How automation through neural machine translation might change the skill sets of translators

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Version 3.1 August 29, 2019

Abstract: The development of neural machine translation systems since 2016 has ushered in a new period of automation in the field of written translation. Claims that machine translation has reached parity with fully human translation are easily questioned, but the fundamental question remains: What impact will high-quality machine translation have on the translation profession? For some, written translators will gradually be reduced to the role of posteditors, working for the improvement of automation rather than for active communication or complex cognitive processing. For others, translators will need to focus on the communication tasks that machines cannot do: text adaptation, rewriting, crosscultural consultancy, and the like; that is, they will be doing things other than low-risk translation. In between those extremes, an analysis of occupation-based skills helps identify places where the work of human translators is relatively automation-resistant, and several strategies that might help those skills find appropriate workplace rewards.

Introduction: The problem to be addressed

The rollercoaster history of machine translation is well known. Times have definitely changed, however, when we learn that Google Translate processes 143 billion words a day (Wood 2018). That means something like seven words per day for every person on the planet. To be sure, the number does not tell us how many words are actually read: if a Google user puts a whole website into another language, all those words are counted even though only three were actually sought. Still, the claim remains impressive, bearing in mind that Google Translate is only one of the freely available machine-translation systems (Microsoft Translator, DeepL, Yandex, Baidu, Youdao, to name a few). The number alone should put paid to any claim that the whole world is being reduced to just one lingua franca or that translation is somehow a marginal activity, only to be used on special occasions. On the contrary, it suggests that translation is a very basic and widespread human activity. When freely available, it enters intimately into countless forms of language learning, physical or mental travel, and general experience of cultural others. But when professionally charged for, what happens exactly?

Let us try another calculation. If there are the equivalent of 333,000 full-time professional translators and interpreters in the world (Pym et al. 2012: 137), give or take 100,000 or so, and if we very generously suppose that each of them renders some 3,000 words a day, then all those human translators and interpreters are producing just under 1 billion words a day – a mere 0.68% of what Google Translate is reported as processing. What does that mean? First, it suggests that a discipline that only looks at the work of paid professionals – and such has so far been the focus of much of translation studies – can have very little to say about the actual uses of translation as the general social activity it has

* Draft written as part of the project Language Competence and Work (RecerCaixa 2016ACUP00020), 2017-2019. Parts of this paper were presented to the conference Translation in the digital era (Kuala Lumpur: Universiti Sains Islam Malaysia, 20-22 August 2019) and are published in the corresponding proceedings.
become. Our models and methods seem woefully tied to a previous age. Second, of course, it means that many translators and interpreters, along with their instructors, are quite legitimately asking whether this is the end of the line for them. As the quality of free online machine translation improves, what will be left for those who still bang out their translations word by word, by hand as it were, as a quaint cottage industry within a postmodern electronic age? Will all professionals soon be out of work?

The practical use of machine translation should be seen as a case of automation, as has happened in many other service-sector occupations. Bank tellers have seen their work move online; machines now take our money in supermarkets. According to neo-classical theory (Deming 2017, Deming and Kahn 2018), when skills are automatized, some activities are no longer done by humans while the ones that cannot be automatized are well rewarded – notably the more complex cognitive and social skills. If you were once a bank teller, you can now make more money by selling home loans; if you were a shop assistant, you might now make less money stacking shelves. So what will happen as automatization takes the place of some translation skills?

I address this question first by trying to determine what is new in neural machine translation and thus what kind of skills it might replace.

Where we are now, more or less

After Barack Obama’s first election as president of the United States, his office put out a “Strategy for American Innovation” that included, among much else, “automatic, highly accurate and real-time translation between the major languages of the world - greatly lowering the barriers to international commerce and collaboration” (Executive Office of the President 2009: 22). At the time, this goal seemed realizable. The logic of statistical machine translation was such that the more people used it, the bigger the database of translations, and the bigger the database, the better the quality, and the better the quality, the more people would use it, and so on. The underlying promise was that the virtuous circle thus formed would spirit us up toward the higher reaches of a technological Tower of Babel.

Statistical machine translation nevertheless remains fallible. For example, if you take Obama’s election slogan “Yes we can” and Google Translate it into Spanish, you get “Si podemos”, and if you translate that back into English it becomes: “If we can” – the promise of paradise remains very much a conditioned by mysterious unnamed factors. Studies on specific language pairs show that the promised qualitative leap did not always occur: in same language pairs quality remained relatively flat in the age of statistical machine translation (see, for example, Lotz and van Rensburg 2016 on MT quality between English and Afrikaans).

Since 2016, however, neural machine translation has brought about a qualitative leap. The adjective “neural” is a motivated metaphor: the systems are using statistical methods on large databases in ways similar to the previous statistical systems in that they involve much more mathematics than linguistics (see, for example, Le and Schuster 2016). They involve many recursive operations, indicating that a word part or word or set of words are mapped in terms to their embedding words, and that those embedding words are similarly mapped, and so on. The effect of this is that the translation process does not work by decomposing a sentence into its component parts, translating those parts, then putting them together to generate a target-language sentence. Instead, pre-existing translations are located and combined on the basis of recursive statistical co-occurrence. The upshot can be seen in several simple experiments.

For example, the English noun dancer can be translated into Spanish as bailarina (feminine) or bailarín (masculine). Without any embedding, there is no way a machine (or a
human) can tell which gender is likely to be correct, and in Spanish the choice cannot easily be avoided (persona que baila remains possible but long). However, if we give a minimal embedding, some kind of decision can be made: strong dancer is rendered as masculine in French, while dainty dancer is rendered as feminine. The decision here is made on the basis of the embeddings and translation pairs with which the adjectives are statistically associated.

