Multiword Unit Hybrid Extraction

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Abstract

This paper describes an original hybrid system that extracts multiword unit candidates from part-of-speech tagged corpora. While classical hybrid systems manually define local part-of-speech patterns that lead to the identification of well-known multiword units (mainly compound nouns), our solution automatically identifies relevant syntactical patterns from the corpus. Word statistics are then combined with the endogenously acquired linguistic information in order to extract the most relevant sequences of words. As a result, (1) human intervention is avoided providing total flexibility of use of the system and (2) different multiword units like phrasal verbs, adverbial locutions and prepositional locutions may be identified. The system has been tested on the Brown Corpus leading to encouraging results.

1 Introduction

Multiword units (MWUs) include a large range of linguistic phenomena, such as compound nouns (e.g. interior designer), phrasal verbs (e.g. run through), adverbal locutions (e.g. on purpose), compound determinants (e.g. an amount of), prepositional locutions (e.g. in front of) and institutionalized phrases (e.g. con carne). MWUs are frequently used in everyday language, usually to precisely express ideas and concepts that cannot be compressed into a single word. As a consequence, their identification is a crucial issue for applications that require some degree of semantic processing (e.g. machine translation, summarization, information retrieval).

In recent years, there has been a growing awareness in the Natural Language Processing (NLP) community of the problems that MWUs pose and the need for their robust handling. For that purpose, syntactical (Didier Bourigault, 1993), statistical (Frank Smadja, 1993; Ted Dunning, 1993; Gaël Dias, 2002) and hybrid syntaxico-statistical methodologies (Béatrice Daille, 1996; Jean-Philippe Goldman et al. 2001) have been proposed.

In this paper, we propose an original hybrid system called HELAS\(^1\) that extracts MWU candidates from part-of-speech tagged corpora. Unlike classical hybrid systems that manually pre-define local part-of-speech patterns of interest (Béatrice Daille, 1996; Jean-Philippe Goldman et al. 2001), our solution automatically identifies relevant syntactical patterns from the corpus. Word statistics are then combined with the endogenously acquired linguistic information in order to extract the most relevant sequences of words i.e. MWU candidates. Technically, we conjugate the Mutual Expectation (ME) association measure with the acquisition process called GenLocalMaxs (Gaël Dias, 2002) in a five step process. First, the part-of-speech tagged corpus is divided into two sub-corpora: one containing words and one containing part-of-speech tags. Each sub-corpus is then segmented into a set of positional ngrams i.e. ordered vectors of textual units. Third, the ME independently evaluates the degree of cohesiveness of each positional ngram i.e. any positional ngram of words and any positional ngram of part-of-speech tags. A combination of both MEs is then used to evaluate the global degree of cohesiveness of any sequence of words associated with its respective part-of-speech tag sequence. Finally, the GenLocalMaxs retrieves all the MWU candidates by evidencing local maxima of association measure values thus avoiding the definition of global thresholds. The overall architecture can be seen in Figure 1.

Compared to existing hybrid systems, the benefits of HELAS are clear. By avoiding human intervention in the definition of syntactical patterns, it provides total

\(^1\) HELAS stands for Hybrid Extraction of Lexical ASSociations.
flexibility of use. Indeed, the system can be used for any language without any specific tuning. HELAS also allows the identification of various MWUs like phrasal verbs, adverbial locations, compound determinants, prepositional locations and institutionalized phrases. Finally, it responds to some extent to the affirmation of Benoît Habert and Christian Jacquemin (1993) that claim that “existing hybrid systems do not sufficiently tackle the problem of the interdependency between the filtering stage [the definition of syntactical patterns] and the acquisition process [the scoring and the election of relevant sequences of words] as they propose that these two steps should be independent”.

Figure 1: Global architecture of HELAS

The article is divided into five main sections: (1) we introduce the related work; (2) we present the text corpus segmentation into positional ngrams; (3) we define the Mutual Expectation and a new combined association measure; (4) we propose the GenLocalMaxs algorithm as the acquisition process; Finally, in (5), we present some results over the Brown Corpus.

