Data-Driven Frame-Semantic Parsing with Tree Wrapping Grammar

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Abstract

We describe the first experimental results for data-driven semantic parsing with Tree Rewriting Grammars (TRGs) and semantic frames. While several theoretical papers previously discussed approaches for modeling frame semantics in the context of TRGs, this is the first data-driven implementation of such a parser.[1] We experiment with Tree Wrapping Grammar (TWG), a grammar formalism closely related to Tree Adjoining Grammar (TAG), developed for formalizing the typologically inspired linguistic theory of Role and Reference Grammar (RRG). We use a transformer-based multi-task architecture to predict semantic supertags which are then decoded into RRG trees augmented with semantic feature structures. We present experiments for sentences in different genres for English data. We also discuss our compositional semantic analyses using TWG for several linguistic phenomena.

1 Introduction

While many user-facing applications of Natural Language Processing such as machine translation or sentiment analysis can these days be performed with state-of-the-art accuracy by syntax-agnostic machine learning models, grammar-based methods are still important. For one thing, they offer more transparency and insight into the decisions of a model, while in many cases having near-state-of-the-art performance (Xia et al., 2019; Kasai et al., 2019; Lindemann et al., 2019; Poelman et al., 2022). Secondly, they tend to be less data-hungry and therefore more readily adapted or transferred to low-resource languages. Symbolic methods for semantic parsing can also greatly contribute to grammar theory studies and to linguistic investigations of different languages.

In this paper, we are interested in developing a methodology for deep semantic parsing (i.e., producing semantic representations for entire sentences) which would also allow easy transfer to different languages, including low-resource ones. We start from the typologically oriented linguistic theory of Role and Reference Grammar (RRG). This theory uses a common inventory of labels and structures to describe languages from different language families (Van Valin and Foley, 1980; Van Valin, 2005). The formalization of RRG using Tree Wrapping Grammar (TWG; Kallmeyer et al., 2013) has paved the way for using this theory in computational linguistics and for developing NLP applications such as syntactic parsers (Bladier et al., 2022; Evang et al., 2022).

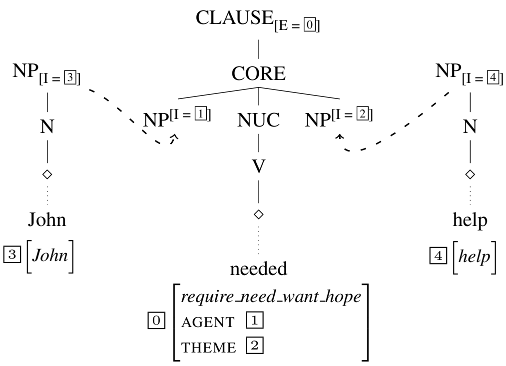

Figure 1: Frame-semantic derivation with TWG for *John needed help*

The TWG formalism is inspired by Tree-Adjoining Grammar (TAG; Joshi and Schabes, 1997) and allows for adequate modeling of long-distance dependencies. Since TWG is closely related to TAG, we can readily apply existing computational methods developed for TAG. In this work, we explore how well the methodology for compositional semantics with a tree-based syntax outlined in several theoretical papers on TAG (Kallmeyer and Osswald, 2012a,b; Zinova and

[1]The code for our semantic parser can be found on https://github.com/TaniaBladier/Frame-Semantic-Parser-with-Lexicalized-Grammars

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Kallmeyer, 2012) is suitable for TWG and can be used for a large scale implementation.

A small-scale frame-semantic parser based on the Tree Adjoining Grammar was already implemented by Arps and Petitjean (2018). Our approach differs from theirs in that it is data-driven and aims for a broad-coverage semantic parser. Our method is based on transformers and contextual embeddings and we do not use a metagrammar in our application, but go for an approach based on supertagging. Our work also differs from Semantic Role Labeling (i.e., shallow semantic parsing) with TAG (Liu and Sarkar, 2009; Kasai et al., 2019) since we are interested in deep semantic representations of the sentences. Figure 1 shows how the semantic representations for the sentence *John needed help* can be produced compositionally with elementary trees in TWG paired with frames, and Figure 3 shows the frame representation for this sentence.

