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

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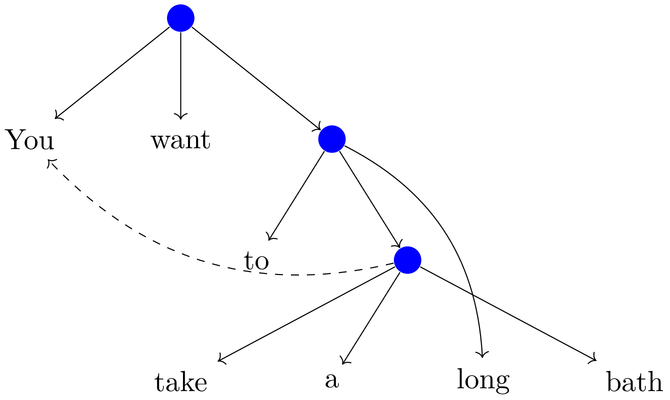
January 9, 2018

TUPA — Transition-based UCCA Parser

The **first parser** to support the combination of three properties:

1. Non-terminal nodes — entities and events over the text



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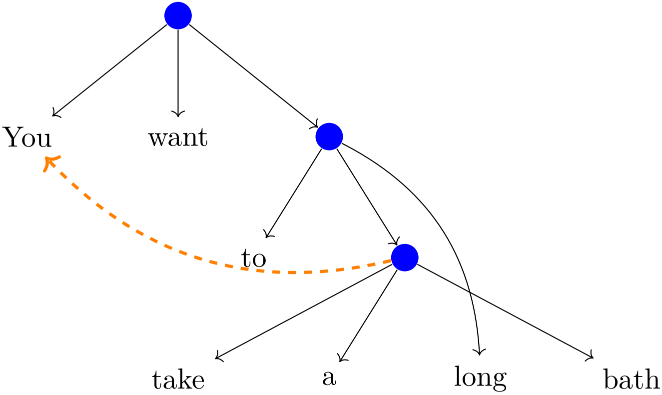
The **first parser** to support the combination of three properties:

1. Non-terminal nodes — entities and events over the text
2. Reentrancy — allow argument sharing

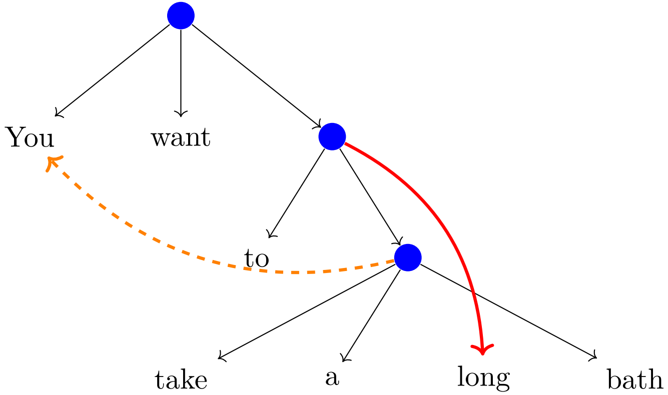


TUPA — Transition-based UCCA Parser

The **first parser** to support the combination of three properties:

1. Non-terminal nodes — entities and events over the text
2. Reentrancy — allow argument sharing
3. Discontinuity — conceptual units are split

— needed for many semantic schemes (e.g. AMR, UCCA).



Introduction

Linguistic Structure Annotation Schemes

- Syntactic dependencies
- Semantic dependencies (Oepen et al., 2016)
- AMR (Banarescu et al., 2013)
- UCCA (Abend and Rappoport, 2013)
- Other semantic representation schemes[1]

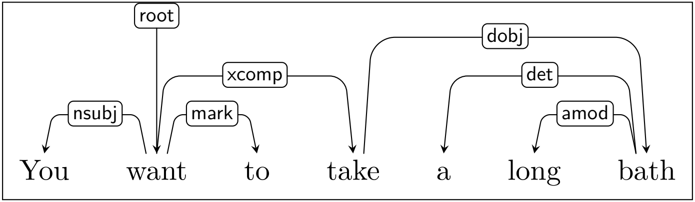
Abstract away from syntactic detail that does not affect meaning:

$$\boxed{\ldots\text{bathed}} = \boxed{\ldots\text{took a bath}}$$

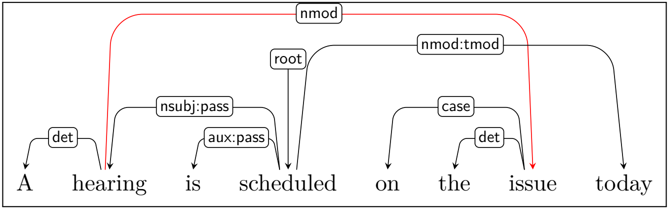
[1] See recent survey (Abend and Rappoport, 2017)

Syntactic Dependencies

- Bilexical tree: syntactic structure representation.
- Fast and accurate parsers (e.g. *transition-based*).

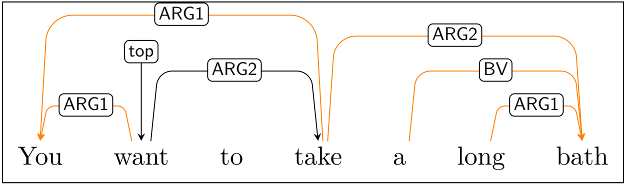


Non-projectivity (discontinuity) is a challenge (Nivre, 2009).

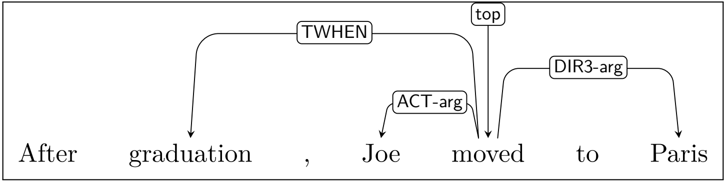


Semantic Dependencies

- Bilexical graph: predicate-argument representation.
- Derived from theories of syntax-semantics interface.



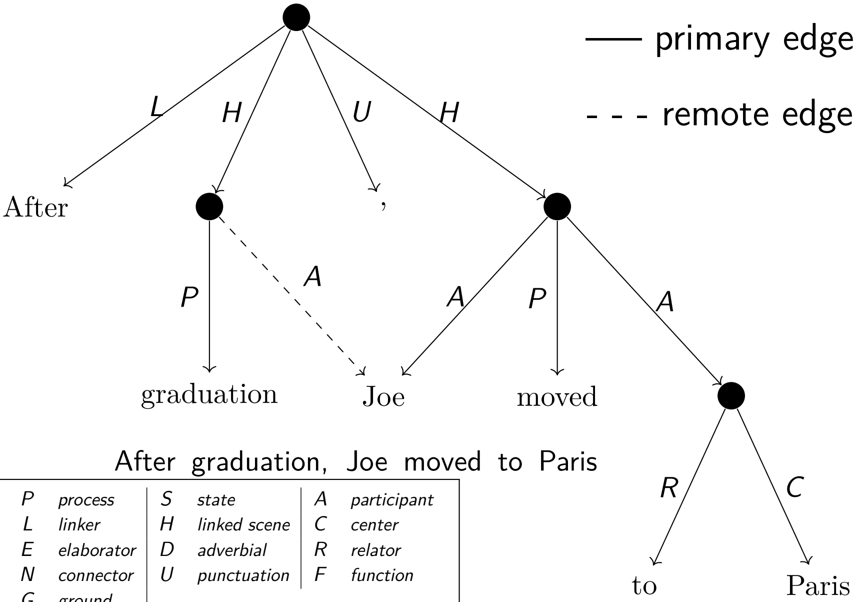
DELPH-IN MRS-derived bi-lexical dependencies (DM).



Prague Dependency Treebank tectogrammatical layer (PSD).

The UCCA Semantic Representation Scheme

Universal Conceptual Cognitive Annotation (UCCA)

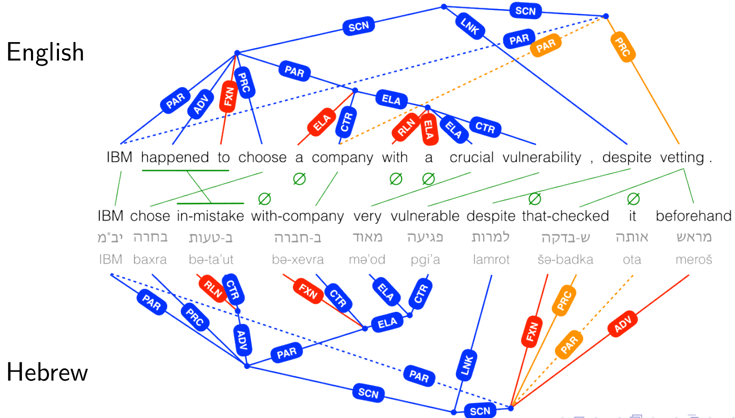


After graduation, Joe moved to Paris

P	*process*	*S*	*state*	*A*	*participant*
L	*linker*	*H*	*linked scene*	*C*	*center*
E	*elaborator*	*D*	*adverbial*	*R*	*relator*
N	*connector*	*U*	*punctuation*	*F*	*function*
G	*ground*				

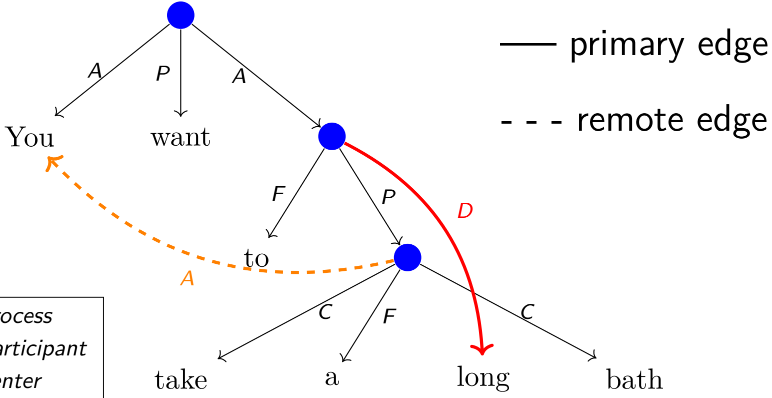
The UCCA Semantic Representation Scheme

- Cross-linguistically applicable (Abend and Rappoport, 2013).
- Stable in translation (Sulem et al., 2015).
- Fast and intuitive to annotate (Abend et al., 2017).
- Facilitates MT human evaluation (Birch et al., 2016).



