https://doi.org/10.24303/lakdoi.2022.30.1.157

A Comparative Error Analysis of Neural Machine Translation Output: Based on Film Corpus

Sungran Koh
(Kookmin University)

Koh, Sungran. (2022). A comparative error analysis of neural machine translation output: Based on film corpus. *The Linguistic Association of Korea Journal, 30*(1), 157-177. This study aims to analyze translation from Korean to English in three mainstream machine translation (MT) systems in Korea and to classify the major error problems of the MT systems. To do this, first, the Korean script of the film *Minari* (2021) was collected and translated by three major machine translators (Google Translate, Papago, and Kakao i). Then, the translation output of the three mainstream online translation systems was manually evaluated by humans. Next, MT errors in Korean to English were classified into four categories: missing words, word order, incorrect words, and unknown words. The 'incorrect words' were subcategorized into 'sense', 'incorrect form', and 'extra words'. The most frequent type of incorrect word error was 'incorrect disambiguation (subject)' and 'wrong lexical choice' in terms of 'sense'. Based on these findings, some suggestions are to use more developed machine translation for both MT system developers and Korean English as a Foreign Language(EFL) learners. This study sheds light on the quality of current MT systems based on the error analysis of this data and offers EFL learners insights into using MT systems better.

Key Words: machine translation, EFL learners, errors, incorrect words, incorrect form

1. Introduction

As the world has been increasingly globalized and technology has been advanced, more people have been interested in cross-cultural and trans-lingual communication.

Accordingly, their need for foreign language translation has been growing, and machine translation plays a critical role in helping with language in their daily lives. Machine Translation (MT), referred to as automatic language translation, is the process that computer programs use to translate sentences from one natural language to another natural one. Ali (2016) states, "machine translation may play a pivotal role in helping language experts in their daily work in general and in aiding non-professionals to understand and create text in target languages in particular" (p.55).

With technological advancement, MT has attracted more interest and has been researched and developed over the last few decades, but it is still a big challenge for both developers and users. Ali (2016) mentions, "machine or a piece of software cannot interpret the sense of anything and more so will not translate if it does not understand the meaning of the text" (p.55). MT can translate texts, but is unable to convey the sense and implications. In addition, MT is not only related to mathematics, computer science, and linguistics but also various syntactic and semantic levels of languages have caused its error problems. MT still lacks in recognizing the proper synonym, collocation or word meaning.

The identification of MT output is a vital and challenging task for the development of this area. Above all, there is no unique reference for translation. Since a unit of words may have more than one correct equivalent in a target language, the texts can have more than one proper translation. Stankevičiūtė, Kasperaviciene and Horbacauskiene(2017) mention, "errors can involve not only single words but also phrases, discontinuous expressions, word order or relationships across sentence boundaries" (p. 77). As MT systems are able to treat flexible syntax, vocabulary, and even a variety of discourses, post-editing by humans is often needed. Post-editing by humans is effort and time consuming in determining which one is correct or wrong. Moreover, every languages does not have the same or similar word order. There are many times that the word order of a source language is different from that of the target language. As an example of this, English and Korean have different word orders. English follows the "subject-verb-object" (SVO) word order, whereas, Korean follows the "subject-object-verb" (SOV) order. This difference often causes inevitable errors in the interlingual basic order.

In addition, Korean is an agglutinative language with rich morphological features such as Turkish, Finnish, Hungarian, and Mongolian. While SVO languages such as English have the semantic content of the particles added to the nouns and verb stems, the agglutinative languages have the chains of particles attached to complicated suffixes, morphemes per word structures showing many syntactic characteristics due to word-form sparsity, and variable word order. Consequently, it has been difficult to translate from one language to another for MT systems. Despite this difficulty, MTs are useful and helpful in providing communication aids or translation tools in an unfamiliar foreign language.

The analysis of translation error is a fundamental task in all natural language processing to diagnosis and develop the MT system. Translation error analysis is the process of questioning the consequence of unsuccessful language. According to Leng & Shan (2019), "it is particularly important to analyze the errors in machine translation to improve the quality of the output text of machine translation and to make appropriate post-editing" (p.30). To the field of MT, Emmanuelle, Francic, and Eady (2019) mention that the analysis of translation error is used to improve translation teaching methodologies. Dulay and Krashen (1983) mention that errors include valuable information that learners use to acquire languages. According to Richards (1974), "At the level of pragmatic classroom experience, error analysis will continue to provide one means by which the teacher assesses learning and teaching and determines priorities for future effort" (p.15).

In order to error analyze MT, this study used a film corpus-based method with the Korean-English subtitles of the film *Minari* (2021) which is a 2020 American drama film. It won the six leading awards at the 93rd Academy Awards: Best Picture, Best Director, Best Original Score, Best Original Screenplay, Best Actor (Yeun), and Best Supporting Actress (Youn). Yeun is the first Korean to win an Academy Award for acting. One of the reasons for using this movie for error analysis in MT is that most of the script in this movie does not use complex sentences but simple and compound sentences. Simple and compound sentences are good for using MT. Lee & Kim (2018) argue pre-editing rules for MT translation, one of which is to simplify the sentence structure by separating a compound sentence with two simple sentences using a connective. They showed the quality of the MT improved greatly when they used this rule. Also, they state that complex sentences with subordinate conjunctions result in wrong or ungrammatical sentences in MT.

