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On the Current State of Machine Translation: Investigating the Statistical Approach Limitations and the Neural Model Implications

قراءةٌ في واقع الترجمة الآلية: بين حدود المنهج الإحصائي وإرهاصات النموذج العصبي

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Abstract

Translation is of increasing interest in our time due to the rapid expansion in the amount of content that should be transferred beyond the linguistic barriers of its mother tongue. Yet, human translation cannot keep up with the continuous flow of documents published today worldwide, which makes it imperative to use the available translation technologies, in particular machine translation tools. Nowadays, and thanks to the improvements made in the field of artificial intelligence, the statistical approach has been eventually replaced by the neural model. This paper attempted to explore this subject from a theoretical and applied point of view in order to determine the motifs and the impact of this change on the quality of machine translation in the target language, by comparing the translation quality produced by 'Reverso' and 'Google Translate'; to conclude that although neural machine translation gave promising results, the raw output is not comparable to a human translation.

ملخص

تزداد أهمية الترجمة الآلية والحاجة إليها مع تعاظم الإنتاج الفكري الإنساني الذي لا يمكن الاستفادة منه على الوجه الأمثل إلا بترجمته من لغاته الأصلية إلى لغات أخرى. وبما أن الترجمة البشرية لا تستطيع مواكبة ما ينتجه العالم من الدفق الهائل من الوثائق يوميا كان لزاما الاستعانة بتكنولوجيات الترجمة المتاحة وبالأخص ما يعرف بنظم الترجمة الآلية باختلاف إصداراتها وطرق عملها. ولقد عرفت أدوات الترجمة الآلية في السنوات الأخيرة تحسنا كبيرا من الجانب التقني واللغوي بفضل ما جدّ في مجال الذكاء الاصطناعي مما مهد لاستبدال المنهج الإحصائي بالنموذج العصبي. ومن هذا المنطلق، يتنزّل بحثنا بالدراسة والتحليل لسبر أغوار هذا الموضوع من الناحية النظرية والتطبيقية بهدف تحديد دوافع هذا التغير وتأثيره على جودة الترجمة الآلية ومقروئيتها في اللغة المنقول إليها من خلال مقارنة نتاج أداة Reverso و Google Translate، لنستنتج أنه وعلى الرغم من أن أداة الترجمة الآلِية العصبية قيد الدراسة قدمت نتائج واعدة، فهي لم تصل بعد إلى مستوى الترجمة البشرية.

الكلمات المفتاحية:

الترجمة الآلية،

الذكاء الاصطناعي،

المنهج الإحصائي،

النموذج العصبي،

الجودة.

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1. Introduction

Machine translation has become a much-needed activity in a globalized world where information accessibility and transfer is on a large scale. Although the concept of machine translation is simple, the science behind it is extremely complex as it integrates together several leading-edge technologies, in particular, machine learning, big data, natural language processing…etc. Thanks to the new findings in the artificial intelligence research field, the performance of machine translation has improved considerably in recent years, paving the way to the emergence of a new model called 'neural machine translation'.

This latter that has taken over the statistical machine translation approach has attracted much research attention in recent years. Yet, many neural machine translation studies have been addressed between major European language pairs, by taking advantage of large scale parallel corpora, but very few research works are conducted on the English-Arabic language pair due to its parallel data scarcity. In this research paper, we will further investigate the reasons behind the shift from SMT to NMT and how this new MT trend has affected English - Arabic machine translation quality.

To address this issue, we divided our research study into two major parts; the first part tackles the theoretical side of the topic, by tracking back the origin of statistical and neural machine translation, introducing the fundamentals of SMT and NMT and studying the advantages of this latter over the former MT approach. Then, we will move to the second part of the study that focuses on comparing the performance of Reverso (SMT) and Google Translate (NMT) to conclude the paper with a set of results and recommendations.

2.Historical Background of Statistical and Neural Machine Translation

The idea of doing translation tasks using computers was formally introduced for the

first time by Warren Weaver in the late 40s, who investigated the ability of using basic bilingual dictionaries to analyze linguistic information of source and target language. Since then, machine translation has been studied extensively under different paradigms over the years leading to the emergence of rule-based and example-based machine translation.

