ADAPT-AND-ADJUST: OVERCOMING THE LONG-TAIL PROBLEM OF MULTILINGUAL SPEECH RECOGNITION

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ABSTRACT

One crucial challenge of real-world multilingual speech recognition is the long-tailed distribution problem, where some resource-rich languages like English have abundant training data, but a long tail of low-resource languages have varying amounts of limited training data. To overcome the long-tail problem, in this paper, we propose the Adapt-and-Adjust (A2), a transformer-based multi-task learning framework for end-to-end multilingual speech recognition. The A2 framework overcomes the long-tail problem via three types of techniques: (1) exploiting a pretrained multilingual language model (mBERT) to improve the performance of low-resource languages; (2) proposing dual adapters consisting of both language-specific and language-agnostic adaptation with minimal additional parameters; (3) overcoming the class imbalance either by imposing class priors in the loss during training or adjusting the logits of softmax output during inference. Extensive experiments on the CommonVoice corpus show that A2 significantly outperforms conventional approaches for end-to-end multilingual speech recognition.

1 INTRODUCTION

Deploying a single Automatic Speech Recognition (ASR) model to recognize multiple languages is highly desired but very challenging for real-world multilingual ASR scenarios due to the well-known long-tailed distribution challenge, i.e., some resource-rich languages like English have abundant training data while low-resource languages have limited varying amounts of training data. The recent popular end-to-end (E2E) monolingual ASR architecture (Graves et al., 2013; Chan et al., 2015; Vaswani et al., 2017) is promising for achieving state-of-the-art performance for resource-rich languages but suffers dramatically from the long tail of low-resource languages due to the lack of training data. This paper aims to investigate an end-to-end multilingual ASR framework where a single model is trained end-to-end from a pooled dataset of all target languages to improve multilingual ASR tasks' overall performance, especially for low-resource languages.

Building an end-to-end multilingual ASR is notoriously challenging due to the long-tail data distribution. This imbalanced dataset setting poses a multitude of open challenges for multi-task training, where the distribution of the training data is very skewed. We can elaborate on this in two aspects. First, there are very limited audio samples available on low-resource languages, such as Kyrgyz, Swedish, and Turkish. Simultaneously, there are vast amounts of high-resource language data, such as English, French, and Spanish. Second, the graphemes or subword labels' distribution follows a long-tailed distribution in ASR since some labels appear significantly more frequent, even for a monolingual setting. Furthermore, a multilingual system may include languages with various writing scripts other than Latin alphabets, such as Chinese or Cyrillic, that eventually maximize the skewness. To further illustrate the long-tail distribution of our study, Figure 1 shows the frequencies of the word piece tokens in the curated multilingual CommonVoice dataset (Ardila et al., 2020).

While a standard end-to-end multilingual multi-task training approach can improve overall performance compared with the monolingual end-to-end approaches, it cannot fully overcome the long-tail problem. One of the key reasons is the class imbalance issue, which will make the multilingual model bias towards the dominant languages. To address the class imbalance issue, one straightforward approach is to resample the training data (Kannan et al., 2019; Pratap et al., 2020) during batch assemble. However, such an ad-hoc approach does not fully resolve the underlying long-tail distribution problem, and only a marginal improvement is obtained in practice.

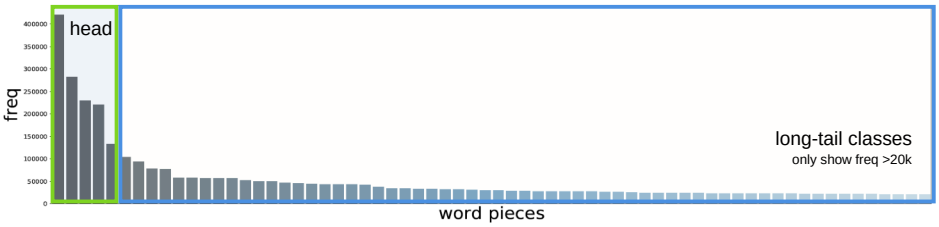


Figure 1: The long-tail distribution of word piece tokens in the curated multilingual CommonVoice dataset. The head classes are tokens have high frequency, otherwise they are classified as tail classes.

In this paper, we propose the Adapt-and-Adjust (A2) framework for multilingual speech recognition using a speech transformer to address the long-tail data distribution issue. For adapting the multilingual network to specific languages, both language-specific and language-agnostic adapters are augmented to each encoder and decoder layer for adaptation of the multilingual model to each language with minimal additional parameters. While the language-specific adapters focus on adapting the shared network weights to a particular language, a common adapter is proposed to learn some shared and language-agnostic knowledge for better knowledge transfer across languages. Moreover, to increase the relative margin between logits of rare versus dominant languages, we perform class imbalance adjustments during multilingual model training or inference by revisiting the classic idea of logit adjustment (Zhou & Liu, 2006; Menon et al., 2020). Class imbalance adjustment (Collell et al., 2016; Menon et al., 2020; Cui et al., 2019) is applied by adjusting the logits of softmax input with the class priors. Lastly, for better language modeling, a distilled mBERT (Devlin et al., 2019) is converted to an autoregressive transformer decoder to jointly explore the multilingual acoustic and text space to improve the performance of low-resource languages.

We conduct experiments and establish a benchmark from the CommonVoice corpus with a realistic long-tailed distribution of different languages. Extensive experiments show that A2 significantly outperforms conventional approaches for end-to-end multilingual ASR. Our key contributions are:

- We propose the Adapt-and-Adjust (A2), a novel end-to-end transformer-based framework for real-world multilingual speech recognition to overcome the long-tail challenge;
- We demonstrate the effectiveness of utilizing a pretrained multilingual language model as a speech decoder to improve multilingual text representations and language adapters to better share the learned information across all languages. To the best of our knowledge, this work is the first to adapt a pretrained multilingual language model for multilingual ASR.
- We show that incorporating class priors during training or inference is effective and essential to address the long-tail issue in multilingual training.
- We establish a reproducible multilingual speech recognition benchmark with long-tailed distributions of 11 languages from different language families for the research community.

We will release the code of our implementations and the data sets as a benchmark to facilitate the research on addressing the long-tail problem of multilingual ASR.