The objective of this paper is to implement a broad-coverage semantic parser based on Tree Rewriting Grammars. Since this is the first broad-coverage implementation of a deep semantic parser for either TAG or TWG, we are particularly interested in modeling linguistic phenomena which we came across during this data-driven implementation. We describe this in §2. We also want to investigate if our syntax-aware methodology allows us to achieve state-of-the-art results on semantic parsing. We describe the theoretical background of our work and introduce our approach to frame-based semantics with TWG in §3 and present experimental results in §4. We discuss future work in §5.

2 Semantic Parsing with TWG

2.1 Tree Wrapping Grammar

TWGs consist of elementary trees which can be combined using the operations of a) *substitution* (replacing a leaf node with a tree), b) *sister adjunction* (adding a new daughter to an internal node), and c) *tree-wrapping substitution* (adding a tree with a d(ominance)-edge by substituting the lower part of the d-edge for a leaf node and merging the upper node of the d-edge with the root of the target tree, see Fig. 2). The latter is used to capture long distance dependencies (LDDs), see the wh-movement in Fig. 2. Here, the left tree with the d-edge (depicted as a dashed edge) gets split; the lower part fills a substitution slot while the upper part merges with the root of the target tree. TWG is more powerful than TAG (Kallmeyer, 2016). The reason is that a) TWG allows for more than one wrapping substitution stretching across specific nodes in the derived tree and b) the two target nodes of a wrapping substitution (the substitution node and the root node) do not have to come from the same elementary tree, which makes wrapping non-local compared to adjunction in TAG.

TWG emerged as a result of the formalization of Role and Reference Grammar (RRG; Van Valin and LaPolla, 1997; Van Valin, 2005). RRG is a linguistic theory strongly inspired by typological concerns. RRG was used to describe languages with diverse syntactic structures such as Lakhota, Tagalog, and Dyirbal. RRG's syntactic structures are rather flat in order to be applicable to all types of different languages. According to RRG, sentence structure is organized in layers: nucleus (containing the predicate), core (containing the nucleus and the arguments of the predicate) and clause (the core and extracted arguments). Each layer can have modifiers (called periphery elements), and operators attach to the layer over which they take semantic scope.

2.2 Frame Semantics and TWG

We adapt the syntax-semantics interface for LTAG proposed by Kallmeyer and Osswald (2013) to semantic parsing with TWG. Kallmeyer and Osswald represent semantic frames as base-labelled, typed feature structures. The frames can be understood as a straightforward representation of the semantic and conceptual knowledge about a situation, while having good computational properties as their composition relies on the unification of attribute-value structures. The frames represent genuine semantic representations, and not logical expressions, whose meaning has to be derived during semantic composition[2].

The elementary trees in a lexicalized TWG are paired with frames via interface feature structures, as shown in Figure 1. Here, the root of the elementary tree for 'needed' is augmented with an interface feature structure whose E (event) attribute value is a frame of type $require\_need\_want\_hope$, which has two attributes: an agent and a theme.

[2]The advantage of the unification is that the order of semantic argument filling is not specified by successive lambda abstraction or the like. Instead, semantic argument slots can be filled in any order (in particular, independently of surface word order) via unifications triggered by syntactic composition). For a more detailed discussion see Kallmeyer and Romero (2004) and Kallmeyer and Osswald (2014)

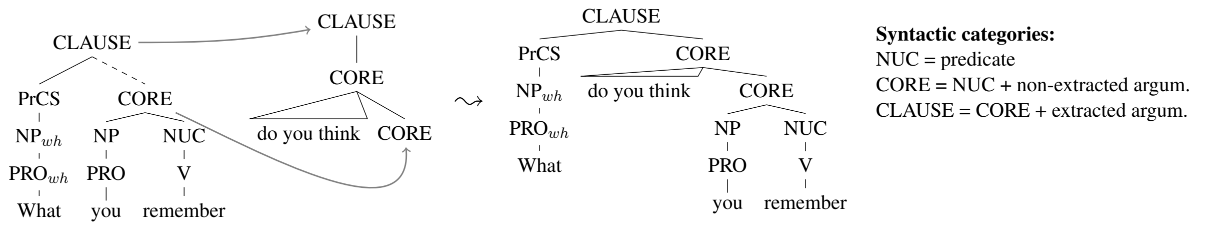

Figure 2: Tree-wrapping substitution for the sentence *"What do you think you remember"* with long-distance wh-movement.

$$\boxed{0}\begin{bmatrix} \textit{require\_need\_want\_hope} \\ \text{AGENT} \;\; \textit{John} \\ \text{THEME} \;\; \textit{help} \end{bmatrix}$$

Figure 3: Frame-semantic representation for *John needed help*.