In the early 90s, with the development of statistics, IBM Research Center published "the Mathematics of Statistical Machine Translation: Parameter Estimation" that presented the first concrete proposal for machine translation based on a corpus-based approach (Brown, P., 1993, p 263). This concept was achieved by developing five sophisticated models for word-for-word translation. However, this latter failed to deal with some linguistic elements related to gender agreement and homonymy (Garg, A., Mayank, A., 2018, p 5) as it didn't take contextual information into account. That is why, the original emphasis on word correlations between source and target language was replaced by correlations between 'phrases' by the inclusion of morphological, syntactic and structural information (Hutchins, J., 2014, p 3) to the system's database.

Since then, SMT became the major focus of MT research until the emergence of neural machine translation with the first serious experience conducted by Castaño, Casacuberta and Vidal (1997, p 160) who tried to design an artificial neural network and use it to train the MT system. However, the idea couldn't be applied in real life until recently thanks to the availability of a high computational power, and a large amount of big data to be trained automatically. Kalchbrenner and Blunsom (2013, p1700) were the first to revive the idea of NMT by introducing the Recurrent Continuous Translation Model, followed by the work of Sutskever (2014, p1) who used deep neural networks for the first time in training NMT models.

In the following year, the first pure neural machine translation project was submitted in the International Conference of Machine Translation (WMT) (Koehn, P., 2015: p10) that was able to translate short sentences correctly, which encouraged the main Language Service Provider (LSP) companies to start implementing the neural model, notably Microsoft, Amazon and Systran. In September 2016, the Google

Brain group published a paper that explains in detail the newly deployed GNMT (Google Neural Machine Translation) showing that "this GNMT system delivers roughly a 60% reduction in translation errors on several popular language pairs" (Yonghui, M., Zhifeng, Ch. et al., 2016, p 2). At the time of our writing, NMT research is progressing at a rapid pace in order to overcome many of the linguistic and technical problems that traditional MT systems couldn't solve.

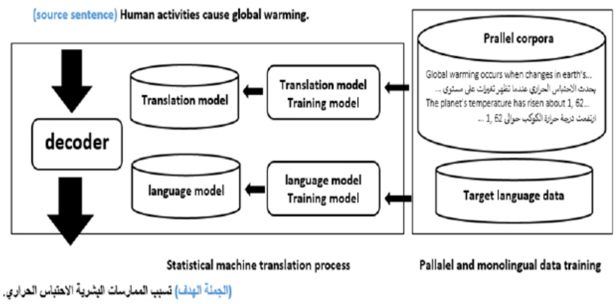
3.Overview of Statistical Machine Translation

The concept of SMT is grounded in the premise that language is so rich and complex that can't be limited in a group of language rules or dictionary entries. Instead, SMT is directed into developing a system that discovers translation rules automatically by implementing the mathematical concept of probability. In fact, "probabilities are used when we have to deal with events with uncertain outcomes, such as a foreign word that may translate into one of many possible English words" (Koehn, P., 2010, p 6). SMT is based on a very large amount of bilingual corpora of approved human translations as well as monolingual data. Therefore, building a credible database is vital to the improvement of SMT quality.

Broadly speaking, most of SMT systems are made of the following three elements: "(01) a translation model that measures probabilities of equivalences in translation rules, (02) a language model that captures the fluency of generated sentences in the target language, (03) a reordering model that deals with word/phrase order differences between source and target language." (Deyi, X., Min, Z., 2015, p 3)

Consequently, the process of SMT starts with: (01) bilingual corpora alignment (i.e. texts in original language and texts in target language), (02) frequency matching of input words against words in the corpus, (03) extraction of most probable equivalents in the target language, (04) reordering of the output according to the most common word sequences using a 'language model', (05) and finally, the production of the output in the target language. (Hutchins, J., 2014, p13)

Fig.1. The process of statistical machine translation



4.The Shortcomings of Statistical Machine Translation

Although effective, SMT suffers from various problems that can be determined as follow:

4.1. Sentence Alignment: since SMT relies on parallel corpora, alignment should be precise in order to prevent all kinds of translation inaccuracy. This is because "in parallel corpora single sentences in one language can be found translated into several sentences in the other and vice versa" (Oransa, O., 2019), especially if the source and target language do not belong to the same language family tree, as in the case of English and Arabic.

