Dependency Tree Representations of Predicate-Argument Structures

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Abstract

We present a novel annotation framework for representing predicate-argument structures, which uses dependency trees to encode the syntactic and semantic roles of a sentence simultaneously. The main contribution is a semantic role transmission model, which eliminates the structural gap between syntax and shallow semantics, making them compatible. A Chinese semantic treebank was built under the proposed framework, and the first release containing about 14K sentences is made freely available. The proposed framework enables semantic role labeling to be solved as a sequence labeling task, and experiments show that standard sequence labelers can give competitive performance on the new treebank compared with state-of-the-art graph structure models.

Introduction

Semantic role labeling (SRL) is the shallow semantic parsing task of identifying the arguments of a predicate, and assigning semantic role labels to them (Gildea and Jurafsky 2002). Predicate-argument structures of a sentence typically form a graph (Hajič et al. 2009; Choi and Palmer 2011), where a noun phrase can be the argument of more than one predicate semantically. For instance, in the sentence in Figure 1, the word “他 (he)” acts as the *A0* of the two predicates “去过 (went to)” and “离开 (left)”, respectively.

Most available semantic resources, such as PropBank (P-B) (Kingsbury and Palmer 2002), adopt this type of graph-structure representation, which makes structured prediction computationally more expensive, compared to linear or tree structures. As a result, many state-of-the-art SRL systems take SRL as several subtasks (Xue 2008; Björkelund, Hafdell, and Nugues 2009), including predicate selection, argument selection and role classification, thereby neglecting the relation between different roles the same word or phrase plays.

In the example in Figure 1, the role *A0* of “他 (he)” on “离开 (left)” can be regarded as the result of a *role transmission*, which passes the *A0* role from “去过 (went to)” to “离开 (left)” via the syntactic coordination between the two predicates. Many phenomena, including raising construction, control construction, relativization and nominalization, cause similar transmissions. By modeling semantic role transmission, incompatibilities between syntactic structures and predicate-argument structures can be resolved. Syntactic constructions here act as a media to transmit semantic information (Steedman 2000).

	他	去过	北京	，	后来	离开	了
去过.01	A0		A1				
离开.01	A0				ADV		

Figure 1: PB-style structures. (“他 (he) 去过 (went to) 北京 (Beijing)， (,) 后来 (then) 离开 (left)了 (le; a function word)” (He went to Beijing, and then left.))

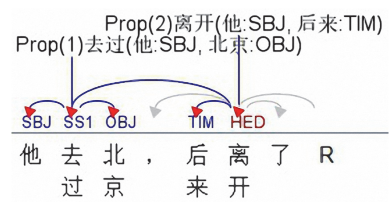

Figure 2: Proposed representation of the same sentence as Figure 1. The arcs are syntactic dependencies and the tags *SBJ, SS1*, etc are semantic tags. Propositions are marked out on the top of predicates; they are not a part of our annotation, but can be derived from it.

Inspired by this, we present a novel annotation framework, which represents predicate-argument information and syntactic dependencies simultaneously using a uniform dependency tree structure. An instance is shown in Figure 2, where each noun phrase is tagged with one semantic role, and the first predicate “去过 (went to)” is tagged with a transmission tag *SS1*, meaning that the subject of the predicate “去过 (went to)” is transmitted to its parent node, the second predicate “离开 (left)”. Based on these semantic role labels and transmission tags, the two propositions “去过 (他:SBJ, 北京:FIN) (went (he:SBJ, Beijing:FIN))” and “离开 (他:SBJ, 后来:TIM) (left (he:SBJ, then:TIM))” can be inferred automatically.

Our annotation has several potential advantages. First, modeling semantic role transmission explicitly allows not only the modeling of all the propositions in a sentence simultaneously, but also the integration of syntactic and semantic information, which can potentially improve SRL, and enable joint parsing and SRL. Second, a tree structure allows sequence labeling to be applied to semantic role labeling for a whole sentence at one step, reducing error propagation compared with the traditional three-step method.