Neural translation will also pick up renditions that might not normally count as straight translations. For example, the Spanish word despacito means slowly or slow, and is normally rendered as such. But when the input follows the word with “quiero respirar tu cuello despacito”, which is the following line in the Luis Fonsi song of the same name, DeepL renders despacito as nice and easy. Why? Because the four syllables can be sung in an English version of the song – the system has used the embedding to retrieve a previous translation of the song, rather than translate the word as such. This is great if you happen to be translating that particular song, but can be puzzling if not.

A further relative novelty in neural systems is the use of strategic omission. If an element has a very low probability of occurring in a particular embedding, then it might simply be omitted. To continue with the song Despacito, one of the Spanish lines is “Quiero desnudarte a besos despacito”, which can be rendered literally as “I want to undress you with kisses slowly”. Old transfer machine translation for this gives “I want to undress you for kisses slowly”, which sounds like a difficult but not impossible romantic relationship; DeepL gives “I want to undress you to kisses slowly”, which could be more possible and starts to makes some sense; but Google Translate has “I want to undress with kisses slowly”, which can be sung well enough but strategically omits the second person, profoundly altering the romance. This kind of surreptitious omission is strangely frequent with respect to pronouns (which tend to be minefields anyway, along with most cohesion markers). It underlies one of the relative traps of the system: the omissions and the various drawings on previous translations mean that the output can sound so good that it tends to be convincing to a fast-reading monolingual reader, who will not know how many errors have been concealed along the way.

The move from statistical to neural systems goes just one jump further in interactive interfaces such as DeepL. There, if you are not happy with bailarín as a rendition of dancer, you click on the doubted translation and a series of alternatives pops up. Select the one you prefer, and the rest of the translation adjusts automatically. And at the bottom of the screen you have a whole lot of linguistic information on the word, with a series of previous translations (from Linguee). Such systems are not just translation machines; they are invaluable learning aids.

Why postediting is the real question

The improvements in machine translation thus mean that there is an increasing proportion of translation tasks that can be done faster and with greater quality by postediting than by translating from scratch. Garcia (2010) reported that the threshold had already been reached for Chinese-English translation with statistical systems, and there have been clear improvements since. It is in this general sense that I predicted, back in 2013, that “statistical-based MT, along with its many hybrids, is destined to turn most translators into posteditors one day, perhaps soon” (Pym 2013: 491). That prediction has been justly criticized for its implicitly restrictive vision of translators as doing nothing but postediting, since such an
evolution would indeed risk making translation boring and underpaid\(^1\), constituting a “downward migration” for talented professionals (Kenny 2018: 66).\(^2\) Postediting might be opposed to an “upward migration” whereby translators move to automation-resistant skills. But is that the only choice to be made?

I suspect that this is a false dichotomy, for many reasons. First, it is possible to do both postediting and the more complex linguistic tasks. Second, since machine translation remains fallible, it has to be checked in any high-risk situation, such that postediting can be seen as a “authorizing” activity, somewhat akin to that of a notary in the field of official documents or a good copyeditor in publishing: potentially boring but ideally well paid.\(^3\) That is, professional translators should be selling trustworthiness rather than words (Pym 2017, and below). And third, there is no need to get hung up on narrow understandings of what “translation proper” is, since “translators can do more than translate” (Pym 2014, 2017), and the wide spaces of the “more than” are quite possibly where the automation-resistance skills lie.

Before getting into those arguments about the future employment of translators, let me run through some of the silly things that are said about machine translation. If you can see through the fog, there might be a path ahead.

**Undoing simple ideas**

**Myth 1.** “Humans will always translate better than a machine.”

Claims of axiomatic human superiority are not hard to find. There are, however, several things wrong with the simple opposition.

First, as we have seen, neural machine translation systems do not really translate: they find previous human translations. If you like, they are operating like sophisticated match-making services, helping the user find the right piece of prior human translation. Or if you prefer a Marxist analogy, the databases are dead human labor, accumulated as translation capital that can be incorporated into future productive processes.

Second, as is too rarely confessed, human translators make mistakes, and in the area of field-specific terminology they sometimes do rather worse than a neural machine translation system with a clean database.

And third, as claimed above, humans can often translate better (faster, with better terminological choices) with the support of machines.

**Myth 2.** “The bigger the database, the better the machine translation output.”

As we have noted, the promise of statistical machine translation was that bigger databases would enable better statistical probabilities and thus constant improvement, thanks to a

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\(^1\) Remarkably, the 1966 ALPAC report included an experiment where it was found that “most of the translators found postediting tedious and even frustrating” although some found it useful, “particularly with regard to technical terms” (1966: 96, 97).

\(^2\) Kenny’s comments on my 2013 article seem to overlook the parts where I allow that translators will need to go beyond technologies, as in: “anyone working with TM/MT will need tons of these suprasentential text producing skills, probably to an extent even greater than is the case in fully human translation” (2013: 491). She seems rather more upset about my deconstruction of Chris Durban’s anti-technology and anti-intellectual discourse on professional translating (Pym 2016a), as if the critique of Durban’s outbursts involved some kind of denial of a whole market segment.

\(^3\) An illustrative example of this is found among patent professionals who use gist MT to decide what needs to be translated by humans (Nurminen 2019). As one of these professionals puts it, “the more important [the] decision, the less you do the decision based only on the MT” (ibid.: 36).
virtuous circle. Over time, it seems that this relation does not necessarily hold. In relatively closed, specific semantic fields, it makes more sense to have a restricted, clean database. For some time, IBM has had in-house machine-translation systems for each of its products, with very exact matches for the items in those products. At that extreme, the logics of translation memories and machine translation converge: the machine-translation system is actually working like a large translation memory. This would seem to be one kind of future for machine translation: in-house systems that can be highly controlled.

