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Methodology Matters: How Translation Theories and Technologies Have Shaped *Journey to the West*

Savannah Fennell

Translation between Chinese and English demonstrates that different language pairs are more difficult for humans and machines to translate. Additionally, difficulties in the translation world center around literary translation, the topic of the Workshop on Machine Translation's (WMT) shared discourse taskforce. The main conference on Machine Translation and MT research, WMT 2023 focused on literary translation, specifically the challenges posed by Chinese literature. The use of entirely vernacular language combined with other literary, cultural, and historical traditions in *Xīyóujì* (西游 or *Journey to the West*), poses a unique translation dilemma. Translation is best described as a spectrum of theories that influence a translator's approach to their work ranging from dynamic to literal. Machine Translation (MT), however, is governed by different approaches based on engineering programs that mimic natural language production. Comparing human and machine translation approaches to Chinese literature can improve classical Chinese-to-English translations through a comparison of translation techniques. This research will focus on the most influential translators of Classical Chinese, Arthur Waley, Anthony C. Yu, and William J. F. Jenner. The influences of a translator's approach to their work through the lens of Liraz Postan's categories and the methodologies of various machine translation engine types are examined with particular interest.

Keywords: Rules-based machine translation (RBMT), Statistical machine translation (SMT), Neural machine translation

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Introduction

Since the advent of translation studies in the fourth century CE, translation theory, methodology, and technologies have expanded past Bible translation, increasing accessibility to different cultures and ideas around the world. Translation is best described as a spectrum of theories that influence a translator's approach to translators' work. In the context of different language pairs, different types of work, and individual goals, translators can fall somewhere along the continuum between dynamic and literal. Some of the most referenced theories are "Sociolinguistic, Communicative, Hermeneutic, Linguistic, Literary, and Semiotic Approaches" (Postan). When discussing Machine Translation (MT) however, Postan's categories and theories of translation are no longer in play. Machine Translation engines are governed by different approaches based on engineering programs that mimic natural language production from one language to another. These are divided into four categories: Rules-based, Statistical-based, Neural, and Generative Artificial Intelligence (AI).

Drastically different language pairs are more difficult for human and machine translation alike, and the history of Chinese-to-English translation is no exception. *Journey to the West* (*Xīyóujì*) composes one of the four classic novels of Chinese literature and is an important part of Chinese cultural history. The use of vernacular language over the standardized classical language of the time poses a unique dilemma for translations that combines culture, history, minority languages, and poetic traditions that differ greatly from the West. Thus, translators' backgrounds and methodology have influenced different understandings of Chinese Literature, particularly *Journey to the West*, leading to various versions of the original text, changing the understanding of Chinese culture through its most recognizable cultural symbol, the Monkey King. By exploring the different effects of translation theory used by humans to that of machine translation engines on Chinese literature, better techniques can be developed to approach Chinese classical literature.

Purpose

The purpose of this project is to discover the strengths and weaknesses of the methodologies used by human translators and their effects on classical Chinese literature compared to the methodologies used by machine translation tools. The goal is to analyze which approaches are most successful in translating classical Chinese literature to modern American English. Specific attention will be given to how vernacular language, alternating literary styles, and cultural elements are presented to English audiences. Noting what would need to be elaborated on and a defense on what is changed or dropped from the original text.

1. Can Machine Translation engines accurately translate classical Chinese Literature?
2. How do Machine Translation approaches compare to human translation in the execution of this task?

Significance of the Research

Researchers in MT are focusing on the discourse of literary translation and how Large Language Models (LLMs) handle this type of translation. According to WMT's publication on the topic in 2023, researchers were invited to an open call to participate in a shared taskforce that experimented with systems trained on a Chinese-English document-level web novels data set. The goals set forth by this group were to: "1) Encourage research in machine translation for literary text, 2) Provide a platform for researchers to evaluate and compare the performance of different machine translation systems on a common dataset, and 3) Advance the state of the art in machine translation for literary texts" (Wang et al., 2023).