This study aims to analyze translation from Korean to English in three mainstream online translation systems in Korea and to classify the major error problems of MT systems, and further to suggest the effective methods in using MT systems for Korean EFL learners. This focus of this study is not on the identification of human translation errors but on that of MT errors.

To achieve this aim, as a first step, the script of the film *Minari* (2021) was collected from the movie and was translated by three mainstream online translation systems in Korea - Google Translate, Papago, and Kakao i. Google Translate by Google are representative translation systems in Korea which provide translation into many languages and are based on neural network technology. Papago, provided by a leading IT company Naver Corporation in Korea, is a multilingual machine translation, using an AI based neural machine to acquire from its mistakes. Kakao i is an AI platform developed by Kakao Corporation. The next step was to evaluate translations of the three mainstream online translation systems in Korea manually by two Korean-Americans who have extensive knowledge and experiences in English translation and compare the three systems. Lastly, MT errors in Korean to English translation are classified into four categories according to the Vilar, Xu, D'Haro, and Ney (2006)'s MT taxonomy.

2. Literature Review

2.1. Machine Translation Taxonomies

Much research has been performed and suggests taxonomies classifying the type of translation errors in MT to find out the typical errors of each MT system. The MT error taxonomy has been used to evaluate the merits and demerits of MT systems. Dulay and Krashen (1983) suggest the two descriptive error taxonomies Linguistic Category Classification (LCC) and Surface Structure Taxonomy (SST). Llitjós, Carbonell & Lavie (2005) suggest a hierarchical taxonomy of errors in making rules of MT translation, but they have no explanation of which types of errors were classified. Mohamed & Shafeen (2017) classify the translation errors into four categories: word, phrase, syntactic, and sematic translation problems. Costa, Correia & Coheur (2016) divide the type of translation errors into five major classifications: orthography, lexis, grammar, semantic, and discourse (See Figure 1).

This demonstrates that the lexis category including omissions, additions, and untranslated items have the highest errors in MT among five categories of their taxonomy. The lowest error frequency shows in the discourse item.

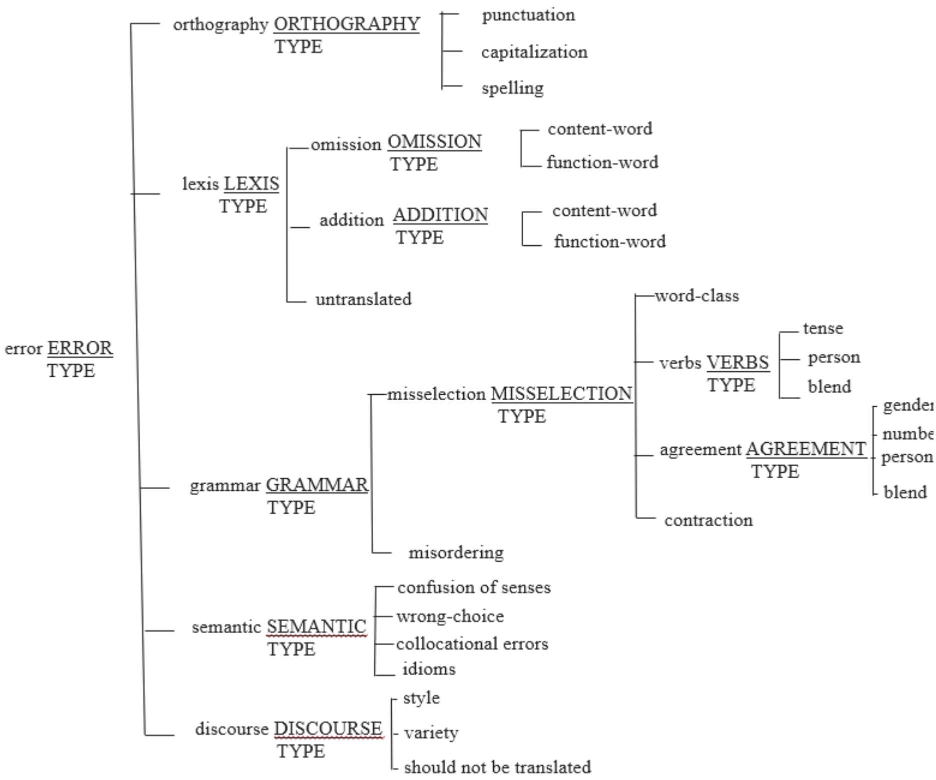

Figure 1. Taxonomy of translation errors
(Costa, Correia & Coheur, 2016, p.12)

Han and Palmer (2005) classified the sources of translation errors into six major types: tagging, spelling, recovery and ambiguity resolution errors, missing entries from the common noun list, the inflectional template list, and the inflection dictionary. Popović and Ney (2007) indicate the basis of the five error classes: inflectional error, reordering error, missing word, extra word, and lexical choice error.

Condon, et al. (2010) carried out translation from English to Iraqi Arabic and classified errors into deletions, insertions, and substitutions for morphology, and types of errors following a similar taxonomy as Vilar, et al. (2006). Costa, et al. (2015) compared Bojar (2011), Vilar, et al. (2006), and Dulay, Burt, and Krashen (1983) as in the following Table 1.