A very different kind of future is opened up by the large public systems that purport to work in many different fields and are thus far more exposed to error. The problem with the public systems is not that the algorithms are faulty; it is that many of the people who use them are often stupid. Once the machine gives a rendition that looks fluent and convincing, users accept the translation as valid and then put it on a website, where it can be picked up by a web crawler and fed back into a database. Rubbish out, rubbish in – the ideally virtuous circle turns into vicious circle and the promises of perpetual improvement come to naught.

This is not to say that the size of a database is not important. A minor language needs basic electronic resources in order to benefit from machine translation, and inadequate resources can have detrimental effects on language maintenance (see Bowker 2009). Yet the economies of scale seem no longer sufficient: smart is better.

Myth 3. “Machine translation has reached parity with humans.”

In March 2018 Microsoft claimed that in Chinese to English news translation “our latest neural machine translation (NMT) system has reached a new state-of-the-art, and that the translation quality is at human parity when compared to professional human translations” (Hassan et al. 2018: 1). Mention of “human parity” sends shockwaves around the translation professions (Wu et al. 2016 had merely claimed that Google’s neural output was “nearly indistinguishable” from human translation). References to parity recall the projected moment of “singularity”, when computer processing capacity surpasses the capacity of the human brain (Kurzweil 2005). Singularity has been achieved in the fields of chess and the game go, so why not in translation as well?

“Parity” here means that users cannot tell the difference between machine translations and human translations (in general accordance with the Turing Test for artificial intelligence); it does not mean that the translations are error-free. So 18M bilingual sentence pairs were evaluated by “bilingual crowd workers”, who were asked whether the candidate translation conveyed “the semantics of the source text” (Hassan et al. 2018: 3). In general (there are several tests involved), no significant difference was found between the human and machine-generated translations.

Does this spell the end of the road for humans? Not necessarily. Note that the testing was of context-free sentence pairs being assessed in terms of content, not form. This means pragmatic, discursive, stylistic or other purpose-based features were excluded. Similarly excluded were the cohesion devices that link isolated sentences, where machine translations typically have problems: a better kind of test would be on continuous text (as argued in Läubli, Sennrich, Volk 2018). In short, the deck was stacked in favor of the machine.

A further limitation on the parity claim ensues from what has been said above about translators selling trustworthiness. There is some evidence that a human translator expends greater effort on the more high-risk passages of a text, reducing the risk of error in them (see Pym 2015). Machine translation processes, on the other hand, invest effort uniformly over the whole text, which means that their probability of error per sentence remains theoretically constant. That is, if a page of human translation and a page of machine-translation output
both have three errors in them, the human translation will probably not have the errors in the high-risk passages but the machine translation might. So when the end-user receives the translations, they can assume all the parity they like, but they will not know exactly where those three errors lie.

Translators will still sell trustworthiness.

**Myth 4. “Machine translation replaces translators.”**

A logical corollary of parity would seem to be that machine translation should replace translators in many fields, especially when the machine is free and the translator is not. This consequence, however, does not necessarily follow from the premise.

Consider Wei’s models of possible change (Figure 1, reported in Li 2018). An optimistic vision (A) predicts that most professional translators will turn to postediting, the use of raw machine translation will increase, and there will remain a mysterious top “premium” market that continues untouched and may even increase a little (perhaps in the way that haute couture actually benefits from the mass production of clothes). On this model, machine translation will take away some of the boring donkeywork at the bottom of the value chain but will pose no real threat to the top. The major predicted change is that the rump of professional translation work will be done with the help of machine translation – which is what a basic economy of effort would predict and was envisaged in Pym 2013. Wei nevertheless also offers us a pessimistic model (B) where much of the work done by professional translators will indeed be done my machine translation, and the new work created for translators is as taggers, marking natural-language strings so that they perform better in MT databases. That is, translators will be working to help machine translation, rather than the other way around. This is the model that Wei considers most likely to be realized.

*Figure 1. Possible models of professional translation (from Wei 2018, cited in Li 2018)*
Wei’s models nevertheless do not really capture the massive social usage of machine translation (of which professional translation could be less than 1%, according to our calculation above). The impact of machine translation would thus appear to lead to something more like Figure 2, which does not contradict Wei’s model but merely attempts to place it in perspective. According to this second model, the major impact of machine translation will not directly be on what professional translators do, but on the myriad low-risk tasks that people use translation for when it is virtually cost-free, when great accuracy is not required, or when user-ignorance reigns. That is, neural machine systems help transform translation into a general social activity, occupying spaces that were not previously worked in by professional translators.

Figure 2. An alternative model of change in translation activities

From this perspective, the great challenges facing translation researchers and teachers might not concern professionals at all: our main task should be to understand the social uses and effects of general non-professional translation, and to teach all language learners about what machine translation can and cannot do – they are virtually all using it, so they might as well know something about it. That, in turn, requires that new forms of translation activities be introduced into all language learning, but those arguments are for another day.

So let us focus on just the tip of the iceberg. What can we expect to happen there?

