

Integration of Linguistic Resources for Verb Classification: FrameNet Frame, WordNet Verb and Suggested Upper Merged Ontology

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Abstract. The work described in this paper was originally motivated by the construction of a lexical semantic knowledge base for analysis of Ideational Metafunction of language in Systemic Functional Grammar and the Generalized Upper Model ontology. The work involves mapping FrameNet Frames with Ideational Meanings and instantiating WordNet Verb as the meaning evoking linguistic elements. As the work evolved, the developed method has allowed the assignment of sense-tagged WordNet verb to FrameNet Lexical Units of each Frame. The task is achieved by linking FrameNet Frames with SUMO (Suggested Upper Merged Ontology) concepts. We describe our method of mapping which reuses and integrates linkages between WordNet, FrameNet and SUMO. The generated verb list is further examined with WordNet::Similarity, a semantic similarity and relatedness measuring system.

1 Introduction

Verb classification is a useful resource for semantic analysis and cognitive linguistics research. Categorization of semantically-related verbs renders assistant in understanding of the meaning construal of natural language in clause level. NLP tasks involving event recognition, discourse polarity analysis and semantic role labeling (SRL) require semantically-related verbs lists for clause pattern and participant role identification.

It is apparent that verb classification is heavily relied by clausal semantic analysis. In view of this, we aim at constructing a lexical semantic resource consists of comprehensive sense-tagged verb lexicons in addition with clause level knowledge.

Rather than start from scratch, we reuse and integrate available resources including WordNet[8], FrameNet[15] and Suggested Upper Merged Ontology (SUMO)[16]. WordNet provides intensive lexical coverage with semantic links among them but lacks information in clausal semantics. FrameNet identifies clause patterns, semantic role, verb argument structure and examples but a lower lexical coverage. SUMO is a non-linguistic upper ontology which has been mapped with WordNet [17]. SUMO is

taken as an interface between FrameNet and WordNet in order to extend the integration of the two linguistic resources.

2 Background and Motivation

The work described in this paper was originally motivated by constructing a verb classification for Ideational Metafunction analysis in Systemic Functional Grammar (SFG). Systemic Functional Grammar [9] is a theory centered on the notion of language function. According to Systemic Functional Grammar, there are three *metafunctions* of language: Ideational Metafunction, Interpersonal Metafunction and Textual Metafunction.

Verb classification is crucial for Ideational Metafunction analysis. Ideational Metafunction can be seen as the construal of an experience, in the other words, the encoding of a happening or an event. The notion focuses on that a clause consists of a *Process* and some *Participants*, i.e. “who did what to whom”. Process, the verbal group, acts as the nucleus of a clause determining the type of experience construed. There are four major process types: Material (construe doing & happening), Mental (construe processes of sensing & perception), Verbal (the processes of saying) and Relational (construe attributive relation between participants).

Systemic Functional Grammar has been computationally formalized into an ontology, Generalized Upper Model (GUM). GUM [3] defined concepts of SFG Ideational Metafunction but lacks lexical information. The ultimate goal of this work is to instantiate verbs to GUM concepts denoting different process types.

The four SFG process types represent four verb categories. Comparing with other verb classifications such as WordNet, VerbNet, FrameNet and Levin’s verb list, the SFG verb classification is much more generic and meta. Thus, the goal of constructing a SFG verb list can therefore achieved by the techniques in ontology reuse and knowledge base mapping rather than starting from scratch. FrameNet’s *Frame* although is “too fine-grained” with respect to the types of happening *construal* in Ideational Metafunction, its notation is highly compatible for mapping with the four meta SFG categories on the basis that both Frames and Process are denoting an event scenario. In FrameNet, verbs which can evoke a Frame are defined in the Frame’s Lexical Units list (LU), which means such verb categorization is motivated by semantic relatedness rather than syntactic similarity. Moreover, Frames in FrameNet are organized hierarchically, although it has a fine-grained categorization, the defined subclass “is-a” relations aid the mapping of Frames with Processes.

However, the verb coverage of FrameNet’s LU is not rich enough. The intensive lexical coverage of WordNet is rather attractive for linguistic analysis. There were various works of mapping WordNet with FrameNet (e.g. [4] [6] [14] [18] [21]). Depending on their intended goal, the mapping focuses on particular set of Frames or FrameNet defined LU, thus, a large number of WordNet verbs were not linked with FrameNet. In order to categorize as much verbs from WordNet as possible, previous WordNet FrameNet Mapping is taken as learning data, we determine an ontology-aided algorithm to automatically populate verb synsets from WordNet into the word list (Lexical Units, LU) of FrameNet Frame. Figure 1 depicts the framework of the project.

