The Potential of Machine Translation to Provide Texts for Extensive Reading

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Machine translation (MT) is part of a technological revolution that presents an existential threat to the language-teaching profession, creating challenges for language teachers who were at first amused at its mistakes and later confounded by students using it for written assignments. It may now be neither possible nor helpful for teachers to try to stop students from using MT, and technologies that have emerged with it; instead teachers need to find reasons for students to continue studying the language, and ways that students can benefit from this technology, for example through considering how language proficiency is attained. Extensive reading (ER) is the practice of reading easy texts to gain language proficiency. Reading at an appropriate level is essential to lower the affective filter, maintain motivation of the learner and allow effective time in the target language for fluency to develop. However, most of the reading content that is immediately available to learners via the internet is above an appropriate level, and often well above a level at which students can read with any fluency. This review paper presents an overview of MT technology and language education and proposes how existing and emerging MT technology may be used to create reading material at appropriate levels for learners.

機械翻訳（MT）は、言語教育という職業に存亡の危機をもたらしかねない技術革命である。教師が学生に、MTやそれに伴って登場した技術の使用を禁止することは、今や不可能であり、有益でもないかもしれない。その代わりに教師は、学生が言語学習を続けるための理由や、言語能力獲得の方法を考え、学生がこれらの技術を使用し利益を得るための方法を見つける必要がある。適切なレベルの文章を多く読むことは、情意フィルターを下げ、学習者のモチベーションを維持し、流暢さを身につけるため、そして有効な言語学習時間を確保するために不可欠であるが、インターネットを通じて学習者がすぐに利用できるリーディング素材のほとんどは、適切なレベルを上回っていることが多い。本稿では、MT技術と言語教育の概要を紹介し、学習者にとって適切なレベルの読み物を作成するために、既存のMT技術や新しいMT技術をどのように利用できるかを提案する。

For language teachers, machine translation first appeared as an amusement, but has steadily increased as a threat. Teachers initially faced the problem of students submitting written work that had been machine-translated. Since written assignments are usually set to encourage students to practise using the target language, this is entirely defeated by students who write in their first language and simply press the translate button. For less motivated students, writing in the native language and using machine translation can save a lot of time. Some highly motivated students may even misunderstand the purpose of writing assignments to be producing high-quality text, and may believe that computers will do a much better job translating into the target language than they could ever do. Considering the power and ubiquity of computers, students can be forgiven for assuming that computers are better than them, and most students do not have sufficient proficiency in the foreign language to judge whether the output is good or not. Further, students may see machine translation as a useful tool in the arsenal of the language user, and one that they need to learn how to use.

Until the late 2010's output from machine translation was very poor, so it was easy for teachers to identify. It was possible to demonstrate this fact to students by using samples of machine translation into their own language. Since around 2019 the quality of freely-available machine translation output has become much better, and it is now no longer possible for teachers to tell whether an assignment was written by the student or translated by computer. There may be clues in pronouns, word choices, names, duplicate translations, or carelessly copied postscripts such as "translated by DeepL", but usually teachers cannot be sure. Software is available that claims to detect if a text has been created by computer or human; however, it is important to note that this software is using the same technology as MT so may be behind the fast-developing systems and at the same time may be informing developers how to make their translations more human.

Fair assessment has become difficult as teachers have no way of knowing if students have completed their foreign language writing assessments by simply writing in their native language or found answers to reading comprehension assignments by translating into their language. Studies by Newfields and Botev (2021) and Ruzicka (2021) suggest well over half of their university students used MT for their English homework. If you set your students a writing assignment, and you are wondering whether they used MT to write it or not, they probably did.

Recent developments in Machine Learning (ML) technology and Large Language Models (LLM) have led to many warnings; for example, Patrick Vallance, Chief Scientific Adviser to the UK Government, has stated "There will be a big impact on jobs and that impact could be as big as the Industrial Revolution was" (Devlin, 2023). As translation quality improves, there is also an existential threat for the language teaching profession: if computers can translate in and out of their native language, what is the point of students learning another language? (Mok & Zinkula, 2023). Many university language courses aim to teach students the "vital" academic skills of reading and writing papers. It must now seem obvious to many in academia, and particularly to students who have grown up in a digital world, that MT can now do a very good job translating reading material into their own language. If they have to write something in English, students can simply write it in Japanese and press translate. If it is for publication it will need to be checked by a native or highly-proficient language user, but in most cases outside the language classroom, it would need to be checked anyway if they had written it themselves. Not only does machine translation allow students to get through their language classes without actually practising the language, it also brings into question the need for those classes in the first place. (See Gally, 2018 and Brierley, 2012 for discussions on the position of language teaching in the Japanese context.)

