A Parameter-efficient Language Extension Framework for Multilingual ASR

Wei Liu*,1, Jingyong Hou2, Dong Yang2, Muyong Cao2, Tan Lee1

 $^{\rm 1}$ Department of Electronic Engineering, The Chinese University of Hong Kong $^{\rm 2}$ GVoice, Tencent

louislau_1129@link.cuhk.edu.hk, {jingyonghou,daviddyang,locwellcao}@tencent.com, tanlee@cuhk.edu.hk

Abstract

Covering all languages with a multilingual speech recognition model (MASR) is very difficult. Performing language extension on top of an existing MASR is a desirable choice. In this study, the MASR continual learning problem is probabilistically decomposed into language identity prediction (LP) and cross-lingual adaptation (XLA) sub-problems. Based on this, we propose an architecture-based framework for language extension that can fundamentally solve catastrophic forgetting, debudded as PELE. PELE is designed to be parameter-efficient, incrementally incorporating an add-on module to adapt to a new language. Specifically, different parameter-efficient fine-tuning (PEFT) modules and their variants are explored as potential candidates to perform XLA. Experiments are carried out on 5 new languages with a wide range of low-resourced data sizes. The best-performing PEFT candidate can achieve satisfactory performance across all languages and demonstrates superiority in three of five languages over the continual joint learning setting. Notably, PEFT methods focusing on weight parameters or input features are revealed to be limited in performance, showing significantly inferior extension capabilities compared to inserting a lightweight module in between layers such as an Adapter.

Index Terms: multilingual speech recognition, continual learning, cross-lingual adaptation, parameter-efficient fine-tuning

1. Introduction

Multilingual automatic speech recognition (MASR) refers to a process in which a single model can transcribe speech in multiple languages [1–4]. It has been shown that tens and even hundreds of languages can be supported in one unified model, given the success of Whisper [5] and USM [6]. Nevertheless, in practice, there are always new languages not currently covered by the model. After collecting the labeled data of new target languages, instead of training a monolingual ASR, extending the original MASR to new languages is an intuitively better choice to leverage the already encoded multilingual knowledge.

Extending an existing MASR to new languages lies in the field of continual learning (CL) [7–14]. CL aims to learn a sequence of tasks incrementally. The major challenge in CL is catastrophic forgetting (CF). The tuned model weights after learning a new task would hinder the performance of the preceding tasks. CL has been investigated in computer vision [15, 16] and natural language processing (NLP) [17–19], mostly on classification tasks. It is far less explored in the scope of ASR [20, 21], especially for multilingual ASR as a class incremental learning (CIL) setting. Unlike domain incremental learning (DIL) where the input data distribution changes and

the output classes remain the same, CIL introduces new class labels, i.e., including new language tokens into vocabulary. Thus supporting transcription in a new language is a more difficult CL problem, compared with adapting to new domains [20] or learning new tasks with much similar inputs [15, 18, 19].

Previous studies categorize the approaches to CL into threefolds: regularization-based [9,10], rehearsal-based [11,12] and architecture-based [13-15, 18, 19]. These methods themselves are usually task-agnostic. Considering the aforementioned challenge, their effectiveness in the ASR language extension remains to be verified. Della [22] recently established a CL benchmark for MASR and explored different CL methods. It was found that rehearsal-based and architecture-based are more effective than regularization-based methods. In [22], 10 hours of adaptation data were used for a new language. The averaged word error rates of the extended MASR systems are above 40% (mostly around 65%). The performance is below the level for practical use. Speech data of ten hours are considered extremely limited in an industrial setting even from the low-resource perspective. It remains unclear whether satisfactory performance can be attained when dealing with a more practical data size or if these methods are simply limited in performance.

