A multi-word term extraction program for Arabic language

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Abstract
Terminology extraction commonly includes two steps: identification of term-like units in the texts, mostly multi-word phrases, and the ranking of the extracted term-like units according to their domain representativity. In this paper, we design a multi-word term extraction program for Arabic language. The linguistic filtering performs a morphosyntactic analysis and takes into account several types of variations. The domain representativity is measured thanks to statistical scores. We evaluate several association measures and show that the results we obtained are consistent with those obtained for Romance languages.

1. Introduction

The development of a terminology extraction tool for Arabic language requires linguistic specifications of terms. Indeed, Arabic being an agglutinative language, statistical methods could not be applied straightforward and should be associated to linguistic treatments.

The aim of this work is to develop a multi-word term (MWT) extraction tool for Arabic. The identification of MWTs is crucial for terminology extraction because MWTs are less polysemous and more numerous than SWTs. For instance, (Nakagawa and Mori, 2002) show that more than 85% of domain-specific terms are multi-word terms.

To extract MWTs from corpora, we adopt the standard approach that combines grammatical patterns and statistical score (Cabrè et al., 2000). First, we defined the linguistic specification of MWTs for Arabic language. Then, we develop a term extraction program and evaluate several statistical measures in order to filter the extracted term-like units for keeping the most representative of domain specific corpus.

This paper is organized as follows: section 2 focuses on related work. In section 3, we present the linguistic specifications of Arabic multi-word terms and we detail in section 4 our methodology of multiword terms extraction. We present our results in section 5 and we conclude in section 6.

2. Related work

Approaches to MWT extraction proposed so far can be divided into three categories: a) statistical approaches based on frequency and co-occurrence affinity, b) symbolic approaches using parsers, lexicons and language filters, and c) hybrid approaches combining different methods (Smadja, 1993) (Church and Hanks, 1990) (Daille, 1994) (Sag et al., 2002) (Maynard and Ananiadou, 2000).

In practice, most statistical approaches employ linguistic filters to extract candidate MWTs (Church and Hanks, 1990). One of the main problems confronting statistical approaches, however, is that they are unable to deal with low-frequency of MWTs. In fact, the majority of the words in most corpora have low frequencies, occurring only once or twice. This means that a major part of multiword terms are excluded by statistical approaches. Lexical resources and parsers are used to obtain better coverage of the lexicon in MWT extraction. For example, In their DEFI Project, (Michiels and Dufour, 1998) used dictionaries to identify English and French multiword terms and their translations in the other language. Like pure statistical approaches, purely knowledge based symbolic approaches also face problems. They are language dependent and not flexible enough to cope with complex structures of MWTs. As (Sag et al., 2002) suggest, it is important to find the right balance between symbolic and statistical approaches. Our main interest in this paper is the development of a hybrid MWT tool for identifying and extracting Arabic MWTs from corpora.

3. Linguistic specifications of Arabic multi-word terms

Arabic words are formed with root-pattern schemes. Multi-word terms (MWTs) defined as idiosyncratic interpretations cross word boundaries (or spaces) (Sag et al., 2002). The main property of MWTs is the morphosyntactic one: its structure belongs to well-known morphosyntactic structures such as N ADJ, N1 N2, etc. that have been studied by Roman (1990) for Arabic.

3.1. MWT patterns

They consist of series of local grammar rules to detect MWTs having two content words. (Grammatical function words such as prepositions and determiners are permitted to intervene between the two content words). Some examples met in our corpus are presented in Table 1. For the description of Arabic terms, we applied Buckwalter’s transliteration system which transliterates Arabic alphabet into Latin alphabet.

3.2. MWT variation

The module for automatic term acquisition takes into account term variations. We followed the typology suggested (Daille, 2005).

\[\text{http://www.qamus.org/transliteration.htm}\]
3.2.1. Graphical variants

By graphical variants, we mean the graphic alternations between the letters p and h. Table 2 shows some examples of graphic alternations.

| Graphic alternation | Arabic MWT | English translation |
|----------------------|------------|---------------------|
| p/h                  | tlwv Altrb p/tlwv Altrb h | ground pollution |

Table 2: Graphical variants

3.2.2. Inflectional variants

In Arabic inflectional variant is a central issue in language processing as Arabic is an agglutinative language, with a very rich inflectional system. The amount of inflectional forms in which a given lemma or the 'canonical form' of a given term can appear in texts is extensive.

Inflectional variants include the number inflection of nouns, the number and gender inflections of adjectives (Jacquemin, 2001; Nenadic and Spasic, 2002), and the definite article that is carried out by the prefixed morpheme (Al).

Table 3 shows some examples of inflectional variants.

| Type       | Arabic MWT   | Variant   | English translation |
|------------|--------------|-----------|---------------------|
| Number     | tlwv AlmĀ’   | tlwv      | water pollution(s)  |
| Definitude | tlwv hwĀy    | Alhūv     | (the) air pollution |

Table 3: Inflectional variants

3.2.3. Morphosyntactic and syntactic variants

Morphosyntactic variants refer to the synonymy relationship between two MWTs of different structures. The example below shows synonymic terms of N1 ADJ and N1 PREP N2 structures.