2 Related Work

For the purpose of MWU extraction, syntactical, statistical and hybrid syntaxico-statistical methodologies have been proposed. On one hand, purely linguistic systems (Didier Bourigault, 1993) propose to extract relevant MWUs by using techniques that analyse specific syntactical structures in the texts. However, these methodologies suffer from their monolingual basis as the systems require highly specialised linguistic techniques to identify clues that isolate possible MWU candidates.

On the other hand, purely statistical systems (Frank Smadja, 1993; Ted Dunning, 1993; Gaël Dias, 2002) extract discriminating MWUs from text corpora by means of association measure regularities. As they use plain text corpora and only require the information appearing in texts, such systems are highly flexible and extract relevant units independently from the domain and the language of the input text. However, these methodologies can only identify textual associations in the context of their usage. As a consequence, many relevant structures cannot be introduced directly into lexical databases as they do not guarantee adequate linguistic structures for that purpose.

Finally, hybrid syntactico-statistical systems (Béatrice Daille, 1996; Jean-Philippe Goldman et al. 2001) define co-occurrences of interest in terms of syntactical patterns and statistical regularities. Thus, such systems reduce the searching space to groups of words that correspond to a priori defined syntactical patterns (e.g. Adj+Noun, Noun+Prep+Noun) and apply statistical scores to identify the most relevant sequences of words. One major drawback of such systems is that they do not deal with a great proportion of interesting MWUs (e.g. phrasal verbs, prepositional locations). Moreover, they lack flexibility as the syntactical patterns have to be revised whenever the targeted language changes.

In order to overcome these difficulties, we propose an original architecture that combines word statistics with endogenously acquired linguistic information. We base our study on two assumptions. On one hand, a great deal of studies in lexicography and terminology assess that most of the MWUs evidence well-known morphosyntactic structures (Gaston Gross, 1996). On the other hand, MWUs are recurrent combinations of words. Indeed, according to Benoît Habert and Christian Jacquemin (1993), the MWUs may represent a fifth of the overall surface of a text. Consequently, it is reasonable to think that the syntactical patterns embodied by the MWUs may be endogenously identified by using statistical scores over texts of part-of-speech tags exactly in the same manner as word dependencies are identified in corpora of words. So, the global degree of cohesiveness of any sequence of words may be evaluated by a combination of its degree of cohesiveness of words and the degree of cohesiveness of its associated part-of-speech tag sequence (See Figure 1).

Compared to existing systems, the benefits of our architecture are clear. By avoiding human intervention in the definition of syntactical patterns, (1) HELAS provides total flexibility of use being independent of the targeted
language and (2) it allows the identification of various MWUs like phrasal verbs, adverbial locutions, compound determinants, prepositional locutions and institutionalized phrases.

3 Text Segmentation

Positional ngrams are nothing more than ordered vectors of textual units which principles are introduced in the next subsection.

3.1 Positional Ngrams

The original idea of the positional ngram model (Gaël Dias, 2002) comes from the lexicographic evidence that most lexical relations associate words separated by at most five other words (John Sinclair, 1974). As a consequence, lexical relations such as MWUs can be continuous or discontinuous sequences of words in a context of at most eleven words (i.e. 5 words to the left of a pivot word, 5 words to the right of the same pivot word and the pivot word itself). In general terms, a MWU can be defined as a specific continuous or discontinuous sequence of words in a context of at most eleven words (i.e. 

\[ F \] words to the left of a pivot word, 

\[ F \] words to the right of the same pivot word and the pivot word itself). This situation is illustrated in Figure 2 for the multiword unit Ngram Statistics that fits in the window context of size \(2.3+1=7\).

