Measuring the comparability of multilingual corpora extracted from Twitter and others

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Abstract. Multilingual corpora are widely exploited in several tasks of natural language processing, these corpora are principally of two sorts: comparable and parallel corpora. The comparable corpora gather texts in several languages dealing with analogous subjects but are not translations of each other such as in parallel corpora. In this paper, a comparative study on two stemming techniques is conducted in order to improve the comparability measure based on a bilingual dictionary. These methods are: Buckwalter Arabic Morphological Analyzer (BAMA) and a proposed approach based on Light Stemming (LS) adapted specifically to Twitter, then we combined them. We evaluated and compared these techniques on three different (English-Arabic) corpora: a corpus extracted from the social network Twitter, Euronews and a parallel corpus extracted from newspapers (ANN). The experimental results show that the best comparability measure is achieved for the combination of BAMA with LS which leads to a similarity of 61\% for Twitter, 52\% for Euronews and 65\% for ANN. For a confidence of 40\% we aligned 73.8\% of Arabic and English tweets.

Keywords: Twitter, Stemming, comparability measure

1 Introduction

Several applications in natural language processing necessitate parallel corpora. For classical issue of machine translation, this type of data is available: Europarl [9], Hansard[13] and Hong Kong [16]. Unfortunately, this kind of data is not available for all languages and especially for under-resourced ones and those used in social networks where the users allow themselves a certain freedom of writing. That is why nowadays, researchers make efforts to investigate comparable corpora because they are more available than parallel corpora which need a human effort to align corresponding sentences.

Comparable corpora require alignment procedure to retrieve parallel segments within these documents. Consequently, we should determine which document is comparable to another one. To achieve this previous task, we need first to define precisely the concept of comparability. Li [10] defines the comparability as follows: Two corpora in two different languages \( L_1 \) and \( L_2 \) are considered as comparable, if the translation of a part of \( L_1 \) respectively \( L_2 \) does exist in \( L_2 \) respectively \( L_1 \). Comparable corpora can be collected from different Internet sources such as newspapers, Wikipedia dump files and from Social networks, but the alignment of these documents remains a challenge in natural language processing.

Nowadays, Twitter has became a popular social network which allows millions of users to share their opinions on various topics. The emergence of this kind of data has led to many research works with the objective to exploit this large quantity of information to build monolingual and multilingual corpora [6], [12]. Another research activity that exploits social networks concerns multilingual sentiment analysis and sentiment classification from tweets [2], [5], [4].

Our objective in this paper is to collect comparable data about Syrian war and refugee problems by crawling a social network in Arabic and English. Obviously, we can not just crawl Twitter, we need to compare the retrieved corpora in order to build a real comparable corpus. For that, we have to measure the comparability between the English and the Arabic corpora. The most used methods for this issue are based on a bilingual dictionary. The drawback of this method is that the bilingual dictionaries can not cover the whole existing corpora and especially those extracted
from social networks. Consequently, the dictionary should cover largely the processed corpora. Otherwise, the comparability measure will be biased by the weak rate of coverage of the bilingual dictionary.

To increase the coverage of the bilingual dictionary, we will use stemming methods in order to rewrite the corpora in terms of lemmas especially for Arabic. For this language, we will be faced, in addition to the classical problems of processing Modern Standard Arabic, to the noisy text which includes misspelled words, Arabic dialects phrases, the stretched or duplicated letters, etc.

This paper is organized as follows: in section 2 we summarize some previous work on comparability measures. We describe the collected multilingual corpora and the preprocessing steps applied to each corpus in Section 3. In section 4 we described a stemming method used by the community (BAMA), we propose a light stemming method and then we combine the two previous approaches. In section 5 we present Li and Gaussier comparability measure that we need for retrieving a comparable documents. Several experiments and results are described in section 6. Finally, we conclude and present some future works.

