

COMP 4446 / 5046

Lecture 5: Inference – Dynamic Programming

Jonathan K. Kummerfeld

Semester 1, 2025

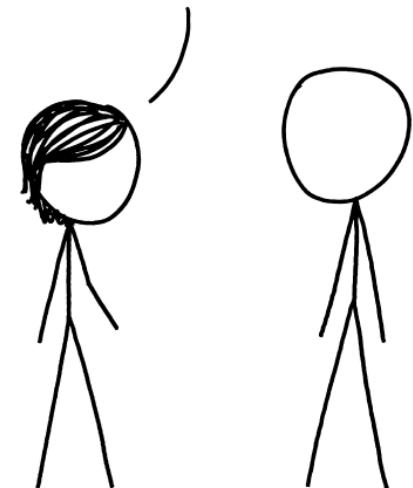


THE UNIVERSITY OF
SYDNEY

[menti.com 6274 6616](https://menti.com/62746616)

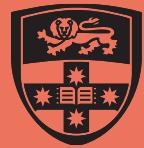
Language Nerd

I DON'T MEAN TO GO ALL LANGUAGE NERD ON YOU, BUT I JUST LEGIT ADVERBED "LEGIT," VERBED "ADVERB," AND ADJECTIVED "LANGUAGE NERD."



[Not to go all sentence fragment on you.]