![Figure 2: 7-word size window context](image)

Thus, any substring (continuous or discontinuous) that fits inside the window context and contains the pivot word is called a positional word ngram. For instance, [Ngram Statistics] is a positional word ngram as is the discontinuous sequence [Ngram __ from] where the gap represented by the underline stands for any word occurring between Ngram and from (in this case, Statistics). More examples are given in Table 1.

| Positional word 2grams | Positional word 3grams |
|------------------------|------------------------|
| [Ngram Statistics]     | [Ngram Statistics from]|
| [Ngram ___ from]       | [Ngram Statistics ___ Large]|
| [Ngram ___ ___ Large]  | [Ngram ___ from Large] |
| [to ___ Ngram]         | [to ___ Ngram ___ from]|

Table 1: Possible positional ngrams

Generically, any positional word ngram may be defined as a vector of words \([p_{11}, u_1, p_{12}, u_2, \ldots, p_{1n}, u_n]\) where \(u_i\) stands for any word in the positional ngram and \(p_{ij}\) represents the distance that separates words \(u_i\) and \(u_{ij}\). Thus, the positional word ngram [Ngram Statistics] would be rewritten as [0 Ngram +1 Statistics]. More examples are given in Table 2.

| Positional word ngrams | Algebraic notation |
|------------------------|--------------------|
| [Ngram ___ from]       | [0 Ngram +2 from] |
| [Ngram ___ ___ Large]  | [0 Ngram +3 Large]|
| [to ___ Ngram]         | [0 to +2 Ngram]   |
| [Ngram Statistics ___ Large] | [0 Ngram +1 Statistics +3 Large] |

Table 2: Algebraic Notation

However, in a part-of-speech tagged corpus, each word is associated to a unique part-of-speech tag. As a consequence, each positional word ngram is linked to a corresponding positional tag ngram. A positional tag ngram is nothing more than an ordered vector of part-of-speech tags exactly in the same way a positional word ngram is an ordered vector of words. Let’s exemplify this situation. Let’s consider the following portion of a part-of-speech tagged sentence following the Brown tag set:

Virtual /JJ Approach /NN to /IN Deriving /VBG Ngram /NN Statistics /NN from /IN Large /JJ Scale /NN Corpus /NN

It is clear that the corresponding positional tag ngram of the positional word ngram [0 Ngram +1 Statistics] is the vector \([0 /NN +1 /NN]\). More examples are in Table 3. Generically, any positional tag ngram may be defined as a vector of part-of-speech tags \([p_{11}, t_1, p_{12}, t_2, \ldots, p_{1n}, t_n]\) where \(t_i\) stands for any part-of-speech tag in the positional tag ngram and \(p_{ij}\) represents the distance that separates the part-of-speech tags \(t_i\) and \(t_j\).

| Positional word ngrams | Positional tag ngrams |
|------------------------|-----------------------|
| [0 Ngram +2 from]      | [0 /NN +2 /NN]        |
| [0 Ngram +3 Large]     | [0 /NN +3 /JJ]        |
| [0 to +2 Ngram]        | [0 /IN +2 /NN]        |
| [0 Ngram +1 Statistics +3 Large] | [0 /NN +1 /NN +3 /JJ] |

Table 3: Positional tag ngrams

So, any sequence of words, in a part-of-speech tagged corpus, is associated to a positional word ngram and a corresponding positional tag ngram. In order to introduce the part-of-speech tag factor in any sequence of words of part-of-speech tagged corpus, we present an alternative notation of positional ngrams called positional word-tag ngrams.

In order to represent a sequence of words with its associated part-of-speech tags, a positional ngram may be represented by the following vector of words and part-
of-speech tags \( [p_1, u_1, t_1, p_2, u_2, t_2, \ldots, p_n, u_n, t_n] \) where \( u_i \) stands for any word in the positional ngram, \( t_i \) stands for the part-of-speech tag of the word \( u_i \) and \( p_i \) represents the distance that separates words \( u_i \) and \( u_j \). Thus, the positional ngram \( \text{Ngram Statistics} \) can be represented by the vector \( [0 \text{ Ngram } /NN +1 \text{ Statistics } /NN] \) given the text corpus in section (3.1). More examples are given in Table 4.

| Positional ngrams | Alternative notation |
|-------------------|----------------------|
| [Ngram ___ from]   | [0 Ngram /NN +2 from /NN] |
| [Ngram ___ Large]  | [0 Ngram /NN +3 Large /JJ] |
| [to ___ Ngram]     | [0 to /IN +2 Ngram /NN] |

Table 4: Alternative Notation

This alternative notation will allow us to defining, with elegance, our combined association measure, introduced in the next section.

