Adapters and Reinforcement Learning for Data-Efficient Machine Translation

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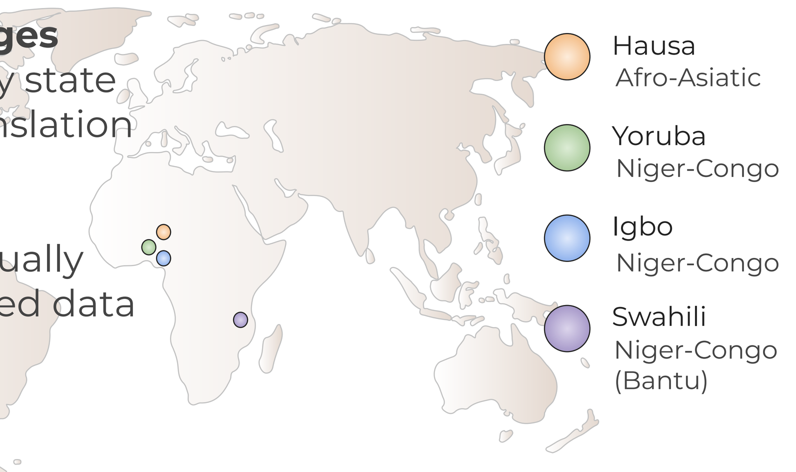
INTRODUCTION

- **Low-resource languages** (LRLs) are neglected by state of the art machine translation systems, **even GPTs**
  - Limited data
  - Expensive to manually annotate unlabelled data
- Explore efficacy of two data-efficient training techniques
  - **Language adapters**
  - **Reinforcement learning**



Languages of interest in this work and their language families

KEY FINDINGS

Monolingual language adapters and reinforced self-training (ReST) improve LRL translation performance over the multilingual M2M-100 model.

- **Data-efficient:** utilize monolingual data using ReST
  - Avoid costly human annotation
- **Compute-efficient:** adapters have a fraction of the trainable parameters compared to traditional finetuning
  - Faster, less GPU-intensive training
- **Cross-lingual transfer:** leverage related language data to strengthen target language translation performance

METHODS

*Base Model: **M2M-100**, Meta's pretrained transformer-based multilingual model[1]*

Monolingual Adapters[2]

- Separating source and target language adapters facilitates incorporation of additional parallel data
  - Effective **zeroshot transfer** to unseen lang pairs
  - E.g. train en-ha, sw-yo => can translate en-yo, sw-ha as well

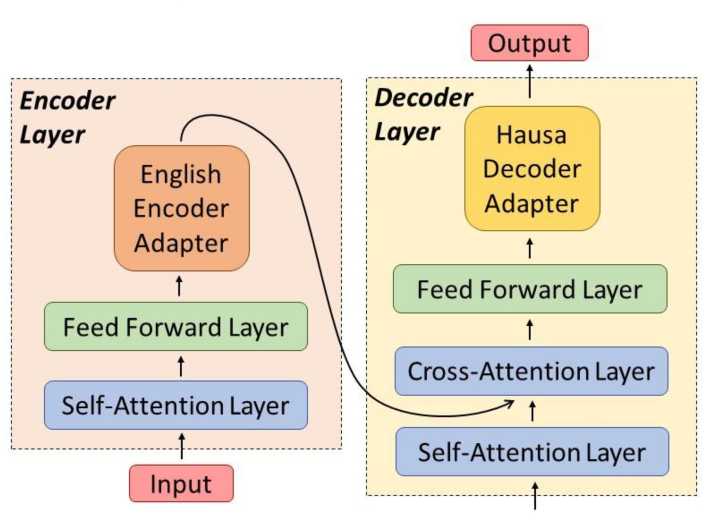


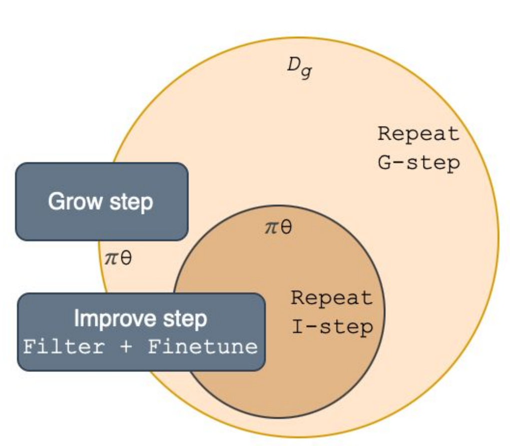
Diagram of monolingual adapters in the en-ha language direction

Model	Num. of Parameters
M2M-100	418.00 million
Monolingual Adapters	4.76 million

- **Parameter-efficient**: Freeze base model, train adapters on each encoder/decoder layer

Reinforced Self-Training[3]

