Building a Case-based Semantic English-Chinese Parallel Treebank

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Abstract

We construct a case-based English-to-Chinese semantic constituent parallel Treebank for a *Statistical Machine Translation* (SMT) task by labelling each node of the *Deep Syntactic Tree* (DST) with our refined semantic cases. Since subtree span-crossing is harmful in tree-based SMT, DST is adopted to alleviate this problem. At the same time, we tailor an existing case set to represent bilingual shallow semantic relations more precisely. This Treebank is a part of a semantic corpus building project, which aims to build a semantic bilingual corpus annotated with syntactic, semantic cases and word senses. Data in our Treebank is from the news domain of Datum corpus. 4,000 sentence pairs are selected to cover various lexicons and part-of-speech (POS) n-gram patterns as much as possible. This paper presents the construction of this case Treebank. Also, we have tested the effect of adopting DST structure in alleviating subtree span-crossing. Our preliminary analysis shows that the compatibility between Chinese and English trees can be significantly increased by transforming the parse-tree into the DST. Furthermore, the human agreement rate in annotation is found to be acceptable (90% for English nodes, 75% for Chinese nodes).

Keywords: English-Chinese semantic constituent parallel Treebank, case tree annotation, semantic machine translation corpus

1. Introduction

The reason of building this corpus is that having a bilingual semantic corpus with refined semantic role information is expected to bring significant benefit to the task of *Statistical Machine Translation* (SMT). Since the semantic constituent is less variant during translation in comparison with the syntactic constituent (Fung et al., 2007), it should lessen the data sparseness problem of translation patterns, which often occur in syntactic SMT.

Researchers have paid attention to constructing semantic resources in the last 20 years. And many useful and high-quality semantic resources have been built, such as FrameNet (Baker et al., 1998), PropBank (Palmer et al., 2005), Academia Sinica Treebank (Huang et al., 2000), NomBank (Meyers et al., 2004) , VerbNet (Schuler, 2005), HowNet (Dong and Dong, 2003), etc. However, each of them only serves its own purpose. Therefore, they are different from each other in many details, such as annotation types (e.g., frame sets in FrameNet, shared semantic arguments in PropBank) and annotation methods (e.g., adding a layer of predicate-argument information to syntactic structures in PropBank, and labeling semantic information on each node as Sinica Treebank does).

Currently, FrameNet and PropBank are the two most commonly used semantic resources in *Semantic Role Labeling* (SRL) and SMT tasks. FrameNet is based on a theory of meaning called Frame Semantics (Fillmore, 1982). The basic idea is that the meanings of most words can best be understood on the basis of their semantic frames, which describe the types of events, relations, and the participants involved. In FrameNet, most sentences are selected manually from British National Corpus and then assigned with their associated frames based on the frame semantics theory. FrameNet was first adopted in the SRL task by Gildea and Jurafsky (Gildea and Jurafsky, 2002). However it has not been widely used in SMT tasks.

On the other hand, PropBank has been widely used in both SRL and SMT since CoNLL-2005 (Carreras and Màrquez, 2005). It annotates the Penn TreeBank with predicate argument structures, and uses shared arguments as semantic labels. But it only labels a part of the nodes in the constituency tree. Therefore, it cannot clearly represent the relation between clauses or the relation between various arguments (e.g., the semantic relation in phrase "everyday [Modifier] life [Head word]" or between clauses "I come back [Result], because of the rain)[Reason]" are not represented).

In previous work, researches had brought semantic relation labeling and tree flattening into the SMT task (Wu and Fung, 2009; Liu and Gildea, 2010; Bazrafshan and Gildea, 2013). However, most of those existing Treebanks are: (1) not in bilingual form (e.g., Sinica Treebank etc.), (2) in bilingual form but the translation direction of the corpus is not from English to Chinese(e.g., PropBank), or (3) annotation coverage is not fine enough (e.g. PropBank). Therefore, inspired by the work of Su et al. (1995), we build this corpus to meet our requirements.

Since the compatibility during tree translation is an important issue for tree-based SMT, we adopt the *Deep Syntactic Tree* (DST) structure (Mel´čuk and Wanner, 2006) in our treebank to reduce span-crossing, and then transform the DST into its corresponding case tree. Also, we label all the tree nodes of the DST (not only nouns and verbs but also clauses, adjectives, adverbs, interjections, etc.) with our semantic case labels. We tailor the *Sinica case set* (Huang et al., 2000) to share the same case set in both Chinese and English case trees, and then annotate each node of our Treebank with them to represent detailed semantic relations.

