Towards Better Chinese Zero Pronoun Resolution from Discourse Perspective

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Abstract. Chinese zero pronoun (ZP) resolution plays an important role in natural language understanding. This paper focuses on improving Chinese ZP resolution from discourse perspective. In particular, various kinds of discourse information are employed in both stages of ZP resolution. During the ZP detection stage, we first propose an elementary discourse unit(EDU) based method to generate ZP candidates from discourse perspective and then exploit relevant discourse context to help better identify ZPs. During the ZP resolution stage, we employ a tree-style discourse rhetorical structure to improve the resolution. Evaluation on OntoNotes shows the significant importance of discourse information to the performance of ZP resolution. To the best of our knowledge, this is the first work to improve Chinese ZP resolution from discourse perspective.

Keywords: Chinese zero pronoun resolution, zero pronoun detection, elementary discourse unit, tree-style discourse rhetorical structure,

1 Introduction

As a gap in a sentence, a ZP exists when a phonetically null form is used to refer to a real world entity. It is well-known that correctly recovering ZP is important to many natural language processing(NLP) tasks. Although Chinese ZP resolution has been much studied in the linguistics literature [16, 17], it was not until recently that it became a hot topic in computational linguistics. Although various kinds of lexical and syntactic features have been successfully employed in ZP resolution to a certain extent [23, 14, 4, 3, 2], the contribution of discourse information has been largely ignored. In this paper, we aim to improve the performance of Chinese ZP resolution from discourse perspective, with various kinds of discourse information considered. During the ZP detection stage, elementary discourse units (EDUs) are detected and used to constrain the generation of ZP candidates. During the ZP resolution stage, a tree-style discourse rhetorical structure is employed to limit the search space of the ZP antecedent by filtering out unlikely antecedent candidates. To our knowledge, this is the first work to improve Chinese ZP resolution from discourse perspective.

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2 Background knowledge

In this section, we introduce two related background knowledge, i.e. Chinese ZP and discourse parsing.

2.1 Chinese zero pronoun

It is well-known that Chinese is a pro-drop language. Due to the lack of hints (e.g. number or gender) about their possible antecedents, the ZP resolution is much more challenging than traditional coreference resolution. Even worse, as noted in Kong and Ng [11], the statistics on OntoNotes v5.0 show that non-anaphoric ZPs account for more than 10% of the mentions in coreference chains.

Example (1) shows an excerpt of coreference annotation from article chtb_0009 in the Chinese part of the OntoNotes corpus with its translated English counterpart provided in the English part of the OntoNotes corpus as shown in Example (2). In this paper, ZPs are denoted by ``Φ'' and the mentions in the same coreference chain are shown in same font style (i.e., italic or underline style).

(1) 针对***甘肃***旅游业的发展需求，<u>人保公司</u>积极推出海外游客保险，还在国内首家推出海外散客保险办法，使`` 八五'' 期间到***甘肃***观光游览的海外游客全部得到保险保障。
甘肃省还积极探索高风险业务，`` 八五'' 期间，Φ 参与卫星发射的共保，<u>Φ</u> 分担的风险金额达一千万元，<u>Φ</u> 支付赔款五百万元，成为西北首家参与航天业务的公司。

(2) Aiming at the development requirements of the ***Gansu*** tourism industry, <u>***People's Insurance Co.***</u> actively promotes travel insurance for overseas tourists, and took the lead at home in providing insurance for individual overseas tourists, which made sure that all those who came sightseeing in ***Gansu Province*** during the ``eighth five-year plan'' period had insurance.
Gansu Province also actively explored high risk business.
During the ``eighth five-year plan'' period, ***it*** participated in the co-insurance of satellite launching, with a shared risk amount reaching 10 million yuan, and paying 5 million yuan in indemnity, became the northwest's first company to participate in the aerospace industry.

From above bilingual example we can find that,

- In Chinese text, one sentence can have multiple ZPs located in different coreference chains (e.g., just as illustrated in Example(1), there are three ZPs in two coreference chains). This accounts for about 6.7% of instances in the Chinese part of the OntoNotes v5.0 corpus.
- The distance between a ZP and its antecedent can be far away (as illustrated in Example (1), the second ZP and its antecedent ``人保公司/People's Insurance Co.'').
- ZPs can be translated into many different forms, e.g. common NP, demonstrative NP, pronoun or even clause in English (e.g., as illustrated in Example (1), the first ZP is translated into pronoun ``it'', while the second and the third ZPs are formulated into clauses).

