Frank Austermühl (Auckland)

On Clouds and Crowds: Current Developments in Translation Technology

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Abstract:

This paper presents two recent developments in translation technology: statistical machine translation (MT) and *massive online collaboration* (MOC), and their impacts on the translation process in general, and on the working conditions of individual translators in particular. Considering machine translation, we will focus on online MT systems and the paradigm of statistical machine translation. Concerning *massive online collaboration*, the discussion will focus on both *crowdsourcing* and on *Wiki* resources for translators. Finally, potential ways of reacting to the challenges posed by MT and MOC for both translation research and teaching will be provided.

Ziel des Artikel ist es, zwei jüngere Entwicklungen im Bereich der Übersetzungstechnologie – Statistik-basierte maschinelle Übersetzung (MÜ) und *massive online collaboration* (MOC) – und ihre Auswirkungen auf den Übersetzungsprozess im Allgemeinen und die Arbeitsbedingungen von professionellen Übersetzerinnen und Übersetzern im Besonderen zu diskutieren. Mit Blick auf die maschinelle Übersetzung liegt der Fokus der Diskussion auf Onlinelösungen sowie bei statistischen MÜ-Ansätzen. Beim Thema *massive online collaboration* stehen sowohl das Konzept des *crowdsourcing* als auch die kollaborative Entwicklung von Wiki-Ressourcen für Übersetzer im Vordergrund. Im Schlussteil des Artikels werden mögliche Wege aufgezeigt, wie in Forschung und Lehre im Bereich der Übersetzungswissenschaft auf die durch MÜ und MOC entstehenden Herausforderungen reagieren kann.

Keywords:

machine translation, statistical machine translation, massive online collaboration, crowdsourcing, social translation, translation wikis.

Maschinelle Übersetzung, statistische Ansätze, Crowdsourcing, Übersetzen und soziale Netzwerke, Übersetzungs-Wikis.

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1 Introduction

The aim of this paper is to analyze the impacts that two recent phenomena in translation technology are having on the lives of current and future professional translators: *statistical machine translation* and *massive online collaboration*, especially *crowdsourcing*. The main thesis of this paper is that these phenomena, like translation technology in general, represent a double-edged sword. Under this umbrella, a discussion ensues that considers the ways in which translation technology is influencing, shaping, and changing the way the business of translation is carried out, as well as the implications that these changes have on the training of future professional translators. This discussion will be conducted within a spectrum of influences, and marked by the polar positions of freedom and constraint. In these regards, this paper can be generally viewed as an extension of my previous works (see Austermühl 2001, 2007, and 2011), and also relates to my keynote address at the 2005 Annual Conference of the New Zealand Society of Translators and Interpreters (NZSTI).

The central considerations here are less focused on the question of how certain types of translation technology and digital resources can contribute to empowering individual translators, including electronic dictionaries, terminological databases, electronic corpora, and the web in general (see Enríquez Raído 2011 for a more thorough discussion of this topic). In contrast, our first goal is an exploration of whether and how the latest developments in machine translation have the potential to disempower or even replace human translators. Secondly, the question arises whether the phenomenon of crowdsourcing might further contribute to this disempowerment of the individual professional through the combined efforts of a collective comprised mostly of amateurs, or whether this collective might succeed in reintroducing the human element into modern translation processes, an element that has been under constant pressure from productivity tools, such as translation memory systems (for more detailed discussion of the notion of productivity tool, see Enriquez and Austermühl 2003 as well as Austermühl 2011).

In the context of this discussion it is essential to point out that my concept of translation principally considers translation as an independent, knowledge-based process of text production, and that, secondly, my research interest lies primarily in the agency of individual

translators within the context of intercultural mediation. This paper should be viewed within a larger research context that is predominantly interested in how individual translators can use electronic tools and resources to optimize both the quality of their professional work as well as the caliber of their professional lives (for a discussion of the psychological aspects of freelance translation work, see Atkinson 2011).

It is also significant to note that thus far machine translation has not been part of this overall research agenda. The reason for this is that machine translation has had essentially nothing to do with translation for much of its existence, as it basically represents a process of rule and lexicon-based replacement, in which individual translators play virtually no role. Nevertheless, with the advent and continuous improvement of statistical machine translation systems and its much stronger human component (see below), the points of contact between machine translation and human translators have reached a level where it is crucial that translation scholars, teachers, and professional associations alike take a greater interest in this topic.

