A User Study of the Incremental Learning in NMT

Miguel Domingo, Mercedes García-Martínez, Álvaro Peris, Alexandre Helle, Amando Estela, Laurent Bié, Francisco Casacuberta, and Manuel Herranz

Abstract

In the translation industry, human experts usually supervise and post-edit machine translation hypotheses. Adaptive neural machine translation systems, able to incrementally update the underlying models under an online learning regime, have been proven to be useful to improve the efficiency of this workflow. However, this incremental adaptation is somewhat unstable, and it may lead to undesirable side effects. One of them is the sporadic appearance of made-up words, as a byproduct of an erroneous application of subword segmentation techniques. In this work, we extend previous studies on on-the-fly adaptation of neural machine translation systems. We perform a user study involving professional, experienced post-editors, delving deeper on the aforementioned problems. Results show that adaptive systems were able to learn how to generate the correct translation for task-specific terms, resulting in an improvement of the user’s productivity. We also observed a close similitude, in terms of morphology, between made-up words and the words that were expected.

1 Introduction

Despite its improvements and obtaining admissible results in many tasks, machine translation (MT) is still very far from obtaining automatic high-quality translations (Dale, 2016; Toral et al., 2018). Thus, a human agent needs to supervise and correct the outputs generated by an MT system. This process is known as post-editing and is a common use case of MT in the industrial environment. As MT systems are continuously improving their capabilities, it has acquired major relevance in the translation market (Guerberof, 2008; Pym et al., 2012; Hu and Cadwell, 2016; Turovsky, 2016).

Throughout the post-editing process, new data are continuously generated. These new data have valuable properties—they are domain-specific training samples. Thus, it can be leveraged to continuously adapt the system towards a given domain or the style of the post-editor. A common way of achieving this consists in following an online-learning paradigm (Ortiz-Martínez, 2016; Peris and Casacuberta, 2019). Each time the user validates a post-edit, the system’s models are updated incrementally with this new sample. Hence, when the system generates the next translation, it will consider the previous post-edits made by the user and it is expected to produce higher quality translations (or, at least, more suited to the post-editor’s preferences).

Domingo et al. (2019b) conducted a preliminary user study for professional post-editors, who had a positive perception of the adaptive systems. However, they noticed that, in some cases, there were occurrences of some made-up words. In this work, we study the impact of this phenomenon. Additionally, we extend their user study by involving three more participants and providing additional measures for the increase in productivity gained with the adaptive system.

2 Related work

Post-editing MT hypotheses is a practice that was adopted in the translation industry a long time ago (e.g., Vasconcellos and León, 1985). Its relevance grew as MT technology advanced and improved. The capabilities of MT post-editing have been demonstrated through many user studies (Aziz et al., 2012; Bentivogli et al., 2016; Castilho et al., 2017; Green et al., 2013a).

Parallel to the rise of the post-editing protocol, using user post-edits to adapt MT systems has also attracted the attention of researches and industry. This was studied in the CasMaCAT (Alabau et al., 2013) and MateCAT (Federico et al., 2014) projects and phrase-based statistical MT systems based on online learning were developed (Ortiz-Martínez, 2016). With the breakthrough in neural MT (NMT) technology (Bahdanau et al., 2015; Wu et al., 2016; Vaswani et al., 2017), research shifted towards constructing adaptive systems by online learning in this post-editing scenario. The use of online learning to adapt an NMT system to a new domain with post-edited samples was proposed by Peris et al. (2017) and Turchi et al. (2017). Other works refined these adaptation techniques and applied them to new use cases (Kothur et al., 2018; Wuebker et al., 2018; Peris and Casacuberta, 2019).

The evaluation of MT post-edits is a hard topic that
is currently being actively researched (e.g., Toral, 2019; Freitag et al., 2020; Läubli et al., 2020). Several works conducted user studies for MT post-editing systems, either phrase-based (Alabau et al., 2013; Green et al., 2013b; Denkowski et al., 2014; Bentivogli et al., 2016) or NMT (Daems and Macken, 2019; Koponen et al., 2019; Jia et al., 2019). Moreover, two studies showed improvements in terms of productivity time and translation quality with the application of an online learning protocol (Karimova et al., 2018; Domingo et al., 2019b). This latter study is tightly related to ours. We extend it by performing a finer-grained evaluation of the outputs of the adaptive systems.

