TweetMT: A parallel microblog corpus

Iñaki San Vicente[1], Iñaki Alegría[2], Cristina España-Bonet[3], Pablo Gamallo[4], Hugo Gonçalo Oliveira[5], Eva Martínez[2], Antonio Toral[6], Arkaitz Zubiaga[7]
[1] Elhuyar, [2] University of the Basque Country, [3] Universitat Politècnica de Catalunya,
[4] Universidade de Santiago de Compostela, [5] University of Coimbra,
[6] Dublin City University, [7] University of Warwick
tweetmt@elhuyar.com

Abstract

We introduce TweetMT, a parallel corpus of tweets in four language pairs that combine five languages (Spanish from/to Basque, Catalan, Galician and Portuguese), all of which have an official status in the Iberian Peninsula. The corpus has been created by combining automatic collection and crowdsourcing approaches, and is publicly available. It is intended for the development and testing of microtext machine translation systems. In this paper we describe the methodology followed to build the corpus, and present the results of the shared task in which it was tested.

Keywords: Machine Translation, Microblogs, Tweets, Social Media

1. Introduction

While machine translation is a mature research field now, the application of machine translation techniques to tweets is still in its infancy. Tweets are often written from mobile devices, which exacerbates the poor quality of the spelling, and include linguistic inaccuracies, symbols and diacritics. Tweets also vary in terms of structure, including features which are exclusive to the platform, such as hashtags, user mentions, and retweets. These characteristics make the application of machine translation to tweets a new challenge that requires specific processing techniques to perform effectively.

Despite the paucity of research in the specific task of translating tweets, an increasing interest can be observed in the scientific community (Gotti et al., 2013; Peisenieks and Skadiņš, 2014). Similarly, a related and highly relevant direction of research is the work on machine translation of SMS texts, such as Munro's study in the context of the 2010 Haiti earthquake (Munro, 2010).

Provided the dearth of benchmark resources and comparison studies bringing to light the potential and shortcomings of today's machine translation techniques applied to tweets, a corpus was compiled in the framework of TweetMT, a workshop and shared task[1] on machine translation applied to tweets. Our parallel corpus includes tweets for the following language pairs: Catalan–Spanish (ca-es), Basque–Spanish (eu-es), Galician–Spanish (gl-es), and Portuguese–Spanish (pt-es).

[1] http://komunitatea.elhuyar.eus/tweetmt/

2. Collecting parallel tweets

To the best of our knowledge, there is no parallel tweet dataset available apart from that produced by (Ling et al., 2013), which differs from our purposes in that they worked on tweets that mix two languages, i.e., providing the translated text within the same tweet. They further improve the quality of the parallel segments by means of crowdsourced annotations (Ling et al., 2014). Since we wanted to work on the translation of entire tweets into new tweets, we generated a corpus for the specific purposes of the TweetMT Workshop.

For corpus generation, we developed a semi-automatic method to retrieve and align parallel tweets. We first identify Twitter authors that concurrently tweet in multiple languages. This could be applied to the *ca-es* and *eu-es* language pairs, but not to the *pt-es* and *gl-es* pairs, due to the lack of accounts that meet those characteristics. In the latter cases, we used crowdsourcing to collect the parallel corpora.

Table 1 provides detailed statistics of the datasets used for the tweetMT shared task. A second release of the dataset contains all the correctly aligned tweets. Details will be give in the final version of the paper.

2.1. Corpus Creation from Multilingual Accounts

2.1.1. Accounts and Collected Data

The initial collection of tweets amounted to 23 Twitter accounts (from 16 authors) for the *eu-es* pair and 19 accounts (from 14 authors) for the *ca-es* pair. In all, 75,000 tweets were collected for *eu-es* and 51,000 tweets for the *ca-es* language pair. The collection includes tweets posted between November 2013 and

March 2015. Test sets for the other languages pairs, *gl-es* and *pt-es* were collected through crowdsourcing.

2.1.2. Alignment

Aligning tweets of an author within and across accounts requires both to find matching translations as well as to occasionally get rid of tweets that have no translations. We perform this process semi-automatically, first by automatically aligning tweets that are likely to be each other's translation, and then by manually checking the accuracy of those alignments.

Before we can even align tweets with their likely translations, we needed to identify the language each tweet is written in through language identification (Zubiaga et al., 2014). We used an ngram-based language identifier[2] trained over Twitter specific data. We defined a set of heuristics and statistics that would help us find matches quite accurately. Specifically, we looked at the following three characteristics to find likely matches:

- **Publication date.** Translations must be published within a certain period range to be flapped as possible translations of each other. The difference between source and target timestamps must not exceed a certain threshold.
- **Overlap of hashtag and user mentions in source and target tweets.** A minimum number of user name and hashtags were required to overlap between source and target parallel tweet candidates. The overlap is computed as the division between the number of entities in the intersection of both tweets and the entities in the union. The threshold is empirically set to 0.76.
- **Longest Common Subsequence ratio (LCSR) between source and target tweets.** LCSR (Cormen et al., 2001) is an orthographic similarity measure, as it tells us how similar two strings are. It is especially reliable when working with closely related languages, as parallel sentences are often very close to each other, because both vocabulary and word order are close.