Graph Structure

UCCA generates a directed acyclic graph (DAG).
Text tokens are terminals, complex units are non-terminal nodes.
Remote edges enable reentrancy for argument sharing.
Phrases may be discontinuous (e.g., multi-word expressions).



P	*process*
A	*participant*
C	*center*
D	*adverbial*
F	*function*

You want to take a long bath

Transition-based UCCA Parsing

Transition-Based Parsing

First used for dependency parsing (Nivre, 2004).
Parse text $w_1 \ldots w_n$ to graph G incrementally by applying transitions to the parser state: stack, buffer and constructed graph.

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Initial state:

stack

●

buffer

You	want	to	take	a	long	bath

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Initial state:

stack | buffer

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.

Example

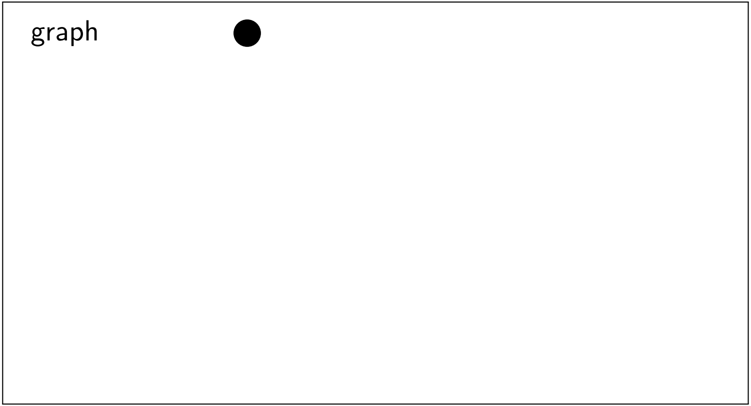
⇒ SHIFT

stack

