Is ChatGPT A Good Translator? A Preliminary Study

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Abstract

This report provides a preliminary evaluation of ChatGPT for machine translation, including translation prompt, multilingual translation, and translation robustness. We adopt the prompts advised by ChatGPT to trigger its translation ability and find that the candidate prompts generally work well and show minor performance differences. By evaluating on a number of benchmark test sets, we find that ChatGPT performs competitively with commercial translation products (e.g., Google Translate) on high-resource European languages but lags behind significantly on low-resource or distant languages. As for the translation robustness, ChatGPT does not perform as well as the commercial systems on biomedical abstracts or Reddit comments but is potentially a good translator for spoken language.

1 Introduction

ChatGPT is an intelligent chatting machine developed by OpenAI upon the InstructGPT (Ouyang et al., 2022), which is trained to follow an instruction in a prompt and provide a detailed response. According to the official statement, ChatGPT is able to answer followup questions, admit its mistakes, challenge incorrect premises, and reject inappropriate requests due to the dialogue format. It integrates various abilities of natural language processing, including question answering, storytelling, logic reasoning, code debugging, machine translation, and so on. We are particularly interested in how ChatGPT performs for machine translation tasks, especially the gap between ChatGPT and commercial translation products (e.g., Google Translate, DeepL Translate).

In this report, we provide a preliminary study of ChatGPT on machine translation to gain a better understanding of it. Specifically, we focus on three aspects:

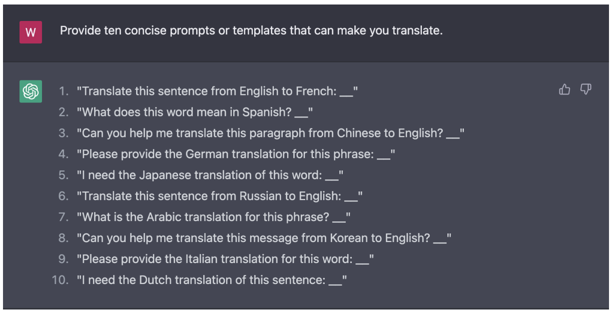

Figure 1: Prompts advised by ChatGPT for machine translation (Date: 2022.12.16).

- **Translation Prompt**: ChatGPT is essentially a large language model, which needs prompts as guidance to trigger its translation ability. The style of prompts may affect the quality of translation outputs. For example, how to mention the source or target language information matters in multilingual machine translation models, which is usually solved by attaching language tokens (Johnson et al., 2017; Fan et al., 2021).
- **Multilingual Translation**: ChatGPT is a single model handling various NLP tasks and covering different languages, which can be considered a unified multilingual machine translation model. Thus, we are curious about how ChatGPT performs on different language pairs considering both the resource difference (e.g., high vs. low) and language family (e.g., European vs. Asian).
- **Translation Robustness**: ChatGPT is developed upon GPT3, which was trained on large-scale datasets that cover various domains. Therefore, we wonder if it can perform robustly well on domain-specific or even noisy sentences.

To trigger the translation ability of ChatGPT, we ask ChatGPT itself for advice and obtain three

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Table 1: Information of adopted test sets.

Test Set	Direction	Domain	Amount
Flores-101	Any	General	1012
WMT19 Bio	De⇒En	Biomedical	373
WMT20 Rob2	En⇒Ja	Reddit	1376
	Ja⇒En		997
WMT20 Rob3	De⇒En	Common Voice	5609

candidate translation prompts. By evaluating on the Chinese⇒English translation task, we find that the candidate prompts generally work well and show minor performance differences. Nevertheless, we adopt the best-performing prompt for the rest parts of the study. By evaluating the translation among four selected languages on the Flores-101 test sets, we find that ChatGPT performs competitively with commercial translation products (e.g., Google Translate) on high-resource European languages but lags behind significantly on low-resource or distant languages. As for the translation robustness, results on three robustness sets suggest that ChatGPT does not perform as well as the commercial systems on biomedical abstracts or Reddit comments but is potentially a good translator for spoken language.

2 ChatGPT for Machine Translation

2.1 Evaluation Setting

We provide a brief introduction of the evaluation setting, which mainly includes the compared baselines and test data.

Baselines. We compare ChatGPT with three commercial translation products, namely, Google Translate[1], DeepL Translate[2], and Tencent TranSmart[3]. So far, the three commercial systems support translation in 133, 29, and 16 languages, respectively.

Data. For multilingual translation, we evaluate the above translation systems on the Flores-101 (Goyal et al., 2021)[4] test sets, which consists of 1012 sentences translated into 101 languages. To test the translation robustness, we adopt the test set of WMT19 Biomedical Translation Task (Bawden et al., 2019, i.e., Bio) and the set2 and set3 of

[1]https://translate.google.com
[2]https://www.deepl.com/translator
[3]https://transmart.qq.com/zh-CN/index
[4]https://github.com/facebookresearch/flores

Table 2: Candidate translation prompts.

