GLOBAL POINTER: NOVEL EFFICIENT SPAN-BASED APPROACH FOR NAMED ENTITY RECOGNITION

Abstract

Named entity recognition (NER) task aims at identifying entities from a piece of text that belong to predefined semantic types such as person, location, organization, etc. The state-of-the-art solutions for flat entities NER commonly suffer from capturing the fine-grained semantic information in underlying texts. The existing span-based approaches overcome this limitation, but the computation time is still a concern. In this work, we propose a novel span-based NER framework, namely Global Pointer (GP), that leverages the relative positions through a multiplicative attention mechanism. The ultimate goal is to enable a global view that considers the beginning and the end positions to predict the entity. To this end, we design two modules to identify the head and the tail of a given entity to enable the inconsistency between the training and inference processes. Moreover, we introduce a novel classification loss function to address the imbalance label problem. In terms of parameters, we introduce a simple but effective approximate method to reduce the training parameters. We extensively evaluate GP on various benchmark datasets. Our extensive experiments demonstrate that GP can outperform the existing solution. Moreover, the experimental results show the efficacy of the introduced loss function compared to softmax and entropy alternatives.

Keywords: Named Entity Recognition, Relation Extraction, Natural Language Processing, Multi-label loss, Deep Neural Networks

1 introduction

Named entity recognition (NER) task aims to recognize entities, also called mentions, from a piece of text that belong to predefined semantic types such as person, location, organization, etc. NER is a key component in natural language processing (NLP) systems for information retrieval, automatic text summarization, question answering, machine translation, knowledge base construction, etc. Guo et al. [2009], Petkova and Croft [2007], Aone [1999], Mollá et al. [2006], Babych and Hartley [2003], Eitzoni et al. [2005]. Note that NER has been introduced in two forms, including flat
and nested entities. Flat NER has been widely addressed as a sequence labeling problem. Nested entities have shown importance in various real-world applications due to their multi-granularity semantic meaning. However, a given token may have multiple labels and thus renders applying sequence labeling-based approaches unattainable.

With the rapid development of deep neural network (DNN), NER task has experienced a shift towards the contextual representation learning. The earlier DNN-based approaches have treated NER as a sequence labeling problem. They commonly attempt to address each token individually by capturing the type and position information. Despite the effectiveness of these approaches, they cannot perform span-based NER, which is called nested NER, in which the entity consists of more than one token. DNN-based approaches for nested NER usually attempt to learn span-specific deep representation in order to classify the corresponding type. There exist some approaches initiated the solution. The authors of Fu et al. proposed to take the span length information into account during the training process. Another work Shen et al. introduced to jointly address span classification and boundary regression in a unified framework to alleviate the boundary information issue. However, the implantation of these approaches is a bit complicated and may be bothersome in real-world scenarios.

In this paper, we propose a novel solution, namely Global Pointer (GP), to address span-based NER task. Specifically, we leverage the relative positions through a multiplicative attention mechanism. The ultimate goal is to enable a global view that considers the beginning and the end positions (i.e., the head and tail information) to predict the entity. To achieve this, we design two modules to identify the head and the tail of a given entity to enable the inconsistency between the training and inference processes. In addition, to alleviate the burden of class imbalance in NER, we extend the softmax and cross-entropy in a universal loss function. It is noteworthy that the number of parameters of the proposed solution increases when a new entity type is added. Note that the introduced loss can be applied to any task suffering from the label imbalance issue. To remedy this issue, we introduce another extension of GP, namely efficient GP, based on an effective approximate method to reduce the number of parameters. We extensively evaluate GP on various benchmark datasets. Our extensive experiments demonstrate that GP can outperform the existing solution. Moreover, the experimental results show the efficacy of the introduced loss function compared to softmax and entropy alternatives.

