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Enhancing Translation of Myanmar Sign Language by Transfer Learning and Self-Training

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Outline

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Background

- There are many deaf or hard-of-hearing people in Myanmar
  - Approximately 1.1 M of the population
  - Population of deaf people with a university education is only 0.0006%
- They mostly rely on Myanmar Sign Language (MSL) for communication
- However, both deaf and hearing people find it rather difficult to learn MSL
- There are few and limited assistive technology available for deaf people

Goal

- To develop a high-quality translation system between Myanmar Sign Language (MSL) and Myanmar Written Language (MWL)
- Technical challenge
  - There are only a few limited parallel corpora between MSL and MWL
- Two techniques are used:
  - Transfer learning
  - Semi-supervised learning with self-training

Related Work (1/2)

1. Machine Translation for Low-Resource Languages Using Transfer Learning

- **Zoph et al. (2016)** [7] proposed transfer learning for low-resource neural machine translation (NMT). Their method involves training the parent model with a high-resource language pair and transferring some information from it to the child model with a low-resource language pair. The parent model's parameters influence the child model, boosting baseline NMT performance by an average of 5.6 BLEU.

- **Kocmi and Bojar (2018)** [9] proposed an innovative transfer learning approach for NMT. Parent model from any language pair improves child model performance, even with unrelated languages and different alphabets.

- **Maimaiti et al. (2022)** [10] proposed language-independent Hybrid Transfer Learning (HTL), which enhances NMT quality for low-resource, morphologically rich languages. HTL shares lexicon embeddings between parent and child languages, outperforming five state-of-the-art methods for Azerbaijani and Uzbek translations.

Related Work (2/2)

2. Myanmar Sign Language (MSL) Translation

- There are only a few previous studies since limited parallel data availability makes MSL translation difficult

- **Moe et al. (2018a)** [11] explored statistical machine translation (SMT) for MSL to MWL translation. Optimal performance was achieved using the Operation Sequence Model and Hierarchical Phrase-based SMT with syllable-based segmentation.

- **Moe et al. (2018b)** [12] compared NMT approaches for MSL translation. The transformer model outperformed Convolutional and Recurrent Neural Networks.

- **Moe et al. (2020)** [13] investigated unsupervised neural machine translation (U-NMT) for MSL and MWL. Among several monolingual corpora, the highest BLEU score is obtained when the myPOS corpus is used.

Characteristics of this study

- Transfer learning from a parent MT model (of high-resource language) to a child model (of low-resource language) is applied to the translation of MSL
  - Although transfer learning is common, it has not been applied to MSL

- In addition, semi-supervised learning by self-training is applied to increase the size of the parallel corpus between MSL and MWL

Myanmar Sign Language (MSL) (1/2)

- Deaf people use MSL as their primary communication language instead of voice
- There are two types of features: manual features (MF) and non-manual features (NMF) to convey meaning

Manual Features (MF)

