

Comparing Distributional and Curated Approaches for Cross-lingual Frame Alignment

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Abstract

Despite advances in statistical approaches to the modeling of meaning, many questions about the ideal way of exploiting both knowledge-based (e.g., FrameNet, WordNet) and data-based methods (e.g., BERT) remain unresolved. This workshop focuses on these questions with three session papers that run the gamut from highly distributional methods (Lekkas et al., 2022), to highly curated methods (Gamonal, 2022), and techniques with statistical methods producing structured semantics (Lawley and Schubert, 2022).

In addition, we begin the workshop with a small comparison of cross-lingual techniques for frame semantic alignment for one language pair (Spanish and English). None of the distributional techniques consistently aligns the 1-best frame match from English to Spanish, all failing in at least one case. Predicting which techniques will align which frames cross-linguistically is not possible from any known characteristic of the alignment technique or the frames. Although distributional techniques are a rich source of semantic information for many tasks, at present curated, knowledge-based semantics remains the only technique that can consistently align frames across languages.

1 Introduction to the Workshop

Broadly speaking, research in computational linguistics encompasses two main streams: (1) work that relies primarily on operationalizing prior knowledge about language and its use, such as rule-based parsers (Bender et al., 2002), scripts (Schank and Abelson, 1977), planning, scenarios, scripts for virtual assistants, and FrameNet (FN) frames (Ruppenhofer et al., 2016), as well as lexical databases like WordNet (Fellbaum, 1998), VerbNet (Kipper et al., 2000), and PropBank (Palmer et al., 2005), among others; and (2) work that seeks to derive knowledge directly from data (text, speech, and increasingly vision) with unsupervised (or distantly

supervised) methods, which are distributional and frequency-based, in linguistics (Biber et al., 2020), cognitive science (Xu and Xu, 2021), and computational linguistics, notably vector embeddings like BERT (Devlin et al., 2019). They are often complementary; e.g. Kuznetsov and Gurevych (2018) combine POS tagging and lemmatization to improve vector embeddings and Qian et al. (2021) combine syntactic knowledge with neural language models to improve accuracy.

Despite great advances in statistical approaches, many questions remain unresolved:

- What are the strengths and limitations of each approach?
- Is extracting different types of knowledge from text/speech possible by one and not the other? Why?
- How well can each represent relations and support reasoning over text?
- What factors limit progress of each approach?
- Would combining the two approaches solve all the problems?

These issues are as pertinent today as they were nearly 30 years ago at “The Balancing Act: Combining Symbolic and Statistical Approaches to Language” (McDonald, 1994). The goal of this workshop is to encourage reporting of research bearing on these issues; we will hear three such papers (listed below), in addition to our own results on cross-lingual frame alignment, described in the remainder of this paper.

In “Multi-sense Language Modelling”, Andrea Lekkas, Peter Schneider-Kamp and Isabelle Augenstein use pretrained embeddings and also calculate new ones, combining them with many facets of the curated WordNet lexicon. They report on extensive testing of five different system architectures against a most-frequent-sense baseline on both next word prediction and WordNet sense prediction, on both the SemCor and SemEval datasets.

Maucha Gamonal’s “A Descriptive Study of

Metaphors and Frames in the Multilingual Shared Annotation Task” shows how FrameNet frames can explain instances of metaphor in 50 sentences from the transcription of a TED talk that members of the respective FrameNet projects annotated in Portuguese, English, and German. The “frame shift” discussed in the paper also has implications for theories of translation. Despite progress on automatic recognition of metaphors (e.g. Veale 2016, Shutova et al. 2015, Chakrabarty et al. 2021), the kind of detail shown here is generally not retrievable computationally.

Lane Lawley and Lenhart Schubert generate “Logical Story Representations via FrameNet + Semantic Parsing”. Lawley and Schubert have previously worked on learning logical representations of events (“event Logic”) from simple stories (Lawley et al., 2021). In this paper, they show how semantic parsing based on FrameNet and implemented in the LOME parser (Xia et al., 2021) can add valuable information to the logical representation, allowing more precise reasoning.

As described in the rest of this paper, the introduction to the workshop presents but one example of the complex interplay between curated and distributional semantics from research at the ICSI FrameNet project: cross-linguistic frame alignment. We compared curated semantics techniques with those of unsupervised distributional ones, intentionally focusing on a very small set of data for one language pair (English and Spanish) to characterize the specific details of such comparisons.

