

BiFrameNet: Bilingual Frame Semantics Resource Construction by Cross-lingual Induction

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Abstract

We present a novel automatic approach to constructing a bilingual semantic network—the BiFrameNet, to enhance statistical and transfer-based machine translation systems. BiFrameNet is a frame semantic representation, and contains semantic structure transfers between English and Chinese. The English FrameNet and the Chinese HowNet provide us with two different views of the semantic distribution of lexicon by linguists. We propose to induce the mapping between the English lexical entries in FrameNet to Chinese word senses in HowNet, furnishing a bilingual semantic lexicon which simulates the “concept lexicon” supposedly used by human translators, and which can thus be beneficial to machine translation systems. BiFrameNet also contains bilingual example sentences that have the same semantic roles. We automatically induce Chinese example sentences and their semantic roles, based on semantic structure alignment from the first stage of our work, as well as shallow syntactic structure. In addition to its utility for machine-aided and machine translations, our work is also related to the spatial models proposed by cognitive scientists in the framework of artifactual simulations of the translation process.

1. Introduction

The merits of translation at the word level or the concept level have long been a cause for debate among linguists. Some linguists suggest that the two languages of a bilingual speaker share a common semantic system (Illes and Francis 1999; Ikeda 1998) and hence translation is carried out at the concept level.

Meanwhile, there has been a gradual convergence of statistical and transfer approaches in machine translation recently (Wu 2003). Statistical MT systems are based on a stochastic mapping between lexical items, assuming the underlying semantic transfer is hidden. Transfer systems use explicit lexical, syntactic and semantic transfer rules.

Consequently, cognitive scientists and computational linguists alike have been interested in the study of semantic mapping between languages (Ploux and Ji, 2003, Dorr et al., 2002, Ngai et al., 2002, Boas 2002, Palmer and Wu, 1995). We propose to automatically construct a bilingual lexical semantic network with word sense and semantic role mapping between English and Chinese, simulating the “concept lexicon”, suggested by cognitive scientists, of a bilingual person.

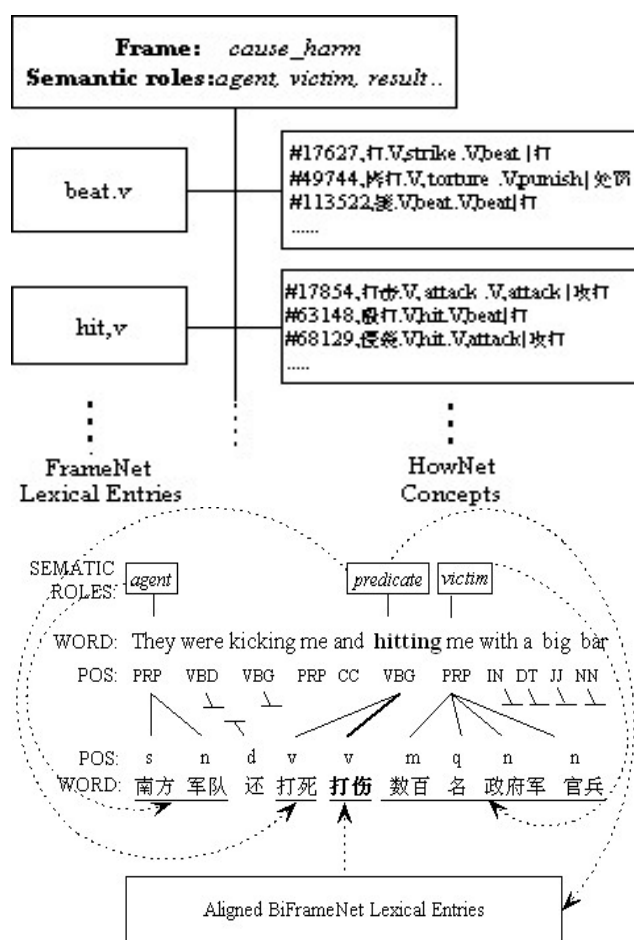


Figure 1. BiFrameNet lexicon and example sentence induction

The linguists-defined ontologies—FrameNet (Baker et al., 1998), HowNet (Dong and Dong, 2000), and bilingual dictionaries are the basis for the induction of the mapping. We automatically estimate

the semantic transfer likelihoods between English FrameNet lexical entries and the Chinese word senses in HowNet, and align those frames and lexical pairs with high likelihood values. In addition, we propose to induce Chinese example sentences automatically to match English annotated sentences provided in the FrameNet. The BiFrameNet thus induced provides an additional resource for machine-aided or machine translation systems. It can also serve as a reference to be compared to cognitive studies of the translation process.

