# **Efficient Unseen Language Adaptation** for Multilingual Pre-Trained Language Models

**Po-Heng Chang & Yun-Nung (Vivian) Chen** https://github.com/MiuLab/UnseenAdapt

#### Motivation

- Apply machine learning application to lowresource language
- Issues  $\bullet$

• The lack of labeled data in low-resource language

- ⇒ Zero-shot cross-lingual transfer is needed Low-resource languages are **unseen** by most mPLMs
- Language adaptation is needed

### Paper Idea

Design parameter-efficient and data-efficient framework to adapt mPLMs to unseen languages and achieve strong cross-lingual transfer performance

#### Train (English)

That's what I think. [SEP] I think so. Hypothesis Premise





The corpora of low-resource languages are small and mPLMs are large

⇒ A data-efficient and parameter-efficient method is needed

#### **Proposed Framework MLM on Unlabeled Data**

#### **Test (Unseen Language – Quechua)**

Chaychusmi yuyani. [SEP] Manam yuyapunichu.

Premise

Hypothesis

#### **Tuning on Source-Language Labeled Data**



#### Experiments

MasakhaNEWS (Adelani+, 2023)		AmericasNLI (Ebrahimi+, 2022)		82.5 -	
Model	Avg. accuracy	Model	Avg. accuracy	80.0 - 77.5 -	
Zero-shot		Zero-shot		8 75.0 -	
Fine-tuning	69.77	Fine-tuning	42.58	ο 72.5 -	
Prompt-tuning	62.54	Prompt-tuning	43.35	TUD 70.0 -	
Zero-shot with adaptatio	n	Zero-shot with adaptation		67.5 -	
Fine-tuning	55.62	Fine-tuning	46.51	65.0 -	Bottom K layers Fine-tuning
MAD-X (Pfeiffer+, 2020)	55.20	MAD-X (Pfeiffer+, 2020)	49.29	62.5 -	Adapter (MAD-X)
Ours	57.56	Ours	48.59		6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 Trainable layers K



## Conclusions

- First extend the generalization of mPLMs to unseen languages using only **soft-prompt** tuning
- We demonstrate the **efficiency** of soft-prompt language adaptation which
  - Outperforms fine-tuning with only **0.28%** of tunable parameter
  - Comparable to adapter-based method while utilizing **17 times** fewer parameters



