International Journal of Academic Research
ISSN: 2348-7666; Vol.7, Issue-4 April, 2020
Impact Factor: 6.023; Email: drtvramana@yahoo.co.in

The role of machine translation in language learning

Bareq Raad Raheem
Ph.D. Research Scholar, Department of English
Aligarh Muslim University, Aligarh, India
barekvip@yahoo.com

Abstract

Machine learning (ML) applications have been used widely in various aspects nowadays and one of them is translation process. Machine translation (MT) facilitates the translation for every one not only for the learners. Dictionaries can be downloaded in our smart phones and computers. They are also available in the most of webs such as Google translate and can use them easily. This study aims to show the role of machine translation in improving the learners ability in translation and the impact of MT in achieving effective learning.

Keywords: Artificial Intelligence, Language Learning, Machine Learning, Translation Machine.

1

. Introduction

Artificial Intelligence is presented as the platform developed with machine intelligence. Artificial Intelligence, being the most advanced technology, is machine based but humanized intelligence. It is completely automated and away from the interference of human. It has been applying in most of the fields. A large number of artificial intelligence applications have emerged with the renewal of artificial intelligence technology such as image recognition, speech recognition, translation, medical care, and even robots.

Recent developments in educational technologies and the wide-spread use of computers in schools fueled innovations in machine learning (ML) and second language (SSL), Hou, Y.T., et al. (2010). ML commonly used in today's software is to study and apply the computer modeling of learning processes in their multiple manifestations, which can ease language learning and encourage the development of intelligent system, Zhang, Z., et al. (2009), Balcan, M.F., et al., (2008).

An impact on the translation industry that also undertakes information exchange and management. Thus, the present study aims at to explore the upcoming role of machine translation in the field of English language learning and translation as well to make it pleasant and interactive activity. The marked impact of ML applications and their significance in educational field specially MT, hence different studies have been carried out in the area of MT.

Briggs, N. (2018). The searcher has aimed to provide language educators with information pertaining to the students' use of, evaluations of, and attitudes towards Web-based machine translation (WBMT) tools. Specifically, the extent to which students rely upon, and value WBMT for the purpose of language are evaluated.

Jonna Sycz-Opon (2016). This study has presented experimental classes devoted to machine translation (MT) with the application of MT Evaluation Protocol, conducted with participation of 45 students at the University of Silesia. The teaching scenario involved theoretical discussion of MT solutions, followed by structured testing of machine translation, during which the students could very the quality of the MT output and come up with their own conclusions about the students with theoretical and practical knowledge of MT tools, based on testing and inductive learning.

Case, M. (2015). This study has examined the question of how language teachers in a highly technology-friendly university environment view machine translation and the implications that this has for the personal learning environments of students. It brings an activity-theory perspective to the question, examining the ways that the introduction of new tools can disrupt the relationship between different elements in an activity system.

Fiederer, R., et al., (2009). This study has focused on the question: how does the quality of the post edited product compare with the quality of human translation? The searcher assumed, on the basis of attitudes in general to machine translation, that most language professionals would predict that the post-edited quality would be inferior to the quality of human translation. The research results has showed that the machine translated, Post-edited output was judged to be of higher clarity and accuracy, while the translations were judged to be of better style. When asked to pick their "favorite" sentence, the majority of the evaluators chose translated (as opposed to machine translated) sentences. Further, sentences where Controlled Language (CL) rules had been applied scored higher on clarity and accuracy, adding further to the claim that the application of CL rules improves MT output.

Gaspari, F. et al., (2007). This study has drawn the background that led to its development, giving an account of its origins and of the early stages of its evolution. Several competitors have entered the field of web-based MT over the last decade, and this study has offered a review of the most significant contributions in the literature with a particular focus on two key issues: firstly, the role that these online MT tools have played in meeting the translation needs of the users, and secondly the impact that they have had on the MT-related industry and business.

