Large SMT data-sets extracted from Wikipedia

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Abstract

The article presents experiments on mining Wikipedia for extracting SMT useful sentence pairs in three language pairs. Each extracted sentence pair is associated with a cross-lingual lexical similarity score based on which, several evaluations have been conducted to estimate the similarity thresholds which allow the extraction of the most useful data for training three-language pairs SMT systems. The experiments showed that for a similarity score higher than 0.7 all sentence pairs in the three language pairs were fully parallel. However, including in the training sets less parallel sentence pairs (that is with a lower similarity score) showed significant improvements in the translation quality (BLEU-based evaluations). The optimized SMT systems were evaluated on unseen test-sets also extracted from Wikipedia. As one of the main goals of our work was to help Wikipedia contributors to translate (with as little post editing as possible) new articles from major languages into less resourced languages and vice-versa, we call this type of translation experiments “in-genre” translation. As in the case of “in-domain” translation, our evaluations showed that using only “in-genre” training data for translating same genre new texts is better than mixing the training data with “out-of-genre” (even) parallel texts.

Keywords: comparable corpora, in-genre translation, similarity-based text mining, Wikipedia

1. Introduction

SMT engines like Moses1 produce better translations when presented with larger and larger parallel corpora. For a given test-set, it is also known that Moses produces better translations when presented with in-domain training data (data sampled form the same domain as the test data, e.g. news, laws, medicine, etc.), but collecting parallel data from a given domain, in sufficiently large quantities to be of use for statistical translation, is not an easy task. To date, OPUS2 (Tiedemann, 2012) is the largest online collection of parallel corpora, comprising of juridical texts (EUROPAL and EUConst)3, medical texts (EMEA), technical texts (e.g. software KDE manuals, PHP manuals), movie subtitles corpora (e.g. OpenSubs) or news (SETIMES), but these corpora are not available for all language pairs nor are their sizes similar with respect to the domain. To alleviate this data scarcity, significant research and development efforts have been invested in parallel texts harvesting from the web (Resnik & Smith, 2003) regarded as a huge multilingual comparable corpus with presumably large quantities of parallel data.

Comparable corpora have been widely recognized as valuable resources for multilingual information extraction, but few large datasets were publicly released and even fewer evaluated in the context of specific cross-lingual applications. One of the most tempting uses of comparable corpora mining is in statistical machine translation for under-resourced language pairs (e.g. Lithuanian-English) or limited/specialized domains (e.g. automotive).

Within the ACCURAT European project we developed LEXACC, a language independent text-miner for comparable corpora (Ştefănescu et al., 2012), able to extract cross-lingually similar fragments of texts, similarity being judged by means of a linear weighted combination of multiple features. The text-miner modules (sentences indexing, searching, filtering), the features and the learning of the optimal weights used by the similarity scoring function which endorses the extracted pairs are largely described in (Ştefănescu & Ion, 2013). Unlike most comparable corpora miners that use binary classifiers, our miner associates each extracted pair (s,t) a symmetric similarity score, sim_score∈[0, 1]. Based on these scores, one can experiment with various subsets of an extracted data set (DS) select only the sentence pairs with similarity scores higher or equal to a decided threshold value. Starting with a minimal threshold value (th) for the similarity score (th=0.1), the experimenter will get the full data set (DSth) which, certainly, contains many noisy pairs. Increasing the th, one gets less sentence-pairs, but more (cross-lingually) similar:DSth1⊂DSth2⊂...⊂DSthn, with 0.1< ... th1< 1.0 and DSthi = {s,t | sim_score(s,t) ≥ th_i}. The parallel text miner was used to extract sentence-pairs from large corpora collected from the web (Skadiņa et al., 2012) for a wide variety of language pairs: English-German, English-Greek, English-Estonian, English-Lithuanian, English-Latvian, English-Romanian and English-Slovene. Although the “optimal” similarity scores slightly differed from one language pair to another, they were comparable, in the interval [0.35, 0.5]. To evaluate the value of the mined parallel sentences, the extracted German-English sentences were used for domain adaptation of a baseline SMT system (trained on EuroParl+news corpus). This experiment, described in (Ştefănescu et al., 2012), showed significant quality improvements over the baseline (+6.63 BLEU points) when translating texts in the automotive domain.