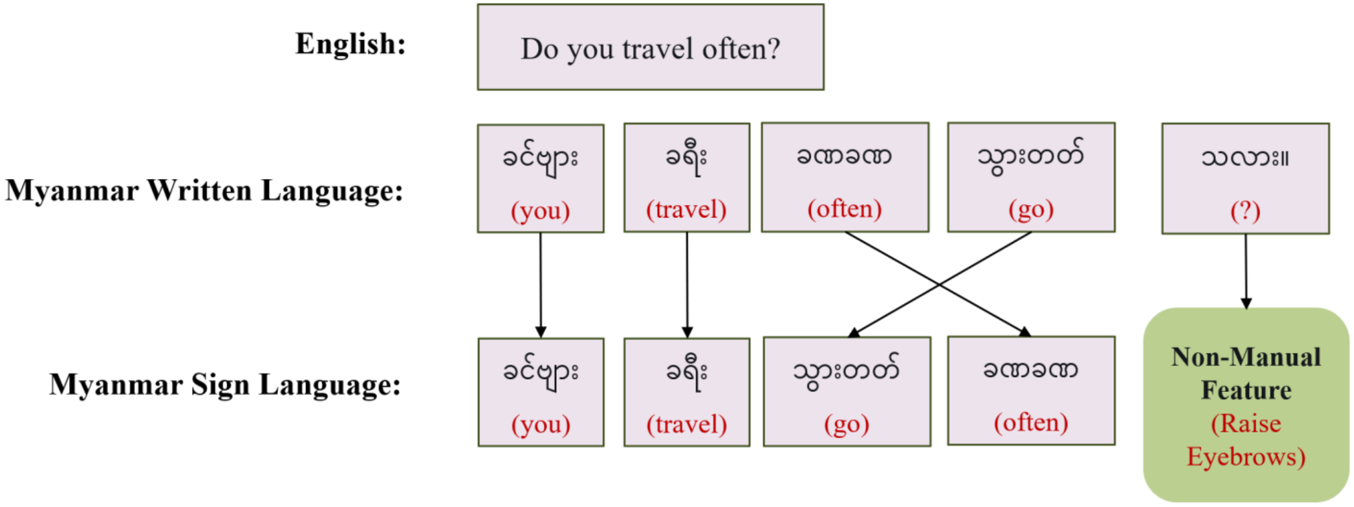
Hand shape, movement, position

Non-manual Features (NMF)

eye, mouth, chin movement, facial expression, & so on

Myanmar Sign Language (MSL) (2/2)

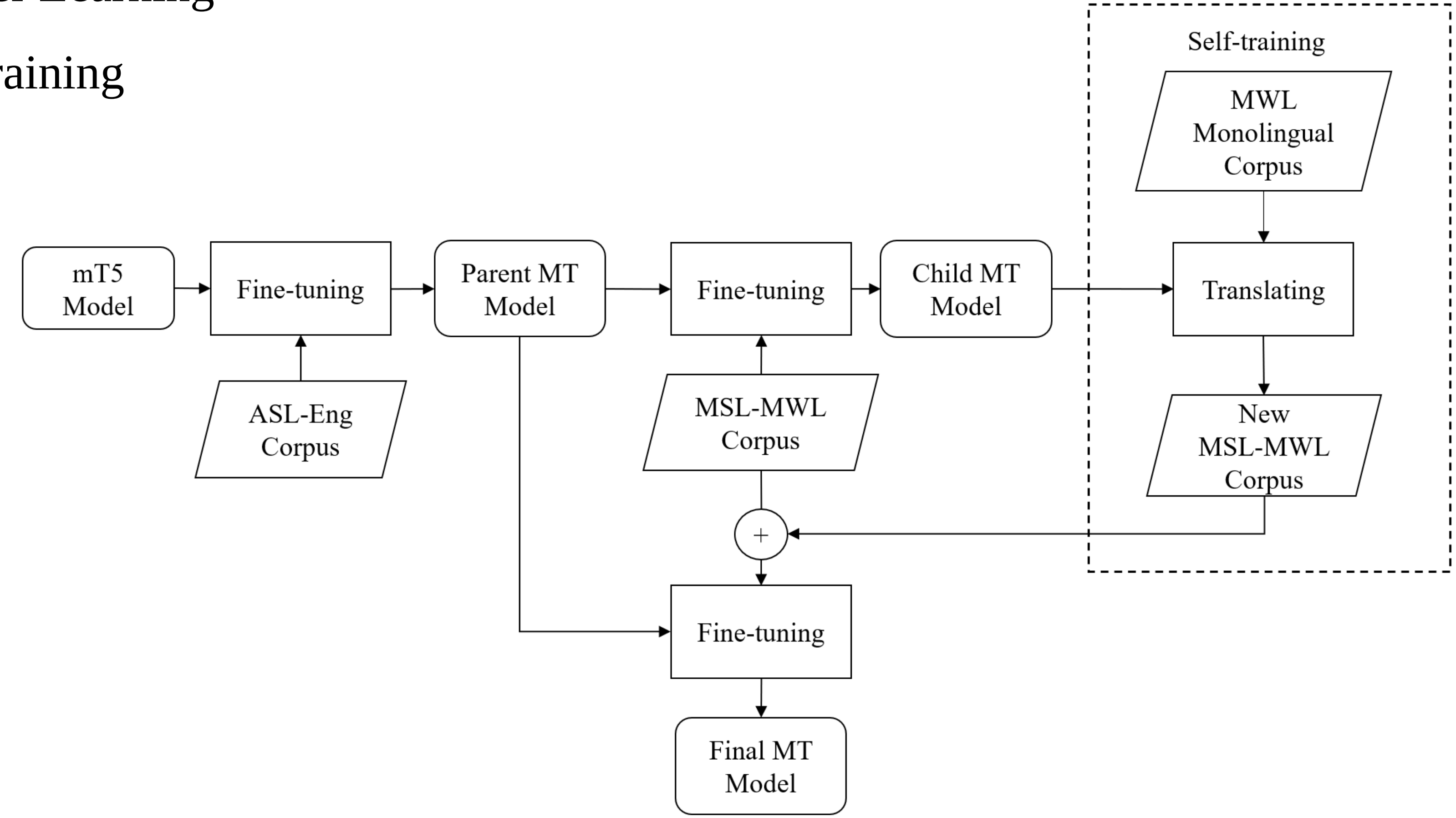
- MWL is tonal and syllable-based, whereas MSL relies on visual-spatial elements to convey meaning
- MSL and MWL are different in grammatical structure