2.Machine Learning System

overall structure of ML framework which consists of four major steps: on-line (packet filtering), data processing, training/testing step, and cross validation has been discussed by Shon, T., & Moon, J. (2007). The first step is "packet filtering" which is connected to on-line processing and includes a real-time traffic filtering using PTF. This step offers better performance for packet

International Journal of Academic Research
ISSN: 2348-7666; Vol.7, Issue-4 April, 2020
Impact Factor: 6.023; Email: drtvramana@yahoo.co.in

preprocessing and diminishes the number of potential attacks of the raw traffic. The second step is "Data Processing" which indicates to the packets that passed the first step are preprocessed with packet relationships based on traffic flow for SVM learning inputs.

The third step is "Training/Testing Step" which contains the enhanced SVM machine learning approach. The SVM model combines two kinds of machine learning methods: soft margin SVM (supervised method) and one-class SVM (unsupervised method). In doing so, the enhanced SVM approach inherits the high performance of soft margin SVM, and the novelty detection capability of one-class SVM.

The final step is "cross validation/real test with Bro and Snort" which requires verifying the approach using both an m-fold cross validation test, and comparing the suggested framework with real world NIDs, as Bro and Snort. The following figure shows the four stages of ML:

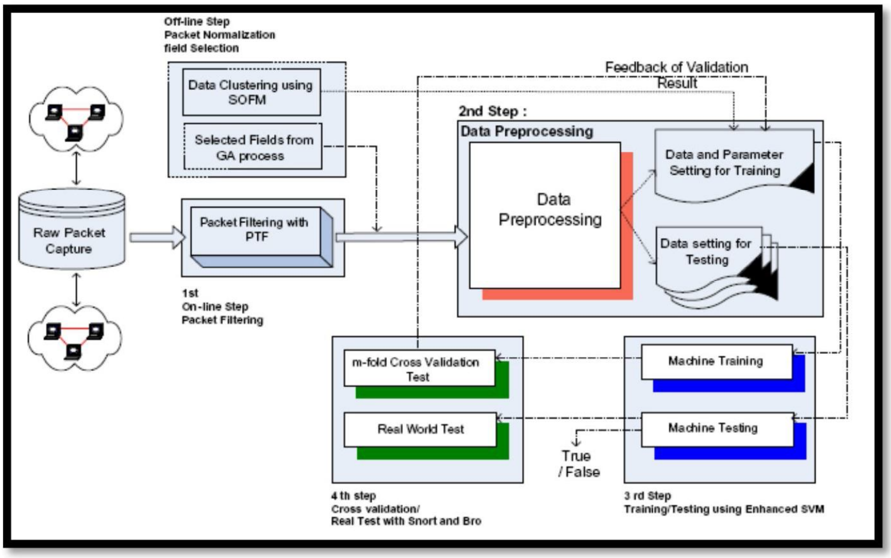

Fig.1 .Model Of Machine Learning Framework

3

. Machine Translation

Machine translation is a sub-field of computational linguistics that explores the use of software to translate text or speech from one language to another. In terms of when and where machine translation started, one can go back almost 70 years. The 1950s considers as introduction of the first translation of words by machine. The first time a sentence translated by a computer when an IBM computer translated sixty Russian sentences into English. The IBM 701 Data Processing Machine made grammatical and semantic decisions that mimicked the work of a bilingual human. Machines are assessed for their ability to emulate human behavior and they are said to demonstrate intelligent behavior if they have the ability to pass the Turing test. Turing I.B.A. (1950). The test is considered passed if the output performed by the machine and by a human, cannot be distinguished by the evaluating judge (Ibid).

Machine Translation models have been developed rapidly in recent years. Its engine is an example of machine that emulates human behavior as it performs tasks usually undertaken by human translators. Machine translation is essentially automated translation and in general terms it is a process in which computer software is used to translate text from source language to target language.

Currently, machine translation engines are extremely popular and used extensively are now easily accessible to everyone with an internet connection. For example, within a click of a few buttons, internet users can translate web pages or snippets of web content. As a result, there is an interest in machine translation (MT), its output and whether it is indistinguishable from what a human translator produces .

