An investigation of challenges in machine translation of literary texts: the case of the English–Chinese language pair

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A thesis presented to Western Sydney University in fulfilment of the requirements for the degree of Master of Research

December 10, 2021

Acknowledgements

I must first thank my supervisor Professor Jing Han, who has been not only a knowledgeable and inspiring role model, but also a supportive and encouraging supervisor for me. I could not have finished this thesis without her guidance. I am grateful she agreed to take me on this wondrous journey of research.

I would like to thank Dr Alex Norman and Dr Jack Tsnois who greeted me when I first started this research course. Nothing feels greater than having learnt from researchers like them who are so passionate, so meticulous, and yet so caring.

I want to thank my family and friends for their ever-lasting support.

Finally, I want to thank myself for loving what I do.

Statement of Authentication

The work presented in this thesis is, to the best of my knowledge and belief, original except as acknowledged in the text. I hereby declare that I have not submitted this material, either in full or in part, for a degree at this or any other institution.

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December 10, 2021

Abstract

In the absence of a focus on literary text translation in studies of machine translation (MT), this study aims at investigating some challenges of this application of the technology. First, the most commonly used types of MT are reviewed in chronological order of their development, and, for the purpose of identifying challenges for MT in literary text translation, the challenges human translators face in literary text translation are linked to corresponding aspects of MT. In investigating the research questions of the challenges that MT systems face in literary text translation, and whether equivalence can be established by MT in literary text translation, a qualitative method is used. Areas such as the challenges for MT in the establishment of corpora, achieving equivalence, and realisation of creativity in literary texts are examined in order to reveal some of the potential contributing factors to the difficulties faced in literary text translation by MT. Through text analysis on chosen sample literary texts on three online MT platforms (Google Translate, DeepL and Youdao Translate), all based on highly advanced neural machine translation engines, this study offers a pragmatic view on some challenging areas in literary text translation using these widely acclaimed online platforms, and offers insights on potential research opportunities in studies of literary text translation using MT.

1. Introduction

Machine translation (MT) is a computer-based approach to automatic translation of a text from a source language to a target language (Poibeau, 2017, p 2). It is also a subfield of computational linguistics (CL) or natural language processing (NLP) that investigates the use of software to translate text or speech from one natural language to another (Liu & Zhang, 2014, Costa-jussà & Fonollosa, 2015).

As Poibeau (2017, p. 189) pointed out, MT systems are often criticised for lacking a theoretical foundation. Even the most advanced neural machine translation (NMT) adopts an empirical approach, from the definition of the architecture of the neural network to other parameters. Even though, in the pursuit of improved translation quality, the number of studies with diverse focuses on machine translation (MT) has been growing since the advent of neural machine translation (NMT), there is still a lack of attention on how MT systems perform in literary text translation. Thus, this study investigates MT with a focus on literary text translation, using the language pair of Chinese and English.

To investigate the challenges to machine translation (MT) of literary texts and to examine whether and how MT can attain equivalence between source text (ST) and target text (TT), it is helpful to look first at the development of machine translation. Accordingly, the first part of this paper is a review of MT types, elucidating the development of MT models from rule-based machine translation (RBMT), statistical machine translation (SMT) and hybrid methods to NMT. Following a chronological order of the development of these systems, it briefly explains the principles on which they are based and how they were modelled. Subsequently, this study looks at some key translation concepts, including equivalence, corpus and creativity in literary translation, after which challenges to these areas when MT systems are applied to literary text translation will be considered. Other challenges, such as comprehensibility, linguistic knowledge and computational ability are also raised as contributing factors to the challenges in literary translation by MT.

Studies on MT to date have been carried out with the common goal of enabling the machine to generate automatic translation with equivalent or better quality to that of a human translator. These studies cover pre-editing the ST (Yoshimi, 2001), post-editing the TT (Jia et al., 2019), data selection and domain adaptation for corpus (Banerjee et al., 2015), legal term terminology translation by phrase-based statistical machine translation (PB-SMT), neural machine translation (NMT) (Haque et al., 2020), and semantic interaction for multi-modal NMT (Su et al., 2021). However, none of these are specifically focused on the challenges of literary translation by MT systems. In response, this study takes a qualitative approach, using a purposefully chosen set of sample literary texts that contain elements of special concern in translations of this type, such as context and genre of ST, culturally or temporally distinct language, word limit on ST input, rhetoric and aesthetic rendition, and consistency. By carrying out analysis of these texts and of translations provided by three online translation platforms offering NMT systems (Google Translate, DeepL Translator and Youdao Translate), this study reveals some of the challenges that current NMT systems are facing and suggests future research directions in MT studies.

2. Review of MT types

There are three main types of machine translation: RBMT, SMT and NMT. Different models of MT are based on different approaches (Sager, 1994), including linguistic, semantic and corpus approaches. These are fundamentally distinct from each other, as reflected in the methods of handling, analysis and generation. Chronologically, the first model of MT was RBMT (early 1930s), followed by SMT (1980s), with NMT emerging last (late 1990s).

2.1 Rule-based machine translation

The first MT system model was built in 1933, when computers were still mechanical (Le Scao, 2020). To perform translation, RBMT, also known as knowledge-based MT, relies on morphological, syntactic, semantic and contextual knowledge about the SL, the TL and the connections between them. In RBMT, the system models are first programmed to parse a source text (ST) in order to identify and analyse the linguistic features, such as the lexico-grammatical elements, while a group of linguists encode a set of rules for the machine system, based on the genre and type of the text (Yu & Bai, 2014, p. 186). After the parsing step, the system will be guided by the encoded rules to generate the equivalent target text (TT), that is, the translation. The rules direct the process of MT in an RBMT system. The collaboration of linguists and computer scientists allows linguistics experts to focus on the construction of rule bases and lexicons, while computer scientists can focus on algorithm design and implementation. Linguistic knowledge assists MT systems through computer-accessible dictionaries and grammar rules based on theoretical linguistic research (Liu & Zhang, 2014, p. 111).

2.1.1 Three models of rule-based machine translation

Vauquois's Triangle (Vauquois, 1968, pp. 254-260) (figure 1) depicts the intermediary representations used in the translation process (direct, transfer and interlingua). These have also been adopted here for the purpose of categorizing the MT approaches, that is, according to the depth of these intermediary representations.

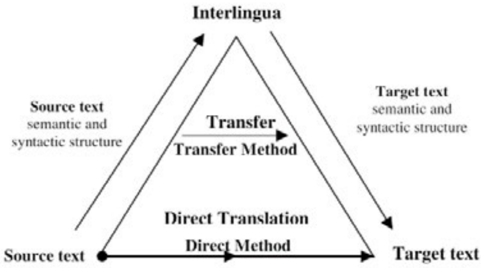

Figure 1. Vauquois's Triangle

In the direct model, the assumption is that translation tasks mainly require a lexical transfer between the languages involved; SL sentences are taken as strings of words before their lexical equivalents in TL can be retrieved from accessible bilingual dictionaries. The identified equivalents will be reorganised into the corresponding TL sentences. Only a minimal amount of morphological, syntactic, analysis and word reordering are carried out in this model, and translation is done either through the dictionaries that contain relevant linguistic knowledge or through the algorithms that describe the knowledge before it is expressed by program codes. The limitation of the direct model is it only provides a finite number of sentence patterns, and only for language pairs with similar syntactic features. As Poileau point out, for translation between genetically distant languages such as Simplified Chinese and English, the transfer rules required must be complex, and the required systems have yet to be invented (Poibeau, 2017, p. 70).

The interlingua model starts from the premise that semantico-syntactic intermediary representations can be found to link different languages. A universal representation for all the ST and TT is essential, yet the interlingua symbols are independent of both SL and TL. In most cases, interlinguas are designed for specific systems (Yu & Bai, 2014. p. 189). Their emergence and development are to serve the purpose of providing translation in multiple languages within the same system. Different languages can share and use the same intermediary representations, reducing the required input for the system. An interlingua can be a structured representation such as a logic expression, a semantic network, a knowledge representation or even an artificial or natural language representation. Researchers (Nirenberg, 1989, pp. 5-24; Carbonell et al., 1978) recognize the interlingua approach as a knowledge-based approach when a knowledge representation is used as an interlingua. Other names for interlingua include pivot language, metalanguage and bridge language.

The transfer model usually adopts a syntactic view, considering the sentence as a structure rather than a linear string. Instead of building an MT system to cover all possible SL sentences for TL translation, which is not feasible, the approach of computer scientists was to find a finite number of structures in one language and their equivalent structures in another language. After this stage of defining the intermediary structures, the system then uses a three-phase process: analysis from ST to the source intermediary structure; transfer from the source intermediary structure to the target intermediary structure; generation from the target intermediary structure to TT. Because of this, the basis of the approach is the structural correspondence between the languages involved in the transfer model (Yu & Bai, 2014, p. 189).

As illustrated by Yu and Bai (2014, pp. 190-192), SL analysis plays an important role in the transfer model and is carried out on both syntactic and semantic levels to cover morphological, syntactic, semantic and contextual aspects. While syntactic analysis determines the grammatical categories of particular words, morphological information is also collected for the same purpose. The syntactic structure of an SL sentence includes the grammatical categories of words, their grouping, and the relations among them, as identified in the syntactic analysis. Once the TL syntactic structure is in place, equivalent TL words will be retrieved from the dictionaries to construct the translation in TL, in which, in most cases, TL words of appropriate morphological forms are derived. However, semantic analysis of SL sentences is still required, due to the ambiguities left unresolved on the syntactic level.

2.1.2 Three phases of rule-based machine translation

From a linguistic perspective, there are three phrases involved in a RBMT process: ST analysis, mode of transfer, and generation of TT synthesis. Lexicon and structure have been used for the segmentation and annotation of the ST. The machine will match the text to a monolingual dictionary that helps to recognise a word, though there can be occasions when such recognition does not occur. During the process of parsing the sentences into structural components, with different constituents marked as nominal, prepositional or verb groups, the embedded dictionary also provides information on potential syntactic functions of words and collocations in which these words can occur.

During the intermediate phase of transfer, both ST and TT are considered. The simplest form involves looking up a bilingual dictionary to find the matching lexical units for the source words while referring to the information established during the analysis. At the end of the transfer phase, there will be a sequence of annotated words or larger units, with a description of their syntactic function and order, in the form of an intermediate representation that corresponds to neither the syntax of the source nor the target language. In the following step, this interim product will be synthesized after the words or large units are ordered and adjusted so that they are syntactically and morphologically appropriate to the TL.

2.1.3 Summary

The development of a RBMT system is time-consuming and labour-intensive, as it takes several years for it to be developed and to become commercialised. Furthermore, rules encoded by humans fail to cover all the possible linguistic phenomena, which results in unsatisfactory translation quality (Liu & Zhang, 2014, p. 111). Web-based translation services such as Google Translate and Bing Translate used English as a pivot language for their interlingua approach to support MT between tens of other languages. However, difficulties occurred when MT systems worked on some large-scale translation projects, indicating that an interlingua approach using a human-defined presentation may encounter uncontrollable complexity when many languages are involved (Nagao, 1989; Patel-Schneider, 1989, pp. 319-351). These problems have led to their later development into a different model of MT.

2.2 Statistical machine translation

While RBMT works on preset linguistics rules, SMT takes a probabilistic approach, rather than an empirical one, using statistical translation models derived from language corpora. The basic idea (Brown et al. 1990, pp. 79-85; Brown et al. 1993, pp. 263-313; Koehn & Knight, 2009) is to mathematically model the probability of a target sentence being the translation of a given source sentence. The probability, based on pattern(s), is the key. The first step is to define and implement the model, after which the problem of translating a source sentence into a target sentence becomes one of locating the target sentence with the highest translation probability (Liu & Zhang, 2014, pp. 113-114).

2.2.1 Statistical machine translation models

As for RBMT, models for SMT can be based on various language units: for example, word-based models, phrase-based models and syntax-based models.

In word-based models, word-to-word translation tables are embedded for calculating the sentence translation probability. In phrase-based models (Och, 2002; Koehn et al., 2003), phrase-to-phrase tables, instead of word-to-word tables, are used for calculation of translation probabilities. Such models outperform word-based ones because they capture local context when translating a word, providing more accuracy. However, long-distance dependency remains a challenge for phrase-based models.

Syntax-based models are based on synchronised grammars; rule tables are used to record the probabilities of synchronised syntax rules. Such rules are different to the preset rules for RBMT; rather, they are extracted from the patterns of current language use. A translation rule consists of a source rule, a target rule and a correspondence between variables in source and target rules. The benefit of adopting syntax-based models is that the long-distance dependencies which cannot be captured by the word-to-word or phrase-to-phrase models can now be captured. They also perform better than phrase-based models with language pairs with highly divergent syntax structures.

