Frame-based Semantic Patterns for Relation Extraction

Angrosh Mandya, Danushka Bollegala, Frans Coenen, Katie Atkinson

Department of Computer Science
University of Liverpool, UK
{angrosh,danushka,coenen,katie}@liverpool.ac.uk

Abstract. This paper presents novel frame-based semantic patterns, exploiting *frame element* and *frame* annotations, provided by FrameNet for relation extraction. The proposed frame-based patterns are evaluated against state-of-the-art dependency based syntactic patterns and lexico-syntactic patterns, on three independent datasets that differ in size and construction. The results show that the proposed frame-based patterns significantly improve performance, both in terms of scoring higher precision and higher recall for relation extraction, in comparison to dependency and lexico-syntactic patterns on all three datasets.

1 Introduction

Pattern-based information extraction methods have a long and established history as a successful approach for domain-specific relation extraction [9, 15]. Although lexico-syntactic patterns are useful for relation extraction [9], these patterns suffer from two distinct problems: (i) *recall problem*: where only a small subset of trained patterns are applied on newer sentences, failing to extract information from a large number of sentences; and (ii) *precision problem*: where significant proportion of extracted information is unreliable, due to extracting incorrect entities for related relations. For example, a lexical pattern such as "*announced the products of*" learnt during the training phase from the sentence "The CEO of the company, **Steve Jobs** announced the products of **Apple** at WWDC", when applied on a test sentence such as "Today, **Amazon** announced the products of **Apple** on their website", results in extracting wrong entities (*Amazon, Apple*) for the CEO-COMPANY relation.

Generalizing patterns using dependency based syntactic parse are shown to be useful in improving recall of the applied pattern set [11]. Patterns using the shortest path between entities in the dependency tree [19] removes significant lexical information to generalize patterns that achieve higher recall. However, dependency patterns are observed to achieve lower precision against lexical patterns [19].

Besides dependency patterns, FrameNet [7] based frame annotations for words in sentences are also useful for defining patterns. FrameNet provide annotations in terms of *semantic frames* comprising *frame elements* (FE) and *lexical units*

(LUs) [7]. Further, SEMAFOR [6], FrameNet based semantic parser helps in automatically obtaining frame annotations for newer sentences. For example, annotations provided by SEMAFOR[1] for an example sentence is as shown below:

[Lee]$_{\text{SELLER}}$ sold [a textbook]$_{\text{GOODS}}$ [to Abby]$_{\text{BUYER}}$.

In the example sentence above, *frame element* annotations such as SELLER, GOODS, BUYER are provided for different *lexical units* in the sentence. These frame elements are associated with a broader *semantic frame* COMMERCIAL_SELL, which is also provided by SEMAFOR. Using this mapping between *semantic frames* and *frame elements* pattern such as "COMMERCIAL_SELL SELLER GOODS BUYER" can be used to extract related entities (*Lee, Abby*) for the relation SELLER-BUYER. Such patterns have greater advantage over lexical and dependency-based patterns, by providing (a) higher precision through extracting specific related entities; and (b) provide better generalisation through removing lexical information. In other words, *these patterns help in achieving higher precision without losing on recall*. Following this motivation, we propose frame-based semantic patterns for relation extraction, exploiting FrameNet annotations. We further evaluate the frame-based patterns against state-of-the-art dependency and lexico-syntactic patterns. The results show that frame-based patterns perform comparatively better for smaller datasets and achieves a statistically higher performance for large datesets. The remainder of this paper is structured as follows: In §2, the related work for this study is described. In §3, we describe the proposed frame-based semantic patterns. In §4, we describe the datasets, evaluation metrics and the results of this study. Finally, in §5, we conclude this paper.

