The Context (not only) for Humans

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Abstract

Our context considerations will be practically oriented; we will explore the specification of a context scope in the Czech morphological tagging. We mean by morphological tagging/annotation the automatic/manual disambiguation of the output of morphological analysis. The Prague Dependency Treebank (PDT) serves as a source of annotated data. The main aim is to concentrate on the evaluation of the influence of the chosen context on the tagging accuracy.

1. English and Czech Tagging Experiments

The corpus-based approaches determine the amount of human work involved in the NLP tasks on the building of training data and on the coming up with an algorithm giving results as precise as possible. The ideas of context specification cannot be left out in the formulation of the algorithm. The scope of context must be specified according to the character of the particular NLP task. As we consider the nature of context from the perspective of the tagging application, an elementary unit we process is a word token. In general, there is no strict rule saying how many preceding and following word tokens we should look at to be sure that we tag the word token properly. Thus, let us have a look at the empirical experience.

| STRATEGY        | TAGGER ID | TRAINING DATA | TA (%) |
|-----------------|-----------|---------------|--------|
| Trigram Markov model (Merlialdo, 1994) | MM_EN | Associated Press (955Kw) | 97.0   |
| Maximum Entropy (Ratnaparkhi, 1996) | ME_EN | WSJ (926Kw) | 96.6   |
| Exponential model (Hajič, Hladká, 1998b) | EXP_EN | WSJ (1.2 Mw) | 96.8   |
| Memory-based (Daelemans, Zavrel, 1996) | MB_EN | WSJ (2Mw) | 96.4   |
| Rule-based (Brill, 1993b) | RB_EN | WSJ (600Kw) | 96.9   |
| Neural Networks (Schmid, 1994) | NE_EN | WSJ (2Mw) | 96.2   |

Table 1: Tagging experiments on English

Let \( W = w_1 w_2 w_3 \ldots w_n \) be an input text to be tagged. As all the presented tagging strategies tag the input text in the left-to-right direction, a word token \( w_i \) is processed when the word tokens \( w_1 w_2 \ldots w_{i-1} \) have already been tagged - \( w_1 \mid w_{i-1} \mid w_i \mid w_{i+1} \ldots w_n \) \(^1\) For the currently processed word token \( w_i \), the context \( c(w_i) \) of the representative corpus-based tagging strategies for tagging Czech (MM_CZ then, MM_CZ exp, EXP_CZ tags - see Tab. 1) and English (MM_EN, ME_EN, EXP_EN, MB_EN, RB_EN, NE_EN tags - see Tab. 2) can be expressed as follows:

| STRATEGY | TAGGER ID | TRAINING DATA | TA (%) |
|----------|-----------|---------------|--------|
| Bigram Markov model | MM_CZ_\text{ex} | PDT (300Kw) | 92.50  |
| Trigram Markov model | MM_CZ_\text{exp} | PDT (300Kw) | 93.38  |
| Exponential model | EXP_CZ | PDT (300Kw) | 93.85  |

Table 2: Tagging experiments on Czech

\(^1\) As the EXP tagger operates on a subtag level let \( m_a \) consist of all possible values of \( i \)-th morphological category within the positional tag.

\(^2\) (Hladká, 2000) provides very detailed view on the issue of Czech language tagging.
side context\(^3\) while the other strategies look not only at the left positions but consider also the right-hand side context. Some authors offer practical experience with a modification of the context scope. In the paper (Schmid, 1994), the author describes the context shrinking to two preceding and one following words together with their tags which causes accuracy reduction only by 0.1%. Enlarging the context gave no improvement. The authors (Daelemans, Zavrel, 1996) do not specify directly the context scope, but they construct a distance metrics between similar environments within modest contexts. We can conclude that the enumerated contexts as a whole are limited up to 4 positions to the left/right.

2. The Context for Humans

At the starting point of the tagging procedure, all tagging strategies are given the same input text. The input text (as a whole) is understood as a whole text context. Consequently, the tagging strategies select from the whole text context any subcontext over which they process the given word token. Let us limit the subcontext to the word tokens \((w_1, w_2, ..., w_{i-1})\) preceding the currently processed word token \((w_i)\) within the input text. For a vocabulary size \(n\) there are \(n^{i-1}\) different subcontexts (for ex. \(n = 1,000\) and \(i = 4\) then \(n^3 = 10^6\)). The problem which immediately appears concerns the matrices (of \(n^{i-1}\) order) representing the counts of particular subcontexts within the training corpus. With regard to the astronomically large number of such subcontexts, a vast majority of the possible subcontexts will never occur in Czech (or other natural language) and that is the reason why the given matrices are sparse. Nevertheless, the computational linguists’ effort is directed to deal with sparseness of data being connected with context specification.

None of the representative corpus-based tagging methods do achieve the magic point of 100% performance (Table 1, 2). It is supposed that the context can reveal almost all the secrets of a language. We stress almost, in some cases the context is not enough to specify the function/meaning of a word form. As we are interested in context-based models of a language, the magic point of such models cannot be 100% because the world knowledge which is hidden somewhere between the lines cannot be read in the set of word forms and tags.

