# Predicting Opinion Dependency Relations for Opinion Analysis

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## Abstract

Syntactic structures have been good features for opinion analysis, but it is not easy to use them. To find these features by supervised learning methods, correct syntactic labels are indispensible. Two possible sources to acquire syntactic structures are parsing trees and dependency trees. For the annotation processing, parsing trees are more readable for annotators, while dependency trees are easier to use by programs. To use syntactic structures as features, this paper tried to annotate on human friendly materials and transform these annotations to the corresponding machine friendly materials. We annotated the gold answers of opinion syntactic structures on the parsing tree from Chinese Treebank, and then proposed methods to find their corresponding dependency relations on the dependency trees generated from the same sentence. With these relations, we could train a model to annotate opinion dependency relations automatically to provide an opinion dependency parser, which is language independent if language resources are incorporated. Experiment results show that the annotated syntactic structures and their corresponding dependency relations improve at least 8% of the performance of opinion analysis.

## 1 Introduction

Opinion analysis has drawn much attention in research communities of machine learning and natural language processing. In the early stages, words in documents were used as the main features (Pang *et al.*, 2002). Some opinion dictionaries were created for this demand (Ku *et al.*, 2007). However, researchers soon realized that word features were not sufficient for acquiring good performances, so they started to include syntactic structures and semantic information (Qiu *et al.*, 2008). Their researches showed that linguistic knowledge is helpful in determining opinions.

For various applications related to opinions, syntactic structures have become powerful tools for extracting useful clues. To find opinions in product reviews, modification relations were used to identify the product and their features (Lu *et al.*, 2009), e.g., a good *price* (feature) of this *camera* (product). To find opinion holders and targets, templates and linguistic rules were adopted (Breck *et al.*, 2007). To find more opinion words, dependency relations were utilized (Qiu *et al.*, 2011). Even when applying the basic negation rule that flips opinion polarity over, we need to find its modified word first by syntactic clues. However, we will show that syntactic relations do not directly suggest opinions.

Syntactic relations are obtained usually from all kinds of syntax trees. Parsing trees (phrase structured) and dependency trees (grammatical) are the most commonly seen ones. Parsing trees are in-order trees which keep the order of words in sentences, so they are more readable for people. Instead, nodes in dependency trees are displayed by the head-modifier relations, in which the sentence sequence probably is not remained. People could find the opinion passages if they can understand the whole sentence, i.e. from parsing trees. However, when the linguistic background is needed, it could be difficult for most people to reconstruct the whole sentence from the dependency trees in order to find the opinion passage. Therefore, if we want to find annotators to build a corpus which could be used to train an opinion relation recognizer, parsing trees are the better materials compared to dependency trees. However, compared to relations between words, complicated tree structures are more challenge to be utilized by algorithms (Doan *et al.*, 2008).



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This paper focuses on extracting opinionated dependency relations from relations generated by the Stanford parser. We design an annotation mechanism on the syntactic structures on the sentence from Chinese Treebank to create an annotation environment with a lower entry barrier so that sufficient annotations can be labeled. Then these annotations are aligned to the relations in the corresponding dependency trees generated by the same parser from the same sentence as the gold standard for training the automatic annotator of the opinion dependency relations. We conduct experiments on the annotated opinion syntactic structures in parsing trees, and on the opinion dependency relations corresponding to them. The proposed process demonstrates a feasible direction toward the development of an opinion dependency parser.

## 2 Problem Definition

Given a set of non-collapsed dependencies parsed from a specific sentence by the Stanford dependency parser (de Marneffe and Manning, 2008; Chang *et al.*, 2009), each associated with a dependency relation between two words in this sentence, our goal is to identify which of them are with sentiment, i.e., those which reveal a part of opinions or the aroused emotions. For example, in the sentence "活动 取得 了 圆满 成功 (Activities scored le perfect success)", the Stanford dependency parser gives three relations: nmod(成功 <success>, 圆满 <perfect>), nsubj(取得 <scored>, 活动 <activities>), dobj(取得 <scored>, 成功<success>), and asp(取得 <scored>, 了<le>). The goal is to identify the former three may bear sentiment or opinions. The corresponding dependency tree is shown in Figure 1. From Figure 1 we can also see that it is not easy to read the original sentence without the linguistic background.