The evaluation of LEXACC in the ACCURAT project encouraged us to explore its efficacy on a well-known
multilingual strongly comparable corpus, namely Wikipedia\(^4\), and to investigate the feasibility of what we called “in-genre” statistical machine translation: translating documents of the same genre (not necessary the same domain) based on training data of the respective genre. Wikipedia is a strongly comparable multilingual corpus and it is large enough to ensure reasonable volumes of training data for “in-genre” translations. One useful property of Wikipedia is that, in spite of covering many domains, articles are characterized by the same writing style and formatting conventions\(^5\). The authors are given precise guidelines content-wise, on the language use, on formatting, and several other editorial instructions to ensure genre unity across various topics as in the traditional encyclopedias. Therefore, we refer to the translation of a Wikipedia-like article, irrespective of its topic, based on training data extracted from Wikipedia, as an “in-genre” (encyclopedic) translation. The parallel data mining processing flow (Ștefănescu & Ion, 2012) was recently improved by what we called “boosted mining” (Tufiş et al., 2013a,b), and a larger and quite different experiment was conducted with the aim of evaluating the usability of texts mined from comparable corpora for statistical translation of texts similar in genre with the extraction corpora.

2. Related work
The interlingual linking in Wikipedia makes it possible to extract documents in different languages such that the linked documents are versions of each other. If the linked documents were always faithful translations of some hub (original) documents, Wikipedia would be a huge multilingual parallel corpus of encyclopedic texts. Yet, this is not the case and, frequently, articles originally written in one language (English, most of the times) are adapted translations (usually, shortened) in other languages. It also happens that there exist articles with no links to other languages or only with links to one or two (major) languages.\(^6\) Thus, Wikipedia is arguably the largest strongly comparable corpus available online and the best data collection for “in genre” translation experiments. The major motivation of the current endeavour is the validation of the idea that it is possible to develop systems capable of supporting the translation (with minimal post-editing) of Wikipedia articles from less-resourced languages into major languages and vice-versa. Currently, Wikipedia does not offer an integrated translation engine to assist the translation task, but this could be an option worthy of consideration.

It is, therefore, not surprising that several researchers were tempted to explore parallel sentence mining on Wikipedia. Among the first, Adafre and Rijke (2006) approached Wikipedia mining for parallel data using a MT system (Babelfish) to translate from English to Dutch and then, by word overlapping, to measure the similarity between the translated sentences and the original sentences. They also experimented with an automatically induced (phrase) translation lexicon from the titles of the linked articles, measuring the similarity of source (English) and target (Dutch) sentences. Experiments were performed on 30 randomly selected English-Dutch document pairs yielding a few hundred parallel sentence pairs. A few years later, Mohammadi and GhasemAghaee (2010), for another language pair (Persian-English) developed the Adafre and Rijke’s method by imposing additional conditions on the extracted sentence pairs: the length of the parallel sentence candidates had to correlate and the Jaccard similarity of the lexicon entries mapped to source (Persian) and target (English) had to be as high as possible. The experiments conducted by Mohammadi and GhasemAghaee did not generate a parallel corpus, but only a couple of hundred parallel sentences intended as a proof of concept.

Gamalo and Lopez (2010) collected the linked documents in Wikipedia (CorpusPedia), building a large comparable corpus (English-Spanish, English-Portuguese and Spanish-Portuguese), with similar documents classified according to their main topics. However, they did not measure the similarity among the aligned documents neither did they extract the “parallel” sentences.

Another experiment, due to Smith et al. (2010), addressed large-scale parallel sentence mining from Wikipedia. Based on binary Maximum Entropy classifiers (Munteanu & Marcus, 2005), they automatically extracted large volumes of parallel sentences for English-Spanish (almost 2M pairs), English-German (almost 1.7M pairs) and English-Bulgarian (more than 145K pairs). According to Munteanu and Marcus (2005), a binary classifier can be trained to differentiate between parallel sentences and non-parallel sentences using various features such as: word alignment log probability, number of aligned/unaligned words, longest sequence of aligned words, etc. To enrich the feature set, Smith et al. (2010) proposed to automatically extract a bilingual dictionary from the Wikipedia document pairs and use this dictionary to supplement the word alignment lexicon derived from existing parallel corpora. Furthermore, they released their English-Spanish and English-German Wikipedia test-sets (but not the training data) and so, a direct comparison was made possible (Section 4).

