Improved Meta Learning for Low Resource Speech Recognition

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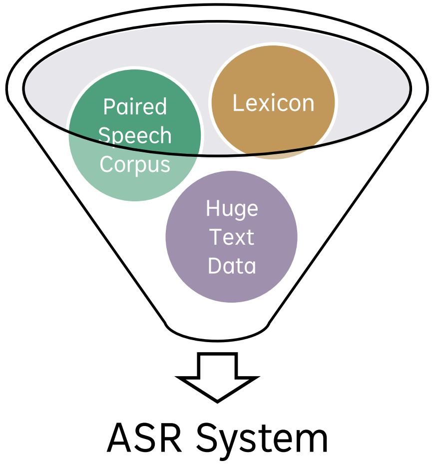
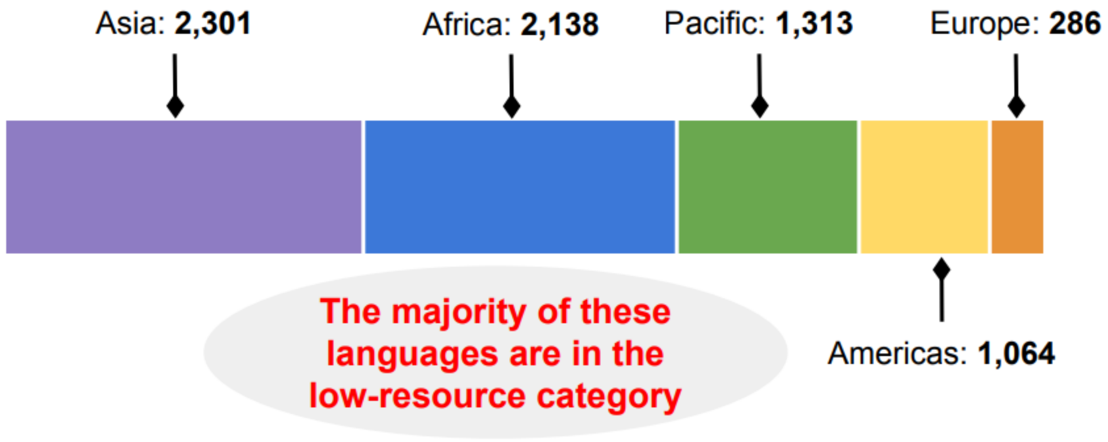
Outline

- Introduction to low resource languages
- Challenges
- Proposed approach
- Experimental setup and results
- Conclusions

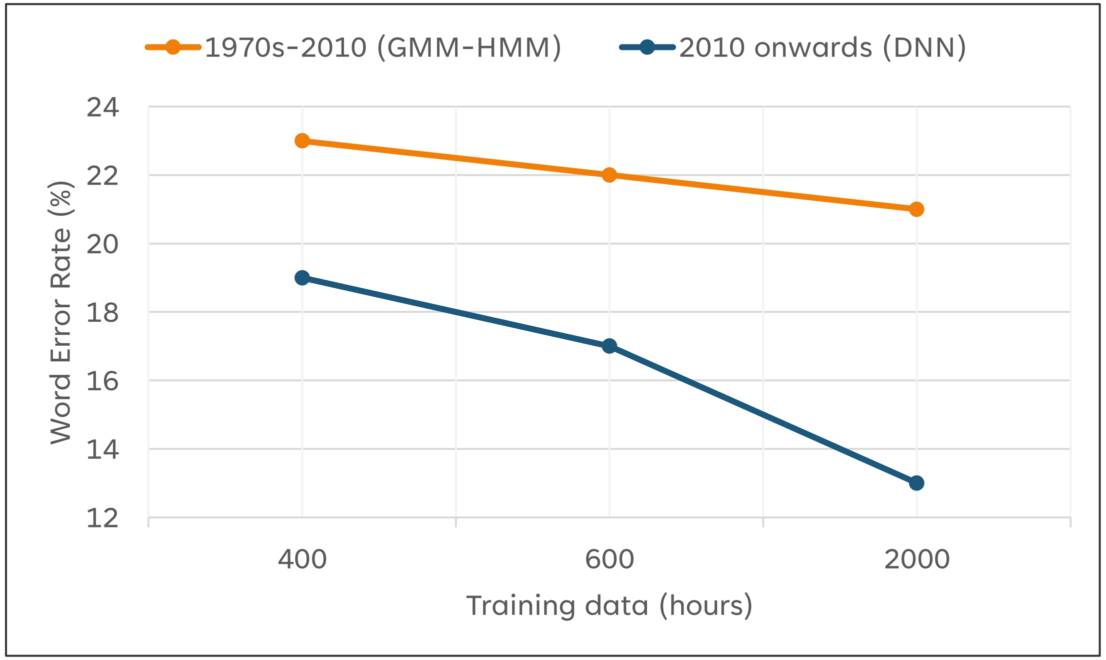
What are Low Resource Languages (LRL)?