In section 2, we introduce the construction of this resource. Section 3 discusses the compatibility between parallel parse-trees and the effect of DST structure in reducing the alignment span crossing. Section 4 introduces the annotation procedure, case set tailoring, and the annotation task management. Finally, section 5 concludes the paper.

2. Semantic Corpus Construction

Our case Treebank is a part of a joint project from five parties (3 national universities in China and 2 institutes of Chinese Academy of Sciences). The goal of this project is to build a corpus which provides both syntactic and semantic information for SMT tasks. This treebank contains 4,000 word-aligned English-Chinese constituent syntactic tree-pairs, their associated DST treebank tree-pairs, and also their annotated case tree-pairs. The word alignment and various kinds of tree-pairs are all annotated by university teachers and graduate students, which were pre-trained for this task.

The text sentences of our treebank are selected from Datum Corpus (total 193,380 sentence-pairs), which is built under China "863" program and consists of high quality translations from English to Chinese. We extract 4,000 sentences pairs from Datum's news domain (34,380 sentence pairs), and they are selected to cover as many POS n-gram-patterns and lexicon-types as possible. In average, each sentence-pair contains 30 English words and 29 Chinese words.

The constituent syntactic trees are first generated with the Berkeley parser (Petrov et al., 2006). Annotators then check the result and add constraints (for guiding the parser to generate the correct parse-tree) to those sentences which are not properly parsed. We then re-parse each sentence which has an incorrect parse tree with those constraints. The above checking and re-parsing process will be iterated until we get a satisfactory result.

The *Deep Syntactic Tree* (DST) is adopted to avoid the divergence resulted from the surface-syntactic discrepancies between different languages, as proposed in the Meaning-Text Theory. A DST example is shown in Figure 1. It is obtained via normalizing the given syntactic tree with some pre-specified rules. The normalization procedure mainly extracts function words, flattens non-terminal nodes according to linguistic rules, and assigns additional syntactic information (e.g., specifying head-child, voice, tense, lemma, etc.). The DST structure helps reduce subtree span-crossing during translation via flattening subtrees and extracting functional words. The experiment results show that adopting DST could reduce translation span-crossing more than 20%.

The case trees are obtained via labeling each node of the DST with its associated semantic role in the corresponding subtree. To save human effort, we use a SRL tool/model to pre-assign the case-labels to some DSTs first, and then ask the annotator to check and correct the labeling errors. Afterwards, we re-train the SRL model with additionally involving those newly corrected case trees. We use the SRL tool to perform case labeling, manually check case trees, and then use the results to improve the pre-labeling model, iteratively. Case tree examples are shown in Figure 2.

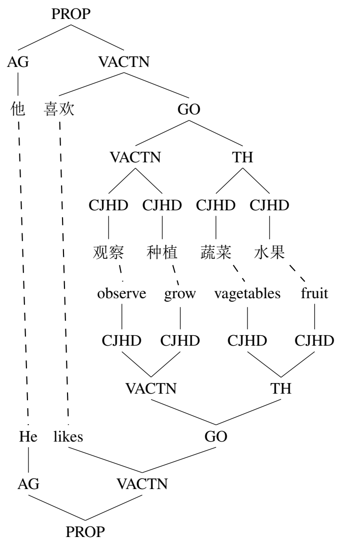

Figure 2: Bilingual examples of case trees

Semantic case grammar was first proposed by Fillmore (Fillmore, 1966). It only focuses on the relations between the predicate and the semantic elements around , but not on their deeper logical relationship or information such as scope or degree, so it can be only taken for presenting shallow semantic relations. We provide detailed semantic information in our case tree such as scope and degree, but not co-reference, as Wu and Fung (2009) had empirically shown that such shallow semantic labels can provide useful information for global reordering. Furthermore, we label every node of the DST with its corresponding case role to provide complete semantic case information for SMT.

We tailor our case set (total 54 cases) from the Academia Sinica case set (Huang et al., 2000) based on our experience in analyzing Chinese and English syntactic treebank. For example, we add new cases such as *Imperative* [XIMP], *Question* [QUES], etc. Also, we refine the Sinica case set to cover every DST node, such as *Scope* [SCOP], and *Conjunction Head* [CJHD].