Building on the discourse in literary translation, this project seeks to further the attention on literary translation through the lens of classical Chinese literature. The three translators selected for this research are Arthur Waley (*Monkey* 1943), William John Francis Jenne (*Journey to the West* 1985), and Anthony C. Yu (*The Monkey and the Monk* 2012). The three translators were influenced by different factors including translation theory and their background. However, translation technology does not have cultural knowledge, theory, or context. Instead, machines use four different methods: Rules-based, Statistical-based, Neural (i.e. Google Translate), and Generative AI (i.e. ChatGPT). By observing what is gained and lost in translation via human application of theory and machine learning, a better understanding of the effects of these methods on the understanding of Chinese literature can be developed. By analyzing the benefits and drawbacks of methodologies applied to the challenges *Journey to the West* poses, one can determine the best method for translating classical Chinese for modern-day readers.

Overview of *Journey to the West*

西游记 (*Xīyóujì*) or *Journey to the West* is perhaps one of the best-known works of classical Chinese literature outside of China. Translated into more than ten different languages to date, Journey to the West's hero 孙悟空 (Monkey King) has become a recognizable cultural symbol of China. Compiled by poet and novelist Wu Cheng'en during the Ming dynasty (1368-1644 CE), the novel chronicles the pilgrimage of Buddhist monk 玄奘 (Xuanzang or Tripitaka) and his disciples on their quest to India for the sacred texts. Though Wu Cheng'en was the first to construct a novel about it, the journey of Xuanzang existed in Chinese folklore and literature long before. Prior to Wu Cheng'en, different parts of the journey were in the form of early *huaben*, or "vernacular story," novelettes and a six-part Yuan drama. One of the four classic novels of Chinese literature, Journey to the West consists of 100 chapters, three major sections, and 81 adventures, making it one of the longest books written in all of Chinese history.

What Is Translation?

Translation is best described as a spectrum of theories that influence a translator's approach to their work. In the context of different language pairs, different types of work, and individual goals, a translation can fall somewhere along the continuum between dynamic and literal. Translation is further broken down into categories of expository text, non-fictional text focused on presenting informational facts on a topic, and literary text—both of which cover one or more domains or topics. In translation, there are many different theories with various names. For this paper, translation methodologies will be divided into Liraz Postan's six groups: "Sociolinguistic, Communicative, Hermeneutic, Linguistic, Literary, and Semiotic Approaches" (Postan 2023).

What Is Machine Translation?

With the advent of rapidly developing technology, it is important first to state that MT and AI are not the same. Google defines AI as "a broad field, in which technology is used to build machines and computers that can mimic human cognitive functions that allow it to understand, learn, and respond to spoken or written language, analyze data, make recommendations, etc." (Google Cloud Tech 2023). Under this umbrella lies machine learning and deep learning which learn and improve from experience. Trained on initial sets of data, the technology predicts outcomes and "learns" from the insights to make informed decisions. AI technologies such as machine learning or deep learning can be utilized when constructing a Machine Translation engine. MT engines, however, are defined as programs engineered as tools to help translate text from a source language to a target language via the models listed above: Rules-based, Statistical, Neural, and Generative AI.

Early MT engines faced two problems: semantic interpretation and natural language production. In the separate field of AI, however, a tool was created with a focus on solving natural language processing problems in computer programs. The MARGIE system, developed in 1973 by R.C. Schank and his students at Stanford University, extracted meaning from input and generated that meaning in output natural language sentences. This was accomplished by using a parser to analyze grammar and the underlying meaning of text. As it became more acceptable to integrate the use of AI tools into MT, Neural and Generative AI approaches further developed into what we consume in the public and private sector today. This technology, while more successful at handling semantic interpretation and natural language production, still struggles with several bugs not withholding word order, translating literary text, recognizing numbers, and identifying idioms and symbolism.