2 Related Work

The use of frames for information extraction (IE) was first investigated as early as 1995 [12] to automatically build a knowledge base of domain-specific linguistic patterns. Following this, there have been very few subsequent studies that have further explored the use of frames for IE. A major bottleneck to this is the absence of tools that can handle the complexity of annotating sentences with frames. However, the recent development of frame-based linguistic resources such as FrameNet [3, 8], and FrameNet based semantic parsing tools such as SEMAFOR [6], has reinstated interest in using frames for IE. FrameNet annotations has been successfully used in various application domains [17, 13]. On the other hand, over the years the field of relation extraction has witnessed significant amount of research. [14] identify at least three learning paradigms in the field of relation extraction, which include (a) supervised approaches focussing on hand-labelled datasets [18]; (b) unsupervised approaches targeting large amounts of text [4]; and (c) bootstrapping method that starts with small seed instances to iteratively learn patterns and entity pairs [5, 1, 15]. Further [14] proposed distant

[1] The online demo of SEMAFOR is available at http://demo.ark.cs.cmu.edu/parse)

supervision method employing Freebase to automatically develop a large dataset from Wikipedia text to exploit relation extraction. [16] proposed to relax the distant supervision method and used mutually exclusive training knowledge base and training text to develop a different dataset for relation extraction.

In relation to the above studies, the present study examines frame-based semantic patterns for pattern-based relation extraction. Although several studies have employed frames for different IE tasks, to the best knowledge of the authors, there are no previous studies that specifically examine frames for pattern-based relation extraction. The proposed frame-based patterns are evaluated on different datasets developed following distant supervision method. The focus of this study is not to develop a classifier that competes with other relation extraction systems that uses the above datasets. However, this study specifically evaluates the usefulness of frame-based semantic patterns for relation extraction. To this end, the proposed frame-based patterns are compared with dependency and lexico-syntactic pattern types, which are the state-of-the-art for pattern-based relation extraction.

3 Frame-Based Semantic Patterns

We present in this section two types of frame-based semantic patterns, based on FrameNet annotations: (i) *Frame Element* patterns and (ii) *Frame* patterns. To aid understanding we commence the section by briefly describing FrameNet, and then explain the proposed patterns.

3.1 FrameNet

FrameNet is a lexical resource primarily designed to support natural language processing. Founded on the theory of frame semantics [7], FrameNet comprises a large collection of *frames*, each identified by a label, and each describing some "happening" (situation). Each *Frame* comprises *Frame Elements* (FEs) describing semantic roles within the context of the situation described by the frame. For example, the `Commercial_sell` frame describes basic commercial transactions involving buyers and sellers, exchanging money and goods. The FEs in this case are `Buyer`, `Seller`, and `Goods`. Words that *evoke* these frames are called Lexical Units (LUs). An example sentence with FrameNet annotations was earlier provided in §1. The FrameNet annotations are used to develop the following two types of patterns (a) *Frame Element patterns* and (b) *Frame patterns*.

3.2 Frame Element Patterns

The *Frame Element* pattern is developed based on the mapping provided between *frames* and *frame element* annotations provided by FrameNet. For example, consider the FrameNet annotations for the sentence "Currently, he works at Twitter in San Francisco" provided in Figure 1.

Fig. 1: Frame annotation for example sentence.

The FrameNet annotations provided for this sentence include *frames* such as `Being Employed` and `Businesses` (marked in blue) and the *frame elements* `Place of Employmnet`, `Business` and `Place`, marked in red. The mapping between these *frames* and *frame elements* can be used to create the following patterns to extract the entities (*Twitter, San Francisco*) for the COMPANY-LOCATION relation: (1) "BUSINESSES BUSINESS PLACE"; (2) "BEING_EMPLOYED PLACE_OF_EMPLOYMENT".

