Prompting Large Language Model for Machine Translation: A Case Study

Biao Zhang, Barry Haddow, Alexandra Birch

Edinburgh
University of Edinburgh
Natural Language Processing
NLP

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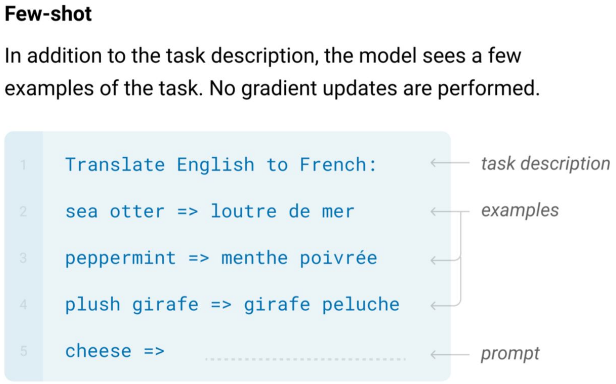
Prompting LLM gains popularity and also works for MT



GPT-3's in-context learning or few-shot prompting for machine translation

		0-shot		1-shot		Few-shot		Supervised
Src	Tgt	Prior SOTA	PaLM 540B	Prior SOTA	PaLM 540B	Prior SOTA	PaLM 540B	Finetuned SOTA
en	fr	32.9[a]	**38.5**	28.3[b]	**37.5**	33.9[a] (9)	**44.0**	45.6[c]
en	de	25.4[a]	**31.8**	26.2[b]	**31.8**	26.8[a] (11)	**37.4**	41.2[d]
en	ro	16.7[a]	**24.2**	20.6[b]	**28.2**	20.5[a] (9)	**28.7**	33.4[e]
fr	en	35.5[a]	**41.1**	33.7[b]	**37.4**	38.0[a] (9)	**42.8**	45.4[f]
de	en	38.9[a]	**43.8**	30.4[b]	**43.9**	40.6[a] (11)	**47.5**	41.2[g]
ro	en	36.8[a]	**39.9**	38.6[b]	**42.1**	37.3[a] (9)	**43.8**	39.1[h]

MT results (BLEU) on WMT datasets for PaLM

Brown et al., 2020; Chowdhery et al. 2022

…… but **it is non-trivial**

Few-shot

In addition to the task description, the model sees a few examples of the task. No gradient updates are performed.

```
Translate English to French:       ← task description
sea otter => loutre de mer          ← examples
peppermint => menthe poivrée
plush girafe => girafe peluche
cheese => ...........               ← prompt
```

GPT-3's in-context learning or few-shot prompting for machine translation

Src	Tgt	0-shot Prior SOTA	0-shot PaLM 540B	1-shot Prior SOTA	1-shot PaLM 540B	Few-shot Prior SOTA	Few-shot PaLM 540B	Supervised Finetuned SOTA
en	fr	32.9[a]	**38.5**	28.3[b]	**37.5**	33.9[a] (9)	**44.0**	45.6[c]
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MT results on WMT datasets for PaLM

A systematic study of how prompting works for MT is still missing!