In the following, we will first concentrate on recent developments in machine translation, in particular with regard to statistical approaches to machine translation. Here, our aim is to consider the performance of online MT systems using such a statistical approach (in particular *Google Translate* and *Microsoft's Bing Translator*) for both assimilation and dissemination purposes (see below for an explanation of these concepts). Secondly, our attention will be on the notions of massive online collaboration (MOC) and crowdsourcing for translation purposes. Based on examples of crowdsourced translations, we will consider both the advantages and disadvantages of such an approach, taking into consideration the possible effects of a commercialized approach to crowdsourcing in translation. Finally, under the heading "Fight or Flight," we will address ways in which translation scholars, teachers, and professionals might or should react to the challenges described in this paper.

2 The Rise of the Machine

With regard to the topic of machine translation (MT), we can start with a simple question, and, at least for now, a simple answer. The question is: "Why has Machine Translation

become so much better?" Most will agree that the quality of machine translation has indeed improved significantly over the course of the last five to ten years. We will try to provide a more detailed answer to this question below, but for now the short and simple answer is that machine translation has become so much better because our expectations as users of MT systems have become so much lower. Indeed, the ideal of machine translation research as expressed in John Hutchins and Harold Somer's classical chart seen in Figure 1, i.e. the ability of a computer to produce fully automatic high quality translation (FAHQT), has now been replaced by yet another acronym, FAUT, or *fully automatic usable translation*, which represents a more realistic view of the abilities of machine translation from the perspectives of both developers and users.

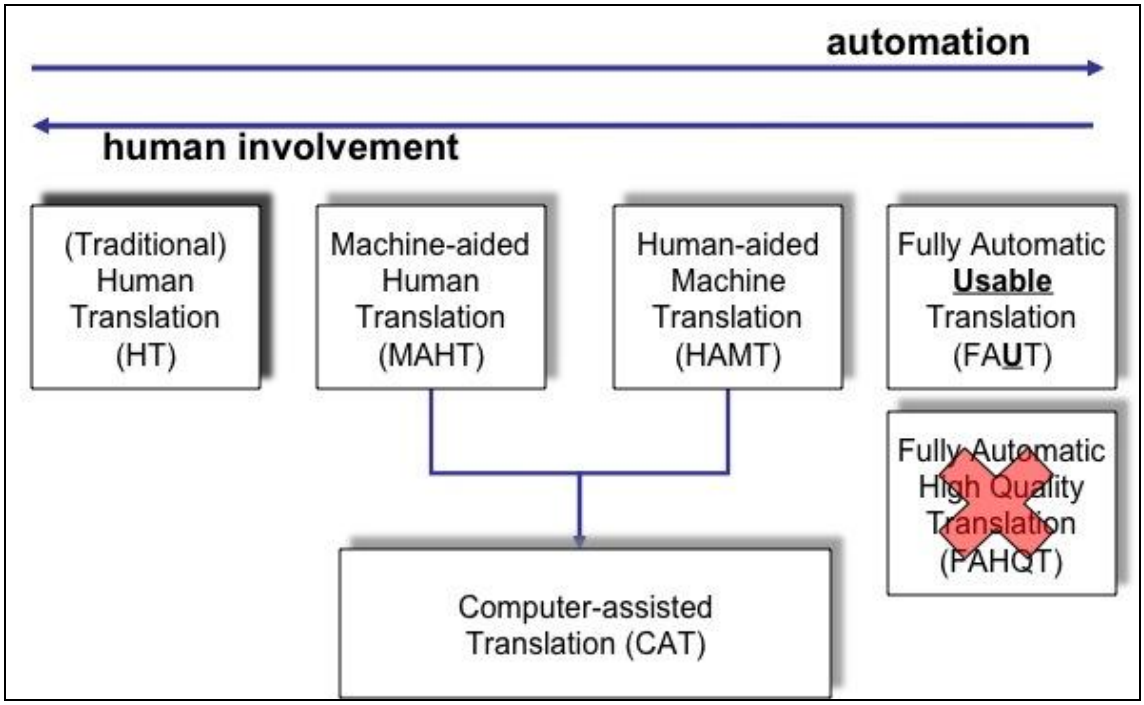

Fig. 1: (adapted from Hutchins and Somers 1992: 148)

Lower user expectations are, however, only one answer to our initial question, and represent instead only part of a larger, more comprehensive answer. Yet, before discussing this in more detail, it is essential to introduce and describe a member of key concepts within the context of machine translation systems in general, and regarding the improvement of machine translation in particular.

These concepts are:

- Assimilation (Gisting)
- Dissemination
- Post-editing (Revising)
- Pre-editing (Controlled language)
- Training (Terminology).