Ploux and Ji, (2003) proposed a spatial model for matching semantic values between French and English. Palmer and Wu (1995) studied the mapping of *change-of-state* English verbs to Chinese. Dorr et al. (2002) described a technique for the construction of a Chinese-English verb lexicon based on HowNet and the English LCS Verb Database (LVD). They created links between HowNet concepts and LVD verb classes using both statistics and a manually constructed “seed mapping” of thematic classes between HowNet and LVD. Ngai et al. (2002) employed a word-vector based approach to create the alignment between WordNet and HowNet classes without any manual annotation. Boas (2002) outlined a number of issues surrounding the planning and design of GermanFrameNet (GFN), a bilingual FrameNet dictionary which, when complete, will have a corpus-based German lexicon following the FrameNet structure.

This paper is organized as follows: Section 2 describes the algorithm for estimating transfer relations between FrameNet and HowNet structures. Section 3 presents our method for selecting BiFrameNet example sentences for a particular frame and automatically inducing semantic role annotations. We conclude in Section 4, followed by a discussion in Section 5.

2. Lexical semantic mapping in BiFrameNet

Dorr et al. (2002) uses a manual seed mapping of semantic roles between FrameNet and LVD to induce a bilingual verb lexicon. In this paper, we propose a method of automatically mapping the English FrameNet lexical entries to HowNet concepts, resulting in the BiFrameNet ontology. We also make use of two bilingual English-Chinese lexicons for this induction. In this section 2, we use an example FrameNet lexical entry “beat.v” in the “*cause_harm*” frame to illustrate the main steps of our algorithm.

μ : lexical entry in FrameNet; ν : concept in HowNet
 F : FrameNet frame; H : HowNet category
 L : links from FrameNet to HowNet
 L_F : links of the frame F ; T_μ : translations of μ
 R is a ranked list; $R[k]$ means the top- k element
 V_F : possible ν linked to $\mu \in F$
 Λ_F : HowNet categories related to frame F
 $\delta(x)$: binary function, return 1 if input is true;
 otherwise return 0.
 For each μ
 $T1_\mu = \{\text{translations of } \mu \text{ in HowNet}\}$
 $T2_\mu = \{\text{translations of } \mu \text{ in dictionary}\}$
 $T_\mu = T1_\mu \cup T2_\mu$
 $L \leftarrow L \cup \{(\mu, \nu) \mid \nu.w_c \in T_\mu, \nu.g_c = \nu.pos\}$
 For each F
 $V_F = \{\nu \mid (\mu, \nu) \in L, \mu \in F\}$
 For each H
 $f(H) = \sum_{\nu} \delta(\nu \in V_F, \nu \in H)$
 R is the ranked list of H sorted by $f(H)$
 $\Lambda_F = R[1] \cup R[2] \dots \cup R[N]$
 $\Lambda_F \leftarrow \Lambda_F \cup \{R[k] \mid Sim(R[l], R[k]) > threshold, l = 1, \dots, N, k = N + 1, \dots\}$
 $L_F = \{(\mu, \nu) \mid \mu \in F, \nu \in V_F \cap \Lambda_F\}$

Figure 2. BiFrameNet ontology induction

2.1. FrameNet and HowNet

The Berkeley FrameNet database consists of frame-semantic descriptions of more than 7000 English lexical items, together with example sentences annotated with semantic roles (Baker et al., 1998). There is currently no frame semantic representation of Chinese. However, the Chinese HowNet (Dong and Dong 2000) represents a hierarchical view of lexical semantics in Chinese.