The values of these attributes are shared with the feature structures paired with the NP substitution nodes for the subject and the object, where they are the values of the I (individual) attribute[3]. The roots of the elementary trees for 'John' and 'help' are augmented with feature structures for whose I attribute values are feature structures for whose types we use the respective lemmas (more detailed semantic representations of NPs are beyond the scope of this paper).

During parsing, as syntactic trees are combined (by adjunction, substitution or wrapping substitution), the semantic representations are also combined. The unification of interface feature structures triggers unification of feature values in the frames. In our example, as the substitution of the subject NP takes place (combining the elementary trees of 'needed' and 'John'), the respective values associated to the attribute I in the interface feature structures are unified. This results in the unification of the feature structures $\boxed{3}$ and $\boxed{1}$, which makes the frame for John become the agent of the event 'needed'. The same happens when the tree for 'help' is substituted at the object NP node of the 'needed' tree: $\boxed{4}$ and $\boxed{2}$ unify to let the frame for 'help' become the value of the theme attribute in the frame $\boxed{0}$.

To build our frame lexicon, we use the inventory of the lexical-semantic resource VerbAtlas (Di Fabio et al., 2019). VerbAtlas covers over 13 700 verbal WordNet (Fellbaum, 2000) senses, but organizes them into a relatively small number of frames (466) with only 25 cross-frame semantic roles, which makes it well suited for training neural language models. The frames in VerbAtlas are mapped to PropBank (Palmer et al., 2005) framesets and multilingual BabelNet (Navigli and Ponzetto, 2010) frames, and can potentially be linked to FrameNet (Baker et al., 1998; Baker, 2014) frames.

[3]The feature I is used as a variable in untyped frames referring to an argument (possibly syntactically complex) which fills the substitution slot.

2.3 Complex linguistic cases

In the process of developing our data-driven semantic parser, we came across several complex linguistic constructions which were not previously described in papers dealing with the combination of Tree Rewriting formalisms and semantics. Depending on the syntactic complexity of the sentences, such constructions occur in about 20% of all sentences in our data, distributed unevenly among the subcorpora we used for the experiments. We describe some of our semantic modeling choices in this section[4].

Control constructions We introduce the variable *pivot* for cases in which an elementary tree does not have an explicit syntactic argument, but shares the argument with an elementary tree it combines with. Figs. 4 and 5 show an example. The *pivot* variable is only assigned to CORE nodes and is used to propagate the semantic representation of the controlled argument.

Constructions with a peripheral subordinate clause The representation of discourse relations is beyond the scope of this work, so for now we generate semantic representations for such clauses separately. Fig. 6 shows the elementary tree-frame pairs and Fig. 7 shows a representation for the sentence *The sheep follow him because they know his voice*.

Constructions with a non-peripheral subordinate clause If a subordinate clause is not a modi-

[4]For the sake of space we only represent the relevant elementary trees in the figures of this section and skip some initial elementary trees that are substituted or adjoined into the larger trees.

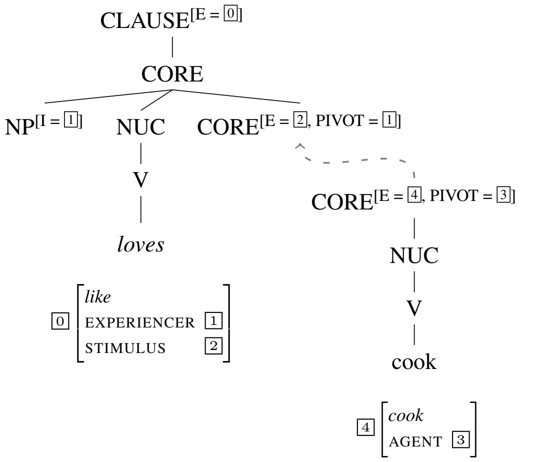

Figure 4: The pivot variable in semantic representation of the sentence *She loves to cook*.