●	You

buffer

want	to	take	a	long	bath



Example

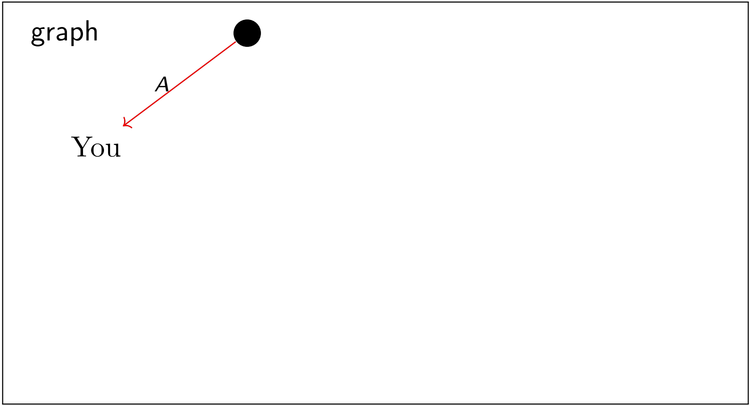
$\Rightarrow$ Right-Edge$_A$

stack

●	You

buffer

want	to	take	a	long	bath



Example

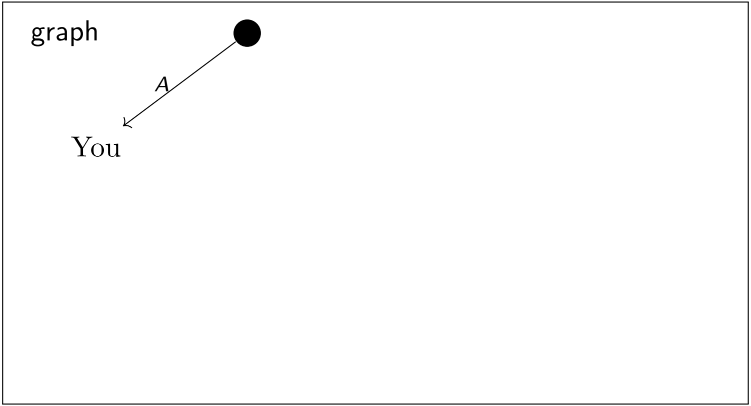
$\Rightarrow$ SHIFT

stack

●	You	want

buffer

to	take	a	long	bath



Example

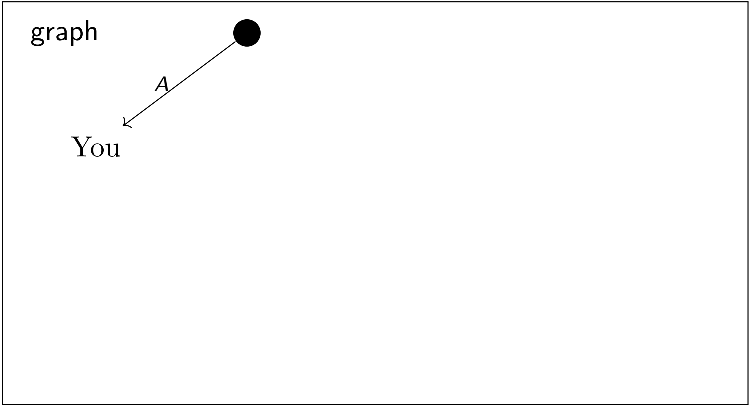
$\Rightarrow$ Swap

stack

●	want

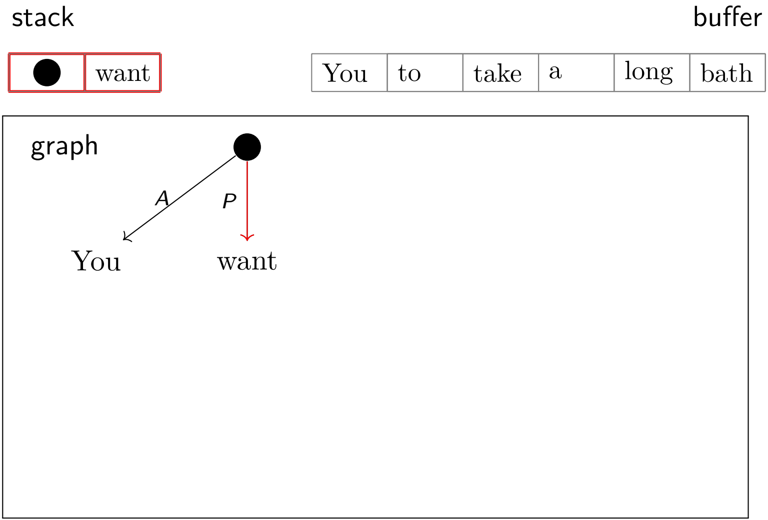
buffer

$\boxed{\text{You}}$	to	take	a	long	bath



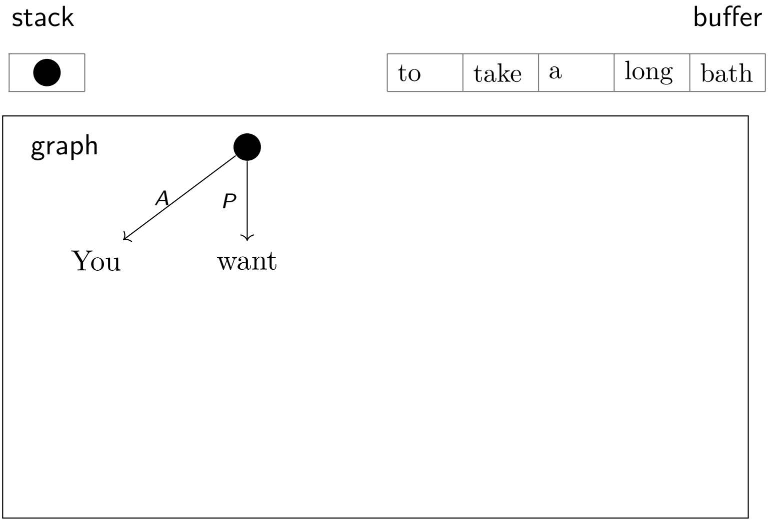
Example

$\Rightarrow$ RIGHT-EDGE$_P$



Example

$\Rightarrow$ REDUCE



Example

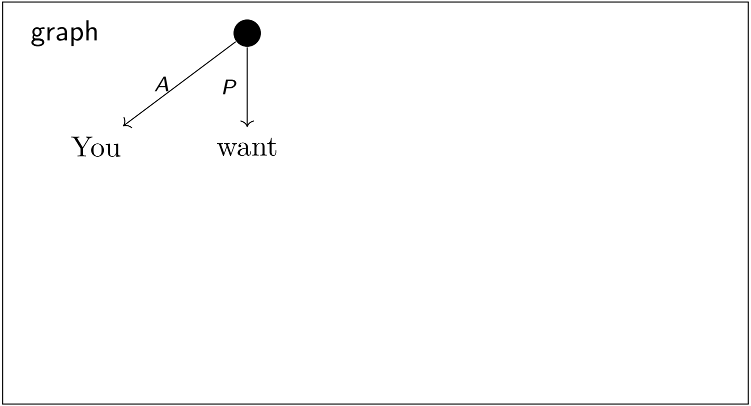
$\Rightarrow$ SHIFT

stack

●	You

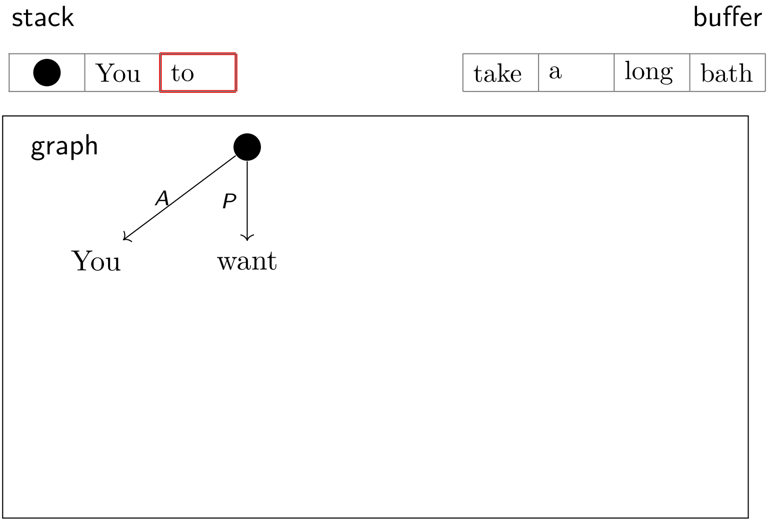
buffer

to	take	a	long	bath



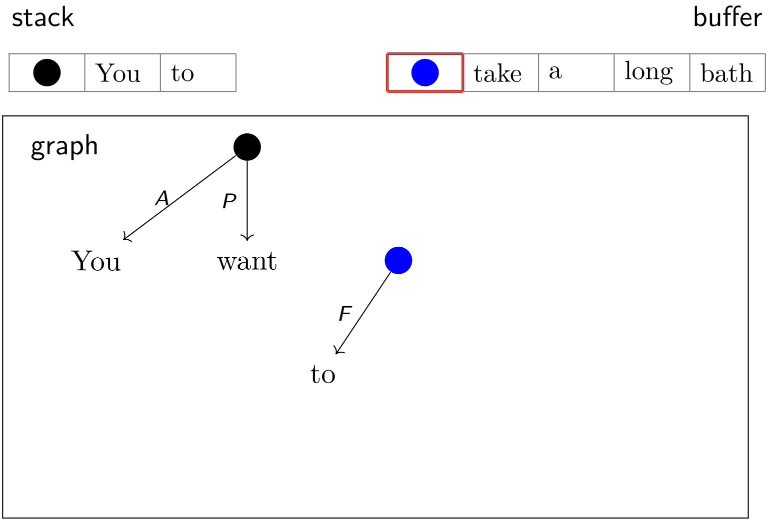
Example

$\Rightarrow$ SHIFT



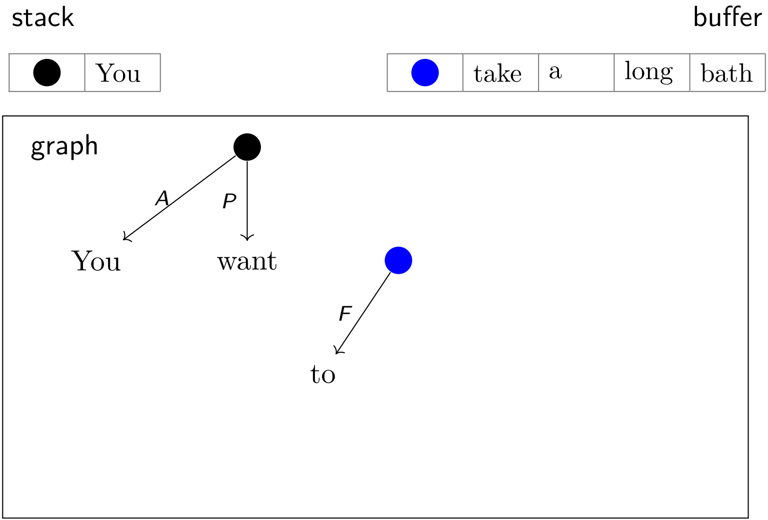
Example

$\Rightarrow$ $\textsc{Node}_F$