The market for professional translators

There is little hard evidence that machine translation inevitably spells the end of the translation profession. Indeed, there is ample evidence that the global translation industry continues to enjoy remarkably healthy expansion. The United States Occupational Outlook Handbook (Bureau of Labor Statistics 2019) predicts an 18% growth from 2016 to 2026; the China language service industry development report (China Academy 2018) claims 10% year-on-year growth; the Slator Language Industry Market Report 2019 predicts a global market growth of 21% from 2019 to 2022; United Kingdom Companies House figures (Bond 2018a) indicate that 265 new language service providers were set up there in 2017 and the 2018 number is on track to be higher. Similar general indicators can be found for other languages and markets. It thus seems that the interlingual transfers resulting from globalization are increasing so fast that, even if 99% of them are indeed done with machine translation alone, the remaining 1% has been growing steadily. Employers still report they need more high-level language skills than they can find (Ubalde and Alarcón 2019). That is,
the share of professional translation is not being taken away – the communication pie is simply growing much larger.

There is nevertheless at least one important caveat to be gleaned from the general statistics. Eurostat data on language service providers from 2010 to 2016 (Nimdzi 2019) show a massive 86% growth in revenue for companies with 250 employees or more, but actually indicate negative growth for companies with under 50 employees. This suggests that the growth could be quite uneven: success at the top end could be statistically hiding turmoil at the smaller scale. This might be because machine translation and associated technologies are benefitting the larger companies that are best able to invest in such things and adapt to them; automation may indeed be hurting smaller companies that cannot make such investments or are otherwise unable to adapt. At the same time, it could be that the large companies are able to attract and maintain clients where translation is a high-risk operation requiring more services than equivalence-based translation. The numbers, unfortunately, do not indicate the causes of the imbalance. Yet they do give a warning.

The future is not easy to predict. It may not be all rosy for those who seek business as usual.

**Which parts of translators’ work are automated?**

In the light of the above, a few things can be said about the way neural machine translation might affect the work of translators, over and above the incorporation of postediting into work flows. To undertake this, we need to know the skills that translators need, and then which of them have a good chance of becoming automatized.

Various models of translation competence have been formulated by translation teachers (for example, Kelly 2002, PACTE 2009, Göpferich 2009, EMT Expert Group 2009, EMT 2017). At least one other is based on surveys of employers (China Academy of Translation 2016). The models include a wide range of knowledges and skills. For example, the one initially developed for the European Masters in Translation (EMT 2009) offers the following: translation service provision competence, language competence, intercultural competence, information mining competence, thematic competence, and technology competence, each with numerous skills or sub-competences within them. As much as that kind of model is undoubtedly useful as a tool for discussing curriculum design among educators, it presents several disadvantages for the task of assessing automation. First, the very plurality of the typologies suggests that they respond to specific socioeconomic contexts or personal visions; second, none of the typologies, to my knowledge, has based its categories on any controlled empirical research on what translators actually do (they have more to do with consensus reached by teachers sitting around a table); and third, since the models have

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4 Further speculation on market turmoil at the lower end can be found in an article in *The Economist* (2017), where not all the causes can be brought back to machine translation. The reality of online work, for instance, means that clients can seek out translators in low-paying countries, driving down global prices. Pym, Orrego-Carmona and Torres-Simón (2016) further attribute market disorder to the ability to copy or forge signals of translator status, which is only indirectly related to machine translation (scammers can steal a translator’s identity and use it to sell machine translations as fully-human translations).

5 The competence model presented by China Academy of Translation (2016: 71) was used in a survey of 423 employers (and as such might be compared with the data for Europe in the EMT Optimale project, see Toudic 2012). PACTE (2009) is presented as a “validation of the competence model” but merely proves the existence of translation competence in general: a group of translation graduates and a group of language graduates did the same translation, and the translation graduates scored better (when graded by the same institution that trained them). This does not validate the categories of the competence model. Göpferich (2009) does carry out longitudinal research following a group of students through their studies, but this does not, to my knowledge,
been developed for translation only (sometimes along with interpreting), they do not readily allow for comparisons with other occupations. They are thus not well-suited comparative sociology; they were never intended to be.

On the other hand, there is much to be gained from working with a collective framework that seeks quantitative comparisons of the knowledges, skills and abilities that are important in numerous occupations. This means starting from a rather wider range of standardized items. A weighted list of items of this kind has been developed for the US Department of Labor (O*Net 2018), which is the main database used in the research project of which the current report forms a part. The US data have the significant advantages of being freely available, based empirically on what employer-identified “job incumbents” themselves say about their work, and having been applied to over 12,000 job titles, including “translation and interpreting”. There are also some major disadvantages, however. First, the database refers to the US market for translators and interpreters only, which differs in important ways from the labor markets in societies where translation is needed for public governance (as in Europe and Canada) or for virtually all trade (as in China): the US market would seem to have a relatively greater proportion of interpreters working in the legal and healthcare systems. Second, since the main analytical categories have been developed over decades, they do not focus on technologies and there is no specific weighting of the role of technologies (as noted in Handel 2016); one merely finds lists of the technologies and tools that employees might use. And third, since the database is presented in a way intended to help people decide on a career or look for jobs corresponding to their skills, it was not designed to help sociologists. This means, among much else, that information on the data collection process is not systematically made available. The information on each occupation is nevertheless reported as being based on responses from at least 15 people working under the title concerned, with an estimated average of “39 respondents per item within each of the 809 occupations in the first complete database” (Handel 2016: 160). That would seem to be very few informants in an occupation like translation and interpreting. Further, since the employers identified the survey respondents, one suspects there could be an over-representation of in-house employees. And fourth, the responses that the employees gave with respect to what they have to know and do (knowledge and skills) were then mapped onto a list of more abstract “abilities” by job analysts, which results in a problematic doubling-up of some items and a merging of others. That said, O*Net data is worth pursuing on an experimental basis.

