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A Comparative Analysis of Japanese-English Machine Translation Outputs Using Neural and Statistical Systems

Google Translate vs. Systran

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ABSTRACT

This study explores the effectiveness and accuracy of Google Translate and Systran in translating Japanese to English, focusing on syntactic and semantic error patterns. It evaluates the translation quality of the text 音楽のテンポが経済的意思決定に及ぼす影響 "*Ongaku no tenpo ga keizaiteki ishi kettei ni oyobosu eikyou*" (The Effect of Music Tempo on Economic Decision-Making) by Kobayashi, Fujikawa, and Foo (2012). The methodology employs a qualitative approach, categorizing errors based on syntactic and semantic criteria. Despite advancements in Neural Machine Translation (NMT), challenges remain in achieving accurate and contextually appropriate translations, particularly for complex language pairs like Japanese-English. The study highlights the persistent issues in maintaining syntactic and semantic accuracy in translations produced by Google Translate and Systran. It underscores the importance of Machine Translation Post-Editing (MTPE) to enhance translation quality. The findings reveal that while MT systems have significantly improved, human intervention remains essential to address nuanced linguistic and cultural elements. The research emphasizes the relevance of Machine-Aided Human Translation (MAHT) as a balanced approach, combining the efficiency of MT with human expertise to ensure high-quality translations. This approach is crucial for fostering better cross-cultural communication and understanding in the translation industry.

KEYWORDS

Machine translation; Neural; Post-editing; Syntax; Semantics.

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INTRODUCTION

The English word 'translation' emerged around 1340, derived from the Old French word "translation" or the Latin "*translation*" (meaning transporting), according to Munday (2016). According to the Cambridge Dictionary, translation refers to the process of converting something from one language to another while retaining the same meaning. Combining these views, translation can be defined as the process of transferring input from the source language (SL) to the target language (TL), aiming to preserve the

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original meaning, form, and style of the SL as much as possible.

The translation process necessitates extensive knowledge of both SL and TL, including cultural adaptations, local idioms, and more. However, achieving a top-notch translation product is challenging even with such knowledge. This is due to the requirement for translators to possess practical skills and apply correct theoretical approaches as guidance to produce satisfactory work. One significant advancement in the translation industry that aids in meeting these demands is the application of machine translation (MT).

LITERATURE REVIEW

Historical Overview

Machine translation (MT) research began in the 1950s, following significant advancements in cryptography during World War II. The Georgetown experiment in 1954 marked a milestone, translating sixty Russian sentences into English (Hutchins, 2005; Norwati, 2019). Initially, researchers anticipated rapid progress, expecting fully automated systems within a few years. However, the complexity of natural language posed significant challenges, leading to a shift from rule-based models to statistical approaches in the late 1980s and 1990s (Kay, 1997).

Despite early setbacks, MT systems evolved, leveraging statistical models to process large bilingual corpora. SMT systems, introduced by IBM's research team, marked a significant advancement by using statistical learning methodologies (Brown et al., 1990). These systems relied on vast multilingual data to build models, enhancing translation quality and efficiency.

In recent years, the advent of Neural Machine Translation (NMT) has revolutionized the field. Google's introduction of NMT in 2016 replaced earlier statistical methods, offering more nuanced and accurate translations by leveraging deep learning techniques (Sutskever, Vinyals, & Le, 2014). Despite these advancements, challenges remain, particularly in maintaining syntactic and semantic accuracy across diverse language pairs (Yamagishi, Kanouchi, Sato, & Komachi, 2016).

Translation Software Background

The rapid advancement of technology and globalization has increased the demand for efficient translation tools. Various MT applications, such as Citcat, Google Translate, and Systran, offer solutions for different language pairs. Google Translate, supporting over 100 languages, and Systran, one of the oldest MT companies, are widely used for their accessibility and comprehensive language support. This study evaluates their effectiveness in translating Japanese-English text, focusing on their syntactic and semantic accuracy (Li, 2015; Zhu, 2015).