The first two concepts on this list, *assimilation* and *dissemination*, refer to different purposes associated with the use of machine translation systems, as well as to different expectations for these, and the requirements for quality in the output of such systems. The second cluster of concepts, *post and pre-editing* as well as *training*, are all related to the improvement of MT output through human intervention.

With regard to the notions of assimilation and dissemination, Somers explains the different perspectives expressed through the two concepts as follows:

> Researchers in MT started to look at ways in which usable and useful MT systems could be developed even if they fell short of this goal. Many commentators now distinguish between the use of MT for assimilation, where the user is a reader of a text written in an unfamiliar language, and dissemination, where the user is the author of a text to be published in one or more languages. (Somers 2003: 6)

2.1 Machine Translation for Assimilation

Assimilation thus describes a process in which the use of an MT system is driven by the needs of the end users, and the translation process is a result of their explicit decision to have the incoming text translated. Included in this decision to have any given text translated is the user's acceptance of a potentially reduced level of quality in the target text. Hutchins describes the particular *skopoi* typically associated with MT usage for assimilation purposes as follows:

> Assimilation [is the] translation of texts for monitoring (or 'filtering') or skimming information, or the translation of texts for occasional users (e.g. nonspecialist general public), where the 'raw' output from the system doesn't need to be edited; in other words, where recipients can

> accept poor quality as long as they can get an idea of what the text conveys. (2005: 7)

This last element of Hutchins's definition, the objective of getting an idea of what a particular text is about, i.e. to get the *gist* of the text, has led to referring to assimilative MT as gisting. As a screening method, gisting through MT serves "to determine whether the text should be translated" at all (Nogueira and Semolini 2010: n. pag.), and can be understood as a preliminary step on the way to a more thorough, human translation.

As Chelo Vargas Sierra and Laura Ramírez Polo describe, machine translation is particularly strong in "areas in which human translation is not able to offer the competitive advantage that Machine Translation does: quick information gisting on the web in languages unknown to the user, chat and instant messaging translation and quick translation of short documents and web pages for internal use" (2011: n. pag.). Which leads to the question: Just how useful is machine translation for gisting purposes?

To probe potential answers to this question a small experiment was conducted that aimed at identifying the quality of machine-translated business letters (for a more in-depth study, with similar results, see Bowker and Ehgoetz 2007). The corpus used in this experiment consisted of 60 sample letters in English taken from a website promoting international trade. These sixty texts fell into three main subject/text type categories (the number of texts per category is provided in parentheses): General (8), Purchase Orders (16), and Payment (36).

Using both *Google Translate* (w^1) and *MS Bing Translator* (w^2), these texts were machine translated from English into German. The MT output was then evaluated by two independent coders, who are both native speakers of German. The coders were asked to apply a simple coding scheme that would indicate whether they considered the translation to be *poor* (i.e. hard to understand or not understandable at all), *confusing* (leaving the reader not knowing what to do, and hence not acceptable), *ok* (understandable, enabling the reader to react to the letter), or *good* (superior to the "ok" category, in that the text was also well written and idiomatic). Figure 2 shows the results for the overall corpus of 60 target texts.

Google Translate			Bing Translator		
Good	**OK**	**Poor**	**Good**	**OK**	**Poor**
7	26	27	8	23	29
11.7%	43.3%	45.0%	13.3%	38.3%	48.3%
55.0%			**51.7%**		

Fig. 2: Overall Acceptability of MT Output

As we can see, with the overall level of acceptability being only slightly more than 50 percent, the question of MT quality seems to resemble a coin toss. However, when the three individual categories are considered, a different picture emerges. As Figure 3 shows, the number of acceptable translations in both the *General* and *Ordering* categories reaches 75 percent for *Google Translate*, and 75 percent and 62.5 percent, respectively, for *MS Bing*. Thus, three out of four letters involved with the initial contact between two parties, inquiries regarding product lines and prices, as well as requests for quotes and product orders, achieved an acceptable standard and were clearly able to fulfill the translation *skopos*.

	Google Translate			Bing Translator		
	Good	OK	Poor	Good	OK	Poor
General	1	5	2	1	4	3
	12.5%	62.5%	25.0%	12.5%	50.0%	37.5%
	75.0%			62.5%		
Ordering	1	11	4	2	10	4
	6.3%	68.8%	25.0%	12.5%	62.5%	25.0%
	75.0%			75.0%		
Payment	5	10	21	5	9	22
	13.9%	27.8%	58.3%	13.9%	25.0%	61.1%
	41.7%			38.9%		

Fig. 3: Acceptability of MT Output per Text Category

Of the three categories, only the texts in the *Payment* category show a negative percentage of acceptable translations. An analysis of the linguistic characteristics of these payment-related sample texts helps to explain the lower quality scores in this category. First, these texts contained a higher number of technical terms, some of which were also ambiguous (e.g.