2.2.2 Key concepts of statistical machine translation

There are three key concepts in SMT: context, translation memory and corpus.

When the context of a TT is determined, that is, when humans 'inform' the machine of the type of text or when the machine determines the type through analysis of the TT, previous translations can provide examples of relevant renditions. For example, in the case of technical translation, uniformity of translation can be enhanced by consulting the terminology, phraseology and style adopted by previous translations. This type of translation is also known as example-based translation, given that the existing translations are analysed and generalised according to various linguistic strategies before being used as a reservoir of knowledge for future translation.

Human language is complex, in the sense that the meaning of a sentence or a text can be delivered by ambiguous words. There are not always clear-cut boundaries between word senses, and most of the time, these word sentences are related to one another. Direct correspondence can, but may not, exist across different languages (Hatim & Munday, 2019, p. 182). Under different contexts or when different languages are considered, the same notion can be expressed by a single word or by a group of words. Consequently, manual specification for an automatic MT system to cover all possible situations is impossible. This partly explains why MT is challenging and computationally expensive.

Since the 1980s, there has been an increase in the number of electronic texts that are directly accessible by computers. Those texts that are translations of each other can be aligned or matched at paragraph or sentence level. The collection of such texts is called a corpus. In addition, the increased number of bilingual texts on the Internet also contributes to the development of a corpus (Poibeau, 2017, pp. 91-92). A machine requires a corpus to calculate probabilities as well as to align words of the SL to those of the TL.

According to Gavrila and Vertan (2011), current SMT systems are dependent on the availability of a very large set of training data for producing the language and translation models. Such a training dataset is different to a translation memory. For individual-user translators, past translations can be accessed via an individual translation memory tool, usually called a CAT (computer-assisted translation) tool, that stores, analyses and tags past translations. Precedent translations can be retrieved from these translation memories, effectively and efficiently improving human translation when a TT term or phrase reoccurs. Mercer et al. (1993, pp. 263-311) and followers of the statistical approach suggested that an SMT system should be based on as much data as possible. However, the accumulated data must also be representative and diversified. Consequently, data from translation memory is insufficient for SMT to estimate probabilities for translations. In terms of the SMT performance, qualitative criteria are difficult to evaluate, and quantitative criteria continue to prevail. It has been shown (Poibeau, 2017) that the increased availability of bi-texts improves the performance of the system.

Effective corpus-based statistical methods emerged at the end of the 1990s (Hutchins, 2011). Corpus-based MT began with Jean-Paul Vinay and Jean Darbelnet's description of a detailed and systematic model for the analysis and comparison of an ST-TT pair using parallel non-translated and translated texts. It involved the identification and numbering of the ST units and the units of translation, followed by a matching of the two (Hatim & Munday, 2019, p. 29).

2.2.3 Corpora and automatic data harvesting

The amount of available data and the feasibility of harvesting enough data to develop a quality bilingual corpus is a central question in corpus construction. If there are sufficient data, parallel corpora can be automatically created. A parallel corpus that can 'harvest' high-quality bilingual text from the Internet can be created by establishing a system capable of following links identified on webpages (Poibeau, 2017, pp. 98-100). The system automatically checks the languages used on the Internet and navigates through webpages to find any equivalent page in the target language.

During this search process, the system either searches for an equivalent at the website address (URL) level – that is, looking for a 'mirror site' in the target language, identified by its URL (for example, the '.en' version of the same website, if the TL is English) – or compares the length of the document or the HTML structure. In order to connect the two texts, the system establishes links between ST and TT so that each sentence in the SL is linked to some or multiple sentences in the TL, which can then be considered a fully connected bi-text. Cognates, lexical correspondences such as personal names, locations, and perhaps proper nouns, can often be identified in given bi-texts. Other elements, including numbers, acronyms, and typography (for example, bold and italics), are also useful elements for the system in establishing the link between ST and TT (Poibeau, 2017, p. 107). Importantly, these search techniques have little to do with linguistics (Poibeau, 2017, p. 99).

Given the automatic nature of this process, it is questionable whether the representativeness of the data and the quality of the sources chosen are reliable. There is no means of guaranteeing quality of bi-texts, except by maximizing the amount of data that is fed to the machine. However, as regards the relationship between quantity and quality, Poibeau (2017) stated the negative consequences of including a website with poor translation will be limited, because the accurate translations provided by a multitude of other websites will mean that the poor translation is statistically negligible, with little or no final influence. One perspective of particular importance to this study was also raised by Poibeau (2017, p. 110): that a literary translation that is unique and original will be discarded because, due to these very qualities, it will not be statistically significant among all the other translation possibilities. Nonetheless, this is not considered an issue for machine translation, which looks only for standard equivalents and does not aspire to originality.

Once the establishment of a corpus is completed, the search for an optimal target sentence from the set of all possible target sentences of a given ST is often referred to as 'decoding and word alignment' (Liu & Zhang, 2014, pp. 113-114). Cross-lingual alignment works reasonably well for pairs of similar languages, because the translation follows the structure of the ST and sentences are usually chained in the same way in the ST and TT (Leng, et al., 2019). However, for a pair of distant languages such as Chinese and English, which do not have similar lexica and syntax and do not share the same alphabets and language branch, errors occur during alignment. The language branch more commonly used by researchers in MT to determine distance language is based on the taxonomies of language families used in the annual *Ethnologue* publication (Paul et al., 2009).

When a mistake in one location spreads to the rest of the text, a global process, in addition to a sentence-by-sentence one, is required. One type of approach used is to find specific patterns in the source language and observe whether the same pattern can be found in the TL (Liu & Zhang, 2014).

The use of statistical calculation and probability estimation reduces the need for the manual input of linguistic rules. For this reason, hybrid methods, offering the benefits of both RBMT and SMT, can give better MT results (see section 2.3).

2.3 Hybrid Methods

Hybrid methods focuses on combining the best properties of two or more MT approaches (Costa-jussà & Fonollosa, 2014). Researchers such as Liu and Zhang (2014, p. 115) believe that almost all practical MT systems adopt hybrid approaches to some extent: for example, an RBMT model using statistical word segmentation or parsing, or an SMT approach utilising human-encoded rules to translate certain types of name entities such as time, date, numerical expressions and names of persons, locations, or organisations. The purpose of adopting a hybrid approach is achieve improved results for translation.

The two main types of hybrid systems are rule-based engines using statistical translation for post-processing and clean-up, and statistical systems guided by rule-based engines. One current dominant paradigm in the field of MT uses a combination of these two approaches, so that a system can be developed based on both lexical indices and sentence length. The hybrid approach aims to provide as many cues as possible between sentences to reinforce confidence when it comes to different local alignment (Poibeau, 2017, p. 108). This is important because, when two texts are being aligned, cognates are rarely sufficient. Nor is sentence length a defining feature, because it is likely that several consecutive sentences have similar length.

The hybrid systems reflect the usefulness of securing the benefits of a symbolic approach, drawing on dictionaries with very wide coverage and enabling transfer of rules between languages, with the benefits of recently developed statistical techniques. Rule-based systems remain dominant for rare languages where too few data are available to develop statistical systems. The adoption of a language model improves the fluency of the generated translation. Statistical information can be integrated in many different ways into systems that otherwise manipulate symbolic information. It is possible, according to Poibeau (2017, p. 108), to design modules in which dictionaries and rules can be made to dynamically adapt to certain domains, such as medical, legal and information technology.

The overall idea behind hybrid systems is to make full use of the richness of all the available resources, which usually are the result of years of research and development, while the statistical approaches improve the efficiency of translation work.

The overlap between RBMT and SMT can include deeper linguistic information at the syntactic and shallow semantic levels. The hybrid approach considers a large number of different linguistic features, including word forms, parts of speech, dependency relationships, syntactic phrases, named entities and semantic roles, and each of these are considered equally important (Ji, 2017, pp. 53-102), overcoming the disadvantage of focussing on only one or two of these linguistic features. For example, one approach in RBMT, the semantic approach, focuses on adding semantic features to syntactic structures, rather than having syntactic analysis as the chief component for other linguistics-based approaches. This type of approach makes semantic parsing the vital part of the system. Analysis of semantic features outweighs or complements linguistics features such as grammatical and lexical categories (Liu & Zhang, 2014, p. 110). Such an approach uses Schank's (1972, pp. 552-61) similar concept of conceptual dependencies, which represents an example of the resolution of ambiguities with reference to an extralinguistic knowledge base. Combined with linguistic analysis techniques, these approaches achieve better system performance (Liu & Zhang, 2014. p. 110). These opportunities for combining the benefits of statistical, rule-based and example-based approaches (Hutchins, 2011) are the fundamental reason why researchers are looking into the possibility of hybrid systems.

2.4 Neural machine translation (NMT)

Over the past decade, a new type of statistical learning called 'deep learning' or 'hierarchical learning' has emerged in the wake of advances in understanding of neural networks. 'Deep learning' refers to a subfield of machine learning based on artificial neural networks, which are algorithms originally inspired by the structure and function of the biological brain (Brownlee, 2020). Neurons transmit and process basic information, from which the brain can build complex concepts and ideas has witnessed rapid progress in recent years (Poibeau, 2017, p. 181). NMT (Bahdanau et al., 2015; Luong et al., 2015; Sutskever et al., 2014; Wu et al., 2016; Gehring et al., 2017; Vaswani et al., 2017), from novel model structure developments (Gehring et al., 2017; Vaswani et al., 2017) to achieving performance comparable to that of humans (Hassan et al., 2018).

In nearly all languages, a sentence is a linguistic unit that is syntactically and semantically autonomous (as opposed to a phrase or any other nonautonomous group of words) (Poibeau, 2017, p. 101). Natural language processing is often based on the notion of the sentence, particularly for MT, which generally operates sentence by sentence, each being considered independently from the others.

MT that adopts deep learning may require few manually specified elements. The best representation is usually automatically inferred from the data (Poibeau, 2017, pp. 183-184). The deep learning model bypasses the use of a group of predefined characteristics. Instead, it works on a very large group of examples to automatically extract the most relevant features, the process of which is what MT refers to. Such learning is considered hierarchical because it first starts with basic elements, such as characters or words of a language, to identify the next level of complex structures, such as sequences of words or phrases, until it obtains an overall analysis of the sentence. To draw an analogy with human perception: the process is similar to our brain simultaneously processing information. MT analyses groups of simple items and identifies higher-level characteristics while recognising complex forms from characteristic features and even extrapolating a complex representation from partial information (Poibeau, 2017, p. 183).

2.5 SMT vs NMT

Deep learning MT or NMT is different from SMT in that the former consist of only an encoder and a decoder; the encoder analyses the training data and the decoder automatically produces a translation according to its analysis of the data. Traditional statistical approaches use a combination of modules, while the encoder and decoder are based uniquely on a neural network. SMT systems can use different optimisation strategies with these different modules, which also manage information of different types simultaneously to ensure more reliable decision-making. When elements of words or phrases are put in richer context, this model works on a multidimensional basis, with context as the critical element. The hypothesis behind this approach is that words appearing in similar contexts may have a similar meaning. Words appearing in similar translational context will be identified and grouped into 'word embeddings'. This solves the problem of translating rare words by using other words appearing in similar context as valuable substitute translations. For polysemic words, the different embedding reflects different contexts of use, thus helping the system to make the appropriate choice.

In short, SMT has different modules managing various parts of a problem simultaneously; the deep learning approach to MT processes the whole sentence directly without decomposing it into smaller segments, and considers all types of relations in the context. These relations include vertical ones among groups of similar words filling a position in a sentence as well as horizontal ones among syntactically related groups of words in a sentence. Such an approach offers flexibility and cognitive interest. However, at the same time it also poses a great computational challenge.

The deep learning approach compares not only words, but also higher linguistic units such as phrases, sentences or groups of words, because similarity can often be found among words that strictly are not synonyms (Poibeau, 2017, pp. 185-188). This comparison process occurs in a continuous space, so the approach can be flexible and able to identify even paraphrase. During the analysis process, where identification and grouping occur, structure of the sentence, that is, relations between words or groups of words, will be discovered by the system. To do so, it will have been fed with thousands of examples during training so that it can 'observe' regularities, which makes the identification of relevant syntactic relations also a part of the automatic process for deep learning systems.