The tables below take the 2018 O*Net list of knowledges, skills and abilities that are pertinent to written translation only, since this is the part of the profession that is most likely to be affected by automation (in the present state of the technologies) and there might be fewer indications of its internal heterogeneity. I thus exclude “active listening”, for example.

text the categories of the model itself. Beyond that, all the teachers might argue that their considerable accumulated experience constitutes a form of research.

6 The US market for translators and interpreters is rather peculiar in that, although the market is large and growing, there is very little dedicated training for translators and there is great diversity within the market. Written translation and spoken interpreting have quite different socioeconomic configurations, since interpreters (who speak their translations) are predominantly employed in the health services and courts, often for recent immigrant groups and with languages that are spoken within such groups, with relatively low social esteem. At the same time, conference interpreters form a reduced group that enjoys quite high social rewards, as do legal interpreters employed, for example, in high-stakes legal cases involving Chinese or Japanese. A somewhat dated snapshot of the salaries of US interpreters (Kelly et al. 2010: 35) shows a curve with three humps: a distinct but small group earning more the USD100,000 a year, a rump earning USD40,000 to USD50,000, and a huge bottom rung (with more than three times the interpreters in the top group) earning less that USD10,000, often interpreting part-time (Kelly et al. 2010: 37). Any statistics that assume the homogeneity of these groups are likely to be misleading.
This is nevertheless a problematic normalizing exclusion, since the importance of spoken language will return later in the analysis.

There are four main categories for the O*Net data: knowledge, language skills, information-processing skills, and social communication skills. Under each category I have joined the lists for “skills” and “abilities”, since the difference is not pertinent to my purposes here. I include only the items with an importance score above 50 in the O*Net data, since there is a long tail of quite minor skills and abilities that do not concern technology. I then broadly estimate whether the remaining skills and abilities can be carried out by human translators and/or neural machine translation (MT), calling the shots based on what we know about translation (from the general competence models just listed) and what we know about neural machine translation (from the above description). The analysis is admittedly rough but might yet be suggestive.

Knowledge

The list of knowledges listed as being needed by translators and interpreters (Table 1) is both obvious (with respect to languages and service provision) and rather peculiar (with respect to the rest).

Table 1. Knowledge pertinent to written translation (O*Net importance weight and descriptors)

<table>
<thead>
<tr>
<th>IMPORTANCE</th>
<th>KNOWLEDGE</th>
<th>DESCRIPTION</th>
<th>HUMAN</th>
<th>MT</th>
</tr>
</thead>
<tbody>
<tr>
<td>98</td>
<td>English Language</td>
<td>Knowledge of the structure and content of the English language including the meaning and spelling of words, rules of composition, and grammar.</td>
<td>YES</td>
<td>YES</td>
</tr>
<tr>
<td>98</td>
<td>Foreign Language</td>
<td>Knowledge of the structure and content of a foreign (non-English) language including the meaning and spelling of words, rules of composition and grammar, and pronunciation.</td>
<td>YES</td>
<td>YES</td>
</tr>
<tr>
<td>77</td>
<td>Customer and Personal Service</td>
<td>Knowledge of principles and processes for providing customer and personal services. This includes needs assessment, meeting quality standards for services, and evaluation of customer satisfaction</td>
<td>YES</td>
<td>NO</td>
</tr>
<tr>
<td>62</td>
<td>Law and Government</td>
<td>Knowledge of laws, legal codes, court procedures, precedents, government regulations, executive orders, agency rules, and the democratic political process</td>
<td>YES</td>
<td>NO</td>
</tr>
<tr>
<td>62</td>
<td>Communications and Media</td>
<td>Knowledge of media production, communication, and dissemination techniques and methods. This includes alternative ways to inform and entertain via written, oral, and visual media.</td>
<td>YES</td>
<td>NO</td>
</tr>
<tr>
<td>60</td>
<td>Education and Training</td>
<td>Knowledge of principles and methods for curriculum and training design, teaching and instruction for individuals and groups, and the measurement of training effects.</td>
<td>YES</td>
<td>NO</td>
</tr>
<tr>
<td>56</td>
<td>Computers and Electronics</td>
<td>Knowledge of circuit boards, processors, chips, electronic equipment, and computer hardware and software, including applications and programming</td>
<td>YES</td>
<td>NO</td>
</tr>
<tr>
<td>51</td>
<td>Clerical</td>
<td>Knowledge of administrative and clerical procedures and systems such as word processing, managing files and records, stenography and transcription, designing forms, and other office procedures and terminology.</td>
<td>YES</td>
<td>NO</td>
</tr>
</tbody>
</table>
The high weighting given to “customer and personal service” could be read in several ways: the “customer” could be the person needing the translation or the client purchasing the translation. It at least serves to remind us that translation involves the provision of a service. And the inclusion of a potpourri of “clerical skills” at the bottom of the list similarly makes basic sense (translators have to keep their business affairs in order).

The remaining kinds of knowledge then seem to reflect the fields in which the unknown respondents were working: law, communications, education and electronics serve only to remind us that there are many potential fields involved and that it is good to know something about the one you are working for.

The message is simple enough as a point of departure: knowledge of languages might be automated, but there are many other kinds of knowledge involved.

**Language skills**

The basic language skills in the repertoire are reading and writing, both considered to be of great importance. Again, this should be news to no one.

