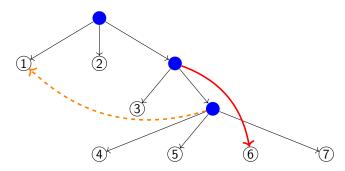
A Transition-Based Directed Acyclic Graph Parser for Universal Conceptual Cognitive Annotation

Daniel Hershcovich, Omri Abend and Ari Rappoport



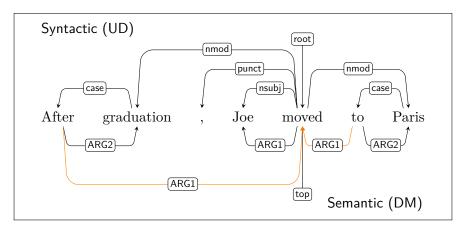
ACL 2017

- 1. Non-terminal nodes
- 2. Reentrancy
- 3. Discontinuity
- needed for many semantic schemes (e.g. AMR, UCCA).



Linguistic Structure Annotation Schemes

- Syntactic dependencies (Nivre, 2005)
- Semantic dependencies (Oepen et al., 2016)



Bilexical dependencies.

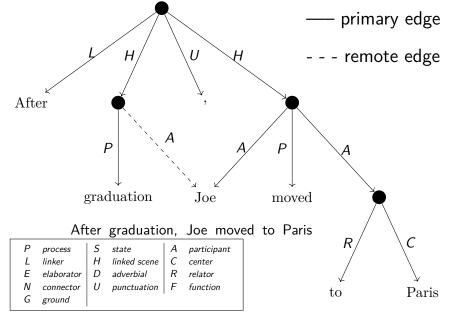


- Syntactic dependencies (Nivre, 2005)
- Semantic dependencies (Oepen et al., 2016)
- AMR (Banarescu et al., 2013)
- UCCA (Abend and Rappoport, 2013)
- Other semantic representation schemes¹

$$\dots$$
 showered = \dots took a shower

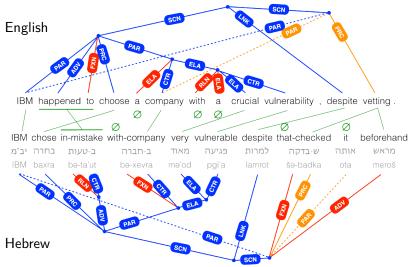
$$\dots$$
's war against crime $= | \dots$ fights crime

Universal Conceptual Cognitive Annotation (UCCA)



The UCCA Semantic Representation Scheme

Cross-linguistically applicable (Abend and Rappoport, 2013). Stable in translation (Sulem et al., 2015).



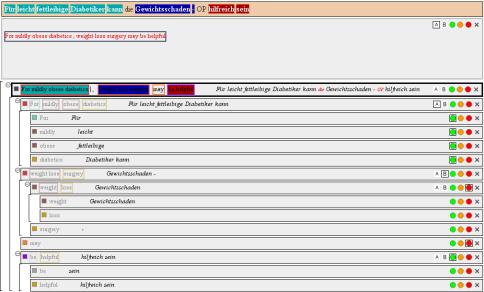
UCCAApp

Rapid and intuitive annotation interface (Abend et al., 2017). Usable by non-experts. http://ucca-demo.cs.huji.ac.il



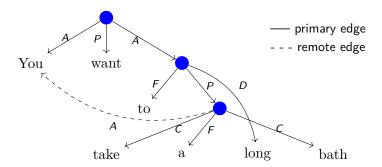
HUME

UCCA facilitates semantics-based human evaluation of machine translation (Birch et al., 2016). http://ucca.cs.huji.ac.il/mteval



UCCA generates a directed acyclic graph (DAG), where the text tokens are terminals. Structural properties:

1. Non-terminal nodes — hierarchy of entities and events



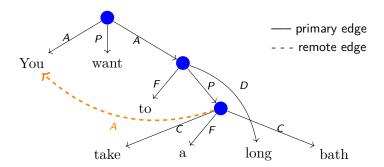
You want to take a long bath



Graph Structure

UCCA generates a directed acyclic graph (DAG), where the text tokens are terminals. Structural properties:

- 1. Non-terminal nodes hierarchy of entities and events
- 2. Reentrancy allow argument sharing

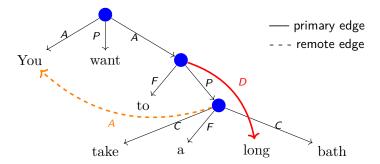


You want to take a long bath

Graph Structure

UCCA generates a directed acyclic graph (DAG), where the text tokens are terminals. Structural properties:

- 1. Non-terminal nodes hierarchy of entities and events
- Reentrancy allow argument sharing
- 3. Discontinuity conceptual units are split



You want to take a long bath

First used for dependency parsing (Nivre, 2004).