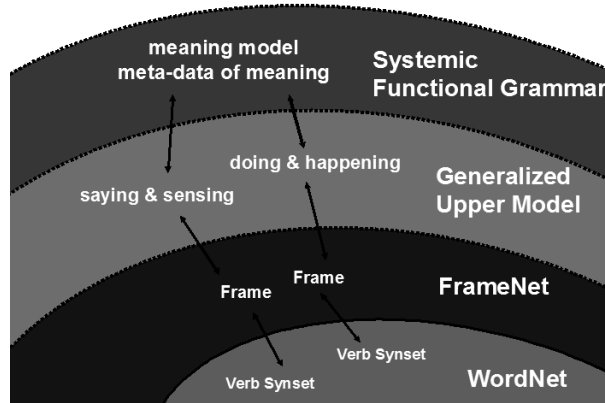
Lexicogrammar – A semantic resource for ideational meaning

Fig. 1. The framework of mapping knowledge bases of different linguistic strata

3 Extension of FrameNet Verb Coverage

A bottom-up knowledge base engineering methodology is applied to construct the lexical semantic resource represented in Figure 1. The primary attention is therefore focused on linking WordNet verbs to FrameNet LU. There are several works done on this area [4], [6], [21]. Our principle is to apply the relations links in WordNet to generate verb candidates for expanding the FrameNet LU and at the same time rely on the FrameNet declared LU which is semantic relatedness motivated. We applied Shi & Mihalcea's [21] mapping (hereafter, FnWnMap) which is verb focused. Verbs in FrameNet LU are tagged with WordNet sense. Taking the mapping as a learning data, we defined several ways of extending the LU verb coverage with WordNet.

3.1 Direct Retrieval – WordNet Synset

WordNet is an extremely large lexical database covers a vast number of English nouns, adjectives, verbs and adverbs. Lexical data are organized into synonym sets, named synset. Each synset carries a concept shared by its included synonyms. There are different relations defined among the synsets including hypernym, hyponym entailment, antonym and etc.

The first extension of LU verb coverage is straightforward. Since all lexemes in the same synset share the same concept, if one of them is capable of evoking a Frame, all lexemes in the same synset is capable of evoking the same Frame due to the synonym relations. By means of the sense-tagged information defined from FnWnMap, for each verb in a Frame's LU, we retrieve its belonged synset and map the whole synset to the frame, i.e. populated all synonyms in the synset to the LU.

For example, the LU of the Frame "STATEMENT" includes a verb "assert". FnWnMap has tagged two senses for it: "to declare or affirm solemnly and formally

as true;...” and ‘state categorically’. The synset carries the former sense includes another 7 verbs {affirm, verify, avow, aver, swan, swear} and the synset of the latter sense has another 2 verbs {asseverate, maintain}. All of these 9 sense-tagged verbs are thus populated into the LU of “STATEMENT”. Unsurprisingly, some of these discovered verbs have been defined in the FnWnMap, for instances “affirm”, “aver” and “avow”. This supports our principle of verb synonyms share the same synset concepts possess the same frame-evoking capability. The synset retrieving methodology has increased the number of verb sense mapping to 7900 from the defined 3652 verb sense in FnWnMap.

3.2 WordNet Relation Links and Frame as Domain

The second extension of verb coverage takes a Frame as a domain and applies the relation links among synsets in WordNet. As the FnWnMap has tagged the WordNet sense of the verb in each Frame’s LU, a list of Frame-specific synsets can be retrieved. Next, we retrieve a set of related synsets which are directly related to each of these Frame-specific synsets as mapping candidates. Unlike other WordNet FrameNet Mapping which focuses on particular types of relation links, all relation links defined in WordNet are taken into account [6] to generate the set of candidate synsets because every type of links (hypernym, troponym, entailment, etc.) does represent a semantic similarity or relatedness.

