Handle with Care: A Case Study in Comparable Corpora Exploitation for Neural Machine Translation

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Abstract

We present the results of a case study in the exploitation of comparable corpora for Neural Machine Translation. A large comparable corpus for Basque-Spanish was prepared, on the basis of independently-produced news by the Basque public broadcaster eitb, and we discuss the impact of various techniques to exploit the original data in order to determine optimal variants of the corpus. In particular, we show that filtering in terms of alignment thresholds and length-difference outliers has a significant impact on translation quality. The impact of tags identifying comparable data in the training datasets is also evaluated, with results indicating that this technique might be useful to help the models discriminate noisy information, in the form of informational imbalance between aligned sentences. The final corpus was prepared according to the experimental results and is made available to the scientific community for research purposes.

Keywords: Comparable Corpora, Basque, Spanish, Neural Machine Translation

1. Introduction

Comparable corpora are an important source of potential parallel data, suitable to train data-driven machine translation systems (Munteanu and Marcu, 2005; Sharoff et al., 2016) or to create bilingual dictionaries (Rapp, 1995). The extraction of parallel sentences from this type of corpora faces a number of challenges, since potential parallel data are immersed in vast amounts of unrelated content which need to be efficiently mined. Over the years, several techniques have been designed to address comparable document alignment (Sharoff et al., 2015; Azpeitia and Etchegoyhen, 2019) and comparable sentence alignment (Munteanu and Marcu, 2002; Fung and Cheung, 2004; Smith et al., 2010; Etchegoyhen and Azpeitia, 2016b; Artetxe and Schwenk, 2019), leading to new parallel datasets that can support machine translation, in particular for under-resourced languages (Etchegoyhen et al., 2016; Schwenk et al., 2019).

Neural Machine Translation (NMT) is currently the dominant paradigm in research and development in the field of machine translation, having led to significant advances in recent years for most language pairs (Bahdanau et al., 2015; Bojar et al., 2016; Bojar et al., 2017; Vaswani et al., 2017). As a data-driven approach where model parameters are estimated and optimised on large volumes of parallel data, NMT is particularly sensitive to the presence of noise in the training data (Belinkov and Bisk, 2018; Sperber et al., 2017; Cheng et al., 2018; Khayrallah and Koehn, 2018). Due to the nature of the task, parallel data extracted from comparable corpora are likely to introduce unwarranted noise in the training process and an evaluation of this potential issue is worth examining.

In this article, we describe the preparation of a large comparable corpus for Basque-Spanish, composed of independently-produced news by the Basque public broadcaster eitb, and focus on the impact of various techniques to exploit the original data for Neural Machine Translation. We show in particular that filtering in terms of alignment thresholds and length-difference outliers have a significant impact on translation quality. The impact of tags identifying comparable data in the training datasets is also evaluated, following the approach proposed by Caswell et al. (2019) for synthetic data, with results indicating that this technique might be useful when there is less information in the target sentence than in the source, but detrimental in the opposite case, where the imbalanced comparable data may still strengthen target-side sequence modelling.

The final corpus is available to the community for research purposes, and the main contributions of our work are thus the following:

- An evaluation of various techniques to exploit comparable corpora for Neural Machine Translation.
- An evaluation of data tagging for comparable corpora, which, to our knowledge, has not been explored yet.
- A large parallel corpus in the news domain for Basque-Spanish, an under-resourced language pair, shared with the scientific community.

The remainder of this paper is organised as follows: Section 2. describes related work on comparable corpora; Section 3. describes the corpora used in this study; in Section 4., we describe the various experiments performed with the comparable and parallel Basque-Spanish corpora: the experimental setup is described in Section 4.1., Section 4.2. discusses the results obtained with different sentence alignment thresholds, Section 4.3. presents the results obtained with length filtering, Section 4.4. describes our tagging approach and its results, and Section 4.5. summarises the characteristics of the final corpus, obtained by combining the optimal methods determined in the previous sections; finally, Section 5. draws conclusions from this work.

2. Related work

A significant body of work has been produced over the years to mine parallel sentences from large collections of

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1 www.eitb.eus
monolingual corpora (Sharoff et al., 2016), starting with seminal work by Resnik (1999) to exploit the World Wide Web as a source of potential parallel data.

