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

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האוניברסיטה העברית בירושלים
THE HEBREW UNIVERSITY OF JERUSALEM

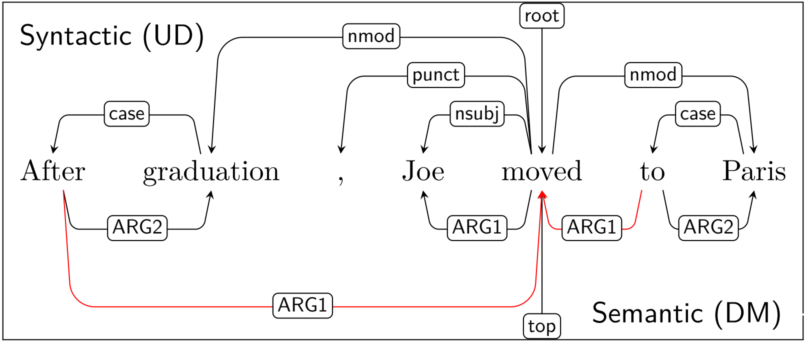
ACL 2017

Linguistic Structure Annotation Schemes

- Dependency grammar: bilexical tree, purely syntactic.

Semantic representation (Abend and Rappoport, 2017):

- Semantic dependencies: bilexical graph, coupled with syntax.



Bilexical dependencies.

Linguistic Structure Annotation Schemes

- Dependency grammar: bilexical tree, purely syntactic.

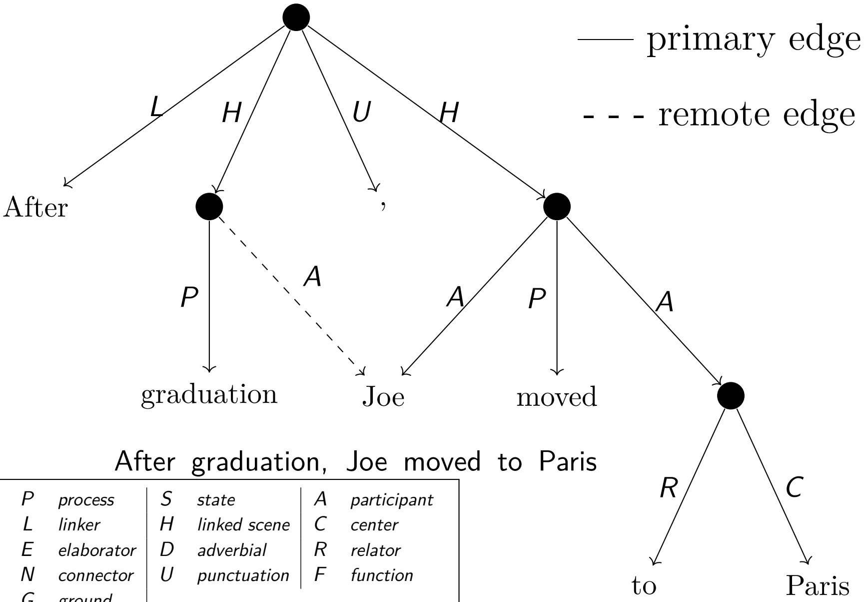
Semantic representation (Abend and Rappoport, 2017):

- Semantic dependencies: bilexical graph, coupled with syntax.
- AMR (Banarescu et al., 2013), UCCA (Abend and Rappoport, 2013): direct semantic representation.

$\boxed{\text{...showered}} = \boxed{\text{...took a shower}}$

$\boxed{\text{...'s war against crime}} = \boxed{\text{...fights crime}}$

Universal Conceptual Cognitive Annotation (UCCA)

