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Investigation of Two Types of Machines Translations Google and Targman in Five Scientific Disciplines based on BLEU Model

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Abstract— In recent years, automatic translation as one of the sub-branches of natural language processing science in our country has been considered by many researchers, including the automatic translators of Targman, Faraazin, etc. In order to localize this technology, these automatic translators need to be evaluated and studied accurately and dynamically. However, large companies such as Google have also worked in this field in order to translate other languages into Persian and vice versa, but due to reasons such as inappropriate figures, calligraphy problems and other problems of Persian language in providing a good and even average translation in Persian language, Google cannot be a good machine translation for Persian language. The purpose of this study is to evaluate different translation machines including Google Translate and Targoman. For this purpose, two sentences in English and Persian in five scientific branches of linguistics, computer, psychology, genetic engineering and chemistry have been randomly selected from the scientific books of these branches. The evaluation criterion in this paper is the BLEU test, which was introduced as a standard method by IBM in 2001. After performing BLEU test on the scores obtained by each translation machine, Google Translate and Targman were ranked first to second .As the results show in a completely statistical and general way, the scores obtained by these machine translators are not satisfactory and the development of these translation machines to reach the desired level requires the efforts of researchers in this field. In addition, the goal of the current research is to examine the methods of improving machine translation using two-level sorting, linguistic features, machine translation evaluation system, semantic ambiguity, semantic similarity, structural reconstruction, as well as computerized linguistics and machine translation software. Due to the widespread increase in regional and international communications and the need for information exchange, the demand for translation has increased in recent years. They also have common and repetitive words, in which case machine translation can be used as an alternative to human translation. There are several ways to improve machine translation which this proposal deals with it.

Keywords — *MT; NLP; BLEU; Google Translate; Targoman; IBM.*

1. Introduction

Evaluation of machines translation is one of the most vital areas of research in natural language processing. Evaluation of factors such as efficiency, accuracy and other factors in translation is very important. Since the advent of these machines, human beings have always sought to evaluate this species. They have been intelligent systems because improving the quality and accuracy of such systems will not be possible except with careful evaluation. Due to rapid technological advances, such systems must also be evaluated quite dynamically. Many methods have been proposed for accurate evaluation of translation machines that will be discussed in this study. In a general category, machine translation evaluation methods and techniques can be divided into three important categories as follow:

Fig.1: Machine translation evaluation methods

Traditionally, there have been two methods for evaluating the translation machine. The first method is called Glass Box, in which the criterion for checking the translation machine is the specifications of the translation machine itself. In contrast, the Black Box method examines the translation (output) by the translation machine, and in this example the internal specifications of the translation machine are not important.

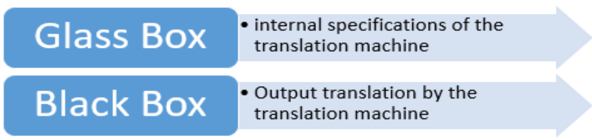

Fig.2: Evaluating the machine translation methods

Over time, the inefficiency of human translation as well as the introduction of computers into human life, traditional and humane methods of translation also led to machine translation. The process of evaluating the translation machine has been of interest to researchers for many years, and the first model of these evaluations was performed in 1966 (Jurafsky, 2009). This example has been one of the human examples that has evaluated the criterion of semantic closeness (Hutchins, 2001). The other two

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most commonly done by humans which are adequacy and fluency. In the first method, the evaluation criterion is whether the important information in the translated sentence can be clearly identified (Stahlberg, 2020). In addition, in the second method, the criterion is using for evaluating the proximity of the language of the translation machine to the natural human language. These two criteria are examined separately on each sentence. (White, 1994).

In the mid-1990s, researchers concluded that human-made evaluations were unreliable for many reasons (King, 1996). Human methods are quite costly and take weeks or even months to complete (Hovy, 1999). In another research, the reason for the development of automated methods for evaluating translation machines is the high cost in the execution process and the unreliability of the results and the low speed in the execution. (Och, 2003). Reasons such as cost-effectiveness, unreliable conclusions, time-consuming, and other reasons have led researchers to develop automated methods and gradually abandon human methods (Homon, 2007).