"account"). Second, the payment-related letters used a number of evasive expressions, and, in general, a longer-winded style aimed at padding the actual purpose of the letter, i.e. to get the addressee to "pay up." Finally, as these letters were samples, they also included placeholders, often occurring in the middle of a sentence, into which the letter writer needed to add information, such as the precise amount invoiced. These placeholders, which are more frequently found in this category than in the other two, led, in turn, to a disruption of individual sentences.

2.2 Machine Translation for Dissemination

While MT for gisting, or translation for assimilation purposes, follows an incoming pathway, the use of MT systems for dissemination represents a reverse direction. Here, the goal of the translation is to produce target texts "of publishable quality; not necessarily texts that are actually published, but rather texts that are of that quality" (Hutchins 2005: 8). Hutchins further explains that

> [s]uch texts are required usually by organizations and usually involve professional translators. The 'raw' untreated output from MT systems is inadequate, and publishable quality means human assistance; e.g. post-editing (revision) of the output text, pre-editing of the input, using a controlled language, or restricting the system to a specific subject domain. In general it has been found (through the experience of using MT) that the more the subject domain of an application can be restricted the more successful the system is, in terms of quality. (Hutchins 2005: 8)

The difference between MT for assimilation and MT for dissemination is hence not only a matter of perspectives and expectations, but also one of human involvement. As Rebecca Fiederer and Sharon O'Brien state:

> If MT is used for 'gisting' purposes, then often no post-editing is required unless, of course, the user would like to see a more polished version of the output. However, when MT is used for publication purposes, then some level of post-editing is normally required. Another method for improving MT output is to apply Controlled Language (CL) rules to the source text in order to reduce ambiguities and complexity. CL rules generally make the source text input more suitable for MT by reducing sentence length, eliminating problematic features such as gerunds, long noun phrases, ambiguous anaphoric referents and so on. (Fiederer and O'Brien 2009: n. pag.)

The post-editing of MT output is thus a form of revision, in Brian Mossop's use of the term, "the process of checking a draft translation for errors and making appropriate amendments" (Mossop 2001: 169). It should be noted, though, that Mossop's definition of revision is smaller in scope than those found in writing-oriented publications. Catherine Haar, for example, points out that "full scale revising may include major new sections of text or even a substantially new try at a document, while editing involves spelling, grammar, mechanics, word-usage, and other local concerns" (Mossop 2001: 16). Future research on the post-editing of MT outputs will need to indicate how much editing and revising (in Haar's definition) is actually involved. (For an early work on post-editing MT output see Krings and Koby 2001).

A second experiment aims at determining whether the use of MT systems could speed up the process of translation while maintaining the same level of quality usually associated with the work of professional translators. First, three translators with different degrees of experience, ranging from one year to four years to more than 15 years were asked to translate a technical text, an instructive text from a software help file. The objective for the translators was to produce a high-quality translation, one that they would be confident to submit to a client for publication. The time required to finalize the translation of this short text (206 words) was then measured.

In a second phase, the same translators, who were working into Chinese, German, and Spanish respectively, were asked to revise a machine translation (*Google*) of a comparable text (214 words long, similar topic, same text type) to a standard that would meet the quality expectations established for the first text. Once again, the time needed to complete the revision was measured.

In the case of the German translators, the time to complete the translation was 14 minutes, while the time for revision was 11 minutes. Extrapolated to 60 minutes, this would lead to words-per-hour rates of 5,297 and 7,004, respectively, representing an increase of 32 percent. The Spanish translator even managed to increase her productivity by a factor 2.2. The Chinese translator, however, did not finish the revision task, as she considered the work

necessary to repair the text, mainly the re-arrangement of sentence parts, to be "not worth it."

The question of increasing translator productivity through the use of pre-translated and post-edited texts is also at the core of a more comprehensive experiment described by Lori Thicke in *MultiLingual* (see Thicke 2011 for details). Thicke's study intended to discover how much the productivity of all her company's in-house translators could be increased through the use of MT systems. In addition, it also sought to understand how the translation process and its product could be impacted by two variables: First, pre-editing, the application of controlled language rules on the source text (see Aikawa et al. 2007 as well as O'Brien and Roturier 2007 for more on controlled language use); and, secondly, training the MT system by entering relevant terms from the source and target languages into the system's dictionary. The source text in this experiment, which was to be translated from English into French, was an 880-word-long passage from the online help system of an Anti-Money Laundering Software developed by *SAS*, a regular client of Thicke's. Thicke then compared the words-per-day rates that translators/revisers were to achieve when working with different types of MT output.