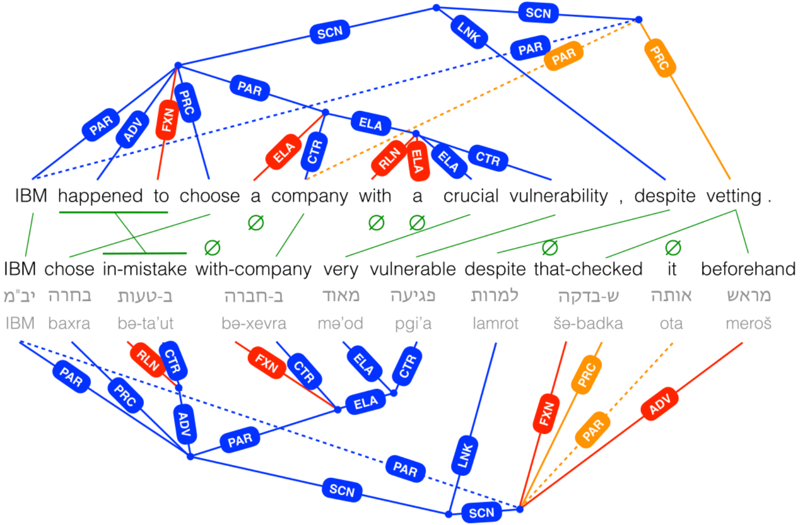


After graduation, Joe moved to Paris

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*				

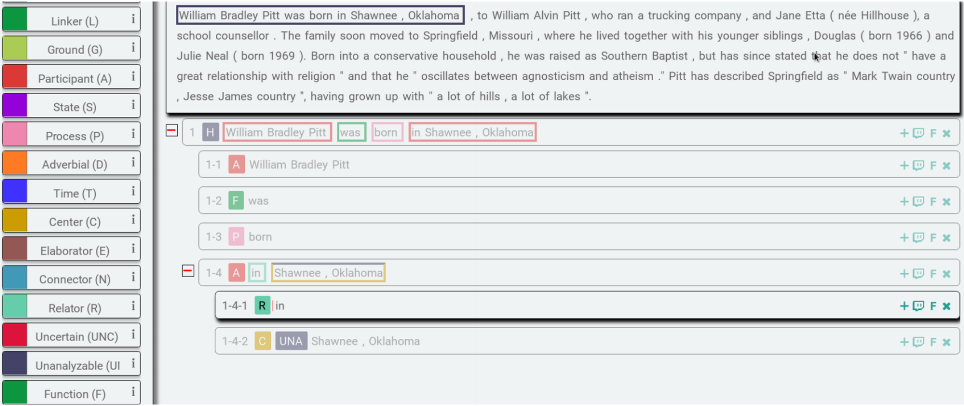
The UCCA Semantic Representation Scheme

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



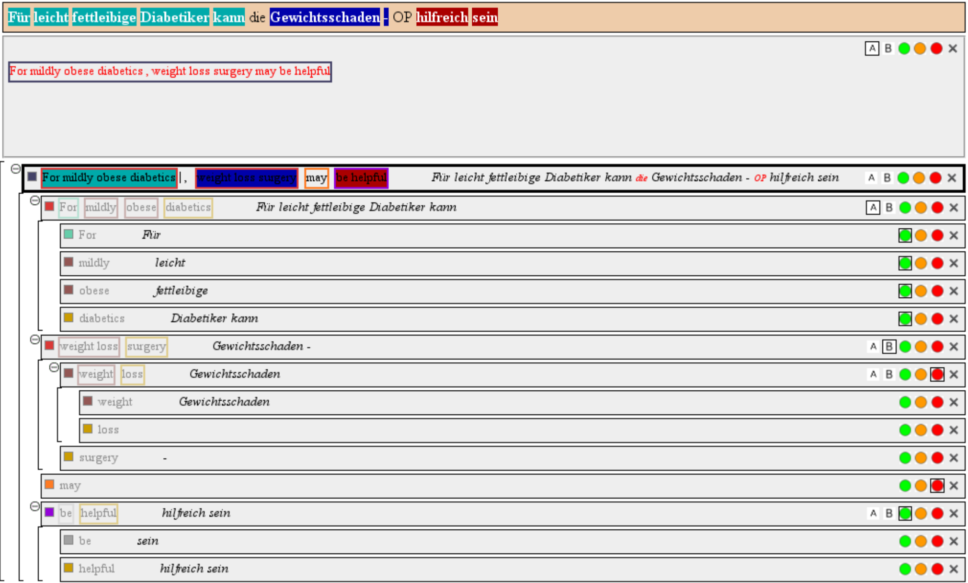
UCCAApp

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



HUME

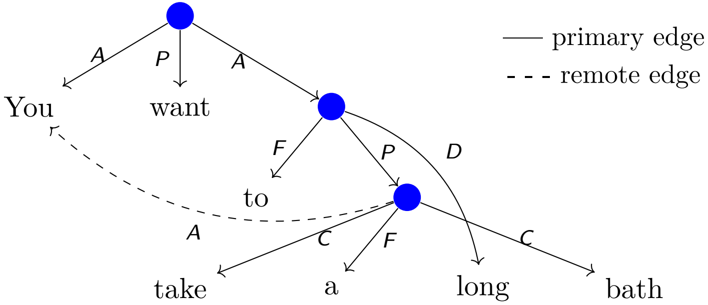
UCCA facilitates semantics-based human evaluation of machine translation (Birch et al., 2016). `http://ucca.cs.huji.ac.il/mteval`



Graph Structure

UCCA forms a directed acyclic graph (DAG). Tokens are terminals.
Structural properties:

1. Non-terminal nodes

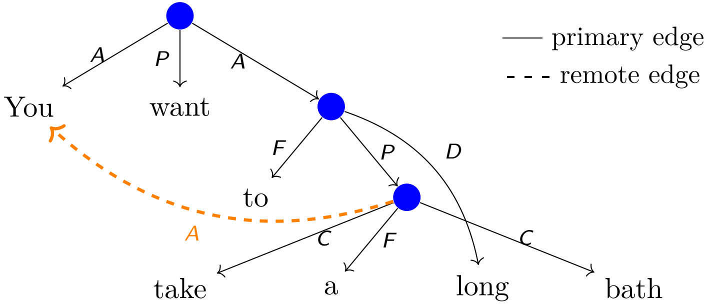


You want to take a long bath

Graph Structure

UCCA forms a directed acyclic graph (DAG). Tokens are terminals. Structural properties:

1. Non-terminal nodes
2. Reentrancy

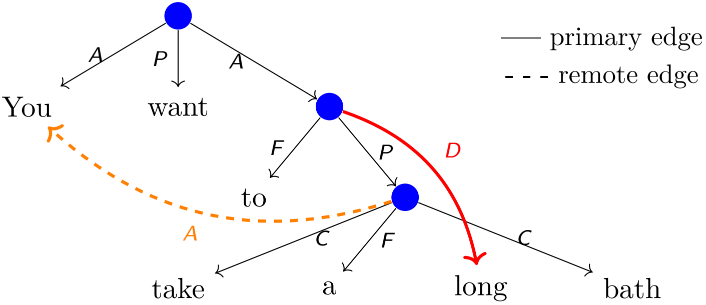


You want to take a long bath

Graph Structure

UCCA forms a directed acyclic graph (DAG). Tokens are terminals.
Structural properties:

1. Non-terminal nodes
2. Reentrancy
3. Discontinuity



You want to take a long bath

Transition-Based Parsing

- Parse text $w_1 \ldots w_n$ to graph $G = (V, E, \ell)$ incrementally.
- Classifier determines transition to apply at each step.
- Trained by an oracle based on gold-standard graph.

Transition-Based Parsing

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Initial state:

stack

●

buffer

You	want	to	take	a	long	bath

Transition-Based Parsing

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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.

