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Improve Chinese Semantic Dependency Parsing via Syntactic Dependency Parsing

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***Abstract*—We address the problem of Chinese semantic dependency parsing. Dependency parsing is traditionally oriented to syntax analysis, which we denote by syntactic dependency parsing to distinguish it from semantic dependency parsing. In this paper, firstly we compare Chinese semantic dependency parsing and syntactic dependency parsing systematically, showing that syntactic dependency parsing can potentially improve the performance of semantic dependency parsing. Thus then we suggest an approach based on quasi-synchronous grammar to incorporate the auto-parsed syntactic dependency tree into semantic dependency parsing. We conduct experiments on the Chinese semantic dependency parsing corpus of SemEval-2012. Finally we achieve 65.25% LAS on test corpus, gaining increases of 2.45% compared to the top result of 62.80% in SemEval-2012.**

***Keywords*-Semantic Dependency Parsing, Syntactic Dependency Parsing, Quasi-synchronous Grammar.**

I. Introduction

Chinese semantic dependency parsing has been proposed to facilitate semantic analysis for a long time [1]. It is supposed that semantic dependency parsing can be useful for many applications such as question answering, textual entailment, machine translation, information extraction, etc. Relatively less work has been done on it. This could be due to two facts. First, there isn't a unified standard since linguistic phenomenons are too difficult to catch comprehensively. Second, there isn't a large scale annotated corpus which is available for public . Fortunately, SemEval-2012 has organized a task for Chinese semantic dependency parsing [2]. Nine systems have been submitted. The top result achieves 62.80%[1] in labeled attachment score (LAS) and 80.45% in unlabeled attachment score (UAS).

In this paper, we suggest to enhance Chinese semantic dependency parsing by syntactic dependency parsing. Seldom works have considered the syntax constraints for Chinese semantic dependency parsing. We expect better performance would be gained if syntactic dependency parsing is done preliminarily. Firstly, we analyze the similarities and differences of the two different dependency parsing problems. We find syntactic dependency parsing can potentially help semantic dependency parsing. Thus secondly we attempt to make use of syntactic dependency parsing for semantic dependency parsing. We adopt the approach mentioned in [3], which generates rich quasi-synchronous grammar (QG) features generated by transformation patterns (TP). Experiments are conducted on corpus of [2]. Our baseline system employs Mate [4], achieving a LAS of 64.65% which is 1.85% higher than the top result in SemEval-2012. Then we use the corpus of CONLL 2009 [5] to train a syntactic dependency parsing model. Guided by results of syntactic dependency parsing, our final system achieves a LAS of 65.25%.

The remainder of the paper is organized as follows. Section 2 gives a comparison between Chinese semantic dependency parsing and syntactic dependency parsing. Section 3 describes our system for Chinese semantic dependency parsing. Section 4 reports the experimental results and error analysis. Section 5 describes the related works. Finally, in Section 6 we conclude this paper.

II. Chinese Semantic Dependency Parsing: A Comparison with Syntactic Dependency Parsing

In this section, we analyze the similarities and differences of Chinese semantic dependency parsing and syntactic dependency parsing by comparing the corpus of [2] and CONLL 2009. Figure 1 shows an example of the two dependency parsing problems. The red part displays the dependency tree of semantic dependency parsing, and the blue part displays the tree of syntactic dependency parsing.

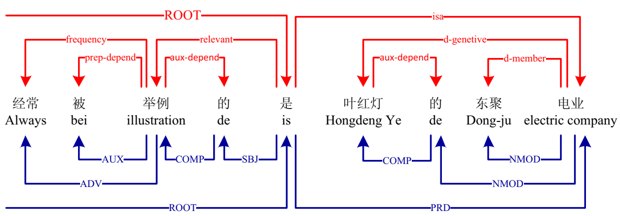

Figure 1. A comparison example between Chinese semantic dependency parsing and syntactic dependency parsing.

[1]Some teams have renewed their results after acquiring the test corpus.

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In the following, we compare them through three aspects respectively: grammar, head and label.

A. Grammar

Both Chinese semantic dependency parsing and syntactic dependency parsing conform to the principles of projected dependency grammar [6]. Thus the two problems can exploit the same methods for decoding and learning.