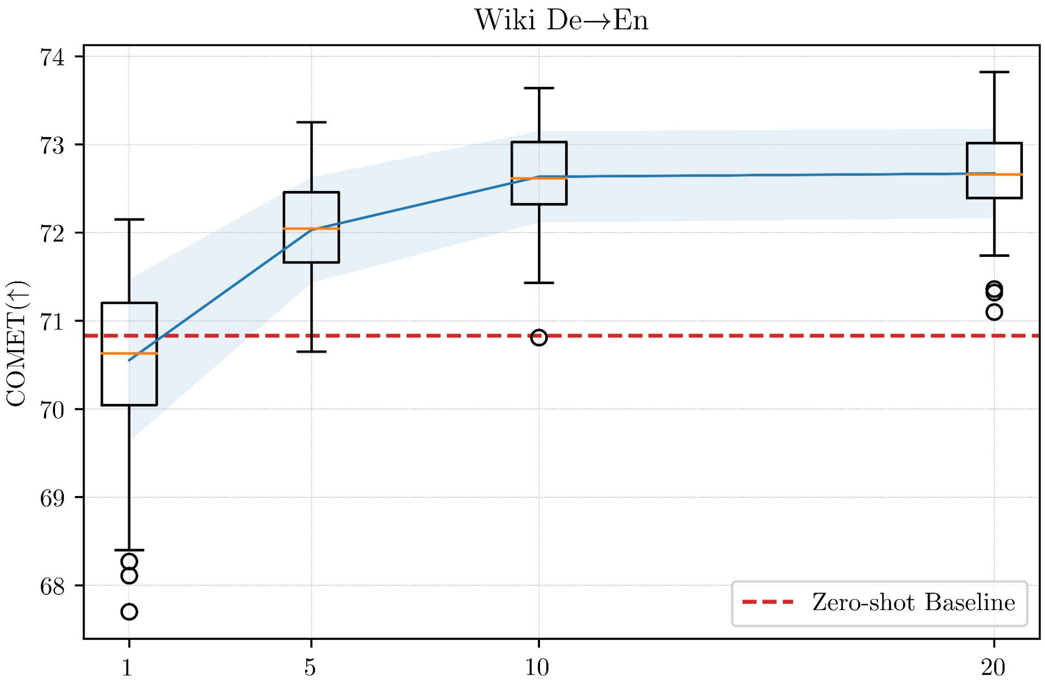
Research Questions

- What’s the best ***prompting strategy*** for MT?
- Can we use ***monolingual data*** for few-shot prompting?
- Can we ***transfer prompt*** across different settings?

Experimental setup

- Model
  - GLM-130B [Chinese and English] (quantized version)
- Languages
  - English (En), German (De), Chinese (Zh)
- Dataset
  - Wiki (Flores, En-De-Zh), WMT21 (En-De, En-Zh), Multi-Domain (IT, Law and Medical, De-En)
  - PDC for document-level translation (En-Zh)
  - Ablation set: 100 samples from dev as ablation test, the rest as ablation dev
- SacreBLEU, COMET and Spearman correlation

Demonstration greatly affects prompting quality



* The curve: **more examples gives better quality**

* Each box: **quality varies greatly over different examples**

* Results on Wiki De→En Ablation sets for few-shot prompting.
* We randomly sample 100 times from the pool.

Example is important; How to select?

Feature	Model	Case dep	Description
SLength	None	No	Source length
TLength	None	No	target length
LMScore	**GLM-130B**	No	log likelihood of GLM
MTScore	**COMET QE**	No	MT quality of prompt example
SemScore	**LASER2**	No	cosine semantic similarity of prompt example
CaseSemScore-Src	**LASER2**	**Yes**	SemScore(source example, test input)
CaseSemScore-Tgt	**LASER2**	**Yes**	SemScore(target example, test input)

