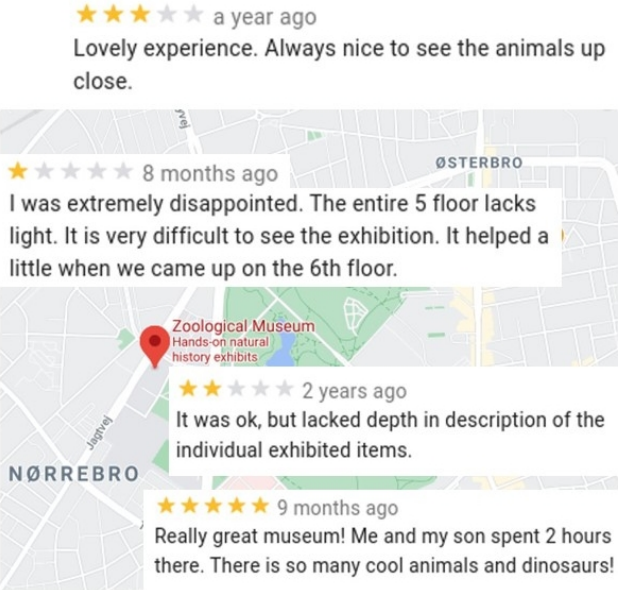
Meaning Representation and Parsing in Natural Language Processing

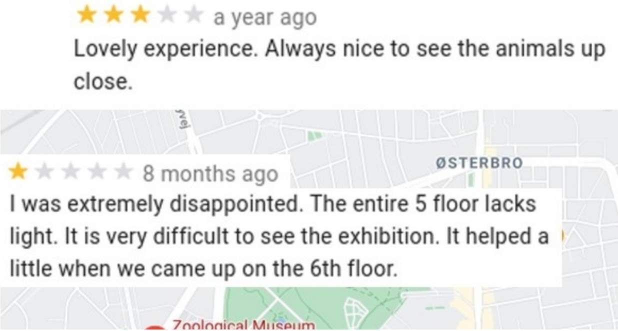
Daniel Hershcovich

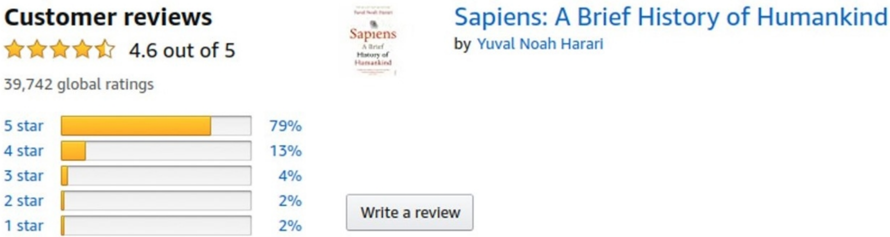
IFRO
4 May 2021

Sentiment Classification

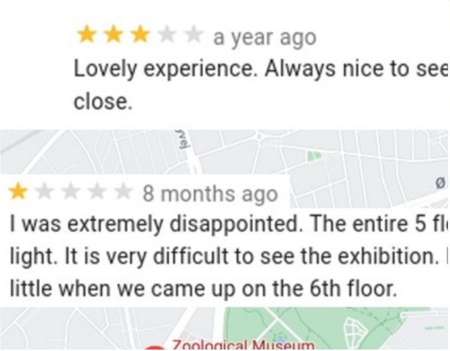


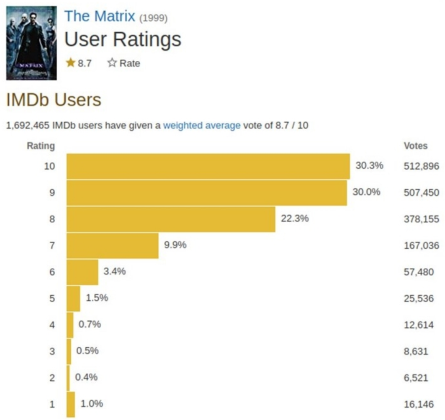
Sentiment Classification





Sentiment Classification





Semantic Parsing

- How long do visitors typically stay?

Semantic Parsing

- How long do visitors typically stay?
- Do people typically come with their kids?

Semantic Parsing

- How long do visitors typically stay?
- Do people typically come with their kids?
- Are there more boys or girls visiting?

Semantic Parsing

- How long do visitors typically stay?
- Do people typically come with their kids?
- Are there more boys or girls visiting?
- Do visitors with kids spend more time there?

Semantic Parsing

- How long do visitors typically stay?
- Do people typically come with their kids?
- Are there more boys or girls visiting?
- Do visitors with kids spend more time there?

Me and my son spent 2 hours there.

Participants Action Time Location

Scaling Up Qualitative Studies

FORMS INTERVIEWS AI

What can we teach computers to do with language?

Translate:

Dave Grossman and Jack Thompson argue that violent games are harmful

↓

Dave Grossman og Jack Thompson hævder, at voldsomme spil er skadelige

Recognize entities:

Dave Grossman and Jack Thompson argue that violent games are harmful

Infer:

Violence in games hardens children to unethical acts

↓ entails

Violent games are harmful

What can we teach computers to do with language?

Translate:

Dave Grossman and Jack Thompson argue that violent games are harmful

↓

Dave Grossman og Jack Thompson hævder, at voldsomme spil er skadelige

Recognize entities:

Dave Grossman and Jack Thompson argue that violent games are harmful

Infer:

Violence in games hardens children to unethical acts

↓ entails

Violent games are harmful

What can we teach computers to do with language?

Translate:

Dave Grossman and Jack Thompson argue that violent games are harmful

↓

Dave Grossman og Jack Thompson hævder, at voldsomme spil er skadelige

Recognize entities:

<u>Dave Grossman</u> and <u>Jack Thompson</u> argue that violent games are harmful

Infer:

Violence in games hardens children to unethical acts

↓ entails

Violent games are harmful

What can we teach computers to do with language?

Translate:

Dave Grossman and Jack Thompson argue that violent games are harmful

↓

Dave Grossman og Jack Thompson hævder, at voldsomme spil er skadelige

Recognize entities:

Dave Grossman and Jack Thompson argue that violent games are harmful

Infer:

Violence in games hardens children to unethical acts

↓ entails

Violent games are harmful

IBM Debater

AI system that can debate humans on complex topics

	Pre-debate: both sides receive the motion and prepare	15 min
	Moderator introduces the motion to the audience	
Opening speeches	Project Debater delivers the ‘government’ opening speech	4 min
	Human debater delivers the ‘opposition’ opening speech and replies	4 min
Second speeches	Project Debater offers rebuttal and additional points	4 min
	Human debater offers rebuttal and additional points	4 min
Summary speeches	Project Debater provides final rebuttal and closing statements	2 min
	Human debater provides final rebuttal and closing statements	2 min

Slonim et al. **“An autonomous debating system.”** *Nature* (2021)

Learning from plain text: masked language modeling

Which Sesame Street $\boxed{\textcolor{red}{?}\quad\quad}$ is your favorite?

Learning from plain text: masked language modeling

Which $\boxed{\textcolor{red}{?}\quad\quad}$ Street character is your favorite?

Learning from plain text: masked language modeling

Which Sesame $\boxed{\color{red}{?}\quad}$ character is your favorite?

Learning from plain text: masked language modeling

$\boxed{\textcolor{red}{?}\quad\quad}$ Sesame Street character is your favorite?

Learning from plain text: masked language modeling

Which Sesame Street character $\boxed{\textbf{?}}$ your favorite?

Learning from plain text: masked language modeling

Which Sesame Street character is $\boxed{\textcolor{red}{?}\quad}$ favorite?

Learning from plain text: masked language modeling

Which Sesame Street character is your $\boxed{\textcolor{red}{?}\quad\quad}$?

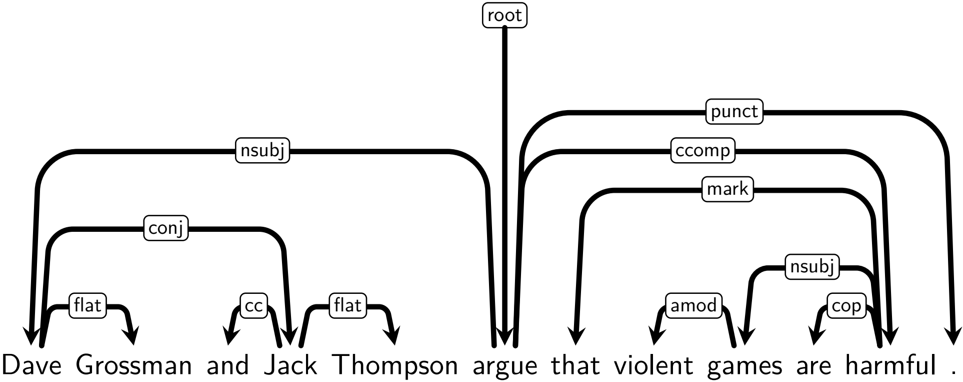
Learning from plain text: masked language modeling

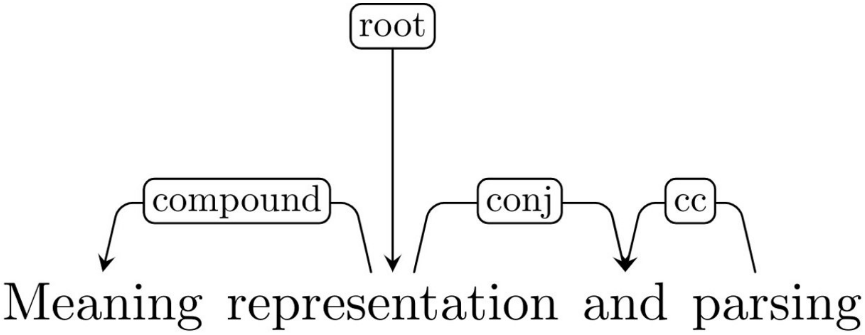
Which Sesame Street character is your favorite?