A standard part in the process is the determination of document pairs, to reduce the space of computation in the typically large datasets involved in the task. Several approaches have exploited metadata information for Web page alignment, including URL, structural tags or publication date (Resnik and Smith, 2003; Chen and Nie, 2000; Munteanu and Marcu, 2005; Papavassiliou et al., 2016). Alternatively, content-based document alignment approaches for comparable corpora have also been proposed, based on vector space models (Chen et al., 2004), token translation ratios (Ma and Liberman, 1999), mutual information (Fung and Cheung, 2004), expectation-maximisation (Ion et al., 2011) or n-gram matching using machine-translated documents (Uszkoreit et al., 2010). Several approaches have used a mixture of content and structural properties, notably the systems in the WMT 2016 document alignment shared task (Buck and Koehn, 2016a). Among those, Gomes and Lopes (2016) proposed a phrase-based approach combined with URL-matching. Buck and Koehn (2016b) used cosine similarity between TF-IDF vectors over machine-translated documents, and Germann (2016) performed alignment via vector space word representations, latent semantic indexing, and URL matching. In (Esplá-Gomis et al., 2016), document alignment is performed via a mixture of URL similarity, structural features such as shared links, and bag of words similarity.

Comparability at the document alignment was notably evaluated in a dedicated shared task of the BUCC workshop series (Sharoff et al., 2015). Among participating systems, Li and Gaussier (2013) used bilingual dictionaries and proportion of matching words to assess comparability, Morin et al. (2015) made use of hapax legomena and pigeon hole reasoning to enforce alignments, and (Zafarian et al., 2015) used several components, including topic modelling, named entity detection and word features. A strictly content-based method was proposed by Etchegoyhen and Azpeitia (2016a), based on Jaccard similarity (Jaccard, 1901) over sets of lexical translations, expanded with surface-based entities and common prefix matching, demonstrating high accuracy in a large number of scenarios, including comparable corpora (Azpeitia and Etchegoyhen, 2019).

The extraction of parallel sentences from comparable corpus has also been addressed via a large variety of approaches, based on suffix trees (Munteanu and Marcu, 2002), maximum likelihood (Zhao and Vogel, 2002), binary classification (Munteanu and Marcu, 2005), cosine similarity (Fung and Cheung, 2004), reference metrics over statistical machine translations (Abdul-Rauf and Schwenk, 2009; Sarikaya et al., 2009) or rich features (Steфанescu et al., 2012; Smith et al., 2010). In recent years deep learning approaches have been applied to the task as well, with bidirectional recurrent neural networks (Grégoire and Langlais, 2017) or cosine similarity over bilingual sentence embeddings (Schwenk, 2018).

The core document alignment method of Etchegoyhen and Azpeitia (2016a) was applied to comparable sentence alignment as well (Etchegoyhen and Azpeitia, 2016b), improving over more sophisticated feature-rich methods. This approach, also based on Jaccard similarity over expanded lexical translation sets, was further extended with lexical weighting (Azpeitia et al., 2017) and a named-entity penalty (Azpeitia et al., 2018), obtaining the best results across the board in the BUCC shared task on parallel sentence identification in comparable corpora (Zweigenbaum et al., 2017; Pierre Zweigenbaum and Rapp, 2018). Improvement over these results were obtained with the margin-based approach of Artetxe and Schwenk (2019), which uses cosine similarity over multilingual sentence embeddings, extended with a filtering mechanism based on nearest neighbours similarity. A first version of the BUCC corpus was prepared and shared with community (Etchegoyhen et al., 2016), to provide further support to the under-resourced Basque-Spanish language pair. In what follows, we exploit a larger version of the corpus, built with news generated in subsequent years, and evaluate the impact of different methods to produce a parallel corpus from the comparable data.

### 3. Corpora

The BUCC corpus is composed of news independently produced in Basque and Spanish by the journalists of the Basque Country’s public broadcast service, to report on the same specific events. The corpus can thus be considered strongly comparable (Skadina et al., 2012) and viewed as a rich source of parallel data for this language pair (Etchegoyhen et al., 2016).

