Applying Collocation Segmentation to the ACL Anthology Reference Corpus

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Abstract

Collocation is a well-known linguistic phenomenon which has a long history of research and use. In this study I employ collocation segmentation to extract terms from the large and complex ACL Anthology Reference Corpus, and also briefly research and describe the history of the ACL. The results of the study show that until 1986, the most significant terms were related to formal/rule based methods. Starting in 1987, terms related to statistical methods became more important. For instance, language model, similarity measure, text classification. In 1990, the terms Penn Treebank, Mutual Information, statistical parsing, bilingual corpus, and dependency tree became the most important, showing that newly released language resources appeared together with many new research areas in computational linguistics. Although Penn Treebank was a significant term only temporarily in the early nineties, the corpus is still used by researchers today. The most recent significant terms are Bleu score and semantic role labeling. While machine translation as a term is significant throughout the ACL ARC corpus, it is not significant for any particular time period. This shows that some terms can be significant globally while remaining insignificant at a local level.

1 Introduction

Collocation is a well-known linguistic phenomenon which has a long history of research and use. The importance of the collocation paradigm shift is raised in the most recent study on collocations (Sertan, 2011). Collocations are a key issue for tasks like natural language parsing and generation, as well as real-life applications such as machine translation, information extraction and retrieval. Collocation phenomena are simple, but hard to employ in real tasks. In this study I introduce collocation segmentation as a language processing method, maintaining simplicity and clarity of use as per the n-gram approach. In the beginning, I study the usage of the terms collocation and segmentation in the ACL Anthology Reference Corpus (ARC), as well as other related terms such as word, multi-word, and n-gram. To evaluate the ability of collocation segmentation to handle different aspects of collocations, I extract the most significant collocation segments in the ACL ARC. In addition, based on a ranking like that of TF-IDF, I extract terms that are related to different phenomena of natural language analysis and processing. The distribution of these terms in ACL ARC helps to understand the main breakpoints of different research areas across the years. On the other hand, there was no goal to make a thorough study of the methods used by the ACL ARC, as such a task is complex and prohibitively extensive.

2 ACL Anthology Reference Corpus

This study uses the ACL ARC version 20090501. The first step was to clean and preprocess the corpus. First of all, files that were unsuitable for the analysis were removed. These were texts containing characters with no clear word boundaries, i.e., each character was separated from the next by whitespace. This problem is related to the extraction of text from .pdf
format files and is hard to solve. Each file in the ACL ARC represents a single printed page. The file name encodes the document ID and page number, e.g., the file name C04-1001_0007.txt is made up of four parts: C is the publication type, (20)04 is the year, 1001 is the document ID, and 0007 is the page number. The next step was to compile files of the same paper into a single document. Also, headers and footers that appear on each document page were removed, though they were not always easily recognized and, therefore, some of them remained. A few simple rules were then applied to remove line breaks, thus keeping each paragraph on a single line. Finally, documents that were smaller than 1 kB were also removed. The final corpus comprised 8,581 files with a total of 51,881,537 tokens.

3 Terms in the ACL ARC related to collocations

The list of terms related to the term collocation could be prohibitively lengthy and could include many aspects of what it is and how it is used. For simplicity’s sake, a short list of related terms, including word, collocation, multiword, token, unigram, bigram, trigram, collocation extraction and segmentation, was compiled. Table 2 shows when these terms were introduced in the ACL ARC: some terms were introduced early on, others more recently. The term collocation was introduced nearly 50 years ago and has been in use ever since. This is not unexpected, as collocation phenomena were already being studied by the ancient Greeks (Seretan, 2011). Table 2 presents the first use of terms, showing that the terms segmentation, collocation and multiword are related to a similar concept of gathering consecutive words together into one unit.

While the term collocation has been used for many years, the first attempt to define what a collocation is could be related to the time period when statistics first began to be used in linguistics heavily. Until that time, collocation was used mostly in the sense of an expression produced by a particular syntactic rule. The first definition of collocation in ACL ARC is found in (Cumming, 1986).