In brief, the main contributions are three-fold:

- We propose a novel solution, namely Global Pointer (GP), to address span-based NER task that leverages the relative positions through a multiplicative attention mechanism.
- We extend the softmax and cross-entropy in a universal loss function to perform class imbalance scenarios. NER is an example. In addition, we propose an effective approximation method to reduce the training parameters when a new entity type is added.
- We extensively evaluate the proposed solution on various benchmark datasets. Our extensive experiments demonstrate that the proposed solution can outperform the existing solutions. Moreover, the experimental results validate the efficacy of the introduced loss function compared to softmax and entropy alternatives.

The remaining of the paper is organized as follows. Section 2 reviews related work. Section 3 describes the propose solution. Section 4 presents the experimental settings and empirically evaluates the performance of the proposed solution. Finally, we conclude this paper with Section 5.

2 Related work

NER has received extensive attention of researchers in the last decades. The earlier solutions include rule-based. Unsupervised learning approaches initiated the solution. The authors of Fu et al. proposed to take the span length information into account during the training process. Another work Shen et al. introduced to jointly address span classification and boundary regression in a unified framework to alleviate the boundary information issue. However, the implementation of these approaches is a bit complicated and may be bothersome in real-world scenarios.
With the rapid development of deep neural networks, various approaches were introduced to address NER task as a classification problem. The key idea is to learn entity-specific representation to model the semantic relation between two entities. Convolutional neural networks Yao et al. [2015], Strubell et al. [2017], Zhai et al. [2017], recursive neural networks Li et al. [2017], Gridach [2017], Wang et al. [2018], Akbik et al. [2018], Liu et al. [2019a], Ghaddar and Langlais [2018] and long-short term memory based approaches Huang et al. [2015], Tran et al. [2017], Jie and Lu [2019]. The authors of Zheng et al. [2017], Zhou et al. [2017] introduced to jointly extract the entities and their relations in a unified framework.

Recently, pre-trained language models (PLMs) have mostly achieved the state-of-the-art performance of various NLP tasks Devlin et al. [2018], Liu et al. [2019b], Yang et al. [2019]. Following this approach, NER has experienced a shift towards PLMs. An end-to-end model based on sequence-to-sequence learning with copy mechanism and the graph convolutional networks, which introduced to jointly extract relation and entity from sentences Zeng et al. [2018], Fu et al. [2019]. A reinforcement learning-based approach Zeng et al. [2019] was proposed to tackle the extraction order of relation extraction task. A cascade binary tagging-based framework Wei et al. [2020] was introduced to treat relations as functions mapping subjects to objects in a sentence to alleviate the overlapping problem in relation extraction. Table-Sequence Wang and Lu [2020] consists of two encoders, including a table encoder and a sequence encoder, that work together to learn the entity-specific representation. A partition filter network-based approach Yan et al. [2021] introduced to model two-way interaction between entity and relation extraction tasks. The authors of Yuan et al. [2021] introduced modeling relevant features by leveraging heterogeneous factors, e.g., inside tokens, boundaries, and related spans to enhance span representation, resulting in accurate classification performance.

3 Approach

In this section, we describe the proposed solution. We begin by defining span-based NER task. Then, we present the technical details of our approach. Finally, we present the approximation method to reduce the number of parameters.

3.1 Problem definition

Named Entity Recognition (NER) task aims to extract the entity segments and then correspondingly identify their types in the given text. Let $S = [s_1, s_2, ..., s_M]$ be the possible spans in the sentence. The span $s$ is represented as $s[i : j]$ where $i$ and $j$ are the head and tail indexes, respectively. The goal of NER is to identify all $s \in E$, where $E$ is the entity type set.