2 Adapt-and-Adjust Framework

2.1 Overview

Figure 2 gives an overview of the proposed Adapt-and-Adjust framework for end-to-end multilingual ASR tasks. Our framework improves a basic transformer-based sequence-to-sequence model by proposing three key novel contributions: (1) mBERT based decoder, (2) language adapters, and (3) class-imbalance adjustments. First of all, we extend the basic transformer framework by replacing the vanilla decoder with an mBERT model for better language modeling, particularly for low-resource languages. Second, the common and language-specific adapters are added to each encoder and decoder layer to learn both the shared and language-specific information for better adaptation capability. Finally, we perform class imbalance adjustments during training or inference

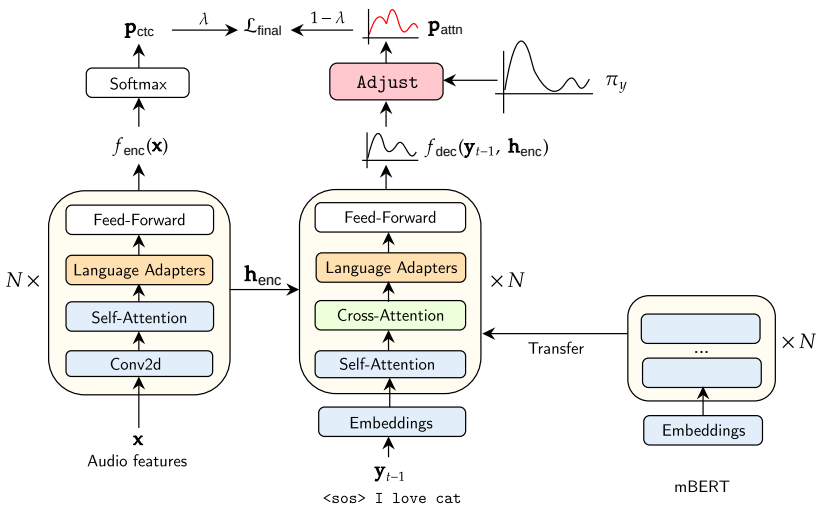


Figure 2: Overview of the Adapt-and-Adjust (A2) framework. Layer norm is omitted to save space. $\mathbf{p}_{\text{ctc}}$ is the output of the connectionist temporal classification (CTC) branch, $\mathbf{p}_{\text{attn}}$ is the output of the decoder, and $\mathbf{y}_{t-1}$ is the previous token. Three key components are: (1) a pre-trained language model mBERT based decoder to improve the performance of low-resource languages; (2) language adaptation via the proposed dual adapters; and (3) class-imbalance adjustment either during training or inference by adjusting the logits $f_{\text{dec}}(\mathbf{y}_{t-1}, \mathbf{h}_{\text{enc}})$ with class priors π_y.

phase, in which the logits to the softmax layer are adjusted with the class priors estimated from the training data. From a Bayesian perspective, the classifier after the logit adjustment minimizes a balanced error where both the head and tail classes contribute equally to the training.

2.2 Base Model: Hybrid CTC-Attention Speech Transformer

A sequence-to-sequence speech transformer model (Dong et al., 2018; Kim et al., 2016; Karita et al., 2019b) based on the hybrid CTC-Attention network is used for acoustic modeling. It takes in the acoustic features $\mathbf{x} \in \mathbb{R}^{T\times F}$ and outputs the sentence piece tokens $\mathbf{y}$, where T, F denote sequence length and feature dimension. The encoder consists of several 2D convolution layers followed by self-attention layers. The convolution layers are used to extract more robust features before they are sent to the transformer. The decoder layers have two attention mechanisms, one for self-attention and the other one for the encoder output. The network is trained in an autoregressive manner by predicting the next token given the current output. In addition, CTC layer (Graves et al., 2006) is added to the encoder output to serve as a regularizer to the attention model.

Training Multi-task loss $\mathcal{L}_{\text{MTL}}$ (Watanabe et al., 2018; Karita et al., 2019b) combining the CTC loss (Graves et al., 2006) and attention loss $\mathcal{L}_{\text{ATTN}}$ is used to train the speech transformer. The multi-task loss is computed as an interpolation of two losses with a hyper-parameter λ ($0 \leq \lambda \leq 1$):

$$\mathcal{L}_{\text{ATTN}} = \text{KL}(\mathbf{p}_{\text{attn}} || \mathbf{p}_y), \tag{1}$$

$$\mathcal{L}_{\text{MTL}} = \lambda \log \mathbf{p}_{\text{ctc}}(\mathbf{y}|\mathbf{h}_{enc}) + (1-\lambda)\mathcal{L}_{\text{attn}}, \tag{2}$$

where $\mathbf{p}_y$ is the label distribution after label smoothing (Müller et al., 2019) to prevent the model from making over-confident predictions. Kullback-Leibler Divergence loss (KL) (Kullback & Leibler, 1951) instead of cross-entropy is used for the attention loss. The probability distribution $\mathbf{p}_{\text{ctc}}(\mathbf{y}|\mathbf{h}_{enc})$ is computed by using dynamic programming.

Decoding Beam search is used to predict the sentence pieces without any additional language models. The decoding score is computed as a weighted sum of both the CTC and attention network probabilities by using β as the decoding parameter to balance them (Karita et al., 2019a).

$$\hat{\mathbf{y}} = \underset{\mathbf{y}\in\mathcal{Y}^*}{\arg\max}\{\beta p_{\text{ctc}}(\mathbf{y}|\mathbf{h}_{\text{enc}}) + (1-\beta)p_{\text{attn}}(\mathbf{y}|\mathbf{h}_{\text{enc}}, \mathbf{y}')\}, \tag{3}$$

where $\mathbf{y}'$ is the decoded sequence so far.

2.3 MULTILINGUAL BERT AS TRANSFORMER DECODER

For better language modeling, especially for low-resource languages, mBERT is used as the transformer decoder. Since mBERT was initially trained on text data, to jointly explore the acoustic and text space, it is essential to augment a cross-attention layer to the encoder output for each mBERT layer and its self-attention layer to "align" the two spaces for the speech recognition task. This is because the text space may diverge significantly from the acoustic space of the encoder output. Another change is that the mBERT is autoregressive: future positions are masked for prediction, given the current output token and the encoder output.

Autoregressive mBERT Figure 3 depicts the changes made to the mBERT so that it can be used as the autoregressive speech transformer decoder. We copy embeddings and self-attention parameters of mBERT into a randomly initialized decoder model. Let t denote the current decoding step. The autoregressive decoder takes the current input token y_t to predict the next token y_{t+1}. The mBERT embedding layer converts the input token to a vector representation, which is used as the key, value, and query of the self-attention layer. Subsequently, the cross-attention layer takes the encoder output $\mathbf{h}_{enc}$ as the key and value, the self-attention output as the query, and compute the attention output.