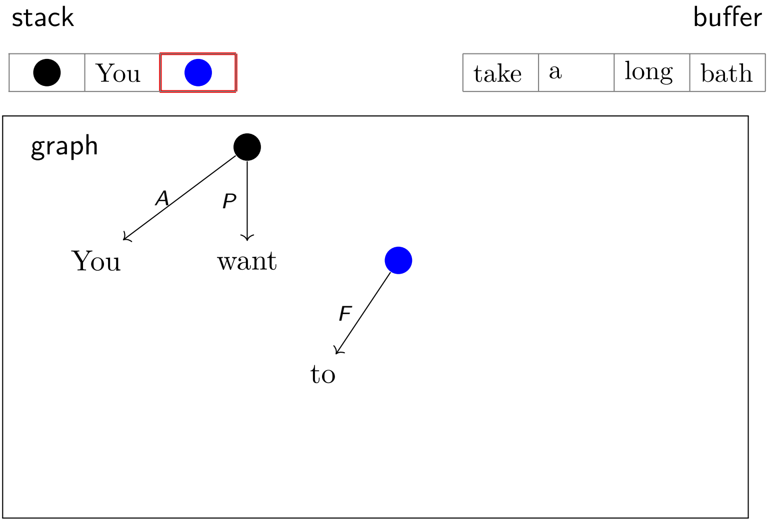
Example

⇒ Reduce



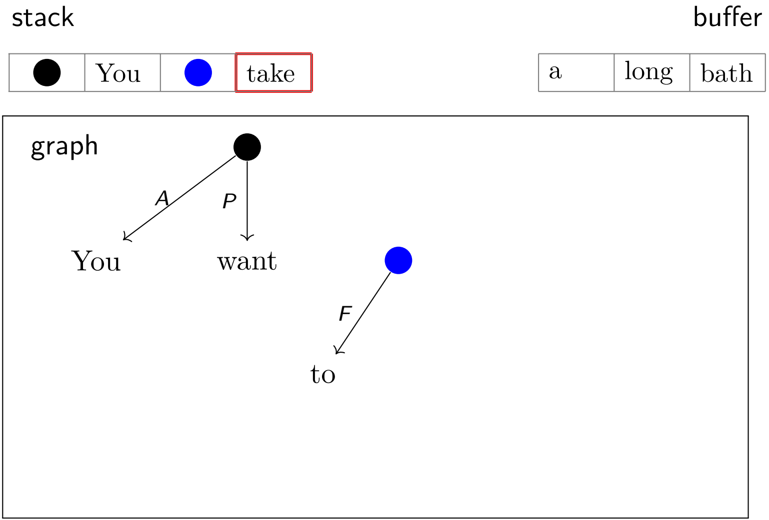
Example

$\Rightarrow$ Shift



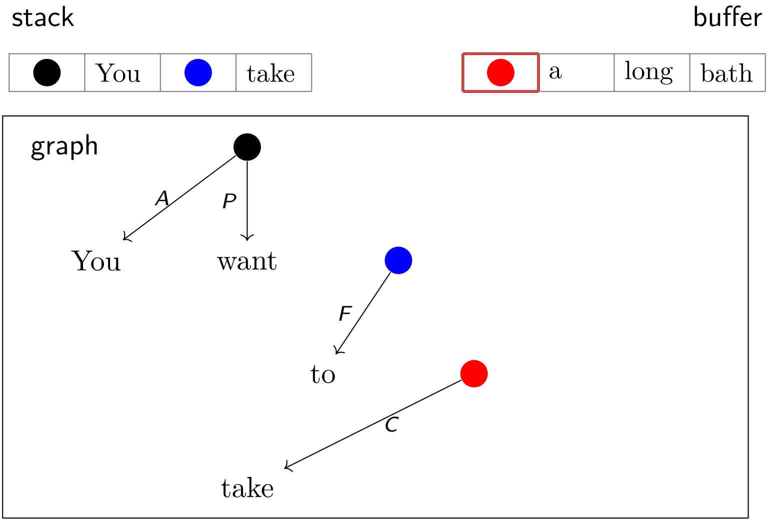
Example

⇒ SHIFT



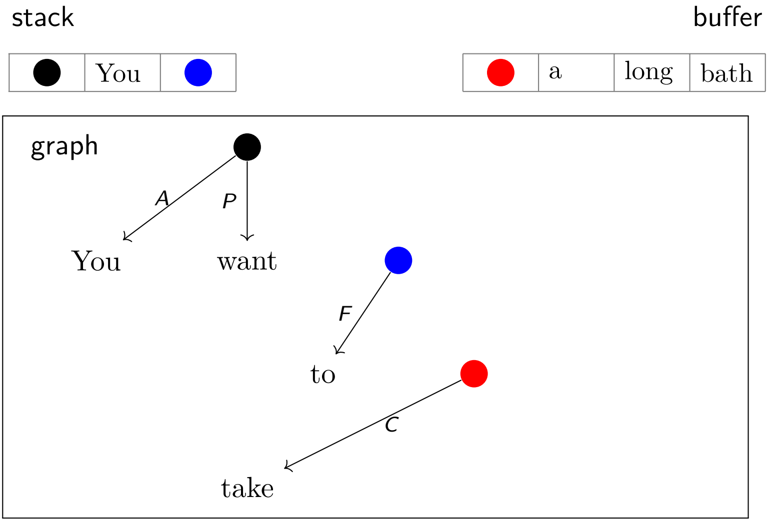
Example

$\Rightarrow$ Node$_C$



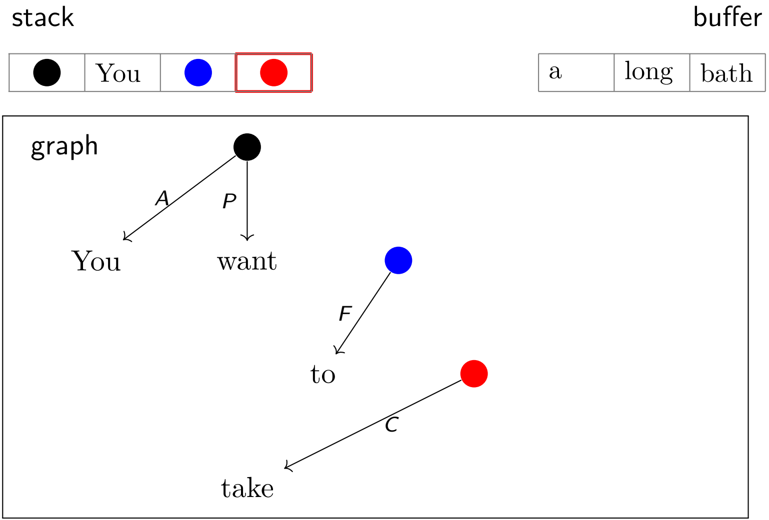
Example

⇒ Reduce



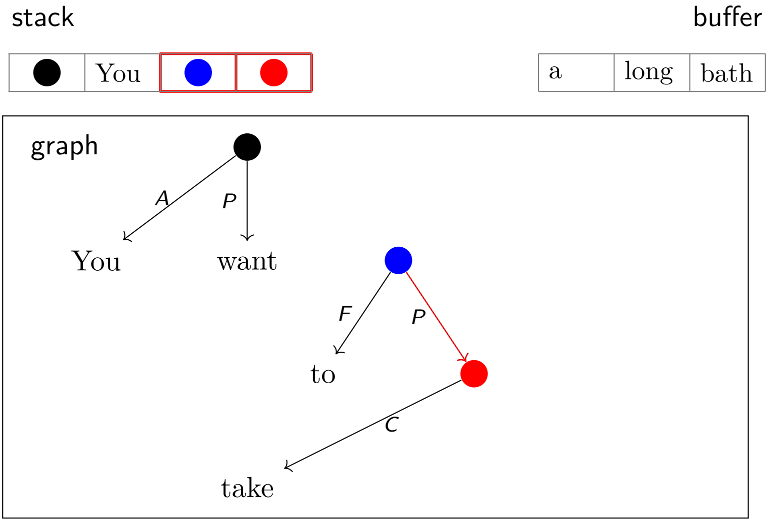
Example

$\Rightarrow$ Shift



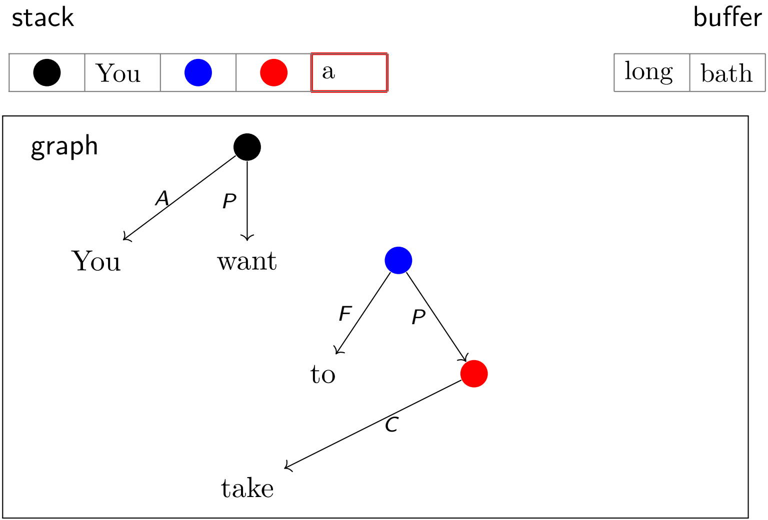
Example

$\Rightarrow$ RIGHT-EDGE$_P$



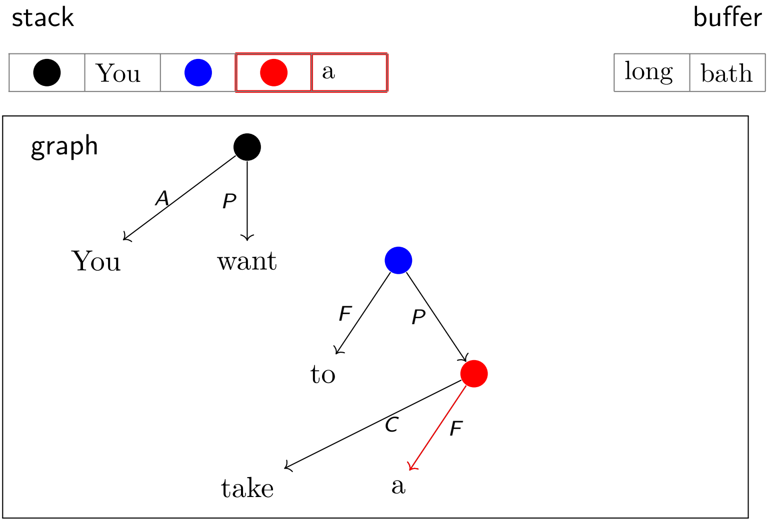
Example

⇒ SHIFT



Example

⇒ $\textsc{Right-Edge}_F$



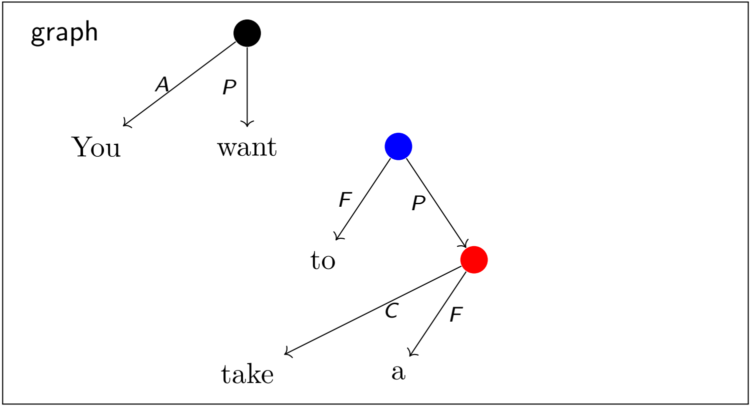
Example

$\Rightarrow$ Reduce

stack

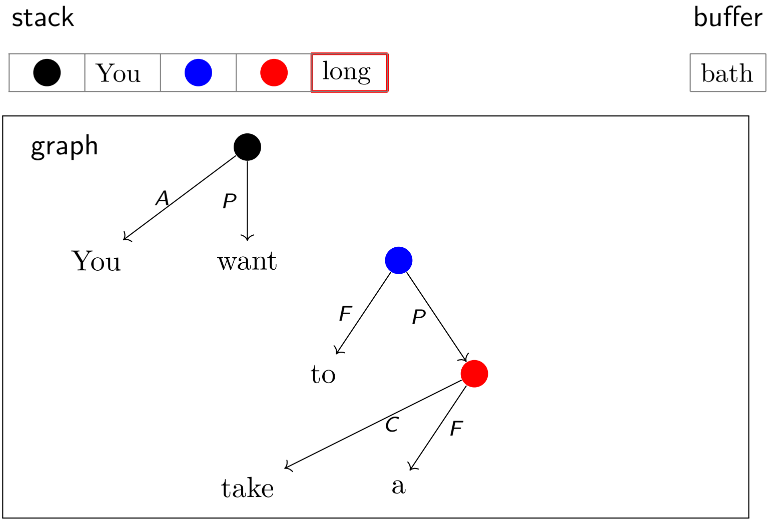
buffer

long	bath



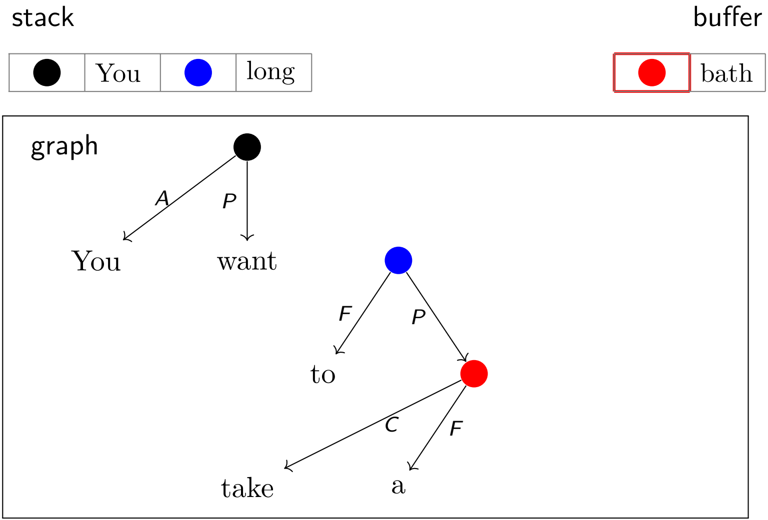
Example

$\Rightarrow$ SHIFT



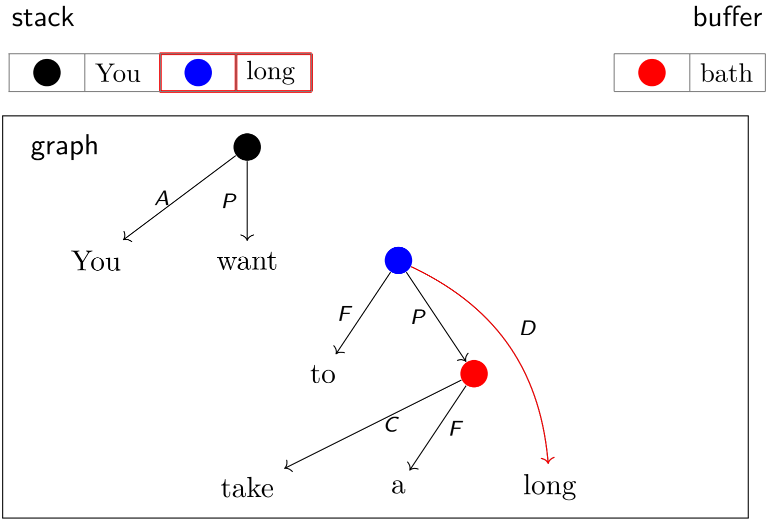
Example

⇒ Swap



Example

⇒ RIGHT-EDGE$_D$

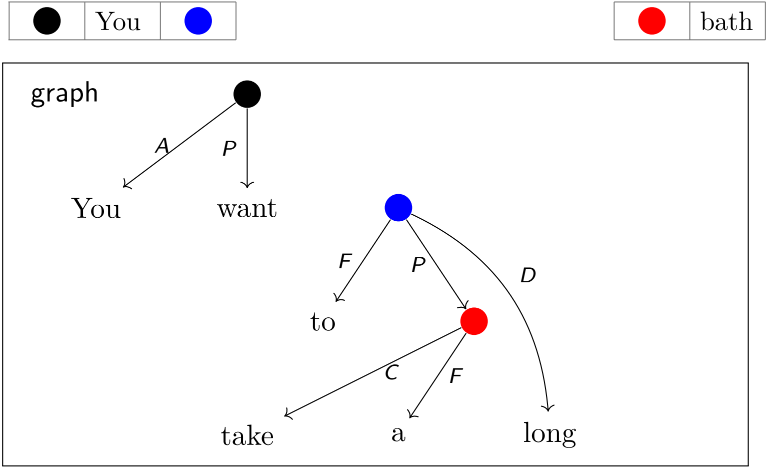