input and model agnostic

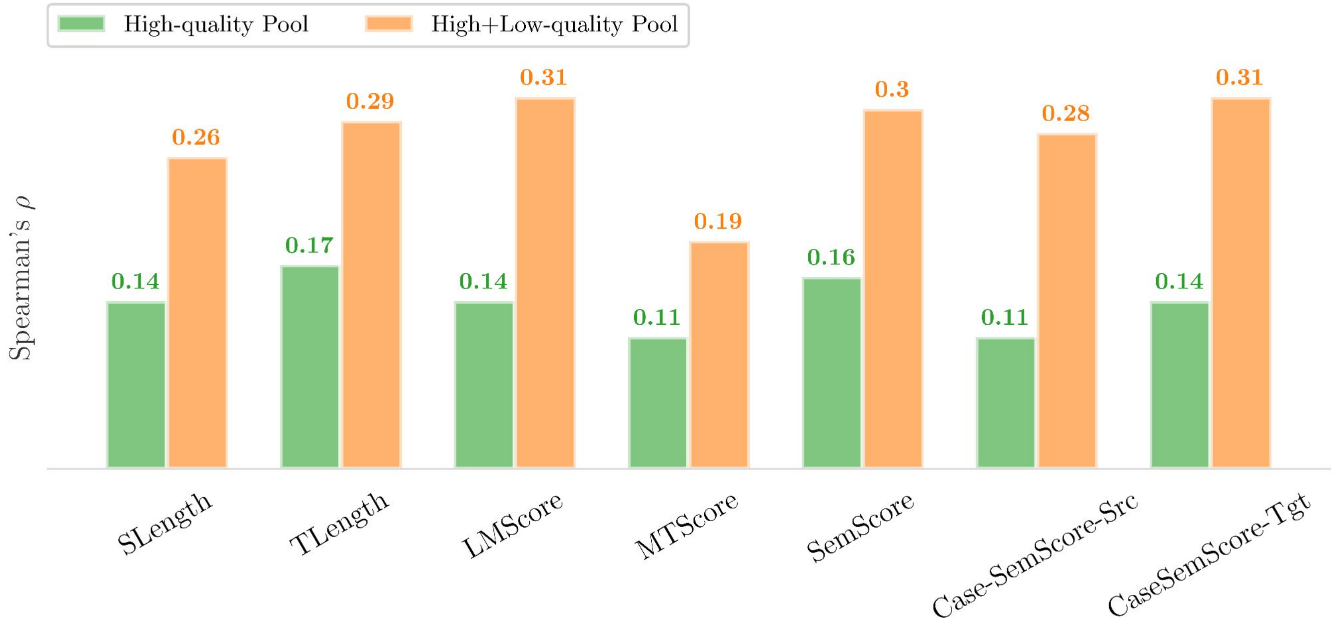
model dependent but input agnostic

input and model dependent

*** We extract a set of features and check their correlation with prompting results**

* We focus on **1-shot prompting** to simplify the setup

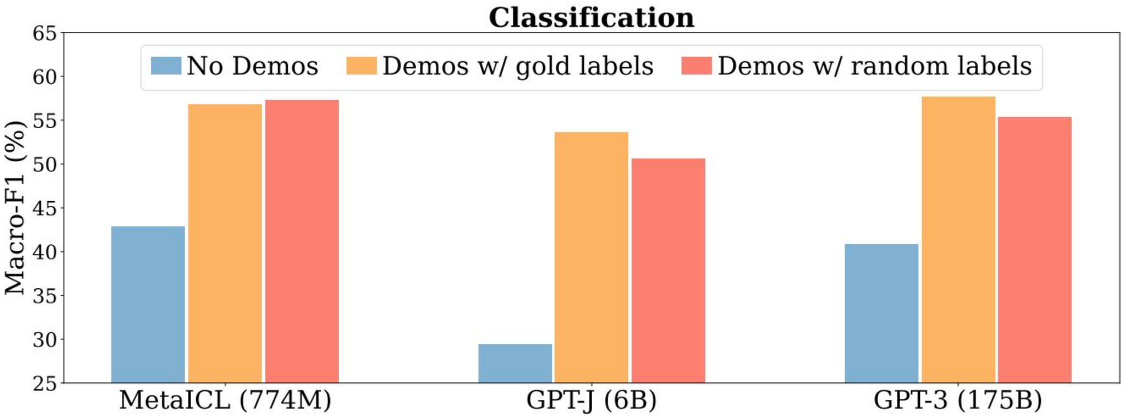
Features show significant yet weak correlation



* Average Spearman scores (over 6 directions) for 1-shot prompting on Wiki Ablation sets.
* **High-quality pool**: FLORES Ablation dev set; **Low-quality pool**: WikiMatrix v1.
* We randomly sample **600 demonstrations** to compute the correlation.

Do we need genuine MT pairs for demonstration?