While working on an unedited source text with an untrained system, the translators achieved a daily output of 5,587 words. Pre-editing the source text by applying SAS's internal style guide led to a more than ten-percent increase in the productivity of translators, who managed to translate 6,208 words. Training the MT system, in this case by adding 56 relevant terms to the system's dictionary, had an even greater impact than the pre-editing exercise: Using the translation of an un-edited version of the source text produced by the trained system led to an overall daily turnover of 7,880. Finally, using the trained system to translate the pre-edited source text led to an overall words-per-day rate of 9,677.

Given that in their assignments as well as in the case of this study, translators are expected to produce 2,500 words per day, this final result represents a productivity increase of 287 percent, a figure that correlates with our own test described above.

It is worth emphasizing that in the studies described above, no loss of quality in the final product was observed (similar to the results observed in Pym 2009 and Garcia 2010), although no clear assessment criteria or even processes had been established in these cases.

Another experiment that was carried out by Fiederer and O'Brien (2009) at Dublin City University offers more insights into the assessment of MT quality and the differences between translation-from-scratch and MT output revision. Fiederer and O'Brien selected 30 sentences from an English-language software user manual, pre-editing 15 of them. For each of the 30 sentences, they produced three human translations and three machine-translated target texts that were then all post-edited by translators into German.

They then asked a total of eleven raters, all translators themselves who were unaware of how the texts had been produced, to assess the quality of the output in terms of clarity, accuracy, and style, criteria proposed by Hutchins and Somers, 1992. The following guiding questions helped the assessors to better understand these criteria:

> Clarity: "How easily can you understand the translation?
> Accuracy: "To what extent does the translation contain the "same" information as the source text?" and "If the sentence contains instructions, do you think someone using the translation could carry out the instructions as well as someone using the original?"
> Style: "Is the language used appropriate for a software product user manual? Does it sound natural and idiomatic? Does it flow well?" (Fiederer and O'Brien 2009)

The results of the assessment indicated that the raters considered the machine-translated and revised texts to be slightly better in terms of accuracy and significantly better in terms of clarity. The human translations were considered to be slightly better in terms style. It should be noted, however, that the post-editors had not been asked to make more comprehensive stylistic revisions. Notably, when they were then asked which of the available solutions to the individual sentences they considered to be superior, all raters selected one of the three human translations.

Comparing the 15 pre-edited sentences with the 50 unedited ones also reveals that the use of controlled language augments the results in the accuracy category discussed above. That is, the post-edited target texts that were based on pre-edited source texts scored

significantly higher in the accuracy and clarity categories, while being slightly inferior to the human translations in terms of style.

2.3 How Statistical Machine Translation Works

The studies described above, and other, similar small scale experiments, such as those carried out by Pym (2009) and Garcia (2010), do indeed support the initial statement about the increased quality of MT output. To return to the original question: Why has machine translation become so much better?

The somehow ironic answer here is that machine translation has improved because it has become so much more human!

To better understand this paradox, let us first consider how the current dominant paradigm in machine translation works, whether *Google Translate* or *Bing Translator.*

This paradigm is known as Statistical Machine Translation, or, more specifically, as Phrase-based Statistical Machine Translation (Ph-SMT). SMT represents a primarily data-driven approach to automatic translation. Its main data resources are two separate corpora: a bilingual parallel corpus, also referred to as a bi-text, and a monolingual target language corpus. The parallel corpus in SMT systems can be populated by data taken from mostly publicly-available text collections, such as the official records of the Canadian parliament, the so-called *Hansards,* a bilingual English/French corpus currently consisting of 1.3 million words taken from debates of the Canadian parliament (w^3), or from the translations of the European Union's *Acquis Communautaire* corpus, the EU's "body of legislative text" with currently about one billion words in 22 languages (w^4).

The target language corpora are usually larger affairs. Examples of these monolingual text collections that are used to train SMT systems include the *British National Corpus* (BNC), with approximately 100 million words (w^5), and the even larger *Corpus of Contemporary American English* (COCA), with about 425 million words (w^6).