2 Previous works

The construction of comparable corpora is performed using similarity measures. These measures can be based on three different approaches: vocabulary overlapping, vectors space and Machine translation. Among existing work to align the comparable corpus we can cite the following: Li and Gaussier in [11] defined the degree of comparability between two corpora as the expectation of finding, for each word of the source corpus, its translation in the target one. They use this definition to propose a measure which estimates the comparability of a parallel corpus, then they showed how the comparability degree has decreased when noises have been added to the parallel corpora. Then this measure has been modified, to take into account the context in order to reduce the issue of polysemy.

Li and Gaussier’s measure has been improved by Guiyao et al in[8] by taking into account the occurrence of a word concerned by the comparability and its different translations.

Saad et al [14] used LSA for measuring the comparability between two corpora. They proved that this approach gives better results than those based on the common vocabulary.

Gamallo in [7] proposed two strategies to build comparable corpora from Wikipedia, they used (binary and TFIDF) Dice to measure the degree of comparability of 30 different comparable corpora. They proved that the Dice score based on TFIDF achieves better results than those based on the binary representation.

3 Corpora and preprocessing

To study the reliability of the techniques proposed in this work, we use several corpora extracted from: Twitter, Euronews and a parallel corpus (ANN)[15].

Our objective is to retrieve comparable corpora from Twitter, this could be considered as a difficult task. In this work, we validate the proposed approach on supposed easier corpora Euronews (comparable) and ANN (parallel).

3.1 Twitter corpus

The objective is to build an English-Arabic comparable corpus. For that, we extract from Twitter by using Talend Studio and Twitter API the most frequent Hashtags for each language concerning the topics War in Syria and The Syrian Refugees. Table 1 and Table 2 show these Hashtags and the corresponding number of the retrieved tweets. We also used related Hashtags to enlarge our corpus, for example: #Syrianarmy, #freesyrianarmy. Due to the particularity of Arabic, we used different Hashtags such as: #سوريا, #سوريا. both of them correspond to the word Syria. In fact, this word could be written in two ways in MSA (Modern Standard Arabic) with symbol Ta (تا) and with symbol alif (ا).
Table 1. Number of English tweets collected for each Hashtag.

<table>
<thead>
<tr>
<th>English Hashtag</th>
<th>$N_{\text{Twts}}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>#SyrianRefugees</td>
<td>10895</td>
</tr>
<tr>
<td>#refugeecrisis</td>
<td>2856</td>
</tr>
<tr>
<td>#Syrianarmy #freesyrianarmy</td>
<td>3760</td>
</tr>
<tr>
<td>#SyriaCrisis</td>
<td>6260</td>
</tr>
<tr>
<td>#syria #syrian</td>
<td>34000</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>57771</strong></td>
</tr>
</tbody>
</table>

Table 2. Number of Arabic tweets collected for each Hashtag.

<table>
<thead>
<tr>
<th>Arabic Hashtag</th>
<th>Translation</th>
<th>$N_{\text{Twts}}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>#اطفال <em>سوريا</em>_</td>
<td>Children of Syria</td>
<td>1599</td>
</tr>
<tr>
<td># الثورة <em>السورية</em></td>
<td>Syrian revolution</td>
<td>10092</td>
</tr>
<tr>
<td>#اللاجئين <em>السوريين</em></td>
<td>Syrian refugees</td>
<td>4000</td>
</tr>
<tr>
<td>#سوريا #سوريا_</td>
<td>Syria</td>
<td>34000</td>
</tr>
<tr>
<td>#الجيش _السوري <em>الحر</em> #الجيش _العربي <em>السوري</em></td>
<td>Syrian arab army, Free Syrian army</td>
<td>5234</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>59452</strong></td>
<td></td>
</tr>
</tbody>
</table>

Table 3 shows the characteristics of all corpora used in this work, where $|S|$ is the number of sentences, and $|V|$ is the vocabulary size.

Table 3. Comparable and parallel corpora characteristics.