Parse text $w_1 \dots w_n$ to graph $G = (V, E, \ell)$ incrementally.

First used for dependency parsing (Nivre, 2004). Parse text $w_1 \dots w_n$ to graph $G = (V, E, \ell)$ incrementally.

Initial state:



You	want	to	take	a	long	bath

First used for dependency parsing (Nivre, 2004). Parse text $w_1 \dots w_n$ to graph $G = (V, E, \ell)$ incrementally.

Initial state:

stack buffer

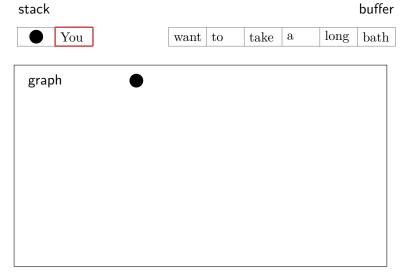
You want to take a long bath

TUPA transitions:

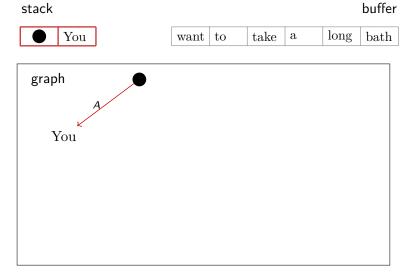
 $\{SHIFT, REDUCE, NODE_X, LEFT-EDGE_X, RIGHT-EDGE_X, LEFT-REMOTE_X, RIGHT-REMOTE_X, SWAP, FINISH\}$

Support non-terminal nodes, reentrancy and discontinuity.

