Vietnamese Named Entity Recognition using Token Regular Expressions and Bidirectional Inference

Phuong Le-Hong
College of Science
Vietnam National University, Hanoi, Vietnam
Email: phuonglh@vnu.edu.vn

Abstract—This paper describes an efficient approach to improve the accuracy of a named entity recognition system for Vietnamese. The approach combines regular expressions over tokens and a bidirectional inference method in a sequence labelling model. The proposed method achieves an overall $F_1$ score of 89.66% on a test set of an evaluation campaign, organized in late 2016 by the Vietnamese Language and Speech Processing (VLSP) community.

I. INTRODUCTION

Named entity recognition (NER) is a fundamental task in natural language processing and information extraction. It involves identifying noun phrases and classifying each of them into a predefined class. In 1995, the 6th Message Understanding Conference (MUC) started evaluating NER systems for English, and in subsequent shared tasks of CoNLL 2002 and CoNLL 2003 conferences, language independent NER systems were evaluated. In these evaluation tasks, four named entity types were considered, including names of persons, organizations, locations, and names of miscellaneous entities that do not belong to these three types.

More recently, the Vietnamese Language and Speech Processing (VLSP) community has organized an evaluation campaign to systematically compare NER systems for the Vietnamese language. Similar to the CoNLL 2003 share task, four named entity types are evaluated: persons (PER), organizations (ORG), locations (LOC), and miscellaneous entities (MISC). The data are collected from electronic newspapers published on the web.

This paper presents the approach and experimental results of our participating system on this evaluation campaign. In summary, the overall $F_1$ score of our system is 89.66% on a development set extracted from the training dataset provided by the organizing committee of the evaluation campaign. Three important properties of our approach include (1) use of token regular expressions to encode regularities of organization and location names, (2) an algorithm to annotate every token in an input sentence with their token regular expression types, and (3) a bidirectional decoding approach to boost the accuracy of the system.

The remainder of this paper is structured as follows. Section [II] gives a brief introduction of multinomial logistic regression, the main machine learning model which is used in our system. Section [III] describes in detail the features used in our model, including common features used in NER and those derived from our newly proposed token regular expressions. This section also presents an algorithm we develop to annotate every token of an input sentence with its regular expression type. Section [IV] introduces a bidirectional decoding scheme and a method to combine forward and backward models to get a better model. Section [V] gives experimental results and discussions. Finally, Section [VI] concludes the paper.

II. MULTINOMIAL LOGISTIC REGRESSION

Multinomial logistic regression (a.k.a maximum entropy model) is a general purpose discriminative learning method for classification and prediction which has been successfully applied to many problems of natural language processing, such as part-of-speech tagging, syntactic parsing and named entity recognition. In contrast to generative classifiers, discriminative classifiers model the posterior $P(y|x)$ directly. One of the main advantages of discriminative models is that we can integrate many heterogeneous features for prediction, which are not necessarily independent. Each feature corresponds to a constraint on the model. In this model, the conditional probability of a label $y$ given an observation $x$ is defined as

$$P(y|x) = \frac{\exp(\theta \cdot \phi(x, y))}{\sum_{y \in \mathcal{Y}} \exp(\theta \cdot \phi(x, y))},$$

where $\phi(x, y) \in \mathbb{R}^D$ is a real-valued feature vector, $\mathcal{Y}$ is the set of labels and $\theta \in \mathbb{R}^D$ is the parameter vector to be estimated from training data. This form of distribution corresponds to the maximum entropy probability distribution satisfying the constraint that the empirical expectation of each feature is equal to its true expectation in the model:

$$\mathbb{E}(\phi_j(h, t)) = \mathbb{E}(\phi_j(h, t)), \quad \forall j = 1, 2, \ldots, D.$$

The parameter $\theta \in \mathbb{R}^D$ can be estimated using iterative scaling algorithms or some more efficient gradient-based optimization algorithms like conjugate gradient or quasi-Newton methods [1]. In this paper, we use the L-BFGS optimization algorithm [2] and $L_2$-regularization technique to estimate the parameters of the model. This classification model is applied to build a classifier for the dependency parser where each observation $x$ is a parsing configuration and each label $y$ is a transition type.
III. Feature Representations

In discriminative statistical classification models in general and the maximum entropy model in particular, features play an important role because they provide the discriminative ability to efficiently disambiguate classes.

In order to facilitate the extraction of various feature types, each lexical token is associated with a surface word and an annotation map containing different information of the text in the form of key and value pairs. The current annotation map includes values for part-of-speech, chunk, token regular expression type and named entity label.

In the context of named entity recognition, the information about surface word, part-of-speech and chunk tag are given; and in a training phrase, named entity tags are also provided. In the next subsection, we describe the regular expression types which are associated with each token to add some helpful semantic information for named entity disambiguation.