3.2 Global Pointer

The architecture of our proposed GP consists of two layers, including token representation span prediction. An illustrative example of GP is shown in Figure 1.
3.2.1 Token Representation

Given a sentence $X = [x_1, x_2, ... x_n]$ with $n$ token, we begin by associating each token in $X$ with its corresponding representation in the pre-training language model (PLM), e.g., BERT. We end up with a new matrix $H \in \mathbb{R}^{n \times v}$, where $v$ is dimension of representation:

$$h_1, h_2, ..., h_n = PLM(x_1, x_2, ..., x_n).$$

3.2.2 Span Prediction

Now that we have already obtained the sentence representation $H$, we then compute the span representation. To this end, we use two feedforward layers that rely on the begin and end indices of the span.

$$q_{i,\alpha} = W_{q,\alpha}h_i + b_{q,\alpha},$$

$$k_{i,\alpha} = W_{k,\alpha}h_i + b_{k,\alpha},$$

where $q_{i,\alpha} \in \mathbb{R}^d$, $k_{i,\alpha} \in \mathbb{R}^d$ is the vector representation of the token which used to identify the entity of type $\alpha$. Specifically, the representation of the start and end position is $q_{i,\alpha}$ and $k_{i,\alpha}$ for span $s[i : j]$ of type $\alpha$. Then, the score of the span $s[i : j]$ to be an entity of type $\alpha$ is calculated as follows:

$$s_{\alpha}(i, j) = q_{i,\alpha}^\top k_{j,\alpha}$$

To leverage the boundary information, we explicitly inject relative position information to the model. We apply ROPE position coding into the entity representation, which satisfies $R_i^\top R_j = R_{j-i}$. In this way, our scoring function is calculated as follows:

$$s_{\alpha}(i, j) = (R_i q_{i,\alpha})^\top (R_j k_{j,\alpha})$$

$$= q_{i,\alpha}^\top R_i^\top R_j k_{j,\alpha}$$

$$= q_{i,\alpha}^\top R_{j-i} k_{j,\alpha}$$

3.3 Parameter Reduction

It is noteworthy to mention that when $W_{q,\alpha}, W_{k,\alpha} \in \mathbb{R}^{v \times d}$, the parameters increase to $2vd$ for each new added entity type. Compared with the method of sequence labeling, the increase of parameters under the same conditions is about $2v$. Generally speaking, $v >> d$, in the bert-base model $v$ is 768, while the common choice of $d$ is 64.

To alleviate this issue, we introduce an approximation technique to enable Global Pointer to perform under fewer parameters settings. In the next sections, we refer to it as Efficient Global Pointer. The key idea is to capture the shared score calculation under each entity type. Specifically, we treat NER task as two subtasks, including extraction and classification. The former extracts segments as entities, and the latter identifies the type of each entity. In this way, the extraction step is equivalent to the NER task with only one entity type. We can complete it with a scoring matrix $(W_q h_i)^\top (W_k h_j)$. The classification step can be read as $w_\alpha[h_i; h_j]$, where $w_\alpha \in \mathbb{R}^{2v}$ denotes the identification of the entity type $\alpha$, and $[h_i; h_j]$ is the span representation, which is the concatenation of the start and end representations. The new scoring function is the combination of:

$$s_{\alpha}(i, j) = (W_q h_i)^\top (W_k h_j) + w_\alpha[h_i; h_j].$$

Note that the extraction task’s parameters are shared by all entity types. Therefore, when a new entity type is added, the parameters of classification task increase by $2v$, which is less compared to the original number of parameters $2vd$.

To further reduce the parameters, we consider using $[q_i; k_i]$ instead of $h_i$ to represent a token. Then, the final scoring function becomes:

$$s_{\alpha}(i, j) = q_{i,\alpha}^\top k_{j,\alpha} + w_\alpha^\top [q_i; k_i; q_j; k_j],$$

where $w_\alpha \in \mathbb{R}^{4d}$, $[q_i; k_i; q_j; k_j]$ is the span representation. Intuitively, the number of parameters increases for each new entity type is $4d$, which is indeed less than $And 4v$. 