3 Experimental framework

As we extended the work of Domingo et al. (2019b), we used their same data and systems. The task at hand consisted of a small medico-technical (description of medical equipment) corpus from their production scenario. It contains specific vocabulary from a very closed domain. It was conformed by two documents of 150 sentences, which contained 1.7 and 2.7 thousand words respectively. The translation direction was English to Spanish. The system was trained using the data from WMT’13’s translation task (Bojar et al., 2013) and samples selected by the feature decay selection technique (Biçici and Yuret, 2015). The data features are summarized in Table 1. We applied joint byte pair encoding (Sennrich et al., 2016), using 32,000 merge operations. The system was built with OpenNMT-py (Klein et al., 2017), using a long short-term memory (Gers et al., 2000) recurrent encoder–decoder with attention (Bahdanau et al., 2015). All model dimensions were 512. The system was trained using Adam (Kingma and Ba, 2014) with a fixed learning rate of 0.0002 (Wu et al., 2016) and a batch size of 60. A label smoothing of 0.1 (Szegedy et al., 2015) was applied. At inference time, we used beam search with size 6.

The adaptation process followed the findings from Peris and Casacuberta (2019). We tuned the hyperparameters for the adaptation process on our development set, under simulated conditions. For each new post-edited sample, we applied two plain SGD updates, with a fixed learning rate of 0.05.

As translation environment we used the one designed by Domingo et al. (2019a). It connects our adaptive NMT engine with the SDL Trados Studio interface, which is used by the post-editors in our production workflow. In addition, it also allowed us to trace the productivity metrics and user behavior.

3.1 Evaluation

We evaluated two main aspects of the adaptation process: productivity of the post-editors and quality of the NMT systems. The former was assessed by computing the average post-editing time per sentence and the number of words generated by the post-editor per hour. For the latter, we employed two well-known MT metrics: (h)BLEU (Papineni et al., 2002) and (h)TER (Snover et al., 2006). In order to ensure consistent BLEU scores, we used sacreBLEU (Post, 2018). Since we computed per-sentence BLEU scores, we used exponential BLEU smoothing (Chen and Cherry, 2014).

We applied approximate randomization tests (Riezler and Maxwell, 2005), with 10,000 repetitions and a p-value of 0.05, to determine whether two systems presented statistically significant differences.

3.2 Human post-editors

Six professional translators were involved in the experiment. Some profiling details about them can be found in Table 2.

| User   | Sex | Age | Professional experience |
|--------|-----|-----|-------------------------|
| User 1 | Male| 24  | 1.5 years               |
| User 2 | Female| 25 | 5 years                 |
| User 3 | Female| 30 | 5 years                 |
| User 4 | Female| 24 | 1 month                 |
| User 5 | Female| 22 | 1 year                  |
| User 6 | Male | 48  | 22 years                |

Table 2: Information about the human post-editors that took part in the experiment, regarding their sex, age and years of professional experience.

The static experiment consisted in post-editing using the initial NMT system, which remained fixed along the complete process. For the adaptive experiment, all users started with the initial system, which was adapted to each user through the process using their own post-edits. Therefore, at the end of the process, each user obtained a tailored system. In order to avoid the influence of translating the same text multiple times, each participant post-edited a different document set under each scenario (static and adaptive), as shown in Table 3.

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### Table 1: Corpora statistics in terms of number of sentences, number of tokens, number of types (vocabulary size) and average sentence length. K denotes thousands and M, millions.

| Corpus  | # Sentences | # Tokens | # Types | Average length |
|---------|-------------|----------|---------|----------------|
| Training | 23.4M       | 702M     | 1.8M    | 30.0 K         |
| Document 1 | 150         | 1.7K     | 618     | 11.3 K         |
| Document 2 | 150         | 2.6K     | 752     | 17.3 K         |
4 User study

In our study, we focus on the differences between static and adaptive systems based on three main aspects: the productivity of post-editors, the quality of post-edits and the generation differences.

4.1 On the productivity of the post-editors

Table 4 shows the average gains obtained in terms of translation quality. These results demonstrate how the adaptive systems benefits from the user post-edits to improve the translation quality, yielding gains of up to 6.7 TER points and 8.0 BLEU points.

| User   | Document 1 | Document 2 |
|--------|------------|------------|
| User 1 | Static     | Adaptive   |
| User 2 | Adaptive   | Static     |
| User 3 | Static     | Adaptive   |
| User 4 | Adaptive   | Static     |
| User 5 | Static     | Adaptive   |
| User 6 | Adaptive   | Static     |

Table 3: Distribution of users, document sets and scenarios. All users conducted first the experiment which involved post-editing document 1 and then document 2 (e.g., user 2 first post-edited document 1 on an adaptive scenario and, then, document 2 on a static scenario).