2. Literature Review

Many writers have written about Machine Translation. Most of the time, however, they have examined the different method for machine translation. Including these articles and books, I can mention Computational Linguistics by Lenhart Schubert (2020), A Novel Reordering Model for Statistical Machine Translation by Saeed Farzi,Heshaam Faili,Shahram Khadivi,Jalal Maleki (2013), Statistical phrase based translation (2003) by PhilippP. Koehn, Franz Josef F.J. Och, and Daniel D. Marcu, Milestones in machine translation by John Hutchins (2013), Machine aided translation with a post-editor by Andrew Donald Booth (2017), SPEECH Speech and LANGUAGE language PROCESSING Processing by Daniel Jurafsky and James H. Martin (2019), Joint Word Alignment and Bilingual Named Entity Recognition Using Dual Decompositionby Mengqiu Wang, Wanxiang Che, and Christopher D. Manning (2013), An overview of research software Related to Computational Linguistics and Library and& Information Sciencesby Falahati Qadimi Fumani (2008), , by PalmiraP. Marrafa and AlejandroA.

Ribeiro (2001), Quantitative Evaluation of Machine Translation Systems: Sentence Level, by P. Marrafa and A. Ribeiro (2003). What is important in any research is the methodology and research foundations. In the humanities field, the results of the research are usually not the same in the same subject, and two researchers may work on a topic and achieve different results. At the same time, the result of both is valuable. The present study was conducted using a descriptive method that gathered by library methodology, which was compiled by studying machine translation, related issues, articles and books which have mentioned in the reference. In a general division, machine translation methods, features, software's have been examined. The purpose of this study is to investigate the methods of improving machine translation using different methods and analyses the function of MT in different platforms such as Google. These methods include two-level sorting, language features, machine translation evaluation system, semantic ambiguity, semantic similarity, structural reconstruction, as well as computer linguistics and machine translation software. The results of this study show that the current machine translation system is based on language rules, sample texts and statistical methods.

3. Methods

The corpus of this review comprised of two principal Machine Translation which is known as Google and Targoman. The information is two Translation of Persian to English and English to Persian from five logical disciplines such as: semantics, software engineering, brain research, hereditary designing, and science. This examination was done as per distinctive machine translations including Google Decipher and Targoman. For this reason, two sentences in English and Persian in five logical parts of semantics, PC, brain science, hereditary designing, and science have been haphazardly chosen from the logical books of these branches. The assessment model in this exploration is the BLEU test. Subsequent to playing out the BLEU test on the scores got by every machine translation, Google Decipher and Targman were positioned first to second. As the outcomes show in a totally measurable and general manner, the scores got by these machine translations are not good and the improvement of these machine translation to arrive at the ideal level requires the endeavors of scientists in this field.

4. Results and Discussion

4.1 Automatic Methods in Machine Translation Assessment

Automatic translation machine evaluation methods are called WER, BLEU, NIST, METEOR, TER, individually, which will be clarified in the following section.

Fig.3: Automatic translation machine evaluation methods

According to Levenshtein, one of the first automated methods developed to evaluate machine translation machines is the word error rate (WER). This standard technique is additionally used to assess discourse acknowledgment frameworks. Levenshtein presented a model called Levenshtein distance. This distance means the difference between the words in the sentence translated

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by man (Reference Translation) and the sentence translated by machine (Machine Translation). However, adjusting the RT and MT sentences which each word should have the equivalent in the RT sentence. Assuming this is the case, the value of one is assigned to the corresponding words and zero is assigned to words that do not correspond. Three operations are performed in this model, each of which is explained separately in the below figure (Levenshtein, 1966).