Transition-Based UCCA Parsing

⇒ SHIFT

stack

●	You

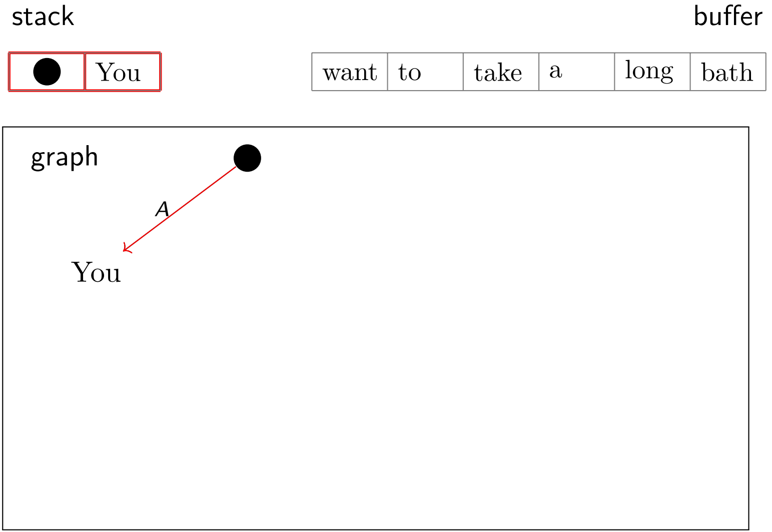
buffer

want	to	take	a	long	bath

graph

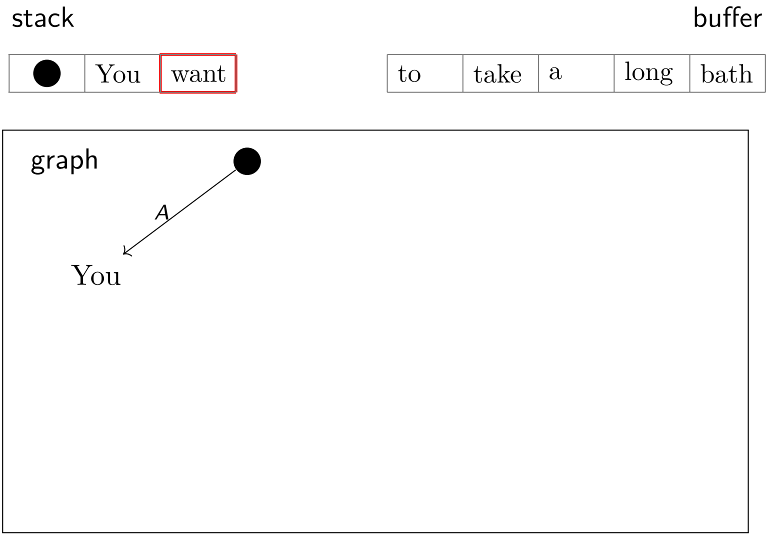
Transition-Based UCCA Parsing

$\Rightarrow$ RIGHT-EDGE$_{\text{A}}$



Transition-Based UCCA Parsing

⇒ Shift



Transition-Based UCCA Parsing

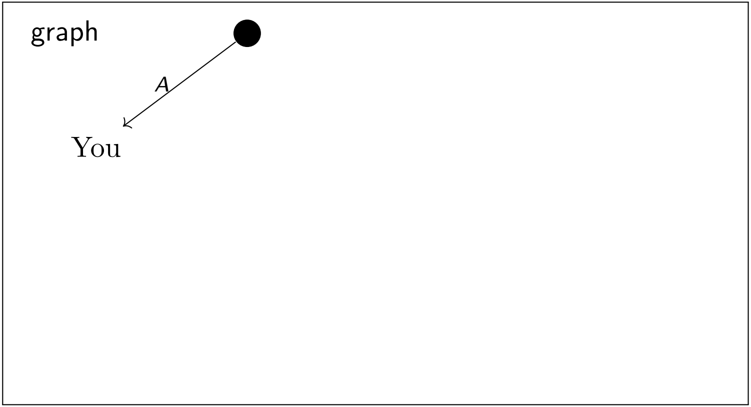
⇒ Swap

stack

●	want

buffer

You	to	take	a	long	bath



Transition-Based UCCA Parsing

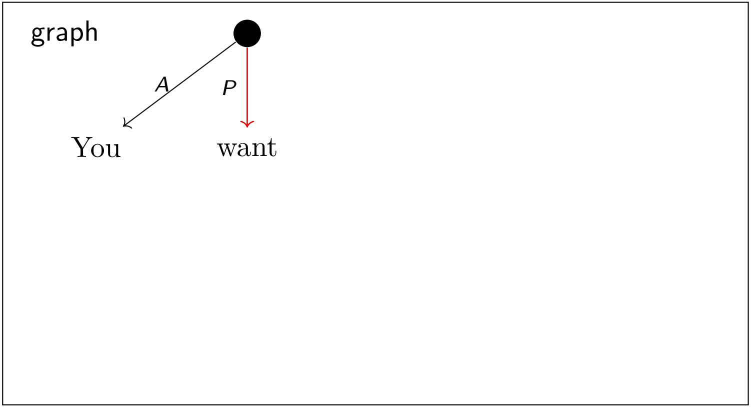
⇒ $\textsc{Right-Edge}_P$

stack

●	want

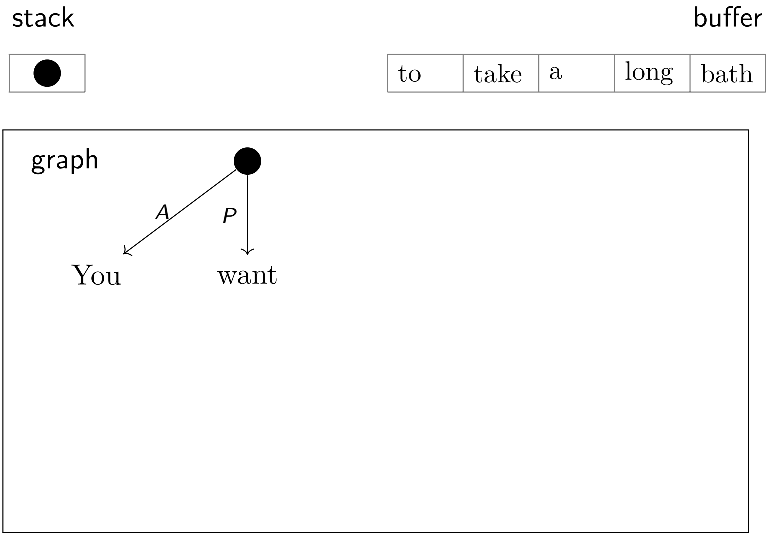
buffer

You	to	take	a	long	bath



Transition-Based UCCA Parsing

⇒ Reduce



Transition-Based UCCA Parsing

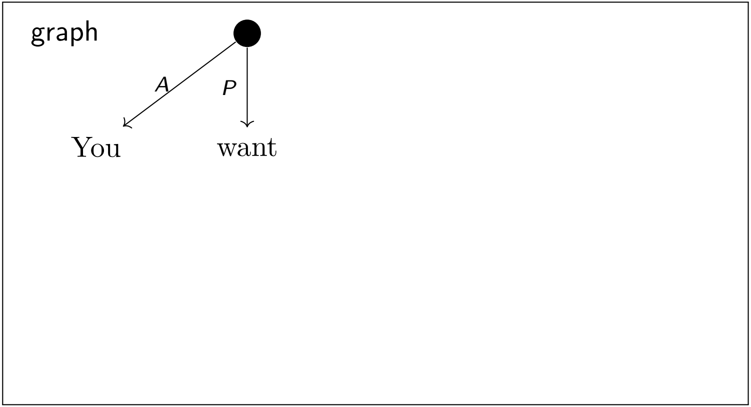