3.3 Frame Patterns

The *frame element* pattern described above provides a very specific mapping between related entities. However, in many instances such fine grained annotations are not available. In such case, the *Frame* pattern is proposed to map entities for a given relation. For example, consider the frame annotations for the example sentence shown in Figure 2. From the figure it can be seen that although various FEs are triggered by the LUs Microsoft Corporation, Redmond and Washington relevant to the COMPANY-LOCATION relation of interest, there is no individual frame that can be used to define a pattern to map entities with respect to this relation. Instead the *frame* names (shown in blue) can be used to define patterns for relation extraction as follows: (1) "BUSINESSES MEMBERSHIP BUSINESSES POLITICAL_LOCALES" ; (2) "BUSINESSES MEMBERSHIP BUSINESSES POLITICAL_LOCALES LOCATION" to extract COMPANY-LOCATION*(Microsoft Corporation, Redmond)* and COMPANY-LOCATION*(Microsoft Corporation, Washington)*. Such Frame patterns also provides the additional advantage that they are more general than *frame element* patterns.

Fig. 2: Frames annotation for example sentence.

4 Evaluation

In this section, we describe the lexico-syntactic and dependency based syntactic patterns against which frame-based patterns are evaluated. The datasets, evaluation metrics and the results of this study is also presented in this section.

4.1 Patterns Evaluated Against

The proposed frame-based patterns (F) are evaluated against the following pattern types:

a. Lexico-syntactic patterns. F is evaluated against the following two types of lexico-syntactic patterns: (a) L1 - patterns using lexical entries between entities; and (b) L2 - patterns replacing lexical entries with their Part Of Speech (POS) tags

b. Dependency-based syntactic patterns. The shortest path between entities in the dependency tree is shown to be useful for relation extraction [19]. F is evaluated against the following three types of dependency-based syntactic patterns based on the shortest path: (a) D1 - patterns using lexical entries between entities; (b) D2 - patterns using dependency relations between entities; and (c) D3 - patterns using both lexical entries and grammatical relations between entities

4.2 Datasets

The proposed frame-based patterns are evaluated on the following three datasets.

SemEval-2010 Task 8 dataset The SemEval-2010 Task 8 dataset [10] is a standard dataset for relation extraction, containing 10,717 examples annotated with 9 different relation types, and an artificial relation 'Other'. The nine relations are: Cause-Effect, Component-Whole, Content-Container, Entity-Destination, Entity-Origin, Instrument-Agency, Member-Collection, Message-Topic and Product- Producer. The dataset is split into 8,000 training examples and 2,717 test examples.The dataset is split into 8,000 training examples and 2,717 test examples, with each sentence marked with two nominals, e_1 and e_2. The task is to predict the relation between the nominals considering the directionality. Thus, the relation Cause-Effect(e_1,e_2) is different from the relation Cause-Effect(e_2,e_1). Considering directionality results in 18 different relations. However, only 17 relations were used since one of the relations had only one annotated instance. The instances are randomly split in the ratio 80:20 to create the training and the test set, respectively.

[16] Dataset. The [16] dataset was developed with a focus to relax the distant supervision assumption to extract relations from newswire instead of Wikipedia. In this study, we considered the ten relations shown in Table 1 from Riedel et al. (2010) dataset to evaluate frame-based patterns. Sentences for each

	Relation	TS
REL_1	people_deceased_person_place_of_death	2541
REL_2	people_person_place_of_birth	4265
REL_3	business_person_company	7987
REL_4	location_administrative_division_country	8860
REL_5	location_country_administrative_divisions	8860
REL_6	location_neighborhood_neighborhood_of	9472
REL_7	people_person_place_lived	9829
REL_8	location_country_capital	11216
REL_9	people_person_nationality	11446
REL_10	location_location_contains	75969
Total number of sentences: 150445		

Table 1: Relations considered from [16] dataset; TS: Total Sentences

of these relations were randomly split in the ration of 80:20 to create the training and test set, respectively.

