NYELVI KÖZVETÍTÉS A KÁRPÁT-MEDENCÉBEN A PANDÉMIA IDEJÉN

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Szerkesztette
SZOTÁK SZILVIA ÉS LEHOCKI-SAMARDZIC ANNA

JEZIČNO POSREDOVANJE U KARPATSKOM BAZENU U VRIJEME PANDEMIJE
Uredile
Szilvia Szoták i Ana Lehocki-Samardžić

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Edited by
Szilvia Szoták and Ana Lehocki-Samardžić

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TARTALOM/SADRŽAJ/CONTENTS

CHALLENGES OF ASSESSING MACHINE TRANSLATION FROM GERMAN INTO CROATIAN LANGUAGE: A CASE STUDY[1]

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Abstract. The present paper discusses the theoretical framework of the assessment of machine translation, and it examines one of the possibilities of evaluating machine translation in a form of a case study. The proposed case study examines a translated legal text done by the automatic language translators Google Translate and Bing Translator from German into Croatian language, and then compares it to the human translation of the same text obtained from the parallel corpora of legal texts EUR–Lex. The language analysis in the sample case study is done according to the Kirchhoff et al.'s error analysis, although there are other options mentioned in the paper.
Keywords: machine translation, legal text, error analysis, assessment

Sažetak: Izazovi evaluacije strojnog prevođenja s njemačkog na hrvatski: studija slučaja. U radu se razmatra teorijski okvir za evaluaciju strojnog prevođenja i ispituje se njegova mogućnost analize u obliku studije slučaja. U izloženoj studiji slučaja ispitali smo pravni tekst preveden pomoću Google Translate-a i Bing Translator-a, automatskih jezičnih prevoditelja s njemačkog na hrvatski jezik, a zatim smo taj tekst usporedili s humanim prijevodom iz paralelnog korpusa EUR-Lex pravnih tekstova. Lingvistička analiza studije slučaja slijedi analizu pogrešaka Kirchhoff et al., no u radu se spominju i druge mogućnosti.
Ključne riječi: strojno prevođenje, pravni tekst, analiza pogrešaka, evaluacija

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Absztrakt: A németről horvát nyelvre történő gépi fordítás értékelésének kihívásai: esettanulmány. A tanulmány a gépi fordítás értékelésének elméleti kereteit tárgyalja, és esettanulmány formájában megvizsgálja annak lehetőségét. Jelen esettanulmányban egy olyan jogi szöveget vizsgáltunk meg, amelyet a Google Translate és a Bing Translator automatikus nyelvi fordítóprogram fordított német nyelvről horvát nyelvre, majd ezt a szöveget összehasonlítottuk az EUR-Lex jogi szövegek párhuzamos korpuszából származó humán fordítással. A esettanulmány nyelvi elemzése Kirchhoff et al. hibaelemzését követi, bár a dolgozatban más lehetőségek is említésre kerülnek.
Kulcsszavak: gépi fordítás, jogi szöveg, hibaelemzés, értékelés

1. Introduction

Before starting to discuss the topic of evaluating machine translation, one must acknowledge the terminology that will be used throughout this paper. It is well known that there are significant differences in the terms machine translation, computer–aided translation, and other forms of interactive translation that combine both machine and human translation.

According to Taravella and Villenevue (2013: 65), *human–aided machine translation* (HAMT) is a kind of automatic translation (AT) that cannot take place without human intervention (BOUILLON (1993) and QUAH (2006) in TARAVELLA AND VILLENEVUE 2013: 65). This means that the human factor is an important aid in machine translation, and that the translation process could not be completed without human intervention. Apart from the automatic translation systems that are human–aided (HAMT), there are also human translation systems that are computer–assisted, the term being *machine aided human translation* (MAHT). Both terms, i.e., HAMT and MAHT, can be found in the literature nowadays under the terminology of *computer–aided translation* (CAT) or *computer–assisted tools* CAT tools (HUTCHINSON AND SOMERS 1992; QUAH 2006 in TARAVELLA AND VILLENEVUE 2013: 65), which are also often being referred to as *machine–aided translation* (MAT) by software engineers and specialists (QUAH 2006:6 in TARAVELLA AND VILLENEVUE 2013: 65). Frequently, HAMT is shortened simply to *machine translation* (MT) (BOWKER 2002: 4 in TARAVELLA AND VILLENEVUE 2013: 65). The main notable difference between MT and CAT tools lies in the responsibility for the final translation, that is, whether the translation is solely the machine output (MT) (AZZANO 2009: 19), delivered by a computer software or an application, or by a human translator who has been using different types of software to produce the translation, such as electronic dictionaries, terminology databases and translation memory systems (HAMT) (WERTHMANN AND WITT 2014: 82). In this paper, we will be discussing the possibilities and opportunities of evaluating MT in the latter sense, and thus

