Framester: A Wide Coverage Linguistic Linked Data Hub

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Abstract. Semantic web applications leveraging NLP can benefit from easy access to expressive lexical resources such as FrameNet. However, the usefulness of FrameNet is affected by its limited coverage and non-standard semantics. The access to existing linguistic resources is also limited because of poor connectivity among them. We present some strategies based on Linguistic Linked Data to broaden FrameNet coverage and formal linkage of lexical and factual resources. We created a novel resource, Framester, which acts as a hub between FrameNet, WordNet, VerbNet, BabelNet, DBpedia, Yago, DOLCE-Zero, as well as other resources. Framester is not only a strongly connected knowledge graph, but also applies a rigorous formal treatment for Fillmore's frame semantics, enabling full-fledged OWL querying and reasoning on a large frame-based knowledge graph. We also describe Word Frame Disambiguation, an application that reuses Framester data as a base in order to perform frame detection from text, with results comparable in precision to the state of the art, but with a much higher coverage.

Keywords: Frame Detection, Framester, FrameNet, FrameNet Coverage, Knowledge Graphs, Frame Semantics, Linguistic Linked Data.

1 Introduction

Many resources from different domains are now published using Linked Open Data (LOD) principles to provide easy access to structured data on the web. There are several linguistic resources which are already part of LOD, two of the most important are WordNet [7] and FrameNet [2]. They have already been formalized several times, e.g. in OntoWordNet [12], WordNet RDF [30], FrameNet DAML [22], FrameNet RDF [24], etc. FrameNet allows to represent textual resources in terms of Frame Semantics. The usefulness of FrameNet is however affected by its limited coverage, and non-standard semantics. An evident solution stands on creating valid links between FrameNet and other lexical resources such as WordNet, VerbNet [19] and BabelNet [23] to create wide-coverage and multilingual extensions of FrameNet. By overcoming these limitations, NLP-based applications such as question answering, machine reading and understanding, etc. would eventually be improved.

This study focuses on a wide coverage resource called "Framester". It is a frame-based ontological resource acting as a hub between linguistic resources such as FrameNet, WordNet, VerbNet, BabelNet, DBpedia, Yago, DOLCE-Zero, and leveraging this wealth of links to create an interoperable *predicate space* formalized according to frame semantics [8], and semiotics [10].

Framester uses WordNet and FrameNet at its core, expands it to other resources transitively, and represents them in a formal version of frame semantics. A frame-detection based application of Framester called as *Word Frame Disambiguation (WFD)* is developed and made available through the *WFD API*. Two evaluations of WFD show that *frame detection by detour* [3] employing large linguistic linked open data is comparable to the state-of-the-art frame detection in precision, and is better in recall.

WFD API uses a simple subset of Framester, which includes a novel set of mappings between frames, WordNet synsets, and BabelNet synsets, and extends frame coverage using semantic relations from WordNet and FrameNet. *WFD* exploits classical Word Sense Disambiguation as implemented in UKB [1] and Babelfy [21], and then uses Framester to create the closure to frames. *WFD* is therefore a new *detour* approach to frame detection and aiming at complete coverage of the frames evoked in a sentence.

This paper is structured as follows: section 2 gives a brief overview of the major existing resources, section 3 details state of the art. Section 4 gives the formal semantics underlying Framester as well as how the resource has been created, while section 5 details the application *WFD* for frame detection based on Framester, along with its evaluation and comparison to the state-of-the-art frame detection algorithm. Finally, section 6 concludes the paper.

2 Linguistic Resources

Some details about the most important linguistic resources forming the core of Framester Cloud are given.

WordNet [7] is a lexical database that groups synonyms into the form of synsets. Each synset is described by a gloss and represents a concept, which is semantically related to other concepts through relations such as hyponymy/hypernymy, meronymy/holonymy, antonymy, entailment, derivation, etc. The conversion of WordNet to RDF has been performed several times; the guidelines and W3C version are described in [31]. OntoWordNet [12] turns the informal WordNet graph into an ontology, representing synsets and the other entities from WordNet as ontology elements (classes, properties, individuals, axioms), and linking them to the DOLCE-Zero foundational ontology[1].