3. Mining Wikipedia
Among the 287 language editions of Wikipedia (http://meta.wikimedia.org/wiki/List_of_Wikipedias \(^7\) ), created under the auspices of WikiLeaks Foundation, the English, German and Spanish ones are listed in the best populated category, with more than 1,000,000 articles: English is the largest collection with 4,468,164 articles, German is the third largest with 1,765,430 articles (it was the second when we downloaded it), while Spanish is the 8th in the top Wikipedias with 1,086,871 articles (it was the sixth before). Romanian Wikipedia is in the medium populated category, and with 241,628 articles is the 28th largest collection (it was the 25th at the time of dump downloading). For our experiments we selected three very large Wikipedias (English, German and Spanish) and a medium-sized Wikipedia (Romanian) intended for the

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\(^4\) http://en.wikipedia.org
\(^5\) http://en.wikipedia.org/wiki/Wikipedia:Manual_of_Style.
\(^6\) http://en.wikipedia.org/wiki/Wikipedia:TONE

\(^7\) Consulted on March 9th 2014. The statistics on Wikipedia naturally varies at different times. All our experiments are based on the dump of December 22nd, 2012.
SMT experiments on three language pairs: English – German, English - Spanish and English - Romanian. With the monolingual Wikipedias selected for parallel sentence mining, we downloaded the “database backup dumps”\textsuperscript{8} for which Wikipedia states that they contain “a complete copy of all Wikimedia wikis, in the form of wiki text source and metadata embedded in XML”. Parsing the English XML dump, we kept only the proper encyclopedic articles which contain links to their corresponding articles in Spanish, German or Romanian. Thus, we removed articles that were talks (e.g. Talk:Atlas Shrugged), logs (e.g. Wikipedia:Deletion log), user related articles (e.g. User:AnonymousCoward), membership related articles (e.g. Wikipedia:Building Wikipedia membership), manuals and rules related articles, etc. For each language, the retained articles were processed, using regular expressions, to remove the XML mark-up in order to keep only the raw, UTF-8 encoded text, which was saved into a separate file. The non-textual entries like images or tables were stripped off. Each text document was then sentence-split using an in-house sentence splitter based on a Maximum Entropy classifier.

Table 1: Linked documents for three language pairs

| Language pair | Document pairs | Size on disk | Size ratio (L1/L2) |
|---------------|----------------|--------------|-------------------|
| English-German | 715,555 | 2.8 Gb (EN) | 2.3 Gb (DE) | 1.22 |
| English-Romanian | 122,532 | 0.78 Gb (EN) | 0.2 Gb (RO) | 3.91 |
| English-Spanish | 573,771 | 2.5 Gb (EN) | 1.5 Gb (ES) | 1.66 |

Table 2: Wiki-base: number of parallel sentences and words for each language pair, for a given threshold

| Sim. score | EN-RO | EN-DE | EN-ES |
|------------|-------|-------|-------|
| 0.9 | Pairs: 42,201 | EN Words: 4.26M | RO Words: 0.81M | EN Words: 0.55M | DE Words: 0.54M | EN Words: 91,630 | EN Words: 1.13 M | EN Words: 1.16 M |
| 0.8 | Pairs: 112,341 | EN Words: 2.36M | RO Words: 2.4 M | EN Words: 2.08M | DE Words: 2.01M | EN Words: 576,179 | EN Words: 10.5M | EN Words: 11.29M |
| 0.7 | Pairs: 142,512 | EN Words: 2.99M | RO Words: 3.04M | EN Words: 190,135 | DE Words: 3.49M | EN Words: 1,198,866 | EN Words: 23.73M | EN Words: 25.93M |
| 0.6 | Pairs: 169,662 | EN Words: 3.58M | RO Words: 3.63M | EN Words: 255,128 | DE Words: 3.89M | EN Words: 1,579,692 | EN Words: 31.02M | EN Words: 33.71M |
| 0.5 | Pairs: 201,263 | EN Words: 4.26M | RO Words: 4.33M | EN Words: 322,011 | DE Words: 4.89M | EN Words: 1,838,794 | EN Words: 36.51M | EN Words: 39.55M |
| 0.4 | Pairs: 252,203 | EN Words: 5.42M | RO Words: 5.48M | EN Words: 412,608 | DE Words: 8.47M | EN Words: 2,102,025 | EN Words: 42.32M | EN Words: 45.57M |
| 0.3 | Pairs: 317,238 | EN Words: 6.89M | RO Words: 6.96M | EN Words: 559,235 | DE Words: 11.8M | EN Words: 2,656,915 | EN Words: 54.93M | EN Words: 58.52M |