(Cumming, 1986): By “collocation” I mean lexical restrictions (restrictions which are not predictable from the syntactic or semantic properties of the items) on the modifiers of an item; for example, you can say answer the door but not answer the window. The phenomenon which I’ve called collocation is of particular interest in the context of a paper on the lexicon in text generation because this particular type of idiom is something which a generator needs to know about, while a parser may not.

It is not the purpose of this paper to provide a definition of the term collocation, because at the moment there is no definition that everybody would agree upon. The introduction of unigrams, bigrams and trigrams in the eighties had a big influence on the use of collocations in practice. N-grams, as a substitute to collocations, started being used intensively and in many applications. On the other hand, n-grams are lacking in generalization capabilities and recent research tends to combine n-grams, syntax and semantics (Pecina, 2005).

The following sections introduce collocation segmentation and apply it to extracting the most significant collocation segments to study the main breakpoints of different research areas in the ACL ARC.

4 Collocation Segmentation

The ACL ARC contains many different segmentation types: discourse segmentation (Levow, 2004), topic segmentation (Arguello and Rose, 2006), text segmentation (Li and Yamanishi, 2000), Chinese text segmentation (Feng et al., 2004), word segmentation (Andrew, 2006). Segmentation is performed by detecting boundaries, which may also be of several different types: syllable boundaries (Müller, 2006), sentence boundaries (Liu et al., 2004), clause boundaries (Sang and Dejean, 2001), phrase boundaries (Bachenko and Fitzpatrick, 1990), prosodic boundaries (Collier et al., 1993), morpheme bound-

| Term                      | Count   | Documents | Introduced in |
|---------------------------|---------|-----------|---------------|
| word                      | 218813  | 7725      | 1965          |
| segmentation              | 11458   | 1413      | 1965          |
| collocation               | 6046    | 786       | 1965          |
| multiword                 | 1944    | 650       | 1969          |
| token                     | 3841    | 760       | 1973          |
| trigram                   | 3841    | 760       | 1973/87       |
| bigram                    | 5812    | 995       | 1988          |
| unigram                   | 2223    | 507       | 1989          |
| collocation extraction    | 214     | 57        | 1992          |

Table 1: Term usage in ACL ARC
"Of the same simplicity and uniqueness is the decomposition of the sentence S in its single words $w_1, w_2, ..., w_k$ separated by interspaces, so that it is possible to write $s = (w_1 w_2 ... w_k)$ like at the text."

A word is the result of a sentence decomposition.

The statement “x is transformed to y” is a generalization of the original fact, and this generalization is not always true. The text should be checked before a transformational rule is applied to it. Some separate steps for this purpose will save the machine time. (1) A text to be parsed must consist of segments specified by the rule. The correct segmentation can be done by finding the tree structure of the text. Therefore, the concatenation rules must be prepared so as to account for the structure of any acceptable string.

We shall include features such as lexical collocation (agent-action agreement) and transformations of semantic equivalence in a systematic description of a higher order which presupposes a morpho-syntactic description for each language [8, pp. 66-71]. The following analogy might be drawn: just as strings of alphabetic and other characters are taken as a body of data to be parsed and classified by a phrase structure grammar, we may regard the string of rule numbers generated from a phrase structure analysis as a string of symbols to be parsed and classified in a still higher order grammar [11; 13, pp. 67-83], for which there is as yet no universally accepted nomenclature.

When title indices and catalogs, subject indices and catalogs, business telephone directories, scientific and technical dictionaries, lexicons and idiom-and-phrase dictionaries, and other descriptive multi-word information are desired, the first character of each non-trivial word may be selected in the original word sequence to form a keyword. For example, the rather lengthy title of this paper may have a keyword as SADSIRS. Several known information systems are named exactly in this manner such as SIR (Raphael’s Semantic Information Retrieval), SADSM (Lindsay’s Sentence Appraiser and Diagrammer and Semantic Analyzing Machine), BIRS (Vinsonhaler’s Basic Indexing and Retrieval System), and CGC (Klein and Simmons’ Computational Grammar Coder).