Recent Advances in Japanese-English Machine Translation

Recent studies have highlighted the progress and challenges in Japanese-English MT. Yamagishi, Kanouchi, Sato, and Komachi (2016) demonstrated the effectiveness of controlling the voice in Japanese-English NMT, achieving a 0.73-point improvement in BLEU score by incorporating voice information. This advancement underscores the importance of context in translation, as tonal and formality nuances significantly affect the translated output. Similarly, Dabre (2018) explored the use of multilingualism and transfer learning to enhance translation quality for low-resource languages, showing significant improvements in translation accuracy through leveraging related languages and transfer learning techniques.

Li (2015) discussed the impact of globalization and information technology on translation, emphasizing the role of computer-aided translation (CAT) technologies in modern translation practices. This study provides a comprehensive overview of CAT tools, including translation memory and terminology management, and their applications in improving translation efficiency and quality.

Evaluating the effectiveness of different MT systems, Zhu (2015) conducted a detailed analysis of Japanese-English translation, comparing the performance of various NMT models. Their findings indicated that while NMT systems offer improved fluency and coherence, challenges in maintaining syntactic and semantic accuracy persist, particularly for complex language pairs like Japanese-English.

Yanase and Lees (2020) categorized errors in academic essays translated from Japanese (L1) to English (L2), highlighting the common issues faced by MT systems in maintaining grammatical accuracy and contextual relevance. Their findings underscore the importance of context-aware translation models for improving overall translation quality.

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Nakazawa (2017) discussed the paradigm shift brought about by NMT, comparing it with SMT and highlighting the significant improvements in translation accuracy. Nakazawa's study also identified unique challenges posed by NMT, such as handling out-of-domain translations and ensuring complete translations without omissions.

Feely, Hasler, and de Gispert (2019) focused on controlling Japanese honorifics in English-to-Japanese NMT, presenting methods to adjust the level of formality in translations. This study addresses the complexity of honorific speech and provides insights into improving the cultural and contextual appropriateness of NMT outputs.

Okita and Kurokawa (2023) investigated the use of MT among graduate students in Japan, emphasizing the ethical implications and the impact on academic writing. Their study revealed a high reliance on MT tools, highlighting both the benefits and challenges of integrating MT into academic workflows.

These studies collectively highlight the significant advancements in Japanese-English MT and emphasize the importance of contextual and cultural factors in achieving high-quality translations. The integration of voice control, honorific management, and the handling of academic writing nuances demonstrates the evolving sophistication of MT systems.

The Concept of Machine Translation Post-Editing (MTPE)

Machine Translation Post-Editing (MTPE) involves human editors refining machine-generated translations to ensure quality. This process is critical in the localization industry, where AI and machine learning advancements necessitate continuous improvement in translation accuracy (Gouadec, 2007). Despite the potential of MT systems, human intervention remains essential to correct errors and enhance the final output.

Although machine translation systems might have improved over time, human translation will always be relevant despite concerns about the possibility of full automation in translation. One of the reasons is that human languages carry polysemous words and are thus susceptible to multiple interpretations, often more than not depending on the interlocutors themselves. This is especially true for literary texts such as idioms and *haiku*/poems as shown in Table 1 and Table 2 respectively – in which certain advanced translation procedures such as adaptation and transposition would be applied. Based on Table 1 and Table 2, proves that MT is not viable for these sociocultural and literary phrases, making human translation as valid as ever.

Table 1: Machine Translation Errors for *Kotowaza* (Proverbs).

Input	MT Output*	Correct Translation	Malay Adaptation (Ramlan, 2021a)
猫に小判 *Neko ni koban*	Oval for cats	*koban* / gold coin to a cat	*Bagai kera diberi kaca*
蛙の子は蛙 *Kaeru no ko wa kaeru*	The frog child is a frog	A frog's offspring is a frog	*Bapa borek, anak rintik*
無くてぞ人は恋しかりける *Nakute zo hito wa koi shikarikeru*	I can't miss people	without people, love can miss (them)	*Jauh di mata, dekat di hati*

*MT outputs from Google Translate

Table 2: Machine Translation Errors for *Haiku* (Poem).