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2 Euskal Irrati Telebista: http://www.eitb.eus.
This version of the original dataset covers ten years of content, and is composed of 168,984 documents in Basque and 174,348 in Spanish, extracted from xml files with the structure described in Etchegoyhen et al. (2018b). With an original amount of over two million sentences per language, it is the largest available corpus for the Basque-Spanish language pair, covering political news, sports and cultural events, among others. Statistics of the original corpus are described in Table 1.

To perform the experiments described in this article, a second corpus was used, based on the translation memories made available by the Basque government.\(^3\) We used the corpus created from these translation memories and shared by Etchegoyhen et al. (2018a),\(^4\) to which we will refer as opendata in what follows. The corpus is constituted mainly by translations of administrative content, notably from the Instituto Vasco de Administración Pública (IVAP). As it consists of professionally produced translations, the opendata corpus was used as a parallel basis for the experiments described in what follows.

The eitb corpus was first aligned at the document level with docal, the efficient component for parallel and comparable document alignment described in Etchegoyhen and Azpeitia (2016a) and Azpeitia and Etchegoyhen (2019). For sentence alignment, we used the stacc system (Etchegoyhen and Azpeitia, 2016b), in its variant with lexical weighting (Azpeitia et al., 2017). To extract the translation tables necessary in these approaches to document and sentence alignment, we used the fastalign toolkit (Dyer et al., 2013) on the opendata corpus. Prior to performing either alignment, the sentences were tokenised and truecased using the scripts available in the moses toolkit (Koehn et al., 2007).

The statistics for the opendata and eitb corpora, in number of aligned sentences are shown in Table 9, where the latter was obtained after enforcing one-to-one alignment but without any filtering based on the alignment scores computed by stacc, i.e. with an alignment threshold set to 0.

| CORPUS    | OPENDATA | EITB\(_{0.0}\) |
|-----------|----------|----------------|
| TRAIN     | 921,763  | 1,337,040      |
| DEV       | 2,000    | 2,000          |
| TEST      | -        | 1,678          |

Table 2: Corpora statistics (number of sentence pairs)

The development and test sets were extracted from the eitb dataset, with manually verified alignments. For the test set, additional Basque translations were manually created by professional translators, to increase the robustness of the test considering the relatively free word order in Basque (Etchegoyhen et al., 2018a). In the Spanish to Basque translation direction, we thus use two translation references, whereas for Basque to Spanish, we use the manually translated sentences as source, to remove any eventual bias that may arise from the original data being comparable.

4. Experiments

In this Section, we first describe the experimental setup, including initial translation models. We then describe the different methods in turn and discuss their results.

4.1. Experimental Setup

All translation models were based on the Transformer architecture (Vaswani et al., 2017), built with the marian toolkit (Junczys-Dowmunt et al., 2018). The models consisted of 6-layer encoders and decoders and 8 attention heads, reproducing the basic transformer described in the original paper. We used the Adam optimiser with \(\alpha = 0.0003\), \(\beta_1 = 0.9\), \(\beta_2 = 0.98\) and \(\epsilon = 10^{-9}\). The learning rate increases linearly for the first 16,000 training steps and decreases thereafter proportionally to the inverse square root of the corresponding step. We set the working memory to 6000MB and automatically chose the largest mini-batch for a given sentence length that fits the specified memory. The validation data was evaluated every 3,500 steps, and the training process ended if there was no improvement in the perplexity of 5 consecutive checkpoints. Embeddings for source, target and output layer are tied and all datasets were segmented with bpe (Sennrich et al., 2016c), using 30,000 operations.

We trained two initial models, on the opendata corpus and on that same corpus merged with the aligned eitb corpus with an alignment threshold set to 0, to measure the initial contribution of the selected comparable data. These models and all subsequent ones were evaluated on the previously described test sets, which cover various topics. The results in terms of bleu (Papineni et al., 2002) for the two initial models are shown in Table 3.

