

Generating and Exploiting Large-scale Pseudo Training Data for Zero Pronoun Resolution

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Abstract

Most existing approaches for zero pronoun resolution are supervised approaches, where annotated data are released by shared task organizers. Therefore, the lack of annotated data becomes a major obstacle in zero pronoun resolution task. The existing approaches mainly face the challenge of costing manpower on labeling the extended data for better training performance and domain adaption. To alleviate the problem above, in this paper we propose a simple but novel approach to automatically produce large-scale pseudo training data for zero pronoun resolution. Furthermore, to avoid the drawbacks of the feature engineering based approaches, we proposed an attention-based neural network model for this task. Experimental results show that our proposed approach outperforms the state-of-the-art methods significantly with an absolute improvement of 5.1% F-score in OntoNotes 5.0 corpus.

1 Introduction

Previous work on zero pronoun (ZP) resolution mainly focused on the supervised learning approaches (Han, 2006; Zhao and Ng, 2007; Iida et al., 2007; Kong and Zhou, 2010; Iida and Poesio, 2011; Chen and Ng, 2013). However, a major obstacle for training the supervised learning models is the lack of annotated data. An important step is the organizing of the shared task on anaphora and coreference resolution, such as the ACE evaluations, SemEval-2010

shared task on Coreference Resolution in Multiple Languages (Marta Recasens, 2010) and CoNLL-2012 shared task on Modeling Multilingual Unrestricted Coreference in OntoNotes (Sameer Pradhan, 2012). Following these shared tasks, the annotated evaluation data can be released for the follow up studies. Despite the success and contribution of these shared tasks, it still face the challenge of costing manpower on labeling the extended data for better training performance and domain adaptation.

To address the problem above, in this paper, we proposed a simple but novel approach to automatically generate large-scale pseudo training data for zero pronoun resolution. As the zero pronoun resolution task mainly deal with nouns, noun phrases, compound noun phrases, pronouns, etc., for each document (\mathcal{D}), we first count the frequency of each noun and pronoun on the document. For the noun or pronoun of which the frequency is equal to or greater than 2, we then randomly choose one position where the noun or pronoun is located on and replace it on that position with a specific symbol $\langle blank \rangle$. Let query q and answer a denote the sentence that contains a $\langle blank \rangle$, and the noun or pronoun which is replaced by the $\langle blank \rangle$, respectively. Thus a pseudo training sample can be represented as a triple:

$$\langle q, a, \mathcal{D} \rangle$$

For the zero pronoun resolution task, a $\langle blank \rangle$ represents a zero pronoun (ZP) in q , and a indicates the corresponding antecedent of the ZP. In this way, we obtain 1.81 million pseudo training samples in total generated from news corpus.

Towards the shortcomings of the previous ap-

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Document:	
1	welcome both of you to the studio to participate in our program , 欢迎 两位 呢 来 演播室 参与 我们的 节目 ,
2	it happened that i was going to have lunch with a friend at noon . 正好 因为 我 也 和 朋友 这个 , 这个 中午 一起 吃饭 .
3	after that , i received an sms from 1860 . 然后 我 就 收到 1860 的 短信 .
4	uh-huh , it was by sms . 嗯 , 是 通过 短信 的 方式 ,
5	uh-huh , that means , er , you knew about the accident through the source of radio station . 嗯 , 就 是 说 呢 你 是 通过 台 里 面 的 一 个 信 息 的 渠 道 知 道 这 儿 出 了 这 样 的 事 故 .
6	although we live in the west instead of the east part , and it did not affect us that much , 虽 然 我 们 生 活 在 西 部 不 是 在 东 部 , 对 我 们 影 响 不 是 很 大 ,
7	but i think it is very useful to inform people using sms . 但 是 呢 , 我 觉 得 有 这 样 一 个 短 信 告 诉 大 家 呢 是 非 常 有 用 的 啊 .
Query:	
8	some car owners said that <blank> was very good. 有 车 主 表 示 , 说 这 <blank> 非 常 的 好 .
Answer:	
sms	
短信	

Figure 1: Example training sample for zero pronoun resolution system. (The original data is in Chinese, we translate this sample into English for clarity)

proaches that are based on feature engineering, we first propose a neural network architecture, which is an attention-based neural network model, for zero pronoun resolution. The proposed approach consists of two training phases. First, it utilizes the produced pseudo training data from a large-scale news corpus to pre-train the proposed neural network model as a **pre-training**. Second, the OntoNotes 5.0 dataset (training set) is used to train the model as an **adaptation**. The test is then also performed on the OntoNotes 5.0 dataset (test set).

