



Minimal Clues, Maximal Understanding: Solving Linguistic Puzzles with RNNs, Transformers, and LLMs

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Problem and Introduction

- Critical gap exists in ability of deep-learning models to mimic human-like reasoning and understanding
- We uncover limits by solving *Rosetta Stone* linguistic puzzles with minimal bidirectional translations
- Experiments: i) **RNNs**, ii) **fine-tuned transformer based models**, and iii) **GPT-4 in-context learning**
- Our methods surpass baselines (with GPT-4 being the best) but lack human-like reasoning

Background and Datasets

- Most NLP research predominantly concentrates on merely 0.2% of known languages (20 out of 7,000)
- Puzzles from **PuzzLing Machines**¹ dataset are solvable without knowledge of chosen diverse languages: Swahili, Georgian, Norwegian, Malay
- Explored two datasets: “large” 10,000-sentence **TedTalk corpus**² and “small” linguistic puzzles
- Dataset did not include puzzle solutions so we performed data curation for training and test sets

Chickasaw	English
Ofi'at kowi'ā lhiyohli.	The dog chases the cat.
Kowi'at ofi'ā lhiyohli.	The cat chases the dog.
Ofi'at shoha.	The dog stinks.
Ihooat hattakā hollo.	The woman loves the man.
Lhiyohlii.	I chase her/him.
Salhiyohli.	She/he chases me.
Hilha.	She/he dances.
Translate the following into Chickasaw:	
?	The man loves the woman.
?	The cat stinks.
?	I love her/him.
Translate the following into English:	
Ihooat sahollo.	?
Ofi'at hilha.	?
Kowi'ā lhiyohlii.	?

Rosetta Stone linguistic puzzle

Methods

- **Baselines:** Implemented *Random Words* and *FastAlign* methods
- **Recurrent Neural Network (RNN)*:** Sequence-to-sequence network with LSTM encoder and decoder plus attention
- **Transformer-Based Models*:** Pre-trained NMT models with self-attention (6 layers each with 8 attention heads)
- **LLM In-Context Learning:** Provided solved puzzles and prompted GPT-4 for translation without language-specific knowledge