 \Rightarrow Shift

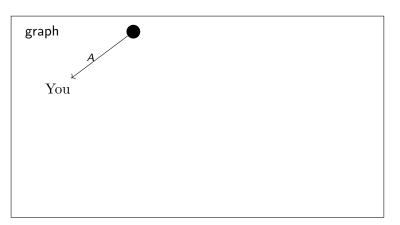


 \Rightarrow Right-Edge_A

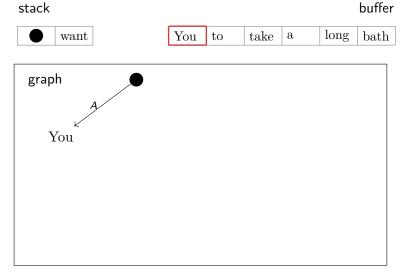


 \Rightarrow Shift

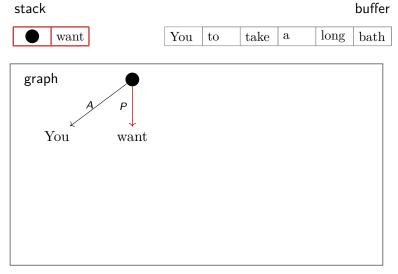




 \Rightarrow SWAP

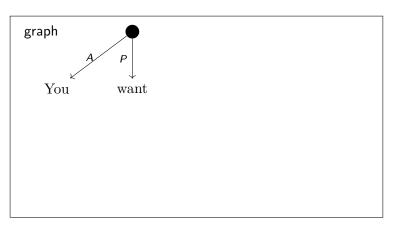


 \Rightarrow Right-Edge_P



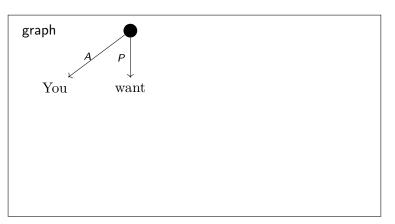
 \Rightarrow Reduce





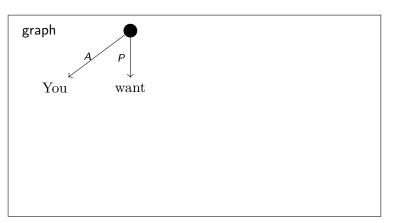
 \Rightarrow Shift



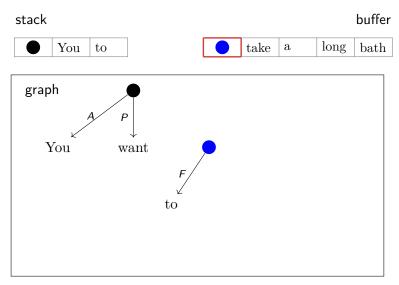


 \Rightarrow Shift

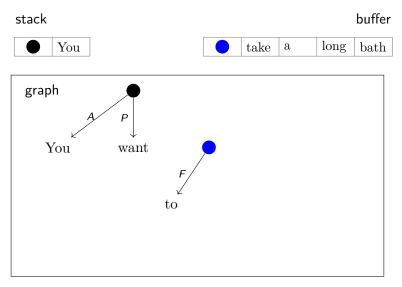




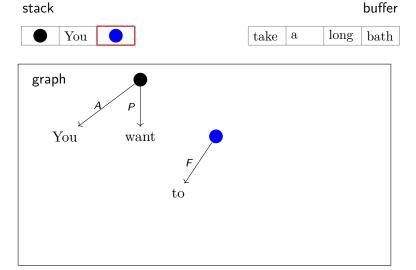
 $\Rightarrow \text{Node}_F$



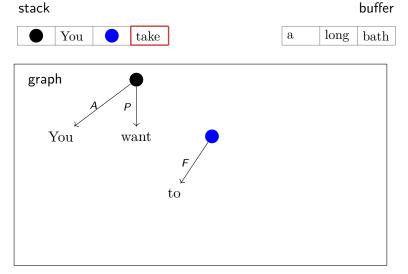
 \Rightarrow Reduce



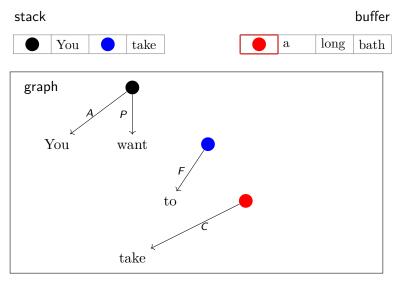
 \Rightarrow Shift



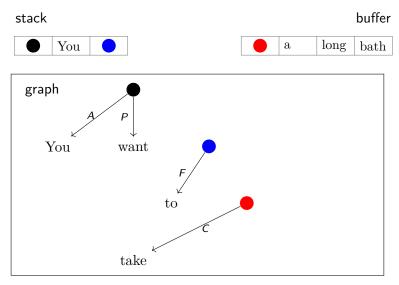
 \Rightarrow Shift



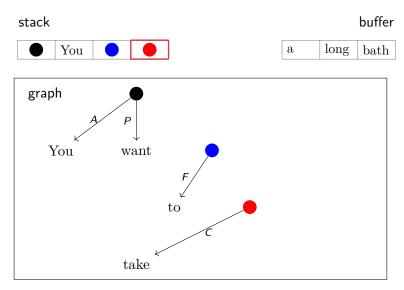
 \Rightarrow Node_C