3.2 Data Preparation

So, the first step of our architecture deals with segmenting the input text corpus into positional ngrams. First, the part-of-speech tagged corpus is divided into two sub-corpora: one sub-corpus of words and one sub-corpus of part-of-speech tags. The word sub-corpus is then segmented into its set of positional word ngrams exactly in the way the tagged sub-corpus is segmented into its set of positional tag ngrams.

In parallel, each positional word ngram is associated to its corresponding positional tag ngram in order to further evaluate the global degree of cohesiveness of any sequence of words in a part-of-speech tagged corpus. Our basic idea is to evaluate the degree of cohesiveness of each positional ngram independently (i.e. the positional word ngrams on one side and the positional tag ngrams on the other side) in order to calculate the global degree of cohesiveness of any sequence in the part-of-speech tagged corpus by combining its respective degrees of cohesiveness i.e. the degree of cohesiveness of its sequence of words and the degree of cohesiveness of its sequence of part-of-speech tags.

In order to evaluate the degree of cohesiveness of any sequence of textual units, we use the association measure called Mutual Expectation.

4 Cohesiveness Evaluation

The Mutual Expectation (ME) has been introduced by Gaël Dias (2002) and evaluates the degree of cohesiveness of links that connect together all the textual units contained in a positional ngram (\( \forall n, n \geq 2 \)) based on the concept of Normalized Expectation and relative frequency.

4.1 Normalized Expectation

The basic idea of the Normalized Expectation (NE) is to evaluate the cost, in terms of cohesiveness, of the loss of one element in a positional ngram. Thus, the NE is defined in Equation 1 where the function \( k(\cdot) \) returns the frequency of any positional ngram\(^3\).

\[
NE([p_1 \ldots u_k \ldots p_n]) = \frac{k([p_1 \ldots u_k \ldots p_n])}{1 + \sum_{j=2}^{n} k([p_1 \ldots u_j])}
\]

Equation 1: Normalized Expectation

In order to exemplify the NE formula, we present in Equation 2 its development for the given positional ngram \([0 A +2 C +3 D +4 E]\) where each letter may represent a word or a part-of-speech tag.

\[
NE([0 A, 2, 3 D, 4 E]) = \frac{k([0 A, 2, 3 D, 4 E])}{k([0 A, 2, 3 D]) + k([0 A, 2, 4 E]) + k([0 A, 3 D, 4 E]) + k([0 C, 1, 2 D])}
\]

Equation 2: Normalized Expectation example

However, evaluating the average cost of the loss of an element is not enough to characterize the degree of cohesiveness of a sequence of textual units. The Mutual Expectation is introduced to solve this insufficiency.

4.2 Mutual Expectation

Many applied works in Natural Language Processing have shown that frequency is one of the most relevant statistics to identify relevant textual associations. For instance, in the context of multiword unit extraction, (John Justeson and Slava Katz, 1995; Béatrice Daille, 1996) assess that the comprehension of a multiword unit is an iterative process being necessary that a unit should be pronounced more than one time to make its comprehension possible. Gäel Dias (2002) believes that this phenomenon can be enlarged to part-of-speech tags. From this assumption, they pose that between two positional ngrams with the same NE, the most frequent positional ngram is more likely to be a relevant sequence.

So, the Mutual Expectation of any positional ngram is defined in Equation 3 based on its NE and its relative frequency embodied by the function \( p(\cdot) \).

\[^3\] The "^" corresponds to a convention used in Algebra that consists in writing a "^" on the top of the omitted term of a given succession indexed from 1 to n.
We will note that the ME shows interesting properties. One of them is the fact that it does not sub-evaluate interdependencies when frequent individual textual units are present. In particular, this allows us to avoid the use of lists of stop words. Thus, when calculating all the positional ngrams, all the words and part-of-speech tags are used. This fundamentally participates to the flexibility of use of our system.

As we said earlier, the ME is going to be used to calculate the degree cohesiveness of any positional word ngram and any positional tag ngram. The way we calculate the global degree of cohesiveness of any sequence of words associated to its part-of-speech tag sequence, based on its two MEs, is discussed in the next subsection.