- The languages that do not have enough linguistic resources are considered as low resource languages.
- There are approximately over 7000 languages being spoken around the world. (Precoda et al., 2004)
- Only around 100 languages have well established speech recognition systems.





Word Error Rate vs Available data



(Huang et al., 2014)

Challenges

- LRL may have few native speakers as only 400 languages have over one million speakers.
- It is tough to record diverse speech data, which is most expensive and time-consuming.
- Transcription process may also take a considerable number of efforts to produce accurate annotated data.
- Linguistic experts must be included in the process to create pronunciation dictionaries.

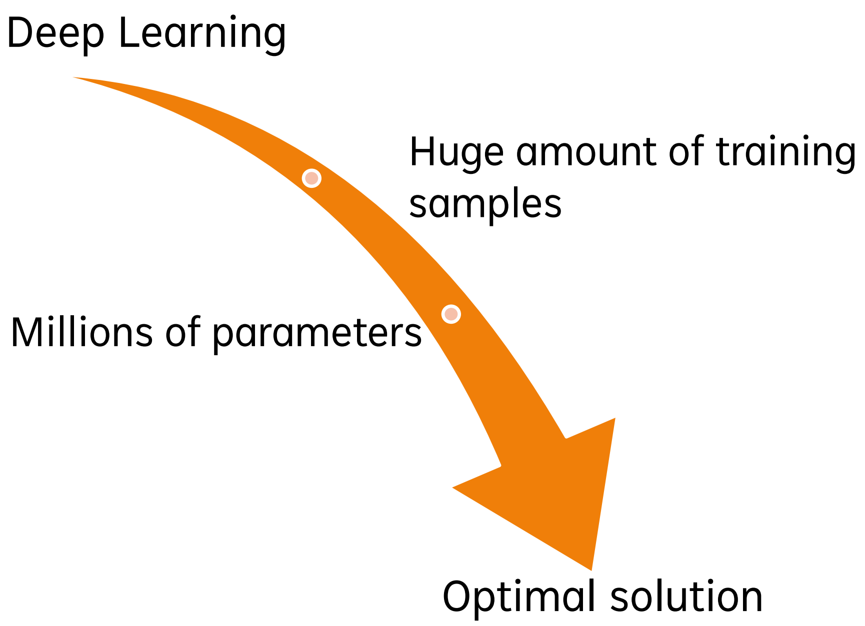
Proposed Solutions

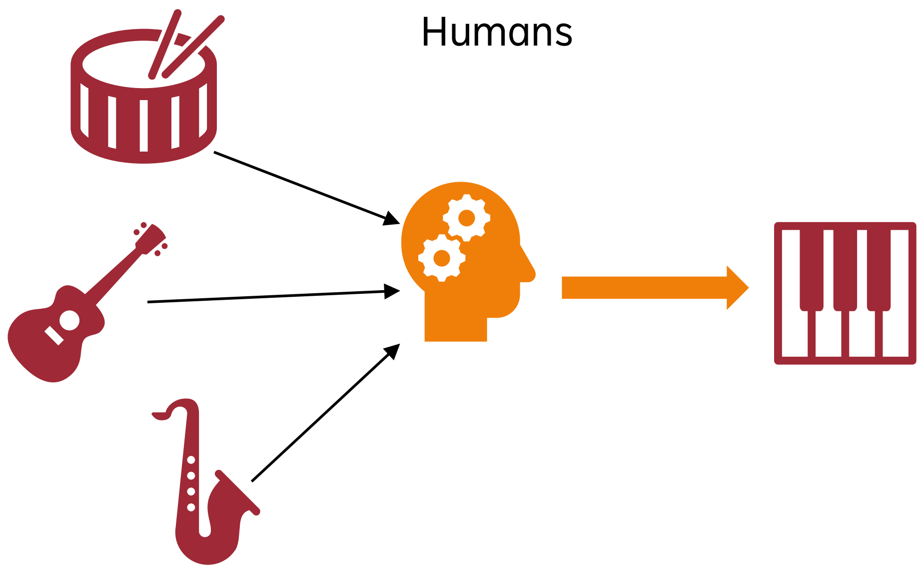
- Data augmentation
- Multilingual systems
- Cross lingual transfer learning
- Semi-supervised learning
- Meta learning

Meta learning

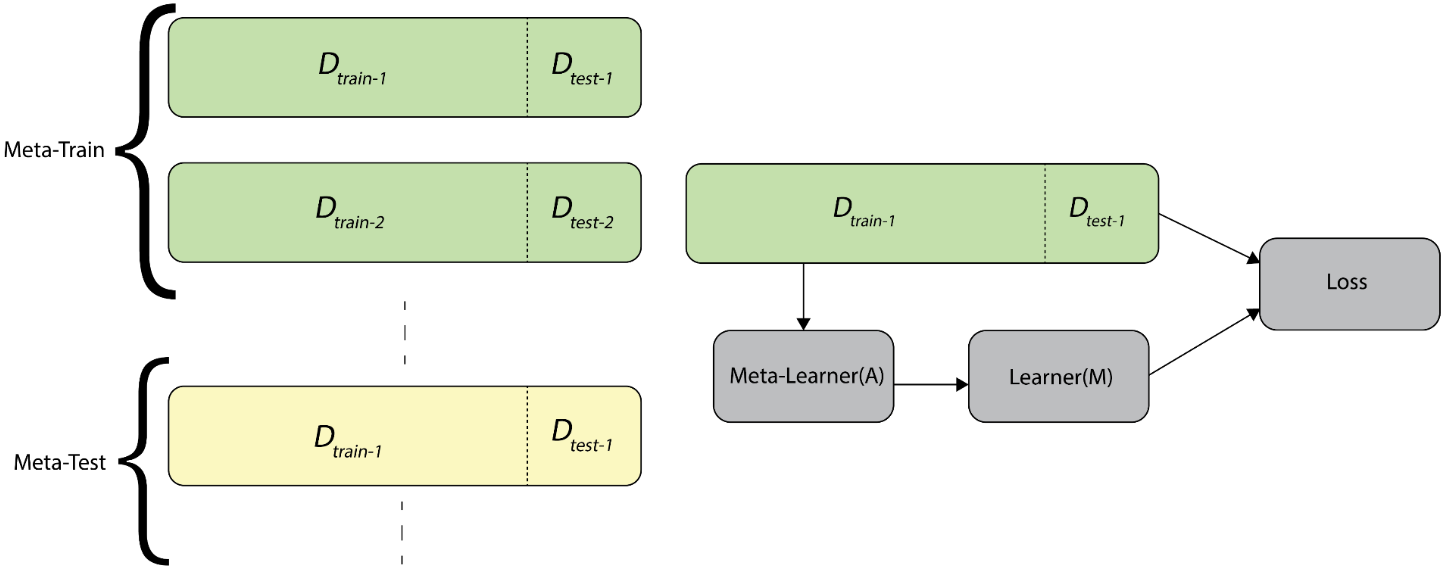
(Motivation)

- Meta-learning, also known as learning to learn, focuses on improving the learning efficiency based on previous experiences on wide variety of tasks.





