Integration of Machine Translation in CAT Tools: State of the Art, Evaluation and User Attitudes

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Abstract

There have been proposed various techniques for combining machine translation (MT) and translation memory (TM) technologies in order to enhance retrieved TM matches and increase translators' productivity. We provide an overview of these techniques and propose a way of classifying them. According to the results of our user survey, many translators are not aware of MT feature in their computer-assisted translation (CAT) tool. However, more than a half of the population perceive such combination as useful. We argue that it is necessary to take into account user perspective when evaluating MT and CAT integration and suggest characteristics of such evaluation.

1. Introduction

Complementing translation memory (TM) software[1] with automatic translation appears to boost translators' productivity. SMT (statistical machine translation) toolkits such as Moses (Koehn et al., 2007), Microsoft Translator Hub[2] and others made it possible for companies to train their own domain-, company- or project-specific engines that provide better results compared to generic engines available for free use. For instance, the Sybase IT company (Bier, 2012) reports productivity increase from combining MT and TM, with the condition that the engine is trained on large-scale company-specific data. In the individual translator scenario, a study was carried out by (Kanavos and Kartsaklis, 2010), which showed significant productivity increase in workflows that involved MT integration.

Indeed, it would be ideal if translators could not only make use of already translated texts (i.e. translation memories), but also have some technology that can help them with new parts, which are not in the TM. For instance, these parts can be automatically translated and presented to the translator. The problem is, however, to decide how exactly we should present these MT suggestions in a CAT (computer-assisted translation) tool environment.

Another problem is that free publicly available engines do not always satisfy the quality requirements, which is even more true for specialised texts, where general SMT systems cannot account for specific vocabulary. While agencies can train domain-specific engines, independent freelance do not have the possibility to do that and often just refuse using any MT at all. In addition, not all agencies have resources to train good-quality engines for all language pairs they need. Finally, some customers restrict translators from using online MT services because of confidentiality issues.

Despite all these issues, most state-of-the-art CAT tools do allow automatic translation integration in one way or the other. Translators receive MT suggestions along with TM matches, termbase matches, online resources, glossaries. Most CAT tools allow to install a plugin from one of the main MT service providers or to connect a proprietary engine. Moreover, it seems to be a trend in the field, as most recent CAT software releases claim to employ advanced MT technologies. The question is how MT can be integrated in the workflow in the most convenient way for users.

In this article we study the state-of-the art techniques used to combine MT and CAT tools. The next section provides an overview of existing machine translation technologies used in popular CAT tools and suggest a classification for types of MT and TM integration. We will also cover some issues regarding the evaluation of such integration. Following that, we discuss results of a user survey on translation technologies which cover the problems of MT integration in CAT tools. We conclude by proposing possible further steps needed to identify users' preferences regarding integration of MT in CAT software.

2. Types of MT integration in CAT

From a general perspective, TM and MT can be combined in two different ways. The more obvious way is to include suggestions from an MT engine along with the other suggestions the user gets from each segment, such as suggestions from the TM data base, term base, etc. It is mostly useful when no exact match or fuzzy match with high score is retrieved from the TM. It has been proven that MT suggestions increase productivity for segments which have matches of lower than 75–80% (Kanavos and Kartsaklis, 2010). We will talk more in detail about this type of integration in section 2.2. The second way of combining TM and MT is using both technologies together to enhance the output results and thus increase the productivity and reduce the post-editing effort. These methodologies are described in section 2.1.

2.1 Internal combining of TM and MT techniques

2.1.1 Combining target segment from assembled matches

Some CAT tools use EBMT (example-based machine translation) or similar techniques to provide so- called segment assembly. These techniques, compared to normal string-based matching of the segment to be translated, search for fragments of the source segment in the translation memory repository, extract their translations and combine them together to obtain a translation for the whole source segment. This feature was included in Déjà Vu X, and also made the necessary substitutions of untranslatables, such as numbers (Lagoudaki, 2008), and in the Swordfish II application (Kanavos and Kartsaklis, 2010). It is now also included in the last versions of MemoQ[3], which searches fragments of the source segments in TMs and term bases. The text chunks for which no match was found in any of the sources are inserted in the translation suggestion as they appear in the source segment. These tools, however, do not use any advanced MT technology and only perform string matching similar to normal TM search.

