

# An Analysis of the Error Translation in Movie Trailers by Youtube Auto-Translate

Noor Prasetyo<sup>1</sup>, Neneng Sri Wahyuningsih<sup>2\*</sup>

Universitas LIA, Jakarta, Indonesia.

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**Abstract:** In this study, the writer discusses common errors done by YouTube Auto-Translate in translating some of movie trailers with Indonesian subtitle as the Target Language (TL). Then, the writer compares the subtitles in the target language to that of a professional translation's output and YouTube's Auto-Translate output and categorizes the errors by referring to the error classification by Vilar et al. The writer found 14 errors on YouTube Auto-Translate output. After observing the 14 data, it showed that commonly errors found from the data are related to lexical level by nine times (63%). The second error type is related to disambiguation which took place four times (27%). The errors found with the lowest frequency are Word Order and Unknown Word with which each of them is only shown once (5%). To sum up, machine translation helps us a lot in looking up words in a dictionary, but it is not recommended to rely on machine translation as it fails to recognize the context. It is then suggested that whenever we use MT, we must have it post-edit by human translator.

**Key Words:** cultural influence; error classification; lexical error; machine translation; movie trailer; translation procedures; YouTube auto-translation.

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**Abstrak:** Dalam penelitian ini, penulis membahas kesalahan umum yang dilakukan oleh salah satu Machine Translations, YouTube Auto-Translate dalam menerjemahkan beberapa trailer film dengan subtitle bahasa Indonesia sebagai Target Language (TL). Kemudian, penulis membandingkan subtitel dalam bahasa target dengan keluaran terjemahan profesional dan keluaran Terjemahan Otomatis YouTube dan mengkategorikan kesalahan dengan mengacu pada klasifikasi kesalahan oleh Vilar et al. Penulis menemukan 14 error pada keluaran YouTube Auto-Translate. Setelah mengamati 14 data, terlihat bahwa kesalahan umum yang ditemukan dari data terkait dengan tingkat leksikal sebanyak sembilan kali (63%). Jenis kesalahan kedua terkait dengan disambiguasi yang terjadi sebanyak empat kali (27%). Kesalahan yang ditemukan dengan frekuensi terendah adalah Word Order dan Unknown Word yang masing-masing hanya ditampilkan satu kali (5%). Singkatnya, terjemahan mesin sangat membantu kita dalam mencari definisi kata dalam kamus, tetapi tidak disarankan untuk mengandalkan mesin penerjemah karena mesin penerjemah gagal mengenali konteks kalimat. Oleh karena itu, terjemahan mesin harus selalu disunting oleh penerjemah manusia.

**Kata Kunci:** pengaruh budaya; klasifikasi kesalahan; kesalahan leksikal; mesin penerjemah; trailer film; prosedur penerjemahan, YouTube auto-translation..

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\*Corresponding author: Neneng Sri Wahyuningsih, [neneng.sri@stbalia.ac.id](mailto:neneng.sri@stbalia.ac.id), Jakarta, Indonesia

## INTRODUCTION

Technology has advanced considerably. It provides us with many kinds of social media in their own platforms and features. Much information can be retrieved instantly from the world wide web. One of them is YouTube. Aero & Noorman (2022) pointed out that YouTube is believed as one of the best platforms to share information in video format. As cited by Aero & Noorman (2022), Butow (2020) believed that one of the reasons YouTube become popular was because it is created for people to share videos online. Many interesting videos coming from many different language backgrounds urges YouTube to provide a feature that can help the viewers understand the language in the said videos. Thus, Machine Translator (MT), can be a helping hand in the making of translation process.

MT is a well-known alternative for translating texts because it supports ease of use, proficiency, and, of course, some of them are free to use. Many translators have used it honorably as a tool to increase their productivity, particularly while translating technical texts (Doherty, 2016). It aids in the creation of translations that enable them to avoid the time-consuming task of looking up unfamiliar words in dictionaries and establishing terminological consistency. Lotz & Van Rensburg (2016) added that online MT allows us to quickly determine the gist of a text in a foreign language (pp. 77-78). As Diab (2021) said that relying on the human factor alone to translate huge amount of content is neither time nor cost-effective. Therefore, many translation agencies offer “the use of MT with different levels of pre- and post-editing for the sake of speeding up the translation process and reducing expenses “(Diab, 2021, p. 183).

Most machine translations are available for free on the internet. Rivera-Trigueros (2022) reported that “neural MT is the predominant paradigm in the current MT scenario, with Google Translator (later mentioned as GT) as the most used system”. The growing demand for tools that provide different types of audiences with multilingual access has made GT famous as it provides the most languages to be translated in its system.