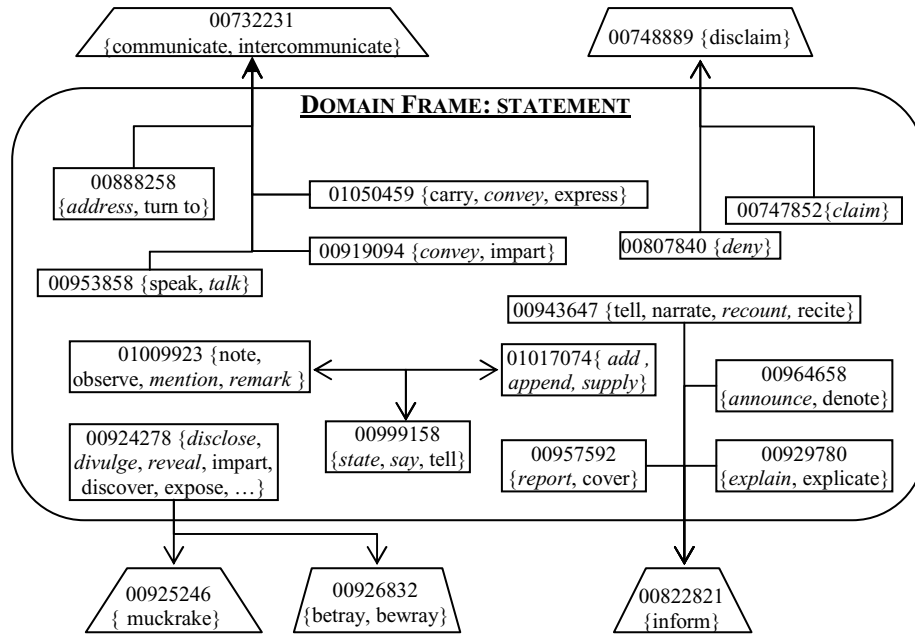
All of the domain-specific synsets have a certain semantic similarity - the same frame-evoking semantics. In addition, the WordNet organized synsets as a semantic network by different semantic links. Thus, the Frame-specific synsets together with the candidates form a small lexical semantic network as shown in Figure 2.

We designed 2 different algorithms for automatic identification of appropriate candidate synsets for mapping to the LU of domain Frame:

1. Map candidate synsets with a high affinity to the domain Frame.
2. Link the domain Frame with SUMO concept.
Retrieve SUMO concepts mapped with WordNet synsets.
Map domain Frame with Candidate synsets which mapped to the Frame linked SUMO.

3.3 Affinity of Candidate Synsets with Domain Frame

This algorithm relies on the semantic relatedness defined by WordNet relation links. Some candidate synsets have more connection links with the verb synsets residing within the Frame domain. This implies that these candidates have a high affinity to the domain and thus are selected to be mapped into the Frame LU [6]. A threshold value is set for the number of connection links representing the affinity of the synsets to the domain. Preliminary test on random selected frames show that that setting the threshold value as greater than 1 is precise enough to draw appropriate synsets to the domain Frame LU. The pseudo-code of the algorithm is shown below Figure 2.



Synset details is given in: “WordNet2.0 SynsetId {lemma1, lemma2, lemmaN}”.
 Italicized lemmas are FrameNet LU and tagged by FnWnMap.

□ Frame-specific Synsets ▤ Related Synsets as Candidates

Fig. 2. A portion of domain-specific synsets and related synsets of STATEMENT Frame

For each Frame F

Retrieve all F related synsets into a set $SYN_F = \{S_1, S_2, \dots, S_n\}$

For each $S_n \in SYN_F$,

$S_{nn} = \text{DirectRelatedSynset}(S_n)$, $S_{nn} \in \text{CandSyn}_F$.

$\text{CandSyn}_F = \{S_{1a}, S_{1b}, \dots, S_{1x}, S_{2a}, S_{2b}, \dots, S_{2x}, S_{3a}, S_{3b}, \dots, S_{3n}, S_{na}, S_{nb}, \dots, S_{nx}\}$,

For each $S_{nn} \in \text{CandSyn}$

If S_{nn} has number of relation links > 1

Then map S_{nn} as F related synsets, populate lexemes in S_{nn} into F’s LU

In figure 2, three synsets, {communicate, intercommunicate} with connection links of 4, {disclaim} with connection links 2 and {inform} with connection links of 5, are drawn and mapped to the Frame STATEMENT as their new sense-tagged LU.

In fact, a recursive methodology may be applied so as to increase the number of synset mapping. However, this will definitely decrease the precision of the mapping because the candidate synsets retrieved in each recursion will be more semantically distant to the domain.

3.4 Linking FrameNet Frame with SUMO Concept

We applied the WordNet-SUMO Mapping [17] (WNSumoMap) to retrieve the SUMO concepts mapped with each of the domain-specific synsets for linking FrameNet Frame and SUMO [7]. Since all of these synsets are drawn from the same domain and share a certain semantic similarity and relatedness, some retrieved SUMO concepts will have a higher frequency of occurrences than the others. A list of SUMO concepts with their occurrences is thus generated, see Figure 3.