As for the performance of the heuristics, publication date proximity is effective for filtering out wrong candidates, but it is not enough to find the correct parallel tweet, so it is applied first. User and hashtag overlap ratio proved successful, up to the point that the contribution of LCSR was minimal. **The final paper will further detail the heuristics.**

The output of this alignment can be manually corrected by native speakers of their respective languages. At this point, we split the initial corpus into two datasets: one development-set C_{dev} composed of 4,000 parallel tweets for each language pair and one test-set C_{test} composed of 2,000 parallel tweets for each language pair.

The development set is limited to accounts with most tweets (2 for *ca-es* and 4 for *eu-es*). Test-sets also contain tweets from the authors in the development set, but tweets from new "unseen" authors are also introduced. This way we have the possibility to evaluate systems both on "in-domain" and "out-of domain" scenarios.

Only test sets were manually corrected. Each tweet is reviewed by a single annotator. The overall error rate over the collections manually reviewed to create the test-sets was 7% for the *ca-es* language pair (12,500 tweets) and 21% for the *eu-es* language pair (15,045 tweets). The error rate in the development-set is estimated as the average error rate of the Twitter accounts that are included in the collection C_{dev} computed from the annotations of those accounts in C_{test}. The error rate in C_{dev} is 3% (*ca-es*) and 33% (*eu-es*). Figure 1 summarizes in a boxplot the distribution of the alignment error rates ac

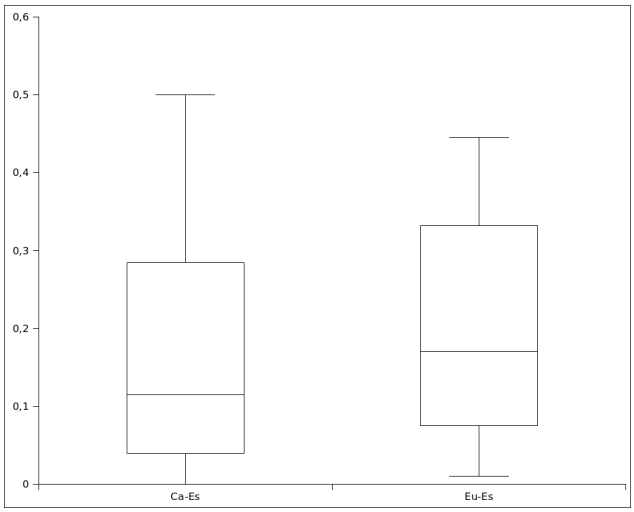

Figure 1: Alignment error rate distribution for *ca-es* and *eu-es* test datasets

2.2. Crowdsourced Corpus Creation using Crowdflower

In the crowdsourcing tasks for *pt-es* and *gl-es*, the contributors had to translate manually, from Spanish to Portuguese and Galician, a dataset with $2,552$ Spanish tweets, taken from both our *ca-es* and *eu-es*

[2]http://www.let.rug.nl/vannoord/TextCat/

Dataset	Tweets	Authors	Tokens	URL	@user
eu-es$_{\text{dev}}$	4,000	4	181K	2,622	1,569
ca-es$_{\text{dev}}$	4,000	2	161K	3,280	823
eu-es$_{\text{test}}$	2,000	16	37K	1556	673
es-eu$_{\text{test}}$	2,000	16	43K	1535	692
ca-es$_{\text{test}}$	2,000	14	45K	1590	417
es-ca$_{\text{test}}$	2,000	14	46K	1567	502
gl-es$_{\text{test}}$	434	-	7K	274	134
es-gl$_{\text{test}}$	434	-	7K	291	159
pt-es$_{\text{test}}$	1,250	-	19K	674	349
es-pt$_{\text{test}}$	1,250	-	21K	919	583

Table 1: Statistics for the datasets generated.

parallel corpora, and divided into working tasks of 10 tweets each.

Instructions were provided to workers in order to make sure that the translations were consistent. For instance, contributors were asked not to translate user mentions (keywords with a leading @) and URLs, while hashtags should only be translated if the contributor considered that it would be natural to use the Portuguese/Galician hashtag.

As a final result, we obtained a parallel corpus with $2,500$ *pt-es* and 777 *gl-es* tweets which were split into two test datasets with $1,225$ entries for each translation direction for *pt-es* and 388 for *gl-es*. To verify the quality of the translations, samples of 30 tweets were evaluated both for Portuguese and for Galician. In both cases they were considered acceptable by the Portuguese and Galician authors of the current paper, even if some errors were detected. In the case of Galician, we found some mistakes derived from the new spelling rules imposed since 2003. In the case of Portuguese, six errors (most of them lexical problems) were found from the 30 tweets evaluated. The final version of the paper will include an error analisys of this evaluation.

