Quality in translation through the combination of CAT tools and CohLitheSP

La calidad en la traducción por medio de herramientas TAO y CohLitheSP

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Resumen
Siempre ha habido profundas discusiones sobre el papel desempeñado por la traducción automática y la traducción humana en procesos de calidad de traducción. ¿Cuál es mejor? O, ¿deben usarse combinadas para obtener una traducción de calidad? El presente trabajo responde a estas cuestiones por medio del cálculo de varias métricas de evaluación para estudiar la calidad que ofrece la traducción automática comparada con la traducción humana. Además, se introduce una herramienta novedosa (CohLitheSP), basada en la comparación de un texto de referencia con el texto traducido por humanos, con índices que incluyen Narratividad, Lecturabilidad, Cohesión Referencial, Cohesión Profunda y Concreción. Toda esta tecnología se ha aplicado en un T. F. G. sobre traducción turística, de un alumno que han acabado el grado de Traducción e Interpretación, no habiendo utilizado nunca estas herramientas previamente.

Palabras clave: Calidad en procesos de traducción, traducción especializada, Inglés para Fines Específicos.

Abstract
There have always been long-winded discussions on the role played by both human and MT in quality translation processes. Which one is better? Or, should they be used in combination to achieve a quality translation? The present paper provides an answer to these matters by...
means of the calculation of several evaluation metrics to study the quality offered by MT compared to human translation. Moreover, there is a implementation of a new tool (CohLitheSP) based upon the comparison between a reference model text with a text translated by humans, with some indexes including Narrativity, Readability, Referential Cohesion, Deep Cohesion, and Concreteness. All mention technology has been applied to the final year dissertations on tourist translation of one student who have already finished a degree in translation and interpreting but have never used this technology before

**Keywords:** Quality in Translation processes, Specialized translation, English for Specific Purposes.

1. **INTRODUCTION**

1.1. **The concept of translation**

The concept of translation has always been difficult to define. The Royal Spanish Academy (rae.es) defines the verb translate as "to express in one language what is written or has been expressed before in another", a simple definition and, from the point of view of a person studying translation, imprecise.

To address the concept of translation, linguistics have been based on four different approaches or conceptions:

- As an activity between languages; translating is going from a language A to a language B to express the same reality (Vinay and Darbelnet 55)
- Its textual character; the replacement of a text in a source language by a semantically and pragmatically equivalent text in the target language (House, "A Model for Translation Quality Assessment" 29)
- As an act of communication; translation is a communicative process that takes place in a social context (Hatim and Mason 1)
- As a process; translating activity is defined as the operation that consists of determining the significance of linguistic signs based on a meaning concretized in a message, and then restoring that message in its entirety through the signs of another language (Delisle 319)

However, if you want to make a good translation, you also have to take into account other crucial aspects such as the purpose of the text, the addressee, the primacy of communication, the appropriateness to the target language, the context, cultural aspects, textual ascription and translation as a mental process (Hurtado 31-37).
For all this, it is necessary to mention at this point the "translation competence" in terms of an expert knowledge that is very necessary for professional translation. This concept is defined as "the combination of abilities, skills and knowledge which are manifested in specific actions in situations" (Hansen 205).

Bearing in mind that English is currently the lingua franca, tourist texts should be well written so that tourists from all over the world get a good image of the country that emits the tourist text. However, the reality is that tourist translation does not receive the importance it deserves. It is due to "the lack of professionalization and inexperience of those who carry out these translations and the scant importance given to them by the tourist agents who order them" (Fuentes 30). On the other hand, tourist translation is mostly done in reverse, something that reduces the quality of the translation; Furthermore, the translator must deal with terms coming from fields of specialization, cultural terms, the subordination of the text to the image and the abundance of double meanings (Durán 355).

Finally, we could add a reason that, in many cases, is the main one: the lack of budget. Many small or local family businesses cannot afford to hire a professional, so the translation is done by a machine translator or an unqualified person. To this we can add the widespread "ignorance" that exists in Spain about the importance of translation and the undervaluation of this work, something that we can easily observe in the rates offered by many companies. Above all, the biggest problem arises when translation is viewed as an expense rather than what it really is: an investment. The fact that tourist translations are carried out by translators with very low professionalism can lead to economic losses and, of course, to the deterioration of the image of our country by tourists, who may come to think that it is about from an uneducated country, which does not care about its tourists and in which the information provided to them is not valued (Fuentes 30). All this can directly affect what we know as «the Spain brand», which is the image that our country gives abroad (Durán 355).