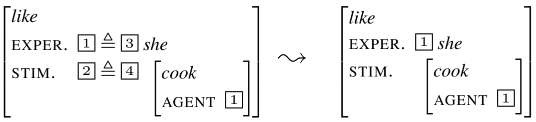

Figure 5: Label unifications and resulting frame for *she loves to cook.*

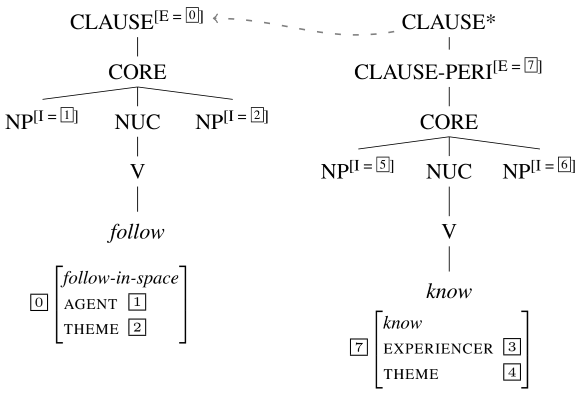

Figure 6: Tree-frame pairs for the sentence *The sheep follow him because they know his voice*

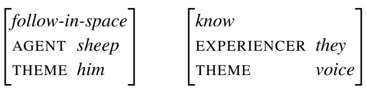

Figure 7: Semantic representations of a main clause and a peripheral subordinate clause in sentence *The sheep follow him, because they know his voice*

fier, but an argument of a main clause, the frame of the subordinate clause fills the corresponding argument slot of the parent frame (see the elementary trees and frame representation in Fig. 8, 9 for the sentence *What people say about themselves means nothing*).

Treatment of prepositional phrases The treatment of prepositional phrases depends on whether

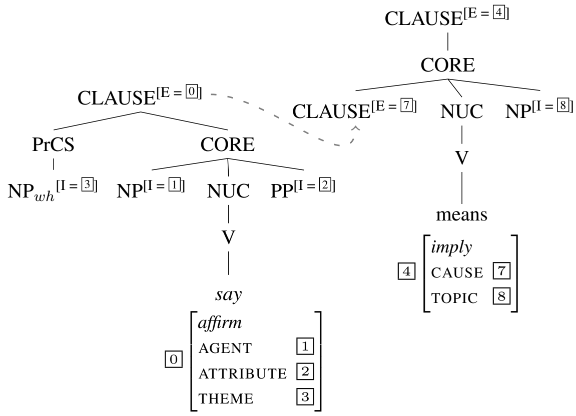

Figure 8: Tree-frame pairs for constructions with subordinate clauses

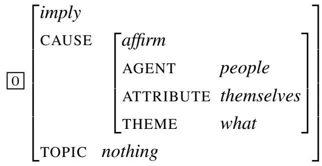

Figure 9: Constructions with subordinate clauses, here *What people say about themselves means nothing*

the PP is an argument or an adjunct of the predicate. In (1-a) below, the PP fills a core role of the predicate *lowered*. However, the role filler *well* for this argument slot should itself be substituted first into the elementary tree of the preposition *into*. Thus, to propagate the filler of the *destination* role to the designated argument slot of *lowered*, we check during the substitution of the PP subtree and the subsequent frame unification that the argument role of the PP corresponds to the required argument role of the sentential predicate (see Fig. 10). If the prepositional phrase is an adjunct of the predicate (as, for example, in (1-b), where *with a check* modifies the predicate *pay*), the subframe of the prepositional phrase is added as an additional semantic role of the predicate after adjoining the PP subtree.

Since we focus on verbal predicates in this work, we do not explore an explicit frame representation of different prepositions, as outlined in Kallmeyer and Osswald (2013). Instead, we leave the representation of prepositions and other non-verbal predicates for future work.

(1) a. Tom lowered the bucket into the well.
b. I want to pay with a check.

Constructions with non-local dependencies Constructions with non-local dependencies (e.g.

long-distance wh-movement or extraposed relative clauses) can be handled via unification during wrapping substitution (see tree-frame pairs in Fig. 11 and the resulting representation in Fig. 12).

	Supertag	Frame	Arg. Link.
she	(NP (PRO ◇))	(entity)	(–)
loves	(CL (CO (NP) (NUC (V ◇)) (CORE)))	(like)	((1, 'Exp.'), (2, 'Stim.'))
to	(CO* (CLM ◇))		(–)
cook	(CO (NUC (V ◇)))	(cook)	((0, 'Agent'))

Table 1: Example of the training data, CL stands for Clause, CO means Core.