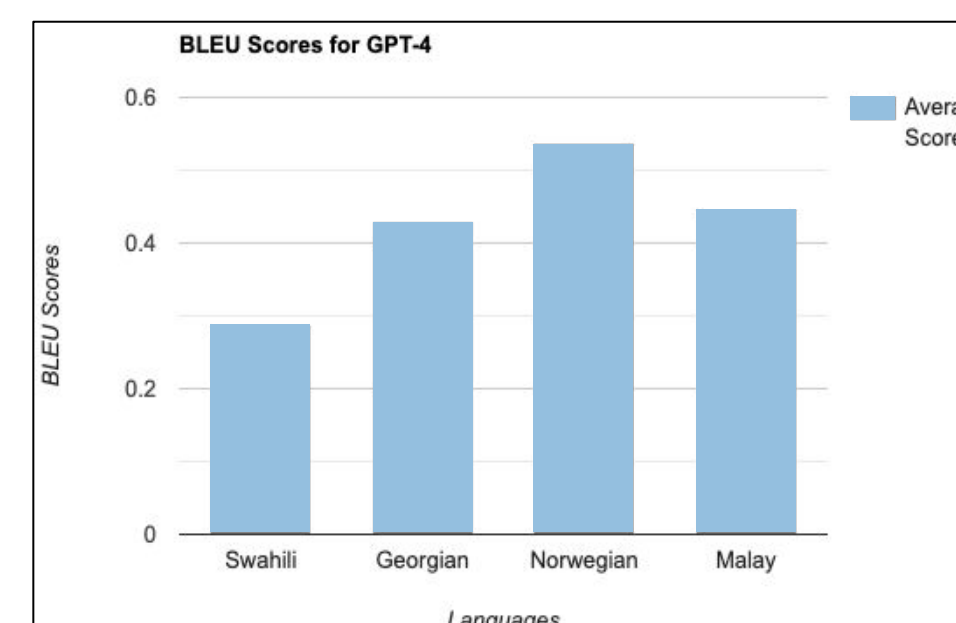
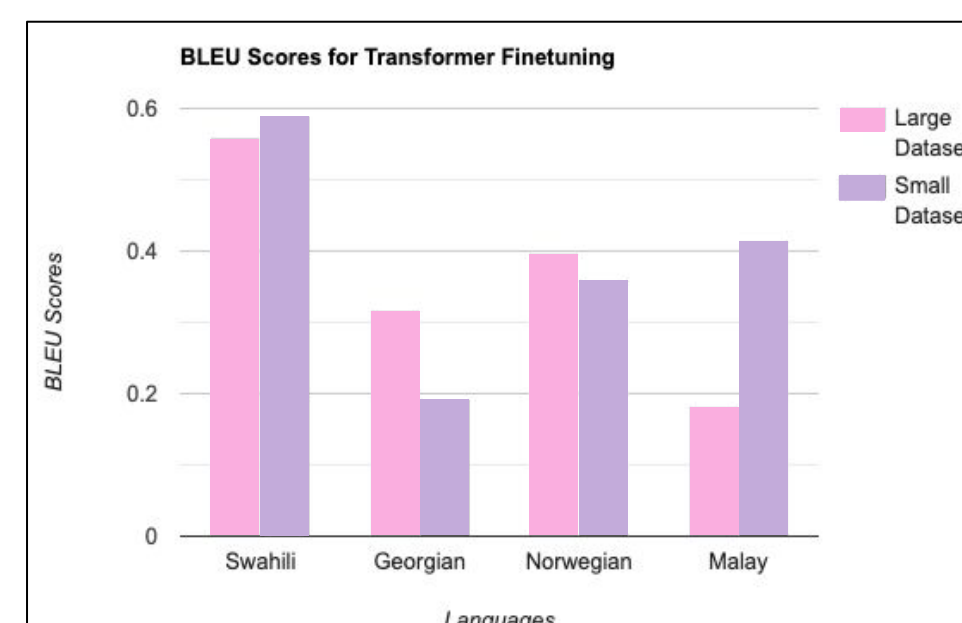
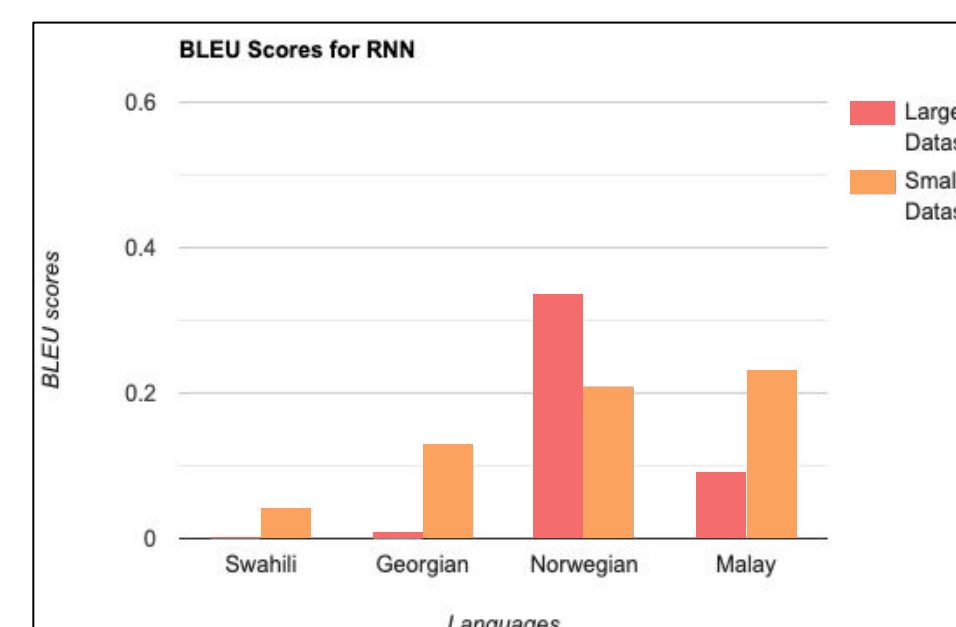