- The resolution of ZPs is difficult, even for a human annotator. In Example (1) the subject of ``sharing the risk and paying the indemnity" should be ``People's Insurance Co." instead of ``Gansu Province" which becomes the subject in its corresponding English annotation due to the wrong resolution of the second ZP.

2.2 Discourse parsing

Since the release of the Rhetorical Structure Theory Discourse Treebank (RST-DT) [1] and the Penn Discourse Treebank (PDTB) [19], English discourse parsing has attracted increasing attention in recent years [10, 12, 9]. Meanwhile, the discourse-level annotation for other languages, such as Chinese, has been carried out and achieved considerable success [7, 18, 24]. With the availability of these discourse corpora, some preliminary research on discourse parsing of other languages has been conducted [22, 8, 15].

In this paper, we employ the Connective-driven Dependency Treebank (CDTB) corpus [18] and the corresponding end-to-end discourse parser [15] to extract gold and automatic discourse information, respectively. The CDTB corpus is constructed using the Connective-driven Dependency Tree (CDT) scheme [18], which attempts to benefit from both the tree structure adopted by RST and connective driven principle adopted by PDTB, and to address special characteristics of Chinese discourse structure. In the CDT scheme, EDUs are regarded as leaf nodes and connectives are viewed as non-leaf nodes. In particular, connectives are employed to directly represent the hierarchy of the tree structure and the rhetorical relationship of a discourse. Guided by the CDT scheme, the CDTB corpus contains 500 Xinhua newswire articles[1] from the Chinese Treebank (CTB) [21] and is built by adding additional one more layer of discourse annotations. A three-level set of discourse relations are recommended by the CDTB corpus. Among them, first level contains four relations: causality, coordination, transition and explanation, which are further clustered into 17 sub-relations in the second level. For example, relation causality contains 6 sub-relations, i.e. cause-result, inference, hypothetical, purpose, condition and background. In the third level, the connectives are under each sub-relation. In this paper, the 17 sub-relations in the second-level are considered.

For more detail about the CDT scheme and the CDTB corpus, please refer to Li et al. [18]. Figure 1 shows the gold-standard discourse tree corresponding to Example (1). From Figure 1, we can find that, although Example (1) consists of 2 sentences, this paragraph contains 8 EDUs from the discourse perspective. The CDT-styled discourse parser can provide three kinds of discourse information, i.e., EDUs, discourse relations with connectives and sense categories, and the discourse rhetorical tree structure.

3 Related work

Although ZPs are prevalent in Chinese, there is only a few works in Chinese ZP resolution. Representative works include Converse [6], Zhao and Ng [23], Kong and Zhou [14], Chen and Ng [4, 3, 2].

[1] Among them, 325 articles overlap with the ``NW" section of the OntoNotes corpus. The following oracle experiments are conducted in this part.