Global Pointer
3.4 Class Imbalance Loss

Inspired by the circle loss, we introduce a loss function to alleviate class imbalance. In single-class classification, the cross-entropy loss function is:

\[
\log \left( \sum_{i=1}^{n} e^{s_i} \right) = - \log \left( \sum_{i=1}^{n} e^{s_i} \right) = \log \left( \frac{n}{\sum_{i=1}^{n} e^{s_i}} \right) = \log \left( 1 + \sum_{i=1, i \neq t}^{n} e^{s_i} \right),
\]

where \(s_i\) is the non-target score and \(s_t\) is the target score. Here, we consider the loss function in the scenario of multi-label classification. The goal is to make the score of the target class not less than that of the non-target class. Therefore, the loss function is:

\[
\log \left( 1 + \sum_{i \in \Omega_{neg}} e^{s_i} \sum_{j \in \Omega_{pos}} e^{-s_j} \right)
\]

where \(\Omega_{pos}\) and \(\Omega_{neg}\) are positive sample set and negative sample set, respectively. Considering the multi-label scenario where the number of classes is not fixed, we introduce an additional class \(TH\) as the threshold value. We expect that the scores of target classes are greater than \(s_{TH}\) and those of non-target classes are less than \(s_{TH}\). Then, the loss function is calculated as:

\[
\log \left( 1 + \sum_{i \in \Omega_{neg}} e^{s_i} + \sum_{j \in \Omega_{pos}} e^{s_{TH} - s_j} \right)
\]

Equation 10 can be further simplified as follows:

\[
\log \left( e^{s_{TH}} + \sum_{i \in \Omega_{neg}} e^{s_i} \right) + \log \left( e^{-s_{TH}} + \sum_{j \in \Omega_{pos}} e^{-s_j} \right)
\]

For sake of simplicity, we set the threshold to 0 and the final loss function:

\[
\log \left( 1 + \sum_{i \in \Omega_{neg}} e^{s_i} \right) + \log \left( 1 + \sum_{j \in \Omega_{pos}} e^{-s_j} \right)
\]

Specifically, the entity type of \(\alpha\) is represented by:

\[
\log \left( 1 + \sum_{(q,k) \in P_{\alpha}} e^{-s_{\alpha}(q,k)} \right) + \log \left( 1 + \sum_{(q,k) \in Q_{\alpha}} e^{s_{\alpha}(q,k)} \right)
\]

where \(q, k\) represent the start and tail indexes of a span, \(P_{\alpha}\) represents a collection of spans with entity type \(\alpha\), \(Q_{\alpha}\) represents a collection of spans that are not entities or whose entity type is not \(\alpha\), \(s_{\alpha}(q,k)\) is the score that a span \(s[q:k]\) is an entity of type \(\alpha\).

In inference step, the segments that satisfy \(s_{\alpha}(q,k) > 0\) are the output of the entity of type \(\alpha\).

4 Experiments and Evaluation

4.1 Experimental Setup

Dataset. To validate the proposed solution, we conduct extensive experiments on various benchmark datasets. Specifically, we rely on three Chinese NER datasets, including The People’s daily, CLUENER [Xu et al., 2020] and CMeEE.
## Global Pointer

| Dataset         | Train  | Test  | Sentence length | Number of Entities |
|-----------------|--------|-------|-----------------|--------------------|
| The People’s daily | 23,182 | 46,36 | 46.93           | 3                  |
| CLUENER         | 10,748 | 1,343 | 37.38           | 10                 |
| CMeE            | 15,000 | 5,000 | 54.15           | 9                  |
| CONLL04         | 4,270  | 1,079 | 28.77           | 4                  |
| Genia           | 16,692 | 1,854 | 25.35           | 5                  |
| NYT             | 56,195 | 5,000 | 128             | -                  |
| WebNLG          | 5,019  | 703   | 128             | -                  |
| ADE             | 4,272 (10-fold) | 128 | 2 |

Table 1: Statistics of datasets.

| Method          | The People’s daily | CLUENER | CMeE | CONLL04 | Genia |
|-----------------|--------------------|---------|------|---------|-------|
| Bert-CRF        | 95.46              | 78.70   | 64.39| 85.46   | 73.02 |
| PFN [Yan et al.] | 94.00              | 79.29   | 63.68| 87.43   | 74.31 |
| Global Pointer  | 95.51              | 79.44   | 65.98| 88.57   | 74.64 |

Table 2: Comparative evaluation on various benchmark datasets for flat and nested NER. The results represent the Macro-F1 scores averaged of five runs with different randomization. The Note that all the results are our implementations and best scores are highlighted in bold.