Such analysis, identification and extrapolation can help in deciding the context and genre of a text, but only when the marking features are sufficiently distinct or when enough training data are provided. It is important to be aware that that the machine is allowed to automatically infer, rather than being given manual specifications. However, in a literary text, the short-distance genre can change constantly and dynamically; for example, when a group of characters are talking, each may be given a unique characteristic or cultural and educational background. All these factors will make machine learning and processing more complicated and challenging.

It is also very important to note that the approach remains empirical, particularly in the definition of the architecture of the neural network used (for example, the number of layers in the neural network or the length of the vectors used) as well as other parameters (for example, the way unknown words are processed); there is little theoretical basis for these choices, which rely on system performance and efficiency. For this reason, these systems are sometimes criticised for lacking a theoretical foundation.

In has been shown that, for simple sentences, deep-learning based MT systems perform better than SMT (Poibeau, 2017, p. 187). However, traditional SMT outperforms NMT for more complex sentences. The Google MT team offers three explanations for this (Wu, et al., 2016). First, the complexity of neural networks makes the training of such systems difficult, particularly as regards the number of parameters that have to be automatically adjusted. Second, for unknown words that are not included in the training data, NMT systems lack robustness, and such words may be overlooked. Third, there are occasions when group words are not translated, which results in inaccurate, incomprehensible or nonsensical translation. Approaches to deep learning have yet solve the problem of unknown words. Poibeau (2017, pp. 189-194) suggested a solution that requires the decomposition of unknown words into smaller units to find relevant cues to help the translation process.

SMT has been the dominant paradigm in machine translation (MT) research for more than two decades, while deep NMT models have been radically improved across many translation tasks for four to five years (Ramesh, et al., 2021). The deployment of deep learning approaches has taken much less time than that needed for the statistical approach to dominate the market and supersede rule-based systems. This indicates that the deep learning approach is steadily and quickly moving forward to be robust and mature enough to outperform statistical approaches for most sentence types.

3. Literature Review

English is the universal international language for communication. Consequently, demand for translation is steadily increasing as the number of non-English-speaking Internet users increases (House, 2009, p. 80). Automated translation tools play a very important role in communication, because they address the needs of disadvantaged and less powerful non-English-speakers (Williams, 2013, p. 3). As Kenny (2001, p. 1) has put it, the translation process involves more than simply replacing a word in one language by a word in another; the type, purpose and readership of the text are also critical considerations. Translation can be considered 'a set of textual practices with which the writer and reader collude' (Bassnett, 1998, p. 39) and that subsets of individuals and institutions are constantly conversing about or disputing in both the source culture (SC) and the target culture (TC) (Susam-Sarajeva, 2006, p. 5). Furthermore, the non-monolithic nature of SC and TC require that the cultures of SL and TL also be considered. In regard to this, House (2009, p. 38) introduced the concept of 'culture filter', defining it as a means of capturing differences in culturally shared conventions of behaviour and communication, preferred rhetorical style and expectation norms in the source and target speech communities.

3.1 Current studies on machine translation

Studies in MT have aimed to support the goal of matching the quality of human translation. As such, they have addressed the challenges of different areas, such as text domain, varied length, style and complexity of SL sentences, and semantic interaction. Some studies focus on improving the system, whereas others take different approaches to improving translation quality.

Yoshimi (2001), who investigated pre-editing ST for improved translation quality, noted differences between texts with a distinctive style, for example, headlines of English news versus ordinary text. The computer system was given a pre-editing module to rewrite the headlines to assist the MT system in providing higher quality translation with minimal or no changes to existing parts of the system.

Jia et al. (2019) compared postediting NMT and phrasebased MT for translation of English to Chinese. Their study covered texts of simple to more complex structure and evaluated MT quality based on the accuracy and fluency of the translated texts. They showed that post-editing significantly reduces the technical and cognitive effort for translators, and that post-editing effort is necessarily correlated with ST complexity.

A study carried out by Banerjee et al. (2015) looked at the test and training data used for SMT systems, focussing on data selection and domain adaptation. This helps with the problem of poor translation quality caused by sparseness of in-domain parallel training data, by suggesting supplementary data from out-of-domain or general-domain bi-text to enhance system functionality. The improved relevance of selected data improves the SMT model and improved translation quality.

Another study done by a group of researchers involved comparative qualitative evaluation and error analysis of terminology translation in domain-specific MT such as phrase-based SMT (PB-SMT) (Haque et al., 2020), with a focus on legal terminology corpora. The findings of this study demonstrated that NMT outperforms PB-SMT. However, it contradicted some previous studies, in which PB-SMT was reported to have outperformed NMT in term translation (Beyer et al. 2017; Burchardt et al. 2017; Macketanz et al. 2017; Specia et al. 2017; Vintar 2018).

To achieve improved performance of unsupervised neural machine translation (NMT) (Artetxe et al., 2017b; Lample et al., 2017, 2018), which uses only monolingual sentences for translation, studies on unsupervised cross-lingual word alignment or sentence alignment have been carried out (Conneau et al., 2017; Artetxe et al., 2017a). NMT involves word embedding mapping (Artetxe et al., 2017b; Lample et al., 2017) and vocabulary sharing (Lample et al., 2018), while PB-SMT involves encoder–decoder weight sharing (Artetxe et al., 2017b; Lample et al., 2018) and adversarial training (Lample et al., 2017) are used for sentence alignment.

A recent study carried out by Su et al. (2021) explored semantic interaction where multi-modal NMT goes beyond the traditional encoder-decoder framework by incorporating spatial visual features. In addition to NMT models learning the semantic representations of text and image and producing two modalities of context vector for word prediction, the joint model with two modalities includes the feature of semantic interaction. Su et al. (2021) also showed that multi-modality models refine the context vectors and significantly improved the baseline of NMT.

3.2 Existing problems and solution strategies

Rao (2018, July 21) identified six areas of concern for current NMT systems: out-of-domain data, small datasets of input data, rare words, long sentences, alignments between SL and TL and quality control. Solution strategies have included stemming (see below) to translate unknown words and word context analysis to avoid errors of word-for-word translation and to clarify ambiguities (Poibeau, 2017, p. 55-65).

In stemming, if a word is unknown to a machine, which means it is not included in the dictionary embedded in the system, the MT system will remove letters successively from the end of the word until it finds a known word. This seemingly simple technique works well for English and continues to be the dominant method for search engines. Stemming enables the identification of pseudo-roots for words without having to perform an advanced morphological analysis. But its application in languages other than English is limited.

To avoid a word-for-word translation, the precise meaning can be decided by analysing the context of words. However, the size of the context to be taken into consideration differs according to the nature of the word and the genre and topic of the text. Ambiguity is the most pervasive problem in natural language processing, although most cases can be solved by examining the near context.

The approach of many research teams to solving word ambiguities has been to enrich the content of their partition vocabulary of their electronic dictionaries by domain, and gradually add multiword expressions. For example, the meaning of the word 'bank' in an environmental corpus will be different to that in a financial corpus. In this way, the storage of multiword expressions and consideration of the domain can help in resolving ambiguity.

Although studies on challenges of MT have covered various fields, research on literary text translation has been limited; the subject tends to focus more on productivity, and little is known about how MT copes with literary texts (Vieira, 2020, June 16). This study runs a preliminary investigation on results in MT of literary texts and of associated challenges.

3.3 Literary translation

The typology of translation distinguishes the following types: commercial translation, which is also called business translation, and concerns any documents translated within the world of business (Hatim & Munday, 2004, p. 112; 2019); legal translation, which concerns not only legal terminology but also differences between legal systems and cultures (Garzone, 2000, p. 395); technical translation, which involves texts from specialist fields such as science and mechanics (Lee-Jahnke, 1998, pp. 83-84); and literary translation, which applies to literary works, for example, of poetry or drama (Trujillo, 1999). Literary translation is inseparable from creativity (Zapała-Kraj, 2019). To keep the mode of expression of the ST and ensure publication, a literary translator must demonstrate an appreciation of and feeling for different styles, tones and nuances in both the SL and TL, thus recreating the mood of the original

(Finlay, 1975, p. 45). Instead of simply replacing words from one language with another, literary translation involves the intricate task of expressing the words of the writer in a way that express the original intention (Clifford, 2001, p. 7).

The complications of literary translation that translators must deal with include the nature of the texts, unspecified target audience, and interlingua and intercultural inequality (Kazakova, 2015). Handling these complications requires and establishes a relationship between the creative achievement of the writer and the creativity of the translator (Boase-Beier & Holman, 1999, p. 7). The translator strives to convey as much as possible of the ST, while processing the limitations of TT at the same time. The translator must first read and understand, and then write – an act of writing that can correct and enrich the original (Manguel, 2020). During this process, when facing the readers in the TL, the translator needs to consider the expectations and understanding of the readers, just as the writer would want from the readers in the SL.

Wills (1998, pp. 57-60) sees literary translation as an ambiguous, subjective and highly personal undertaking. They believe translators make their choices and decisions by constantly considering the purpose of the elements in the ST and how to ensure that the TT reflects the same purpose. A holistic view is necessary, so that the translators work on the translation not only at a microcontextual level, where they make choices in relation to syntax, lexicon, style, etc., but also at a macrocontextual level where decisions to adhere to overall strategies are made (Karimzadeh, et al., 2015). The translator's interpretation of stylistic and semantic features decides how the text as a whole is interpreted (Snell-Hornby, 2006, p. 24). Translators may adopt strategies from extremely foreignising to domestication in one piece of translation (Hervey & Higgins, 1995, pp. 19-20), because although prescriptive strategies work well on isolated linguistic and grammatical units, the translation of linguistic structures still requires the communicative and situational context to be considered (Snell-Hornby, 2006., pp. 24-25).

If the translator adopts a functional point of view, not only the meaning but also the style and form matter (Moruwamon, & Kolawole, 2007). But even when it is possible to translate the sense, it is not always possible to translate the form. As Hatim & Munday (2019, p. 10) explained, untranslatability occurs when form contributes to sense, which is most likely to happen in poetry, song, advertising, and punning, where sound, rhyme and double meanings can make full re-creation in TL very challenging. A good example of the form-content problem is the name of a character in J.K. Rowlings's *Harry Potter and the Chamber of Secrets*: 'Tom Marvolo Riddle'. The hidden clue 'I am Lord Voldemort' can be found if the readers shuffle the letters. in most cases, such creativity, labelling and representing done by the author is not possible to replicate in a different language.

As Tourniaire (1996) explained, for texts of all literary types, it depends on the reader whether an allusion the author uses is 'picked up'; it depends on the readers' educational level whether a scientific implication can be understood. Other linguistic characteristics, such as phonological elements, are themselves subject to lexical, syntactic, semantic and stylistic conventions, which creates more difficulties in the interpretation and translation of such texts. This explains the concept of 'thumbprint' introduced by Li (2017) in an investigation of translator subjectivity and its relation to a distortion or unintended interpretation of the SL. It has been found that a translator leaves a trace, the 'thumbprint', in all the work that he or she has done. The group of features in a translator's work establishes what can be considered as the translation style. These features are believed to arise from the translator's subconscious habitual use of language, independent of the ST.

In Skopos theory, the concept of translation shifts from being linguistically oriented to being functionally and socioculturally oriented (Prunc, 2003 in de Leon, 2008, p. 1; Schaffner, 1998, p. 235). Skopos theory regards a ST as an ‘offer of information’ that will eventually be simulated, as a whole or partially, into an offer of information in a TT by considering the target language and culture (Reiss & Vermeer 1991 in Sunwoo, 2007, P.2; Munday, 2008). The demand of fidelity is subordinate to the Skopos rule. For example, if the Skopos rule demands a change of function, intertextual coherence to the ST is no longer the required standard; rather, it will be subordinate to adequacy or appropriateness, or both (cf. Reiss & Vermeer, 1984, p. 39).

Under certain circumstances, in the interests of cultural adaptability, the translation text can become a derived version of a text departing so radically from the original (House, 2009, p. 25) – for example, in the translation of advertisements – that it is difficult to determine whether the derived text is a translation or a text that owes its existence to some other textual operation, such as paraphrasing, summarising or popularising an original text. Sometimes, the derivation is so significant that the work is so often viewed as going beyond the proper limits of translation and consequently making ‘the contours of translation, as the object of study ... steadily vaguer and more difficult to survey.’ (Koller, 1995 in Nord, 2012, p. 27). This may bring a translation product closer to an ‘adaptation’ rather than a ‘translation’ (Nord, 1997 in Green, 2012, p. 111; Schaffner, 1998, p. 237).