When MT engines translate material, they approach it first through analysis of the source text. This analysis includes syntactic analysis, semantic analysis, identification of idioms, and format analysis, among others. This initial phase is also referred to as parsing, during which MT engines label the characteristics of the text based on its grammatical framework algorithm. Various methods have been experimented with when analyzing text from Context analysis to Thesaurus codes, and Constituency analysis to Semantic analysis. However, each method proved to struggle with different aspects of natural language such as polysemy or multiple meanings of the same word. To combat these issues, engines use a method that consists of giving the computer a database of word meanings and the connections among them so that it "understands" the context of the word in the text. The system can then operate within the permissible combinations of semantics bonds. Once this step is completed, the engine takes that information and creates an Interlingua. Interlingua is an intermediate language created by the analysis of the source language but independent of any target language structure; in other words, it is the language of the MT engine. The engine then moves to synthesize the information by choosing definite and indefinite articles, establishing word order, and flagging missing words.

Hypothesis

1. Can MT engines adequately translate classical Chinese Literature?

Because MT engines are historically bad at dealing with literary works and cultural context, it is not believed that the translations rendered by them would be reliable. Additionally, MT engines are either trained to translate between specific language pairs and domains or trained on a wide variety of data across different language pairs. This will present a problem for translating *Journey to the West*, because it is a very specific story with references to various vernacular dialects of Chinese and ancient cultural references. This level of complexity will fare better with an engine trained specifically in the domain of classical Chinese literature of which there is currently a deficiency of training data.

2. How do MT approaches compare to human translation?

As mentioned in previous sections, MT engines rely on their ability to learn and predict patterns in languages via a more word-for-word linguistic approach. While this approach tends to fare well with expository texts, it is not as successful across all available language pairs or when considering literary text. Though MT engine companies claim that their technology can "learn," the reality is that machines look at language through the lens of probability matching. Another way to think about how MT engines work is to see them as working with language as if it were a puzzle. The engines do not consider cultural context and have very limited abilities to consider the context of a single sentence in the whole text because of word count limitations on text input. Due to an MT engine's approach, it takes more time to catch up with changes in language usage such as slang or cultural references compared to human translators. It is because of these factors that this research argues that human translation is still preferable over MT engines in various language pairs and domains. MT engines remain a useful tool but require the skill sets that only humans possess to make them as productive as possible by means of either pre- or post-editing.

Methodolgy

To test the quality of MT engines' approach to Classical Chinese, Phrase (a neural MT engine), Kantan (a statistical MT engine), and ChatGPT (an LLM) computer platforms were used to translate Chapter 16 of *Journey to the West*. Using the Phrase tool to segment the paragraphs, segments with 6-19 characters were selected for comparison between all three machine translations and the three human translations. Each segment was assigned a difficulty of accuracy score by Phrase, which informs the translator of the difficulty of being able to translate a segment ranging from 0, being the hardest, and 100, being the easiest. Using the Phrase segments, matching segments from the original Chinese text, ChatGPT, Kantan, Aurthur. Waley, Anthony. Yu, and William. Jenne were arranged side by side in an Excel sheet. Anthony. Yu's *The Monkey and The Monk*, 2012 edition, was selected as the standard for which Python code was created to analyze the BLEU (word count/word matching accuracy), COMET (semantic matching and accuracy), and METEOR (vector based) scores of each version of the segments. A. Yu's translation was chosen as the standard because it is the most recent human translation done by a native speaker of Mandarin Chinese at the time of this study. In the following table, Phrase assigned difficulty scores with zero being hardest and one hundred being easiest to match:

Table 1

A comparison of human and machine translated segments from *Journey to The West* and their associated translation difficulty scores.