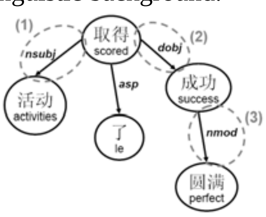


Figure 1. A sample dependency tree with three aligned opinion dependency relations.

Formally, the collection of the non-collapsed dependency relations of a sentence *S*, generated by the Stanford dependency parser, is denoted by *Rdep(S)* = {$r_1$, $r_2$, …}, where each $r_i \in Rdep(S)$ is associate with an opinion judgment of *op(r)*.

**Definition: Dependency Relation** The dependency relation *r*, generated by the Stanford parser, is composed of the type of relation *rel*, the head word $w_h$ and the modifier word $w_m$ in the form of $rel(w_h, w_m)$. $w_h$ and $w_m$ are two individual words in *S*. For example, in one relation in Figure 1, *r* = nmod(成功 <success>, 圆满 <perfect>), where *rel* = nmod, $w_h$ =成功 <success>, and $w_m$ =圆满<perfect>. A list of *rel* is available in Stanford Parser Manual (de Marneffe and Manning, 2008; Chang *et al.*, 2009).

**Definition: Opinion Judgment** The opinion judgment *op(r)*, generated by the proposed system, indicates whether the corresponding dependency relation *r* is opinionated, and $op(r) \in \{true, false\}$. For example, when *r* = nmod(成功 <success>, 圆满<perfect>), *op(r)* = *true*.

**Definition: Gold Opinion Judgment** The gold opinion judgment, generated by mapping from manually annotated data, indicates whether the corresponding dependency relation *r* is opinionated, and $gop(r) \in \{true, false\}$.

The gold answers come from the annotations on Chinese Treebank 5.1. In a parsing tree *T* of the sentence *S*, generated by the Stanford parser, an in-ordered set of tree nodes *O* = {$o_1$, $o_2$, …} is used to draw a parsing tree for the annotation process, and its corresponding order, i.e., its index, is used as the node ID to record the annotations.

The way we annotate an opinion relation on a parsing tree is annotating an opinion trio (Ku *et al.*, 2009). An opinion trio *tri* = $(triID, o_{parent}, o_{left}, o_{right}, t) \in Tri$ is a structure containing a left node $o_{left}$ and a right node $o_{right}$ in a parsing tree, between them there is a syntactic inter-word relation $t \in Rpt$, and a nearest parent node $o_{parent}$ of these two nodes. *Rpt* is an inter-word relation set where $Rpt \in$ {*Substantive-Modifier*, *Subjective-Predicate*, *Verb-Object*, *Verb-Complement*, *Other*}. A sample parsing tree and opinion trios within the sentence in Figure 1 are shown in Figure 2. The literal output of opinion trios are shown in

Figure 3. In the trio *tri* = (3, *NP-OBJ*, 圆满, 成功, *Substantive-Modifier*), *triID* = 3, $o_{parent}$ = *NP-OBJ*, $o_{left}$ =圆满 (perfect), $o_{right}$ =成功(success), and *t* = *Substantive-Modifier*.

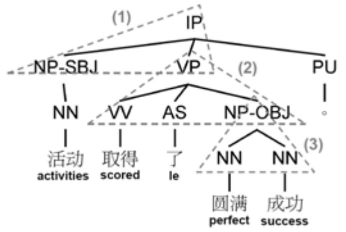


Figure 2. A sample parsing tree with trios.

| | | | |
|---|---|---|---|
| 1, IP | 活动 | VP | Subjective-Predicate |
| 2, VP | 取得 | NP-OBJ | Verb-Object |
| 3, NP-OBJ | 圆满 | 成功 | Substantive-Modifier |

Figure 3. Opinion trios

Note that because the annotation of trios is on nodes of parsing trees, which appear in-orderly, $o_{left}$ will always appear before $o_{right}$ in a sentence, and keeping this in mind will help understand the meaning of each inter-word relation *t*.

Now for the sentence *S*, we have its parsing tree *T*, the annotated opinion trios *Tri(S)* on it, and its dependency relations *Rdep(S)*. The next step is to mark the *op(r)* on *Rdep(S)* according to its corresponding *Tri(S)*. For each trio *tri*, if any descendent of its left node $o_{left}$ and any descendent of its right node $o_{right}$ together build a relation $r \in Rdep(S)$, the opinion judgment of *gop(r)* of the relation *r* is set to *true*. Otherwise, *gop(r)* is set to *false*. Now we have *gop(r)* for each *r* in *Rdep(S)*, our goal is to find good methods to generate *op(r)* so that it can predict *gop(r)* as precisely as possible. We propose methods to achieve this goal in Section 3.