| User   | System  | Time [s] | Words per hour [wph] |
|--------|---------|----------|----------------------|
| User 1 | Static  | 37.9     | 1685                 |
|        | Adaptive| 33.0\ddagger | 1935\ddagger         |
| User 2 | Static  | 30.5     | 2091                 |
|        | Adaptive| 30.4     | 2097\ddagger         |
| User 3 | Static  | 38.0     | 1678                 |
|        | Adaptive| 27.0\ddagger | 2364\ddagger         |
| User 4 | Static  | 37.5     | 1701                 |
|        | Adaptive| 47.4\ddagger | 1346\ddagger         |
| User 5 | Static  | 80.2     | 795                  |
|        | Adaptive| 46.7     | 1367\ddagger         |
| User 6 | Static  | 53.7     | 1188                 |
|        | Adaptive| 49.7\ddagger | 1284\ddagger         |

Table 5: Results of the user experiments, in terms of productivity. Static system stands for conventional post-editing, without adaptation. Adaptive system refers to post-editing in an environment with online learning. Time corresponds to the average post-editing time per sentence, in seconds. Words per hour represents the number of words generated by the post-editors per hour. Users 4 to 6 has less experience, in this particular domain, than users 1 to 3. \ddagger indicates statistically significant differences between the static and the adaptive systems.

Table 4: Results of the user experiments, in terms of translation quality. These numbers are averages over the results obtained by the different post-editors. Static system stands for conventional post-editing—without adaptation. Adaptive system refers to post-editing in an environment with online learning. hTER and hBLEU refer to the TER and BLEU of the system hypothesis computed against the post-edited sentences. \ddagger indicates statistically significant differences between the static and the adaptive systems.

| Test   | System  | hTER [ ] | hBLEU [ ] |
|--------|---------|----------|-----------|
| Document 1 | Static  | 39.5     | 47.9      |
|         | Adaptive| 32.8\ddagger | 55.9\ddagger |
| Document 2 | Static  | 36.2     | 42.9      |
|         | Adaptive| 34.3\ddagger | 50.5\ddagger |

of words generated per hour, the adaptive systems achieved significant gains for all cases except for user 4—which is coherent with the results obtained in terms of time per sentence. These gains range from 6—for user 2, who took the same average time for both scenarios—to 686 words per hour. Therefore, both metrics showcase how adaptive systems are able to significantly improve productivity.

4.1.1 User feedback

Following Domingo et al. (2019b) post-editors filled a questionnaire (see Appendix A) regarding the task they had just performed. We asked them about their level of satisfaction of the translations they had produced; whether they would have preferred translating from scratch instead of post-editing; and their opinion about the automatic translations, in terms of grammar, style and overall quality. Additionally, we also requested them to give, as an open-answer question, their feedback on the task.

While post-editors were generally satisfied with the system and the translations they produced (as also reported by Domingo et al. (2019b)), they spotted some issues regarding the adaptive NMT system: they noticed that domain-specific term were “forgotten” by the system, being wrongly translated. In addition, the users spotted the occurrence of some nonexistent words in the target language (e.g., “absolvido”). We delve deeper into these problems in Section 5.

4.2 On the quality of the post-edits

In order to assess and compare the quality of the human post-edits using the static and adaptive systems, a
human evaluation was conducted with the help of two professional translators—who had not taken part in the user study. In this evaluation, the evaluators were given a source sentence and the post-edits produced by each user—three of which had used the static system, and the other three the adaptive system.

Following Castilho et al. (2019) and TAUS adequacy/fluency guidelines\(^1\), they were asked to assess, on a 4-point scale, the adequacy (how much of the meaning is represented in the translation) and the fluency (the extent to which the translation is well-formed grammatically, has correct spellings, adheres to common use of terms, titles and names, is intuitively acceptable and can be sensibly interpreted by a native speaker) of each post-edit.

In total, they evaluated 600 sentences: the post-edits of the first 50 sentences of Document 1 and the post-edits from the first 50 sentences of Document 2 (see Section 3). To avoid biases, evaluators were not given any information regarding the origin of the translations. Figs. 1 and 2 present the results of the evaluation.

In terms of adequacy, results show that, for both systems, most of the post-edits convey the full meaning of the original sentence or most of it (represented by the scores 4 and 3). Just a few of them convey little or none of the original meaning (represented by the scores of 2 and 1). While both system behave similarly, we observe that a larger amount of the post-edits generated using the adaptive system have the highest adequacy score. This difference is more noteworthy for the post-edits from document 1 than for those from document 2. Similar conclusions can be reached according to fluency: Most post-edits, independently of the system used, are either flawless or good (represented by scores 4 and 3) regarding the extent to which they are constructed. Just a few are considered to be dis-fluent or incomprehensible (represented by a score of 2). Again, both systems are perceived to be similar in document 2, while the adaptive system is perceived as slightly more fluent.