Earlier the dictionary books were using in translation process but nowadays the technology rapid development has helped to use the dictionaries in mobiles and computer easily, such as Google's online computer-assisted translation platform also supports translation from English to more than 50 languages (Online Computer Aided Translation System).

The Google Translator Toolkit (GTT) integrates the Google Translate, WYSIWYG editor, open rating system, sharing system, Wikipedia, and Knol. Currenty, GTT translations support some common file types, including: HTML file (.html), Word file (.doc), Open office file (.odt), Text file (.txt), Rich text file (.rtf) format. The translation tools of GTT are mainly translation memories and Glossaries. The auxiliary tools are Google's original machine translation tools (Google Translate) and dictionaries.

Neutral Machine Translation (NMT) is the newest phase of machine translation with the development of artificial intelligence. Its theory is based on the theory and techniques of natural language understanding (NLU), Natural Language Processing (NLP) machine translation (MT) translation memory (TM), and statistics-based machine translation (SWT) as well as deep learning. As a new theory and a new discipline, it broke through the bottleneck of computer translation technology and achieved high-quality machine translation . Its characteristics are using big data and cloud computing backstage as computing platforms based on the new developments in the field of neutral networks, continuously receiving numerous training data to the backstage based on the mobile Internet, and carrying out features data mining and rapid training through deep learning capabilities. Anastasiou, D., et al., (2011).

4. Mt In Language Learning

Significant modifications are expected due to the applications of Artificial Intelligence in our daily life and the field of English language learning. It has always been observed that technology is considered as a great support system in learning of English language. It's clear that of machine translation contribution has great value in the field of learning. Machine translation can provide tens of millions of translations per day, and its ability to quickly grasp new terminology customizations is difficult for learners to do. Some of machine translation provide the learners facilities which is checking the spelling mistakes and grammar mistakes as well.

Moreover, the combination of machine learning (MT) and second language Learning (SLL) can facilitate language learning and encourage the development of intelligent system, thus promoting the users' understanding of the system and improving the high accuracy of ML systems. Generally speaking, ML aims to study and apply the computer modeling of learning processes in their multiple manifestations. The combined advantages of learning from examples and learning by observation benefit the development of ML. The human-computer collaboration via on-the-spot interactions is shown as a promising direction in SLL domain because ML systems can enhance the effectiveness and users can simultaneously share intelligence.

Translation has had a bad reputation in second language learning and teaching. It is often associated with the Grammar Translation Method that for centuries guided the discipline, and mostly involved translating source texts from the second language (L2) into the native one (L1). This practice has gone as it was gradually replaced by the communicative methodologies of the 1960s. There are, however, a growing number of voices which claim that given the right parameters, as the fifth macro-skill to complement the other four (speaking and listening, reading and writing), which all educated bilinguals, not just translators, should master Campbell, S. (2002). In any case, it is a learning method that is proposed for advanced learners, certainly not for beginners. Kaye, P. (2009).

Conventional translation should not be confused with MT. When translating, someone conveys meaning into the other language manually, directly from the source text. with MT, the machine itself generates a draft, which most likely will not be perfect and will often require someone to fix grammar and lexis to make sure the meaning is adequately rendered – a task commonly referred to as post-editing. When applied to the language learning situation, MT produces a draft, which is the case of translating into L1,L2, the learners may comprehend depending on their level of knowledge of the L2, when the translating is being done into L1, the machine rendition may help the learners to comprehended the source.

Researchers have been aware of the possible uses of MT in language learning. i.e., of MT as computer-assisted language learning (CALL), since the 1980s. Somers, H. (2003) and Nin O.A. (2008). have offered a background of this literature.