## 3 Methods

As mentioned, our goal is to predict opinion dependency relations as precisely as possible. However, to use more readable materials, opinion trios are first annotated on Chinese Treebank 5.1, and then they are mapped to the corresponding dependency relations. Before the aligning process, we use the annotated trios for training to predict the opinion trios in Section 3.1. Using these predict trios for opinion analysis shall show the performance before the aligning process. After that, the aligned dependency relations, i.e., the gold opinion dependency relations are adopted for training to predict the opinion dependency relations in Section 3.2. Because the parsing tree and the dependency tree are generated by the same parser, we can always align them by the provided word ID numbers.

After prediction, the opinion dependency relations are available, and they can provide necessary information for many applications. However, we go one step further to test whether they benefit the opinion analysis. To fulfill this purpose, a basic method which uses the opinion dependency relations to extract opinionated sentences and determine their polarities is proposed in Section 3.3.

### 3.1 Predicting Opinion Trios

We predict the opinion trios by the sequential labeling model Conditional Random Field (*CRF*, Lafferty *et al.*, 2001). In a parsing tree, the tag of the internal node is the syntactic structure of its sub-tree, and the tag of the leaf node contains its part of speech and the content word. For each node, tags of its first four children (the first level), first four children of them (the second level), and their three children are used as features of this node. Features of its siblings (the window size is five) are considered, too.

The labels $\ell$ we would like the *CRF* to predict labels for each node, which are *N* or labels of the form *t-C*, where $t \in Rpt$, $C = \{L, R\}$, *L* indicates that the current node is $o_{left}$ in some opinion trio and *R* indicates $o_{right}$. The label *N* indicates that the current node does not belong to any $tri \in Tri$. The cardinality of the set *Rpt* is five, so that a total of 11 labels are used in *CRF*. *CRF++*[1] is selected for experiments.

### 3.2 Predicting Opinion Dependency Relations

After aligning the opinion trios to the dependency relations, we will have *gop(r)* for each one of them. In the previous research, usually only some relations were selected for opinion analysis. No statistical numbers showed the connection between the dependency relations and the opinions. We believe that it is because

[1] http://crfpp.sourceforge.net/

the opinion annotation on dependency relations is more difficult than on words, sentences, or documents. However, because of this alignment, we are able to see the distribution of different dependency relations in opinion sentences and opinion segments (opinion trios). We then predict opinion dependency relations based on these distributions: the *op(r)* of the relation *r* is set to *true* when its corresponding *gop(r)* appears massively frequently to be *true* in opinion sentences. To make this method reasonable, the assumption that *there are no opinion trios in non-opinionated sentences* must hold. A similar assumption that there are no opinion segments in non-opinionated sentences was made when annotating the NTCIR MOAT corpus, too (Seki *et al.*, 2008). Under this assumption, the relation that is in most case opinionated in opinion sentences is also in most case opinionated in all sentences. We believe that this assumption holds because intuitively if there is an opinion segment in one sentence, this sentence should be opinionated.

### 3.3 Using Syntactic Information for Opinion Extraction

In the previous research, relations were usually extracted automatically and then were used in various applications. As these relations are available after the prediction (or alignment) and as our purpose is to provide easy to use opinion dependency relations for further applications, we simply design rules for these relations in opinion analysis to show the baseline enhancement of using them.

#### 3.3.1 Using opinion trios

In the past, Ku *et al.* (2009) have conducted rule based experiments for opinion trios. They designed formula for trios of each $t \in Rpt$. Therefore, we adopted their rules on our augmentative experiment materials. We define the opinion scoring function *S(.)*, and its output opinion score varies with the input variables. These rules are shown by trio types as follows.