The contributions of this paper are as follows:

- To our knowledge, we are the first to proposed an approach to automatically generate large-scale training data for zero pronoun resolution.
- We proposed a two-phase training approach, namely pre-training-then-adaptation, which benefits from the automatically produced pseudo training corpus.
- Towards the shortcomings of the feature engineering approaches, we first proposed an attention-based neural network model for zero pronoun resolution.

2 The Proposed Approach

In this section, we will detail the approach to generating pseudo training data (Section 2.1), the two-phase training approach (Section 2.2), the proposed

attention-based neural network model (Section 2.3) as well as the unknown words processing approach (Section 2.4).

2.1 Generating Pseudo Training Data

In order to get large quantities of training data for neural network model, we proposed an approach, which is inspired by (Hermann et al., 2015), to automatically generate large-scale pseudo training data for zero pronoun resolution. However, our approach is more simple and general than that of (Hermann et al., 2015).

As we may recall from Section 1, a pseudo training sample can be represent as a triple $\langle q, a, \mathcal{D} \rangle$. Next, we will introduce the details of generating the pseudo training data for zero pronoun resolution.

First, we collect a large number of documents that are relevant (or homogenous in some sense) to the released OntoNote 5.0 data for zero pronoun resolution task in terms of its domain.

Given a certain document \mathcal{D} , which is composed by a set of sentences $\mathcal{D} = \{s_1, s_2, \dots, s_n\}$, we randomly choose an answer word a in the document. Note that, we restrict an answer word a to be either a noun or pronoun¹, as well as the answer word should appear at least twice in the document. Second, after the answer word a is chosen, the sentence that contains a is defined as a query q , in which the answer

¹The part-of-speech is identified using LTP Toolkit (Che et al., 2010).

word a is replaced by a specific symbol $\langle blank \rangle$. Third, given the query q and document \mathcal{D} , the target of the prediction is to recover the answer a . That is quite similar with the zero pronoun resolution task. Therefore, the automatically generated training samples is called *pseudo* training data. Figure 1 shows an example of a pseudo training sample.

In this way, we can generate tremendous triples of $\langle q, a, \mathcal{D} \rangle$ for training the proposed neural network, without any assumptions on the nature of the original corpus.

2.2 Two-phase Training

It should be noted that, though we have generated large-scale pseudo training data for neural network training, there is still a gap between pseudo training data and the real zero pronoun resolution task in terms of the query style. So we should do some adaptations to our model to deal with the zero pronoun resolution problems ideally.

In this paper, we used an effective approach to deal with the mismatch between pseudo training data and zero pronoun resolution task-specific data. Generally speaking, in the first stage, we use large amount of the pseudo training data using the way described in previous section, to train a fundamental model, and choose a best model according to the validation accuracy. Then we continue to train from the previous best model using the zero pronoun resolution task-specific training data, which is exactly the same domain and query type as the standard zero pronoun resolution task data.

The using of the combination of proposed pseudo training data and task-specific data, i.e. zero pronoun resolution task data, is far more effective than using either of them alone. Though there is gap between these two data, they share many similar characteristics to each other as illustrated in the previous part, so it is promising to combine these data together, which compensate to each other.

The whole domain adaptation procedure can be concluded as,

- Pre-training stage: by using large-scale training data to train the neural network model, we can learn richer word embeddings, as well as relatively reasonable weights in neural networks than just using a small amount of zero pronoun

resolution task training data;

- Adaptation stage: by continuing to train with task-specific data, we can force the previous model to adapt to the new data, without losing much information that have learned in the previous stage.