In fact, when searching for texts to be translated, we frequently find on a considerable number of official and unofficial web pages the option of "Google Translate service"; In other words, they have not hired a professional or bet on quality - especially in English-speaking countries. Many others are translated in parts, but not complete, which shows the undervaluation of the translation and the ignorance of the impact of not offering a quality translation to the potential tourist. Besides, the quality of tourist texts is also diminished by other factors unrelated to and not so related to translation. The tourist agents that issue these texts have to consider a series of parameters to attract and persuade travellers. Therefore, the marketing department of the company issuing the text will be in charge of meeting all the necessary requirements to achieve it. If, on the contrary, it is not achieved,
it is that the text is not fulfilling its objective, so it does not have the quality that it should have. In this way, the tourist texts that want to fulfil their objective of persuading the tourist, must comply with the parameters established by the AIDA sequence (attention, interest, desire and acquisition). Thus, from a psychological point of view, the texts in which a product is advertised are intended to produce this sequence in the potential customer: "to capture their attention, enliven their interest, generate their desire and achieve the acquisition" (Beltrán 57). In this way, the translator must be aware that he has to transmit this sequence in order to fulfil the objective of the text and not deteriorate its quality. If this is not taken into account, the translator could "be responsible" for the deterioration in quality and the text not working in the target culture in the eyes of the tourism agents who hired him. However, this does not mean that the quality of the text is based on maintaining everything that is established in the source text, but that it must be adapted to a new culture, always taking into account the format, images and other extra linguistic elements. In fact, the translator, as an expert in both languages —source text and target text—, must cooperate with the team for which he works in order to adapt the text. By this we mean that it is important to notify clients of possible inadequacies of the text—for example, for religious reasons or sensitive topics or taboos in certain countries— (Beltrán 57). Finally, we will emphasize that currently there is practically no academic training for tourist translators. In this way, when considering tourist translation as a general translation, the tourist translator will not fulfil the necessary skills to carry out this work, due to his low knowledge of the characteristic features of the tourist discourse (Durán 2).

House starts most of her works with questions such as "What is a good translation?" ("A Model for Translation Quality Assessment” 127). In fact, it should be "one of the most important questions to be asked in connection with translation". Also, House ("Translation: The Basics” 2) defines translation as 'the result of a linguistic-textual operation in which a text in one language is re-contextualized in another language'. For her, there are some interaction factors which should be taken into consideration ("Translation: The Basics” 2-3):

- the structural characteristics, the limitations of two languages (source and target language);
- the extra-linguistic world
- the source text with its features;
- the linguistic-stylistic-aesthetic norms of the target language;
- the target language rules;
• intertextuality in the target text;
• traditions, principles, etc., in the target language;
• the translation company’s instructions given to the translator;
• the translator’s workplace conditions;
• the translator’s knowledge and expertise;
• the translation receptors’ knowledge and expertise.

House (“Translation: The Basics” 5) also insists on the cognitive aspects of translation, and specifically, the process of translation in the translator’s mind; a matter studied over the last 30 years. O’Brien (‘The Borrowers: Researching the Cognitive Aspects of Translation” 6) states that any translation process has a lot of connections with other disciplines such as linguistics, psychology, cognitive science, neuroscience, reading and writing research and language technology.

Equivalence is another key point in translation, and authors such as Jakobson (“On Linguistic Aspects of Translation” 233) and Nida (”Toward a Science of Translation” 159) stating on ‘different kinds of equivalence’, and Catford (“A Linguistic Theory of Translation” 20); House (“Translation Quality Assessment: A Model Revisited” 37); Neubert (“Elemente einer allgemeinen Theorie der Translation” 451–56, “Text and Translation” 18); Pym (”European Translation Studies, une science qui dérange, and why Equivalence Needn’t Be a Dirty Word” 153–76); and see Koller (“The Concept of Equivalence and the Object of Translation Studies” 191–222, “Einführung in die Übersetzungs wissenschaft” 29-45.). On the contrary, Hatim and Mason (“Discourse and the Translator” 36-38) and Reiss and Vermeer (”Grundlegung einer allgemeinen Translationstheorie” 114) do not give equivalence much importance. Riccardi (“Translation studies: Perspectives on an emerging discipline” 86) says, “The translated text is well anchored in the target culture and, in transposing the original; the translator will often be confronted with culture-bound expressions or situations”, and for Ahikary (oapub.org) this means that “The term equivalence refers to the sameness, similarity or correspondence between SLT and TLT in terms of form and meaning. Equivalence can be observed at various levels in linguistic units”.

1.2. The introduction of MT

Quality translation should be mentioned here associated to the goals of MT and new ‘interactive’ and/or ‘adaptive’ interfaces have been proposed for post-editing (Vashee Benjamin.com). Therefore, in this case, human and MT are inextricably linked. Some recent studies mention that MT is almost ‘human-like’ or that it ‘gets closer to that of average
human translators’ (Wu et al. arxiv.org) and, also that MT quality is at human parity when compared to professional human translators” (Hassan et al. arxiv.org). Ahrenberg (“Comparing machine translation and human translation: A case study” 1) states that the aim of MT is ‘overcoming language barriers’, although human translation is aimed at producing ‘texts that satisfy the linguistic norms of a target culture and are adapted to the assumed knowledge of its readers’. In order to do that, MT is used with human post-editing (O’Brien et al. 200-218).