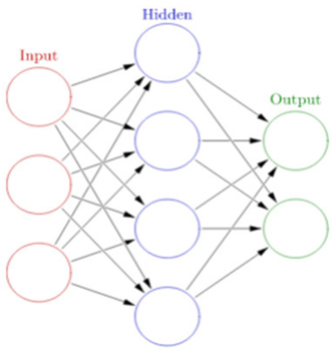
4.2. Idiomatic Expressions: Idiomatic expressions aren't often translated idiomatically in statistical machine translation tools. For example, the idiomatic expression 'hear! hear!' that is used in the British parliament to designate 'bravo! bravo!' is translated literally by Reverso to 'اسمع! اسمع!' instead of 'أحسنت!أحسنت!'.

4.3. Word Order: word order differs from one language to another depending on the syntactic rules of a language. In SMT, the more the source sentence is long and complex, the less the system succeeds in reordering it correctly in the target language.

5. Neural Machine Translation as the New State-of-the-art

In recent years, machine translation has served great purposes and improved the efficiency and productivity of human translators thanks to the adoption of what is known to be neural machine translation. NMT system uses a bidirectional recurrent neural network, also called an encoder, to process a source sentence into vectors for a second recurrent neural network, called the decoder (Cheng, Y., 2019, p 2). The encoder-decoder structure is generally made of three layers: the input layer, the output layer and the hidden layer, and the more hidden layers there are, the less errors are expected to occur (Koehn, P., 2015, p 8-9).

Fig.2. The three layers of the artificial neural network



Source : (Sujin P., Jaewook, L. et al., 2017, p 4)

Like other corpus-based approaches, neural machine translation engines are trained to translate between languages based on a large number of stored translations, called training data. However, the key trait of the NMT approach is that a single system is trained directly between source and target text; in other words, "unlike the traditional phrase-based translation system which consists of many small sub-components that are tuned separately, neural machine translation attempts to build and train a single, large neural network that reads a sentence and outputs a correct translation." (Bahdanau, D., Kyunghyun, C., et al, 2015, p 1). Thus, NMT engines operate from end-to-end with no intermediate stages between source and target sentence.

Besides, and as its name indicates, the architecture of neural machine translation is inspired by biological neural networks. This has been achieved by using the latest trends of artificial intelligence to train neural networks on how to learn on their own from the stored data each time the user/ translator translates a new document (Krzysztof, W., Krzysztof M., 2015, p 2). In other words, neural networks are compared to a child who learns language basics from his surroundings, and then starts using all the acquired information to express longer and more complicated sentences and thoughts. Besides, neural machine translation tends to mimic human skills of reflection, analysis, memory and decision taking in an automated manner.

6.The Advantages of Neural Machine Translation

Neural machine translation was launched a mere four years ago but it has achieved remarkable results in terms of quality and speed. This is mainly due to the following elements:

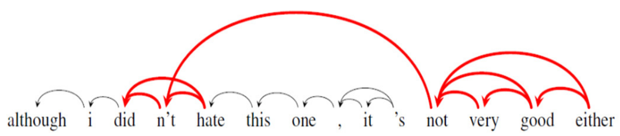
6.1. Deep Learning: Deep learning technology has revolutionized several areas including speech recognition, face detection and remote interpreting. Fortunately, the MT field hasn't remained invariant. Deep learning is defined as part of machine learning that is governed by "a set of methods that permits computers to learn from data without human supervision and intervention" (Kamath, U., 2019, p 5). In NMT, deep learning is divided into two main categories: supervised learning that relies on adding labels to the training data (Kamath, U., 2019, p 5), such as the addition of syntactic rules, word's typology, term's meaning; and unsupervised learning that "determines categories from data where no labels are present" (Kamath, U., 2019, p 6), such as word embedding, clustering and data association.

In their study research, Vanmassenhove, Hardmeier and Way (2018, p 3007) investigated the integration of gender information into an NMT system; and found out that adding a gender information to the source text (by using personal pronouns, adjectives) significantly improves English – French translation quality over time. This study makes it clear that deep learning highly improves morphological agreement between source and target text.

6.2. Prediction: NMT tools are designed in the same way as text completion techniques found in smartphone keyboards. When the user types a word, the smartphone gives him a suggestion for the next word, and it is up to him to accept the word or discard it. Based on this principle, NMT engines use the concept of prediction to produce translations "by using the decoder to predict the best possible target word considering the part of the sentence that a professional translator has already typed" (Forcada, M., 2017, p 296) and the general context of the source text.

