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A Review on Machine Translation Models and Challenges and Issues Faced

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Abstract
Language plays a major role in the world economy and businesses and the need for language translation is highly demanding. Due to a growth in the interchange of information across various regions utilizing distinct regional languages, the demand for translation has increased in recent years. In today's modern and increasingly globalized society, translation has become critical. Machine translation is a great resource for both corporations and people. While machine translation is unlikely to completely replace humans in any industry where quality is critical, a rising number of examples demonstrate how effective and beneficial it can be. Machine translation can be used in conjunction with human proofreaders and post-editors or on its own. Machine translation has been one of the most widely used applications of modern deep learning techniques, making language translation both simple and accurate. This article presents a review of machine translation models and investigates the issues and challenges faced and the applications of machine translation.

Introduction

Nowadays machines can understand text, respond to speech, listen to human commands, and map out the sentiment of a human being and whatnot. All this is made possible by NLP (Natural Language Processing). NLP is a branch of AI (Artificial Intelligence) that is focused on providing computers the ability to understand human speech and text as humans do. Machine translation is one of the applications of NLP that is changing the world today.

Machine translation is the translation of speech or text from one language to another automatically without any human intervention. Machine translation offers a wide range of uses in everyday life. In operations applications like translating official documents, an erroneous translation might have unfavorable or even fatal implications. As we tend to move to a state of affairs within which machines habitually translate tongue sentences, the potential for misunderstandings could become magnified.

Machine translation systems like Data-driven machine translation largely rely on the textual domain used to train them. In a typical in-domain MT state of affairs, the number of texts from one domain won't be enough to train a highly accurate translation system, even if it's for neural machine translation. To tackle these problems some models are trained on a mixture of parallel texts from completely different domains and later fine-tune the in-domain texts.

This has prompted new studies into machine translation testing approaches. To determine the validity of translation outcomes, existing approaches primarily rely on metamorphic relations built at the textual level of syntactic level. These metamorphic relationships, on the other hand, do not take into account whether the original and translated sentences have the same meaning.

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History

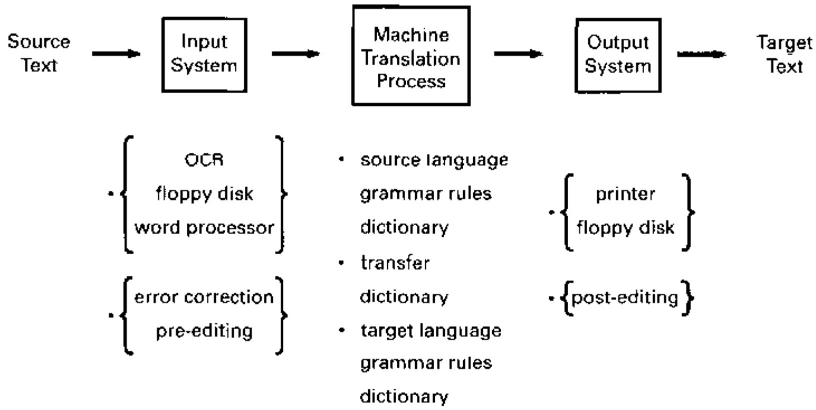
The concept of machine translation can be traced all the way back to the seventeenth century. René Descartes proposed a universal language in 1629, with similar thoughts in many languages using the same symbol. Warren Weaver's Memorandum on Translation introduced the topic of "machine translation" in 1949. Yehoshua Bar-Hillel, the field's initial researcher, began his work at MIT in 1951. After a public demonstration of their method in 1954, a Georgetown MT research team followed up in 1951. In Japan and Russia (1955), MT research programs arose, and the first MT conference was conducted in London in 1956. In the United States, the Association for Machine Translation and Computational Linguistics was founded in 1962, and the National Academy of Sciences established the Automatic Language System Processing Advisory Committee (ALPAC), Modern machine translation software frequently allows for customization by domain or profession (for example, weather reports), which improves translation accuracy by restricting the number of alternatives allowed. This method is especially effective in areas where formal or formulaic language is used. It follows that machine translation of government and legal documents easily produces more usable output than conversation or less standardized text.

Translation process

The meaning of a text in the original (source) language must be fully restored in the target language, i.e., the translation, to process any translation, whether human or automated. While it appears simple on the surface, it is significantly more complicated.
For example, the human translation process can be summarized as follows:
1. Decoding the meaning of the source text; and
2. Re-encoding this meaning in the target language.

This seemingly simple method conceals a sophisticated cognitive operation. To fully decode the meaning of the source text, the translator must interpret and analyze all of the text's features, a process that necessitates extensive knowledge of the source language's grammar, semantics, syntax, idioms, and other features, as well as the culture of its speakers. To re-encode the meaning in the target language, the translator requires the same level of expertise.