- This study focuses on translating word sequences from MSL to MWL and vice versa, where a word in MSL represents a sign
- Currently, our approach can convert an MSL gloss into a sign or gesture, it doesn't consider for non-manual features

Proposed Method

- Multilingual Pre-trained Text-to-Text Transfer Transformer (mT5) model is used as a based translation system
- Our method consists of two basic methodologies
  1. Transfer Learning
  2. Self-Training



Preprocessing

- Sentences in MSL and MWL are segmented into a sequence of tokens as a preprocessing step
- Three segmentation schemes are used:
  - **Word-based Segmentation**: A sentence is manually divided into a word sequence by using spaces
  - **Syllable-based Segmentation**: The regular expression (RE)-based Myanmar syllable segmentation tool, called **sylbreak**, is used
  - **Byte-pair Encoding (BPE)-based Segmentation**: The BPE-segmentation model is built from the large monolingual corpus of MWL, myPOS

	MWL	MSL
No Segmentation:	ကျေးဇူးပြု၍ဖိနပ်ချွတ်ပါ။ (Please take off your shoes.)	ဖိနပ်ချွတ်ပါကျေးဇူးပြု၍။ (Please take off your shoes.)
Word-based Segmentation:	ကျေးဇူးပြု၍ (Please) ဖိနပ် (Shoes) ချွတ် ပါ (Take off) ။	ဖိနပ် (Shoes) ချွတ်ပါ (Take off) ကျေးဇူးပြု၍ (Please) ။
Syllable-based Segmentation:	ကျေး ဇူး ပြု ၍ ဖိ နပ် ချွတ် ပါ ။	ဖိ နပ် ချွတ် ပါ ကျေး ဇူး ပြု ၍ ။
BPE-based Segmentation:	ကျေးဇူးပြု၍ ဖိနပ် ချွတ် ပါ ။	ဖိနပ် ချွတ်@@ ပါ ကျေးဇူးပြု၍ ။

Transfer Learning

- The pre-trained mT5-Base model, which has 580 million parameters, is used

- Two-step fine-tuning of the mT5 model:
  - The parallel corpus of American Sign Language (ASL) and English is used to build the parent MT model
  - The parent MT model is fine-tuned again using a parallel corpus of MSL and MWL to obtain the child MT model
  - The knowledge in the parent MT model is transferred to the child MT model, which can compensate for the sparseness of the data of a Myanmar parallel corpus