In this paper, we investigate an architecture-based CL framework to facilitate language extension on a MASR model. The existing MASR model acts as a base model, incrementally integrating an add-on module for adapting to a new language. Without the need to access the original training data of previous languages, the parameters of the base model are frozen to fundamentally avoid CF. Experiments on language extension are carried out with 5 new languages, for which the amount of data ranges from 22 to 284 hours. To reduce the storage overhead in deployment, the proposed framework PELE (abbreviating Parameter Efficient Language Extension) is designed to be parameter-efficient and scalable in terms of the number of extended languages. While [22] did not specifically consider this scalability. It is shown that, with around 10M parameters per language, the best add-on module candidate in PELE can exhibit superior performance on three of five languages compared to the continual joint training setting. To conclude, the major contributions of this study are summarized below:

- We propose a theoretically inspired [23] CL framework for language extension in multilingual ASR, in which the original MASR continual learning problem is probabilistically decomposed into two sub-problems, language identity prediction (LP) and cross-lingual adaptation (XLA).
- We propose utilizing the parameter-efficient fine-tuning (PEFT) methods and their variants to adapt to new languages in PELE to achieve a trade-off between the method's scalability and representation capacity.

^{*} This work was done during an internship at Tencent.

Our proposed PELE exhibits significantly better performances compared to several competitive baselines, with a very limited increase in the number of parameters. The experiments are conducted using a wider range of low-resourced data sizes, making the conclusions more instructive.

2. PELE

2.1. CL-MASR Problem Decomposition

Denote an input speech feature sequence as X and its corresponding transcription as Y, speech recognition can be formulated as p(Y|X). In the multilingual scenario, a latent variable l is introduced to represent spoken language identity. According to the Bayesian formula, MASR can be formulated as:

$$p(\mathbf{Y}|\mathbf{X}) = \sum_{l \in L} p(\mathbf{Y}, l|\mathbf{X}) = \sum_{l \in L} p(l|\mathbf{X})p(\mathbf{Y}|\mathbf{X}, l), \quad (1)$$

where L is the set of all supported languages. Let's consider a new target language l_i that we aim to extend. We make an assumption, denoted as **Asmp. 1**, that " $p(\mathbf{Y}, l_j | \mathbf{X}) = 0$ for all pairs (\mathbf{X}, \mathbf{Y}) that belong to language l_i , if $l_j \neq l_i$ ". Under this assumption, the conditional probability $p(\mathbf{Y} | \mathbf{X}) = p(\mathbf{Y}, l_i | \mathbf{X})$. This assumption simplifies the interaction of information, such as language-specific modules and vocabulary, between the new language l_i and other languages. Thus when we want to support a new language l_i based on an existing MASR model, the negative log-likelihood $-\log p(\mathbf{Y} | \mathbf{X})$ serves as the continual learning loss \mathcal{L}_{CL} to be minimized. Based on Eq. 1 and **Asmp. 1**, \mathcal{L}_{CL} can be decomposed into two separate terms:

$$\mathcal{L}_{CL} = \mathcal{L}_{LP} + \mathcal{L}_{XLA} = -logp(l_i|\mathbf{X}) - logp(\mathbf{Y}|\mathbf{X}, l_i).$$
 (2)

Here the first term \mathcal{L}_{LP} signifies the loss for language identity prediction (LP) and the second term \mathcal{L}_{XLA} represents the loss of cross-lingual adaptation (XLA) for the language l_i . The overall loss \mathcal{L}_{CL} is upper-bounded by \mathcal{L}_{LP} and \mathcal{L}_{XLA} . Therefore, improving either of these two terms would contribute to the performance of newly supported languages. With this in mind, we break down the CL-MASR problem into two sub-problems for more effective analysis and modeling. They are (i) LP, to identify the spoken language of input speech; and (ii) XLA, to adapt the original MASR model for the new language.

2.2. CL Modification to MASR

In this section, we demonstrate how to enable CL on an existing MASR model by explicitly incorporating LP and XLA. In this study, the existing MASR model, before CL modifications, adopts a typical hybrid CTC-attention architecture [24], consisting of an encoder, a decoder, and a CTC layer. The encoder first converts the speech feature \mathbf{X} to hidden representation \mathbf{H} . Then \mathbf{H} is forwarded to two output branches, the CTC layer and decoder, for obtaining the final transcription \mathbf{Y} .

LP is a classification task that can be trained separately. To seamlessly incorporate this function, leveraging the existing encoder to classify LID is expected. Without any changes to the base model, the n-th layer output $\mathbf{H}^{(n)}$ is extracted as features to discriminate languages. We attempt two kinds of approaches: (1) neural network-based (MLP): A three-layer MLP takes $\mathbf{H}^{(n)}$ as input for LID classification. (2) Gaussian discriminative analysis (GDA) [19]: a non-parametric method that models each language class as a Gaussian distribution with the estimated mean and covariance from $\mathbf{H}^{(n)}$ s. The classification is then performed by comparing the test sample's $\mathbf{H}^{(n)}$ with all languages' Gaussians and choosing the nearest one.