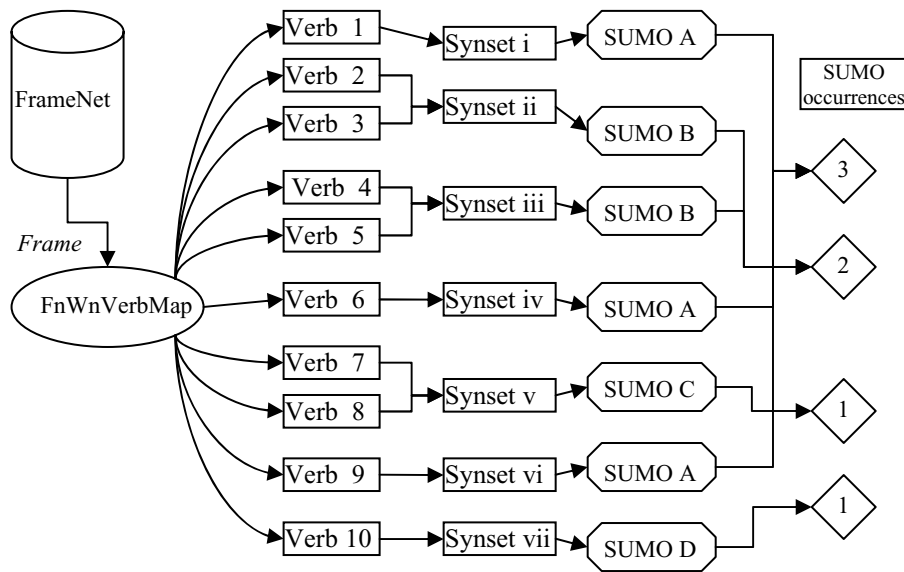


Fig. 3. The relational network of FrameNet Frames, WordNet Synsets and SUMO Concepts

A statistical distribution analysis [18] is proceeded to categorize the listed SUMO concepts according to degree of prominence for Frame Mappings. The linking of Frames and SUMO concepts is classified into three types according to the standard distribution:

1. Core SUMO concepts have an occurrence with a positive standard score greater or equal to 1 in the distribution of the occurrence.
2. Peripheral SUMO concepts have an occurrence with a positive standard score between 0 and 1 in the distribution of the occurrence.
3. Irrelevant SUMO concepts have an occurrence with a negative standard score in the distribution.

The higher the occurrence of a SUMO concept, the more prominent is it to the Frame. It should be remarked that it is a relational linkage between FrameNet Frames and SUMO concepts *but neither* a mapping of equivalence *nor* subclass mapping. The retrieved SUMO concepts are world concept of the verb synsets but not the Frame.

The Core linkage defined above can be stated as “The lexical realization of the SUMO concepts is highly capable of evoking the Frame” or represented in F-Logic, an ontology engineering program code, as a parameterized relation:

`SUMO[evoked(Core) ->Frame] . Frame[evokedBy(Core) ->SUMO] .`

In fact, if a Frame is to be mapped to SUMO as equivalence or subclass, it is likely to be mapped with the concept PROCESS.

In many cases, the mappings are unproblematic. Frames with more mapped verbs yield reliable and satisfying SUMO mappings. On the basis of statistical analysis and automatic knowledge acquisition, larger learning data returns better result. A small number of Frames possessing relatively small number of FnWnMap synsets poses a null result. For instances the JUSTIFYING Frame, it has only five FnWnMap synsets returned and each of them was mapped with different SUMO Concepts: &%Arguing+, &%Communication+, &%Process+, Stating+ and &%Reasoning+. A standard deviation of zero is found due to their equal occurrences. In such case, the equivalence of occurrences means all of them possess the same weight in the distribution, therefore we categorize all of the SUMO concepts as Peripheral SUMO to the Frame implying that neither of the SUMO concepts are Core nor Irrelevant to the frame.

Candidate synsets mapped with the Frame Core SUMO concept is determined as appropriate synsets to be populated into the Frame LU list. The designed algorithm is supported by WordNet semantic relations in drawing candidate and the consistency of the frame-evoking semantics between the mapped synsets and candidates interfaced by SUMO world concepts. The frame-evoking semantics is, however, determined by statistical distributional prominence rather than philosophical and semantic mappings. Thus, to achieve a reliable resulting extended Frame LU, only Frame Core SUMO concepts is taken in the automatic learning process. The establishment of the Frame Peripheral SUMO concept is for loosening the selection criteria which is not suggested for the automatic machine mapping but serves as an aid for case by case human mapping.