Table 1. Comparison with other taxonomies

Error types		Bojar	Vilar	Dulay
Orthography	Punctuation	√	√	√
	Capitalization	x	x	x
	Spelling	x	x	√
Lexis	Omission	√	√	√
	Addition	√	√	√
	Untranslated	√	√	√
Grammar	Word class	√	x	√
	Verb	√	√	√
	Agreement	x	√	√
	Contraction	x	x	√
	Misordering	√	√	√
Semantic	Confusion of senses	√	√	√
	Wrong choice	√	√	√
	Collocational errors	x	x	x
	Idioms	x	√	√
Discourse	Style	x	√	√
	Variety	x	x	x
	Should not be translated	x	x	x

(Costa, et al., 2015, p.13)

One of the most used classifications in MT is the taxonomy by Vilar, et al. (2006). Vilar, et. al. (2006) identify the taxonomy and use translation errors from Spanish to English and Chinese to English and show an abundant source of generalizations regarding the translation errors in MT. They classify errors into five categories: missing words (some words are omitted), word order (wrongly positioned), incorrect words, unknown words (copied without translation), and punctuation (See Figure 2).

‘Missing words’ is essential only when making a grammatically correct sentence. Most of the ‘missing words’ type errors are due to missing main words, or content words. The next category is ‘word order’ which is divided into two reorderings such as word level and phrase level. It is difficult to define the difference between local and long range. Local range means the reordering within the same syntactic chunk and long range means moving the words into another chunk. The third category of error is the ‘incorrect words’

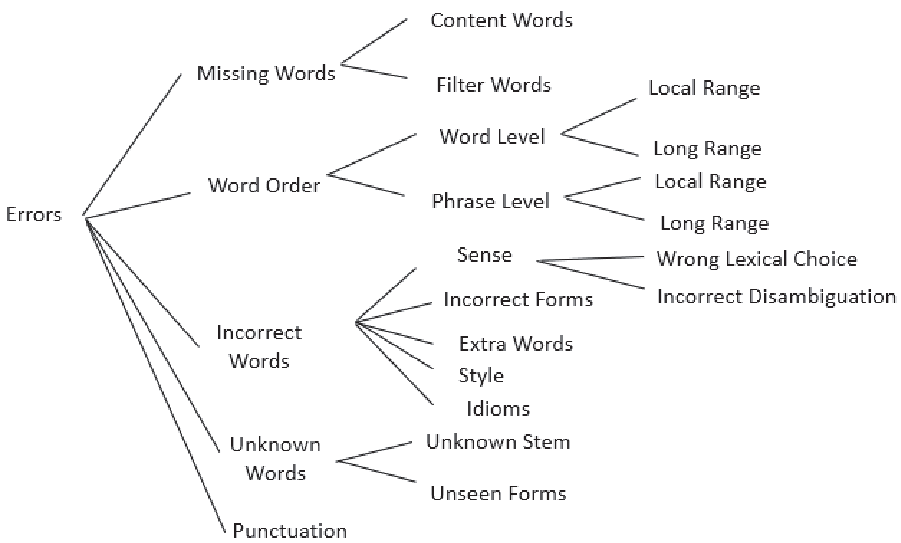

Figure 2. Classification of translation errors
(Vilar, Xu, D'Haro & Ney, 2006, p. 699)

which has five subcategories. Incorrect words alter or disrupt the meaning of the sentence. In the meaning or sense in a sentence, the MT system chooses the wrong translation or disambiguate the correct meaning of a word. Incorrect disambiguation means that the system misunderstands the source word and choose a clearly discrete wrong meaning. Next, the incorrect form subcategory is the errors caused by an incorrect form of a word. This is important for inflectional languages which lead to a hard problem for MTs. The next subcategory, extra words, is often found in the translation of spoken language input. The remaining two subcategories are less important. Style errors are not totally incorrect but choose a bad word, and the meaning of the sentence is unchanged. An example of this is the repetitive word use in a close context. An idiom error subcategory happens when MT systems do not know the idiomatic expression, which leads to errors in the translation. The 'unknown words' category concerns unknown proper names such as location or person and unseen forms of known stems. Lastly, 'punctuation' errors cause minor problems in MT, and this study does not include this error category. Bojar (2011) is in line with Vilar, et al.'s (2006) proposal except for the "unknown words" category.

This present study also draws on a similar study to the taxonomy proposed by Vilar, et al. (2006) for error classification in MT, but eliminates the "punctuation" category because punctuation is vital only when it is interfere with the logical structure of sentences. As mentioned above, many taxonomies are impacted by the idiosyncrasies of the languages with which they are dealing.

2.2. Google, Papago, and Kakao i

Vanjani (2020) mentions that Google Translate was most accurate as compared to the other seven automatic language translators with the source language and target language being similar languages.

Lyons (2016) evaluates the output of five MT systems such as Google Translate, Baidu, Naver MT (Line), a communications app, the Microsoft Translator (Bing) and freetranslation.com (Free) and demonstrates the result of error classification. The 'incorrect lexical choice' category took up over half the errors (54.8%), whereas the 'missing words' category accounted for only 5.3% of the errors (See Table 2).