<table>
<thead>
<tr>
<th>IMPORTANCE</th>
<th>SKILL/ABILITY</th>
<th>DESCRIPTION</th>
<th>HUMAN</th>
<th>MT</th>
</tr>
</thead>
<tbody>
<tr>
<td>75</td>
<td>Reading Comprehension</td>
<td>Understanding written sentences and paragraphs in work related documents.</td>
<td>YES</td>
<td>YES</td>
</tr>
<tr>
<td>69</td>
<td>Writing</td>
<td>Communicating effectively in writing as appropriate for the needs of the audience.</td>
<td>YES</td>
<td>YES</td>
</tr>
</tbody>
</table>

Missing is the ability to translate (or interlingual mapping skills, which were also remarkably absent from the 2009 EMT model). On the face of it, though, machine translation should be able to automate just about everything we might want to include here, with the main area of doubt being the phrase “appropriate for the needs of the audience” included under “writing”. NMT cannot really adjust in that way in cases where the audience for the translation is very different from the audience for the start text (although Systran does nominally offer separate renditions for default, legal and IT discourses). More important, what is missing here is the levels of these skills that are required for specific tasks: the risks of error value and the corresponding value of trustworthiness are not taken into account. But an employer or sociologist, looking at the deceptively smooth outputs of neural machine translation, might be forgiven for thinking that translators’ basic linguistic skills have indeed been automatized.

**Information-processing skills**

The skills and abilities that can be listed under information processing cover a wide range of items, which could easily be expanded (the list of less important items would include deductive and inductive reasoning, originality, speed of closure, and so on). Many of these items seem to address spoken more than written translation, raising challenging questions about the extent to which the two can or should be separated.
Table 3. Information-processing skills and abilities pertinent to written translation (O*Net importance weight and descriptors)

<table>
<thead>
<tr>
<th>IMPORTANCE</th>
<th>SKILL/ABILITY</th>
<th>DESCRIPTION</th>
<th>HUMAN</th>
<th>MT</th>
</tr>
</thead>
<tbody>
<tr>
<td>69</td>
<td>Information Ordering</td>
<td>The ability to arrange things or actions in a certain order or pattern</td>
<td>YES</td>
<td>NO</td>
</tr>
<tr>
<td></td>
<td></td>
<td>according to a specific rule or set of rules (e.g., patterns of numbers,</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>letters, words, pictures, mathematical operations).</td>
<td></td>
<td></td>
</tr>
<tr>
<td>66</td>
<td>Critical Thinking</td>
<td>Using logic and reasoning to identify the strengths and weaknesses of</td>
<td>YES</td>
<td>NO</td>
</tr>
<tr>
<td></td>
<td></td>
<td>alternative solutions, conclusions or approaches to problems.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>66</td>
<td>Problem Sensitivity</td>
<td>The ability to tell when something is wrong or is likely to go wrong.</td>
<td>YES</td>
<td>NO</td>
</tr>
<tr>
<td></td>
<td></td>
<td>It does not involve solving the problem, only recognizing there is a problem.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>63</td>
<td>Monitoring</td>
<td>Monitoring/Assessing performance of yourself, other individuals, or</td>
<td>YES</td>
<td>NA</td>
</tr>
<tr>
<td></td>
<td></td>
<td>organizations to make improvements or take corrective action.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>60</td>
<td>Selective Attention</td>
<td>The ability to concentrate on a task over a period of time without being</td>
<td>YES</td>
<td>NA</td>
</tr>
<tr>
<td></td>
<td></td>
<td>distracted.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>56</td>
<td>Active Learning</td>
<td>Understanding the implications of new information for both current and</td>
<td>YES</td>
<td>NO</td>
</tr>
<tr>
<td></td>
<td></td>
<td>future problem-solving and decision-making.</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

This list of ways to process information is intriguing because, in principle, all a machine translation system does is process information. MT should probably bring in automation on all counts. Yet one struggles to imagine that machine translation can apply critical reasoning (as described here), and one would indeed hope that this is the kind of thing that might be expected of translators when postediting and text tailoring. In general, the kind of information-processing skills listed here are not those that are easily automated by machine translation.

**Social communication skills**

The social communication skills considered pertinent to translation are rather restricted in nature and are well down the list in terms of importance scores:

Table 4. Social-communication skills and abilities pertinent to written translation (O*Net importance weight and descriptors)

<table>
<thead>
<tr>
<th>IMPORTANCE</th>
<th>SKILL/ABILITY</th>
<th>DESCRIPTION</th>
<th>HUMAN</th>
<th>MT</th>
</tr>
</thead>
<tbody>
<tr>
<td>53</td>
<td>Social Perceptiveness</td>
<td>Being aware of others' reactions and understanding why they react as they do.</td>
<td>YES</td>
<td>NO</td>
</tr>
<tr>
<td>53</td>
<td>Coordination</td>
<td>Adjusting actions in relation to others' actions.</td>
<td>YES</td>
<td>NO</td>
</tr>
<tr>
<td>53</td>
<td>Service Orientation</td>
<td>Actively looking for ways to help people.</td>
<td>YES</td>
<td>NO</td>
</tr>
<tr>
<td>53</td>
<td>Judgment and Decision</td>
<td>Considering the relative costs and benefits of potential actions to choose</td>
<td>YES</td>
<td>NO</td>
</tr>
<tr>
<td></td>
<td>Making</td>
<td>the most appropriate one.</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

These are all clearly automation-resistance skills, yet their low scores indicate that they are considered of little importance in the translation profession. And below the 50-point cut-off level, the O*Net repertoire includes a long list of social communication skills that are
considered of even less importance for translators: negotiation, persuasion, resolving conflicts, “communicating with persons outside the organization”, and so on. The list of “social communication skills” is a potpourri of things people can do with language, mainly concocted with the idea that the worker is employed in a rather large company where internal communications are important. They would seem to apply rather less in an occupation where, on the global scale, 74% of professionals are freelancers and 60% of them work part-time (Pym, Grin, Sfreddo and Chan 2012). Freelancers nevertheless do have to maintain contacts with clients, negotiate contracts, be aware of their social setting, resolve conflicts and the rest, as do those who navigate the politics of large companies. Those are indeed language skills, and translators do use them. Machines do not use them – so these are potential names for a substantial set of automation-resistant skills.