Source: <https://xkcd.com/1443/>

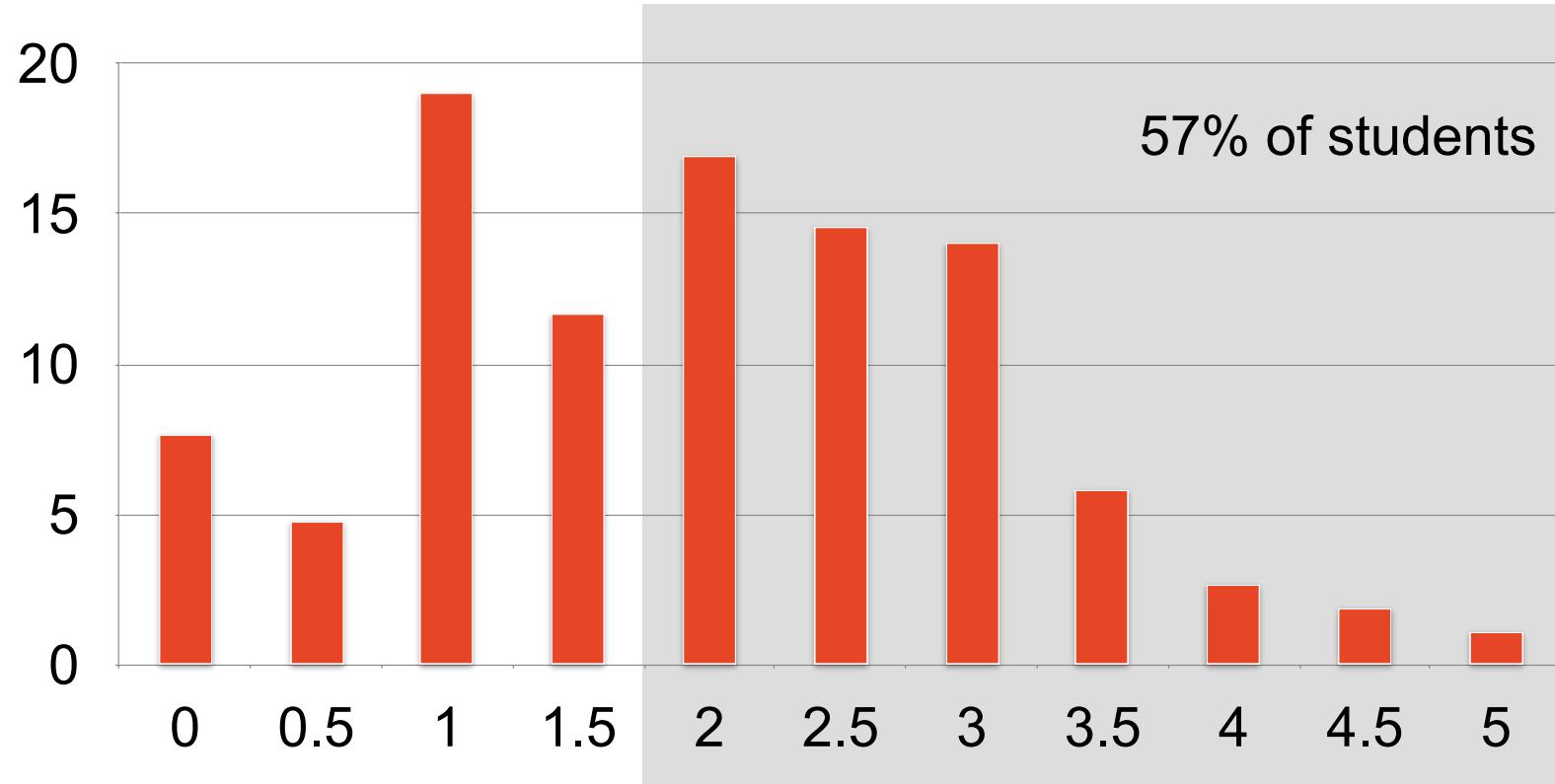


Sequence Tagging
Graph Parsing
Coreference
Workshop Preview



menti.com 6274 6616

The quiz was representative of the exam and 43% of students scored under 2. What next?



Me: Working to give more support

You: Engage with all components of the unit



COMP 4446 / 5046
Lecture 5, 2025

Sequence Tagging

Graph Parsing

Coreference

Workshop Preview



[menti.com 6274 6616](https://menti.com/62746616)

Sequence Tagging

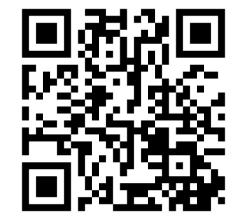


Sequence Tagging

Graph Parsing

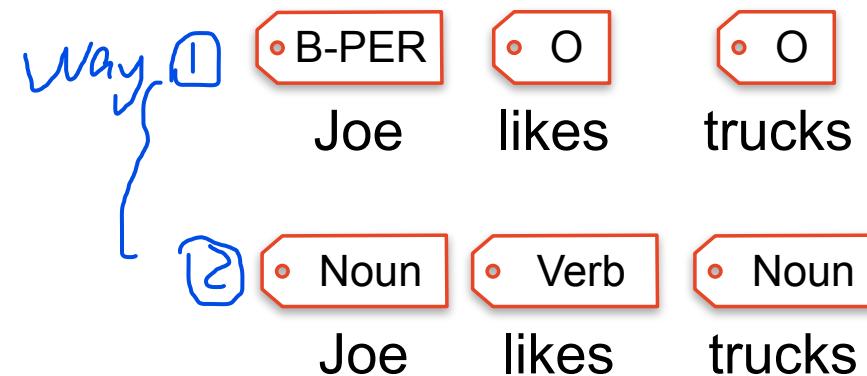
Coreference

Workshop Preview



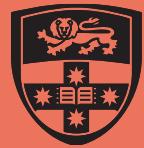
menti.com 6274 6616

We will consider various sequences and tags



input
Should be small, otherwise, computational cost ↑

Sequences are a fixed, known, length
Tags are from a small-ish, fixed, set



Sequence Tagging
Graph Parsing
Coreference
Workshop Preview



[menti.com 6274 6616](https://menti.com/62746616)

Independent predictions can be inconsistent

Possible
independent
predictions:

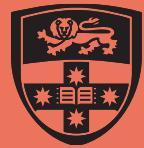
B-ORG I-ORG O B-LOC O O O O ...

2 mistake

True labels:

B-ORG I-ORG I-ORG I-ORG O O O O ...

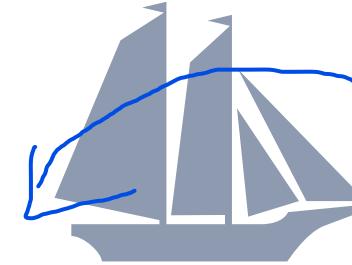
The University of Sydney is located in ...