BERT, RoBERTa, XLM-R, ...
GPT, GPT-2, GPT-3

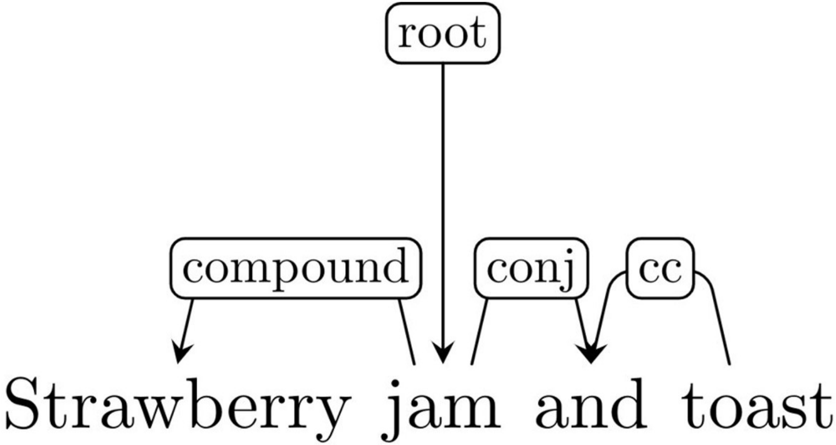
What can we teach computers to do with language?

Identify relations between concepts (**parsing**, various frameworks):




root
compound
conj
cc
Meaning representation and parsing

Dependency Parsing



Breaking It Down

[Meaning], [Representation] and [Parsing]
1. What we mean, 2. How to represent (something), 3. How to parse (something)

or

[Meaning Representation] and [Parsing]
1. How to represent what we mean, 2. How to parse (something)

or

[Meaning [Representation and Parsing]]
1. How to represent what we mean, 2. How to parse what we mean

or

[Meaning Representation] and [Parsing *(to Meaning Representation)*]
1. How to represent what we mean, 2. How to parse (1)

Breaking It Down

[Meaning], [Representation] and [Parsing]
1. What we mean, 2. How to represent (something), 3. How to parse (something)

or

[Meaning Representation] and [Parsing]
1. How to represent what we mean, 2. How to parse (something)

or

[Meaning [Representation and Parsing]]
1. How to represent what we mean, 2. How to parse what we mean

or

[Meaning Representation] and [Parsing *(to Meaning Representation)*]
1. How to represent what we mean, 2. How to parse (1)

Breaking It Down

[Meaning], [Representation] and [Parsing]
1. What we mean, 2. How to represent (something), 3. How to parse (something)

or

[Meaning Representation] and [Parsing]
1. How to represent what we mean, 2. How to parse (something)

or

[Meaning [Representation and Parsing]]
1. How to represent what we mean, 2. How to parse what we mean

or

[Meaning Representation] and [Parsing *(to Meaning Representation)*]
1. How to represent what we mean, 2. How to parse (1)

Breaking It Down

[Meaning], [Representation] and [Parsing]
1. What we mean, 2. How to represent (something), 3. How to parse (something)

or

[Meaning Representation] and [Parsing]
1. How to represent what we mean, 2. How to parse (something)

or

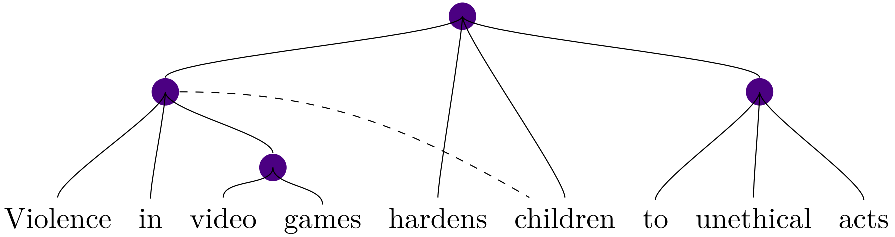
[Meaning [Representation and Parsing]]
1. How to represent what we mean, 2. How to parse what we mean

or

[Meaning Representation] and [Parsing *(to Meaning Representation)*]
1. How to represent what we mean, 2. How to parse (1)

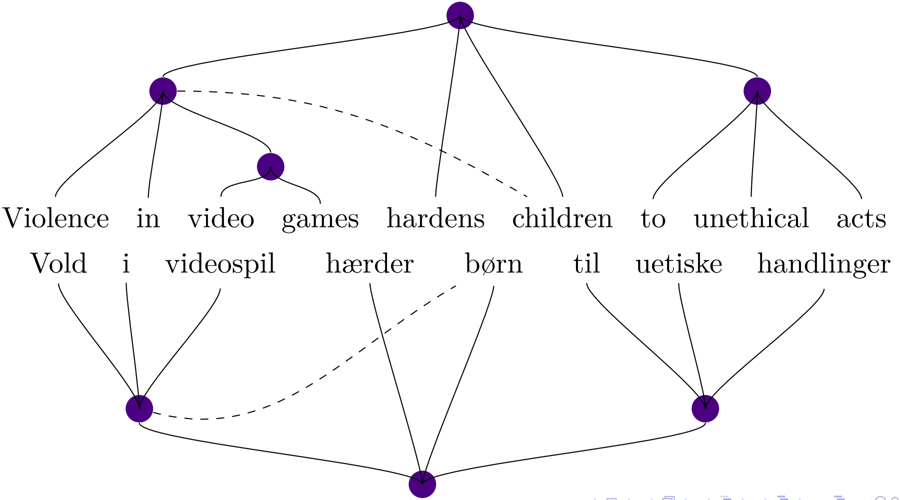
Meaning Representation Graphs

Abend and Rappoport. **"Universal Conceptual Cognitive Annotation (UCCA)"**. *ACL* (2013)

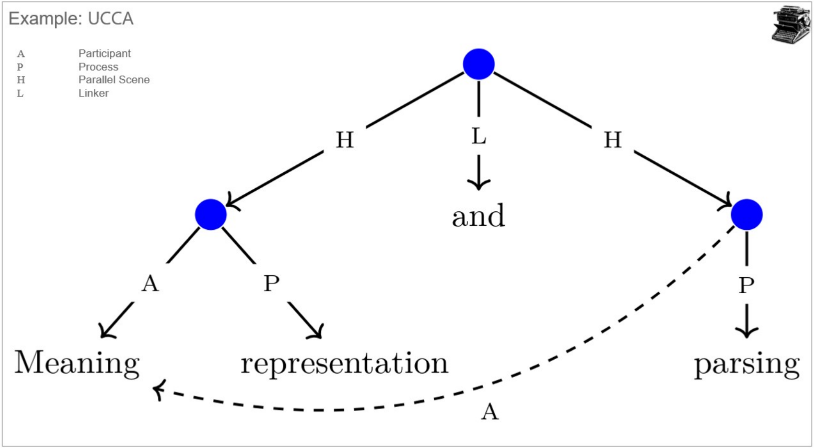


Meaning Representation Graphs

Abend and Rappoport. **"Universal Conceptual Cognitive Annotation (UCCA)"**. *ACL* (2013)



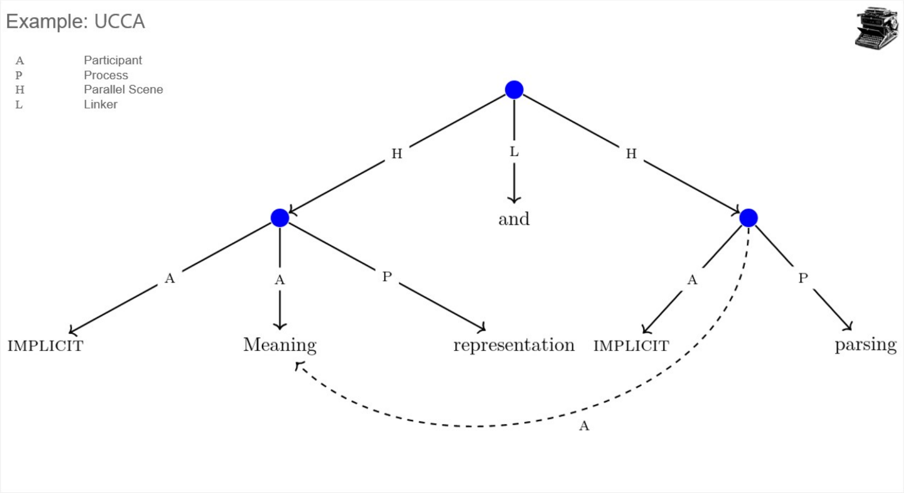
Meaning Representation Graphs



Hershcovich et al. **"Content Differences in Syntactic and Semantic Representations"**. *NAACL* (2019)

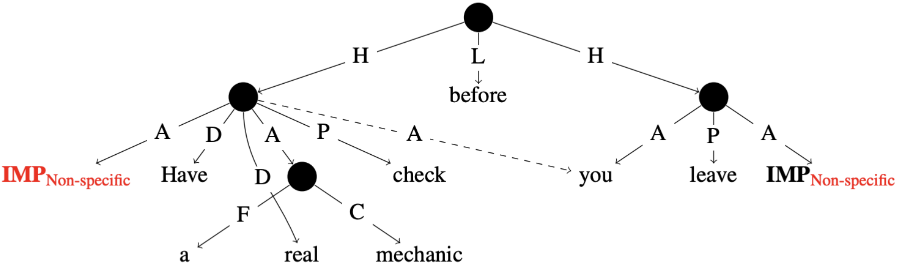
Hershcovich et al. **"Comparison by Conversion: Reverse-Engineering UCCA from Syntax and Lexical Semantics"**. *COLING* (2020)