So should we stop teaching languages?

We now have a reasonably detailed list of the automation-resistant parts of the translator’s activities. These are also very useful labels for the kinds of training activities that we might use to make the translation profession even more automation-resistant, as indeed might all the items that are listed under “social-communication skills” (Table 4).

The fact remains, though, that the language knowledge and skills that employers consider to be of most weight in the translation profession are precisely the ones that seem the least automation-resistant. So should we just give up on teaching languages and the core translation skills? That is, should we retreat from the conceptual territory that we can no longer defend?

This is indeed what seems to be happening in parts of the translator-training community. The network known as the European Masters in Translation has accepted member programs where under 20% of the contact hours are on language-specific translation, especially in the UK (Torres and Pym 2019). The revised competence model elaborated by the same European Masters in Translation (EMT 2017) not only recognizes the usefulness of machine translation in the translation process but also places increased emphasis on precisely the “personal-interpersonal” and “service provision” skills that appear to be the most automation-resistant. And the translator certification system operative in Australia has opened the way to have postediting and revision included as activities that it evaluates (NAATI 2019), which might be seen as an enlightened displacement of some of the emphasis on basic language skills.

It would nevertheless be shortsighted to abandon language knowledge as the basis of translator competence. To understand why, let us consider a few other occupations. When we visit a family doctor, their basic activity is linguistic: they listen, talk, and perhaps write something on a piece of paper. Same for a lawyer: they basically talk, write, and charge fees. But when these professionals access information, when they put it in a new order and adapt it to a new user, their information-processing and social-communication skills are highly rewarded not just because those activities are well executed, but more importantly because they are based on access to a highly specialized and complex knowledge base: medicine and laws. The access to the knowledge may be highly automatized these days (in searches of case law, for example) but the mastery of the knowledge itself is still highly valued, especially in high-risk situations. So too with translation, potentially: the algorithms of machine translation can locate good candidate translations automatically, but mastery of translation enables reasoned choices between those candidates, adaptation to specific situations, and incorporation into linguistic exchanges at various levels of risk. The point is this: If you throw away knowledge of languages and mastery of translation solutions, it is like training a doctor who knows no medicine or a lawyer who does not know the law – third-rate television
actors would perform just as well. Even when they are not highly rewarded in direct terms for knowing languages or being able to translate from scratch, translators still need those things. That is why all their other skills are potentially of value.

Justa Holz-Mänttäri (1984) theorized this long ago: translators work with clients who have expertise in the various fields concerned, while the expertise of the translator, their prime knowledge base and field of mastery, should be interlingual communication. If we do not know the languages, and know them extremely well, and know the many ways they can be mapped onto each other and used to effect in specific situations, then we have no basis for everything else we can offer.

This does not mean, of course, that translators should somehow refuse to become conversant in the specific fields in which they work: the areas of knowledge mapped in Table 1 (including a fairly random selection of education, law, and electronics) indicate that area expertise does play a role and should not be ignored.

The real question, though, is what we can then do with the rest of the list, the automation-resistant skills and abilities that our analysis lists as being more peripheral in the activities of translators. I offer a few general suggestions.

Possible strategies for future rewards

The fundamental question here is not what translators can or cannot do, but how they might obtain appropriate social rewards for automation-resistant skills. Or more generally, which particular language activities are likely to be rewarded in a market where automation has taken hold? To tackle this question, I approach from the perspective of an organization that is distributing rewards.

Feely and Harzing (2003) see the global information economy as generating three kinds of linguistic challenges facing anyone who wants to get a message out across languages: diversity (the number of languages a company needs services in), penetration (what market sectors have to be reached), and sophistication (form and complexity in processing language). These criteria may occur separately or in combination. This analysis can be applied to translation in the following ways:

1. If language diversity is the only challenge, then machine translation is fine. Many cities do indeed make their websites freely available in as many languages as machine translation provides, without any human intervention, and the criterion of diversity is thereby satisfied. There is thus no need to reward translators for diversity alone, at least not at any level beyond the economics of the supply and demand of skills in a particular language pair.

2. If market penetration is the only criterion, then machine translation might go part of the way toward the goal but will probably need further editing, explanations and/or adaptation to specific registers. In order to reach particular market niches, machine translation is limited; the human skills categorized as “information processing” (Table 4 above) come into their own.

3. If sophistication is a criterion, with respect to either the complexity of cognitive operations or the formal qualities of a presentation, then human translators with advanced language skills should once again be automation-resistant (even when we use many technologies to help us write better). The reason has to do with the consequences of error: even if a minor typo or syntactic error has no actual consequences for the understanding or use of a text, such things have a negative
impact on company image and can be disastrous for branding – the communication loses value, even though it might have diversity and penetration. This is where high-level language skills return to a sphere of value, even when only in forms of postediting.

This analysis seems logical enough. The more substantial problem lies in communicating its consequences to employer groups, who tend to see automation as little more than a great cost-reducing factor. And this is where translators need, more than ever, the social-communication skills (Table 5) that are not being directly rewarded in themselves. The communication skills can thus partly be seen as means to rewards – we need to be good at them so that our other virtues can be appreciated.