Given our framework, a semantic treebank, the Chinese Semantic Treebank (CST), containing 14,463 sentences, is constructed. This corpus is based on the Peking University Multi-view Chinese Treebank (PMT) release 1.0 (Qiu et al. 2014), which is a dependency treebank. CST can be converted into PropBank format without loss of information. In standard PB-style evaluation, CST allows sequence labeling algorithms to give competitive accuracies to state-of-the-art graph-structured SRL systems.

Semantic Role Transmission

Motivations

The goal of our semantic annotation is three-fold:

(1) to give the same annotation for different syntactic variations with the same predicate-argument structure. This is consistent with the goal of PropBank (Xue 2008).

(2) to make syntax and semantics compatible, annotating semantic information using the same structure as syntactic annotation. In many cases, the predicate-argument structure is compatible with the syntactic structure. For example, syntactic subjects typically act as semantic agents, and syntactic objects act as semantic patients. In other cases, however, semantic and syntactic structures are incompatible. In Chinese, this type of incompatibility is typically caused by prepositional phrases, light verb structures, relativization, nominalization, raising and control constructions. Resolving such incompatibilities is the main goal of our scheme.

(3) to include the semantic roles of zero pronouns in tree structures, which is a very important issue for Chinese treebanking. In the English (Marcus, Marcinkiewicz, and Santorini 1993) and Chinese Penn Treebanks (Xue et al. 2005), null elements (empty categories) are used to mark the extraction site of a dislocated item, and represent dropped pronouns. As shown by Kim (2000), 96% English subjects are overt, while the ratio in Chinese is only 64%. This demonstrates there is added importance in Chinese null elements. Zero-pronoun resolution has been studied by a line of work recently (Yang and Xue 2010; Cai, Chiang, and Goldberg 2011). Due to their frequency, the resolution is useful for many tasks, such as machine translation (Xiang, Luo, and Zhou 2013).

The first goal is the underlying goal of all semantic role labeling resources, which can be achieved by a well-designed set of semantic role tags together with a detailed annotation guideline. The other two goals are achieved by modeling semantic role transmission, which is our main contribution.

Semantic Role Transmission

The key innovation of our framework is a semantic role transmission model, which annotates semantic role transmissions via a path in a syntactic dependency tree, rather than direct predicate and argument relations .

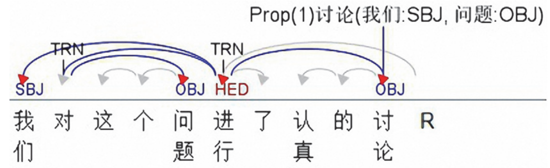

Figure 3: Intra-predicate transmissions using the preposition "对 (on)" and the light verb "进行 (do)" as media words. ("我们 (we) 对 (on) 这个 (this) 问题 (topic) 进行 (do) 了(finish, a function word) 认真 (serious) 的 (of; a function word) 讨论 (discussion)") (We made a serious discussion on this topic.)

Semantic role transmission can be classified into *intra-predicate transmission* and *inter-predicate transmission*. The former happens within the dependents of a predicate, using function words (e.g. the preposition "于 (in)") and light verbs (e.g. "进行 (do)") as media. The latter runs across at least two predicates, using predicates as media.

Intra-predicate transmission is used to model the roles of function words and light verb structures. Here a *light verb* is a verb that has little semantic content of its own, and typically forms a predicate with a noun (Butt 2003). In intra-predicate transmission, a media word transmits a semantic role from its child to its parent or another child.

For instance, in Figure 3, the preposition '对 (on)'" and light verb "进行 (do)" are two media words. The subject "我们 (we)" is transmitted by the light verb to the nominalized predicate "讨论 (discussion)" and acts as its *SBJ* semantically. The prepositional object "这个 (this) 问题 (topic)" is transmitted first by the preposition "对 (on)", and then by the light verb "进行 (do)" to the verb "讨论 (discussion)", and acts as its *OBJ* semantically.

