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Neural machine translation and the indivisibility of culture and language

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Neural machine translation (NMT) is becoming a common resource both for professional translators and for people who need small, occasional translations. The wide use of NMT for professional purposes reshapes the conditions of translation assignments. Moreover, the effects on the target text and language are not well known, although some studies already suggest a stronger influence of the source language on them. On the other hand, since many NMT tools are easily and freely available and even accessible via mobile devices, they are being increasingly used by non-professionals to carry out short translations mostly. These occasional translators use these tools both to understand a text originally written in a language they do not fluently speak (translation into their first language) and to publish a text in the language they do not master (translation into their second language or even into a language in which the user has poor or no knowledge at all). Finally, NMT is also present in everyday digital products even without users being aware of its intervention, for example in specific apps on smart devices. This article proposes a reflection on the effects of NMT in all these scenarios, with a special focus on the effects on the reception of the target text and on the target language standard.

Keywords: neural machine translation, NMT, translationese, post-editese, NMT reception, ethics, language as Intangible Cultural Heritage

1. Introduction

Machine Translation (MT) is within the reach of any user of a smartphone or any other type of digital device. The different languages of potential users of any digital product may have been an obstacle for the activity of global companies at one point, however, with MT, these companies have turned linguistic diversity

into a business opportunity. As a result, they are revolutionising the market and, by extension, society. These companies have revolutionised access to MT applications for non-translators that are also being integrated into new types of digital products and services, such as smart home devices. These devices allow for a human-machine interaction based on questions and answers that uses processed structured data to create new natural messages in one given language, usually English, which in turn are machine translated into the user's language. From an information point of view, these messages are intended to be equally informative and natural-sounding to any user, regardless of the target language.

Language is part of the business model of global companies such as Google, Facebook, Microsoft, Amazon, Alibaba and many others (Vasiljevs et al., 2019). Their aim is to get clients used to “linguistically agnostic” systems (Edunov et al., 2019). This agnosticism consists of using languages correctly, albeit devoid of the nuances specific to each language. The risk of using linguistically agnostic systems lies in users having an impoverished perception of their own mother tongues, in which case, one likely outcome could be an impoverished way of using their own language. The same could happen when these systems are used as a starting point for professional translation.

In the last five years, Neural machine translation (NMT) has brought about a revolution in the localisation industry: previously MT systems performed poorly, but NMT achieves much higher levels of fluency and for this reason it gives the impression of being much more efficient than the best performing system until this advent, namely, Statistical machine translation (SMT) (Castilho et al., 2017).

The application of Artificial Intelligence (AI) to machine translation has created a new technological paradigm for researchers and language professionals (ibid.). Unlike previous paradigms, NMT makes it easy to achieve fluency levels in the target language with near-perfect grammatical accuracy. Nowadays, achieving complete fluency (understood as grammatical accuracy) is only a matter of increasing the power and processing capabilities of the software and hardware used: the greater the processing capacity of a system and the volume of data available for translation, the better the results produced by MT systems. In fact, current technological research in translation is focused on improving the way currently available data is processed. These data are translations with different levels of quality and generated under specific contexts, which are aligned as bilingual corpora.

Research on the application of NMT also focuses on how to improve the specific corpora used to create synthetic linguistic data (Freitag, 2019). These data are used in contexts where no previous data exist, such as poorly documented language combinations. However, current research does not focus on generating specific real and natural linguistic data for translating that also respects, or even cultivates, the complexity of the target language.

2. Data in Neural Machine Translation

NMT systems are based on artificial neural networks which are composed of thousands of artificial units extracted from the corpora used for training (Forcada, 2017). Like any data-based artificial intelligence (AI) system, it will be able to perform to the same level as the quality of the data used. Consequently, the nature of the data used is particularly relevant.

NMT has reached quality levels that are valid for the localisation industry, which mainly measures quality sentence by sentence in terms of adequacy and fluency (Rossi and Carré, 2022; Gar Bailo and Sánchez-Gijón, 2022). NMT systems are particularly successful in language combinations with a significant volume of aligned data that mainly comes from previous translations. However, these translations are the product of specific translation commissions for only a few different text genres. In most of these cases they are rather stereotypical documents from very specific genres and generally of limited use, which do not reach a general audience readership. They may reflect a high degree of interference from the MT system that was used, their quality is measured in terms of fluency and adequacy, and while they contain correct translations, they are not necessarily appropriate or natural (Frytzała, 2022). These are translations of texts that have an elevated instrumental function, such as documentation from the field of information technologies or texts from the fields of law, administration or economics.

