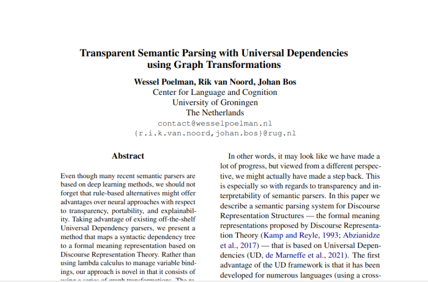
Transparent Semantic Parsing with Universal Dependencies using Graph Transformations

Wessel Poelman
Rik van Noord
Johan Bos

Center for Language and Cognition
University of Groningen
The Netherlands

September 25, 2022


Transparent Semantic Parsing with Universal Dependencies using Graph Transformations

Wessel Poelman, Rik van Noord, Johan Bos
Center for Language and Cognition
University of Groningen
The Netherlands
contact@wesselpoelman.nl
{r.i.k.van.noord, johan.bos}@rug.nl

Abstract

Even though many recent semantic parsers are based on deep learning methods, we should not forget that rule-based alternatives might offer advantages over neural approaches with respect to transparency, portability, and explainability. Taking advantage of existing off-the-shelf Universal Dependency parsers, we present a method that maps a syntactic dependency tree to a formal meaning representation based on Discourse Representation Theory. Rather than using lambda calculus to manage variable bindings, our approach is novel in that it consists of

In other words, it may look like we have made a lot of progress, but viewed from a different perspective, we might actually have made a step back. This is especially so with regards to transparency and interpretability of semantic parsers. In this paper we describe a semantic parsing system for Discourse Representation Structures — the formal meaning representations proposed by Discourse Representation Theory (Kamp and Reyle, 1993; Abzianidze et al., 2017) — that is based on Universal Dependencies (UD, de Marneffe et al., 2021). The first advantage of the UD framework is that it has been developed for numerous languages (using a cross-

COLING 2022

Objective

Semantic parsing: from Universal Dependencies to Discourse Representation Structures

Overview

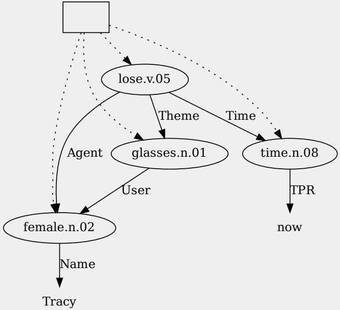
- Recent DRS notation developments
- Graph transformations
- Full example
- Experiments and results

Recent DRS notation developments

Following work by Bos (2021), we recast a traditional DRS as a direct acyclic graph

x e y t
female.n.02(x)
Name(x,"Tracy")
lose.v.02(e)
Agent(e,x)
Theme(e,y)
Time(e,y)
glasses.n.01(y)
User(y,x)
time.n.08(t)
t $\prec$ now

$\longrightarrow$

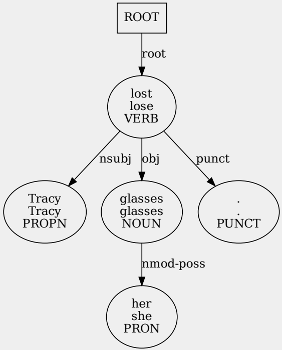


"Tracy lost her glasses."

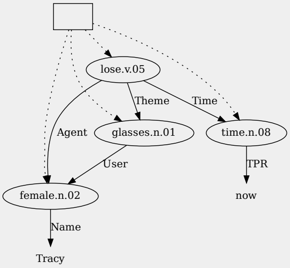
Benefits of new notation

- No variables
- Structure is simple, previous DRSs as graphs were more verbose (Abzianidze et al., 2020; Oepen et al. 2020)
- Somewhat resembles a UD parse tree

Recent DRS notation developments



Slightly unorthodox visualization of a UD parse tree



DRS in simple graph format

Graph Transformations

- SOTA in semantic parsing uses neural seq2seq models
- No guarantee for structure
- Requires lots of training data
- Performance for lower resource languages often lacking

(van Noord et al., 2020; Zhou et al., 2021; Bevilacqua et al., 2021; Bai et al., 2022)