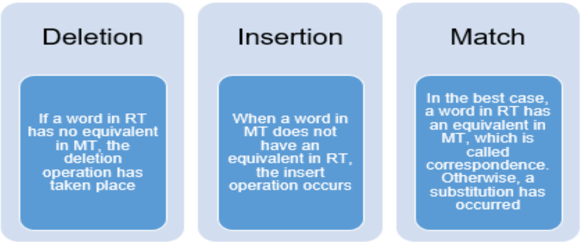

Fig.4: Three operations on the WER model

The formula for calculating WER is as follows:

$$WER= i+D+S$$

This method was presented by Papenieni at IBM in USA. BLEU is considered as a standard method for evaluating translation machines. One of the key features of this model is the use of several reference sentences (sentences translated by human RT). The output value of this test is determined by counting N-Grams or a sequence of words that occur in RT. The BLEU method emphasizes the accuracy of the translation machine (Papenieni, 2002). The problems of the BLEU method have always been criticized by many activists and researchers in this field. One of the disadvantages of BLEU is that this method is not suitable for short sentences and does not provide a reliable output. If there are words with the same meaning in a sentence, BLEU is unable to recognize these words. However, in this method, if the length of the output sentence of the translation machine is shorter than the length of the reference sentence, a value of Brevity Penalty is applied in the formula which is one of the weaknesses of this evaluation method. With all these shortcomings, it is the only standard method for evaluating a MT. However, this method was proposed by Banerjee to correct the defects of the BLEU model. This method is highly dependent on retrieval while BLEU is an accuracy-based model. Unlike the BLEU model, which only examines accuracy in translation, this method examines both accuracy and retrieval and combines the two variables (Banerjee, 2005). In this method, alignment takes place in different layers, which is described in the figure below.

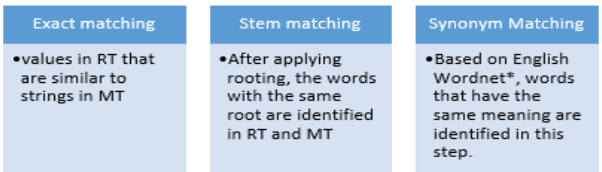

Fig.5: METEOR layers

In each of these stages, words that were not aligned in the previous steps are allowed to be aligned. In alignment operations, only Uni-grams are aligned. The ratio of the number of words equal to the number of words in the output indicates the accuracy of this method. Retrieval is calculated by dividing the aligned words by the number of words in the human-translated sentence. This method, like the BLEU method, uses the Fragmentation Penalty value. This formula is used because the machine translated sentence may be a shorter reference sentence called chunks. Other automated methods include Turian et al., 2003.

4.2. Comparison of Translation of Scientific Disciplines in three Translation Machines

4.2.1. Linguistic Sentences

In this section, two linguistic sentences from the book entitled "An Introduction to the Sociology of Language" are examined.

Table 1. Linguistic sentences

Original Persian sentence	Google	Targoman	Human Translation
ریشه‌شناسی، دانشی است که به کمک آن، تاریخ یک واژه از دید تلفظ و معنی ثبت می‌شود	Etymology is the science by which the history of a word is recorded in terms of pronunciation and meaning.	ریشه‌شناسیis the knowledge in which the history of a word is recorded in terms of pronunciation and meaning	Etymology is the science by which the historical backdrop of a word is recorded as far as articulation and importance
In linguistics and grammar, a sentence is a linguistic expression, such as the English example "The quick brown fox jumps over the lazy dog."	در زبان شناسی و دستور زبان، جمله یک عبارت زبانی است، مانند مثال انگلیسی "روباه قهوه ای سریع از روی سگ تنبل می پرد".	در زبان‌شناسی و دستور زبان، یک جمله یک عبارت زبانی است، مانند مثال انگلیسی "روباه قهوه‌ای سریع بر روی سگ تنبل می‌پرد."	جمله یک عبارت زبانی در زبانشناسی و دستور زبان محسوب میشود که به عنوان مثال میتوان اثر""روباه قهوه ای سریع از روی سگ تنبل می پرد" را در زبانشناسی انگلیسی نام برد

As noted above, with the exception of Google Translate, Targoman can no longer translate perfectly fluently and they cannot even translate all words in English.

4.2.2. Computer Sentences

In this section, two computer sentences from the paper entitled “Integrity and Confidentiality in Cloud Outsourced Data “are examined.