XLA is the core function of extending a new language for MASR. Architecture-based CL suggests incrementally assigning a specific module for each language. On the other hand, many parameter-efficient fine-tuning (PEFT) modules exhibit powerful learning capacity on par with full fine-tuning on a wide range of NLP tasks [25–27]. The scalability of PEFT makes it easy to extend more languages. Thus PEFT can serve as a potential candidate to perform high-quality XLA. PEFT essentially injects a small set of trainable parameters into the original model in various forms, while keeping the original base model frozen. According to the different injection positions, they can be divided into three categories: (1) parameter composition, (2) function composition, and (3) input composition.

2.3. PELE Formulation

To coordinately enable LP and XLA together, a general framework PELE is thus proposed. The multilingual information interaction among the add-on PEFT modules of XLA and the base model can be naturally included in this framework without considering **Asmp. 1**. According to Eq. 1, our PELE can be written in a module-level formulation as follows:

$$\mathbf{m}^* = \sum_{l=0}^{L'} \alpha_l \mathbf{m}_l, \tag{3}$$

where \mathbf{m}_l indicates a specific PEFT module to adapt on the language l and α_l is the corresponding weight coefficient. L' denotes the number of new extended languages. L'+1 addon modules are placed in parallel, similar to the structure of mixture-of-expert (MoE) [28], for the extension of multiple languages. l=0 represents the base languages that the original MASR model supported. Note that \mathbf{m}_0 serves as a dummy forward, lacking trainable parameters but being a module equivalent in form to $\{\mathbf{m}_l\}_{l=1}^{L'}$. In this manner, it can seamlessly revert to the original MASR without any adaptation effect when $\alpha=[1,0,...0]$ (we denote the vector $\alpha=[\alpha_0,\alpha_1,...,\alpha_{L'}]$).

By comparing Eq. 3 with Eq. 1, \mathbf{m}_l can be regarded as a module-level realization of $p(\mathbf{Y}|\mathbf{X},l)$ for language adaptation, and the coefficient α_i is viewed to approximate $p(l|\mathbf{X})$. It is worth noting that the coefficient vector $\boldsymbol{\alpha}$ is not necessarily to be derived from LP posterior. Other choices like the ground-truth one-hot vector (pre-know the language identity) or entirely the learnable vector can also be attempted. With a certain $\boldsymbol{\alpha}$, the output \mathbf{m}^* represents the final module-level adaptation.

Different PEFT choices result in different formulations of \mathbf{m} . Specifically, (1) in parameter composition PEFT, \mathbf{m} is usually the injected parameter matrix, such as the incremental update $\Delta \mathbf{W}$ of LoRA [25] or the mask weight of Mask tuning [29, 30]. (2) In function composition PEFT, \mathbf{m} is exactly the inserted lightweight module in-between layers, such as $Adapter(\mathbf{H}^n)$ [26]. (3) In input composition PEFT, \mathbf{m} can be the virtual token sequence of prompt tuning [27]. In general, Eq. 3 is flexible to be implemented and incorporated into any specified layer/sub-layer of the base model for adaptation.

3. Experimental Setup

3.1. Base Model & Dataset

Consider a given MASR base model that adopts a hybrid CTC-attention architecture [24]. It has 12 conformer layers [31] as encoder and 6 transformer layers [32] as decoder. The attention dimension is 512. The based model is trained on a dataset which is a mixture of 10 languages with 4714.1 hours in total. The

language includes English (en), French (fr), Spanish (es), Chinese (zh), Italian (it), Russian (ru), Portuguese (pt), Turkish (tr), Dutch (nl), and Tatar (tt) from the Common Voice 13.0 [33]. In our CL MASR experiments, we select 5 'never-seen' languages in the Common Voice, to perform language extension. They are German (de, 284.3h), Polish (pl, 131.7h), Welsh (cy, 101.5h), Japanese (ja, 55.5h), and Czech (cs, 22.4h). The number in brackets denotes the training data size in terms of hours.