The bigram and trigram MMs employ the smallest left-hand side context size relatively to the other corpus-based methods; at the same time, their performances are the best (Table 1, 2). We believe that a further improvement of MMs lies in a better selection of the analysed context. Not to limit ourselves only to experiments modifying the context size and in order to discover certain guidelines we explore how people handle the information coming from the predefined left-hand side context.

2.1. Prerequisites

The annotation of the test file was assigned to a group of 5 students: 2 undergraduate students (S1, S2) with rich experience learned during the annotation of the PDT; 3 computational linguistics graduate students (S3, S4, S5) - one of them (S5) with an experience with various tagging strategies and one of them (S4) being bilingual not educated in Czech. The test file that was given to the students comprised a 283 word token subset (141 unambiguous tokens and 142 ambiguous tokens) of the test file which we used in the tagging experiments mentioned above (MM\(_{CZ\_tri}\), MM\(_{CZ\_bi}\), EXP\(_{CZ}\)). For purposes of evaluation of the tagging and annotation, the given test file was annotated independently by another annotator upon an unlimited context.

2.1.1. Formalism

Let \(S = w_1w_2...w_s\) be a sentence\(^4\) (a sequence of word tokens) we tag/annotate in the left-to-right direction, \(S_{\text{tokens}} = (w_i)_{i=1,s}\) be a list of word tokens occurring in the sentence \(S\). While tagging the \(i\)-th word, the \(i-1\) preceding word tokens are already tagged by tags \(t_1, t_2, ..., t_{i-1}\); let \(T\) be a list of tags \((t_j)_{j=1...i-1}\).

The contexts which come into play during the experiments of annotation (BC, TC, SC) and the experiments of tagging (TTC, BTC) can be defined as functions:

- **Bigram Context (BC)** as a function

  \[
  BC : S_{\text{tokens}} \rightarrow 2^{S_{\text{tokens}}},
  \]
  \[
  BC(w_i) = \{w_{i-1}\}, BC(w_1) = \emptyset
  \]

- **Tag Bigram Context (TBC)** as a function

  \[
  TBC : S_{\text{tokens}} \rightarrow 2^T,
  \]
  \[
  TBC(w_i) = \{t_{i-1}\}, TBC(w_1) = \emptyset
  \]

- **Trigram Context (TC)** as a function

  \[
  TC : S_{\text{tokens}} \rightarrow 2^{S_{\text{tokens}}},
  \]
  \[
  TC(w_i) = \{w_{i-1}, w_{i-2}\}, TC(w_1) = \emptyset,
  \]
  \[
  TC(w_2) = \{w_1\}
  \]

- **Tag Trigram Context (TTC)** as a function

  \[
  TTC : S_{\text{tokens}} \rightarrow 2^T,
  \]
  \[
  TTC(w_i) = \{t_{i-1}, t_{i-2}\}, TTC(w_1) = \emptyset,
  \]
  \[
  TTC(w_2) = \{t_1\}
  \]

- **Sentence Context (SC)** as a function

  \[
  SC : S_{\text{tokens}} \rightarrow 2^{S_{\text{tokens}}},
  \]
  \[
  SC(w_i) = \{w_1, ..., w_{i-1}\}, SC(w_1) = \emptyset
  \]

To illustrate the defined terms, let us assume a sample of the sentence fragment *O další Stříbrné medvědy se podělily...* [lit. about – further – Silver – Bears – Refl. – they-shared ... E. The remaining (Prizes of) Silver Bears were obtained by ...] and let us suppose that the first four word tokens are already tagged O[RR–4--——- další|AAMP4-----1A---- Stříbrné|AAMP4-----1A----

\(^3\)In the end, the incorporation of the Viterbi algorithm to find the best tag sequence means the usage of the right-hand side context.

\(^4\)We consider a context within a sentence, we do not cross the sentence boundaries.
medvědy]\text{NNMP}4------A----. Then the word token \textit{se} is to be tagged/annotated. According to the chosen particular context, the word token \textit{se} is being processed within the context information embodied in one of the sets \textit{BC} (se) = \{medvědy\}, \textit{TC} (se) = \{Šťábrné, medvědy\}, \textit{SC} (se) = \{O, další, Šťábrné, medvědy\}, \textit{TTC} (se) = \{AAMP---1A----, NNMP4------A----\}, \textit{BTC} (se) = \{NNMP4------A----\}.

