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Human translation vs machine translation: The practitioner phenomenology

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***Abstract*---**The paper aimed at exploring the current phenomenon regarding human translation with machine translation. Human translation (HT), by definition, is when a human translator—rather than a machine—translate text. It's the oldest form of translation, relying on pure human intelligence to convert one way of saying things to another. The person who performs language translation. Learn more about using technology to reduce healthcare disparity. A person who performs language translation. The translation is necessary for the spread of information, knowledge, and ideas. It is absolutely necessary for effective and empathetic communication between different cultures. Translation, therefore, is critical for social harmony and peace. Only a human translation can tell the difference because the machine translator will just do the direct word to word translation. This is a hindrance to machines because they are not advanced to the level of rendering these nuances accurately, but they can only do word to word translations. There are different translation techniques, diverse theories about translation and eight different translation services types, including technical translation, judicial translation and certified translation. The translation is the process of translating the sequence of a messenger RNA (mRNA) molecule to a sequence of amino acids during protein synthesis. The genetic code describes the relationship between the sequence of base pairs in a gene and the corresponding amino acid sequence that it encodes.
***Keywords*---**communication, human, machine, services, translation.

Introduction

Machine Translation (MT) is considered the paradigm task of Natural Language Processing (NLP) by some researchers because it combines almost all NLP research areas: syntactic parsing, semantic disambiguation, knowledge representation, language generation, lexical acquisition, and morphological analysis and synthesis. However, the evaluation methodologies for MT systems have heretofore centered on black-box approaches, where global properties of the system are evaluated, such as semantic fidelity of the translation or comprehensibility of the target language output. There is a long tradition of such MT black-box evaluations (Van Slype, 1979; Nagao, 1985; JEIDA, 1989; Wilks, 1991), to the point that Yorick Wilks has stated: "MT Evaluation is better understood than MT" (Carbonell & Wilks, 1991; Amancio, Nunes, Oliveira, Pardo, Antiqueira, & Costa, 2011).

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While these evaluations are extremely important, they should be augmented with detailed error analyzes and with component evaluations in order to produce causal analyzes pinpointing errors and therefore leading to system improvement. In essence, we advocate both causal component analysis as well as global behavioral analysis, preferably when the latter is consistent with the former via the composition of the component analysis.

The advent of Knowledge-Based Machine Translation (KBMT) facilitates component evaluation and error attribution because of its modular nature, although this observation by no means excludes transfer-based systems from similar analyzes. After reviewing the reasons and criteria for MT evaluation, this paper describes a specific evaluation methodology and its application to the KANT system, developed at CMU's Center for Machine Translation (Mitamura *et al.,* 1991; Huang, 2011; Hutchins, 1995). The KANT KBMT architecture is particularly well-detailed for a detailed evaluation because of its relative simplicity compared to other KBMT systems, and because it has been scaled up to industrial-sized applications.

Discussion

The statistical framework has allowed a breakthrough in machine translation (MT) and new systems provide admissible results for many tasks. However, in other scopes the quality of fully-automated systems is insufficient. In such cases, MT is used to obtain translation hypotheses, which must be supervised and corrected by a human agent in a post-editing (PE) stage. This working method is more productive than a completely manual translation since the translator starts from an initial hypothesis that must be corrected. Nevertheless, this is a decoupled strategy in which computers and human agent work independently. Higher efficiency rates can be reached if human and system collaborate on a joint strategy. Seeking for this human–computer collaboration, Foster *et al.* (1997) introduced the so-called interactive-predictive MT (IMT), further developed by Alabau *et al.* (2013), Barrachina *et al.* (2009), Bender *et al.* (2005), Langlais & Lapalme (2002) & Macklovitch (2006).

This approach consists in an iterative prediction–correction process: each time the user corrects a word, the system reacts offering a new translation hypothesis, expected to be better than the previous one. In the basic IMT proposal, the user was constrained to follow a left-to-right protocol. Always was corrected the left-most wrong word from a translation hypothesis. This word, together with the previous ones, formed a validated prefix. At each iteration, the user validated a larger prefix and the system produced an appropriate suffix for completing the translation.