⇒ SHIFT

stack

●	You

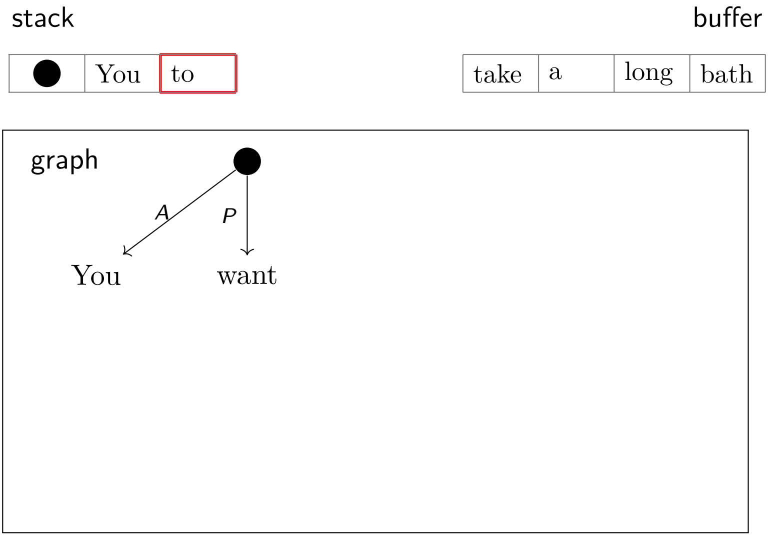
buffer

to	take	a	long	bath



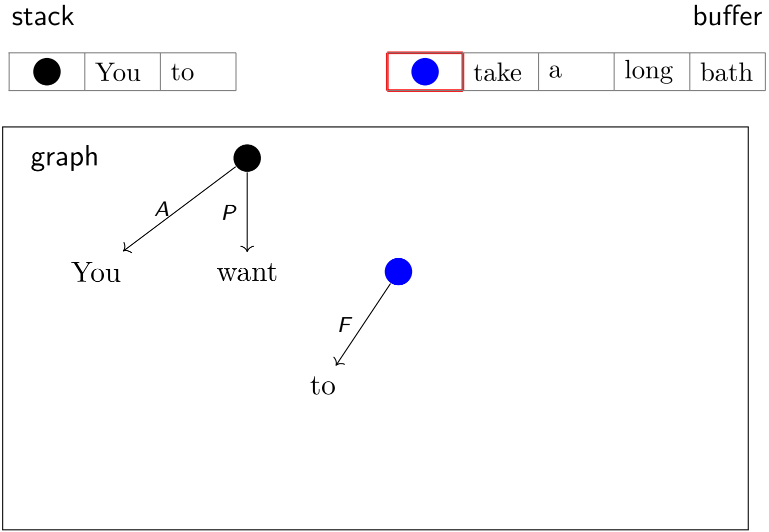
Transition-Based UCCA Parsing

⇒ SHIFT



Transition-Based UCCA Parsing

$\Rightarrow$ $\textsc{Node}_{\text{F}}$

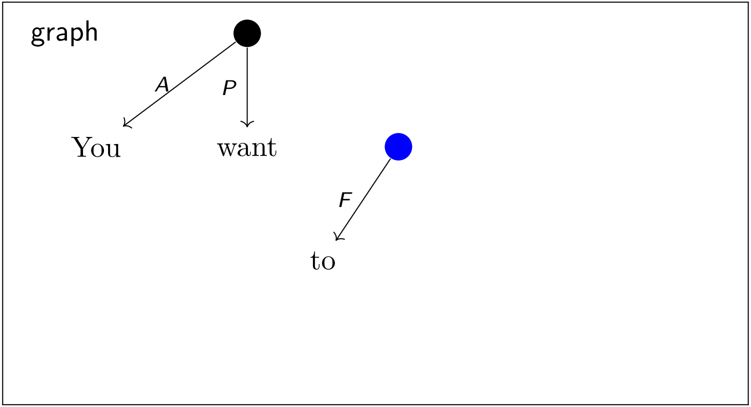


Transition-Based UCCA Parsing

⇒ Reduce

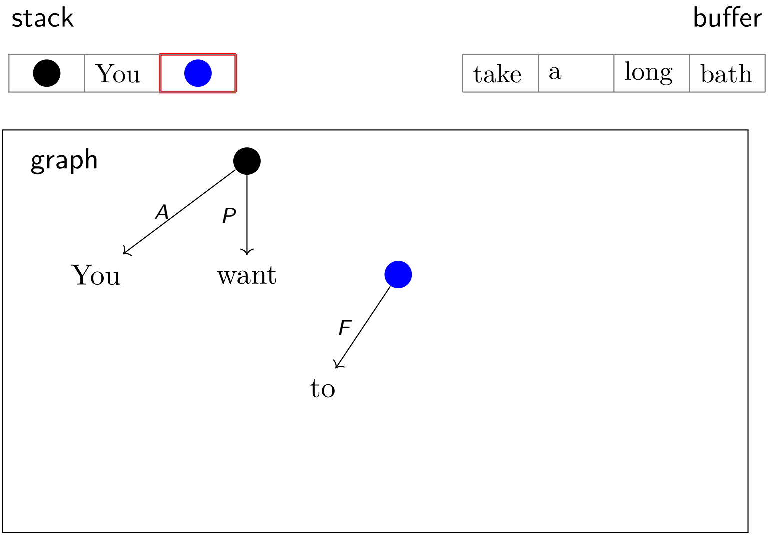
stack	
●	You

buffer				
●	take	a	long	bath



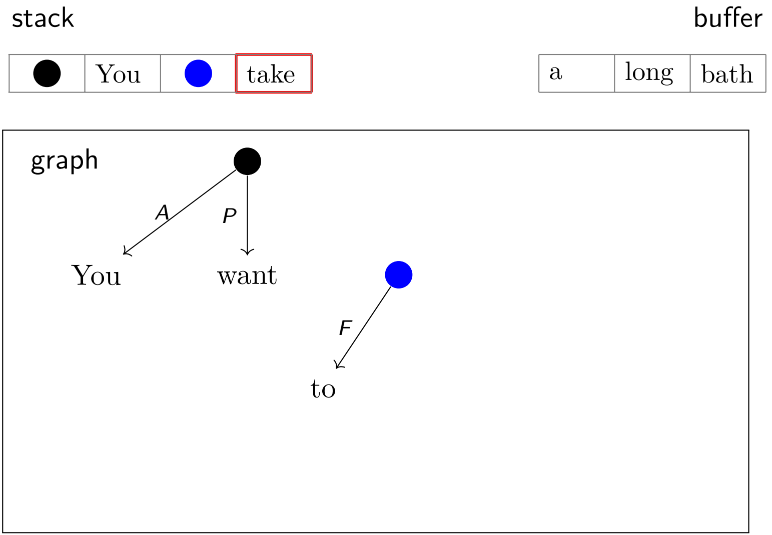
Transition-Based UCCA Parsing

⇒ Shift



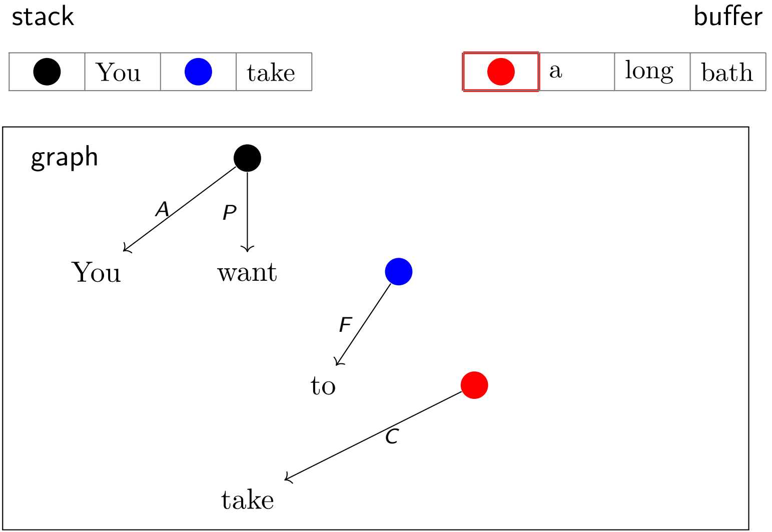
Transition-Based UCCA Parsing

$\Rightarrow$ SHIFT



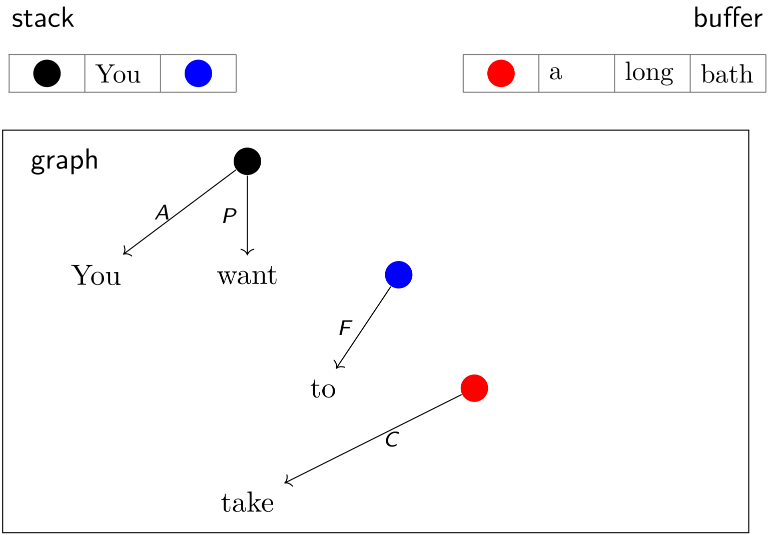
Transition-Based UCCA Parsing

$\Rightarrow$ $\textsc{Node}_C$