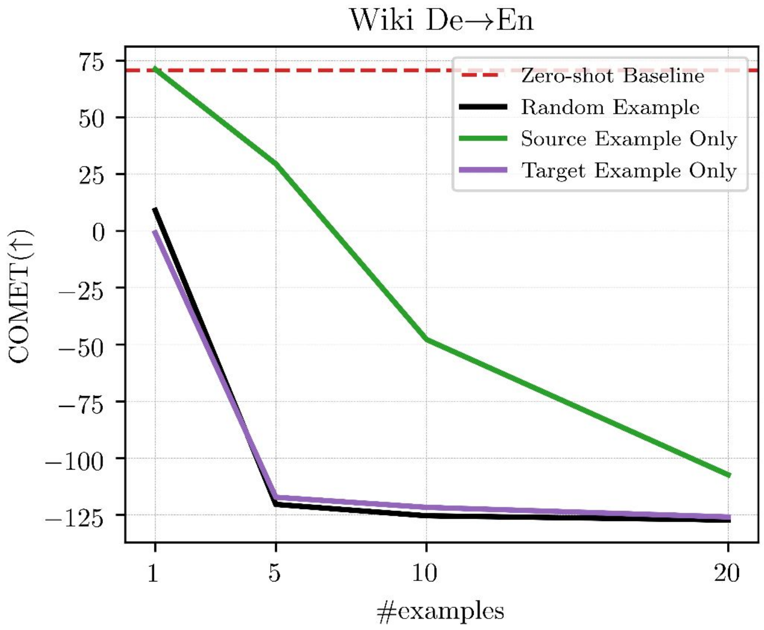
- Ground truth demonstrations may be unimportant (Min et al., 2022).



Does this also apply to MT? Further, can we use monolingual data for prompting?

Example taken from *Rethinking the Role of Demonstrations: What Makes In-Context Learning Work? (Min et al., 2022)*

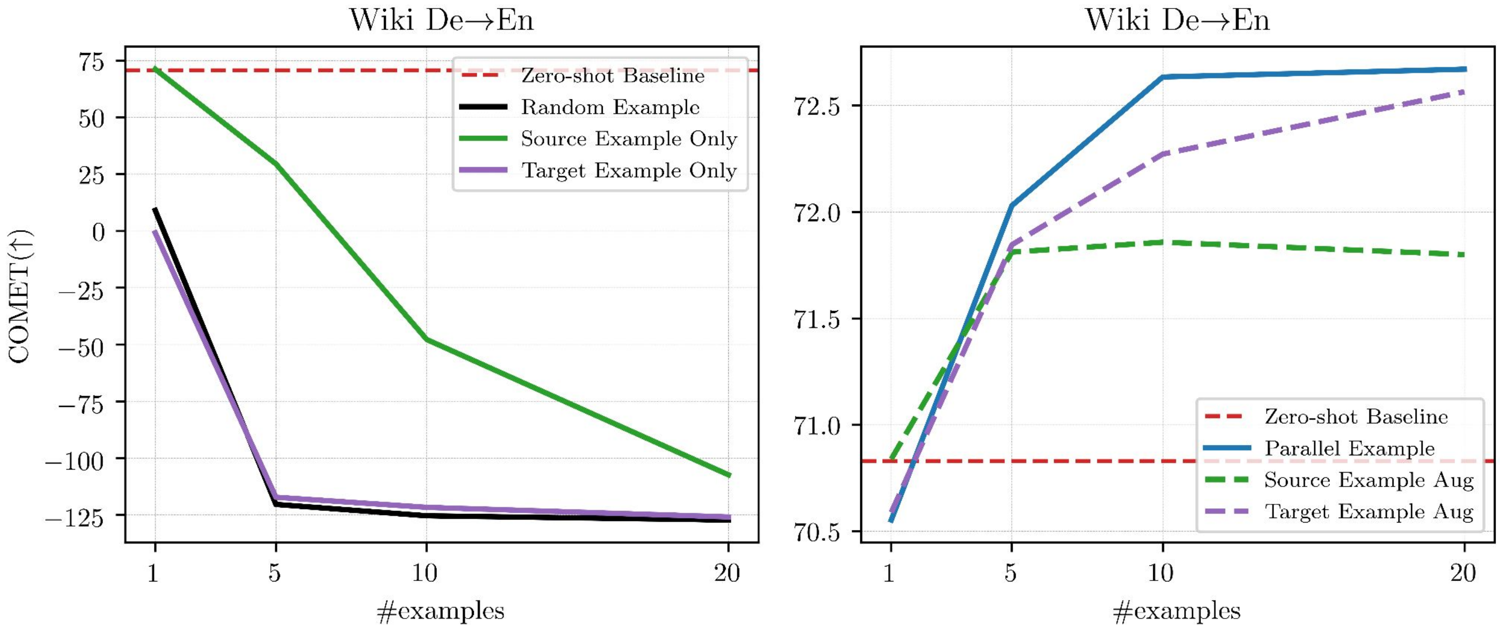
MT prompting requires genuine input-output mapping