3 Method

3.1 Argument linking

As outlined in the previous section, our approach to semantic parsing requires two components which are used to compositionally produce a deep semantic representation of the sentences: TWG elementary trees and the corresponding semantic frames. We divide prediction of semantic frames into two subtasks: prediction of the correct frame and learning the argument linking within those frames.

The argument linking mechanism relies on the elementary tree of the predicate and predicts which substitution slot of the supertag carries which semantic role. For example, in Table 1 the argument linking for the predicate *likes* means that the first substitution slot of the corresponding supertag should get the role label "Experiencer" and the second slot gets the label "Stimulus", hence the numbers 1 and 2. In case an elementary tree has a semantic role with no local filler, as in control or raising constructions (see Figure 4) or in sentences with conjoining predicates, we mark the semantic role with the index 0, indicating that there is no substitution slot for this role (see, for example the frame *cook* in Table 1). For non-predicative frames we learn the frame with the dummy type ENTITY and resolve the type of the frame to the corresponding lemma after parsing.

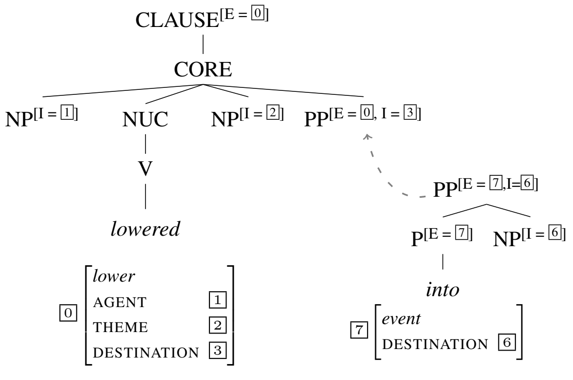

Figure 10: Propagating the role of the argument PP *into* to the main frame *lower* for the example (1-a)

3.2 Reducing the size of TWG grammars

Since the TWG grammars are usually large and contain several thousands distinct elementary trees, which is potentially hard for a neural model to learn, we reduce the size of the grammar by flattening the elementary trees and thus simplifying the syntactic structure of the trees from which we induce the TWG grammar. We collapse the internal structure of the trees, so that it preserves the relevant syntactic information about the lexical anchor and its argument structure. In particular, we delete the internal nodes of the tree which are not relevant for syntactic composition (i.e. the nodes are not involved in any tree combination operations) while leaving the root node and unlexicalized leaves untouched. We delete all SENTENCE nodes while keeping however the spine of CLAUSE, CORE and NUC since these are important targets for modifier and operator adjunctions. Figure 13 shows an example. After flattening the trees, we extract a TWG elementary trees using the automated grammar extraction approach of Bladier et al. (2020a). Since the syntactic trees in TWG grammars can have crossing branches, but the algorithm for TWG parsing (Bladier et al., 2020b), which we use to obtain syntactic representations for our data, does not support crossing branches, some nodes in trees have to be reattached before grammar extraction and re-attached to the correct nodes after parsing.

3.3 Multi-task transformer-based learning

We use the MaChAmp toolkit (van der Goot et al., 2021) to build a multi-task neural model for simultaneous learning of the elementary tree templates (i.e. supertags), frame selection, and argument linking, all cast as sequence labeling tasks. The MaChAmp multi-task models share a BERT-based encoder, but use task-specific decoders for the subtasks. Table 1 shows an example of the input for the multi-task neural model. We initially experimented with training a single-task model for each subtask and tried out different combinations of multi-task models. Since the results of a multi-task model turned out to be comparable with the single-task models (showing only around 0.1 percent of difference), we therefore carry out our ex-