Wikipedia dataset. The Wikipedia dataset was specifically developed for this study, following the distant supervision method. Specifically, we find all sentences that mentions a pair of entities in the seed dataset, and consider those sentences as describing the semantic relationship between the two entities specified in the seed dataset. DBpedia [2] was used to obtain seed entity pairs for ten different relations, which were further used to obtain sentences from Wikipedia dump. Sentences with a mention of at least one entity pair was retained. The dataset was randomly split in the ratio of 80:20 to create the training and the test set, respectively. The number of sentences extracted for different relations are as follows: (1) ACTOR-MOVIE-3147; (2) COMPANY-LOCATION-6908; (3) COMPANY-PRODUCT-9122; (4) DIRECTOR-MOVIE-10651; (5) AUTHOR-BOOKTITLE-12245; (6) COMPANY-FOUNDER-14489; (7) ALBUM-ARTIST-20961; (8) BIRTHPLACE-PERSON-21737; (9) ALBUM-GENRE-22934; and (10) COUNTRY-CITY-45981.

4.3 Evaluation Metrics

As previously discussed in §1, the evaluation of a pattern set, besides considering its ability to match test sentences, should also examine how correctly, the patterns extract related entities for a given relation. The precision and recall measures employed in this study are designed to include this aspect. Thus, given a pattern $l \in \mathcal{L}$, the pattern set obtained from train data, and a test sentence $s \in \mathcal{S}$, the following types of patterns are defined:

(a) *matched pattern*: the pattern l is defined as a *matched pattern* for the test sentence s, iff (if and only if) the pattern l matches the test sentence s.

(b) *correct pattern*: a pattern l is defined as a *correct pattern* for the test sentence s, iff the pattern l matches the test sentence s and correctly extracts the two arguments (e_1, e_2) for a given relation r.

The precision of a pattern l is defined as the ratio of number of times the pattern l is seen as a *correct pattern* to the number of times it is seen as a matched pattern on the test set $\mathcal{S}$. Thus, the precision of a pattern l on the test set $\mathcal{S}$ is given by:

$$\text{Precision }(l) = \frac{\#\text{ pattern } l \text{ is a } \textit{correct pattern} \text{ in } \mathcal{S}}{\#\text{ pattern } l \text{ is a } \textit{matched pattern} \text{ in } \mathcal{S}}.$$

The overall precision P of the pattern set is obtained by:

$$P = \frac{1}{|\mathcal{L}|} \sum_{l \in \mathcal{L}} \text{Precision }(l),$$

where $|\mathcal{L}|$ is the total number of patterns in the pattern set.

The recall of a pattern set is measured in terms of its effectiveness or coverage in applying correct patterns on the test set and is defined as the ratio of of the total number of test sentences on which *correct patterns* are applied to the total number of test sentences. Thus, the recall R of a pattern set is given by:

$$R = \frac{\#\text{ of test sentences with } \textit{correct patterns}}{\#\text{ of test sentences}}.$$

Given Precision P and Recall R, the F-score of a pattern set is obtained by: F-Score $= \frac{2 \times PR}{P+R}$.

4.4 Results

The following are the evaluation results.

Pattern sets applied in isolation. The F-score values of various pattern sets (L1, L2, D1, D2, D3, F), when applied in isolation on three different datasets for relation extraction are shown in Tables 2, 3 and 4. As seen, the frame-based pattern set (F) perform comparatively better for Semeval 2010 Task 8 dataset (Table 2) achieving an average F-score of 0.64, against other pattern types. With respect to the Wikipedia and Riedel et al. (2010) [16] datasets (Tables 3 and 4), F achieves a statistically significant F-score of 0.66 and 0.76 ($p \leq 0.05$; Wilcoxon Signed-Rank Test) against other pattern types.

Frames vs. dependency patterns. As seen in Tables 2, 3 and 4 the dependency-based patterns using grammatical relations (D2) achieves the second best performance among the different patterns evaluated. To evaluate the performance of D2 against F, we compare their precision and recall scores for relations in Wikipedia dataset (results are presented only for Wikipedia dataset due to space constraints) in Table 5. As seen in Table 5, F achieves statistically significant precision and recall in comparison to the scores achieved by D2 ($p \leq 0.05$; Wilcoxon Signed-Rank Test). As explained previously (§4.3), the precision metric considered both to *match* test sentences and extract *correct* entities. Thus, the precision scores (Table 5) shows that F patterns are more precise than D2. Similarly, the recall metric measured the coverage of applying *correct patterns* on test sentences. The recall scores in Table 5 shows that F patterns apply more *correct patterns* as against D2 patterns.