Input	MT Output*	Phrasing (Ramlan, 2021b)
さくらより *Sakura yori*	From Sakura	comparing the cherry blossoms
桃にしたしき *Momo ni shitashiki*	I made it a peach	peach blossoms underneath (would fit)
小家哉 *Koie nari*	Yasushi Koie	this small house I wonder

*MT outputs from Google Translate

METHODOLOGY

This study employs a qualitative methodology to assess the effectiveness and accuracy of Google Translate and Systran in translating texts, specifically focusing on error patterns in their outputs. The chosen text sample was 音楽のテンポが経済的意思決定に及ぼす影響 "*Ongaku no tenpo ga keizaiteki ishi kettei ni oyobosu eikyou*" (The Effect of Music Tempo on Economic Decision-Making) by Kobayashi, Fujikawa, and Foo (2012), translated from Japanese (source language, SL) to English (target language, TL). The text was specifically used as a sample for gauging the adaptability of machine translation to its equal mix of social science and arts (musical) content. Errors

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were categorized based on syntactic and semantic criteria, allowing us to evaluate the quality of translations produced by these tools.

The article investigates the intriguing observation that rhythmic sound can influence behavioral economics, specifically decision-making. It also considers the reactions and states of subjects as they listen to music while buying or choosing products. The specific reason for choosing the Japanese-English pair is that, according to Norwati (2019), Japanese-Malay translation development is still underdeveloped compared to other language pairs like Korean and Arabic.

Our evaluation framework incorporates insights from Popović (2018), who underscores the resource-intensive nature of manual error classification and the potential for automatic tools to supplement human evaluators by estimating error distributions and facilitating pre-annotation. We utilized Machine Translation Post-Editing (MTPE) and detailed tables to present our findings.

The relevance of using qualitative methods for evaluating MT systems is supported by recent research. For instance, Popović (2018) emphasizes the importance of qualitative analysis in understanding the nuances of MT errors. Freitag, Foster, Grangier, Ratnakar, Tan, & Macherey (2021) highlight the necessity of robust evaluation methods, illustrating that inadequate procedures can lead to erroneous conclusions about the quality of MT systems. They recommend using the Multidimensional Quality Metrics (MQM) framework for explicit error analysis, which provides a more reliable assessment of translation quality by involving professional translators and detailed error categorization. Additionally, Li et al. (2019) stressed the importance of qualitative analysis in handling the noisy and informal text common on social media, further underscoring the need for thorough error categorization in MT evaluations.

Through this qualitative lens, our study categorizes and examines error patterns in Google Translate and Systran outputs, providing a comprehensive assessment of their translation accuracy and identifying areas for improvement in MT systems.

RESULTS AND DISCUSSION

Errors in Translation Due to Inaccurate Choice of Semantic Correspondence

For this error acquired, we have found out that the translation output for this language pair has an emphasis on its output orientation. This error may have been caused by this application that is no longer being able to identify the meaning of the word the user wants to translate. This is because there are several words in the source language that have a lot of synonyms in the target language as shown in Table 3.

For the first one, the word コマーシャル (*komāsharu*) directly means "commercial" and this is due to its Katakana orthography – a Japanese writing system that explicitly indicates foreign words. However, the output for the word from Google is also "commercials" which is redundant to the following word in the input 宣伝 (*senden*). It should be "advertisement" as in Systran's output. This redundancy highlights a common issue in neural machine translation systems where contextual appropriateness is not adequately addressed (Koehn & Knowles, 2017).

