Cross-lingual Linking of Automatically Constructed Frames and FrameNet

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Abstract

A semantic frame is a conceptual structure describing an event, relation, or object along with its participants. Several semantic frame resources have been manually elaborated, and there has been much interest in the possibility of applying semantic frames designed for a particular language to other languages, which has led to the development of cross-lingual frame knowledge. However, manually developing such cross-lingual lexical resources is labor-intensive. To support the development of such resources, this paper presents an attempt at automatic cross-lingual linking of automatically constructed frames and manually crafted frames. Specifically, we link automatically constructed example-based Japanese frames to English FrameNet by using cross-lingual word embeddings and a two-stage model that first extracts candidate FrameNet frames for each Japanese frame by taking only the frame-evoking words into account, then finds the best alignment of frames by also taking frame elements into account. Experiments using frame-annotated sentences in Japanese FrameNet indicate that our approach will facilitate the manual development of cross-lingual frame resources.

Keywords: semantic frame, cross-lingual frame linking, FrameNet

1. Introduction

A semantic frame is a conceptual structure describing an event, relation, or object along with its participants. Semantic frames have been shown to be useful for many natural language processing applications such as recognizing textual entailment (Tatu and Moldovan, 2005), question answering (Shen and Lapata, 2007), and knowledge extraction (Søgaard et al., 2015). Thus, several semantic frame resources, such as FrameNet (Baker et al., 1998), VerbNet (Kipper et al., 2000), and PropBank (Palmer et al., 2005), have been manually elaborated. In addition, various systems have been proposed for automatic construction of frame knowledge from raw corpora (Korhonen et al., 2006; Kawahara et al., 2014; QasemiZadeh et al., 2019; Yamada et al., 2021). Among them, FrameNet is a representative resource of manually crafted cognitive frames, which provides rich semantic representations of the core English vocabulary based on Fillmore's frame semantics (Fillmore, 1976) with more than 200K frame-annotated sentences and has been extended to languages other than English. Resources based on FrameNet have now been created for roughly a dozen languages (Baker et al., 2018).

However, manually developing such lexical resources is labor-intensive. In particular, defining frames, which entails considering their relationship to the definition of frames designed for another language, is a laborious process and thus it is difficult to develop such resources on a large scale. For example, Japanese FrameNet (JFN) (Ohara, 2013), consisting of cognitive frames, lexical units, and frame-annotated sentences, has been developed for two decades, but its coverage is still limited. Table 1 shows the statistics of FrameNet and JFN. The number of frame-annotated sentences in JFN is much smaller than that in English FrameNet and efficient ways to expand them are required.

	FrameNet	JFN
# of cognitive frames	1222	947
# of lexical units (LUs)	13572	4957
# of annotated sentences	200751	7905

Table 1: Statistics of FrameNet and JFN.

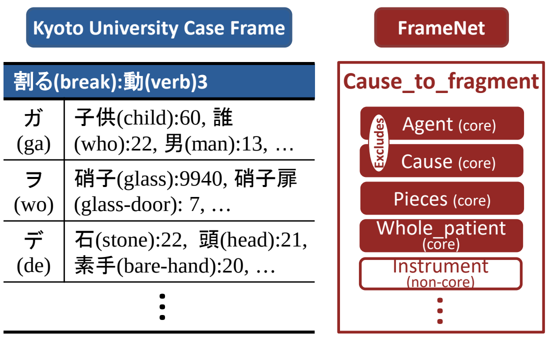

Figure 1: Corresponding KCF and FrameNet frames.