Hongying et al. [2020], which has been widely used in the literature. Moreover, we also experiment with various English datasets, including CONLL04 Roth and Yih [2004], Genia Ohta et al. [2002], NYT Riedel et al. [2010], WebNLG Zeng et al. [2018] and ADE Gurulingappa et al. [2012]. Note that CMeE and Genia were designed for nested NER task, while the others are flat task. Table 1 shows the statistics of the datasets.

### Evaluation Metrics
We use strict evaluation metrics that if the entity type and the corresponding entity boundary are correct, the entity is correct. We use F1-score to evaluate the performance of our model.

### Parameter Settings
We use 12 heads and layers and keep the dropout probability at 0.1 with 30 epochs. The initial learning rate is $2e^{-5}$ for all layers with a batch size of 32. Note that we used the bert-base model Devlin et al. [2018] to initialize the weights of our GP with Adam optimizer.

### Comparative Baselines
We validate the performance of our Global Pointer by comparing it with its alternatives:

- **Bert-CRF**: A baseline for entity extraction task that incorporates pre-trained language model BERT Devlin et al. [2018] and the additional Conditional Random Field (CRF) layer Lafferty et al. [2001].
- **CopyRE** Zeng et al. [2018]. An end-to-end model based on sequence-to-sequence learning with copy mechanism, which introduced to jointly extract relation and entity from sentences.
- **GraphRel** [Fu et al. 2019]. An end-to-end relation extraction model built upon the graph convolutional networks to jointly learn named entities and their corresponding relations.
- **CasRel** Wei et al. [2020]. A cascade binary tagging-based framework introduced to treat relations as functions mapping subjects to objects in a sentence to alleviate the overlapping problem in relation extraction.
- **PFN** Yan et al. A partition filter network-based approach introduced to model two-way interaction between entity and relation extraction tasks.

Moreover, we also compare to the baselines that achieve competitive performance, including Multi-head Bekoulis et al. [2018a], Multi-head + AT Bekoulis et al. [2018b], Rel-Metric Tran and Kavuluru [2019], SpERT Eberts and Ulges [2019].

### 4.2 Main results
We use the Dev set to select the best model and report the average of five runs on each dataset as shown in Table 2 from which we have made the following observations: (1) our proposed solution gives the best Macro-F1 scores compared to the baselines across all datasets; (2) our Global Pointer can significantly outperform BERT-CRF with more challenging datasets. For example, Global Pointer can achieve even about 0.74 and 1.59 with CLUENER CMeE datasets, respectively, over BERT-CRF. Due to the widely recognized challenge of these datasets, the achieved improvements can be deemed very considerable. Moreover, the experimental results in Table 2 have shown that our proposed solution can achieve a competitive performance compared to the state-of-the-art baselines with less training and inference costs.
### Table 3: Comparative evaluation, †, ‡ and § denotes the use of BERT, ALBERT and SCIBERT [Devlin et al. 2018], [Lan et al. 2019], [Beltagy et al. 2019] pre-trained embedding. △ and ▲ denotes the use of micro-F1 and macro-F1 score.

| Dataset        | Training Speed | Inference Speed | Logistic Regression Score |
|----------------|----------------|-----------------|--------------------------|
|                | BERT-CRF       | Global Pointer  | BERT-CRF                 | Global Pointer  |
| The People’s daily | 1x             | 1.56x           | 1x                       | 1.11x           |
| CLUENER        | 1x             | 1.22x           | 1x                       | 1x              |
| CMeEE          | 1x             | 1.52x           | 1x                       | 1.13x           |

Table 4: Comparative evaluation in terms of computational cost between the proposed Global Pointer and BERT-CRF

Furthermore, we compared Global Pointer to its alternative Bert-CRF in terms of computational costs of both training and inference steps. The comparative results are reported in Table 4. As can be seen, our Global Pointer is faster than CRF, especially, with large datasets, such as the People’s daily and CMeEE.