IMT evolved during the years, introducing advances related to the generation of the new suffix (Azadi & Khadivi, 2015; Cai *et al.,* 2013; Green *et al.,* 2014b; Koehn *et al.,* 2014; Ortiz-Mart´ınez, 2011), and the possibility of suggesting more than one suffix (Koehn & Senellart, 2010; Torregrosa *et al.,* 2014). Other novelties came from profiting the use of the mouse, validating a prefix and suggesting a new suffix each time the user learning techniques was also studied, aiming to improve the system with the user feedback (Mathur *et al.,* 2014; Nepveu *et al.,* 2004; Ortiz-Mart´ınez, 2016). Related to this, Gonz´alez-Rubio *et al.* (2012) explored the active learning protocol in an interactive post-edition stage. An interactive approach was also developed for hierarchical translation models (Gonz´alez-Rubio *et al.,* 2013; Dorr, Jordan & Benoit, 1999; Germann, Jahr, Knight, Marcu & Yamada, 2004).

Multimodal interaction integrated handwriting recognition/speech recognition into the IMT environment (Alabau *et al.,* 2011, 2014; Wołk & Marasek, 2015). Green *et al.* (2014a) investigated the interactive use of translation memories. Nonetheless, the core of the user protocol remained the same in all these cited works. Recent works (Gonz´alez-Rubio *et al.,* 2016; Peris, Domingo & Casacuberta, 2017), strove to overcome the prefix-based approach.

One of the interactive protocols proposed in our work, relies on these latter ideas of breaking down the prefix constraint.

The prefix-based protocol suffered from three main issues: first, it was quite restrictive. The human translator was forced to always follow the left-to-right validation direction. This could be unnatural for the users or even inadequate in many cases. Second, the IMT system could produce worse suffixes, which also should be corrected by the user. Apart from increasing the human effort of the process, this introduced an annoying behaviour: the user had to correct words that were right in previous iterations, leading to user exasperation. The third issue was the computational cost of the (prefix-constrained) search for alternative hypotheses, which prevented the use of regular decoders. The increase of the computational power has alleviated this problem, allowing the use of more complex models and search strategies, in order to reach real-time generation of successive hypotheses.

Pursuing to overcome both first problems, in this work we propose an alternative protocol: when a hypothesis is generated, the user can select correct word sequences, called segments, from all over the sentence. These segments are considered to be valid and will remain in future iterations. The user can also correct wrong words, as in the classical approach. The system offers then an alternative hypothesis, that takes into account the corrected word together with the validated segments. Thus, correct parts of the hypothesis are kept during successive interactions, offering a more comfortable user experience and an increase in the productivity.

Up to now, the IMT approaches were based on discrete representations of words and sentences. Nevertheless, in the last years, continuous representations of words and sentences have gained much the attention of the natural language processing community. Distributed representations are richer than classical ones, yielding encouraging results. Although neural models were already applied to MT long ago (Castan˜o & Casacuberta, 1997), they finally took off recently and its use has dramatically increased. Bengio *et al.* (2003) proposed to project words into a distributed space and estimate the probabilities of a language model in such space. From here, continuous models have been used profusely in a wide range of tasks like language modelling (Mikolov *et al.,* 2010; Schwenk, 2007; Sundermeyer *et al.,* 2012), handwritten text recognition (Graves *et al.,* 2009) or automatic speech recognition (Graves *et al.,* 2013). In the MT field, neural models have been successfully introduced into the current statistical machine translation (SMT) pipeline, both in the phrase-based and hierarchical approaches (Devlin *et al.,* 2014; Sundermeyer *et al.,* 2014; Martínez-Gómez, Sanchis-Trilles & Casacuberta, 2012).

In addition to this, a neural approach to MT has been recently proposed (Cho et al., 2014; Kalchbrenner & Blunsom, 2013; Sutskever *et al.,* 2014). Neural machine translation (NMT) has emerged as one of the most promising technologies to tackle the MT problem. It is based on the use of neural networks for building end-to-end systems. The translation problem is addressed by a single, large neural network, which reads an input sentence and directly generates its translation. This is opposed to classical approaches to MT (e.g. Koehn & Knight, 2003), made up of multiple decoupled models. Most architectures are based on recurrent neural networks (RNN). In order to properly deal with long-term relationships, RNNs use gated units, such as long short-term memory (LSTM) units (Hochreiter & Schmidhuber, 1997) or gated recurrent units (GRU) (Cho *et al.,* 2014; Das, Agrawal, Zitnick, Parikh & Batra, 2017).