4.3 Combined Association Measure

The drawbacks shown by the statistical methodologies evidence the lack of linguistic information. Indeed, these methodologies can only identify textual associations in the context of their usage. As a consequence, many relevant structures cannot be introduced directly into lexical databases as they do not guarantee adequate linguistic structures for that purpose.

In this paper, we propose a first attempt to solve this problem without pre-defining syntactical patterns of interest that bias the extraction process. Our idea is simply to combine the strength existing between words in a sequence and the evidenced interdependencies between its part-of-speech tags. We could summarize this idea as follows: the more cohesive the words of a sequence and the more cohesive its part-of-speech tags, the more likely the sequence may embody a multiword unit.

This idea can only be supported due to two assumptions. On one hand, a great deal of studies in lexicography and terminology assess that most of the MWUs evidence well-known morpho-syntactic structures (Gaston Gross, 1996). On the other hand, MWUs are recurrent combinations of words capable of representing a fifth of the overall surface of a text (Benoi\'t Habert and Christian Jacquemin, 1993). Consequently, it is reasonable to think that the syntactical patterns embodied by the MWUs may endogenously be identified by using statistical scores over texts of part-of-speech tags exactly in the same manner as word dependencies are identified in corpora of words. So, the global degree of cohesiveness of any sequence of words may be evaluated by a combination of its own ME and the ME of its associated part-of-speech tag sequence. The degree of cohesiveness of any positional ngram based on a part-of-speech tagged corpus can then be evaluated by the combined association measure (CAM) defined in Equation 4 where $\alpha$ stands as a parameter that tunes the focus whether on words or on part-of-speech tags.

$$\text{CAM}(\text{W}) = \left( \prod_{i=1}^{n} \text{ME}(\text{W}_i) \right)^{\alpha} \prod_{i=1}^{n} \text{ME}(\text{W}_i)$$

Equation 4: Combined Association Measure

We will see in the final section of this paper that different values of $\alpha$ lead to fundamentally different sets of multiword unit candidates. Indeed, $\alpha$ can go from a total focus on part-of-speech tags (i.e. the relevance of a word sequence is based only on the relevance of its part-of-speech sequence) to a total focus on words (i.e. the relevance of a word sequence is defined only by its word dependencies). Before going to experimentation, we need to introduce the used acquisition process which objective is to extract the MWUs candidates.

5 The Acquisition Process

The GenLocalMaxs (Gaël Dias, 2002) proposes a flexible and fine-tuned approach for the selection process as it concentrates on the identification of local maxima of association measure values. Specifically, the GenLocalMaxs selects MWUs from the set of all the valued positional ngrams based on two assumptions. First, the association measures show that the more cohesive a group of words is, the higher its score will be. Second, MWUs are localized associated groups of words. So, we may deduce that a positional word-tag ngram is a MWU if its combined association measure value is higher or equal than the combined association measure values of all its sub-groups of $(n-1)$ words and if it is strictly higher than the combined association measure values of all its super-groups of $(n+1)$ words. Let $\text{cam}$ be the combined association measure, $W$ a positional word-tag ngram, $\Omega_{n}$, the set of all the positional word-tag $(n-1)$-grams contained in $W$, $\Omega_{n+1}$, the set of all the positional word-tag $(n+1)$-grams containing $W$ and $\text{sizeof}(.)$ a function that returns the number of words of a positional word-tag ngram. The GenLocalMaxs is defined as:

\[
\forall x \in \Omega_{n+1}, \forall y \in \Omega_{n+1}, \text{sizeof}(W) > \text{sizeof}(x) \land \text{cam}(W) > \text{cam}(y) \]

Definition 1: GenLocalMaxs Algorithm

Among others, the GenLocalMaxs shows one important property: it does not depend on global thresholds. A
direct implication of this characteristic is the fact that, as no tuning needs to be made in order to acquire the set of all the MWU candidates, the use of the system remains as flexible as possible. Finally, we show the results obtained by applying HELAS over the Brown Corpus.