	Patterns applied in isolation						Augmented Patterns		
Relation	L1	L2	D1	D2	D3	F	FAD	FAL	LAD
					F-score				
CAUSE_EFFECT_e1_e2	0.34	0.42	0.60	0.62	0.59	0.64	0.66	0.68	0.60
CAUSE_EFFECT_e2_e1	0.41	0.52	0.49	0.56	0.56	0.59	0.62	0.67	0.58
COMPONENT_WHOLE_e1_e2	0.62	0.64	0.19	0.62	0.62	0.70	0.64	0.74	0.58
COMPONENT_WHOLE_e2_e1	0.48	0.62	0.45	0.71	0.70	0.66	0.70	0.72	0.73
CONTENT_CONTAINER_e1_e2	0.38	0.50	0.44	0.59	0.49	0.55	0.63	0.58	0.57
CONTENT_CONTAINER_e2_e1	0.54	0.63	0.40	0.65	0.57	0.67	0.73	0.72	0.72
ENTITY_DESTINATION_e1_e2	0.27	0.27	0.70	0.58	0.69	0.62	0.67	0.71	0.48
ENTITY_ORIGIN_e1_e2	0.32	0.59	0.59	0.63	0.58	0.68	0.68	0.74	0.66
ENTITY_ORIGIN_e2_e1	0.74	0.79	0.28	0.79	0.68	0.87	0.85	0.76	0.78
INSTRUMENT_AGENCY_e1_e2	0.42	0.52	0.39	0.54	0.53	0.72	0.75	0.67	0.57
INSTRUMENT_AGENCY_e2_e1	0.23	0.41	0.39	0.69	0.42	0.44	0.56	0.52	0.69
MEMBER_COLLECTION_e1_e2	0.50	0.5 0	0.42	0.66	0.56	0.65	0.71	0.69	0.70
MEMBER_COLLECTION_e2_e1	0.63	0.83	0.37	0.75	0.72	0.87	0.78	0.88	0.76
MESSAGE_TOPIC_e1_e2	0.14	0.43	0.43	0.53	0.37	0.57	0.63	0.65	0.59
MESSAGE_TOPIC_e2_e1	0.01	0.27	0.59	0.57	0.44	0.33	0.63	0.38	0.60
PRODUCT_PRODUCER_e1_e2	0.39	0.65	0.41	0.69	0.58	0.72	0.78	0.81	0.74
PRODUCT_PRODUCER_e2_e1	0.14	0.51	0.62	0.68	0.61	0.71	0.74	0.77	0.65
AVERAGE	0.38	0.53	0.45	0.63	0.57	**0.64**	**0.69**†	**0.68**†	0.64

Table 2: F-score values for relations in Semeval 2010 Task 8 dataset. † statistically significant against F.