6.3. Attention: one major problem that early NMT models suffered from is the production of wrong translations for long sentences. However, this issue seems to be solved thanks to the integration of the attention mechanism that focuses on parts of the source sentence during the translation process, which makes a soft selection over source words and yields an attentive vector to represent the most relevant source parts for the current decoding state (Zaixiang, Z., 2018, p 145).

Example:



As illustrated in this example, the attention process takes place in two levels: the first level links the words to the ones preceding them in the sentence, such as: ‘although’ with ‘I’, unlike the second level that links similar words in terms of their function in the sentence, such as: ‘not’ with ‘didn’t’. Hence, the decoder pays attention not only to the last representation built by the encoder but also to the whole sequence of representations built during encoding through an appropriate additional set of neural connections and layers (Forcada, M., 2017, p 299) .

However, and despite its undeniable success, neural machine translation still faces some fundamental challenges. The first problem is related to the ambiguity of natural languages. Human translators always interpret statements in their contexts, especially when dealing with highly metaphorical texts that are full of idiomatic expressions and figures of speech. Besides, NMT system has a steeper learning curve with respect to the amount of training data, resulting in worse quality in low resource languages, but better performance in high resource languages (Koehn, P., Knowles, R., 2017, p28). Unfortunately, the available NMT tools show ineffectiveness in dealing with rare and newly coined words, and sometimes fail in translating all words in the source sentence.

7.Challenges for Arabic Machine Translation

Arabic and English are two different languages that do not belong to the same language family. That is why, machine translation is bound to face some problems in producing meaningful and coherent translations, namely because:

7.1. Diacritization

This concept is defined as a set of “symbols over and underscored letters, which are used to indicate the proper pronunciations as well as for disambiguation purposes.” (Gashaw, I., Shashirekha, H., 2019, p 5). In Arabic, diacritic is added to the character of a word in order to convey its exact meaning and its function in the sentence, for example: ‘فقد’ can mean to lose or a conjunction. However, and despite the importance of diacritization usage on the Arabic sentence readability and understanding, it is rarely used in Arabic writings, which raises a real challenge for Arabic natural language processing and machine translation, leading to a high rate of ambiguity in passive and active verbs translation as in : يُقدَّر   يُقدِّر – and puns as in:

كَلَّمَ أحمَدُ أخَاهُ.

Translation: Ahmed talked to his brother.

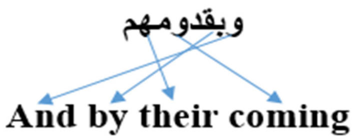
كَلَمَ أحمَدُ أخَاهُ.

Translation: Ahmed wounded his brother.

To solve this problem, using an electronic diacritization tool) for example: Mishkal - مشكال or Sakhr - صخر للتشكيل الآلي) to automatically diacritize Arabic texts has the potential to remarkably improve the results of Arabic machine translation.

7.2. Morphological Complexity

Arabic language is characterized by a complex system of affixation that includes prefixes, suffixes, infixes, and circumfixes. For example, the Arabic sentence ‘وبقدومهم’ and its English translation ‘and by their coming’ is challenging because “(01) it increases the number of out-of-vocabulary tokens, (2) it consequently worsens the issue of data sparsity, (3) it complicates the word-level correspondence between Arabic and another language in translation” (Almahairi, A., Kyunghyun C. et al., 2016, p 2).



Besides, and unlike English language, Arabic is considered as a pro-drop language where the subject can be embedded in the verb (Almahairi, A., Kyunghyun C. et al., 2016, p 142). For example, the sentence: ‘She went to university.’ is translated into Arabic to ‘ذهبت إلى الجامعة’. The subject ‘she’ and the verb ‘went’ are represented in Arabic by the single verb-form ‘ذهبت’. Moreover, MT system finds it harder to determine proper nouns, titles, acronyms and abbreviations in Arabic because of the absence of the element of capitalization.

7.3.Lexical Ambiguity

Arabic Language conveys several levels of ambiguity, some Arabic words and expressions have no equivalence in English (Alkhatib M., Shaalan, K., 2017, p140), such as the word: ‘تَيَمُّم’ that designates the Islamic act of dry ablution using a purified sand or dust (Alkhatib M., Shaalan, K., 2017, p140). Other Arabic expressions have an equivalent meaning but in a different cultural context, such as in the idiomatic expression: ‘it’s raining cats and dogs’ that is translated into Arabic to ‘إنها تمطر كأفواه القرب’, and ‘at the end of the day’ that is translated to ‘في نهاية المطاف’. This kind of cultural expressions can be easily translated by humans, however, “MT requires more complex analysis and computation in order to correctly identify the meaning; this process is called Word Sense Disambiguation (…) which means the task of automatically determining the meaning of a word by considering the associated context” (Almahairi, A., Kyunghyun C. et al., 2016, p 152).