- **Grow** - Generate augmented dataset using the current policy $y \sim \pi_\theta(y|x)$ and $x \in$ monolingual source data
- **Filter** - Filter augmented dataset $\mathcal{D}_g$ using reward function $R(x, y)$
- **Improve** - Finetune policy π_θ using reward filtered augmented data $\mathcal{D}_g$

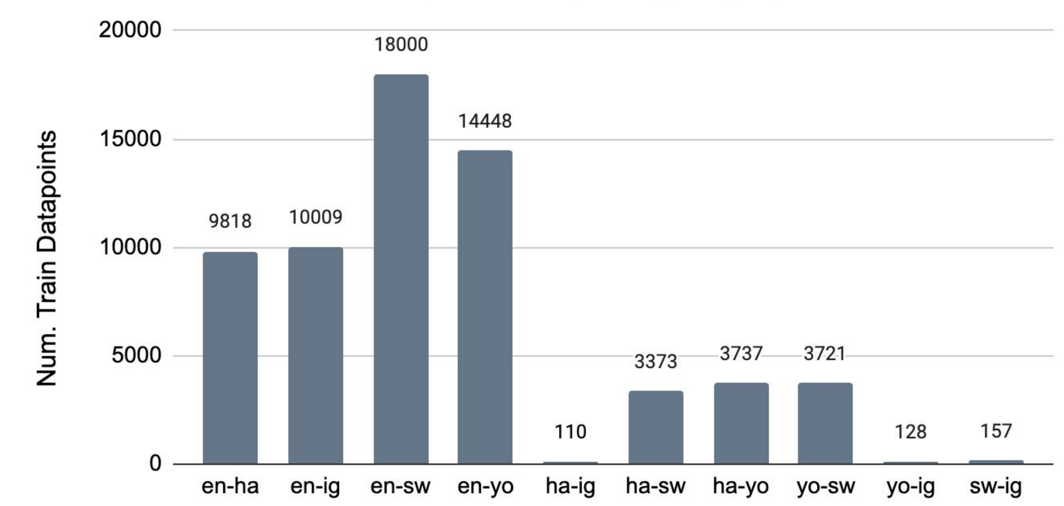


RESULTS

Data

- Combined Lafand-MT[4] and WebCrawl[5] datasets for train and dev splits
  - Simulated low-resource for English-Swahili by randomly selecting 20,000 datapoints
- Flores-200[7] for evaluation
  - 1002 datapoints per language pair

Train datapoints by language pair



Baselines

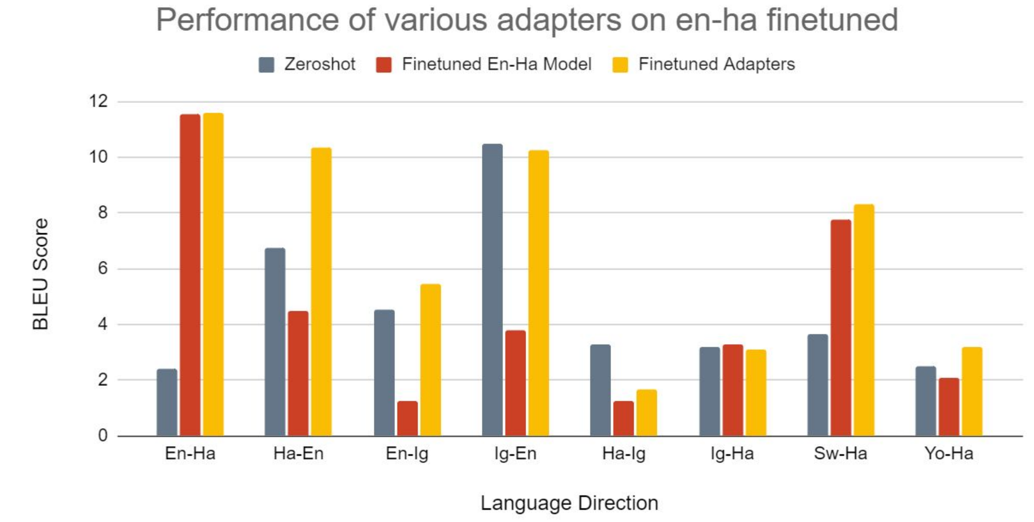
- **Weak Baseline**: Zeroshot evaluation of M2M-100 on English-Hausa (en-ha) and Hausa-English (ha-en)
- **Strong Baseline**: Finetuned evaluation of M2M-100 on en-ha and ha-en

Model	Language Direction	BLEU
M2M Zeroshot	English - Hausa	2.39
M2M Zeroshot	Hausa - English	6.76
M2M Finetuned	English - Hausa	11.53
M2M Finetuned	Hausa - English	15.34