	Translation Prompt
TP1	`Translate these sentences from [SRC] to [TGT]:`
TP2	`Answer with no quotes. What do these sentences mean in [TGT]?`
TP3	`Please provide the [TGT] translation for these sentences:`

Table 3: Comparison of different prompts for ChatGPT to perform Chinese-to-English (Zh⇒En) translation.

System	BLEU↑	ChrF++↑	TER↓
Google	31.66	57.09	56.21
DeepL	31.22	56.74	57.84
Tencent	29.69	56.24	57.16
ChatGPT w/ TP1	23.25	53.07	66.03
ChatGPT w/ TP2	24.54	53.05	63.79
ChatGPT w/ TP3	**24.73**	**53.71**	**62.84**

WMT20 Robustness Task (Specia et al., 2020, i.e., Rob2 and Rob3). We obtain the first two test sets through SacreBLEU and the third pre-processed by Wang et al. (2021)[5]. Table 1 lists the information of these test sets. However, obtaining the translation results from ChatGPT is time-consuming since it can only be interacted with manually and can not respond to large batches. Thus, we randomly sample 50 sentences from each set for evaluation.

Metric. We adopt the mostly used BLEU score (Papineni et al., 2002) as our primary metric and also report ChrF++ (Popović, 2017) and TER(Snover et al., 2006) in some cases. These three metrics are all supported by SacreBLEU (Post, 2018)[6].

2.2 Translation Prompts

To design the prompts for triggering the machine translation ability of ChatGPT, we seek inspiration from ChatGPT by asking it for advice. Specifically, we ask ChatGPT with the following prompt:

```
Provide ten concise prompts
or templates that can make you
translate.
```

and obtain the results as shown in Figure 1. The generated prompts look reasonable but share similar formats. Thus, we summarize them into three

[5]https://github.com/hsing-wang/WMT2020_BioMedical/tree/master/Bio-18-19-testset
[6]https://github.com/mjpost/sacrebleu

Table 4: Performance of ChatGPT for multilingual translation.

System	De-En		Ro-En		Zh-En	
	⇒	⇐	⇒	⇐	⇒	⇐
Google	45.04	41.16	50.12	46.03	31.66	43.58
DeepL	49.23 (+9.3%)	41.46 (+0.7%)	50.61 (+0.9%)	48.39 (+5.1%)	31.22 (-1.3%)	44.31 (+1.6%)
Tencent	n/a	n/a	n/a	n/a	29.69 (-6.2%)	46.06 (+5.6%)
ChatGPT	43.71 (-2.9%)	38.87 (-5.5%)	44.95 (-10.3%)	24.85 (-46.0%)	24.73 (-21.8%)	38.27 (-12.1%)

System	De-Zh		Ro-Zh		De-Ro	
	⇒	⇐	⇒	⇐	⇒	⇐
Google	38.71	21.68	39.05	25.59	33.31	32.27
DeepL	40.46 (+4.5%)	22.82 (+5.2%)	38.95 (-0.2%)	25.39 (-0.7%)	35.19 (+5.6%)	34.27 (+6.1%)
Tencent	40.66 (+5.0%)	19.44 (-10.3%)	n/a	n/a	n/a	n/a
ChatGPT	34.46 (-10.9%)	19.80 (-8.6%)	30.84 (-21.0%)	19.17 (-25.0%)	33.38 (+0.2%)	29.89 (-7.3%)

candidate prompts as shown in Table 2, where `[SRC]` and `[TGT]` represent the source and target languages of translation. Note that we add an extra command into TP2 to ask ChatGPT not to generate double quotes around the translation, which often occurs with the original format. Nevertheless, it is still unstable such that sentences in a batch (in multiple lines) are translated into a single line occasionally.

We compare the three different candidate prompts on the Chinese-to-English (Zh⇒En) translation task with the test set from Flores-101. Table 3 shows the results of ChatGPT and three commercial systems. While ChatGPT provides reasonably good translations, it still lags behind the baselines by at least 5.0 BLEU points. Concerning the three candidate prompts, TP3 performs the best in terms of all the three metrics. Thus, we use TP3 throughout this report by default.

2.3 Multilingual Translation

We select four languages to evaluate the capability of ChatGPT in multilingual translation, including German (De), English (En), Romanian (Ro), and Chinese (Zh), which are commonly adopted in both research (Wang et al., 2022; Jiao et al., 2021, 2022b) and competitions (Bojar et al., 2016; Farhad et al., 2021). The first three languages come from the same family with Latin scripts while the last is from another family with Chinese scripts (Fan et al., 2021). We test the translation performance between any two languages, which involves 12 directions in total. For clarity and comparison, we report the BLEU scores and the improvement or drop of performance (i.e., +/-) relative to Google Translate. Table 4 presents the results.