[1] `http://www.ontologydesignpatterns.org/ont/d0.owl`

FrameNet [2] containing descriptions and annotations of English words following Frame Semantics (see Section 4.1). FrameNet contains *frames*, which describe a situation, state or action. Each frame has semantic roles called *frame elements*. Each frame can be evoked by *Lexical Units (LUs)* belonging to different parts of speech. In version 1.5, FrameNet covers about 10,000 lexical units and 1024 frames. For example in frame **Reshaping** the argument for the role **Deformer** deforms the argument of the role **Patient** in a way that it changes its original shape into a **Configuration** i.e. a new shape. Deformer can also be replaced by a **Cause** i.e., any force or event that causes an effect of changes the shape of the **Patient**. Lexical units such as **bend**, **crumple**, **crush** etc. are example words, typically used to denote reshaping situations in text, as in the sentence

$$[Hagrid]_{Deformer}\ [rolled]_{lexical\ unit}\ up\ the\ [note]_{Patient}.$$

BabelNet is a wide coverage multilingual graph derived from WordNet, Wikipedia, and several other sources [23]. It is a directed labeled graph consisting of nodes and edges where nodes are the concepts and the edges connect two concepts with a semantic relation such as `is-a`, `part-of` etc.

Predicate Matrix [5] is a lexical resource created by integrating multiple sources containing predicates: WordNet, FrameNet, VerbNet and PropBank. VerbNet (VN) [29] is a broad coverage verb lexicon organized as a hierarchy of verb classes grouped by their sense and their syntactic behaviour. Each verb class contains verb senses, and is associated with thematic roles, and selectional restrictions on the role arguments. Proposition Bank [18] adds semantics to the Penn English Treebank (PTB) by specifying predicate-argument structure. Predicate Matrix uses SemLink [26], a resource containing partial mappings between the existing resources having predicate information as a base, and then extends its coverage via graph-based algorithms. It provides new alignments between the semantic roles from FrameNet and WordNet.

3 State of the Art

The integration between Natural Language Processing (NLP) and Semantic Web under the hat of "semantic technologies" is progressing fast. Most work is however opportunistic: on one hand exploiting NLP algorithms and applications, (typically named-entity recognizers and sense taggers) to populate SW datasets or ontologies, or for creating NL query interfaces, and on the other hand exploiting large SW datasets and ontologies (e.g. DBpedia, YAGO, Freebase [28], etc.) to improve NLP algorithms. For example, large text analytics and NLP projects such as Open Information Extraction (OIE, [6]), Alchemy API,[2] and Never Ending Language Learning (NELL, [15]) recently started trying to ground extracted named entities in publicly available identities such as Wikipedia, DBpedia and Freebase. Most famous, IBM Watson [16] has succeeded in reusing NLP and SW

[2] `http://www.alchemyapi.com`

methods in a creative and efficient way. Opportunistic projects for integrating NLP and SW are perfectly fine, but realistic SW applications require a stable semantics when reusing NLP results. At this very moment, that semantics is largely left to the needs of the specific application, and this makes it difficult any comparison between tools or methods.

Standardization attempts are happening since a while, and the recent proposal of Ontolex-Lemon by the OntoLex W3C Community Group[3] will possibly improve resource reuse as Linguistic Linked Data. In addition, platforms exist since a long time which help operational integration of NLP algorithms (GATES, UIMA), or reuse of NLP components as linked data (Apache Stanbol[4], NIF [17], NERD [27], FOX[5]). However, interoperability efforts mainly concentrated on the direct transformation of NLP data models into RDF, so assuming that linguistic entities populate a universe disjoint from the universe of factual data. In the case of W3C OntoLex, a link is established by using so-called "semantics by reference", which allows e.g. to assert that a WordNet synset "references" a class from an existing ontology. In other words, the formal semantics of plain Linguistic Linked Data is delegated to possible mappings that a developer or user wants to make. This approach is conservative and simply avoids the problem of addressing natural language semantics, but has limitations, since it is based on local decisions, which are necessarily arbitrary, and dedicated to a specific task.