Table 2. Error classification results

Error Category	Baidu	Free	Google	Bing	Line	Total	Total(%)
Inflectional errors	58	61	56	64	42	281	5.8
Incorrect word order	168	197	174	192	183	914	19.0
Missing words	62	22	62	59	51	256	5.3
Extra words	96	252	80	132	163	723	15.0
Incorrect lexical choice	488	571	467	534	579	2640	54.8

(Lyon, 2016, p. 267)

Bojar (2011) performed a manual evaluation of four systems to translate from English to Czech: Google, PC Translator12, TectoMT13 and CU-Bojar, CU-Bojar, and PC Translator needed to fix the morphology most frequently, whereas Google did better in terms of necessary fixes. The most frequent fix concerns morphology. Since Czech is a very rich morphological language, it is hard to choose the correct form of words in translating from English to Czech.

Costa et al. (2015) performed the MT from English to Portuguese and analyzed the errors analysis of the four MTs by two online translation systems (Google Translate and Systran) and two in-house MT systems using Moses (Moses-PSMT and Moses-HSMT). The result shows that Google Translate consistently performs better than the other systems with the only exception for Discourse as shown in Table 3.

Table 3. Errors per category in MT systems

	Google	Systran	PSMT	HSMT	Total
Orthography	34	69	218	233	554
Lexis	380	883	606	700	2569
Grammar	404	629	649	713	2395
Semantics	334	783	486	489	2092
Discourse	186	134	37	36	393

(Costa, et al., 2016, p. 290)

Mohamed (2019) carried out the translation from Arabic to English and analyzed the two MT systems Google Translate and Microsoft Bing. Google Translate outperformed Microsoft Bing in minor errors (71.8%) while Microsoft Bing outperformed in major errors (19.2%) (See Table 4).

Table 4. Number of major and minor errors in the two MT system

Type of Error	Google Translate		Microsoft Bing	
	Major	Minor	Major	Minor
Content-related	25	26	18	23
Grammar-related	7	57	4	66
Incorrect terms	20	28	35	27
Hygiene	-	37	-	141
Style	10	10	8	20
Total	62 (28.2%)	158 (71.8%)	65 (19.2%)	273 (80.8%)

(Mohamed, 2019, p.3)

Leng & Shan (2019) performed MT by Papago and Google Translate and classified the lexical errors in MT into general vocabulary error (substitution and omission error), culture-related vocabulary error (idiomatic lexical error) and spacing words error. The results show that general vocabulary error (substitution and omission error) has the highest error rate but does not concentrate on comparing the two.

3. Methodology

The corpus data of this research did not use an original English film but a Korean into English translated film, *Minari* (2021). This study is largely divided into three stages. The first stage is to collect the Korean script from the film *Minari* (2021), and the data was translated into English by the three MT systems: Google Translate, Papago, and Kakao i, which are three online platforms with the most frequent evaluation rates in Korea.

The next stage is that the output of MT is assessed through manual evaluation by a human translator. To have more corpus for reasonable findings, the data from the film scripts were evaluated by a Korean-American translator who is fluent in both Korean and English. Even though the manual evaluation has the weakness of objectively assessing the results of MT and is a time-consuming task, it has the strength to assess the output of MT precisely and to point out the error problems, compared to automatic evaluation. A total of 1,346 sentences of subtitle data were evaluated, except for phrases less than two words from the film *Minari* (2021)

The final stage analyzes error classification to identify and categorize the errors in the output of MT systems. Some words have more than one error and the cases were counted in the total number of errors. To categorize and quantify the number of errors, the present study adopted Vilar, et al.'s (2006) error taxonomy and examined frequencies contained in the MT output.

Lastly, the individual output of the MT systems are compared and analyzed, focusing on the advantages and disadvantages of the translation of individual MT systems and some suggestions are presented for Korean EFL learners to utilize the MT systems more effectively and efficiently based on the results of this study.

4. Result and Discussion

4.1. The Evaluation of the Machine Translation Output

The findings in error classification are used to identify and categorize the errors in the output of MT systems. This present study adopted Vilar, et al.'s (2006) error taxonomy, but this classification is simplifier than that of Figure 2 in parts of sub-classification. Punctuation among the major parts is excluded. Popović and Burchardt (2011) state that the selection between wrong lexical choice and missing or extra words is especially difficult, but this is not the case in this assessment. There is confusion between 'missing words' and 'incorrect disambiguation' in this study. However, 'incorrect disambiguation' with the most frequent errors is divided into three subcategories: subject, object, and others as shown in Table 5.

Table 5. Error analysis of MT output

				Google Translate	Papago	Kakao i
Missing Words				31	12	33
Word Order				2	0	0
Incorrect Words	Sense	Wrong Lexical Choice		52	32	63
		Incorrect Disambiguation	Subject	99	48	81
			Object	5	7	7
			Others	19	16	17
	Incorrect Form			9	4	9
	Extra Words			1	0	0
Unknown Words				7	7	7
Total Error Rate				225 (40%)	126 (22%)	217 (38%)

Among the three MTs, Google Translate has the highest error rate at 40%, and the next one is Kakako i. Papago has the least error rates, and it shows the rate agrees with the Papago use frequency (80%) of ELF learners' respondents on the questionnaires. It implies that the Korean EFL learners would already recognize it.