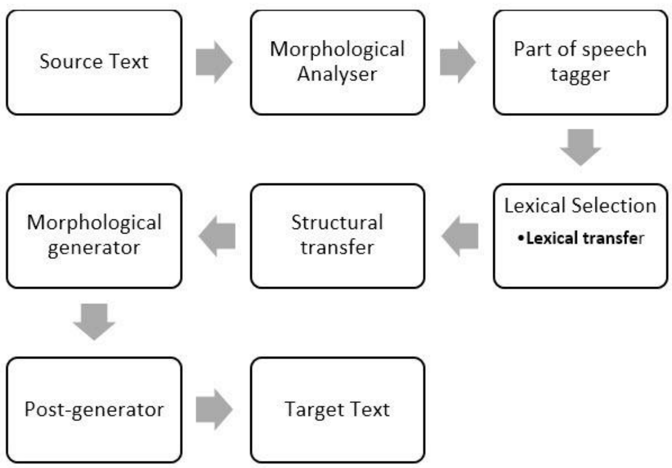
Because natural languages are so complex, machine translation becomes a difficult undertaking. Many words can have several meanings, sentences can have multiple interpretations, and some grammatical relationships in one language may not exist in another.



The figure depicts all of the stages involved in the Machine Translation process.

Classification of Machine Translation

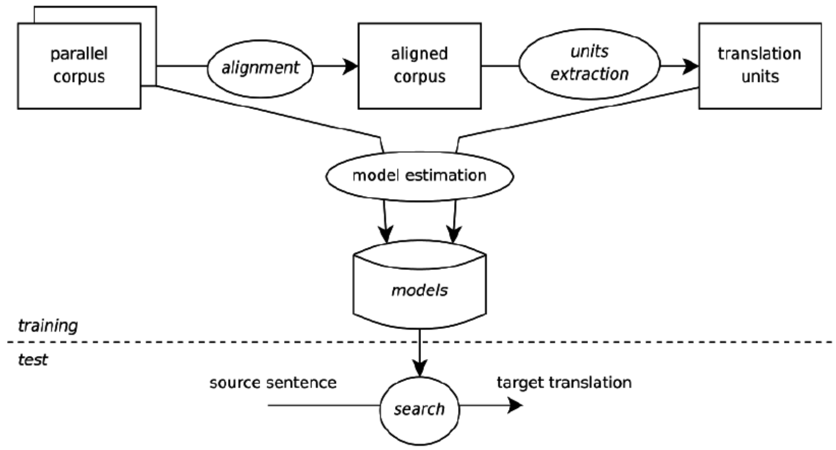
Rules-based machine translation (RBMT)



Architecture for RBMT based approach

Rule-based machine translation systems are based on linguistic information about the source and target languages that are mainly retrieved from dictionaries and grammar covering the main semantic, morphological, and syntactic regularities of each language. An RBMT system can generate sentences in a target language from source sentences based on morphological, syntactic, and semantic analysis of both the source and the target languages involved in a translation task.

Statistical machine translation



Architecture for SMT based approach

Statistical Machine translation (SMT) is a process by which a machine can learn how to translate by analyzing existing human translations. Most modern SMT systems use phrase-based translation techniques, which assemble translations by overlapping phrases. In phrase-based translation, the goal is to reduce the restrictions of word-based translation by translating whole sequences of words, where the lengths may vary. Phrases are made up of words, but they are not always linguistic phrases. Sometimes they are phrases found using statistical methods from bilingual text corpora. A genuine illustration of this is Google Translate.

Currently, SMT is good for basic translation, but it has a major disadvantage in that it doesn't take context into account, which means translations can often be wrong or you won't get high-quality translations. There are several types of machine translation models that are based on statistical data. These include hierarchical phrase-based translation, syntax-based translation, phrase-based translation, and word-based translation.

Neural Machine Translation

This is a large neural network that is trained to translate one language to another. An NMT model considers the conditional probability of translating an encoder sequence into a decoder output. NMT mainly is made up of two components

a. An encoder which generates a representation for the input text sequence.
b. b. A decoder that generates the translation of the representation into a different language.

Issues of RBMT Approach:

The following are some of the drawbacks of using the RBMT method:

a. There aren't enough truly decent dictionaries.
b. It is expensive to create new dictionaries.
c. Some linguistic data must still be manually entered.
d. It's difficult to cope with rule interactions, ambiguity, and idiomatic expressions in large systems.
e. Adapting to new domains is proving to be difficult. Although most RBMT systems have a mechanism for creating new rules and extending and adapting the vocabulary, changes are usually quite expensive, and the results are frequently unsatisfactory.