In both translation directions, the contribution of the comparable data was significant, with large improvements in bleu scores. Although this is not unexpected, since the opendata model was trained on data in the administrative domain, this confirms the potential of the strongly comparable eitb data as a means to improve Basque-Spanish translation, as previously established in Etchegoyhen et al. (2016).

| MODEL          | ES-EU | EU-ES |
|----------------|-------|-------|
| OPENDATA       | 28.6  | 34.0  |
| OPENDATA+EITB\(_{0.0}\) | 36.1  | 46.5  |

Table 3: BLEU results with initial models

4.2. Alignment Thresholds

Methods to extract parallel data from comparable corpora rely on metrics that measure translation equivalence in some forms. The scores assigned by the core metrics usually need to be complemented with some form of filtering, based on thresholds determined over the training or development datasets (Etchegoyhen and Azpeitia, 2016b; Artetxe and Schwenk, 2019). This is necessary since similarity varies between comparable sentences and comparability metrics usually assign a continuous score to comparable sentence pairs.

To determine the impact of threshold selection, we extracted different subsets of the aligned eitb corpus after applying

\(^3\)https://opendata.euskadi.eus

\(^4\)In the version shared for the wrcr 2018 shared task, available at: https://sites.google.com/site/iwslt2018/TED-tasks
different thresholds, selected according to the ranges of the \textsc{stacc} metric which produced significant amounts of data. Each subset was then used to fine-tune the model based on the \textsc{opendata} corpus, with the results shown in Table 4 in terms of \textsc{bleu} score and number of aligned sentences.

| Threshold | Aligned | BLEU   |
|-----------|---------|--------|
| 0.0       | 1,337,040 | 34.8  |
| 0.15      | 1,122,890 | 35.3  |
| 0.17      | 930,839   | 36.1  |
| 0.20      | 580,478   | 35.6  |

Table 4: Alignment threshold results

As these results demonstrate, selecting subsets extracted with higher alignment thresholds is beneficial overall, although the loss of data incurred with more restrictive thresholds can be sub-optimal. For the experiments in the next sections, we selected the dataset extracted with a threshold of 0.17, as it provided the optimal balance in terms of \textsc{bleu} for the two translation directions.\footnote{As a side note, the results obtained via fine-tuning \cite{luong2015} are lower than those obtained via training over merged datasets, as shown by the results in Table 3 compared to those in Table 4 with threshold 0. This is not unexpected \cite{crego2016} and does not impact the relative comparisons established between the fine-tuned models using different thresholds.}

4.3. Length Filtering

Due to the nature of the task, aligned comparable sentences may display information imbalance, with one of the sentences in a pair missing part of the information in the other. In this section we evaluate the impact of information mismatch, via filtering based on length differences measured on the aligned sentence pairs.

We based our approach to length-based filtering on the method described in Iglewicz and Hoaglin (1993), which aims to identify statistical outliers in terms of length differences between aligned sentences. We first computed the median and standard deviation over length differences, measured in terms of tokens. These reference statistics were computed on the parallel \textsc{opendata} corpus, to establish the relevant length-difference indicators on parallel human translations. A length-difference score (\textsc{lgs}), based on a modified z-score, was then computed on the aligned \textsc{eitb} corpus with threshold 0, according to the formula in Equation 1:

\[
\text{\textsc{lgs}} = \frac{0.6745 \times (x - \bar{y})}{\text{median}(|y_i - \bar{y}|)}
\]  

(1)

where \(x\) is the length difference of a sentence pair in the \textsc{eitb} corpus, \(\bar{y}\) is the median length difference in the reference corpus, and the denominator is the median absolute deviation, computed over the reference corpus as well.

The modified z-score was then used to identify outliers in the aligned \textsc{eitb} corpus, with sentence pairs having an absolute score over a given threshold identified as cases of information imbalance. Iglewicz and Hoaglin (1993) recommend a value of 3.5 to identify outliers when using a modified z-score, and we selected this value as our default to filter all identified outliers in the aligned \textsc{eitb} corpus with threshold 0.17, selected after the results in the previous section. Additionally, we selected two more thresholds with lower values, namely 2.0 and 1.5, to evaluate the impact of a more restrictive identification of length imbalance.\footnote{Length imbalance could have been computed by simply taking the average absolute difference for each sentence pair. However, this method would not lead to the identification of statistically significant deviations from the mean determined on a reference corpus, which was our goal for these experiments.}