Some systems attempted to use more sophisticated techniques to construct target segments from shorter fragments extracted from TM bases. An example of these so-called second-generation TM systems is SIMILIS (Planas, 2005), which uses some linguistic analysis to enhance the matching results. The idea is to store syntactic units ('chunks') such as noun phrases and verb phrases in the TM database instead of processing entire sentences. These units can then be assembled to suggest a translation for a new segment. Masterin (Gro ̈nroos and Becks, 2005), another second-generation TM systems, adapts the segmentation to the segments available in the TM database. Each segment in the source text is also annotated using a POS-tagger. Translations for new segments are generated taking into account its syntactic structure ('translation pattern'), semantics, and also use frequency and domain information.

Systems of this type are able to provide better recall by retrieving subsegments and constructing new sentences from multiple TM matches. However, to our knowledge, they have not been evaluated in terms of user experience nor have they been proven to increase translators' productivity.

2.1.2 Enhancing reusability of fuzzy matches with SMT techniques

With the development of statistical machine translation it became possible to use it to enhance the TM system output by translating the parts that are missing in the MT. The idea is to retrieve the fuzzy matches, identify the elements of the source sentence that are not covered by the match, and translate them using SMT techniques. Thus, in (Biçici and Dymetman, 2008), a methodology was proposed, which uses the fuzzy matches from the TM, along with their word-alignment matrices (obtained while training an SMT engine on the same TM). These fuzzy matches and their alignments are used to produce a bi-phrase which is then added to the other bi-phrases extracted by the MT system and assigned a strong value to its associated feature in order to prioritise it over other bi-phrases. This methods shows significant improvements compared to both only TM matching and the MT system alone for different fuzzy-match scores.

Similar research was carried out by (Zhechev and van Genabith, 2010), who, instead of alignment matrices, used precise subtree-based alignments of the fuzzy matches retrieved from the TM to determine the correspondeces between the input source sentence and the match. The parts which are not aligned are then also translated with an SMT system. This research also showed improvements compared to the SMT system with fuzzy match score over 80%.

2.2 External combining of MT and TM

2.2.1 Online vs. offline

Reinke (2013) distinguishes two ways of applying MT in CAT workflow: batch processing (also called the offline method) and interactive processing (the online method). The offline method consists in applying MT before the translation for the segments which did not match with any segment in the TM. These source segments are translated with an MT engine and then added to the project as another TM file (or merged with an existing TM). In order to account for the MT quality, which is lower than the human translation quality in a normal TM, MT-generated TMs are sometimes assigned penalty scores. Finally, the translator gets these results along with other suggestions.

On the other hand, the online method allows the translator to see MT suggestions directly produced for the current segment via a plugin or an API. The translator is free to use these suggestions or discard them depending on their quality. The problem with this method is that it is not easy to decide which position in the ranking these suggestions should appear on, and what match percentage they should be equivalent to. The offline method, in its turn, is more time-consuming and adds additional stages in the project preparation process.

An attempt to compare these two workflows was carried out by (Kanavos and Kartsaklis, 2010). The authors compare productivity in different translation setups: without any MT system, with the offline and online application of MT (they used Moses, Google Translate and Systran) with three different TM applications. They report significant productivity gains in all workflows which included MT. They also claim that "the application of MT in real time, segment by segment, seems to be more efficient and better controlled"

(Kanavos and Kartsaklis, 2010, p. 17). This is not, however, properly demonstrated, as the two approaches, even though compared with the same MT engine (Moses), were carried out with different CAT tools. In addition, no direct comparison with a quantitative measure (like, for instance, translation speed in terms of words per hour) is provided in the paper.

Smilar works include (Koehn and Senellart, 2010), (Simard and Isabelle, 2009), (Kranias and Samiotou, 2004), among others. One of the drawbacks that they have in common is that they normally use automatic metrics such as BLEU (Papineni et al., 2001) or NIST (Doddington, 2002) to evaluate the improvements of the system compared to normal string-based match retrieval and to the baseline SMT system. Even though some of these metrics have shown high correlation with the human judgment, it is not clear to which extent these systems can be useful for translators, i.e. whether these methods actually increase users' productivity and reduce the post-editing effort.