	Patterns applied in isolation						Augmented Patterns		
Relation	L1	L2	D1	D2	D3	F	FAD	FAL	LAD
				F-score					
ACTOR-MOVIE	0.27	0.48	0.34	0.57	0.65	0.67	0.72	0.71	0.66
COMPANY-LOCATION	0.37	0.51	0.36	0.59	0.38	0.68	0.73	0.70	0.65
COMPANY-PRODUCT	0.22	0.40	0.40	0.61	0.36	0.69	0.76	0.72	0.66
DIRECTOR-MOVIE	0.23	0.30	0.56	0.65	0.60	0.71	0.75	0.73	0.70
AUTHOR-BOOKTITLE	0.26	0.49	0.48	0.63	0.52	0.69	0.74	0.73	0.68
COMPANY-FOUNDER	0.45	0.61	0.41	0.72	0.80	0.72	0.82	0.80	0.78
ALBUM-ARTIST	0.27	0.50	0.48	0.60	0.47	0.64	0.72	0.71	0.66
BIRTHPLACE-PERSON	0.27	0.45	0.24	0.53	0.28	0.56	0.65	0.65	0.6
ALBUM-GENRE	0.33	0.41	0.42	0.56	0.49	0.65	0.68	0.71	0.63
COUNTRY-CITY	0.42	0.55	0.33	0.64	0.42	0.68	0.75	0.72	0.70
AVERAGE	0.30	0.47	0.40	0.61	0.49	**0.66***	**0.73****†	**0.71****†	0.67

Table 3: F-score values for relations in Wikipedia dataset. * statistically significant against L1, L2, D1, D2, D3. ** statistically significant against LAD. † statistically significant against F.

Frame element patterns vs. frame patterns. The precision and recall scores achieved by *frame element* patterns and *frame* patterns (described in §3)

	Patterns applied in isolation						Augmented Patterns		
Relation	L1	L2	D1	D2	D3	F	FAD	FAL	LAD
				F-score					
people_deceased_person_place_of_death	0.21	0.36	0.26	0.35	0.28	0.68	0.63	0.61	0.52
people_person_place_of_birth	0.37	0.44	0.52	0.57	0.50	0.78	0.78	0.52	0.67
business_person_company	0.42	0.25	0.64	0.54	0.51	0.88	0.91	0.89	0.71
location_administrative_division_country	0.60	0.63	0.52	0.59	0.50	0.84	0.93	0.82	0.82
location_country_administrative_divisions	0.59	0.65	0.19	0.28	0.12	0.70	0.67	0.72	0.69
location_neighborhood_neighborhood_of	0.85	0.86	0.33	0.67	0.66	0.79	0.93	0.93	0.85
people_person_place_lived	0.53	0.59	0.44	0.67	0.55	0.82	0.83	0.82	0.75
location_country_capital	0.53	0.55	0.11	0.19	0.19	0.61	0.50	0.60	0.59
people_person_nationality	0.65	0.69	0.45	0.70	0.61	0.82	0.86	0.85	0.81
AVERAGE	0.52	0.55	0.37	0.51	0.43	**0.76***	**0.78****†	**0.75****†	0.71

Table 4: F-score values for relations in [16] dataset. * statistically significant against L1, L2, D1, D2, D3. ** statistically significant against LAD. † statistically significant against F.

Relation	D2-P	F-P	D2-R	F-R
ACTOR-MOVIE	0.60	**0.67**	0.55	**0.69**
COMPANY-LOCATION	0.62	**0.74**	0.58	**0.64**
COMPANY-PRODUCT	0.76	**0.79**	0.52	**0.62**
DIRECTOR-MOVIE	0.63	**0.73**	0.69	**0.70**
AUTHOR-BOOKTITLE	0.64	**0.73**	0.63	**0.66**
COMPANY-FOUNDER	0.86	**0.88**	0.62	**0.80**
ALBUM-ARTIST	0.60	**0.64**	0.62	**0.64**
BIRTHPLACE-PERSON	0.51	**0.54**	0.56	**0.60**
ALBUM-GENRE	0.50	**0.58**	0.64	**0.74**
COUNTRY-CITY	0.70	0.7 0	0.60	**0.67**
AVERAGE	0.64	**0.70***	0.60	**0.67***

Table 5: Precision and recall values of D2 and F pattern sets for relations in Wikipedia dataset. * statistically significant.

individually are presented in Table 6. As seen in Table 6, both *frame element* and *frame* patterns achieve a similar precision score. However, in terms of recall, the *frame element* patterns have a lower coverage (0.26) as against *frame* patterns (0.57). This shows that *frame element* patterns apply *correct patterns* on lesser number of test sentences as against *frame* patterns.