Despite its being famous, it does not mean that it is without flaws. GT still has many flaws as it does not follow grammatical rules. This situation has identical mechanism with YouTube’s Auto-Translate. It makes use of algorithms which are primarily based on statistical analysis rather than conventional rule-based analysis. YouTube's Auto-Translate gathers patterns in hundreds of millions of documents to select the optimal translation during the translation process. It looks for patterns in papers that have previously been translated by humans to make educated estimates about appropriate translation. Statistical Machine Translation (SMT) is the technique of looking for patterns in vast amounts of text. However, Google Translate has been more advanced nowadays and has been evolving as Neural Machine Translation (NMT) which not only gathers data from statistical data, but also requires more training and larger corpus. NMT is better than SMT at handling morphology, syntax, word order, and concordance. Thus, Wu et al. (2016) as cited by Diab (2021) when compared to the statistical phrase-based model, using the neural model in Google Translate reduces errors by an average of 60% for English-French, English-Spanish, and English-Chinese language pairs.

Although YouTube's Auto-Translate feature is simple and effective, some linguists argue that translation should not be based only on statistics. YouTube Auto-Translate feature has many benefits besides providing a fast translation. Bowker (2020) found that MT has been used by Chinese speakers to write English in a scholarly context, while Steigerwald et.al (2022) shown that the multilingual services that MT offers can serve as “both a short- and a long-term solution for making science more resilient, accessible, globally representative, and impactful beyond the academy.” There are other machine translators available free on the Internet, such as Microsoft Bing Translate, Yandex Translate, DeepL, and Reverso Translation; however, none of them are embedded or linked to that of YouTube. As YouTube and Google Translate

are in the same domain of Google, therefore, they are linked in the system. However, there are differences on the technology or data used between Google Translate and YouTube Auto-Translate. As mentioned earlier, Google Translate has been trained and used a larger corpus than YouTube Auto-Translate, thus Google Translate can translate better than YouTube Auto-Translate. According to Wu et al. (2016), Google Translate is an NMT that can address many of the problems of standard MT systems. The capacity of NMT to learn directly from input text to associated output text is its strength.

As noted by Hall et al. (2015, p. 224), translation involves not just linguistic substitution but also semantic, pragmatic, and cultural processes. In this case, the meaning of the source words calls attention to the true structure and meaning of the message. It is critical that the message in the receptor language closely matches the various components of the source language. Nida published the idea (as stated in Munday, 2022, p. 56), which claims that the meaning of an orthographic word is defined by its context and subject to cultural fluctuation.

Understanding that languages are influenced by cultural systems implies that translation is not only a problem of language but also of culture. Since each language has a distinct grammatical structure, the problem of computer translation may be tough for languages spoken by various forefathers. English, for example, features verb tenses because the language's speakers place a high value on timeliness. In contrast, honorifics are used in place of proper nouns in Indonesian to express social standing rather than tenses. Given the differences between these languages, Google Translate may struggle to create accurate translations. Furthermore, the nature of the text influences how well SL is converted to the TL (Newmark, 1988).

Today, MT is used in both professional and leisure contexts, such as those found in movies. It plays significant roles in offering films in all the several languages that the in-house production targets. For instance, the house production does market their films by giving movie buffs access to the trailers, which then informs them about upcoming releases. On occasion, the home production advertises the film's trailers on YouTube. However, occasionally they do not provide subtitles in different languages. As a result, YouTube offers an option to address this issue. It is referred to as auto-translation. With MT, this feature operates in the same way. On the movie trailers, the auto-translation will automatically give subtitles in the target language as the viewers wish.

Automatic bilingual subtitle production can be provided not just for movie trailers, but also for lecture videos, particularly for MOOCs. According to Che, Luo, Yang & Meinel (2017), the lecture videos are translated using MT, and they confirmed that this can reduce the total working time in generating bilingual subtitles by around 1/3 while maintaining quality. As a result, MT has been shown to aid in translation.

However, the target language sometimes has mistranslations. For example, in the Final Trailer of Doctor Strange in The Multiverse of Madness, Wanda said "Oh, I knew sooner or later you'd show up," but the auto-translate feature translated it into Indonesian "nanti Anda akan datang," which is not quite right. Something is missing from the translation. The correct translation should be "Sudah kuduga cepat atau lambat kau pasti akan datang." Thus, this study aims to investigate the common error types found in MT, specifically on YouTube Auto-Translate feature. The study uses 14 cut scenes from six movie trailers on YouTube. There are Lightyear (2022), Loki (2021), Shang-Chi (2021), Doctor Strange in The Multiverse of Madness (2022), Black Widow (2021), and Jurassic World Dominion (2022).

The error classification proposed by Vilar et al. (2006) is used in this study. They classified errors into four big categories: punctuation, missing words, word place, and incorrect words. This study will not look at punctuation. Missing words are separated into two categories: missing auxiliary words and missing content words. The word order is then divided into two levels: word level and phrase level, with short and long ranges within each level. Incorrect terms

are classified as extra words, incorrect word choice, untranslated, and poor word sense. Poor lexical choice and poor disambiguation are the two basic types of poor word sense.