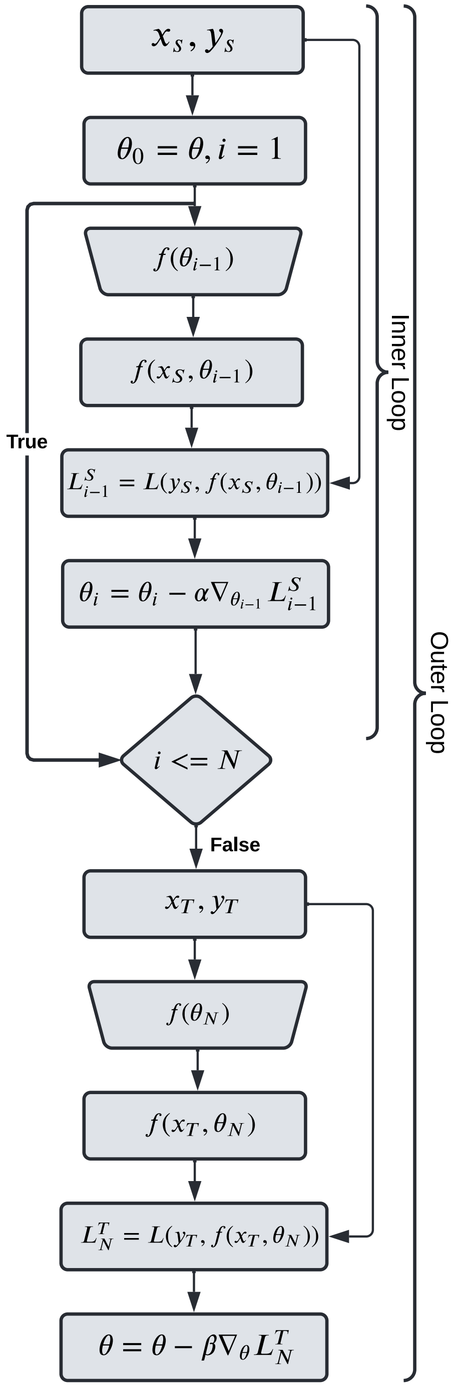
Meta learning
(Formulation)



- **Input:** Meta-training set $\mathscr{D}_{meta-train} = \{(D^{(n)}_{train}), (D^{(n)}_{test})\}^{N}_{n=1}$
- **Output:** Parameters θ algorithm A (Meta-learner)
- **Objective:** Good performance on $\mathscr{D}_{meta-test} = \{(D'^{(n)}_{train}), (D'^{(n)}_{test})\}^{N'}_{n=1}$

Model Agnostic Meta learning (MAML)

(Finn et al., 2017)



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What has been Done?

- MAML for low resource ASR (Hsu et al., 2020)
  - Outperformed no-pretraining and multilingual training settings
- MAML for accent adaptation (Winata et al., 2020)
  - Outperformed joint training setting across various English accents in few shot scenarios