### 4.3 Relative Position & Class Imbalance loss Evaluation

To illustrate the affect of encoding the relative position information, we conduct an ablation study on the CONLL04 dataset as follows. We drop Non-ROPE encoding component of our Global Pointer and compare the performance as shown in Table 7. As can be seen, the Macro-F1 scores drop even about 11.43%, and thus suggests that a well-designed mechanism that leverages the relative position information can boost the performance on NER task. Moreover, we validate the efficacy of the proposed class imbalance loss function as follows. We replace the proposed loss function with the binary cross-entropy (BCE). We observe that the performance of Global Pointer with BCE drops in terms of precision and F1 scores and thus demonstrates the effectiveness of our proposed loss function.

### Table 5: Comparison of the Efficient Global Pointer with the original Global Pointer in F1 score. Best scores are highlighted in bold.

| Dataset        | Global Pointer | Efficient Global Pointer |
|----------------|----------------|--------------------------|
| The People’s daily | **95.51**      | **95.36**                |
| CLUENER        | 79.44          | **80.04**                |
| CMeEE          | 65.98          | **66.54**                |
### 4.4 Reduce Parameters Evaluation

In Section 3.3, we introduce a new variant of the proposed solution, namely Efficient Global Pointer, which can perform under less parameters settings. We conduct empirical experiments on the people’s daily, CLUENER and CMeEE datasets to evaluate the performance of both variants. The comparative results are shown in Table 5 from which we have made the following observations. (1) Overall, Efficient Global Pointer can mostly give the best F1 scores. (2) Despite the limited number of parameters, Efficient Global Pointer can still be competitive on the easy dataset, e.g., People’s daily dataset. (3) CLUENER and CMeEE were annotated with 10 and 9 entity types, respectively, which are widely recognized as more challenging datasets; however, Efficient Global Pointer with less parameters can still perform better than its alternative with all parameters. The performance is expected as the number of parameters increases with each entity type leading to an overfitting problem. In brief, the experimental results suggest that a carefully-designed mechanism to reduce the number of parameters can enhance the performance of NER.

### 4.5 Empirical Analysis

In the section, we perform in-depth analysis in terms of entity length and entity density. Specifically, we conducted relevant experiments on CONLL04 dataset to evaluate the performance of Global Pointer and PFN [Yan et al.]. First, we map the sentences into three groups according to their length: $L < 3$, $3 \leq L < 6$, and $L \geq 6$, denoted as $L_1$, $L_2$ and $L_3$, respectively. Second, we categorized the sentences according to their density: dense $<=$ 0.1, 0.1 < dense $<=$ 0.3, dense $>$ 0.3, denoted as $D_1$, $D_2$ and $D_3$. Note that we use the ratio of the number of entity words to the total number of text words as the index of entity density.

The comparative evaluation is depicted in Table 6. We observe that when the entity length exceeds the half (e.g., 6), Global Pointer can achieve even about 7% improvements higher than PFN in terms of F1 score. These improvements demonstrate the importance of relative position information in the large number of entities recognition. In addition, we also observe that when the density of entities in the text is at the middle level, both models give the worse scores. However, as can be seen, Global Pointer performs better in most scenarios.

### 5 Conclusions

In this paper, we presented a novel solution to address span-based NER framework, namely Global Pointer (GP), by leveraging the relative positions through a multiplicative attention mechanism. GP is designed of two modules that aim to identify the head and the tail of a given entity to enable the inconsistency between the training and inference processes. Moreover, GP contributed with a novel loss function to address the imbalance label problem. To reduce the training cost, we introduced a new variant of GP based on approximate method to reduce the training parameters. We extensively evaluated GP on various benchmark datasets. Our extensive experiments demonstrate that GP can outperform the existing solution. Moreover, the experimental results show the efficacy of the introduced loss function compared to softmax and entropy alternatives.
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