Automatic construction of complex features in Conditional Random Fields for Named Entities Recognition

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Abstract

Conditional Random Fields (CRFs) have been proven to be very useful in many sequence labelling tasks from the field of natural language processing, including named entity recognition (NER). The advantage of CRFs over other statistical models (like Hidden Markov Models) is that they can utilize a large set of features describing a sequence of observations. On the other hand, CRFs potential function is defined as a linear combination of features, what means, that it cannot model relationships between combinations of input features and output labels. This limitation can be overcome by defining the relationships between atomic features as complex features before training the CRFs. In the paper we present the experimental results of automatic generation of complex features for the named entity recognition task for Polish. A rule-induction algorithm called RIPPER is used to generate a set of rules which are latter transformed into a set of complex features. The extended set of features is used to train a CRFs model.

1 Background

Named entity recognition (NER) is an information extraction task and its goal is to identify and categorize text fragments which refer to some objects. Objects can be referred to by proper names, definite descriptions and noun phrases (LDC, 2008). From the perspective of information extraction tasks proper names are the most valuable as they identify the objects by their unique (to some extent) name. In this paper we will focus on identification of proper names for Polish.

There exist several tools for named entity recognition for Polish, including Liner2¹ (Marcińczuk et al., 2013) and Nerf² (Savary and Waszczuk, 2012). So far, the existing tools do not solve the problem of named entity once and for all. For a limited set of named entities (first names, last names, names of countries, cities and roads) the results are 70.53% recall with 91.44% precision (Marcińczuk and Janicki, 2012). Results for a wider range of entities are even lower, i.e. recall of 54% with 93% precision for 56 categories of named entities (Marcińczuk et al., 2013). Savary and Waszczuk (2012) presented a statistical model which obtained 76% recall with 83% precision for names of people, places, organizations, time expressions and name derivations tested on the National Corpus of Polish³ (Przepiórkowski et al., 2012).

The recent works on named entity recognition focus mainly on improving the machine learning-based approaches. One direction is to decompose the task into two stages: named entity boundary detection and classification (Marcińczuk and Kocoń, 2013). The other is identification of new features which will provide better information to identify the named entities (Marcińczuk and Kocoń, 2013). Another direction is combination of different machine learning methods into a single classifier (Speck and Ngonga Ngomo, 2014). There is also another tendency which is based on increasing the size of training data by their automatic generation from Wikipedia (Al-Rfou et al., 2015). Last but not least direction is improvement of named entity recognition for noisy data, like “tweets” (Piskorski and Ehrmann, 2013; Küçük et al., 2014).

In our study we will follow another route whose goal is to generate a set of complex features based on an existing set of token features. In Section 2

¹Web page: http://nlp.pwr.wroc.pl/liner2.
²Web page: http://zil.ipipan.waw.pl/Nerf.
³Home page: http://nkjp.pl
we present the motivation for complex features generation and explain, why the current state-of-the-art approach based on Conditional Random Fields cannot model complex dependencies between features and classes on its own. In Section 3 we present a baseline set of features and propose three new auxiliary token features. Section 4 presents a procedure for generation complex features for a predefined set of basic features utilizing an existing algorithm for rule induction called RIPPER. In Section 5 we present the results of empirical evaluation and, finally, in Section 6 we discuss the obtained results.

2 Motivation for complex features

CRFs are type of discriminative models which are trained to maximize the conditional probability of observations \( (x) \) and classes \( (y) \) sequences \( P(y|x) \). The conditional probability distribution is represented as a multiplication of feature functions exponents:

\[
P(y|x) = \frac{1}{Z_0} exp \left( \sum_{i=1}^{n} \sum_{k=1}^{m} \lambda_k f_k(y_{i-1}, y_i, x) \right.
\]

\[
+ \sum_{i=1}^{n} \sum_{k=1}^{m} \mu_k g_k(y_i, x) \right)
\]

where \( Z_0 \) is a normalization factor, \( f_k(y_{i-1}, y_i, x) \) and \( g_k(y_i, x) \) are feature functions, and \( \lambda_k, \mu_k \) are weights of feature functions which are set during learning process. This probability distribution does not model the relationships between combinations of feature functions and classes. In other words, if a combination of two or more feature functions is a good class indicator, the CRFs will not be able to discover the relationship. However, if the relationship between observation features is known then it can be presented to the CRFs as a set of feature functions. The feature functions which are a combination of two or more observation features will be called complex features. The complex feature functions can be represented as:

\[
f_k(y_{i-1}, y_i, x) = y_{i-1} \circ y_i \circ \text{concat}(h_1(x), ..., h_j(x))
\]

\[
g_k(y_i, x) = y_i \circ \text{concat}(h_1(x), ..., h_j(x))
\]

where \( h_1(x), ..., h_k(x) \) are some observation features. This leads to a conclusion, that the complex dependences between observation features and classes must be predefined in a form of separate feature functions.