The most frequent errors were found in the 'incorrect words': 'subject' part of the 'incorrect disambiguation' (M =76, SD = 21.12) in 'sense' and 'wrong lexical choice' (M =49, SD = 12.83) in 'sense'. The reason the 'subject' part has the highest frequent errors is because the Korean language usually does not identify 1st person and 2nd person subjects in a sentence, especially in an informal way. Lee and Kim (2018) mention that subject omission often occurs in Korean which is a high-context language, and it is considered as an obstacle to translate from Korean to English which subject always should be in place. As a result, the result of the MT is more likely to make differences depending on the existence of a subject. The error frequency in the subject part of the incorrect disambiguation in 'sense' is the highest in Google Translate, and next are Kakao i and Papago.

The 'wrong lexical choice' subcategory of 'sense' has the second frequent errors. In this part, Kakao i has the most frequent errors rather than Google Translate. Lee and Kim (2018) mention that Google Translate tends to use relatively specialized and higher difficulty level words. This study shows this tendency, but it did not reach the quality of Papago's translation.

4.2. A Closer Error Examination

In this section, some items with higher error rates are analyzed through a closer examination: incorrect disambiguation (subject), wrong lexical choice, and missing words. Some detail points are described in the following.

4.2.1. Incorrect Disambiguation (Subject)

4.2.1.1. Subject Omission

There are many cases where subjects in Korean are omitted in a sentence, whereas, subjects in English should be specified in most sentences. That is why the most frequent errors were found in this aspect. Korean '아무 집도 안 보이는데' should be *I don't see any houses*, but Google Translate (GT) and Kakao i (Ki) are translated as *Can't you see any houses* which has a different meaning. As another example, 캘리포니아에서 돈 좀 많이 벌었겠는데' is wrongly translated as *I must've made a lot of money in California* in GT and *I must've made a lot of money in California* in Ki, but PA translated it correctly as *You must have made a lot of money in California*. In terms of subject omission, GT had the most frequent error rates, whereas, PA had the least frequent errors. The other data is in the following Table 6.

Table 6. Subject omission in MT

Korean	Original English Subtitle	Google Translate(GT)	C* or I	Papago (PA)	C or I	Kakao i (Ki)	C or I
수컷은 파란박스에 암컷은 하얀박스에 넣으면 됩니다.	We put the males in the blue bin and the females in the white bin.	Males are placed in blue boxes and females are placed in white boxes.	C	The male can put the female in the white box in the blue box.	I	Males are placed in blue boxes and females are placed in white boxes.	C
누나한테 가 있어	Go to your sister.	I'm going to my sister	I	Go to your sister.	C	I'm going to my sister	I
숫놈은 맛이 없어	Male chicks don't taste good.	males have no taste	I	He doesn't taste good.	C	males have no taste	I
누가 누구더라 미쳤대?	Who's calling who crazy?	Who was that crazy?	I	Who was it? Crazy?	W	Who was that crazy?	I

Korean	Original English Subtitle	Google Translate(GT)	C* or I	Papago (PA)	C or I	Kakao i (Ki)	C or I
벌써 처녀가 다됐네	Already such a lady!	I'm already a virgin	I	You're already a virgin.	C	You're almost a virgin!	C
데이빗. 할머니한테 인사해야지	David, say hello to Grandma.	David. I have to say hi to my grandma	I	David, say hello to your grandmother.	C	David, I'm gonna say hi to Grandma	I
내가 그렇게 보고 싶었니?	You missed me that much?	Did I miss you like that?	I	Did you miss me that much?	C	Did you miss me that much?	C
먼길 오느라 고생했네	Must've been hard for you to travel so far.	I struggled to come a long way.	I	You've had a hard time coming this far.	C	I've been through a long way	I
그걸로 점수 못 따	You won't get points that way.	I can't score it	I	You can't score that.	C	That won't score	C
일하러 간다	I'm going to work.	go to work.	I	I'm going to work.	C	I'm going to work.	C

* 'C' means 'Correct' and 'I' means 'Incorrect'.

4.2.1.2. Third Person Subject Representation of First Person Subject

The Korean language often uses the third person subject instead of the first person. However, English uses 3rd person verbs according to the subject when the 3rd person subject is used. Consequently, the cases translating from Korean into English lead to meaning changes. Daddy(아빠) is the subject in a Korean sentence, 'daddy (아빠) 나갔다 온다', and 아빠 is the speaker and should be the subject 'I' in the sentence. However, MT translated 'daddy' or 'dad' as the subject of the sentence and resulted in an incorrect translation of the meaning as shown in Table 7 below.