However, to Kazakova (2015), to consider literary translation as free rather than literal is a misconception, because some meanings in literary texts are very far from the dictionary or common grammar, and are perceived and interpreted when humans process the text for information. The meaning in a text brings not only information but also feeling, imagination and experiences to people. When achieving these effects, a text can be straightforward and simple, or ambiguous and complex. How the text is received, however, depends on the language of the text and on the readers. A literary work appeals to both sense and sensations, with the intention of troubling the reader or providing a form of catharsis.

3.3.1 Equivalence

Equivalence is defined by Shuttleworth & Cowie (1997, p. 49) as the nature and the extent of the relationship between SL and TL texts or smaller linguistic units. Palumbo (2009, p. 42) defined it more simply as 'the relationship existing between a translation and the original text.' In translation, appropriate equivalence, which transfers the meaning from ST into TT, has always been an issue of heated debate (Boushaba, 1988). Among the efforts from scholars to eschew the conflict between literal and free translation, an important one revolves around the issue of equivalence (Munday, 2012).

During the translation process, translators constantly strive for equivalence between ST and TT. In a bid to resolve the inherent 'fuzziness' of the concept of equivalence, scholars have introduced various definitions (Snell-Hornby, 1986, p. 16): for example, formal equivalence and dynamic equivalence (Nida, 1964; Hatim & Munday, 2019, pp. 41-44). These have included Koller and House's denotative, connotative, text-normative, pragmatic and formal equivalence (1979, p. 187ff., cf. also Koller, 1995; House, 2009, pp. 31-35) as well as Neubert's text-bound equivalence (1984). Many of those concepts have been used to compensate for non-equivalent translations on lower ranks, that is, at word or phrase level (Nord, 2005).

Literal translation can be a norm between two closely related languages in which the lexical and syntactic structures are almost identical, but such a literal translation is not so common when the language in question is more distant, like the language pair of English and Chinese (Hatim & Munday, 2019, pp. 10-14).

Formal equivalence is also understood as 'structural correspondence', where formal replacement of only the word or phrase in the SL by another in the TL takes place. For example, preservation of the ambiguity of an ST is one legitimate use of formal equivalence. However, formal equivalence should also be distinguished from 'literal translation', which tends to retain formal features almost by default, regardless of the context, meaning or the implication of a given utterance. The drawback of such literal translation is that it often fails to take one simple fact of language and translation into account: that not all text users are the same. Target audience and the purpose of the translation will decide whether a literalism is acceptable or not, even though turgid adherence to form and almost obsession with total accuracy still can be the case in the translation in all parts of our life (Hatim & Munday, 2019).

Formal equivalence is a context-driven approach of translation that translators adopt to preserve certain linguistic or rhetorical effects (Hatim & Munday, 2019, p. 42). It is an essential part of the stylistic approach to literary translation (Huang, 2011). The purpose of such adherence to form is to bring the target reader closer to the linguistic or cultural preferences of the ST. The more form-bound a meaning is, such as the case of ambiguity through word play, the more formal the equivalence relation will have to be, which will be a crucial aspect for MT to consider in literary text translation, given that there is a lack of such studies in MT research. Take an extreme case quoted by Venuti (1995, 215ff), for example; in Zukofsky and Zukofsky's translation of the Latin poetry of Catullus (ca. 74 B. C. E. /1969) the overriding goal of the translators was to reproduce as closely as possible the sound of the Latin original, even at the expense of meaning. As a result of this requirement for formal equivalence, Venuti (1995, 215ff) considered that the translation could hardly be considered English.

When formal equivalence proves unattainable, translators may seek other options, such as referential or denotative equivalence, in which the SL form is replaced by a TL form which refers to the same thing (Hatim & Munday, 2019, p. 50), or dynamic equivalence, where the 'relationship between receptor and message should be substantially the same as that which existed between the original receptors and the message' (Nida 1964, p. 159). However, considerations of linguistics, rhetoric and culture may still hinder faithful rendering of the text where dynamic or referential equivalence are not options. In such cases, translators will seek other types of equivalence until they are satisfied with the result.

According to Koller (1979, p. 100), the hardest problem in translation is connotative equivalence, which is the result of focusing on the connotations transmitted by means of word choice, with respect to level of style, the social and geographical dimensions, frequency, etc. Nida and Taber (1982, p. 91) consider that the connotative meaning can be understood as the emotional response evoked in the reader. The difficulty is to investigate or measure whether the translator's choice achieved the same or similar results as the ST intended.

As Hatim and Munday (2019, p. 43) pointed out, the choice of a certain type of equivalence is not an 'either–or' choice; the types are not absolute techniques, but general orientations for translators. The constant pursuit of equivalence aims to ensure the function of the original text is accessible to the readers of the translation to a different language with a different associated culture (House, 2009, p. 32). Whether such constant pursuit is part of the translation process of MT systems requires further investigation.

Besides the equivalence at the level of individual words and phrase, there is also a focus on meaning in broader contextual categories, such as culture and audience in both ST and TT. Human translators constantly encounter problems not present in the original writing: differences in linguistic code, cultural values, the world and how the text is perceived, its style and aesthetics all need to be reconciled and constitute limitations and constraints in translation (Hatim & Munday, 2019, p. 40).

When less experienced translators endeavour to deliver the meaning of every single word or phrase, the overemphasis on 'fidelity' to the original can result in odd-sounding TL (Landers, 2001, p. 54). There can be occasions when the readability of the translation is reduced to uphold fidelity to the source language and the culture (Landers, 2001, p. 52). Sometimes, to make sure the translation does not lead to odd perceptions, translators smooth out hindrances to readability, even when the original is odd. However, in such cases, cultural and academic considerations outweigh literary and aesthetic concerns, and distort the TL reader's perception of the author.

3.3.2 Creativity in literary text translation

The creative achievement of the writer and the creativity of the translator are at the centre of literary translation study (Boase-Beier & Holman, 1999, p. 7). O'Sullivan (2013, pp. 42-46) argues that creativity is an intrinsic part of the translating process. Creativity begets uniqueness, which leads to a lack of adequate bilingual and monolingual corpora from which MT can derive patterns or statistics for translation. The convention or norms of daily communication are not always applicable to literary text (Yousif, 2018). Also, there have been cases in which another form with the same meaning and that preserves the essential and non-arbitrary link between form and sense cannot be found (Jerrold, 1980, p. 1-41).

The language used in an original literary text will creatively deviate from standard language (Moniek & Frank, 2018). Translation can also be a form of deviation from the original as the standard. But the cultural context in which the TT is to be embedded will lead to varied perceptions of deviation (Boase-Beier & Holman, 1999). Researchers on literary translation, such as Kussmaul (1995, p. 39-53), Beylard-Ozeroff et al., (1998), Kemble & O'Sullivan (2006) and Perteghella & Loffred (2006), do not agree that translation is the subordinate activity 'in the light of creativity'. It is agreed that creativity is not something that can be taught, and that creativity is a spontaneous phenomenon (Boase-Beier, & Holman, 1999). According to Kant's 10 characteristics of creativity (1790/2000), there are no rules for creativity.

Boase-Beier & Holman (1999, p. 15) illustrated how different readers might interpret a writer's creative writing in different ways. Different readers' interpretations of the same text can be creatively varied according to their experience and cognitive ability. This is also the case for translators, because they also have the identity of reader. Translators may not necessarily realise it, but they cannot be free from unconscious and creative interpretation. Given their dual identity as reader and a writer, translators rewrite the ST after their own interpretation, which will also have an impact on the TL after the creative act of translation: for example, through borrowing and adaptation. Translation, in this aspect, acts as an agent for change, modifying and expanding perception, knowledge and language in the TC and bringing risks to the status quo (Hewson & Martin, 1997, p. 49).

When translators start the translating process after analysing the SL text, their identity or function changes from reader to writer because they produce their own version by delivering as much accurate information as possible in the TL environment, in a linguistically and culturally appropriate way. Their writing competence will be challenged as they deploy their translation skills and demonstrate their mastery of their own language. How a piece of translation will be approached and executed will be largely decided by a translator's personal preparation and training. Upbringing, education, knowledge, sensibilities, predilections and beliefs all contribute to the formation of the individual personality of the translator, limiting, defining and also facilitating the translation process, from the initial selection of the SL text right the way through to the final release into the world of its TL progeny (Hewson & Martin, 1997, p. 52).

In an example given by Boase-Beier & Holman (1999, p. 15), for the term 'dog-bark stillness' in a poem by Hughes (1983, p. 56), readers establish varied understanding of the relationship between 'dog-bark' and 'stillness', from the straightforward to the metaphorical.

3.3.3 Constraints

Writers are constrained by various factors, such as the medium through which their work can be presented to the readers and the broad context of their activity. During the transfer process from SL to TL, there are many constraints, including culture, history, genre and linguistic conventions (de Saussure, 1916, p. 8). The translator is subject to both the present model of the SL text and the TL text which operates in the context realised under limitations. Translators need to be informed and literary critics sensitive to not only the SL text itself, but also the linguistic and cultural environment to which the text was exposed (Boase-Beier & Holman, 1999, pp. 7-8): only when translator understands the TL audience and is aware of their expectations will he or she be able to understand the concern of the writer to earn acceptance and approval from their readers. In order to deliver what was meant to be delivered by the SL text, the translator needs to be able to identify whether the SL represents a particular type of genre or whether it is typical or unique for its time. Thus, constraints on translators are not only cultural, linguistic and political, but also genre-determined, stylistic, historical, philosophical, psychological and pragmatic, which all play a critical part in the creative achievement of translators (Boase-Beier & Holman, 1999, p. 8).

3.3.4 Cultural, spatial, and temporal elements

According to Nida and Taber, ‘Anything which can be said in one language can be said in another, unless the form is an essential element of the message’ (Nida & Taber, 1969, p. 4). Dynamic equivalence is a result of this view of translatability and comprehensibility. But what about that which exist, as opposed to merely ‘be said’, in one culture or time which does not exist in another? For example, to translate a text from ancient China that predates other cultures, languages or civilisations, would establishing equivalence in English be possible or justified? Skopos rules will decide whether translators should view such a text through our modern eyes or whether they should consider the particular social circumstances at the time of writing. It is quite unlikely that a translator's linguistic and cultural competence is the same as those of the audience and the writer of the SL (Nida, 1964). All of these factors have a bearing on the final decision that a translator makes.

In addition, there are occasions where informational components cannot be rendered. For example, once the style, vocabulary or grammar go beyond readers' linguistic competence, the text becomes overburdened with information, and is unable to achieve the intended effect. Poetry (sophisticated style), refined essays (sophisticated grammar) or popular science (sophisticated terminology) are all examples of this. But it should be born in mind that sometimes the stylistic elements are as important as the logical meaning of the message, thus requiring extra effort from the translator. Texts representing personal symbols can also be very complex and require an analysis of not only the text of concern but also the writer's entire oeuvre (Boase-Beier & Holman, 1999).

3.3.5 Summary

In summary, the type of translation determines what type of equivalence translators should adopt. Intercultural communication also differs between an overt translation and covert translation. The former leaves the original sociocultural frame as intact as possible, while the latter adapts the ST to the communicative norms of the target culture. In overt translation, intercultural transfer is explicitly present and so likely to be perceived by recipients, whereas covert translation is intended to function as if it were not a translation. The original text and its covert translation do not have to be equivalent at the levels of text and register, but they should be equivalent at the levels of genre and the individual text's functional profile (House, 2009, p. 38).

Equivalence is not an 'either/or' choice, nor does it follow a linear relationship. Equivalence relations are characterised by a 'double-linkage' to ST and the communicative conditions of the recipient's side (Hatim & Munday, 2019, pp. 49-50). As Eugene Eoyang (1993) claimed, ‘Art in translation is what hides art.’ In fact, simple and inevitable expressions in one language can be difficult to render in another language if the same level of simplicity is to be maintained. The art of translation lies in ensuring that the difficulties a translator has during the translation process are kept behind the scenes rather than being reflected in the translation.

3.4 Challenges to machine translation

The divergence between human translation (HT) and MT lies where creativity is confronted by rules, probabilities and statistics. Researchers such as Baker (1998) believed that what hinders machines from delivering a ready-for-use translation are semantic problems and the sociocultural constraints in translation. Shei (2002) identified limitations in structural, lexico-semantic, idiomatic, cultural and reorganisation aspects in his study of pre-editing (by humans) for MT. Over the past two decades, due both to the significant increase in available language data for the establishment of both parallel and monolingual corpora and to the development of information technology, machine training and learning have taken MT quality to a new, higher level (Abdul-Rauf & Holger, 2009).