Original (traditional Mandarin Chinese)	A. Waley	A. Yu	W. Jenner	Phrase	Kantan (my engine)	ChatGPT 2nd time	Scores Assigned by Phrase
"三藏大喜"	N/A	"Tripitaka was most delighted (367)."	"...to Sanzang's great joy (266)."	Tripitaka was overjoyed.	三藏 大喜.	The Tang Monk was overjoyed	17
"行者道：「莫忙，莫忙"	N/A	"'No need to rush like that,' said Pilgrim (367)."	"'Not so fast, not so fast,' Monkey replied (266)."	The traveler said: 'Don't be busy, don't be busy."	行者道：「莫 busy, 莫 busy.	The Monkey King replied, "No rush, no rush."	74
"今日將晚，不是走路的時候，且待明日早行"	"'Wouldn't it be a good plan to see if we can't sleep there to-night?' (146)."	"'It's getting late, hardly the time to travel. Let's wait until tomorrow morning before we leave.'" (367)	"'It's already evening, too late to hit the road. Let's set out tomorrow morning' (266)."	'It will be late today and it is not the time to walk. Let's go early tomorrow."	今日 will night, not to be go, road of 时候 且 待 明日 早 row.	"It's getting late today, not a good time to travel. Let's set off early tomorrow."	56

Results

After running all 155 segments from A. Waley, W. Jenne, Phrase, Kantan, and ChatGPT in comparison to A. Yu's translation, the Python code generated BLEU, METEOR, and COMET scores for each segment. The median of all the segments in each translation was used to represent the overall BLEU, METEOR, and COMET scores for each translation method.

Waley AE Scores

For clarity's sake, all scores have been changed from a 0-1 scale to a 0-100 scale. The median METEOR score of A. Waley's translation is 13, which indicates low translation quality based on word matching using n-grams. This makes sense given the amount of missing matching segments to the original Chinese text that were omitted or simplified by the presentation style of A. Waley. The median COMET score is 53.5, which indicates a mid-quality translation based on the semantic similarity and accuracy between the A. Waley and A. Yu texts' tokens. Lastly, the median BLEU score is 0, which indicates that there was no substantial overlap between the Waley text and the experiment's standard.

Table 2

Segments translated by A. Waley from Traditional Chinese into English (*Monkey* 1943) and his translation's Automatic Evaluation Scores weighed against A. Yu's translation (*The Monkey and the Monk* 2012).

A. Waley	BLEU A. Waley	METEOR A. Waley	COMET A. Waley
N/A	0	0	34
"'You can proceed,' Monkey reported presently. 'I am certain that good people live there(146).'"	20	55	67
"Tripitaka urged on the white horse and soon came to a gate leading into a lane (146)."	0	14	52
"'Where are you off to?' said Monkey stopping him (146).'"	0	26	64

W. Jenne AE Scores

For clarity's sake, all scores have been changed from a 0-1 scale to a 0-100 scale. The median METEOR score of W. Jenne's translation is 33, which indicates low translation quality based on word matching using n-grams. Unlike A. Waley, this translation kept the poetry sections intact, which brought its word correlation higher than A. Waley's but lower overall. The median COMET score is 69, which indicates a higher quality translation based on the semantic similarity and accuracy between the W. Jenner and A. Yu texts' tokens. Lastly, the median BLEU score is 0, which indicates there was no substantial overlap between the W. Jenner text and the experiment's standard.

Table 3

Segments translated by W. Jenner from Traditional Chinese into English (*Journey to the West* 1985) and his translation's Automatic Evaluation Scores weighed against A. Yu's translation (*The Monkey and the Monk* 2012).

W. Jenner	BLEU W. Jenner	METEOR W. Jenner	COMET W. Jenner
"Well-fed chickens and pigs sleep under the eaves, While the drunk old man sings his song next door (268)."	0	60	83
"When he had surveyed the scene, Brother Monkey said, 'Go ahead, master. It's definitely a good village. We can spend the night there (268).'"	0	34	63
"Sanzang urged his horse forward, and in a few moments they were at the beginning of the main street (268)."	0	30	79
"Monkey grabbed him and asked, 'Where are you going? (268).'"	0	25	70

Phrase AE Scores

For clarity's sake, all scores have been changed from a 0-1 scale to a 0-100 scale. The median METEOR score of Phrase's translation is 35, which indicates low translation quality based on word matching using n-grams. The median COMET score is 70, which indicates a higher quality translation based on the semantic similarity and accuracy between the Phrase and A. Yu texts' tokens. Lastly, the median BLEU score is 0, which indicates there was no substantial overlap between the Phrase text and the experiment's standard.