<table>
<thead>
<tr>
<th></th>
<th>Twitter</th>
<th>Euronews</th>
<th>Parallel</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>English</td>
<td>Arabic</td>
<td>English</td>
</tr>
<tr>
<td>$</td>
<td>S</td>
<td>$</td>
<td>12624</td>
</tr>
<tr>
<td>$</td>
<td>V</td>
<td>$</td>
<td>108K</td>
</tr>
</tbody>
</table>

3.2 Preprocessing corpora

Natural Language preprocessing for MSA (Modern Standard Arabic) are available, but the challenge in this work is the nature of the processed data. In fact, tweets are short messages, restricted to 140 characters, these messages often contain misspelled words, abbreviations and dialectal words where the analyzer is unable to produce the morphological form of these messages. Furthermore, Arabic language is morphologically rich because in the majority of cases, a word is composed by the concatenation of a root and affixes. A root in Arabic is considered as a producer of words, that is why from a single root, several words can be composed. For example: the root كتب to write with specific affixes produces different words with different meanings: كتب, كتب, كتب, كتب.

In the following we will present the different cleaning operations related to English and Arabic.

3.2.1 Preprocessing English We present below several procedures applied to the English part of Twitter corpora.
- Since Twitter is used by millions of users, people take some freedom in writing. That is why we use an SMS dictionary which contains abbreviations, acronyms and their literal corresponding text. We use this dictionary to replace abbreviations by their literal forms. For example ppl will be replaced by people.
- In order to remove foreign Twitter in the English part of the corpora, we developed a tool based on stop words and ASCII code to filter the foreign phrases.
- Contrary to Arabic corpus, the English one contains many Hashtags embedded in the Tweet itself. A Hashtag is composed of several words #SyrianArabArmy, #SyrianCivilians, etc which should be split in order to obtain a larger Tweeter vocabulary. In the case where words are separated by capital letters or special characters it is easy to determine the words composing the Hashtag, such as in the examples: #SyrianArabArmy #Syrian_Arabic_army. But, when the Hashtag is completely written in lowercase, we use a dictionary of words, sorted alphabetically and by length which allows to find the different words which match best with the content of the Hashtags.

3.2.2 Preprocessing Arabic For Arabic, the preprocessing is achieved in order to reduce the ambiguity due to the fact that people write some words differently. In the following we present some rules used for that issue.

- We replace the letter ë by ë only at the end of words. This could be very surprising since these two letters are grammatically different, but graphically they are similar except that the first one has two dots above. For convenience, some people use indifferently both of them. This is why we homogenize the script in all the tweets. For almost the same reason, we replace all the forms of symbol Alif with Hamza such as in: 

- All the diacritics have been removed since people can read without these vowels.
- In social networks, sometimes users stretch words to accentuate their opinion or just write the words such as they pronounce them, we need to normalize the way of writing these words. The stretched or duplicated letters are removed such as in: 

In opposite to Twitter corpora, Arabic parallel and comparable corpora used in this work do not need all these preprocessing steps, because these corpora are collected from newspapers. Consequently, they do not contain noisy data as in Twitter corpora. Nevertheless, we removed special characters, Latin characters and stops words. We also transform as above all the Alif with Hamza by a simple Alif.

4 Stemming

For documents such as Twitter, the vocabulary is not large, in order to use statistical methods, in general we segment the words by using lemmatization or stemming. The idea is to replace different words which share the same root by this root itself. These methods consist in reducing inflectional and sometimes derivational forms of a word to a common base form. In Arabic, this task becomes more complex compared to other languages, because, this language has some particularities such as agglutination, using diacritics, etc. In fact, Arabic words can be formed by attaching affixes to a root. Affixes in Arabic are: prefixes, antefixes, suffixes and postfixes. Prefixes and antefixes are attached at the beginning of the words, where suffixes and postfixes are attached at the end. For example the word لتفاوضونهم which means to negotiate with them is composed by the elements shown in Table 4. To improve the dictionary coverage rate, in this work, we applied different techniques to retrieve the most representative form of words. For English corpora, we used TreeTagger and for Arabic corpora, we used the two following methods.