Therefore, we aim to support the development of such frame resources by associating automatically constructed frames for a language other than English with English FrameNet. Specifically, we attempt to link automatically constructed Japanese frames called Kyoto University Case Frames (KCF) (Kawahara and Kurohashi, 2006) to FrameNet. KCF is a set of example-based Japanese semantic frames, which are constructed by clustering examples of predicates and their arguments collected from a large corpus according to semantic similarity. Figure 1 shows an example of KCF with the corresponding FrameNet frame. In KCF, frames are constructed for each meaning of each predicate. Each frame describes the surface cases[1] that each predicate takes, such as *ga* (nominative), *wo* (accusative), and *ni* (dative) and instances that can fill a case slot. In this example, the *ga*, *wo*, and *de*[2]-cases correspond to *Agent*, *Whole_patient*, and *Instrument* in FrameNet, respectively. If such linking can be performed automatically, it will be possible to enumerate predicates of other languages that can be the lexical unit of a FrameNet frame and possible fillers of each frame element of the frame, which will facilitate the manual development of frame resources.

2. Related Work

There have been several studies on linking different types of frame knowledge. SemLink (Palmer, 2009) manually connects PropBank, VerbNet, and FrameNet. Fung and Chen (2004) presented an automatic approach to constructing a bilingual semantic network, where English FrameNet entries are mapped to concepts listed in HowNet, an online ontology for Chinese. Faralli et al. (2018) enriched frame representations with semantic features extracted from distributionally induced sense inventories. Ohara et al. (2018) linked KCF with JFN using crowdsourcing. They aimed to link automatically constructed lexicalized frames to manually crafted knowledge, which is similar to our setting, but their setting is not cross-lingual.

Annotation projection is another popular framework for transferring frame knowledge from one language to another by exploiting the structural equivalences present in parallel corpora. For example, Padó and Lapata (2009) transferred FrameNet-style semantic role annotations from English onto German and Johansson and Nugues (2006) from English onto Swedish. Akbik et al. (2015) presented a method to generate PropBanks for seven languages from English PropBank by exploiting multilingual parallel data. Yang et al. (2018) presented an approach to transferring frames from English FrameNet to construct Chinese FrameNet by using a sentence-aligned bilingual corpus. Marzinotto (2020) presented an approach to project FrameNet annotations into other languages using attention-based neural machine translation models.

The cross-lingual translatability of the frame knowledge has also been investigated in several studies (Baker and Lorenzi, 2020). Boas (2005) suggested frame semantics as an inter-lingual meaning representation and constructed multilingual lexical databases. Majewska et al. (2018) examined the cross-lingual translatability of VerbNet-style classification and showed that VerbNet classes have strong cross-lingual potential. Sikos and Padó (2018) used cross-lingual embeddings for comparing FrameNet frames across languages to investigate the cross-lingual applicability of the frames.

3. Cross-lingual Frame Linking

We link KCF frames, which are included in the Japanese predicate argument structure analyzer KNP 4.19,[3] to the frames defined in FrameNet 1.7 (Ruppenhofer et al., 2016). KCF frames are constructed not only for verbs but also for adjectives and nouns with copula but we focus on frames for verbs in this study. Since KCF frames are constructed for each meaning of each predicate, KCF frames are more fine-grained and the number of KCF frames is much larger than that of FrameNet. Thus, we link each KCF frame to one of the FrameNet frames.

The proposed method is divided into two steps: 1) extract candidate frames by taking only the verb into account and then 2) find the optimal alignment between the given KCF frame and a FrameNet frame. As the preprocessing, we extracted instances of frame-evoking words, called lexical units (LUs), and instances of frame elements (FEs) from the frame-annotated sentences in FrameNet. We extracted only the head words by using the Stanford parser.[4]

3.1. Candidate Frame Extraction

In this step, we extract candidate frames by taking only the verb into account to reduce the processing time. Suppose a KCF frame CF_{v_j} of a Japanese verb v_j is given. For each FrameNet frame FN_i, we calculate the cross-lingual similarities between verb v_j and each of the LUs by using cross-lingual word embeddings. In this study, we used the cosine similarity of supervised cross-lingual word embeddings.[5] We use the mean of the top three similarity scores as the similarity score between verb v_j and a set of LUs, hereinafter referred to as $\text{sim}(v_j, LU_i)$, and then rank the FrameNet frames by the similarity score and extract the top-k frames as the candidate frames for the given KCF frame.