3.2. MASR Continual Learning

Extending the tokens for unseen languages is a crucial step in CL-MASR. To construct an expanded token embedding matrix, the embeddings of new tokens are usually randomly initialized and then concatenated with the original matrix. In our experiments, for simplicity, the Whisper [5] tokenizer is used to generate the output vocabulary at once. In the base model, only the tokens of those 10 seen languages were explicitly trained.

In the CL training procedure, Adam [34] optimizer with an initial learning rate of 1e-3 is used. The warmup steps are 2000. The batch_size is 12 with an $accum_grad$ of 8. Eight V100 GPUs are used for DDP training. If not specified otherwise, the number of training epochs is 50 and the CTC greedy decoding results are reported. For the evaluation metric, Word or character error rate (WER/CER) is adopted to measure the performance of different extended MASR systems.

3.2.1. Baselines

Mono: A monolingual ASR model is trained for each language. The attention dimension is 256. Raw: Directly use the base model for recognition. FullFT: Fully fine-tune the base model with the data of 5 new languages. CJT: Continually joint training with the mixture of 5 new languages and the original 10 languages on top of the base model. ER: Experience Replay is a typical rehearsal-based CL method, showing the best CL-MASR performance in [22]. To alleviate CF, a certain amount of historical data per language is allowed to be stored for mixing with the current new language data in fine-tuning.

3.2.2. PELE

In LP, at most 100k utterances per language are randomly selected to perform MLP or GDA based LID prediction. For the original 10 base languages, we assume the LID label can be obtained. By observing LP results, the 6th encoder layer output \mathbf{H}^6 is selected as the feature to identify LID. For XLA, the adaptation modification is thus performed starting from the 7th encoder layer. Different PEFT modules are explored in the PELE framework to perform cross-lingual adaptation. We illustrate them as follows: (a) For parameter composition type, BitFit [35]: Only the bias parameters of the base model are updated. LoRA [25]: The incremental update $\Delta W = BA$ is assumed to be low-rank decomposed, where $\mathbf{B} \in \mathbb{R}^{d_2 imes r}$ and $\mathbf{A} \in \mathbb{R}^{r imes d_1}$. In our experiments, another low-rank decomposed matrix \mathbf{W}_s is introduced to adjust the original weight matrix \mathbf{W}_0 , i.e., $\mathbf{W} = \mathbf{W}_0 \odot \mathbf{W}_s + \Delta \mathbf{W}$, where \odot denotes the element-wise product. We applied this improved LoRA version with r=32 on all weight matrices of attention layers and feedforward layers. LoRA*: Increase the rank of LoRA to 128 for the output matrix of attention layers and the down projection matrix of feedforward layers. *Mask* [30]: Instead of adjusting the weight values, mask tuning opts to change the weight connection by multiplying \mathbf{W}_0 with a binary mask $\mathbf{B} \in \{0,1\}^{d_2 \times d_1}$. \mathbf{B} is derived by a learnable ma-

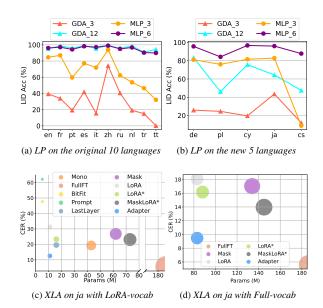


Figure 1: First row: The accuracy of different LID prediction methods. (a) on the original 10 languages; (b) on the new 5 languages. Second row: The CER results of different PEFT methods and baselines when performing XLA on the unseen language Japanese (ja). (c) the vocabulary layer is low-rank updated; (d) the vocabulary layer is fully updated.

trix with a threshold. The weight matrices this method works on are the same as LoRA, and the masking threshold is set as 0.05. *MaskLoRA**: We propose the combination of Mask and LoRA*, i.e., $\mathbf{W} = (\mathbf{W}_0 \odot \mathbf{W}_s + \Delta \mathbf{W}) \odot \mathbf{B}$. (b) For *function composition* type, *Adapter* [26]: Inserted after the self-attention layer and feedforward layer sequentially. The bottleneck dimension is 256. (c) For *input composition* type, *Prompt* [27]: A sequence of 20 learnable token embeddings are prepended to input speech feature sequences to serve as new inputs.