There has been a significant effort for improving the NMT model. Thus, attention mechanisms were included to the model (Bahdanau *et al.,* 2015; Luong *et al.,* 2015b), allowing the model to focus on different parts of the input sentence. The out-of-vocabulary problem was tackled by Jean *et al.* (2015), Luong *et al.* (2015a) and Sennrich *et al.* (2016). Jean *et al.* (2015), also investigated the use of large target vocabularies. Gulcehre *et al.* (2015), included additional monolingual resources into the system. NMT at character-level has also obtained promising results (Chung *et al.,* 2016; Costa-Juss`a & Fonollosa, 2016; Ling *et al.,* 2015; Güvenir & Cicekli, 1998; Church & Hovy, 1993).

In translation studies faithfulness in literary translation exists only to some degree. Since unfaithfulness in literary translation is a matter of definition, the acceptance of relatively faithful but imperfect translation acquires new contexts in digital humanities (see, e.g., Scott; Huang). From an intermedial point of view, a translated text may be considered a new or hybrid product that does not have to be evaluated solely against the primary standards of the source language or its author's culture. Instead, such primary standards may be reduced to secondary in quality assessment. In this article, I address the issue of imperfection in machine translation (MT) versus human translation (HT). Both forms of translation involve a process of the transfer of meaning or knowledge including culture and other elements, and are thus treated as equals.

Since its beginning in the 1950s and 1960s, the use of machine translation includes technical documentation (see, e.g., Hutchins, "Computer-based Translation"). Methodologically, research has gone through the beginning a trial-and-error stage followed by corpus based approaches in the late 1980s. There have been the "direct translation" model and the "interlingua" (indirect) model, including a large number of systems many of which have been used by government departments and corporations. The 1980s then saw the growing interest in spoken language translation. After two decades of research and development backed up by fast-speed computers, MT has been available to many individual internet users. However, what may be described at present is that much of online automatic translation is inaccurate (Nyberg, Mitamura & Carbonell, 1994).

Nonetheless, one is reminded that since authors, such as the Chinese literary icon Lu Xun (see Huang, "The Translatologese Syndrome"), also experience difficulty in expressing their ideas, and that since translators never produce perfect translations, one has no reason to expect flawless translations from the computer. The process of transferring meaning in the translation from one language to another, from print to electronic form, leads to a fundamental change in communication (see, e.g., Sager 256-58) resulting in another medium. Moving electronically translated texts to the internet, including the yet unpopular simultaneous speech translation, presents itself as a third medium. All of these intertwine, interline, depending upon each other (see, e.g., Chapple; Chapple and Kattenbelt; López-Varela and Tötösy de Zepetnek).

One bottleneck problem that remains unresolved is the lack of standardized quality assessment. Although MT evaluation has become an important aspect of research, no formula or easy-to-apply model has been created either for MT or HT quality assessment (see Hutchins, "Machine Translation"). By and large, frontline evaluators assess translated texts on a piece-by-piece basis, while scholars attempt to create models and approaches that measure TT against a non-existent perfect product and are unaware of the dividing line between acceptability and unacceptability.

In the present article, the data used in the quantification of the relevant issues come from an international survey where three literary excerpts translated into English from the Chinese were surveyed: about 300 professional translators — including 15 senior United Nations translators — completed the different versions or different parts of the international survey (see Huang, A Model for Translation). One question was to find the maximum rate of inaccuracy in HT that can be tolerated by the international community of translators, writers, editors, and translation scholars.

This maximum number thus becomes the ceiling under which a TT may not be rejected, but over which a TT is considered a failure. Expressed in numerical terms, this ceiling becomes the dividing line between TT acceptability and unacceptability. Another question was to discover the maximum inaccurate rate in MT which the professionals could tolerate before flatly rejecting it. It should be noted that individuals were asked to answer only questions they felt comfortable with. Thus, not all data would show the same number of participants. The number of participants who were comfortable with MT questions was small, but given the small number of qualified professionals who were willing to participate the data is deemed sufficient.