- **Substantive-Modifier Type:** $o_{left}$ of this trio type modifies $o_{right}$, so that the trio's opinion weight comes from the absolute opinion score of $o_{left}$, while the opinion polarity is determined by the occurrence of negative $o_{left}$ or $o_{right}$. If at least one of them is negative, the trio is negative, else it is positive.

$$\begin{array}{l} \text{if } (S(o_{\text{left}}) \neq 0 \text{ and } S(o_{\text{right}}) \neq 0) \text{ then} \\ \quad \text{if } (S(o_{\text{left}}) > 0 \text{ and } S(o_{\text{right}}) > 0) \text{ then } S(o_{\text{left}} o_{\text{right}}) = S(o_{\text{left}}) \\ \quad \text{else } S(o_{\text{left}} o_{\text{right}}) = -1 \times |S(o_{\text{left}})| \\ \text{else } S(o_{\text{left}} o_{\text{right}}) = S(o_{\text{left}}) + S(o_{\text{right}}) \end{array} \tag{1}$$

- **Subjective-Predicate Type:** $o_{left}$ of this trio type is a subject and $o_{right}$ is the action it performs, so that the action decides the opinion score of the trio. If the action is not an opinion or it is neutral, the subject determines the opinion score of this trio.

$$\begin{array}{l} \text{if } (S(o_{\text{right}}) \neq 0) \text{ then } S(o_{\text{left}} o_{\text{right}}) = S(o_{\text{right}}) \\ \text{else } S(o_{\text{left}} o_{\text{right}}) = S(o_{\text{left}}) \end{array} \tag{2}$$

- **Verb-Object Type:** $o_{left}$ of this trio type acts upon $o_{right}$. The effect depends not only on the action but on the target. The weight is determined by the action, but the polarity is the multiplication of the signs of opinion scores of $o_{left}$ and $o_{right}$.

$$\begin{array}{l} \text{if } (S(o_{\text{left}}) \neq 0 \text{ and } S(o_{\text{right}}) \neq 0) \\ \quad \text{then } S(o_{\text{left}} o_{\text{right}}) = |S(o_{\text{left}})| \times SIGN(S(o_{\text{left}})) \times SIGN(S(o_{\text{right}})) \\ \quad \text{else } S(o_{\text{left}} o_{\text{right}}) = S(o_{\text{left}}) + S(o_{\text{right}}) \end{array} \tag{3}$$

- **Verb-Complement Type:** The scoring function for trios of this type is defined the same as that of a Subjective-Predicate type in Formula (2). The complement node is the deciding factor of the opinion score.

#### 3.3.2 Using opinion dependency relations

The *usages* of opinion dependency relations were seen in several researches (Bikel and Castelli, 2008). In these researches, rules for a small number of major dependency relations were proposed in different papers but they were not listed together for a better utilization. Some rules were not ever mentioned in pervious researches. Instead, all relations are analyzed in this paper. For each relation *r* of which *gop(r)* equals *true* (when gold opinion relations are used for opinion analysis) or *op(r)* equals *true* (when predicted opinion relations are used for opinion analysis), we calculate its opinion score *ops(r)*. Let *RM(w)* be a function to return the dependency relations of word *w*'s modifiers one at a time, *n* is the total number of relations *RM(w)* returns, and *S(.)* is also the defined opinion scoring function then *ops(r)* is defined as in Formula (4).

$$ops(r) = S(rel, w_h, w_m) + \frac{1}{n}\sum ops(RM(w_m)) \qquad (4)$$

That is, the opinion score of a dependency relation is an average of the aggregate scores of its descendent dependency relations. In practice, we design different rules for calculating opinion scores by the current relation type *rel* in *S(.)*. Here to simplify the problem, we adopted Formula (1) and treated $w_m$ as $o_{left}$ and $w_h$ as $o_{right}$ in it.

## 4 Experiments

Though there were researches which predicted opinion dependency relations, they did not predict directly from the parsing results. Instead, they predicted from documents or sentences according to the context and a large quantity of training instances were needed. They did not predict on all dependency relations either. Therefore, there is no existing dataset containing correct opinion labels on dependency relations. In this section, we describe how to generate opinionated syntactic dataset on parsing trees, and align the annotated labels to dependency trees. After that, qualitative and quantitative analyses of opinion dependency relations are provided. At the end, we discuss the evaluation results of the proposed methods.

### 4.1 Data Set and Preprocessing

To use the Stanford parser as our tool to generate dependency tree for experimental sentences and to avoid errors as possible, we adopted Chinese Treebank 5.1 as experiment materials. Sentences in Chinese Treebank are already segmented and part of speech tagged, and its tagging set is the same with the one Stanford parser uses. Therefore, the Stanford parser can take the data from the Chinese Treebank to generate more accurate dependency trees.