On the contrary, a few attempts have been made to formally transform NLP data and lexical resources into regular ontologies and data. On one hand, examples of lexical resources include OntoWordNet [12], FrameNet-OWL [24], FrameBase [28], etc. On the other hand, FRED [13] is a tool that creates formal knowledge graphs (using five-star linked data patterns) from both NLP results and lexical resources.

4 Framester as a Linked Linguistic Predicate resource

Despite the active development of linguistic linked open data in recent years, there are still few linguistic resources, and they are not linked as intensely as they could be. Figure 1 shows a simplification of the current state of the linguistic resources present in the LOD cloud that are relevant for frame-oriented knowledge. These datasets have heterogeneous schemas that pose inconvenience in their direct and interoperable use.

Framester provides a dense interlinking between existing resources, adds new ones (recently ported to linked data in the context of the Framester project), and provides a homogeneous formalization of those links under the hat of frame semantics. Framester is intended to work as a knowledge graph/linked data hub to connect lexical resources, NLP results, linked data, and ontologies. It is bootstrapped from existing resources, notably the RDF versions of FrameNet [24],

[3] http://www.w3.org/community/ontolex/wiki/Main_Page

[4] http://stanbol.apache.org

[5] http://aksw.org/Projects/FOX.html

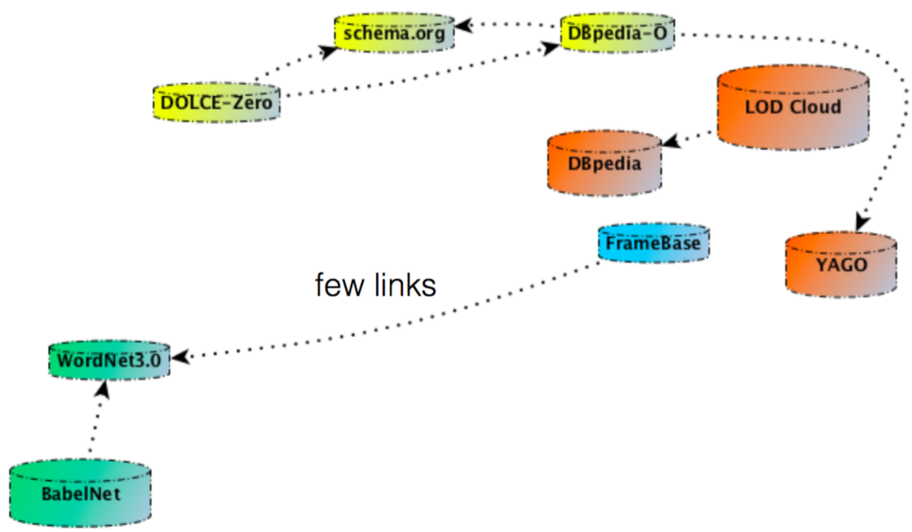

Fig. 1: Current state of Linguistic Linked Data and connections to other resources. Blue, red, green and yellow color represent role-oriented lexical resources, fact-oriented data, wordnet-like lexical resources and ontology schemas respectively.

OntoWordNet, VerbNet, and BabelNet, by interpreting their semantics as a subset of (a formal version of) Fillmore's frame semantics [8], and semiotics [10], and by reusing or linking to off-the-shelf ontological resources including OntoWordNet, DOLCE-Zero, Yago, DBpedia, etc. A complete depiction of the current state of Framester is shown in Figure 2. Many resources in the picture, and their linking, are not described in this paper because of limited space. Further details along-with a SPARQL endpoint and a demo of WFD-API are available on-line from `http://lipn.univ-paris13.fr/framester/`.

The closest resources to Framester are FrameBase and Predicate Matrix. FrameBase is aimed at aligning linked data to FrameNet frames, based on similar assumptions as Framester's: full-fledged formal semantics for frames, detour-based extension for frame coverage, and rule-based lenses over linked data. However, the coverage of FrameBase is limited to an automatically learnt extension (with resulting inaccuracies) of FrameNet-WordNet mappings, and the alignment to linked data schemas is performed manually. Anyway, Framester could be combined with FrameBase (de)reification rules so that the two projects can mutually benefit from their results.