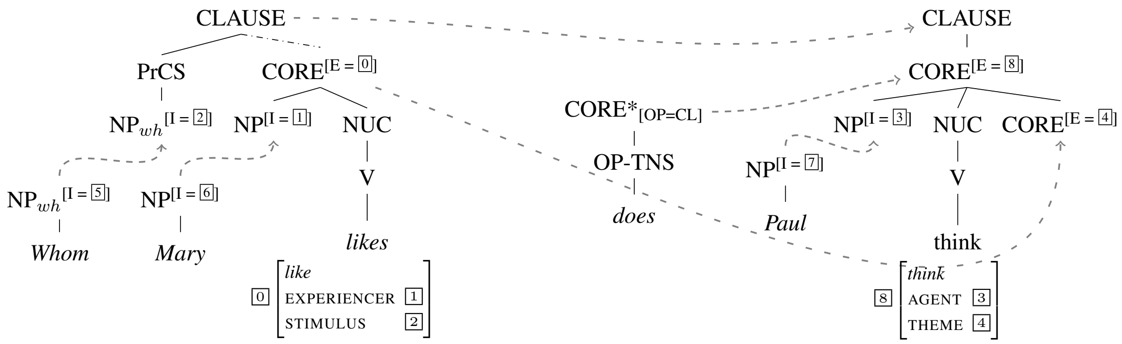

Figure 11: Wrapping substitution for wh-LDD in sentence *Whom does Paul think Mary likes?* The OP=CL notion means that the node will be attached to the CLAUSE node of the parent tree after the parsing step.

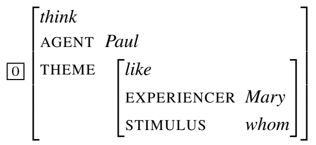

Figure 12: Semantic representation for an LDD construction in *Whom does Paul think Mary likes?*

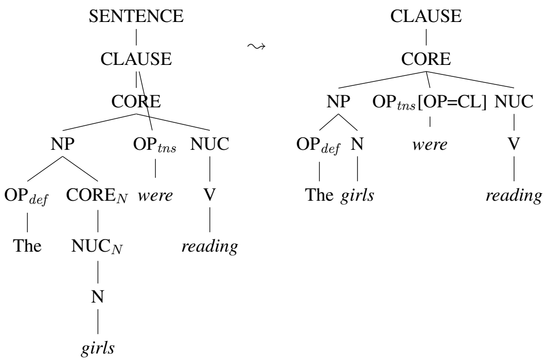

Figure 13: Example of a transformed tree before grammar extraction: the crossing branch from the original tree (on the left) is reattached and some of the internal nodes are removed. OP=CL indicates that the OP$_{tns}$ node was originally immediately below CLAUSE.

periments with the multi-task model. This model has the advantage of predicting all the components of our semantic parsing approach at once, resulting in lower training and prediction times. We tried to apply different weights on the loss function of each subtask to see if it affects the performance of the multi-task model, however the results did not change significantly. Apart from experimenting with different loss functions, we used the default values of the MaChAmp Bert model for training. The model is trained for 10 epochs, and we select the model with the highest F1-checkpoint for the evaluation.

4 Experiments and Discussion

4.1 Data

Since there is currently no manually annotated gold dataset for semantic parsing with TWG, we use alternative resources to train our model. We use the statistical neural TWG parser ParTAGe (Bladier et al., 2020b) developed for syntactic parsing with TWGs and train it on multilingual data from RRGparbank, the first large resource for TWG and Role and Reference Grammar (Bladier et al., 2022). The ParTAGe parser predicts the syntactic trees based on predicted n-best supertags for each sentence and also predicts the dependency heads based on the produced syntactic tree. The performance of this parser is different for sentences with different sentence length, but is sufficiently high for shorter sentences. We measured the ParTAGe performance on English sentences from the RRGparbank corpus (since the parser was originally trained on this data). We found that the performance of the parser on sentences with less then 7 tokens had the labeled F1 score of 93.52 for the produced syntactic trees, and the labeled F1 score of longer sentences was around 85.26.

We use the Parallel Meaning Bank v3.0.0 (PMB; Abzianidze et al., 2017) and the CoNLL-2012 English dataset based on OntoNotes 5.0 (Pradhan et al., 2012) for the frame-semantic parsing experiments. The PMB provides deep semantic representations of sentences following Discourse Representation Theory. It has rather short sentences (around 6.7 tokens on average) consisting of Web texts, newspaper articles and the Bible. The English part of the CoNLL-2012 corpus is a large resource which includes over 94 000 sentences from different genres, including journal articles, web data, broadcast news and phone conversations. We use the pre-defined train, development and test sets for both resources (see Table 2).

	PMB	OntoNotes
# sents (train, dev, test)	6654, 886, 902	75187, 9480, 9260
avg. sent length	6.94	16.71
# tokens	54205	201300
# lemmas	5463	10975
# dist. frames	350	436
# dist. frame/lemma pairs	949	2965
# frame occurrences	4783	34930
# role occurrences	13495	45496
# supertags	782	4158
# supertags occ. once	354	2204

Table 2: Statistics on the used data.