This study will compare the translation by YouTube Auto-Translate to the official translation of the movie trailers. The objective of the study is to identify the different kinds of translation errors made by YouTube's Auto-Translate when translating from English to Indonesian in several movie trailers. This information will be used as a teaching tool to help language learners develop their critical thinking skills in relation to language use. As a result of the study, it is anticipated that linguists will become more conscious of the learners as they get more adept at identifying text types and their distinguishing traits, determining the purpose of translation, and creating alternative translations.

### Machine Translation (MT)

One of the translation tools used to speed up translation is Machine Translation (Holmes in Munday, 2022). MT is unique among translation aids because it tries to automate the translator's primary duty (Munday, 2022). The complete source texts are translated into the target texts by MT in a very short amount of time, something human translators cannot do. Because of its simplicity and usefulness, as well as the more recent broad use of MT by the translation business and the public, MT has become one of the most attractive tools for producing a fast, large-volume, low-cost translation (Doherty, 2016).

The Auto-Translate tools on YouTube function in a similar manner to past Google Translate or Bing Translate in terms of translation. As Doherty (2016) reported that it uses "complex statistical algorithms to analyze large amounts of data to generate a monolingual language model for each of the two given languages, and a translation model for the translation of words and phrases from one of these languages into the other" (p. 953). It does not adhere to grammatical norms because its algorithms are based on statistical analysis rather than traditional rule-based analysis. Google Translate analyses trends in hundreds of millions of documents to determine the optimal translation. It looks for patterns in texts that have already been translated by humans to produce educated guesses for an appropriate translation. The process of looking for patterns in large amounts of text is referred to as statistical machine translation.

MT is not only having difficulties in delivering successful translation for a bigger part of a sentence, even it can fail in translating nouns. Nouns, as Hardmeier & Guillou (2018) highlighted, are troublesome for all MT approaches. They stated that there is no evidence that using neural techniques in MT alone leads to considerably superior performance on this type of issue. Furthermore, they added that MT system developers must handle the language's pronoun function and referential features.

### Machine Translation Error

The behaviorist theory of language learning, on which error analysis was based, stated that errors were indicators that language learners were simply not aware of the target language's rules sufficiently (Brown, 2014). With this idea, linguists concentrate on mistakes as evidence of inefficient language learning. Error analysis is described as "the reality that learners do make mistakes and that these mistakes may be observed, evaluated, and classed to reveal something of the system operating within the learner that led to a boom of study of learners' errors" by Brown (2014). For example, error analysis is a method for methodically identifying, categorizing, and interpreting mistakes made by second language learners. Error analysis highlights the importance of errors in learners' interlanguage system as a result (Brown and Lee, 2015). The term "interlanguage" itself describes the systematic acquisition of a second language

(L2) that is unrelated to either the learners' native tongue or the intended language (TL). However, mistakes and errors in language learning is different, especially if this error is done by machine translator.

Martins and Caseli (2015) noted that several errors are still present in the texts produced by modern MT systems for many language pairs. However, Lee & Cha (2020) disagreed to this idea by saying that auto-generated captions on YouTube have proven effective in assisting viewers in better understand the words uttered. However, they occasionally lack correct captions, which causes confusion. These machine translation errors are divided into many categories.

Popović (2018) stated that manual error classification is a resource- and time-intensive operation with low inter-evaluator agreement. Sudoh, Takahashi and Nakamura (2021) agreed with this approach, citing low-quality MT translation outputs as another issue. They claimed that assessing incorrect translations on a 100-point scale would be difficult and unstable since the extent of errors could not be easily transferred into a one-dimensional space (p.46). As a result, these are difficulties in doing research on MT error translation.

Meanwhile, Vilar et al. (2006, p. 698) categorized the errors into five main categories as "Missing Words," "Word Order," "Incorrect Words," "Unknown Words," and "Punctuation." "Missing words" refers to the components of a phrase that are necessary but are absent. Filler words and material make up this mistake. Filler words are concerned with missing words that are only required to make a statement that is technically correct, as opposed to content words, which are concerned with missing words that are necessary to convey the sense of a sentence. "Word Order" error points to the incorrect sentence structure. The word and phrase-based orderings of this mistake are separated into local and long-range reordering within each of these categories. In contrast to long range, which transfers the words into a different chunk of the source text, local reorders the words within the same syntactic chunk of the text. "Incorrect Words" error refers to the mistranslated phrase. This mistake can be broken down into lexical, disambiguation, form, extra-word, stylistic, and idiomatic faults. Untranslated words are pointed out by the "Unknown Words" error. This error can be divided into two categories: unknown stem and hidden shape. Unknown stem occurs when the source lexeme prevents MT from recognizing the correct translation, whereas unseen form occurs when MT is unable to distinguish the morphologically complex words of SL. "Punctuation" error refers to the errors related to marks used in writing.