2.2.2 MT plugins and APIs

At the beginning of 2000s many TM tools already had MT plugins (Wordfast version 3, SDLX version 4, Trados version 5) (Garcia, 2009). However, this technology was not well adopted, probably due to the low quality provided by the MT systems, and was neglected in subsequent software versions. Nowadays, though, it has changed and most popular CAT tools on the market come with MT plugins and even provide a possibility to develop a plugin for a DIY MT system.

The research conducted by (Federico et al., 2012) compares translators' productivity with and without MT suggestions in a common CAT setting when they have access to translation memories. They authors used a popular CAT tool and the MyMemory[4] plugin, which retrieves suggestions from a publicly available TM database and, when no TM match is available, it provides suggestions from the Google Translate system. The plugin also records translation time for each segment, which allows to measure translation speed. The other productivity indicator used in the experiment was post-editing effort, which is computed as the edit distance between the suggestion and the final translation. Using MT led to productivity gains for all translators. However, the results varied significantly among translators depending on their working style (some translators correct more including subtle stylistical errors, while others only performed light post-editing) and the configuration of their user interface. This work provides interesting insights on the evaluation of MT integration in CAT. On one hand, it attempts to investigate how it affects translators' productivity in a real-world setting with a popular CAT tool and a commercial MT engine. On the other hand, this setting introduces some factors, which make the experiment less controlled and introduces significant variation in the results.

A problem that has not been discussed in much detail in this context is how exactly to present the MT suggestions generated by the plugin among the suggestions from other sources (like TM, term bases, glossaries). How do we rank the MT results relative to other suggested segments or, in other words, what percentage should be assigned to them? Should it always be the same score (for instance, 80%), or should it be calculated for each translated segment? Can these scores be calculated using quality estimation techniques? And finally, will this score depend on the language pair?

2.2.3 Autocompletion with MT and Interactive Machine Translation

Autocompletion is a popular feature included in many CAT tools on the market, and very much favoured by translators (Zaretskaya et al., 2015). It consists in suggesting words or phrases to complete the segment that the translator has started typing. The translator, if she wants to discard the suggestions, can simply overtype them, or accept them. However, to our knowledge only few commercial CAT tools use MT techniques to generate autocompletion suggestions. One of these tools is SDL Trados Studio 2015, which was released in July 2015. It describes the MT suggestions in the Autosuggest feature as one of the main novalties of this new version of the software[5].

In research, the first attempt to use MT in autocompletion was made by (Langlais et al., 2000) in the TransType system. The authors refer to this process as Iteractive Machine Translation (IMT). The system provides suggestions in real time while the user is typing. The suggestions are computed each time a character is typed, and the user can accept them by pressing a special key or reject them by continuing typing. This way the system continuously adapts the suggestions while the user is typing. The system was shown to help reduce the number of typed characters to less than 40%, and translators who participated in the evaluation generally found it very useful. However, the average speed did not increase. The authors make a very important observation that the usefulness of such feature depends significantly on the general usability of the prototype and on combination with other editing features.

The Caitra[6] system developed at the University of Edinburgh (Koehn and Haddow, 2009) follows the same vein. It uses phrases from a MT phrase table as suggestions for predictive typing. Similarly, these phrases are chosen based on the prefix already typed by the user. The suggestions are normally short phrases, which reflects the underlying phrase-based SMT method. In addition to the autocomplete suggestions, the user can also see the most probable suggestions from the phrase table for the whole sentence. And finally, the system also offers a post-editing function, when the users are given an entire automatically translated sentence and have to correct it. The system was evaluated in terms of translation speed and translation quality. The fastest translation was achieved with post-editing, although autocompletion also increased the translation speed. The best quality was observed with post-editing and with the setting that includes autocompletion and phrase-table options. These results were also complemented by a questionnaire for the participants in order to identify their opinion on the features. The combination of autocompletion together with the phrase-table options was reported to be the most enjoyable and helpful for the users and also produced the most accurate translations. It has to be stressed that this work is one of the few that not only compares results with and without MT functionality, but also compares different types of MT integration (post-editing and autocompletion).