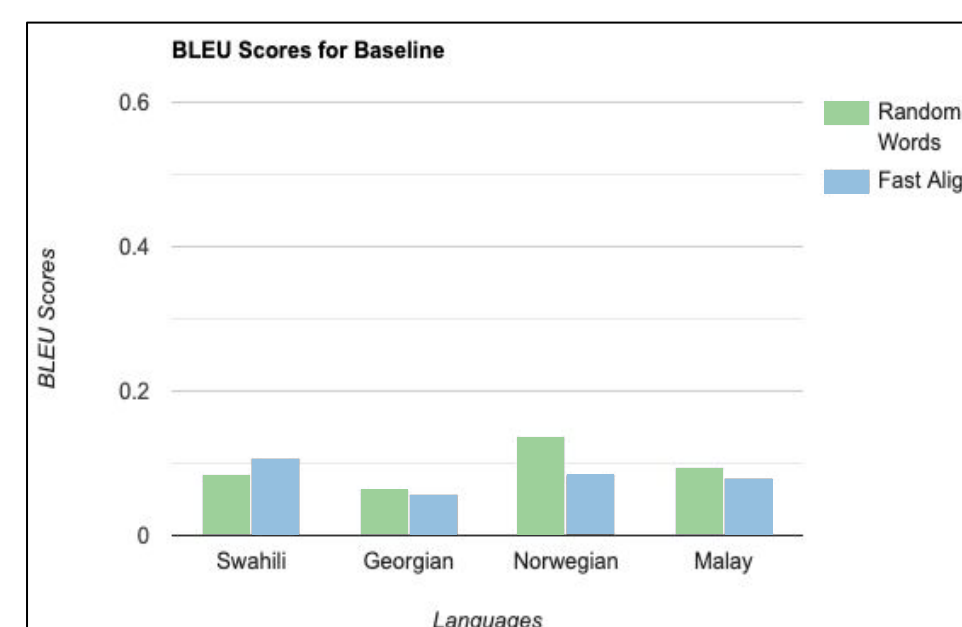
* fine-tuned on either TEDTalk external corpus or small set of solved linguistic puzzles