Greedy predictions can make mistakes that become clear too late

Predictions:

Det	Adj.	Noun	Det	Noun
-----	------	------	-----	------



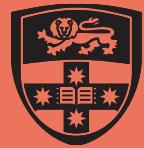
True labels:

Det	Noun	Verb	Det	Noun
-----	------	------	-----	------

The old man the boat

A greedy method can't go back and undo the choices Adj & Noun!

"The old man" originally good
goes bad latter



Sequence Tagging
Graph Parsing
Coreference
Workshop Preview



[menti.com 6274 6616](https://menti.com/62746616)

Considering each tag sequence separately is not feasible

17 tags in Universal Dependencies

$$\text{Options} = |\text{tags}|^{\text{|words|}}$$

For the last example,

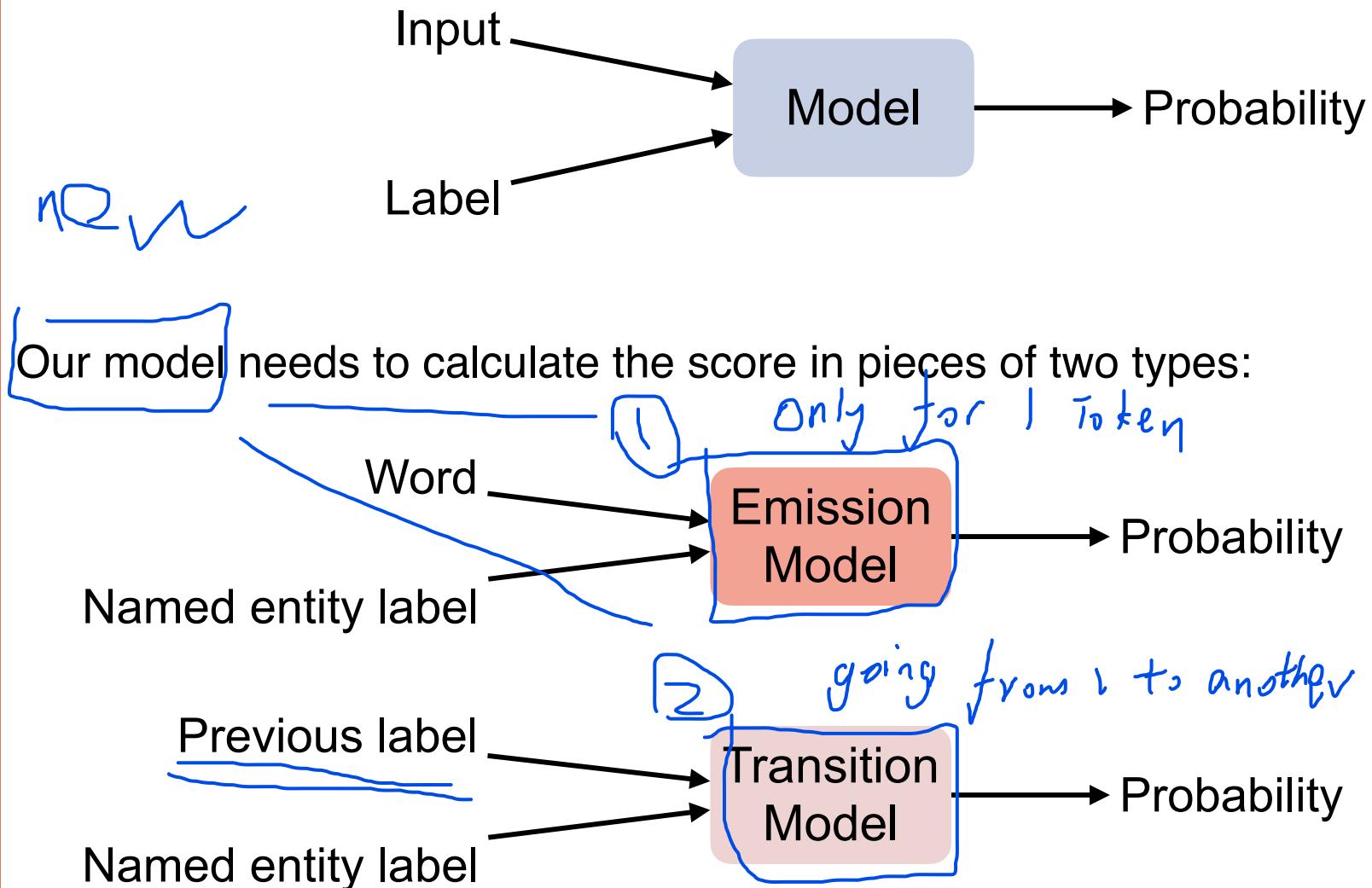
$$17^5 = 1,419,857 \text{ options}$$

For a 20 word sentence (average length in news):