Inter-predicate transmission is mainly used to transfer the semantic role of a source phrase to a null element. This type of transmissions can be classified into two subtypes according to the direction: *out-transmission*, which transmits a semantic role from the current predicate to a target predicate, and *in-transmission*, which transmits a semantic role from a source predicate to the current predicate.

An example out-transmission is shown in Figure 2, where the subject "他 (he)" is transmitted from the first predicate "去过 (went to)" to the second predicate "离开 (left)", with "去过 (went to)" being the medium. An example in-transmission is shown in Figure 4, where the nominalized predicate "制作 (production)" inherits the subject "他 (he)" from the predicate "参加 (participate)".

Annotation Framework

POS Tags and Dependency Labels

Our annotation is based on the Peking University Multi-view Treebank (Qiu et al. 2014), which consists of 33 POS tags and 32 syntactic tags, respectively. The POS tagset is a simplified version of the basic PKU POS tags, which contains over 100 tags (Yu et al. 2003). The syntactic dependency tagset, including *SBV* (subject), *TPC* (topic), *VOB* (direct object), *ACT* (action object), *POB* (prepositional object),

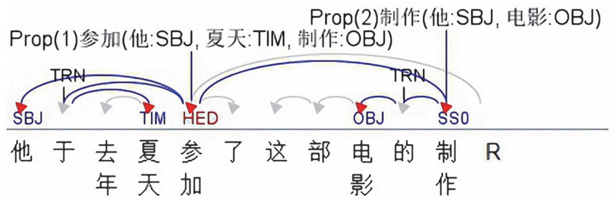

Figure 4: Preposition phrase and in-transmission. ("他 (he) 于 (in) 去年 (last year) 夏天 (summer) 参加 (participate) 了 (le; a function word) 这部 (this) 电影 (movie) 的 (de; a function word) 制作 (production)") (He attended the production of the movie last summer.)

COS (sharing-object coordinate), *COO* (non-sharing-object coordinate), *DE* (modifier of 的(special function word)) and *HED* (root of a sentence), serves as the basis for the design of our semantic annotation framework.

Semantic Roles and Transmission Tags

Each word bares at most one *semantic tag* in our annotation. It can be either a conventional *semantic role*, or a *transmission tag* if the word acts as a transmission medium. If a word does not have a semantic role to a predicate or act as a transmission medium, it is not tagged semantically.

Semantic role set induction. PropBank (Kingsbury and Palmer 2002), FrameNet (Baker, Fillmore, and Lowe 1998) and VerbNet (Schuler 2005) choose different types of semantic role sets. For English, the existence of a semantic dictionary makes it possible to map semantic roles from PropBank to VerbNet. For Chinese, the construction of PropBank is not based on a semantic dictionary (Xue 2008), which makes it impossible to map the six core semantic roles of PropBank to fine-grained semantic roles.

We choose HowNet (Dong and Dong 2006) as the base dictionary for our treebank construction, which classifies verbs into hundreds of categories, each bearing different semantic role frames. There are 51 semantic roles in HowNet, including *agent* and *patient*. To reduce the workload of human annotation, we infer a coarse-grained role set based on the HowNet semantic role frames. Following the phoneme inducing procedure of Wells (1982), the role set inducing strategy is as follows.

- *Rule 1*: *If two semantic roles co-occur in any frame, they are* opposite. *Otherwise, they are* complementary.
- *Rule 2*: *If two semantic roles are complementary, they can be taken as the same semantic role.*

For instance, *agent* and *experiencer* never co-occur in any frame, and so are *complementary*; *agent* and *patient* co-occur in many frames, and so are *opposite*. According to *Rule 2*, we take *agent* and *experiencer* as one semantic role, but differentiate *agent* from *patient*.