As we will see in the experiment section that the proposed domain adaptation approach is effective and brings significant improvements.

2.3 Attention-based Neural Network Model

In this section, we will introduce our attention-based neural network model for zero pronoun resolution.

Our model is primarily an attention-based neural network model, which is similar to *Attentive Reader* proposed by (Hermann et al., 2015). Formally, when given a set of training triple $\langle q, a, \mathcal{D} \rangle$, we will construct our network in the following way.

Firstly, we project one-hot representation of document \mathcal{D} and query q into a continuous space with a shared embedding matrix W_e . Then we input these embeddings of document and query into different bi-directional RNN to get their contextual representations. In our model, we used the bidirectional Gated Recurrent Unit (GRU) as RNN implementation(Cho et al., 2014).

$$e(x) = W_e * x, \text{ where } x \in \mathcal{D}, q \quad (1)$$

$$\vec{h}_s = \overrightarrow{GRU}(e(x)) \quad (2)$$

$$\overleftarrow{h}_s = \overleftarrow{GRU}(e(x)) \quad (3)$$

$$h_s = [\vec{h}_s; \overleftarrow{h}_s] \quad (4)$$

For the query representation, instead of concatenating the final forward and backward states as its representations, we directly get an averaged representations on all bi-directional RNN slices, which can be illustrated as

$$h_{query} = \frac{1}{n} \sum_{t=1}^n h_{query}(t) \quad (5)$$

For the document, we place a soft attention over all words in document (Bahdanau et al., 2014), which indicate the degree to which part of document

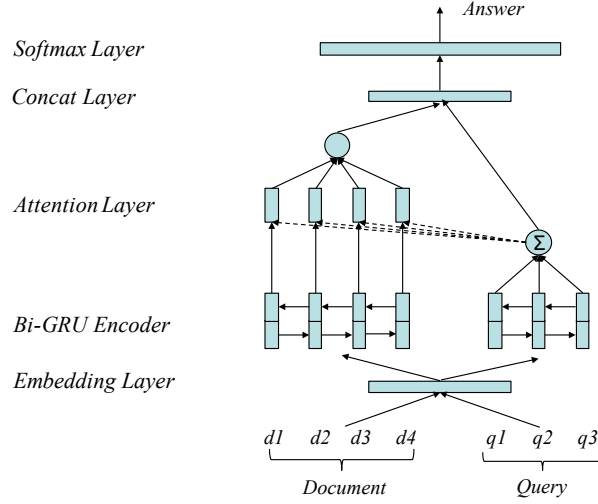


Figure 2: Architecture of attention-based neural network model for zero pronoun resolution task.

is attended when filling the blank in the query sentence. Then we calculate a weighted sum of all document tokens to get the attended representation of document.

$$m(t) = \tanh(W * h_{doc}(t) + U * h_{query}) \quad (6)$$

$$\alpha(t) = \frac{\exp(W_s * m(t))}{\sum_{j=1}^n \exp(W_s * m(j))} \quad (7)$$

$$h_{doc.att} = h_{doc} \cdot \alpha \quad (8)$$

where variable $\alpha(t)$ is the normalized attention weight at t th word in document, h_{doc} is a matrix with each column being the composite representation $h_{doc}(t)$

$$h_{doc} = [h_{doc}(0), h_{doc}(1), \dots, h_{doc}(t)] \quad (9)$$

Then we use attended document representation and query representation to estimate the final answer, which can be illustrated as follows, where V is the vocabulary,

$$r = \text{concat}[h_{doc.att}, h_{query}] \quad (10)$$

$$P(a|\mathcal{D}, q) \propto \text{softmax}(W_r * r) \text{ , s.t. } a \in V \quad (11)$$

Figure 2 shows the proposed neural network architecture.