Implicit Elements



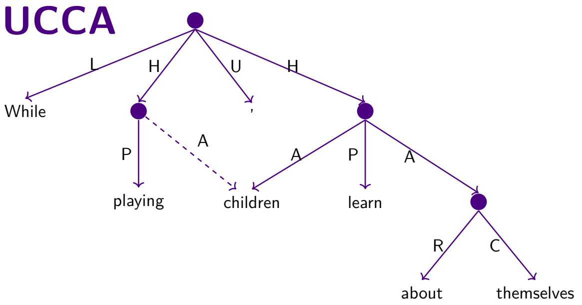
Cui and Hershcovich. **“Refining Implicit Argument Annotation for UCCA.”** *DMR* (2020)

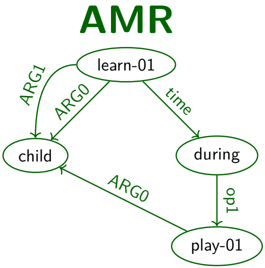
Implicit Elements

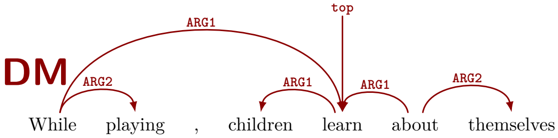


Cui and Hershcovich. **"Refining Implicit Argument Annotation for UCCA."** *DMR* (2020)

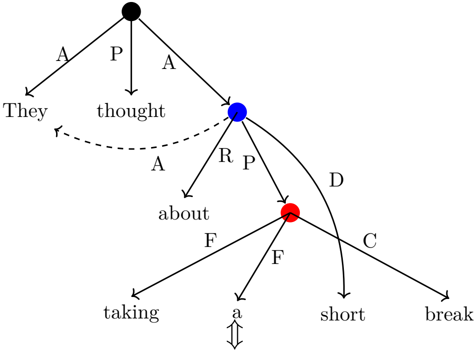
Different Frameworks to Represent Meaning







Parsing



SHIFT, RIGHT-EDGE$_A$, SHIFT, SWAP, RIGHT-EDGE$_P$, REDUCE, SHIFT, SHIFT, NODE$_R$, REDUCE, LEFT-REMOTE$_A$, 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, REDUCE, SHIFT, RIGHT-EDGE$_C$, FINISH

Hershcovich et al. **"A Transition-Based Directed Acyclic Graph Parser for UCCA"**. *ACL* (2017)

TUPA: Transition-based UCCA Parser

Parses text to graph incrementally by applying transitions to its state.

TUPA: Transition-based UCCA Parser

Parses text to graph incrementally by applying transitions to its state.

Initial state:

stack ●

buffer

They	thought	about	taking	a	short	break

TUPA: Transition-based UCCA Parser

Parses text to graph incrementally by applying transitions to its state.

Initial state:

stack

●

buffer

They	thought	about	taking	a	short	break

Transitions:

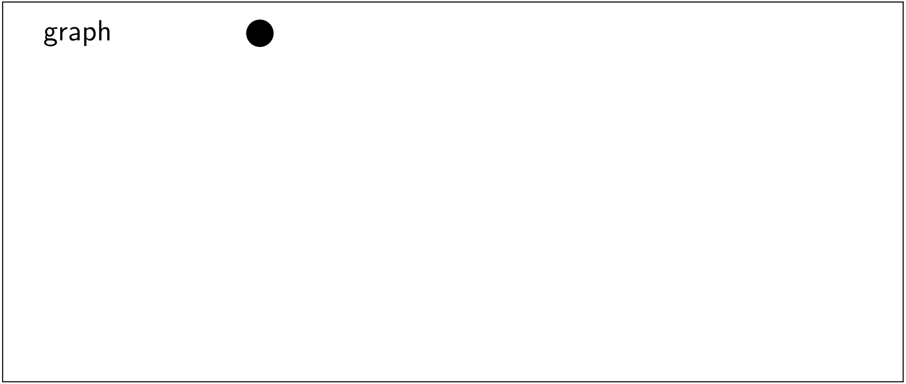
{SHIFT, REDUCE, NODE$_X$, LEFT-EDGE$_X$, RIGHT-EDGE$_X$, LEFT-REMOTE$_X$, RIGHT-REMOTE$_X$, SWAP, FINISH}