The type/token ratio is calculated by dividing the number of discrete entries by the total number of syntagms in the row.

sort of phoneme triples (trigrams), giving list of clusters and third-order information-theoretic values.

Bigrams are in general too short to contain any useful identifying information while tetragrams and larger n-gram are already close to average word length.

Our goal is to develop a methodology for extending an n-gram model to an (n+1)-gram model. We regard the model for unigrams as completely fixed before beginning to study bigrams.

Collocation segmentation is a new type of segmentation whose goal is to detect fixed word sequences and to segment a text into word sequences called collocation segments. I use the definition of a sequence in the notion of one or more. Thus, a collocation segment is a sequence of one or more consecutive words that collocates and have collocatability relations. A collocation segment can be of any

| Term                      | Source and Citation |
|---------------------------|---------------------|
| word                      | (Culik, 1965) : 3. Translation ‘word by word’. |
| segmentation              | (Sakai, 1965): The statement “x is transformed to y” is a generalization of the original fact, and this generalization is not always true. The text should be checked before a transformational rule is applied to it. Some separate steps for this purpose will save the machine time. (1) A text to be parsed must consist of segments specified by the rule. The correct segmentation can be done by finding the tree structure of the text. Therefore, the concatenation rules must be prepared so as to account for the structure of any acceptable string. |
| Collocation                | (Tosh, 1965): We shall include features such as lexical collocation (agent-action agreement) and transformations of semantic equivalence in a systematic description of a higher order which presupposes a morpho-syntactic description for each language [8, pp. 66-71]. The following analogy might be drawn: just as strings of alphabetic and other characters are taken as a body of data to be parsed and classified by a phrase structure grammar, we may regard the string of rule numbers generated from a phrase structure analysis as a string of symbols to be parsed and classified in a still higher order grammar [11; 13, pp. 67-83], for which there is as yet no universally accepted nomenclature. |
| multi-word                | (Yang, 1969): When title indices and catalogs, subject indices and catalogs, business telephone directories, scientific and technical dictionaries, lexicons and idiom-and-phrase dictionaries, and other descriptive multi-word information are desired, the first character of each non-trivial word may be selected in the original word sequence to form a keyword. For example, the rather lengthy title of this paper may have a keyword as SADSIRS. Several known information systems are named exactly in this manner such as SIR (Raphael’s Semantic Information Retrieval), SADSM (Lindsay’s Sentence Appraiser and Diagrammer and Semantic Analyzing Machine), BIRS (Vinsonhaler’s Basic Indexing and Retrieval System), and CGC (Klein and Simmons’ Computational Grammar Coder). |
| token                     | (Beebe, 1973): The type/token ratio is calculated by dividing the number of discrete entries by the total number of syntagms in the row. |
| trigram                   | (Knowles, 1973): sort of phoneme triples (trigrams), giving list of clusters and third-order information-theoretic values. (D’Orta et al., 1987): Such a model it called trigram language model. It is based on a very simple idea and, for this reason, its statistics can be built very easily only counting all the sequences of three consecutive words present in the corpus. On the other hand, its predictive power is very high. |
| bigram                    | (van Berkelt and Smedt, 1988): Bigrams are in general too short to contain any useful identifying information while tetragrams and larger n-gram are already close to average word length. (Church and Gale, 1989): Our goal is to develop a methodology for extending an n-gram model to an (n+1)-gram model. We regard the model for unigrams as completely fixed before beginning to study bigrams. |
| unigram                   | the same as bigram for (Church and Gale, 1989) |
| collocation extraction    | (McKeown et al., 1992): Added syntactic parser to Xtract, a collocation extraction system, to further filter collocations produced, eliminating those that are not consistently used in the same syntactic relation. |

Table 2: Terms introductions in ACL ARC.
Figure 1: The collocation segmentation of the sentence *a collocation is a recurrent and conventional fixed expression of words that holds syntactic and semantic relations.* (Xue et al., 2006).