Other authors, Popovic’ and Burchardt (“From human to automatic error classification for machine translation output” 265–272) emphasize the fact that errors produced by MT are useful since the comparison of human and MT can be an excellent exercise, and they claim for automatic error classification. Moreover, we should include here studies on effects of mentioned tools on translations (Jimenez-Crespo 79–102; Lapshinova- Koltunski aclweb.org; Besacier and Schwartz 114–122).

Nevertheless, there are authors who claim that it is almost impossible to overcome the perfection of human translation (Melby and Warner jbe-platform.com) and Giammarresi and Lapalme (“Computer science and translation: Natural languages and machine translation” 205–224). MT Translation has gone through three stages ’from early dictionary-matched machine translation to corpus-based statistical computer-aided translation, and then to neural machine translation with artificial intelligence as its core technology in recent years’ (Zhaorong iopscience.iop.org). Papineni et al. (aclweb.org) focus mainly on ’developing metrics whose ratings correlate well with human ratings or rankings’ Ahrenberg (“Comparing machine translation and human translation: A case study” 2).

In accordance with Christensen and Schjoldager (“Computer-aided translation as a distributed cognitive task.” 443–464) it is known that professional translators, when working, only interact with computers, although we have very little information on what is really happening between translators and machines (Muñoz Martín 70), up to the point that “when we ask what translators really do with translation memories and machine translation, there is not an enormous amount of empirical data to speak of” (Pym “What technology does to translating” 2). In this paper, we are studying the role of CAT tools in the translation processes from a translator-computer interaction (TCI) approach, if we use a term first used by O’Brien (journals.sagepub.com), which is connected to an area of study within the scope of computer science, which is human-computer interaction (HCI), and applied psychology (Carroll “Human-Computer Interaction: Psychology as a Science of Design” 61–83 and interaction-design.org). Now, we are referring to some experiments carried out within this framework of research. We should first refer to the comparison
established between the quality of post-edited MT output and human translation by Fiederer and O’Brien (“Quality and Machine Translation: A Realistic Objective?” 52-74). They discovered that skilled evaluators place the same value on the quality of post-edited texts and the quality of human translations, if we refer to accuracy and coherence. Then, we should mention the experiment by Guerberof Arenas (“Productivity and quality in the post-editing of outputs from translation memories and machine translation.” 11–21), in which it is shown that higher productivity is achieved by professional translators when using MT matches than when processing fuzzy matches, making fewer errors in MT matches than in TM matches. The same study shows that there were significantly more errors when translating from scratch. It is also interesting to refer to Tatsumi’s research (doras.dcu.ie), focused on editing speed and degree of editing. She reached the conclusion that MT matches are faster to edit than 75–79% of fuzzy matches. It is also a fact that the usage of CAT tools is dramatically changing the procedures and content in translators’ translations (Folaron “Translation tools.” 429–436; Muñoz Martín “A blurred snapshot of advances in translation process research” 70). Moreover, we should not forget the experiment by Garcia (Translating by post-editing: is it the way forward?” 217–237), in which there was a comparison between post-editing of MT-generated text with human translation, resulting in marginal productivity gains when using MT. Furthermore, there is a shift in the role of the translator, moving from a phase based exclusively on linguistic transfer to a constant interaction with computers without forgetting linguistic matters. This could be illustrated with the process of segment-by-segment translation using CAT tools, which is more linear as translation is accomplished, as opposed to “traditional” translation, which was constantly going backward and forward (Bowker and Fisher “Computer-aided translation” 4). It was also found that the process of segment-by-segment translation gives rise to the reproduction of source-text structures (Jiménez-Crespo “Conventions in localisation: a corpus study of original vs. translated web texts” 233, and Dragsted “Computer-aided translation as a distributed cognitive task.” 443–464). It is also worth remembering that there was a study on student-translators’ impact on TM tools when translating by Christensen (“Studies on the Mental Processes in Translation Memory-assisted Translation – the State of the Art.” 137-160), in which it was found that MT is more efficient, easier, more interesting, and obviously faster. It was also found that MT is more consistent, and conversely, the results were not so creative and personal, being also more mechanical. There was also an experiment by Teixeira (Knowledge of Provenance and its Effects on Translation Performance in an Integrated TM/MT Environment.” 119–130) in which the speed and quality of the translation is not greatly affected if translators are given MT or TM...
matches. Guerberof Arenas’ 2012 research (researchgate.net) was called into question by herself at the moment she discovered no striking differences in quality or productivity between MT and TM matches (Guerberof Arenas “The Role of Professional Experience in Post-Editing from a Quality and Productivity Perspective.” 51–76, and “Correlations between productivity and quality when post-editing in a professional context.” 165–186). Another fact to be taken into consideration is the time saved when translators are supplied with MT and TM matches, since the post-editing effort is diminished Federico et al. (“Measuring user productivity in machine translation enhanced computer assisted translation.” amta2012.amtaweb.org). Finally, quality and translation speed was analysed by Läubli et al. (arxiv.org), reaching the conclusion that the translation time was reduced by 17.4 % when adding MT matches to other translation aids, and that the quality was also superior.