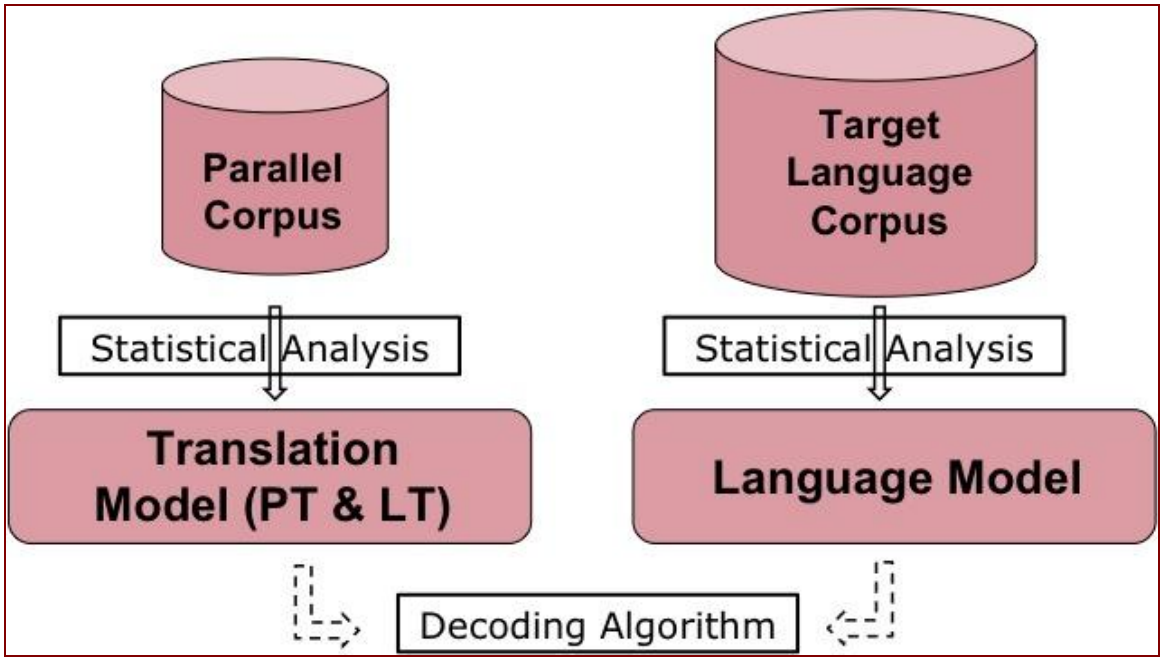

Fig. 4: How SMT Works (Source: Koehn 2007)

As Mary Hearne and Andy Way explain, translating with SMT systems involves a two-step process of "training and decoding" (2011: 205). The training of an SMT system consists of developing a translation model and a target language model through a statistical analysis of the two corpora. The translation model is essentially a table of source language words and phrases and their potential target language translations. However, unlike "a conventional dictionary where plausible entries only are permitted, many of the entries [in the translation model] represent translations that are unlikely but not impossible, and the associated probabilities reflect this" (Hearne and Way 2011: 205). Similarly, the target language model that results from the analysis of the target language corpus is "a database of target-language word sequences (usually ranging between 1 and 7 words in length), each of which is also associated with a probability" (Hearne and Way 2011: 205).

Jointly, the two models are applied in the decoding of a new source text. Based upon the data contained in the system's translation and target language models, the translation of a sentence, phrase or word becomes a straightforward process of identifying the translation solution that has been "assigned the highest overall probability according to the translation

and language models" (Hearne and Way 2011: 205; see also Koehn 2010 for an in-depth discussion of SMT).

Notably, this process of generating a significant number of potential translations and then selecting the one with the highest probability may remind the reader of Pym's two-part "minimalist definition" of translation competence, i.e. (1) "[t]he ability to generate a series of more than one viable target text (TT_I, TT_2 … TT_n) for a pertinent source text (ST); [and (2)] [t]he ability to select only one viable TT from this series, quickly and with justified confidence" (2003: 489).

The corpora that SMT systems are based upon are compilations of texts produced by human writers and translators. Machine translation, similar to translation memory systems, thus depends on and owes its current success to high-quality human input. Way and Hearne stress this human basis of SMT by stating: "[T]he role of the translators in SMT is a crucial one: they provide all the knowledge upon which our models are based" (Way and Hearne 2011: 238; emphasis in the original). Consequently, one approach to improving the quality of SMT lies in better understanding and representing (through annotation) decisional patterns in human translations (Way and Hearne 2011). Through adding rules identified by humans or automatically derived from an analysis of relevant bi-texts, it is hoped that typical MT problems, such as the need for re-ordering MT output, can be dealt with successfully (Way and Hearne 2011).

Translation agencies around the world have started shifting to business models that integrate, and are often based upon, the use of machine translation systems. In such a scenario, MT systems provide a draft translation that is then, depending on the quality needs of the client, revised by human translators, who often bid for these translation/revision tasks in an online auction. Thus, additional financial pressures are added to an already deflated job profile.