8.Case Study

As a continuation of the theoretical part of the study, we performed an experiment on a short text that was translated on Reverso (SMT) and Google Translate (NMT) to diagnose and compare the two systems’ translation errors, find out the reasons, and try to shed light on the areas where the right translation solution is made.

8.1. The text of the study

Is translation technology changing our life?

Today, it is no exaggeration to boldly state that technological developments in translation, driven by the two major technological innovations of computer-assisted translation tools and machine translation, have fundamentally changed how we communicate. While the introduction of AI to translation may still be in its infancy, it has already achieved promising results; NMT has just landed, and with the involvement of deep learning, it is here to stay. Real-time translation has also experienced a quantum leap in the world of business and audiovisual industry and tends to move us closer to ‘language transparent’ society. Besides, cloud machine translation enables translators to collaborate on projects in real time and share resources in the easiest way.

However, we are still not sure whether, in near future, neural machine translation can hold a candle to the depth of experience and bicultural understanding that a human translator applies to translate the source text.

8.2. Google Translate Output

هل غيرت تكنولوجيات الترجمة حياتنا؟

اليوم، ليس من المبالغة أن نقول بجرأة أن التطورات التكنولوجية في الترجمة، مدفوعة بالابتكارين التكنولوجيين الرئيسيين لأدوات الترجمة بمساعدة الكمبيوتر والترجمة الآلية، قد غيّرت بشكل أساسي طريقة تواصلنا. في حين أن إدخال الذكاء الاصطناعي في الترجمة قد لا يزال في بدايته، فقد حقق بالفعل نتائج واعدة؛ لقد هبطت NMT للتو، وبإشراك التعلم العميق، فهي موجودة لتبقى. شهدت الترجمة الفورية أيضًا قفزة نوعية في عالم الأعمال والصناعة السمعية والبصرية وتميل إلى تقريبنا من مجتمع "اللغة الشفافة". إلى جانب ذلك، تتيح الترجمة الآلية السحابية للمترجمين التعاون في المشاريع في الوقت الفعلي ومشاركة الموارد بأسهل طريقة.

ومع ذلك، ما زلنا غير متأكدين مما إذا كانت الترجمة الآلية العصبية في المستقبل القريب يمكن أن تحمل شمعة إلى عمق التجربة والفهم ثنائي الثقافة الذي يطبقه مترجم بشري على ترجمة النص المصدر.

8.3.Reverso Output

هل تغير تكنولوجيا الترجمة حياتنا؟

واليوم، ليس من قبيل المبالغة أن نقول بجرأة إن التطورات التكنولوجية في مجال الترجمة التحريرية، مدفوعة بالابتكارات التكنولوجية الرئيسية في أدوات الترجمة بمساعدة الحاسوب والترجمة الآلية، قد غيرت بشكل جوهري طريقة تواصلنا. ورغم أن إدخال

الذكاء الاصطناعي إلى الترجمة ربما لا يزال في مرحلة الطفولة المبكرة، فإنه حقق بالفعل نتائج واعدة؛ فقد هبط فريق التدريب الوطني للتو، وبمشاركة التعلم العميق، فقد وصل إلى هنا لكي يظل قائما. كما شهدت الترجمة في الوقت الحقيقي قفزة نوعية في عالم الأعمال والصناعة السمعية البصرية وتميل إلى تقريبنا من المجتمع "الشفاف للغة". بالإضافة إلى ذلك، تمكّن الترجمة الآلية السحابية المترجمين من التعاون في المشاريع في الوقت الحقيقي ومشاركة الموارد بالطريقة الأسهل.

ومع ذلك، ما زلنا غير متأكدين مما إذا كان في المستقبل القريب، إن الترجمة الآلية العصبية من الممكن أن تحمل شمعة إلى عمق الخبرة وفهم الثقافة التي تنطبق عندما يترجم المترجم النص المصدر.