It is noted that to achieve the overall parameter efficiency, the vocabulary layer with large parameters is suggested to have a low-rank update. For this purpose, Eq. 3 is implemented on the vocabulary layer, where \mathbf{m}_l adopts LoRA (r=32) to apply on the token embedding matrix for the language l.

4. Results and Analysis

4.1. Results of the Decomposed Sub-problems

4.1.1. Language Prediction (LP)

Fig. 1 (a) and (b) plot the LID prediction accuracy on the original 10 languages and the new 5 languages, respectively. GDA and MLP are two kinds of language classification methods; the former is a non-parametric approach. The suffix number represents which encoder layer output is utilized as the feature. In the original 10 languages, GDA_12 approaches 100% accuracy, while the results of GDA_3 are mostly under 50% accuracy. Similarly, MLP_6 largely outperforms MLP_3. It implies that the higher encoder layer has richer information to discriminate languages. In the new 5 languages, the performance of GDA_12 exhibits significant degradation. It is hypothesized that the layer representation of the base model is hard to generalize to unseen languages without any training. In contrast, MLP_6 maintains a reasonable prediction accuracy. Not using MLP_12 is because of the trade-off that several higher encoder layers have to be

kept to perform adaptation modification.

4.1.2. Cross-lingual Adaptation (XLA)

In XLA, a never-seen language, Japanese (ja), is utilized as the target language for adaptation. Fig. 1 (c) shows the XLA results of various PEFT methods and some baselines by training 100 epochs. The y-axis denotes the CER performance, the lower, the better. The x-axis denotes the number of trainable parameters to measure the parameter efficiency. The circles with different colors represent different adaptation methods. The scalability of the method is better if the corresponding circle is smaller as fewer parameters are required to adapt to a new language.

Prompt and BitFit exhibit the two smallest circles, showing the worst adaptation performance. We argue that their representation capacity is quite limited to realize the MASR language extension. LoRA gives a CER of around 30% and the enhanced LoRA* further decrease the CER to 23.3%, demonstrating the importance of the PEFT's capacity. For the method of mask tuning, it can be seen that Mask gives a CER result in between LoRA and LoRA*. At the cost of more trainable parameters, MaskLoRA* surpasses Mask and LoRA* by marrying the strengths of both sides. The method *LastLayer* denotes updating the last encoder and decoder layer of the base model, achieving a strong result. The blue circle located in the bottom left corner, in particular, draws our attention. This Adapter method can attain 12.5% CER with 11M parameters. Its performance only left behind FullFT, while significantly increasing the adaptation scalability. In Fig. 1 (d), instead of low-rank updating the vocabulary (LoRA-vocab), several potential PEFT methods are selected to perform adaptation with the vocabulary fully updated. We observe that Adapter still keeps the obvious CER advantage and shows the least performance decrease when comparing LoRA-vocab to Full-vocab.

The overall XLA results suggest that different from the previous CL problems studied in NLP, for the ASR language extension, *parameter* and *input composition* type of PEFT methods, e.g., *LoRA* [25], *Mask* [30], *Prompt* [27], are performance-limited, showing significantly less representation capacity than *Adapter* [26], a *function composition* PEFT method.

4.2. Comparison between PELE and Baselines

Tab. 1 presents the performance comparison of different methods on the MASR language extension. Five never-seen languages, namely German (de), Polish (pl), Welsh (cy), Japanese (ja), and Czech (cs), are utilized for MASR continual learning. Compared to Raw, FullFT significantly increases the recognition performance on the new languages by fully fine-tuning. However, without access to the original languages' data, the CF issue is obvious. In this way, to extend a new language each time, a copy of the base model is required. In experience reply (ER), ER (10k) alleviates the CF phenomenon more than ER (1k) due to the relatively larger cached data size of the historical data. With no access limitation to previous languages' data, CJT can naturally solve the catastrophic forgetting. It can be observed that CJT further improves the recognition of the original 10 languages by continual training, while the performance on the new languages degrades compared to FullFT.