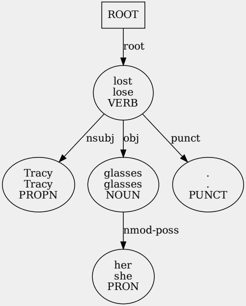
The approach (*UD-Boxer*)

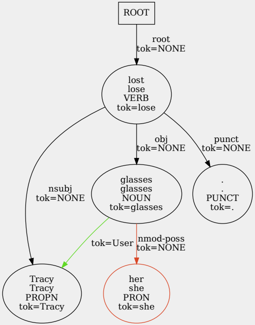
- Use graph transformations to convert UD structurally
- Map syntactic concepts to semantic roles and concepts
- Target language-neutral UD features as much as possible

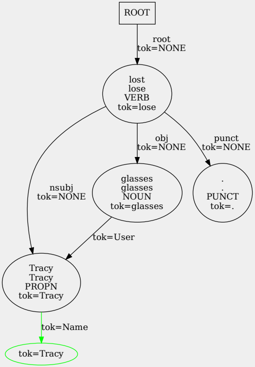
Overview UD-Boxer

- 19 language-neutral, structural transformations
- 4 language-dependent, structural transformations (negation, quantifiers)
- Extracted node and edge mappings from isomorphic graphs in gold training data

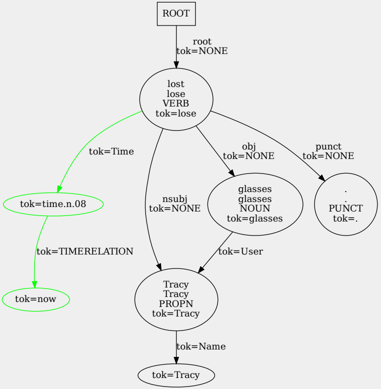
Full example

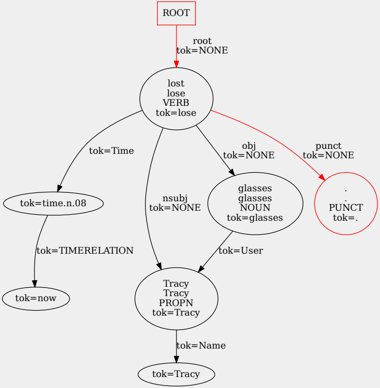






Full example





Full example

- Combine *lemma* and *UPOS* features from UD to construct WordNet synsets (senses are most frequent from the training data)
- Use most frequent triple mapping from training data (UPOS-deprel-UPOS to DRS role or operator)
- Other strategies to convert morphological and syntactic features

lose.v	->	02
glasses.n	->	01
VERB-nsubj-PROPN	->	Agent
VERB-obj-NOUN	->	Theme

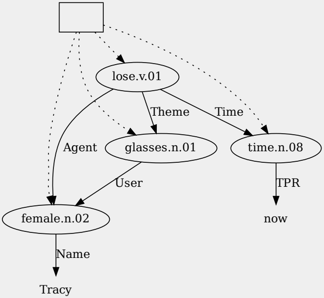
Full example

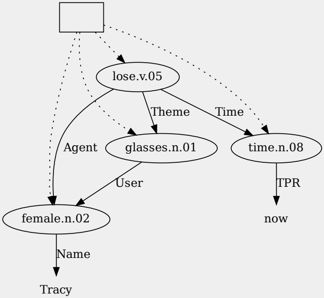
- Combine *lemma* and *UPOS* features from UD to construct WordNet synsets (senses are most frequent from the training data)
- Use most frequent triple mapping from training data (UPOS-deprel-UPOS to DRS role or operator)
- Other strategies to convert morphological and syntactic features

lose.v	->	02
glasses.n	->	01
VERB-nsubj-PROPN	->	Agent
VERB-obj-NOUN	->	Theme

These are baselines! Not actual word sense disambiguation or role labeling!