\textsuperscript{8} http://dumps.wikimedia.org/backup-index.html of December 2012

\textsuperscript{9} We deliberately avoid using the term “parallel sentences”, because, as will be shown, in our experiments we consider not only parallel sentences.
By random manual inspection of the generated sentence pairs, we saw that, in general, irrespective of the language pair, sentence pairs with a translation similarity measure equal or higher than 0.7 are parallel. Those pairs with a translation similarity measure between 0.3 and 0.6 have extended parallel fragments which an accurate word or phrase aligner easily detects. Further down the threshold scale, below 0.3, we usually find sentences that roughly speak of the same event but are not actual translations of each other. The noisiest data sets were extracted for the 0.1 and 0.2 similarity thresholds and we dropped them from SMT experiments.

3.2 SMT experiments with Wiki-Base

In order to select the most MT useful parts of Wiki-Base for the three considered language pairs, we built three baseline Moses-based SMT systems using only parallel sentences, that is those pairs extracted with a similarity score higher or equal to 0.7 (see Table 2). We incrementally extended the training data by lowering the similarity score threshold and, using the same test-set, observed the variation of the BLEU score. The purpose of the evaluation of the SMT systems was only to indicate the best threshold for selecting the training set from the Wiki-Train for subsequent building of the Wiki-Translators. As the standard SMT system we chose Moses surface to surface translation, lexical reordering wbe-msd-bidirectional-fe model, a maximum 4 words phrase-length, and the default values for the rest of parameters.

The target language model (LM) for all experiments was trained on all monolingual, sentence-split English Wikipedia after removing the administrative articles as described in Section 3. The language model was limited to 5-grams and the counts were smoothed by the interpolated Knesser-Ney method. Since we experimentally noticed that the additional sentence pairs extracted for a threshold of 0.6 were almost as parallel as those extracted for higher thresholds we included this interval too in the sampling process for test-set design. Thus, we proceeded to randomly sample 2,500 sentence pairs from similarity intervals ensuring parallelism ([0.6, 0.7], [0.7, 0.8], [0.8, 0.9] and [0.9, 1]). We obtained 10,000 parallel sentence pairs for each language pair. Additionally, we extracted 1,000 parallel sentence pairs as development set (dev-set). These 11,000 sentences were removed from the Wiki-Base (L1, L2) that were meant as training corpora for each language pair. When sampling parallel sentence pairs (test- and dev-sets), we were careful to observe the Moses’ filtering constraints: both the source and target sentences must have at least 4 words and at most 60 words and the ratio of the longer sentence (in tokens) of the pair over the shorter one must not exceed 2. The duplicates were also removed. Further on, we trained seven translation models (TM), for each language pair, over cumulative threshold intervals beginning with 0.3: TM0 for [0.3, 1], TM2 for [0.4, 1] …, TM5 for [0.9, 1]. The resulting seven training corpora were filtered with Moses’ cleaning script with the same restrictions mentioned above. For every language, both the training corpora and the test-set were tokenized using Moses’ tokenizer script and true-cased. The quality of the translation systems was measured as usual in terms of their BLEU score (Papineni et al., 2002) on the same test data.