Other positive results were achieved by implementing an MT-based autocompletion component in the HanyCAT tool (Hokamp, 2015). The MT-based component was compared with the whole-language autocompletion, which makes suggestions based on the whole language vocabulary. The average time per segment was almost 10 seconds less with the MT-backed suggestions, which is a very significant result from the point of view of time saving. However, the quality of translations was not evaluated. Furthermore, it would be interesting also to see how this feature works together with other common CAT tools functionalities like TM suggestions.

2.2.4 Recent developments: towards adaptive MT

A topic that has become popular recently both in SMT research and in the context of commercial CAT tools is so-called adaptive MT or incremental learning in MT. The idea is to have an MT system which would adapt its parameters based on users' interaction with the system, in other words learn in real time from the user's corrections and thus reduce further translating effort. This type of systems can be implemented both in the IMT scenario and in the post-editing scenario.

One such SMT model is defined in (Ortiz-Martinez et al., 2010) and can be implemented with the CasmaCat[7] translation tool (Ortiz-Martinez and Casacuberta, 2014). The incremental learning algorithm proved to reduce user effort compared to the conventional interactive MT.

The MateCat[8] web-based CAT tool, which was developed in collaboration with the CasmaCat project, allows advanced Moses integration that has adaptive MT. There are two possible ways of adaptation: the offline or project adaptation is performed after a day of work, and takes into account statistics about the translated document to build more accurate translation models. The online adaptation, on the other hand, occurs almost instantly and helps to avoid the cases when the user has to correct the same MT errors multiple times within one document.

Finally, the leader on the CAT tool market SDL Trados Studio has also promised to release the language learning capability of their "next-generation machine translation technology", which will be able, according to their web site, to "learn user preferences"[9].

2.3 Classification summary

All the methods discussed above can be summarised in the following classification scheme (Figure 1). First, they are largely divided into internal and external integration. The internal methodologies are those that aim at enhancing the quality of the TM system's suggestions by using some MT techniques. On the other hand, external integration provides one more source of suggestions apart from the TM matches and other sources like term bases and glossaries. The internal methods can be implemented as segment assembly using EBMT-like techniques, or using SMT methods to translate the "gaps" that are not covered by the TM fuzzy matches.