Meanwhile teachers, as language users themselves often in a foreign-language environment, are very likely to have used machine translation in their professional or personal lives. Indeed, professional translators have been using MT technologies since the 1990s (Urlaub & Dessein, 2022). Teaching students how to use MT may therefore be a priority. Not only is it too late to tell students to stop using this technology, but it may also not be in their best interests to shield them from a very useful tool.

The technology also presents opportunities. At an epistemological level, MT and related technologies may be able to teach us something about the way that language proficiency is attained. At a practical level these technologies may be used to provide the kind of graded reading material essential to language acquisition. There is no guarantee that this will save the language teaching profession, but now that machines are learning language in a similar way to humans, they may also be able to produce materials that can help humans to learn languages.

A Brief History of Machine Translation

The history of machine translation goes back at least seventy years and can be seen at the beginning of the development of the modern computer, which came from work breaking codes during the Second World War. Warren Weaver's 1949 Memorandum suggested that the task of translating from a foreign language could be seen as decoding an encoded text in the target language (Hutchins, 1999). Perhaps justified among those who had seen unprecedented technological developments during the war, there was early optimism with some researchers believing the "problem" of machine translation would be cracked in five years. However, by 1965, the National Academy of Sciences (ALPAC) decided that MT could not compete with human translation quality, and would not be able to for the foreseeable future (Mandal, 2019). This conclusion probably slowed development by decades.

MT did find some useful avenues over the next twenty years, with the French Textile Institute translating abstracts between French, English, German, and Spanish from 1970, Brigham Young University translating Mormon texts from 1971, and Xerox translating manuals from 1978. In 1992 the first online public machine translation service was available between English and German. Systrans appeared on the web in 1996, followed by Babel Fish on Altavista in 1997, then Google Translate in 2006. The earlier systems were based on sets of rules, but later statistical approaches were used to analyse large monolingual and bilingual corpora and determine which words and combinations of words were most likely. Statistical approaches produced better output than rule-based approaches; however, the recent improvements can be attributed to deep learning especially with the use of neural networks (Mandal, 2019).

A Brief History of Machine Learning

"Machine learning" was first coined by Arthur Samuel (1959) and is often used interchangeably with "artificial intelligence", coined in 1956 (Schmidhuber 2022). The latter term is broader, leading us into questions of what is artificial, and what intelligence means, often with the flimsy definition that "intelligence" is what humans can do, but machines cannot (yet). "Machine learning" has the more precise meaning of giving a task to a computer, providing training data, then providing test data to see if the task has been achieved. Machine learning techniques began in the 1960s, but progress stalled in the 1970's as there was more focus on AI, culminating in IBM Big Blue's 1997 defeat of Garry Kasparov at chess, which until then had been considered a sign of "intelligence" and therefore impossible for humans to lose at (Greenmeirer, 2017). Kasparov himself considered chess to require art and intuition; qualities which computers could never have (Liethauser, 1990). As an example of the shift from knowledge-based approaches to data-based approaches and "Deep learning" (coined by Geoffrey Hinton in 2006), in 2016, DeepMind's AlphaGo (later acquired by Google) beat Go champion Lee Sedol (Krieg & Kohs, 2017). IBM had built Big Blue with circuitry specifically designed for playing chess, 4000 openings and 700,000 games in its memory, four chess grandmasters on the programming team and a redesign after losing its first match. AlphaGo, on the other hand, used a general neural network processor, the rules of Go, and a 30-million-move database, and then learned by playing against itself. Lee Sedol credited AlphaGo with creative moves (Krieg & Kohs, 2017).

Neural networks are built by creating computing pathways analogous to how synapses are connected in the human brain. The first neural networks were made by connecting multiple devices together, but computers are now available with neural networks on single chips. It is important to note that neural networks are not programmed as such. They are essentially pathways that are optimized through reinforcement techniques based on large amounts of data. The resulting network is thus a 'black box' that the programmer herself would not understand, any more than a brain surgeon could look at a brain and understand why it produces output. In essence, the training of a neural network tweaks the pathway settings until it matches the desired output in supervised learning or detects a pattern in unsupervised learning. (See Schmidhuber 2022 for a history of neural networks.)