In the PELE block, Adapter, as the best PEFT candidate shown in Sec. 4.1.2, are mainly experimented with different α settings. The WER performance in the original 10 languages remains 16.3%, the same as Raw for all the PELE configurations. Note that previous languages' data are not required in PELE. The CF issue is fundamentally solved due to the

Table 1: The WER (%) performance comparison of MASR continual learning between baselines and the proposed PELE. base10 represents the average recognition performance on the original 10 languages that the base model is trained with. Avg represents the averaged WER of all 15 languages. Inc. Params denotes the averaged parameters that increased by supporting a new language. ER (1k) denotes 1k utterances per language are cached for experience replay, and ER (10k) is similar. In the α column, LP post means α adopts the LID prediction posterior, while LP ohot denotes the one-hot vector derived by LP post is used. GT ohot means adopting the ground-truth one-hot vector and GT learn represents the learnable vector parameters that first initialized as GT ohot.

Methods		Inc. Params (M)	base10	de	pl	су	ja	cs	Avg
Mo	Mono		21.1	15.1	10.8	15.5	19.3	83.8	22.2
Raw		-	16.3	90.8	104.0	99.7	104.2	103.1	41.6
Full	FullFT		99.8	12.8	8.0	10.5	8.5	24.5	66.4
ER (ER (1k)		48.3	14.9	11.6	13.3	10.5	29.5	35.1
ER (ER (10k)		23.4	15.2	14.0	14.2	11.1	30.9	20.0
CJT		-	14.8	15.2	12.5	15.9	13.3	32.0	14.8
α	PEFT		PELE framework						
LP post	Adapter	11.2	16.3	23.0	24.4	17.1	15.1	35.4	17.4
LP ohot	Adapter	11.2	16.3	24.1	27.9	16.9	14.6	32.4	17.4
GT ohot	LoRA	11.3	16.3	31.0	33.3	29.0	29.7	49.2	21.0
	LoRA*	16.2	16.3	28.1	26.4	24.5	22.7	43.1	19.2
	Adapter	11.2	16.3	19.6	14.2	13.9	12.7	26.5	15.6
GT learn	Adapter	11.2	16.3	18.3	12.8	13.9	12.4	29.9	15.7

architecture-based CL design. Regarding LP, MLP_6 is utilized to produce LID posterior or onehot. The overall average recognition performance only left behind CJT. To observe the performance upper bound, GT ohot is introduced to exclude the language prediction (LP) error effect. In addition, LoRA and LoRA*, as the representative type of parameter composition PEFT, are also reported. Adapter achieves at least 10% absolute WER reduction per new language compared to LoRA-related methods. The overall WER performance arrives at 15.6%, approaching 14.8% of CJT. Particularly, in three of five new languages, our best PELE system surpasses CJT. By comparing LP ohot with GT ohot, we can see the performance degradation caused by the LP error. The frozen encoder layers make the MLP_6 accuracy limited, thus affecting the overall CL performance. Better LP, maybe an external predictor, is expected to have less degradation. Furthermore, we attempt α a learnable weight coefficient vector (GT learn), which is initialized as GT ohot. By explicitly leveraging the interaction of multilingual module-level information, most languages exhibit performance improvement except the language Czech (cs).

5. Conclusions

In this paper, we present a theoretically inspired architecture-based framework, PELE, for language extension in MASR. PELE is designed to be parameter-efficient for the framework's scalability. Many different PEFT modules are explored as candidates to perform cross-lingual adaptation. Experiments carried out on 5 never-seen languages show the effectiveness and efficiency of PELE. The best-performing PEFT module configuration attains an overall satisfactory performance, surpassing the continual joint learning setting on three of five languages. Importantly, it is found that the performance of PEFT in language extension is limited when working on weight parameters or input features. The PELE framework is flexible and more configurations (e.g., other PEFTs/coefficient vectors, curriculum training scheme, and the order of extended languages, etc) are expected to be further explored in future works.