The second one involves two parallel inputs - 詳細なメカニズム (*shōsaina mekanizumu*) and 複合作用 (*fukugō sayō*) which mean "complex mechanism" and "detailed mechanisms" for Systran and "compound action" on the "detailed mechanism" for Google. As it is, both agree on the output "detailed mechanism" for the input 詳細なメカニズム. Despite that, the second input has the 1=> feature in which 作用 (*sayou*) is also a "mechanism" redundant to the previous word メカニズム (*mekanizumu*) due to its similar nature as the first case - its Katakana orthography explicitly indicates foreign or loaned words and thus should be highly restrictive to the sole meaning of the original language. This issue is also discussed in studies exploring the translation of semantically redundant phrases and the impact of language-specific orthographic conventions (Dabre, Chu & Kunchukuttan, 2020).

The third one shows two synonyms, 条件 (*jōken*) and 状態 (*jōtai*). By default, two different Kanji characters mean two different words. Therefore, Systran's outputs of "condition" and "state" for the respective inputs are correct, yet Google conceives both as "condition". This difficulty in differentiating synonyms and producing contextually accurate translations is a known challenge for NMT systems (Toral & Way, 2018).

The fourth is related to the position of the word in the sentence according to TL. The input 。そして… (*soshite*…) is actually a discourse marker in the Japanese Language and thus has two meanings "and" as well as "then". But since the word is after a full stop, the output "then" would be more appropriate considering English as TL, not the output "and" put forth by both translation software. The importance of context-aware translation models is critical for accurately translating discourse markers (Läubli, Sennrich, & Volk, 2018).

The fifth one is the wrong choice of lexis for the input リスク選好 (*risuku senkō*) and 時間選好 (*jikan senkō*). Since the context of the article revolves around economic matters, the output for 選好 (*senkō*) should be "preference" as in Systran but Google wrongly chose "appetite" as its output instead. This highlights the challenges of translating domain-specific terminology and the importance of context in choosing the correct lexical equivalents (Arcan & Buitelaar, 2017).

Table 3: Errors in Translation Due to Inaccurate Choice of Semantic Correspondence.

Input	SMT (Systran)	NMT (Google)	MTPE Process
コマーシャルをはじめとした**宣伝**やアイキャッチ、 *komāsharu wo hajime to shita senden ya aikyattchi,*	such as commercials, **advertisements,** the eye catches,	such as commercials and **commercial**, eye-catching,	コマーシャル *komāsharu* Literally means 'commercial' -should be "and advertisement" but comes out as "and commercials" (Systran), redundant to the previous Katakana word.
詳細なメカニズムについては**複合作用**についても今後考慮する必要がある。 *Shōsaina mekanizumu ni tsuite wa fukugō sayō ni tsuite mo kongo kōryo suru hitsuyō ga aru*	and it is necessary to consider the **complex mechanism** for **detailed mechanism** in the future. There is.	and it is necessary to consider the **compound action** in the **detailed mechanism** in the future.	**詳細なメカニズム** *Shōsaina mekanizumu* **複合作用** *Fukugō sayō* Both words in the noun contribute to the 1=> category.
実験は一人の被験者につき一つの**条件**のみで計測し、独立して計測を行う。 *Jikken wa hitori no hikensha ni tsuki hitotsu no jōken nomi de keisoku shi, dokuritsu shite keisoku wo okonau.* 実験中は通してその**状態**を維持し、 *Jikkenchū wa tōshite sono jōtai o iji shi,*	In the experiment, one subject is measured under only one **condition** and is measured independently. Throughout the experiment, that **state** is maintained,	The experiment is carried out independently by measuring only one **condition** per subject. During the experiment, the **condition** is maintained,	**条件** – *jōken* **状態** – *jōtai* By default, two different Kanji characters mean different words. But Systran depicts **状態** j*ōtai* as a 'condition' as well.
ミクロ経済学ではしばしば個々人の経済的意思決定を効用という統一された指標によって説明する**。そして**… *Mikuro keizaigaku de wa shibashiba kokojin no keizaiteki ishi kettei wo kōyō to iu tōitsu sa reta shihyō ni yotte setsumei suru. Soshite…*	In microeconomics, individual economic decisions are often explained by a unified indicator of **utility. And…**	In microeconomics, individual economic decisions are often explained by a unified measure of **utility. And…**	**そして** – *soshite* And/then But more appropriate to be 'then', since it is after the full stop.
リスク**選好**と**時間選好**はしばしば同列に扱われる事象であり、… *Risuku senkō to jikan senkō wa shibashiba dōretsu ni atsukawareru jishō de ari, …*	Risk **appetite** and time **appetite** are events that are often treated in the same line, …	The risk **preference** and the time **preference** are often treated in the same class, …	**選好** – *senkō* Appetite/preference -Should be a preference based on the context