We divide our case-set into 5 classes (by their properties and usages) for helping annotators analyze and annotate case labels more efficiently. These classes include: (1) central word class (such as action verb constituent [VACTN]); (2) core semantic case class (e.g. agent [AG]); (3) secondary semantic case class (e.g., possessive

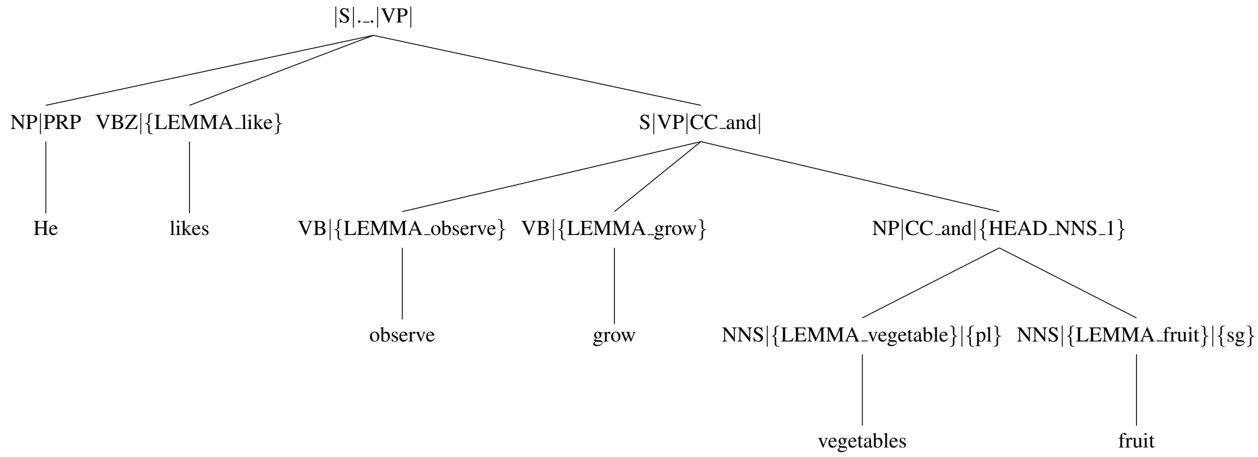

Figure 1: The DST example for the sentence "He likes to observe and grow vegetables and fruit."

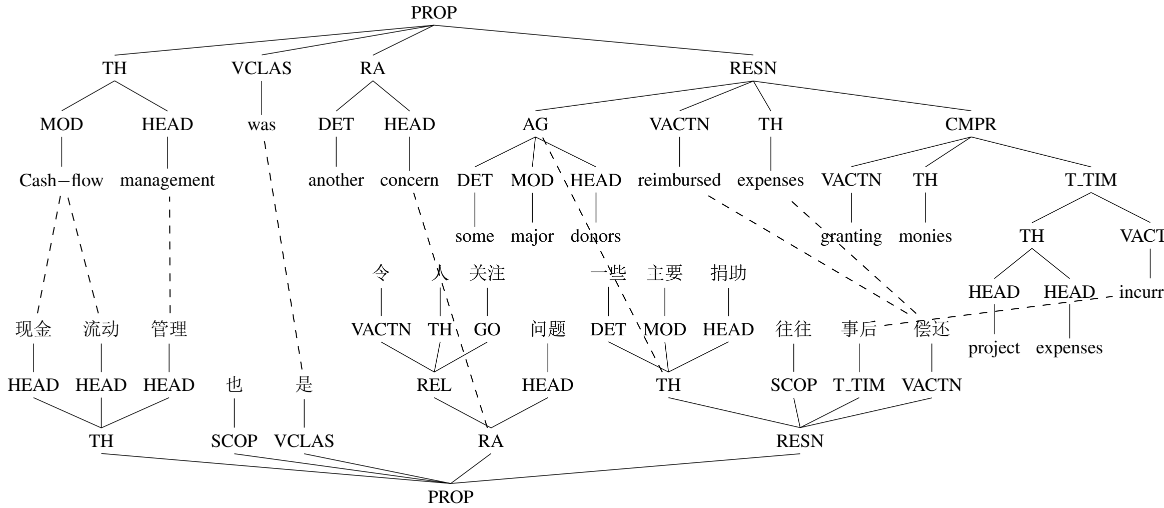

Figure 3: An example of aligned case trees

[POS]); (4) modality semantic case class (e.g., manner [MANR]), and (5) semantic relation case class (e.g., concession [CONC]). The adopted case set covers: (1) semantic relation between verb predicate (such as VACTN: Action predicate; VCLAS: classified predicate) and their arguments (such as AG: Agent; RA: Range; CMPR: Comparison), (2) modality (such as SCOP: Scope; DEGR: Degree), (3) relation between non-verb words (such as HEAD: non-verb head word; POS: Possession), (4) phrase and clause level relations (such as RESN: Reason; CONC: Concession). An aligned case tree pair example with each kind of case classes is given at Figure 3.