We have to emphasize that the removal of the test and development set sentences from the training corpora does not ensure an unbiased evaluation of the BLEU scores since their context still remained in the training corpora. This requires some more explanations. For each extracted sentence pair, LEXACC stores in a book-keeping file the ID of the document-pair out of which the extraction was done. This information could be used for identification and elimination from the training set of all the pairs coming from the same documents from which the development and evaluation sets were selected. Yet, due to the nature of the Wikipedia article authoring, even this strategy of filtering the development and evaluation would not ensure an unbiased evaluation. The Wikipedia contributors are given specific instructions for authoring documents10 and because of complying with these instructions, inevitably one could find in different documents almost identical sentences except for a few name entities. Indeed we found examples of such sentence pairs in the train-set similar, but not identical, to sentences in the test-set, yet coming from different document-pairs. Certainly one could build a tough test-set by removing all similar (pattern-based) sentences from train-set, but we did not do that because it would have been beyond the purpose of this work. As we mentioned before, this evaluation was meant only for estimating most useful extraction level for the second phase of training the WIKI-Translators.

| TM based on Wiki-Base | BLEU SCORE RO->EN | BLEU SCORE DE->EN | BLEU SCORE ES->EN |
|-----------------------|-------------------|-------------------|-------------------|
| TM(0.3, 1)            | 37.24             | 39.16             | 47.59             |
| TM(0.4, 1)            | 37.71             | 39.46             | 47.52             |
| TM(0.5, 1)            | **37.99**         | **39.52**         | 47.53             |
| TM(0.6, 1)            | 37.85             | 39.5              | 47.44             |
| TM(0.7, 1)            | 37.39             | 39.24             | 47.28             |
| TM(0.8, 1)            | 36.89             | 38.57             | 46.27             |
| TM(0.9, 1)            | 32.76             | 34.73             | 39.68             |

Table 3: Comparison among SMT systems trained on various parts of Wiki-Base

Table 3 summarizes the results of this first step experiment, with the best BLEU scores (bold figures) identifying the most MT useful parts of Wiki-Base (L1,L2). We considered TM (0.7, 1) as the baseline for all language pairs.

3.3 Phase 2: Building Wiki-Train (L1, L2)

The experiments on Wiki-base revealed that the most useful training data was extracted by using LEXACC with 0.5 similarity score for German-English and Romanian-English language pairs and 0.3 for Spanish-English pair (see Table 3). We re-ran GIZA++ on these subsets of Wiki-Base to extract new lexicons. The new lexicons were merged with the initial ones and the LEXACC extraction was repeated with the resulted mined comparable sentence-pairs denoted as Wiki-Train.

10 http://en.wikipedia.org/wiki/Wikipedia:Translation
Both translation directions. The results are presented in pairs in the training set. Anyway, the English-Spanish process. As one can see, the extracted data, at each evaluation on the respective test sets (10,000 pairs) in training of each translation system was followed by the in-domain experiments).

Most of the results we are aware of (for in-genre or ones), but still the BLEU scores are very high, better than the target language (most of the errors are morphological duplicates was not the best filtering option.

As expected, the translations into non-English languages are less accurate due to a more complex morphology of the target language (most of the errors are morphological ones), but still the BLEU scores are very high, better than most of the results we are aware of (for in-genre or in-domain experiments).

### Table 4: Wiki-Train: number of similar sentences and words for each language pair, for a given threshold

| Sim. score | EN-RO | EN-DE | EN-ES |
|-----------|-------|-------|-------|
| 0.9       | Pairs 66,777 | EN Words 1.08M | EN Words 1.07M | EN Words 1.04M | Pairs 97,930 | EN Words 1.07M | EN Words 1.04M | EN Words 1.01M |
| 0.8       | Pairs 152,015 | EN Words 2.69M | EN Words 3.7M | EN Words 3.6M | Pairs 272,358 | EN Words 5.93M | EN Words 9.73M | EN Words 10.51M |
| 0.7       | Pairs 189,875 | EN Words 3.36M | EN Words 6.2M | EN Words 5.93M | Pairs 434,019 | EN Words 8.94M | EN Words 19.94M | EN Words 21.82M |
| 0.6       | Pairs 221,661 | EN Words 3.96M | EN Words 8.94M | EN Words 8.53M | Pairs 611,868 | EN Words 9.4M | EN Words 25.07M | EN Words 27.41M |
| 0.5       | Pairs 260,287 | EN Words 4.72M | EN Words 12.36M | EN Words 11.79M | Pairs 814,041 | EN Words 7.4 M | EN Words 28.99M | EN Words 31.57M |
| 0.4       | Pairs 335,615 | EN Words 6.33M | EN Words 18.09M | EN Words 17.31M | Pairs 1,136,734 | EN Words 19.09M | EN Words 33.62M | EN Words 36.73M |
| 0.3       | Pairs 444,102 | EN Words 8.71M | EN Words 31.41M | EN Words 30.18M | Pairs 1,848,651 | EN Words 44.02M | EN Words 35.18M | EN Words 47.18M |