B. Head

Through the example of Figure 1, we find that the dependencies related with word "的(de)" are different. This is caused by that semantic dependency parsing builds dependency structures in terms of parataxis [7], thus some words such as "的(de)", " 被(bei)", " 把(ba)" and " 和(and)" are neglected in semantic analysis, however they usually play an important role in syntax.

We analyze the head consistency of the two problems in detail. The overall consistency is 49.09%. To carefully look into the two problems, we also compute the head consistencies considering the part-of-speech (POS) tag pairs of syntactic dependency parsing. We expect that the semantic dependencies should be more consistent with the syntax dependencies if both words of a dependency are notional words. Similarly, if one of the words of a syntactic dependency belongs to the neglected words of semantic analysis, then the head consistency should be relatively lower. As is shown in Table I, our expectation is truly reflected. We only list the top five and the least five POS tag pairs of which the appearance frequency is high than 600.

POS Tag Pair (Top Five)	Consistency (%)	POS Tag Pair (Least Five)	Consistency (%)
AS⌒VV	98.31	DEG⌒NN	0.00
JJ⌒NN	98.21	VV⌒DEC	0.00
AD⌒VE	98.11	NN⌒DEG	0.00
AD⌒VC	96.89	NN⌒CC	0.00
NN⌒VE	93.14	VA⌒DEC	0.00

Table I
HEAD CONSISTENCY BETWEEN SEMANTIC DEPENDENCY PARSING AND SYNTACTIC DEPENDENCY PARSING.

C. Label

Semantic dependency parsing has totally different label set compared to syntactic dependency parsing. The semantic relations amount to 123, while the number of syntactical labels in CONLL 2009 is 41. This indicates that semantic dependency parsing would be more difficult than syntactic dependency parsing.

However, we can find some regularities by studying the corpus of two problems deeply. For example, "SBJ" is always mapped into "agent" or "experiencer", and "AMOD" is always mapped into "d-attribute" or "d-restrictive". Table II lists some top frequency mapping patterns. These patterns can be potentially useful for semantic dependency parsing.

Syntax Label	Semantic Labels	Syntax Label	Semantic Labels
NMOD	d-restrictive,aux-depend	AUX	model
ADV	aux-depend	TMP	time, aux-depend
SBJ	agent, experiencer	PRT	aspect
ROOT	ROOT, s-succession	PRD	isa
DMOD	d-quantity, d-deno	CJTN	aux-depend
RELC	aux-depend	LOC	prep-depend
AMOD	d-attribute, d-restrictive	cCJTN	aux-depend

Table II
SOME OF THE MOST FREQUENT MAPPING PATTERNS BETWEEN SYNTAX LABELS AND SEMANTIC LABELS.

III. METHOD

Given an input sentence of n words, denoted by $\mathbf{x} = w_1 \cdots w_n$, and their corresponding POS tags $\mathbf{t} = t_1 \cdots t_n$, the goal of semantic dependency parsing is to find a semantic dependency tree as is depicted by red part in Figure 1. We denote the semantic dependency tree by $\mathbf{y} = \{(h, m, l) \mid 0 \leq h \leq n, 0 < m \leq n, l \in \mathscr{L}\}$, where (h, m, l) means a directed arc from the *head word* (also called *father*) w_h to the *modifier* w_m with a dependency label l, and $\mathscr{L}$ is the semantic label set(In syntactic dependency parsing, $\mathscr{L}$ is the syntax label set).

A. Baseline Model

Chinese semantic dependency parsing is a typical problem of dependency parsing. Graph-based dependency parsing has achieved state-of-the-art performance in Chinese. Thus we adopt graph-based models in this work. Graph-based dependency parsing models the problem by finding the highest scoring tree from a directed graph. The score of a dependency tree is factored into scores of small parts (subtrees) such as dependency, sibling, grandchild, grand-sibling and tri-sibling [8]. According to the size of subtrees, a graph-based model can be either first-order, second-order or third order. It efficiently finds an optimal tree in a huge search space via dynamic programming decoding.

In this work, we employ Mate[2] [4] to train our dependency parsing models since it can incorporate rich label related features. Mate implements a second-order model including dependency, sibling and grandchild features.

B. Syntax QG Features

The conception of QG features is first presented for machine translation problems [9]. The key idea is to guide the forming of a semantic dependency parsing tree by its syntactic dependency tree.