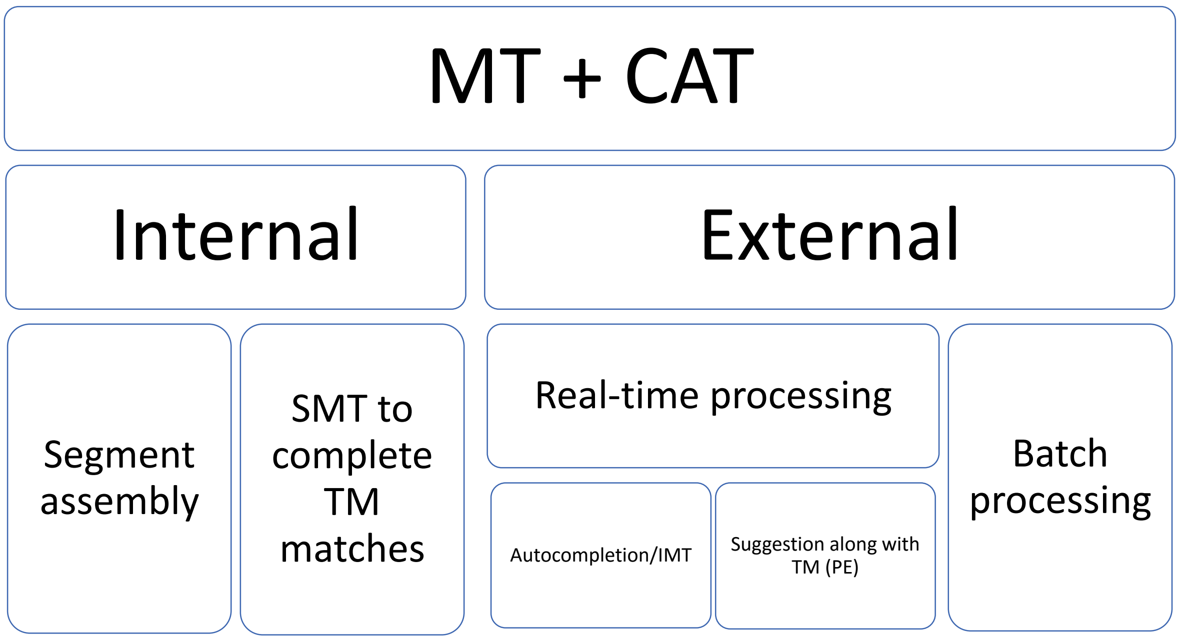

Figure 1 *Integration of MT in CAT tools*

The right side of the scheme (external integration) is divided according to the stage when the translation is performed: batch processing, or offline pre-translation of the whole text, and real-time (online) processing. And finally, in real-time processing, MT suggestions can be presented to the user in form of autocompletion or interactive MT, or as additional suggestions for each segment together with the suggestions from TM and other sources. This scenario, in case when the MT suggestion is accepted by the user, is also referred to as the post-editing (PE) scenario: the user makes necessary changes in the MT output to correct translation errors. The key difference between the autocompletion method and the post-editing method is the user interaction part: in the autocompletion scenario the MT suggestions appear based on the prefix typed by the user and adapt while the user is typing, while in the PE scenario the user works with a final suggestion.

3. Users' perception of the MT and CAT integration

There are various methods of identifying how useful a specific functionality in software is. In the case of CAT tools, as has been partially mentioned in previous sections, one can measure translators' speed, post-editing effort, average number of keystrokes per segment, cognitive load (e.g. measured with eye-tracking techniques), and estimate user satisfaction by means of a questionnaire.

The user survey "Computer Tools for Translators: Users' Needs" (Zaretskaya et al., 2015) aimed at identifying user needs and attitudes regarding various types of translation software, including MT, TM systems, textual corpora and related tools, among others. In this section we will focus on the findings related to the MT integration in CAT tools.

The survey was built online and the link to it was distributed through translation companies, mailing lists and social media groups for translators, translation blogs and translation associations. We received 736 completed responses and 1304 responses in total. This indicates a high response rate but a low completion rate, which is mainly due to the large size of the questionnaire. The participants responded actively and many provided feedback and comments.

As far as the participants' profile is concerned, we received replies from 88 different countries, about a half of them being from Italy, Spain, Germany, USA, UK, Brazil, Belgium, Finland and Portugal. The vast majority of translators worked as freelancers. The two largest subgroups were freelancers who had an agency but also worked independently apart, and freelancers who only worked independently. Only 12% just worked with an agency, 3% as in-house translators in a translation company and other 3% in a non-translation company.

The questionnaire data was analysed in three steps. The first step included descriptive analysis of the quantitative data, i.e. the answers were described with the help percentages and graphs in order to show the data distribution. These results are summarised in (Zaretskaya et al., 2015). Secondly, we analysed the qualitative data obtained from the open-ended questions (i.e. respondents' comments in their own words) using a coding methodology described in (Auerbach and Silverstein, 2003). And finally, we performed bivariate analysis to find dependencies between pairs of questions (Lee and Forthofer, 2006).

From the total of 736 respondents only 36% reported using MT system or service at the moment of the study, which is mainly due to bad quality of the MT output and to the confidentiality agreements with the client.