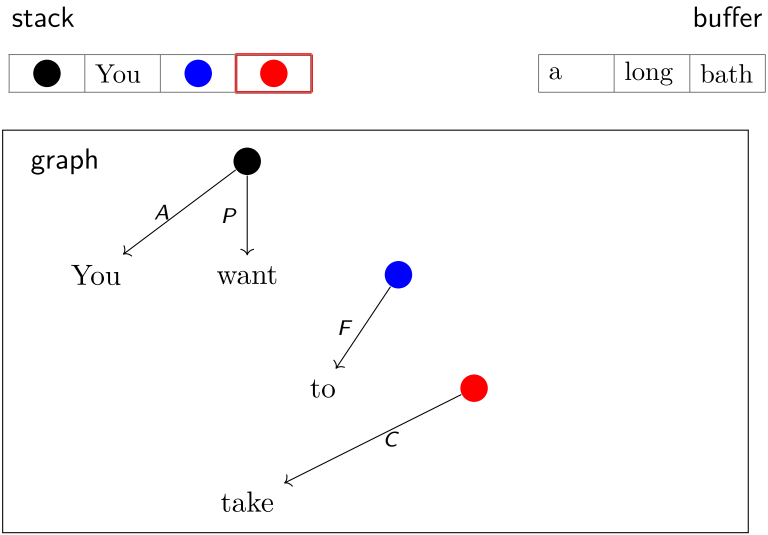
Transition-Based UCCA Parsing

⇒ REDUCE



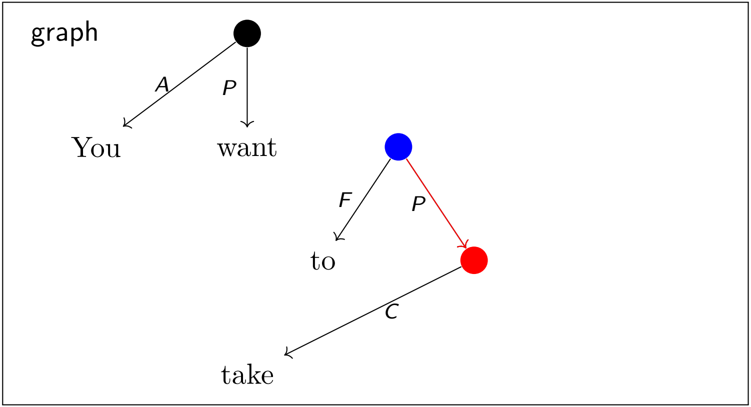
Transition-Based UCCA Parsing

⇒ Shift



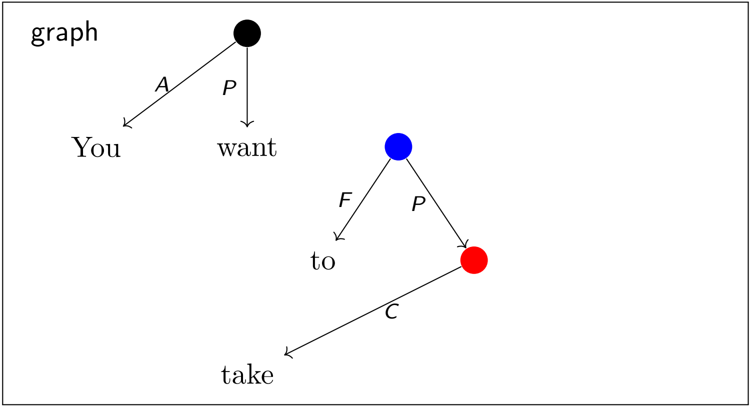
Transition-Based UCCA Parsing

⇒ RIGHT-EDGE$_{P}$



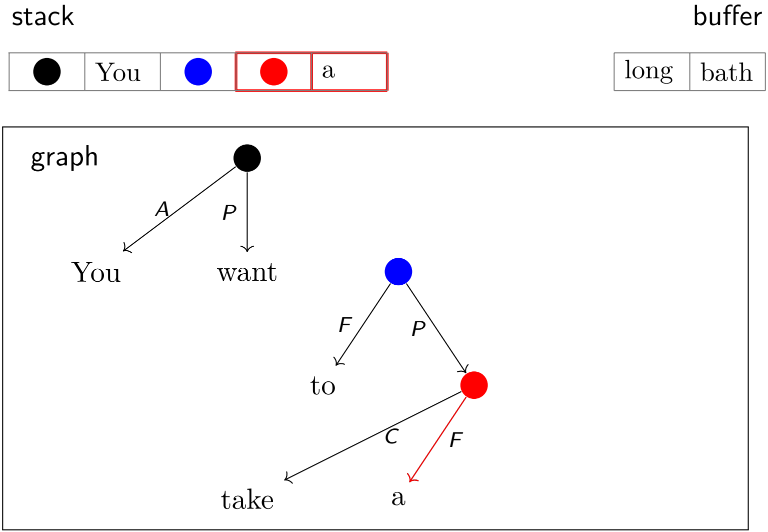
Transition-Based UCCA Parsing

$\Rightarrow$ SHIFT



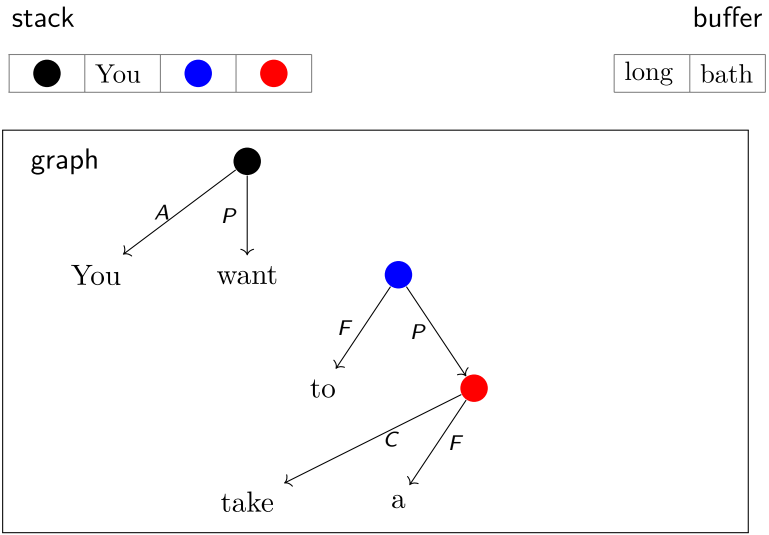
Transition-Based UCCA Parsing

⇒ RIGHT-EDGE$_F$



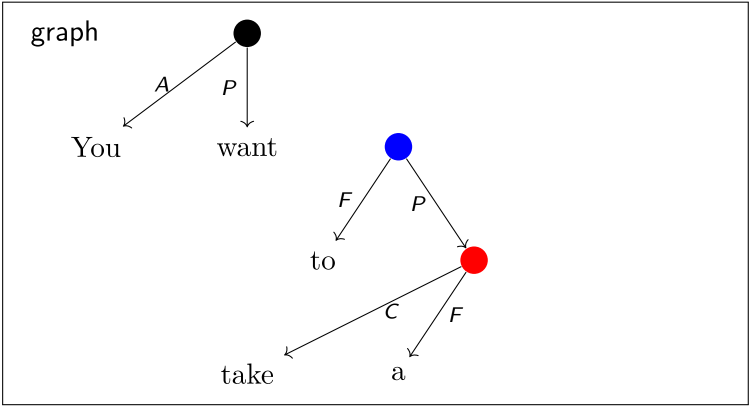
Transition-Based UCCA Parsing

$\Rightarrow$ REDUCE



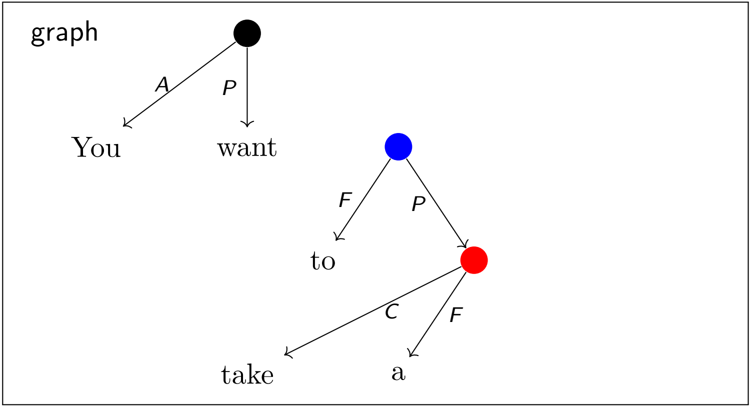
Transition-Based UCCA Parsing

⇒ SHIFT



Transition-Based UCCA Parsing

⇒ SWAP

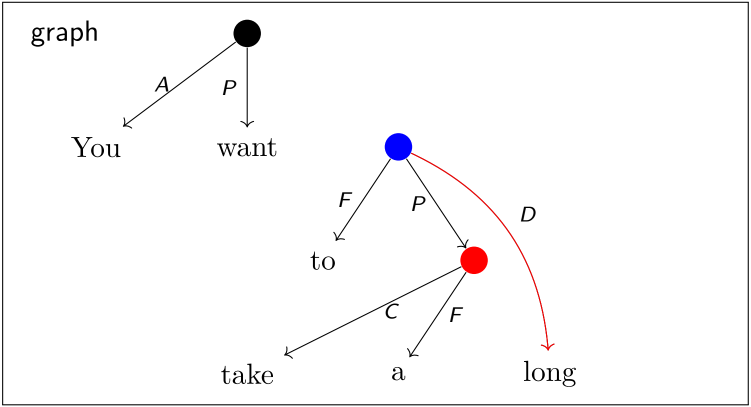