The dataset Chinese Treebank 5.1 contains 507,222 words, 824,983 Hanzi, 18,782 sentences, and 890 data files. For the opinion analysis experiments, opinionated labels, i.e., opinionated, non-opinionated, positive, neutral, negative, were annotated on all sentences in Chinese Opinion Treebank. Afterward 57,706 trios were annotated on the parsing trees of gold opinion sentences, i.e., sentences which were annotated as opinionated. Methods for generating the gold opinion sentences proposed by Ku *et al.* (2007) were adopted.

Next, the Stanford parser took all sentences in Chinese Treebank as input to generate their dependency trees. A total of 416,581 dependency relations were generated, and 284,590 of them were in opinion sentences. Then the annotated trios were aligned to their corresponding dependency relations, and because trios were only annotated on opinionated sentences, the *gop(r)* of these aligned relations were set to *true*. At the end, a total of 54,753 relations *gop(r)* were set to *true*.

| | Opinion | | |
|---|---|---|---|
| Polarity | Positive | Neutral | Negative |
| # | 6,916 | 1,824 | 1,937 |
| % | 64.78 | 17.08 | 18.14 |
| Total # | 10,677 | | |
| Total % | 56.84 | | |

Table 1. Statistics of opinions.

| *Rpt* | Number | Percentage |
|---|---|---|
| Substantive-Modifier | 21,317 | 36.94 |
| Subjective-Predicate | 15,860 | 27.48 |
| Verb-Object | 18,010 | 31.21 |
| Verb-Complement | 1,208 | 2.09 |
| Other | 1,311 | 2.27 |
| Total | 57,706 | 100.00 |

Table 2. Statistics of structural trios.

Table 1 shows the distribution of the opinion and polarity labels. Table 2 shows the statistics of trios. Trios of the Substantive-Modifier and Verb-Object types are the majority in opinion sentences, while trios of the Verb-Complement type are few.

Table 3 further shows the distribution of dependency relations. It shows that previously the most adopted dependency relations for opinion analysis, e.g., *amod* (adjective modifier) or *advmod* (adverb modifier), do not certainly bear opinions or appear in opinion sentences. In Section 4.3, we will further test the performance of finding the opinionated relations with the help of the opinion word dictionary, which was also widely adopted by previous work (Feng *et al.*, 2009).

### 4.2 Evaluation of Opinion Trio Prediction

In this section, results of predicting opinion trios by CRF mentioned in Section 3.1 are shown. We first predicted the appearance of

$o_{left}$ and $o_{right}$ in trios, and then predicted the trio type $t \in Rpt$ for each trio.

The performance in Table 4 is not promising. Therefore, we consider the structure of trios, that is, $o_{left}$ and $o_{right}$ should appear as an ordered pair, and otherwise the label was viewed as illegal. The performance is shown in Table 5. Table 5 shows that all predicted trios were opinionated, and this tells that some opinion trios are of certain structures, but not all of them. We observed that the precisions 1.00 came from the collocations of specific words and structures, while the low recalls were from other trios which were not identified. However, these results still confirmed that we can find opinion trios by phrase structures and they may benefit in the opinion analysis process.