Example: TUPA Transition Sequence

⇒ Shift

stack | | | buffer

●	They	thought	about	taking	a	short	break



Example: TUPA Transition Sequence

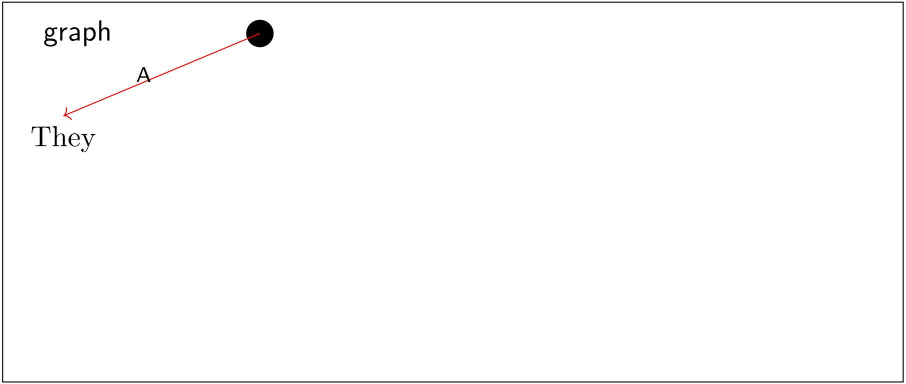
$\Rightarrow$ Right-Edge$_A$

stack

●	They

buffer

thought	about	taking	a	short	break



Example: TUPA Transition Sequence

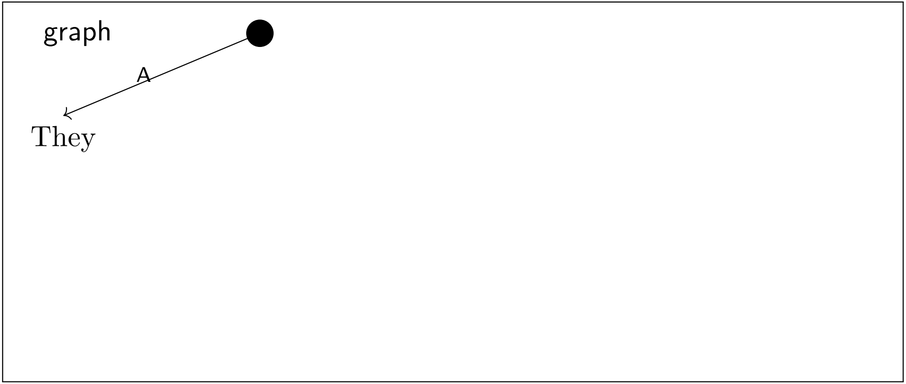
⇒ Shift

stack

●	They	thought

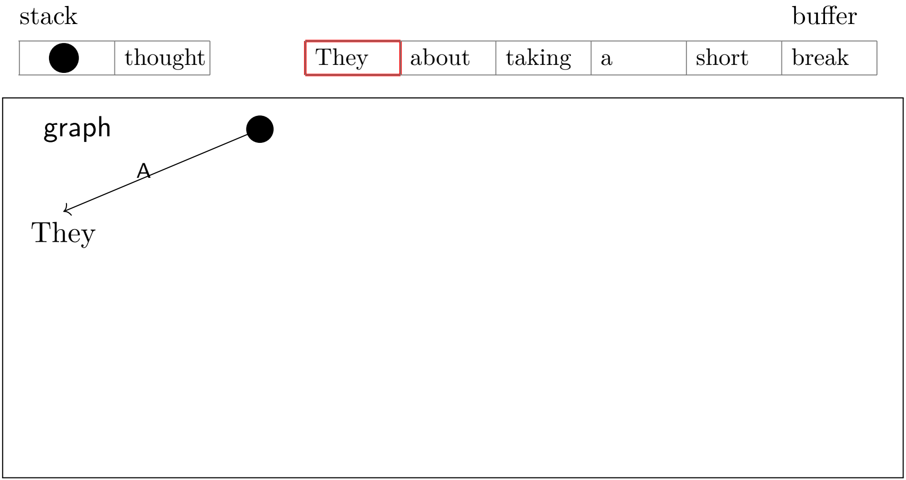
buffer

about	taking	a	short	break



Example: TUPA Transition Sequence

⇒ SWAP



Example: TUPA Transition Sequence

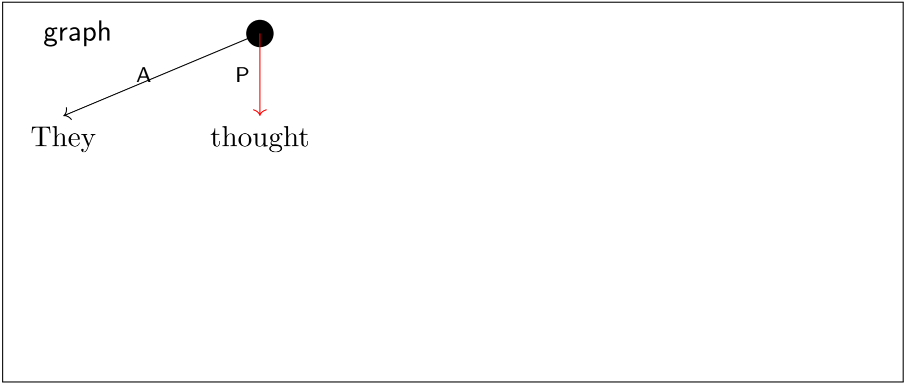
$\Rightarrow$ RIGHT-EDGE$_P$

stack

●	thought

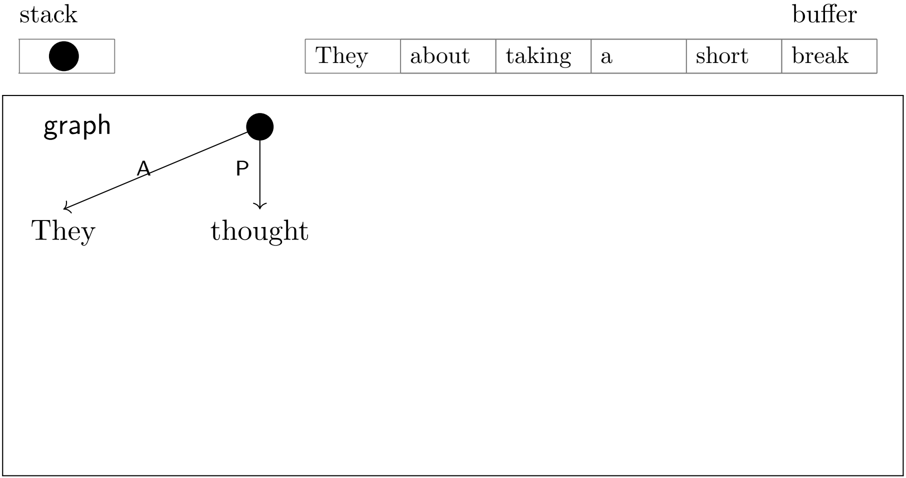
buffer

They	about	taking	a	short	break



Example: TUPA Transition Sequence

⇒ REDUCE



Example: TUPA Transition Sequence

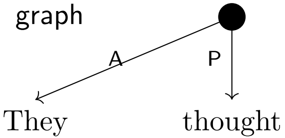
⇒ SHIFT

stack

●	They

buffer

about	taking	a	short	break

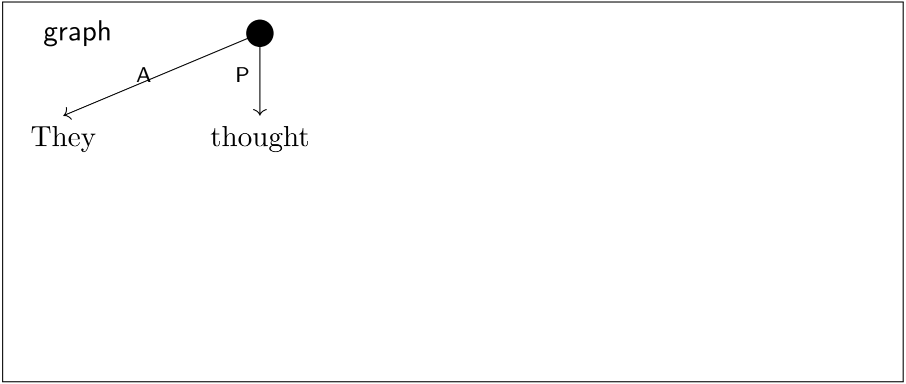


Example: TUPA Transition Sequence

⇒ SHIFT

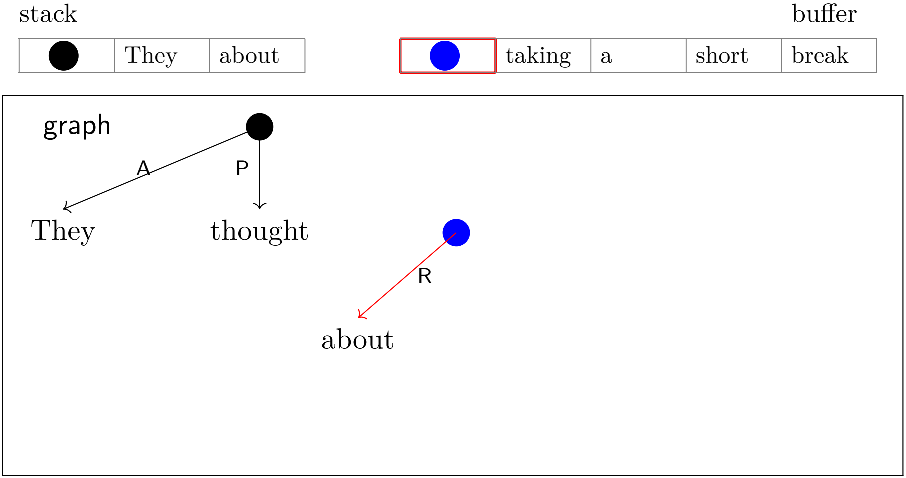
stack		
●	They	about

			buffer
taking	a	short	break



Example: TUPA Transition Sequence

$\Rightarrow$ NODE$_R$