PMB and OntoNotes are not explicitly annotated with VerbAtlas frames, but PMB provides WordNet senses and VerbNet semantic roles, and OntoNotes is annotated with PropBank framesets and semantic roles. Since VerbAtlas provides manually created mappings to these resources, we used these mappings to create a sufficient amount of semantically annotated data. In order to obtain syntactic representations needed for our frame-semantic parser, we parse all sentences with the pretrained ParTAGe models available from Bladier et al. (2022).

4.2 Frame-semantic parsing experiments

Our frame-semantic parser predicts supertags needed to produce syntactic trees in parallel with the frame labels and corresponding semantic roles. We predict only heads of the semantic roles, since the full spans can be reconstructed deterministically from the predicted syntactic trees. We use the constituent trees produced by our parser to reconstruct the full spans of semantic roles[5].

VerbAtlas has 466 frames, 350 of which we observe in PMB and 436 in the OntoNotes data. The distribution of the frames is relatively even, without any frames occurring particularly more frequent then other frames. We do not consider frames associated with modal verbs. Since some of the frames occur only in test or development set and thus cannot be learned, we calculate the upper bound for the data to determine what would be the highest possible achievable score. The evaluations show a long tail of prediction errors without particular errors occurring more often then the others. Table 4 shows some of the most frequent mistakes.

[5]We reconstructed full spans of semantic roles only for OntoNotes, since the data from PMB are not annotated with full-span semantic roles.

The distribution of the supertags is uneven with a couple of most frequent ones occurring in the majority of the cases. We found 225 distinct predicative supertags in the PMB data, and 1358 in OntoNotes. Table 5 shows that the first three most common predicative supertags make up around two thirds of all predicates in PMB. A similar distribution is also present in the larger OntoNotes corpus, although the frequency of the most common supertags is less prominent.

The results of the frame-semantic parsing show that we achieve results comparable with the baseline Semantic Role Labeling (SRL) results on the OntoNotes and show a slight improvement on the PMB data (see Table 3[6]). The results on different genres in OntoNotes show a significant increase in performance on the Bible data and the worst results for the web texts. This result is due to the greater sentence length for the web data and a high amount of internet slang and deviations from standard English orthography and syntax.

4.3 Error analysis

Although VerbAtlas has rather coarse-grained frame lexicon, the number of frames (466) is still large and some frame pairs have only a subtle difference in its definition (e.g. the frame pairs GO-FORWARD and LEAVE_DEPART_RUN-AWAY or AFFIRM and SPEAK). Also there are some verbs, like for example *go*, which are polysemous and can be assigned different frames which appear more or less frequent in the annotated data. Since the majority of the frames appear only a couple of times in the training data, the model sometimes predicts the wrong frame which appears more frequently, as for example the frame LEAVE_DEPART_RUN-AWAY is wrongly predicted instead of CONTINUE in example (2).

(2) [...] but they're determined to keep going$_{\text{[leave_depart_run-away]}}$

Each frame in VerbAtlas comes with its own set of semantic roles. Although the number of the roles is small (26), the model has to learn the correct labels for each of the 466 frames. Since for most frames in VerbAtlas, the agentive and patientive role have the labels AGENT and THEME, the

[6]We use the following terms while describing our semantic parsing experiments: the term *trigger* stands for a lexical unit that can evoke a frame, the term *role* for frame element, and *role candidate* for the sequence of words that instantiates a role.

	PMB	OntoNotes					
		avg.	bn+bc	nw+mz	pt	tc	wb
frame trigger detection	93.75	92.92	92.35	92.14	96.41	94.79	91.56
frame label selection (w. *entity* and *event* labels)	89.75	89.57	88.56	88.65	95.81	92.5	86.15
frame label selection (only VA-labels)	83.9	89.06	87.93	87.78	97.11	92.06	85.48
*upper bound	99.81	99.46	99.59	99.38	99.71	99.65	98.88
role candidate detection	91.1	87.47**	86.54**	87.91**	91.45**	86.45**	86.25**
role label selection (head)	**86.15**	89.67**	88.36**	90.08**	93.16**	89.56**	88.15**
role label selection (full span)	–	**88.34****	87.61**	88.63**	92.11**	88.82**	86.43**
role label selection (baseline, head)	85.8 Bladier et al. (2021)	**92.1** InVeRo-XL (Conia et al., 2021)					
role label selection (baseline, full span)	–	86.8 InVeRo-XL (Conia et al., 2021)					
avg. sent. length	5.99	14.73	14.36	20.09	11.02	8.04	16.71
# sents	902	9260	2968	2568	1051	1618	1055