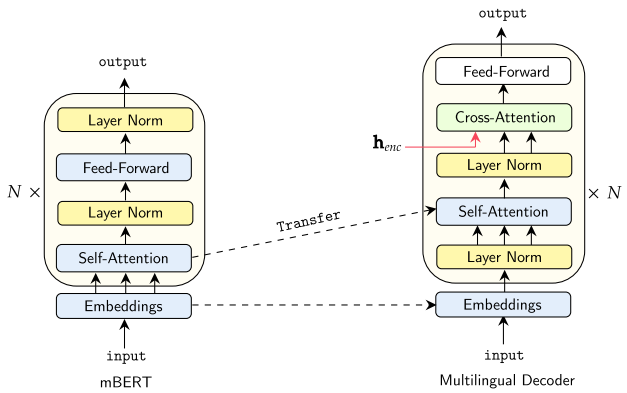


Figure 3: Parameter transfer from a pre-trained multilingual language model to a speech recognition decoder. The dotted line shows the transfer direction from a specific module of the model.

Vocabulary Mapping The vocabulary size of the vanilla mBERT is too large (119,547 tokens) for training the end-to-end speech recognition system. Therefore, vocabulary mapping is performed to reduce the number of targets for the speech transformer. In this work, sentence pieces (SP) (Kudo, 2018) are used as the target tokens for all the end-to-end ASR systems. The SP models are trained on the transcriptions with a preset number of vocabulary size. In this work, we use a shared set of 5,237 tokens as the multilingual system's vocabulary. The minimum number of the token set for the sentence piece model is 150 for all the monolingual systems, except Chinese with 2,265 tokens. The generated sentence piece tokens are then matched against the mBERT token set. During training, the embeddings of all tokens in the mBERT vocabulary are initialized with mBERT embeddings.

2.4 LANGUAGE ADAPTERS

Similar to Kannan et al. (2019), lightweight residual language adapters are used to mitigate the data imbalance issues. As shown in Figure 4, in addition to the language-specific adapter for capturing the language-intrinsic knowledge, a common shared adapter is also trained to learn language-agnostic information in the multilingual data; we call this **Dual-Adapters**. The language-specific and common adapters are denoted as A_{lang} and A_{com} respectively. Each adapter of layer l consists of a down-projection layer $\mathbf{W}_d^l$, followed by a ReLU activation function, and an up-projection layer $\mathbf{W}_u^l$. The adapters take $\mathbf{h}^l$ as the input, where $\mathbf{h}^l$ is the self attention output of layer l. We compute the output of the adapter $\text{Adapter}(\mathbf{h}^l)$ as following for both language-specific and common adapters:

$$\text{Adapter}(\mathbf{h}^l) = \mathbf{W}_u^l(\text{ReLU}(\mathbf{W}_d^l(\text{LayerNorm}(\mathbf{h}^l)))) + \mathbf{h}^l. \tag{4}$$

Afterwards, the final adapter output $\mathbf{o}^l = \mathbf{o}^l_{\text{lang}} + \mathbf{o}^l_{\text{com}}$. Then, $\mathbf{o}^l$ is used as the input to the next encoder or decoder layer. We create a language mask to specify the language-specific adapters.

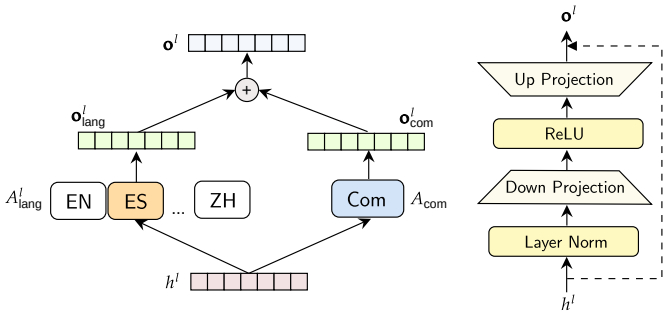


Figure 4: Dual-Adapters. The orange box presents the active language-specific adapter and the blue box presents the common adapter. The figure on the right shows the language adapter structure.

2.5 Word Piece Class Imbalance Adjustments

In addition to the architecture extension with language adapters, the class imbalance problem is addressed to incorporate the class priors during training or inference via logit adjustments. Derived from a Bayesian classifier point of view in Menon et al. (2020) for computer vision tasks, the softmax classifier with adjusted logits as input minimizes the balanced error across all classes. A natural adjustment is to scale the logits $f_y(x)$ by the inverse of its class prior π_y. In log domain, the logit adjustment can be performed as following:

$$f_y^{\text{adj}}(x) = f_y(x) - \tau \cdot \log \pi_y, \tag{5}$$

where $\tau > 0$ is a hyper-parameter. The adjustment can be viewed as applying a class-dependent offset to re-weight each logit according to its class prior. The logit adjustment can be performed either during both model training or inference.

Class priors The class priors are the natural frequencies of the sentence piece tokens estimated from the multilingual training data. To form a valid prior distribution, smoothing is applied to the raw counts according to Equation 6 for zero occurrence tokens:

$$\pi_y = \begin{cases} \frac{C_i}{C} - \frac{1}{(N-n_0)\times C}, & c_i > 0 \\ \frac{1}{n_0 \times C}, & \text{otherwise}, \end{cases} \tag{6}$$

where C is the total number of counts for all labels, n_0 is the number of labels with zero occurrences, N is as the number of classes and c_i is the raw count of class i.

Training phase: class imbalance adjustments To incorporate the priors during training, the logits $f^{\text{dec}}_{y_t}$ of the last decoder layer are adjusted before softmax according to the following:

$$f^{\text{dec}}_{y_t} = w_y^T \cdot \text{Decoder}(\mathbf{h}_{\text{enc}}, \text{Embedding}(y_{t-1})) \tag{7}$$

$$f^{\text{adj}}_{y_t} = f^{\text{dec}}_{y_t} - \tau \cdot \log \pi_{y_t}, \tag{8}$$

$$p^{\text{adj}}_{y_t} = \frac{\exp(f^{\text{adj}}_{y_t})}{\sum_{y'_t \in [N]} \exp(f^{\text{adj}}_{y'_t})} \tag{9}$$

The adjusted softmax output vector $\mathbf{p}^{\text{adj}}_y$ of the sequence is used to compute the KL loss and perform the backward propagation to update the model. y_{t-1} is the previous label available only during training. To reduce the training and inference discrepancy, scheduled sampling (Bengio et al., 2015) is commonly used for the sequential classification tasks like speech recognition. During later training iterations, instead of using the ground truth label y_{t-1} for computing the logits, y'_{t-1} is chosen from the maximum prediction output of the current model to simulate the inference:

$$y'_{t-1} = \underset{y}{\text{argmax}}\, \mathbf{p}^{\text{adj}}_{y_{t-1}} \tag{10}$$

If the scheduled sampling is used, the adjusted logits at step t will have influence over all following tokens in the current sequence. This is a crucial difference from the image classification task in Menon et al. (2020). If τ is set to be 1, the training phase logit adjustment becomes similar to the widely used label smoothing technique Müller et al. (2019). However, in conventional label smoothing, the prior π_y is usually a uniform distribution that is independent of the data. The logit adjustment applies a class-specific "smoothing" based on the class prior and has shown to be superior than the baseline with the standard label smoothing.