The remainder of the paper proceeds as follows: Section 2 provides a brief overview of FrameNet; Section 3 describes the work of developing cross-lingual frame alignments; Section 4 presents the results of different methods for aligning some Spanish and English frames; and Section 5 offers concluding remarks and future directions to pursue cross-linguistic frame alignment.

2 Overview of FrameNet

FrameNet (Ruppenhofer et al., 2016) is a research and resource development project in corpus-based computational lexicography grounded in the theory of **Frame Semantics** (Fillmore, 1985).

The **semantic frame**, a script-like knowledge structure that facilitates inferencing within and across events, situations, states-of-affairs, relations, etc., is at the core of the theory (Petrucci, 1996). FN defines a semantic frame in terms of its **frame ele-**

ments (FEs), or participants (and other concepts) in the scene that the frame captures; a **lexical unit** (LU) is a pairing of a lemma and a frame, characterizing that LU in terms of the frame that it evokes. The definition of a frame, represented both in prose and in structured relations between frames, is a bundle of inferences relating the frame elements whenever the frame is evoked.

Example 1 illustrates the Frame Semantics analysis for the verb **buy**, which FN defines in the `Commerce_buy` frame, with the FEs **BUYER**, **SELLER**, **GOODS**, and **MONEY**.¹

1. **Chuck** **BUYER** **bought** **a car** **GOODS** **from Jerry** **SELLER** **for \$2,000** **MONEY**

3 Cross-Linguistic Frame Alignment

As interest in Frame Semantics (Fillmore, 1982) and the original FrameNet for English (Fillmore, 2014) grew, research groups around the world started developing FN-like resources for their languages. Such resources in many languages have made it possible to address the question of whether semantic frames are universal or merely language-specific lexical phenomena. With these databases at hand, we may operationalize the question as: To what extent can these lexical databases be aligned to form a multilingual FrameNet lexical database connecting all of the languages, while also accounting for language-specific differences and domain-specific extensions to FrameNet?

The goal of the Multilingual FrameNet (**MLFN**) project (Gilardi and Baker, 2018) was to answer this question by building a cross-linguistic database. Though this database succeeded in partially aligning frames, the question remained of how to assess the validity and utility of the alignments. Baker and Lorenzi (2020) described a database of vectors that represent alignments between pairs of frames in different languages (e.g., English-Spanish, English-Japanese, etc.).² Baker and Lorenzi (2020) also described developing ViToXF, a freely available visualization tool for all of the alignments.³ The tool allows interactive exploration of the alignments between English and one of seven other languages

¹This paper uses these typographical conventions: Frame names are in typewriter font; FE Names are in SMALL CAPS; and lexical units are in boldface.

²The latest release of this database is available on Github. <https://github.com/icsi-berkeley/framenet-multilingual-alignment/releases/tag/1.0.3-2>.

³<https://github.com/icsi-berkeley/framenet-multilingual-alignment>.

in the database. The alignments were created using 11 different methods, four (4) resource-based and seven (7) vector-based. The rest of this section characterizes these alignment methods; this is a revised version of the descriptions of alignment methods in [Baker and Lorenzi \(2020\)](#).

3.1 Alignment by Frame Name/ID Number

At first glance, the alignment problem might seem trivial: if other FNs have used Berkeley FrameNet (BFN) frame names. Can we assume that a frame in a language other than English with the same name as a BFN frame represents the same concept, and just ignore any that don't have matching names? Furthermore, some of the other resources used target-language frame names, rather than English ones, a situation that would mean aligning just the names themselves by translation between the two languages. Sometimes, the non-English language frame data also included a field for the BFN frame name or BFN frame ID, which could be used independently for alignment. Also, even when the names (or IDs) match, the non-English frame may be defined differently or have a different number of core FEs than the BFN frame. By definition, a different number of core FEs between the (English and non-English) frames amounts to different frames, so such alignments are, at best, imperfect.

3.2 Alignment by LU Translation

A second way of approaching alignment is to take all the LUs from a source language frame and find translation equivalents in the target language. If frames are equivalent across languages, we expect the translations of LUs in one source language frame to fall in the same target language frame, but the success of this method depends on the accuracy of the translations. By definition, a LU represents one sense of a lemma, a fact that should, in principle, greatly narrow the range of possible translations. However, exploiting frame information in the translation process remains a challenge.