Predicate Matrix is an alignment between predicates existing in FrameNet, VerbNet, WordNet, and PropBank. It does not assume formal semantics, and its coverage is limited to a subset of lexical senses from those resources. The intended meaning of "frames" and "roles" defined in the aligned resources is assumed to be equivalent, though the alignment matrix does not state explicitly the formal conditions, under which such equivalence may hold. An RDF version

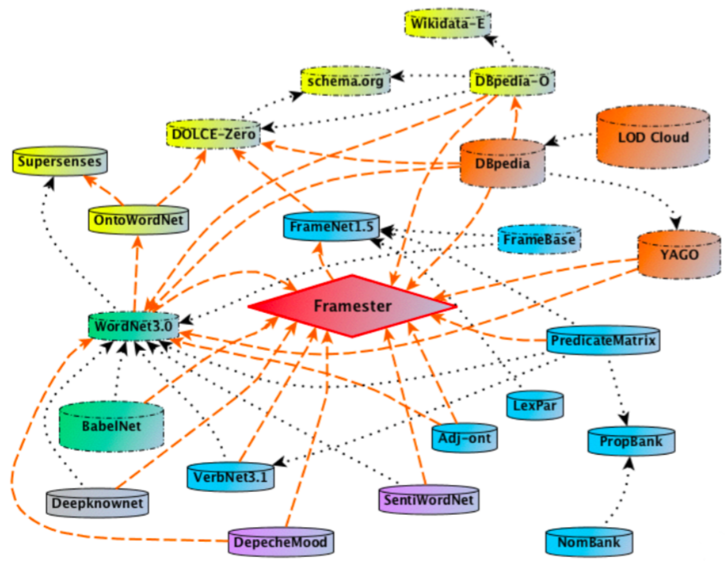

Fig. 2: Framester Cloud. Red color represents the main hub i.e., Framester, Purple represents the links to data sets for Sentiment Analysis. Black and orange arrows represent the existing and Framester specific links respectively.

of Predicate Matrix has been created in order to add it to the Framester linked data cloud, and to check if those equivalences can be reused in semantic web applications.

4.1 Frame Semantics in OWL

Framester pushes the formalization game further, using the D&S (Descriptions and Situations [11]) knowledge pattern. D&S allows to distinguish the reification of the intension of a predicate (a *description*) from the reification of the extensional denotation of a predicate (a *situation*). A description d can define or reuse *concepts* $c^1, \ldots, c^n$ that can be used to *classify* entities $e^1, \ldots, e^m$ involved in a situation s that is expected to be compatible with d. D&S has been applied in many different ontology design contexts, e.g. proving its flexibility, and eventually being an ideal schema for punning operations in OWL2. As an example, a same set of facts (e.g. a boy pushing another) can be viewed either as an accident, a joke, or voluntary harm: such views are different (intensional) descriptions of different (extensional) situations, consisting of the same entities and relations among them.

D&S perfectly fits the core assumptions of Fillmore's frame semantics, by which a frame is a schema for conceptualizing the interpretation of a natural language text, its denotation (a frame occurrence) is a situation, and the elements (or semantic roles) of a frame are aspects of a frame, which can be either obligatory, optional, inherited, reused, etc. Constructive D&S [9] is an extension of D&S that takes into account a semiotic theory to integrate linguistic and formal semantics. It can therefore support additional frame semantics assumptions such as *evocation* and *semantic typing*.

As described in [24], several recipes can be designed to interpret FrameNet frames and frame elements as OWL classes, object properties, or punned individuals. Both FrameBase and Framester make use of the basic recipe that interprets frames as classes and frame elements as properties. However, Framester goes deeper in providing a two-layered (intensional-extensional) semantics for frames, semantic roles, semantic types, selectional restrictions, and the other creatures that populate the world of lexical resources. The two-layered representation is based on the Descriptions and Situations pattern framework, and exploits OWL2 punning, so enabling both (intensional) navigation in the linked lexical datasets, and the reuse of lexical predicates as extensional classes or properties. The main assumptions for Framester knowledge graphs are as follows:

Frame as a multigrade intensional predicate: A frame is a *multigrade intensional predicate* [25] $f(e, x_1, ..., x_n)$, where f is a first-order relation, e is a (Neo-Davidsonian) variable for any *eventuality* or *state of affairs* described by the frame, and x_i is a variable for any *argument place*, which could admit several *positions* in case multiple entities are expected to be classified in a place. For example in *"Hagrid rolled up a note for Harry"*, multigrade intensional predicate is represented as $Roll(e, Hagrid, note, Harry)$. OWL2 punning allows to represent a frame as either a class $f \sqsubseteq$ `dands`[6]`:Situation` (a subclass of the dands:Situation class, having situations as instances) or as an individual $f \in$ `framester`[7]`:Frame` (an instance of the framester:Frame class) (see Figure 3).