The syntactic variants modify the internal structure of the base-term, without affecting the grammatical categories of the main item which remain identical. We distinguish modification and coordination variants. Table 5 shows some examples of syntactic variants.

| Structure alternation | Arabic MWT | English translation |
|-----------------------|------------|---------------------|
| N1 ADJ ↔ N1  b) nfty ↔ b) n mn | oil wells |

Table 5: Syntactic variants

4. Multi-word term extraction

The term extraction process is performed in two major steps: the selection of MWT-like units, using part-of-speech that has been assigned by the diab’s tagger (Diab et al., 2004), and the ranking of MWT-like units by means of statistical techniques, log-likelihood ratio (LLR) (Dunning, 1994), FLR (Nakagawa and Mori, 2003), Mutual Information (MI) (Kenneth and Hanks, 1989) and t-scores (Church et al., 1991). To filter the MWT-like units, we used their part-of-speech that has been assigned by the diab’s tagger (Diab et al., 2004). The MWT-like string patterns are described through morphosyntactic rules presented in Table 6.

Association measures are used in order To rank MWT like strings that have been collecting in the first step, The well-known association measures rely on different concepts. So, we compute several measures: log-likelihood ratio (LLR) (Dunning, 1994), FLR (Nakagawa and Mori, 2003), Mutual Information (MI) (Kenneth and Hanks, 1989) and t-scores (Church et al., 1991). Mutual Information (MI)
MWT Pattern | Part of speech pattern
--- | ---
N1 N2 | NN[P]? | NNs[P]?
N1 ADJ | NN[P]? | NNs[P]? | JJ
N1 PREP N2 | NN[P]? | NNs[P]? | IN | NN[P]? | NNs[P]?

Table 6: Pattern and Part-of-speech Mapping

(Kenneth and Hanks, 1989) was taken from Information Theory. Other measures such as the log-likelihood ratio (LLR) (Dunning, 1994) and t-score (Church et al., 1991) are based on hypothesis testing. FLR (Nakagawa and Mori, 2003) make the hypothesis that MWTs are often built around a limited number of single words and measures how many distinct words are part of MWTs.

5. Experimentation and Evaluation

5.1. Corpora used

Document retrieval experiments for Arabic language are done on general language corpora gathering newspaper articles are available. As it does not exist specialised domain corpora, we built a specialised corpus: the texts are taken from the environment domain and are extracted from the Web sites "Al-Khat Alakhdar" and "Akhabar Albai". The environment domain covers various environmental topics such as pollution, noise effects, water purification, soil degradation, forest preservation, climate change and natural disasters. The corpus contains 1.062 documents, 475.148 words from which 54.705 are distinct. The length of these documents varies between a paragraph and 40 pages.

5.2. Reference list

We create a reference list to automatically annotate the results of the statistical measures in section 5.3.. The reference list is collected from a list of known Arabic terms from the environmental domain such as Agrovoc. In total we compiled a list of 65,000 MWTs.

5.3. Comparing statistical measures

Before proceeding to the statistical analysis, however, one more step is required which is generating the bigrams and the corresponding frequency counts. In generating the bigrams, the program starts first by extracting strings using the pattern shown in the previous section. We compare four commonly-used approaches (defined in Table 7) to measure the strength of association of bigram word strings. Formulae are defined in terms of the contingency table. In this table, n11 is the frequency of the bigram xy, n12 is the frequency of x followed by any word other than y, and n1p is the total frequency all bigrams with x as the first word. n11 is the expected value of the bigram xy (n11 = n12 n1p / n1p). And for FLR score, XY = N1 N2N L, where Ni (i= 1,.., L) is a simple word. Then a geometric mean: LR of XY is defined as follows.

\[ LR-CN = \prod_{i=1}^{L} ((LN(N_i) + 1)(RN(N_i) + 1))^{\frac{1}{2}} \]  

Where

\[ LN(N) = \sum_{i=1}^{#LDN(N)} \#L_i \]  
\[ RN(N) = \sum_{j=1}^{#RDN(N)} \#R_j \]

\# LDN(N) and \# RDN(N) : These are the number of distinct MWTs.

5.4. Selecting the best measure

We evaluate the statistical algorithms against the environmental corpus (section 5.1.). We compute the association scores of the candidate multiword terms. We take from each produced ranking a set of 100 true terms, that match with our reference list, and calculate the precision as shown in equation:

\[ \text{precision} = \frac{\text{attested multiword terms}}{\text{all extracted sequences}} \]

We attested that a term is relevant to the environment domain if it has already been listed in existing terminology database. We note that the LLR, FLR and t-score measures, that are based on the significance of association measure, outperform the \( MI^3 \) measure. Note that LLR outperform other methods. These results are consistent with those reported in (Daille, 1994) (Hong et al., 2001) The results are shown in Table 8.

6. Conclusion

In this paper we presented our approach for the extraction of term candidates from Arabic technical texts. We have applied an hybrid approach for the extraction of MWT in Arabic for environment domain, combining the detection of term candidates through linguistic techniques with
the subsequent ranking of candidates according to different statistical measures. We defined the linguistic specification of MWTs for Arabic language. Results obtained for Arabic are similar to that of Romance languages.

Further works have still to be made to evaluate this approach in different domains and applications such as information retrieval or information extraction. Since MWTs have been useful for various applications of terminology processing (Ibekwe-SanJuan and Condamines, 2007) (Marcelline et al., 2003) and in IR (Haddad, 2002) (Ahlgren and Keklinen, 2006), we believe that our Arabic term extraction program will fill a gap in Arabic specialized language processing.

7. References

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