1.3. CohLitheSP

Apart from MT, to analyze the appropriateness of the texts as regards reading, a code in Python language has been developed. The first operation carried out by this code is sequencing words of the text to recover the number of paragraphs, sentences, words and syllables in total, and later, it determines five metrics based on the studies in Coh-Metrix, but simplified. Coh-Metrix (cohmetrix.com), in accordance with its web page, is «a Computer tool which produces indexes in linguistic and discourse representations of a text». It is important to say that these mentioned indexes «are used in many different ways to research cohesion of the explicit text and coherence of the mental representation». Cohesion is understood here as «the features of an explicit text which plays a role helping the reader to connect ideas in the text mentally» (Graesser, McNamara, and Louwerse, “What do readers need to learn in order to process coherence relations in narrative and expository text? ” 82–98). Coherence, in this context, is «the interaction among linguistic and knowledge representations». When the focus is in the text, coherence coincides with the characteristics of the text which can contribute to the coherence of the mental representation. It is important to consider that Coh-Metrix was originally created to analyze texts written in English, being this reason why a new technique was developed to analyze texts written in Spanish.

This new technique is called CohLitheSP since it is based upon Coh-Metrix, and does not need large dictionaries nor corpuses formed by thousands of words to offer consistent results. Furthermore, on the other hand, specific formulae have been introduced for tests written in Spanish, when just a few changes have to be made to adapt it to any language without any extra cost. For example, to calculate the number of syllables in a text, it is
imperative to know the language it belongs to. In this case, it is needed to calculate how many vowels there are and subtract the diphthongs that, according to Spanish language, are formed by open and close vowels. Furthermore, additional exceptions should be calculated, bearing in mind the rule of hiatus when there is stressed close vowel, among others.

In the course of this didactic experience, four tourist texts will be translated using the CAT tool called Matecat. Next, the evaluation metrics will be calculated from the comparison between the translation options given by the machine and the human translation. Then, the CohLitheSP tool will be introduced to calculate a series of indices of the translations obtained. The last step will be the comparison of the data obtained from the evaluation metrics with the data from the CohLitheSP tool to study the improvement or not of the quality and readability of translations from English into Spanish.

In accordance with the present experiment on the use of CAT tools combined with CohLitheSP, and bearing in mind the previous research, the following research question is formulated: can we improve quality of translation and readability of translated texts by the combination of the different tools mentioned?

2. METHODOLOGY

2.1. Contextualization and sample

This didactic experience was implemented in a final dissertation on the university course of Translation and Interpreting at the University of Murcia, in the academic year 2017-2018. For this work, four tourist texts translated from English into Spanish have been selected: Dartmoor, English Food, Royal Collection and Venture Extreme. Dartmoor is a text from the National Park of Dartmoor (dartmoor.gov.uk), where we can find terminology on Geography and Geobotany. English Food is related to the English cuisine webpage (essentially-england.com). The intention of this text is to trigger a potential customer to know and try the typical cuisine. It has basic information on the typical food. The text Royal Collection comes from the official website of the Royal Collection (rct.uk) and offers information on the history of Windsor Castle. And Venture Extreme has been found on another website (venture-xtreme.com) and deals with adventure sports. It describes the current situation of the tourist and sports sectors.

2.2. Development of the experiment

The steps followed in this didactic experience were:

- Evaluation metrics for MT compared to the reference translation (student’s translation)
- Calculation of the amplification constant for each specific corpus
• Calculation of marks of easibility of texts

2.2.1. Evaluation metrics for MT

In order to check the results of applying a translation environmental tool and study the advantages and disadvantages, we are introducing Matecat, to the final year dissertation mentioned above. The reasons of choosing Matecat are:

• “Matecat is a free and open source online CAT tool. It is free for translation companies, translators and enterprise users.” (Matecat, 2014). The founders and main contributors of Matecat are the international research center FBK (Fondazione Bruno Kessler), the translation company Translated srl, the Université du Maine and the University of Edinburgh.

• In Matecat translation, assignments are organized into projects in which the user specifies the source language and the target language. One project comprises one or several texts to be translated, and each project has a translations memory.