The earliest studies focused on translation in the L1, to L2 direction and saw MT output typically as a "bad model", which involved the risk of providing the learner with ill-formed examples of L2. It could, however, help contrast grammatical dissimilarities between the languages, as Higgins, J., et al., (1984), wrote by "asking the students to spot the machine's howlers and account for them" (1984, p. 95). Not that most learners, or indeed teachers, had many opportunities to test whether it was of any use, since at that stage, MT technology was not only rudimentary but difficult to access. Already in the 1990s, Richmond boidily proposed "doing it backwards", predating, modifying the L1 sentence until an adequate L2 was obtained while dismissing the risk of reinforcing L2 errors by placing "the emphasis on linguistic processes and linguistic input rather than on linguistic forms and output" (1994, in Somers, H (2003), p. 328). The "Bad Model" unease was further defused by authors who suggested that it could also train learners in revision techniques (French, R.J. (1991) and encourage independent learning. La Torre, M.D. (1999).

In the following decade, Shei, C.C. (2002) referred to the advantages of pre-editing (which "can boost student learning in the cognitive and affective domain"), and Kliffer, M. (2005) and Nin O.A (2008) those of post-editing Kliffer's study indicated that students post-editing into L2 markedly improved the MT output, with the weaker students valuing the experience the most and definitely preferring post editing to translating from scratch. Nin O.A study (2008) presented that students produced fewer errors when translating into the L2 by post-editing than when they translated the traditional way.

All of these mentioned studies on MT for language learning and the others referred to by Somers, H. (2003) and Nin O.A. (2008), gathered data using advanced language learners or even translation trainees, never beginners or early intermediate learners. Also, these studies have limited the application of MT to pre-editing with the aim of gaining a satisfactory MT output, or post-editing as an alternative to translating directly from the source text. Thus, all previous literature sits in this blurred area where language learning overlaps with translation training. To these bodies of research, we could then add other work with a focus on translation trainees or indeed on professional translators, which has been published (Fiederer, R., & O'Brien, S. (2009), Garcia, I. (2010), Guerberof, A. (2009), among others). MT could help in other ways. Outside the classroom, it helps millions to at least make partial sense of a source that otherwise would not have been understood at all. It may also aids as a reading comprehension tool within the classroom. It may even works with the production of "free" writing, i.e., writing that does not need the existence of a previous source text to work on.

Two studies (Cohen, A., & Brooks-Carson, A. (2001), Kobayashi, H., & Rinnert, C. (1994), have already observed the effects of composing a text in L1 and then translating it into L2. In the present study ,the searcher reviewed these studies which has done in the area of MT and considers a good background to show the significance of MT in learning process for different levels and different purposes.

5. Conclusion / Suggestions

ML applications became a part of our daily life and MT can be considered as advanced approach in language learning. The searcher in this study has shown the significance of MT in learning English as second language and in translation as well. The study has given an evidence by reviewing a set of studies which shown how MT important in learning English and the role of it in assistance the translation. Using MT has great value in field of learning English and it's effective and easy way in translation and teachers who are using MT during the class and encouraging the student to use it also gives enthusiasm in learning English.

Suggestions

Using Machine translation helps in moving towards higher English level in translation and learning as well . Allocating time for self enhancement of the language is a requirement. We need to be cautious in applying MT, and then being mindful of using the MT in learning. Encouraging students in downloading number of *dictionary apps* and use them can make the journey towards learning pleasing and interesting. Thus, initiating self-learning. As the study states that there are clear significance in using MT in learning and in translation, it important to suggest that the teachers should start using MT in the class to make the class active and interest.