Example

$\Rightarrow$ REDUCE

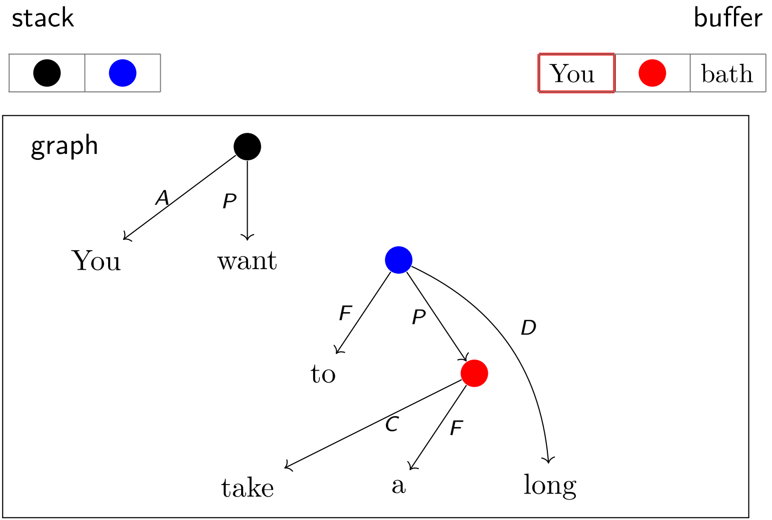
stack

buffer



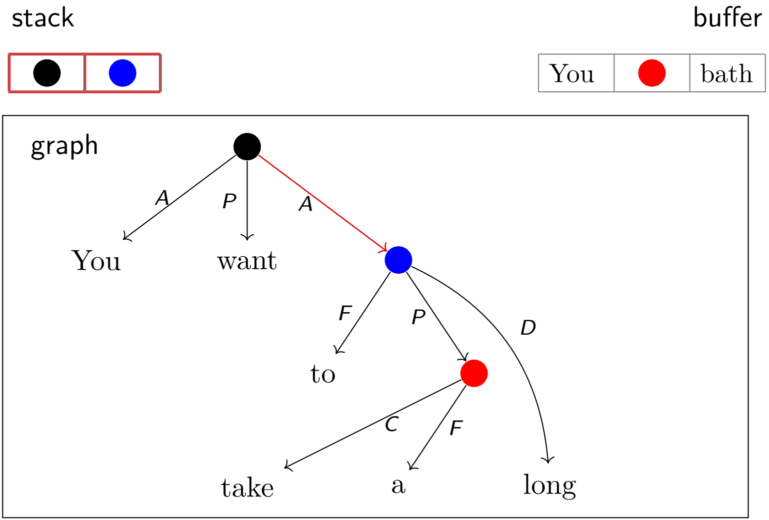
Example

$\Rightarrow$ Swap



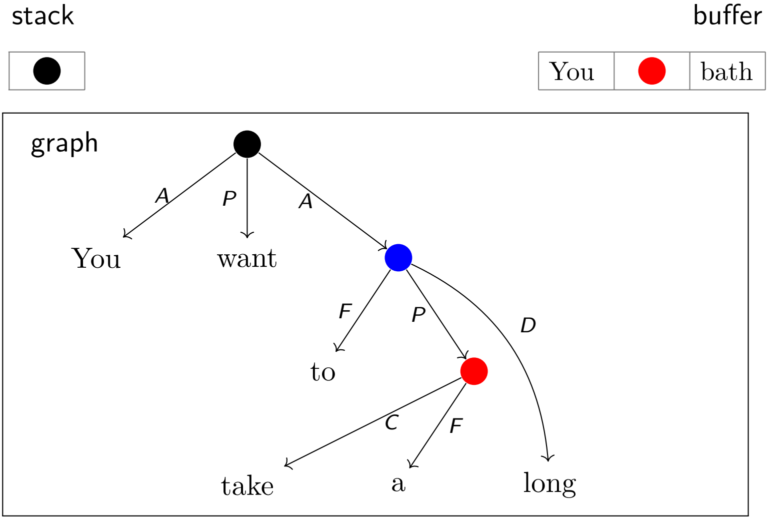
Example

$\Rightarrow$ RIGHT-EDGE$_A$



Example

$\Rightarrow$ REDUCE



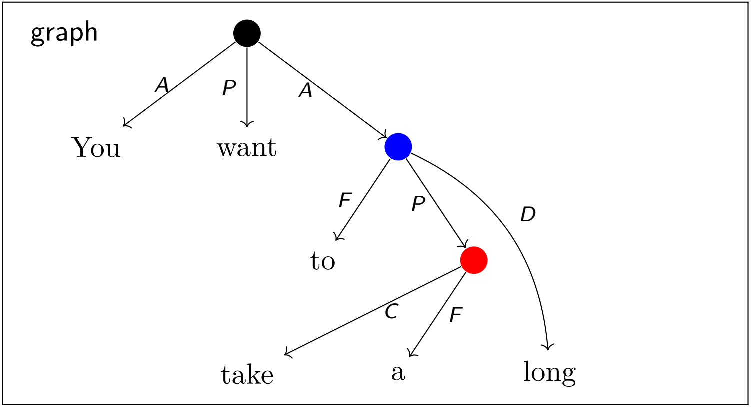
Example

$\Rightarrow$ REDUCE

stack

buffer

You	●	bath



Example

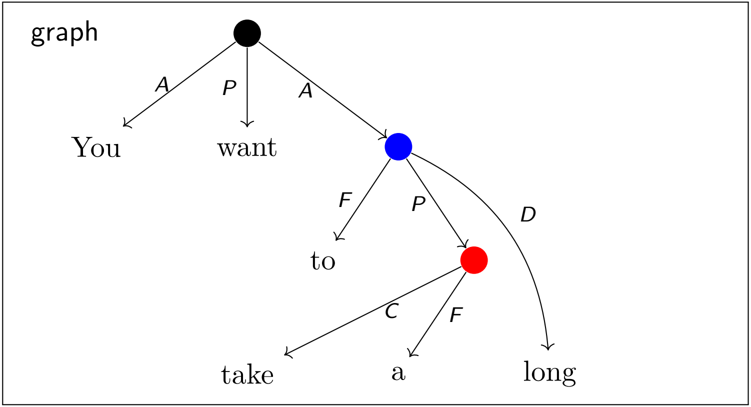
⇒ SHIFT

stack

You

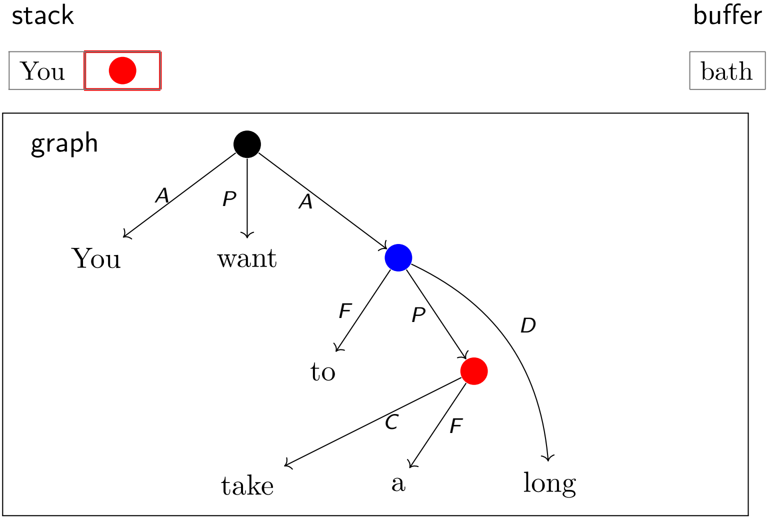
buffer

	bath



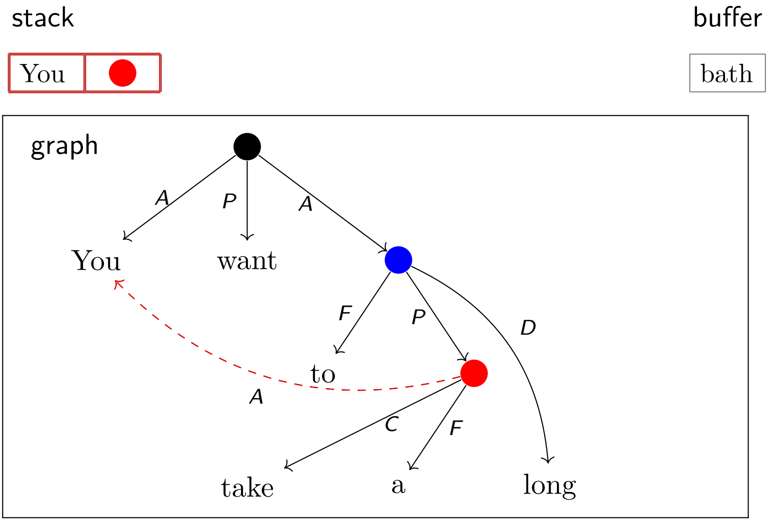
Example

$\Rightarrow$ Shift



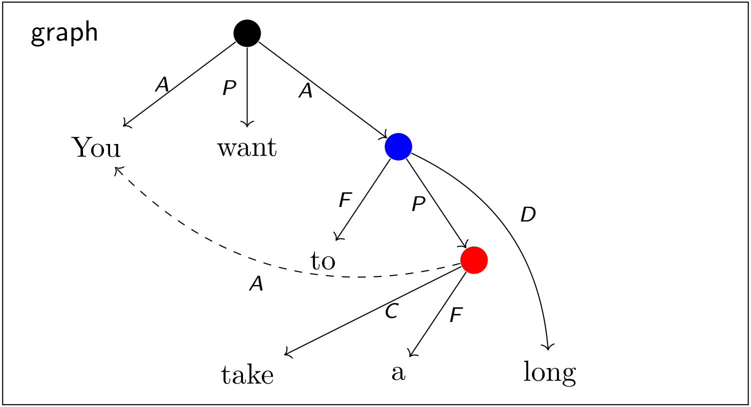
Example

$\Rightarrow$ Left-Remote$_A$



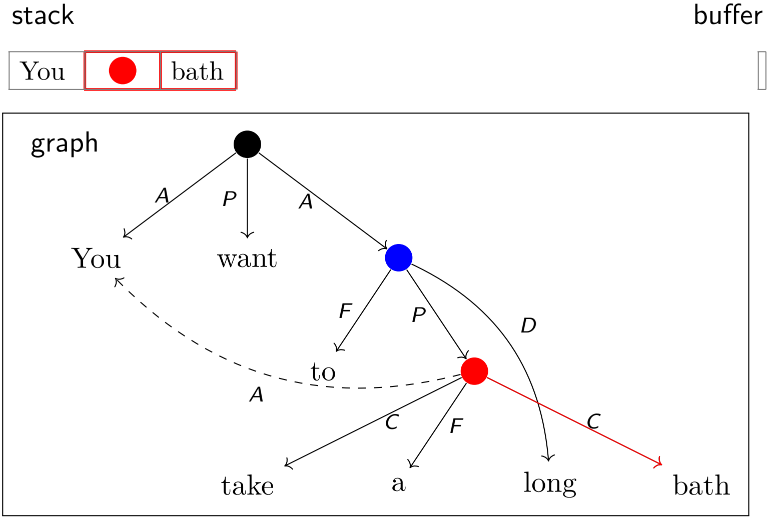
Example

$\Rightarrow$ Shift



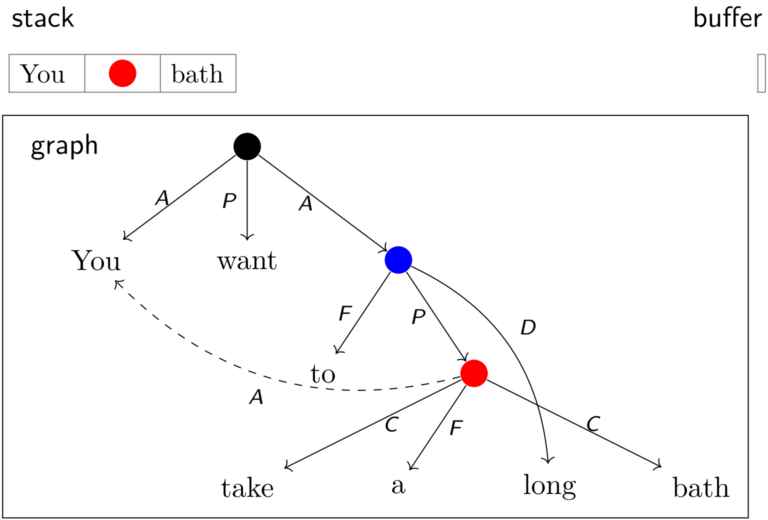
Example

$\Rightarrow$ RIGHT-EDGE$_C$



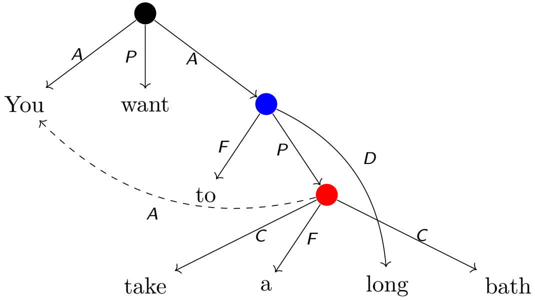
Example

$\Rightarrow$ FINISH



Training