A. Regular Expressions over Tokens

We use regular expressions at both character level and token level to infer useful features for disambiguating named entities. While character-level regular expressions are used to detect word shape information, which was shown very important in NER, token-level regular expressions are very helpful to detect word sequence information in many long named entities [3].

Common word shape features that our system uses include:
- is lower word, e.g., “tỉnh”
- is capitalized word, e.g., “Tổng_cục”
- contains all capitalized letters (allcaps), e.g., “UBND”
- is mixed case letters, e.g., “iPhone”
- is capitalized letter with period, e.g., “H.”, “Th.”, “U.S.”
- ends in digit, e.g., “A9”, “B32”
- contains hyphen, e.g., “H-P”
- is number, e.g., “100”
- is date, e.g., “20-10-1980”, “10/10”
- is code, e.g., “21B”
- is name, where consecutive syllables are capitalized, e.g., “Hà_Nội”, “Đồng_Quê”

Using the word shape features presented above, we then introduce regular expressions over a sequence of words to capture its regularity. Suppose that fPress(w) is a boolean function which returns true if w is in a set of predefined words related to press and newspaper domain, for example {“báo”, “tờ”, “tap_chī”, “dài”, “thông_tấn_xã”}, and returns false otherwise. And suppose that fName(w) is a boolean function which returns true if w is a name or an allcaps, and returns false otherwise. Then, we can define the following token regular expressions to capture the name of a news agency:

\[[fPress, fName]\]

This sequence pattern matches many different, probably unseen news agency names, such as “báo Tuổi_Tre, thông_tấn_xã Việt_Nam”, or “tờ Batam”.

In a similar way, suppose that we have a function fProvince which matches common names of administrative structure at various levels such as “{tỉnh, thành_phố, quận, huyện, xã…}”, we can build a sequence pattern

\[[fAllcaps, fProvince, fName]\]

which matches many corresponding organization names such as “UBND thành_phố Đà_Nâng”, “HDND huyện Mù_Căng_Chải”, etc.

Note that an elementary token pattern can be reused in multiple sequence patterns. For example, the following sequence pattern

\[[fProvince, fName]\]

can match provincial names, which are usually of type location, such as “tỉnh Quảng_Ninh”, “thành_phố Hồ Chí_Minh”.

By examining the training data, we have manually built a dozen of regular expressions to match common organization names, and six regular expressions to match common location names. These regular expressions over tokens are shown to provide helpful features for classifying candidate named entities, as shown in the experiments.

B. Regular Expression Type Annotation

Once regular expressions over tokens have been defined, we add a regular expression type for each word of an input sentence by annotating its corresponding annotation map key. Together with word identity, word shape, part-of-speech and chunk tag information, regular expression types provide helpful information for better classifying named entities, as shown in the latter experiments.

We use a greedy algorithm to annotate regular expression type for every word if it has. Basically, the algorithm works as follows. Given a sequence of T tokens (or words) \([w_1, w_2, \ldots, w_T]\) and a map of regular expressions over tokens, each key name defines a pattern sequence: (patternName, patternRegExp), we first search for all positions of the sentence which begins a pattern match, and select the longest match, say, patternPatternName which ranges from token \(w_i\) to token \(w_j\) for \(1 \leq i < j \leq T\). Then, all the tokens \(w_i, w_{i+1}, \ldots, w_j\) are annotated with the same regular expression type patternPatternName. And finally, the algorithm recursively annotates types for tokens in the remaining two halves of the sequence \([w_1, w_2, \ldots, w_{i-1}]\) and \([w_{j+1}, w_{j+2}, \ldots, w_T]\).

Note that this is a greedy method in that we always choose the longest pattern in each run. This is a plausible approach since if there are multiple matches, longer patterns tend to be more correct than shorter ones. For example, there are two matches on the token sequence “UBND tỉnh Đồng_Nâi”, one is an organization name over the entire sequence, and another is a location name over the last two tokens; the longer one is the correct match.

C. Feature Set

In this subsection, we describe the full feature set that is used in our system to classify a token at a position of a sentence.
• Basic features: current word \(w_0\), current part-of-speech \(p_0\), current chunk tag \(c_0\), previous named entity tags \(t_{-1}\) and \(t_{-2}\) (or a special padding token “BOS” – begin of sentence);
• Word shape features, as described in the previous subsection;
• Basic joint features: previous word \(w_{-1}\) (or “BOS”), joint of current and previous word \(w_0 + w_{-1}\), next word \(w_{+1}\) (or “EOS” – end of sentence), joint of current and next word \(w_0 + w_{+1}\), previous part-of-speech \(p_{-1}\), joint of current and previous part-of-speech \(p_0 + p_{-1}\), next part-of-speech \(p_{+1}\), joint of current and next part-of-speech \(p_0 + p_{+1}\), joint of current word and previous named entity tag \(w_0 + t_{-1}\);
• Regular expression types: current regular expression (regexp) type \(r_0\) (or “NA” – not available), previous regexp type \(r_{-1}\) (or “NA”/“BOS”), joint feature \(r_0 + r_{-1}\), next regexp type \(r_{+1}\) (or “NA”/“EOS”), joint feature \(r_0 + r_{+1}\), joint features between current word and regexp types \(w_0 + r_0\), \(w_0 + r_{-1}\), \(w_0 + r_{+1}\), and lastly, joint features between current part-of-speech and regexp types \(p_0 + r_0\), \(p_0 + r_{-1}\), and \(p_0 + r_{+1}\).