| A | B | C | D | E (%) | F (%) | A | B | C | D | E (%) | F (%) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Dvpmod | 590 | 501 | 413 | 84.92 | 82.44 | Attr | 3,869 | 2,666 | 140 | 68.91 | 5.25 |
| Pass | 560 | 399 | 224 | 71.25 | 56.14 | Pobj | 12,285 | 8,067 | 322 | 65.67 | 3.99 |
| Dobj | 32,949 | 24,294 | 13,192 | 73.73 | 54.30 | clmpd | 2,343 | 1,902 | 69 | 81.18 | 3.63 |
| Npsubj | 137 | 84 | 41 | 61.31 | 48.81 | tcomp | 2,839 | 1,588 | 53 | 55.94 | 3.34 |
| Ba | 757 | 575 | 263 | 75.96 | 45.74 | Nmod | 60,335 | 37,476 | 1,194 | 62.11 | 3.19 |
| Top | 2,256 | 1,458 | 661 | 64.63 | 45.34 | Asp | 4,176 | 2,889 | 79 | 69.18 | 2.73 |
| Nsubj | 36,902 | 26,102 | 11,058 | 70.73 | 42.36 | numod | 14,264 | 7,643 | 187 | 53.58 | 2.45 |
| Neg | 2,982 | 2,699 | 1,143 | 90.51 | 42.35 | Clf | 7,998 | 4,635 | 94 | 57.95 | 2.03 |
| Amod | 12,425 | 8,177 | 3,376 | 65.81 | 41.29 | Dvpm | 642 | 544 | 11 | 84.74 | 2.02 |
| Rcmod | 14,823 | 10,452 | 4,079 | 70.51 | 39.03 | partmod | 1,328 | 1,039 | 19 | 78.24 | 1.83 |
| Rcomp | 1,341 | 934 | 306 | 69.65 | 32.76 | Det | 6,021 | 4,083 | 74 | 67.81 | 1.81 |
| Advmod | 34,058 | 26,184 | 7,845 | 76.88 | 29.96 | ordmod | 1,220 | 553 | 10 | 45.33 | 1.81 |
| Mmod | 5,752 | 4,908 | 1,405 | 85.33 | 28.63 | prnmod | 770 | 320 | 5 | 41.56 | 1.56 |
| Range | 2,816 | 946 | 269 | 33.59 | 28.44 | plmod | 3,482 | 2,381 | 12 | 68.38 | 0.50 |
| Assmod | 12,365 | 9,106 | 1,669 | 73.64 | 18.33 | Cc | 7,462 | 5,031 | 17 | 67.42 | 0.34 |
| Ccomp | 40,712 | 31,338 | 4,377 | 76.97 | 13.97 | Lobj | 6,205 | 4,126 | 11 | 66.49 | 0.27 |
| Vmod | 866 | 613 | 79 | 70.79 | 12.89 | Conj | 11,414 | 6,967 | 17 | 61.04 | 0.24 |
| Dep | 17,295 | 8,222 | 887 | 47.54 | 10.79 | Cpm | 12,586 | 9,262 | 16 | 73.59 | 0.17 |
| Xsubj | 1,514 | 1,230 | 114 | 81.24 | 9.27 | Assm | 12,488 | 9,182 | 9 | 73.53 | 0.10 |
| Comod | 755 | 533 | 44 | 70.60 | 8.26 | tclaus | 1,583 | 1,140 | 1 | 72.02 | 0.09 |
| Lccomp | 3,102 | 2,063 | 155 | 66.51 | 7.51 | Etc | 1,164 | 663 | 0 | 56.96 | 0.00 |
| Cop | 625 | 519 | 37 | 83.04 | 7.13 | xcomp | 114 | 84 | 0 | 73.68 | 0.00 |
| Prep | 16,395 | 11,001 | 776 | 67.10 | 7.05 | acomp | 16 | 11 | 0 | 68.75 | 0.00 |

Table 3. Distributions of dependency relations and opinion dependency relations.

(A: type of dependency relations (*rel*); B: total occurrences in generated dependency trees; C: total occurrence in generated dependency trees of opinions; D: total occurrence in generated dependency trees of opinions when it bears opinions (*gop(r)* equals *true*); E: percentage that this relation appears in generated dependency trees of opinions; F: percentage that this relation appears in generated dependency trees of opinions when it bears opinions (*gop(r)* equals *true*).)

### 4.3 Evaluation of Opinion Dependency Relation Prediction

To predict which dependency relations are opinionated, we start with analyzing the distribution of them. Table 3 presented the distribution of dependency relations. The percentage of a relation appearing in dependency trees of opinion sentences when bearing opinions (*gop(r)* equals *true*), i.e., the value in F column, is taken as the support value. The support value indicates that in what degree this relation bears opinions. If the support value is high, it is confident to say that the relation is opinionated; otherwise, considering the content words is necessary. This idea conforms to the previous observation in Section 4.2: some of the opinions are structural, but not all of them.

According to the support value, dependency relations were divided into four categories. The Chinese opinion word dictionary *NTUSD* (Ku *et al.*, 2007) is involved to help identify opinion dependency relations when the support value is not high. The selecting criteria are listed as follows.