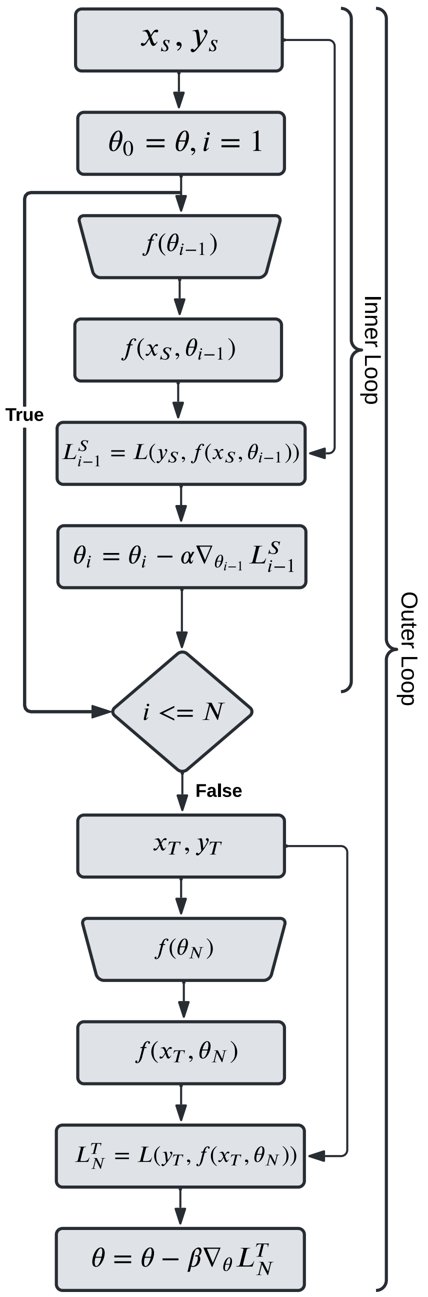
Issues with MAML

- Inconsistent training behaviour
- Slower convergence speed

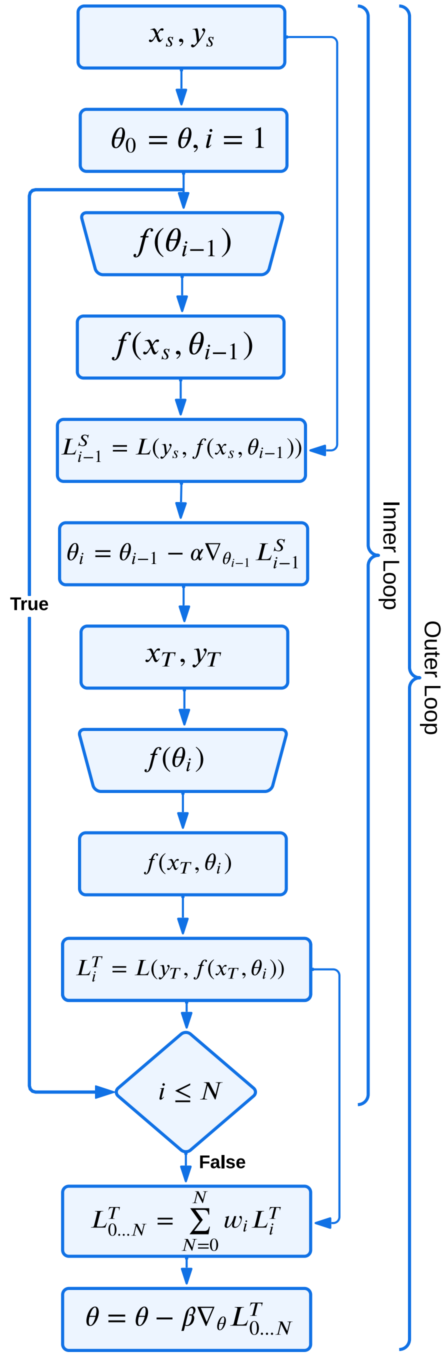
Proposed Solution

- Multi-step loss (MSL) (Antoniou et al., 2018)
  - Originally, proposed for the image classification task.
  - It calculates the inner loss after every inner step updates.
  - Then computes the weighted sum of all the inner losses.