Let $\mathbf{y}'$ denote the syntactic dependency tree, the score function of graph-based models change into:

$$\text{Score}(\mathbf{x}, \mathbf{t}, \mathbf{y}', \mathbf{y}) = \mathbf{w}_{\text{bs}} \cdot \mathbf{f}_{\text{bs}}(\mathbf{x}, \mathbf{t}, \mathbf{y}) + \mathbf{w}_{\text{qg}} \cdot \mathbf{f}_{\text{qg}}(\mathbf{x}, \mathbf{t}, \mathbf{y}', \mathbf{y})$$

where $\mathbf{f}_{\text{bs}}(\cdot)$ denotes the baseline features, $\mathbf{f}_{\text{qg}}(\cdot)$ denotes the QG features, and $\mathbf{w}$ is the parameter vector.

[2]http://code.google.com/p/Mate-tools/

In this paper, we follow the work of [3], using TP to generate QG features. Simply speaking, a TP is a mapping mode from a semantic dependency subtree to its corresponding syntactic dependency subtree. All the TPs in this work are identical with that in [3], including dependency, sibling and grandchild TPs.

Table III shows the QG feature templates used in this work, where $\psi(\mathbf{y}', \cdot)$ denotes the TP from semantic dependency subtree to syntactic dependency subtree, *dir* denotes the arc direction between head and child, l_{syn} denotes syntax label, and l_{sem} denotes semantic label.

	Feature Templates
Dependency	$\psi_{\text{dep}}(\mathbf{y}', h, m) \circ t_h \circ t_m \circ dir \circ l_{\text{sem}} \circ l_{\text{syn}}$
	$\psi_{\text{dep}}(\mathbf{y}', h, m) \circ w_h \circ t_m \circ dir \circ l_{\text{sem}} \circ l_{\text{syn}}$
	$\psi_{\text{dep}}(\mathbf{y}', h, m) \circ t_h \circ w_m \circ dir \circ l_{\text{sem}} \circ l_{\text{syn}}$
	$\psi_{\text{dep}}(\mathbf{y}', h, m) \circ w_h \circ w_m \circ dir \circ l_{\text{sem}} \circ l_{\text{syn}}$
Sibling	$\psi_{\text{sib}}(\mathbf{y}', h, m, s) \circ t_h \circ t_m \circ t_s \circ dir \circ l_{\text{sem}} \circ l_{\text{syn}}$
	$\psi_{\text{sib}}(\mathbf{y}', h, m, s) \circ w_h \circ t_m \circ t_s \circ dir \circ l_{\text{sem}} \circ l_{\text{syn}}$
	$\psi_{\text{sib}}(\mathbf{y}', h, m, s) \circ t_h \circ w_m \circ t_s \circ dir \circ l_{\text{sem}} \circ l_{\text{syn}}$
	$\psi_{\text{sib}}(\mathbf{y}', h, m, s) \circ t_h \circ t_m \circ w_s \circ dir \circ l_{\text{sem}} \circ l_{\text{syn}}$
	$\psi_{\text{sib}}(\mathbf{y}', h, m, s) \circ t_m \circ t_s \circ dir \circ l_{\text{sem}} \circ l_{\text{syn}}$
Grandchild	$\psi_{\text{grd}}(\mathbf{y}', h, m, \text{gr}) \circ t_h \circ t_m \circ t_{\text{gr}} \circ dir \circ l_{\text{sem}} \circ l_{\text{syn}}$
	$\psi_{\text{grd}}(\mathbf{y}', h, m, \text{gr}) \circ w_h \circ t_m \circ t_{\text{gr}} \circ dir \circ l_{\text{sem}} \circ l_{\text{syn}}$
	$\psi_{\text{grd}}(\mathbf{y}', h, m, \text{gr}) \circ t_h \circ w_m \circ t_{\text{gr}} \circ dir \circ l_{\text{sem}} \circ l_{\text{syn}}$
	$\psi_{\text{grd}}(\mathbf{y}', h, m, \text{gr}) \circ t_h \circ t_m \circ w_{\text{gr}} \circ dir \circ l_{\text{sem}} \circ l_{\text{syn}}$
	$\psi_{\text{grd}}(\mathbf{y}', h, m, \text{gr}) \circ t_h \circ t_{\text{gr}} \circ dir \circ l_{\text{sem}} \circ l_{\text{syn}}$

Table III
QG FEATURES USED IN OUR MODELS. DEP , SIB, GRD DENOTE DEPENDENCY, SIBLING AND GRANDCHILD RESPECTIVELY.