Table 4

Segments translated by Phrase from Traditional Chinese into English and the translation's Automatic Evaluation Scores weighed against A. Yu's translation (*The Monkey and the Monk* 2012).

Phrase	BLEU Phrase	METEOR Phrase	COMET Phrase
"I also saw the well-fed chicken and dolphin sleeping in the corner of the house, and the drunk neighbor singing."	0	11	58
"The traveler looked at it and said, 'Master, please come. There must be a good family in the village, and you can stay overnight.'"	21	45	72
"The elder urged the white horse to arrive at the entrance of the street early."	0	46	88
"The traveler grabbed him and said, 'Where are you going?'"	0	27	58

Kantan AE Scores

For clarity's sake, all scores have been changed from a 0-1 scale to a 0-100 scale. The median METEOR score of Kantan's Translation is 5, which indicates low translation quality based on word matching using n-grams. The median COMET score is 42.5 and indicates a lower quality translation based on the semantic similarity and accuracy between the Kantan and A. Yu texts' tokens. Lastly, a BLEU score of 0, which indicates there was no substantial overlap between the Kantan text and the experiment's standard.

Table 5

Segments translated by Kantan from Traditional Chinese into English and the translation's Automatic Evaluation Scores weighed against A. Yu's translation (*The Monkey and the Monk* 2012).

Kantan (my engine)	**BLEU Kantan**	**METEOR Kantan**	**COMET Kantan**
又见那食饱 chicken 豚眠屋角, tipple 酣 O 叟 singing to.	0	0	32
行者 look 罢道：「师父请 row, 定 to be 一村 good 人家, positive could 借宿.」	0	4	30
那 elder 催动白马, 早 to 街衢之 mouth.	0	5	58
行者顺手一把 garnetting staying 道：「那裡 going ？	0	5	31

ChatGPT AE Scores

For clarity's sake, all scores have been changed from a 0-1 scale to a 0-100 scale. The median METEOR score of ChatGPT's translation is 33, which indicates low translation quality based on word matching using n-grams. The median COMET score is 70, which indicates a higher quality translation based on the semantic similarity and accuracy between the ChatGPT and A. Yu texts' tokens. Lastly, the median BLEU score is 0, which indicates there was no substantial overlap between the ChatGPT text and the experiment's standard.

Table 6

Segments translated by ChatGPT from Traditional Chinese into English and the translation's Automatic Evaluation Scores weighed against A. Yu's translation (*The Monkey and the Monk* 2012).

ChatGPT 2nd time	**BLEU ChatGPT**	**METEOR ChatGPT**	**COMET ChatGPT**
"They also saw chickens and pigs full from their meals, sleeping in the corners of the houses, and neighbors, inebriated, singing songs joyfully."	0	29	66
"The venerable monk urged his white horse and soon reached the village's entrance."	0	27	73
"The Monkey King reached out and stopped him, saying, 'Where are you going?'"	55	80	73
"Let me ask you something: 'what place is this?'"	0	46	88