6 The Experiments

In order to test our architecture, we have conducted a number of experiments with 11 different values of \( \alpha \) for a portion of the Brown Corpus containing 249 578 words i.e. 249 578 words plus its 249 578 part-of-speech tags. The limited size of our corpus is mainly due to the space complexity of our system. Indeed, the number of computed positional ngrams is huge even for a small corpus. For instance, 21 463 192 positional ngrams are computed for this particular corpus for a 7-word size window context. As a consequence, computation is hard. For this experiment, HELAS has been tested on a personal computer with 128 Mb of RAM, 20 Gb of Hard Disk and an AMD 1.4 Ghz processor under Linux Mandrake 7.2. On average, each experiment (i.e. for a given \( \alpha \)) took 4 hours and 20 minutes. Knowing that our system increases proportionally with the size of the corpus, it was unmanageable, for this particular experiment, to test our architecture over a bigger corpus. Even though, the whole processing stage lasted almost 48 hours.

We will divide our experiment into two main parts. First, we will do a quantitative analysis and then we will lead a qualitative analysis. All results will only tackle contiguous multiword units although non-contiguous sequences may be extracted. This decision is due to the lack of space.

6.1 Quantitative Analysis

In order to understand, as deeply as possible, the interaction between word cohesiveness and part-of-speech tag cohesiveness, we chose eleven different values for \( \alpha \), i.e. \( \alpha \in \{0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1\} \), going from total focus on words (\( \alpha = 1\)) to total focus on part-of-speech tags (\( \alpha = 0\)).

First, we show the number of extracted contiguous MWU candidates by \( \alpha \) in table 5. The total results are not surprising. Indeed, with \( \alpha = 0 \), the focus is exclusively on part-of-speech tags. It means that any word sequence, with an identified relevant part-of-speech sequence, is extracted independently of the words it contains. For instance, all the word sequences with the pattern [\( JJ \) /\( NN \)] (i.e. Adjective + Noun) may be extracted independently of their word dependencies! This obviously leads to an important number of extracted sequences. The inclusion of the word factor, by increasing the value of \( \alpha \), progressively leads to a decreasing number of extracted positional ngrams. In fact, the word sequences with relevant syntactical structures are being filtered out depending on their word statistics. Finally, with \( \alpha = 1 \), the focus is exclusively on words. The impact of the syntactical structure is null and the positional ngrams are extracted based on their word associations. In this case, the word sequences do not form classes of morpho-syntactic structures being the reason why less positional ngrams are extracted.

We are already working on an efficient implementation of HELAS using suffix-arrays and the concept of masks.

| \( \alpha \) | 0     | 0.1   | 0.2   | 0.3   | 0.4   | 0.5   |
|-------------|-------|-------|-------|-------|-------|-------|
| 2gram       | 23146 | 21980 | 20074 | 17689 | 15450 | 13461 |
| 3gram       | 297   | 467   | 567   | 351   | 1188  | 1693  |
| 4gram       | 86    | 108   | 127   | 163   | 225   | 326   |
| 5gram       | 79    | 81    | 81    | 82    | 77    | 62    |
| 6gram       | 82    | 57    | 56    | 57    | 56    | 58    |
| TOTAL       | 23670 | 22603 | 20905 | 18342 | 16996 | 15620 |

**Table 5:** Number of extracted MWU candidates

A deeper analysis of table 5 reveals interesting results. The smaller the values of \( \alpha \), the more positional 2grams are extracted. This situation is illustrated in Figure 3.

Once again these results are not surprising. The Mutual Expectation tends to give more importance to frequent sequences of textual units. While it performs reasonably well on word sequences, it tends to over-evaluate the part-of-speech tag sequences. Indeed, sequences of two part-of-speech tags are much more frequent than other types of sequences and, as a consequence, tend to be over-evaluated in terms of cohesiveness. As small values of \( \alpha \) focus on syntactical structures, it is clear that in this case, small sequences of words are preferred over longer sequences.
By looking at Figure 3 and Table 5, we may think that a
great number of extracted sequences are common to
each experiment. However, this is not true. In order
to assess this affirmation, we propose, in Table 6, the
summary of the identical ratio.