According to this strategy, we acquire a set of 22 semantic roles, including both *core* and *peripheral* roles. It is relatively unambiguous to map the roles to fine-grained roles. A brief description for each semantic role is shown in Table 1 together with its frequency in the semantic treebank.

	Tag	Content				Freq
c	ACT	action object				1803
o	DAT	contrast, beneficiary, partner, target				5546
r	FIN	location finite, state finite, time finite				1644
e	OBJ	content, isa, patient, possession, result, OfPart				31169
	POS	possessor acted by topic				538
	SBJ	agent, coagent, existent, experiencer, possessor, relevant, whole				28523
	Tag	**Content**	**Freq**	**Tag**	**Content**	**Freq**
p	CAU	cause	381	COS	cost	22
e	DEG	degree	10	DIR	direction	127
r	BSS	basis	585	INS	instrument	279
i	LOC	location	3283	MAN	manner	385
p	MAT	material	13	PUR	purpose	331
h	QUN	quantity	702	RAN	range	164
e	SCO	scope	700	THR	location through	108
r	TIM	time, duration	5043			
a						
l	INI	location initial, state initial, time initial				618

Table 1: Canonical semantic roles.

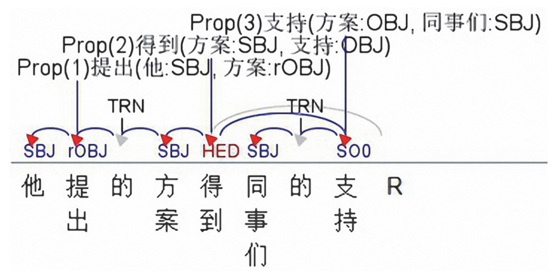

Figure 5: Reverse semantic role. ("他 (he) 提出 (propose) 的 (de; a function word) 方案 (scheme) 得到 (gain) 同事们 (colleagues) 的 (of; a function word) 支持 (support)") (The scheme he proposed gained support from his colleagues.)

Each semantic role tag might appear in two forms: canonical semantic role (on nouns) and reverse semantic role (on verbs). The two types of tags (*a* and *b* below), together with the two types of transmission tags as introduced earlier (*c* and *d* below), form the full semantic tagset.

(a) Canonical semantic roles denote the semantic roles of syntactic subjects, objects and prepositional objects upon their predicates. For instance, in the example sentence in Figure 2, "他 (he)" and "北京 (Beijing)" act as the *SBJ* and *OBJ* role of the predicate "去过 (went to)", respectively. Both are canonical roles, which are acted by a syntactic subject and object, respectively.

Among the 22 canonical semantic roles in Table 1, the top 6 roles tend to occur in the subject or object position, and take the predicates as their parent node in dependency trees. Most of them are induced from several fine-grained roles in HowNet. The bottom 17 peripheral roles tend to occur as prepositional objects or adverbials.

(b) Reverse semantic roles are used in relative clauses, where the predicate modifies the argument (directly or indirectly) syntactically. In Figure 5, "方案 (scheme)" acts simultaneously as the *OBJ* roles of the two predicates “提出 (propose)” and “支持 (support)”, and the *SBJ* role of the predicate “得到 (gain)”. The semantic relations between the noun and the predicate “得到 (gain)” can be annotated by tagging the noun with a canonical semantic role.

As for the relation between the noun and the predicate “提出 (propose)”, we tag the predicate with the semantic role *OBJ* and add a prefix “r” before the role to indicate that the relation has been annotated in the reverse direction. We determine whether a role is canonical or reverse through the following rule:

- *Rule 3*: *If a verb or adjective is tagged with a semantic role, its syntactic label is DE, and the syntactic label of its parent word is ATT, then the role is reverse; otherwise, the role is canonical*.