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



$\Downarrow$

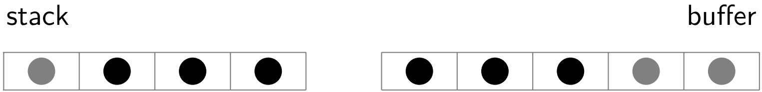
Shift, Right-Edge$_A$, Shift, Swap, Right-Edge$_P$, Reduce, Shift, Shift, Node$_F$, Reduce, Shift, Shift, Node$_C$, Reduce, Shift, Right-Edge$_P$, Shift, Right-Edge$_F$, Reduce, Shift, Swap, Right-Edge$_D$, Reduce, Swap, Right-Edge$_A$, Reduce, Reduce, Shift, Shift, Left-Remote$_A$, Shift, Right-Edge$_C$, Finish

TUPA Model

Learn to greedily predict transition based on current state.
Experimenting with three classifiers:

Sparse	Perceptron with sparse features (Zhang and Nivre, 2011).
MLP	Embeddings + feedforward NN (Chen and Manning, 2014).
BiLSTM	Embeddings + deep bidirectional LSTM + 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)



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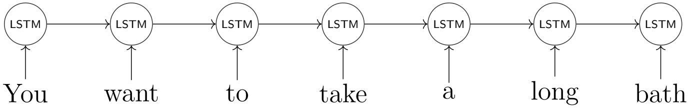
Effective "lookahead" encoded in the representation.