4 http://www.cis.uni-muenchen.de/ schmid/tools/TreeTagger/


**Table 4. Example of Arabic Affixes**

<table>
<thead>
<tr>
<th>Word</th>
<th>Antefixe</th>
<th>Prefixe</th>
<th>Stem</th>
<th>Suffixe</th>
<th>Postfixe</th>
</tr>
</thead>
<tbody>
<tr>
<td>هم ون فاوش ي ل ليفاوضعهم</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

4.1 Buckwalter Arabic Morphological Analyzer

This analyzer is one of the most referenced in the literature, coded with Perl language by Tim Buckwalter [3]. It is designed as a main database of 40,648 lemmas supplemented by three morphological compatibility tables used for controlling affix-stem combinations [1]. For each word entered, BAMA provides: the different possible lemmas of the word with its diacritics, grammatical label of each lemma and their corresponding translation in English, as shown in Figure 1.

![Fig. 1. BAMA output of Arabic word يتكلمون they speak](image)

4.2 Method based on Light Stemming (LS)

Arabic Light stemming consists in removing all affixes attached to the Arabic word. However, this approach may face to several ambiguities. For instance, when a word contains a sequence of letters that seems to be an affixe but which is not. For example, the sequence نذ in the word: نذ they speak/talk/discuss + suffix: [masc.pl.] suffix=بIV SUFF_SUBJ:MP,MOOD:I prefix=":IV3MP\] type="" impartial="" transitive="" pos=VERB,IMPERFECT root="" pattern="" stem=نذ").

That is why, we proposed a new method of light stemming, which removes all affixes attached to the Arabic word according to a specific order. We start by removing the external affixes of the word then those connected directly to the stem, as shown in Figure 5. Each time an affix is removed the remaining lemma is kept for the further processing steps as described in Algorithm 1 and 2. Using the affix categories shown in table 5, Algorithm 1 removes firstly, only the Antefix (Fig. 2. Topology of an Arabic word)
RAntefix(W) attached to the Arabic word, secondly only the Postfix (RPostefix(W)) and finally, it removes both of them (RPostfixAntefix(W)). After each removal operation, the achieved lemma is kept. The same procedure is then applied to remove the prefix (RPrefix(l_i)), suffix (RSuffix(l_i)) and finally, it removes both of them (RPrefixSuffix(l_i)) from each lemma kept in the previous step.

Algorithm 1 Generation of lemmas
1: $S_l \leftarrow \emptyset$
\hspace{1cm} // Removing External affixes by using $T_{Antefix}$ and $T_{Postfix}$ affixes tables:
\hspace{1cm} $S_l \leftarrow RAntefix(W)$;
\hspace{1cm} $S_l \leftarrow RPostfix(W)$;
\hspace{1cm} $S_l \leftarrow RPostfixAntefix(W)$;
\hspace{1cm} // Removing Internal affix by using $T_{Prefix}$ and $T_{Suffix}$ affixes tables:
2: for each $l_i$ in $S_l$ do // $i = 1 \ldots 3$
\hspace{1cm} $S_l \leftarrow RPrefix(l_i)$;
\hspace{1cm} $S_l \leftarrow RSuffix(l_i)$;
\hspace{1cm} $S_l \leftarrow RPrefixSuffix(l_i)$;
3: end for
4: Filtering ($S_l$)

Consequently, for each word, we get twelve lemmas, they may contain wrong and duplicated segmentation hypotheses. The filtering algorithm will remove the duplicated lemmas and those which are not present in a huge corpus as explained in Algorithm 2.