Currently, over 2,000 case-tree pairs had been annotated with an acceptable human agreement rate (75% for Chinese case-nodes and 90% for English case-nodes), and other 2,000 case-tree-pairs are under annotation process. Since the usage of Chinese lexicons is more flexible than that of English, the human agreement rate for the Chinese case-tree is lower than that for the English case. The case tree in our Treebank is represented similarly to the syntactic tree adopted in Penn Tree Bank (PTB) (Marcus et al., 1993). For example: "vegetables and fruit" will be represent as "(TH (CJHD vegetables) (CJHD fruit))", where "TH", "CJHD" denote Theme and Conjunction-Head, respectively.

The word alignment and word sense of the treebank are annotated by another group. To get word alignment, they pre-align the bilingual corpus with Giza++ (Och and Ney, 2000). After that, annotators manually correct the alignment result and format it into a human readable form. Our partner also labels the word senses in that corpus with the Synset from WorldNet 3.0. All those resources mentioned above will be presented in our project.

3. The compatibility between Parallel Parse-trees

It is well-known that the language pairs across different language families are less compatible, which thus causes the difficulty of translation. The incompatibility may result from various linguistic phenomena (e.g., the use of function words, difference in word order, grammar, idiom, word-formation rules, etc.). For example, the task of SMT between Chinese and English is more difficult than that