3 Massive Online Collaboration: Charybdis to MT's Scylla or a Two-faced Janus?

The notion of Massive Online Collaboration (MOC) in translation represents the second technological phenomenon to be addressed. Ignacio Garcia (2010) from the University of Western Sydney, likens machine translation and massive online collaboration to Homer's mythical monsters Scylla and Charybdis, insinuating that if the one monster (MT) does not defeat us human, freelance translators, then the other threat, the maelstrom of MOC ,will surely do us in. With regard to massive online collaboration, at least, we propose to take a less pessimistic, more Roman perspective, in which these latest technological phenomena can be likened to the two-faced god Janus. Accordingly, MOC, especially through translation-oriented wikis and crowdsourced translations, is a two-faced creature. One the one hand, it clearly adds a humanizing dimension to processes of intercultural communication by clearly demonstrating the power of the crowd to help others and to do good, as evidenced by crowdsourced translations in the aftermath of the Haitian and Japanese earthquakes. On the other hand, the power and skills of the amateur threatens the professional livelihoods of translators around the world, as evidenced in the free-of-charge localization of *Facebook* interfaces.

The notion of *massive online collaboration*, or MOS, is an umbrella term referring to the joint implementation of tasks by a large crowd connected via social networking technologies (see Désilets 2007 and 2010 for on overview).From a translation perspective, MOC is of particular interest with regard to i) crowdsourced translations and ii) the collaborative creation of translation resources.

Crowdsourcing in translation generally refers to the translation of user- and community-generated content, or, as Donald DePalma and Nataly Kelly (2008) define it, "translation of, for, and by the people." Designations for this phenomenon vary widely in the literature. Some of the ways in which translation scholars refer to this type of translation include the following:

> collaborative translation, fan translation, user-based translation, lay translation, citizen translation, participative translation, volunteer translation, CT3 (community, crowdsourced and collaborative translation), pool translation, hive translation, social translation, Web 2.0 translation.

Prominent examples of large-scale application of crowdsourcing in translation include the translation of *Facebook*'s interface into a number of languages (see Sawers 2009) and the use of so-called collaborative translation platforms by leading IT companies such as Sun, Cisco, and Microsoft (Wooten 2011). In all of these cases, the actual translation work is done without pay by volunteer members from the respective social networks. Project consulting and management is carried out on the client's end, either directly in-house or through external language service providers. This type of collaborative business model seems to suggest that while the need for individual, paid translators is reduced, the demand for qualified translation consultants and project coordinators has increased alongside the need to build an adequate technological infrastructure. While crowdsourcing represents a job threat to many professional translators who are unable to be a paid part of large translation projects, the collaborative nature of such translation work and its potential usages reveal the softer side of our modern Janus. Seen from this perspective, crowdsourcing strengthens the human dimension of translation, as evidenced by collaborative translation of emergency text messages from Kreole into English in the aftermath of the Haitian earthquake (Munro 2010). Further examples include fan-subtitling of the prestigious, online academic TED talks, joint translations of political blogs (*The Economist* 2010), and the use of community translation by the non-profit organization *Translators Without Borders* (Petras 2011: 41).

In addition, it is also noteworthy that translators benefit from access to online resources created through massive online collaboration. Among these are digital marketplaces such as *Proz.com*, translation environments such as *XMT Cloud*, and *CLWE*, general reference sites like *Wikipedia*, terminological resources, such as *TermWiki* (w[7]), with more than 1.275 million terms in 75 languages, and *OmegaWiki* (w[8]), *with* more than 46,000 terms in 290+ languages, publicly accessible corpora and translation memories like *My Memory* (w[9]) with about 440 million stored segments and *Wordfast's VLTM* (w[10]).

Yet, the same kind of collaboration that produces these resources also provides data to feed the very same tools, the TM and MT systems that threaten to take a big chunk out of the translators market. A significant amount of research on the collaborative creation of resources used in the development and optimization of MT systems is especially revealing

(see for example Biçici and Dymetman 2008 and Callison-Burch 2009), as is the increasing transfer of TM content from servers to the cloud (see Garcia 2007). Other areas of research further underscore the close links between MOC and MT systems development, including corpora compilation, semantic tagging of MT input data, and using MOC sites for evaluating MT output. Indeed, many business models in translation now feature a combination of MT, community translation, and traditional professional translation, with agencies offering matching levels of target text quality (Sanchez Zampaulo 2011: 26).

Another feature that has become a part of the modern translation business involves agencies that (reverse) auction translation jobs, in which freelance translators must bid for jobs on source texts that have already been fed through MT systems. Here, we witness the so-called *human intelligence task* (*HIT*) concept of Amazon's Mechanical Turk (w[11]) become a part of professional translation processes.