$$17^{20} = 4,064,231,406,647,572,522,401,601 \\ (4.1 \text{ Septillion})$$



For certain models we can find the highest scoring sequence efficiently

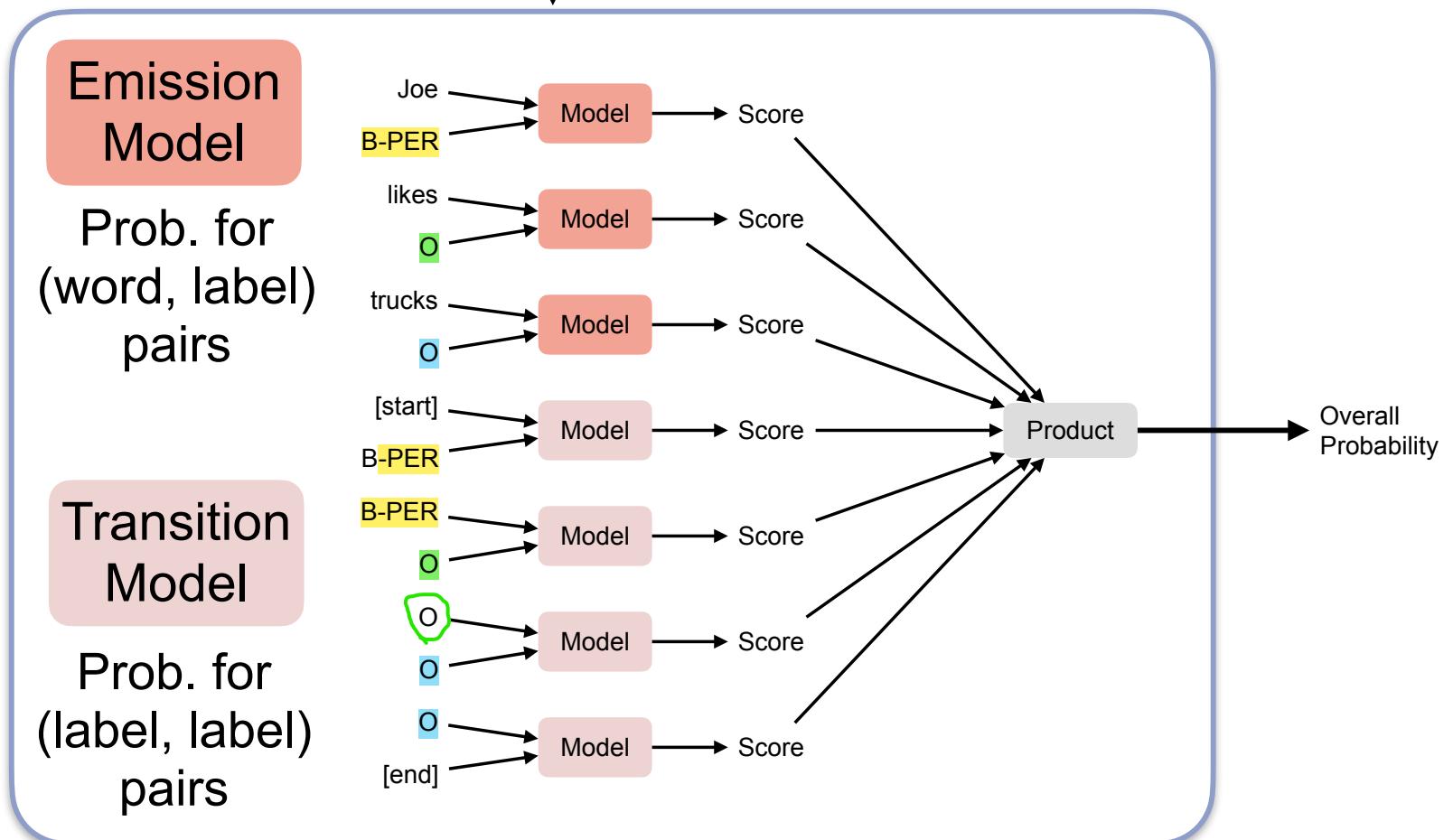


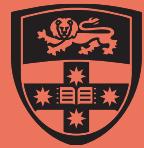


We can still think of it as a model for whole sequences

B-PER O O
Joe likes trucks
↓

We'll consider just 1 entity type for simplicity