### Table 5: Best translation SMT systems, trained on Wiki-Train

| | Wiki-Train | TM | TM | TM |
|---|---|---|---|---|
| TM based on Wiki-Train | BLEU | TM (0.5, 1) | TM (0.5, 1) | TM (0.3, 1) |
| Wiki-Train | 41.09 | 40.82 | 46.28 |
| EN->EN | 41.09 | 40.82 | 46.28 |
| EN->RO | 29.61 | 35.18 | 46.00 |
| EN->DE | 29.61 | 35.18 | 46.00 |
| EN->ES | 29.61 | 35.18 | 46.00 |

### 4. Comparison with other works

Translation for Romanian-English language pair was also studied in (Boroș et al., 2013; Dumitrescu et al., 2012; 2013) among others. In these experiments we had explicit interests in experiments on using in-domain vs. out-of-domain test/train data, and various configurations of the Moses decoder in surface-to-surface and factored translation. Out of the seven domain-specific corpora (Boroș et al., 2013) one was based on Wikipedia. The translation experiments on Romanian-English, similar to those reported here, were surface based with training on parallel sentence pairs extracted from Wikipedia by LEXACC at a fixed threshold: 0.5 (called “WIKI5”), without MERT optimization. A random selection of unseen 1,000 Wikipedia Romanian test sentences was translated into English using combinations of:

- a WIKI5-based translation model (240K sentence pairs)/WIKI5-based language model;
- a global translation model (1.7M sentence pairs)/global language model named “ALL”, trained on the concatenation of all seven specific corpora.

Table 6 gives the BLEU scores for the Moses configuration similar to ours.

### Table 6: BLEU scores (RO->EN) on 1000 sentences

| | WIKI5 TM | ALL TM |
|---|---|---|
| WIKI5 LM | 29.99 | 29.95 |
| ALL LM | 29.51 | 29.95 |

Boroș et al. (2013)’s results confirm the conclusion we claimed earlier: the ALL system does not perform better than the in-genre WIKI5 system. The large difference between the herein BLEU score (41.09) and 29.99 in (Boroș et al., 2013) may be explained by various factors. First and more importantly, our current language model was entirely in-genre for the test data and much larger: the language model was built from entire Romanian Wikipedia (more than 500,000 sentences), while the language model in (Boroș et al., 2013) was built only from the Romanian sentences paired to English sentences (less than 240,000 sentences). Our translation model was built from more than 260,000 sentence pairs versus 234,879 sentence pairs of WIKI5). Another explanation might be the use of different Moses filtering parameters (e.g. the

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11 For a fair comparison with data in Table 3 we did not use here the MERT optimization

12 The test-set construction followed the same methodology described in this article
length filtering parameters) and different test-sets. As suggested by other researchers, Wikipedia-like documents are more difficult to translate than, for instance, legal texts. Boroş et al. (2013) report BLEU scores on JRC-Acquis test-sets (with domain specific training) almost double than those obtained on Wikipedia test-sets.