The results on fine-tuned models trained on each selected sub-corpus filtered by length outliers are shown in Table 5. Also indicated in this table are the size of the filtered corpus, the \textsc{bleu} brevity penalty (bp), and the proportion of sentences where the length of the Spanish sentence is larger than that of the Basque sentence, for Basque to Spanish translation, in terms of \textsc{bleu} scores, length filtering improved over the unfiltered corpus, showing that information imbalance was significantly detrimental. For Basque to Spanish, the results were reversed, with a gradual decrease of \textsc{bleu} scores with additional filtering. One interpretation of these results may be based on the fact that the length of filtered Spanish sentences is systematically longer than that of Basque sentences. Although this is the case in general, given the morphological system of Basque, where for instance determiners are suffixes, more aggressive filtering of length-difference outliers lowers the proportion of Spanish sentences that are longer than their Basque counterparts, indicating that the overall tendency in the corpus is for information imbalance to affect the Basque data more than its Spanish counterpart. In other words, the news in the \textsc{eitb} corpus tend to summarise the information more in Basque than in Spanish. Translating from the latter language to the former would thus have the effect of orienting the models towards summarisation, with an impact on translation quality that needs to be compensated with more length-based filtering. This conjecture is supported by the results in terms of brevity penalty, with lower brevity scores correlating with less length-based filtering.

For Basque to Spanish, translation quality seems to correlate instead with the volumes of data. This may be attributed to the fact that there is no marked tendency towards summarisation in this translation direction, given the fact that the target sentences are longer than the source, for the most part. The target monolingual data can thus contribute relevant information in a way that is similar to synthetic data based on back-translations or on empty source sentences \cite{sennrich2016}, where the models can improve its modelling of the target sequences in the face of degenerate source input.

Selecting a single corpus based on these results faces a difficult choice. Although the Basque to Spanish results tend to indicate that the non-filtered output provides significant improvements in terms of \textsc{bleu}, for the reasons hypothesised above, the opposite translation direction would favour the selection of a corpus based on length filtering with a 2.0 outliers threshold, as it provides the best \textsc{bleu} score and lower impact in terms of brevity than a 3.5 threshold. In what follows, we will select the corpus based on the 2.0 threshold,
4.4. Data Tagging

The use of tags identifying specific aspects of the data in the training corpora has proved effective in Neural Machine Translation. Thus, Sennrich et al. (2016a) used markers to control the translation of honorifics, Kubus et al. (2017) model domain control via tags identifying different domains, Yamagishi et al. (2016) use tags to control voice translation in Japanese to English Translation, and Caswell et al. (2019) employ tags for back-translated synthetic data, among others.

The latter work in particular demonstrates that tagging techniques can prove more effective than noise approaches, indicating also that the impact of noising for back-translated data essentially acts as an indicator of the type of data used for training and helps the models discriminate between natural and synthetic data. We extend their approach to comparable data, by prepending a \(<cc>\) tag to all source sentences of the comparable eitb training set.

We trained models by combining the opendata corpus with selected variants of the eitb corpus, with and without tags indicating comparable data. The results of these experiments are shown in Table 7.

to favour the translation direction with lower results overall, noting that the filtered sentence pairs could be used to train a separate model for Basque to Spanish only. Selecting this filtering threshold also improves the overall quality of the corpus to be shared, as it removes imbalanced pairs of the type shown in Table 6, where the information in the Spanish sentence that is missing in the Basque counterpart of the aligned pair is marked in italics.

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We trained models by combining the opendata corpus with selected variants of the eitb corpus, with and without tags indicating comparable data. The results of these experiments are shown in Table 7.

For Spanish to Basque, tagging was only effective on the noisier datasets, i.e. the eitb variant with no filtering of length-difference outliers. For the less noisy dataset, based on a higher alignment threshold and length-based filtering, the use of tags was detrimental. Interestingly, the use of tags in this translation direction had a significant impact in terms of shortness of translations, from a brevity penalty of 0.812 for the untagged model based on the eitb variant with no filtering of length differences, to 0.984 for the tagged variant based on the same corpus.