8.4.Results and Evaluation

After examining Reverso and Google Translate performance and comparing them in terms of the number of grammatical- structural, lexical, semantic errors and correct words, we found that Google Translate (NMT) outperformed Reverso (SMT) in all aspects but in small percentages because of the novelty of the NMT model compared to the SMT approach. By analyzing the translated text on Reverso, we deduced that statistical MT doesn't reflect the real meaning of translation as it uses stored parallel corpora to recycle new translations, unlike NMT that shows some creativity in translation as it relies on the concept of deep learning and data training.

8.4.1.Syntactic and Structural Level

The main problems related to syntax and structure in the English-Arabic machine translation are word order, verb tense, prepositions, definite articles and wrong analysis of grammatical categories. Google Translate (NMT) was more accurate than Reverso (SMT) in using the right verb tenses in Arabic thanks to the technology of deep learning that trains the artificial neural network to take the right grammatical decision, as in the use of the present tense (neural machine translation **can** hold → **يمكن** أن تحمل), and the present perfect (it **has** already **achieved** promising results → (**فقد** (**حقق** بالفعل نتائج واعدة) and in the correct translation of the modal verb 'may' in (while the introduction of AI to translation **may** still be in its infancy→ في حين أن إدخال الذكاء الاصطناعي في الترجمة **قد** لا يزال في بدايته).

Beside verb tenses, the translation of prepositions is regarded as a thorny issue in machine translation. The MT tool has to render prepositions according to the output and not according to the input. Reverso output was not syntactically correct because of the misuse of the preposition 'of' in (the two major technological innovations **of** computer-assisted translation tools and machine translation → بالابتكارات التكنولوجية الرئيسية (**في** أدوات الترجمة بمساعدة الحاسوب والترجمة الآلية) and the conjunction 'that' in (it is no exaggeration to boldly state **that** technological → ليس من قبيل المبالغة أن نقول بجرأة **إن** التطورات), contrary to Google Translate that used the correct Arabic prepositions /conjunctions with regard to the neighboring words thanks to the technique of attention, leading to the creation of more coherent sentences.

Nevertheless, both translations need a better word reordering as Google Translate and Reverso arranged the words in the target sentence according to their positions in the source sentence without considering that the verbal sentence (VSO) is the default word order in Arabic or more widely used, and not considering it can produce awkward nominal sentences, as in (**today**, it is no exaggeration → **اليوم**، ليس من المبالغة).

Another important drawback that was observed in Reverso is the addition of the conjunction 'و' at the beginning of the text (Today,→**و**اليوم)، This phenomenon is alarming since this is a machine work that deals with a written text, and hence there is no apparent reason as to why the system adds words.

Another element that contributes in the well-formedness of Arabic translation is the use of the definite article 'ال'. Both MT tools failed in adding the definite article in the sentence (technological developments in translation **driven** by→ (التطورات التكنولوجية في الترجمة **مدفوعة**) that has to be translated into 'المدفوعة' because adjectives and attributes in Arabic must have the same syntactic structure.

8.4.2. Lexical Level

One important feature of machine translation is to maximize meaning, so that minimum effort and less time are required to understand the output. Google Translate (NMT) succeeded in translating many of the text's words and expressions correctly according to its general context (experience / real time → التجربة/ الوقت الفعلي); yet, the tool's output was less accurate when translating words with multiple meanings, as in the verb ‘tends to’ that means ‘move to a particular direction’ and ‘be liable to possess a particular characteristic’. Google Translate opted for the first meaning, which doesn’t correspond with the sentence general idea (Real-time translation (…) **tends to** move us closer to language transparent society→ **تميل إلى** تقريبنا من مجتمع اللغة الشفافة). We noticed the same problem in Reverso but with a high percentage, this is mainly because the statistical approach depends on monolingual and parallel corpora to produce the output in other languages, which makes it harder for low resource languages– like Arabic - to get updated and accurate translations because of the lack of Arabic numeric data to be used in machine translation.

Besides, the noun ‘إشراك’ used for the translation of the word ‘involvement’ by Google Translate and Reverso doesn’t fit the context of the sentence (NMT has just landed, and with the **involvement** of deep learning, it is here to stay). Instead, the words ‘استعمال/ استثمار’are more likely to express the idea of involving deep learning technology in neural machine translation.