Google Translate changed to neural MT with deep learning in 2016 and was able to translate among 133 languages by July 2022. In 2017 DeepL was launched based on Linguee bilingual texts, translating among 26 languages by July 2022. The earliest attempts at MT relied on prescribed lists of equivalent words, and later attempts were based on rules provided by programmers or assumptions such as the existence of a universal grammar. In contrast, deep learning is immune to prescribed translations and agnostic to linguistic theories, instead finding existing patterns in massive bodies of language. DeepL is often considered a better translator than Google, and this may be because it trained on European Union texts, which have been translated to a very high accuracy since EU policy defines documents in different languages as having legally identical meaning. On the other hand, in *Building machine translation systems for the next thousand languages*, Bapna et al. (2022) give evidence of Google's deep learning now being able to translate a new language based not on a bilingual corpus, but on a smaller monolingual corpus.

Lessons from Deep Learning

First, we should be cautious in deciding what technology will never be able to do, or how many years developments will take. Of course, wise people have always made predictions that seem foolish in hindsight. In 1895 Lord Kelvin, president of the Royal Society, stated that heavier-than-air flying machines were impossible (Cerf & Navasky, 1984, p 236). In 1927, H. M. Warner, the oldest of the Warner Brothers said, "Who the hell wants to hear actors talk?" (Warner, 1965, p. 167). In 1977 Ken Olson, president, chairman and founder of Digital Equipment Corp. said, "There is no reason for any individual to have a computer in their home" (Cerf & Navasky, 1984, p. 209). Considering the developments in AI, as we see progress from impossible to possible, laughable to serious, and inferior to humans to superior to humans, we would be ill-advised to suggest that humans will always be better at languages, or even that computers can never understand context. Some computer developments are abrupt and non-linear so we should also be cautious in assuming that technologies will only come several years in the future. This is especially true when we consider that AI can now be used to develop AI programming itself. Andrej Karpathy (2022), founding member of OpenAI says that 80% of his programming is performed by AI.

Another consequence of this technology is that we may need to consider a change in focus in language teaching. Many students will see little benefit of writing in a second language when a machine can do it better. On the other hand, a student who wants to meet people at an international conference, appreciate songs on YouTube, or read Shakespeare would likely eschew the use of AI even if it were available. AI may have 'solved' chess but nobody would send an AI bot to enjoy a game with a partner. The personal need for interaction and appreciation of humanity and culture are still parts of the language learning process and perhaps they should be the main focus if language learning is to have a future.

Regarding language learning, the most important lesson from the development of MT may be that high-quality output comes not from the learning and application of a few prescribed rules and translations based on simple assumptions about language, but by having access to a massive corpus of texts and language models combined with supervised and reinforcement learning techniques. Language is highly complex, and we cannot simply write down a succinct and comprehensive set of rules under a monolithic theory of language to tell computers how to use it. If the greatest computer-science minds over 50 years of research failed to develop an effective rule-based approach to language translation, it's not surprising that language learners should also fail in such approaches. Indeed, it is through exposure to massive amounts of the target language that AI has succeeded in producing both translations and natural responses, and this perhaps can inform how learners will improve: large amounts of exposure being more effective than rule-based approaches.

Humans are not computers and while it's trivial to load dictionary translations and grammar rules into a computer's databanks or add a corpus of millions of words, humans cannot be given such a head start, and will take time to cover texts. Research does however show that human language ability is based on exposure to large amounts of language, for example Hart and Risley (2003) finding a *difference* of 30 million words between children of different social groups heard by the age of three. While the large language models behind MT have been built on huge corpuses, recent work on less well represented languages suggests that language can be acquired from smaller monolingual samples (Bapna et al. 2022; see also Blin, 2021). Some advocates of Extensive Reading have proposed a million words as a reading target for second language learners of English, based on the amount a typical native language user will read in a year (Sakai & Kanda, 2005).

What is Extensive Reading?

Extensive reading (ER) is the practice of reading large amounts of easy and enjoyable texts which research has shown leads to improvements in language proficiency. ER is usually practiced not as a form of active study, but an immersion into fluent language practice. There is evidence that starting with low-level books leads to faster improvements in language ability (Takase, 2012). In order to read fluently, readers need to know at least 98% of the words they see (Nation, 2001). For learners to gauge whether a text is too difficult they can use the "Five finger rule" whereby they count one finger for each word they don't know. If the page is 200 words, five words means that the coverage is below 98% and they will not be able to read fluently.

A major issue in native texts is that generally language follows Zipf's Law (Piantadosi, 2015) regarding frequency: the nth word is n times less common than the 1st word. A practical corollary of this is that the first word is 1000 times more common than the 1000th word, but the 1000th word is only twice as common as the 2000th word. In a given text, this will leave a very long tail of less frequent words, and typically half of the headwords in the text will only appear once. This long tail will cover at least 5% of the running words meaning the students have less than 95% coverage. While over 98% signifies that a text is suitable for extensive reading, Waring (2012) has referred to texts with less than 95% coverage as "reading pain". As headword vocabularies get larger in a native text, whether the 10,000th word or 20,000th word is chosen will be more dependent on context than pure frequency, so it's difficult to predict which low-frequency words will appear and this long tail renders native texts essentially unreadable to learners with a vocabulary of perhaps one or two thousand words. Thus, texts for ER must remove or replace low frequency words.