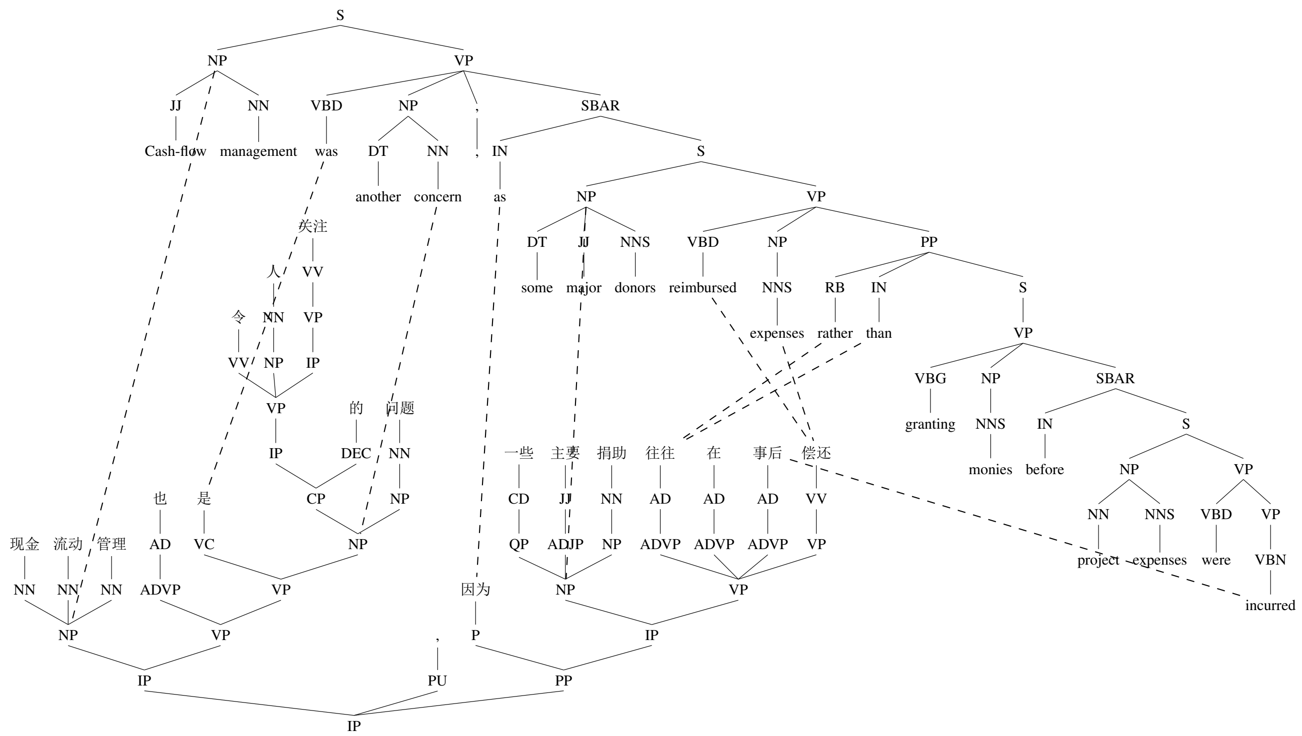

Figure 4: An example of aligned syntactic trees

between English and other fusional languages (such as Arabic and French). Correspondingly, the incompatibility between parse-trees of these two languages greatly raises the difficulty of performing syntactic SMT.

Due to the above reason, we want to improve the compatibility between Chinese and English syntactic trees. The subtree span-crossing in aligned syntactic trees (marked in red lines) is shown in Figure 5. The target sentence will not be "reachable" under compositional transformation when there is a span-crossing. In practice, span-crossing increases the size of subtrees involved in the translation patterns of syntactic SMT (Liu and Gildea, 2010), which makes the sparseness problem even worse. And our case tree can alleviate the span-crossing problem.

As an example, the bilingual tree pairs in Figure 3 and Figure 4 have the same semantic meaning. The tree pair in Figure 3 is our aligned semantic case tree; and the tree pair in Figure 4 is its corresponding syntactic tree pair. Please note that Chinese sentence and English sentence are different from each other greatly in syntactic structures. But when we transform the syntactic tree into their corresponding semantic case trees, the incompatibility between these two trees is dramatically reduced (as shown in Figure 3). Furthermore, the tree-node labels between these two case trees became more compatible by using semantic case labels, such as RA (Range), TH (Theme), VCLAS (Classification Verb), RESN (reason), and T_TIM (Time). Therefore, adopting case-trees will benefit semantic alignment and the extraction of transfer rules.

As the result, the span-crossing can be alleviated by transforming the syntactic tree into its corresponding DST. Figure 5 shows that the left syntactic tree pair contains span-crossing (target sentence is thus not reachable through compositional transformation). After having extracted function words (the word "of" in English and " 的" in Chinese) and flattened non-terminal nodes (NP and PP in English and DNP in Chinese), the original span-crossing is eliminated.

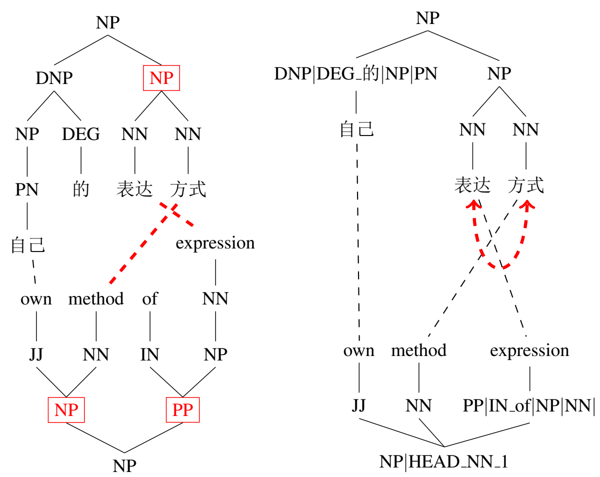

Figure 5: Span-crossing is eliminated by adopting DST (the tree-pair to the right)

We conduct an experiment to evaluate the effect of increasing reachability by adopting the DST. Table 1 shows the reachability comparison between PTB style syntactic tree-pairs and DST tree-pairs. The test is done on our English-

Chinese corpus, in which the sentence length is about 30 English words in average. In this experiment, the DST significantly reduces the span-crossing and increases the sentence reachability about 19% (from 37.5% to 56.3%). In Table 2, we show the same experiment on another technical domain corpus[1] which possesses shorter English sentences (each sentence contains about 13 words in average.). The results show that DST also increases its sentence reachability about 13% (from 67.9% to 80.8%). These two experiments demonstrate that DST could effectively increase the sentence reachability.