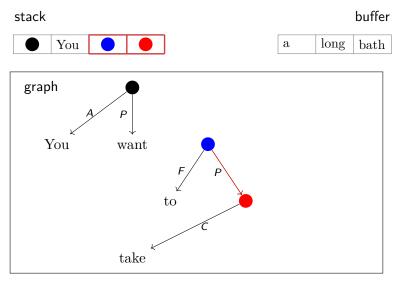
 \Rightarrow Reduce



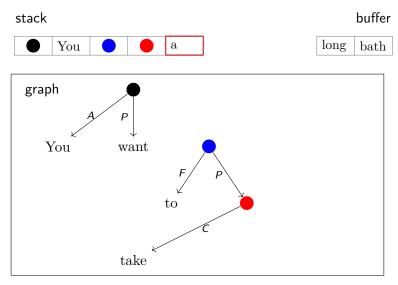
 \Rightarrow Shift



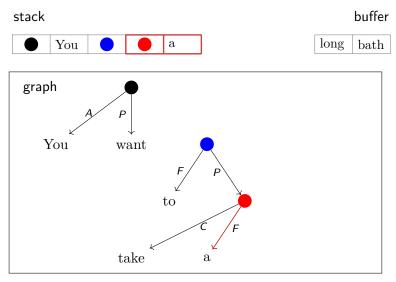
 \Rightarrow Right-Edge_P



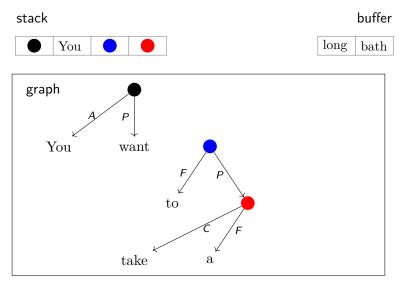
 \Rightarrow Shift



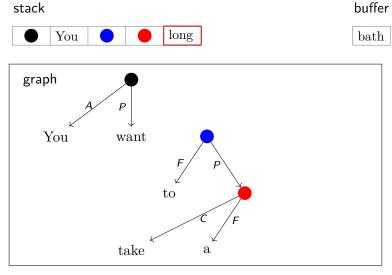
 \Rightarrow Right-Edge_F



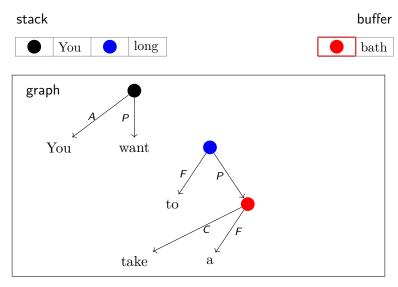
 \Rightarrow Reduce



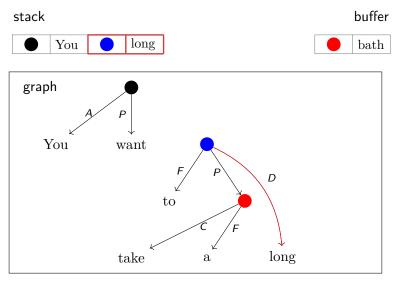
 \Rightarrow Shift



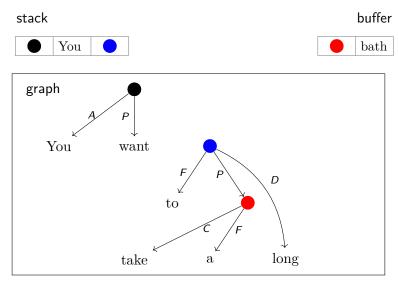
 \Rightarrow SWAP



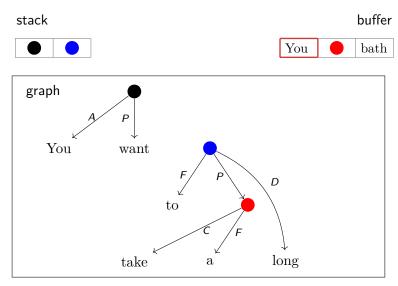
 \Rightarrow Right-Edge_D



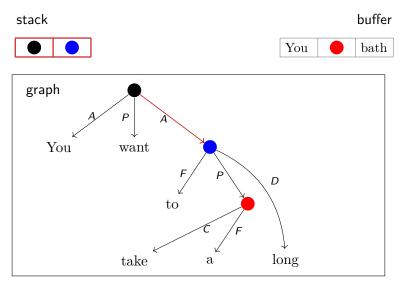
 \Rightarrow Reduce



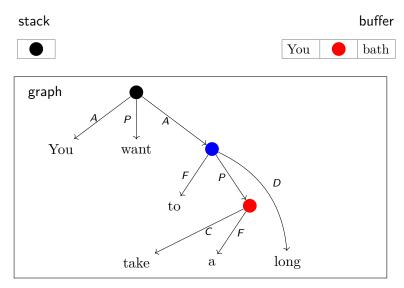
 \Rightarrow SWAP



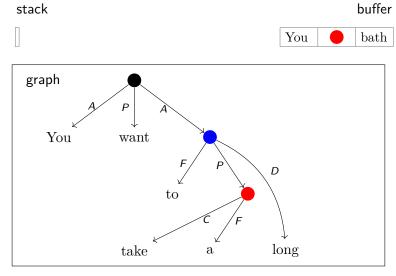
 \Rightarrow Right-Edge_A



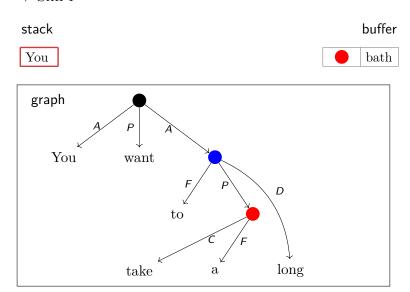
 \Rightarrow Reduce