FrameNet is a collection of lexical entries grouped by frame semantics. Each lexical entry represents an individual word sense, and is associated with semantic roles and some annotated sentences. Lexical entries with the same semantic roles are grouped into a “frame” and the semantic roles are called “frame elements”. For example:

Frame: *Cause_harm*
 Frame Elements: *agent, body_part, cause, event, instrument, iterations, purpose, reason, result, victim.....*
 Lexical Entries:
bash.v, batter.v, bayonet.v, beat.v, belt.v, bludgeon.v, boil.v, break.v, bruise.v, buffet.v, burn.v,....
 Example annotated sentence of lexical entry “beat.v”:
 [agent I] lay down on him and **beat** [victim at him]
 [means with my fists].

HowNet is a Chinese ontology with a graph structure of word senses called “concepts”, and each concept contains 7 fields including lexical entries in

Chinese, English gloss, POS tags for the word in Chinese and English, and a definition of the concept including its category and semantic relations (Dong and Dong, 2000). For example, one translation for “beat.v” is 打:

NO. = 17645
W_C = 打
G_C = V
E_C = ~架, ~斗, ~仗, ~敌人, ~死, ~伤, ~得好
W_E = attack
G_E = V
E_E =
DEF = fight 争斗

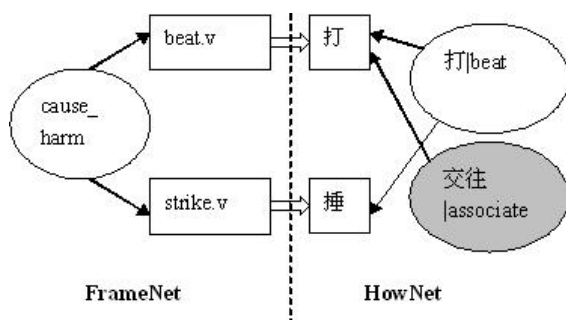
Whereas HowNet concepts correspond roughly to FrameNet lexical entries, its semantic relations do not correspond directly to FrameNet semantic roles.

2.2. Initial mapping based on bilingual lexicon (step 1)

We use the bilingual lexicon from HowNet and LDC dictionary to first create all possible mappings between FrameNet lexical entries and HowNet concepts whose part-of-speech (POS) tags are the same. Here we assume that syntactic classification for the majority of FrameNet lexical entries (i.e. verbs and adjectives) are semantically motivated and are *mostly* preserved across different languages. For example “beat” can be translated into {搥, 败, 冲击, 出手, 难倒, 骗取, 赢, 战败...} in HowNet and {打, 打败, 捣, 敲打, 赢...} in the LDC English-Chinese dictionary. “beat.v” is then linked to all HowNet concepts whose Chinese word/phrase is one of the translations and the part of speech is verb “v”.

2.3. Refined mapping based on semantic contexts in both languages (step 2)

At this stage, each FrameNet lexical entry has links to multiple HowNet concepts and categories. For example, “beat.v” in “cause_harm” frame is linked to “打” in both the “beat” category and the “associate” category (as in “打电话/make a phone call”). We need to choose the correct HowNet concept (word sense). Many word sense disambiguation algorithms use contextual words in a sentence as disambiguating features.



In this work, we make use of contextual lexical entries from the same semantic frame, as illustrated above. In this example, the “cause_harm” frame contains two lexical entries—“beat.v” and “strike.v”. From the previous step, “beat.v” and “strike.v” is each linked to a number of Chinese candidates. “beat.v” is linked to “打” with membership in two different HowNet categories, namely “打|beat” and “交往|associate”. To disambiguate between the above these 2 candidate categories, we make use of the other lexical entries in “cause_harm”, in this case “strike.v” which is linked to “捶”, in the “打|beat” HowNet category. Now, “□|beat” receives two votes (from “□” and from “□”), and “□□|associate” only one (from “□”). We therefore choose the HowNet category “□|beat” to be aligned to the frame “cause_harm”, and eliminate the sense of “打” in the “交往|associate” category. Consequently, “beat.v” in “cause_harm” is linked to all HowNet concepts that are translations of “beat” which are verbs, and which also belong to the HowNet category “□|beat” (but not “□□|associate”).