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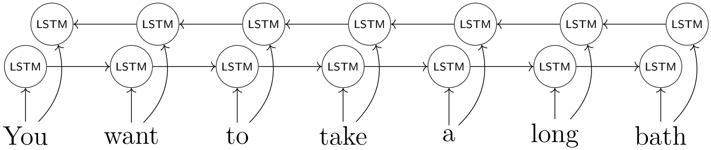

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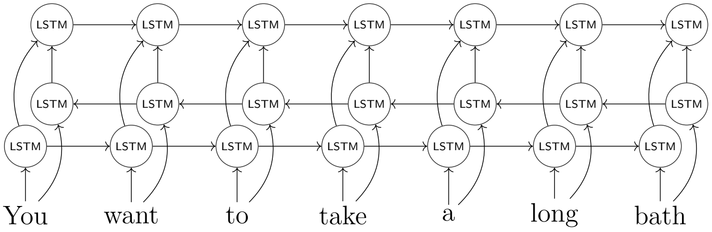

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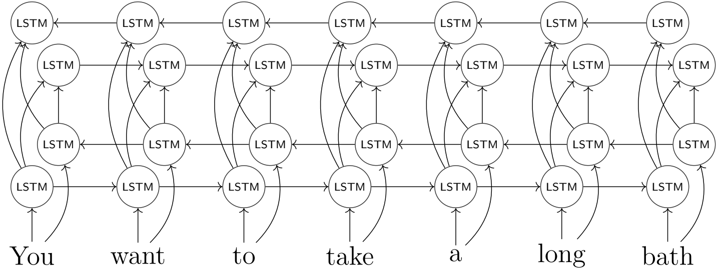
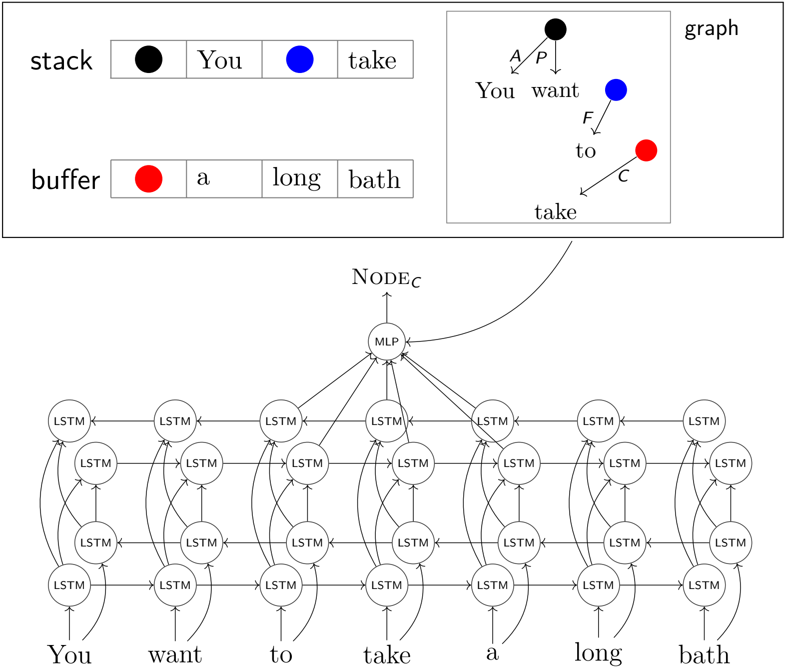
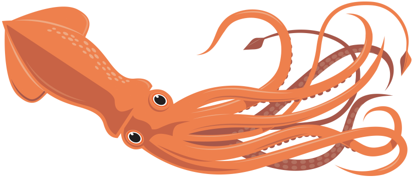



stack
You
take
buffer
a
long
bath
graph
A
P
You
want
F
to
C
take
NODE$_C$
MLP
LSTM
You
want
to
take
a
long
bath

Experiments

Experimental Setup

- UCCA Wikipedia corpus ($\overset{\text{train}}{4268} + \overset{\text{dev}}{454} + \overset{\text{test}}{503}$ sentences).
- Out-of-domain: English part of English-French parallel corpus, *Twenty Thousand Leagues Under the Sea* (506 sentences).



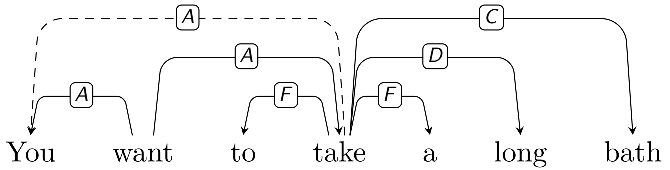
Baselines

No existing UCCA parsers ⇒ conversion-based approximation.
Bilexical DAG parsers (allow reentrancy):

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

Tree parsers (all transition-based):

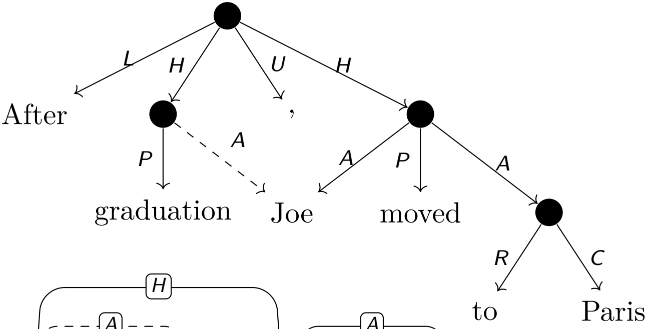
- MaltParser (Nivre et al., 2007): bilexical tree parser.
- Stack LSTM Parser (Dyer et al., 2015): bilexical tree parser.
- UPARSE (Maier, 2015): allows non-terminals, discontinuity.

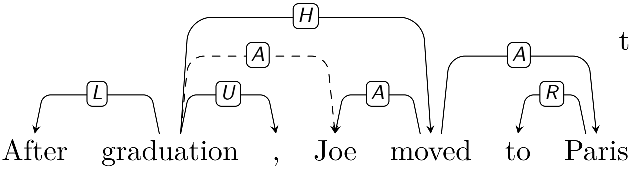


UCCA bilexical DAG approximation (for tree, delete remote edges).

Bilexical Graph Approximation

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

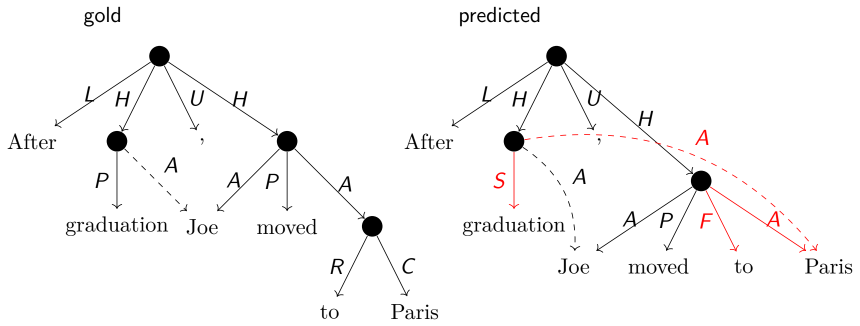




Evaluation

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:

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

Remote:

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

Results

$\text{TUPA}_{\text{BiLSTM}}$ obtains the highest F-scores in all metrics:

	Primary edges			Remote edges		
	LP	**LR**	**LF**	**LP**	**LR**	**LF**
$\text{TUPA}_{\text{Sparse}}$	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
$\text{TUPA}_{\text{BiLSTM}}$	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	–	–	–
Stack LSTM	73.2	66.9	69.9	–	–	–
Tree			(100)			–
UPARSE	60.9	61.2	61.1	–	–	–

Results on the Wiki test set.

Results

Comparable on out-of-domain test set:

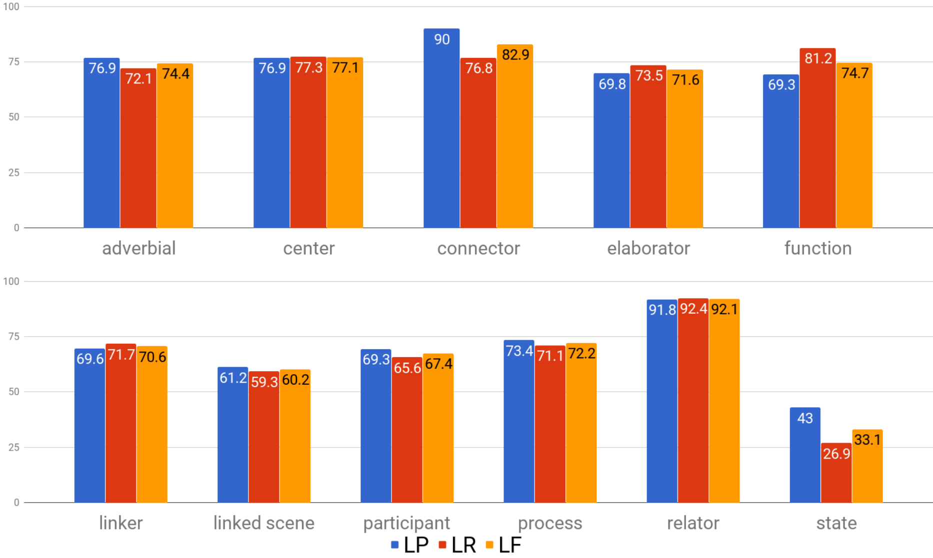
	Primary edges			Remote edges		
	LP	**LR**	**LF**	**LP**	**LR**	**LF**
TUPA$_{\text{Sparse}}$	59.6	59.9	59.8	22.2	7.7	11.5
TUPA$_{\text{MLP}}$	62.3	62.6	62.5	20.9	6.3	9.7
TUPA$_{\text{BiLSTM}}$	68.7	68.5	**68.6**	38.6	18.8	**25.3**
Bilexical DAG			(91.3)			(43.4)
DAGParser	56.4	50.6	53.4	–	0	0
TurboParser	50.3	37.7	43.1	100	0.4	0.8
Bilexical tree			(91.3)			–
MaltParser	57.8	53	55.3	–	–	–
Stack LSTM	66.1	61.1	63.5	–	–	–
Tree			(100)			–
UPARSE	52.7	52.8	52.8	–	–	–

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

Discussion

Fine-Grained Analysis

Evaluation of $\text{TUPA}_{\text{BiLSTM}}$ per edge type:



Online Demo

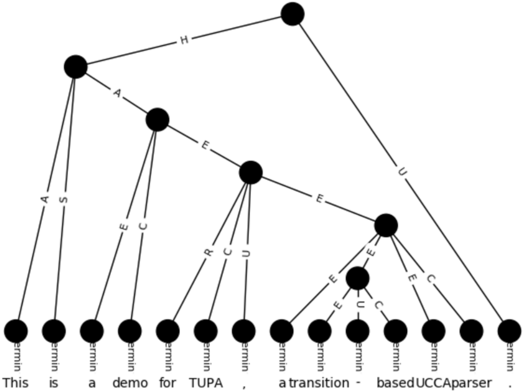
`http://bit.ly/tupademo`

Input text:

This is a demo for TUPA, a transition-based UCCA parser.