compare it with human translation of the same text. The aim of the paper is to discuss the challenges of assessing machine translation of European Union legal documents. The reason for choosing a legal text lies in the fact that the referenced human translations have been accredited, revised, approved, and are part of the EUR–Lex multilingual legal text corpus obtainable by the tool SketchEngine[2]. The evaluation of the machine translation will not be made from the viewpoint of software engineers, but from the perspectives of linguists and translators. Since there have already been numerous papers published on the topic of machine translation from or into the English language, the present paper will evaluate another official language pair of the European Union, namely the German and Croatian language sample. Due to the limited constraints of the present paper, we will concentrate only on the translation from German into Croatian language, thus creating a case study.

2. A brief history of Machine Translation

Contrary to common belief, the first ideas on obtaining a machine–aided translation date back to the 17th century, when Latin slowly began to lose its status as science lingua franca and was replaced by other languages such as the French, thereby causing a rise in interests in the idea of mechanical devices which would help overcome linguistic obstacles (RAMLOW 2009: 54). In the 19th century, George Bole invented the mechanical calculator which was used in the process of coding, whereas in 1933 the French Georges Artsrouni and Russian Petr Petrovich Smirnov–Troyanski obtained patents for their translation machines independently of one another. Both these machines were used for composing mechanical dictionaries (RAMLOW 2009: 55). In 1946 Andrew Donald Booth and Warren Weaver developed the first computer–driven translation system based on dictionary comparison. Thereafter, in 1948, a newer version of this system was developed by R. H. Richens and Andrew Donald Booth. The developed system had other functions; in addition to the word–for–word translation, it was also able to carry out a syntactic analysis (RAMLOW 2009: 57). Yehoshua Bar–Hillel became known as a first scientist in the field of machine translation in 1951, he later worked with IBM on a project, presented to the public in 1954, in which 49 sentences were automatically translated from Russian into English. Although it may be considered invaluable in a scientific sense, this presentation had attracted investors and motivated other countries to develop their own systems. In 1955 and 1956, research projects dealing with machine translation were started up in England, Italy, Russia, China, and Japan (HUTCHINS 1995: 432). In the 1980s, MT became commercialized, and research branched out in several directions. These systems were computerized and

[2] https://www.sketchengine.eu/

mostly made for Japanese and English, transfer–based and limited to the syntactic and morphological analysis of the source text (cf. HUTCHINS 1995). At the end of the 1980s, research went in a different direction, in addition to the rule–based translation systems, corpus–based and artificial intelligence-oriented methods were also implemented. Since the 1990s, the usage of computers became much more widespread. Machine translation systems were used by professional translators more frequently, in as much as different translation tools, such as translation memory systems, terminology databases and word processing programs, that were also introduced in the 1990s. (RAMLOW 2009: 35–36). However, the contemporary usage of MT tools has had its modern breakthrough in the twenty-first century with the advanced usage of mobile and electronic devices and online resources and databases.