In the fields of both literary and non-literary translation, translators’ retrospection and empirical, onscreen experiments have shown that, time permitting, translators usually return repeatedly to their translation, frequently switching their decisions in the light of later ones and in the light of further reflection, (Shih, 2015; Göpferich et al., 2009). Given that automatic MT systems aim to provide real-time translation (*SummaLinguae*, 2020, January 01), it is questionable whether MT system can perform the same constant revision and self-correction. In the text analysis carried out in the later part of this study, the lack of translation consistency in MT also reflects this lack of revision and self-correction, and the area is identified as one requiring further investigation.

Translators also function as a rewriters in the act of translation, because they determine the implied meaning of the TL text before redetermining the meaning of the SL text via the act of rewriting (Álvarez & Vidal, 1996). It is to be borne in mind, though, as Pound (1934) once claimed, that no single language is capable of expressing everything that humans could comprehend. Therefore, creativity is harnessed to find the most appropriate and acceptable equivalence in two languages. During the translation process, in the struggle to find a way to deliver the meaning in the TL, the translator will usually have to think 'out of the box' and break free of constraints such as form, culture or even the type of the ST. MT, however, relies on data and statistics interpreted after training and analysis. Anything that is not considered in specific rules or algorithms is unlikely to be captured, which limits machines' capability of thinking out of the box. In effect, the ST and the built-in data or corpora restrict MT, because the logic being used may restrict the kinds of expressions that are allowed (Cok, 2013).

3.4.1 Corpora

A corpus was defined as a collection of texts, selected and compiled according to specific criteria (House, 2009). These texts can be held in an electronic format, which allows analysis from different aspects and for different purposes. A corpus approach allows a focus on the combination of lexical, syntactic and discoursal features, while it is possible to compare a large number of translations into different languages by different translators in different sociocultural settings and across different time frames.

If a corpus consists of text from only one language, it is referred to as a monolingual corpus. A corpus with texts in multiple languages is referred to as a multilingual corpus. In multilingual corpora, parallel corpora and comparable corpora are distinguished.

Parallel corpora contain native language (L1) source texts and their (L2) translations (McEnery & Hardie, 2012). With parallel corpora, the type of routine translation shifts can be identified after comparison between lexical or syntactic structures in both ST and TT (St

John, 2001). For human translators, a search can be run through the corpus for a word or phrase, the results of which will yield all occurrences (or a selection of them) with the surrounding text displayed on a line.

Usually, two parallel texts will have been 'aligned' before the data can be extracted. 'Being aligned' that means units of text in one language have been linked with units of text in the other language. The benefits of having an aligned corpus are that translation effects can be precisely located and generalisations about the translation-related difficulties for a specific language pair can be derived (House, 2009).

A comparable corpus is a set of texts in two or more languages on the same topic, but which are not translations of one another (Delpech, 2014). Typically, a comparable corpus contains components in two or more languages that have been collected using the same sampling method, for example, the same proportions of texts of the same genres in the same domains and in a range of different languages over the same sampling period.

Newmark (2003, p. 96) coined the term 'translatorese' to mean the automatic choice of the most common 'dictionary translation' of a word when a less frequently used alternative would be more appropriate. Such cases represent the 'lifeless' form of the TL that homogenises different ST authors, and which is not uncommon in the absence of a parallel corpus. A comparable corpus can be used to established whether certain patterns are either restricted to translation or occur with different frequency in them (House, 2009, pp. 77-79).

Recent progress with corpus-based approaches in MT have followed suggestions by Baker (1992) to investigate universals using larger corpora (electronic databases of texts) in an attempt to avoid the anecdotal findings of small-scale studies. Corpora consisting of millions of aligned sentences are nowadays commonplace (Poibeau, 2017, p. 166).

The establishment of monolingual corpora in the TL allows MT to reflect the historical development of target culture literary norms. With the help of comparable or parallel corpora, the changeable nature of translation over time and across cultures can also be identified, because texts can be continually renewed in conformity with different cultural norms (House, 2009, p. 25). Whilst human translators are stranded in a certain segment of social and economic history, machines can easily study different translations of one source text across time and space on a broader spectrum. It has been shown (Poibeau, 2017, p. 178) that statistical analysis realises a direct modelling of polysemy, idioms and frozen expression without a predefined linguistic theory. The representation extracted from a statistical analysis can be more appropriate and cognitively more plausible than the result of a formal approach. Given that ambiguity and polysemy are related to usage and context, a statistical approach helps in understanding the relevant context and in better selecting the meaning.

3.4.2 Challenges of corpora

When the translation is specifically targeted at a certain group of recipients or when the translation has a specific, narrow purpose, for example, advertisement, an approach of pragmatic equivalence will better fulfil the special communicative function. Pragmatic equivalence is concerned with the way words and phrases are used in communicative situations and the way they are interpreted in context. It is very important to translate the mood and feel that are expressed in the source text (Aruna, 2018). That is why, from what people can see on TV, on billboards and on their mobile phones, translation in such fields offers limited or minimal reference to daily communication (House, 2009). Such genres require different identification and realisation in ST and TT, following the linguistic and textual norms of usage that characterise them (Koller, 1979; House, 2009). Domain adaptation, which concerns genres of texts for MT, particularly in literary translation, has already been tested by researchers working on translation of novels (Toral & Way, 2015).

However, there is still a lack of automatic domain adaptation for the MT systems, that is, adaptation without manual narrowing or selection of certain domain.

Koehn (2009) proposed that when the SMT retains a simple view of language, the system usually analyses texts to break them into shorter structures such as words, phrases or short sentences. Subsequently, the machine pairs such structures with those from the corpus. From the linguistics aspect, in languages characterised by rich inflectional morphology, such as Chinese, without spaces to separate the words, the definition of what constitutes a word is less clear. To identify and categorise the words based on parts of speech (for example, noun, verb, adjective) or their meaning can be difficult, resulting in a need for a large vocabulary in the corpus.

A parallel corpus can usually provide a training environment for the MT system, so that parameters can be set (Liu & Zhang, 2014, p. 109). A translation can be generated by several specific models guided under a certain framework. In such doing the translation can be used in these models to calculate probability in different aspects. Translation models and language models are the most important models in SMT. The former deals with realising equivalence between ST and TT, while the latter makes sure the translation is accurate and appropriated in the TL.

Poibeau (2017) has questioned the possibility of the statistical approach of translation simply by putting together sequences of words extracted from very large bilingual corpora. It has been shown that sentence alignment works better for language pairs of closer proximity. This is because these languages share a similar linguistic structure, as a result of which translational equivalents at word or segment levels obtain better results. But the question remains of what impact will there be on MT performance SL is genetically distant from the TT.

Using statistical methods, a significant number of phenomena of high frequency and importance can be processed, and a better result can be achieved. This applies to the search for translation at word level, control of local ambiguities, and the relative contribution of different linguistic constraints when they seem to contradict one another, etc. However, on the other hand, the statistical systems fall short on complex analysis of linguistic phenomena. The key challenge is how to define or characterize the notion of 'context'. Does the usage in a large corpus decide the differentiated meaning of a given word? Can machines extract a usage pattern from the corpus? New research has proved that lexical meaning (the meaning of words) is formalised, but the meaning of sentences and relations between sentences, known as the propositional semantics, remains a problem to be resolved (Poibeau, 2017, pp. 175-177).

Polysemy was seen from the beginning as one of the major problems. Once the MT system is able to establish the context within which such words occur, it becomes easier to clarify their meanings.

Machines and humans respond differently to situations where a translation is almost impossible. Pressured by factors such as clients and market, a human translator will have to come up with a solution, while MT, when it is not able to pair with anything in its corpus, often generates a non-translated part. Thus, in sentence alignment, different strategies are devised to limit the problem of cascading misalignment. One consists of aiming to locate homogeneous texts or text portions. Nowadays, most texts can be retrieved from the Internet, and those containing HTML or tags can also be used for text alignment. However, the challenge is that whether the texts retrieved from the Internet are of sufficient quality to serve as translation and language models.

It has also been shown in current practice that there are more non-fiction types that introduce personal judgement than those that contain merely logically proved concepts or ideas. If emotive information is missing or distorted in the translation, the result can be shifting or replacement of the emphasis or the concept (Boase-Beier & Holman, 1999). If corpora cannot be regularly updated to reflect the changes of language usage, it will be difficult for the system to deliver an accurate and appropriate translation.

Additionally, under the pressure of the cost- and profit-driven market, designers or owners of machine translation systems are not sharing their established corpora. Rather, their corpora has become what enhances their competitiveness in the market. Even though corpus-sharing would create a larger resource, covering more comprehensive language use in both the source and target languages, it is currently unrealistic.

Machines derive from statistics and patterns a collection or a combination of results of translators' constraining and enabling filter identities. Whether this can provide good and sufficient reference for the translation of the TL when it comes to realising equivalence, regardless of the form, remains an area requiring further investigation. In the process of calculating statistics from data, the creative process of literary translation done by previous translators may or may not be taken into account by the machine. Such uncertainty and insignificance of data may be the reason that MT is unable to provide satisfactory results in literary text translation.

3.4.3 Comprehensibility and Translatability

Before a human translator starts a translation, the first step is to comprehend and interpret the text. According to Sperber and Wilson (1986), understanding is constructed based on one's personal knowledge and cognition. When it comes to the interpretation of a word or phrase, a translator needs to identify not only the explicit assumption, but also the contextual effects of this assumption, which is often made according to a certain context defined by previous comprehension (House, 2009, p. 75). Contextual effect is at an essential element of the comprehension process. When a written text is transferred from SL to TL, cognitive, linguistic, visual, cultural and ideological phenomena will always play an integral part.

In most cases, readers of translations are not in a position to compare ST and TT. They can only assume that the language of the translator is identical to and coincides with the language of the original. But all translation is a type of manipulation or (mis)representation by the translator (Boase-Beier & Holman, 1999). The translator acts as a reader first, to disambiguate the potential senses of the ST, before identifying the appropriate TL equivalent (Hatim & Munday, 2019).

The challenge and difficulty in literary translation stem mainly from the fact that literary texts abound in essentially elusive connotations. As House (2009, p. 40) put it, there is no direct correlation between language, thought and reality, rather, the three are in continual dynamic interaction with each other. But, in the face of creativity, language or the users of languages are all free. When individuals adopt certain expressions, associations, referred to as private connotations, are established via the link between these expressions and their emotions. These private connotations defy explicit definitions and vary within one person's mind, according to different mood and experience, which make matters more complicated. To help the translators reduce the burden of interpreting such connotation, Kenny (2001) raised the importance of classifying contexts of situation in literary translation. However, classifying contexts of situation is one problem; abstracting from actual experience is another. Comprehensibility and translatability are limited when language departs from its 'normal' communicative function. For example, in poetry, the linguistic form is an essential element of the text because the meaning and form are inseparable. In this case, paraphrases, commentaries, explanations, coining or borrowing of new words and phrases are not sufficient in literary translation, even though they probably would suffice in translation of other genres (House, 2009).

Roman Jakobson's (1959, p. 238) claim that 'all cognitive experience and its classification can be conveyed in any existing language' expressed a classical dichotomy in translation between sense and content on one hand and form and style on the other (Hatim & Munday, 2019, p. 10). But this dichotomy fails to take into consideration the temporal and cultural elements or the varied targeted audience. For example, translators will be challenged to produce a justified rendition of a document written thousands of years ago by an emperor of a dynasty of China to his ministers and chancellors about a policy response to a particular event at that particular time using a unique way of expression. Who are the targeted readers of such a translation? How do we assess and justify whether the interpretation is correct, given that the interpreter cannot verify the initial intention of the author? Will the meaning conveyed make sense to readers from those countries which didn't have a history or civilization formed at that time? Can a generic understanding of the original text be achieved via the use of a currently existing language?

Nonetheless, translatability is still a relative notion. Despite differences in linguistic structures such as grammar and morphological forms, meaning can still be expressed across languages (Hatim & Munday, 2019, p. 14). For various types of texts, translators consider both the diverse range of readers and the purposes of translation. Thus, there is often a need for a certain level of ST explication and adjustment. Once a form of words does not appear to be transparent enough to the translator, the latter authors consider that such lack of transparency will produce unintended and unmotivated opaqueness, posing a potential risk to comprehensibility. Translator intervention then becomes necessary, in which the translator might renounce preservation of the form and resort to a different type of equivalence (Hatim & Munday, 2019, p. 43).