Semantic corpus	PTB	DST
Numbers of sentences	250	250
Unreachable sentences	143	100
Ratio of reachable sentences	37.5%	56.3%
Number of subtrees	4,547	2,318
Subtrees with crossing	471	186

Table 1: Reachability test on our corpus

BDC corpus	PTB	DST
Numbers of sentences	1,528	1,528
Unreachable sentences	490	293
Ratio of reachable sentences	67.9%	80.82%
Number of subtrees	13,621	5,246
Subtrees with crossing	1,346	432

Table 2: Reachability test on BDC corpus

Adopting the case tree also can increase the comparability between Chinese and English subtrees. In Figure 6, the upper 3 syntactic trees have the same semantic meaning but their syntactic structures are very different until we transform them into their corresponding case trees (the lower 3 case trees). After the transformation, not only the tree structure has been simplified, but also the syntactic structure difference caused by adopting different voices (one in active and another in passive) has been reduced. We hope using case tree could provide a better alignment and ease transfer rule extraction for SMT task.

4. Annotation Procedure

4.1. corpus preparation

The raw sentences of our case trees are selected from Datum Corpus, which is under China ”863” program and consists of high quality translations from English to Chinese. We filter the original corpus to select 10,000 sentence-pairs only in the news domain as follows: (1) Take every 20 sentences as a document, then use Gibbs LDA (Wei and Croft, 2006) to divide the corpus into 3 classes (news, others, combination of news and others). (2) If a document is classified as “news” with probability great

[1]BDC corpus, which is provided by Taiwan Behavior Design Corp.

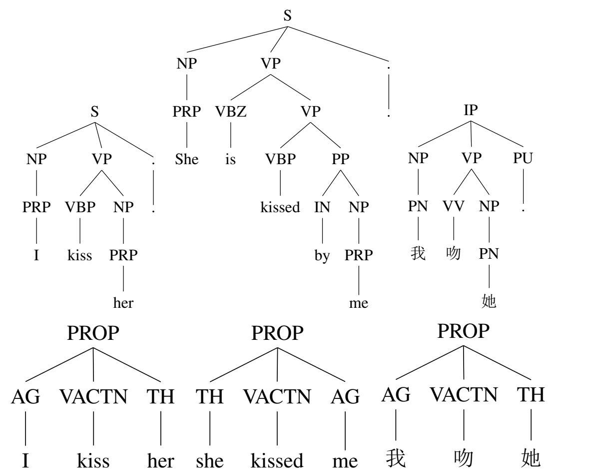

Figure 6: Comparability is increased through adopting case tree representation form

than 0.5, label it as a news document. The obtained news corpus ends up with 34,380 sentence pairs. (3) Randomly select 3,000 sentence-pairs for the development-set and also do it for the test-set. (4) Perform stemming and POS tagging on the remaining 28,380 English sentences (within sentence-pairs). Afterwards, their unigrams and bigrams of stems are extracted to measure lexicon coverage (the trigrams and quadgrams of POS-tags are also extracted to measure syntactic-pattern coverage). (5) Iteratively select 4,000 sentence-pairs with their English sentences possess the highest lexicon and syntactic-pattern coverage rate at each extraction.

4.2. Case tree annotation procedure

For those selected sentence-pairs, the annotation task will be conducted according to the following steps: (1) We first manually annotate those sentences with their PTB style syntactic trees. (2) We then normalize each syntactic tree into its corresponding DST by rules. (3) Afterwards, we manually annotate a seed corpus with their case labels (total 500 sentence-pairs), and train a SRL model with the Conditional Random Field approach (Lafferty et al., 2001). (4) Use the obtained SRL model to pre-label an amount of remaining sentence-pairs. (5) The annotator is then asked to manually edit those pre-labeled case trees. (6) Re-train a new SRL model additionally with those newly annotated case trees. The steps (4) to (6) will be repeated iteratively until all sentence-pairs are annotated with their case labels. With this iterative process, we incrementally improve our SRL model and save annotator’s effort via providing more accurate pre-labeled case trees.

In building the SRL model, the following features are adopted:

Features related to the current node: the syntactic node label, the extracted functional word, the extracted syntactic labels which are extracted from the subtree node during flattening, the linguistic features (such as voice, tense, aspect, etc.), and the lexical features (i.e., head word and lemma).

Sibling nodes and the Parent node features: They will adopt the same set of features as that for the current node.

We randomly collect 3 different test sets (each includes 100 sentence-pairs) to test the case pre-labeling accuracy rate. The results show that our pre-labeling achieves averaged 91% node accuracy rate for English and 68% for Chinese. We also provide guidelines and online training lectures to train the annotators. After our training and with the help of pre-labeling, the annotation speed had been improved from 23 minutes to 10 minutes per sentence.