3. Assessment of Machine Translation of Texts from German into Croatian

There has been a dearth of publications on the discourse and analysis of MT of texts into Croatian from the linguistic point of view. The available ones that discuss MT into Croatian were mostly MA theses written by students of information studies. For instance, BAKOVIĆ (2018)[3] in her MA thesis analyzes the efficiency of Google Translate and Yandex Translators from German into Croatian and concludes that both translators presented lots of errors in the field of discourse, recognition of coherent group of words, understanding of the syntactic function of each word, understanding of selective relations between words, phrases, word ambiguity, ability to identify previous events, and context, whereas Google Translate has proven to be a more reliable and better machine translator that made less errors and offered better quality translations from German into Croatian and vice versa (BAKOVIĆ 2018:55). POPADIĆ (2017)[4]. On the other hand, parallel evaluation of Google Translate, Bing Translate and Yandex on three texts from English into Croatian (an original research paper, a popular-scientific paper, and a newspaper article) brought forth a conclusion that Google Translate was the most efficient machine translation tool.
Because of the above stated reasons and the fact that next to the professional translation CAT tools the wider public nowadays uses mostly the automated MT tools such as Google and Bing, in this paper we will present a sample of a

[3] BAKOVIĆ, DAJANA 2018. Usporedba prijevoda s njemačkog jezika na hrvatski jezik putem besplatnih strojnih prevoditelja. Rijeka: Filozofski fakultet (MA–Thesis). https://repository.ffri.uniri.hr/islandora/object/ffri:2133, obtained on March 20, 2022.
[4] POPADIĆ, DRAGANA 2017. Usporedna analiza alata za strojno prevođenje. Osijek: Fakultet elektrotehnike, računarstva i informacijskih tehnologija Osijek (diplomski rad). https://repozitorij.etfos.hr/islandora/object/etfos:1635, obtained on March 20, 2022.

German legal text translated by Google Translate[5] and Bing Translator[6] into Croatian, that will subsequently be evaluated and analyzed from the linguistic point of view.

3.1. Assessment Criteria of MT

When evaluating MT, one must consider several aspects and several approaches of assessing the automated translation. One approach is by using the SAE J2450 quality metric. This metric has been developed to assess any type of specialized language. It was mainly created to assess only "automotive service information" (SAE J2450, 2001: 2[7]), but it can now be applied to any other specialized language, regardless of the source language or the method of translation (i.e., human translation, computer assisted translation or machine translation). The metrics allow an evaluator to tag errors in a translation and compute a weighted, numeric score that represents the quality of the translation. It consists of four parts: seven error categories, two sub-categories, two meta-rules to help decide ambiguities on the assignment of an error to the categories and subcategories and the numeric weights. Evaluators must follow five steps to assess a translation. Once the errors are identified by the evaluator, he must indicate if the errors are serious or minor. In this case, it is necessary that the evaluator gives a judgment call about the level of seriousness of the error. The error categories are wrong term, syntactic error, omission, word structure or

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[5] *Google Translate* is a free online translator, and perhaps the most used MT tool. It is a statistic–based system that incorporates 108 languages. The system works on translation of 59 language pairs even without an internet connection, it can also translate texts on photographs into 90 languages and handwriting into 96 languages. Google translator has access to the largest database in the world, namely the Google search engine, which serves as a corpus for the Google translator. Since 2016, Google has been using a neural model (WU 2016: 1-2) named Google Neural Machine Translation (GNMT). GNMT improves translation quality by using an example–based machine translation method (EBMT) in which the system "learns from millions of examples". It translates whole sentences at once, not just piece by piece and uses a broader context to help identify the 25 most relevant translations, which are then rearranged and adapted to be as similar as possible to human speech with proper grammar (GERS, SCHMIDHUBER, CUMMINS 2000). GOUGH (2018) suggests that Google Translator as a machine translation tool has improved significantly over the years. The data from June 2018 according to Google's translation accuracy test and user reviews say that for most major languages in the world Google Translate received an average score of 5.43 out of a possible 6 (for example, English to Spanish translation via Google Translate was rated with the score 5.43, while the Chinese to English translation was rated 4.3).

[6] *Microsoft Bing Translator* is also a free internet translator and the direct competitor of Google Translate. It also has many languages in its database, more precisely 90 languages and dialects, can recognize the voice and translate texts on photographs. Like its competitor, Google Translate, this translator also works without an internet connection.

[7] SAE J2450 2001. Translation Quality Metric. SAE International. http://www.apex-translations.com/documents/sae_j2450.pdf, obtained on March 20, 2022.

agreement error, misspelling, punctuation error, and miscellaneous error (Table 1).