Wikipedia vs. Riedel et al. (2010) [16] dataset. As seen from Tables 3 and 4, the performance of F is significantly higher for Riedel dataset in comparison to Wikipedia dataset. While F achieves an average F-score of 0.66 as against an average F-score of 0.61 obtained by D2 for Wikipedia dataset, F achieves a higher average F-score of 0.76 against the average F-score of 0.51 achieved by D2 for the Riedel dataset. These results are significant since the two datasets are developed following different methods. While the Wikipedia dataset follows distant supervision method, the Riedel dataset is developed by relaxing the distant supervision method. As seen from these Tables (3 and 4), the performance of D2 decreases for Riedel dataset in comparison to Wikipedia dataset (0.61 vs. 0.51),

	Frame element Patterns		*Frame* Patterns	
Relation	P	R	P	R
ACTOR-MOVIE	0.60	0.63	0.72	0.17
COMPANY-LOCATION	0.69	0.53	0.70	0.32
COMPANY-PRODUCT	0.74	0.48	0.75	0.34
DIRECTOR-MOVIE	0.70	0.64	0.66	0.17
AUTHOR-BOOKTITLE	0.68	0.60	0.64	0.24
COMPANY-FOUNDER	0.80	0.53	0.78	0.32
ALBUM-ARTIST	0.59	0.53	0.64	0.32
BIRTHPLACE-PERSON	0.51	0.52	0.51	0.22
ALBUM-GENRE	0.56	0.66	0.55	0.23
COUNTRY-CITY	0.66	0.58	0.65	0.35
AVERAGE	0.65	0.57	0.66	0.26

Table 6: Precision and recall values of *frame element* and *frame* patterns.

showing that dependencies are less useful for datasets where mutually exclusive training knowledge base and training text is employed for relation extraction. On the other hand, the performance of F is higher for Riedel dataset, indicating that frame-based patterns can generalize well for such datasets.

Augmenting dependency patterns and lexico-syntactic patterns with frames.

The results of augmenting dependency and lexical patterns with frames is also provided in Tables 2, 3 and 4. A cascaded method was followed to sequentially apply one pattern set after another on the test set.The patterns from the second pattern set was applied on those test sentences, where the first pattern set failed to apply *correct patterns* (i.e., not only *match* but also apply *correct* patterns). Accordingly, two types of frame-based augmented patterns were examined: FAD - frame (F) augmented dependency (D2) patterns; and FAL - frame (F) augmented lexical (L2) patterns. These patterns were evaluated against dependency patterns (D2) augmented with lexical patterns (L2). The D2 and L2 were chosen as these patterns achieved higher performance among related pattern types. The F-score values of FAD and FAL in all three datasets (Tables 2, 3 and 4) shows that FAD and FAL achieve statistically significant performance against using frame-based patterns (F) in isolation. Interestingly, FAD and FAL achieves a higher performance against combining dependencies and lexical patterns. This indicates that augmenting dependency and lexical patterns with frames are useful for relation extraction. The precision and recall values (not shown here) of augmented patterns indicates that augmented patterns achieve higher recall, thus applying *correct patterns* on larger number of test sentences.

5 Conclusion

To conclude, we presented in this paper frame-based semantic patterns for relation extraction. More specifically, we proposed *frame element* and *frame* patterns exploiting the FrameNet annotations for relation extraction, which were evaluated against lexico-syntactic and dependency-based syntactic patterns, on three independent datasets . The evaluation results shows that frame-based patterns achieves significantly higher performance against state-of-the-art dependency and lexical patterns, both in terms of precision and recall on all three datasets. Experiments conducted to augment dependency and lexical patterns with frame-based patterns shows that the augmentation helps in achieving higher recall.