We use The Open Multilingual WordNet (OMWN) ([Bond and Foster, 2013](#)) to find translation equivalents between languages. The first step is to create a mapping $S(\ell)$ from each LU in each language to a set of synsets one of which may represent its sense. That mapping requires finding OMWN synsets that contain the lemma+POS of the given LU. Let L_e and L_f be the lists of LUs in any two frames in the source language (e)

and the target language (f). Equation 1 defines the matching of LUs between L_e and L_f .

$$m_1(L_e, L_f) = \{a \in L_e \mid b \in L_f, S(a) \cap S(b) \neq \emptyset\} \quad (1)$$

To evaluate the alignment between the two frames, this function calculated three different scores (selectable in ViToXF under the name "LU translations using WordNet"). The first is a metric that considered LUs from both frames (Equation 2), but this method gives too much weight to frames containing more LUs. Avoiding this problem required breaking the alignment into two scores, accounting for the direction of alignment. Specifically, the score of the alignment from English to the target language might be different from the reverse. Equation 3 presents the formula for one of those scores. (Simply switching the two arguments will obtain the other score.)

$$s_1(L_e, L_f) = \frac{|f(L_e, L_f)| + |f(L_f, L_e)|}{|L_e| + |L_f|} \quad (2)$$

$$s_2(L_e, L_f) = \frac{|f(L_e, L_f)|}{|L_e|} \quad (3)$$

We also explored an alternative scoring method based on synsets rather than LUs (by selecting "Synset count" in ViToXF). Equation 4 defines the matching set in this case, with the scores calculated in a manner similar to that of Equation 3.

$$m_2(L_e, L_f) = \bigcup_{a \in L_e} S(a) \cap \bigcup_{b \in L_f} S(b) \quad (4)$$

3.3 Alignment by Frame Element Similarity

Recalling that frames are defined in terms of the entailments of their FEs, for two frames to be the same across languages, they must minimally have the same number and type of FEs. Some FrameNets, like Spanish FN and Japanese FN, simply used the same FEs that BFN named and defined; that is, the names and definitions of FEs are identical to those of the English resources. Others, e.g., Chinese, translated the names and the definitions into the target language or created completely new ones in the target language. These cases required aligning the FEs according to the proximity of the names and definitions from the two languages in a shared vector space. French created FE names

and definitions in English, although many of those frames do not correspond to those in BFN. Swedish FN used FE names in English and adopted the BFN definitions. Both the Brazilian Portuguese and German FN projects include FEs in a mixture of English and the target language. In these last two cases, developing the alignment required grouping the FEs according to the language of their name (English or the target language), calculating the similarity separately for the FEs in each language, and then combining the scores.⁴

3.4 Alignment by Distributional Similarity of Lexical Units

Another approach uses cross-lingual word embeddings to find alignments; this appears in ViToXF under the options “LU translations using MUSE” and “MUSE centroid similarity”. Currently, ViToFX is based on fastText word embeddings from various languages trained on Wikipedia data and aligned to a single vector space (Bojanowski et al., 2017). The spaces were aligned by an unsupervised adversarial approach, where the discriminator tries to predict the embedding origin and the generator aims to create transformations that the former cannot accurately classify (Lample et al., 2018). The transformed fastText vectors of many languages mapped to English space are available in the MUSE library.⁵ MLFN uses these pre-trained cross-lingual word embeddings for two different scoring techniques. The first, “LU translations using MUSE” (like those in Section 3.2), uses the word embeddings as a way to obtain translation equivalents. We define $n(\vec{v}, k, t)$, the k -neighborhood of \vec{v} in the target language with cosine similarity greater than t . Equation 5 defines the alignment score between a pair of frames given their LU lists L_e and L_f .

$$s_3(L_e, L_f) = \frac{|\{a \in L_e \mid b \in L_f, \vec{v}(b) \in n(\vec{v}(a), k, t)\}|}{|L_e|} \quad (5)$$

The second distributional technique, “MUSE centroid similarity”, calculates the alignment between two frames by finding the average vector of their LUs vectors (i.e. the centroid vector of each

frame) and computing the cosine similarity of those centroids, like Sikos and Padó (2018).