These results tend to support the hypothesis that tagging helps the model discriminate between natural and noisy data, and becomes counterproductive when the tagged comparable data are closer to the natural translations, as in the heavily filtered variants.

For Basque to Spanish, tagging was detrimental overall in terms of BLEU, despite minor improvements regarding the brevity of translations. The tendency was the same across dataset variants, irrespective of filtering. This can be viewed in light of the previous hypothesis that the overall higher quantity of information in the Spanish target sentences is a dominating factor for this translation direction.

The negative impact caused by tagging in this case seems to indicate that comparable data with less source information in the source than in the target are actually not noisy for the translation models, as discriminating between natural and comparable data leads to lower translation quality results in this case. Determining whether this hypothesis is correct could be further examined by comparing tagged back-translated data with tagged comparable data, an exploration we leave for future research.

### Table 5: Fine-tuning results with length filtering thresholds

|_corpus | aligned es-eu bleu bp | aligned eu-es bleu bp | len(filt_{es}) | len(filt_{eu}) |
|--------|------------------------|------------------------|----------------|----------------|
| eitb0.17 | 930,839 36.1 0.811 | 44.2 0.919 | - |
| eitb0.17_{lg=3.5} | 773,755 37.7 0.916 | 43.6 0.919 | 98.84% |
| eitb0.17_{lg=2.0} | 637,183 37.7 0.960 | 42.2 0.907 | 98.65% |
| eitb0.17_{lg=1.5} | 580,448 37.0 0.979 | 41.8 0.900 | 98.48% |

### Table 6: Examples of filtered sentence pairs with modified z-score above 2.0

| model | es-eu | eu-es |
|-------|-------|-------|
| opendata | - | 28.6 1.0 | - | 34.0 0.98 |
| opendata+eitb0.0 | 38.6 0.984 | 36.1 0.812 | 45.4 0.970 | 46.5 0.939 |
| opendata+eitb0.17 | 39.5 0.989 | 35.7 0.828 | 44.7 0.965 | 46.1 0.943 |
| opendata+eitb0.17_{lg=2.0} | 38.2 0.992 | 38.9 0.973 | 43.4 0.970 | 44.1 0.927 |

### Table 7: Results on merged datasets with and without tags

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The negative impact caused by tagging in this case seems to indicate that comparable data with less source information in the source than in the target are actually not noisy for the translation models, as discriminating between natural and comparable data leads to lower translation quality results in this case. Determining whether this hypothesis is correct could be further examined by comparing tagged back-translated data with tagged comparable data, an exploration we leave for future research.
**4.5. Shared Corpus**

In view of the results discussed in the previous sections, the optimal variants of the datasets in terms of BLEU scores of the resulting models are different depending on the translation direction. For Basque to Spanish, the corpus without either alignment or length-difference filtering would provide the best objective scores, whereas from Spanish to Basque the variant with an alignment threshold of 0.17, augmented with tags, would lead to the best results in translation metric scores.

Our aim in sharing a prepared dataset was however to select a unique parallel corpus with the highest alignment quality which could be beneficial in both translation directions, without tagging nor the indirect BLEU improvements obtained from the ability of NMT models to exploit degenerate information as input. We therefore selected the variant of the CTE corpus based on an alignment threshold of 0.17 and length-based filtering with a threshold of 2.0, as it complied with this requirement. With 637,183 aligned sentences, it will be the largest parallel corpora for Basque-Spanish in the news domain, covering a large amount of topics.

Table 8 provides some examples of aligned sentences in the final corpus. These examples illustrate the quality of the parallel resource obtained from the original comparable datasets, and the variety of topics covered in the corpus, including politics, world affairs, weather, sports and culture.

The specific challenges presented by the morpho-syntactic properties of Basque, including agglutinative morphology, ergativity or relatively free word order, among others, make it even more necessary to prepare additional parallel resources for this language. We hope that the corpus prepared and described in this work will help advance research and development for the under-resourced Basque-Spanish language pair.