Table 7. Third person subject representation of first person subject in MT

Korean	Original English Subtitle	Google Translate (GT)	C or I	Papago (PA)	C or I	Kakao i (Ki)	C or I
아빠 나갔다 온다.	I'll be outside.	daddy goes out	I	Dad's out. I'm coming back.	I	daddy goes out	I
싫어요. 아빠 코 골잖아요	No, Dad! You snore!	I do not like it. Daddy are you snoring?	I	No, you snore.	C	I do not like it. Daddy are you snoring?	I
엄마가 기도해봐	You pray, Mommy.	pray for mama	I	Mom, pray for me.	C	Mommy prays	I

Korean	Original English Subtitle	Google Translate (GT)	C or I	Papago (PA)	C or I	Kakao i (Ki)	C or I
엄마가 가서 하늘나라 보고 와요	You go and see Heaven.	Mom goes and sees heaven	I	Mom, go see the sky.	C	Mommy goes and see the sky	I
엄마가 이기적이라 이렇게 된 거야	This happened because I was selfish.	It happened because my mother was selfish	I	She's selfish. That's what happened.	I	This is how you got to be selfish	I

4.2.1.3. Indefinite Question

Some wh-words in Korean are considered pure indefinite pronouns void of any inherent interrogative. As seen in Table 8 below, '왜' in '왜 미련하게 덩치만 큰 애 있잖아' in Korean has the 'why' meaning in English, but in this case, 'why (왜)' is a pure indefinite pronoun. However, GT and Ki did not recognize the fact and translated it as a question word which led to the wrong translation. Not so for PA.

Table 8. Question word subject in MT

Korean	Original English Subtitle	Google Translate (GT)	C or I	Papago (PA)	C or I	Kakao i (Ki)	C or I
왜 미련하게 덩치만 큰 애 있잖아	That big, dumb kid.	Why do you have a foolishly big boy?	I	You know, there's a kid who's stupidly big.	C	Why is he so big?	I
우리가 어떻게 될지 불 보듯 뻔한데 당신만 바라보면서 버티기엔	I know this won't end well and I can't bear it.	It's so obvious what we'll be like, but I can't stand looking at you.	I	It's obvious what's going to happen to us, but I can't stand it looking at you.	I	It's obvious what we're going to do, but I can't stand to look at you	I

4.2.2. Wrong Lexical Choice

4.2.2.1. Homonym

Homonyms in Korean bring out the translation errors in MT. In Korean, '밤' can mean 'chestnut' or 'night', and 'It's a chestnut' is incorrectly translated as 'It's night' or 'It's night time'. Besides, '일어나다' is also a Korean homonym meaning 'stand' or 'wake up', and 'Would you wake up if you're new today?' should be 'Would you stand up if you're new today?' as shown in Table 9.

Table 9. Homonyms in MT

Korean	Original English Subtitle	Google Translate (GT)	C or I	Papago (PA)	C or I	Kakao i (Ki)	C or I
머리를 썼지	We used our minds!	did my hair	I	I used my brain.	C	I used my hair	I
밤이다	It's a chestnut!	it's night	I	It's night time	I	It's night	I
좋은거 다 들었어	Anything good for you.	I heard all the good things	I	I've heard everything good.	I	I heard all the good stuff	I
쌌지?	Sucks for you!	cheap?	I	Did you wrap it?	I	You packed it, right?	I
오늘 처음 오신분들 계시면 일어나 주시겠어요?	If you're here with us for the first time, please stand.	If you are here for the first time today, could you please stand up?	C	Can you stand up if you're new here today?	C	Would you wake up if you're new today?	I
태워줘요?	Do you need a ride?	burn me?	I	You want a ride?	C	You want a ride?	C
여기 기름을 좀 바르고	I'm gonna put some oil in here.	put some oil on it	C	I'll put some oil on it.	C	I'm gonna put some gas on this	I
고추를 영어로 뭐라고 그러니?	What is his thing called in English?.	How do you say chilli in English?	C	How do you say chili in English?	C	What do you say in English?	I

4.2.2.2. The Confusion of Similar Meaning or Pronunciation

In Korean, '천당' and '천장' have similar pronunciations, and MT mistranslated them using ' heaven' and 'ceiling' as 'You don't have to go see Heaven' and 'You don't have to look at the ceiling'. Also, '탄내' and '탄피' having similar pronunciations were mistranslated as 'Looks like a bullet', which should be 'It smells like smoke'.

Table 10. The confusion of similar meaning or pronunciation in MT

Korean	Original English Subtitle	Google Translate (GT)	C or I	Papago (PA)	C or I	Kakao i (Ki)	C or I
천당같은거 안봐도 돼	You don't have to go see Heaven.	I can't see anything like heaven	I	You don't have to look at the ceiling.	I	You don't have to watch the heavenly party	I

Korean	Original English Subtitle	Google Translate (GT)	C or I	Papago (PA)	C or I	Kakao i (Ki)	C or I
홀가분 할 거예요	It feels like, lighter.	I'm going to go crazy	I	You'll be relieved.	C	I'm gonna be a little bit	I
탄내 같은데	It smells like smoke.	It smells like burnt	C	It smells burnt.	C	Looks like a bullet	I
생시가 아냐	This isn't real.	not live	I	It's not real.	C	It's not a birth poem	I
잘 생긴 거지	I'm good-looking!	handsome beggar	I	He's handsome.	C	He's a handsome man	I
그렇게 무거운 걸 혼자 들었어?	And you put it back, all by yourself?	Have you ever heard something so heavy by yourself?	I	Did you carry that heavy thing all by yourself?	C	Did you hear that heavy?	I
저 물은 어디서 저렇게 길어왔어?	where did you get all that water?	where did that water come from?	C	But where did that water come from?	C	Where did that water get so long?	I
용도 들어가고 다 들어갔어	It has everything, even deer antlers.	It went into use and everything went in.	I	It's a dragon. It's all in.	I	I'm in the system and I'm in the system	I

4.2.2.3. English Use in Korean

In Korean, English is often mixed with Korean and MT seems confused. Penis, '페니스' in Korean, is confused and mistranslated as 'Fennis Fault' in PA. 'Peepee, '피피' in Korean, is mistranslated as 'bleeding' which is '피'in Korean.