3. The corpus in use: Shared Task Results

The generated dataset has been used in the framework of the TweetMT machine translation shared task. Before release, test datasets were preprocessed to replace all user mentions by `IDIDID` and all URLs by `URLURLURL`. Participants, had a window of 72 hours to return their translated results. The translated texts would then be extracted, cut down to 140 characters, for automated evaluation. A thorougher analysis of the results will be presented in the final paper, here we summarize them.

System	ca2es	es2ca	eu2es	es2eu	pt2es	es2pt
DCU1	76.73	75.79	25.30	23.22	43.36	36.13
DCU2	76.52	77.75	25.30	**24.44**	43.67	**37.25**
DCU3	**77.70**	75.25	25.44	23.42	**44.28**	36.94
EHU1	–	–	**28.61**	24.34	–	–
EHU2	–	–	–	19.54	–	–
UPC1	68.20	**77.93**	–	–	–	–
UPC2	63.12	–	–	–	–	–

Table 3: BLEU score for all the participant systems and language pairs. Results are obtained only considering the first 140 characters per tweet.

3.1. Overview of the Systems Submitted

Out of the 5 registered participants, three teams ended up submitting their results: DCU (Dublin City University) for 3 tracks (*ca-es*, *eu-es*, *pt-es*) (Toral et al., 2015); EHU (University of the Basque Country) for the *eu-es* track (Alegria et al., 2015); and UPC (Universitat Politècnica de Catalunya) for the *ca-es* track (Martínez-Garcia et al., 2015).
The main characteristics of the systems submitted are compiled in Table 2.

3.2. Results

Participants were allowed to submit up to three results per track. Here we outline the BLEU (Papineni et al., 2002) performance results (see Table 3) for all the tracks and systems.
DCU3 system was the best for the *ca-es* direction, a system combining two kinds of SMT engines plus a RBMT one. For the *es-ca* direction, the two simplest pure phrase-based SMT systems, UPC1 and DCU2, obtained the highest scores. The two teams used very similar corpora in their experiments, so the techniques they used make the difference in this case. The best translator for the *es-eu* language pair is the statistical system EHU1 in both directions. When translating from Spanish into Basque, however, DCU2 with the combination of 5 different systems gets very similar scores. Finally, DCU3 was the best in the *pt-es* direction. As in the *ca-es* track, their best system is again a combination of two kinds of SMT engines and a RBMT one. On the opposite direction the best system, DCU2, does not include translation options from the RBMT, probably reflecting a lower quality for this engine on tweets.
The analysis of the results enables us to draw the following conclusions:

- The evaluations for the genre of formal tweets show better results than for other genres such as news in the same language pairs (Alegria et al., 2015).

System	Main Engine	Distinctive features
DCU1	System combination or SMT	Moses and Apertium (ES↔CA), Moses, cdec and Apertium (ES→EU), cdec (EU→ES), Moses (ES↔PT).
DCU2		Moses (ES→CA), Moses, cdec and Apertium (CA→ES, EU→ES), Moses, cdec, ParFDA, Matxin and Morph (ES→EU), Moses and cdec (ES↔PT).
DCU3		Moses, cdec and Apertium (ES→CA, ES↔PT), Moses, ParFDA and Apertium (CA→ES), Moses, cdec, Matxin and Morph (ES→EU), Moses, cdec, Apertium and Morph (EU→ES).
EHU1	SMT	Specific language model and pre- and post-processing for tweets
EHU2	RBMT	Adaptation to Tweets (mainly hashtags)
UPC1	SMT	Moses system
UPC2	SMT	Document-level system (Docent), semantic models

Table 2: Summary of the systems developed by the participants.

- Combining techniques, including RBMT and SMT, can lead to improvements (Toral et al., 2015).
- Expanding the context by using a user's tweets within the same day can be of use to boost the performance of the MT system (Martínez-Garcia et al., 2015).

4. Conclusion

The corpus developed as part of the TweetMT shared task has enabled us to come up with a benchmark parallel corpus of tweets for translation applied to four language pairs: *ca-es*, *eu-es*, *gl-es* and *pt-es*. The corpus is publicly available and can be downloaded from the workshop's website[3], which we expect that will enable further research in the field. The *ad hoc* methodology we used to collect the parallel tweets has proven very useful and effective for the language pairs that have accounts that concurrently tweets in these languages, but it is a limitation for the rest of the languages.

The results achieved by the participants of the shared task are surprisingly high, especially considering that we are dealing with tweets. Still, it is worthwhile noting that the tweets considered in this shared task can largely be deemed formal and would be difficult to generalize the results to other tweet translation tasks. However, the fact that formal tweets can be accurately translated encourages its use by community managers who tweet in different languages, by making their work easier. One of our main objectives for future work is to further generalize the machine translation task by including a more representative collection of tweets, to assess the ability of MT systems to translate informal tweets too.

[3] http://komunitatea.elhuyar.eus/tweetmt/resources/

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