This fluidity shown by human translators in switching between different forms of equivalence is not an explicit part of algorithms for MT. Machines are trained based on corpora, which consist of previous choices. They skip the process of juggling with options, instead selecting the most likely or probable choice in the language that human use. The option for varying degrees of dynamic equivalence by human translators is based on their judgement that form is not significantly involved in conveying a particular meaning or when it is impossible or unnecessary for formal rendering. Dynamic equivalence is sought after human translators exhaust formal possibilities for rendering the intended effect. But for machines, the question is whether there is enough training data for machines to evaluate whether such choices made by previous human translators are the most appropriate and accurate: does high frequency of usage guarantee quality? Dynamic equivalence makes it possible for human translators to cater for a wide variety of contextual values and effects carried within texts. However, because it is dynamic, it is hard to establish a correlation for the machine, either for training or for translation.

In situations of poetic ambiguity and cryptic concision, the translator may need to know whether an author had any overriding aim, or a hierarchy of interlocking aims that need to be observed and preserved in the translation. They may have the option of consulting the writer, but not usually. For machines, such clarification and amendment can only happen in a manual post-editing stage – if, and only if, a human translator is engaged to proofread and make necessary changes to the finished MT.

Even if an exact match does not exist and something is impossible to translate, if a text has been submitted to MT to be translated, entities in the SL will have to be mapped on to entities in the TL. Several dimensions define the translation decisions. They include, but are not limited to, temporal, spatial, and cultural ones, within which a match is sought' (Boase-Beier & Holman, 1999).

There are always situations where the connotation of the ST cannot be conveyed to the audience in TL in the same way it was conveyed to the audience in SL. An example is a joke told by an English-speaking primary student: Why is 6 scared of 7? Because 7 ate (8) 9. The sound of number 8 is the same as the sound of the past tense of the verb 'eat', therefore creating the ambiguous meaning of the number 7 'eating' the number 9 when children are reading the three numbers of 7, 8, and 9 together. The creative use of sound leads to the funny effect, which cannot be maintained when the numbers are translated into Chinese, simply because the sound which is the root cause of the effect will be lost in a different language that uses different phonetic systems.

When compromises are necessary, decisions vary at different times. A solution is usually a reflection of the translator's individual assessment of the respective perception of SL and TL audiences. In order not to offend potential readers, a translator or the publisher may sometimes have to decide to what extent they can make changes to the original.

3.4.4 Linguistic knowledge and proficiency

Another aspect that might be overlooked due to the growing dependence on statistics is whether programmers or coders of MT algorithms have sufficient linguistic knowledge. In an example quoted by Yu & Bai (2014, p. 192), a subtle linguistic issue was noticed in the ST example:

他像个被破获的扒手。(He looks like a captured pickpocket).

The Chinese verb '破获' means 'solve' in English and usually co-occurs with the noun '案件', meaning 'a case'. However, in this translation, the verb was accompanied by the noun '扒手', meaning 'a pickpocket or thief', which can be considered as linguistically incorrect. There are similar linguistic rules in English, for example, the verb 'solve' cannot have 'a thief' as direct object, whereas 'a case' is feasible. The English translation is accurate and appropriate; however, the issue in the ST is not reflected. An advantage of having machines make decisions based on statistics is that the programmer who designs the system need not be a linguist. However, during the process of establishing a corpus, a lack of quality control of language usage may cause the system to be fed with terms and expressions that do not meet linguistic standards. If the purpose of the example text was to reveal the language issue in current expression, the statistical representation of such mismatch in English is so small that it did not become an option for the machine. Thus, this characteristic of the SL is lost.

3.4.5

Computational ability

As pointed out by Stambolieva (2015), the principal obstacle to the success of rule-based translation tasks is the first part: the formulation by one or more humans of a working set of instructions, of the ‘instruction book’ type, which would include an algorithm for correct parsing and generation at the levels of morphology, syntax, semantics and pragmatics, and which would consider context, world knowledge and the culture of the speaker or hearer.

In SMT, machines do not work on rules, but on statistics drawn from corpora (both bilingual and monolingual), because continuous representations for words are able to capture their morphological, syntactic and semantic similarity (Collobert & Weston, 2008). As Quigley (2010) pointed out ′… Once the computer finds a pattern, it can use this pattern to translate similar texts in the future. When you repeat this process billions of times you end up with billions of patterns and one very smart computer program. For some languages however we have fewer translated documents available and therefore fewer patterns that our software has detected. This is why our translation quality will vary by language and language pair.’ Many translation corpora rely on easily available published texts and their translations, because the construction of a parallel corpus depends on the availability of texts and their translations. A goal of compiling a perfectly balanced bidirectional corpus is difficult, because of the lack of balance between translated texts between two languages in equal quantities. In most cases, the nature and range of texts translated in the two directions may differ greatly in different language pairs (House, 2009, p. 77).

Koehn (2009) considered that, faced with the richness and complexity of language, it is impossible to fully analyse language and distil it into a set of rules to be encoded into a computer program.

When working on a translation job, the first decision a translator has to make is whether the text calls for a ‘normal’ translation or whether it requires adaptation. Words can belong to various registers under different contexts. Only a careful perusal of the entire text can answer this question (Landers, 2001). However, non-commercial (free) machine translation tools usually set a maximum word count, for example, 5000 words for Youdao.dict users. As the present study did not use commercial machine translation engines, it was hard to test whether a machine translation tool can be fed with a complete novel and how long it would take the machine to finish processing the whole book and render a translation.

Also, forms of texts are evolving. There has seen a significant growth in online novels, which are updated more frequently than formal publications. From a reader's point of view, readers in the TL wish for the same instant reading experience that the readers in the SL expect. There are numerous machine translation sites for novels aimed at meeting this demand (for example, Dragneelclub.com). Online novels are automatically translated by online MT systems while the authors are still writing and uploading the novels, so confusing lexical and grammatical problems are quite common. For machine translation system designers, there are more divergent options available for algorithms, models and approaches, which also indicate that there will not be a universal system for all types of literary texts.

For the translation between English and a language that is structurally different to English, a hybrid system integrating a statistical component with advanced linguistic modules that take language specificities into account may be more optimal. For morphologically rich languages – that is, languages from which many different surface forms can be generated from one basic linguistic form, language-specific modules dealing with morphology issues are used to improve the performance of natural language processing systems.

When Google struggled to find the equivalent expression in Italian of the English phrase 'It's raining cats and dogs', it opted for a word-for-word translation, the result of which was poetic but not accurate. But Google has been constantly updating its system to attempt to tackle the problem of frozen and multiword expressions because it is recognised that these are not suitable for literal translation (Poibeau, 2017, pp. 165-168).

Some of the algorithms used for today's deep learning approaches were developed as early as the 1980s, but the computing power at that time was insufficient to support their use, thus limited the adoption of deep learning in the field of SMT (Poibeau, 2017, p. 170).

How human translators understand and interpret, as well as their strategies to solve problems and make decisions, are still being studied. Statistical machine translation uses the end product of such processes, bypassing the step of establishing how a human brain functions to arrive at the product (House, 2009, p. 76). Currently, it is hoped that the study of natural language processing will one day enable machines to replicate the human mental processes.

3.4.6 Evaluation

Differences in evaluation between HT and MT are also of interest to researchers. Evaluation differs between HT and MT in that, even with an evaluation program in place, the evaluation of a MT system focuses on the performance and function of the MT, rather than the translation product itself.

3.4.6.1 HT Evaluation

Although the evaluation of translation quality is difficult to verify empirically, House (2009, p. 43) proposes three evaluation criteria: general efficiency of the communication process, comprehension of intent and equivalence of response. House believes that human translation quality depends on whether the translation has conveyed the temperament of the writer of the SL and on the readers' potential interpretation. Translation evaluation cannot depart from the intended effect of the text. If a translation can achieve the same effect on its recipients in the TL as the original would have in the recipients in the SL, it is considered a good one.

During translation, evaluation is present behind every utterance and is constantly happening. The choice made by translators will reflect and indicate their ideology and values as well as those of the authors (Munday, 2012). Translation choices are drawn from a group of competing equivalents. The preferred equivalent types are not immutable; rather, the translators may aim for varied types of equivalents to realize the intended meaning. This process of evaluation is constant and multidimensional (Halliday, 1978).

The translators bring cultural relevance to the original, because human beings perceive texts through a cultural filter. For readers, interpretation of a text is more than simple deciphering of the constituent sentences (House, 2009). Each translator is under the impact of their own personal preferences and personalities. The decisions and compromises they make in terms of faithfulness and freedom vary (Boase-Beier & Holman, 1999), as does the evaluation.

Frequently, translations are judged to be successful based on the degree to which they 'don't read like a translation.' This seems to be the only most important aspect for the majority of readers, while the view among translators may be less uniform (Landers, 2001). People may rightfully question who may want to read prose that has a heavy imprint of foreign grammar, idiom, or syntax, other than scholars. And the answer might be: Does fewer mean negligible? And there can never be a justified answer to that.

3.4.6.2 Machine Evaluation and Training

The evaluation process for MT systems is not aimed solely at assessing per se, but is also a vital step in machine learning and system improvement. The process for training of MT systems is similar to the training that a human translator would receive in order to reach a higher standard of work. MT evaluation can usually operate in the combined form of an automatic embedded program coupled with manual post-editing by human translators of the translation done by MT systems. The latter can be done during or after translation. A very fundamental difference between MT evaluation and human evaluation is that MT evaluation focuses on the function of the MT system (that is, the performance of the system) rather than the translation product itself (Maučec & Donaj, 2019).

Parallel corpora are used for evaluating and training the translation model for MT. As parallel corpora are considered by theorists such as Delpech (2014) as a collection of unnatural ways of expression, access to monolingual corpora is usually facilitated for the process of evaluating or training the language models (Liu & Zhang, 2014, p. 109). The key to the training and evaluation process for SMT translation engines is a very large volume of both bilingual corpora (source texts and their translations) and monolingual corpora (either texts in the SL or texts in the TL). To build a translation model, the system looks for statistical correlations between source texts and its translations, both for entire segments and for shorter phrases within each segment. Scores can then be generated for the probability of a given ST mapping to a translation (Bussey, 2020). Increasingly, developers hold yearly evaluation conferences, during which measurement on the progress of systems is carried out. Fierce competition and short time frames are challenging developers, as there does not seem to be sufficient time for them to reflect on current and previous status.

4. Research questions and methodology

4.1 Research questions

This study explores two research questions:

Research question 1: What are some of the challenges that MT systems face in literary texts translation?

Research question 2: Can equivalence be established by MT in literary text translation?

4.2 Methodology

4.2.1 Qualitative method and text analysis

The aim of this study is to reveal and analyse the areas of literary text translation with which MT is currently struggling or with which it will struggle in the future.

A qualitative method is adopted for this study, using deliberate sampling strategies rather than random ones (Busetto et al., 2020). With purposive sampling, sampled units are predefined – in the case of this study, the types of texts selected for this study were based on relevance, previous experience, or theory (Russell & Gregory, 2003; Jansen, 2007). A qualitative method suits this study because it investigates the chosen subjects, that is, literary texts for translation, and looks at their 'quality, different manifestations, the context in which they appear or the perspective from which they can be perceived' (Philipsen & Vernooij-Dasen, 2007). In other words, this study involves data in the form of words rather than numbers (Punch, 2013). Document study is also an essential part of this study, which the written materials are first reviewed (Russel & Gregory, 2003), before performing text analysis (sampling, analysis and interpretation) (Fossey et al., 2002).

The conceptual part of this study is based on an effort to link concepts in literary translation by human translators with the process of literary translation in MT, as well as how these concepts form into larger systems (Williams & Chesterman, 2002, p. 58). The empirical part seeks new information derived from textual analysis.

Following selection of the literary text samples and their translations by different MT systems, lexical and textual analysis were carried out of translation outcomes in the language pair of Chinese and English, as well as to compare their natural language forms to their translation form. The analysis followed a procedure proposed by Keshavarz (2011, p. 14): first, selection of specific features to analyse; second, identification of relevant devices and characteristics in literary text translation; third, comparison of work across different MT systems; four, explanation of the identified issues.

4.2.2 Selection of sample texts

Samples were selected from a broad definition of literary texts which represent certain characteristics of texts in this domain, such as temporal and cultural uniqueness, creativity, etc. in the ST. The purpose is to illustrate how translators can be challenged by ambiguities in languages and different cultures. The challenge in common to this type of translation is that all these texts require the translator, whether human or not, to have a certain degree of creativity in the translating process if an equivalent relationship is to be established.