- **Very supportive**: with the support value above 0.8, e.g., *dvpmod*. Relations in this category are viewed as opinionated and their *gop(r)* are automatically set to *true*.
- **Supportive**: with the support value above 0.35 but lower than 0.8, e.g., *pass*, *dobj*, *npsubj*, *ba*, *top*, *nsubj*, *neg*, *amod*, *rcmod*. *RH(w)* is a function to return the word *w*'s

head in other relations of the same sentences, and *RM(w)* returns *w*'s modifier. For each $r = \{rel, w_h, w_m\}$ in this category:

$$\begin{aligned}&\textit{if} \text{ any of } w_h, w_m, RH(w_h), RM(w_m) \textit{ is in NTUSD},\\ &gop(r) = true,\\ &else\ gop(r) = false.\end{aligned}$$

- **Minor supportive**: with the support value above 0.2, e.g., *rcomp*, *advmod*, *mmod*, *range*. For each $r = \{rel, w_h, w_m\}$ in this category:

$$\begin{aligned}&\textit{if} \text{ all of } w_h, w_m, RH(w_h), RM(w_m) \textit{ is in NTUSD},\\ &gop(r) = true,\\ &else\ gop(r) = false.\end{aligned}$$

- **Not supportive**: with the support value less than 0.2. Relations in this category are viewed as non-opinionated and their *gop(r)* are automatically set to *false*.

| Experiment Settings | P | R | f-Score |
|---|---|---|---|
| Appearance: $o_{left}$ and $o_{right}$ | 0.60 | 0.52 | 0.56 |
| *t* = Substantive-Modifier | 0.59 | 0.41 | 0.49 |
| *t* = Subjective-Predicate | 0.53 | 0.46 | 0.49 |
| *t* = Verb-Object | 0.62 | 0.65 | 0.64 |
| *t* = Verb-Complement | 0.44 | 0.13 | 0.20 |

Table 4. Prediction of the appearance of children nodes in trios.

| Experiment Settings | P | R | f-Score |
|---|---|---|---|
| *t* = Substantive-Modifier | 1.00 | 0.25 | 0.40 |
| *t* = Subjective-Predicate | 1.00 | 0.25 | 0.41 |
| *t* = Verb-Object | 1.00 | 0.39 | 0.56 |
| *t* = Verb-Complement | 1.00 | 0.13 | 0.23 |

Table 5. Prediction of trios.

| All dependency relations | | | |
|---|---|---|---|
| *Rel* | P | R | f-Score |
| Nsubj | 0.4507 | 0.7028 | 0.5492 |
| Advmod | 0.3675 | 0.6851 | 0.4784 |
| Dobj | 0.6097 | 0.8566 | 0.7124 |
| Rcmod | 0.4195 | 0.8509 | 0.5620 |
| Amod | 0.5031 | 0.7953 | 0.6163 |
| Mmod | 0.3289 | 0.7388 | 0.4552 |
| Neg | 0.4313 | 0.6404 | 0.5155 |
| Range | 0.3630 | 0.5762 | 0.4454 |
| Top | 0.4833 | 0.5461 | 0.5128 |
| Rcomp | 0.3371 | 0.5817 | 0.4269 |
| Ba | 0.4286 | 0.5817 | 0.4935 |
| Dvpmod | 0.8244 | 1.0000 | 0.9037 |
| Pass | 0.5819 | 0.7455 | 0.6536 |
| Npsubj | 0.5000 | 0.7073 | 0.5859 |
| **Total** | **0.4713** | **0.6178** | **0.5347** |
| Modification dependency relations | | | |
| **Total** | **0.4070** | **0.2371** | **0.2997** |

Table 6. Performance of predicting opinion dependency relations.

The results of two experiment settings are listed: prediction performed on all dependency relations and on only modification-related dependency relations (in the form of *lex*-mod, e.g., *amod*, *rcmod*, etc.) The later are the relations adopted in many previous researches. Table 6 shows the performance of predicting opinion dependency relations. It indicates that if only modification related relations were considered, the f-score dropped nearly half because more than half of the opinion dependency relations were expelled in this case. In other word, results show that predicting on all relations instead of taking only modification-related dependency relations as clues can capture more opinion relations, and hence the prediction of opinion relations is necessary.

### 4.4 Evaluation of Opinion Extraction Using Predicted Opinion Trios and Dependency Relations

In this section, predicted opinion trios and predicted opinion dependency relations were utilized in an opinion extraction system. In order to make use of these structural cues, opinion analysis methods proposed by Ku *et al.* (2007) were selected. Their methods calculated opinion scores of sentences from characters and words accumulatively, so syntactic cues can be added in and function jointly.