The most similar experiments to ours were reported by Smith et al. (2010). They mined for parallel sentences from Wikipedia producing parallel corpora of sizes even larger than ours. While they used all the extracted sentence pairs for training, we used only those subsets that observed a minimal similarity score. We checked to see if their test-sets for English-Spanish (300 pairs) and for English-German (314 pairs) contained sentences in our training sets and, as this was the case, we eliminated from the training data several sentence pairs (about 200 sentence pairs from the English-Spanish training corpus and about 140 sentence pairs from the English-German training corpus). We retrained the two systems on the slightly modified training corpora. Since they used MERT-optimized translation systems in their experiments, we also optimized, by MERT, our new TM[0.5,1] for German->English and new TM[0.4,1]13 for Spanish->English translation systems, using the respective dev-sets (each containing 1,000 sentence pairs, as described in Section 3.2).

Their test-sets for English-Spanish and for English-German were translated (after being true-cased) with our best translation models and also with Google Translate (as of mid-February 2013).

Table 7 summarizes the results. In this table, “Large+Wiki” denotes the best translation model of Smith et al. (2010) which was trained on many corpora (including Europarl and JRC Acquis) and on more than 1.5M parallel sentences mined from Wikipedia. “TM[0.5,1]” and “TM[0.4,1]” are our Wiki-Train translation models as already explained. “Train data size” gives the size of training corpora in multiples of 1,000 sentence pairs.

| Language pair      | Train data size (sentence pairs) | System               | BLEU |
|--------------------|----------------------------------|----------------------|------|
| English-Spanish    | 9,642K                           | Large+Wiki           | 43.30|
|                    | 2,288K                           | LM[0.4,1]            | 50.19|
|                    | --                               | Google               | 44.43|
| German-English     | 8,388K                           | Large+Wiki           | 23.30|
|                    | 814K                             | TM[0.5,1]            | 24.64|
|                    | --                               | Google               | 21.64|

Table 7: Comparison between SMT systems on the Wikipedia test-set provided by Smith et al. (2010)

For Spanish-English test-set of Smith et al. (2010) our result is significantly better (6.89 BLEU points) than theirs, in spite of almost 4 times less training data. For the German-English pair, the BLEU score difference between TM[0.5,1] and Large+Wiki systems is smaller, but still statistically significant (1.34 points), and one should also notice that our system used 10 times less training data.

Surprisingly, our TM[0.5,1] for German-English performed on the new test-set much worse than on our test-set (24.64 versus 40.8214 BLEU points), which was not the case for the Spanish-English language pair. We suspected that some German-English translation pairs in the Smith et al. (2010) test-set were not entirely parallel. This idea was supported by the correlation of the evaluation results between our translations and Google’s for Spanish-English and German-English. Also, their reported results on German-English were almost half of the ones they obtained for Spanish-English.

Therefore, we checked the German-English and Spanish-English test-sets (supposed to be parallel) by running the LEXACC miner to see the similarity scores for the paired sentences. The results confirmed our guess. The first insight was that the test-sets contained many pieces of texts that looked like section titles. Such short sentences were ignored by LEXACC. While out of the considered sentence pairs (ignoring the sentences with less than 3 words), for Spanish-English LEXACC identified more than 92% as potentially useful SMT pairs (with a similarity score higher than or equal to 0.3 – this was the extraction threshold for Spanish-English sentence-pairs), for German-English LEXACC identified only 35% potentially useful SMT pairs (a similarity score higher than or equal to 0.5 – this was the extraction threshold for German-English sentence-pairs). Even if the threshold for German-English was lowered to 0.3 and titles included only 45% passed the LEXACC filtering.

As for parallelism status of the sentence pairs in the test-sets (i.e. similarity scores higher than 0.6 for both languages) the percentages were 78% for Spanish-English and only 29% for German-English. Without ignoring the short sentences (easy to translate) these percentages were a little bit higher (80.8% for Spanish-English and 32.82% for German-English). These evaluations also outline that LEXACC is too conservative in its rankings: we noticed almost parallel sentences in the test-set for Spanish-English even for a similarity score of 0.115, while in the German-English the same happens for similarity scores lower than 0.316. The most plausible explanation was that one of the LEXACC’s parameters (cross-linking

14 Note that this value for our TM[0.5,1] was obtained on a very different and much larger test-set and also without MERT optimization. Yet, the difference is large enough to raise suspicions on the test-set used for this comparison.