Issues of SMT Approach:

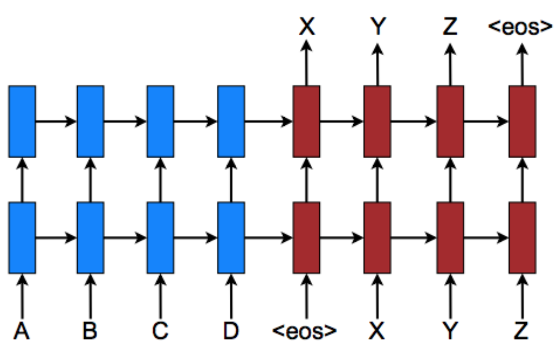
a. For users with limited resources, creating a corpus can be costly, and the outcomes can be surprising. Fluency on the surface can be deceiving.
b. Between languages with considerably divergent word ordering, statistical machine translation does not operate well (e.g., Japanese and European languages).
c. The advantages of European languages are overestimated.

Issues of NMT Approach:
d. Decoding is substantially slower than Statistical Machine Translation and takes a week to train.
e. No post-edit customization: it's difficult to figure out "what's wrong," and mistakes are difficult to correct.
f. Hardware requirements (GPU) are very expensive.

Neural Machine Translation Models

Sequence to sequence Model

The sequence-to-sequence model is a huge network of two completely distinct neural network models. One is an encoder, and the other is a decoder network. A sequence of mapping is generated at the decoder end from the input to the output. The decoder encrypts the text and provides meaning to the string.



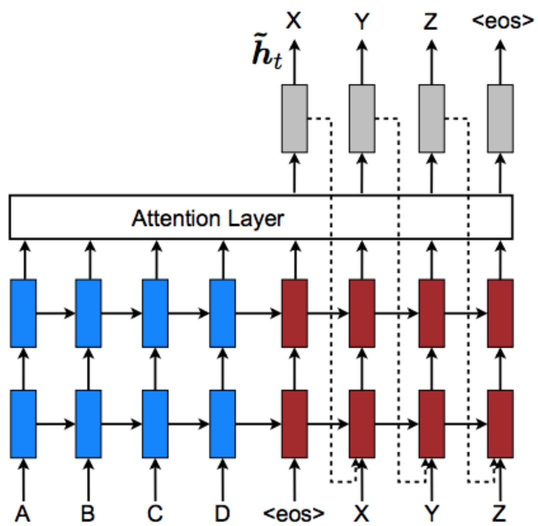
Translation of a source sequence A B C D into a target sequence X Y Z with neural machine translation as a stacking recurrent architecture. <eos> is used to indicate the end of a sentence in this case.

In neural machine translation, the encoder-decoder method encodes a sequence of input texts into a vector using which the translation is decoded. On a wider view, the job of the encoder network is to analyze and evaluate the input text sequence to get a logical understanding and to represent the input text sequence in a smaller dimension. This representation is then fed to the decoder network. The sequence-to-sequence problems even known as seq2seq are powered by Encoder-Decoder LSTM (Long Short-Term Memory) recurrent neural network. The LSTM is an architecture used in deep learning specifically it is a recurrent neural network architecture.

Attention model

By selectively focusing on sub-parts of the text during translation, attention mechanisms are increasingly being employed to enhance the performance of Neural Machine Translation (NMT).
In an attention model, the encoder feeds all the hidden states to the decoder network instead of passing only the last hidden stage.
This mainly uses two approaches

a. Global attention
b. Local attention

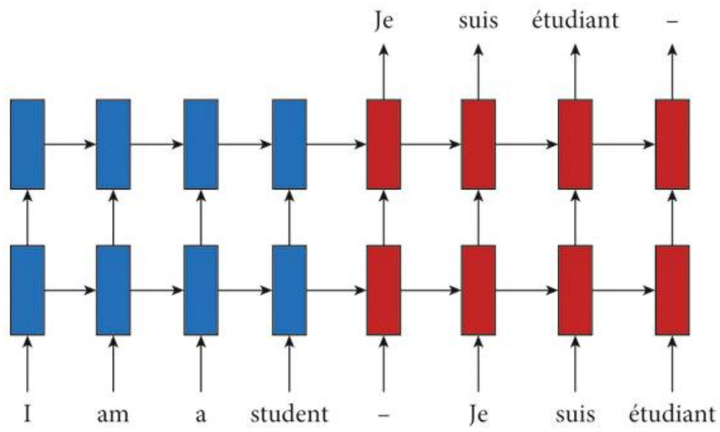


Attention and input-feeding method to NMT

In global attention, all sources receive attention whereas in local attention only a few source positions receive attention. Both the attention models differ from the sequence-to-sequence or the encoder-decoder approach only in the decoder phase.