Algorithm 2 Filtering($S_l$)
1: $S_{Out} \leftarrow \emptyset$
\hspace{1cm} $S'_{l} \leftarrow RemoveDuplicatedLemma(S_l)$
\hspace{1cm} for each $l_i$ in $S'_l$ do $F \leftarrow CalculateFrequency(l_i, C_A)$ // $C_A$ is a huge corpus
\hspace{2cm} if $F \neq 0$ then $S_{Out} \leftarrow l_i$
\hspace{1cm} end if
\hspace{1cm} end for

Table 5. Affixes categories most used in Arabic.

<table>
<thead>
<tr>
<th>Arabic affixes</th>
<th>ARabic affixes</th>
</tr>
</thead>
<tbody>
<tr>
<td>$T_{Antefix}$</td>
<td>لـ، بـ، وـ، فـ، نـ، بـ، فـ، نـ، بـ، فـ، نـ، بـ، فـ، نـ</td>
</tr>
<tr>
<td>$T_{Prefix}$</td>
<td>تـ، قـ، نـ</td>
</tr>
<tr>
<td>$T_{Suffix}$</td>
<td>تـ، نـ، تـ، نـ</td>
</tr>
<tr>
<td>$T_{Postfix}$</td>
<td>يـ، هـ، كـ، هـ، كـ، هـ، كـ</td>
</tr>
</tbody>
</table>

4.3 Combining BAMA and LS
Because BAMA processes a standard Arabic, consequently it fails in analyzing misspelled words which are very frequent especially in Twitter. In the following we give some examples of them:

5 Corpora: Mourad Abbas (14M) and Saad Motaz(15M) http://aracorpus.e3rab.com
they do not speak is actually constituted with two words لا يتكلمون which should be separated by a space. This is not the case that makes BAMA failing in the analysis.
- The word لا ياعبدو should be written such as لا ياعبدها. Obviously, BAMA is unable to analyze this misspelled word.
- Other words in Twitter are written in Syrian dialect such as : بتحقق bombarding. This is not supported in BAMA.
- Some forms of imperative verbs such as: أفصوا bomb are not used in BAMA [1].

In Figure 3, we present how LS can analyze the word لا يتكلمون for which BAMA fails. The words

Fig. 3. Lemmas produced by LS for incorrect word لا يتكلمون They do not speak, A: Antefix, Pr: Prefix, S: Suffix, P: Postfix.

in red indicate wrong lemmas and in green correct lemmas. Contrary to BAMA, LS gives for this word two lemmas: أتكلم I speak and تكلم He speaks.

LS also has some limitations, for instance, it is unable to analyze correctly the agglutinated words including plural forms. It is able to segment them by identifying the pronoun and the plural form but it fails to identify the root form such as in the example: قلوب فهم their heart, where LS provides only هم and قلوب.

To overcome the drawbacks of the two methods, we propose to combine them. The limitations of both methods justifies the use of a hybrid method based on BAMA and LS. This justification is strengthened by the fact that BAMA is able to analyze correctly 88% of the content of our Twitter Arabic corpus while LS processes correctly 91%.

In this hybrid method, both approaches cooperate in order to produce all the potential lemmas for each word in order to increase the coverage of the dictionary.

5 Estimating the comparability

In this work, we used Li and Gaussier measure [11] to study the impact of the methods of stemming on the comparability measure. This measure defined the similitude between two corpora as follows: Let assume that $C$ is an Arabic-English corpora consisting of an Arabic part $C_a$ and an English part $C_e$. The comparability measure can be defined as the expectation of finding, for each English word $W_e$ (respectively $W_a$) in the vocabulary $V_e$ of $C_e$ (respectively $V_a$ of $C_a$), its translation in the vocabulary $V_a$ of $C_a$ (respectively $V_e$ of $C_e$).