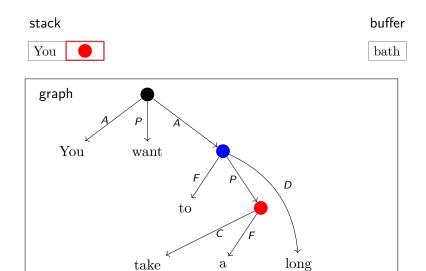
 \Rightarrow Reduce



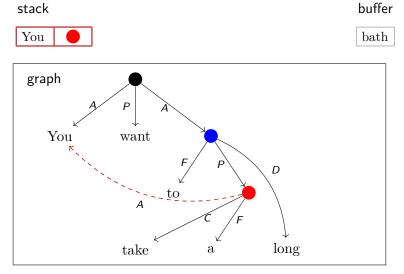
 \Rightarrow Shift



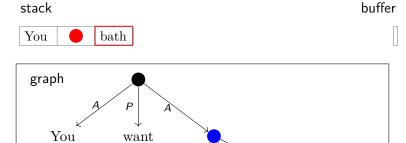
 \Rightarrow Shift



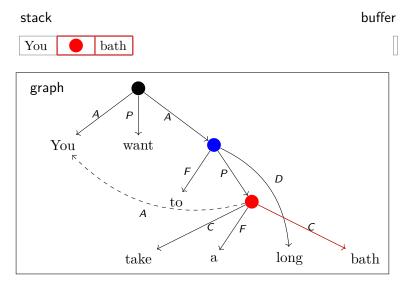
 \Rightarrow Left-Remote_A



 \Rightarrow Shift

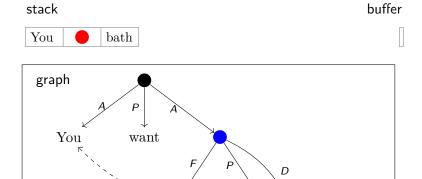


 \Rightarrow Right-Edge_C



take

 \Rightarrow Finish



a

bath

long

TUPA Model

Greedy parsing, experimenting with three classifiers:

Sparse Perceptron with sparse features.

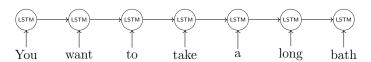
 $\begin{tabular}{ll} \textbf{MLP} & Embeddings + feedforward NN classifier. \end{tabular}$

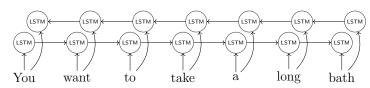
 $\textbf{BiLSTM} \quad \text{Embeddings} + \text{deep bidirectional LSTM} + \text{MLP}$

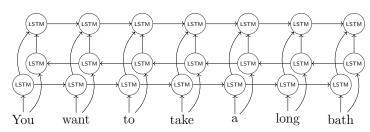
(Kiperwasser and Goldberg, 2016).