Another lexical problem that was noticed in Google Translate and Reverso is related to terminology. The lexicon of the MT database has to include the target language terminology to be used in its output. Reverso dictionary didn’t have the target language equivalent for the term ‘real-time translation’; thus, it provided a literal translation for it ‘الترجمة في الوقت الحقيقي’. The same problem was observed in Google Translate in the translation of the term ‘computer-aided translation’ that was wrongly translated to ‘الترجمة بمساعدة الكمبيوتر’ instead of the common Arabic term ‘الترجمة بمساعدة الحاسوب’. Terminological errors negatively affect the translation of specialized texts more than any other error type, this is because experts primarily rely on terminology to express ideas and explain information to the target reader; hence, producing wrong terminological equivalents by the machine can reduce the specialized texts accuracy and decrease their scientific value.

8.4.3. Semantic Level

When evaluating machine translation output, finding the right cultural equivalent in the target language is the most significant point of focus because any cultural mistranslation can lead to a complete deviation of the sentence general idea. Both Google Translate and Reverso tools seem to have a problem in translating figures of speech correctly, which makes it imperative for human translators/ reviewers to interfere and retranslate them properly. Whereas Google Translate succeeded in translating one figurative expression out of three (in its infancy→لا يزال في بدايته), Reverso failed in translating all of them (NMT **has just landed**→ **هبط للتو** فريق التدريب الوطني / hold a candle→ تحمل الشمعة). This is because MT algorithms can’t detect the connotative meaning of such expressions as they differ from one culture to another.

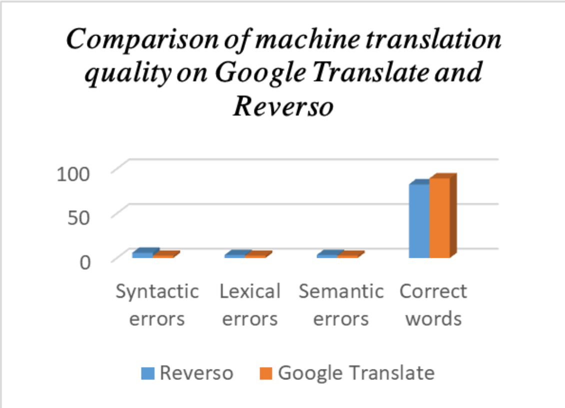
Besides, both Google Translate and Reverso translated the following metaphorical expression literally (language transparent society→مجتمع اللغة الشفافة) into Arabic without taking into account the rhetoric aspect of it. The literal translation of figures of speech produced by MT tools makes the task of human post-editing so comprehensive and time-consuming.

Finally, Google Translate and Reverso translate abbreviations differently, as in the case of the abbreviation ‘NMT’ that was wrongly translated by Reverso to ‘فريق التدريب الوطني’ instead of ‘الترجمة الآلية العصبية’, which means that the Arabic database used in Reverso is not properly updated. However, Google Translate left ‘NMT’ with no target language equivalent, and used it as it is in the target text (هبطت للتو**NMT**) which means that Google Translate doesn’t translate unknown abbreviations out of context when no appropriate equivalent is found in its database.

Table (01): Google Translate and Reverso translation quality comparison

	Reverso			
Errors	**Syntactic**	**Lexical**	**Semantic**	**Correct words**
Number	7	4	4	99
Percentage	5,83%	3,33%	3,33%	82,5%

	Google Translate			
Errors	**Syntactic**	**Lexical**	**Semantic**	**Correct words**
Number	3	3	3	107
Percentage	2,5%	2,5%	2,5%	89,16%



9.Conclusion

In recent years, neural machine translation has gained a foothold in theory and practice by showing superior performance to the traditional SMT approach. In this paper, we tried to study the motives behind the shift from the statistical to the neural MT by investigating English to Arabic machine translation quality of Google Translate and Reverso as being two of the most used online free MT tools.

Hence, in order to conceptualize the paradigm shift from SMT to NMT, it is vital to help translation students in the Arab World understand the strengths and weaknesses of this new MT technology and come to a deep understanding on how to evaluate its trustworthiness in their professional career. This can be achieved by enhancing the academic sphere of translation technology through the organization of more machine translation-based conferences, seminars and workshops, and the building of university curricula around the issues of machine translation theory and practice. Besides, diversifying the Arabic digital content and facilitating its access and usage can increase the chance of proceeding deep learning techniques into Arabic as NMT primarily relies on training data to acquire linguistic knowledge; which eventually leads to a better Arabic machine translation quality.

Conflict of Interest

The authors declare that they have no conflict of interest

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