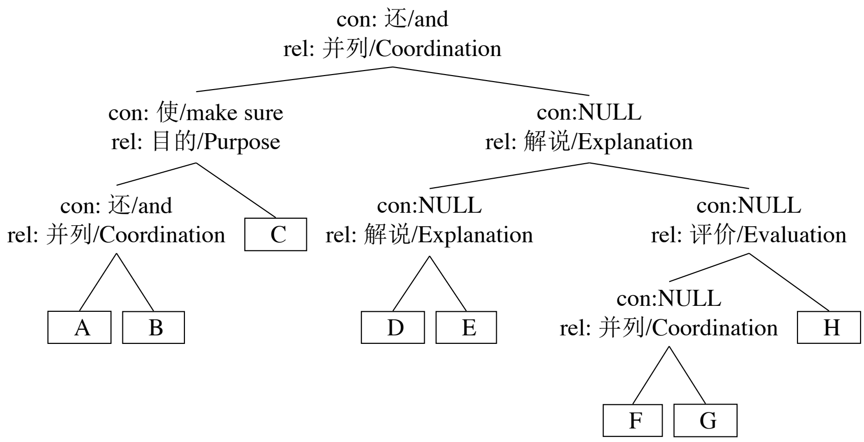

Fig. 1. The gold-standard discourse tree corresponding to Example (1) (There are eight terminal nodes corresponding to EDUs, denoted as A to H. Meanwhile each non-terminal node contains a connective and its corresponding discourse relation category. A. 针对甘肃旅游业的发展需求，人保公司积极推出海外游客保险/Aiming at the development requirements of the Gansu tourism industry, People's Insurance Co. actively promotes travel insurance for overseas tourists B. 还在国内首家推出海外散客保险办法/and took the lead at home in providing insurance for individual overseas tourists C. 使``八五" 期间到甘肃观光游览的海外游客全部得到保险保障/which made sure that all those who came sightseeing in Gansu Province during the ``eighth five-year plan" period had insurance D. 甘肃省还积极探索高风险业务/Gansu Province also actively explored high risk business E. ``八五" 期间，Φ 参与卫星发射的共保/During the ``eighth five-year plan" period, it participated in the co-insurance of satellite launching F. Φ 分担的风险金额达一千万元/with a shared risk amount reaching 10 million yuan G. Φ 支付赔款五百万元/paying 5 million yuan in indemnity H. 成为西北首家参与航天业务的公司/became the northwest's first company to participate in the aerospace industry)

Converse [6] developed a Chinese ZP corpus, which only deals with dropped subjects/objects and ignores other categories. Zhao and Ng [23] proposed a feature-based method to ZP resolution on the same corpus. Kong and Zhou [14] proposed a unified framework for ZP resolution. In particular, appropriate syntactic parse tree structures are designed to better represent the feature space using tree kernel-based methods.

Chen and Ng [4] built the first end-to-end ZP resolver. In order to eliminate the reliance on annotated data, Chen and Ng [3] presented a generative model for unsupervised Chinese ZP resolution. Chen and Ng [2] further proposed an unsupervised probabilistic model for this task, which tried to jointly identify and resolve ZPs. In particular, some discourse information provided by a salience model is combined in their ZP resolution system. Chen and Ng [5] further proposed an approach to Chinese ZP resolution based on deep neural networks to reduce feature engineering efforts involved in exploiting lexical features.

In summary, although various kinds of lexical, syntactic and contextual features are employed in the literature, the discourse information has been largely ignored. In this paper, we attempt to improve the performance from discourse perspective.

4 Baseline

Our baseline approach is similar to the state-of-the-art as described in Chen and Ng [2], which consists of two components, a ZP detector and a ZP resolver, and works as follows: after generating ZP candidates according to some heuristic rules, the ZP detector is first employed to identify the true ones from the candidates and the ZP resolver is then used to determine the referential chain for each ZP.

4.1 ZP detection

In our baseline, the ZP detector contains two steps, i.e., ZP candidate generation and ZP identification.

In order to further improve the performance of our baseline, a clause-based approach is employed to generate ZP candidates similar to Kong and Zhou [13]. First, a simplified semantic role labeling (SRL) framework (only including predicate recognition, argument pruning, and argument identification) is adopted to determine clauses from a parse tree. Here, clauses are classified into terminal or non-terminal clauses according to whether covering sub-clauses. Then, ZP candidates are generated for each clause in a bottom-up way. Particularly, for non-terminal clauses, all the sub-clauses having been resolved are viewed as an inseparable ``constituent''.

After generating the ZP candidates, a learning-based classifier is adopted to identify whether a given candidate is a true ZP, with the help of following features.

- Lexical: two words and their POSs before or after the candidate, and their various combinations.
- Syntactic: whether the lowest clause covering the given candidate has a subject; whether the given candidate is the first gap of the clause; whether the clause is a terminal clause or non-terminal clause; whether the clause has a sibling immediately to its left; whether the left siblings of the clause contain an NP; whether the clause has a sibling immediately to its right; whether the right siblings of the clause contain a VP; whether the syntactic category of the immediate parent of the clause is an IP or VP; whether the path from the clause to the root of the parse tree contains an NP or VP or CP; whether the clause is a matrix, an independent, a subordinate clause, or others.
- Semantic: whether the clause has an agent or patient argument.

4.2 ZP resolution

After ZP detection, a mention-pair model is employed to determine whether the given ZP and a candidate antecedent are coreferent. Obviously, the keys to the success of the ZP resolver are the generation of antecedent candidates and the features employed in this resolver. In this paper, we consider all NPs preceding the given ZP as the antecedent candidates only excluding those having the same head as its parent NP in current and previous two sentences. Besides, we create training instances in the typical way as illustrated in Soon et al.[20], which adopts the closest-first resolution strategy, and adopt following features.