The pseudo-code of the algorithm is shown below:

For each Frame F, as defined in previous code:

$SYN_F = \{S_1, S_2, \dots S_n\}$

For each $S_n \in SYN_F$,

$Sumo_n = SUMO(S_n)$, $Sumo_n \in FrameSUMOS_F$

Core F SUMO = $Sumo_n$ with standard score ≥ 1 in $FrameSUMOS_F$

Periph SUMO = $Sumo_n$ with standard score ≥ 0 & < 1 in $FrameSUMOS_F$

Irrel F SUMO = $Sumo_n$ with standard score < 0 in $FrameSUMOS_F$

$CandSyn_F = \{S_{1a}, S_{1b}, \dots S_{1n}, S_{2a}, S_{2b}, \dots S_{2n}, S_{3a}, S_{3b}, \dots S_{3n}, S_{na}, S_{nb}, \dots S_{nn}\}$

If $SUMO(S_{nn}) = Core F SUMO$

Then populate lexemes in S_{nn} into F's LU

Table 1 shows the data of the STATEMENT Frame. It has 94 FnWnMap verbs belonged to 75 synsets. These 75 synsets are mapped with 30 different SUMO concepts*. It yields three Core SUMO concepts: Communication+, Stating+ and Stating= and one Peripheral SUMO concept: Expressing+.

Table 1. SUMO concepts statistical distribution of the STATEMENT Frame

SUMO Concepts	Occurrences	Standard Score	Frame SUMO Mappings Types
Arguing+	1	-0.456	IRRELEVANT
BodyMotion+	2	-0.168	IRRELEVANT
Committing+	1	-0.456	IRRELEVANT
Communication+	12	2.706	CORE
ContentDevelopment+	2	-0.168	IRRELEVANT
Declaring+	2	-0.168	IRRELEVANT
Declaring=	2	-0.168	IRRELEVANT
Disseminating+	2	-0.168	IRRELEVANT
Disseminating=	1	-0.456	IRRELEVANT
EmotionalState+	1	-0.456	IRRELEVANT
Expressing+	3	0.119	PERIPHERAL
ExpressingDisapproval+	1	-0.456	IRRELEVANT
IntentionalProcess+	1	-0.456	IRRELEVANT
IntentionalPsychologicalProcess+	1	-0.456	IRRELEVANT
Lecture=	2	-0.168	IRRELEVANT
LinguisticCommunication+	2	-0.168	IRRELEVANT
Publication+	1	-0.456	IRRELEVANT
Questioning+	1	-0.456	IRRELEVANT
ReligiousProcess+	2	-0.168	IRRELEVANT
Requesting=	2	-0.168	IRRELEVANT
Speaking+	2	-0.168	IRRELEVANT
Speaking=	1	-0.456	IRRELEVANT
Stating+	16	3.855	CORE
Stating=	9	1.843	CORE
Supposing+	1	-0.456	IRRELEVANT
Testifying=	1	-0.456	IRRELEVANT
Translating=	1	-0.456	IRRELEVANT
agent+	1	-0.456	IRRELEVANT
refers=	1	-0.456	IRRELEVANT
Arguing+	1	-0.456	IRRELEVANT

4 Data Evaluation

Linking an upper ontology (generic world concepts) to a domain-specific linguistic resources (frame-semantics) base on statistical analysis of concept distribution is a novel mapping approach. In order to evaluate the precision of our data, the FnWnMap defined frame-mapped synsets are taken as the golden standard, we applied a word sense similarities and relatedness measuring system, WordNet::Similarity[19], to determine the semantic relatedness between the SUMO interfaced mapped synsets with the golden standard.

WordNet::Similarity (WNS) [19] provides 6 similarity measures and 3 relatedness measures which uses WordNet information including path lengths for various WordNet relations (hypernym, meronym, etc.) and overlap among glosses and examples, semantic density, information content, depth of is-a hierarchy to determine the degree of relatedness of a pair of given words. Giving a pair of words, WNS can return a relatedness score according to the measure type chosen.