Example: TUPA Transition Sequence

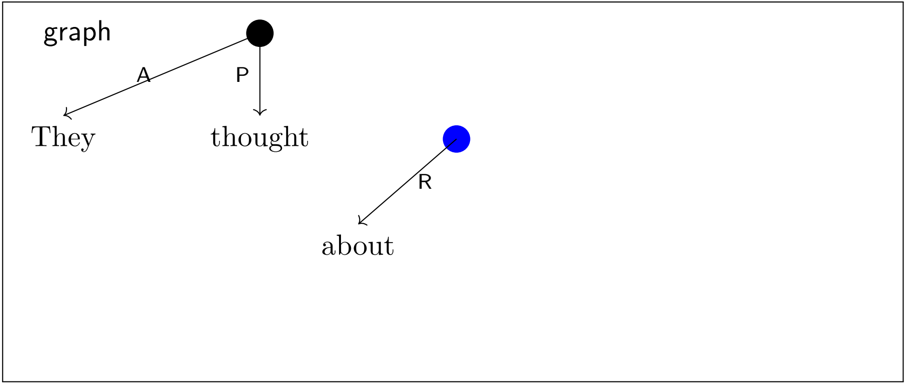
⇒ REDUCE

stack

●	They

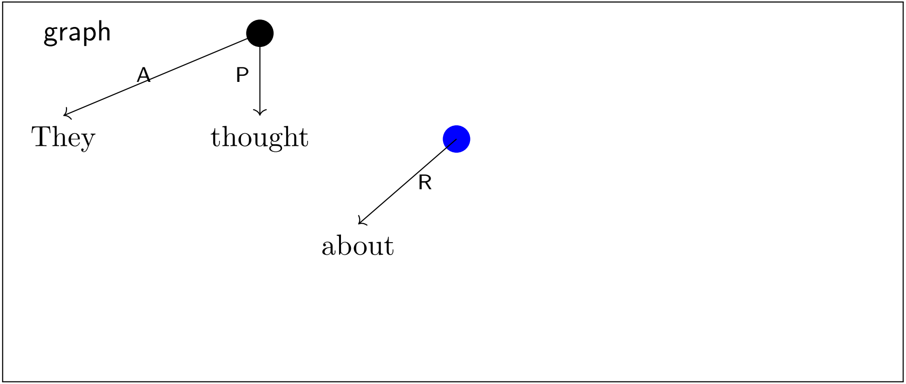
buffer

●	taking	a	short	break



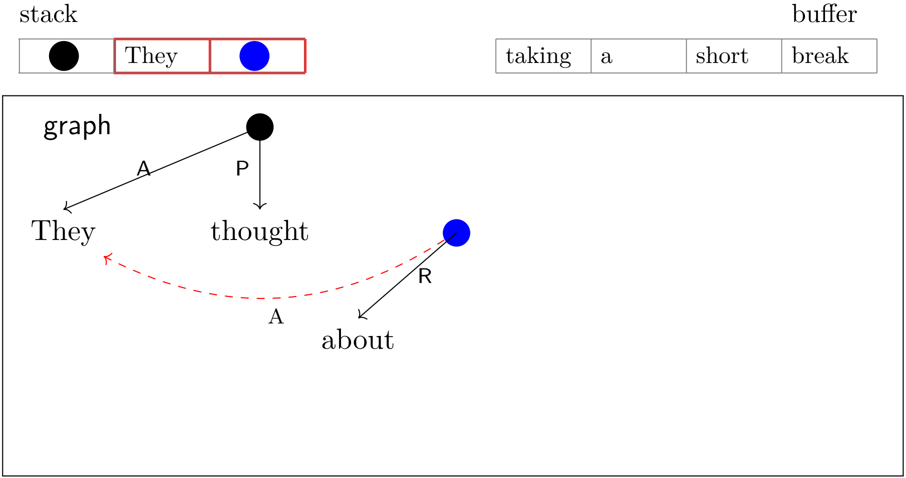
Example: TUPA Transition Sequence

⇒ SHIFT



Example: TUPA Transition Sequence

⇒ LEFT-REMOTE$_A$



Example: TUPA Transition Sequence

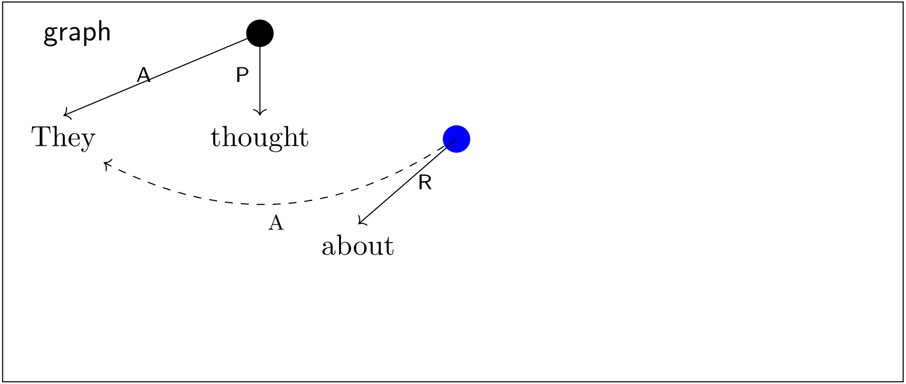
⇒ SHIFT

stack

	They		taking

buffer

a	short	break



Example: TUPA Transition Sequence

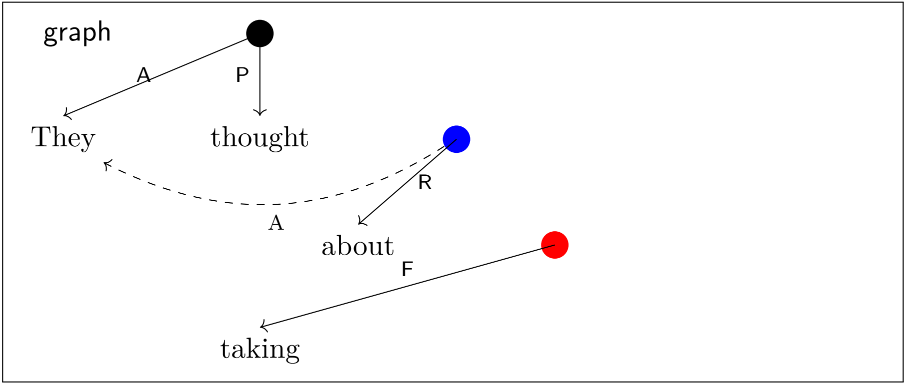
$\Rightarrow$ NODE$_C$

stack

	They		taking

buffer

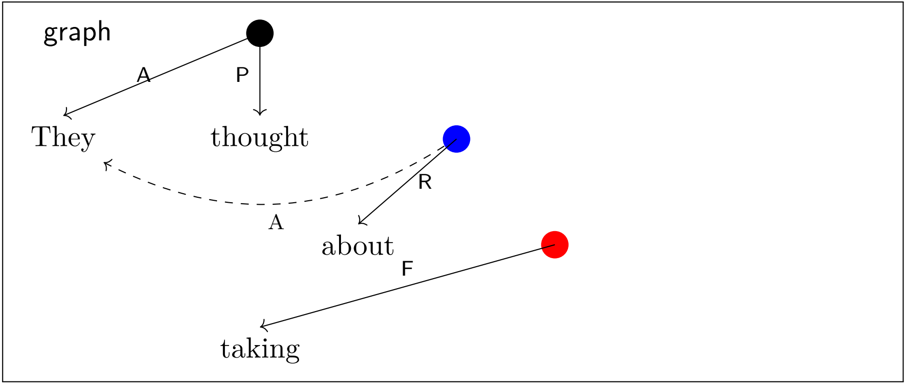
	a	short	break



⇒ REDUCE

stack

buffer



Example: TUPA Transition Sequence

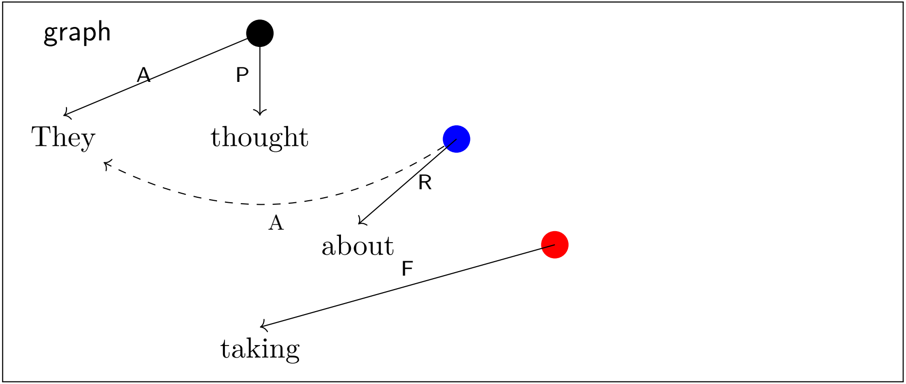
⇒ SHIFT

stack

	They		

buffer

a	short	break



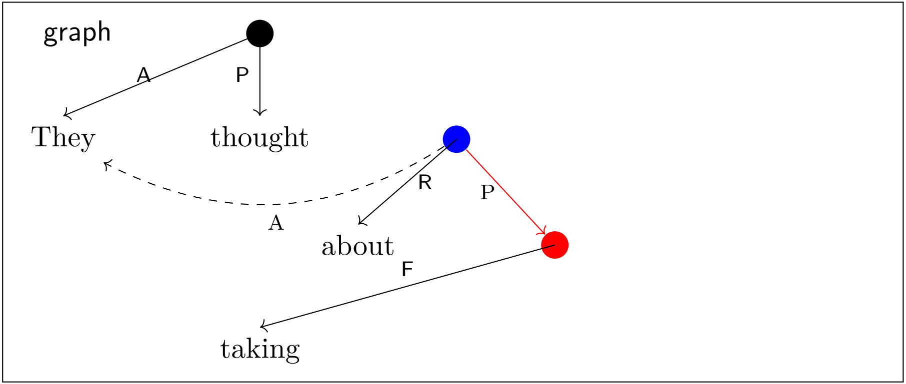
$\Rightarrow$ RIGHT-EDGE$_P$

stack

	They		

buffer

a	short	break



Example: TUPA Transition Sequence

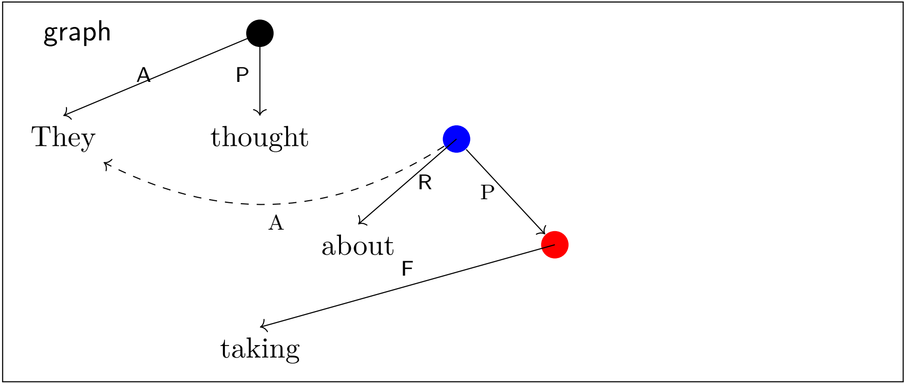
⇒ SHIFT

stack

●	They	●	●	a

buffer

short	break



Example: TUPA Transition Sequence

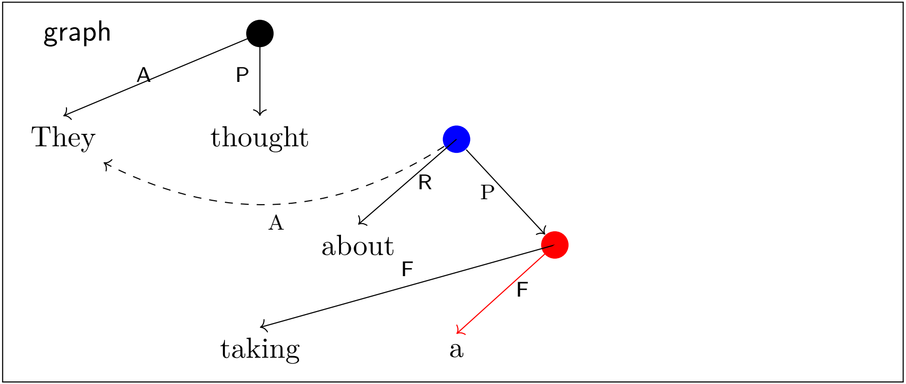
$\Rightarrow$ Right-Edge$_F$

stack

●	They	●	●	a