- Features on ZP: whether the path of nodes from the ZP to the root of the parse tree contains NP, IP, CP, or VP; whether the ZP is the first or last ZP of the sentence; whether the ZP is in the headline.
- Features on antecedent candidate (CA): whether the CA is a first person, second person, third person, neutral pronoun, or others; whether the CA is a subject, object, or others; whether the CA is in a matrix clause, an independent clause, a subordinate clause, or none of the above; whether the path of nodes from the CA to the root of the parse tree contains NP, IP, CP, or VP.
- Features between ZP and CA: their distance in sentence[2]; whether the CA is the closest preceding NP of the ZP; whether the CA and the ZP are siblings.

5 Discourse-based approach

Although various kinds of lexical and syntactic features have been employed in the literature to capture the context of a ZP and achieved some success in Chinese ZP resolution, the performance of the state-of-the-art ZP resolution is still far from satisfaction. In this section, we introduce the motivation of this study and propose a new approach towards better Chinese ZP resolution from discourse perspective.

5.1 Motivation

From a corpus study, we make a statistic analysis on the overlap part of the OntoNotes and the CDTB corpus. The statistics shows that this part contains 7455 EDUs, and among them, 1639 discourse trees are built covering 1310 explicit discourse relations and 3807 implicit discourse relations. We can have following observations:

- M1: One EDU has at most one ZP. There is only one case that one EDU has multiple ZPs. This indicates the appropriateness of generating ZP candidates on EDU-level.
- M2: There exists close relationship between discourse relation categories and zero anaphora. For example, in the case of two EDUs with the coordination discourse relation, although they always have similar grammar pattern and share the subject, such subject sharing is not considered as ZP phenomenon according to the annotation guideline (e.g., in Example (1), EDU A and B, F and G).
- M3: Due to the hierarchical nature of the discourse rhetorical structure, it is more appropriate to employ the number of discourse relations extracted from a discourse parse tree instead of the linear number of sentences, clauses or EDUs.

Above observations suggest we can move towards better ZP resolution from discourse perspective.

[2] if the CA and the ZP are in the same sentence, the value is 0; if they are one sentence apart, the value is 1; and so on

5.2 A EDU-level approach to Chinese ZP detection

In our baseline system, a simplified SRL framework is employed to detect the clauses from syntactic parse trees. Since the achieved clauses can be nested, we generate ZP candidates in a bottom-up way. During subsequent processing, all the resolved clauses are viewed as an inseparable ``constituent''. It is interesting to notice that none of ``constituent'' clauses have ZPs. Therefore, our baseline may introduce much more negative instances. This largely harms the performance of our baseline system.

Motivated by the observations in Section 5.1 (M1), we skip the clause detection and generate at most one ZP candidate for each EDU. Besides those traditional features capture the context of the EDU from syntactic perspective, additional discourse features as shown in Table 1 are employed in ZP detection from discourse perspective. The third column lists the feature values viewing EDU F in Example (1) as current EDU.

Feature	Description	Value
PreEduZP	Whether previous EDU has a ZP	true
PreEduRel	the discourse relation category between previous and current EDUs.	none
NxtEduRel	The discourse relation type between next and current EDUs.	Coordination
FstCoorRel	Whether current EDU is the first EDU of a coordinating discourse relation.	true

Table 1. Discourse features employed in our ZP detector

5.3 A discourse rhetorical structure-based approach to Chinese ZP resolution

In accordance with ZP detection, a discourse rhetorical structure-based approach is employed to address ZP resolution, extending our baseline system in three aspects:

Extension 1: One more constraints are deployed during the generation of antecedent candidates. The EDUs having the direct coordination discourse relation with the ZP's EDU are not considered. (M2)

Extension 2: The distance between a ZP and its antecedent candidate is redefined. Since the comma in Chinese can function as the English period due to frequent occurrence of long sentences in Chinese, it is not appropriate to employ the number of sentences to measure the distance. Instead, we redefine the distance as the height of the minimal subtree in the discourse rhetorical tree from discourse perspective. Here, the subtree is governed by the EDU containing the given ZP and the EDU containing the antecedent candidate. In Example (1), we can calculate the distance between the second ZP and its antecedent(`` 人保公司/People's Insurance Co.'') using the discourse rhetorical tree as shown in Figure 1. First, we find the two EDUs, i.e.,A and F. Then, we extract the minimal subtree covering these two EDUs, i.e., the complete discourse tree. Finally, we can have the height of the minimal subtree 4. In this way, we can get the distance between the second ZP and its antecedent as 4. (M3)