A critical challenge for setting up ER programmes is building a library and this library must be large enough to provide books at a range of levels and varied content to satisfy all the learners. Most challenging is providing books at a suitable level, and particularly low-level books, which have a limited market and the difficulty of writing compelling stories within narrow lexical confines.

An Opportunity for Deep Learning in Extensive Reading

While MT presents teachers with challenges in the short term and an existential threat in the long term, there may be an opportunity for MT technology to help those who are motivated to learn by providing texts at a level suitable for ER. As MT develops into more languages, if English at various levels could be added as target languages—for example 1000 headwords, 2000 headwords, 3000 headwords—it would be possible to automatically convert a wide range of texts into reading material at a level suitable to the learner while dealing with the long tail problem noted above.

Text Difficulty

In order to realise this opportunity, bodies of language at appropriate levels need to be identified. Data already exists on the level of difficulty of published graded readers that have been specifically written for learners of English as a second language (Brierley et al. 2019). The measure of text difficulty is not straightforward since there are many factors involved and no definitive unit of measurement (Gillis-Furutaka, 2015).

Vocabulary is one factor, with higher-frequency words tending to be easier to understand. The number of headwords in a book may be a useful yardstick and this is the basis of the ERF (Extensive Reading Foundation) reading levels. As well as the range of words used in a text, the way the words are used with each other will also affect difficulty. Simple words can be used in complex combinations or in idioms that may only be comprehensible to readers of higher proficiency. The Gunning Fog Index (Gunning, 1952) includes the ratio of multisyllabic words as well as the length of sentences in its calculation of the difficulty of a text, and Flesch Reading Ease considers the average number of words in a sentence and average number of syllables per word. (See Carrell, 1987.)

In addition to these linguistic features, the nature and content of the longer text will affect reading difficulty, for example the genre, setting and voice. If it is fiction, the cultural, political and social background will make a difference. Stories with more characters are more difficult to understand, and may be radically so, since the number of relationships between characters grows more rapidly as the number of characters increases, and it is relationships that require understanding in a story.

Perhaps the most accurate measure is the impression of learners who have read the books. Impressionistic difficulty level is a double-ended ruler since the apparent level of difficulty depends both on the level of difficulty of a text and the level of proficiency of a reader. It may be further clouded by the age, gender and social background of the reader. Holster, Lake and Pellowe (2017) compared various features of 1016 books with the impressions of 668 Japanese university students who had read at least five of them. One feature considered was Yomiyasusa Level (YL), a scale based on the impressions of readers in Japan (Sakai & Kanda, 2005). They found that word frequency was not effective in predicting the impressionistic difficulty of a text, while YL was effective, and the length of the book was the most reliable indicator. This may have a superficial meaning that students find shorter books easier, because they will simply be spending less time reading, and reading itself is difficult. An alternative interpretation considers the correlation between the length of the books and the level of difficulty. We do not need to look far along a children's bookshelf to see that the books grow longer as their level goes up.

In Sakamoto, Niimura and Brierley (2023), deep learning was used to analyse text features to predict the YL of 32 graded readers, which it did with a high correlation of .91. This demonstrates that deep learning has potential to identify texts at appropriate levels in order to build a monolingual corpus for an MT system to learn how to translate to language at a level.

Conclusion

AI is set to change many aspects of life, and these changes may come with alarming speed. High quality machine translation has recently presented challenges to language teachers, and presents an existential threat if the goal of language learning is perceived as the transfer of functional skills in academic writing, or even communication during travel since real-time interpreting software is upon us. If the reason to study language can be rehabilitated to less utilitarian and more humanitarian goals, then we may find uses rather than threats from MT.

One such use may be to quickly generate texts that are tuned to the reading level ideal for the student's improvement. A large quantity of material for Extensive Reading could be made available to students using emerging MT technology, after prescribing levels of difficulty and identifying texts at that level, with assistance from deep learning tools that will identify other texts within those levels. Several graded readers have been adapted from original texts, often with editions at different levels, which can provide a bilingual corpus.

As well as offering the opportunity of producing more texts for learners to read, the development of MT can teach us that language proficiency comes not from following prescribed rules within a dogmatic theory of language but from exposure to large quantities of text.

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Bio Data

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