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Errors in Phrasal/Syntactic Structures

Several outputs in the article from both translation software have spotted discrepancies with the supposed syntax of the respective SLs, as shown in Table 4. Their syntax is usually reciprocal to the actual order or maybe premature/incomplete sentences. Since English syntax vastly differs from Malay as in Japanese syntax to English, phrase structure errors done by Google Translate and Systran in the translation process would be inevitable. The output will be difficult to read and understand when the translation of the translation sentence is inaccurate and riddled. This in turn causes the users to misinterpret the exact meaning of the translated sentence resulting in a misunderstanding of the context of the translated text. This problem may be due to the lack of word storage data for this application which results in incompletely translated sentences in terms of sentence structure. This problem of incorrect sentence arrangement is also due to the less systematic translation process by this application. Therefore, the quality of the output produced by this application becomes poor and incomprehensible.

Table 4: Errors in Phrasal/Syntactic Structures.

No.	Input	SMT (Systran)	NMT (Google)
1.	詳細なメカニズムについては複合作用についても今後考慮する必要**がある。** *Shōsai na mekanizumu ni tsuite wa fukugō sayō ni tsuite mo kongo kōryo suruhitsuyō* ***ga aru****.*	and it is necessary to consider the compound action in the detailed mechanism in the future.	and it is necessary to consider the complex mechanisms for detailed mechanisms in the future. **There is.**
2.	結果として時間選好は割引率によるリスクと等価とする考え方**である。** *Kekka to shite jikan senkō wa waribiki-ritsu ni yoru risuku to tōka to suru kangaekata* ***de aru****.*	the time preference is considered to be equivalent to the risk by the discount rate.	time appetite is equivalent to risk by the discount rate. **is there.**
3.	単なる音刺激が影響**したものかは分離が困難**である。 *Tan naru oto shigeki ga eikyō* ***shita mono ka wa bunri ga konnan de aru****.*	but **it is difficult to separate** whether this is essentially music or just sound stimulation.	or simple sound stimulation has an effect**. It is difficult to separate.**
4.	娯楽施設ではアップテンポなロックやポップスが流れやすいように、**経験的には**使い分けられている。 *Goraku shisetsu dewa apputenpona rokku ya poppusu ga nagare yasui yō ni,* ***keiken-teki ni wa*** *tsukaiwakerarete iru.*	and in entertainment facilities, there is a lot of up-tempo rock and pop music that are used **differently empirically.**	and entertainment facilities have been used **differently** to make it easier to play up-tempo rock and pop.

For the first and second inputs, がある。(*ga aru*) and である。(*de aru*), both respective outputs of "there is." and "is there." at the end of the sentences are unconventional and instead should be embedded in the early part of the sentence in the proper order (e.g. there is…). The third example, 離が困難である。(*hanare ga kon'nandearu.*) has the correct output for Systran "but it is difficult to separate…" but the wrong syntax for Google Translate's "it is difficult to separate." since that "separate" is a transitive verb and thus the sentence structure is unsuitable. The fourth input, 経験的には (*Keiken-teki ni wa*) has the output for Systran "differently empirically' which is incorrect since there are two adverbials and adverbials cannot end a sentence. Thus, the correct output syntactically would be "empirically different.". These issues signify the challenges MT systems face in maintaining syntactic accuracy across different language pairs (Bentivogli, Bisazza, Cettolo, & Federico, 2016; Sennrich, 2017).