Transition-Based UCCA Parsing

⇒ RIGHT-EDGE$_{\text{D}}$

stack

buffer



Transition-Based UCCA Parsing

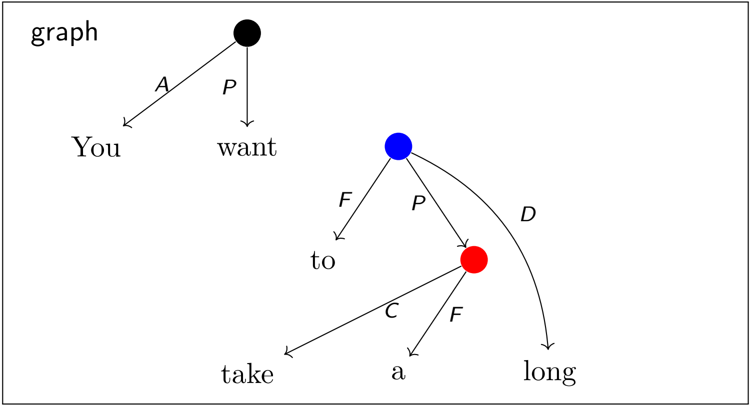
⇒ REDUCE

stack

●	You	●

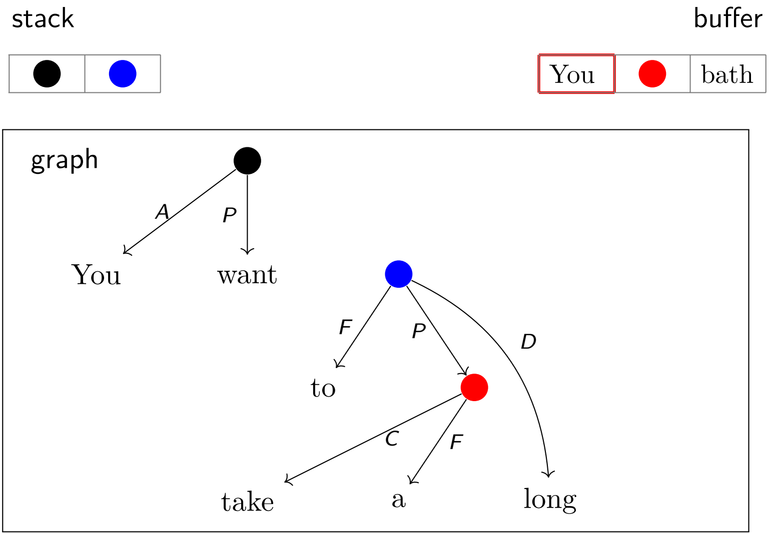
buffer

●	bath



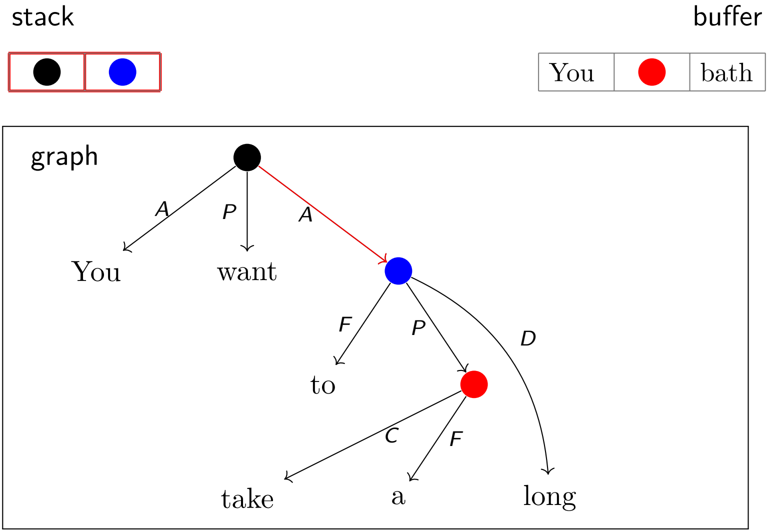
Transition-Based UCCA Parsing

$\Rightarrow$ SWAP



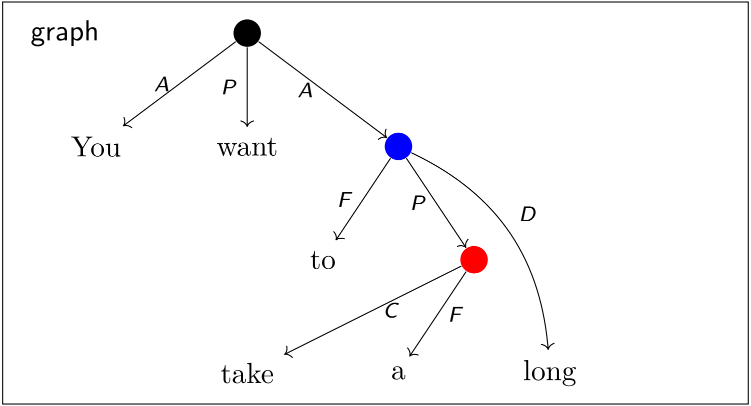
Transition-Based UCCA Parsing

$\Rightarrow$ RIGHT-EDGE$_{\text{A}}$



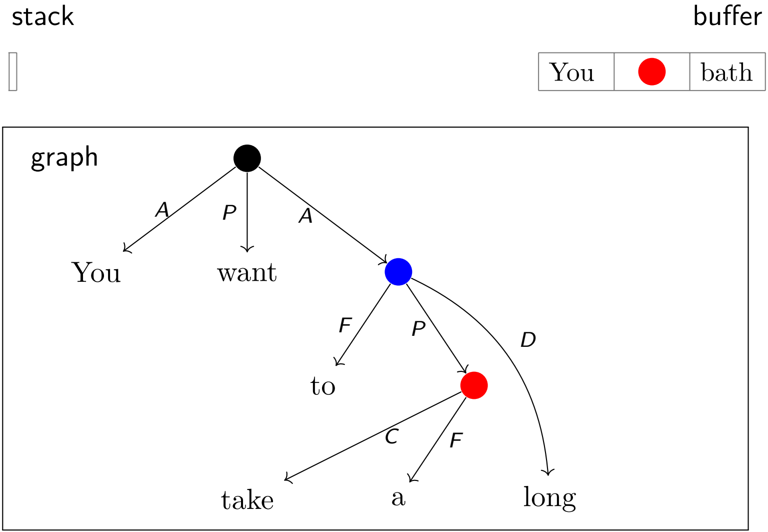
Transition-Based UCCA Parsing

⇒ REDUCE



Transition-Based UCCA Parsing

⇒ Reduce



Transition-Based UCCA Parsing

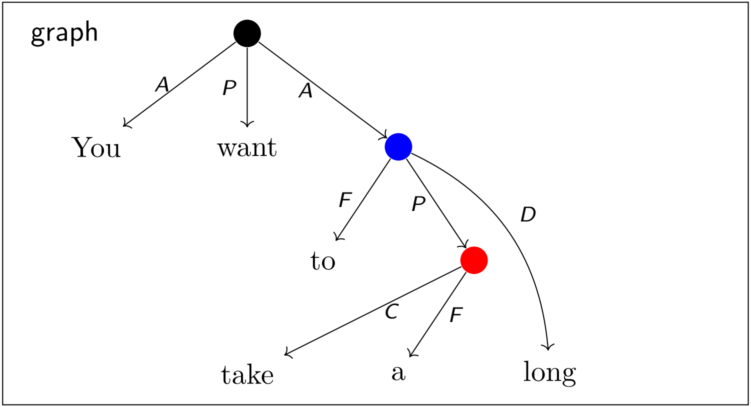
⇒ SHIFT

stack

You

buffer

bath



Transition-Based UCCA Parsing

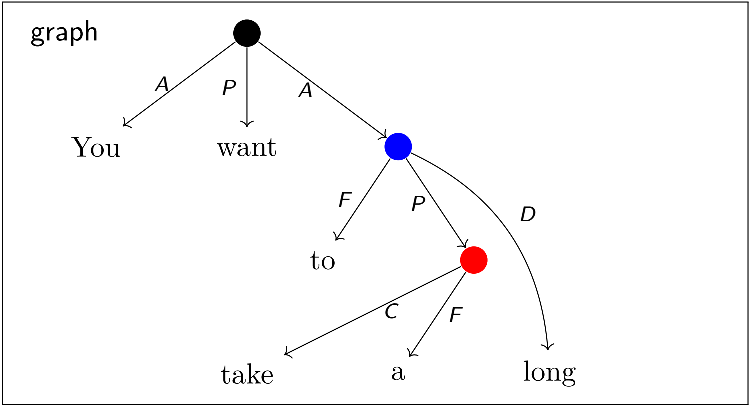