The use of these corpora to train NMT engines already makes it possible to obtain translations with almost total grammatical accuracy. Nevertheless, this product is far from being a natural text in the target language. Like any system based on AI, NMT decisions are based on a large amount of data. The linguistic data currently used are generally translations from English of specific text genres produced in specific professional contexts, are data validated by human translators, but only serve one purpose: the translation commission in which they were produced. Kersting and Meyer (2018) have drawn up a list of opportunities and risks of the use of AI. In their paper, Kersting and Meyer (*ibid.*) introduce the opinion of Deepak Ajwani (Nokia Bell Labs, Ireland). The authors point out that “[i]f the learning systems leveraging these Big Data sets are not designed carefully, they may end up coding our biases and stereotypes (e.g., possible racial biases in automated airport profiling) and this may result in these biases getting even more deeply ingrained” (*ibid.*: 7).

The data used by current MT systems are biased by the nature of the projects for which they were created and the main source language used (English). It has already been proven that MT systems have an impact on target languages (Gar Bailo and Sánchez-Gijón, 2022). Consequently, will the use of supervised and unsupervised MT influence the standard target languages? Should these lan-

guages be protected by creating appropriate machine translation quality thresholds based on criteria beyond adequacy and fluency? Should MT become a resource which is more respectful of the target languages and of greater value to any user (professional or not) in any context (supervised or not)? And from a translation point of view, how can MT adapt its translation to the purpose of the translation commission, the function of a text or the characteristics of the target language audience? Can an MT system create a translation strategy adapted to the communicative situation? Machine Translation has already proved that it can do error-free translations, but can it deliver accurate translations according to their context of use?

3. What translation has already taught us

Research in both the academic world and the translation industry are exploring whether machine translation works beyond the translation of purely instrumental texts (technical, legal or administrative documentation) (for example, Fritzala, 2022). In both cases, current research continues to focus on the technological development of the systems, evaluation of their quality (in terms of the lack of errors) and the perception of quality by professional or end users. However, from professional, technological and academic perspectives, MT is already considered a common resource in professional contexts. It is also considered one of the technologies, probably the most relevant one, in the Augmented Translation workbench professionals already work in (O'Brien, 2022a).

The possibility of achieving correct translations, both in terms of meaning and form, was the goal of those researchers that dreamed of Fully Automated Machine Translation (FAMT, Frederking and Zampolli, 1999), not only within controlled domains and under specific circumstances, but also of systems capable of translating any type of text. Farajian et al. (2017) explore the performance of different MT systems with texts from any domain. Moorkens et al. (2018) consider how translators of literary texts could incorporate MT as a resource and what results they would obtain. Large (2018) has managed to test whether MT systems can provide valid translations of literary texts. These are some examples of approaches to MT that go beyond the limitations of its typical use and explore its performance beyond the controlled contexts in which it has been used so far. All these examples come from the academic or professional world. However, users who install translation apps on their mobile devices to translate everything they do not understand do not question the naturalness of the translation: if the translation is error-free and the meaning is contextually valid, they will not question

whether the use of language is the most authentic or whether it has been affected by the nature of the data used by the MT system.

The main companies that develop and market MT as a service and as part of other products they develop (Google, Facebook and Microsoft), have very recently started to focus the debate on a phenomenon called “translationese” (Freitag, Caswell & Roy, 2019; Edunov et al, 2019; Junczys-Dowmunt, 2019). Translationese is a phenomenon that has been detected in translated texts (Baker, 1993), namely that they reflect a more basic use of language compared to texts originally written in that same language and this due to the influence of both the source text and the source language. Compared to originally written texts, translated texts tend to have lower rates of lexical and syntactic variety, a more limited selection of linguistic structures and a higher level of explicitness.

Translationese is a phenomenon that translators learn to avoid as much as possible to meet both the linguistic standards of the target language usage as well as the expectations and requirements of their clients. These expectations determine the translation strategy for each commission and consider aspects such as the purpose of the translation commission, the text function, the communicative situation or the characteristics of the end reader. Unfortunately, over the last three decades, the requirements of clients in multilingual translation and localisation projects have given priority to lexical, terminological, syntactic and discursive coherence over the naturalness of the target language and the adaptation of the text to different communicative and cultural circumstances. In fact, MT automatic quality metrics do not explicitly consider these factors. Comparing MT with a single validated human translation makes it possible to assess the similarity between these two translations, but not necessarily the quality regarding the naturalness of the translation and its suitability for a communicative situation. Multilingual translation projects were planned and implemented bearing in mind the context and function for which the translations were to be used. These were instrumental and functional texts – legal or technical documentation that accompanied any type of service or product – and most of them were intended to be understood by experts. They were translated with the help of computer-assisted translation (CAT) tools based on translation memories. These translations were created to facilitate understanding in particular communicative situations (i.e., texts with low visibility, used by a restricted readership and with an essentially instrumental function), and are now used as a starting point for NMT.