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Table 2. Computer sentences

Original Persian sentence	Google	Targoman	Human Translation
رشد روزافزون حجم داده ها و نداشتن امکانات کافی محاسباتی و ذخیره سازی، سازمان ها را با چالش های مدیریتی متنوعی رو به رو کرده است	Increasing data volume and lack of sufficient computing and storage facilities have faced organizations with a variety of management challenges.	The growing growth of data volumes and the lack of adequate computational resources and storage have faced a variety of managerial challenges	Expanding information volume and absence of adequate processing and storage spaces have confronted associations with an assortment of the board difficulties
A computer is used for various purposes. It is used for making Software, documents, invoices, list s, etc.	کامپیوتر برای اهداف مختلف استفاده می شود. برای تهیه نرم افزار، اسناد، فاکتورها، لیست ها و غیره استفاده می شود.	یک کامپیوتر برای اهداف مختلف استفاده می‌شود. از آن برای ساخت نرم‌افزار، اسناد، فاکتورها، فهرست‌ها، و غیره استفاده می‌شود.	کاپیوتر برای اهداف مختلفی استفاده میشود، مانند: ساختن نرم افزار، اسناد، فاکتورها، لیست ها و...

It is indisputable fact that both machine translations are not capable of fluent translation. In addition, the Targoman translation machine is not even able to recognize prepositions that should not be translated into Persian.

4.2.3. Psychology Sentences

In this section, two psychological sentences from the paper entitled “How not to be perfectionist “are examined.

Table 3. Psychology sentences

Original Persian sentence	Google	Targoman	Human Translation
هدف از کسب این مهارت ها، رسیدن به سلامت جسمی و روانی و در نهایت موفقیت های فردی و اجتماعی است یادگیری این مهارت ها انقدر برای موفقیت ضروری است که 60 % عملکرد در همه شغل ها را شامل می شود	The goal of acquiring these skills is to achieve physical and mental health and ultimately individual and social success. Learning these skills is so essential to success that it accounts for 60% of performance in all jobs	The purpose of acquiring these skills is to achieve physical and mental health and ultimately individual and social success; learning these skills is so essential to success that 60 % of the performance is included in all jobs.	The goal of acquiring these skills is to achieve physical and mental health and ultimately individual and social success. However, Learning these skills is so essential to success that it accounts for 60% of performance in all jobs.
Studying psychology helped the teacher better understand the minds of her students	مطالعه روانشناسی به معلم کمک کرد تا ذهن دانش آموزان خود را بهتر درک کند	تحصیل روانشناسی به معلم کمک کرد تا ذهن دانشجویان خود را بهتر درک کند.	تحصیل در رشته روانشناسی به معلمان توانایی میبخشد تا درک بهتری از شرایط ذهنی دانشجویان داشته باشند

Again, it is clear that both translation machines are not able to recognize and translate fluently, and again, Google offers more accurate translation.

4.2.4. Genetic engineering Sentences

In this section, two Genetic engineering sentences from the paper entitled “ABC of Clinical Genetics are examined.

Table 4. Genetic engineering sentences

Original Persian sentence	Google	Targoman	Human Translation
این نوع سلول ها، سلول های تمایز نیافته ای هستند که هیچ گونه تخصصی ندارند و می توانند به انواع سلول های گوناگون تقسیم شوند	These types of cells are undifferentiated cells that have no specialization and can be divided into different types of cells	These types of cells are germ cells that have no specialized species and can be divided into different types of cells	These sorts of cells are undifferentiated cells that have no specialization which can be isolated into various kinds of cells.
Turning the tide on the brave new world genetic engineering biotechnology is not just about food production	چرخش جزر و مد در دنیای جدید و شجاع بیوتکنولوژی مهندسی ژنتیک فقط مربوط به تولید غذا نیست	تبدیل جزر و مد به تکنولوژی‌های جدید مهندسی ژنتیک در دنیای جدید، تنها مربوط به تولید مواد غذایی نیست.	در دنیای جدید، تبدیل پدیدهٔ کِشَند به تکنولوژی های جدید مهندسی ژنتیک تنها مربوط به تولید فرآورده های غذایی نیس.

Again, it is obvious that the word “Tide” could be better translated, and the placement of sentences in both translation machines is not fluent.