Basic features and terminology

The term 'machine translation' (MT) refers to computerized systems responsible for the production of translations with or without human assistance. It excludes computer-based translation tools which support translators by providing access to on-line dictionaries, remote terminology databanks, transmission and reception of texts, etc. The boundaries between machine-aided human translation (MAHT) and humanaided machine translation (HAMT) are often uncertain and the term computer-aided translation (CAT) can cover both, but the central core of MT itself is the automation of the full translation process.

Although the ideal goal of MT systems may be to produce high-quality translation, in practice the output is usually revised (post-edited). It should be noted that in this respect MT does not differ from the output of most human translators which is normally revised by a second translator before dissemination. However, the types of errors produced by MT systems do differ from those of human translators (incorrect prepositions, articles, pronouns, verb tenses, etc.). Post-editing is the norm, but in certain circumstances MT output may be unedited or only lightly revised, e.g. if it is intended only for specialists familiar with the text subject. Output might also serve as a rough draft for a human translator, i.e. as a 'pre-translation'.

The translation quality of MT systems may be improved either, most obviously, by developing more sophisticated methods or by imposing certain restrictions on the input. The system may be designed, for example, to deal with texts limited to the sublanguage (vocabulary and grammar) of a particular subject field (e.g. biochemistry) and/or document type (e.g. patents). Alternatively, input texts may be written in a controlled language, which restricts the range of vocabulary, and avoids homonymy and polysemy and complex sentence structures. A third option is to require input texts to be marked (pre-edited) with indicators of prefixes, suffixes, word divisions, phrase and clause boundaries, or of different grammatical categories (e.g. the noun cónvict and its homonymous verb convíct). Finally, the system itself may refer problems of ambiguity and selection to human operators (usually translators) for resolution during the processes of translation itself, in an interactive mode.

Systems are designed either for two particular languages (bilingual systems) or for more than a single pair of languages (multilingual systems). Bilingual systems may be designed to operate either in only one direction (unidirectional), e.g. from Japanese into English, or in both directions (bidirectional).
Multilingual systems are usually intended to be bidirectional; most bilingual systems are unidirectional.

In overall system design, there have been three basic types. The first (and historically oldest) type is generally referred to as the 'direct translation' approach: the MT system is designed in all details specifically for one particular pair of languages, e.g. Russian as the language of the original texts, the source language, and English as the language of the translated texts, the target language.

Translation is direct from the source language (SL) text to the target language (TL) text; the basic assumption is that the vocabulary and syntax of SL texts need not be analyzed any more than strictly necessary for the resolution of ambiguities, the correct identification of TL expressions and the specification of TL word order; in other words, SL analysis is oriented specifically to one particular TL. Typically, systems consist of a large bilingual dictionary and a single monolithic program for analysing and generating texts; such 'direct translation' systems are necessarily bilingual and unidirectional.

The second basic design strategy is the interlingua approach, which assumes that it is possible to convert SL texts into representations common to more than one language. From such interlingual representations texts are generated into other languages. Translation is thus in two stages: from SL to the interlingua (IL) and from the IL to the TL. Procedures for SL analysis are intended to be SL-specific and not oriented to any particular TL; likewise programs for TL synthesis are TL-specific and not designed for input from particular SLs.

A common argument for the interlingua approach is economy of effort in a multilingual environment. Translation from and into n languages requires n(n-1) bilingual 'direct translation' systems; but with translation via an interlingua just 2n interlingual programs are needed. With more than three languages the interlingua approach is claimed to be more economic. On the other hand, the complexity of the interlingua itself is greatly increased. Interlinguas may be based on an artificial language, an auxiliary language such as Esperanto, a set of semantic primitives presumed common to many or all languages, or a 'universal' language-independent vocabulary.

The third basic strategy is the less ambitious transfer approach. Rather than operating in two stages through a single interlingual representation, there are three stages involving underlying (abstract) representations for both SL and TL texts. The first stage converts SL texts into abstract SL-oriented representations; the second stage converts these into equivalent TL-oriented representations; and the third generates the final TL texts. Whereas the interlingua approach necessarily requires complete resolution of all ambiguities in the SL text so that translation into any other language is possible, in the transfer approach only those ambiguities inherent in the language in question are tackled; problems of lexical differences between languages are dealt with in the second stage (transfer proper). Transfer systems consist typically of three types of dictionaries (SL dictionary/ies containing detailed morphological, grammatical and semantic information, similar TL dictionary/ies, and a bilingual dictionary relating base SL forms and base TL forms) and various grammars (for SL analysis, TL synthesis and for transformation of SL structures into TL forms).