Parse

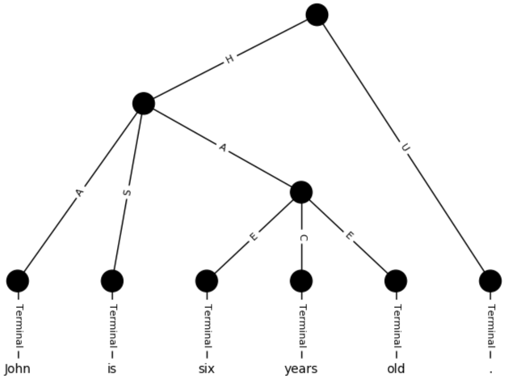
Download



Legend	
P	process
S	state
A	participant
L	linker
H	linked scene
C	center
E	elaborator
D	adverbial
R	relator
N	connector
U	punctuation
F	function
G	ground

Error Analysis

Copular clauses tend to be parsed as identity.



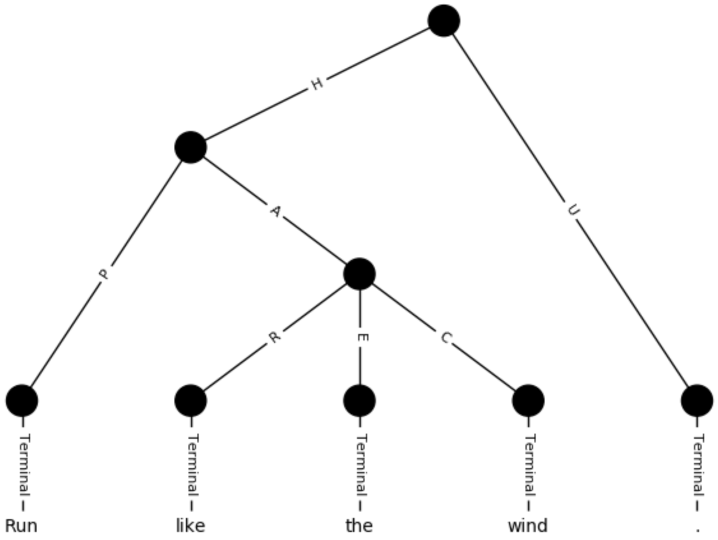
But, from the guidelines[2]:

$$\text{John}_A \left[\text{is}_F \left[[\text{six}_E \text{years}_C]_E \text{old}_C \right]_C \right]_S$$

[2] http://www.cs.huji.ac.il/~oabend/ucca/guidelines.pdf

Error Analysis

The *participant* category is used when *adverbial* should be.

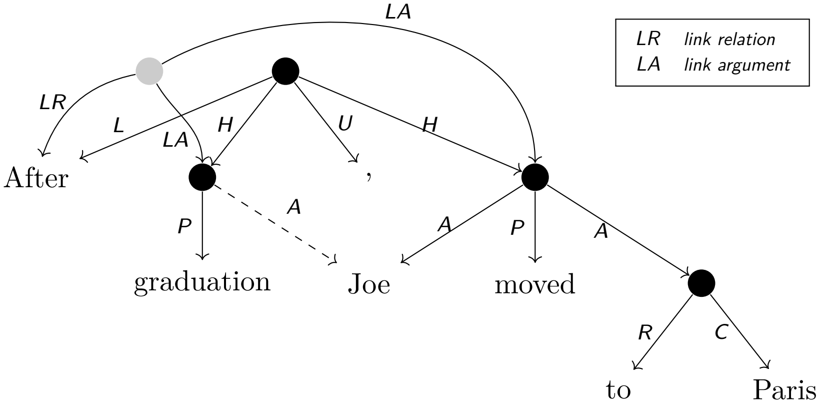


Future Work

Broad-Coverage UCCA Parsing

Already annotated in UCCA, but not yet handled by TUPA:

- Linkage: inter-scene relations (see example).
- Implicit units: units not mentioned at all in the text.
- Inter-sentence relations: discourse structure.

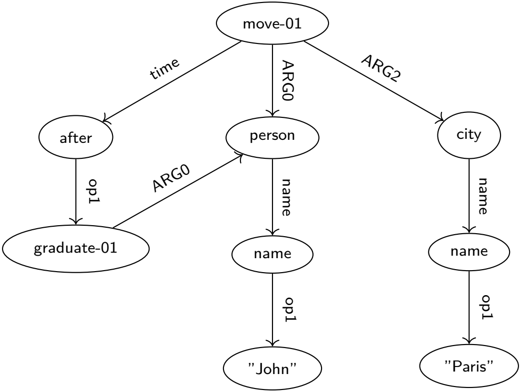


UCCA graph with a Linkage relation.

AMR Parsing

Similar in structure and content, but poses several challenges:

- Node labels: not just edges, not also nodes are labeled.
- Partial alignment: orphan tokens, implicit concepts.



AMR graph.

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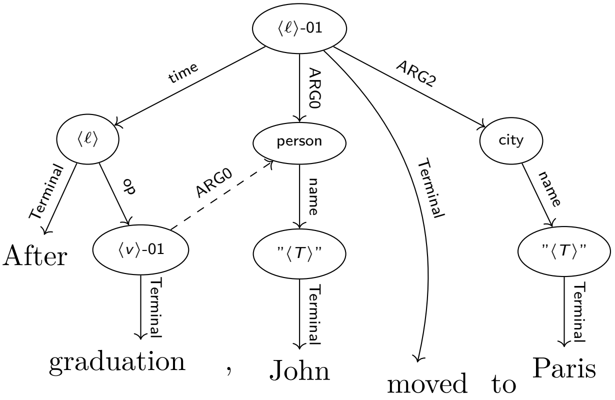
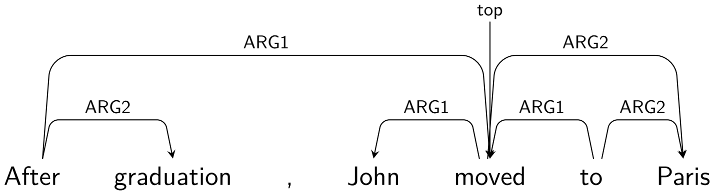


AMR graph in UCCA++ format.

Semantic Dependency Parsing

Similar structure, but without non-terminal nodes.
By applying bilexical conversion in reverse, TUPA can be used.



SDP graph (in the DM formalism).

Semantic Dependency Parsing

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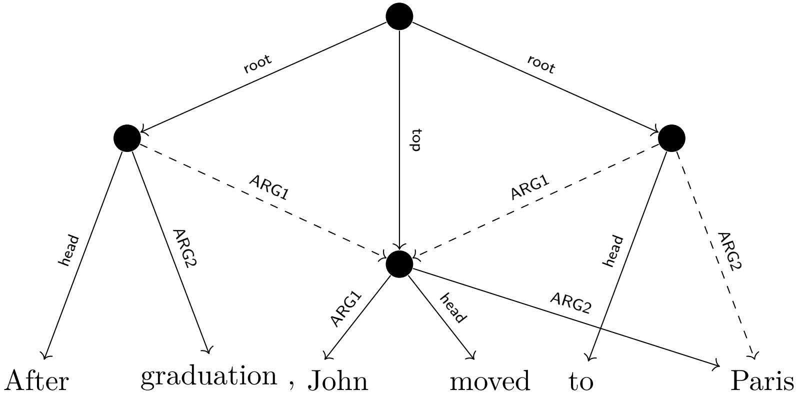

SDP graph in UCCA++ format.

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 UCCA and any DAG over the text tokens.
- Outperforms strong conversion-based baselines.

Code: `github.com/danielhers/tupa`
Demo: `bit.ly/tupademo`
Corpora: `cs.huji.ac.il/~oabend/ucca.html`

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Future Work:

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

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Thank you!

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Backup

UCCA Corpora

	Wiki Train	Wiki Dev	Wiki Test	20K 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 $W = \{w_1, \ldots, w_n\}$:

$$M(G_p, G_g) = \left\{(e_1, e_2) \in E_p \times E_g \;\middle|\; y(e_1) = y(e_2) \wedge \ell_p(e_1) = \ell_g(e_2)\right\}$$

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:

$$\mathrm{LP} = \frac{|M(G_p, G_g)|}{|E_p|}, \quad \mathrm{LR} = \frac{|M(G_p, G_g)|}{|E_g|},$$

$$\mathrm{LF} = \frac{2 \cdot \mathrm{LP} \cdot \mathrm{LR}}{\mathrm{LP} + \mathrm{LR}}.$$

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