buffer

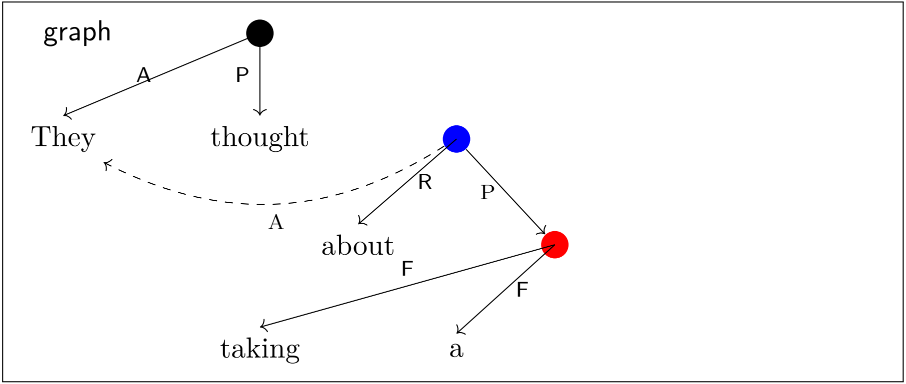
short	break



⇒ Reduce

stack			
●	They	●	●

buffer	
short	break



Example: TUPA Transition Sequence

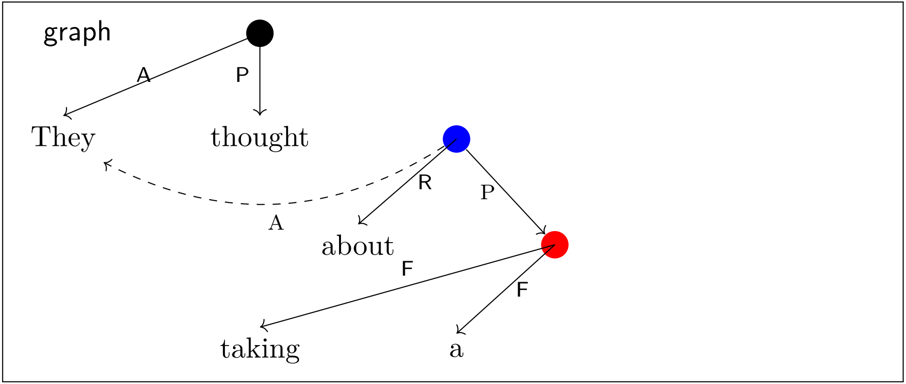
⇒ SHIFT

stack

●	They	●	●	short

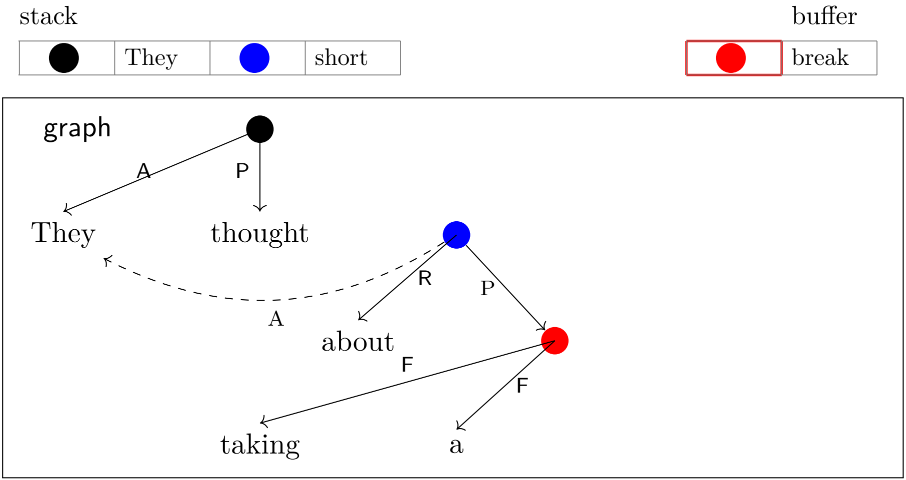
buffer

break



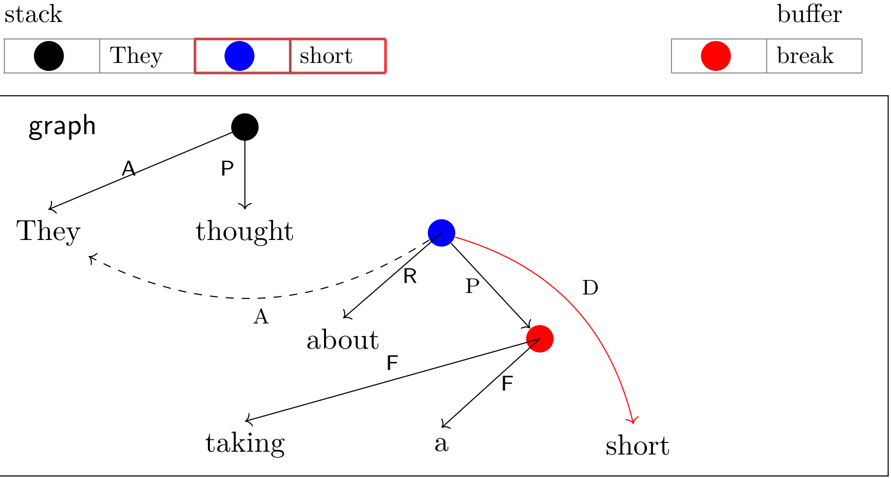
Example: TUPA Transition Sequence

$\Rightarrow$ SWAP



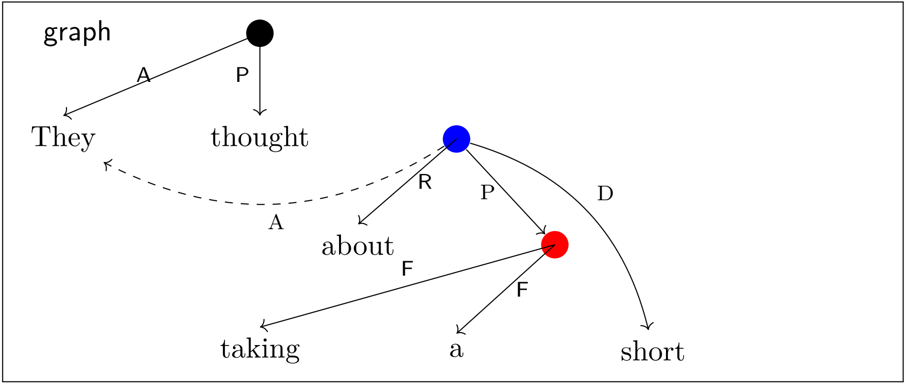
Example: TUPA Transition Sequence

⇒ RIGHT-EDGE$_D$

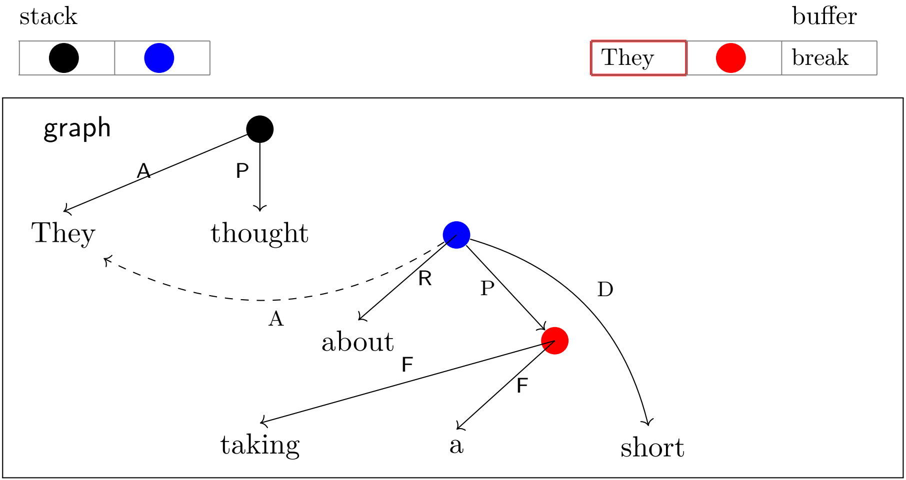


⇒ REDUCE


stack
They
buffer
break


graph
A
P
They
thought
R
P
D
A
about
F
F
taking
a
short

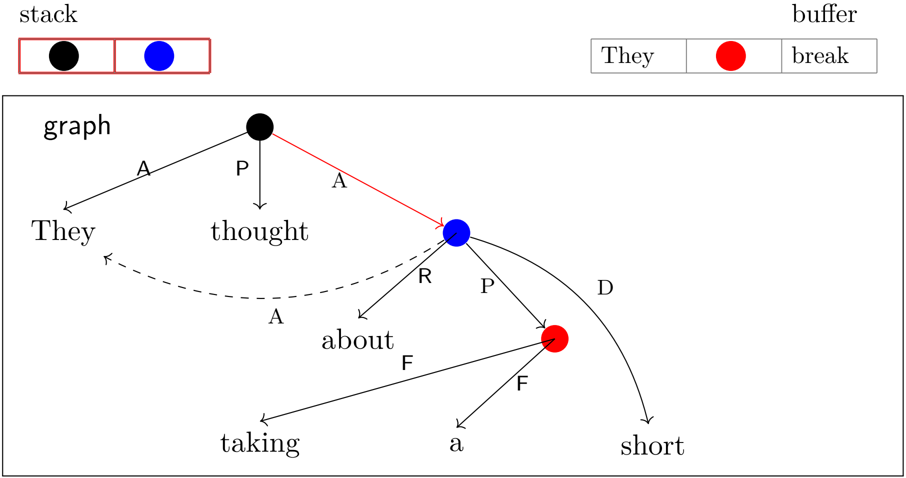
⇒ Swap



stack
buffer
They
break
graph
A
P
They
thought
R
P
D
A
about
F
F
taking
a
short

Example: TUPA Transition Sequence

$\Rightarrow$ RIGHT-EDGE$_A$

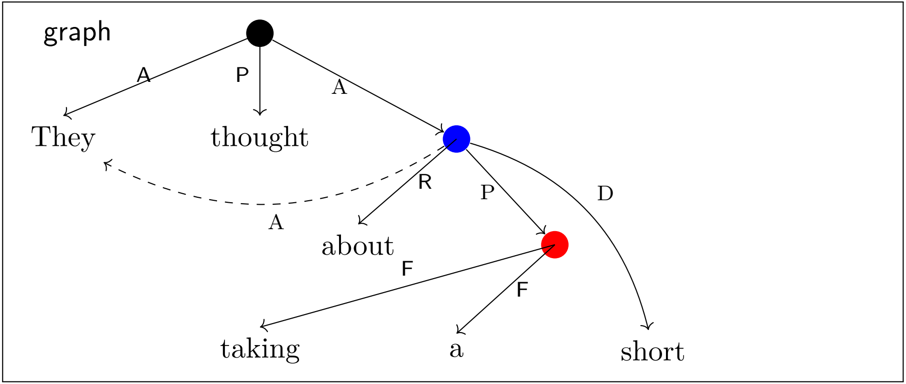


Example: TUPA Transition Sequence

⇒ Reduce

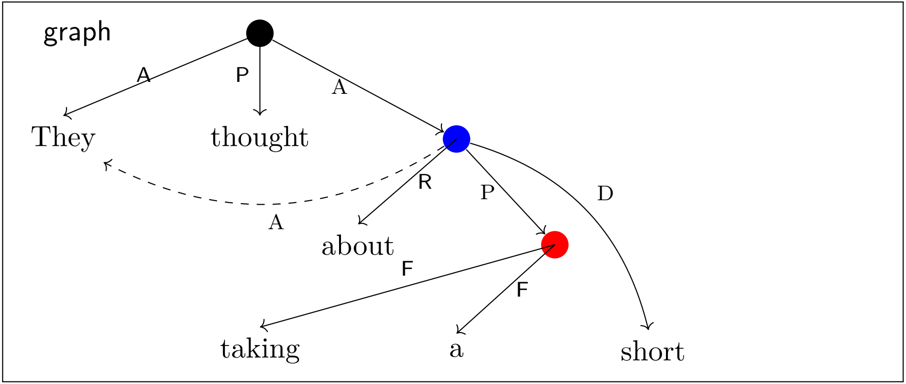
stack

buffer



Example: TUPA Transition Sequence

⇒ Reduce



Example: TUPA Transition Sequence

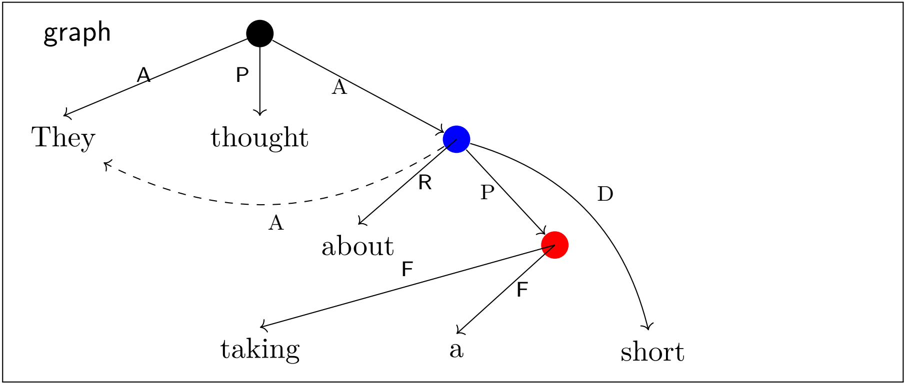
⇒ SHIFT

stack

They

buffer

●	break

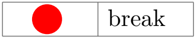