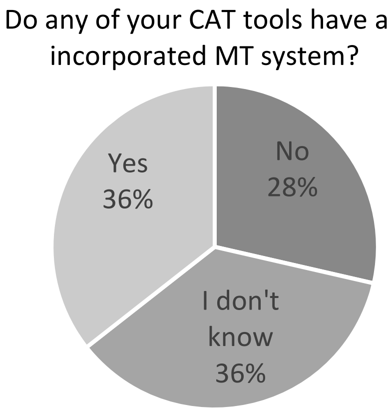

Figure 2 *Integration of MT in CAT tools*

The population subgroup of MT users was asked whether their translation software had integration of MT. Figure 2 shows that 35% of the respondents reported having an MT feature in their CAT tool, while 29% did not have it. Surprisingly, a big part of respondents (36%) said that they did not know whether there is an MT system integrated in their CAT tool. This makes us assume that there are a number of users who are not aware of MT integration in their software, which is, consequently, one of the factors preventing them from adopting this technology in the most convenient and useful way. Even though MT integration in CAT is becoming more and more popular in commercial tools, and there is a considerable amount of research on the subject, it is still not clear for the users how it works. Raising awareness of such technology and its potential benefits can be a way of improving the user attitudes towards MT technology: if the users become more aware of this feature and start using it more actively, they will understand the advantages and benefit it brings.

Furthermore, in general, integration of MT in translation software is perceived as something useful only by about a half of respondents (including both MT users and non-users). On a scale from 1 to 5, where 1 is "inconvenient" and 5 is "essential", the weighted average score received from respondents was 3.35, with 46% viewing this feature as "useful", and almost equal number (about 10%) chose "essential" and "inconvenient" (Figure 3).

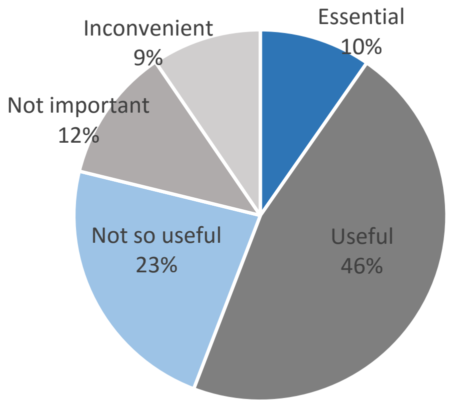

Figure 3 *Usefulness of MT functionality in CAT software*

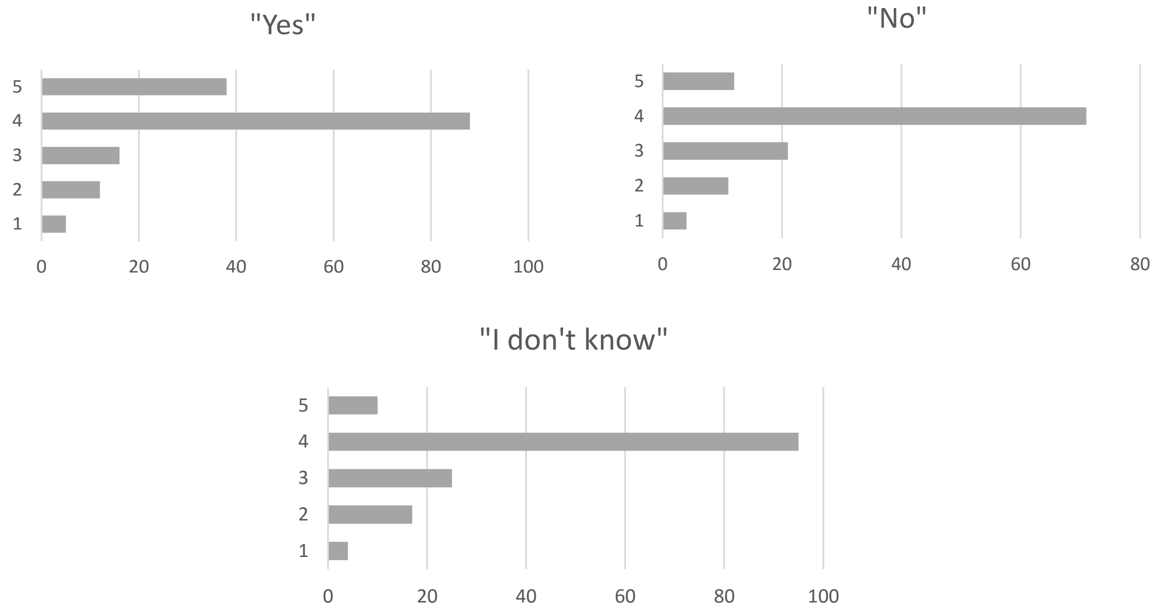

Figure 4 *Usefulness of MT functionality in CAT software for users who have it 4a, do not have it 4b, and do not know 4c*