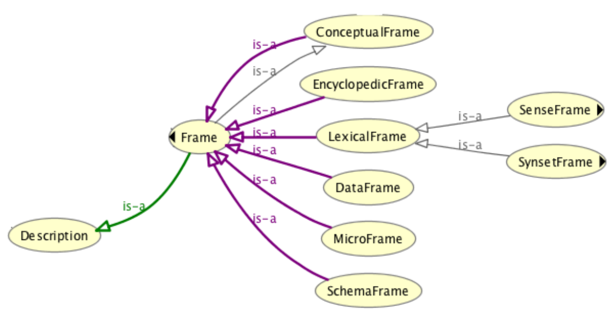

Fig. 3: Framester Frame Class.

WordNet synsets are interpreted in a twofold way: as specialized frames, and as semantic types. As equivalence classes of word senses, whose words can evoke one or more frames, they are cloned as instances of `framester:SynsetFrame`, which inherits their semantic roles from the core frames cloned from FrameNet.

[6] `http://www.ontologydesignpatterns.org/cp/owl/descriptionandsituation.owl#`

[7] `http://www.ontologydesignpatterns.org/ont/framester/framester.owl#`

Following the OntoWordNet semantics, they are promoted as OWL classes, unary projections of the corresponding synset frames.

Any word or multiword can evoke a frame: this is represented by means of a property chain that connects a word entity to a (punned) frame. A *frame occurrence* (a situation denoted by text or data) $s \in f$ is an instance of f and the entities $\{e, x_1...x_n\}$ involved in a situation are individuals. In $Roll(e, Hagrid, note, Harry)$, the frame evoked by the lexical unit "Roll" is the situation i.e., an occurrence of the frame "Reshaping" and the entities $\{e, Hagrid, note, Harry\}$ are the individuals.

Frame Projections include any projections of a frame relation. Assuming frame semantics, each meaning consists of activated frames, whose formal counterparts are multigrade intensional predicates. When only some aspect of that frame is considered, it can be formalized as a (typically unary or binary) projection of a frame relation. Semantic roles as well as co-participation relations are the *binary projections* of a frame. A semantic role is a binary projection $rol(e, x_i)$ of frame f, where e is the reified eventuality i.e., the Neo-Davidsonian variable of a multigrade predicate. A co-participation relation is a binary projection $cop(x_i, x_j)$ of f. Selectional restriction and the semantic type are unary projections of a frame. A selectional restriction is denoted as $res(x_i)$ of f that provides a typing constraint to an argument place. A semantic type $typ(x_i)$ for an external frame f' is reused as one of the domains of f. Figure 4 shows the hierarchy of frame projections. Table 1 shows the examples of each of the frame projections based on the running example.

Frame Projections	Example
Unary Projections	
Semantic Type	$Rolls(e, Hagrid, note, Harry) \wedge agent(e, Hagrid) \wedge theme(e, note)$ $\wedge recipient(e, Harry) \wedge Person(Hagrid, Harry) \wedge Text(note)$
Binary Projections	
Semantic Role	$Rolls(e, Hagrid, note, Harry) \wedge agent(e, Hagrid) \wedge theme(e, note)$ $\wedge recipient(e, Harry)$ semantic roles = {agent,theme,recipient}
Co-participation Relation	$rolls(Hagrid, note)$

Table 1: Frame Projections for the example *"Hagrid rolled up the note for Harry."*. The first column keeps the names of the Frame Projections (i.e., Unary and Binary Projections) and the second column shows the corresponding example.