Five settings for opinion analysis were experimented:

- **C+W+N**: characters, words, and negations were used as cues for calculating opinion scores. It was the original method proposed by Ku *et al.*
- **C+W+N+goldTrio**: annotated opinion trios were utilized additionally.
- **C+W+N+Trio**: predicted opinion trios were utilized additionally.
- **C+W+N+goldDep**: opinion dependency relations aligned from the annotated trios were utilized additionally.
- **C+W+N+Dep**: predicted opinion dependency relations were utilized additionally.

The results were shown in Table 7. The performance of the opinion extraction improves 10.40% (0.7162->0.7993) when utilizing opinion trios and 8.66% (0.7162->0.7782) when utilizing opinion dependency relations. These results clearly indicate that the syntactic information benefit opinion analysis. Because of the possible information loss in the automatic alignment process, that the performance of using trios is a little better than using dependency relations matches our expectation.

| Setting | f-Score |
|---|---|
| C+W+N | 0.7162 |
| C+W+N+goldTrio | 0.7922 |
| C+W+N+Trio | 0.7993 |
| C+W+N+goldDep | 0.7784 |
| C+W+N+Dep | 0.7782 |

Table 7. Performance of using syntactic information for opinion analysis.

## 5 Related Work

For all we know, no previous work has annotated opinion information on all dependency relations, or mapped annotated opinionated structures to dependency relations on a large quantity of documents or sentences. Therefore, to the best of our knowledge, no statistically analysis of opinion dependency relations involving manually annotations has been conducted. Researchers designed ruled or extracted dependency relations as features for opinion analysis based on their linguistic knowledge (Qiu *et al.*, 2011).

Yet there are still several lines of related work, including (i) opinion analysis (ii) opinion corpora (iii) syntactic information. Several dozen papers have been published on the topic of opinion analysis. Two general approaches have been proposed previously. They are machine learning approaches and heuristic-rule approaches. For both approaches, syntactic structures could be utilized. For the former, they can be used as features (Abbasi *et al.*, 2008); for the later, rules can be designed according to them (Ku *et al.*, 2009). We can see from the previous work that syntactic structures can help to enhance the performance.

As to the experimental corpora, some researchers managed to generate annotated materials and gold standards under constraints. Somasundaran (2007) annotated discourse information from meeting dialogs to train a sentiment model. MPQA annotated opinions and their sources (Wiebe *et al.*, 2002). NTCIR annotated opinions, polarities, sources, and targets for its multilingual opinion analysis task (MOAT, Seki *et al.*, 2008). However, none of them were annotated on materials with syntactic structures, and it caused the lack of analysis of opinion syntactic structures.

Researchers have acquired syntactic structures (Zhou, 2008), but few of them have tried to associate syntactic structures with opinions. The most similar previous work to ours was proposed by Ku *et al.* (2009). Compared to it, the proposed process made the development of opinion dependency parser feasible. As dependency relations and the predicted opinion dependency relations are of the same form, no extra knowledge or integration is needed for the use of them.

## 6 Conclusions and Future Work

The proposed new process is the main contribution of this paper. It annotated opinion syntactic structures on phrase structure trees, which are more readable for annotators, and aligned these structures to grammatical structures, which facilitates their usage. Chinese Treebank was selected as the source of phrase structure trees, and dependency relations as the grammatical structures. They are both widely used in natural language processing.

Though the experiments were implemented on Chinese materials, this process is language independent. It can be applied to materials in different languages without modifications.

By predicting opinion dependency relations, we can say that a basic opinion dependency parser has been developed. Experiments have shown that the predicted opinion dependency relations are beneficial for opinion extraction. Although we still need a parser to generate syntactic structures, parsing is relatively a mature technique in natural language processing. For a comparably new research problem like opinion analysis, it is common that tools are not handy. The best of the proposed method is that it can function in a multilingual environment by incorporating a domain or language specific resources (here, NTUSD for Chinese).

Through the alignment, we made a large quantity of opinion dependency relations available. According to their distributions shown in this paper, researchers can select suitable relations to use according to their diverse needs, such as extracting evaluative features in product reviews or comments, opinions or their polarities.

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