3.2. Frame Alignment

For each of the candidate FrameNet frames FN_i, we calculate the frame alignment score against the given KCF frame CF_{v_j}. We treat five cases in KCF, *ga*, *wo*, *ni*, *to*,[6] and *de*, as the target of the alignment; that is, we try to find the corresponding FE for each case if CF_{v_j} has that case. Note that, all cases except *ga* are allowed to not be aligned to any FEs in order to avoid generating inappropriate alignments.[7] As for the FEs, we examined two settings: CORE-ONLY and ALL-FEs. We

[1] In the case frame introduced in Fillmore's case grammar (Fillmore, 1968), "case" refers to deep case, whereas "case" in KCF refers to surface case.

[2] *De* is a Japanese case particle that typically indicates location or instrument.

[3] http://nlp.ist.i.kyoto-u.ac.jp/EN/index.php?KNP

[4] https://nlp.stanford.edu/software/lex-parser.shtml

[5] https://github.com/facebookresearch/MUSE

[6] *To* is a Japanese case particle that typically indicates accompaniment or comparison target.

[7] Japanese *ga* is the nominative case marker and usually represents a core role. Thus we impose a constraint that the *ga* case must be aligned to one of the core FEs.

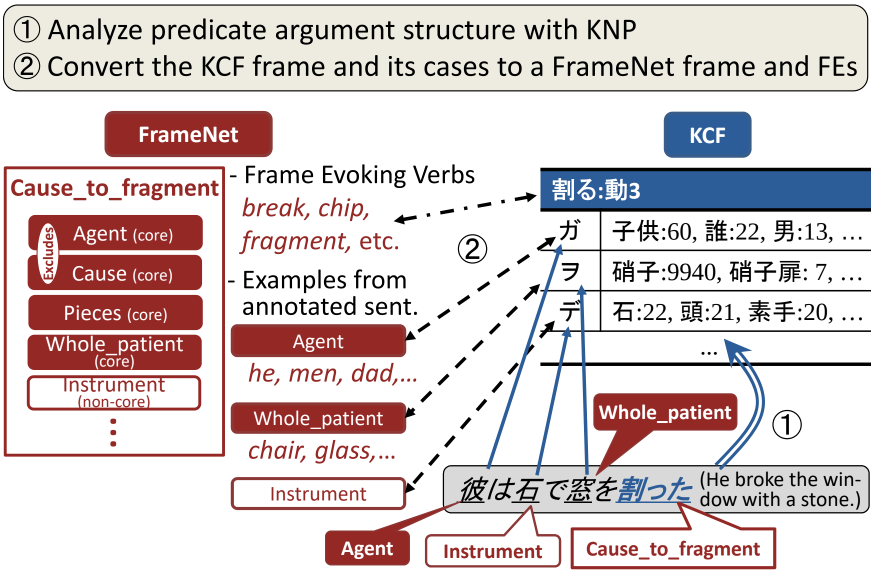

Figure 2: Overview of the procedure for evaluating the linking results.

consider only the core FEs as the target of the alignment in the CORE-ONLY setting and consider both core and non-core FEs in the ALL-FEs setting.

We generate all possible combinations of the corresponding pairs of target FEs and cases and then calculate the alignment score for each combination. Note that two different cases are not allowed to be aligned to the same FrameNet FE. The alignment score is calculated as the product of $\text{sim}(v_j, LU_i)$ and the sum of the individual case alignment scores. Considering CA_k, the case alignment that corresponds the m-th FE to the n-th case, the case alignment score is defined as:

$$\mathit{score}(CA_k) = \cos(\text{emb}(\mathit{FE}_m), \text{emb}(c_n)) \cdot \text{wt}(c_n),$$

where $\text{emb}(\mathit{FE}_m)$ is the average of the English word embeddings that are included in the instances of the m-th FE and $\text{emb}(c_n)$ is the average of the Japanese word embeddings that are included in the instances of the n-th case. $\text{wt}(c_n)$ is the weight of case c_n defined as the square root of the total frequency of the case instances. To avoid generating inappropriate alignments, we also give a fixed score λ to cases that are not aligned to any FEs.