The corpus will be made available on OPUS⁹ (Tiedemann, 2012) under the Creative Commons CC-BY-NC-SA license. The statistics for the shared version of the corpus are shown in Table 9.

| LANG | EXAMPLE |
|------|---------|
| ES   | aíntx asintx, los partidos minoritarios buscan convertirse en, que los terceros fuerza política del 12,13 país. |
| EU   | halai, etai, guztii, ere, gutxiengo alderdiak herialdeko, hiri, hitza, indar politikoak izateko, borrokatzen dira. |
| EN   | even, so, minority, parties, seek to become the third political force in, in the final corpus. |

| LANG | EXAMPLE |
|------|---------|
| ES   | Nasserallak defiende que el productor altera contenido del filme similitud con, conocimiento. |
| EU   | ekoizleak filmearen, bera onirtziak jaso gabe, aldatu zuela adierazi du Nasserllak. |
| EN   | Nasserallak argues that the producer altered the content of the film in without his knowledge. |

| LANG | EXAMPLE |
|------|---------|
| ES   | la sequía unida, las altas temperaturas, las bajas humedad, las intensidad del viento durante los próximos días, hará que la probabilidad de que se produzcan 20,21 incendios forestales. |
| EU   | Lehorteak, temperaturas altas, hezetasunak, erlatibo baxak, eta, haizearekin intentsitateak datorren, 12,14,15 egunetan, bateau suteak izateko, arriskuak handitzea, ergingoak, dute. |
| EN   | drought coupled with high temperatures, low relative humidity and wind intensity over the next 13 days will increase the likelihood of 20,21 fires. |

| LANG | EXAMPLE |
|------|---------|
| ES   | el luxemburgués aceleró el, quedó, atascado, por, la mecánica. |
| EU   | Luxemburgotarak, azeleratuk, zuela, aitatuk, geratuz, zen, arazotz, mekaniko mototzak. |
| EN   | the Luxembourian accelerated, and got stuck, by, mechanics. |

| LANG | EXAMPLE |
|------|---------|
| ES   | el, 851 % de 3 Nueva Orleans, quedó bajo el agua, en, algunas zonas, 6, 7 metros, de la profundidad. |
| EU   | New Orleansko, lurraldearen, 4,5 %, 851 urpean, geratuz, zuela, zenbait, gunean, 7,11 metrotako, sakoneran. |
| EN   | 851 % of New Orleans was underwater, in 3 some areas, 7,11 meters deep. |

Table 8: Examples of aligned sentences in the final corpus, with English translations

|     | ES     | EU     |
|-----|--------|--------|
| SENTENCES | 637,183 | 637,183 |
| WORDS   | 13,365,220 | 10,882,709 |

Table 9: Shared CTE corpus statistics

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⁷ To facilitate the understanding of the Basque and Spanish examples, we include a likely English translation in each case, along with indexes to indicate approximate word correspondences between the English sentence, where each token (excluding punctuation) is assigned a separate index, and the Basque and Spanish sentences.

⁸ See (Etchegoyen et al., 2018a) and references therein for more details on Machine Translation of Basque.

⁹ http://opus.nlpl.eu/
selection of an optimal subset which could serve models in both translation directions. Additionally, the impact of further filtering based on length-difference outliers was also measured, with the notable result that such filtering is necessary for Spanish to Basque translation, given information imbalance in the data, but not in the other translation directions, as nmt models proved able to benefit from target language information despite degenerate comparable source information.

Another result of this study was the tendency of nmt models to gear towards summarisation when provided with impoverished target information, a phenomenon which is likely to arise with comparable corpora and needs to be controlled for an optimal exploitation of the data.

Results on the impact of tagging for comparable data were also presented, a topic which had not been previously studied, to the best of our knowledge. Tagging was shown to be effective only in helping the models discriminate noisy comparable data, identified to be data with degenerate information in the target language. In all other cases, with either filtered datasets or higher informational content in the target side, tagging was detrimental and further experiments will be necessary, in particular to determine the precise types of comparable data which constitute noise for nmt models.

The usefulness of comparable corpora, in particular for under-resourced languages, has been comforted in this work, with large improvements in translation quality resulting from their use. Additionally, our results indicate that this type of data needs to be handled with care to benefit Neural Machine Translation approaches.

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