4.2.5. Chemistry Sentences

In this section, two Chemistry sentences from the paper entitled “Organic Chemistry "are examined.

Table 5. Chemistry sentences

Original Persian sentence	Google	Targoman	Human Translation
مروری برمبانی شیمی و تکنولوژی فوم پلی	An overview of the	A review of یورتان	An outline of the

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یورتان	chemistry and technology of polyurethane foam	chemistry and پلی فوم technology	science and innovation of polyurethane froth
The definition of chemistry is a branch of science that deals with the form and properties of matter and substances or the interaction between individuals.	تعریف شیمی شاخه‌ای از علم است که به شکل و ویژگی‌های ماده و مواد یا تعامل بین افراد می‌پردازد.	تعریف شیمی شاخه‌ای از علم است که با فرم و خواص ماده و مواد و یا تعامل بین افراد سر و کار دارد.	شیمی به عنوان شاخه ای از علم تعریف میشود که به شکل، و ویژگی های ماده و مواد یا تعامل بین افراد میپردازد

It is apparent that again translation is not fluent in both translation machines. In addition, it is reasonable to surmise that both of these machine translations do not have the ability to translate accurately.

4.3 Data Analysis

The following tables compare the two translation machines.

Table 6. Paired Samples Test

				Paired Differences
	Mean	Deviation	Error	Interval of the Difference
				Lower
Pair1 Google - Targoman	50 50	.1533912 .103246	.007 .013	.0013772 .0218067

As can be seen in this table, the results were obtained from Asia Testbed Data. In this method we have four variables that the results are obtained for us by the software itself. The first variable is Mean, which changes based on the number of sentences entered. In this study, we entered two sentences from five different disciplines. The next variable is Deviation, which is the amount of deviation from the main meaning of the sentence. The next variable is Error, which indicates the amount of translation error by the two machines. The last variable is Interval of the Difference, which shows the distance between the two translation machines. As you can see, the accuracy of Google Translate is higher than that of Targoman. This initial review is called Lower.

Table 7. Paired Samples Test -2

Paired			Difference	Significance
		P $\frac{D}{S\ 2}$		
				Upper
Pair 1 Google-Targoman			.0575852 .1089933	1.916 3.015 5.281
Google				Targoman

In this table, the intention is to get the score and full accuracy between these two translation machines. The first variable is Difference, which indicates the difference between the two translations of both translation machines. Significance then deals with the accuracy of these two translation machines in each of the five disciplines. The set of these two variables is known as Upper. At this time, Lower is compared with Upper Open by the software to obtain P number and Average. P number is, in fact, the degree of accuracy of each of these two machines, and the average score of each of these two translation machines is given by the software based on the variables. Eventually it turned out that Google's translation machine was much more accurate.

Table 8. Google and Targoman performance in translating five fields' sentences

No.	List of fields	Google	Targoman	
1	Linguistic Sentences	.05 .168	.004 .103	P number Average
2	Computer Sentences	.05 .168	.004 .103	P number Average
3	Psychology Sentences	.05 .168	.004 .103	P number Average
4	Genetic engineering Sentences	.05 .168	.004 .103	P number Average
5	Chemistry Sentences	.05 .168	.004 .103	P number Average

As can be seen from the tables above, the comparison result of these two machine translations is as follow:
According to the P number obtained and considering the probability we get between Google and Targman (.05 > .004 p value =), we conclude that the difference between the performance and accuracy of these two machines are significant. This means that according to the average obtained by Google (.168) and Targman (.103), we conclude that Google performs much better than Targman in these five scientific fields and according to the BLEU system of higher accuracy. At last, we conclude that Google and Targman translation machines are ranked first to second in terms of accuracy and efficiency according to the BLEU method, respectively.