Table 3: Frame-semantic parsing results. We use the frame inventory from VerbAtlas (VA; Di Fabio et al., 2019) in our semantic representations. The role label selection for full spans is not evaluated for the PMB experiment, since only semantic heads of role spans are annotated in gold PMB data. *Since some labels from the test set are not present in the training data, we measure the highest possible upper bound for the VA-label selection. **We measure the scores for OntoNotes only for pre-identified predicates to make the evaluations comparable with the reported baseline. bn+bc = broadcast, nw+mz = newswire, pt = bible, tc = telephone conversations, wb = web.

Gold frame	Predicted frame	%
GO-FORWARD	LEAVE_DEPART_RUN-AWAY	0.7
CONTINUE	LEAVE_DEPART_RUN-AWAY	0.48
INCITE_INDUCE	EXIST-WITH-FEATURE	0.42
KNOW	MEET	0.42
RESULT_CONSEQUENCE	ARRIVE	0.42

Table 4: Most frequent frame label prediction mistakes with the percentage from the overall frame label prediction errors, measured on OntoNotes data.

Supertag	% (PMB)	% (ON)
(CL (CO (NP) (NUC (V ⋄)) (NP)))	38.82	8.5
(CL (CO (NP) (NUC (V ⋄))))	14.37	6.64
(CL (CO (NP) (NUC (V ⋄)) (PP)))	10.62	3.3
(CL (CO (NP) (NUC (V ⋄)) (NP) (NP)))	7.6	0.1
(CL (CO (NP) (NUC (V ⋄)) (P) (NP)))	5.28	0.01

Table 5: Most common predicative supertags for PMB and OntoNotes (ON) data.

model frequently picks these two labels instead of some less frequent frame-specific role labels. For example in (3), the correct role set for the COME-AFTER_FOLLOW-IN-TIME frame is THEME and CO-THEME, but the model predicts the more common AGENT and THEME role labels.

(3) That$_{\text{[agent]}}$ follows$_{\text{[come-after_follow-in-time]}}$ a decline$_{\text{[theme]}}$ in the prior six months [. . .]

As for the errors in prediction of argument linking, the most errors emerge when an infinitive modifies a noun or an adjective (see an example in (4)). The supertag for the verb in such constructions has the type of an auxiliary tree and thus lacks the agentive argument slot. In these cases, the semantic role corresponding to the PIVOT variable sometimes is not predicted (we described the PIVOT in greater detail in Section 2.3). For example, in (4) for the MANAGE frame, only the role THEME is predicted, but not the AGENT role for *strategy*.

(4) A time-honored strategy to control$_{\text{[manage]}}$ the masses$_{\text{[theme]}}$.

5 Conclusion and Future Work

In this paper, we presented the first broad-coverage frame-semantic parser with Tree Wrapping Grammar, a grammar formalism closely related to Tree Adjoining Grammar. To develop our parser, we adapted the theoretical approach of Kallmeyer and Osswald (2013) to semantic parsing with TAG and transferred it to TWG. We explored parsing strategies for several complex linguistic constructions. We developed our transformer-based language model based on the VerbAtlas frame lexicon, and experimented with English data in several genres. We could see that our semantic parser shows results close to the state-of-the-art semantic parsers.

In future work we want to explore the transferability of our approach to different languages, including low-resource ones. Our approach to semantic parsing starts from statistical syntactic parsing for TWG proposed by Waszczuk (2017); Bladier et al. (2020b). A recent work by Evang et al. (2022) presents a modification of this method for cross-lingual syntactic parsing based on word embeddings and English glosses. The underlying idea is to transfer supertag information from an English translation to the target sentence via word alignments. We plan to extend this method to semantics.

The frame lexicon VerbAtlas, which we use as a frame inventory for the semantic representations, lacks relations between frames. In order to enable semantic inference and logical reasoning with our parser, we currently investigate possibilities to develop a rule-based mapping from VerbAtlas frames to FrameNet frames, which would then yield also hierarchical relations between frames.

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