Lastly, we take the highest frame alignment score for each FrameNet frame as the frame score and rank the FrameNet frames by their scores. In contrast with the ranking in Subsection 3.1, this ranking takes not only the verb similarity but also the similarities of all corresponding pairs of FEs and cases into account.

4. Experiments

We evaluated the performance of our approach through frame-semantic parsing by using the frame-annotated examples in Japanese FrameNet. Out of the 947 frames defined in JFN, 43 are defined only in JFN but 904 are also defined in FrameNet. We used the examples whose frame evoking words are verbs that are annotated with the shared frames for estimating the linking accuracy. The detailed procedure is as follows.

1. Perform predicate argument structure analysis with KNP to determine a KCF frame and alignment between arguments of the frame-evoking verb and cases in the KCF frame.
2. Convert the KCF frame and its cases to a FrameNet frame and FEs by using the linking results and estimate the accuracy of the frame and semantic role identification.

Figure 2 shows the overview of the evaluation procedure. We used the annotated FEs only when KNP analyzed that the words and the frame-evoking verb had a dependency relation. If no FEs satisfied this condition, we did not use the examples. In addition, we did not use examples where the frame-evoking verb was used in the passive voice or was used in a compound verb to reduce mismatches caused by factors other than frame linking errors. After applying constraints above, we obtained 1182 examples for evaluation from the 2234 annotated frame-evoking verbs in JFN.[8] KNP selects appropriate frame and alignment in most cases for these examples, and thus the estimated accuracy can be considered to be roughly equivalent to the frame linking accuracy. Note that the reason for applying these constraints is to reduce mismatches caused by factors other than frame linking errors and frame linking itself is applicable to all KCF frames.

As for parameters, we set the number of candidate frames $k = 100$. The score for non-aligned case

[8] Of the 7905 frame-evoking words in the annotated sentences in JFN, 5453 are nouns, 218 are adjectives, and 2234 are verbs.

Setting \ Recall	@1	@3	@5	@10	@30	@100
VERB-ONLY	0.367 (434/1182)	0.575 (680/1182)	0.629 (744/1182)	0.717 (847/1182)	0.804 (950/1182)	**0.910** (1076/1182)
CORE-ONLY	0.398 (471/1182)	0.573 (677/1182)	0.641 (758/1182)	0.719 (850/1182)	0.815 (963/1182)	**0.910** (1076/1182)
ALL-FEs	**0.437** (517/1182)	**0.595** (703/1182)	**0.657** (777/1182)	**0.726** (858/1182)	**0.828** (979/1182)	**0.910** (1076/1182)

Table 2: Frame ranking results.

Setting	Frame	*ga*	*wo*	*ni*	*to*	*de*	total
FRAME-GIVEN	1.000 (1182/1182)	0.764 (371/485)	0.521 (203/390)	0.527 (87/165)	0.482 (27/56)	0.333 (6/18)	0.623 (694/1114)
CORE-ONLY	0.398 (471/1182)	0.741 (166/224)	0.604 (84/139)	0.500 (23/46)	0.429 (9/21)	0.429 (3/7)	0.652 (285/437)
ALL-FEs	0.437 (517/1182)	0.785 (197/251)	0.576 (80/139)	0.540 (27/50)	0.429 (9/21)	0.429 (3/7)	0.675 (316/468)

Table 3: Accuracy of semantic role identification.

$\lambda \in \{0.2, 0.3, \ldots, 0.6\}$ was tuned via two-fold cross-validation, that is, we divided 1182 examples into two parts and set λ that achieved the highest frame identification score in the other part.