4 Fight or Flight?

At first glance, the dramatic developments described above might seem alarming for those involved in the translation profession. Yet, a few questions remain: What has changed, and how much? How should translators, trainers and professional translators react to these changes? *The Economist* (2010) refers to this new generation as "cyborg translators." Even though the rise of machine translation and crowdsourcing comes with bright futuristic labels, these developments represent more of an evolution in the way that the translation business is conducted than any kind of startling revolution.

First, a new technology application, phrase-based statistical machine translation, is changing both how source texts are being processed, and the forms in which these texts reach the translator. In the extreme, this development means that translating is reduced to a process of editing and revising, a situation not unfamiliar for translators who have made a career move to reviser, especially for language combinations in which the translator does not work into the direction of his or her mother tongue. Even when they are not revising entire target text drafts, translators are faced with patchwork source texts, with chunks of translation already processed and provided by the MT system. Notably, this again is not a new scenario,

as a similar situation occurs when translators apply the pre-translate feature of suitably filled translation memory systems.

Secondly, translators now frequently bid for jobs in reversed online auctions, making the job procurement process more openly competitive, but not different in its nature. Jobs have a tendency to end up with service providers who offer a better deal, not necessarily a cheaper offer. Continuing this trend, crowdsourcing means that some translation jobs will be carried out by those who offer their services not only cheaper, but entirely free of cost while also providing clients with additional rewards generally associated with social media marketing.

Thirdly, translators, engaged in crowdsourced translations work in virtual teams, dealing with only parts of a larger translation project, and they often do not even know their fellow team members. Yet this type of dissociative team work cannot be considered as new. Translators involved in software localization, for example, have always had to work with large number of disconnected files that represent a mere fraction of the global source text.

Translation agencies around the world have integrated these developments into their business models. As a result, agencies now offer increasingly different levels of translation quality, from machine translations to community translations, and professional translations. The latter, presumably done by professional translators, are thus still regarded as superior, although research seems to indicate that both MT revisions and collaborative translations can compete in quality. In addition, agencies are already offering services that assist companies in implementing and managing crowdsourced translation projects.

What does all this mean for professional translators and for the future of the translation process? What challenges will they confront and how can they best prepare for these? First of all, from a teaching perspective it is essential that students are made aware of the latest developments, and that they have opportunities to critically reflect on the reality of a highly automated and increasingly restrictive industry and how it intersects with their personal understanding of translation. As Atkinson (2011) as well as Sarah Dillon and Janet Fraser (2006) have demonstrated, modern translation procedures, especially the necessity of using CAT solutions such as translation memory systems, need not be detrimental to the

translator's self-image. Indeed, as Atkinson reveals from his survey of 135 freelance translators, technological prowess and a positive attitude towards translation technology correlates with higher levels of job satisfaction. Although further studies are required, it would seem plausible that a similar positive approach would benefit translators-turned-revisers. Despite the results of selected MT experiments, the usefulness of MT systems is currently limited by parameters such as language combinations, text types, and subject areas. Nevertheless, it is safe to assume that increasing numbers of translators will be working with MT output, and this leads to the need to develop the editing and revising skills required for machine prepared drafts. Thus, in this new scheme, translators become "curators" (*The Economist* 2010). Similarly, important goals in translator training should include competence in pre-editing, the application of controlled language rules to optimize MT input or to improve the understandability of source texts. In pursuit of this goal, existing editing and revising courses can be easily adapted to include MT as well.

Modern teaching methods in translation practice can also be readily adapted to the demands of crowdsourced translation. Collaborative approaches, such as the ones proposed by Don Kiraly (2000) and María González Davies (2004), have long been available to translator trainers. These collaborative approaches effectively simulate real-life translation projects and foster in-class cooperation in small groups as well as the implementation of distributed projects in virtual teams. Integrating project management skills, both technical and social, into such an approach logically represents the next step (see Dunne and Dunne 2011).

Developments discussed above offer additional opportunities for translation graduates to demonstrate their refined set of competences. Managing crowdsourced projects requires an intricate understanding of the totality of a translation project, including the use of sophisticated localization technologies. These technical competencies are vital for the success of any project, and particularly essential in one that is the product of a virtual community of amateurs. Furthermore, participation in crowdsourcing projects as volunteer translators offers students as well as graduates valuable opportunities to gain practical experiences, making them highly sought-after on the professional market. MT evaluation

and development represent further critical areas in which the insights of well-trained, critical translation graduates can be valuable in identifying the translation patterns typical of the specific language combinations mentioned by Way and Hearne above.

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