To verify the above conclusion we performed the following experiment. Let assume we have a training instance with eight observations \( (x_1, ..., x_8) \), two observation features \( h_1 \) and \( h_2 \), and two possible classes \( A \) and \( B \). The vectors with observation feature values are presented in Table 1. If we treat every observation as a separate one-element sequence the CRFs model trained with only simple feature functions \( (g_k(y_i, x) = y_i \circ h_j(x)) \) will not learn to distinguish between classes \( A \) and \( B \).

| \( x \) | \( h_1(x) \) | \( h_2(x) \) | \( y \) |
|-------|-------|-------|-------|
| \( x_1 \) | 0 | 0 | \( A \) |
| \( x_2 \) | 0 | 1 | \( B \) |
| \( x_3 \) | 1 | 0 | \( B \) |
| \( x_4 \) | 1 | 1 | \( A \) |
| \( x_5 \) | 0 | 0 | \( A \) |
| \( x_6 \) | 0 | 1 | \( B \) |
| \( x_7 \) | 1 | 0 | \( B \) |
| \( x_8 \) | 1 | 1 | \( A \) |

Table 1: Feature vectors for observations \( x_1, ..., x_8 \) and features \( h_1(x) \) and \( h_2(x) \).

We can observe, that there is a relationship between \( h_1, h_2 \) and \( y \), i.e. \( y = B \) if \( h_1(x) \leftrightarrow h_2(x) \). This relationship can be transformed into a complex function, i.e.:

\[
h_3(x) = (h_1 \circ h_2)(x) = \text{concat}(h_1(x), h_2(x))
\]

If we include the feature \( h_3(x) \) (see Table 2) and repeat the training and testing procedure, then the CRFs model will correctly classify the observations. This confirms that the complex dependences between observation features and classes must be beforehand identified and included in the training procedure as a separate set of feature functions.

In the context of named entity recognition tasks the observation is a single token. The \textit{class} is a label from a predefined set of labels, i.e. \{ \textit{B-nam}, \textit{I-nam}, \textit{O-nam} \}, where \textit{B-nam} is assigned to tokens starting a named entity, \textit{I-nam} is assigned to tokens which are part of a named entity and \textit{O} is assigned to tokens which are not part

\footnote{Here we used the CRF++ tool to train and test the model.}
of any named entity. An observation feature is a token attribute, for example an orthographic form, a part of speech or a presence in a gazetteer. A complex feature will be a combination of observation features, for example the current token is upper case and the preceding token is lower case.

3 Feature space

3.1 Baseline set of features

The baseline set of features contains features used by Marciničuk and Kocôń (2013) in recognition of named entities boundaries for Polish. It contains orthographic, morphological, lexicon-based and wordnet-base features. The set contains only one complex feature, i.e. agreement. This feature checks the number, case and gender agreement between adjacent tokens.

3.2 New features

Before generating complex features we revised the baseline set of features. After error analysis we have identified three main types of errors which are related to incorrect boundaries detection. The errors are:

- names which are split into several tokens which are not separated by white spaces are partially recognized. For example “EX-8.5” (name of an engine model) is split into five tokens: [EX][h][8][.][5] and only the first token is marked as a named entity, i.e. “EX”.
- names which are quoted are partially recognized. For example in “(...) lecture ’New media and social changes’ (...)” only “New media” is annotated.
- names in brackets are also partially recognized.

To solve the above problems we introduced three new basic features: quotation, bracket and nospace. The features are described in the following subsections.

3.2.1 The Nospace feature

Nospace feature indicates if there is or not a space (or any white space character) between the current and the preceding token.

\[
nospace(n) = \begin{cases} 
1 & \text{if there is a whitespace character between } n-1\text{-th and } n\text{-th tokens} \\
0 & \text{otherwise} 
\end{cases}
\]

3.2.2 The Quotation feature

Quotation feature indicates if the token is between an opening and a closing quotation marks.

\[
\text{quotation}(n) = \begin{cases} 
B & \text{if } n\text{-th token is an opening quotation mark} \\
I & \text{if } n\text{-th token is between an opening and a closing quotation marks} \\
E & \text{if } n\text{-th token is a closing quotation mark} \\
O & \text{otherwise} 
\end{cases}
\]

3.2.3 The Bracket feature

Bracket feature indicates if the token is between an opening and a closing bracket.

\[
\text{bracket}(n) = \begin{cases} 
B & \text{if } n\text{-th token is an opening bracket} \\
I & \text{if } n\text{-th token is between an opening and a closing brackets} \\
E & \text{if } n\text{-th token is a closing bracket} \\
O & \text{otherwise} 
\end{cases}
\]

4 Complex feature generation

RIPPER (Repeated Incremental Pruning to Produce Error Reduction) is a rule learning algorithm that can efficiently handle large and noisy datasets. According to Cohen (1995) RIPPER scales nearly linearly with number of examples in a dataset.