One thing to notice is that for zero pronoun resolution task, antecedents of zero pronouns are always

noun phrases (NPs), while our model generates only one word (a noun or a pronoun) as the result. To better adapt our model to zero pronoun resolution task, we further process the output result in the following procedure. First, for a given zero pronoun, we extract a set of NPs as its candidates utilizing the same strategy as (Chen and Ng, 2015). Then, we use our model to generate an answer (one word) for the zero pronoun. After that, we go through all the candidates from the nearest to the far-most. For a NP candidate, if the produced answer is its head word, we then regard this NP as the antecedent of the given zero pronoun. By doing so, for a given zero pronoun, we generate a NP as the prediction of its antecedent.

2.4 Unknown Words Processing

Because of the restriction on both memory occupation and training time, it is usually suggested to use a shortlist of vocabulary in neural network training. However, we often replace the out-of-vocabularies to a unique special token, such as $\langle unk \rangle$. But this may place a obstacle in real world test. When the model predict answer as $\langle unk \rangle$, we do not know what is the exact word it represents in the document, as there may have many $\langle unk \rangle$ s in the document.

In this paper, we propose to use a simple but effective way to handle unknown words issue. The idea is straightforward, which can be illustrated as follows.

- Identify all the unknown words inside of each $\langle q, a, \mathcal{D} \rangle$ triple;

- Instead of replacing all these unknown words into one unique token $\langle unk \rangle$, we make a hash table to project these unique known words to numbered tokens, such as $\langle unk1 \rangle, \langle unk2 \rangle, \dots, \langle unkN \rangle$ in terms of its occurrence order in the document. Note that, the same words are projected to the same unknown word tokens, and all these tokens are only valid inside of current sample. For example, $\langle unk1 \rangle$ indicate the first unknown word, say “apple”, in the current sample, but in another document the $\langle unk1 \rangle$ may indicate the unknown word “orange”. That is, the unknown word labels are indicating position features not the exact word;
- Insert these unknown marks in the vocabulary. These marks may only takes up dozens of slots, which is negligible to the size of shortlists (usually 30K \sim 100K).

- (a) 今天的天气没有昨天的天气那么宜人。

(b) 今天的 $\langle unk \rangle$ 没有昨天的 $\langle unk \rangle$ 那么 $\langle unk \rangle$ 。

(c) 今天的 $\langle unk1 \rangle$ 没有昨天的 $\langle unk1 \rangle$ 那么 $\langle unk2 \rangle$ 。

Figure 3: Example of unknown words processing. a) original sentence; b) original unknown words processing method; c) our method

We take one sentence “今天的天气没有昨天的天气那么宜人。” / The weather of today is not as pleasant as yesterday.” as an example to show our unknown word processing method, which is shown in Figure 3.

In the testing phase, if the model predict a $\langle unkX \rangle$ as entity answer, we can simply scan through the original document and identify its position according to its unknown word number X and replace the $\langle unkX \rangle$ with the real word. For example, in Figure 3, if the model predict an answer as $\langle unk1 \rangle$, from the original text, we can know that $\langle unk1 \rangle$ represents the word “天气/weather”.

3 Experiments

3.1 Corpus

In the first training stage, i.e. general model training, we choose a selection of news data which is pub-

licly available². In the domain adaptation stage, we employ the dataset used in the official CoNLL-2012 shared task, from the OntoNotes Release 5.0³, to carry out our experiment. The CoNLL-2012 shared task dataset consists of three parts, i.e. a training set, a development set, and a test set. Documents in the corpus come from six sources, namely Broadcast News (BN), Newswires (NW), Broadcast Conversations (BC), Telephone Conversations (TC), Web Blogs (WB), and Magazines (MZ). Specially, in ZP resolution, considering that only the training set and the development set are annotated with ZPs, we thus utilize the training set for training and the development set for testing, in a way similar to (Chen and Ng, 2015). The statistics of training and testing data is shown in Table 1 and 2 respectively.

	Sentences #	Query #
General Train	18.47M	1.81M
Domain Train	122.8K	9.4K
Validation	11,191	2,667

Table 1: Statistics of training corpus.