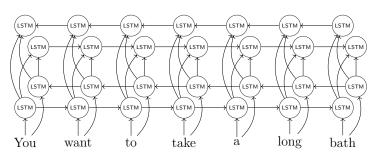
Features: words, POS, syntactic dependencies, existing edge labels from the stack and buffer + parents, children, grandchildren; ordinal features (height, number of parents and children)

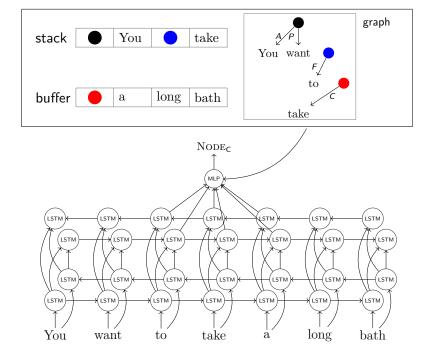
stack buffer





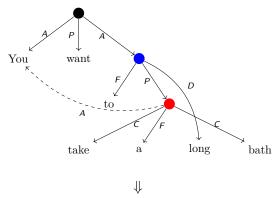






Training

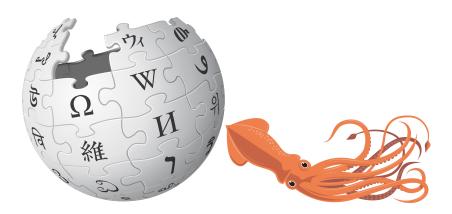
An *oracle* provides the transition sequence given the correct graph:



SHIFT, RIGHT-EDGE_A, SHIFT, SWAP, RIGHT-EDGE_P, REDUCE, SHIFT, SHIFT, NODE_F, REDUCE, SHIFT, SHIFT, NODE_C, REDUCE, SHIFT, RIGHT-EDGE_P, SHIFT, RIGHT-EDGE_F, REDUCE, SHIFT, SWAP, RIGHT-EDGE_D, REDUCE, SWAP, RIGHT-EDGE_A, REDUCE, REDUCE, SHIFT, SHIFT, LEFT-REMOTE_A, SHIFT, RIGHT-EDGE_C, FINISH

Experimental Setup

- UCCA Wikipedia corpus (4268 + 454 + 503 sentences).
- Out-of-domain: English part of English-French parallel corpus, Twenty Thousand Leagues Under the Sea (506 sentences).



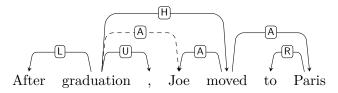
Baselines

Bilexical DAG parsers (allow reentrancy):

- DAGParser (Ribeyre et al., 2014): transition-based.
- TurboParser (Almeida and Martins, 2015): graph-based.

Tree parsers (all transition-based):

- MaltParser (Nivre et al., 2007): bilexical tree parser.
- LSTM Parser (Dyer et al., 2015): bilexical tree parser, NN.
- UPARSE (Maier, 2015): allows non-terminals, discontinuity.



Bilexical DAG approximation (for tree, delete remote edges).

Results

TUPA_{BiLSTM} obtains the highest F-scores in all metrics:

	Primary		Remote			
	LP	LR	LF	LP	LR	LF
TUPA _{Sparse}	64.5	63.7	64.1	19.8	13.4	16
TUPA _{MLP}	65.2	64.6	64.9	23.7	13.2	16.9
$TUPA_{BiLSTM}$	74.4	72.7	73.5	47.4	51.6	49.4
Bilexical DAG			(91)			(58.3)
DAGParser	61.8	55.8	58.6	9.5	0.5	1
TurboParser	57.7	46	51.2	77.8	1.8	3.7
Bilexical tree			(91)			_
MaltParser	62.8	57.7	60.2	_	_	_
LSTM Parser	73.2	66.9	69.9	_	_	_
Tree			(100)			_
UPARSE	60.9	61.2	61.1	_	_	_

Results on the Wiki test set.

Results

Comparable out-of-domain test set:

	Primary		Remote			
	LP	LR	LF	LP	LR	LF
TUPA _{Sparse}	59.6	59.9	59.8	22.2	7.7	11.5
TUPA _{MLP}	62.3	62.6	62.5	20.9	6.3	9.7
$TUPA_{BiLSTM}$	68.7	68.5	68.6	38.6	18.8	25.3
Bilexical DAG			(91.3)			(43.4)
DAGParser	56.4	50.6	53.4	_	0	0
TurboParser	50.3	37.7	43.1	100	0.4	8.0
Bilexical tree			(91.3)			_
MaltParser	57.8	53	55.3	_	_	_
LSTM Parser	66.1	61.1	63.5	_	_	_
Tree			(100)			_
UPARSE	52.7	52.8	52.8	_	_	_

Results on the 20K Leagues out-of-domain set.