The text analysis in this study agrees with the notion that semantic and syntactic features of texts are subordinate to the communicative function (Nord, 2005, p. 41). A contextualized qualitative translation analysis (House, 2009) and comparison of the chosen examples will look at both the syntactic features of the text as well as the semantic meaning. The predominant step of the text analysis in this study is to identify the communicative situation for the ST. The sample analysis covers factors such as sender, sender's intention, audience, place of communication, time of communication, motive of communication, text function (and genre), text composition and sentence structure (Nord, 2005).

4.2.3 Selection of machine translation platforms

The MT platforms used for text analysis for this study are Google Translate, DeepL Translator and Youdao Translate, all of which claim to have adopted NMT systems. Among the various MT platforms offering free service to online users, it is possible that the hybrid approach of adopting both RBMT and SMT are still in use in specific fields between short-distance language pairs, such as English and French. However, because of the limited scope and resources available for this study, only the free translation services of these MT platforms were selected for the study. DeepL and Youdao Translate also offer fee-paying service, but the questions of whether these services function differently and whether there is a quality variation between the free service and the fee-paying service are beyond the scope of this study.

5. Textual analysis and overall implications

5.1 Analysis of sample translation of literary texts

5.1.1 Context and the Genre of ST

An important concept in translation is the unit of translation, sometimes called the lexicological unit or the unit of thought, which refers to 'linguistic level at which ST is recodified in TL' (Shuttleworth & Cowie, 1997, p. 192; Beaugrande, 1978). The unit of thought may comprise an individual word, phrase, clause, sentence or even the whole text (Hatim & Munday, 2019, p. 17). To Vinay and Darbelnet (1958/1995, p. 21), the unit is identified as the smallest segment of the utterance. They are linked in such a way that, if translated individually, the meaning that these grouped lexical elements aim at will be lost. The meaning of the unit of translation can vary, depending on the context or among different genres. This is illustrated by dictionary entries, in which, next to each individual narration, there are discriminators describing or summarizing the main use, field or collocation of each translation equivalent. This demonstrates how the translation unit is not fixed to an individual word across languages. Rather, it depends on the semantic meaning of a word or group of words.

In most situations of literary text translation, the sentences cannot be dealt with in isolation. Thus, it is important to establish the context by first identifying the authorial voice. When a translator decides the correct register for a given expression, they need to consider questions such as the following: Does the point of view stay unchanged throughout the whole text? Is the tone informal or formal? Are there any shifts? Even a single word in the wrong register may have a disturbing effect. An identified context to clarify ambiguity for both human translators and MT.

5.1.1.1 Example 1

Example 1 (Table 1) is a remark by a person to his friend in a different country It is intended to produce a humorous and sarcastic effect.

Table 1. **Textual analysis, Example 1**

Source text:	你们那里快完了吗？ 我们是快完了。
Literal translation to English:	You there soon finish? We are soon finish.
Intended meaning:	Has it come to an end over there? We are doomed.
Google[a]:	Are you almost done there? We are almost done.
DeepL[b]:	Are you almost done there? We're almost done.
Youdao[c]:	Are you almost done there? We are almost done.

[a]Accessed 11:09am, 6 March 2021; [b]accessed 11:02am, 6 March 2021; [c]accessed 10:57am, 6 March 2021

The sentence '你们那里快完了吗？ 我们是快完了。' can occur in multiple situations:

1. Person A is asking about person B's progress, for example, on Person B's assignment or work project, to find out whether it is going to be completed soon.
2. Person A and Person B are both threatened by the same danger, for example, a flood. Person A believes herself or himself to be helpless, and is asking Person B whether he or she is in the same position.
3. Person A is asking Person B about the situation where Person B lives. Person A is now in a bad situation, while, for Person B, the same bad situation has almost passed.

The context of this dialogue is as follows: the sample sentence is extracted from a short conversation between two friends, one based in China and one in Italy during the COVID-19 pandemic. Their conversation takes place when the situation in China is under control while the situation in Italy is getting out of control.

Because of the absence of previous communication, the systems embedded in these MT platforms are unable to analyse the whole scenario of the conversation and therefore cannot infer the context of the discourse. As a result, the machine translations are syntactically and grammatically correct, but do not convey the intended meaning. The ambiguity and humour here results from the Chinese word ‘完了’, which, depending on context, can mean ‘finished’, ‘completed’, ‘doomed’ or ‘done’. The first ‘完了’ refers to something that has come to an end, that is China had COVID under control, whilst the second ‘完了’ refers to the situation where the impact of COVID in Italy was so bad that people there considered themselves ‘doomed’.

5.1.1.2 Example Two

In Example Two (Table 2), the word ‘pandemic’ is added into the first part of the text. However, it does not help the machines to correctly identify the meaning of ‘完了’ because the machine does not ‘know’ that there are two persons using the word ‘完了’, that they are in different locations with totally different situations, and that therefore, the two occurrences of the same word carry different meanings.

Table 2. **Textual analysis, Example 2**

Source text:	你们那里<ins>**疫情**</ins>快完了吗？我们快完了。
Literal translation to English:	You there epidemic soon finish? We soon finish.
Intended meaning:	Has the pandemic in your area come to an end? We are doomed.
Google[a]:	Is the epidemic almost over in your place? We are almost done.
DeepL[b]:	Is the epidemic almost over where you are? We are almost done.
Youdao[c]:	Is the epidemic almost over in your place?? We are almost done.

[a]Accessed 11:10am, 6 March 2021; [b]accessed 11:05am, 6 March 2021; [c]accessed 10:57am, 6 March 2021

In this example, the writer of the ST uses the different meanings of the same word under different contexts to produce humour and sarcasm. Lexical ambiguities are often used to in comedy to produce funny effects. Comedy usually demands adaptation more than any other features in a text because humour often derives from a secondary sense of the text, with a different, surface meaning on top. The task for the translator is to identify whether the humour, or the same level of humorous effect, can be achieved in the translation (Landers, 2001). Example 2 is a good illustration of House's (2009, p. 34) claim that the separate situations of text and context interact with each other via the link between the social environment and the functional organisation of language.

To achieve the desired humorous effect for the above example, both formal equivalence and semantic equivalence should be sought, which is a significant challenge for both human and machine. While human translators, having knowledge of the pandemic, will be able to clarify the ambiguity if they are told the geographic locations of the participants and the time the conversation occurred, MT by itself is challenged to link these data and establish the context of this conversation.

5.1.2 Culturally or temporally distinct language

When translators aim at transferring their comprehension and interpretation in an appropriate way, the linguistic and cultural environment of the TL must be considered (Boase-Beier & Holman, 1999). The building of monolingual corpora in the TL may establish a linguistic and cultural environment that allows the machine to 'consider' – but only if there are enough data for the corpus to be built. For language pairs that are close to each other, for example English and Latin, in the case of the lack of common equivalents for native animals and plants, translators commonly leave the original in the translation, providing that the context makes the meaning clear. For example, animal and plant names anglicised to appear in the Oxford English Dictionary are treated as English words even though they are strange to many readers (Landers, 2001). But this is not suitable for languages like Chinese, which is morphologically different to English. The achievement of a balance between literalism and comprehensibility is crucial in ensuring that the text is not incomprehensible or unreadable to today's audience, while also ensuring that an overzealous modernisation does not vitiate the exoticism and richness of vocabulary of the original (Landers, 2001).

5.1.2.1 Example Three

《哪吒》(Nezha) is a well-known mythical character that can be found in both Indian and Chinese mythologies. Different versions of his life and fate in different cultural backgrounds give him varied names, nicknames, titles and varied personal relationships with other characters in his life. When MT corpora are being established for such culturally and temporally unique contents, the first challenge is whether an equivalent can be established in another culture and language to deliver the same intended meaning and achieve the same artistic effect in the recipients in the target language and culture. Even for similar cultures and backgrounds like those of China and India, where similar storylines about the same character exist, the differentiated existing or established translations in English of stories about him raise issues of inconsistency and ambiguity. Cultural and temporal uniqueness make it difficult for MT to provide a consistent and comprehensible translation in English. The following example is an imperative clause, the English translation of which has been the subject of heated debate. It is usually used at the end of an official order or law issued by the emperors in the Han Dynasty, to emphasize the urgency for the order to be executed in a timely order without any mistakes or delays. It is also used by Taoist priests at the end of their magic spells, to either order the spirits or ghosts to follow their magic order or to cast a spell on someone or something after a rune paper is burnt. The phrase does not carry much substantive meaning, but has unique cultural and temporal associations.

Table 3. **Textual analysis, Example 3**

Source text:	急急如律令
Literal translation to English:	Hurry hurry as law orders
Intended meaning:	Follow the order, off you go
Google[a]:	hurried as a law (accessed at 4:32pm, 4 July 2021)
DeepL[b]:	as urgent as a law (accessed at 4:32pm, 4 July 2021)
Youdao[c]:	quickly quickly your mother call you (accessed at 4:33pm, 4 July 2021)
Human Translator[d]:	Abracadabra (accessed at 4:35pm, 4 July 2021)

[a]Accessed 4:32pm, 4 July 2021; [b]accessed 4:32pm, 4 July 2021; [c]accessed 4:33pm, 4 July 2021; [d]ChinaDaily, 26 August 2019

The text production and reception in the TC usually follow conventions or norms, which will have a strong impact on translators. Such convention or norms can be found in a 'socially and culturally accustomed web of relationships' not only between translation texts in the TC, but also between translators, their critics and readers (House, 2009, p. 24). These conventions are demonstrated by different versions of translations by different translators at different times, and disagreements and agreements on the acceptability of alternative translations also reflect the silent unconscious rules influencing a translator's decision process. For MT systems built on and learning from accepted human translation or natural language, the challenge is how they can recognise and identify the temporal and cultural background of the text and deliver a translation that is comprehensible and appropriate in the TL and TC as well as in temporal context of the target audience.

As demonstrated by Example One, a text relates via genre to the larger cultural context of the linguistic and cultural community (House, 2009, p. 34). A society is usually of a polysystemic nature, containing both literary and extra-literary systems. Any writing within a given culture, from its central canonical texts to the most marginal and to 'imported' translated texts, are situated in that culture. Translators are thus considered ‘cultural importers’, bringing in innovative influences on the literary traditions and conventions of the target cultural system via their translation work.

5.1.3 Word Limit for ST Input

It is worth noting that online MT platforms which offer free services to the general public usually impose a word limit of 5000 words for the ST. For example: Google Translate has a word limit of 5,000 characters (Rody, 2021, May 25). Youdao Translate has the same word count restriction (Youdao Translate, n.d.) whilst DeepL offers 100,000 characters for free to its users (DeepL, n.d.). Another translation platform developed in China called Caiyunapp (彩云小译) (caiyunapp.com), allows a free service of 50,000 words per month. Document translation going beyond this word limit will incur a cost of 4 Chinese yuan per 10,000 words if users need to download the translated document (Caiyunapp, n.d.).

Such limitations reflect, from a different perspective, that MT systems for the general public only analyse and process the opposite documents. If the length of the ST exceeds the word limit of the MT system, there will be a lack of comprehensive understanding of the whole context. As a result, the MT system will be using incomplete data for analyzing the ST and establishing the equivalence in the TL, which, consequently, affects the translation in the TL.

5.1.3.1 Example Four

Example 4 (Table 4) is based on a short passage from the first paragraph of Charles Dickens’s collection *Night Walk*, translated to Chinese by Yunping Niu and Zhenqin Ding (Dickens, 1861/2013): ‘Some years ago, a temporary inability to sleep, referable to a distressing impression, caused me to walk about the streets all night, for a series of several nights. The disorder might have taken a long time to conquer, if it had been faintly experimented on in bed; but it was soon defeated by the brisk treatment of getting up directly after lying down, and going out, and coming home tired at sunrise.'