	Documents	Sentences	Words	AZPs
Test	172	6,083	110K	1,713

Table 2: Statistics of test set.

3.2 Neural Network Setups

Training details of neural network models are as follows.

- **Embedding:** We use randomly initialized embedding matrix with uniformed distribution in the interval $[-0.1, 0.1]$, and set units number as 256. No pre-trained word embeddings are used.
- **Hidden Layer:** We use GRU with 256 units, and initialize by random orthogonal matrices (Saxe et al., 2013). As GRU still suffers from gradient exploding problem, we set gradient clipping threshold to 10.
- **Vocabulary:** As the whole vocabulary is very large (over 800K), we set a shortlist of 100K and unknown words are mapped to 20 different symbols, which is described in Section 2.4.

²<http://www.sogou.com/labs/dl/cs.html>

³<http://catalog.ldc.upenn.edu/LDC2013T19>

	Kong and Zhou			Chen and Ng(2014)			Chen and Ng(2015)			Our Approach [†]		
	R	P	F	R	P	F	R	P	F	R	P	F
Overall	44.9	44.9	44.9	48.4	48.9	48.7	50.0	50.4	50.2	55.3	55.3	55.3
NW (84)	34.5	34.5	34.5	38.1	38.1	38.1	46.4	46.4	46.4	59.2	59.2	59.2
MZ (162)	32.7	32.7	32.7	30.9	31.1	31.0	38.9	39.1	39.0	51.3	51.3	51.3
WB (284)	45.4	45.4	45.4	50.4	50.4	50.4	51.8	51.8	51.8	60.5	60.5	60.5
BN (390)	51.0	51.0	51.0	45.9	45.9	45.9	53.8	53.8	53.8	53.9	53.9	53.9
BC (510)	43.5	43.5	43.5	53.8	53.8	53.8	49.4	49.4	49.4	55.5	55.5	55.5
TC (283)	48.4	48.4	48.4	53.7	56.1	54.9	52.7	52.7	52.7	52.9	52.9	52.9

Table 3: Experimental result on the test data. The strongest F-score in each row is in boldface. [†] indicates that our approach is statistical significant over the baselines (using t-test, with $p < 0.05$).

- **Optimization:** We used the ADAM update rule (Kingma and Ba, 2014) with an initial learning rate of 0.001, and used negative log-likelihood as the training objective. The batch size is 32.

We trained model for several epochs and choose the best model according to the performance of validation set. All models are trained on Tesla K40 GPU. Our model is implemented with Theano (Theano Development Team, 2016) and Keras (Chollet, 2015).

3.3 Experimental results

Same to the previous researches that are related to zero pronoun resolution, we evaluate the our system performance in terms of recall (R), precision (P), and F-score (F).

Table 3 shows our results. We focus on AZP resolution process, where we assume that gold AZPs and gold parse trees⁴ are given. The same experimental setting is utilized in (Chen and Ng, 2014b).

Our system performance is given in the first row of Table 3, and it follows the results in different sources in test data. The parenthesized number beside each domain indicate the number of AZPs. We employ three Chinese ZP resolution baseline systems, i.e. (Kong and Zhou, 2010; Chen and Ng, 2014b; Chen and Ng, 2015). We can see that the best baseline is (Chen and Ng, 2015)’s system. It outperforms the other baselines by 5.3% and 1.5% in overall F-score respectively.

We can observe that our approach significantly outperform the best previous system (Chen and Ng, 2015) by 5.1% in F-score, beats the other base-

lines by 10.6%, and 6.6% in F-score, respectively. By looking at the performance of six per-source results, our approach beats the best baseline in all domains. All these results approve that our proposed approach achieves a significant improvement in AZP resolution. However, as our approach outperforms the baseline system with more than ten percent in F-score in source NW and MZ, it can only surpass 0.1% and 0.2% in the domain of TC and BN over the best previous system. We believe that such a fluctuation in performance is caused by the difference of words distributions in different sources. One possible reason is that the average document length of TC and BN quite larger than other domains, and this may produce more unknown words in them, which is relatively less accurate than normal word in the shortlist. And also, we found that in source TC (Telephone Conversations) and BN (Broadcast News) where texts are often in colloquial form, which means that there are lots of useless and meaningless words in their contexts. Therefore, it will be more difficult for our approach to capture the useful information in these contexts, and thus performances are not so well in these sources. Such phenomena indicates that further improvements can be gained by filtering useless words in contexts, or increasing the size of domain adaptation data.