Monolingual Adapters

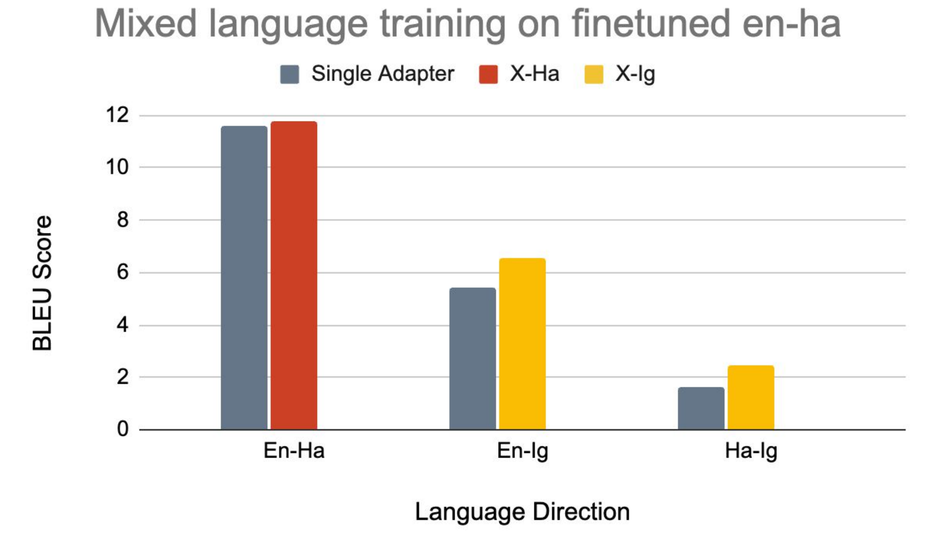
- Changing target language leads to significant performance gains

Performance of various adapters on en-ha finetuned



- Adapters learn better in **mixed language** (X-Target) setup
  - Exposes adapters to more diverse data

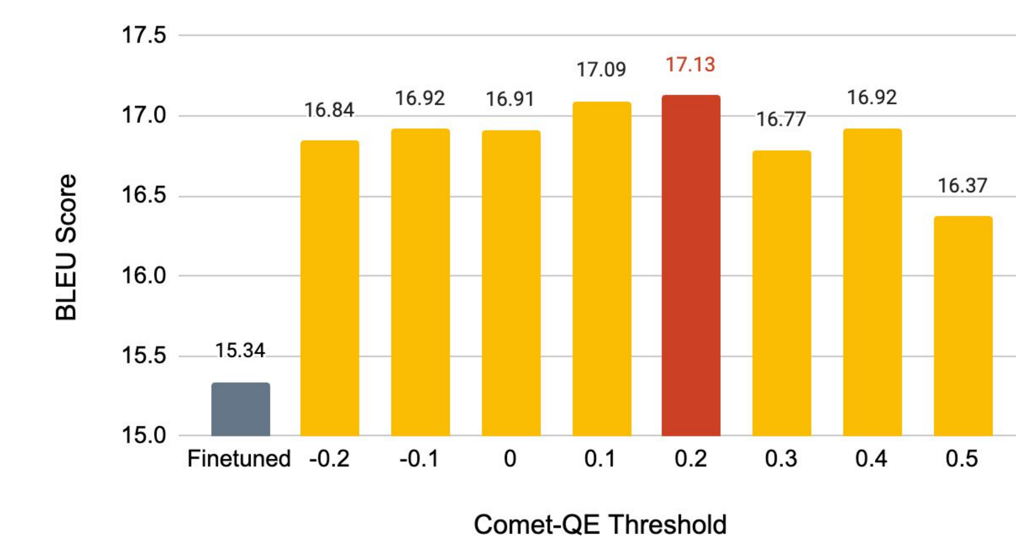
Mixed language training on finetuned en-ha