Conclusion

- UCCA's semantic distinctions require a graph structure including non-terminals, reentrancy and discontinuity.
- TUPA is an accurate transition-based UCCA parser, and the first to support any DAG over the text's tokens.
- Outperforms strong conversion-based baselines.

Code: https://github.com/danielhers/tupa

Demo: http://bit.ly/tupademo

Corpora: http://www.cs.huji.ac.il/~oabend/ucca.html



Conclusion

- UCCA's semantic distinctions require a graph structure including non-terminals, reentrancy and discontinuity.
- TUPA is an accurate transition-based UCCA parser, and the first to support any DAG over the text's tokens.
- Outperforms strong conversion-based baselines.

Future Work:

- More languages (German corpus construction is underway).
- Parsing other schemes, such as AMR.
- Text simplification, MT evaluation and other applications.

Code: https://github.com/danielhers/tupa

Demo: http://bit.ly/tupademo

Corpora: http://www.cs.huji.ac.il/~oabend/ucca.html



Thank you

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UCCA Corpora

		20K					
	Train	Dev	Test	Leagues			
# passages	300	34	33	154			
# sentences	4268	454	503	506			
# nodes	298,993	33,704	35,718	29,315			
% terminal	42.96	43.54	42.87	42.09			
% non-term.	58.33	57.60	58.35	60.01			
% discont.	0.54	0.53	0.44	0.81			
% reentrant	2.38	1.88	2.15	2.03			
# edges	287,914	32,460	34,336	27,749			
% primary	98.25	98.75	98.74	97.73			
% remote	1.75	1.25	1.26	2.27			
Average per non-terminal node							
# children	1.67	1.68	1.66	1.61			

Corpus statistics.

Evaluation

Mutual edges between predicted graph $G_p = (V_p, E_p, \ell_p)$ and gold graph $G_g = (V_g, E_g, \ell_g)$, both over terminals $W = \{w_1, \dots, w_n\}$:

$$M(G_p, G_g) = \{(e_1, e_2) \in E_p \times E_g \mid y(e_1) = y(e_2) \wedge \ell_p(e_1) = \ell_g(e_2)\}$$

The yield $y(e) \subseteq W$ of an edge e = (u, v) in either graph is the set of terminals in W that are descendants of v. ℓ is the edge label.

Labeled precision, recall and F-score are then defined as:

$$\begin{aligned} \mathsf{LP} &= \frac{|M(G_p, G_g)|}{|E_p|}, \quad \mathsf{LR} &= \frac{|M(G_p, G_g)|}{|E_g|}, \\ \\ \mathsf{LF} &= \frac{2 \cdot \mathsf{LP} \cdot \mathsf{LR}}{\mathsf{LP} + \mathsf{LR}}. \end{aligned}$$

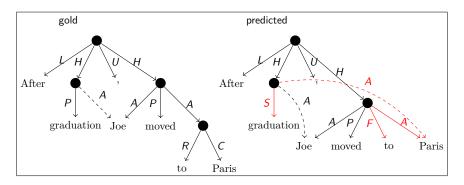
Two variants: one for primary edges, and another for remote edges.



Evaluation

Comparing graphs over the same sequence of tokens,

- Match edges by their terminal yield and label.
- Calculate labeled precision, recall and F1 scores.
- Separate primary and remote edges.



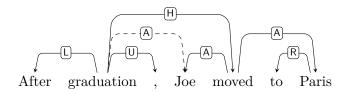
Primary:
$$\frac{LP}{\frac{6}{9} = 67\%} \frac{LR}{\frac{6}{10} = 60\%} \frac{LF}{64\%}$$

Remote:
$$\frac{\text{LP}}{\frac{1}{2} = 50\%} \frac{\text{LR}}{\frac{1}{1} = 100\%} \frac{\text{LF}}{67\%}$$

Bilexical Graph Approximation

No existing UCCA parsers \Rightarrow compare to bilexical parsers:

- 1. Convert UCCA to bilexical dependencies.
- 2. Train bilexical parsers and apply to test sentences.
- 3. Reconstruct UCCA graphs and compare with gold standard.



Bilexical DAG approximation (for tree, delete remote edges).