15 Similarity score (ES-EN) 0.1: Sin embargo, el museo, llamado no fue terminado sino hasta el 10 de abril de 1981, dos días antes del vigésimo aniversario del vuelo de Yuri Gagarin. -> However, it took until April 10, 1981 (two days before the 20th anniversary of Yuri Gagarin’s flight) to complete the preparatory work and open the Memorial Museum of Cosmonautics.

16 Similarity score (DE-EN) 0.29: Die 64,5 Prozent , welche die SPD unter seiner Führung erzielte , waren das höchste Ergebnis , welches je eine Partei auf Bundeslandsebene bei einer freien Wahl in Deutschland erzielt hatte . -> In the election that was conducted in the western part of Berlin two months later , her popularity gave the SPD the highest win with 64.5 % ever achieved by any party in a free election in Germany.
factor) strongly discourages long-distance reordering (which was quite frequent in the German-English test-set and has also a few instances in the Spanish-English test-set).

5. Conclusions

Wikipedia is a rich resource for parallel sentence mining in SMT. Comparing different translation models containing MT useful data, ranging from strongly comparable to parallel, we concluded that there is sufficient empirical evidence not to dismiss sentence pairs that are not fully parallel on the suspicion that the inherent noise they contain might be detrimental to the translation quality.

On the contrary, our experiments demonstrated that in-genre comparable data are strongly preferable to out-of-genre parallel data. However, there is an optimum level of similarity between the comparable sentences, which, according to our similarity metrics (for the language pairs we worked with), is around 0.4 or 0.5.

Additionally, the two step procedure we presented, demonstrated that an initial in-genre translation dictionary is not necessary, and it can be constructed subsequently, starting with a dictionary extracted from whatever parallel data.

We want to mention that it is not the case that our extracted Wikipedia data is the maximally MT useful data. First of all, LEXACC may be improved in many ways, which is a matter for future developments. For instance, although the cross-linking feature is highly relevant for language pairs with similar word ordering, it is not very effective for language pairs showing long distance re-ordering. We also noticed that a candidate pair which did not include in both parts the same numeric entities (e.g. numbers, dates, and times) was dropped for further consideration. Thirdly, the extraction parameters of LEXACC were not re-estimated for the Wiki-Train construction. Additionally, we have to mention that LEXACC evaluated and extracted only full sentences: a finer-grained (sub-sentential) extractor would be likely to generate more MT useful data. Also, one should note that the evaluation figures are just indicative for the potential of Wikipedia as a source for SMT training. In previous work it was shown that using factored models for inflectional target languages (Boroș et al, 2013) and cascading translators (Tuțiș & Dumitrescu, 2012) may significantly improve (several BLEU points) the translation accuracy of an SMT system. Some other techniques may be used to improve at least translations into English. For instance, given that English adjectives and all functional words are not inflected, a very effective way, for a source inflectional language would be to lemmatize all words in these categories. Another idea is to split compound words of a source language (such as German) into their constituents. Both such simplifications are, computationally, not very expensive (and for many languages appropriate tools are publicly available), and may significantly reduce the number of out-of-vocabulary input tokens.

The parallel Wiki corpora, including the test-sets (containing 10,000) and the dev–sets (containing 1,000 sentences) are freely available on-line\(^\text{17}\).

The archives contain all the extracted sentence pairs, beginning with the similarity threshold 0.1 (see Table 8), thus much more, but, to a large extent, noisy data. Yet, as said before, several useful sentence pairs for each language pair might be recovered.

| Sim. score | EN-RO | EN-DE | EN-ES |
|-----------|-------|-------|-------|
| 0.1       | Pairs 2,418,227 | En Words 63.99M | Pairs 11,694,784 | En Words 295.22M |
|           | Ro Words 63.96M | De Words 292.56M | Pairs 3,280,305 | En Words 84.30M |
|           |                   |                     | Es Words 87.37M |           |

Table 8: Full unfiltered data-sets

The LEXACC text miner plus other miners are freely available on ACCURAT project site\(^\text{18}\) with the newest version on the RACAI’s META-SHARE clone\(^\text{19}\).

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\(^{17}\) http://dev.racai.ro/dw

\(^{18}\) http://www.accurat-project.eu/

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