Conclusion

According to the results of the experiment, Phrase, a neural MT engine, outperformed both ChatGPT, an LLM, and Kantan, a statistical MT engine. However, all three failed to obtain a median BLEU score higher than zero. This indicates a less than substantial amount of overlap between the translations the engines produced compared to that of Anthony C. Yu's work from 2012. Both Phrase and ChatGPT produced output that sounded and read like natural English and achieved a COMET score of 70, indicating shared meaning with A. Yu's text. Surprisingly, both kept the poetry within the original text's format without additional prompting. The slight difference in n-gram matching between the two can be seen in the variations of names used for the characters and how they are referred to when their proper names are not being used. In this regard and other word choices, Phrase had more in common with Yu's translation. Thus, it obtained the highest median METEOR score of 35, still indicating a low-quality score in terms of word matching. The results indicate that larger amounts of training data, like the billions of parameters used to train LLMs, do not equate to better scores. Additionally, better-quality translation outputs tend to be produced by task and domain- specific trained tools. Neural MT engines are built on a few hundred million parameters in a language pair which can be expanded by post-training to improve its quality and by working in a specific domain or language utilizing human input from post-editing. Thus, Neural MT engines trained on Classical Chinese literature are the best tools to help translate from Chinese to English, resulting in the least amount of human post-editing compared to other MT engines and LLMs.

The results of applying Automatic Evaluation helped highlight the afore-mentioned difference and the choices made by each translator. A. Waley's text scored low in word-matching (METEOR 13 & BLEU 0) and semantic similarity and accuracy (COMET 53.5) compared to Yu's translation. W. Jenner's translation had slightly more words in common with Yu's translation compared to A. Waley's, earning it a METEOR score of 33, but was not significant enough to raise the BLEU score from zero. It is important to remind the reader that all three human translators are from different time periods, which influences the dialect of English used in each instance. In turn this affects the translation's word-for-word accuracy more than sematic similarity.

Although A. Waley is notorious for paraphrasing and cutting out the large sections of poetry from *Journey to the West*, W. Jenner's median COMET score was only 15.5 points higher. The Automatic Evaluation scores of MT engines were much closer to each other in general when enough training data was used. This is due to the lack of cultural influence and conscious or subconscious decision-making on the part of machine translation. Phrase's median METEOR score (35) outperformed ChatGPT (33) by 2 points, both sharing a median COMET score of 70. Kantan on the other hand, with resources limited to its original training data set, obtained a median METEOR score of 5 and a COMET score of 42.5. Kantan's translation left many words untranslated, made easily recognizable structural errors, and could not produce a natural-sounding translation. Though the other methods proved more effective, there is a lack of reasoning and informed decision-making behind elements of the translation such as the names of characters and how idioms were translated.

Thus, solely relying on any of these tools leaves the reader at the mercy of the engines' randomly choosing how to handle more culturally sensitive topics and information based on their training data. Unlike human translators, these tools do not have a goal in mind when translating, like Yu's goal to create a culturally informed and rich translation or A. Waley's goal of accessibility of Asian art for public consumption. The "why?" behind MT engines' choices is difficult to parse and can at times lead to questions of equity towards the representation of other languages and cultures being handled by a tool that cannot fully comprehend either. Thus, while these tools are very useful in terms of time-cost effectiveness, they need to be paired with a human copilot who can supervise cultural and linguistic interpretations.

Acknowledgement of Limitations

This research focused on the quantitative aspect of comparing human and MT translations. No TAUS or other types of human driven qualitative analysis took place. While there is biographical information on the approaches and reasonings behind the choices of all three human translators, many MT engines, particularly Generative AI, are created in a black box. This means that the training data used and the innerworkings of the tools are not available for public knowledge, leaving decisions opaque and unexplainable. As language changes and develops, so does translation. The use of a source or target language in one generation can change, altering understanding of the original text and culture. However, MT engines are static in that they cannot automatically update their information on language use but rely on parroting the input they were trained on. This can lead to biased representations of either language or culture that can lead to ethical implications of an MT engine's decisions. The study was limited by the number of human translators and MT engines used.

Recommendations for Future Research

To further this research, it is suggested that a qualitative aspect of analysis be incorporated to observe the quality assigned by human readers. Additionally, testing the success of Neural and Generative MT engines trained specifically in classical Chinese literature would be beneficial. Doing so would provide greater insight concerning how specialization in language pairs and domains reduces both qualitative and quantitative errors in the post-editing process. Future research should extend the sample set of translations to include more human input as well as additional MT engines.