### 2.2. How Humans Treat the Context Information

A specially developed tool for morphological annotation (Hajič, Hladká, 1998b), which offers an easy disambiguation of lemmas and tags (which are outputs of the automatic morphological analysis), was used as a disambiguation tool, which displays, for the currently annotated ambiguous word token, its morphological information and the whole text context. For our aims, we have modified the disambiguation tool in the sense of the visibility of a partial context; in case of Bigram Context only the previous word token is visible, for Trigram Context only two previous word tokens are, and finally, for Sentence Context the preceding word tokens up to the beginning of the sentence are at the annotator’s disposal. We have to stress that unambiguous word tokens remain obviously untouched by the annotator and while annotating the given ambiguous word token the annotators have no information on the assigned tags of the word tokens which are included in the context; annotators just suggest a hypothesis of the tags of the context word tokens themselves. On the other hand, the presented Markov models working over Tag Trigram/Bigram Context do not deal with the word tokens.

### 3. Discussion of the Results

Table 3 provides information on the evaluation of the annotation and tagging of the given test file. Reading the table horizontally, we observe that all the students are getting better as the context enlarges. Reading the table vertically, we speculate that the learned experience in the course of the annotation over the whole context comes into play (students S1, S2 vs. students S3, S4, S5). On the other hand, the knowledge of the tagging methods seems not to be so important (student S5). The bigram MMs beat the students annotating over the bigram context TBC. However, the situation is inverse for the trigram contexts TTC, TC - annotation almost beats tagging.

Tables 4 and 5 give a detailed view on the annotation/tagging on a subtag level. A more interesting observation concerns the way how the error rate over these MCs changes as the context enlarges.

Looking at Tab. 6, the numbers represent decreasing/increasing (positive/negative numbers) of the error rates over the MCs \textit{gender}, \textit{number}, \textit{case} for each student and the MM taggers. For example, for student S3, the error rate over \textit{gender} decreases by 0.36\% if the bigram context (BC) is enlarged to the trigram context (TC) and at the same time it decreases by 0.7\% if the trigram context (TC) is enlarged to the sentence context (SC). Given the Czech typical word order and given the assumed left-hand side contexts, the improvement of the \textit{case} error rate is more expressive than the changes of the \textit{gender} and \textit{number} error rates. Again, given the Czech word order, it is necessary to include the right-hand side context to identify the \textit{gender} and \textit{number} of the word token.

The strategy of human annotation described above can be understood only as a simulation of the MMs. The humans work with the left-hand side context from the beginning till the end; the MMs assign to the currently processed word token tags with regard to the left-hand side context as well, but the incorporation of the Viterbi algorithm to find the best tag sequence which means, in fact, the usage of the right-hand side context in fact.

Putting together this fact and the insufficiently represen-
Table 5: Error rates (%) over the gender, number, case

| annotator/tagger | context | g   | n   | c   |
|------------------|---------|-----|-----|-----|
| S3               | BC      | 4.95| 3.18| 8.13|
|                  | TC      | 4.59| 1.77| 2.83|
|                  | SC      | 3.89| 1.41| 2.47|
| S4               | BC      | 6.36| 3.53| 13.43|
|                  | TC      | 4.24| 3.18| 8.83|
|                  | SC      | 4.95| 2.47| 6.36|
| S1               | BC      | 4.59| 1.77| 5.65|
|                  | TC      | 2.83| 1.77| 4.24|
|                  | SC      | 2.12| 1.06| 1.41|
| S2               | BC      | 2.83| 0.35| 3.53|
|                  | TC      | 1.06| 0.35| 1.06|
|                  | SC      | 1.41| 0.35| 1.06|
| S5               | BC      | 6.36| 2.47| 6.01|
|                  | TC      | 4.95| 2.12| 3.89|
|                  | SC      | 4.59| 2.47| 3.89|
| MM_CZ_A         | BTC     | 2.47| 0.71| 6.71|
| MM_CZ_Ari       | TTC     | 2.12| 0.35| 5.30|

Table 6: The error rate changes (%) due to the context enlarging

| morphological category | context enlarging | the error rate improvement (%) |
|------------------------|-------------------|--------------------------------|
| annotator/tagger       |                   |                                |
| TC→-BC                 | S3                | 0.36                           |
| SC→-TC                 |                   | 1.41                           |
|                       |                   | 5.3                            |
| TC→-BC                 | S4                | -0.71                          |
| SC→-TC                 |                   | 0.35                           |
|                       |                   | 4.6                            |
| TC→-BC                 | S1                | 1.76                           |
| SC→-TC                 |                   | 0.71                           |
|                       |                   | 1.41                           |
| TC→-BC                 | S2                | 1.77                           |
| SC→-TC                 |                   | 0.71                           |
|                       |                   | 2.83                           |
| TC→-BC                 | S5                | -0.35                          |
| SC→-TC                 |                   | 0.35                           |
|                       |                   | 2.12                           |
| TC→-BC                 | MM_CZ             | 1.68                           |
| SC→-TC                 |                   | 0.35                           |
|                       |                   | -0.35                          |
| SC→-TC                 |                   | 0.00                           |
|                       |                   | 2.47                           |
| SC→-TC                 | MM_CZ             | 0.35                           |
| TTC→-TBC               |                   | 0.36                           |
|                       |                   | 1.41                           |

Table 5: Error rates (%) over the gender, number, case

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