IV. EXPERIMENTS

A. Experimental Settings

We evaluate the performance of our baseline and syntax QG models on the corpus of [2]. The model of syntactic dependency parsing is trained on CONLL 2009 [5]. We exclude the sentences that also exist in the semantic corpus. Table IV shows the corpus statistics.

Corpus	Section	# sent.	# words.
Semantic	Train	8301	250311
	Devel	534	15329
	Test	1233	34311
Syntax	Train	15280	409225
	Devel	1762	49620

Table IV
STATISTICS OF SEMANTIC AND SYNTAX CORPUS.

B. Final Results

Table V shows the final results on the test set. We list some results in SemEval-2012 in the bottom for comparison: **ICT** refers to the results of [10], **Zhijun Wu** refers to the results of [11], **Zhou qiaoli** refers to the results of [12], and **NJU** refers to the results of [13]. **Baseline** denotes the results of our baseline model, and **Syntax QG** denotes the results after using syntax QG features. The model of syntactic dependency parsing achieve a LAS of 86.54% and a UAS of 88.32% on syntax development set. As is shown in Table V, our baseline model outperforms the top system participated in SemEval-2012 by 1.85%($p < 10^{-4}$). After incorporating the syntax QG features, the LAS gains a further increase by 0.6% (p-value is 0.001).

System	LAS	UAS
Baseline	64.65	82.21
Syntax QG	**65.25**	**83.01**
ICT	62.80	80.45
Zhijun Wu	62.72	78.69
Zhou qiaoli	62.08	N/A
NJU	61.64	80.29

Table V
FINAL RESULTS ON THE TEST SET.

C. Discussion and Analysis

Table VI shows the number of error reduction of head finding in semantic dependency parsing after applying syntax QG features in terms of POS tag pairs of semantic dependency. We only list the top eight pairs which decrease most. The related POS tags of these pairs are all notational words. It indicates that when the syntax QG model can process better for dependencies of notational words, as these dependencies are more consistent with syntactic dependencies.

POS Tag pair	Baseline	Syntax QG	↓
NN⌒NN	494	460	34
AD⌒VV	297	271	26
NN⌒VV	666	642	24
VV⌒VV	947	924	23
NR⌒NN	178	162	16
VV⌒NN	168	158	11
P⌒NN	78	67	11
VC⌒VV	94	84	10

Table VI
ERROR NUMBERS OF HEAD FINDING IN SEMANTIC DEPENDENCY PARSING.

Table VII shows the impact on labeled attachment of semantic dependency parsing after applying syntax QG features. We only list the top six semantic labels which decrease most. We can find that all these semantic labels listed are included in Table II, which denotes that syntactic label is a good indication to predict semantic label.

Semantic Label	Baseline	Syntax QG	↓
d-restrictive	805	774	31
aux-depend	512	289	23
s-succession	616	598	18
ROOT	244	230	14
agent	418	404	14
prep-depend	192	181	11

Table VII
ERROR NUMBERS OF LABELED ATTACHMENT IN TERMS OF SEMANTIC LABELS.

V. Related Works

Chinese semantic dependency parsing is first presented by reference [14]. This work annotates a corpus containing a number of sentences however it is not available for public. In SemEval-2012, an evaluating task has been organized for Chinese semantic dependency parsing [2]. The task organizer has labeled 100,68 sentences and splits the corpus into three parts for training, developing and testing respectively. The task attracts five teams to participate and finally they submitted nine systems. The best system achieves 62.80% in LAS [10]. In this work, we suggest a better model for semantic dependency parsing, and then make use of syntactic dependency structures to further improve the performance.

Our approach is inspired mainly by [3], which aims to enhance syntactic dependency parsing of one style by parsing results of another style. [3] exploits QG features to align dependency trees of different styles. We simply treat the semantic dependency corpus of [2] and the corpus of CONLL 2009 as two different styles for dependency parsing. However, our problem is different with that of [3].