Diab (2021) further stated that most of the research comparing the quality of machine translation technologies rely on automatic evaluation methods, specifically the bilingual evaluation understudy (BLEU), which is performed without any human assessment. She went on to say that, while BLEU is a good indicator of the overall performance of MT systems, it does not provide any linguistics concepts into the types of errors created by MT models because only humans can do it. She demonstrated an analysis that employs the DQF-MQM Harmonised Error Typology, a shared industry standard for classifying and counting translation errors sentence by sentence based on eight major categories such as accuracy, fluency, terminology, style, design, locale convention, verity, and other issues.

Some writers have studied similar topic about YouTube Auto-Translate. They are Laksana & Siegfrieda (2018) and Putri (2014). Both writers used classification errors by Vilar et al. Laksana used YouTube Auto-Translate, like the writer, as the subject and Gustika used Google Translate as the subject. The first study was conducted by Laksana and Siegfrieda (2018). The study entitled "An error types of analysis on YouTube Indonesian English auto-translation in Kok Bisa? channel". This study discussed the common errors by YouTube Auto Translate. In this study, they used the similar theory from Vilar et al which classified the error into five main categories. The method conducted by the writers was qualitative and quantitative

method. The data collecting technique was watching the 14 chosen video from Kok Bisa? YouTube channel and find any errors in the English subtitle by YouTube Auto-Translate. After the data collected, they analyze the English subtitle. By analyzing the data, they can classify the errors and count how many errors occurred in those 14 videos. In the end of the study, the writers conclude that YouTube Auto Translate weakness is in lexical and grammar. In the analysis, wrong lexical choice took the first place at 24.14% followed by bad word form at 21.93%. From what they found, they suggested to analyze the source of the errors found in the translation produced by YouTube Auto-Translate.

The second study was done by Putri (2014). The study examines the most common types of errors made by Google Translate using texts from Indonesian folklore. The descriptive method is used to conduct the research. Three Indonesian folklore manuscripts were selected as the source text for the research's data. Google Translate then converts them into English. The folklores are Si Pitung (from DKI Jakarta), Sangkuriang (from West Java), and Manik Angkeran (from Bali). After that, the writer analyzed the translated text by Google Translate. She concludes that Google Translate generates the most incorrect word errors when translating folklore texts. The grammatical and structural differences between ST and TT led to this error. Furthermore, the distinctive qualities of folklores, such as cultural words, contents, and structures, became the source of differences that resulted in translation problems.

To fill the gap in the current research, this research is conducted by focusing on the YouTube Auto-translate on famous movie trailers that are available on the Internet. This study also compares the translation from YouTube Auto-translates with their official subtitles from their official trailers. Thus, readers of this study will realize that YouTube Auto-translate can or cannot be reliable.

## METHOD

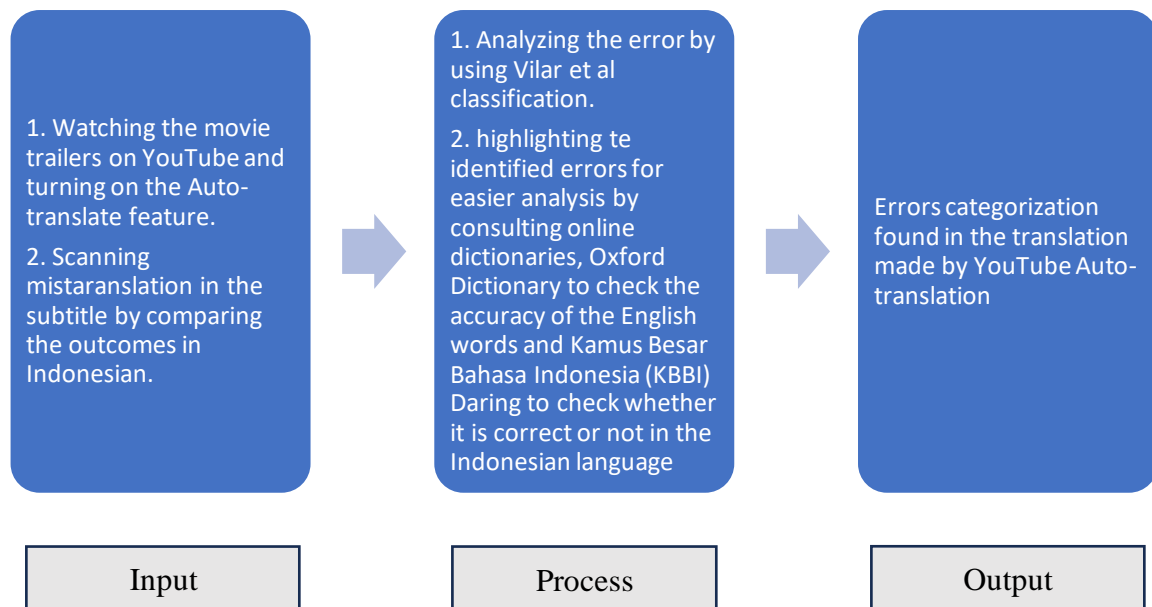
This research is descriptive qualitative research since the data was described in words and analyzed using error analysis. Data from qualitative descriptive research are produced that provide a subjective account of the "who," "what," and "where" of events or experiences (Kim et al., 2017, p.23). Only the research situation, issues, phenomena, and any other study-related facts can be described and reported by the researcher. The primary objective of this study was to examine the errors made by YouTube's Auto-Translate feature.