⇒ SHIFT

stack

You	●

buffer

bath



Transition-Based UCCA Parsing

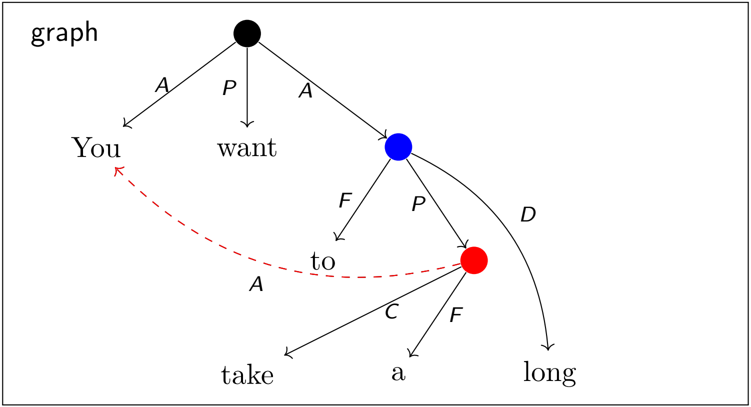
⇒ LEFT-REMOTE$_A$

stack

You	

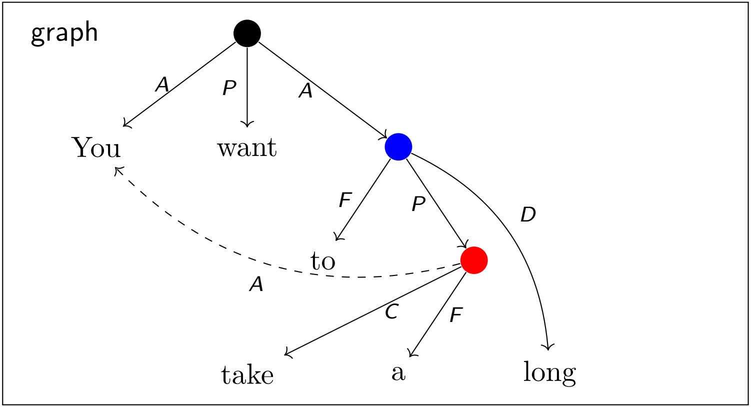
buffer

bath



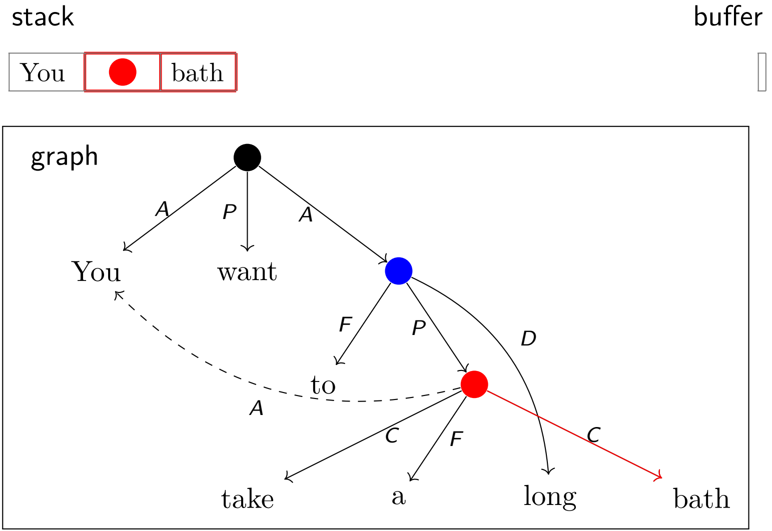
Transition-Based UCCA Parsing

⇒ Shift



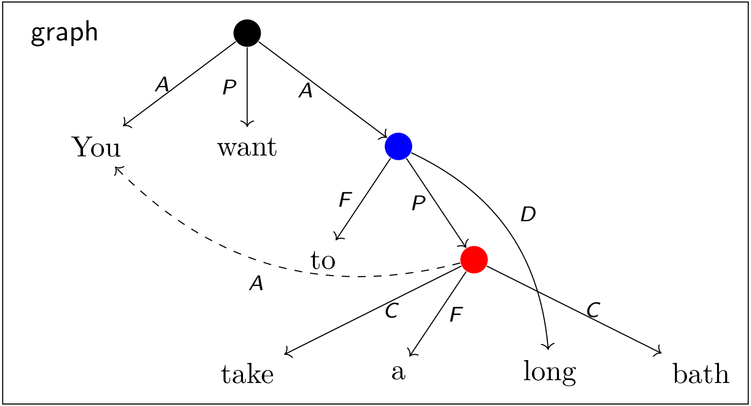
Transition-Based UCCA Parsing

⇒ RIGHT-EDGE$_C$



Transition-Based UCCA Parsing

⇒ FINISH

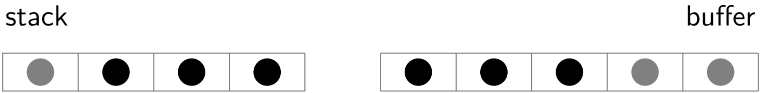


TUPA Model

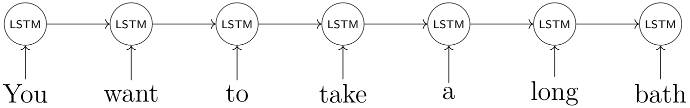
Greedy parsing, experimenting with three classifiers:

Sparse	Perceptron with sparse features.
MLP	Embeddings + feedforward NN classifier.
BiLSTM	Embeddings + deep bidirectional LSTM + MLP.