With the spread of MT, these professional translation commissions have a new requirement: to increase productivity as much as possible, by editing raw MT errors (O’Brien, 2022b). Here, an error is understood as any lack of fluency in the target language usage, or accuracy when reproducing the message. While MT post-editing has increased productivity exponentially, it has also caused a

significant loss of naturalness in the target texts, which is now beginning to be called “post-edited” (Daems et al., 2017). These translations do not contain grammatical errors but are increasingly moving away from the peculiarities of the target language (TL) (Toral, 2019). In other words, the rates of standardisation and interference are even higher than translations which do not use MT, while also exhibiting even lower rates of lexical variation. Consequently, target languages might be exposed to a rapid process of impoverishment and degradation caused by previous translations. In other words, old translations of texts and functional genres that have been generated under specific quality criteria are used as representative data for the target language standard, which means that widespread use of MT is going to turn them into the target language standard: the new standard.

4. Moving towards a target language-and-culture friendly model

The impact of AI systems decisions on the way humans behave has already been studied in other fields of applied AI. These studies conclude that the application of AI has a profound impact on any human strategy and how they are implemented (Ayoub and Payne, 2016), so that it is already possible to consider how this will affect the decision-making capacity of humans. So, it begs the question as to what the impact of NMT will be, not only for sporadic users of these systems, but also for professional translators who use it on a regular basis.

The task of the professional translator is complex and is not simply a matter of changing the linguistic code of the text. The translator’s task begins with analysing the translation commission and the text. The translator considers the intention of the author and the client, the purpose of the commission and the various functions of the text, as well as the communicative situation of the target text and the characteristics of the target reader. With this information in mind, the translator draws up a translation strategy which makes it possible to systematically solve the translation problems posed by the text and gives the text coherence. In addition, the translation strategy achieves three further objectives. First, to respect the intertextual references in the text. Second, to identify and deal with any use of language that is not merely informative and functional (such as rhetorical devices, figurative meanings, connotations, etc.) in an appropriate and coherent manner. Third, to identify all those source text elements related to the source culture and to look for ways to reproduce them in the target text. In the case of close cultural references, they may be understandable for the target language reader but, in any case, including or modifying them will have been subject to the criteria of an expert who knows both cultures in contact.

The use of MT was limited to very specific translation commissions, such as technical documentation and other types of highly standardised text. Some studies have focused on the reception of target languages audiences to post-edited machine translation and human translation. In the case of specialised texts (Information Technology manuals), a study by Fiederer and O'Brien (2009) showed that users preferred post-editing to human translation because of its accuracy, while they preferred the style of human translation. In a study by Bowker (2009) conducted in Canada on translation in each language group in the country, French speakers preferred human translation to post-editing, while English speakers preferred post-editing.

In 2003, the UNESCO adopted the Convention for the Safeguarding of the Intangible Cultural Heritage (Unesco, Ich 2020). The first domain in which Intangible Cultural Heritage is manifested is "(a) oral traditions and expressions, including language as a vehicle of the intangible cultural heritage;" (Article 2, Paragraph 2). Paragraph 3 in the same article claims that "Safeguarding" means measures aimed at ensuring the viability of the intangible cultural heritage, including the identification, documentation, research, preservation, protection, promotion, enhancement, transmission, particularly through formal and non-formal education, as well as the revitalization of the various aspects of such heritage.' Those measures were probably thought to safeguard those languages in risk of disappearance. But the Fully Automated Machine Translation (FAMT) may end up putting at risk of denaturing all target languages, including those which are majority languages, or which are not in danger of disappearing.