One thing deserves to mention is that, as we mentioned in Section 2.4, there are lots of UNKs in the training data. To better handle these UNKs, we apply the UNK processing mechanism to map these UNKs into real words. Table 4 shows the results with and without the UNK replacement. As we can see that, by applying the our UNK processing mechanism, the performance has gained an improvement by 3 percent in F-score, which indicates the effec-

⁴All gold information are provided by the CoNLL-2012 shared task dataset

tiveness of our proposed approach.

	R	P	F
With UNK replacement	55.3	55.3	55.3
Without UNK replacement	52.2	52.2	52.2

Table 4: The performance of unknown words processing.

We also tested whether our domain adaptation method is effective. We used the three different types of training data: only pseudo training data, only task-specific data, and our domain adaptation method (using both of them sequentially). The results are shown in Table 5. As we can see that, by using our domain adaptation method, our model could give a significant improvement over either of the other models. So it seems that combining pseudo training data and task-specific data is much more promising than just using either of them.

	R	P	F
Only General Train	41.1	41.1	41.1
Only Task-Specific Train	28.9	28.9	28.9
Domain Adaptation	55.3	55.3	55.3

Table 5: Comparison of different training data.

4 Error Analysis

To better evaluate our proposed approach, we perform a qualitative analysis of its errors. Two major errors are revealed by our analysis, as discussed below.

First, our approach fails when there are lots of $\langle unk \rangle$ s in contexts of ZPs, especially when the words near before and after a ZP are $\langle unk \rangle$ s. Follows is an example, where words with # are regarded as $\langle unk \rangle$ s by our model. To ease to understand, we replace $\langle unk \rangle$ s with certain words.

ϕ 登上# 太平山# 顶, 将 香港岛# 和 维多利亚港# 的美景 尽收眼底。
 ϕ Successfully climbed# the peak of [Taiping Mountain]#, to have a panoramic view of the beauty of [Hong Kong Island]# and [Victoria Harbour]#.

In this case, the words “登上/climbed” and “太平山/Taiping Mountain” that appears immediately after the ZP “ ϕ ” are all regarded as $\langle unk \rangle$ s by our model. As we model sequence of words by RNN, the $\langle unk \rangle$ s make the model more difficult to capture

the semantic information of the sentence, which in return can influence the overall performance. Especially for these words that are near a ZP, which play an essential role when modeling contexts information for a ZP. If these words are $\langle unk \rangle$ s, by looking at the words “顶/peak”, there are little information can be obtained, so that our model produces the incorrect answer. Such $\langle unk \rangle$ s can be avoided if we increase the size of shortlists, and we should made a trade of between system performance and efficiency.

Second, our model makes incorrect decisions when the correct antecedents of ZPs are long-distance antecedents. As our model chooses answers from words in the contexts, if there are lots of words between a ZP and its antecedent, more noise information are induced in, and learning difficulty can be increased. For example:

我帮不了那个人 ... 那天结束后 ϕ 回到家中。
 I can't help that guy ... After that day, ϕ return home.

In this case, the correct antecedent of ZP “ ϕ ” is the NP candidate “我/I”. By seeing the contexts, we observe that there are totally 30 more words between ZP and its antecedent. Although our model does not intend to fill the ZP gap only with the words near the ZP, as most of antecedents appear just a few words before the ZPs, our model prefers the nearer words as correct antecedents. Hence, once there are lots of words between ZP and its nearest antecedent, our model can sometimes make wrong decisions. To correctly handle such cases, our model should learn how to filter the useless words and enhance the learning of long-term dependency.