MAML vs MAML with MSL



MAML



MAML with MSL

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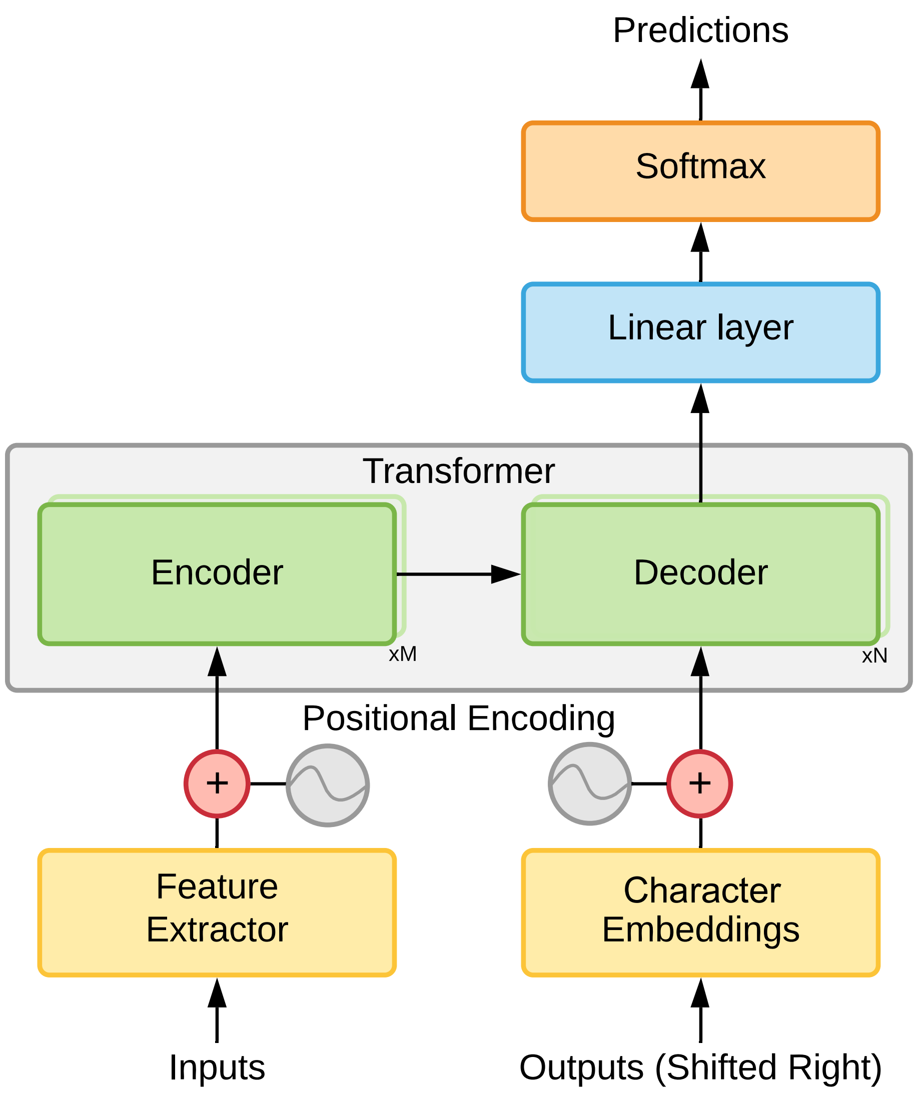
The ASR model

- Transformer based model
  - 6 layered VGG extractor
  - 2 encoder layers
  - 4 decoder layers
  - 8 heads for multi-head attention



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Experimental Setup

Datasets

- Common Voice V7.0
- Source language sets
  - [fa, ar, ta], [ar, mn, lt], [or, pa-IN, hi, ur, as]
- Target language set
  - hi, mn, fa, ar, ta

Methodology

- Pretrain
  - 100K iterations on 3 source sets
- Fine-tune
  - Fine-tune for 10 epochs with beam size of 5.

Table 1: The selected low resource languages from the Common Voice dataset v7.0 and the total amount of speech data in terms of hours.