The data for this study were Indonesian translations of English movie trailers obtained from YouTube. 14 clips from seven YouTube teaser videos serve as the data sources. These data will be categorized into Vilar et al., error categorization (2006). The official YouTube channel for each house production of a movie trailer is where the target texts were found. The indicators were developed based on the theories to simplify the study and classification of the data.

This study is using Vilar et al. (2006) error's classification in analyzing the data as it is more applicable to the data that has been obtained. The four primary categories of errors identified by Vilar et al. (2006) are (a) missing words, (b) word order, (c) wrong words, and (d) punctuation. When a word in the phrase being created is missing, a missing word is produced. There are two categories: missing auxiliary words and missing content words. By rearranging words or phrases inside a sentence, word order can be distinguished. There are word level errors and phrase level errors. Once more, short range and long range are differentiated for each level. When the system is unable to identify the accurate translation of a given word, an incorrect term is discovered. It is classified as an extra word, a bad word form, an untranslated word, or a bad word sense. The two categories of poor word sense are poor lexical choice and poor disambiguation. There would also be a punctuation error. However, for languages without

established punctuation standards, these constitute relatively minor annoyances for the output quality of machine translation at this time.

The following procedures are used to collect and analyze the data starting from the input to the output:



As we can see from the chart above, the study is started by the researcher watching the movie trailers on YouTube with the Auto-Translation subtitle feature turned on to see the translation outcome in Indonesian. The data is then analyzed by scanning the subtitle for mistranslations by comparing YouTube Auto-Translation output with the official subtitle from the movie trailers; then, highlighting identified errors for easier analysis by consulting online dictionaries, such as Oxford Dictionary to check the accuracy of the English words and Kamus Besar Bahasa Indonesia (KBBI) Daring to check whether it is correct or not in the Indonesian language; and finally, analyzing the error by using the classification provided by Vilar et al (2006). This study is important to be done as many movie viewers depend on YouTube Auto-Translate feature without being aware that the translation result is inaccurate.

## RESULTS

This chapter consists of data analysis of the errors occurred in YouTube's Auto Translate. The analysed data were taken from 14 dialogues in six different movie trailers and the TL were generated from YouTube's Auto Translate. All of the data taken were the mistranslations generated by YouTube's Auto-Translate. The data were analysed by using translation errors types according to Vilar et al. (2006 p.698). The 14 errors were classified as word order (phrase level), incorrect word (incorrect disambiguation, wrong lexical choice), and unknown word. Here are the examples of the data analysis based on the findings on the 14 cut scenes in four movie trailers.

The data analysis revealed that the most common errors detected in the data are related to lexical level by nine times (63%). The second type of error is disambiguation, which occurred four times (27%). The errors with the lowest frequency are Word order and Unknown Word, both of which appear only once (5%).