IV. BI DIRECTIONAL DECODING

The standard decoding algorithm for sequence labelling is the Viterbi algorithm, which is a dynamic programming algorithm for finding the most likely sequence of tags given a sequence of observations. In this work, we also use the Viterbi algorithm to find the best tag sequence for a given word sequence. However, we found a significant improvement of tagging accuracy when combining two decoding directions, both forward decoding and backward decoding. In this section, we describe our bidirectional decoding approach.

Given a sequence of \(T\) words \([w_1, w_2, \ldots, w_T]\), for each word \(w_j\), a pre-trained multinomial logistic regression model computes a conditional probability distribution over possible tags \(y_j \in \mathcal{Y}\):

\[
P(y_j | c_j) = \frac{\exp(\theta \cdot \phi(c_j, y_j))}{\sum_{y_j \in \mathcal{Y}} \exp(\theta \cdot \phi(c_j, y_j))}, \quad \forall j = 1, 2, \ldots, T,
\]

where \(\phi(c_j, y_j)\) is the feature function which extract features from context \(c_j\) containing known information up to position \(j\). As described in the previous section, \(c_j\) encodes useful features for predicting \(y_j\), including those extracted from a local word window \([w_{j-2}, \ldots, w_{j+2}]\), two previous tags \(y_{j-1}, y_{j-2}\), and joint features between them.

The probability of a tag sequence given a word sequence is approximated by using the Markov property. In a log scale, we have

\[
\log P(y_1, \ldots, y_T | w_1, \ldots, w_T) \approx \sum_{j=1}^{T} \log P(y_j | c_j).
\]

The Viterbi algorithm is then used to find the best tag sequence \(\hat{y}_1, \hat{y}_2, \ldots, \hat{y}_T\) corresponding to the max-probability path on a lattice of size \(K \times T\) where \(K = |\mathcal{Y}|\) is the size of the tag set.

Note that in the second-order Markov model as above, each context \(c_j\) uses the two tags \(y_{j-2}\) and \(y_{j-1}\) which have been inferred in the previous steps. That said, this is a left-to-right inference scheme. In the experiments, we use a greedy update at each position \(j\) where the tag \(y_j\) is chosen as the best tag of each local probability distribution computed by the maximum entropy model.

A reversed inference scheme does the same decoding procedure but in a right-to-left fashion, where two tags \(y_{j+2}, y_{j+1}\) are inferred before decoding \(y_j\). In essence, when performing backward decoding, we can use the same Viterbi decoding procedure as in the forward counterpart, but now using a backward maximum entropy model to compute the probability of a tag given its following tags. It turns out that both the training and decoding procedure for this model can be reused simply by reversing the word and tag sequences at both training and test stages.

An important finding in our experiments is that the backward model is much better than the forward model in recognizing location names while it is much worse in recognizing person names. We therefore propose a method to combine the strength of the two models to boost the accuracy of the final model. The combination method will be presented in detail in the experiments.

V. EXPERIMENTS

A. Datasets

We evaluate our system on the training dataset provided by the VLSP NER campaign\footnote{http://vlsp.org.vn/evaluation_campaign_NER}. This dataset contains 16,858 tagged sentences, totaling 386,520 words. The dataset contains four different types of named entities: person (PER), location (LOC), organization (ORG), and miscellaneous (MISC). Since the real test set has not been released, we divide this training set into two parts, one for training and another for development. The training dataset has 306,512 tokens (79.3% of the corpus), and the development dataset has 80,007 tokens (20.7% of the corpus).

B. Parameter Settings

The multinomial logistic regression models used in our system are trained by the L-BFGS optimization algorithm using the \(L_2\)-regularization method with regularization parameter fixed at \(10^{-6}\).\footnote{Using a larger regularization parameter underfits the model.} The convergence tolerance of objective function is also fixed at \(10^{-6}\). The maximum number of iterations of the optimization algorithm is fixed at 300. That is, the training terminates either when the function value converges or when the number of iterations is over 300. We use the feature hashing technique as a fast and space-efficient method of vectorizing features. The number of features for our models are fixed at 262,144 (that is, \(2^{18}\)).