We used Java implementation of RIPPER called JRip, which is a part of Weka software (Hall et al., 2009). The set of rules was induced on the tune part of the KPWr corpus (Broda et al., 2012) which contains 62k instances of O class, 3.7k instances of B − nam class and 3k instances of I − nam class. For each token feature we used

| $x$ | $h_1(x)$ | $h_2(x)$ | $h_3(x)$ | $y$ |
|-----|----------|----------|----------|-----|
| $x_1$ | 0        | 0        | 00       | A   |
| $x_2$ | 0        | 1        | 01       | B   |
| $x_3$ | 1        | 0        | 10       | B   |
| $x_4$ | 1        | 1        | 00       | A   |
| $x_5$ | 0        | 0        | 00       | A   |
| $x_6$ | 0        | 1        | 01       | B   |
| $x_7$ | 1        | 0        | 10       | B   |
| $x_8$ | 1        | 1        | 00       | A   |

Table 2: Feature vectors for observations $x_1, \ldots, x_8$ and features $h_1(x), h_2(x)$ and $h_3(x)$.
five features for the adjacent tokens — two preceding tokens, the current token and two following tokens. A sample of token feature vectors for a single feature orth is presented in Table 3.

| n | orth | orth-2 | orth-1 | orth-0 | orth+0 | orth+1 | orth+2 |
|---|------|--------|--------|--------|--------|--------|--------|
| 1 | Tom  | NULL   | NULL   | Tom    | lives  | NULL   | NULL   |
| 2 | lives | NULL   | Tom    | lives  | in     | Paris   | NULL   |
| 3 | in   | Tom    | lives  | in     | Paris  | NULL   | NULL   |
| 4 | Paris | lives  | in     | Paris  | NULL   | NULL   | NULL   |

Table 3: Token feature vectors for a sample sentence and a single feature orth (orthographic form of token).

The rule induction process took 2.5 hours on a single 2.4 GHz CPU. The final set of rules consists of 29 rules for B-nam class and 24 rules for I-nam class. The accuracy of the rules on the tune part was 96.6%. The detailed results are presented in the Table 4.

| Class | P   | R   | F   |
|-------|-----|-----|-----|
| B-nam | 82.5% | 79.2% | 80.8% |
| I-nam | 86.2% | 63.8% | 73.3% |
| O     | 97.7% | 99.1% | 98.4% |
| All   | 96.6% | 96.6% | 96.4% |

Table 4: Evaluation of the rules on the tune part of the KPWr corpus.

A sample rule generated by JRip is presented on Figure 1. The rule says: the current token starts a named entity (B-nam) if the current token has an upper case letter (has_upper_case+0 = 1) and the preceding token does not have only upper case letters (all_upper-1 = 0) and the preceding token have only lower case letters (pattern-1 = ALL_LOWER) and the following token has an upper case letter (has_upper_case+1 = 1).

(has_upper_case+0 = 1) and (all_upper-1 = 0) and (pattern-1 = ALL_LOWER) and (has_upper_case+1 = 1) => iobtag=B-nam

Figure 1: A sample rule generated by JRip on the tune part of KPWr.

(has_upper_case:0/all_upper:-1/pattern:-1/has_upper_case:1

Figure 2: A complex feature converted from the sample rule from Figure 1.

5 Evaluation

We have evaluated three set of features: baseline (described in Section 3.1), baseline with new features (described in Section 3.2) and baseline with complex features (baseline features with new features and automatically generated complex features according to the procedure presented in Section 4).

We decided not to evaluate the set of rules generated by JRip on their own as we did not expect to obtain good results. The performance of the rules on the tune set (set on which the rules were generated) was relatively low and on unseen data it might be even lower.

The evaluation was performed by training CRF++ implementation of CRFs which generates all possible combinations of feature values for given feature template during the training process. This way CRF++ can explore all combinations of feature values (including the one generated by JRip) and evaluate them in the context of sequence labelling task. The final evaluation of the generated complex features is presented in Section 5.