* Using random examples hurts prompting
* Source-only or target-only monolingual prompting doesn’t work

Results on Wiki De→En Ablation sets; we randomly sample 50 demonstrations and report average performance.

Can we use mono data? Yes! For/backward translation



* Pseudo parallel data (based on zero-shot prompting) benefits prompting

* Back-translation performs better than forward-translation

Choosing demonstrations is hard; can we transfer it?

Setting *A*

We have rich resources and found good demonstrations, D_1 and D_2 , and

$$\text{perf}(D_1) > \text{perf}(D_2)$$

Setting *B*

1. $\text{perf}(D_1)$ or $\text{perf}(D_2) >$ zero-shot prompting ?
2. $\text{perf}(D_1) > \text{perf}(D_2)$?

Cross-lingual transfer

e.g. En→De ⇒ De→Zh

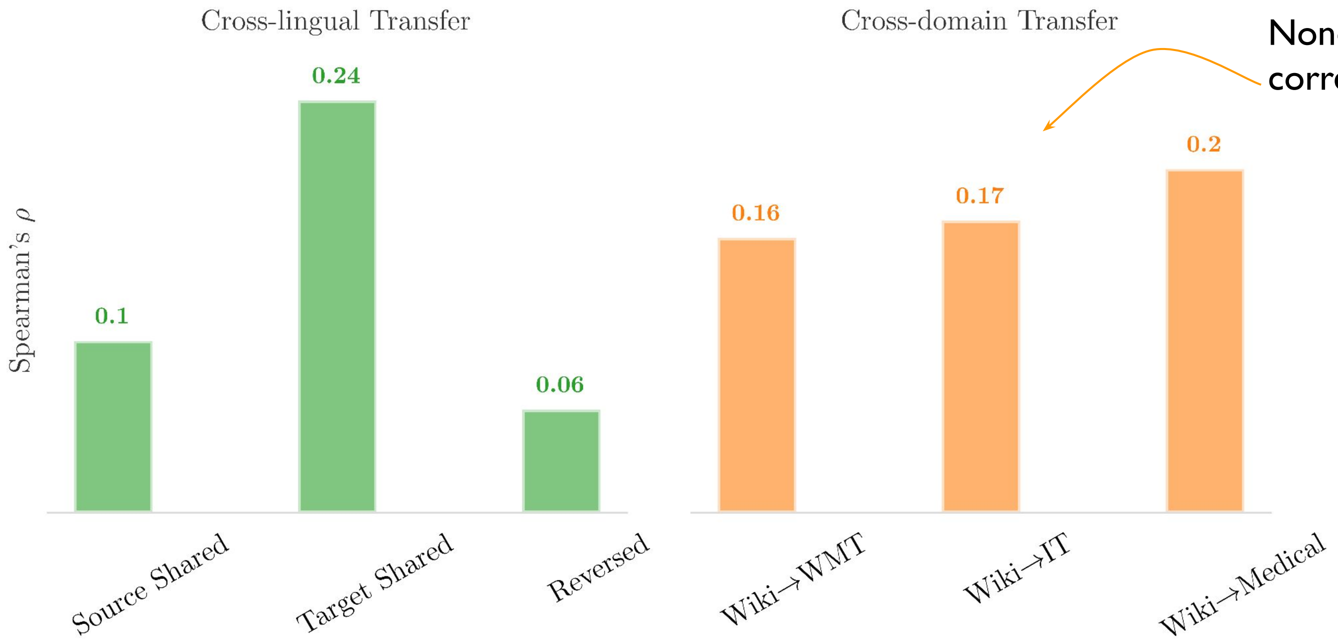
Cross-domain transfer

e.g. Wiki to WMT, IT, Medical

Sentence-to-document transfer

e.g. Sent-MT to Doc-MT