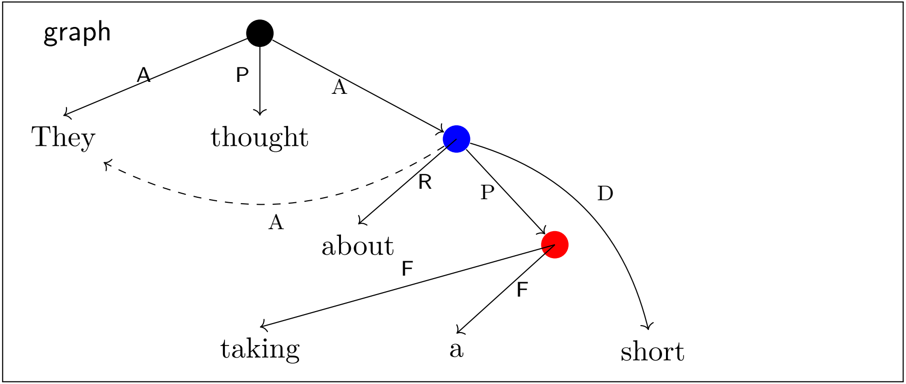
Example: TUPA Transition Sequence

⇒ REDUCE

stack

buffer





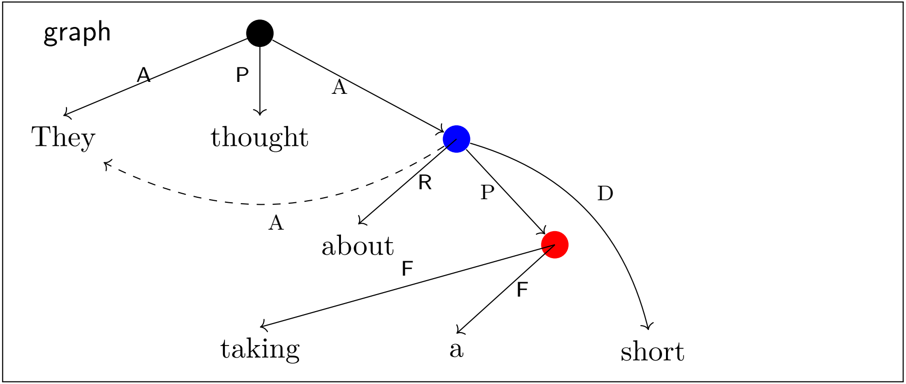
Example: TUPA Transition Sequence

⇒ Shift

stack

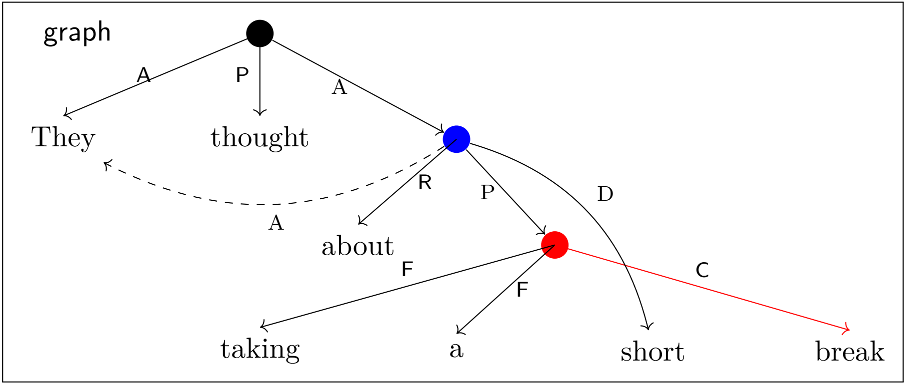
buffer

break



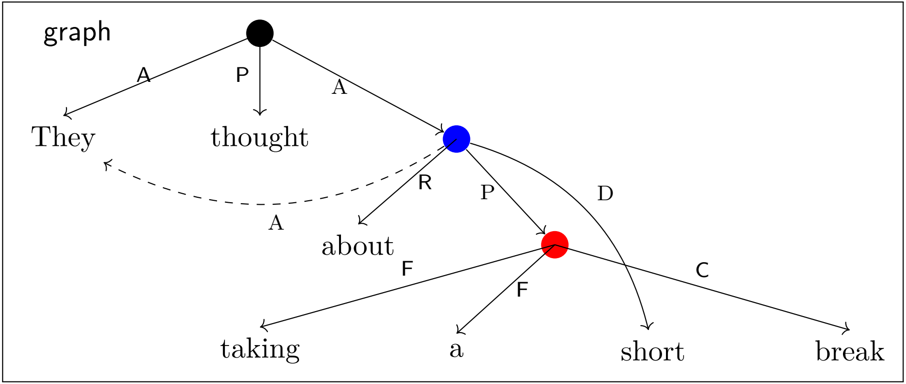
Example: TUPA Transition Sequence

$\Rightarrow$ RIGHT-EDGE$_C$



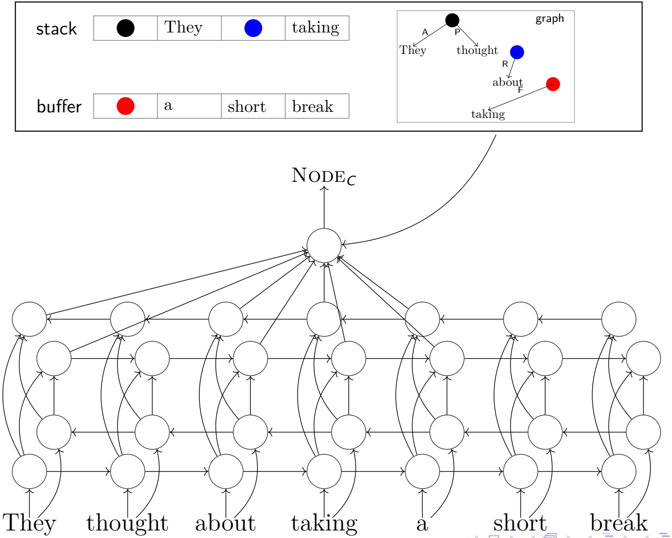
Example: TUPA Transition Sequence

⇒ FINISH

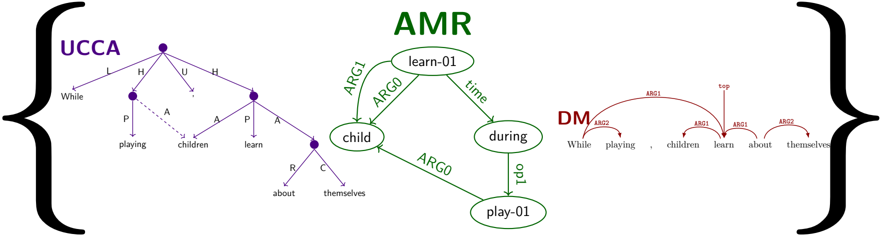


TUPA Model

Learns to predict next transition based on current state.

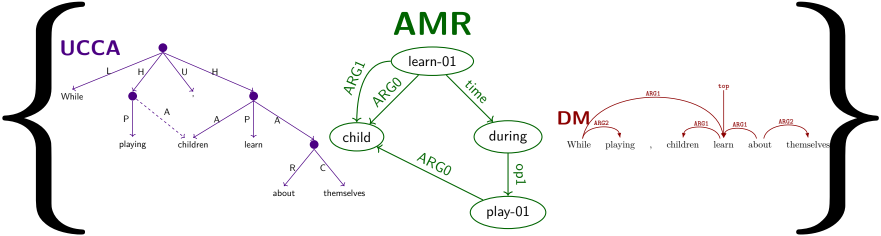


Sharing



UCCA
L
H
U
H
While
P
A
,
A
P
A
playing
children
learn
R
C
about
themselves
AMR
learn-01
ARG1
ARG0
time
child
during
ARG0
op1
play-01
DM
ARG1
top
ARG2
ARG1
ARG1
ARG2
While
playing
,
children
learn
about
themselves

Sharing



Improves UCCA parsing in English, French and German.

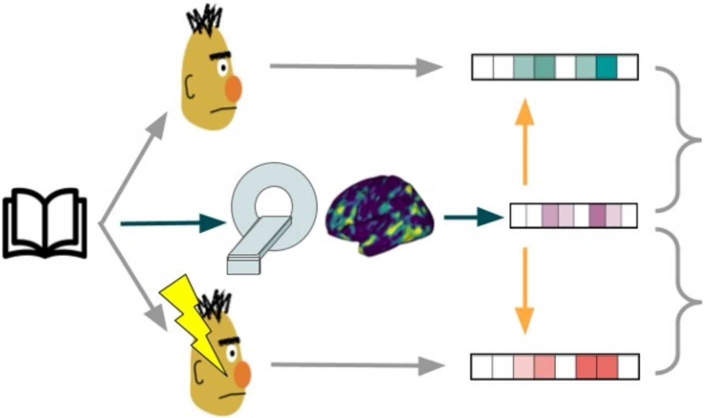
Hershcovich et al. **"Multitask Parsing Across Semantic Representations"**. *ACL* (2018)

Parsing Competitions

Improvements in 5 frameworks and 5 languages (English, French, German, Chinese and Czech).