5Web page: http://crfpp.googlecode.com/svn/trunk/doc/index.html
Table 5: A list of features used to construct the set of rules with a number of rules in which the feature appeared.

| Feature               | Count |
|-----------------------|-------|
| has_upper_case        | 29    |
| starts_with_lower_case| 24    |
| starts_with_upper_case| 23    |
| ctag                  | 14    |
| pattern               | 14    |
| agr1                  | 12    |
| class                 | 12    |
| dict_person_first_name| 10    |
| all_upper             | 9     |
| orth                  | 9     |
| case                  | 8     |
| parenthesis           | 8     |
| nospace               | 8     |
| has_lower_case        | 7     |
| gender                | 6     |
| length                | 7     |
| all_alphanumeric      | 4     |
| all_digits            | 2     |
| all_letters           | 3     |
| has_digit             | 2     |
| number                | 2     |
| suffix-1              | 2     |
| struct                | 2     |
| no_letters            | 1     |
| prefix-1              | 1     |
| quotation             | 1     |
| starts_with_digit     | 1     |
| suffix-2              | 1     |

We also validate the generality of the feature sets by training the model on the train and tune part of KPWr and testing on the test part of KPWr (see Table 6).

We present results for strict and partial matching evaluation (Chinchor, 1992). In the strict matching the boundaries of recognized annotations must be exactly the same as in the reference corpus. In the partial matching the recognition of annotations presence and its boundaries are evaluated separately. This means that annotations which do not exactly match the expected boundaries are treated as partial success.

To check the statistical significance of difference between results we used Student’s t-test with a significance level $\alpha = 0.05$ (Dietterich, 1998).

Application of the new three features (nospace, quotation and bracket) improved the F-measure for strict evaluation from 80.30% to 81.13%. The difference is statistically significant for $\alpha = 0.05$ what means that the additional features are useful for the recognition of named entities boundaries. Further improvement was achieved by extending the feature set with the complex features generated with RIPPER algorithm. The F-measure increased to 82.61% and the difference is also statistically significant.

Similar increase of F-measure was observed for the test part of KPWr. The initial value of F-measure increased from 82.40% for baseline set of features to 84.50% for the baseline set of features extended with complex features.

| Evaluation               | P  | R  | F  |
|--------------------------|----|----|----|
| Baseline                 |    |    |    |
| Strict                   | 81.92% | 78.74% | 80.30% |
| Partial                  | 88.11% | 84.83% | 86.44% |
| Baseline with new features|    |    |    |
| Strict                   | 82.79% | 79.54% | 81.13% |
| Partial                  | 88.52% | 85.22% | 86.84% |
| Baseline with complex features|    |    |    |
| Strict                   | 84.10% | 81.16% | 82.61% |
| Partial                  | 89.07% | 86.25% | 87.64% |

Table 6: 10-fold cross validation on the train part of KPWr corpus.

| Evaluation               | P  | R  | F  |
|--------------------------|----|----|----|
| Baseline                 |    |    |    |
| Strict                   | 84.25% | 80.63% | 82.40% |
| Partial                  | 89.78% | 85.80% | 87.74% |
| Baseline with new features|    |    |    |
| Strict                   | 84.94% | 81.72% | 83.29% |
| Partial                  | 90.22% | 86.75% | 88.45% |
| Baseline with complex features|    |    |    |
| Strict                   | 86.04% | 83.02% | 84.50% |
| Partial                  | 90.73% | 87.63% | 89.15% |

Table 7: Evaluation on the test part of the KPWr corpus.

6 Conclusions

A rule learning algorithms such as RIPPER can be successfully used to improve the performance of a CRF-based statistical model. RIPPER can find a dependences between token features and their
classes. The dependences can be expressed as a set of rules which can be latter transformed into a set of feature templates for CRFs.

Despite the improvement we achieved, the final performance of named entity recognition is still far from perfect. There are same possible reasons for that. First of all, the complex features generated by RIPPER have form of conjunction of positive assertions. This means that RIPPER will not produce rules with negation (i.e. if \( h_j(x) \) \(<\rangle\) \( b' \) then \(...\)). This can be achieved by enumerating all possible values for feature \( h_j \) and constructing a set of negated features but this approach might be ineffective due to large space of possible values (especially orthographic and base forms).

The other limitation of this approach is lack of long distance dependences modelling. For example, if a sequence of tokens \( T \) in one sentence has labelling \( L \), then there is high probability that the same sequence in another sentence will have the same labelling. In the current approach there is no linking between the same sequences of tokens.

Also the discrepancy between strict and partial matching evaluation shows, that there is still a problem with proper boundary detection of named entities. This is a problem for long names, like titles which are not quoted. In such cases there is no orthographic indication, where the title ends and its ending is recognized incorrectly.

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