6. References

- V. Pratap, A. Sriram, P. Tomasello, A. Y. Hannun, V. Liptchinsky, G. Synnaeve, and R. Collobert, "Massively multilingual ASR: 50 languages, 1 model, 1 billion parameters," in *Proc. Interspeech*. ISCA, 2020, pp. 4751–4755.
- [2] B. Li, R. Pang, T. N. Sainath, A. Gulati, Y. Zhang, J. Qin, P. Haghani, W. R. Huang, M. Ma, and J. Bai, "Scaling end-to-end models for large-scale multilingual ASR," in *Proc. ASRU*. IEEE, 2021, pp. 1011–1018.
- [3] B. Li, R. Pang, Y. Zhang, T. N. Sainath, T. Strohman, P. Haghani, Y. Zhu, B. Farris, N. Gaur, and M. Prasad, "Massively multilingual ASR: A lifelong learning solution," in *Proc. ICASSP*. IEEE, 2022, pp. 6397–6401.
- [4] H. Yadav and S. Sitaram, "A survey of multilingual models for automatic speech recognition," in *Proc. LREC*. European Language Resources Association, 2022, pp. 5071–5079.
- [5] A. Radford, J. W. Kim, T. Xu, G. Brockman, C. McLeavey, and I. Sutskever, "Robust speech recognition via large-scale weak supervision," in *Proc. ICML*. PMLR, 2023, pp. 28 492–28 518.
- [6] Y. Zhang, W. Han, J. Qin, Y. Wang, A. Bapna, Z. Chen, N. Chen, B. Li, V. Axelrod, G. Wang et al., "Google USM: Scaling automatic speech recognition beyond 100 languages," arXiv preprint arXiv:2303.01037, 2023.
- [7] A. Awasthi and S. Sarawagi, "Continual learning with neural networks: A review," in *Proc. CoDS-COMAD*, 2019, pp. 362–365.
- [8] M. De Lange, R. Aljundi, M. Masana, S. Parisot, X. Jia, A. Leonardis, G. Slabaugh, and T. Tuytelaars, "A continual learning survey: Defying forgetting in classification tasks," *IEEE transactions on pattern analysis and machine intelligence*, vol. 44, no. 7, pp. 3366–3385, 2021.
- [9] J. Kirkpatrick, R. Pascanu, N. Rabinowitz, J. Veness, G. Desjardins, A. A. Rusu, K. Milan, J. Quan, T. Ramalho, A. Grabska-Barwinska et al., "Overcoming catastrophic forgetting in neural networks," *Proceedings of the national academy of sciences*, vol. 114, no. 13, pp. 3521–3526, 2017.
- [10] Z. Li and D. Hoiem, "Learning without forgetting," *IEEE transactions on pattern analysis and machine intelligence*, vol. 40, no. 12, pp. 2935–2947, 2017.
- [11] D. Rolnick, A. Ahuja, J. Schwarz, T. Lillicrap, and G. Wayne, "Experience replay for continual learning," *Proc. NeurIPS*, vol. 32, 2019.
- [12] A. Chaudhry, M. Ranzato, M. Rohrbach, and M. Elhoseiny, "Efficient lifelong learning with A-GEM," in *Proc. ICLR*, 2019.
- [13] A. A. Rusu, N. C. Rabinowitz, G. Desjardins, H. Soyer, J. Kirk-patrick, K. Kavukcuoglu, R. Pascanu, and R. Hadsell, "Progressive neural networks," arXiv preprint arXiv:1606.04671, 2016.
- [14] A. Mallya, D. Davis, and S. Lazebnik, "Piggyback: Adapting a single network to multiple tasks by learning to mask weights," in *Proc. ECCV*, 2018, pp. 67–82.
- [15] M. Wortsman, V. Ramanujan, R. Liu, A. Kembhavi, M. Rastegari, J. Yosinski, and A. Farhadi, "Supermasks in superposition," *Proc. NeurIPS*, vol. 33, pp. 15173–15184, 2020.
- [16] H. Qu, H. Rahmani, L. Xu, B. Williams, and J. Liu, "Recent advances of continual learning in computer vision: An overview," arXiv preprint arXiv:2109.11369, 2021.
- [17] M. Biesialska, K. Biesialska, and M. R. Costa-jussà, "Continual lifelong learning in natural language processing: A survey," in *Proc. COLING*. International Committee on Computational Linguistics, 2020, pp. 6523–6541.
- [18] A. Razdaibiedina, Y. Mao, R. Hou, M. Khabsa, M. Lewis, and A. Almahairi, "Progressive prompts: Continual learning for language models," in *Proc. ICLR*, 2023.
- [19] Z. Wang, Y. Liu, T. Ji, X. Wang, Y. Wu, C. Jiang, Y. Chao, Z. Han, L. Wang, X. Shao *et al.*, "Rehearsal-free continual language learning via efficient parameter isolation," in *Proc. ACL*, 2023, pp. 10933–10946.