We compared the average scores of usefulness between the three groups: participants who had an MT system integrated in their CAT tool, participants who did not, and participants who did not know whether they had it. The means were very similar: 3.9, 3.6 and 3.6 respectively, but we can see that the translators who already had the MT feature found it slightly more useful. Figure 4 shows the distribution of the usefulness scores for the three groups, where 5 is the highest score meaning that it is essential, and 1 is the lowest meaning that it is inconvenient. All three groups found MT integration in their CAT tool useful (score 4), although the subgroup who already have it (4a) are more likely to find it essential than the other two groups. This means that once translators get to try this functionality, they are more likely to find its advantages and continue using it. Furthermore, since there are translators who think it might be useful, but still have not adopted it, it is probably because they have not found any simple way to do so. Therefore, making MT integration into CAT tools more accessible and user-friendly might improve the situation.

In addition, the respondents were asked to name their favourite feature of their CAT tool. Out of 403 respondents who provided their comments only two mentioned automatic translation. On the other hand, only few respondents mentioned MT as their most hated feature (five out of 311). This means that at this point, the MT functionality is not considered very useful compared to other features (for instance, autopropagation) and is not perceived as very productivity-boosting and time-saving. At the same time it is not annoying to the users and does not cause many problems.

As it appears from the survey findings, only about a third part of translators consciously use MT functionality in their CAT tool. On the other hand, more translators find it useful, especially the ones who already have it in their CAT tool.

4 Conclusions and future work

Machine translation and translation memory are both the two most developed and most popular among translation technologies nowadays. Nevertheless, there is still space for their improvement in the direction of user satisfaction. There have been proposed methods for combining the two technologies, which can increase translators' productivity by enhancing the quality and usability of retrieved matches or by making the integration more user-friendly.

We proposed a classification of methods of MT integration in CAT tools and discussed how these methods were evaluated. Some work was done on evaluating translators' performance with specific type of MT integration, and very little was done to compare different types. Another problem is to decide not only on which integration type works best, but rather on how it should be integrated in a real work setting and combined with other CAT tool functionalities. This has to be taken into account when measuring users' productivity with MT integration.

Our user study showed that despite of the significant advancements of the recent years in the field of machine translation, this technology is still used only by a small percentage of professional translators. Furthermore, MT functionality in CAT tools, while becoming a more and more popular topic in research and in CAT software industry, is unknown to many users or ignored by them. However, almost a half of the translators who participated in the survey thought that this functionality was useful, and those who did have it were more likely to see it as an asset. This is a positive finding that makes us assume that comparing user experience and productivity gains of MT and CAT integration in different settings and user scenarios can bring significant benefits to professional translators and language service providers.

We suggest that, in order to take into consideration all aspects of the user requirements regarding such integration, the evaluation of such systems should conform to the following characteristics.

1. It should measure translators' productivity in terms of speed (average speed per segment)
2. It should measure translators' effort in terms of keystrokes or edit distance
3. User experience needs to be evaluated, for instance, by the means of a user survey.
4. As it has been proven that most types of MT integration increase productivity, the next step would be to compare different implementations among them.
5. The evaluation should be carried out in a real-life setting with professional translators and a complete CAT tool user interface with a common set of functionalities, such as TM suggestions, spell-checker, glossaries, etc.

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Notes:
1 In this article, we use the term TM software in the same context as CAT tool, as most such programs nowadays include more than just the TM functionality.
2 https://hub.microsofttranslator.com/
3 http://kilgray.com/memoq/2013/help- en/index.html?fragment_assembly.html

4 https://mymemory.translated.net/
5 http://www.translationzone.com/products/sdl-trados-studio/sdl-autosuggest.html
6 http://www.caitra.org/
7 http://casmacat.eu/
8 https://www.matecat.com/
9 http://www.sdl.com/cxc/language/machine- translation/xmt.html

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