In our example, HowNet concepts under two HowNet categories—“beat” and “damage” are linked to the “cause_harm” frame in FrameNet. Only the concepts in the top N categories are considered as correctly linked to the lexical entries in the “cause_harm” frame. We heuristically chose N to be three in our algorithm.

2.4. Final mapping adjusted by taxonomy distance (step 3)

Using frame context alone in the above step can effectively prune out incorrect links, but it also prunes some correct links whose HowNet categories are not in the top three categories. In this next step, we aim to recover this kind of pruned links by finding other categories with high similarity to the chosen categories. We introduce the category similarity score (Liu and Li, 2002), which is based on the HowNet taxonomy distance:

$$\text{Sim}(\text{category1}, \text{category2}) = \frac{\alpha}{\alpha + d}$$

Where d is the path length from category1 to category2 in the taxonomy. α is an adjusting parameter, which controls the curvature of the similarity score. We set $\alpha=1.6$ in our work following the experiment results in Liu and Li (2002). If the similarity of category p and one of the top three categories is higher than a threshold t, the category p is also considered as a valid category for the frame.

In our example, some valid categories, such as “firing|射击” is not selected in the previous step even though it is related to the “cause_harm” frame. Based

on the HowNet taxonomy, the similarity score between “firing|□□” and “beat|□” is 1.0, which is above the threshold set. Hence, “firing|□□” is also chosen as a valid category and the concepts in this category are linked to the “beat.v” lexical entry in the “*cause_harm*” frame. However, using taxonomy distance can cause errors such as 打 in the “weave” category to be aligned to “beat.v” in the “*cause_harm*” frame.

2.5. BiFrameNet lexicon evaluation

We evaluate our work by comparing the results to a manually set golden standard of transfer links for some lexical entries in FrameNet, and use the precision and recall rate as evaluation criteria. Manual evaluation of all lexical entries is a slow process and is currently still on-going. However, to show the *lower bound* of the system performance, we chose FrameNet lexical entries with the highest number of transfer links to HowNet concepts as the test set. Since each link is a word sense, these lexical entries have most ambiguous translations. Since the number of lexical entries in a FrameNet parent frame (i.e. frame size) is an important factor in the disambiguation step, we analyze our results by distinguishing between “small frames” (a frame with less than 5 lexical entries) and “large frames”. 24% of the frames are “small frames”. Referring to Tables 2 and 3, we can see a weighted average of $(0.649*0.24+0.874*0.76) = 82\%$ F-measure.

lexical entry	Parent frame	#candidate HowNet links	#lexical entries in parent frame
beat.v	cause_harm	144	51
move.v	motion	132	10
bright.a	light_emission	126	44
hold.v	containing	145	2
fall.v	motion_directional	127	5
issue.v	emanating	124	4

Table1. Lexical entries test set

lexical entry	Precision step3/step1	Recall step3/step1	F-measure step3/step1
beat.v	88.9/36.8%	90.6/100%	89.7/53.8%
move.v	100/49.2 %	72.3/100%	83.9/66.0%
bright.a	79.1/54.0%	100/100%	88.3/70.1%
Overall	87.1/46.3%	87.6/100%	87.4/52.3%

Table 2. Performance on large frames

lexical entry	Precision step3/step1	Recall step3/step1	F-measure step3/step1
hold.v	22.4/7.6%	100/100%	36.7/14.1%
fall.v	87.0/49.2%	81.1/100%	83.9/66.0%
issue.v	31.1/12.3%	100/100%	47.5/20.3%
Overall	52.1/25.0%	85.9/100%	64.9/40.0%

Table 3. Performance on small frames

	Step 1	Step 2	Step 3

Precision	36.81%	95.24%	88.89%
Recall	100%	75.47%	90.56%
F-measure	53.81%	84.21%	89.72%

Table 4. Average performance on “beat.v” at each step of the algorithm

Table 4 shows the system performance in each step of the alignment between the FrameNet “beat.v” to HowNet concepts with the final F-measure at 89.72.