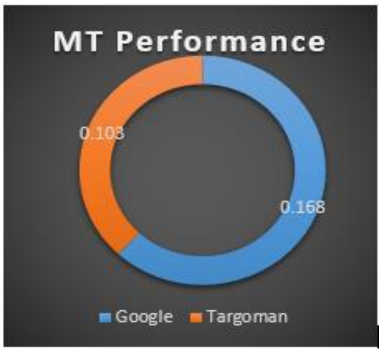

Fig.6: Comparison among Google and Targman translation machines in terms of performance

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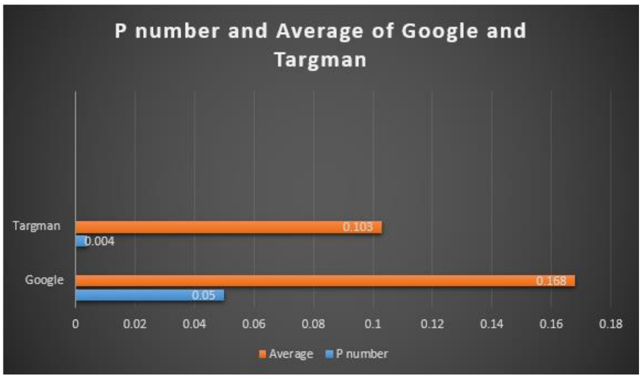

Fig.7: Comparison among Google and Targman translation machines in terms of P number and Average

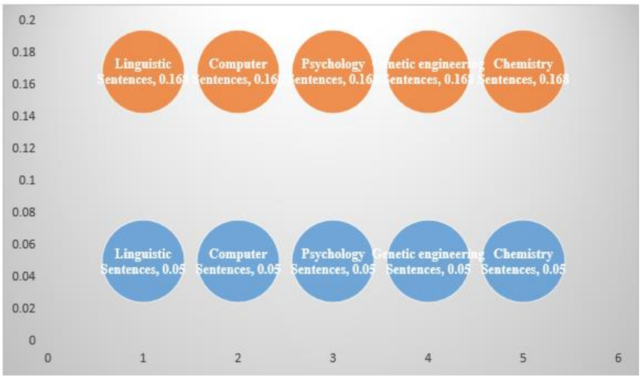

Fig.8: P number and Average in Google Translate based on fields

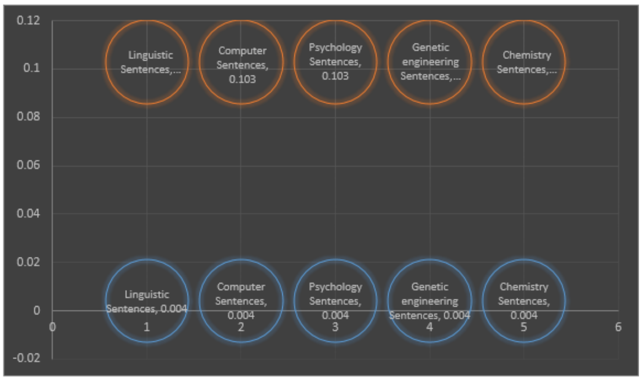

Fig.9: P number and Average in Targoman Translate based on fields

5. Conclusion

Due to the rapid advancement of technology and the introduction of computers into daily life, human beings have always sought to speed up their daily tasks with sufficient care. One of these dimensions is translation from one language to another. Efforts to mechanize translation began in the early 1960s and have continued to this day. Automatic translation systems will only improve with accurate and dynamic tracking. In this research, an attempt has been made to examine the existing translation machine by presenting a suitable, fast and accurate method. In this study, two machine translations such as Google and Targoman were evaluated by BLEU evaluation method. The results show that Google is more accurate than Targoman in the five scientific areas studied in this research. Translation machines may vary in accuracy in different genres. The results of this study also showed that machine translations have a long way to go to provide more accurate and quality translation, and human translation is still the best way to translate. Due to the shortcomings in all areas, we can try to eliminate the shortcomings of such smart machines. In this study, two translation machines, Targman and Google, were examined through BLEU. In this research, five disciplines of linguistics, computer, psychology, genetic engineering and chemistry were evaluated and all the research questions were answered. The study concluded that translation machines could not currently replace human translation. Among the translation machines evaluated, Google performed much more accurately and was able to provide a more accurate translation than Targman. The future of translation machines is likely to be a combination of machine translation and human translation. Examining the data of both machines translation, it turned out that Google performed much better than Targman because it scored better in all areas. In the near future, the main investment can be on Google translation machine, which is the largest translation machine in the world.

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