Reference

1. Anastasiou, D., & Gupta, R. (2011). Comparison of crowdsourcing translation with Machine Translation. Journal of Information Science, 37(6), 637-659.
2. Briggs, N. (2018). Neural Machine Translation Tools in the Language Learning Classroom: Students' Use, Perceptions, and Analyses. JALT CALL Journal, 14(1), 2-24.
3. Campbell, S. (2002). Translation in the Context of EFL-The Fifth Macro shill?. TEFLIN Journal, 13(1), 58-72.
4. Case, M. (2015). Machine translation and the disruption of foreign language learning activities. eLearning Papers, (45), 4-16.
5. Case, M. (2015). Machine translation and the disruption of foreign language learning activities. eLearning Papers, (45), 4-16.
6. Cohen, A., & Brooks-Carson, A. (2001). Research on direct versus translated writing:
7. Fiederer, R., & O'Brien, S. (2009). Quality and machine translation: A realistic objective. The journal of Specialized translation, 11(11), 52-74.
8. Fiederer, R., & O'Brien, S. (2009). Quality and machine translation: A realistic objective. The journal of Specialized translation, 11(11), 52-74.
9. French, R.J. (1991). Machine translation. In W. Brierley & I.R. Kemble (Eds.), Computers as a tool in language learning (pp. 55–69). Chichester: Ellis Horwood.
10. Garcia, I. (2010). Is machine translation ready yet?. Target. International Journal of Translation Studies, 22(1), 7-21.
11. Gaspari, F., & Hutchins, J. (2007). Online and free! Ten years of online machine translation: origins, developments, current use and future prospects. Proceedings of the Machine Translation Summit XI, 199-206.
12. Guerberof, A. (2009). Productivity and quality in the post-editing of outputs from translation

memories and machine translation. Localization Focus, 7(1), 11–21.
13. Higgins, J., & Johns, T. (1984). Computers in language learning. Aylesbury: Adison-Wesley.
14. Joanna Sycz-Opoń Ksenia Gałuskina,(2016) MT Evaluation Protocol as an educational tool for teaching machine translation: experimental classes. Journal of Translator Education and Translation Studies, (1)1, pp. 35-49 http://www.testsjournal.org.
15. Kaye, P. (2009). Translation activities in the language classroom. Teaching English.
16. Kliffer, M. (2005). An experiment in MT post-editing by a class of intermediate/advanced French majors. In Proceedings EAMT 10th Annual Conference (pp. 160-165).
17. Kobayashi, H., & Rinnert, C. (1994). Effects of first language on second language writing: Translation versus direct composition. In A.H. Cumming (Ed.), Bilingual performance in reading and writing (pp. 223–255). Ann Arbor, MI: Research Club in Language Learning.
18. La Torre, M. D. (1999). A web-based resource to improve translation skills. RECALL-HULL-, 11(3), 41-49.
19. Language Writing, vol.18, June 2009, pp.103-118.
20. Lykourentzou, I., Giannoukos, I., Nikolopoulos, V., Mpardis, G., & Loumos, V. (2009). Dropout prediction in e-learning courses through the combination of machine learning techniques. Computers & Education, 53(3), 950-965.
21. M. Temmerman, "Communicative aspects of definitions in classroom
22. N. Storch, "The impact of studying in a second language (L2) medium
23. Nin˜ o, A. (2008). Evaluating the use of machine translation post-editing in the foreign language class. Computer Assisted Language Learning, 21(1), 29–49.
24. Ning, Y., & Zhu, X. (2016, September). Deep Learning in Effective English Teaching Strategy of Senior High. In 2016 4th International Education, Economics, Social Science, Arts, Sports and Management Engineering Conference (IEESASM 2016). Atlantis Press.
25. Shei, C. C. (2002). Teaching MT through pre-editing: Three case studies. In Proceedings of the 6th EAMT Workshop Teaching Machine Translation (pp. 89-98).
26. Shon, T., & Moon, J. (2007). A hybrid machine learning approach to network anomaly detection. Information Sciences, 177(18), 3799-3821.
27. Somers, H. (2003). Machine translation in the classroom. In H. Somers (Ed.), Computers and translation. A translator's guide (pp. 319–340). Amsterdam/Philadelphia: Benjamins.
28. Students' strategies and their results. The Modern Language Journal, 85, 169–188.
29. Turing, I. B. A. (1950). Computing Machinery And Intelligence-Am Turing. Mind, 59(236), 433.
30. university on the development of L2 writing," Journal of Second
31. Ye, Q., Zhang, Z., & Law, R. (2009). Sentiment classification of online reviews to travel destinations by supervised machine learning approaches. Expert systems with applications, 36(3), 6527-6535