Inference phase: class imbalance adjustments Alternatively, the class priors can be incorporated during inference via logit adjustments. The decoding score is computed as following:

$$\hat{\mathbf{y}} = \arg\max_{\mathbf{y} \in \mathcal{Y}^*} \{\beta p_{\text{ctc}}(\mathbf{y}|\mathbf{h}_{\text{enc}}) + (1-\beta) p_{\mathbf{y}}^{\text{adj}}\} \tag{11}$$

During beam search, the attention decoding scores $p_{\mathbf{y}}^{\text{adj}}$ are computed in the same way as the scheduled sampling from the adjusted logits.

3 EXPERIMENTS

3.1 EXPERIMENTAL SETUP

Dataset The CommonVoice dataset (Ardila et al., 2020) is a multilingual corpus collected by Mozilla. Similar to (Conneau et al., 2020), we use 11 languages: *English (en), Spanish (es), French (fr), Italian (it), Kyrgyz (ky), Dutch (nl), Russian (ru), Swedish (sv), Turkish (tr), Tatar (tt),* and *Chinese (zh)*. The dataset is split into training, dev, and eval set according to the ESPnet recipe. The transcriptions are tokenized using the SentencePiece model with the unigram algorithm. We train our SentencePiece model using our transcription data, and the size of the vocabulary is shown in Table 10. We then add special tokens, such as <unk>, <sos>, <eos>, and a blank token for the CTC objective. The data split is shown in Table 6.

Network configurations We use six transformer encoder layers with a hidden size of 2048 units and eight attention heads, each with an attention dim of 256. For the decoder, distil-mBERT (Sanh et al., 2019) is used. The mBERT decoder consists of six transformer decoder layers with a hidden size of 3072 and an attention dim of 756, and four attention heads. We train our model with a batch size of 32 and accumulate the gradient in two steps to have a larger batch size in a single GPU NVIDIA V100 16GB with Adam optimizer with a warm-up step of 25000. Particularly, for the balance sampling, we take six samples for each language and construct a balanced batch by accumulating gradient 11 times. Gradient clipping of 5 is applied to stabilize the training.

Training and Evaluation We evaluate our model using beam-search with a beamwidth of 10 and $\lambda = 0.3$ and $\beta = 0.5$. The hyperparameter τ is set to 0.3 for both training and inference phase class imbalance adjustments. The multilingual models are trained with 150K iterations. We compute the average over the last ten checkpoints as the decoding model. For the monolingual setting, we stop after 100 epochs of training. Models are evaluated using the character error rate (CER) to simplify the evaluation and have a universal metric for all languages.

Baselines As baseline approaches, we consider **Monolingual**: we train monolingual models; **SMT**: Standard Multilingual Training, we randomly sample the batch from the data distribution; **BS**: Balanced Sampling, we sample the same number of utterances for each language in a batch so that they have roughly equal contributions to the training; **LAN-Specific Adapters**: language-specific adapters proposed by Kannan et al. (2019); and language conditioning with one-hot language vectors **LID** proposed by Li et al. (2018).

3.2 RESULTS

In Table 1, we present the test results on the CommonVoice dataset. Compared to the monolingual models, even SMT models improve the performance of the low-resource languages significantly. We conjecture that this may be because the multilingual model can capture common sub-phonetic articulatory features (Kirchhoff et al., 2002; Metze, 2005; Livescu et al., 2007; Wang & Sim, 2014) that are shared by different languages and beneficial for the low-resource languages recognition.

Balanced Sampling We observe the same trend as in Kannan et al. (2019): compared to the MT, the tail classes performance has been significantly boosted. However, the head classes suffer from the balanced sampling due to fewer occurrences during training and possibly model overfitting to the tail classes. Consequently, the overall performance is the same as MT. In fact, even after balanced sampling, the sentence piece tokens still have a long-tailed distribution as shown in Appendix.

Table 1: Test results in CER (%) on the CommonVoice dataset.

	high-resource			**intermediate**					**low-resource**			
	en	**fr**	**es**	**it**	**ru**	**zh**	**tt**	**nl**	**tr**	**ky**	**sv**	**avg**
Train hour	80	50	40	20	15	15	15	15	10	9	4	
Monolingual	21.6	19.8	16.8	24.7	26.6	38.4	22.0	44.2	30.3	31.6	57.7	30.3
SMT	**20.1**	**17.4**	**13.0**	**12.5**	13.7	**34.1**	**12.2**	**18.7**	**13.9**	**14.4**	**26.4**	**17.9**
BS	25.2	20.3	14.5	12.7	13.2	32.6	11.5	18.0	12.9	13.4	22.8	17.9
LAN-Specific Adapters	**24.2**	19.4	13.9	12.3	11.8	32.0	10.7	16.9	11.8	12.7	**21.7**	17.0
LID	25.7	19.2	13.7	12.0	12.0	31.6	10.8	16.4	12.0	12.5	21.8	17.1
LID + Adjust-Train	24.7	**18.5**	**13.0**	**11.3**	**11.6**	**31.2**	**10.4**	**16.4**	**11.6**	**12.4**	22.0	**16.6**
A2 (Adjust-Inference)	22.6	17.9	12.7	**11.2**	11.2	**30.1**	10.2	**15.8**	11.4	12.2	**21.1**	**16.0**
A2 (Adjust-Train)	**22.0**	**17.7**	**12.5**	11.3	**11.1**	30.4	**10.0**	15.9	**11.3**	**12.1**	21.3	**16.0**

Language Adapters We then compare different language adaptation techniques, including the LAN-Specific Adapters (Kannan et al., 2019), the one-hot language vector (Li et al., 2018), and the Dual-Adapters. Note that all adapters are based on the BS + mBERT, which has a better performance than the BS only model. We study the impact of mBERT in a separate part. Different from findings in Kannan et al. (2019), where a marginal 0.2% LAN-Specific Adapters, adding adapters helps all the languages. Adding the language-specific adapters without common adapters significantly outperform the BS baseline with 0.9% absolute performance gain. Another way of injecting language information is to augment a one-hot language vector. We observe the same results as Kannan et al. (2019), where the language-specific adapters perform slightly better than the language vector. Interestingly, if word piece class imbalance adjustment (LID + Adjust-Train) is applied to the language vector, a significant CER improvement is achieved.