Self-Training

- The sentences in the monolingual corpus are translated into MSL sentences using the trained child MT model
- The pairs of the original monolingual sentences and the translated sentences form a new parallel corpus
- To improve the quality of the automatically constructed parallel corpus, we filtered out the unreliable translations
  - The score of the translated sentence *s* is calculated using the following equation:

$$score\ (s) = \log P(s) \cong \sum_{w_i \in s} \log P_{mT5}(w_i)$$

  - $P(s)$ is the probability of generating s, while $P_{mT5}(w_i)$ is the probability of generating i-th token w_i estimated by the fine-tuned mT5 model
  - The top *N* translations with the highest scores are kept to make the new parallel corpus
- Finally, the original and new parallel corpus is used to fine-tune the child MT model

Evaluation (1/2)

Dataset

i. **Parallel Corpus of English:** A part of English-ASL Gloss Parallel Corpus2012 (ASLG-PC12) is used for training the parent MT model

ii. **Parallel Corpus of Myanmar Language:** Only one parallel corpus of MSL and MWL, which was collected from 30 sign language trainers and deaf people

iii. **Monolingual Corpus of Myanmar Language:** The myPOS corpus consists of 43,196 sentences that have been manually word-segmented and POS-tagged for the purpose of NLP research and development

	Parallel				Mono	Parallel*
	ASL–Eng		MSL–MWL		MWL	MSL–MWL
	Training	Test	Training	Test		
Sentence	85,710	2,000	2,836	300	43,196	10,000
Word	2,131,033	50,072	36,164	3,999	537,272	92,336
Character	11,828,933	278,499	472,044	51,905	7,534,916	1,085,076

* automatically constructed by self-training.

Evaluation (2/2)

1. **Bilingual Evaluation Understudy (BLEU) score**
   - To compare MT systems using different segmentation schemes, it is measured by counting the overlap of character n-gram

2. **Word Error Rate (WER)**

$$WER = \frac{S + D + I}{N}$$

S = the number of substitution errors

D = the number of deletion errors

I = the number of insertion errors

N = the total number of tokens in the reference

Result and Discussion (1/4)

- Several MT models between MSL and MWL are trained and compared
  - Three segmentation schemes (word, syllable, BPE)
  - The models trained with and without transfer learning
  - The models trained with and without the enlarged parallel corpus obtained by self-training

- The BLEU scores are calculated with confidence interval values at the **significance level of 0.95**

Result and Discussion (2/4)

- Comparing the models mT5 and mT5+T, an improvement of **0.62 points in MSL → MWL** and **5.06 points in MWL → MSL** with the syllable-based segmentation
- Comparing the models mT5 and mT5+S, the maximum improvement is **4.7 points of the MT model for MWL →MSL** with the syllable segmentation
- Combining transfer learning and self-training can further boost MT performance, the highest BLEU scores are **56.60 and 57.11 for MSL → MWL and MWL → MSL**, which are 5.93 and 5.88 points higher than the baseline model

BLEU score (↑)

Model	Parent Model	Self-Training	MSL→MWL word	MSL→MWL syllable	MSL→MWL BPE	MWL→MSL word	MWL→MSL syllable	MWL→MSL BPE
mT5			47.77 [43.95,50.70]	50.67 [46.14,54.06]	46.30 [43.26,50.11]	52.79 [48.80,55.94]	51.23 [47.51,54.44]	49.62 [45.56,53.00]
mT5+T	✓		49.62 [45.83,52.58]	51.29 [41.89,54.77]	46.42 [43.29,49.11]	52.01 [47.46,55.22]	56.29 [51.80,59.03]	50.73 [40.77,54.58]
mT5+S		✓	50.19 [45.99,54.27]	52.26 [48.60,55.89]	48.00 [44.47,50.25]	49.40 [45.96,52.54]	55.93 [52.31,59.37]	49.61 [45.94,52.96]
mT5+T+S	✓	✓	51.65 [47.71,55.29]	**56.60** [52.72,59.76]	53.48 [49.98,56.91]	56.53 [52.92,59.84]	**57.11** [52.61,60.62]	51.02 [47.79,52.54]

Result and Discussion (3/4)

- The lowest WER is obtained by mT5+T+S with the syllable segmentation scheme
- The results of WER are similar to BLEU, that is,
  1. The syllable segmentation is the best
  2. Both transfer learning and self-training are effective
  3. The contributions of those two techniques are comparable