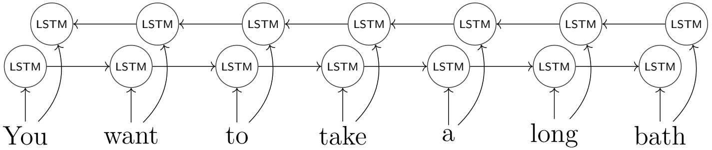
Features: words, POS, syntactic dependencies, existing edge labels from the stack and buffer + parents, children, grandchildren; ordinal features (height, number of parents and children)



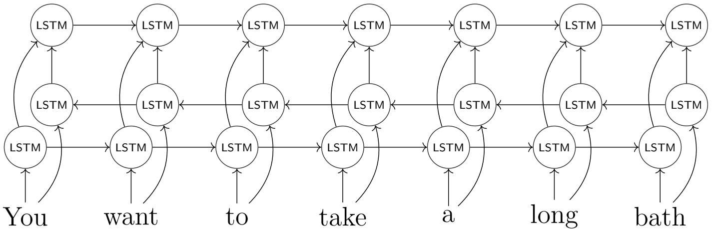
BiLSTM


LSTM
LSTM
LSTM
LSTM
LSTM
LSTM
LSTM
You
want
to
take
a
long
bath

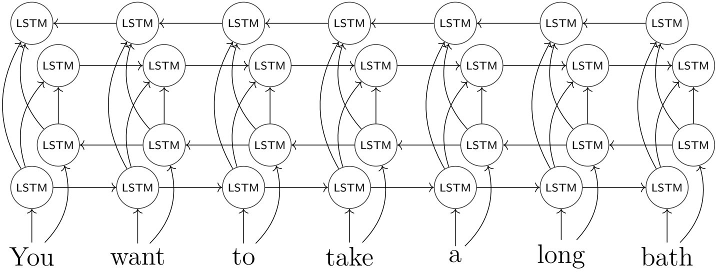
BiLSTM

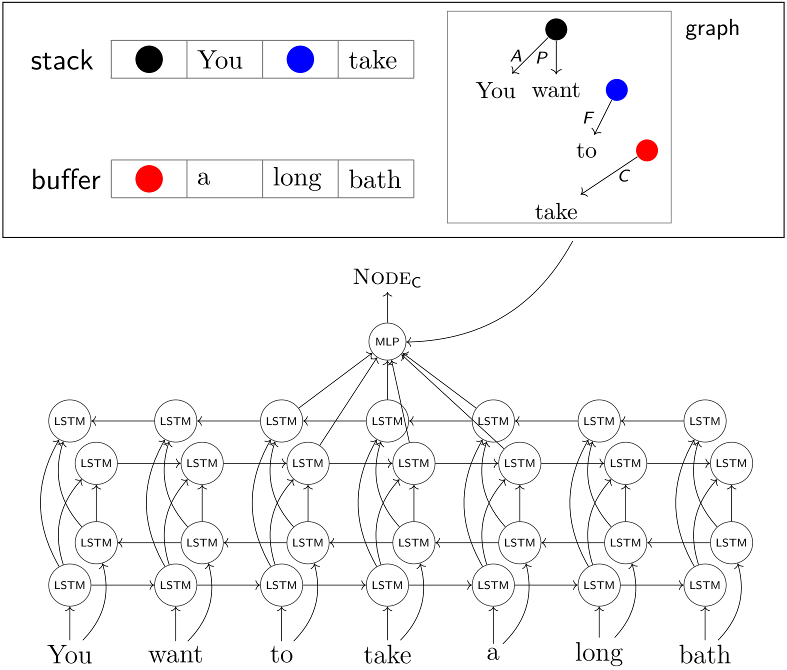


BiLSTM



BiLSTM

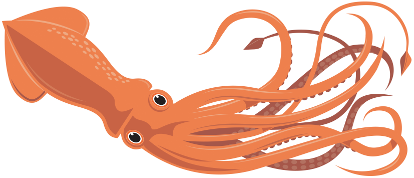




stack
You
take
buffer
a
long
bath
graph
A
P
You
want
F
to
C
take
NODE$_C$
MLP
LSTM
You
want
to
take
a
long
bath

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).



Results

	Primary			Remote		
	LP	**LR**	**LF**	**LP**	**LR**	**LF**
Sparse	64.5	63.7	64.1	19.8	13.4	16
MLP	65.2	64.6	64.9	23.7	13.2	16.9
BiLSTM	74.4	72.7	**73.5**	47.4	51.6	**49.4**

Results on the Wiki test set.

Results

	Primary			Remote		
	LP	**LR**	**LF**	**LP**	**LR**	**LF**
Sparse	64.5	63.7	64.1	19.8	13.4	16
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Results on the Wiki test set.

	Primary			Remote		
	LP	**LR**	**LF**	**LP**	**LR**	**LF**
Sparse	59.6	59.9	59.8	22.2	7.7	11.5
MLP	62.3	62.6	62.5	20.9	6.3	9.7
BiLSTM	68.7	68.5	**68.6**	38.6	18.8	**25.3**

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

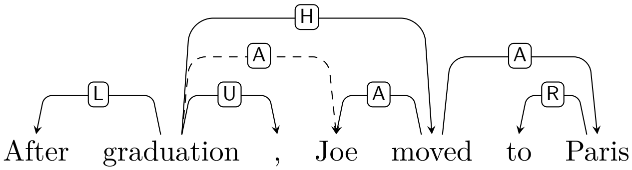
Baselines

Bilexical DAG parsers:

- 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.
- UPARSE (Maier, 2015): allows non-terminals, discontinuity.



Bilexical DAG approximation.

Results

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

	Primary			Remote		
	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	–	–	–
LSTM Parser	73.2	66.9	69.9	–	–	–
Tree			(100)			–
UPARSE	60.9	61.2	61.1	–	–	–

Results on the Wiki test set.

Results

Similar on out-of-domain test set:

	Primary			Remote		
	LP	**LR**	**LF**	**LP**	**LR**	**LF**
$\text{TUPA}_{\text{Sparse}}$	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
$\text{TUPA}_{\text{BiLSTM}}$	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	–	–	–
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 challenging structural properties.
- TUPA is a transition-based parser suitable for UCCA, achieving high accuracy with BiLSTM model.
- Outperforms conversion-based parsing with a variety of strong bilexical DAG and tree baselines.

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

Conclusion

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Future Work:

- More languages (German corpus construction is underway).
- Parsing other schemes, such as AMR.
- Application to text simplification and other tasks.

Corpora: `http://www.cs.huji.ac.il/~oabend/ucca.html`
Code: `https://github.com/danielhers/tupa`
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Thank you

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UCCA Corpora

	Wiki			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 $W = \{w_1, \ldots, w_n\}$:

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

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:

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

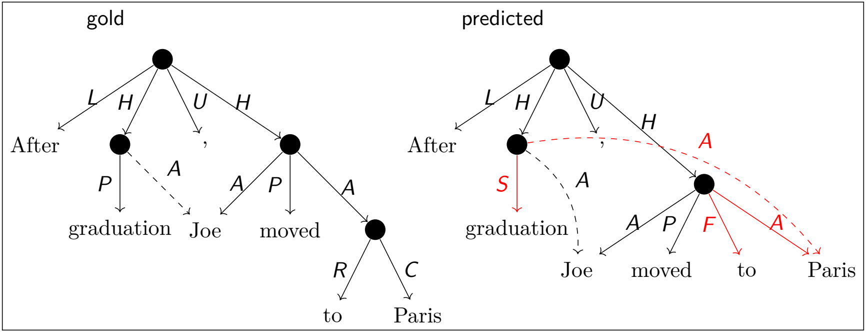
$$\mathrm{LF} = \frac{2 \cdot \mathrm{LP} \cdot \mathrm{LR}}{\mathrm{LP} + \mathrm{LR}}.$$

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

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%