Within the stages of analysis and synthesis (or generation), many MT systems exhibit clearly separated components involving different levels of linguistic description: morphology, syntax, semantics. Hence, analysis may be divided into morphological analysis (identification of word endings, word compounds), syntactic analysis (identification of phrase structures, dependency, subordination, etc.), semantic analysis (resolution of lexical and structural ambiguities); synthesis may likewise pass through semantic synthesis (selection of appropriate compatible lexical and structural forms), syntactic synthesis (generation of required phrase and sentence structures), and morphological synthesis (generation of correct word forms). In transfer systems, the transfer component may also have separate programs dealing with lexical transfer (selection of vocabulary equivalents) and with structural transfer (transformation into TL-appropriate structures). In some earlier forms of transfer systems analysis did not involve a semantic stage, transfer was restricted to the conversion of syntactic structures, i.e. syntactic transfer alone.

In many older systems, particularly those of the 'direct translation' type the components of analysis, transfer and synthesis were not always clearly separated. Some of them also mixed data (dictionary and grammar) and processing rules and routines. Later systems have exhibited various degrees of modularity, so that system components, data and programs can be adapted and changed without damage to overall system efficiency. A further stage in some recent systems is the reversibility of analysis and synthesis components, i.e. the data and transformations used in the analysis of a particular language are applied in reverse when generating texts in that language.

The direct translation approach was typical of the "first generation" of MT systems. The indirect approach of interlingua and transfer based systems is often seen to characterise the "second generation" of MT system types. Both are based essentially on the specification of rules (for morphology, syntax, lexical selection, semantic analysis, and generation). Most recently, corpus-based methods have changed the traditional picture (see below). During the last five years, there is beginning to emerge a "third generation" of hybrid systems combining the rule-based approaches of the earlier types and the more recent corpus-based methods. The differences between direct and indirect, transfer and interlingua, rulebased, knowledge-based and corpus-based are becoming less useful for the categorization of systems.

Transfer systems incorporate interlingual features (for certain areas of vocabulary and syntax); interlingua systems include transfer components; rule-based systems make increasing use of probabilistic data and stochastic methods; statistics- and example-based systems include traditional rule-based grammatical categories and features; and so forth. These recent developments underline what has always been true, namely that MT research and MT systems adopt a variety of methodologies in order to tackle the full range of language phenomena, complexities of terminology and structure, misspellings, 'ungrammatical' sentences, neologisms, etc. The development of an operational MT system is necessarily a long-term 'engineering' task applying techniques which are well known, reliable and well tested.

One of the most promising approaches to machine translation consists in formulating the problem by means of a pattern recognition approach. By doing so, there are some tasks in which online adaptation is needed in order to adapt the system to changing scenarios. In the present work, we perform an exhaustive comparison of four online learning algorithms when combined with two adaptation strategies for the task of online adaptation in statistical machine translation. Two of these algorithms are already well-known in the pattern recognition community, such as the perceptron and passive-aggressive algorithms, but here they are thoroughly analyzed for their applicability in the statistical machine translation task. In addition, we also compare them with two novel methods, i.e., Bayesian predictive adaptation and discriminative ridge regression. In statistical machine translation, the most successful approach is based on a log-linear approximation to a posteriori distribution.

Conclusion

The gold standard of translation in the future may be some kind of computer-assisted human translation—or, of you will, human-assisted computer translation. So, the answer seems to be that no, human translators will never be completely replaced. Translation is a mental activity in which a meaning of given linguistic discourse is rendered from one language to another. Google Translate's NMT system uses a large artificial neural network capable of deep learning. By using millions of examples, GNMT improves the quality of translation, using broader context to deduce the most relevant translation. The result is then rearranged and adapted to approach grammatically based human language. In a full translation the entire text is submitted to the translation process; that is, every part of the source language text is replaced by target language text material.You can even point your smartphone at a sign or other text written in a foreign language, and the app displays the translation for you. Google Translate works on iOS and Android devices; iPhone and iPad users can download it from Apple's App Store, while Android users can snag it from Google Play.

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