Word Piece Class Imbalance Adjustment In addition, the long-tail distribution issue is further addressed with class imbalance adjustments. Both the training and inference phase adjustments provide a significant performance gain over the LAN-Specific Adapters with 1% absolute CER reduction. The gains are mostly due to the improved performance of the head languages, although tail languages also benefit from the logit adjustments. More importantly, the gap between the monolingual and multilingual performance for the head classes is greatly reduced, leading to a better "balanced error" performance. This strongly justifies the importance of class imbalance adjustments. Some examples of transcriptions from models with different techniques are given in Appendix D.

3.3 Ablation Studies

3.3.1 Multilingual BERT

The effectiveness of mBERT is presented in Table 2. The performance of mBERT depends heavily on the quality of acoustic models. Without adapters and logit adjustments, the improvement over BS is marginal and mBERT performance is even worse if standard multilingual training is used. This may indicate that with better acosutic models like A2, the text space of the vanilla mBERT is better aligned with the acoustic space, which leads to improved recognition performance across all languages, especially for low-resource languages. It is also interesting to note that even without adapters or balanced sampling, the "SMT + mBERT + Adjust-Train" system yields the same overall performance as the best adapter system (BS + mBERT + Dual-Adapters).

3.3.2 Language Adapters

In this section, we investigate the impacts of different language adapter configurations. The results and parameter sizes are given in Table 3. Generally speaking, adding adapters in the decoder

Table 2: Ablation Study on mBERT for multilingual speech recognition

	en	fr	es	it	ru	zh	tt	nl	tr	ky	sv	avg
SMT	**20.1**	**17.4**	**13.0**	**12.5**	**13.7**	**34.1**	**12.2**	**18.7**	**13.9**	14.4	26.4	**17.9**
SMT + mBERT	20.4	17.9	13.4	13.0	14.0	34.8	12.4	18.9	14.0	**14.3**	**26.2**	18.1
BS	25.2	20.3	**14.5**	12.7	**13.2**	**32.6**	11.5	18.0	12.9	13.4	**22.8**	17.9
BS + mBERT	**25.0**	**20.0**	15.4	**12.6**	**13.2**	32.9	**11.1**	**17.3**	**12.6**	**12.8**	**22.8**	**17.8**
BS + Dual-Adapters	23.5	18.9	13.5	12.1	12.3	31.0	10.9	16.5	12.0	12.9	21.6	16.8
BS + Dual-Adapters + mBERT	**23.4**	**18.6**	**13.4**	**11.8**	**11.7**	**30.8**	**10.8**	**16.2**	**11.6**	**12.4**	**21.5**	**16.5**
SMT + Adjust-Train	20.2	16.9	12.5	11.9	13.1	32.9	11.3	18.5	13.5	13.9	25.3	17.3
SMT + Adjust-Train + mBERT	**19.4**	**16.5**	**12.1**	**11.7**	**12.2**	**31.1**	**11.0**	**17.5**	**12.7**	**13.2**	**24.6**	**16.5**

layers is not as effective as in the encoder layers, indicating adaption of acoustic space is much more effective than the text space. Therefore, considering the extra computation and parameters, it is advisable to apply only the encoder adapters with only 2M increase in parameters. We

Table 3: Ablation Study on language adapters impacts in BS + mBERT models

	Params	en	fr	es	it	ru	zh	tt	nl	tr	ky	sv	avg
No Adapter	76M	25.0	20.0	15.4	12.6	13.2	32.9	11.1	17.3	12.6	12.8	22.8	17.8
Decoder Adapter Only	82M	23.6	19.2	13.7	12.2	**11.7**	32.5	**10.3**	16.7	11.7	**12.2**	21.4	16.8
Encoder Adapter Only	78M	**23.1**	**18.5**	**13.3**	**11.8**	**11.7**	31.1	10.6	**16.0**	**11.5**	12.6	**21.3**	**16.5**
Encoder + Decoder	84M	23.4	18.6	13.4	**11.8**	**11.7**	**30.8**	10.8	16.2	11.6	12.4	21.5	**16.5**

then investigate the effectiveness of the common language adapters as shown in Table 4. The Dual-Adapters outperforms the language specific adapters significantly by a 0.5% absolute CER reduction, indicating the knowledge transfer with common adapter is effective.

Table 4: Ablation Study of common and language-specific adapters. *The difference of parameters between LAN-Specific Adapters (Kannan et al., 2019) and Dual-Adapters is very small (<1M).

	Params	en	fr	es	it	ru	zh	tt	nl	tr	ky	sv	avg
LAN-Specific Adapters	84M*	24.2	19.4	13.9	12.3	11.8	32.0	**10.7**	16.9	11.8	12.7	21.7	17.0
Dual-Adapters	84M*	**23.4**	**18.6**	**13.4**	**11.8**	**11.7**	**30.8**	10.8	**16.2**	**11.6**	**12.4**	**21.5**	**16.5**

3.3.3 CLASS-IMBALANCE ADJUSTMENTS: TRAINING VS. INFERENCE

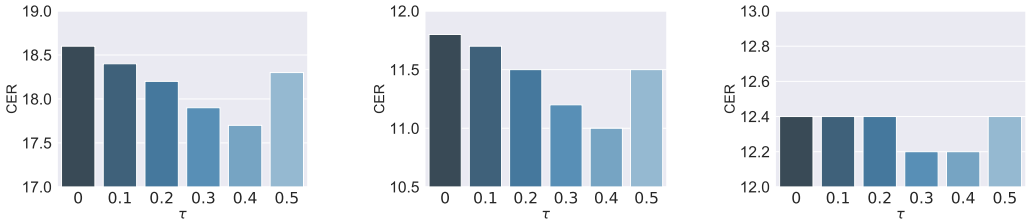
The two logit adjustment variants are compared with different network configurations in Table 5. For the standard multilingual training system, the training phase adjustment shows a clear advantage over the inference phase adjustment. Under the convex assumption, the solution of the two adjustment approaches is the same. However, deep neural network optimization is a non-convex problem, they may converge to different local minima. Therefore, for the standard training, the model is heavily biased towards the head classes. Training phase class imbalance adjustment can help the training more focus on the tail classes, leading to much balanced and lower errors. With more efforts devoted to the long-tail problem, for example, balanced sampling or language adapters, although the initial models still perform worse, the inference phase adjustment can better calibrate the raw classification scores and yield similar performance to the training phase adjustment.