Feature	Description	Value
MdZP	The number of other ZPs between the given ZP and current candidate.	1
MdZERel	If MidZP is larger than 0, the direct discourse relation category between the EDU containing the nearest other ZP and current EDU.	none
NtERel	The direct discourse relation category between next EDU (skipping all the direct coordinating EDUs) and current EDU.	Evaluation
DscType	The direct discourse relation category between the EDU containing the given ZP and the EDU containing current candidate.	none
DscPath	The list of discourse relations between the EDU containing the given ZP and the EDU containing current candidate.	$Coordinate \uparrow$ $Evaluation \uparrow$ $Explanation \downarrow$ $Explanation$

Table 2. Discourse features employed in our ZP resolver

Extension 3: Discourse features as shown in Table 2 are introduced in ZP resolution. The third column in Table 2 lists the feature values viewing the ZP in EDU F in Example (1) as the anaphor and the mention ``甘肃省" in EDU D as the antecedent candidate.

6 Experiments and discussion

In this section, we evaluate the contribution of discourse information comprehensively.

6.1 Experimental Setup

Following Chen and Ng [5], we employ the Chinese portion of the OntoNotes 5.0 corpus, which was used in the official CoNLL-2012 shared task. Since only the training set and development set in the CoNLL-2012 data contain ZP coreference annotations, we train our models on the training set and perform evaluation on the development set. We report our performance using traditional precision, recall and F1-measure. In addition, maximum entropy is employed as our learning-based algorithm. All our maximum entropy classifiers are trained using the OpenNLP maximum entropy package[3] with the default parameters (i.e. without smoothing and with 100 iterations). To see whether an improvement is significant, we conduct significance testing using paired t-test.

6.2 Experimental Results and Discussion

We first compare our discourse-based system with our baseline system to show the contribution of the discourse information. Then we compare our discourse-based system with the state-of-the-art system as described in Chen and Ng's [5].

[3] http://maxent.sourceforge.net/

Contribution of discourse information

In order to better understand the contribution of the discourse information to ZP resolution, we conduct a set of experiments on the overlap portion of the OntoNotes and the CDTB corpora (i.e., 325 texts). Considering the limited number of the available texts, we conduct these experiments using 10-fold cross-validation. Compared to our baseline system, all the following improvements are statistically significant ($p < 0.005$).

It should be noted that the performance of the discourse parser depends on that of the syntactic parser. This paper employs the automatic parse trees provided by the CoNLL-2012 shared task as the default one. Besides, we train and evaluate the discourse parser [15] under the default automatic parse trees. As a result, we achieve the performance of 93.8% in F-measure for EDU detection, 52.3% for discourse tree generation, and 53.6% for discourse relation classification. For details, please refer to Kong et al. [15].

	on gold parse trees			on auto parse trees		
	R(%)	P(%)	F	R(%)	P(%)	F
baseline	58.2	72.9	64.7	39.4	62.7	48.4
+gold dp	78.4	72.6	75.4	68.1	64.4	66.2
+auto dp	71.4	70.5	70.9	50.2	59.4	54.4

Table 3. Performance of Chinese ZP detection

In order to evaluate the contribution of the introduced discourse information to ZP detection. Table 3 shows the performance of our ZP detector under gold standard and automatic parse trees respectively. From the results we can find that,

- In comparison with using gold standard parse trees, the performance of ZP detection using automatic parse trees drops significantly. This indicates the dependency of our ZP detector on the quality of syntactic parsing.
- In comparison with our baseline system, incorporating gold discourse information can improve our ZP detector about 10.7% and 17.8% in F-measure under gold and automatic parse trees, respectively.
- In comparison with using gold discourse information, the performance of ZP detection using automatic discourse information drops about 4.5% and 11.8% in F-measure under gold and automatic parse trees respectively. Just as reported in Kong et al. [15], the performance of discourse parser much depends on the results of syntactic parser. In spite of this, in comparison with the baseline system, the introduced discourse information also improve the performance of ZP detection about 6.0% in F-measure under automatic setting.