| \( \alpha \) | 0   | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 |
|------------|-----|-----|-----|-----|-----|-----|
| 0          | 14.64 | 5.74 | 2.99 | 1.73 | 1.17 | 1.0 |
| 0.1        | 9.99  | 3.77 | 2.08 | 1.35 | 1.0  | 1.0 |
| 0.2        | 9.99  | 3.77 | 2.08 | 1.35 | 1.0  | 1.0 |
| 0.3        | 8.2   | 2.83 | 1.69 | 1.0  | 1.0  | 1.0 |
| 0.4        | 4.99  | 2.36 | 1.0  | 1.0  | 1.0  | 1.0 |
| 0.5        | 3.51  | 1.0  | 1.0  | 1.0  | 1.0  | 1.0 |
| 0.6        | 0.83  | 0.54 | 0.49 | 0.47 | 1.0  | 1.0 |
| 0.7        | 0.70  | 0.59 | 0.54 | 0.52 | 1.0  | 1.0 |
| 0.8        | 0.81  | 0.61 | 0.61 | 0.69 | 1.0  | 1.0 |
| 0.9        | 1.0   | 1.0  | 1.0  | 1.0  | 1.0  | 1.0 |
| 1.0        | 1.0   | 1.0  | 1.0  | 1.0  | 1.0  | 1.0 |

Table 6: Identical Ratio

The identical ratio calculates, for two values of \( \alpha \), the
quotient between the number of identical extracted se-
quencies and the number of different extracted se-
quencies. Thus, the first value of the first row of table 6,
represents the identical ratio for \( \alpha = 0 \) and \( \alpha = 0.1 \), and
means that there are 14.64 times more identical ex-
tracted sequences than different sequences between both
experiments.

Taking \( \alpha = 0 \) and \( \alpha = 1 \), it is interesting to see that there are
much more different sequences than identical sequences
between both experiments (identical ratio = 0.47). In
fact, this phenomenon progressively increases as the
word factor is being introduced in the combined asso-
ciation measure to reach \( \alpha = 1 \). This was somewhat unex-
pected. Nevertheless, this situation can be partly
decrypted from Figure 3. Indeed, figure 3 shows that
longer sequences are being preferred as \( \alpha \) increases. In
fact, what happens is that short syntactically well-
founded sequences are being replaced by longer word
sequences that may lack linguistic information. For in-
stance, the sequence \( \text{Blue Mosque} \) was extracted with
\( \alpha = 0 \), although the longer sequence \( \text{the Blue Mosque} \)
was preferred with \( \alpha = 1 \) as whenever \( \text{Blue Mosque} \) appears
in the text, the determinant \( \text{the} \) precedes it.

Finally, a last important result concerns the frequency of
the extracted sequences. Table 7 gives an overview of the
situation. The figures are clear. Most of the ex-
tracted sequences occur only twice in the input text cor-
pus. This result is rather encouraging as most known
extractors need high frequencies in order to decide
whether a sequence is a MWU or not. This situation is
mainly due to the GenLocalMaxs algorithm.

| \( \alpha \) | 0   | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 |
|------------|-----|-----|-----|-----|-----|-----|
| 0.1        | 12355 | 13095 | 12335 | 11061 | 10803 | 10458 |
| 0.2        | 42003 | 39852 | 38156 | 31184 | 27533 | 23848 |
| 0.3        | 1952 | 1828 | 1949 | 1350 | 1166 | 980 |
| 0.4        | 1091  | 1019 | 917 | 743  | 608  | 511 |
| 0.5        | 28998 | 26999 | 24868 | 2070 | 16966 | 1307 |
| TOTAL      | 23670 | 22603 | 20905 | 18342 | 16996 | 15620 |

Table 7: Number of extracted MWUs by frequency

6.2 Qualitative Analysis

As many authors assess (Frank Smadja, 1993; John
Justeson and Slava Katz, 1995), deciding whether a se-
quence of words is a multiword unit or not is a tricky
problem. For that purpose, different definitions of mul-
tiword unit have been proposed. One of the most suc-
sessful attempts can be attributed to Gaston Gross
(1996) that classifies multiword units into six groups
and provides techniques to determine their belonging.
As a consequence, we intend as multiword unit any
compound noun (e.g. interior designer), compound deter-
minant (e.g. an amount of), verbal locution (e.g. run
through), adverbial locution (e.g. on purpose), adjectival
locution (e.g. dark blue) or prepositional locution (e.g. in
front of).