5 Related Work

5.1 Zero pronoun resolution

For Chinese zero pronoun resolution, early studies employed heuristic rules to Chinese ZP resolution. (Converse, 2006) proposes a rule-based method to resolve the zero pronouns, by utilizing Hobbs algorithm (Hobbs, 1978) in the CTB documents. Then, supervised approaches to this task have been vastly explored. (Zhao and Ng, 2007) first present a supervised machine learning approach to the identification and resolution of Chinese zero pronouns. In

their study, (Kong and Zhou, 2010) develop a tree-kernel based approach for Chinese ZP resolution. More recently, unsupervised approaches have been proposed. (Chen and Ng, 2014b) develop an unsupervised language-independent approach, utilizing the integer linear programming to using ten overt pronouns. (Chen and Ng, 2015) propose an end-to-end unsupervised probabilistic model for Chinese ZP resolution, using a salience model to capture discourse information. Also, there have been many researches on ZP resolution for other languages. These studies can be divided into rule-based and supervised machine learning approaches. (Ferrández and Peral, 2000) proposed a set of hand-crafted rules for Spanish ZP resolution. Recently, supervised approaches have been exploited for ZP resolution in Korean (Han, 2006) and Japanese (Isozaki and Hirao, 2003; Iida et al., 2006; Iida et al., 2007; Sasano and Kurohashi, 2011). (Iida and Poesio, 2011) developed a cross-lingual approach for Japanese and Italian ZPs where an ILP-based model was employed to zero anaphora detection and resolution.

In sum, most recent researches on ZP resolution are supervised approaches, which means that their performance highly rely on large-scale annotated data. Even for the un-supervised approach (Chen and Ng, 2014b), they also utilize a supervised pronoun resolver to help resolve ZPs. Therefore, the advantage of our proposed approach is obvious. We are able to generating large-scale pseudo training corpus for ZP resolution, and also our approach benefits from the automatically produced pseudo training corpus.

5.2 Document-level Reading Comprehension

Recently, many neural network based reading comprehension task have been proposed. And it should be noticed that all of them are attention-based models, which indicate that attention mechanism is important in text understanding. By using attention mechanism, the model can learn the relations between document and query, indicating at which part of the document might be relevant to answering the question.

Hermann et al., (2015) have proposed a methodology for obtaining a large quantities of document-query-answer triples, which is the essential in reading comprehension task. By using this method, a

large number of training data can be obtained without much human intervention, and make it possible to train a reliable neural network to study the inner relationships inside of these triples. They used attention-based neural networks for this task. Evaluation on CNN/DailyMail datasets showed that their approach is much effective than traditional baseline systems.

Our work is different from Hermann et al.(2015) in the following aspects. Firstly, though we both utilize the large-scale corpus, Hermann et al. require that the document should come along with a brief summarization of it, while this is not always available in most of the document, and this may place an obstacle in generating limitless training data. In our work, we do not assume any prerequisite of the training corpus, and directly extract query from the document, which makes it possible to get infinite corpus for neural network training. Secondly, their work mainly focus on reading comprehension in general domain. We are able to exploiting large-scale training corpus for solving problems in specific domain, and the proposed method can be easily adapted to other domains as well.

6 Conclusion

In this study, we propose a effective way to generate and exploit large-scale pseudo training data for zero pronoun resolution task. The main idea behind our approach is to automatically generate large-scale pseudo training data and then utilizing an attention-based neural network model to resolve zero pronouns. For training purpose, two training phases are employed, i.e. an **pre-training** phase and an **adaptation** phase, and this can be also applied to other tasks as well. The experimental results on OntoNotes 5.0 corpus is encouraging. It shows that our proposed approach significantly outperforms the state-of-the-art method.

The future work will be carried out on two main aspects: First, as experimental results show that the unknown words processing improve the overall results, we will carry out more work on dealing with unknown words within contexts in a more effective way; Second, we will research on developing other neural network architecture to make it more appropriate for zero pronoun resolution task.

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