How many elements of intangible cultural heritage can be found in a computer programme's user manual? Probably few, or even none. It is a textual genre that has been shaped in a global context, dissociated from elements specific to each culture in contact. In this context, the use of machine translation seems ideal in all senses: quality in translation accuracy, correct formal use in the target text and intertextual coherence. But in which texts and commissions are elements of the intangible cultural heritage of each language and culture so important that an accurate and fluid translation is insufficient? Can an AI system establish a translation strategy like that of a professional translator? In theory, yes, but today there are no appropriate linguistic data collections that allow this level of decision-making and which would generate translations as fluent and accurate as the current corpora do. From another perspective, can language users eventually perceive the style of machine translated texts as an evolution of their mother tongue and consequently, increasingly renounce their intangible cultural heritage? In practice, the answer is yes. The machine translated text accompanies a socio-economic and cultural reality that is new to the target culture and is perceived as new. By way of example, the answers from a smart device gener-

ated through machine translation about the results of a football match will give the same information as the news in the local newspaper but will not say the same thing. The risk lies in the fact that users identify the digital device language usage with evolution and the future, thus determining their own perception of the language.

5. Concluding remarks

There is an ideal environment for using NMT: highly functional texts which use purely informative linguistic resources and no cultural or social references. NMT systems trained to translate with such texts can perform better than a human translation, but what happens when the translation job does not match these characteristics exactly? We may be faced with the kind of bias caused by data as stated by Kersting and Meyer (2018).

An AI system for translation should be able to make translation decisions within the framework of an explicit translation strategy, as translators do. In this way, its translation decisions would not only respond to mathematical calculations about linguistic options within the limits of the sentence, but also be determined by the limits of the text and the characteristics of the translation commission. Furthermore, the use of biased training information (the corpus) should be avoided. The bias of current data is twofold. The first level of bias is related to the nature of the translated texts used (functional and purely informational genres). The second level of bias, which has been less explored in MT, could be caused by the position of power of one of the two languages in contact. As it is a translated text, the very effect of the translation (Translationese) generates a degree of SL interference on the TL regarding linguistic issues, but not only. This second level of bias is more intangible to the end user of the translation and even the professional translator may end up being insensitive to this level of bias.

It does not seem that research in AI applied to translation will take these concerns into account either for the short or the medium term. So, it would be necessary to consider the real limits of MT applied to any context. In our view, using MT in any context would only be possible under specific circumstances. First of all, translation quality cannot be limited to measuring the accuracy and fluency of each individual sentence of the translation. The aim of a translation is not only to avoid errors; in a translation, translators seek to find the most appropriate solutions. The principles of quality control that are currently applied attempt to certify the absence of errors, but do not take correct translations into account, that is, those solutions that are optimal considering all the commission's features. Secondly, we doubt whether the productivity ratios achieved in some translation pro-

jects can be extrapolated to other types of projects. If translating is not just about avoiding errors, performance cannot be measured only in the number of edits and the corresponding time invested in them. Consequently, in our opinion, the most urgent matter in the conscious use of MT is to establish a consensus regarding the concept of quality.

In the meantime, if end readers become more and more accustomed to a different use of their mother tongue, to what extent will the standard of this language change? To what extent will the use of MT change and bring the target languages closer to the dominant source language? Are we in time to establish the appropriate rules of the game so that technological development, economic viability and respect for the intangible cultural heritage can coexist?

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Résumé

Alors que la traduction automatique neuronale (NMT) devient une ressource courante, l'utilisation généralisée de cet outil technologique modifie les conditions d'exercice de la traduction. D'une part, les effets de la NMT sur le texte et sur la langue cibles n'ont pas été précisément identifiés, bien que certaines études suggèrent que dans le cadre de la NMT, l'influence de la langue source sur le produit cible est plus marquée que dans la traduction humaine. D'autre part, l'accessibilité à titre gratuit de nombreux outils de NMT, y compris à partir des appareils mobiles, ouvre la pratique de la traduction à des traducteurs non professionnels. Ces derniers se servent occasionnellement de la NMT pour comprendre des textes, le plus souvent courts, écrits dans une langue qu'ils ne maîtrisent pas (traduction vers la langue maternelle) ou pour publier des textes dans une langue qu'ils maîtrisent peu ou pas du tout (traduction vers une langue étrangère). Enfin, la NMT est présente dans les produits numériques du quotidien, tels que de nombreuses applications pour smartphone, sans même que les utilisateurs en aient conscience. Cet article propose une réflexion sur les effets de la NMT dans l'ensemble des contextes évoqués et souligne les impacts de la traduction automatique neuronale sur la réception du texte cible et sur la norme de la langue cible.

Mots-clés : traduction automatique neuronale, NMT, « translationese », « post-editedese », réception de la NMT, éthique, langue comme patrimoine culturel immatériel

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