References

1. Agichtein, E., Gravano, L.: Snowball: Extracting relations from large plain-text collections. In: Proceedings of the fifth ACM conference on Digital libraries. pp. 85–94. ACM (2000)
2. Auer, S., Bizer, C., Kobilarov, G., Lehmann, J., Ives, Z.: Dbpedia: A nucleus for a web of open data. In: In 6th Intl Semantic Web Conference, Busan, Korea (2007)
3. Baker, C.F., Fillmore, C.J., Lowe, J.B.: The berkeley framenet project. In: Proceedings of the 17th international conference on Computational linguistics-Volume 1. pp. 86–90. Association for Computational Linguistics (1998)
4. Banko, M., Cafarella, M.J., Soderland, S., Broadhead, M., Etzioni, O.: Open information extraction for the web. In: Proceedings of IJCAI. vol. 7, pp. 2670–2676 (2007)
5. Brin, S.: Extracting patterns and relations from the world wide web. In: The World Wide Web and Databases, pp. 172–183. Springer (1998)
6. Das, D., Chen, D., Martins, A.F., Schneider, N., Smith, N.A.: Frame-semantic parsing. Computational Linguistics 40(1), 9–56 (2014)
7. Fillmore, C.: Frame semantics. Linguistics in the morning calm pp. 111–137 (1982)
8. Fillmore, C.J., Johnson, C.R., Petruck, M.R.: Background to framenet. International journal of lexicography 16(3), 235–250 (2003)
9. Hearst, M.A.: Automatic acquisition of hyponyms from large text corpora. In: Proceedings of the COLING. pp. 539–545. Association for Computational Linguistics (1992)
10. Hendrickx, I., Kim, S.N., Kozareva, Z., Nakov, P., Ó Séaghdha, D., Padó, S., Pennacchiotti, M., Romano, L., Szpakowicz, S.: Semeval-2010 task 8: Multi-way classification of semantic relations between pairs of nominals. In: Proceedings of the Workshop on Semantic Evaluations: Recent Achievements and Future Directions. pp. 94–99. Association for Computational Linguistics (2009)
11. Jijkoun, V., De Rijke, M., Mur, J.: Information extraction for question answering: Improving recall through syntactic patterns. In: Proceedings of the COLING. p. 1284. Association for Computational Linguistics (2004)
12. Kim, J.T., Moldovan, D., et al.: Acquisition of linguistic patterns for knowledge-based information extraction. Knowledge and Data Engineering, IEEE Transactions on 7(5), 713–724 (1995)

13. Liu, S., Chen, Y., He, S., Liu, K., Zhao, J.: Leveraging framenet to improve automatic event detection. In: Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers). pp. 2134–2143. Association for Computational Linguistics, Berlin, Germany (August 2016), http://www.aclweb.org/anthology/P16-1201
14. Mintz, M., Bills, S., Snow, R., Jurafsky, D.: Distant supervision for relation extraction without labeled data. In: Proceedings of the Joint Conference of the 47th Annual Meeting of the ACL and the 4th International Joint Conference on Natural Language Processing of the AFNLP: Volume 2-Volume 2. pp. 1003–1011. Association for Computational Linguistics (2009)
15. Ravichandran, D., Hovy, E.: Learning surface text patterns for a question answering system. In: Proceedings of the COLING. pp. 41–47. Association for Computational Linguistics (2002)
16. Riedel, S., Yao, L., McCallum, A.: Modeling relations and their mentions without labeled text. In: Joint European Conference on Machine Learning and Knowledge Discovery in Databases. pp. 148–163. Springer (2010)
17. Søgaard, A., Plank, B., Alonso, H.M.: Using frame semantics for knowledge extraction from twitter. In: Proceedings of AAAI (2015)
18. Surdeanu, M., Ciaramita, M.: Robust information extraction with perceptrons. In: Proceedings of the NIST 2007 Automatic Content Extraction Workshop (ACE07) (2007)
19. Wu, F., Weld, D.S.: Open information extraction using wikipedia. In: Proceedings of COLING. pp. 118–127. Association for Computational Linguistics (2010)