The comparability measure is estimated as follows:
\[
LG = \frac{\sum_{w \in V_e \cap D_e} \sigma(w, V_a) + \sum_{w \in V_e \cap D_a} \sigma(w, V_e)}{|V_e \cap D_e| + |V_a \cap D_a|} 
\]  

(1)

where \(D_e\) (respectively \(D_a\)) is the English side (respectively Arabic side) of a bilingual dictionary.

Let \(\sigma\) a function which indicates whether a translation of a word \(w\) represented by a list of potential translations \(T(w)\) does exist in the vocabulary \(V_x\).

\[
\sigma(w, V_x) = \begin{cases} 
1 & \text{if } T(w) \cap V_x \neq \emptyset \\
0 & \text{else} 
\end{cases} 
\]  

(2)

5.1 The coverage rate

We study hereinafter the influence of stemming techniques on the dictionary coverage rate, this parameter is important which influences directly the comparability of corpora as it will be shown in the following experiments. We define the coverage rate of a dictionary \(D\) compared to a corpus \(C\) represented by a vocabulary \(V\) by the quantity:

\[
C_v(V, D) = \frac{|V \cap D|}{|V|} 
\]  

(3)

Because, we work in a bilingual context (English-Arabic), we calculated a symmetric coverage rate \(C_{v_{sy}}\) as follows:

\[
C_{v_{sy}}(V, D) = \frac{C_v(V_s, D_s) + C_v(V_t, D_t)}{2} 
\]  

(4)

Where: \(v_s\) (respectively \(v_t\)) the source and the target vocabulary and \(D_s\) (respectively \(D_t\)) the source and the target part of the bilingual dictionary.

For all experimentation, we calculated the dictionary coverage rate by using OMWN (Open Multilingual WordNet) which contains 17 785 pairs of Arabic and English entries.

6 Experimental Results

In the following we describe the experiments we conducted. In the first one, no stemming has been used to process the English part of Twitter while for the Arabic part, we used BAMA and LS in order to study the impact of these stemming techniques on the coverage rate.

In the second one, we used comparable and parallel corpora collected from newspapers to conduct similar experiments except that in this case we have more clean corpora than Twitter.

For both experiments we calculated the comparability measure between English and Arabic for both categories of corpora.

Figure 4 illustrates the impact of using stemming techniques on the coverage rate of the bilingual dictionary on the Arabic Twitter corpus. Obviously, for Arabic and more especially for Twitter, this result is expectable, in fact the stemming procedure is very useful and necessary.

In Figure 5, we introduce the stemming process (by using TreeTagger) on the English part of Twitter. We show that the stemming for English is also important since the results of coverage have been improved respectively for BAMA with 2.6% and for LS with 2.9%.

Since, the coverage rate is important in the calculation of the comparability measure, we decided to estimate the coverage for corpora which are supposed to be more clean than Twitter.
Fig. 4. The dictionary coverage rate by using BAMA and LS stemming techniques only on Arabic part of Twitter corpora.

Fig. 5. The dictionary coverage rate by using BAMA and LS stemming techniques on Arabic part and Treetagger for English part of Twitter.

Fig. 6. The dictionary coverage rate by using all the stemming techniques on all corpora.

and for which the documents are strongly related. In Figure 6, we illustrate the coverage rate for three different corpora, the previous Twitter corpus, a comparable one (Euronews) and a parallel corpus (ANN).

This figure shows that the combination of BAMA, LS and TreeTagger achieves the best results whatever the corpus used. The second conclusion is that the best coverage rate is obtained for the
parallel corpus which is not surprising. In the opposite, we were expecting that for Twitter the results would be the worst, but it is not the case since it is extracted from Twitter by fixing the Hashtags. Consequently, both English and Arabic are related to the same topic which leads to the use of a narrow vocabulary. The worst results are achieved for the comparable corpora which is in this case the most difficult corpus for the coverage. In fact, it contains different documents related to several topics. This makes the vocabulary rich and disparate.