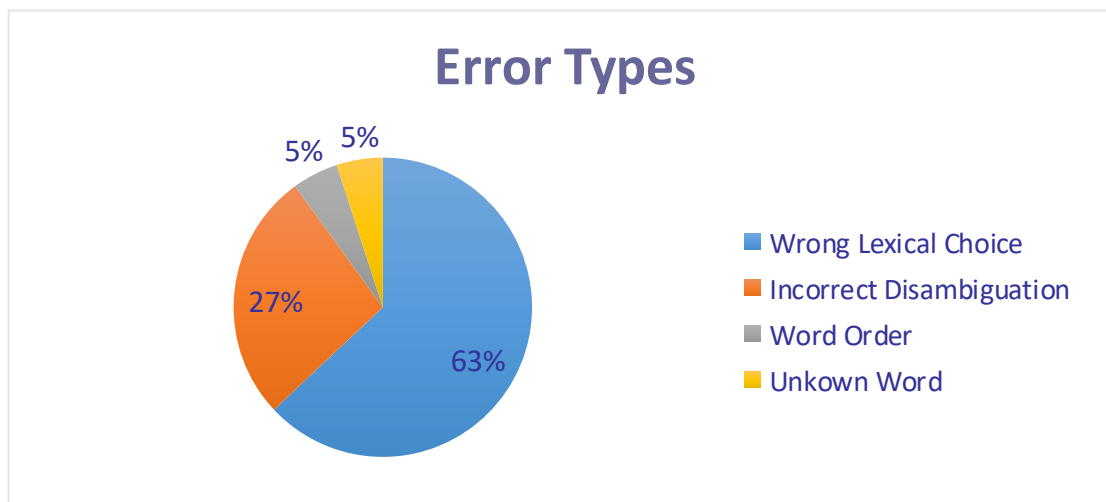


Figure 1 Error types

The major errors found in the research were incorrect words, to be exact wrong lexical choice. This happened because of YouTube's Auto-Translate to translate phrases from the given contexts. **The system cannot recognize what happened beyond the context because it does not apply grammatical rules.** It utilizes algorithms which are based on statistical analysis rather than traditional rule-based analysis.

The writer found YouTube's Auto Translate failed to provide proper word order in the TL. It is due to its failure to recognize proper word order in the TL, for this case Indonesian language which is seen as Asian language group. As noted by Aiken and Balan, whereas MT provides strong translations across European languages, it provides rather mediocre translations between Asian languages. In this study, MT was unable to translate phrases in the target language in the correct order.

## DISCUSSION

Below is the discussion on the findings which is divided by the errors found.

The first error found from the total data set is on wrong lexical choice error. As we can see from the table below, the five movie trailers: Lightyear, Loki, Shang-Chi, Doctor Strange in the Multiverse Madness, and Jurassic World Dominion have this type of error in their YouTube Auto-Translate. The explanation is given after Table 1.

Table 1. Wrong Lexical Choice Error

Lightyear			
SL Subtitle	YouTube's Auto-Translation TL Subtitle		Official TL Subtitle
A year of work for a four-minute flight. Isn't that something?	Satu tahun kerja penerbangan empat menit. Bukankah itu sesuatu?	untuk kami	Setahun kerja untuk penerbangan empat menit. Luar biasa.
Our first test flight is a go.	Penerbangan uji pertama adalah pergi.		Uji terbang pertama kami sudah siap.



<b>Loki</b>		
SL Subtitle	YouTube's Auto-Translation TL Subtitle	Official TL Subtitle
The timekeepers have built <b>quite the circus</b> .	Pencatat waktu telah membangun <b>sirkus yang cukup</b> .	Para Penjaga Waktu membuat <b>sirkus yang luar biasa</b> .
<b>Big metaphor guy</b> . I love it. Makes you sound super smart.	<b>Pria metaphora besar</b> . Saya suka itu membuat anda terdengar sangat pintar	<b>Suka membuat metafora</b> . Aku suka itu. Membuatmu terdengar sangat cerdas.
<b>You are not big on trust, are you?</b>	<b>Anda tidak besar pada kepercayaan apakah</b>	<b>Kau tak mudah percaya, ya?</b>
<b>Shang-Chi</b>		
SL Subtitle	YouTube's Auto-Translation TL Subtitle	Official TL Subtitle
You are <b>a product</b> of all who came before you.	Anda adalah <b>produk</b> dari semua yang datang sebelum Anda.	Kau <b>hasil</b> dari semua yang ada sebelum dirimu.
<b>You are your mother</b> .	<b>Anda adalah Ibu Anda</b> .	<b>Kau seperti ibumu</b> .
<b>Doctor Strange in The Multiverse of Madness</b>		
SL Subtitle	YouTube's Auto-Translation TL Subtitle	Official TL Subtitle
Well, I knew <b>sooner or later</b> you'd show up.	Saya tahu <b>di suatu tempat</b> nanti Anda akan muncul.	Sudah kuduga <b>cepat atau lambat</b> kau akan datang.
<b>Jurassic World Dominion</b>		
SL Subtitle	YouTube's Auto-Translation TL Subtitle	Official TL Subtitle
<b>You didn't come out all this way just to catch up</b> .	<b>Anda tidak keluar sejauh ini hanya untuk mengejar ketinggalan</b> .	<b>Kau tidak kemari hanya untuk mengobrol, bukan?</b>

There were nine Wrong Lexical Choice errors. The errors happened when YouTube's Auto-Translate failed to translate a phrase which includes the context of the text. It cannot find the best equivalences in the TL. Therefore, it is just generated a literal translation. Laksana and Putri (2018, p. 77) supported this finding as they also found that this is "the most commonly found error type produced by YouTube Auto-translate".

On the SL, Ying Nan (Shang-Chi's Aunt) in the movie was trying to tell Shang-Chi that he is just like his mother (for this context is his mother the ideology, facial feature, or other thing related to his mother). However, YouTube's Auto-Translate generated those sentences literally into the TL as *Anda adalah ibu Anda* which is not quite correct. Meanwhile, in the official translation, they bring the message and the context that Ying Nan was going to deliver. That is why YouTube's Auto-Translate fails to translate this sentence, because it cannot see through the context.