• Matecat provides, by default, a connection with Google Translate as a machine translation system, and a connection with MyMemory as a public translation memory. It is important to mention that MyMemory is an open, available translation memory including the translation memories of the European institutions, the United Nations and automatically extracted data from multilingual websites. The first operation to be carried out is the analysis of the project. By clicking Analyze, Matecat shows how many words need to be translated in the preliminary analysis report it produces. In this report, the total number of words of the source text is displayed under Total Word Count. Then the post-editing is started and it is possible to see some translation suggestions.

• The translator has to decide how to adjust the translation and click Translated when the work is done. Matecat also offers the concordance function to look up words and phrases in the active translation memories. Once the post-editing is finished in the last segment, we can download the translated text and the translation memory. The Editing Log allows the translator to view adjustments made to the MT suggestions in the whole process.

• Finally, the average Post-Editing Effort (PEE) can be observed. It is important to mention that Matecat counts words according to industry standards, so “words or phrases with a 100% Translation Memory match are given a weighting of 30% and words or phrases with a partial TM match are given a weighting of 60%” (Matecat, matecat.com).
At this point it is important to reiterate that we are comparing a reference translation with a machine translation within the context of the underlying idea that “the closer a machine translation is to a professional human translation, the better it is” (Papineni, Roukos, Ward and Zhu "BLEU: a method for automatic evaluation of machine translation" 311-318).

The first evaluation metrics we are introducing here are Precision and Recall. First, we must count the number of words in both the machine and the reference translation. In order to do a calculation with Precision, the number of common words is divided by the number of words in the machine translation. The calculation of Recall is achieved by dividing the number of shared words by the number of words in the reference translation. We consider a system to be good if scores are high, so the best system is the one with the highest scores.

WER (Word Error Rate) is another metric we are implementing. In this method, differences such as substitutions, insertions and deletions are taken into account. This metric is based on Levenshtein distance calculated at word level. In this case, the lower the WER result, the better.

The most common metric used is BLEU (Bilingual Evaluation Understudy). This method discovers how many n-grams are overlapping between the machine translation and the reference translation. This metric is based upon the idea that the larger the number of n-grams overlapping between the machine translation and the reference translation, the better the machine translation is. The machine translations should be as near to 1 as possible to be considered good translations. The formula to calculate BLEU is:

\[
\text{BLEU} = \min \left( 1, \frac{\text{number of words in MT}}{\text{number of words in ref}} \right) \prod_{i=1}^{4} \text{precision}_i
\]

In order to obtain the results, a programme\(^1\), written in Python language, was used to implement the WER, BLEU, Precision and Recall functions from the information dumped in a file. The file recognized a header, followed by different text segments corresponding to the original, a reference translation and several translations to be compared. The code proceeded to calculate each function by combining the reference with each translation to generate another file in table format that could be used directly and sent to a spreadsheet.

When performing translation tasks, three different machine translations were offered. The average is calculated for each suggestion offered by the machine, taking into account the above metrics. We can go a step further and consider students’ translations as a reference translation and compare them to the MT. Then, when calculating the above-mentioned

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evaluation metrics (WER, BLEU, Precision and Recall), the results are refined. Following this, a mark can be calculated using this formula:

\[(3*(1-W) + 1*B + 1*P + 1*R) \cdot 10/6\]

When W=0 no mistakes, maximum mark 1-W

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When W=0 no mistakes, maximum mark 1-W.

**2.2.2. Definition of the tool used to calculate easibility of the text**

To obtain the metrics by means of CohLitheSP, the following are needed:

- A reference text conforming to a valid corpus,
- A glossary of technical or specific terms which is helping to know which words are specific within a corpus. These terms will not include measurement units nor “words of stop” (prepositions, determiners, etc), and
- A set of connectors allowing to know when, in a sentence, something is being inferred from something previously said.

The selected metrics and their changes are:

- **PCNARL. Narrativity.** It is calculated determining which words of the text to be evaluated are already being recognized in the reference text.
- **PCSYNL. Readability.** It determines the simplicity of the text in its language. In the case of Spanish, the readability of Fernández (“Medidas sencillas de lecturabilidad” 29-32) has been chosen (based on Flesch), which is using a number of sentences, syllables and words. If someone wants to do it for the English language, it only needs to be changed with the Flesch-Kincaid2, whose formula is also based on a similar calculation.
- **PCREFL. Referential Cohesion.** In this version, the same referential cohesion as in Coh-Metrix is calculated; but instead of considering all nouns, it is only applied in technical or specific terms recognized in the glossary.
- **PCDCL. Deep Cohesion.** It determines the incidence of the connector over the recognized sentences.
- **PCCNCL. Concreteness.** In this version, instead of calculating the concreteness over the whole corpus of the language, the incidence of the terms of the glossary is determined from the recognized words in the reference text within the text to be evaluated.
This reduction in the cost of programming also requests to adopt mechanisms of compromise to be able to recognize the belonging of a word within large sets in such a way that the closest word is given back within some margins of tolerance.