Resource Difference. We consider the resource difference of languages in the same family. In machine translation, German⇔English translation is usually regarded as a high-resource task supported by over ten million sentence pairs (Farhad et al., 2021) while Romanian⇔English translation is supported by much less data (Bojar et al., 2016). As shown in Table 4, ChatGPT performs competitively with Google Translate and DeepL Translate for both German⇒English and English⇒German translations. However, it lags behind them significantly on Romanian⇒English and English⇒Romanian. Specifically, ChatGPT obtains a BLEU score on English⇒Romanian that is 46.4% lower than Google Translate and the value is 10.3% on Romanian⇒English. We speculate that the huge resource difference of monolingual data between English and Romanian limits the language modeling capability of Romanian, which partially explains the poor performance on English⇒Romanian. On the contrary, Romanian⇒English can benefit from the strong language modeling capability of English such that the resource gap of parallel data can be somewhat compensated.

Language Family. We also take the impact of language families into account. In machine translation, translating between different language families is often considered harder than that within the same language family, due to the differ-

Table 5: Performance of ChatGPT for translation robustness.

System	WMT19 Bio	WMT20 Rob2		WMT20 Rob3
	De⇒En	En⇒Ja	Ja⇒En	De⇒En
Google	37.83	29.72	19.21	42.91
DeepL	37.13	26.25	19.83	41.29
ChatGPT	33.22	22.36	18.34	44.59

ent cultures and writing scripts. By comparing German⇔English with Chinese⇔English or German⇔Chinese translation, we find that the gap between ChatGPT and the commercial systems becomes larger. We attribute to the better knowledge transfer within the same family (i.e., from English to German) than between different families (e.g., from English to Chinese). For language pairs that are both low-resource and from different families (e.g., Romanian⇔Chinese), the performance gap can be further enlarged. Since ChatGPT handles different tasks in one model, low-resource translation tasks not only compete with high-resource translation tasks (Jiao et al., 2022a), but also with other NLP tasks for the model capacity, which explains their poor performance.

2.4 Translation Robustness

We further evaluate the translation robustness of ChatGPT on the WMT19 Bio and WMT20 Rob2 and Rob3 test sets, which introduce the impact of domain bias and potentially noisy data. For example, WMT19 Bio test set is composed of Medline abstracts, which require domain-specific knowledge to handle the terminologies. WMT20 Rob2 are comments from the social media website `reddit.com` that could contain various errors, including spelling/typographical errors, word omission/insertion/repetition, grammatical errors, spoken languages, Internet slang, and so on (Michel and Neubig, 2018).

Table 5 lists the BLEU scores. Obviously, ChatGPT does not perform as well as Google Translate or DeepL Translate on the WMT19 Bio and WMT2 Rob2 test sets. The reason may be that commercial translation systems like Google Translate often need to continuously improve their ability to translate domain-specific (e.g. biomedical) or noisy sentences, since they are real-world applications that require better generalization performance over out-of-distribution data. However, these may not be done in ChatGPT.

Table 6: Examples from WMT20 Robust Set3.

	Example
SRC	Haben wir noch Nudeln?
REF	Do we still have noodles?
Google	Do we still have pasta?
DeepL	Do we have any noodles left?
ChatGPT	Do we still have noodles?
SRC	Tatsächlich ist der zu häufige Gebrauch von Seife schlecht für die Haut.
REF	Actually, very frequent usage of soap is bad for the skin.
Google	In fact, using soap too often is bad for your skin.
DeepL	In fact, using soap too often is bad for the skin.
ChatGPT	In fact, the frequent use of soap is bad for the skin.

An interesting finding is that ChatGPT outperforms Google Translate and DeepL Translate significantly on WMT20 Rob3 test set that contains a crowdsourced speech recognition corpus. It suggests that ChatGPT, which is essentially an artificial intelligent chatting machine, is capable of generating more natural spoken languages than these commercial translation systems. We provide some examples in Table 6.

3 Conclusion

We present a preliminary study of ChatGPT for machine translation, including translation prompt, multilingual translation, and translation robustness. By evaluating on a number of benchmark test sets, we find that ChatGPT performs competitively with commercial translation products (e.g., Google Translate) on high-resource European languages but lags behind significantly on low-resource or distant languages. As for the translation robustness, ChatGPT does not perform as well as the commercial systems on biomedical abstracts or Reddit comments but is potentially a good translator for spoken language. Future work may include investigating the impact of historical context on translation results and iterative refinement of translation.

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