(c) Intra-predicate transmission tags. We use the tag *TRN* to indicate intra-predicate transmission. Six types of words are used as intra-predicate media: (1) prepositions such as “于 (in), 向 (to)”, (2) the verb “是 (be)” when used to indicate focus, (3) the auxiliary word “的 (de)” in relative clauses, (4) light verbs such as “进行 (do)” and “予以 (give)”, (5) location words such as “后 (after)”, and “来 (since)”, and (6) the noun morpheme “时 (when)”. In the example sentence in Figure 4, the two words “于 (in)” and “的 (de; a function word)” are tagged as intra-predicate media, belonging to type (1) and (3) above, respectively. In the sentence in Figure 5, the two auxiliary words “的 (de; a function word)” belong to type (3) above.

(d) Inter-predicate transmission tags can be classified according to: (1) the syntactic role of the transmitted phrase upon the source predicate, (2) the semantic role of the transmitted phrase upon the target predicate, and (3) the direction of transmission (i.e. inward or outward). We use tags such as *SS1* and *SS0* to represent inter-predicate transmissions, in which the three letters corresponds to (1), (2) and (3) above, respectively.

Specifically, the first letter can be “S”,“T” or “O”, which denote the source syntactic roles *SBV*, *TPC* and *VOB*, respectively. The second letter can be “S”, “T”, “D” or “O”, which denote the target semantic roles *SBJ*, *POS*, *DAT* and *OBJ*, respectively. The third letter can be “0” or “1”, which denote in-transmission and out-transmission, respectively. In total, only three syntactic roles can be transmitted, and the transmitted constituents can only act as four semantic roles. Popular inter-predicate transmission tags (frequency>10) include *SS0, SS1, SO0, OS1, TS1, SO1, OS0, TT0, TS0, TT1, SD1, ST0*.

For instance, the tag *SS1* in Figure 2 means that the media predicate “去过 (went to)” transmits its syntactic *subject* “他 (he)” to another predicate “离开 (left)”, and the transmitted constituent acts as the *SBJ* role of the target predicate. The tag *SO0* in Figure 5 differs in that it is an in-transmission tag rather than an out-transmission tag.

Representation of Various Constructions

Below are cases for the semantic representation of several special constructions, which are the main cases of multiple heads in semantic role labeling.

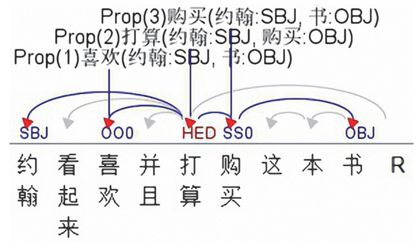

Figure 6: Special constructions. (约翰 (John) 看起来 (seems) 喜欢 (to like) 并且(and) 打算 (plan) 购买 (to buy) 这 (this) 本 (a classifier) 书 (book) (John seems to like and plan to buy this book.)

In a **subject control construction**, the subject of the main clause is co-referential with a null element that belongs to an embedded predicate. For instance, in “约翰 (John) 不愿(is reluctant) 离开 (to leave) (John is reluctant to leave)”, there is a PRO before “离开(to leave)”, and it is co-referential with the subject of the main clause “约翰 (John)”. Under our framework, the embedded predicate “离开 (to leave)” is tagged as *SS0*, which means that it inherits the syntactic subject of the main predicate “不愿(is reluctant)” and takes it as an *SBJ* argument.

In an **object control constructions (pivotal sentences)**, the object of the main clause is co-referential with a null element that belongs to an embedded predicate. For instance, in “约翰 (John) 说服 (persuaded) 汤姆 (Tom) 离开 (to leave)”, there is a PRO before “离开 (to leave)”, which is co-referential with the object of the main clause “汤姆 (Tom)”. In Chinese, object control constructions are also known as *pivotal sentences*, and we differentiate them from other constructions by tagging the embedded predicates (e.g. “离开 (to leave)” as *ACT* in the syntactic level.