Table 5: Training and inference phase logit adjustments with different A2 models

	Params	en	fr	es	it	ru	zh	tt	nl	tr	ky	sv	avg
SMT + mBERT +	76M	20.4	17.9	13.9	13.0	14.0	34.1	12.4	18.9	14.0	14.3	26.2	18.1
Adjust-Inference	76M	20.1	17.2	13.4	12.2	13.2	34.0	11.5	18.3	13.4	**13.2**	26.1	17.6
Adjust-Train	76M	**19.4**	**16.5**	**12.1**	**11.7**	**12.2**	**31.1**	**11.0**	**17.5**	**12.7**	**13.2**	**24.6**	**16.5**
BS + mBERT +	76M	25.0	20.0	15.4	12.6	13.2	32.9	11.1	17.3	12.6	12.8	22.8	17.8
Adjust-Inference	76M	24.1	19.3	13.5	12.0	12.1	32.3	10.6	**16.7**	12.2	**12.6**	22.2	17.0
Adjust-Train	76M	**23.8**	**19.1**	**13.4**	**11.9**	**11.8**	**32.4**	**10.5**	**16.7**	**12.1**	**12.6**	**21.5**	**16.9**
BS + mBERT + Dual-Adapters +	84M	23.4	18.6	13.4	11.8	11.7	30.8	10.8	16.2	11.6	12.4	21.5	16.5
Adjust-Inference	84M	22.6	17.9	12.7	**11.2**	11.2	**30.1**	10.2	**15.8**	11.4	12.2	**21.1**	**16.0**
Adjust-Train	84M	**22.0**	**17.7**	**12.5**	11.3	**11.1**	30.4	**10.0**	15.9	**11.3**	**12.1**	21.3	**16.0**

3.3.4 EFFECTS OF τ ON INFERENCE PHASE LOGIT ADJUSTMENT

Figure 5 depicts the CERs of the systems with different τ for inference phase logit adjustment with the best A2 configuration: balanced sampling with mBERT and dual adapters. We choose one language from each group and other languages demonstrate the same trend. From Figure 5, the advantage of the logit adjustment is clearly shown compared to the baseline without logits adjustment ($\tau = 0$). All languages achieve their best CER with a τ value of $\tau = [0.3, 0.4]$. Performance saturates with heavier smoothing ($\tau >= 0.5$).



(a) High-resource (fr) (b) Intermediate (it) (c) Low-resource (ky)

Figure 5: Comparison of models with different τ.

4 RELATED WORK

Long-Tail Conventional approaches for addressing the long-tail problem are focused on data sampling methods (Kubat & Matwin, 1997; Chawla et al., 2002; Wallace et al., 2011). On the other hand, normalization approaches for balancing loss have been extensively studied (Morik et al., 1999; Menon et al., 2020). Recently, the long-tail distribution issue has received interest in the context of neural network models, and several approaches are proposed, such as weight normalization (Kang et al., 2019), adaptive margin (Cao et al., 2019), and equalized loss (Tan et al., 2020).

Adapters Adapters were first proposed to learn domain-specific representations in computer vision in a parameter-efficient way (Rebuffi et al., 2017). It was subsequently adopted for NLP tasks to avoid fine-tuning a new model for each task by training an adapter module for each task while sharing the pre-trained language model parameters (Houlsby et al., 2019; Lin et al., 2020). The invertible adapters were proposed in Pfeiffer et al. (2020a;b) to effectively adapt an existing pre-trained multilingual model to unseen languages for multi-task cross-lingual transfer.

Multilingual ASR E2E architectures like LAS (Toshniwal et al., 2018) and Recurrent Neural Transducer (Kannan et al., 2019) have been used for building a multilingual ASR system for a group of Indian languages. In Kannan et al. (2019), language adapters are used to tackle the data imbalance problem, although the improvement of using language adapters is marginal compared to the language vector augmentation. Acoustic vector quantization is also used in a recent work Conneau et al. (2020) for multilingual ASR. A massive multilingual ASR study with more than 50 languages and more than 16,000 hours of speech is presented in Pratap et al. (2020). The two main techniques are data resampling and language clusters, which bear some similarities with our balanced sampling and language adapters. Unfortunately, their datasets are not publicly available.

5 CONCLUSION

In this paper, we introduce the Adapt-and-Adjust (A2), an end-to-end transformer-based framework to address the crucial challenge of long-tail data distribution issues in multilingual speech recognition. A2 consists of three major components, namely language adapters, class imbalance adjustments, and a pretrained multilingual language model. Extensive experiments on the CommonVoice corpus show that A2 significantly outperforms conventional approaches for end-to-end multilingual speech recognition due to 1) better acoustic modeling with adapters and class imbalance adjustments; 2) better language modeling with pretrained multilingual BERT.

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A A2 ALGORITHM

The full algorithm of A2 framework with Adjust-Train training phase is outlined in Algorithm 1.

Algorithm 1 Adapt-and-Adjust (A2) with Adjust-Train

Require: $p(\mathcal{T})$: distribution of tasks
Require: θ: an encoder-decoder model
Require: α, λ: step size hyperparameters

randomly initialize θ
transfer language model parameters to decoder parameters in θ
compute class priors π from $p(\mathcal{T})$
while not done **do**
    Sample batch of tasks $\mathbf{x} \sim p(\mathcal{T})$
    Generate language adapter mask $\mathbf{m}$ using the language information from $\mathbf{x}$
    Compute encoder hidden states $\mathbf{h}_{enc}$ using $\mathbf{x}$ and $\mathbf{m}$ by forward propagation on the encoder
    Compute attention logits $\mathbf{y}$ using $\mathbf{h}_{enc}$ and $\mathbf{m}$ by forward propagation on the decoder
    Adjust logit generated from decoder in Equation (5)
    Compute CTC posteriors $P_{\text{CTC}}(\mathbf{y}|\mathbf{h}_{enc})$
    Compute attention loss $\mathcal{L}_{\text{ATTN}}$ in Equation (1)
    Compute multi-task loss $\mathcal{L}_{\text{MTL}}$ using $P_{\text{CTC}}(\mathbf{y}|\mathbf{h}_{enc})$, $\mathcal{L}_{\text{ATTN}}$, and λ in Equation (2)
    Update model $\theta \leftarrow \theta - \alpha \nabla_\theta \mathcal{L}_{\text{MTL}}$
end while

B ASR MODEL STRUCTURE

We present description of our transformer-based speech recognition model.

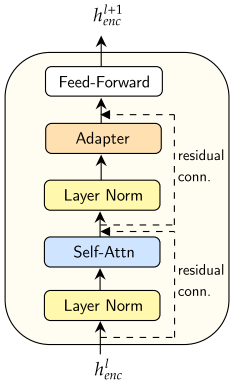

Figure 6: Encoder structure.