WER (%) (↓)

Model	Parent Model	Self-Training	MSL→MWL word	MSL→MWL syllable	MSL→MWL BPE	MWL→MSL word	MWL→MSL syllable	MWL→MSL BPE
mT5			53.5	50.3	52.8	57.4	51.8	51.2
mT5+T	✓		53.1	49.2	51.6	56.5	48.3	52.6
mT5+S		✓	53.9	49.7	51.2	55.9	47.9	50.8
mT5+T+S	✓	✓	51.1	$\boxed{\textbf{48.2}}$	50.4	55.2	$\boxed{\textbf{46.5}}$	49.2

Result and Discussion (4/4)

- Comparison between our best method (mT5+T+S, syllable) and three previous studies
- Syllable-based BLEU score is measured due to the consistency with previous work
- Our method is better than or comparable to the previous studies
  - It is not a fair comparison since the size of the datasets used for the evaluation are different

Method		MSL→MWL	MWL→MSL
mT5+T+S	syllable	37.83	$\boxed{39.97}$
(Moe et al., 2018a)	Supervised, SMT	34.78	35.11
(Moe et al., 2018b)	Supervised, NMT	$\boxed{38.21}$	32.92
(Moe et al., 2020)	Unsupervised, NMT	10.47	29.53

Error Analysis

E1:	Input:	သူ တို့ (they) နောက် (next) ရာ သီ (weather) နွေ (summer) လက် ထပ် (marry) ။ (end word)
	Output:	**သူ တို့** (they) က (preposition) နွေ (summer) ရာ သီ (weather) မှာ (PPM-TIME$_1$) လက် ထပ် (marry) တယ် (PPM-FUTURE) ။ (end word)
	Reference:	နောက် (next) လာ မယ့် (coming) နွေ (summer) ရာ သီ (weather) ဆို (PPM-TIME$_2$) **သူ တို့** (they) လက် ထပ် (marry) တော့ မှာ (PPM-PAST) ။ (end word)
	English:	They will get married next summer.
E2:	Input:	ဟင့် အင်း (no) အ ပျို (single girl) ။ (end word)
	Output:	ဟင့် အင်း (no) **ကျွန် တော်** (he) အ ပျို (single girl) ပါ (am) ။ (end word)
	Reference:	ဟင့် အင်း (no) **ကျွန် မ** (she) အ ပျို (single girl) ပါ (am) ။ (end word)
	English:	No, I am a single girl.
E3:	Input:	ခင် ဗျား (you$_1$) လက် (hand) လှုပ် (move) ရ (can) လား (?) ။ (end word)
	Output:	**မင်း** (you$_2$) လက် (hand) လှုပ် (move) တတ် (can) လား (can ?) ။ (end word)
	Reference:	**ခင် ဗျား** (you$_1$) လက်(hand) လှုပ် (move) လို့ ရ (can) သေး (still) လား (?) ။ (end word)
	English:	Can you move your hand?

- Investigating the errors of the best model mT5+T+S for translating from MSL to MWL with the syllable segmentation scheme

- Example E1 shows that the model generates the word **"they"** as the first word, despite it being the sixth word in the reference
- This highlights the model's struggle in capturing grammatical structure differences between MSL and MWL

- In example E2, the word **"she"** in the reference is replaced with **"he"**, causing a gender inconsistency with "girl"

- In example E3, the Myanmar word **"you$_1$"** is replaced with the other word **"you$_2$"**
- Both words have almost the same meaning but are used in different situations
- This indicates that some substitution errors are acceptable, even if the output differs from the reference

Conclusion

Summary

- A novel method is proposed to train a machine translation (MT) model for translating between Myanmar Sign Language (MSL) and Myanmar Written Language (MWL)

- To tackle the problem posed by the fact that MSL is an extremely low-resource language, transfer learning and self-training were applied where mT5 pre-trained model was used as the backbone

- The results of the experiments showed that both transfer learning and self-training could contribute to improving MT performance

Future Work

- We will extend our method for the translation of MSL to include both manual and non-manual features

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Thank You!

Your time and attention are greatly appreciated.

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