In the semantic level, the object of the main clause always acts as the OBJ role of the main predicate (e.g. “说服 (persuaded)”), while the semantic role of the object upon the embedded predicate can differ. As a result, we tag the semantic role of the object to the embedded predicate on the object node.

Verbal coordinate constructions can be syntactically classified into two types: sharing-object coordinate constructions (COS) and non-sharing-object coordinate constructions (COO). They differ in whether the two coordinate verbs share an object on the right. The dependent verb in a COS construction inherits both the subject and object from the head verb, but the dependent verb in a COO construction can only inherit the subject. Intuitively, the dependent verb of a COO construction should be tagged as *SS0*, and the dependent verb of a COS construction should be tagged as both *SS0* and *OO0*. However, this is unnecessary. Since we differentiate the two types of constructions in the syntactic level using *COO* and *COS*, the transmission tags *SS0* and *OO0* can be inferred from the syntactic tags, and we do not annotate these transmission tags explicitly at all in the semantic level.

Combination of special constructions. In some cases, several types of special constructions co-occur in a clause, bringing challenges to linguistic analysis. For instance, the sentence in Figure 6 contains a raising construction, a verbal coordinate construction, and a control construction, and thus is difficult to analyze in a simple context-free-grammar tree or a dependency tree. Under our framework, the raising-to-subject verb “看起来 (seems)” is tagged as an adverbial in the syntactic level and thus does not needed to be tagged in the semantical level, and the two dependent verbs “喜欢 (to like)” (a special COO construction) and “购买 (to buy)” (the embedded predicate in a subject control construction) are tagged as *OO0* and *SS0*, respectively.

Proposition Generation

From a semantic dependency tree under our framework, PB-style propositions can be generated for each predicates without information loss. A transfer algorithm can take two passes. The first pass recursively traverses each node to find its predicate, recording the predicate-argument pairs. The second pass recursively traverses each node to recover null elements. If the node is tagged with an out-transmission or in-transmission tag, the function transmits a semantic role from the source predicate to the target, and then adds the predicate-argument pair into the result.

Take the sentence in Figure 5 for example. The original sentence contains 8 nodes, each being tagged with a semantic role or transmission tag, with the word “得到 (gain)” being the root node. The first pass finds two overt arguments “他 (he)” and “方案 (scheme)” for the predicate “提出 (propose)”, two overt arguments “方案 (scheme)” and “支持 (support)” for the predicate “得到 (win)” , and one overt argument “同事们 (colleagues)” for the predicate “支持”. Then, the second pass recovers the argument “方案 (scheme)” for the nominalized predicate “支持 (suppot)”.

Annotation Process

We construct Chinese Semantic Treebank (CST) 1.0 based on the 14K sentences in the Peking University Multi-view Treebank. Each syntactic dependency arc is annotated with a semantic role or transmission tag in Section 3. The inter-annotator agreement of CST 1.0 is 89.2% (tested on 500 sentences).

To speed up the annotation, a visualized annotation platform is developed. For quality control, a detailed annotation guideline is provided with abundant instances of different types of syntactic and semantic structures in Mandarin Chinese. Following the strategy for the construction of the Penn Chinese Treebank (Xue et al. 2005) — one annotator corrects an automatic labeled tree before a second annotator verifies the annotation.

Experiments

We compare the performances of two simple sequence labeling models trained on our treebank with those of a state-of-the-art SRL system on its equivalent PB-style conversion, demonstrating the effectiveness of the novel semantic representation.

$w_c; t_c; d_c; w_p; t_p; d_p; w_g; t_g; d_g; hs_c; ht_c$
$w_c t_c; w_c w_p; w_c w_g; t_c t_p; t_c t_g;$
$d_c d_p; d_c d_g; d_c d_p d_g; hs_c ht_c; d_c hs_c;$

Table 2: Feature templates for sequence labeling. *w*=word; *t*=POS tag. *d*=dependency label. *hs*=whether the token has a child syntactically tagged as *SBV*. *ht*=whether the token has a child syntactically tagged as *TPC*. The subscripts *c, p* and *g* denote the current token, the parent token and the grandparent token, respectively.