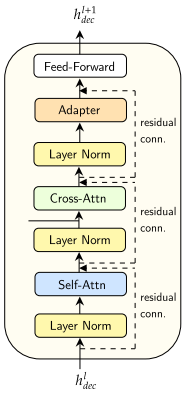

Figure 7: Decoder structure.

Encoder Layer Figure 6 shows the structure of the encoder layer. We use a transformer encoder layer and add an adapter layer on top of the layer norm and self-attention module. We apply two residual connections after the self-attention layer and the adapter layer.

$$o = \text{SelfAttn}(\text{LayerNorm}(\mathbf{h}_{\text{enc}}^{l})) + \mathbf{h}_{\text{enc}}^{l}, \tag{12}$$

$$\mathbf{h}_{\text{enc}} = \text{FeedForward}(\text{Adapter}(\text{LayerNorm}(o)) + o), \tag{13}$$

where $\mathbf{h}_{\text{enc}}^{l}$ is the encoder hidden states of layer l and $\mathbf{h}_{\text{enc}}$ is the output of the encoder layer.

Decoder Layer Figure 7 shows the structure of decoder layer. We place the adapter layer on top of the cross-attention model.

$$o_1 = \text{SelfAttn}(\text{LayerNorm}(\mathbf{h}^l_{\text{dec}})) + \mathbf{h}^l_{\text{dec}}, \tag{14}$$

$$o_2 = \text{CrossAttn}(\mathbf{h}_{\text{enc}}, \text{LayerNorm}(o_1)) + o_1 \tag{15}$$

$$\mathbf{h}^{l+1}_{\text{dec}} = \text{FeedForward}(\text{Adapter}(\text{LayerNorm}(o_2)) + o_2), \tag{16}$$

where $\mathbf{h}^l_{\text{dec}}$ is the decoder hidden states of layer l, and $\mathbf{h}^{l+1}_{\text{dec}}$ is the output the layer.

C Dataset Distribution

Table 6 shows the data split used for training, validation, and testing. Table 7 shows the frequencies of the labels in the original data and our estimates on the balance sampling. There are only a few data with an occurrence of more than 50k (around 1%). The class distribution on the balance sampling is shifted to the 10k-50k range; thus, there are more labels in the middle of the distribution.

Table 6: Dataset split information

	high-resource			**intermediate**					**low-resource**		
	en	**fr**	**es**	**it**	**ru**	**zh**	**tt**	**nl**	**tr**	**ky**	**sv**
Train (hours)	80.0	50.0	40.0	20.0	15.0	15.0	15.0	10.0	10.0	9.0	4.0
Valid (hours)	109.0	34.0	16.5	8.3	7.3	4.2	2.5	2.5	1.3	1.1	0.5
Test (hours)	10.0	10.0	10.0	8.3	7.3	4.3	2.5	2.5	1.3	1.1	0.5

Table 7: Class frequency in the original data and after applying balanced sampling

	>100k	50k-100k	10k-50k	1k-10k	<1k
Original data	6	9	152	1164	3905
Balance sampling	12	30	306	960	3243

Figure 8 and Figure 9 visualizes the long-tail distribution in more detailed. To better visualize them, we ignore the classes fewer than 20k.

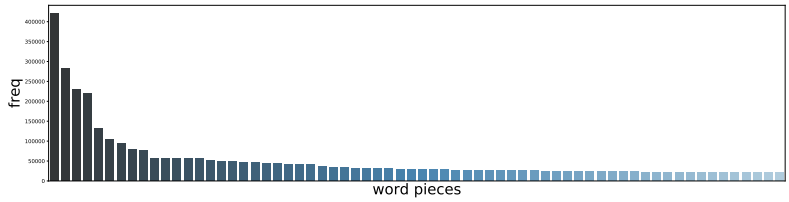

Figure 8: Class Frequency. We only show labels more than 20k

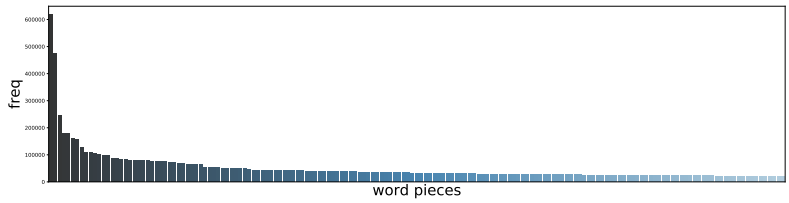

Figure 9: Class Frequency with Balance Sampling. We only show labels more than 20k

D TRANSCRIPTION EXAMPLES

We provide samples on some languages generated from different models, including a resource-limited language *zh* (traditional Chinese scripts and Mandarin speaking in Taiwan) and a resource-rich language *en* (English).

Table 8: Transcriptions of a testing traditional Chinese utterance with different models

Reference	困難與挑戰是激發我們的原動力	
Pinyin	Kun4 Nan2 Yu3 Tiao3 Zhan4 Shi4 Ji1 Fa1 Wo3 Men2 De0 Yuan2 Dong4 Li4	
Model	**Hypothesis**	**CER**
BS + mBERT	困難與挑戰是資料我們的員動力	21.4
+ Dual-Adapters	困難與挑戰是機發我們的員動力	**14.3**
+ Dual-Adapters + Adjust-Train	困難與挑戰是機發我們的員動力	**14.3**
Monolingual	負能一票佔是機發我的能員動力	64.3
SMT	可能與調站是機發我們的員動力	42.9

The reference in Table 8 roughly translates to English as "Obstacles and challenges are the sources of power that motivate us". The monolingual output is rather poor, not only did it miss an important character 們 for distinguishing "my" and "our", the sounding of the sentence is also quite different from the reference (Fu4 Neng2 Yi2 Piao4 Zhan4 Shi4 Wo3 De0 Yuan2 Dong4 Li4). The standard multilingual training (SMT) improves the monolingual by predicting the character 與(Yu3) in place of 一(Yi2). In addition, the output of 調站 (Tiao2Zhan4) sounds almost the same as the reference 挑戰(Tiao3Zhan4) (The monolingual system output 票佔 (Piao4Zhan4) not only does not make any sense in terms of word meaning, the pronunciation is also quite different from the reference). This shows that the multilingual training helps improve the acoustic modelling compared to the monolingual if the monolingual training data is limited. The mBERT model further helps the language modeling by correcting 可能與調站 (literally translates to "possibility and changing stations") to 困難與挑戰 ("Obstacles and challenges"). However, the mBERT also replaces 機發(Ji1Fa1) to 資料(Zi1Liao4) since 資料("documents/materials") is a more common word than 機發 which is a wrong word with correct pronunciations with the reference. Lastly, the adapters successfully convert 資料(Zi1Liao4) to 機發(Ji1Fa1) so that it sounds the same as the reference with one wrong character. This demonstrates the adapter's capability of better acoustic modelling. Finally the errors including the wrong characters in 機發(Ji1Fa1) and 員動力(Yuan2Dong4Li4) can be easily corrected by a decent external language model during decoding, *e.g.,* a RNN-LM trained on the training transcriptions.