Another example of wrong lexical choice is from Loki when one of the timekeepers, Mobius, told that Loki is Big Metaphor Guy. Once more, YouTube's Auto-Translate cannot see through the context that it generated literal translation. This phrase referred to Loki, who always used metaphor when he speaks, and Mobius sarcastically told him with Big Metaphor Guy. In the official translation, it is "Suka membuat metafora" which is the best translation for the phrase. It delivered the message from Mobius that Loki always used metaphor when speaking.

These wrong lexical choice errors are also confirmed by Taufik (2018) that some words cannot be delivered well by YouTube Auto-Translate as it cannot identify the SL concept into

the TL concept. Fan (2017) has a similar opinion of it as MT fails in translating content with cross-cultural aspects so that human translators must edit the work of MT and they should not only convey the meaning of the content, but also take the culture factors into considerations.

The second error found is in category of incorrect disambiguation. The errors found in the YouTube Auto-Translate of movie trailers of Lightyear, Loki, Black Widow, and Jurassic World Dominion as follows:

**Table 2.** Incorrect Disambiguation

Lightyear		
SL Subtitle	YouTube's Auto-Translation TL Subtitle	Official TL Subtitle
We've got a <b>breach</b> in the perimeter.	Kita mendapat <b>pelanggaran</b> dalam perimeter.	Ada <b>kebocoran</b> perimeter.
Loki		
SL Subtitle	YouTube's Auto-Translation TL Subtitle	Official TL Subtitle
It is <b>adorable</b> , that you think you could possibly manipulate me.	Itu <b>menggemaskan</b> bahwa Anda pikir Anda mungkin bisa memanipulasi aku.	<b>Lucu sekali</b> kau mengira kau bisa memanipulasi.
Black Widow		
SL Subtitle	YouTube's Auto-Translation TL Subtitle	Official TL Subtitle
I am sorry. We had our <b>orders</b> , and we played our roles.	Maaf. Kami mendapat <b>pesanan</b> kami dan kami memainkan peran kami.	Maaf, kami terima <b>perintah</b> dan jalani peran kami.
Jurassic World Dominion		
SL Subtitle	YouTube's Auto-Translation TL Subtitle	Official TL Subtitle
<b>You coming or what?</b>	<b>Anda datang atau apa</b>	<b>Kau ikut atau tidak?</b>

There were four errors of Incorrect Disambiguation occurred on YouTube's Auto-Translate translation. This error occurred when the system chooses an incorrect word for the translation. Like Wrong Lexical Choice error, YouTube's Auto-Translate failed to recognize context on the SL, thus the error occurred when choosing the word in TL. This happened when the system was not able to disambiguate the correct meaning of a source word in each context.

On the Black Widow, Melina Vostokoff (Natasha's mother) said "I am sorry we had our orders, and we played our roles." to Natasha. In this sentence, she said "orders" which can be translated into pesanan. In this case, then according to the Oxford Dictionary, "orders are a request for food or drinks in a restaurant, bar, etc. However, this is not what Melina talked about. Referring to the Oxford Dictionary, "orders" which Melina mentioned was something that somebody is told to do by somebody in authority. Then, pesanan is not the equivalent for "orders" in this context because pesanan, according to KBBI Daring, is a request made when buying something (to be delivered or made, etc.). It would be more sensical if "orders" is translated into perintah because Melina was instructed to do something.

Another example was on Jurassic World Dominion when Ellie Sattler confirmed to Alan Grant whether he wanted to join her by saying "You coming or what?". This sentence confused YouTube's Auto-Translate because it does not follow the rule of proper sentence. A proper sentence, in this context is an interrogative sentence, must have to be to make sense – because the verb is gerund. Moreover, "what" cannot be placed at the end of a sentence in an

interrogative sentence. That is why YouTube's Auto-Translate generated it as a question word *apa* to the TL while the intention of this sentence is asking Alan whether he is coming with Ellie. Thus, if the sentence is changed to "Are you coming with me or not?", YouTube's Auto-Translate would generate the right translation to the TL. However, this is the spoken language which somehow does not always follow the grammar rules. The official translation of this utterance is *Kau ikut atau tidak* which makes more sense for Indonesian. The difficulty for this research is that YouTube Auto-translate cannot differentiate the correct equivalence for certain expressions. Moreover, YouTube Auto-Translate does not follow the protocol of good subtitling conduct, such as use of more than 36 characters per line, incorrect sentence chunking, and inability to soften down the taboo words (Budiharjo and Saptaningsih, 2020).