So what kinds of things can be said to those who distribute rewards? What strategies can be formulated to work with automation rather than against it?

_Sell trustworthiness rather than words_

This is basic: automation means that translators should not be paid according to the numbers of words they produce, since the machine can produce the words. This is actually one of the recommendations of the Fédération Internationale des Traducteurs: translators “should seek to charge for their services on an hourly or project basis and not per word, line or page translated” (FIT 2017: 2).

More generally, the need for postediting and checking should allow qualified translators to act as authorities, authorizing the results of postediting. This “notary” function clearly sells trustworthiness more than words, and it may be limited to the high-risk areas in which high levels of trust are required: at key points in workflows in the legal, medical, pharmaceutical fields, for example, or wherever image is at stake.

Social communication skills are needed to build trust, and trust can then be converted into higher rewards for non-automatized language and information-processing skills. If this can be done, then there is no need to eschew postediting as a mindless activity that is somehow beneath the dignity of professional translators (as seems to be argued in Kenny 2018). It will have its place in the range of services that can be offered.

_Play with the full orchestra of translation solutions_

In tasks with a promotional or marketing component, machine translations might provide a good point of departure, but there are many more things that can and should be done to ensure that a text functions well in a new culture. Translators need concepts and terms (a metalanguage) able to communicate the wider range of options to people who are likely to reward them.

One way of thinking about this is to consider a standard list of the kinds of solutions that translators use when solving problems (this one is from Pym 2016, but it follows the general order of the classical list by Vinay and Darbelnet 1958/1995):

- Copying words
- Copying structure
- Perspective change
- Density change
- Cultural correspondence
- Text tailoring
This very simplified list goes from interventions that are close to the start text through to radical adaptations to the target culture. Neural machine translation these days does fairly well in the middle of the list, in solutions ranging from copying structure to cultural correspondence (the solutions involving corresponding idioms are sometimes truly impressive). The machines do produce translations. Yet they tend not to use the solutions at the top or bottom of the list, or the more interventionist solutions in the middle: they tend not to import words or create new ones; they struggle to adopt the discursive perspective of a new receiver; they have few criteria for adding explicitations, applying implicitation, making major shifts in cultural references, or adding or deleting the content of a text. A human translator with a mandate for intervention can make all those changes, playing with the complete orchestra of solution types rather than the quartet offered by sophisticated algorithms.

Once again, this logic is captured in the FIT recommendations: “these professionals should act as language services advisors or language consultants, advising their customers on the best approach to a particular assignment and explaining the benefits or drawbacks of certain translation methods” (FIT 2017: 2). To give that advice, we need to be able to apply all the translation solutions.

*Engage in automation-related activities*

The giving of advice may obviously be related to machine translation in a very direct sense: we can say when and how automation should be used. Yet there is also a range of professional activities that are more directly related to the use of machine translation.

As noted above, machine translation is being used in sectors where professional translators were not previously employed: much language learning (and hopefully more in the future), tourism, gist translation for many everyday purposes, multilingual conversations, and a long list of activities right through to the security surveillance that is able to check on all of them. That list does not really help anyone who wants to make a living out of translation: it basically maps out the places one should *not* want to go (although security surveillance will hopefully need human expertise at many points). It can nevertheless be opposed to a list of areas in which machine translation helps to create new kinds of professional activities:

- Postediting (selling trustworthiness/authority)
- Pre-editing (technical writing)
- Revision and reviewing
- Project management
- Terminology
- Database management
- Interpreting translated data
- Rewriting (public relations, marketing, cross-cultural consulting)

Those are the areas where we should be investing new training efforts, working with the technology rather than against it.

*Do more than translate*

At the same time, neural machine translation should push us towards professional activities with higher value added, many of which are on the borders of translation or blend translation with other skill sets. We thus find a proliferation of new names for the new things that
translators can do. Bond (2018b) scoured LinkedIn for the job titles of people who work for language service providers, coming up with over 600 different titles. Some of these play on concepts wider than translation, such as localization (localization manager, localization strategy consultant) or transcreation (in marketing), and then there is a wide range of titles that emphasize the importance of addressing clients’ specific needs, and indeed intensive communication with clients (something the larger companies tend to recognize). For instance, here are some of the job titles derived from the simple idea of solving clients’ problems (still from Bond 2018b): solutions architect, director of client solutions, solutions consulting and director of technology solutions, cloud solutions architect, or solutions manager for machine intelligence. The people bearing such titles may have a background in translation and probably work with technologies, but they are certainly not postediting machine translation.

Beyond the creative nomenclatures of company culture, the academic literature offers an array of instances where the core tasks of translation are joined to skills in neighboring fields, giving new names for perhaps new activities. We thus find, for instance:

Translation and journalism: “journalistic translation” (or “journalation”) (Filmer 2014; Valdeón 2015)
Translation and editing: “transediting” (from Stetting 1989)
Translation and artistic creation: “transcreation” (e.g. Pedersen 2014)
Translation and adaptation: “transadaptation” (in audiovisual translation and language testing)
Translation and audiodescription: “accessibility management” (e.g. Orero 2017)
And so on.

No one should suggest that these names and activities are a direct consequence of machine translation, or indeed of any particular technology. There are numerous factors behind each of these developments. The basic message should nevertheless remain clear: as machine translation systems automate many everyday translation tasks and can be expected to meet them better each day, there is no overwhelming need to compete with it directly in those fields. Translators should seek work on high-risk communicative situations (which may include postediting work) and combinations with the many neighboring skill sets.

Former bank-tellers are now selling fancy financial products; former supermarket check-out personnel are now stacking shelves. We should be training our students to do more than stack shelves.

References