For each Frame, we create a set of pairs $P_F = L_i \times L_j$, $i \neq j$, where L are the lexemes from all of the frame-mapped synsets defined by the FnWnMap and P_F is inputted to WNS. The mean score $MEAN_F$ and the standard deviation $STDEV_F$ is computed from

the result scores. These values represent the average semantic relatedness between lexemes appropriate to the domain Frame and the tolerable deviation to this average relatedness respectively. The two scores are then used to evaluate the semantic relatedness of the list of lexemes generated by the SUMO interfaced mapping results.

Similarly, for each Frame, and for each lexeme drawn by SUMO interfacing is paired with the list of lexemes defined by FnWnMap. The set of pair, $P_{sumo} = V \times L_i$, where V is each SUMO mapped lexeme and L are the FnWnMap lexemes, is fed to WNS. From the returned set of scores, the mean score $MEAN_V$ is computed and then compared with the $MEAN_F$. If the $MEAN_V$ value is lower than one negative $STDEV_F$ of $MEAN_F$, the semantic relatedness of lexeme V is evaluated as insufficiently semantically related to the Frame and is out-classified for mapping with the Frame.

Preliminary experimentation confirmed that the *lesk* [20] measure provided the most accurate results [14] among the nine measures in WNS. There is another reason for designating the *lesk* measure for the evaluation. It is because *lesk* assigns relatedness score by gloss overlaps of the pair of the two senses and the senses of other words linked to the pairs, for instances the first word and the related word of second and vice versa, overlaps scoring can also be made between gloss-gloss, example-gloss or gloss-example. In the other words, weight is given to the information content overlaps rather than path length measurement. As mentioned, the SUMO interfaced mapping is supported by WordNet semantic links in drawing candidates. Bias will occur if the scoring measure focuses on path length.

In FnWnMap, there are 313 Frames with 3652 verbs sense-tagged mapped. The above lexical coverage extension is performed to all of the Frames. Number of new lexeme yielded from our mapping varies among Frames due to the different number of sense-tagged learning data. For example, the Multi-Link and SUMO-interfacing extension together generates 263 new WordNet sense-tagged verb lexemes mapped to the STATEMENT Frame, 23 in the ATTACK Frame and 123 in the GIVING Frame.

4.1 Evaluation Result

The evaluation result is satisfying. There are 7359 new WordNet sense-tagged lexemes drawn. 1772 of them are recalled by the multi-WordNet links extension, 6121 are recalled by the SUMO interfacing extension and 534 were recalled by both. It is predictable that the verbs recalled by both extension methodologies possess the highest precision rate, 99.63%, by the WNS evaluation. The precision of SUMO interfaced mapping scores a very high precision rate as well, 99.17%. The Multi-WordNet links mapping also has an acceptable rate of 97.18%, see table 2.

Table 2. Precision of new verb-sense mapping evaluated by WordNet::Similarity

FrameNet WordNet Mapping Extension Methodology	Mapped Verb Sense	Out-classified by WNS <i>lesk</i> measure	Precision Rate
Multi-WordNet-links	1772	50	97.18%
SUMO interfacing	6121	51	99.17%
Multi-WordNet-links and SUMO interfacing	534	2	99.63%
Overall verb recruitment	7359	99	98.65%

5 Conclusion

On the basis of available linguistic resources, ontologies and different mappings and linking between these knowledge bases, building a task-oriented semantic resource can be achieved by techniques of information reuse and integration. Non-linguistic ontology like SUMO can be applied for interfacing between linguistic resources. Mapping or linking ontology and linguistic database is generally established by conceptual mapping which is an intensive work involves philosophic, semantic and axiomatic issues. Under an evaluation based on semantic relatedness, the work shed lights on the role of statistical distribution analysis in mapping between linguistic knowledge base and ontology. Manual evaluation of these sense-tagged verb mapping is expensive but worth as not only due to the product knowledge base but also evaluating the statistical mapping approach.

A relative larger lexical semantic knowledge base is generated. The extended verb classification serves as a more useful resource for various semantic analysis tasks. It is significant that the work constructs a usable sense-tagged inventory for NLP, as suggested by [14], this would contribute the future of automatic WSD.

Continuing the work of building a Systemic Functional Grammar lexical semantic knowledge base, similar approach shall be applied in exploiting mapping FrameNet Frame with Generalized Upper Model concepts of CONFIGURATION which denotes event happenings based on not only to the semantic of experience construal but also the lexico-grammar of language as in the Systemic Functional Grammar Ideational Lattice [9]. WordNet sense-tagged lexical instantiation will at the same time be a portion of the final outcome linguistic resource.

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