Experimental Setup

Data. Our treebank is used for all tests. Sentences 12001-13000 and 13001-14463 are used as the development and test sets, respectively. The remaining sentences are used as the training data. We use the transition-based dependency parser of MATE-tools (Bohnet and Nivre 2012) to provide automatic dependency parse trees for the development and test data.

Systems. We use the Conditional Random Fields (Lafferty, McCallum, and Pereira 2001)[1] and Markov Logic Network (Richardson and Domingos 2006; Riedel 2008)[2] for labeling the semantic tag of each word given a dependency tree, defining a simple set of features, as shown in Table 2. The semantic role labeler of MATE-tools (Björkelund, Hafdell, and Nugues 2009)[3], which obtained the best accuracy on the Chinese data of CONLL2009 Shared Task on Semantic Role Labeling, is used as the baseline system. MATE-tools is trained on the PB-style conversion of our treebank, while the sequence labelers are trained on its original corpus.

Evaluation. The accuracies of dependency parsing and semantic role labeling is calculated using the evaluation metric of the CoNLL 2009 shared task scorer (Hajič et al. 2009), which evaluates the accuracy of syntactic dependency parsing with UAS (unlabeled attachment score) and LAS (labeled attachment score), and measures the F1 score (SF1) of the recovered semantic dependencies. The accuracy of full propositions (i.e. a predicate with all its arguments) is also measured in F1 score (PF1). We refer to this evaluation as PB-style evaluation. To satisfy the PB-style evaluation, the results of the SRL systems are converted into PB style using the proposition generation procedure in Section 4.

In addition, we directly evaluate the proposed SRL systems on CST-style annotation with precision, recall and F1 score of semantic role tagging. We also evaluate semantic roles (SR, consisting of canonical and reverse semantic roles) and transmission tags (TRN, consisting of in- and out-transmission tags), respectively.

Results

Table 3 shows the PB-style evaluation results. The MATE-tools parser achieves 85.69% UAS and 82.82% LAS on syntactic parsing. The baseline SRL system achieves a 74.07%

[1]http://crfpp.googlecode.com
[2]http://code.google.com/p/thebeast/
[3]http://code.google.com/p/mate-tools

	Syntax	LAS	UAS	PF1	SF1 (%)
Baseline	auto	82.82	85.69	43.35	74.07
	gold	—	—	61.42	83.87
CRF	auto	82.82	85.69	44.69	74.16
	gold	—	—	64.00	84.50
MLN	auto	82.82	85.69	**46.33**	**75.21**
	gold	—	—	**66.50**	**85.73**

Table 3: Main results of PB-style evaluation. "SF1" and "PF1" denote the F1 scores of semantic roles and propositions, respectively.

	Syntax	P(%)	R(%)	F1(%)
SR	auto	74.39	74.57	74.48
TRN	auto	73.11	75.17	74.13
All	auto	73.97	74.77	74.36
SR	gold	84.66	83.86	84.26
TRN	gold	83.81	85.75	84.77
All	gold	84.37	84.48	84.42

Table 4: CST-style evaluation using the MLN model. "SR" and "TRN" are canonical/reverse semantic roles and transmission tags, respectively.

F1 score of semantic role labeling, and a 43.35% F1 score of proposition generation. When gold syntactic parse results are used, SF1 and PF1 reach 83.87% and 61.42%, respectively. Compared with the baseline system, our MLN-based and CRF-based SRL systems achieve competitive results. In particular, when using gold syntactic parse results, the SF1 and PF1 of the MLN system are higher by 1.86% and 5.08%, respectively.