As presented before, the coverage rate has a serious impact in the calculation of Li and Gaussier comparability measure. That is why all the previous experiments have been presented. In Table 6, we present the comparability measure on the three previous corpora. The achieved results are correlated to the ones presented in the previous experiments. In fact, the best results concern the parallel corpus and the best method is the one which combines BAMA, LS and TreeTagger.

<table>
<thead>
<tr>
<th>Corpus</th>
<th>BAMA</th>
<th>LS</th>
<th>BAMA+ LS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Twitter</td>
<td>58.8</td>
<td>58.4</td>
<td>61</td>
</tr>
<tr>
<td>Euronews</td>
<td>49.6</td>
<td>49.9</td>
<td>51.6</td>
</tr>
<tr>
<td>Parallel</td>
<td>63.8</td>
<td>63.6</td>
<td>65</td>
</tr>
</tbody>
</table>

Table 6. The comparability measure of Li and Gaussier

The comparability measure is not a final objective, we would like to extract for future work comparable tweets and comparable documents. That is why we conducted an experiment which looks for each tweet in Arabic its best corresponding tweet in English. In Table 7, we give respectively the maximum and the average value of comparability between a tweet in Arabic and the set of English tweets. The corresponding results are given also for a supposedly comparable corpus (Euronews) at respectively a sentence and document level. In this case, globally, the average comparability measure is better, at a document level for Euronews than for Twitter at a tweet level. In table 8, we give a sample of Arabic and their corresponding extracted English tweets ExtTweet by using LG comparability measure. We give also the reference Reference which corresponds to the translation of the original tweet in Arabic.

In Figure 7, we give a chart describing the rate of pair of sentences for which the LG measure is greater than a certain threshold $\alpha$ for Twitter, Euronews and a Parallel corpus. This parameter could be considered such as a confidence measure that could be used in a future work to extract the best comparable and correlated tweets. We can notice that for $\alpha = 0.6$, we extract only 5% of comparable tweets, tweets supposed to handle the same idea. Only 8% from the parallel corpus are supposed to be comparable. This is an aberration, but this could be explained easily, in fact $LG$ is based only on a bilingual dictionary while in parallel corpus a sentence is not obtained by a word by word translation of the other one. When we relax the constraints by accepting an $LG$ greater than 0.3, we get for Twitter more than 98% of comparable tweets.

<table>
<thead>
<tr>
<th>Corpus</th>
<th>Max</th>
<th>Average</th>
</tr>
</thead>
<tbody>
<tr>
<td>Twitter</td>
<td>66</td>
<td>32.6</td>
</tr>
<tr>
<td>Euronews</td>
<td>60</td>
<td>27.3</td>
</tr>
<tr>
<td>Euronews document</td>
<td>65.8</td>
<td>35.8</td>
</tr>
</tbody>
</table>

Table 7. Comparability values between Arabic and English documents
Table 8. A sample of Arabic and the extracted corresponding English tweets

<table>
<thead>
<tr>
<th>Tweet</th>
<th>ExtTweet</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>ألفية العامة للجيش تعزى السيطرة على المحطة الحرارية بريف حلب</td>
<td>Syrian army has retaken completely under its control the thermal power plant east aleppo via</td>
<td>General Command of the Army announces the control of the thermal station in the countryside of Aleppo</td>
</tr>
<tr>
<td>الهيكل الأمريكية الروسية سوريا</td>
<td>The american russian and iranian strategic triangle in syria</td>
<td>US Russian Truce Syria</td>
</tr>
<tr>
<td>عاجل وقف إطلاق النار في سوريا لن يتبع ما لم تغير دمشق وموسكو</td>
<td>Urgent ceasefire in Syria will not succeed if Damascus and Moscow do not change their behavior in Syrian crisis</td>
<td></td>
</tr>
</tbody>
</table>
and English tweets close. In addition, with this simple method we retrieved tweets which could be considered as comparable. This result will be used in a future work to retrieve parallel phrases to build a machine translation system based on social network data.

References


