer available, with Group B languages degrading significantly by nearly 4 times. Models *W2V-BERT* and *Joint W2V-BERT* perform very similar to each other on the languages in Group B while on Group A languages, *Joint W2V-BERT* is significantly worse. The difference between these two models is that the former is fine-tuned on supervised data from Group A languages, while the latter eliminates fine-tuning by including a supervised RNN-T loss in the pretraining stage of *W2v-BERT*, a design previously explored in [39–41].

The last two rows in the table clearly demonstrate the value of text injection. The proposed Maestro-U method significantly improves over both a speech-only baseline *W2V-BERT* and the text-injection method proposed in [14], referred to as *Standard Maestro* in this table. The proposed method in the supervised setting yields the best possible performance (*oracle*) with a 9.7% average CER on Group B languages. With no text injection and no supervised speech

for Group B languages, the best performance that can be obtained is an average CER of 64.8% (*no text baseline*). Injecting text using Maestro-U results in an average CER of 30.8%, closing the gap to oracle performance significantly by 68.5% relative.

Table 3. Average CER Performance of various models on South Asian Languages from Group A and B.

method	SA Group A	SA Group B
Grapheme Maestro	9.7	59.0
+ G2P	8.9	14.1
+ byte	9.4	18.3
Oracle maestro	11.2	11.6
No text baseline	13.7	100.0

5.2. Analysis of Maestro-U on unseen writing systems

We analyze the behavior of the proposed model using a subset of the 13 South Asian languages (SAs) with very little to no graphemic overlap with the target languages (Note that the presence of some latin script is unavoidable due to code-switching in these target languages). The unseen grapheme ratio (defined in Section 2) of the 6 languages with zero-supervised-speech ranges from 5% to 56% and the average is 37.2%.

Figure 3 illustrates the behavior of several text injection methods using an utterance from *Tamil*. When the model is trained only with untranscribed speech from the set of Group B languages but without any form of text injection, there is no hypotheses produced during inference in the writing system of the target language (H2). In this extreme case, the model produces no output as it is impossible to learn a correlation between the writing system and the speech signal. Meanwhile, when the model is free to produce a hypothesis unconstrained by a language embedding, it babbles in the closest *sounding* language seen in the training data (H3).

With a duration model trained on graphemes from Group A languages (H4), the model is able to output graphemes in the target language. Graphemes in the target language are hypothesized only when the target language’s embedding is available to the model during training and inference. However, the model can still output graphemes from random languages and even form invalid words in

data. Using a massively multilingual setting comprising of 102 languages, of which 50 languages have zero supervised training data, we show that Maestro-U is capable of multilingual knowledge transfer. On these 50 languages, Maestro-U successfully brings the CER of **9 languages below 10%** and **19 languages below 15%** closing the gap to oracle performance by 68.5% relative. We show significant improvements on languages with and without overlapping writing systems, thereby making Maestro-U a viable solution for expanding to new languages and serving as a foundation model for massively multilingual ASR.

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