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Technical Errors

It is observed that MT systems produced erroneous outputs that differ conventionally from those of human translators – incorrect prepositions, articles, pronouns, verb tenses, etc. (Hutchins, 1995). Therefore, this section focuses solely on this claim and we would verify them as well through our findings from the article using the translation software as shown in Table 5.

Table 5: Errors in Technicalities.

No.	Input	Outputs	MTPE Process
1.	実験は一人の**被験者につき一つ**の条件のみで計測し、独立して計測を行う。 *Jikken wa hitori no* ***hikensha ni tsuki*** *hitotsu no jōken nomi de keisoku shi, dokuritsu shite keisoku wo okonau.*	The experiment is carried out independently by measuring only one condition **per one subject. (Systran)**	**被験者につき一つ** *- Hikensha ni tsuki hitotsu* per one subject -Per subject (one is omitted or vice versa) since 'per' already means 'for every single'
2.	**音楽の持つ他のコンテキストと**の複合によって強く作用することが考えられる。 ***Ongaku no motsu ta no kontekisuto to*** *no fukugō ni yotte tsuyoku sayō suru koto ga kangaerareru.*	It is thought that it acts strongly by the combination of. (Google Translate) and it seems to act strongly by the combination **with other context of the music.** (Systran)	**音楽の持つ他のコンテキストと** – *Ongaku no motsu ta no kontekisuto* Google Translate omits the whole phrase, and thus the correct output should be like Systran's.
3.	リスク選好の度合いと時間選好の度合いについての**み調べる。** *Risuku senkō no doai to jikan senkō no doai ni tsuite no****mi shiraberu.***	the degree of risk and time preference for economic decision **making.**	One full-stop suffices
4.	テンポ以外の**ヴェロシティー**や音量、その他の余韻などは同じ条件になるようにした。 *Tenpo igai no* ***veroshitī*** *ya onryō, sonohoka no yoin nado wa onaji jōken ni naru yō ni shita.*	**Velocity** other than tempo, volume, and other reverberations are the same. (Google Translate) The **verocity**, volume, and other aftertones other than the tempo were made to have the same conditions. (Systran)	ヴェロシティー *- Veroshiti* Systran has the wrong spelling for the output "verocity"; The correct one should be like Google's "velocity"
5.	原曲を以下のように制御**した。まず**、. . *Genkyoku o ika no yō ni seigyo* ***shita. Mazu, …***	we controlled the original as **follows. First…**	した。 *- shita.* English convention would best be colon (:) rather than full stop

CONCLUSION

The quality of machine translation for Japanese-English pairs remains a significant concern. Despite the advancements in MT technologies, such as Google Translate and Systran, there are still notable challenges in achieving accurate and contextually appropriate translations. These systems often struggle with linguistic nuances, including syntactic and semantic accuracy, which are critical for producing high-quality translations.

Systran, with its long history and experience in machine translation, has shown fewer errors and better handling of technical and academic texts compared to Google Translate. This is likely due to its extensive development and refinement over the decades. Conversely, Google Translate, although relatively newer, has made significant

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improvements in lexical selection and sentence structure consistency. Nonetheless, both tools have substantial room for improvement, especially in handling the intricacies of the Japanese language and its translation into English.

The concept of Machine-Aided Human Translation (MAHT) is particularly relevant in this context. MAHT leverages the strengths of machine translation for speed and efficiency while relying on human expertise to ensure accuracy and contextual appropriateness. This approach is essential for translating texts that require a deep understanding of both languages' cultural and linguistic subtleties.

In conclusion, while machine translation has undoubtedly enhanced the process of translating Japanese to English, it is not yet a substitute for human translation. Continued development and refinement of MT systems are crucial to improving their accuracy and reliability. By combining the capabilities of MT with human expertise, we can achieve translations that are both efficient and of high quality, thereby fostering better cross-cultural communication and understanding.

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