Appendix

MT Engine Types:

- **Rules-based machine translation (RBMT)**: This is the earliest rendition of translation technology first developed by Georgetown University in 1954. It functioned based on a large set of predefined grammatical rules to extract meaning and translate between languages. This approach, however, led to the need for large amounts of human post-editing and adding languages manually. Due to its low translation quality, RBMT is rarely used today but is useful in basic situations where a quick understanding of meaning is all that is required.

- **Statistical machine translation (SMT)**: "Developed in the 1990s, Statistical machine translation (SMT) builds a statistical model to create relationships between text words, phrases, and sentences. It then applies this translation model to a second language and converts the same elements to the new language" (Phrase). SMT improves somewhat on RBMT but still shares many of the same problems including sentence alignment, word alignment, statistical anomalies, idioms, and different word orders.

- **Neural machine translation (NMT)**: NMT engines began to replace SMT engines in 2010 by employing artificial intelligence to learn languages and improve that knowledge constantly. The concept was to create neural networks that mimicked the structure of the human brain by introducing an encoding and decoding approach. NMT is much faster than its predecessors and once trained, it allows for more language pairs and is less dependent on post-editing. However, it still struggles with numbers, idioms, long sentences, word alignment, and rare words.

- **Generative Language Module engines or Large Language Models (LLM)**: This is a subset of Deep Learning AI. These are pre-trained on large amounts of data for the general purpose of text classification, question answering, document summarization, and text generation. Due to the large amount of training data, LLMs do not need to be trained on domain specific data. Like NMTs, Generative Language Modules use neural networks. However, the type of model used is a Transformer model that involves a mathematical technique called self-attention, which helps the machine better detect subtleties in sequences. Self-attention builds on deep learning's use of probabilistic analysis of unstructured data, which enables the model to recognize distinctions between pieces of content without human intervention. Though this model is considered the most effective, like the MT engines before it, LLMs are also better with expository than literary text. Additionally, LLMs are prone to "hallucinate" or create fake information when they are unable to produce an accurate answer. It also produces natural sounding language that can make it difficult to detect false or incorrect outputs.

References

Jenner, William John Francis. “The Tang Priest Is Rescued in the Guanyin Temple The Great Sage Removes a Monster from Gao Village.” *Journey to the West*, 1st ed., vol. 1, Foreign Languages Press, 1985, pp. 262–271.

“Introduction to Generative AI.” AI and Machine Learning with Google Cloud, Google Cloud Tech, 2023. https://www.cloudskillsboost.google/course_templates/536

“Introduction to Large Language Models.” Google Cloud Tech, 2023. https://www.cloudskillsboost.google/course_templates/539

Postan, Liraz. “Basic Theory of Translation: Explained for Beginners: Blend.” *BLEND*, 2023. https://www.getblend.com/blog/basic-theory-translation/

Sturgeon, Donald. “西遊記《觀音院唐僧脫難　高老莊大聖除魔》.” Chinese Text Project, https://ctext.org/. Accessed 17 Nov. 2024.

Waley, Arthur, translator. “Chapter XVIII.” *Monkey*, Grover Press, 1943, pp. 146–152.

Wang, Longyue, et al. “Findings of the WMT 2023 Shared Task on Discourse-Level Literary Translation: A Fresh Orb in the Cosmos of LLMs.” arXiv [Cs.CL], Cornell University, 6 Nov. 2023, http://arxiv.org/abs/2311.03127.

Yu, Anthony C, translator. “At Guanyin Hall the Tang Monk Leaves His Ordeal; At Gao Village the Great Sage Casts out the Monster.” *Journey to the West*. Revised ed., vol. 1., The University of Chicago Press, 2012, pp. 367–398.