Category Name: (abbreviation)	Sub-Classification: (abbreviation)	Weight: serious/minor
a. Wrong Term (WT)	serious (s)	5/2
b. Syntactic Error (SE)	minor (m)	4/2
c. Omission (OM)		4/2
d. Word Structure or Agreement Error (SA)		4/2
e. Misspelling (SP)		3/1
f. Punctuation Error (PE)		2/1
g. Miscellaneous Error (ME)		3/1

Table 1: *Reference guide to error categories, classifications and weights (SAEJ2450 2001:5)*

Another approach is the LISA QA Model (Localization Industry Standards Association Quality Assessment). This model establishes seven error categories – mistranslation, accuracy, terminology, language, style, country, and consistency - in order to tag them in a translation. It contains a list of language codes and language names, a predefined list of severity levels and weights, a list of error categories, a list of tasks performed by reviewers, and predefined metrics to define a Pass/Fail grade (STEJSKAL, 2006: 21).

One further possibility to be considered is the TAUS (Translation Automation User Society) Dynamic Quality Evaluation Model. It is a metric created from practices, reports, templates, and several tools used to evaluate translations made both by human translators and MT engines (GÖRÖG, 2014: 445). TAUS applies an error typology on the LISA QA and differentiates between mistranslation, accuracy (omission, addition, cross-references), terminology (glossary adherence, context), language (grammar, semantics, punctuation, spelling), style (general style, register/tone, language variants), country (country standards, local suitability), and consistency. The penalty points in relation to the severity level are 1 = minor errors; 5 = major errors; 10 = critical errors. To use TAUS, it is necessary to create an account in its website and upload the translation to assess its quality. However, TAUS leaves out certain types of texts, for instance technical, legal, or economic texts. (MARTÍNEZ 2014: 84).

Although the presented translation quality assessment metrics aim to make the process automatic and devoid of human decision, one must admit that one of the major drawbacks of the proposed models is the subjectivity of the evaluator. MARTÍNEZ (2014: 86) states that the human activity cannot be detached from these models since it is a person (reviser/rater) who has the final word in error detection and tagging. Due to the fact that this was the first attempt in evaluating MT of legal texts form German into Croatian and therefore we would not be able to provide the weights of the errors MT used in the SAE J2450 and LISA QA metrics discussed above, we decided for the purpose of this paper to

evaluate the MT manually by using Kirchhoff et al. conjoint model of linguistic and error analysis (KIRCHHOFF ET AL. 2012 in POPOVIĆ 2018: 136) with the two-level error categorization as can be seen in Table 2.

level 1	level 2
missing words	content words function words
extra words	content words function words
word order	local range long range
morphology	verbal nominal
word sense error	
punctuation	
spelling	
capitalization	
untranslated	medical term proper term other
pragmatics	
diacritics	
other	

Table 2: *KIRCHHOFF ET AL. error categories*

3.2. Case Study

For the purpose of the paper, a legal text was randomly chosen from the EUR–Lex German and Croatian parallel corpora by using the corpus analysis tool SketchEngine which has previously been translated and validated by a human translator.

The first step in evaluating the machine translation was to present the output to bilingual human evaluators who understand both source and target language to assign a quality score for a given task, e.g., from 1=poor to 5=perfect, i.e., for each source sentence the evaluator should say if the version A or version B is better by assigning an absolute score (cf. POPOVIĆ 2018). The next step was the error classification which was carried out manually by using different sources of information: source language text, target language text and reference validated human translation. Table 3 presents one part of the output of both MT and the human reference text.