In the annotation process, the annotators are presented with sentence pairs and their associated parallel DST trees. If the DST structure is not confused to the annotators, they will annotate the DST nodes with appropriate cases; otherwise, the tree structure will be carefully analyzed. For each sentence-pair, its associated case trees are labeled twice independently by two annotators. If the results are inconsistent, then they will be judged by the third annotator. The obtained case-tree is then combined with the annotated word senses to form a complete semantic tree.

4.3. Annotation Task Management

We have done two experiments on our annotation task. The first is inter-annotator agreement (IAA) test for evaluating the annotation quality. We evaluate the precision, recall and F1-measure for every case tag between the two case trees built by the two annotators. Table 3 reveals that our inter-annotator agreement rate is reasonable (about 75% F1 score for Chinese and 90% for English), which implies that the quality of our case annotation is acceptable. The second experiment is efficiency test for checking the benefit brought by having case pre-labeling. Table 4 shows that performing case pre-labeling not only accelerates the annotation speed about 3 times, but also improves the labeling precision about 20% (in average).

Ideally, we need the annotators who are not only familiar with the syntax but also with the case grammar. However, this strict requirement puts a serious constraint on selecting annotators. Therefore, we recruit those Chinese students who are fluent in both English and Chinese instead, and they are supervised by a professor with corpus construction experience. Furthermore, we prepare a training course for them to introduce the syntax and the case tree we adopt.

For each DST, we have three annotators work on it. The first two annotators are requested to independently annotate the case tree. And the third annotator makes the judgment and the final decision while the first two annotators disagree with each other. At the moment of this writing, we had completed 2,000 sentence-pairs annotation.

During the pilot run of this project, we found that it is difficult to fix the mistake and ensure quality after the annotation has been done. Therefore, we set up an online discussion group to answer the questions raised from the annotators, and given them feedback when a mistake is found during the inspection stage. It is found that this arrangement significantly improves the agreement rate and the annotation quality. Besides, it is also found that the work of those early stages (e.g., syntactic tree and word alignment annotation) notably influences our work. Therefore, the annotation quality management should be set up in each step of this kind of project.

Node Tag	Precision	Recall	F1 score
Head(Chinese)	94.25%	94.54%	94.39%
Head(English)	98.60%	98.53%	98.57%
VACTN(Chinese)	87.76%	89.89%	88.81%
VACTN(English)	98.30%	98.86%	98.58%
TH(Chinese)	89.10%	91.56%	90.31%
TH(English)	92.25%	94.80%	93.51%
AG(Chinese)	76.38%	80.17%	78.23%
AG(English)	89.67%	91.95%	90.79%
MOD(Chinese)	91.33%	91.86%	91.59%
MOD(English)	98.93%	99.15%	99.03%
POS(Chinese)	70.59%	51.06%	56.26%
POS(English)	97.93%	98.86%	98.39%
MANR(Chinese)	63.93%	66.10%	65.00%
MANR(English)	94.48%	94.48%	94.48%
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Average(Chinese)	73.52%	77.19%	75.31%
Average(English)	88.70%	91.73%	90.19%

Table 3: Inter-annotator agreement (IAA) test

Annotation modes	averaged precision	averaged time cost (minutes/sentence)
Annotator-1 without case pre-labeling	75%	25
Annotator-1 with case pre-labeling	90%	8
Annotator-2 without case pre-labeling	70%	30
Annotator-2 with case pre-labeling	95%	12

Table 4: Efficiency test for having case pre-labeling

5. Conclusion

A case-based English-Chinese semantic constituent parallel Treebank for the SMT task is built by labelling each node of the deep syntactic tree with our refined semantic cases. It is a part of a semantic corpus building project, which aims to build a semantic bilingual corpus annotated with word alignment, syntactic trees, semantic cases and word senses. 4,000 sentence pairs from the news domain are selected for annotation to cover various lexicons and part-of-speech (POS) n-gram patterns as much as possible.

The main contributions of this paper are: (1) We construct a case-based English-Chinese semantic constituent parallel Treebank for machine translation (SMT) task, which contains raw texts, word alignment, constitute syntactic trees, deep syntactic trees and case trees. (2) We tailor a case set to represent bilingual shallow semantic relations more precisely. (3) We show that transforming a parse-tree into its corresponding DST could enhance the reachability of compositional transformation.

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