Table 9: Transcriptions of a testing English utterance with different models

Reference	FOUND A LITTLE CROWD OF ABOUT TWENTY PEOPLE SURROUNDING THE HUGE HOLE	
Model	**Hypothesis**	**CER**
BS + mBERT	I SOUND THE LITTLE CROWD OF THE ABOUT TWENTY PEOPLE SURROUNDING THE HUGE HOLE	13.6
+ Dual-Adapters	I SOUND A LITTLE CROWD IS ABOUT SPENT PEOPLE SURROUNDING THE HUGE HOLE	11.9
+ Dual-Adapters + Adjust-Train	I SOUND THE LITTLE CROWD OF ABOUT TWENTY PEOPLE SURROUNDING THE HUGE HOLE	**8.5**
Monolingual	SAW THE LEVEL CROWD AS ABOUT TWENTY PEOPLE SURROUNDING THE FUISH FOR	33.9
SMT	SOUND THE LITTLE CROWD AS ABOUT TWENTY PEOPLE SURROUNDING THE HUGE HOLE	13.6

Table 9 shows the transcriptions of different models applied to an English testing utterance. Different from Table 8 where the only limited training data is available, mBERT does not provide any improvement over SMT except it makes the sentence more grammatical by adding a subject "I". The Dual-Adapters improves the performance compared to mBERT by successfully decoding the word piece "ENT" in "SPENT", which is more closer to "TWENTY" in terms of characters. Lastly, the class imbalance adjustment system yields the best CER.

E VOCABULARY COVERAGE

Table 10: Vocabulary Coverage

	high-resource			intermediate					low-resource			
	en	**fr**	**es**	**it**	**ru**	**zh**	**tt**	**nl**	**tr**	**ky**	**sv**	**multi**
Coverage (%)	74.4	73.6	70.8	73.9	90.2	97.7	91.3	64.7	57.1	91.1	53.8	54.9
# Match	181	281	192	164	156	2,330	157	110	93	154	86	2,875
# Vocab	243	382	271	222	173	2,386	172	170	163	169	160	5,237

F LOSS DYNAMICS

We plot the validation losses from A2 and other baselines in Figures 10 and 11.

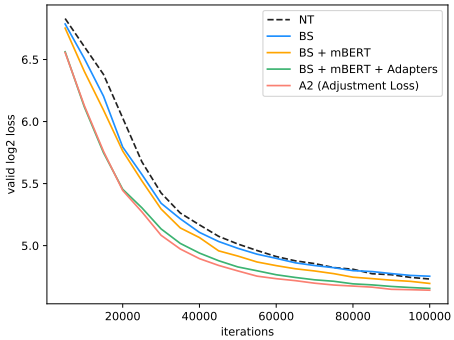

Figure 10: Validation losses

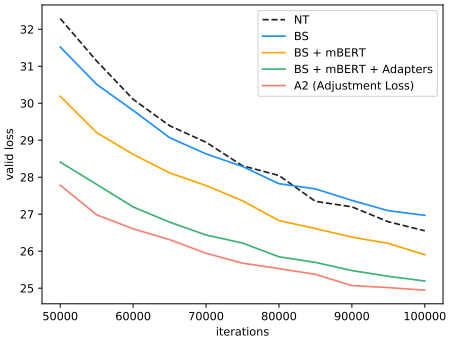

Figure 11: Closer look on Validation losses

G FEW-SHOT SETTING

We also investigate the effectiveness of the A2 framework in the few-shot setting. We take five-hour speech data on each language. The test results are shown in Table 11. Using mBERT as the speech decoder consistently improves the performance of the low-resource monolingual scenario. Interestingly in Chinese, without using mBERT as a decoder, the model seems not to be able to learn useful information. The mBERT decoder yields an absolute CER reduction of 17.2%.

Further performance gain can be achieved with mBERT as the decoder, indicating the multilingual language model is complementary to the shared acoustic knowledge learned from the multilingual speech data. Our proposed A2 framework with language adapters and adaptive loss leads to consistent performance gain across all languages. The average performance translates to a significant CER reduction of 4% compared to the baseline. We can further improve the performance by applying the Adjust-Inference.

Table 11: Character Error Rate (CER) on five hour CommonVoice Training data

	high-resource			**intermediate**					**low-resource**			
	en	**fr**	**es**	**it**	**ru**	**zh**	**tt**	**nl**	**tr**	**ky**	**sv**	**avg**
Monolingual												
SMT	69.6	61.1	56.5	49.8	49.6	96.4	32.8	57.5	49.6	43.7	56.1	56.5
SMT + mBERT	67.3	56.1	51.0	45.4	42.8	73.2	29.6	52.9	46.1	39.6	55.1	50.8
Multilingual												
SMT	41.4	33.5	25.2	22.3	21.9	43.0	15.5	24.9	18.7	18.9	28.9	26.7
SMT + mBERT	40.9	32.6	24.3	21.0	19.9	42.1	14.5	23.8	17.3	17.4	26.7	25.5
SMT + mBERT + Adapters	36.7	28.6	21.3	18.3	17.2	38.2	12.9	20.9	15.1	15.1	23.9	22.6
A2 (Adjust-Inference)	**36.5**	**28.4**	**21.0**	**18.0**	**16.9**	**38.0**	**12.7**	**20.6**	**14.8**	**15.0**	**23.7**	**22.3**

H HYPER-PARAMETER SETTING

The hyper-parameters used in the training is The hyper-parameters used in training are shown in Table 12.

Table 12: Hyper-parameter Setting for Training

hyper-parameters	**value**
encoder-layer	6
encoder-units	2048
decoder-layers	6
decoder-units	3072
encoder-attention-dim	256
decoder-attention-dim	756
attention-heads	4
label-smoothing	0.1
batch-size	32 (for random sampling) 6 (for balanced sampling)
maximum-length-in	512
maximum-length-out	150
optimizer	noam
warmup-step	25000
accum-grad	2 (for random sampling) 11 (for balanced sampling)
grad-clip	5