length (even a single word) and the length is not defined in advance. This definition differs from other collocation definitions that are usually based on n-gram lists (Tjong-Kim-Sang and S., 2000; Choueka, 1988; Smadja, 1993). Collocation segmentation is related to collocation extraction using syntactic rules (Lin, 1998). The syntax-based approach allows the extraction of collocations that are easier to describe, and the process of collocation extraction is well-controlled. On the other hand, the syntax-based approach is not easily applied to languages with fewer resources. Collocation segmentation is based on a discrete signal of associativity values between two consecutive words, and boundaries that are used to chunk a sequence of words.

The main differences of collocation segmentation from other methods are: (1) collocation segmentation does not analyze nested collocations it takes the longest one possible in a given context, while the n-gram list-based approach cannot detect if a collocation is nested in another one, e.g., *machine translation system*; (2) collocation segmentation is able to process long collocations quickly with the complexity of a bigram list size, while the n-gram list-based approach is usually limited to 3-word collocations and has high processing complexity.

There are many word associativity measures, such as Mutual Information (MI), T-score, Log-Likelihood, etc. A detailed overview of associativity measures can be found in (Pecina, 2010), and any of these measures can be applied to collocation segmentation. MI and Dice scores are almost similar in the sense of distribution of values (Daudaravicius and Marcinkeviciene, 2004), but the Dice score is always in the range between 0 and 1, while the range of the MI score depends on the corpus size. Thus, the Dice score is preferable. This score is used, for instance, in the collocation compiler XTract (Smadja, 1993) and in the lexicon extraction system Champollion (Smadja et al., 1996). Dice is defined as follows:

\[
D(x_{i-1}; x_i) = \frac{2 \cdot f(x_{i-1}; x_i)}{f(x_{i-1}) + f(x_i)}
\]

where \(f(x_{i-1}; x_i)\) is the number of co-occurrence of \(x_{i-1}\) and \(x_i\), and \(f(x_{i-1})\) and \(f(x_i)\) are the numbers of occurrence of \(x_{i-1}\) and \(x_i\) in the training corpus. If \(x_{i-1}\) and \(x_i\) tend to occur in conjunction, their Dice score will be high. The Dice score is sensitive to low-frequency word pairs. If two consecutive words are used only once and appear together, there is a good chance that these two words are highly related and form some new concept, e.g., a proper name. A text is seen as a changing curve of Dice values between two adjacent words (see Figure 1). This curve of associativity values is used to detect the boundaries of collocation segments, which can be done using a threshold or by following certain rules, as described in the following sections.
| length | unique segments | segment count | word count | corpus coverage |
|--------|-----------------|---------------|------------|----------------|
| 1      | 289,277         | 31,427,570    | 31,427,570| 60.58%         |
| 2      | 222,252         | 8,594,745     | 17,189,490| 33.13%         |
| 3      | 72,699          | 994,393       | 2,983,179 | 5.75%          |
| 4      | 12,669          | 66,552        | 266,208   | 0.51%          |
| 5      | 1075            | 2,839         | 14,195    | 0.03%          |
| 6      | 57              | 141           | 846       | 0.00%          |
| 7      | 3               | 7             | 49        | 0.00%          |
| Total  | 598,032         | 41,086,247    | 51,881,537| 100%           |

Table 3: The distribution of collocation segments

| 2 word segments | CTFIDF | 3 word segments | CTFIDF |
|-----------------|--------|-----------------|--------|
| machine translation | 10777  | in terms of      | 4099   |
| speech recognition  | 10524  | total number of  | 3926   |
| training data       | 10401  | th international conference | 3649   |
| language model      | 10188  | is used to       | 3614   |
| named entity        | 9006   | one or more      | 3449   |
| error rate          | 8280   | a set of         | 3439   |
| test set            | 8083   | note that the    | 3346   |
| maximum entropy     | 7570   | it is not        | 3320   |
| sense disambiguation| 7546   | is that the      | 3287   |
| training set        | 7515   | associated with the | 3211   |
| noun phrase         | 7509   | large number of  | 3189   |
| our system          | 7352   | there is a       | 3189   |
| question answering  | 7346   | support vector machines | 3111   |
| information retrieval| 7338   | are used to      | 3109   |
| the user            | 7198   | extracted from the | 3054   |
| word segmentation   | 7194   | with the same    | 3030   |
| machine learning    | 7128   | so that the      | 3008   |
| parse tree          | 6987   | for a given      | 2915   |
| knowledge base      | 6792   | it is a          | 2909   |
| information extraction| 6675   | fact that the    | 2876   |