Experiments and Results

- Four RNN and four fine-tuned transformer models per language
- Trained for 16.5 hours on NVIDIA A100 GPUs with 80GB RAM

Averaged results by model type

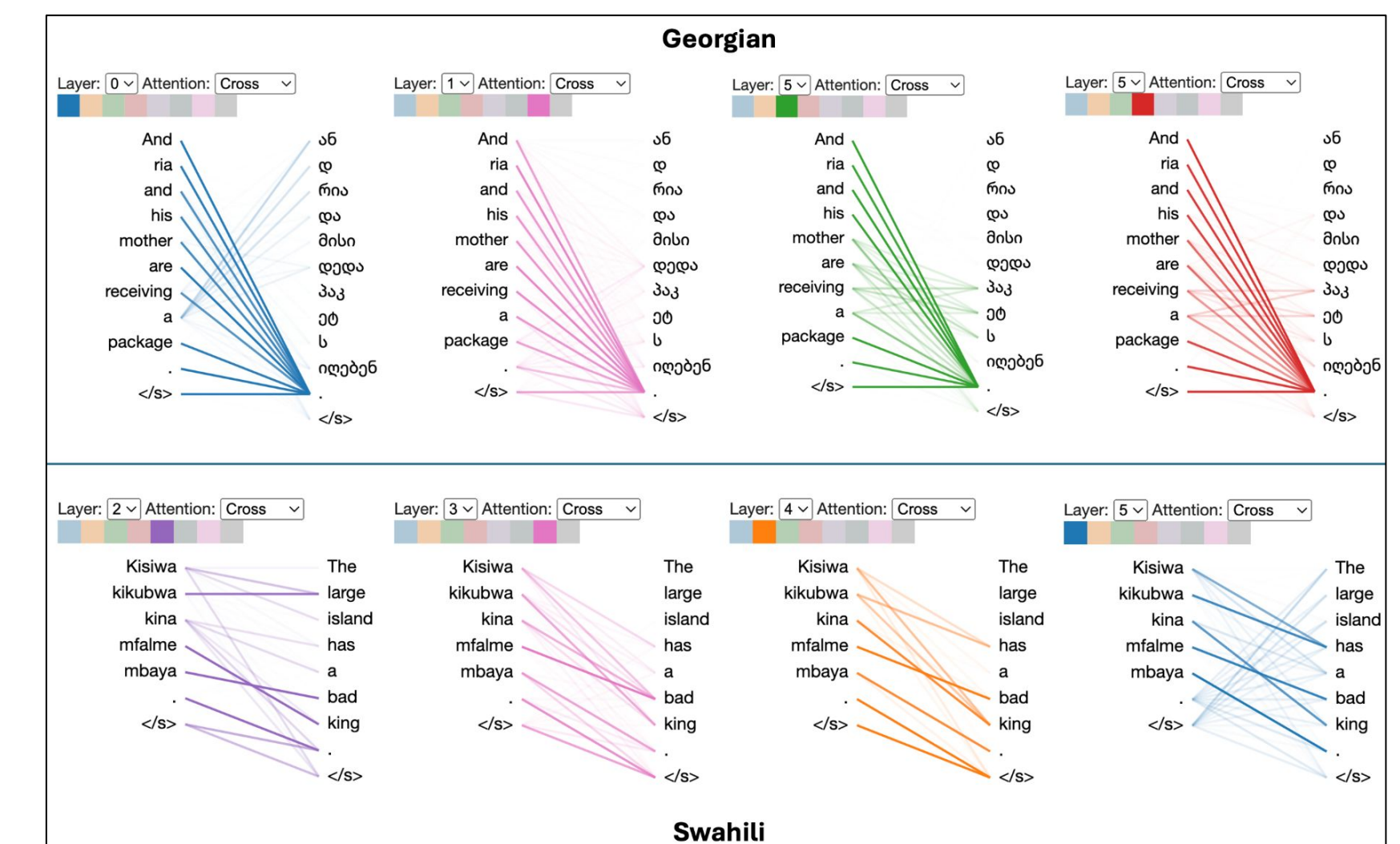
Model	BLEU	CHRF	CTER	EM
Random Words	0.083	0.271	0.188	0.000
Fast Align	0.096	0.295	0.237	0.000
RNN	0.132	0.295	0.059	0.000
Transformer Finetuning	0.387	1.710	11.142	0.000
GPT-4	0.420	0.793	0.243	0.000



BLEU score comparisons by language across model types

Analysis

- RNN and GPT-4 perform best on Norwegian plausibly due to close proximity to English (both Germanic languages with Latin alphabet)
- Performance varies with language *i.e.*, Georgian’s subject-object-verb grammar vs. subject-verb-object for English
 - Shows importance of model adaptability to infer linguistic patterns
- Most Georgian model attention heads focus on “.” punctuation mark
- Swahili model attention shows strong links between correct translation pairs such as “mfalme” — “king” and “mbaya” — “bad”



Attention for Georgian and Swahili fine-tuned transformers

Conclusions and Future Work

- Best performances achieved by transformer fine-tuning and GPT-4, with BLEU scores of 0.387 and 0.420, respectively
- **Research limitation:** variability in puzzle difficulty across different languages. We suggest standardization using human benchmarks
- **Future work:** propose meta-learning techniques to surpass the limitations of current deep-learning models and LLMs

References

- 1) Sahin *et. al.* 2020. PuzzLing Machines: A Challenge on Learning From Small Data.
- 2) <https://opus.nlpl.eu/NeuLab-TedTalks/corpus/version/NeuLab-TedTalks>.