VI. Conclusion

We aim to improve the performance of Chinese semantic dependency parsing by syntactic dependency parsing. First we compare the two different dependency parsing problems systematically. We demonstrate that the two problems share many similarities, thus syntactic dependency parsing can be potentially useful for semantic dependency parsing. Then we suggest an approach to make use of syntactic dependency parsing for semantic dependency parsing. Experimental results show that the performance of Chinese semantic dependency parsing has been increased by 0.6% on a much better baseline than the best system participated in SemEval-2012. Detailed analysis also demonstrates that the improvements are brought by the similarities of these two problems.

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References

[1] M. Li, J. Li, Z. Dong, Z. Wang, and D. Lu, "Building a large chinese corpus annotated with semantic dependency," in *Proceedings of the second SIGHAN workshop on Chinese language processing*, ser. SIGHAN '03. Association for Computational Linguistics, 2003, pp. 84–91.

[2] W. Che, M. Zhang, Y. Shao, and T. Liu, "Semeval-2012 task 5: Chinese semantic dependency parsing," in **SEM 2012: The First Joint Conference on Lexical and Computational Semantics*. Association for Computational Linguistics, 2012, pp. 378–384.

[3] Z. Li, T. Liu, and W. Che, "Exploiting multiple treebanks for parsing with quasi-synchronous grammars," in *Proceedings of the 50th Annual Meeting of the ACL*. Association for Computational Linguistics, 2012, pp. 675–684.

[4] B. Bohnet, "Very high accuracy and fast dependency parsing is not a contradiction," in *Proceedings of the 23rd International Conference on Computational Linguistics*, no. August, 2010, pp. 89–97.

[5] J. Hajič, M. Ciaramita, R. Johansson, D. Kawahara, M. A. Martí, L. Màrquez, A. Meyers, J. Nivre, S. Padó, J. Štěpánek, P. Straňák, M. Surdeanu, N. Xue, and Y. Zhang, "The conll-2009 shared task: Syntactic and semantic dependencies in multiple languages," in *Proceedings of the Thirteenth Conference on Computational Natural Language Learning (CoNLL 2009): Shared Task*. Association for Computational Linguistics, 2009, pp. 1–18.

[6] S. Kübler, R. McDonald, and J. Nivre, "Dependency Parsing," in *Synthesis Lectures on Human Language Technologies*, 2009.

[7] S. Zhiping, "Aspects of parataxis vs. hypotaxis between english and chinese," *Journal of Northeast Normal University (Philosophy and Social Sciences)*, vol. 2, pp. 92–98, 2003.

[8] T. Koo and M. Collins, "Efficient third-order dependency parsers," in *Proceedings of the 48th Annual Meeting of the ACL*, no. July, 2010, pp. 1–11.

[9] D. Smith and J. Eisner, "Quasi-synchronous grammars: Alignment by soft projection of syntactic dependencies," in *Proceedings on the Workshop on Statistical Machine Translation*. Association for Computational Linguistics, 2006, pp. 23–30.

[10] H. Xiong and Q. Liu, "Ict:a system combination for chinese semantic dependency parsing," in **SEM 2012: The First Joint Conference on Lexical and Computational Semantics*. Association for Computational Linguistics, 2012, pp. 514–518.

[11] z. qiaoli, z. ling, l. fei, c. dongfeng, and z. guiping, "Zhou qiaoli: A divide-and-conquer strategy for semantic dependency parsing," in **SEM 2012: The First Joint Conference on Lexical and Computational Semantics*. Association for Computational Linguistics, 2012, pp. 506–513.

[12] Z. Wu, X. Wang, and X. Li, "Zhijun wu: Chinese semantic dependency parsing with third-order features," in **SEM 2012: The First Joint Conference on Lexical and Computational Semantics*. Association for Computational Linguistics, 2012, pp. 430–434.

[13] G. Tang, B. Li, S. Xu, X. Dai, and J. Chen, "Njuparser: Achievements on semantic dependency parsing," in **SEM 2012: The First Joint Conference on Lexical and Computational Semantics*. Association for Computational Linguistics, 2012, pp. 519–523.

[14] L. Mingqin, L. Juanzi, D. Zhendong, W. Zuoying, and L. Dajin, "Building a large chinese corpus annotated with semantic dependency," in *Proceedings of the second SIGHAN workshop on Chinese language processing*, 2003.