Transformer Model

A sequential computation cannot be parallelized as it must await for the previous step to complete before proceeding to the next step. This process increases the time taken to train and produce inference. The use of Convolutional Neural Networks (CNNs) instead of RNNs avoids the challenges faced by



sequential computation.
Recurrent diagram of neural machine translation model

Transformer is a network that uses Convolutional Neural Networks in conjunction with attention models and lets away recurrence and convolutions of any kind. With both large and small training data, it has been demonstrated to generalize effectively well to additional language comprehension and modeling problems.

REAL-TIME APPLICATIONS OF MACHINE TRANSLATION

Machine translation can basically be classified into two major types:

A. **MACHINE TRANSLATION IN INDUSTRY FOR BUSINESS USE**
If some domains or industries are not satisfied with the accuracy that Google Translate or Microsoft Translator provide and they need a more specific type of training for their data in specific domains they train their own data that can provide them with high accuracy, and performance, and relevancy. These domain-specific translators can be used by small, medium, and large enterprises. Few enterprises require a multi-domain translation which means they can customize solutions across multiple domains and other enterprises require translation for specific domains. Both these solutions being automated still require human translators for pre and post-editing processes.

Some fields that use domain-specific machine translation solutions are:

- Government
- Software and technology
- Military and defense
- Healthcare
- Finance
- Legal
- E-discovery
- Ecommerce

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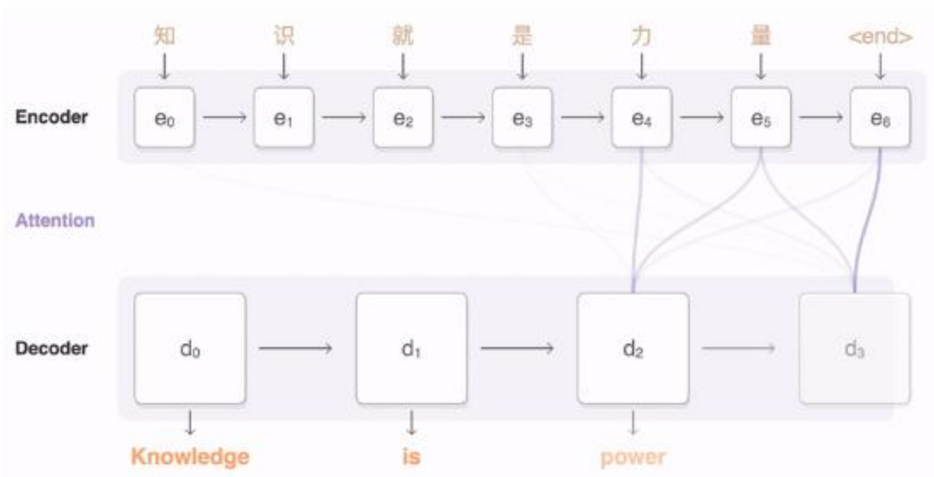
B. ONLINE / APP MACHINE TRANSLATION FOR CONSUMER USE

The machine translation applications provide instant translation for texts, audio, and image files from a source language to any desired language. These are generally built with a high translation accuracy. These applications are mostly cloud-based apps that are trained in the cloud. These are mostly used by individual customers. These apps most commonly offer:

- Text-to-text: Translation of a given text in a specific language to a text in another specified language.
- Text-to-speech: Translation of a given text to speech(audio) mode.
- Speech-to-text: Translation of a speech(audio) to a written text.
- Speech-to-speech: Translation of a speech(audio) in a specific language to a form of speech(audio) in another specified language.
- Image (of words)-to-text: Translation of an input image file with the text of words to a normal text file.



A simple visualization of how Google's translation "Decoder" works

Conclusion

For years, machine translation has been a subject of discussion in artificial intelligence research.
Because natural languages are immensely complex, many words have several meanings and plausible translations, sentences can have multiple readings, and relationships between linguistic components are frequently ambiguous, machine translation (MT) is a difficult challenge. Furthermore, it is occasionally required to consider conceptual understanding. There are growing use-cases in which the human translator/post-editor has no role to play, and translation quality can only be measured in terms of the translation output fitness for purpose. Nonetheless, many use-cases will continue to necessitate human post-editing of MT system translations. As a result, it is incumbent upon the entire MT developer community to deliver. This paper reviewed the history, the classification of Machine Translation, and the issues accompanied by them, briefed about Neural Machine Translation models and the application of Machine Translation in real-time.

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