- [20] S. Vander Eeckt and H. Van Hamme, "Continual learning for monolingual end-to-end automatic speech recognition," in *Proc.* EUSIPCO. IEEE, 2022, pp. 459–463.
- [21] S. V. Eeckt and H. V. hamme, "Weight averaging: A simple yet effective method to overcome catastrophic forgetting in automatic speech recognition," in *Proc. ICASSP*. IEEE, 2023, pp. 1–5.
- [22] L. Della Libera, P. Mousavi, S. Zaiem, C. Subakan, and M. Ravanelli, "CL-MASR: A continual learning benchmark for multi-lingual asr," arXiv preprint arXiv:2310.16931, 2023.
- [23] G. Kim, C. Xiao, T. Konishi, Z. Ke, and B. Liu, "A theoretical study on solving continual learning," *Proc. NeurIPS*, vol. 35, pp. 5065–5079, 2022.
- [24] S. Watanabe, T. Hori, S. Kim, J. R. Hershey, and T. Hayashi, "Hybrid CTC/attention architecture for end-to-end speech recognition," *IEEE Journal of Selected Topics in Signal Processing*, vol. 11, no. 8, pp. 1240–1253, 2017.
- [25] E. J. Hu, Y. Shen, P. Wallis, Z. Allen-Zhu, Y. Li, S. Wang, L. Wang, and W. Chen, "LoRA: Low-rank adaptation of large language models," in *Proc. ICLR*, 2022.
- [26] N. Houlsby, A. Giurgiu, S. Jastrzebski, B. Morrone, Q. De Laroussilhe, A. Gesmundo, M. Attariyan, and S. Gelly, "Parameter-efficient transfer learning for NLP," in *Proc. ICML*. PMLR, 2019, pp. 2790–2799.
- [27] B. Lester, R. Al-Rfou, and N. Constant, "The power of scale for parameter-efficient prompt tuning," in *Proc. EMNLP*, 2021, pp. 3045–3059.
- [28] Q. Liu, X. Wu, X. Zhao, Y. Zhu, D. Xu, F. Tian, and Y. Zheng, "Moelora: An moe-based parameter efficient finetuning method for multi-task medical applications," arXiv preprint arXiv:2310.18339, 2023.
- [29] Y. Fu, Y. Zhang, K. Qian, Z. Ye, Z. Yu, C.-I. J. Lai, and C. Lin, "Losses can be blessings: Routing self-supervised speech representations towards efficient multilingual and multitask speech processing," *Proc. NeurIPS*, vol. 35, pp. 20902–20920, 2022.
- [30] Z. Yu, Y. Zhang, K. Qian, C. Wan, Y. Fu, Y. Zhang, and Y. C. Lin, "Master-ASR: achieving multilingual scalability and low-resource adaptation in ASR with modular learning," in *Proc. ICML*. PMLR, 2023, pp. 40 475–40 487.
- [31] A. Gulati, J. Qin, C. Chiu, N. Parmar, Y. Zhang, J. Yu, W. Han, S. Wang, Z. Zhang, Y. Wu, and R. Pang, "Conformer: Convolution-augmented transformer for speech recognition," in *Proc. Interspeech.* ISCA, 2020, pp. 5036–5040.
- [32] A. Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A. N. Gomez, Ł. Kaiser, and I. Polosukhin, "Attention is all you need," *Proc. NeurIPS*, vol. 30, 2017.
- [33] R. Ardila, M. Branson, K. Davis, M. Kohler, J. Meyer, M. Henretty, R. Morais, L. Saunders, F. M. Tyers, and G. Weber, "Common voice: A massively-multilingual speech corpus," in *Proc. LREC*. European Language Resources Association, 2020, pp. 4218–4222.
- [34] D. P. Kingma and J. Ba, "Adam: A method for stochastic optimization," in *Proc. ICLR*, 2015.
- [35] E. B. Zaken, Y. Goldberg, and S. Ravfogel, "Bitfit: Simple parameter-efficient fine-tuning for transformer-based masked language-models," in *Proc. ACL*, 2022, pp. 1–9.