We first evaluated the frame ranking results. Table 2 shows the recall@k in the three settings. VERB-ONLY corresponds to the ranking for candidate frame extraction. Both CORE-ONLY and ALL-FEs take frame alignment into consideration but CORE-ONLY exploits only the core FEs whereas ALL-FEs exploits both core and non-core FEs. These results demonstrated that taking FEs, including non-core FEs, into account was beneficial for ranking the FrameNet frames. Our approach that considered both core and non-core FEs achieved a frame identification accuracy of 43.7% and ranked the annotated frame in the top 5 for 65.7% and the top 10 for 72.6% of the examples, respectively, which would help the manual expansion of the frame-annotated sentences in JFN. We evaluated statistical significance with McNemar (1947)'s test with Bonferroni correction and a significance level of 0.05, and confirmed that all the differences in the recall@1 were statistically significant.[9]

Example (1) is an example for which the frame improved by taking FEs into account. The most common meaning of '向けた' is 'toward' or 'aiming' and thus the top-ranked frame in the VERB-ONLY setting was Aiming and the annotated frame Purpose was ranked third. However, Purpose was ranked first when taking the case alignment score into account.

(1) 機能の 発揮に 向けた 整備 · · ·
functions demonstrate to maintenance
(Maintenance to demonstrate functions . . .)

In the cases where different frames were annotated on the same Japanese verb depending on the context, it was rare that the different frames were correctly ranked first according to the context. Examples (2) and (3) are the few successful cases. The original forms of the frame evoking words are the same verb '生ずる' and our approach successfully top-ranked Coming_to_be frame for Example (2) and Causation frame for Example (3). However, in most of these cases, the frames that were more typical for the verb were ranked higher, regardless of context.

(2) 企業にとって 活動することに
for companies to be active
限界が 生じて きている
limiting become has
(It has become limiting for companies to be active.)

(3) 大量破壊兵器が 使用された 場合、 · · ·
WMDs are used in case
汚染を 生ずる 可能性がある
pollution result may
(In case WMDs are used, pollution may result.)

The annotated frames were not ranked even in the top 100 for 9% of the examples. Even when we checked the top 300, the annotated frames for 5% of the examples were not included in the candidate frames. After checking the frame-evoking verbs of these examples, we found that a significant portion of them are used as functional verbs such as '基づき (based on)' or '応じて (according to)'. Thus, the frame identification accuracy for standard verbs is considered a bit higher.

We then evaluated the accuracy of the converted semantic roles for the examples whose frames are successfully identified. In addition to CORE-ONLY and ALL-FEs, we also conducted an experiment with the settings where the annotated frames are given. Table 3 shows the results. Although it is not possible to make a simple comparison because of the difference in the

[9] The p-values were 0.011 (VERB-ONLY/CORE-ONLY), 3.8×10^{-8} (VERB-ONLY/ALL-FEs), and 2.0×10^{-9} (CORE-ONLY/ALL-FEs), respectively.

data to be evaluated, the result that ALL-FEs achieved higher accuracy than CORE-ONLY indicates that taking all FEs into account was also beneficial for semantic role identification. ALL-FEs achieved a semantic role identification accuracy of 67.5% in total, and 78.5% for the *ga*-case without using either manually annotated Japanese frame knowledge or parallel texts. One reason for the relatively low accuracy of *Frame-Given* is that KCF is a frame resource constructed independently of FrameNet, and thus it does not necessarily have an appropriate corresponding FrameNet frame.

5. Conclusion and Future Work

In this paper, we presented an attempt of automatic cross-lingual linking of KCF and FrameNet frames with the aim of supporting the development of cross-lingual frame resources. Through experiments on frame-semantic parsing, we demonstrated that both core and non-core FEs need to be taken into account for precise linking. The frame identification accuracy was not very high but our method can enumerate candidate frames and thus we can say that our method will aid in the manual development of cross-lingual frame resources. In addition, our method can also be applied in finding frames that are specific to the language.