Table 4: Top 20 segments for the segment length of two to five words.
4.1 Setting segment boundaries with a Threshold

A boundary can be set between two adjacent words in a text when the Dice value is lower than a certain threshold. We use a dynamic threshold which defines the range between the minimum and the average associativity values of a sentence. Zero equals the minimum associativity value and 100 equals the average value of the sentence. Thus, the threshold value is expressed as a percentage between the minimum and the average associativity values. If the threshold is set to 0, then no threshold filtering is used and no collocation segment boundaries are set using the threshold. The main purpose of using a threshold is to keep only strongly connected tokens. On the other hand, it is possible to set the threshold to the maximum value of associativity values. This would make no words combine into more than single word segments, i.e., collocation segmentation would be equal to simple tokenization. In general, the threshold makes it possible to move from only single-word segments to whole-sentence segments by changing the threshold from the minimum to the maximum value of the sentence. There is no reason to use the maximum value threshold, but this helps to understand how the threshold can be used. (Daudaravicius and Marcinkeviciene, 2004) uses a global constant threshold which produces very long collocation segments that are like the clichés used in legal documents and hardly related to collocations. A dynamic threshold allows the problem of very long segments to be reduced. In this study I used a threshold level of 50 percent. An example of threshold is shown in Figure 1. In the example, if the threshold is 50 percent then segmentation is as follows: a collocation is a recurrent and conventional fixed expression of words that holds syntactic and semantic relations. To reduce the problem of long segments even more, the Average Minimum Law can also be used, as described in the following section.

4.2 Setting segment boundaries with Average Minimum Law

(Daudaravicius, 2010) introduces the Average Minimum Law (AML) for setting collocation segmentation boundaries. AML is a simple rule which is applied to three adjacent associativity values and is expressed as follows:

\[
\text{boundary}(x_{i-2}, x_{i-1}) = \begin{cases} 
\text{True} & \frac{D(x_{i-3}; x_{i-2}) + D(x_{i-1}; x_i)}{2} < D(x_{i-2}; x_{i-1}) \\
\text{False} & \text{otherwise}
\end{cases}
\]

The boundary between two adjacent words in the text is set where the Dice value is lower than the average of the preceding and following Dice values. In order to apply AML to the first two or last two words, I use sequence beginning and sequence ending as tokens and calculate the associativity between the beginning of the sequence and the first word, and the last word and the end of the sequence as shown in Figure 1. AML can be used together with Threshold or alone. The recent study of (Daudaravicius, 2012) shows that AML is able to produce segmentation that gives the best text categorization results, while the threshold degrades them. On the other hand, AML can produce collocation segments where the associativity values between two adjacent words are very low (see Figure 1). Thus, for lexicon extraction tasks, it is a good idea to use AML and a threshold together.

5 Collocation segments from the ACL ARC

Before the collocation segmentation, the ACL ARC was preprocessed with lowercasing and tokenization. No stop-word lists, taggers or parsers were used, and all punctuation was kept. Collocation segmentation is done on a separate line basis, i.e., for each text line, which is usually a paragraph, the average and the minimum combinability values are determined and the threshold is set at 50 percent, midway between the average and the minimum. The Average Minimum Law is applied in tandem. The tool CoSegment for collocation segmentation is available at (http://textmining.lt/).