Due to the expressivity limitations of OWL, some refactoring is needed to represent frame semantics: frames are represented as both classes and individuals, semantic roles and co-participation relations as both (object or datatype) properties and individuals, selectional restrictions and semantic types as both classes and individuals, situations and their entities as individuals. Frames and other predicates are represented as individuals when a schema-level relation is needed (e.g. between a frame and its roles, or between two frames), which cannot be represented by means of an OWL schema axiom (e.g. subclass, subproperty, domain, range, etc.).

Framester Role Hierarchy: Framester preserves the information about the Frame Element inheritance originally present in FrameNet. Additionally, it provides a mapping to generic frame elements which further connects to a more abstract role hierarchy provided by Framester. Figure 4(right) shows the hierarchy of semantic roles as defined in Framester.

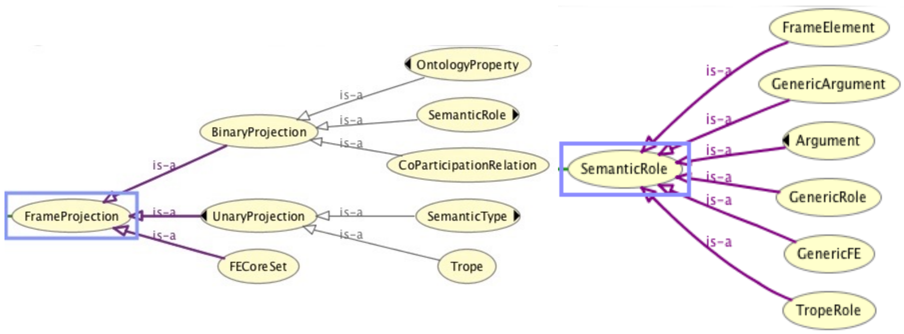

Fig. 4: Hierarchy of (a) Frame Projections (left) (b) Semantic Roles (right).

4.2 Resource Generation

The extensions to FrameNet were created using the semantic relations already present in WordNet. A set of *base-mappings* was produced by deeply revising existing FrameNet-WordNet mappings (eXtended WordFrameNet [5], FrameBase, and other existing sources found on the Web), and enriching them with new ones. This dataset, called Framester Base, has been manually curated to rectify mapping errors and evocations. Based on these basic mappings further links to other resources were generated. Due to space limitations we only discuss the base mappings. Further extensions were automatically performed based on:

1. WordNet hyponymy relations between noun and verb synsets, where each frame is extended with direct hyponyms of the noun or verb synsets mapped to frames in the Framester Base dataset
2. "Instance-of" relations between WordNet noun synsets
3. Adjective synset similarity
4. Same verb groups including verb synsets
5. Pertainymy relations between adverb synsets and noun or adjective synsets
6. Participle relations between adjective and verb synsets
7. Morphosemantic links between adjective and verb synsets
8. Transitive WordNet hyponymy relations
9. Unmapped siblings of mapped noun or verb synsets
10. Derivational links between different kinds of synsets

The Word Frame Disambiguation subset The part of Framester used in the WFD frame detector was bootstrapped by cloning a subset of FrameNet frames (the *core frames*) and its relations, and extending them by means of a manually curated mapping to WordNet synsets. The current experiments used four different Framester profiles to firstly check the impact of automatic extensions on precision and recall of Word Frame Disambiguation API (see next section). The subset of Framester consists of: *(i)* **Base (B)**: just the manually curated mappings, *(ii)* **Direct (D)**: the B profile plus extensions (1) to (7), *(iii)* **Transitive (T)**: the D profile plus extensions (8) to (10) and *(iv)* **FrameNet (F)**: a subset of the B profile that only contains the mappings whose synsets have a direct mapping in FrameNet lexical units. Let us consider the running example, *Hagrid rolled up a note for Harry*, following are the annotations based on each profiles in WFD (the frames unique to Profile D and T are represented in bold and (*) respectively, where as frames evoked by Profile F and B are represented in normal case):

Hagrid [[rolled]$_{\{CauseMotion,\mathbf{CauseChange},...\}}$ up]$_{\{\mathbf{Reshaping},UndergoChange*\}}$ a [note]$_{\{Text*\}}$ for Harry.