The baseline system utilizes a large number of features to address the graph-structured SRL task (Björkelund, Hafdell, and Nugues 2009). In contrast, we achieve competitive results using sequence labeling with a simple set of features. This experiment verifies the effectiveness of our tree-structured semantic role annotation framework in information integration and reducing error propagation. Another advantage of our treebank is that it allows joint syntactic and semantic parsing, which we leave for future work.

Table 4 shows the results of the CST-style evaluation for the MLN system. The F1 score of semantic roles (SR) on auto parse is 0.35% higher than that of transmission tags (TRN), while the F1 score on gold parse is 0.51% lower than that of TRN. This demonstrates that the annotation of TRN is more sensitive to the parsing quality.

Error Analysis

On the semantic role level, the precision:recall of the baseline MATE tools and our MLN system are 85.61%:86.64% and 82.20%:84.84%, respectively. Detailed analysis demonstrates that the improvements of the MLN system are mainly involved with three types of phenomena: subject ellipsis, relative clauses and object control constructions. In particular, the improvement in recall is mainly because of subject ellipsis and relative clauses, where the arguments detected by the MLN system are often missed by the baseline system.

First, as described in Section 2, only 64% of Chinese subjects are overt, and thus subject ellipsis is very popular. Our MLN system performs much better than the baseline system in recovering omitted subjects, mainly because the semantic role transmission in the proposed framework can model the co-referential relation between the transmitted subjects and the omitted subjects.

Second, for an object control construction (Chinese pivotal sentence), the baseline system tends to add a redundant *SBJ* argument to the embedded predicate, while our MLN system does not make the mistake, thanks to the inter-predicate semantic role transmission model. Third, the predicate-argument relations represented by relative clauses are missed frequently by the baseline system, while our MLN system does not make this mistake, because of the intra-predicate semantic role transmission model.

Related Work

Semantic Resources with annotated predicate-argument structures include the PropBank (Kingsbury and Palmer 2002; Hovy et al. 2006; Xue 2008) and FrameNet (Baker, Fillmore, and Lowe 1998). PropBank is an important lexical resource for semantic role labeling, and a part of the OntoNotes resource (Hovy et al. 2006), which include semantic corpora for English, Chinese and Arabic. In PropBank, each sentence is annotated with verbal predicates and their arguments. The semantic role labels for arguments include core argument labels from ARG0 to ARG5, and dozens of peripheral labels such as ARGM-ADV.

For Chinese, there are two semantic resources: the PKU NetBank (Yuan 2007) and HIT Semantic Treebank (Che et al. 2012). Neither of the two treebanks have annotations of null elements, which is very important for the Chinese Language.

Automatic Semantic Role Labeling based on PropBank is typically considered as a pipeline or integration of several classification tasks. To address the SRL task, many machine learning techniques, including Maximum Entropy (Xue and Palmer 2004), logistic regression (Johansson and Nugues 2008), Markov Logic Network (Che and Liu 2010), SVM (Sun et al. 2009) and tree Conditional Random Fields (Cohn and Blunsom 2005) have been utilized. All these methods process the propositions in a sentence separately. CST-based SRL differs in that all the propositions in a sentence can be processed jointly using a sequence labeler.

Besides pipelined methods, there are also systems (Henderson et al. 2008; Lluís and Màrquez 2008) that process parsing and SRL using a joint approach, typically leveraging ILP. Our baseline system, MATE tools, gives comparable accuracies to such joint systems. Our tree structure can facilitate more efficient systems for joint parsing and SRL.

Conclusion

We studied the semantic role transmission by syntactic structures, presenting a tree-structured annotation framework for representing Chinese predicate-argument structures. We built a syntax-compatible semantic treebank according to the framework, allowing SRL to be solved as a sequence labeling task. Preliminary experiments show the effectiveness of our annotation on information integration and error reduction. Our semantic transmission model can be useful for other languages also, and our unified syntactic and shallow semantic tree enables joint parsing and SRL algorithms, which we leave for future work. We make our treebank and the proposition generation script freely available at klcl.pku.edu.cn or www.shandongnlp.com.

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