Table 3 presents the distribution of segments by length, i.e., by the number of words. The length of collocation segments varies from 1 to 7 words. In the ACL ARC there are 345,455 distinct tokens. After segmentation, the size of the segment list was 598,032 segments, almost double the length of the single word list. The length of the bigram list is...
4,484,358, which is more than 10 times the size of the word list and 7 times that of the collocation segment list. About 40 percent of the corpus comprises collocation segments of two or more words, showing the amount of fixed language present therein. The longest collocation segment is described in section 2.2, which contains seven words (when punctuation is included as words). This shows that collocation segmentation with a threshold of 50 percent and AML diverges to one-, two- or three-word segments. Despite that, the list size of collocation segments is much shorter than the list size of bigrams, and shorter still than that of trigrams.

After segmentation, it was of interest to find the most significant segments used in the ACL ARC. For this purpose I used a modified TF-IDF which is defined as follows:

$$CTFIDF(x) = TF(x) \times \ln \left( \frac{N - D(x) + 1}{D(x) + 1} \right)$$

where $TF(x)$ is the raw frequency of segment $x$ in the corpus, $N$ is the total number of documents in the corpus, and $D(x)$ is the number of documents in which the segment $x$ occurs. Table 4 presents the top 20 collocation segments for two-, three-, four- and five-word segments of items that contain alphabetic characters only. The term machine translation is the most significant in CTFIDF terms. This short list contains many of the main methods and datasets used in daily computational linguistics research, such as: error rate, test set, maximum entropy, training set, parse tree, unknown words, word alignment, Penn Treebank, language models, mutual information, translation model, etc. These terms show that computational linguistics has its own terminology, methods and tools to research many topics.

Finally, 76 terms of two or more words in length with the highest CTFIDF values were selected. The goal was to try to find how significant terms were used yearly in the ACL ARC. The main part of the ACL ARC was compiled using papers published after 1995. Therefore, for each selected term, the average CTFIDF value of each document for each year was calculated. This approach allows term usage throughout the history of the ACL to be analysed, and reduces the influence of the unbalanced amount of published papers. Only those terms whose average CTFIDF in any year was higher than 20 were kept. For instance, the term machine translation had to be removed, as it was not significant throughout all the years. Each term was ranked by the year in which its average CTFIDF value peaked. The ranked terms are shown in Table 5. For instance, the peak of the CTFIDF average of the term statistical parsing occurred in 1990, of the term language model in 1987, and of the term bleu score in 2006. The results (see Table 5) show the main research trends and time periods of the ACL community. Most of the terms with CTFIDF peaks prior to 1986 are related to formal/rule-based methods. Beginning in 1987, terms related to statistical methods become more important. For instance, language model, similarity measure, and text classification. The year 1990 stands out as a kind of breakthrough. In this year, the terms Penn Treebank, Mutual Information, statistical parsing, bilingual corpus, and dependency tree became the most important terms, showing that newly released language resources were supporting many new research areas in computational linguistics. Despite the fact that Penn Treebank was only significant temporarily, the corpus is still used by researchers today. The most recent important terms are Bleu score and semantic role labeling.

This study shows that collocation segmentation can help in term extraction from large and complex corpora, which helps to speed up research and simplify the study of ACL history.

6 Conclusions

This study has shown that collocation segmentation can help in term extraction from large and complex corpora, which helps to speed up research and simplify the study of ACL history. The results show that the most significant terms prior to 1986 are related to formal/rule based research methods. Beginning in 1987, terms related to statistical methods (e.g., language model, similarity measure, text classification) become more important. In 1990, a major turning point appears, when the terms Penn Treebank, Mutual Information, statistical parsing, bilingual corpus, and dependency tree become the most important, showing that research into new areas of compu-
tational linguistics is supported by the publication of new language resources. The Penn Treebank, which was only significant temporarily, it still used today. The most recent terms are Bleu score and semantic role labeling. While machine translation as a term is significant throughout the ACL ARC, it is not significant in any particular time period. This shows that some terms can be significant globally, but insignificant at a local level.

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Table 5: The list of selected terms and the yearly importance in terms of CTFIDF.