The analysis of the results has been done \textit{intramuros}
although we are aware that an external independent
cross validation would have been more suited. How-
ever, it was not logistically possible to do so and by
using Gaston Gross’ classification and methodology,
we narrow the human error evaluation as much as pos-
sible. Technically, we have randomly extracted and ana-
lysed 200 positional 2grams, 200 positional 3grams and
100 positional 4grams for each value of \( \alpha \). For the spe-
cific case of positional 5grams and 6grams, all the se-
quences have been analysed.

Precision results of this analysis are given in table 8 and
show that word dependencies and part-of-speech tag
dependencies may both play an important role in the
identification of relevant sequences. Indeed, values of \( \alpha \)
between 0.4 and 0.5 seem to lead to optimum results.
Knowing that most extracted sequences are positional
2grams or positional 3grams, the global precision results
approximate the results given by 2grams and 3grams. In
these conditions, the best results are for \( \alpha = 0.5 \) reaching
an average precision of 62 %. This would mean that
word dependencies and part-of-speech tags contribute equally to multiword unit identification.

| ngram | 0.0 | 0.1 | 0.2 | 0.3 | 0.4 |
|-------|-----|-----|-----|-----|-----|
| 2gram | 29 % | 22 % | 30 % | 44 % | 53 % |
| 3gram | 32 % | 77 % | 74 % | 73 % | 80 % |
| 4gram | 38 % | 32 % | 32 % | 46 % | 41 % |
| 5gram | 34 % | 28 % | 29 % | 31 % | 33 % |
| 6gram | 29 % | 22 % | 18 % | 24 % | 31 % |

Table 8: Precision in % by alpha

A deeper look at the results evidences interesting regularities as shown in figure 4. Indeed, the curves for 4grams, 5grams and 6grams are reasonably steady along the X axis evidencing low results. This means, to some extent, that our system does not seem to be able to tackle successfully multiword units with more than three words. In fact, neither a total focus on words or on part-of-speech tags seems to change the extraction results. However, the importance of these results must be weakened as they represent a small proportion of the extracted structures.

Figure 4: Precision by alpha and ngram

On the other hand, the curves for 2grams and 3grams show different behaviours. For the 3gram case, it seems that the syntactical structure plays an important role in the identification process. Indeed, precision falls down drastically when the focus passes to word dependencies. This is mainly due to the extraction of recurrent sequences of words that do not embody multiword unit syntactical structures like [been able to] or [can still be]. As 2grams are concerned, the situation is different. In fact, it seems that too much focus on either words or part-of-speech tags leads to unsatisfactory results. Indeed, optimum results are obtained for a balance between both criteria. This result can be explained by the fact that there exist many recurrent sequences of two words in a corpus. However, most of them are not multiword units like [of the] or [can be]. For that reason, only a balanced weight on part-of-speech tag and word dependencies may identify relevant two word sequences. However, not-so-high precision results show that two-word sequences still remain a tricky problem for our extractor as it is difficult to filter out very frequent patterns that embody meaningless syntactical structures.

7 Conclusion

This paper describes an original hybrid system that extracts multiword unit candidates by endogenously identifying relevant syntactical patterns from the corpus and by combining word statistics with the acquired linguistic information. As a result, by avoiding human intervention in the definition of syntactical patterns, (1) HELAS provides total flexibility of use being independent of the targeted language and (2) it allows the identification of various MWUs like compound nouns, compound determinants, verbal locutions, adverbal locutions, prepositional locutions and adjectival locutions without defining any threshold or using lists of stop words. The system has been tested on the Brown Corpus leading to encouraging results evidenced by a precision score of 62 % for the best configuration. The system will soon be available on http://helas.di.ubi.pt.

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