5 Word Frame Disambiguation: Evaluation setting and results

Word Frame Disambiguation, a framework based on frame detection, has been implemented for evaluation purposes. It is implemented as a pipeline including tokenisation, POS tagging, lemmatization, word sense disambiguation, and finally frame detection by detour using the four WFD profiles. Framester frames have been expanded (when applicable) by using the semantic relations present in FrameNet: `isPerspectivizedIn`, `seeAlso`, `inheritsFrom`, `perspectiveOn` and `uses`.

The four WFD-profiles have been evaluated in a frame detection task, and compared to other sets of mappings (XWFN [5] and FrameBase [28]), as well as to Semafor [4], the state of the art in machine-learning-based frame detection, whose model has been learnt on the annotations of the FrameNet annotated lexicon (see below).

Two textual corpora are used for evaluation: the FrameNet annotated lexicon version 1.5 released in 2010 (78 documents with 170,000 manually annotated sentences), and a corpus (called here the "independent corpus") of 100 heterogeneous texts taken from New York Times news, tweets, Wikipedia definitions, and scientific articles. The texts in the corpora were disambiguated by using two WSD algorithms: (i) Babelfy [21] and (ii) UKB [1]. The word senses provided by the WSD algorithms were then matched against Framester, and the evoked Framester frames were retrieved by following the links provided by the different profiles introduced in section 4.2.

The annotated FrameNet lexicon can be considered a gold standard, since FrameNet developers have a rigorous manual procedure to annotate it. All words that are listed as FrameNet lexemes, and are found in the text, are annotated with exactly one frame. This contrasts with the fact that multiple frames might be evoked by a same word, and that many words that are not FrameNet lexemes can actually evoke a frame.

The independent corpus has been collected for machine reading evaluation purposes [14], and is not a gold standard for frame detection. This means that frame annotations (its ground truth) should be provided from scratch. In this experiment we used the tools intended to be compared, merged their results, asked two experts to judge the correctness of the detected frames, as well as any missing detection, and a third expert to take decisions when the two raters had different opinions.

On one hand, we expected that Semafor would be highly performant on the annotated FrameNet lexicon (since it has been trained on it), and we wanted (Experiment 1) to verify how close we can perform with a detour approach. On the other hand, the second corpus was used to verify (Experiment 2) if any difference in performance between Semafor and detour-based approaches is sensible to the specific Semafor training, or not.

5.1 Experiment 1: FrameNet Annotated Corpus

For Experiment 1, the frames already present in the FrameNet annotated lexicon were used as ground truth. The performance of Word Frame Disambiguation with all its profiles, as well as Semafor's, were computed, and the results are shown in Table 2: recall obtained for each of the profiles (the values in bold represent the best results). The results were consistent for both the WSD algorithms.

	UKB				Babelfy			
Framester Profiles	Recall	Precision	F_1	New Annotations	Recall	Precision	F_1	New Annotations
eXtended WFN	0.511	**0.810**	0.627	832	0.580	**0.820**	0.680	8129
FrameBase	0.719	0.714	0.716	1132	0.621	0.71	0.661	11035
Profile-F	0.688	0.777	0.702	1148	0.673	0.749	0.704	10962
Profile-B	0.671	0.799	**0.729**	1251	0.662	0.780	**0.715**	11661
Profile-D	0.750	0.641	0.690	1929	0.790	0.569	0.660	20382
Profile-T	**0.860**	0.520	0.648	2728	**0.870**	0.444	0.588	26108

Table 2: Results for different WFD-profiles FN-WN mappings when applied to frame detection against the FrameNet 1.5 full text annotations. Values in **bold** represent the best results.

There was a significant increase in the newly annotated words in Profile-D and Profile-T as these two profiles extend the coverage of FrameNet. This leads to higher recall for these two profiles. The best recall was obtained for the profile created using transitive hyponymy relation (Profile-T).

The system used as a baseline in our experiments is Semafor [4]. It is a frame-semantic parser, which given a sentence aims at predicting frame-semantic representation using statistical models. As a first step, it extracts targets from the sentences and disambiguates it to a semantic frame. For doing so, it uses semi-supervised learning for frame disambiguation of unseen targets. Then an evoked frame is selected for each predicate.