In order to evaluate the contribution of the introduced discourse information to ZP resolution, Table 4 shows the performance of our Chinese ZP resolution under gold parse trees. We can find that,

	Gold ZPs			Auto ZPs		
	R(%)	P(%)	F	R(%)	P(%)	F
baseline	50.4	50.4	50.4	30.2	31.4	30.8
+gold dp	62.3	62.3	62.3	44.8	45.6	45.2
+auto dp	54.8	54.8	54.8	37.8	35.6	36.7

Table 4. Performance of Chinese ZP resolution using gold standard parse trees

- Using gold standard ZPs, the gold standard discourse information can outperform the baseline system by about 12% in F-measure. This shows the effectiveness of our three extensions during ZP resolution. When the automatic discourse information is employed, the performance improvement drops to about 4.4% in F-measure.
- Using automatic ZPs, the gold standard discourse information can outperform the baseline system by about 14.5% in F-measure, more significant than using gold standard ZPs. When the automatic discourse information is employed, the performance improvement drops to about 6% in F-measure.

	R(%)	P(%)	F
baseline	18.2	20.1	19.1
discourse-based system	20.4	25.6	22.7

Table 5. Performance of end-to-end Chinese ZP resolution

Table 5 shows the performance of our end-to-end Chinese ZP resolution system. That is for the given text, our system first conducts syntactic parsing, then employs our ZP detector to identify the ZPs using automatic parse trees, and finally, employs our ZP resolver to determine the antecedents of ZPs. From Table 5, we can find that, the automatic discourse information can improve the performance of the end-to-end ZP resolution system by about 3.6% in F-measure. In comparison with the gold standard parse trees, the improvement decreases by about 14.0% in F-measure. Although as reported in Kong et al. [15], the performance of discourse parser much depends on that of syntactic parser, the improvement achieved by the discourse information is still significant.

Comparison with the state-of-the-art

In order to fairly compare our ZP resolution system with the state-of-the-art system, as described in Chen and Ng [5], we conduct following experiments with the same setting as theirs. Table 6 compares the performance on the OntoNotes corpus. From the results we can find,

- In comparison with Chen and Ng [5], which adopts deep learning approach and achieves the best performance on Chinese ZP resolution up to now, our baseline performs slightly inferior by about 0.6% in overall F1-measure. With the discourse information, our discourse-based system outperforms the state-of-the-art by about 4.5% in overall F-measure.

- Over different sources, our baseline system performs better than Chen and Ng [5] on NW, almost same on MZ and BC, only much worse than Chen and Ng[5] on WB, BN and TC. With the discourse information, our discourse-based system significantly outperforms Chen and Ng [5] on 3 sources (i.e.,NW,MZ and BC) by about 9.4%, 2.4% and 5.0% in F-measure, respectively, only slightly inferior by about 0.3% on TC, and much worse than the-state-of-the-art on WB and BN by about 2.1% and 1.6% in F-measure.

	Chen and Ng [5]			Baseline			Discourse-based System		
Source	R(%)	P(%)	F	R(%)	P(%)	F	R(%)	P(%)	F
NW	11.9	12.8	12.3	13.4	15.7	14.5	19.7	24.1	21.7
MZ	9.3	7.3	8.2	8.9	7.8	8.3	9.3	12.4	10.6
WB	23.9	16.1	19.2	14.2	11.4	12.6	19.2	15.4	17.1
BN	22.1	23.2	22.6	18.5	24.1	20.9	19.4	22.9	21.0
BC	21.2	14.6	17.3	21.6	14.3	17.2	24.3	20.6	22.3
TC	31.4	15.9	21.1	30.1	15.6	20.5	30.7	16.4	21.4
Overall	21.9	15.8	18.4	20.3	15.8	17.8	26.1	20.4	22.9

Table 6. Performance of three end-to-end Chinese ZP resolution systems over different sections of the OntoNotes corpus.

7 Conclusion

In this paper, we focus on improving Chinese ZP resolution from discourse perspective. During ZP detection, we first generate ZP candidates based on EDU, and then extract various kinds of features to model the context of the EDU from both syntactic and discourse perspective. During ZP resolution, the discourse tree structure is employed to improve the resolution performance. Evaluation on OntoNotes shows that the discourse information can significantly improve Chinese ZP resolution. To our best knowledge, this is the first work to improve Chinese ZP resolution from discourse perspective.

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