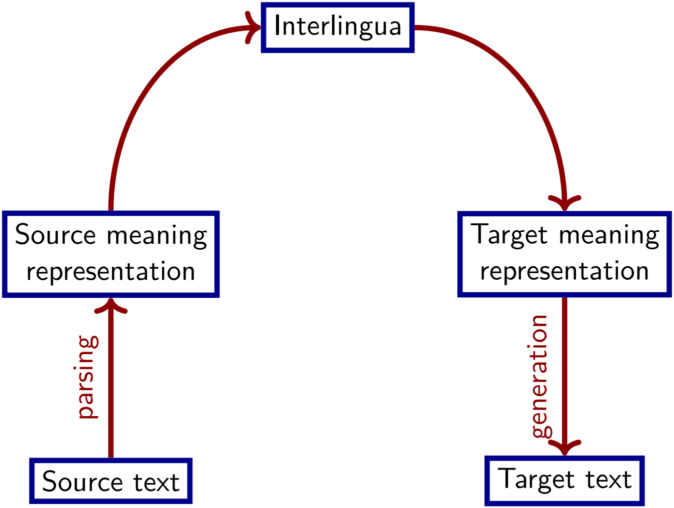
- Hershcovich et al. **"SemEval-2019 task 1: Cross-lingual semantic parsing with UCCA"**. *SemEval* (2019)
- Oepen et al. **"MRP 2019: Cross-Framework Meaning Representation Parsing"**. *CoNLL* (2019)
- Oepen et al. **"MRP 2020: The Second Shared Task on Cross-framework and Cross-Lingual Meaning Representation Parsing"**. *CoNLL* (2020)

Meaning Representations Explain *Human* Language Processing



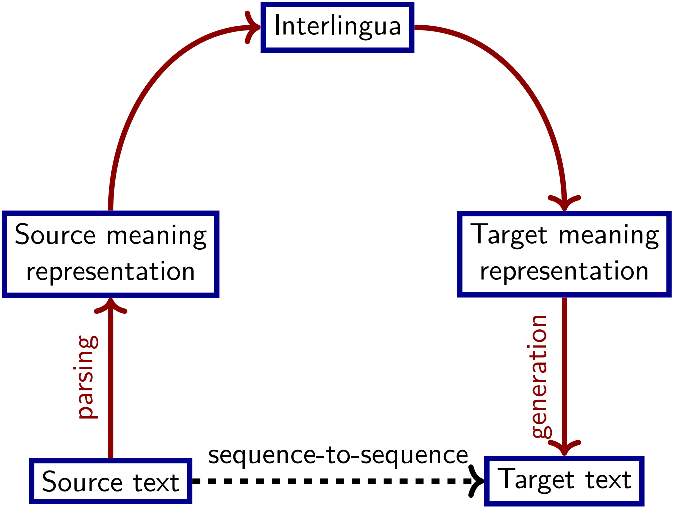
Abdou et al. **"Does injecting linguistic structure into language models lead to better alignment with brain recordings?"**. (2021)

Meaning Representations Make NLP Interpretable



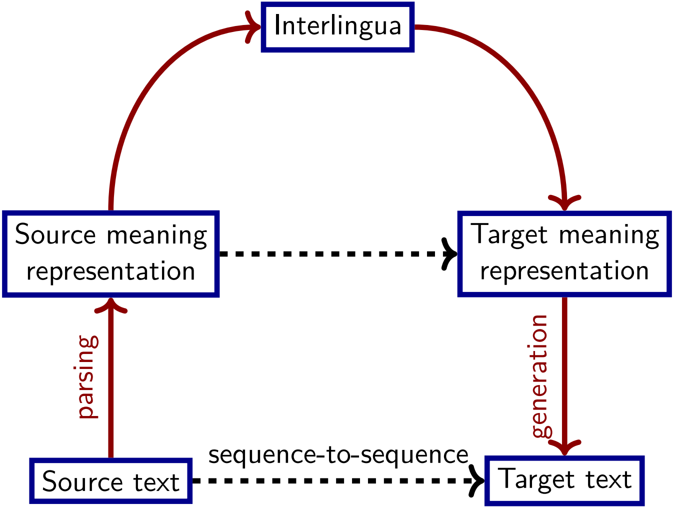
Work in progress

Meaning Representations Make NLP Interpretable



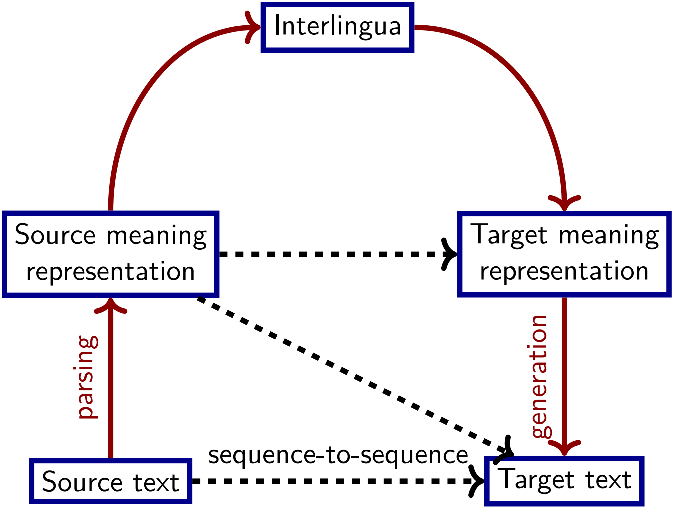
Work in progress

Meaning Representations Make NLP Interpretable



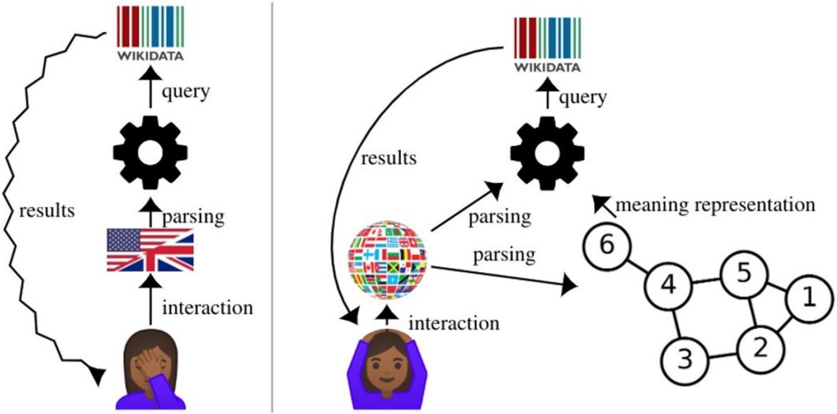
Work in progress

Meaning Representations Make NLP Interpretable

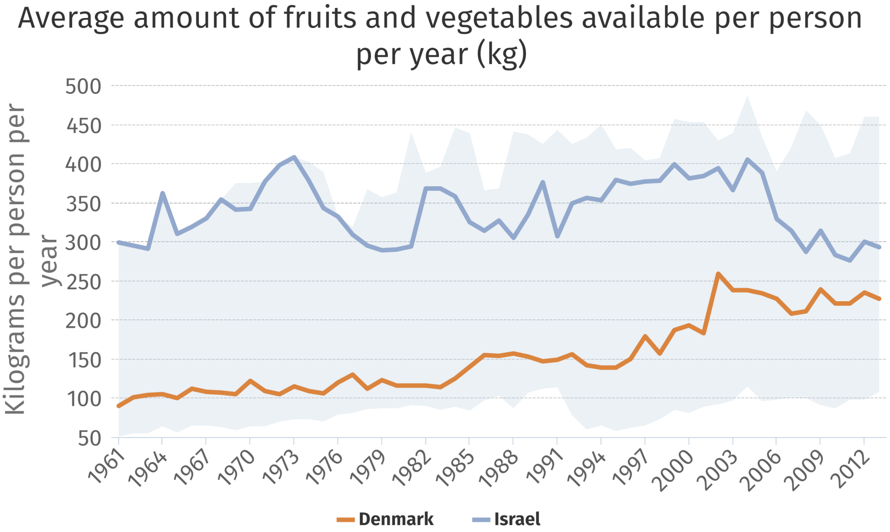


Work in progress

Meaning Representations Help Answering Questions

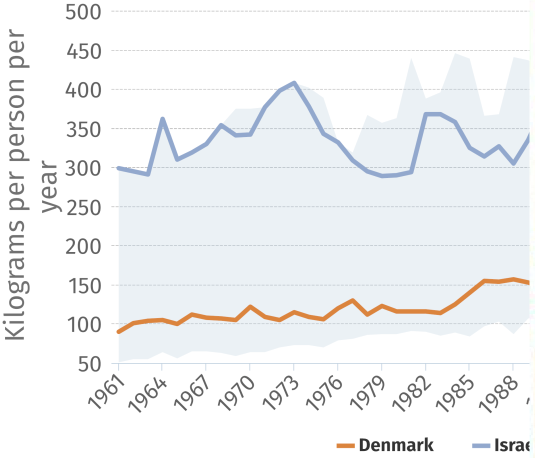


Other Ideas



Source: WHO

Average amount of fruits and vegetables available per person per year (kg)



Source: WHO

Conclusion

Symbolic meaning representation

- Scales qualitative studies
- Can be generated accurately by parsers
- Makes NLP interpretable
- Facilitates question answering

Conclusion

Symbolic meaning representation

- Scales qualitative studies
- Can be generated accurately by parsers
- Makes NLP interpretable
- Facilitates question answering
- **Can do a lot more!**

`dh@di.ku.dk`