In the current evaluation, we provide the sentences from the FrameNet 1.5 corpus to Semafor, which generates frame-tagged output and the precision, recall and the $F_1 - measure$ of the system are computed. The results are reported in Table 3. The recall for Framester (Profile-B with Babelfy as disambiguator on BabelNet as target) is .87, higher than Semafor's (.76), as expected, since the coverage of Framester is much wider. On the other hand, the precision of Semafor is very high (.96), but it cannot be compared to Framester on this corpus, since Framester can give multiple frames for a same word, and also annotates the words that are not annotated in the FrameNet corpus: all these annotations would be calculated as false positives, just because the gold standard did not address them.

In order to investigate if the precision of Framester is comparable to Semafor, and if Semafor performs well also on an independent corpus, we have performed the experiment in section 5.2.

	Recall	Precision	$F_1 - Measure$	New Annotations
Semafor	0.76	0.96	0.85	16520

Table 3: Results for the baseline (Semafor) on FrameNet 1.5 full text annotations.

5.2 Experiment 2: Independent Unannotated Corpus

In the second experiment, we wanted to assess the portability of Semafor results out of the training corpus, as well as the accuracy of Framester profiles. We used an independent corpus collected for machine reading evaluation purposes [14]. Frame annotations have been collected by merging the results of all the compared frame detection methods, then asking two experts to judge the correctness of the detected frames, as well as any missing detection, and asking a third expert to take decisions when the two raters had different opinions. The raters were asked to judge the frames detected on a scale including Valid, Metaphorical, or Invalid[8]

The inter-rater agreement before the third judgement has been measured by using weighted Cohen's K (WKAPPA) in order to adjust for the different weight of disagreement between absolute differences (valid vs. invalid evocation), and nuanced differences (valid/invalid vs. metaphorical evocation), and its value is 0.532, which is acceptable considering that frame annotation rating is difficult, and semantic annotations in general are accompanied by typically low interrater agreement.

The results are in Table 4, and show the performance of Framester profiles as well as Semafor. As expected, and noticed in Experiment 1, the recall grows significantly with extended profiles, but it's in general lower than with the FrameNet

[8] Many frames are not really wrong, but they are evoked as metaphorical or metonymical interpretations, e.g. the frame Travelling in a sentence like *Our love traveled distances.*

annotated corpus, except for the Profile-T. There is anyway a confirmation that Framester and the detour by WSD approach seems more appropriate for optimizing recall in frame detection. The doubt on the ability of Semafor to be very precise also on an independent corpus is confirmed: Semafor is still precise, but only at .79 against .95 on the corpus used for training. In addition, the best precision for Framester (Profile-B) is almost identical to Semafor's, and both Profile-D and Profile-T outperform Semafor on F1 measure.

	TP	FP	Precision	Recall	F1
eXtended WFN	327	98	0.770	0.277	0.523
FrameBase	434	183	0.703	0.359	0.531
Profile-B	435	126	0.776	0.366	0.571
Profile-D	825	346	0.705	0.622	0.663
Profile-T	1204	664	0.644	**0.781**	**0.713**
Profile-F	452	151	0.750	0.377	0.564
Semafor	365	95	**0.794**	0.334	0.564

Table 4: Results for our resource based on different extensions on the data set from Newspaper . Values in **bold** represent the best results. 'TP' and 'FP' stand for True Positives and False Positives respectively.

6 Conclusion

Framester is a novel linguistic linked data resource. It is based on frame semantics, and provides a whole new set of formally represented and linked lexical resources. Because of its adherence to frame semantics, FrameNet is the entry point for Framester, but it needs a well-built mapping to WordNet, which is at the core of existing lexical resources. Unfortunately, the quality of FrameNet-WordNet mappings is not high, and is largely incomplete.

In this work, we have described a new mapping between FrameNet and WordNet, and shown that this mapping is so good that a simple detour-based frame detector performs comparably to the state-of-the-art, machine-learning-based frame detector.

Ongoing work is about extending the experiments, and making use of the many linked datasets composing Framester with inferences provided by the full frame semantics of Framester's. Abstractive text summarisation, machine understanding and text similarity are some of the tasks that are being addressed.

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