4 Results

To evaluate the alignments created by the various techniques described in Section 3 (above), FN researchers defined a set of “gold-standard” frame alignments for a small set of frames from Spanish FrameNet (SFN) aligned to English frames from BFN.⁶ We determined gold-standard frame matches manually by comparing all of the information associated with the frames of each language, including frame definition, frame elements, lexical units with their translations, and frame relations (if any). Since the time for a manual review precludes comparing all frames to all other frames, we only considered those frames with lexical translation overlap.⁷

For each gold-standard alignment, we examined the full set of alignment techniques provided by ViToXF for the SFN frame. With ViToXF, each technique will align a SFN frame to different list of BFN frames, and each such pairing will have a score. The techniques have very different scores, even when normalized, so the best way to compare techniques is by how they order the proposed BFN frames to align. In what follows, we simplify the evaluation of a technique to the relative rank (1st, 2nd, etc.) of the gold-standard BFN frame.

Table 1 compares alignments of five SFN frames (ending in *.es*) with those of BFN (ending *.en*). The first two rows show the gold standard alignments; in four cases, the frames have the same name in both languages. However, SFN *Motion_manner* corresponds most closely with BFN’s *Self_motion*. The other four rows show the rank (1st, 2nd, etc.) of the English gold standard frame in the output of each of four alignment algorithms:

1. Proportion of matching core FE names or IDs
2. WordNet synset count (mapped from Spanish to English synsets)
3. MUSE LU centroid similarity
4. Average core FE name/definition similarity (using MUSE vectors)

Note that the first two of the above-mentioned algorithms are entirely based on curated resources, the

⁴The process used Michal Danilak’s python library for language recognition <https://pypi.org/project/langdetect/>

⁵<https://github.com/facebookresearch/MUSE>

⁶The data derive from SFN (Subirats-Rüggeberg and Truck, 2003) and V.1.7 of BFN (Ruppenhofer et al., 2016).

⁷Some of these results were also described in the Call for Papers for this workshop.

Spanish Frames	Desiring.es	Motion manner.es	Performers and roles.es	Similarity.es	Activity finish.es
Gold standard English match	Desiring.en	Self-motion.en	Performers and roles.en	Similarity.en	Activity finish.en
Matching core FE names/IDs	1st	No match	1st	1st	1st-8th
WN synset count (es-> en)	1st	1st	1st	1st	2nd-3rd
MUSE LU centroid similarity	1st	2nd	2nd	1st	2nd
Average core FE MUSE similarity	1st	>10th	1st	1st	1st

Table 1: Rank of Gold-standard Frame Match by Alignment Method

third is purely distributional, and the last of these combines the two approaches.

All the techniques show promise in accurately aligning certain frames and all perform less well on the inexact match, i.e., SFN *Motion_manner* to BFN *Self_motion*. Unlike the English frame, the SFN frame does not allow complex path information, although many LUs in the SFN frame have translation equivalents in BFN *Self_motion* (e.g. Spanish *correr.v* -> English *run.v*). Also, no single technique ranks the gold standard as the strongest match for all of the listed frames. SFN *Desiring* and *Similarity* align correctly by all of the techniques listed; in contrast, SFN *Activity_finish* only aligns unambiguously using just one technique, i.e., Average core FE MUSE similarity.

At least based on this limited data, it is not possible to predict which techniques will do a good job of aligning which frames cross-linguistically from any known characteristic of the alignment technique or the frames. This is just one example of the complex questions involved in comparing different approaches to alignment.

5 Concluding Remarks and Future Work

This paper has introduced the workshop exploring the strengths and weaknesses of different techniques for modeling meaning. Specifically, the research of the Berkeley FrameNet group has compared distributional approaches and curated approaches for cross-lingual frame alignment, illustrating the results from four different alignment techniques for five Spanish FrameNet and BFN

frames, finding that no distributional technique reliably predicts the gold-standard alignment.

This initial study on a small set of frames in only two languages is suggestive, and points to the need for wider exploration of techniques for aligning lexical units and frames across languages in frame-based resources. We look forward to further development of hybrid semantic representations combining the advantages of distributional and curated semantic techniques, both for the alignment task and a wider range of applications.

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- Spanish FN (Subirats, 2009)
- SALSA (Burchardt et al., 2006)
- Japanese FrameNet (Ohara et al., 2004)
- Chinese FN (You and Liu, 2005)
- FrameNet Brasil (Torrent et al., 2018)
- Swedish FN++ (Borin et al., 2010)
- French FN (Candito et al., 2014)
- Dutch FN (Vossen et al., 2018)

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