ID	Languages	Hours
ar	Arabic	85
as	Assames	1
hi	Hindi	8
lt	Lithuanian	16
mn	Mongolian	12
or	Odia	0.94
fa	Persian	293
pa-IN	Punjabi	1
ta	Tamil	198
ur	Urdu	0.59
Total		615.53

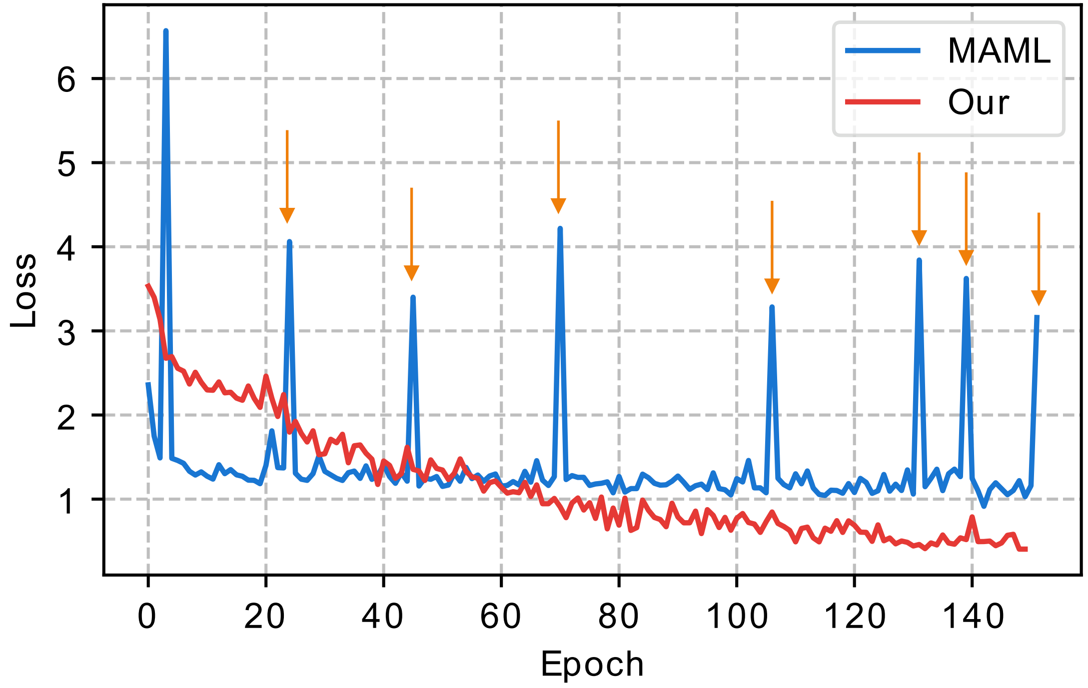
Experimental Results

Table 2: The average experimental results in terms of character error rate (CER in %) on 5 target languages. We have not fine-tune our model on the languages that are present in the pretrain source language sets. These cells are represented by hyphen (-).

Pretrain languages	Finetune									
	Hindi		Mongolian		Persian		Arabic		Tamil	
	MAML	Our	MAML	Our	MAML	Our	MAML	Our	MAML	Our
[fa, ar, ta]	70.51	**70.47**	61.05	**60.52**	-	-	-	-	-	-
[ar, mn, lt]	71.61	**71.37**	-	-	47.96	**45.45**	-	-	40.96	**35.17**
[or, pa-IN, hi, ur, as]	-	-	62.26	**59.50**	52.42	**52.41**	**36.00**	36.09	**45.96**	46.60

Training performance (MAML vs MAML with MSL)

- MAML approach with MSL improves the training consistency.



Conclusions

- Multi step loss indeed improves the training stability.
- It also has positive impact on the overall accuracy of the model.
- In the future, we plan to conduct more experiments with more low resource languages.

Thank you!