In order to do that, a structure (a decision tree) has been created to order words in such a way that we know instantly whether words are included in the structure or not: we are interested in this version not only in the lexemes of Spanish, but also in their cases. That is, considering that we have not been working with an extensive dictionary of Spanish language, nor the rules determining its lexemes, when it is masculine or feminine, in singular or plural. Furthermore, if it is a verb, it should recognize its verbal tense (present, past, future, conditional, etc.). The algorithm proceeds to repeat, as it were, a process of stressing a word, the first characters in every word several times, and more times than the last ones. In this way, when calculating the movements (Levenshtein's distance), errors will have less weight at the end of the word (morphemes) and more weight at the beginning (root).

By using this mechanism under a tolerance of 25% (the words whose ratio of Levenshtein is not below 75% are accepted) an approximation closely related to a process of lematization is obtained.

For the calculation of the narrativity, it is necessary to use these techniques, as well as for the calculation of the concreteness – to be able to generate two decision trees.

The following ideas have been considered to separate in sentences:

A sentence is formed by more than ONE word.

After a dot a sentence begins in upper case.

The sentences that do not comply with 1 and 2 will be separated by “; ·¿? ¡!:”

If a sentence complies with 1 or 2, it will be added to next sentence.

2.2.3. Determination of the weights

By analysing the different students’ texts, it is interesting to point out that the best marks should come from metrics where each student has the most dissenting marks and those metrics where students have better marks should weigh more. Therefore, after multiplying the media and standard deviation of each metric and normalizing the results, the following weights have been generated:

<table>
<thead>
<tr>
<th></th>
<th>Narrativity</th>
<th>PCNARL</th>
<th>49%</th>
</tr>
</thead>
</table>

Table 1. Percentage of Weights
2.2.4. Calculation of the amplification constant for each specific corpus

Below, the results of evaluating the reference texts can be seen.

<table>
<thead>
<tr>
<th>Text Easibility Lithe Version</th>
<th>PCNARL</th>
<th>PCSYNL</th>
<th>PCREFL</th>
<th>PCDCL</th>
<th>PCCNCL</th>
<th>ENTRY</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dartmoor</td>
<td>1000</td>
<td>188.02</td>
<td>39</td>
<td>184</td>
<td>87</td>
<td></td>
</tr>
<tr>
<td>English Food</td>
<td>1000</td>
<td>185.25</td>
<td>61</td>
<td>162</td>
<td>214</td>
<td></td>
</tr>
<tr>
<td>Royal Collection</td>
<td>1000</td>
<td>188.34</td>
<td>0</td>
<td>275</td>
<td>6</td>
<td></td>
</tr>
<tr>
<td>Venture Extreme</td>
<td>1000</td>
<td>181.92</td>
<td>359</td>
<td>133</td>
<td>169</td>
<td></td>
</tr>
</tbody>
</table>

As we can observe, with the exception of Narrativity, the maximum mark is not achieved in each parameter, so, first, the weights for each case are applied and, later, a rule of three with the maximum mark (10). The result will be the constant by which all texts using this reference document are multiplied. For example, if the amplification constant ($K_{TEC}$) over the texts of the technological corpus as reference is needed, then this formula is being used, after calculating the coefficients from the programme:

$$K_{TEC} = \frac{PCNARL_{TEC}}{1000} \cdot 0.49 + \frac{PCSYNL_{TEC}}{200.82} \cdot 0.2 + \frac{PCREFL_{TEC}}{1000} \cdot 0.09 + \frac{PCDCL_{TEC}}{1000} \cdot 0.17 + \frac{PCCNCL_{TEC}}{1000} \cdot 0.05$$

Under these weights, marks of the fourth reference texts have been studied, and it has been found an amplification of 1.39.
For that reason, if we do not want to multiply the amplifier within its corpus, it seems that it is not inexact to multiply by 1.39, regardless of the reference text.