Reinforced Self-Training

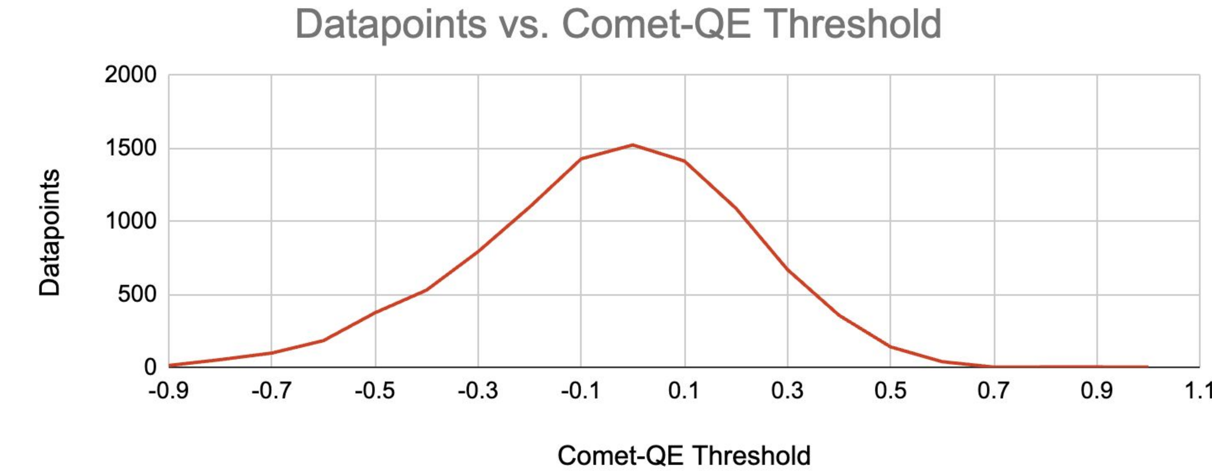
- Optimally selecting the reward function and filter threshold yields significant performance boost over finetuned model
  - Available **monolingual Hausa data**[6]: 1 million datapoints
  - **Reward Function**: Comet-Quality-Estimator[8]

Performance at different thresholds of finetuned ha-en



- How to find the optimal threshold?

Datapoints vs. Comet-QE Threshold

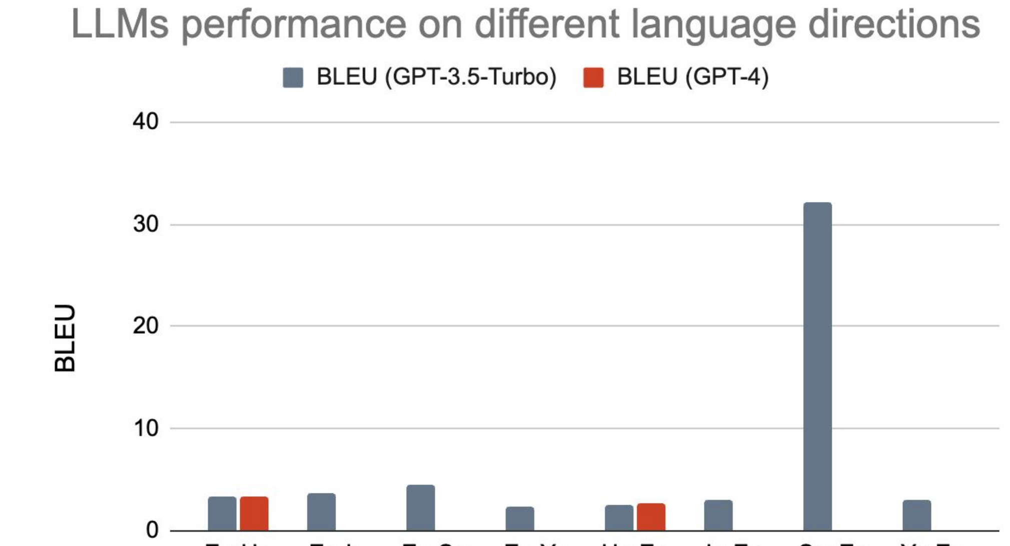


What about LLMs?

Large Language Models for LRL Translation

- LLMs like GPT-3.5-Turbo[9]/GPT-4 generally **don't perform well** for low-resource languages
- Why is **Swahili-English** BLEU score exceptionally high?
  - Translation is modeled as conditional generation problem, heavily influenced by…
    - Powerful target language model
      - LLMs are remarkably good English language models
    - High quality source-target parallel corpus
      - Vast, high quality Swahili-English data

LLMs performance on different language directions



CONCLUSION

Monolingual adapters and reinforced self-training methods show promise for low-resource X-X translation using English-centric translation data.

Adapters

- Most significant gains in performance when adapters are exposed to many different language directions
  - Allows for **incorporation of more data**
- Results indicate underlying model may need sufficient related language knowledge for adapters to build upon
  - May be necessary to finetune model on similar language pair

Reinforced Self-Training

- ReST improves over base supervised training
- Do additional grow steps improve the reward model?
  - Yes, but **progressively diminishing improvements**

FUTURE WORK

Adapters

- Experiment with **different base models** for adapters to determine the extent of the impact pretraining has on adapters' performance
  - E.g. DeltaLM, SeamlessM4T
- Use **family adapters** to explore the impact of linguistic relationships on adapter training

Reinforced Self-Training

- Learning from **weak supervision** of a combination of multiple reward functions
- Enhance performance by additional grow steps using **diverse monolingual data**
  - Domains are important, e.g. more news data
- Efficient hyper-parameter search to improve the policy at each improve step

Adapters + Reinforced Self-Training

- Investigate benefits of using **ReST** method to **finetune monolingual adapters**

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