The superiority of a demonstrate **doesn't generalize**



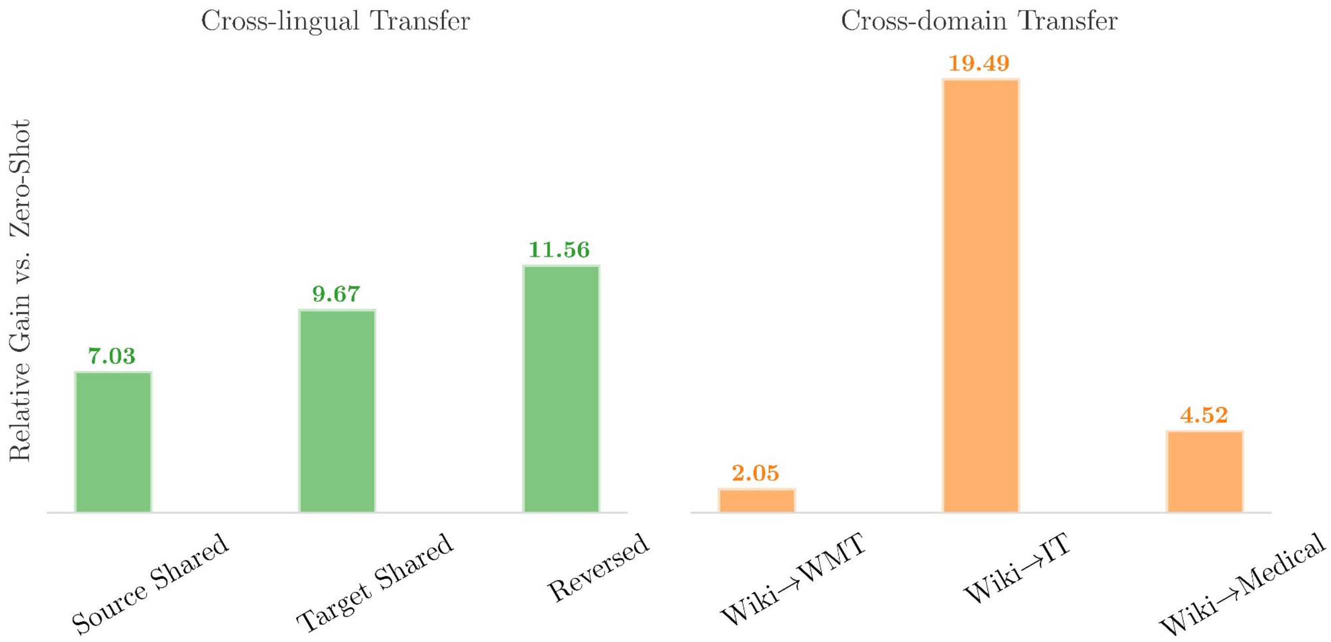
None of the correlations are strong.

* Source/target shared: transfer when source/target language is the same.

* Reversed: transfer between reversed language pairs.

* We randomly sample 200-300 demonstrations to obtain the correlation on Ablation sets.

Out-of-setting demonstration **beats** zero-shot MT



Few-shot prompting with out-of-setting demonstrations is preferred than zero-shot prompting

Takeaways:

- Prompting performance varies greatly across templates
- Selecting examples via simple features is not very promising
- MT prompting doesn't work with monolingual data alone; Use pseudo parallel examples instead.
- Transfer learning of prompting is feasible
- Prompting LLMs for MT still faces problems

Check out our paper for more details
https://arxiv.org/abs/2301.07069