3. Cross-lingual induction of example annotated sentences in BiFrameNet

In the second stage of our proposed work, we aim to automatically induce Chinese example sentences that are appropriate for each semantic frame. Together with English example sentences that already exist in the English FrameNet, they form part of the BiFrameNet, and serve to provide concrete examples of bilingual usage of semantic roles. They can be used either as a resource for machine-aided translation or training data for machine translation.

FrameNet is a collection of over 100-million words of samples of written and spoken language from a wide range of sources, including British and American English. All the example sentences are chosen by linguists for their representative-ness of particular semantic roles, grammatical functions, and phrase type. The current FrameNet contains on average 30 annotated example sentences per predicate, which is still inadequate for automatic semantic parsing systems (Fleischman et al., 2003). Each FrameNet example sentence contains a predicate. The semantic roles of the related frame elements are manually labeled. The syntactic phrase type (e.g. NP, PP) and their grammatical function (e.g. external argument, object argument) are also labeled. An example annotated sentence containing the predicate “beat.v”, in the “*cause_harm*” frame, is shown below:

Example sentence type: trans-simple We are fighting a barbarian, and [<i>agent</i> : we] must [<i>predicate</i> : beat] [<i>victim</i> : him].
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In order to provide a representative set of Chinese example sentences automatically for a particular frame, our method must fulfill the following criteria:

- 1) It must find real sentences occurring naturally in Chinese texts;
- 2) It should find sentences that cover as many different usage and domain as possible;
- 3) It must find sentences that have the same semantic roles as the English example sentences;

\mathbf{e} : English sentence; \mathbf{c} : Chinese sentence
 Ω_F : \mathbf{e} for frame F ; Ψ_F : \mathbf{c} for frame F
 CA : Candidate \mathbf{c} for frame F
 DP : Dynamic Programming alignment (Figure 5)
 For each F
 $CA = \{\mathbf{c} \mid \nu \in \mathbf{c}, \mu \in F, (u, \nu) \in L_F\}$
 For each $\mathbf{e} \in \Omega_F$
 $\hat{\mathbf{c}} = \underset{\mathbf{c} \in CA}{\operatorname{argmax}} \{DP(\mathbf{e}, \mathbf{c})\}$
 $\Psi_F \leftarrow \Psi_F \cup \{\hat{\mathbf{c}}\}$

Figure 3. BiFrameNet example sentence induction

- 4) It should require no manual annotation of any kind.

There are at least three different (semi-)automatic approaches for mining Chinese example sentences:

i) *Translate all English example sentences into Chinese by automatic means, and annotate the semantic roles by word alignment;*

This approach is not appropriate because machine translation can be erroneous and this method does not satisfy criteria (1) and (2).

ii) *Construct an English semantic parser and a Chinese parser independently, and use them to annotate the sentences in a sentence aligned, parallel corpus;*

Apart from the high cost of building two semantic parsers, which itself requires semantically annotated Chinese data; it would be necessary to create artificial links between independent human annotations manually.

iii) *Mine Chinese sentences from a monolingual corpus that are syntactically similar to the English example sentence, and induce semantic roles from the syntactic transfer function between English and Chinese.*

This is the approach we take. Inspired by previous work on syntax-driven semantic parsing (Gildea and Jurafsky, 2002; Fleischman et al., 2003), and syntax-based machine translation (Wu, 1997; Cuerzan and Yarowsky, 2002), we postulate that syntactically similar sentences with the same predicate also share similar semantic roles. In this paper, we present our first experiments on inducing semantic roles based on shallow syntactic information. We mine Chinese example sentences from naturally occurring monolingual corpus, and rank them by their syntactic similarity to our English

example sentences. A dynamic programming algorithm then annotates the aligned syntactic units with the same semantic roles. The example Chinese sentences are not translations of the English sentences. Therefore, the set of example sentences within a frame is enriched, providing better coverage for MT and CLIR systems.