Table 4. **Textual analysis, Example 4**

Translator	Target text	Back Translation
Human[a]	因心事烦扰，曾短暂失眠。连续几晚，我都整夜在街游。倘若我只是虚弱地躺在床上尝试各种入睡方法，也很长时间才能克服病症。所幸我用了一种积极疗法，很战胜了失眠症：刚躺下就起床、出门，日出时再筋疲力回家来。	Some years ago, bothered by things on my mind, I suffered from temporary insomnia. For a series of several nights, I walked about the streets all night. If I just had just lain in bed weakly and tried all sorts of ways to try to fall asleep, it might have taken much longer for me to conquer the condition. Luckily, I tried a positive treatment and quickly defeated the insomnia: by getting up directly after lying down, and going out, and coming home tired at sunrise.
Google[b]	几年前，由于暂时无法入睡，这给人留下了令人痛苦的印象，这使我整夜在街上走了几个晚上。如果在床上进行了微弱的实验，这种疾病可能需要花费很长时间才能克服。但是很快就被轻快的治疗方法击败了，这种方法是躺下后马上起来，出去然后在日出时疲倦回家。	Some years ago, because of temporary inability to sleep, this left a distressing impression, this made me walk through the night on the street for a few nights. If in the bed performed a weak experiment, this illness may require a very long time to be conquered. But soon was defeated by a brisk treatment, this method is to get up straight after lying down, then go out and exhaustedly come back home at sunrise.
DeepL[c]	几年前，由于一个令人痛苦的印象，暂时无法入睡，使我整夜在街上走来走去，一连几个晚上都是如此。如果在床上稍作试验，可能要花很长时间才能克服这种障碍；但很快就被躺下后直接起床，然后出门，日出时疲惫地回家的快速治疗所打败 。	Some years ago, because of a distressing impression, temporarily unable to fall asleep, which made me walk about the streets all night, for a few consecutive nights it happened. If slightly carry out an experiment on the bed, it might take a long time to conquer such disorder; but soon defeated by a prompt treatment of getting out of bed straight after lying down and going out and coming back home exhaustedly at sunrise.
Youdao[d]	几年前，我有一次暂时无法入睡，那是一种痛苦的感觉，使我连续好几天整夜在街上游荡。如果在床上稍微试验一下，这种失调可能要花很长时间才能克服;但是，他很快就被他的敏捷处理打败了，他躺下后立即起床，出门，在太阳升起的时候疲倦地回家。	Some years ago, there was one time I couldn’t fall asleep. That was a distressing feeling, which made me wander about on the streets the whole nights for quite a few days. If slightly carrying out an experiment on the bed, this disorder might take a long time to conquer; but he was soon defeated by his brisk handling, he got up immediately after he lay down, went outside and came back home exhaustedly at sunrise.

[a]Dickens (1861/2013); [b]accessed 11:27am, 6 March 2021; [c]accessed 11:24am, 6 March 2021; [d]accessed at 11:26am, 6 March 2021.

This short piece provides a good example of how the context, temporal characteristics and word limit affect the performance of MT systems. The partial text is unable to provide the MT system with sufficient data for analysis, so it is impossible for the MT system to infer that the work was written in the 1870s. The usage of the SL is different to current usage, and the historical and geographical elements of London in the late 1800s were provided in later passages. Without such information, the identification of the appropriate corpus for SL analysis and, therefore, the generation of an accurate and appropriate translation in the TL becomes a challenge for these systems. Even a layperson would be able to detect that, before any post-editing by a human translator, the MT is unsatisfactory.

5.1.4 Rhetorical and aesthetic rendition

In addition to context, cultural and temporal elements, and word limit, Example Four also demonstrates that, in literary translation, the rhetorical and aesthetic rendition plays a critical part in readers' experience. Translators will commonly struggle to find a formal equivalence in the TT that realises the rhetorical and aesthetic creativity of the ST. Doing so involves a complex decision-making process. Translators 'pick' the most appropriate potential answer out of all the available options, which will then influence subsequent choices.

This decision-making process is not sequential; instead, it is usually iterative in that, a translator may always return to previous decisions to look at them with a different view and make corresponding changes (Hatim & Munday, 2019, p. 52). While human translators will be driven by their own aesthetic standards (Levý, 1967) and their socio-cognitive systems to allow some minor decisions to be overridden, machines are not programmed to carry out such hierarchical and iterative decision-making. If the machine is unable to process the text as a whole due to its length, there is no opportunity for the machine to modify or correct any discrepancies and inappropriateness. Other factors influencing decision-making of human translators, such as cognition, knowledge background and specific requirements from the clients, do not concern the machine.

5.1.5 Consistency

Another issue detected by users of MT systems is the inconsistency of word choices in the translation. Machines need to understand the direction of translation, because the ST is defined as the reference text for the machine at the stage of aligning the sentences (Poibeau, 2017, p. 92). As a result, the TT of a ST done by a machine may not end up with the same ST when being translated back to the SL. A significant consequence of this incapacity to 'remember' the ST is that the same form of the ST with the same meaning may have different forms of TT with the same or different meaning(s) when they occur in different scenarios.

There is a prototypical example where a biblical sentence was taken to be translated into Russian. The sentence in English says, 'The spirit is willing, but the flesh is weak.' However, once the sentence is translated back into English from its Russian translation, it became, 'The whiskey is strong, but the meat is rotten.' The comical effect illustrates well Poibeau's (2017, p. 167) important observation that when the translation steps multiply, the meaning will stray from the ST until it becomes impossible to comprehend.

5.1.5.1 Example 5

The issue of inconsistency in MT can be illustrated by a well-known example posted by an official WeChat account (Translation Study of Community (翻译学习共同体), 2020)),

posted on 7 June 2020 (Table 5). A video on the Chinese video website bilibili.com 'went viral' because of a very humorous effect caused by the back translation of a Chinese paragraph. In the video in question, a blogger used Google Translate to translate the ST into TT, then used the same platform to translate the TT back to ST. After repeating this process 20 times, the meaning of the final version of the text in SL diverged completely from the ST.

Although, with MT, this amount of repetition is neither likely nor necessary in practice, it is not uncommon in the case of human translators. Thus, it illustrates how the machine fails to 'remember' its own work as human translators do. As yet, it is not possible for machines to recognize their own work, because they lack a memory reservoir for this purpose. Even for those machine translation systems which record the selected translation, for example, DeepL, such inputs to their corpora are not updated in real time, due to the limitations of computational ability.

Table 5. **Textual analysis, Example 5**

Original text in Chinese	深蓝的天空中挂着一轮金黄的圆月，下面是海边的沙地，都种着一望无际的碧绿的西瓜。其间有一个十一二岁的少年，项戴银圈，手捏一柄钢叉，向一匹猹用力地刺去。那猹却将身一扭，反从他的胯下逃走了。	On the deep blue sky hangs the golden moon, underneath which is a sandy area close to the sea. There, green melons can be seen as far as one's eye can reach. There is a boy, aged 11 or 12, wearing a silver collar and holding a steel fork.
Final version of back-translated Chinese	在绿色天空中几乎到处都是无尽的金色月亮，沙滩上满是沙子。那时，这个 11 岁的男孩尽可能地用金属皮带系住他的手，并将其放在金属把手上。叔叔关上身体，逃离叔叔。	In the green sky endless moons lying everywhere. Sands are all over the beach. At that moment, this 11-year-old boy tried all his might to tie his hands with the metal belt before placing it on the metal handle. The uncle closed his body, escaped the uncle.

Similar issues have also been noted for translation texts in Example 1 in this study. Even when the exact same ST with the same meaning and connotation is put into the MT system, the same MT platform generated different translations.

As Poibeau (2017, 164) mentioned, for the same language pair, major differences can be identified when translation happens in different directions.

5.1.6 Summary of exemplary analysis

The above examples and their analysis show that it is very often the target readers who may have been deprived of a quite significant part of the ST meaning. During the process of human translation, translators need to consider whether preserving or omitting elements of the ST meaning will be appreciated by the readers the same way as by the translators (Hatim & Munday, 2019, p. 16). But, for machines, the challenges are first, whether they 'know' how to intentionally omit or preserve certain part(s), and, second, whether such omission or preservation will be considered equally significant to a target reader. If MT is to replace human translators and connect with readers using natural language, the essential requirement is for machines to understand human language. Only then will MT be able to produce in the TL readers the same emotional and psychological reactions, such as boredom, that are produced in the original SL readers (Landers, 2001).

To enable machines to understand natural language processing, various strategies have been attempted. In Quillian's attempt (1996) to model a human memory, it was found that memory can facilitate the disambiguation of word sense. Once human memory can be replicated, the inconsistency and ambiguity in MT can be greatly reduced. Researchers (Furth, 1966; Lenneberg, 1967; Schank, 1972) have established that natural language is built on an interlingual conceptual basis existing in persons' minds. The linguistic structure of a language is constructed on this basis during the understanding process, after which the generation process of the linguistic structure will take place. What really remains in human memory is usually the conceptual content of an utterance rather than a visual image or a linguistic representation (Anderson, 1971). The actual language is only an indicator of the underlying conceptual content, in other words, of the meaning of an utterance (Schank, 1972, p. 3). Whilst the term interlingua was used in one of the RBMT models, it was used to only represent the link between different languages, rather than being used to identify the basis for understanding and generating natural languages. Machine learning and understanding relies on whether the system is capable of conceptualization in the same way that humans establish their basis of thoughts (Singer, 2021). The system design and algorithms determine whether the machine can establish the interlingual conceptual basis based on natural language learning and processing. The human translator's art is creativity guided and controlled in a whole variety of different ways. Yet, there are gaps between languages that cannot always be bridged. MT's ability to learn and understand as well as reproduce such creativity in literary text translation remains a big challenge.

5.2 Implications and future research

Translators, as well as readers, are always under the influence of extra-linguistic factors, such as exigencies of the market, censorship, etc. The Zeitgeist has endowed translators with the role of interculturally active, socially and politically committed communicators. Texts to be translated can sometimes be given historical and social significance. At different times, translators have taken on responsibilities for revealing sociocultural and political differences and inequalities. If ideological skewing is inevitable due to a human translator's subjectivity (House, 2009, p. 73), such problems can be avoided if the work is done by a machine. MT has proved its advantages in speed of translation, even though this does not guarantee higher efficiency, because human intervention is currently still required. But, as the term 'automatic machine translation' suggests, the whole process of MT aims to generate translations with only minimal, or ideally, no human intervention at all. For literary text translation, MT still faces many challenges.

By reviewing the development of MT and investigating the existing issues and challenges in literary text translation for MT, this study offers some insight for future MT study in relation to the establishment of corpora, equivalence and the reproduction of creativity.

For human translators, information such as the genre of the ST, the specific time and culture in which the ST exists, the time of the translation assignment and the recipient of the TT is essential for the establishment of the context of the ST, which then ensures a more accurate and satisfactory rendition in the TT. However, only when MT systems no longer require manual input to identify the abovementioned information does it mean that the machine can independently learn and recognise such information based on merely its algorithms, system and training data. To do so, the training data for the MT system need to include significant amounts of high-quality bi-texts and monolingual texts. For this reason, corpus establishment is critical for the training of MT systems. While the corpora built based on online users' contributions may reflect the most current and prevailing language usage and expressions, it should not be overlooked that these usages and expressions only reflect a portion of language usage; that is, that existing in a particular era among a particular group of people for a set type of communication (online communication, which is usually less formal and shorter in length than other types). As more online resources are made available, covering a broader spectrum of texts, the question will become one of whether online data can provide sufficient coverage of high-quality data for the training of MT systems. There will still need to be some type of categorization for the machine to separate or distinguish certain sets of language usage and expressions from the others that occur at different times or in different cultures by various people from different backgrounds. If MT system can attain this level of understanding, it will be able to replicate the process of human memory, and it will become possible to render by MT the creative elements that authors, as part of their writing goals, have incorporated in their literary work.The current constraints set by the boundaries of a given corpus or corpora restrict MT systems to 'picking from the available' rather than creating something of their own. Human translators working on literary text translation are constantly creating, as well as following the established norms based on their background, experience, cognition, etc. The fundamental difference between human translators and machine translation is that the former are capable of creating something novel, be it a word, a way of expression or a method adopted in translation, while the latter relies heavily on what has already been done and made available to the system, and is limited by the computational power of the system. Unless machines can become capable of natural language learning, and as long as probability and statistics remain the basis of MT, several factors will hinder the delivery of satisfactory and independent results. These include the lack of parallel and monolingual corpora in the field of literary text translation, the incapability to establish various types of equivalence and to constantly assess and modify the established equivalence in a translation work, and the challenges in reproduction of creativity. This will particulary be the case when huge discrepancies exists between the cultures and languages of ST and TT or when the literary texts are presented to audiences from different generations at different times.

Although social norms exist in literary text, they are not always followed by the author, the characters, and the subjects, nor are they always expected by the readers, given the creativity and freedom such texts are privileged to have. The gradual replacement of SMT by NMT shows that MT system development has shifted from making the machine to work on what is available – that is, the analysis and statistics – to working on how translation happens, that is, natural language learning and acquisition. . In-depth research in the future on natural language learning in MT can offer the opportunity to look at the challenges in literary text translation for MT again, using professional or commercial NMT platforms.

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Appendix

Table A1. Initialisms

HT	Human Translation
MT	Machine translation
NMT	Neural machine translation
RBMT	Rule-Based machine translation
SC	Source Culture
SL	Source Language
SMT	Statistical machine translation
ST	Source Text
TC	Target Culture
TL	Target Language
TT	Target Text