2.2.5. Calculation of marks of easibility of texts

Regarding the calculation of the marks of the texts, the amplification constant must be applied by the addition of each metric divided by its maximum and multiplied by its weight. For example, the following formula can be observed over the technology texts:

\[
\text{Score}_{\text{PE}} = K_{\text{TEC}} \left( \frac{\text{PCNL}_{\text{PE}}}{1000} \cdot 0.49 + \frac{\text{PCSY}_{\text{PE}}}{206.82} \cdot 0.20 + \frac{\text{PCREF}_{\text{PE}}}{1000} \cdot 0.09 + \frac{\text{PCDC}_{\text{PE}}}{1000} \cdot 0.17 + \frac{\text{PCCNC}_{\text{PE}}}{1000} \cdot 0.05 \right)
\]

3. RESULTS

3.1. Evaluation metrics

The tourist texts had the following results:

<table>
<thead>
<tr>
<th></th>
<th>W1</th>
<th>B1</th>
<th>P1</th>
<th>R1</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dartmoor</td>
<td>0.5992</td>
<td>0.1980</td>
<td>0.8916</td>
<td>0.9206</td>
</tr>
<tr>
<td>English Food</td>
<td>0.6742</td>
<td>0.0755</td>
<td>0.8282</td>
<td>0.9212</td>
</tr>
<tr>
<td>Royal Collection</td>
<td>0.6790</td>
<td>0.0899</td>
<td>0.8974</td>
<td>0.8752</td>
</tr>
<tr>
<td>Venture Extreme</td>
<td>0.6165</td>
<td>0.2648</td>
<td>0.7884</td>
<td>0.8466</td>
</tr>
</tbody>
</table>
Table 4. Marks obtained from table 3

<table>
<thead>
<tr>
<th>Text</th>
<th>Mark</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dartmoor</td>
<td>5.35</td>
</tr>
<tr>
<td>English Food</td>
<td>4.67</td>
</tr>
<tr>
<td>Royal Collection</td>
<td>4.71</td>
</tr>
<tr>
<td>Venture Extreme</td>
<td>5.08</td>
</tr>
</tbody>
</table>

3.2. Evaluation of the documents using CohLitheSP

After applying the corresponding formulas already described above in 2, the following results are achieved:

Table 5. Marks obtained by pupil from table 2

<table>
<thead>
<tr>
<th>Text</th>
<th>Mark</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dartmoor</td>
<td>6.42</td>
</tr>
<tr>
<td>English Food</td>
<td>7.04</td>
</tr>
<tr>
<td>Royal Collection</td>
<td>7.67</td>
</tr>
<tr>
<td>Venture Extreme</td>
<td>6.96</td>
</tr>
</tbody>
</table>

Table 6. Marks obtained by machine from table 1

<table>
<thead>
<tr>
<th>Text</th>
<th>Mark</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dartmoor</td>
<td>7.31</td>
</tr>
<tr>
<td>English Food</td>
<td>7.22</td>
</tr>
<tr>
<td>Royal Collection</td>
<td>7.65</td>
</tr>
<tr>
<td>Venture Extreme</td>
<td>6.61</td>
</tr>
</tbody>
</table>

Figure 2. Evaluation amplified by its reference
Evaluation amplified by its reference

Figure 3.

Figure 4. Evaluation amplified by its reference

Figure 5. Evaluation amplified by its reference
4. DISCUSSION

4.1. Evaluation metrics

The aforementioned pieces of research show the pros and cons of CAT tools concerning the translation process. The first advantage to be taken into consideration is the so-called recycling process with previous translations that translation memories accomplish. Therefore, specialized texts including many repetitions benefit from this system. Another advantage to be considered is efficiency. The aforementioned specialized texts, which have a high degree of repetition, are translated very rapidly with these translation memory systems. Translation memories also support different file formats, keep the original layout of the text and make search queries easier with the bilingual concordancer. Considering terminology, it is important to stress the consistency in translations of translation memories. Moreover, one of the most important advantages is the time gained during the translation process. Taking disadvantages into consideration, the translated texts may show inconsistencies in cohesion and coherence, since this system divides the source text into segments, and the translator may lose the importance of the text as a whole. In addition, emphasis should be placed on inaccurate translations because they could be saved and reused later.

If we compare the translated texts from the precision metrics offered in table 3 to establish correlations using the hypothesis F-test, it is observed that the tool distinguishes two classes of documents under a very high level of correlation.
Table 7. Correlations obtained by precision

<table>
<thead>
<tr>
<th></th>
<th>Dartmoor</th>
<th>English Food</th>
<th>Royal Collection</th>
<th>Venture Extreme</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dartmoor</td>
<td>100.000%</td>
<td>78.763%</td>
<td>79.688%</td>
<td>91.460%</td>
</tr>
<tr>
<td>English Food</td>
<td>78.763%</td>
<td>100.000%</td>
<td>99.039%</td>
<td>87.095%</td>
</tr>
<tr>
<td>Royal Collection</td>
<td>79.688%</td>
<td>99.039%</td>
<td>100.000%</td>
<td>88.043%</td>
</tr>
<tr>
<td>Venture Extreme</td>
<td>91.460%</td>
<td>87.095%</td>
<td>88.043%</td>
<td>100.000%</td>
</tr>
</tbody>
</table>

However, if we look at the correlations generated from the results in Table 1, then the documents are classified as highly correlated in another way.