3.1. Induction from aligned predicate bilingual lexical pair

Since frames are disjoint, we propose a method for finding example sentences one frame at a time. In this paper, we focus on finding Chinese example sentences for the largest frame “*cause_harm*” and the main semantic roles in this frame—“agent”, “predicate” and “victim”¹.

For each English lexical entry and its target translation candidates in the BiFrameNet, we first extract sentences that contain the translation candidates from a large Chinese monolingual corpus. Figure 4 shows some initial Chinese example sentence candidates under “beat.v”. There are many sentences that do not have the “agent-predicate-victim” structure. Our next step is to find the Chinese sentences that have the “agent”, “predicate” and “victim” semantic roles and annotate them automatically.

南方军队还打死打伤数百名政府军官兵 (the southern army killed and maimed hundreds of government soldiers)
 土军在进攻中伤害了无辜的平民 (soldiers harmed innocent civilians during the attack)
 农民砍掉自留山上树木 7 0 多棵 (farmers cut down more than 70 trees)
 使用针刺破葫芦 (use the needle to prick the squash)
 *媒体捅出一份调查报告 (the media exposed/produced an investigation report)
 *一些出版社采取“先斩后奏”的做法 (some publishers adopt a “idiom” method)

Figure 4. Some Chinese example sentence and glosses

3.2. Inducing semantic roles from cross-lingual POS transfer

Among all the Chinese sentences containing the target predicate words, we need to identify those that contain the same semantic roles as those of the English example sentences in FrameNet. Current automatic semantic parsing algorithms (Gildea and Jurafsky 2003, Fleischman et al., 2003) are all based on syntactic parse trees showing a close coupling of semantic and syntactic structures.

Without carrying out full syntactic parsing of the Chinese sentences, we postulate that the semantic

¹ As an example, for “beat.v”, 73% of the English example sentences have these three semantic roles, only 27% also have other semantic roles such as “tools”.

roles of a sentence are generated by the underlying shallow syntactic structure of the sentence such as POS tag sequences. We therefore focus on finding bilingual sentence pairs that are comparable in POS structure, though not necessarily having any lexical comparability. Note that this constitutes only a subset of all possible Chinese example sentences for each frame. The expansion of this set remains the objective of our future research

Given an English example sentence, its semantic role sequence, and its POS tag sequence; and a set of Chinese sentences and their POS tag sequence, we use a dynamic programming method (Figure 5) to find the Chinese sentence whose POS sequence is most likely to be generated from the English POS sequence, and the alignment path. The Chinese word aligned to the English word will assume the latter’s semantic role.

Initialization
$S[0,0]=0; S[0,j-1]+\sigma(\varepsilon,c_j); S[i-1,0]+\sigma(e_i,\varepsilon)$
Recursion
$S[i,j]=\max \begin{cases} S[i-1,j]+\sigma(e_i,\varepsilon) \\ S[i-1,j-1]+\sigma(e_i,c_j) \\ S[i,j-1]+\sigma(\varepsilon,c_j) \end{cases}$
$T[i,j]=\arg \max \begin{cases} S[i-1,j]+\sigma(e_i,\varepsilon) \\ S[i-1,j-1]+\sigma(e_i,c_j) \\ S[i,j-1]+\sigma(\varepsilon,c_j) \end{cases}$
where $\sigma(e_i,c_j)$ is the transfer cost of an English POS tag from a Chinese POS tag; ε is an empty word. M and N are the lengths of the English and Chinese POS sequences respectively; $1 < i < M$; $1 < j < N$;
Termination
$S[N,M], T[N,M]$ are the final alignment score and final point on the path;
Path Backtracking
Output the final English-Chinese POS alignment path by tracing back from the terminal points. Also output the final alignment score normalized by the path length.