The third error falls under the category of word order. Apparently, this error only occurred in one movie trailer translated using YouTube Auto-Translate, that is *Lightyear*. The error can be seen as follow:

**Table 3.** Word Order

<b>Lightyear</b>		
SL Subtitle	YouTube's Auto-Translation TL Subtitle	Official TL Subtitle
<b>Our first test flight is a go</b>	<b>Penerbangan uji pertama kami adalah pergi</b>	<b>Uji terbang pertama kami sudah siap.</b>

This category showed that the error directs to the wrong structure of the sentence. The error can be distinguished between word or phrase-based reordering. To generate a correct sentence, the writer just moves individual words, independently of each other. While a phrase-based reordering is needed, blocks of consecutive words should be moved together to form a right translation. From all the data provided, there was only one error classified as word order error. The error is classified into phrase level error. This happened because the Auto-Translate failed to recognize the noun phrase to target language, Indonesian. As Laksana and Putri (2018) concluded in their study, this error produced by YouTube Auto Translate as no one provides the revision. In other words, it proves that MT lacks in providing the correct TL structure.

The word "flight" means "penerbangan" in the target language. It is correct if we translate it literally, but "flight" is modified by "test" which takes the role as an adjective. Therefore, in the target language, You-Tube Auto-Translate places the noun and the adjective in the wrong position. Thus, the correct position in target language should be "uji terbang" as the equivalent of "test flight".

The fourth error in under the category of unknown word. This error is found in the translation of the dialog in *Doctor Strange in the Multiverse of Madness*. The datum can be seen in Table 4 below:

**Table 4.** Unknown Word

<b>Doctor Strange in The Multiverse of Madness</b>		
SL Subtitle	YouTube's Auto-Translation TL Subtitle	Official TL Subtitle
What do you know about the <b>multiverse</b> ?	Apa yang kamu ketahui tentang <b>multiverse</b> ?	Apa yang kau ketahui tentang <b>multi jagat</b> ?

This category happened when the system could not find the best translation from the given word. YouTube's Auto-Translate may fail because it does not have any records of the stem or form of the word, in consequence they just take the given word to the target language. In this research, the writer found that the system cannot generate translation when it finds a

portmanteau word. Portmanteau is when two words merge into one which results in a new word with new meaning.

The word “multiverse” is a portmanteau word. It consists of “multi”, referring to the Oxford dictionary, it means many; more than one and “verse” clipped form the word universe means a whole space and everything in it according to the Oxford Dictionary. Then, combined and it becomes a multiverse. According to Britannica, multiverse is **hypothetical diverse and observable universes**. However, we can refer to what Marvel studio’s concept about multiverse. As cited from Marvel Cinematic Universe Wiki, multiverse is **the aggregate of all existing dimensions and parallel universes coexist**.

By knowing the root of the word, we can create a new portmanteau word in the target language. “Multi” has a similar meaning in target language, “multi” (it pronounces differently with the English version). Cite from KBBI Daring, multi is a suffix that means a lot; many. Afterwards, the word universe is equivalent to “jagat” in target language. Referring to KBBI, jagat is earth; world; universe. Then, combine these two words into one, “multi jagat”. Thus, the equivalent for “multiverse” is generated as “multi jagat”.

YouTube’s Auto-Translate feature failed to recognize portmanteau words. The system fails because it does not have any records of the stem or form of the word. In consequence they just take the given word to the target language. Therefore, when the system finds new words that consist of two words combined – making a portmanteau word, it cannot analyze the word and find difficulties to find equivalent to target language. Rivera-Trigueros (2022) highlighted that failure in rendering the correct vocabulary is one of the errors made by MT. Other errors found are related to concordance, style, and confusion in word meaning.

## CONCLUSION

There are a total of 14 errors found on YouTube’s Auto-Translation. They were word order (phrase level), incorrect word (incorrect disambiguation, wrong lexical choice), and unknown word. By observing the data, it showed that the commonly errors found from the data are related to lexical level by nine data (63%). The second error type is related to disambiguation which took place four times (27%). The errors found with lowest frequency are Word order and Unknown Word which each of them only shown once (5%).

To sum up of this research, errors made by YouTube Auto-Translate are word order (phrase level), incorrect word (incorrect disambiguation, wrong lexical choice), and unknown word errors. Lexical level is YouTube Auto-Translate of weakness. The emphasis in the original language may also be a contributing factor in the inaccuracy. Analyzing the root of the faults discovered in the YouTube Auto-Translate translation is advised as further research.

Suggestion for the next research in finding error types in YouTube’s Auto-Translate is to find longer videos minimum of 10 minutes for it is giving a bigger change in obtaining the errors in the subtitles. The writer is not recommending analyzing the data from movie trailers for its content is too short and the context is difficult to understand. Future researchers should also use not only human evaluator in assessing the MT errors, but also must make use of automated metrics revisor such as Word Error Rate (WER) which was based on the Levenshtein or edit distance and Translation Error Rate (TER) metrics. The use of these automated metrics can add to the precision of identifying the MT errors. Besides that, the writer reminds the language learners not to rely on any machine translators for doing translation due to many errors found in accordance with context recognition failure by the machine translators.

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