Table 8. Correlations obtained by CohLitheSP

<table>
<thead>
<tr>
<th></th>
<th>Dartmoor</th>
<th>English Food</th>
<th>Royal Collection</th>
<th>Venture Extreme</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dartmoor</td>
<td>100.000%</td>
<td>96.882%</td>
<td>94.818%</td>
<td>94.542%</td>
</tr>
<tr>
<td>English Food</td>
<td>96.882%</td>
<td>100.000%</td>
<td>91.712%</td>
<td>91.437%</td>
</tr>
<tr>
<td>Royal Collection</td>
<td>94.818%</td>
<td>91.712%</td>
<td>100.000%</td>
<td>99.724%</td>
</tr>
<tr>
<td>Venture Extreme</td>
<td>94.542%</td>
<td>91.437%</td>
<td>99.724%</td>
<td>100.000%</td>
</tr>
</tbody>
</table>

4.2. Evaluation of the texts

As can be seen in Figures 2 through 5, MT gets better results than reference translations (student's translations). This may be due to the fact that the Spanish translation mechanisms used by the machine are well conditioned to evaluate its easibility. However, this easibility may not match the accuracy of the translation.

Without going any further, when verifying that the tool that determines the precision is so different from the Coh-metrix tool as seen in tables 7 and 8 due to the fact that they correlate the texts in a very different way, perhaps we should think that both tools evaluate not so much quality but two different elements of it.
However, as soon as we collect the results of tables 5 and 6, only by increasing the precision results so that they have the same mean as CohLitheSP, it can be verified, as seen in figure 6, that the correlation of both systems of evaluation is 94.71% under a Chi square hypothesis test.

![Figure 6. Correlation of both evaluation Systems](image)

It is observed that students’ evaluation approximately coincides with the CohLitheSP’s evaluation.

5. CONCLUSION

In this work, a new and different tool has been shown which adds a supplementary challenge for students: the possibility of improving the readability of their own translations from English into Spanish.

Given the facts, the technique explained before is working properly mainly due to two results: on the one hand, it is proved that different texts coming from different jargons in the same typology, including MT texts, get good or bad marks in the same metrics. On the other hand, the Figure 6 also show that, after refining the final mark, the result is approximate to a student’s evaluation.

Moreover, it is important to stress the easy programming, which does not require large corpuses, despite the fact it comes from systems needing an enormous extra charge in the development of programming. This last feature is complemented by the fact that it is easily transformed to be working in any language.

The procedure used to test the new tool implemented with the use of MT and the calculation of its evaluation metrics (Precision, Recall, WER and BLEU) should also be highlighted.
Finally, in response to the research question (can we improve quality of translation and readability of translated texts by the combination of the different tools mentioned?) it should be concluded that this combination offers a proper and stimulating procedure for students and translators to check their translations from English into Spanish.

6. SOFTWARE

The programme written in Python used to calculate the statistics with commentaries in English can be found in the following address: mailto: https://archive.org/details/coh-lithe-sp-012

NOTES

1 This programme was developed by Juan Manuel Dato Ruiz (qualified computer technician) taking into consideration the evaluation metrics mentioned above.

WORKS CITED


---."Necesidades de mejora y adecuación en la traducción de textos turísticos promocionales". Hermeneus, 2012a, pp. 2-3.


Graesser, Arthur, McNamara, Danielle, and Louwerse, Max. What do readers need to learn in order to process coherence relations in narrative and expository text? In A. P. Sweet & C. E. Snow (Eds.), Rethinking reading comprehension. 2003, pp. 82–98. New York: Guilford.


www.researchgate.net/publication/320467106_Productivity_and_quality_in_MT_post-editing.


Matecat https://site.matecat.com/benefits/?gclid=Cj0KCQjw6uT4BRD5ARIwAQbDv3DU_dHUMG-rxM2J_XsFG6QaAk0yEALw_wcB. Accessed 21 April 2021.


Wu, Yonghui, Schuster, Mike, Chen, Zhifeng, Le, Quoc, Norouzi, Mohammad, Macherey, Wolfgang, Krikun, Maxim, Cao, Yuan, Gao, Qiu, Macherey, Klaus, Klingner, Jeff, Shah, Apurva, Johnson, Melvin, Liu, Xiaobing, Kaiser, Łukasz, Gouws, Stephan, Kato, Yoshikiyo, Kudo, Taku, Kazawa, Hideto, Stevens, Keith, Kurian, George, Patil, Nishant, Wang, Wei, Young, Cliff, Smith, Jasson, Riesa, Jasson, Rudnick, Alex, Vinyals, Oriol, Corrado, Greg, Hughes, Macduff and Dean, Jeffrey. “Google’s neural machine translation system: Bridging the gap between human and machine