Table 11. English use in Korean in MT

Korean	Original English Subtitle	Google Translate (GT)	C or I	Papago (PA)	C or I	Kakao i (Ki)	C or I
페니스 고장	Penis-uh broken.	penis failure	C	Fennis Fault.	I	penis failure	C
할머니, 왜 침대 에서피피 쌌어요?	Grandma, why did you wet the bed?	Grandma, why were you bleeding in bed?	I	Grandma, why did you pee in bed?	C	Grandma, why are you bleeding in bed?	I
절대 노라고 못해요	They won't say no.	I can never sing	I	I can't say no.	C	I can't say no!	C

4.2.3. Missing Words

There are often the cases where one or more words are missing in MT resulting in a different meaning. 'Because of the dirt color?' is mistranslated into 'Because of the dirt?' which gives rise to a different meaning (See Table 12).

Table 12. Missing words in MT

Korean	Original English Subtitle	Google Translate (GT)	C or I	Papago (PA)	C or I	Kakao i (Ki)	C or I
흙 색깔 때문에?	Because of the dirt color?	Because of the color of the soil?	C	Because of the color of the soil?.	C	Because of the dirt?	I
아무튼 계속 체크해 보자	But we'll keep checking.	Anyway, let's check	I	Anyway, let's keep checking	C	Anyway, let's check	I
뼈 빠지게 일했어	Working myself to the bone!	worked hard	I	I've worked my ass off.	C	worked hard	I
우리엄마 돈 많이 썼겠네	You must've spent a lot.	My mother must have spent a lot of money	C	My mom must have spent a lot of money.	C	My mom spent a lot of money	I

4.2.4. Unknown Words

The word '회초리' in Korean is not used in English, and it is difficult to translate even by human translators because of the cultural difference. It is translated as 'stick' and 'cane', but Ki mistranslated as 'fly'. Also, the word is used informally as aslang, and that causes mistranslation, as shown in Table 13.

Table 13. Unknown words in MT

Korean	Original English Subtitle	Google Translate (GT)	C or I	Papago (PA)	C or I	Kakao i (Ki)	C or I
가서 회초리 갖고 와	Go get the stick.	go and get a stick	C	Go get the cane.	C	Go get the fly	I
빽났다	Now they're mine!	got tired	I	It's stiff.	I	be agitated	I

5. Conclusion

The main concern in this study is to classify a taxonomy that covers all idiosyncrasies of Korean and analyze the problem of translation errors in MT translation based on the corpus of the film. This study adopted Vilar, et al.'s (2006) error taxonomy but it is more simplified to fit into the Korean language. The highest frequent errors in three MTs were found in 'incorrect words': 'incorrect disambiguation (subject)' and 'wrong lexical choice' in 'sense'. The reason 'subject' has the most frequent errors is that the Korean language, in many cases, does not express the 1st person and 2nd person subjects in a sentence, especially in an informal way.

A closer error examination categorized the common errors of MT from Korean into English. 'Incorrect disambiguation (subject)' is subcategorized into 'subject omission', 'third person subject representation of first person subject', and 'indefinite question'. In addition, 'wrong lexical choice' is subcategorized into 'homonym', 'the confusion of similar meaning or pronunciation', and 'English use in Korean'.

Costa, Correia & Coheur (2016) mention, "The motivation to build a corpus annotated with errors and translation quality was to help determine future research directions in the MT area, allowing, for instance, to highlight" (p.288). This present research that carried out a MT error analysis study can help what types of errors have an effect on translation quality for the MT developers. Some suggestions are provided based on these findings for both MT developers and Korean EFL learners.

Firstly, GT does not offer appropriate punctuation and capitalization even though they could result in meaning confusion and difference. However, PA provides appropriate punctuation and capitalization regardless of their existence of the origin text, whereas, Ki provides them depending on their existence of the source text. Providing proper punctuation and capitalization in GT and Ki is suggested to their developers.

Next, the Korean language has many cases where subjects are omitted in a sentence, whereas, subjects in English should usually be specified in a sentence. It is suggested that Korean EFL learners using MT should include a proper subject when translating from Korean to English through MT even though a subject is not needed in the Korean sentence. For example, Korean '그랬니?' does not specify a subject, and it could be translated 'Did you?/ Did I?/ Did he?' if the context is not offered. Therefore, users knowing the specific subject in Korean should add it to translate from Korean into English.

According to Lyons (2016), "the general goal of translation is a well-formed (fluent) translation expressing the same meaning (adequacy) as the source text" (p. 261). Mistranslated sentences by MT can prevent understanding the content, and it would give rise to misunderstanding. This study found some deficiencies of MT due to the infinite variety between natural languages and could shed light on the quality of the current MT systems based on the error analysis of this data and give insight to provide a more developed MT system to EFL learners.