Finally, it is worth noting some particularities of the task that may have influenced the results of the evaluation: the task consists in the description of medical equipment and, thus, contains several singularities such as specific acronyms (with which the target audience may be more familiar in their original language than with their translation) or description of parts of an equipment (taking into account that the physical equipment may have tags in its original language). Since the evaluators were given no specific instruction about how

\(^1\)https://www.taus.net/academy/best-practices/evaluate-best-practices/adequacy-fluency-guidelines.
to solve those particularities, their personal criteria may had an impact in the evaluation results.

4.3 On differences in the generation

Next, we compare both adaptive and static systems in terms of the translations generated. To this end, we employed the discriminative language model method (Akabe et al., 2014) implemented in the compare-mt (Neubig et al., 2019) tool, comparing sentence-level BLEU and word $n$-grams.

In terms of translation quality, we show a histogram of sentence-level BLEU scores in Fig. 3. For both documents, we observe similar trends: the static system generated low-scored sentences more frequently than the adaptive systems. The adaptive systems placed more hypotheses from bucket $[50, 60)$ onward, for both test documents. Moreover, the differences in frequencies between adaptive and static systems were kept at a similar proportion along all high-score buckets. Hence, adaptive systems were able to outperform the static one in these high-score ranges.

The study of the different $n$-grams helped us to identify common patterns across all users: adaptive systems were able to effectively learn ad-hoc sequences for the task at hand. We discovered several phenomena among the most common $n$-gram matches of adaptive systems: the correct translation of acronyms, entities relating a particular device and specific task terminology. See Fig. 4 for examples of these phenomena. We found these common constructions to be one of the major causes of the differences in terms of translation quality.

5 Generation of made-up words

On their feedback, the users reported that, in some cases, the system’s hypothesis contained words which were not real words (e.g., “absolvido”). This phenomenon, although infrequent, was a bit cumbersome. Most likely, it is caused by an incorrect segmentation of a word via the byte pair encoding process which, according to their frequency, splits words into multiple tokens. In order to assess its impact, we start by quantifying the issue. Table 6 shows the total of made-up words generated per user.

| User | System | Words |
|------|--------|-------|
| User 1 | Static | 3     |
|       | Adaptive | 6     |
| User 2 | Static | 8     |
|       | Adaptive | 5     |
| User 3 | Static | 3     |
|       | Adaptive | 17    |
| User 4 | Static | 8     |
|       | Adaptive | 5     |
| User 5 | Static | 3     |
|       | Adaptive | 14    |
| User 6 | Static | 8     |
|       | Adaptive | 4     |

Table 6: Total made-up words generated per user.

While this phenomenon is not very frequent (it represents from 0.2 up to 0.8% of all the words generated by a given system), it is present in all systems. Depending on the user, this problem was more present using the static or the adaptive system. Since users were using a different document set for each scenario (see Table 3) and there is a significant difference between documents in terms of total words and vocabulary (see Table 1), we need to compute the average per document in order to evaluate how the problem of made-up words generation affects the different scenarios. These results are shown in Table 7.

Although it could be expected for the adaptive sys-
The phenomenon system example

### Acronyms

| Source | QSE Number | Post-edit | Número de ESC | Adaptive | Número de ESC | Static | Número QSE |
|--------|------------|-----------|---------------|----------|---------------|--------|------------|

### Entities

| Source | Show the R Series ALS | Post-edit | Mostrar la serie R ALS | Adaptive | Mostrar la serie R ALS | Static | Mostrar el R Series ALS |
|--------|------------------------|-----------|------------------------|----------|------------------------|--------|------------------------|

### Terminology

| Source | There are several steps involved with sidestream end tidal CO2 setup. | Post-edit | La configuración del CO2 espiratorio final de flujo lateral se realiza en varios pasos. | Adaptive | Hay varias etapas de la configuración del CO2 espiratorio final del ajuste. | Static | Hay varias etapas que involucran la configuración del CO2 marenoto del CO2 marenoto |
|--------|---------------------------------------------------------------------|-----------|------------------------|----------|------------------------|--------|------------------------|

**Phenomenon System Example**

| Document | System | Words |
|----------|--------|-------|
| Document 1 | Static | 5     |
|           | Adaptive | 4     |
| Document 2 | Static | 8     |
|           | Adaptive | 12    |

**Table 7:** Average of made-up words generated per document for all users.

1. La zona verde es para pacio.
2. Roll al paciente a su lado, y luego rodar el electrodo hacia la espalda del paciente a la izquierda de su columna y debajo de la escaga.
3. Presione la tecla del softón.
4. Sin embargo, el metrónomo absolvido si las comprensiones son inferiores a las directrices.
5. Que el dispositivo puede hacer un choque de prueba de 30 julios.