In the future, we plan to expand the work as follows: 1) using other kinds of cross-lingual word embeddings (Ruder et al., 2019) and comparing their performance; 2) exploring the machine learning-based approach with additional features such as FrameNet hierarchy or the characteristics of each role, such as that *agent* is often linked to the *ga*-case; 3) extending the scope of linking to non-verbal case frames, such as case frames for nominal case frames (Sasano et al., 2004); and 4) exploiting our approach for manual expansion of the annotated sentences in JFN.

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7. Biblrliographical References

Akbik, A., Chiticariu, L., Danilevsky, M., Li, Y., Vaithyanathan, S., and Zhu, H. (2015). Generating high quality proposition Banks for multilingual semantic role labeling. In *Proceedings of the 53rd Annual Meeting of the Association for Computational Linguistics and the 7th International Joint Conference on Natural Language Processing (ACL-IJCNLP)*, pages 397–407.

Baker, C. F. and Lorenzi, A. (2020). Exploring crosslinguistic frame alignment. In *Proceedings of the International FrameNet Workshop 2020: Towards a Global, Multilingual FrameNet*, pages 77–84.

Baker, C. F., Fillmore, C. J., and Lowe, J. B. (1998). The Berkeley FrameNet project. In *Proceedings of the 36th Annual Meeting of the Association for Computational Linguistics and 17th International Conference on Computational Linguistics (ACL-COLING)*, pages 86–90.

Baker, C., Ellsworth, M., Petruck, M. R. L., and Swayamdipta, S. (2018). Frame semantics across languages: Towards a multilingual FrameNet. In *Proceedings of the 27th International Conference on Computational Linguistics: Tutorial Abstracts*, pages 9–12.

Boas, H. C. (2005). Semantic frames as interlingual representations for multilingual lexical databases. *International Journal of Lexicography*, 18(4):445–478.

Faralli, S., Panchenko, A., Biemann, C., and Ponzetto, S. P. (2018). Enriching frame representations with distributionally induced senses. In *Proceedings of the 11th International Conference on Language Resources and Evaluation (LREC)*, pages 587–592.

Fillmore, C. J. (1968). The case for case. In Emmon Bach et al., editors, *Universals in Linguistic Theory*, pages 0–88. Holt, Rinehart and Winston.

Fillmore, C. J. (1976). Frame semantics and the nature of language. *Annals of the New York Academy of Sciences: Conference on the Origin and Development of Language and Speech*, 280:20–32.

Fung, P. and Chen, B. (2004). BiFrameNet: Bilingual frame semantics resource construction by cross-lingual induction. In *Proceedings of the 20th International Conference on Computational Linguistics (COLING)*, pages 931–937.

Johansson, R. and Nugues, P. (2006). A FrameNet-based semantic role labeler for Swedish. In *Proceedings of the 21st International Conference on Computational Linguistics and 44th Annual Meeting of the Association for Computational Linguistics (COLING-ACL)*, pages 436–443.

Kawahara, D. and Kurohashi, S. (2006). Case frame compilation from the web using high-performance computing. In *Proceedings of the Fifth International Conference on Language Resources and Evaluation (LREC)*, pages 1344–1347.

Kawahara, D., Peterson, D., Popescu, O., and Palmer, M. (2014). Inducing example-based semantic frames from a massive amount of verb uses. In *Proceedings of the 14th Conference of the European Chapter of the Association for Computational Linguistics (EACL)*, pages 58–67.

Kipper, K., Dang, H. T., and Palmer, M. (2000). Class-based construction of a verb lexicon. In *Proceedings of the Seventeenth National Conference on Artificial Intelligence and Twelfth Conference on Innovative Applications of Artificial Intelligence (AAAI)*, pages 691–696.

Korhonen, A., Krymolowski, Y., and Briscoe, T. (2006). A large subcategorization lexicon for natural language processing applications. In *Proceedings of the Fifth International Conference on Language Resources and Evaluation (LREC)*, pages 3000–3006.