Figure 5. Dynamic programming (DP) alignment

We train $\sigma(e,c)$ in Figure 5 from a sentence aligned, POS tagged, parallel corpus (Hong Kong News), and a bilingual dictionary. For each bilingual word pair in the dictionary, we estimate the prior distributions of the POS tags of the Chinese words from the Chinese side of the parallel corpus, and that of the English words from the English side. A $V \times W$ POS tag “confusion matrix” is generated, where V is the vocabulary of the Chinese POS tags, and W is the vocabulary of the English POS tags. Table 5 shows some example English-Chinese POS mapping and Figure 6 shows some example annotated sentences in Chinese.

English POS	Chinese POS	$\sigma(e,c)$
PRP	N	3.16-e2
NN	N	4.0-e6
JJ	N	1.74-e4
NNP	Nr	4.257-e2
JJS	V	2.15-e4
VB	V	7.2-e5
VBG	Ad	1.34-e3
VBG	m	6.74-e3

Table 5. Example POS tag transfer

[agent 南方军队]还[predicate 打死打伤][victim 数百名政府军官兵]
[agent 土军]在进攻中[predicate 伤害]了[victim 无辜的平民]
[agent 农民][predicate 砍掉][victim 自留山上树木 7 0 多棵]
使用[agent 针][predicate 刺破][victim 葫芦]

Figure 6. Example Chinese annotated sentences

3.3. BiFrameNet example sentence evaluation

We estimate the syntactic POS transfer probabilities from the HK News Corpus. We use two state-of-the-art POS taggers—a maximum entropy based English POS tagger (Ratnaparkhi, 1996), and an HMM based Chinese POS tagger.² We perform two sets of experiments: (1) For each example English sentence in the “cause_harm” frame from FrameNet, we extract a corresponding Chinese sentence annotated with the same semantic roles; (2) rank all the Chinese sentences that have been aligned to the English sentences by alignment score. The highest ranking Chinese sentences are used for the BiFrameNet. Table 6 shows that the average annotation accuracy of all top Chinese sentence candidates for each English example sentence is 68%. Table 7 shows that the annotation accuracy of the top 100 Chinese example sentences, sorted by DP score, is 71.8%.

Semantic roles	Accuracy
Predicate	77.63%
Agent	68.75%
Victim	52.72%
(Overall)	68%

Table 6. Annotation accuracy of the selected Chinese sentences

Semantic roles	Accuracy
Predicate	81.69%
Agent	63.24%
Victim	70.77%
(Overall)	71.8%

Table 7. Annotation accuracy of the top 100 Chinese sentences with the highest DP alignment scores

² <http://mtgroup.ict.ac.cn/~zhp/ICTCLAS/index.html>

4. Conclusion

We have presented a first quantitative and automatic approach of constructing a bilingual lexical semantic resource—the BiFrameNet. BiFrameNet consists of mappings between FrameNet semantic frames and HowNet concepts, as well as English and Chinese example sentences for a particular frame, with annotated semantic roles in the English FrameNet labels. Evaluation results show that we achieve a promising 82% average F-measure on lexical entry alignment, for the most ambiguous lexical entries; and a 68-72% accuracy in Chinese example sentence induction, for the largest frame. The initial results are available at <http://www.cs.ust.hk/~hltc/BiFrameNet> and will be updated as further improvements and evaluations are implemented.

5. Discussion

There are a number of possible directions for future work. One obvious extension is to use syntactic parse tree representations instead of POS sequences in example sentence alignment. Second, there are many other Chinese sentences that share the same semantic roles, but not the same POS sequences, which are not included. Using additional features to correctly identify these sentences and the constituent semantic roles is a topic of our ongoing research. Moreover, we note that Chinese is a highly idiomatic and metaphoric language. Compounded by the ambiguity of word boundaries, many predicate usages in Chinese are highly unexpected. It is worth considering using other Chinese linguistic resources to enhance the example sentence extraction and annotation. Finally, BiFrameNet needs to be further evaluated and manual post-processing is perhaps required.

We expect the final complete BiFrameNet, in addition to the various FrameNet and PropBank resources being developed manually, will be a valuable resource for statistical and interlingua transfer-based MT systems, as well as to human translators in a machine-aided translation scenario. We are also motivated to investigate the relationship between our results and those of semantic mapping models proposed by cognitive scientists.

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