**Figure 4:** Examples of the n-gram differences between adaptive and static systems. In **boldface** we highlight the differences introduced by adaptive systems.

**Figure 5:** Example of sentences with made-up words (denoted in **bold**) from the static system. The first word should have been estimulación, the second one omóplato, the third one RCP, the fourth one sonará and the fifth one julios.

1. Al mover el Selector de modo a Pacer se activará la puerta del **pidante** para abrir.
2. Coloque el sensor con el adaptador instalado fuera de todas las fuentes de CO2 (incluidos los válvulos de aire de respiración y respiratorio) exhalado.
3. Las marcapasas de estimulación deben producirse aproximadamente cada centímetro en la tira.
4. El conector de autopregunta funciona solo cuando el envase del electrodo es inabierto y conectado a la serie R Series.
5. Para aplicar los electrodos OneStep, introduzca primero el electrodo trasero para evitar la **herración** del electrodo delantero.

**Figure 6:** Example of sentences with made-up words (denoted in **bold**) from the adaptive systems. The first word should be marcapasos, the second one válvulas, the third one marcadores, the fourth one cerrado and the fifth one deformación.

The adaptive systems generate similar made-up words (see Fig. 6 for some examples). However, in this case we observe that some made-up words are almost correct: while los válvulos does not exist (valve is a feminine word in Spanish), it would be correct, from a morphological point of view, if valve were masculine. Something similar, but with the opposite gender, happens with las marcapasas (which should be los marcapasos for a masculine word).
productivity—measured in terms of post-editing time and number of words generated. We also conducted, with the help of two additional professional translators, a human evaluation that verified the quality of the post-edits generated during the user study.

The users were pleased with the system. They noticed that corrections applied on a given segment generally were reflected on the successive ones, making the post-editing process more effective and less tedious. When comparing the translations generated by both kinds of systems, we identified that adaptive systems were able to generate the correct translation of acronyms, entities relating a particular device and specific task terminology.

An undesirable side effect mentioned by the users was the sporadic apparition of made-up words. We studied this phenomenon and reached the conclusion that due to the increase in the number of out-of-vocabularies as part of the post-editing process, adaptive systems suffer this problem more than static systems. Furthermore, sometimes these made-up words are very similar, in morphological terms, to the correct words—such as a feminine word converted into its non-existent masculine equivalent—which made them harder to detect. However, the cognitive impact in the post-editors will need to be assessed before reaching categorical conclusions.

In regards to future work, we should try to assess the cognitive impact of the made-up words phenomenon. We would also like to study the degradation of domain-specific terms, and analyze the impact on the amount of work required to post-edit subsequent sentences as the user provides corrected examples. Additionally, we will integrate our adaptive systems together with other translation tools, such as translation memories or terminological dictionaries, with the aim of fostering the productivity of the post-editing process. With this feature-rich system, we would like to conduct additional experiments involving more diverse languages and domains, using domain-specialized NMT systems, testing other models (e.g., Transformer, Vaswani et al., 2017) and involving a larger number of professional post-editors. Finally, we also intend to implement the interactive–predictive machine translation protocol (Lam et al., 2018; Peris and Casacuberta, 2019) in our translation environment, and compare it with the regular post-editing process.

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6 Conclusions and future work

In this work, we extended a previous user study of an adaptive NMT system. We conducted new experiments with the help of professional translators, and observed significant improvements of the translation quality—measured in terms of hTER and hBLEU—and significant improvements of the user’s productivity—measured in terms of post-editing time and number of words generated. We also conducted, with the help of two additional professional translators, a human evaluation that verified the quality of the post-edits generated during the user study.

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Appendix A  User Questionnaire

How satisfied are you with the translation you have produced?

- Very satisfied.
- Somewhat satisfied.
- Neutral.
- Somewhat dissatisfied.
- Very dissatisfied.

Would you have preferred to work on your translation from scratch instead of post-editing machine translation?

- Yes.
- No.

Do you think that you will want to apply machine translation in your future translation tasks?

- Yes, at some point.
- No, never.
- I’m not sure yet.

Based on the post-editing task you have performed, how much do you rate machine translation outputs on the following attributes?

| Grammaticality | Style | Overall quality |
|---------------|-------|-----------------|
| Well below average | Below average | Average | Above average | Well above average |

Based on the post-editing task you have performed, which of these statements will you go for?