Original text from the German corpus EUR–Lex[8]	Human translation from the Croatian parallel corpus EUR_LEX	Google Translate	Bing Translator
In der Richtlinie 85/577/EWG des Rates vom 20. Dezember 1985 betreffend den Verbraucherschutz im Falle von außerhalb von Geschäftsräumen geschlossenen Verträgen (4) und der Richtlinie 97/7/EG des Europäischen Parlaments und des Rates vom 20. Mai 1997 über den Verbraucherschutz bei Vertragsabschlüssen im Fernabsatz (5) sind eine Reihe von vertraglichen Rechten der Verbraucher verankert.	Direktivom Vijeća 85/577/EEZ od 20. prosinca 1985. za zaštitu potrošača u pogledu ugovora sklopljenih izvan poslovnih prostorija (4) i Direktivom 97/7/EZ Europskog parlamenta i Vijeća od 20. svibnja 1997. o zaštiti potrošača s obzirom na sklapanje ugovora na daljinu (5) utvrđuje se niz ugovornih prava za potrošače.	U Direktivi Vijeća 85/577 / EEZ od 20. prosinca 1985. o zaštiti potrošača u slučaju ugovora sklopljenih izvan poslovnih prostora (4) i Direktivi 97/7 / EZ Europskog parlamenta i Vijeća od 20. svibnja 1997. o Zaštita potrošača pri sklapanju ugovora o prodaji na daljinu (5) sadržana je u nizu ugovornih prava potrošača.	Direktiva Vijeća 85/577/EEZ od 20. prosinca 1985. o zaštiti potrošača u slučaju ugovora izvan poslovnih prostorija (4) i Direktive 97/7/EZ Europskog parlamenta i Vijeća od 20. svibnja 1997. o zaštiti potrošača u slučaju ugovora na daljinu (5) sadrži niz ugovornih prava potrošača.

Table 3: *The original German text with MT and the human translation as the reference text*

Having analyzed the MT of the German text, it can be concluded that the overall translation was very successful. The first level of the analysis by three independent researchers gave the overall succession rate of 4,6 to Google Translate and 4,8 to Bing Translator. The texts are well translated with almost no syntactic errors in an almost perfect Croatian language. However, if we

[8] https://eur–lex.europa.eu/legal–content/DE/TXT/HTML/?uri=CELEX:32011L0083&from=EN, obtained on Dec. 2, 2021

analyze the machine translations further, according to Kichhoff et al.'s criteria presented in Table 2, that is compare them to the human translation, we can see there are some discrepancies (Table 4).

Table 4: *Error analysis from the sample text according to the categories by Kirchhoff et al.*

level 1	**level 2: Google Translate difference compared to HT**	**level 2: Bing Translator difference compared to HT**
missing words		**content word**: the word *sklopljenih* was omitted the word *sklapanje* omitted, consequently the meaning also altered, changed. *U slučaju ugovora izvan poslovnih prostorija.*
extra words	**function word**: The preposition u before the word *Direktivi* was inserted by the Google translator. content word: The phrase *o prodaji* has been added to the last sentence.	
word order		
morphology	**nominal**: noun not inflected *o Zaštita* **nominal:** different preposition and case used: *u Direktivi Vijeća*	**nominal:** different case used: *Direktiva Vijeća*
word sense errors	*utvrđuje se* was translated as *sadržana je*	*utvrđuje se* was translated as *sadržani*
punctuation		
spelling		
capitalization	*Zaštita* was capitalized	
untranslated		
pragmatics	the usage of passive form of the verb *sadržiti: sadržana je u nizu*	
diacritics		
other different word used than HT	*u slučaju ugovora*	*u slučaju ugovora*

As we can see from the analysis, Google Translate made more errors overall than Bing Translator. Based on this sample of translating legal texts of the EU-Law, we can conclude that Bing Translator is closer to the human translation. If we assess the quality of the translation with reference to the human translation, we can see that by inserting extra words Google Translate made a translation closer to the original German text. However, it cannot be claimed that the

human translation was perfect, since the solution in the category *other different word used than HT* proposed by both Google Translate and Bing Translator was evaluated by our assessors as far more appropriate than the human translation itself.

4. Conclusion

The assessment of machine translation, as can be seen from the theoretical framework and the practical example provided by the case study, is a rather complex issue that cannot be answered in one scholarly article. The case study provided indicates a huge improvement in the quality of the MT of specialized, legal texts from German into Croatian language, with significant reliability and immense progress in the last decade. The first round of linguistic evaluation labelled both machine translations of a sample EU-legal text from German into Croatian as almost perfect. Whereas the assessment criteria of MT in the previous years have been mostly composed and outlined by computational linguists, it has been evident that the translation tools must be evaluated by additional criteria provided by translation studies experts. The next step in testing machine translations will be to compare the results of the evaluations from the case study with the SAE J2450 and the LISA QA metric tools to establish a unique evaluation criteria matrix applicable to the evaluation of both MT and HAMT of all sorts of texts and languages.

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