For further research, it is hoped that the solutions to making errors in relation to present perfect tense not existing in Korean are found. Also, it is suggested that future study would focus on classifying the major error problems in each MT (GT, PA, and Ki), and then it is expected to be able to make a contribution to improving the quality of each MT.

References

Ali, A. (2016). Exploring the problems of machine translation from Arabic into English language faced by Saudi University student of translation at The Faculty of Arts, Jazan University, Saudi Arabia. *IOSR Journal of Humanities and Social Science, 21*(4), 55-66. doi: 10.9790/0837-2104025566

Bojar, O. (2011). Analyzing error types in English-Czech machine translation. *The Prague Bulletin of Mathematical Linguistics, 95*(1). 63–76. doi: 10.2478/v10108-011-0005-2

Condon, S., Parvaz, D., Aberdeen, J., Doran, C., Freeman, A., & Awad, M. (2010). Evaluation of machine translation errors in English and IRAQI ARABIC. *LREC, European Language Resources Association*. doi: 10.21236/ada576234

Costa, Â., Correia, R., & Coheur, L. (2016). Building a corpus of errors and quality in machine translation: Experiments on error impact. *Proceedings of the Tenth International Conference on Language Resources and Evaluation* (pp. 288-292). European Language Resources Association (ELRA). http://www.lrec-conf.org/proceedings/lrec2016/pdf/283_Paper.pdf

Costa, Â., Ling, W., Luís, T., Correia, R., & Coheur, L. (2015). A linguistically motivated taxonomy for machine translation error analysis. *Machine Translation, 29*(2), 127-161. doi: 10.1007/s10590-015-9169-0

Dulay, H., Burt, M., & Krashen, S. (1983). *Language two.* New York, NY: Oxford

University Press.

Emmaanuelle, E.-R., Francic, B.-M., & Eady, S. (2019). SCCOLE: A collaborative platform of error annotation for aligned corpora. 27-35

Han, C.-H., & Palmer, M. (2005). A morphological tagger for Korean: Statistical tagging combined with corpus-based morphological rule application. *Machine Translation, 18*(4) 275-297. https://www.jstor.org/stable/20060455

Lee, I.-C. (Director). (2020). *Minari* [Movie]. United States: Plan B Entertainment

Lee, S., & Kim, S. (2018). Pre-editing rules to enhance output quality of machine TRANSLATION: English-Korean and Korean-English. *The Journal of Translation Studies, 19*(5), 121-154. doi: 10.15749/jts.2018.19.5.005

Leng, L., & Shan, G. (2019). Analysis and research on lexical errors in machine translation in Chinese and Korean translation. Retrieved from https://francis-press.com/index.php/papers/1019

Llitjós, A., Carbonell, J., & Lavie, A. (2005). A framework for interactive and automatic refinement of transfer-based machine translation. In *Proceedings of the 10th Annual Conf. of the European Association for Machine Translation* (EAMT), Budapest, Hungary.

Lyons, S. (2016). Quality of Thai to English machine translation. Retrieved September 16, 2021, from https://link.springer.com/chapter/10.1007/978-3-319-42706-5_20

Mohamed, A. (2019). Neural and statistical machine translation: A comparative error analysis. *17th International Conference on Translation* https://www.researchgate.net/publication/335608441_Neural_and_Statistical_Machine_Translation_A_comparative_error_analysis

Mohamed, Z. H., & Shafeen N. M. (2017). A brief study of challenges in machine translation. *International Journal of Computer Science Issues, 14*(2), 54-57. https://doi.org/10.20943/01201702.5457

Popović, M., & Burchardt, A. (2011). From human to automatic error classification for machine. Retrieved September 20, 2021, from https://www.researchgate.net/publication/270878261_From_human_to_automatic_error_classification_for_machine_translation_output

Popović, M. & Ney, H. (2007). Word error rates: Decomposition over POS Classes and applications for Error Analysis. In *Proceedings of the Second Workshop on Statistical Machine Translation (pp. 48-55).* Association for Computational Linguistics.

Richard, J. (1974). *Errors analysis: Perspectives on second language acquisition.* London, UK: Longman

Stankevičiūtė, G., Kasperaviciene, R., Horbacauskiene, J. (2017). Issues in machine translation. *International Journal on Language, Literature and Culture in Education, 4*(1), 75-88. https://www.semanticscholar.org/paper/Issues-in-Machine-Translation-Stankevi%C4%8Di%C5%ABt%C4%97-Kasperaviciene/8c8489bb5e1514931f7284b9b89c0236b877a6b7

Vanjani, M. (2020). A comparison of free online machine language translators. *Journal of Management Science and Business Intelligence*, *5*(1), 26-31.

Vilar, D., Xu, J., d'Haro, L. F., & Ney, H. (2006). Error analysis of statistical machine translation output. *Proceedings of the 5th international Conference on Language Resources and Evaluation (LREC)*, 697-702.

Sungran Koh
Instructor
Kookmin University
77 Jeongneung-ro, Seongbuk-gu, Seoul 02707, Korea
Email: sungran@kookmin.ac.kr

Received on November 12, 2021
Revised version received on February 10, 2022
Accepted on March 31, 2022