Full example





Using SMATCH (Cai and Knight, 2013), the result (left) achieves an F1-score of 96.7 compared with the gold graph (right)

Number of documents per language
in the Parallel Meaning Bank version 4.0.0

	Gold			Silver	Bronze
	Train	Dev	Test	Train	Train
English	7,668	1,169	1,048	127,303	151,493
German	1,738	559	547	6,355	156,286
Italian	685	540	461	4,088	100,963
Dutch	539	491	437	1,440	28,265

Experiments and results

	English		German		Italian		Dutch	
	Dev	**Test**	**Dev**	**Test**	**Dev**	**Test**	**Dev**	**Test**
UD-Boxer (Stanza)	82.1 (0.3)	82.0 (0.0)	**78.4 (0.0)**	77.3 (0.0)	76.2 (1.9)	78.4 (0.9)	75.5 (0.0)	**75.8 (0.0)**
UD-Boxer (Trankit)	81.9 (0.3)	81.8 (0.0)	**78.4 (0.0)**	**77.5 (0.0)**	**77.8 (0.0)**	**79.1 (0.0)**	**75.8 (0.0)**	**75.8 (0.0)**
Neural Boxer (gold)	82.8 (4.6)	84.0 (3.7)	64.2 (0.4)	63.8 (0.2)	55.5 (1.5)	55.7 (1.5)	51.2 (0.2)	51.1 (0.4)
Neural Boxer (best)	**92.5 (2.0)**	**92.5 (2.3)**	74.6 (0.4)	74.7 (0.5)	75.6 (0.0)	75.4 (0.0)	71.9 (0.9)	71.6 (1.0)

Details

- SOTA neural seq2seq method (van Noord et al., 2020) (pre-train gold and silver, finetune gold)
- *Best* is trained on gold, silver and bronze data (German, Italian, and Dutch) or gold and silver (English)
- Parentheses are percentages of ill-formed graphs
- UD parsers Stanza (Qi et al., 2020) and Trankit (Nguyen et al., 2021)

Experiments and results

	English		German		Italian		Dutch	
	Dev	**Test**	**Dev**	**Test**	**Dev**	**Test**	**Dev**	**Test**
UD-Boxer (Stanza)	82.1 (0.3)	82.0 (0.0)	**78.4 (0.0)**	77.3 (0.0)	76.2 (1.9)	78.4 (0.9)	75.5 (0.0)	**75.8 (0.0)**
UD-Boxer (Trankit)	81.9 (0.3)	81.8 (0.0)	**78.4 (0.0)**	**77.5 (0.0)**	**77.8 (0.0)**	**79.1 (0.0)**	**75.8 (0.0)**	**75.8 (0.0)**
Neural Boxer (gold)	82.8 (4.6)	84.0 (3.7)	64.2 (0.4)	63.8 (0.2)	55.5 (1.5)	55.7 (1.5)	51.2 (0.2)	51.1 (0.4)
Neural Boxer (best)	**92.5 (2.0)**	**92.5 (2.3)**	74.6 (0.4)	74.7 (0.5)	75.6 (0.0)	75.4 (0.0)	71.9 (0.9)	71.6 (1.0)

Details

- SOTA neural seq2seq method (van Noord et al., 2020) (pre-train gold and silver, finetune gold)
- *Best* is trained on gold, silver and bronze data (German, Italian, and Dutch) or gold and silver (English)
- Parentheses are percentages of ill-formed graphs
- UD parsers Stanza (Qi et al., 2020) and Trankit (Nguyen et al., 2021)

UD-Boxer only needs gold data!

Conclusions

- Competitive performance for English with little data
- Strong cross lingual performance while requiring small amount of data
- Transparent parsing with simple transformations and mappings

Conclusions

- Competitive performance for English with little data
- Strong cross lingual performance while requiring small amount of data
- Transparent parsing with simple transformations and mappings

Future work

- Handeling of named entities, date expressions and numeric expressions
- Support more complex DRS concepts (negation scope, box referents)
- Actual word sense disambiguation instead of baseline approach

Sources and contact

- UD-Boxer source: https://github.com/WPoelman/ud-boxer
- MSc thesis about UD-Boxer: https://wesselpoelman.nl
- Neural Boxer source: https://github.com/RikVN/Neural_DRS
- Parallel Meaning Bank: https://pmb.let.rug.nl
- Contact: contact@wesselpoelman.nl