Majewska, O., Vulić, I., Mccarthy, D., Huang, Y., Murakami, A., Laippala, V., and Korhonen, A. (2018). Investigating the cross-lingual translatability of verbnet-style classification. *Language Resources and Evaluation*, 52(3):771–799.

Marzinotto, G. (2020). FrameNet annotations alignment using attention-based machine translation. In *Proceedings of the International FrameNet Workshop 2020: Towards a Global, Multilingual FrameNet*, pages 41–47.

McNemar, Q. (1947). Note on the sampling error of the difference between correlated proportions or percentages. *Psychometrika*, 12:153–157.

Ohara, K., Kawahara, D., Sekine, S., and Inui, K. (2018). Linking Japanese FrameNet with Kyoto University Case Frames using crowdsourcing. In *Proceedings of the International FrameNet Workshop 2018: Multilingual Framenets and Constructicons*, pages 56–61.

Ohara, K. H. (2013). Toward constructicon building for Japanese in Japanese FrameNet. *Veredas: Frame Semantics and Its Technological Applications*, 17(1):11–27.

Padó, S. and Lapata, M. (2009). Cross-lingual annotation projection of semantic roles. *Journal of Artificial Intelligence Research*, 36(1):307–340.

Palmer, M., Gildea, D., and Kingsbury, P. (2005). The Proposition Bank: A corpus annotated with semantic roles. *Computational Linguistics*, 31(1):71–105.

Palmer, M. (2009). Semlink: Linking PropBank VerbBet and FrameNet. In *Proceedings of the 5th International Conference on Generative Approaches to the Lexicon*, pages 9–15.

QasemiZadeh, B., Petruck, M. R. L., Stodden, R., Kallmeyer, L., and Candito, M. (2019). SemEval-2019 task 2: Unsupervised lexical frame induction. In *Proceedings of the 13th International Workshop on Semantic Evaluation (SemEval)*, pages 16–30.

Ruder, S., Vulić, I., and Søgaard, A. (2019). A survey of cross-lingual word embedding models. *Journal of Artificial Intelligence Research*, 65:569–631.

Ruppenhofer, J., Ellsworth, M., Petruck, M. R. L., Johnson, C. R., Baker, C. F., and Scheffczyk, J. (2016). FrameNet II: Extended theory and practice.

Sasano, R., Kawahara, D., and Kurohashi, S. (2004). Automatic construction of nominal case frames and its application to indirect anaphora resolution. In *Proceedings of the 20th International Conference on Computational Linguistics (COLING)*, pages 1201–1207.

Shen, D. and Lapata, M. (2007). Using semantic roles to improve question answering. In *Proceedings of the 2007 Joint Conference on Empirical Methods in Natural Language Processing and Computational Natural Language Learning (EMNLP-CoNLL)*, pages 12–21.

Sikos, J. and Padó, S. (2018). Using embeddings to compare FrameNet frames across languages. In *Proceedings of the First Workshop on Linguistic Resources for Natural Language Processing*, pages 91–101.

Søgaard, A., Plank, B., and Alonso, H. M. (2015). Using frame semantics for knowledge extraction from twitter. In *Proceedings of the Twenty-Ninth AAAI Conference on Artificial Intelligence*, pages 2447–2452.

Tatu, M. and Moldovan, D. (2005). A semantic approach to recognizing textual entailment. In *Proceedings of Human Language Technology Conference and Conference on Empirical Methods in Natural Language Processing (HLT-EMNLP)*, pages 371–378.

Yamada, K., Sasano, R., and Takeda, K. (2021). Semantic frame induction using masked word embeddings and two-step clustering. In *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (ACL-IJCNLP)*, pages 811–816, August.

Yang, T.-H., Huang, H.-H., Yen, A.-Z., and Chen, H.-H. (2018). Transfer of frames from English FrameNet to construct Chinese FrameNet: A bilingual corpus-based approach. In *Proceedings of the 11th International Conference on Language Resources and Evaluation (LREC)*, pages 868–872.