These parameters values are chosen according to a series of experiments, for example, using a smaller number of features...
(say, $2^{17}$) reduces slightly the performance of the models, while using a larger number does not result in an improvement of accuracy but increase the training time.

C. Main Results

We train our proposed models on the training set and test them on the development set as described in the previous subsection. The performance of our system is evaluated on the development set by running the automatic evaluation script of the CoNLL 2003 shared task\(^3\) The main results are shown in Table I.

Table I: Performance of our system

| Type   | Precision | Recall | $F_1$  |
|--------|-----------|--------|--------|
| All    | 89.56%    | 89.66% | 89.66% |
| LOC    | 84.97%    | 91.13% | 89.32% |
| MISC   | 93.02%    | 81.63% | 86.96% |
| ORG    | 79.75%    | 52.72% | 63.48% |
| PER    | 94.82%    | 92.15% | 93.77% |

Our system achieves an $F_1$ score of 89.66% overall. Organization names are the most difficult entity type for the system, whose $F_1$ is the lowest of 63.48%. Person names are the easiest type for the system whose both precision and recall ratios are high and the $F_1$ score of this type is 93.77%.

D. Effect of Bidirectional Inference

In this subsection we report and discuss the results using unidirectional inference, either forward and backward. The performance of the forward model is shown in Table II and that of the backward model is shown in Table III.

Table II: Performance of the forward model

| Type   | Precision | Recall | $F_1$  |
|--------|-----------|--------|--------|
| All    | 88.08%    | 87.10% | 87.59% |
| LOC    | 81.01%    | 86.34% | 84.00% |
| MISC   | 97.09%    | 86.71% | 91.30% |
| ORG    | 79.75%    | 52.72% | 63.48% |
| PER    | 94.38%    | 93.45% | 93.91% |

Table III: Performance of the backward model

| Type   | Precision | Recall | $F_1$  |
|--------|-----------|--------|--------|
| All    | 88.03%    | 87.94% | 87.98% |
| LOC    | 86.60%    | 91.80% | 88.50% |
| MISC   | 101.00%   | 83.67% | 91.11% |
| ORG    | 66.45%    | 43.10% | 52.28% |
| PER    | 92.15%    | 92.34% | 92.34% |

We see that the backward model is better than the forward model by 4.6 point of $F_1$ score in recognizing location names. This is surprising since the only difference between the two models is a reverse of input sentences. One possible explanation of this effect is that when recognizing location names of a token sequence $w_1, w_2, \ldots, w_n$, if we already know about the type of $w_n$, it is easier to predict its previous token $w_{n−1}$ and so on. We conjecture that this is due to the natural structure of Vietnamese location names.

However, the backward model underperforms the forward model in recognizing the organization names by a large margin. Its $F_1$ score of this type is only 52.28%, while that of the forward model is 63.48%. This is understandable because our token regular expressions are designed to capture regularities in many organization names, as described in the subsection II-A but these expressions do not work anymore if an input token sequence is reversed.

Either of the two unidirectional models achieves an overall $F_1$ score of 88.00% but when they are combined, our system achieves an overall score of 89.66%, as presented in the previous subsection. The combined model has both the strong ability of recognizing location names of the backward model and is good at recognizing organization names of the forward model.

E. Effect of Token Regular Expressions

In this subsection, we report the effectiveness of token regular expressions to our model. We observe that using token regular expressions significantly improves the performance of the system.

If the token regular expressions for ORG type are not used, its $F_1$ score of the forward model is 62.94%. Adding token regular expressions for this type help boost this score to 65.01%. Similarly, when token regular expressions for LOC are not used, its score of the forward model is 82.19%. Adding six token regular expressions for this type improves its score to 83.07%. However, we observe that when all the regular expressions for this two named entity types are used together, they interact with each other and make their scores slightly different, as shown in the Table II.

F. Software

The named entity recognition system developed in this work has been integrated into the Vitk toolkit, which includes some fundamental tools for processing Vietnamese texts. The toolkit is developed in Java and Scala programming languages, which is open source and freely downloadable for research purpose\[^4\]. An interesting property of this toolkit is that it is an Apache Spark application, which is a fast and general engine for large scale data processing. As a result, Vitk is a very fast and scalable toolkit for processing big text data.

VI. CONCLUSION

We have introduced our approach and its experimental result in named entity recognition for Vietnamese text. We have shown the effectiveness of using token regular expressions, of bidirectional decoding method in a conditional Markov model for sequence labelling, and of combining the backward and forward models. Our system achieves the overall $F_1$ score of 89.66% on a test corpus.

\[^3\]http://www.cnts.ua.ac.be/conll2003/ner/

\[^4\]https://github.com/phuonglh/vn.vitk
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