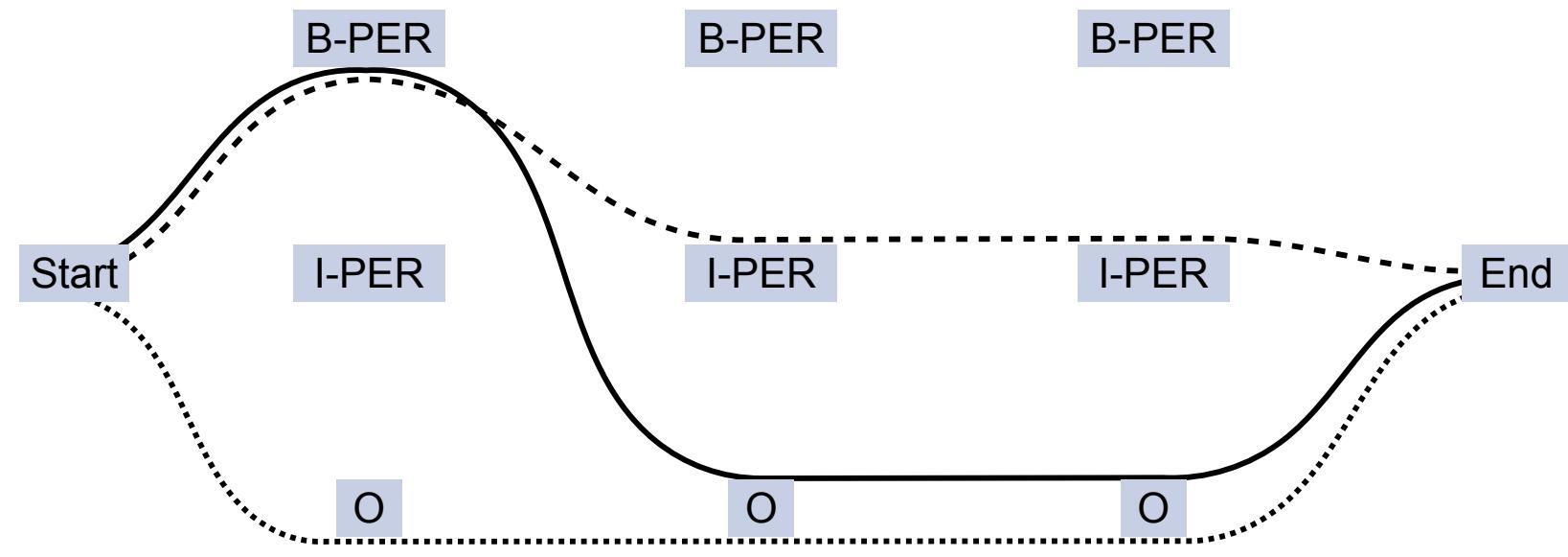


Sequence Tagging
Graph Parsing
Coreference
Workshop Preview

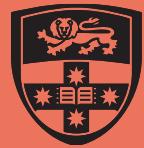


[menti.com 6274 6616](https://menti.com/62746616)

To understand the algorithm, we can draw paths through a grid of labels



Joe	likes	trucks	—
I	like	chocolate
Jonathan	Kay	Kummerfeld	----

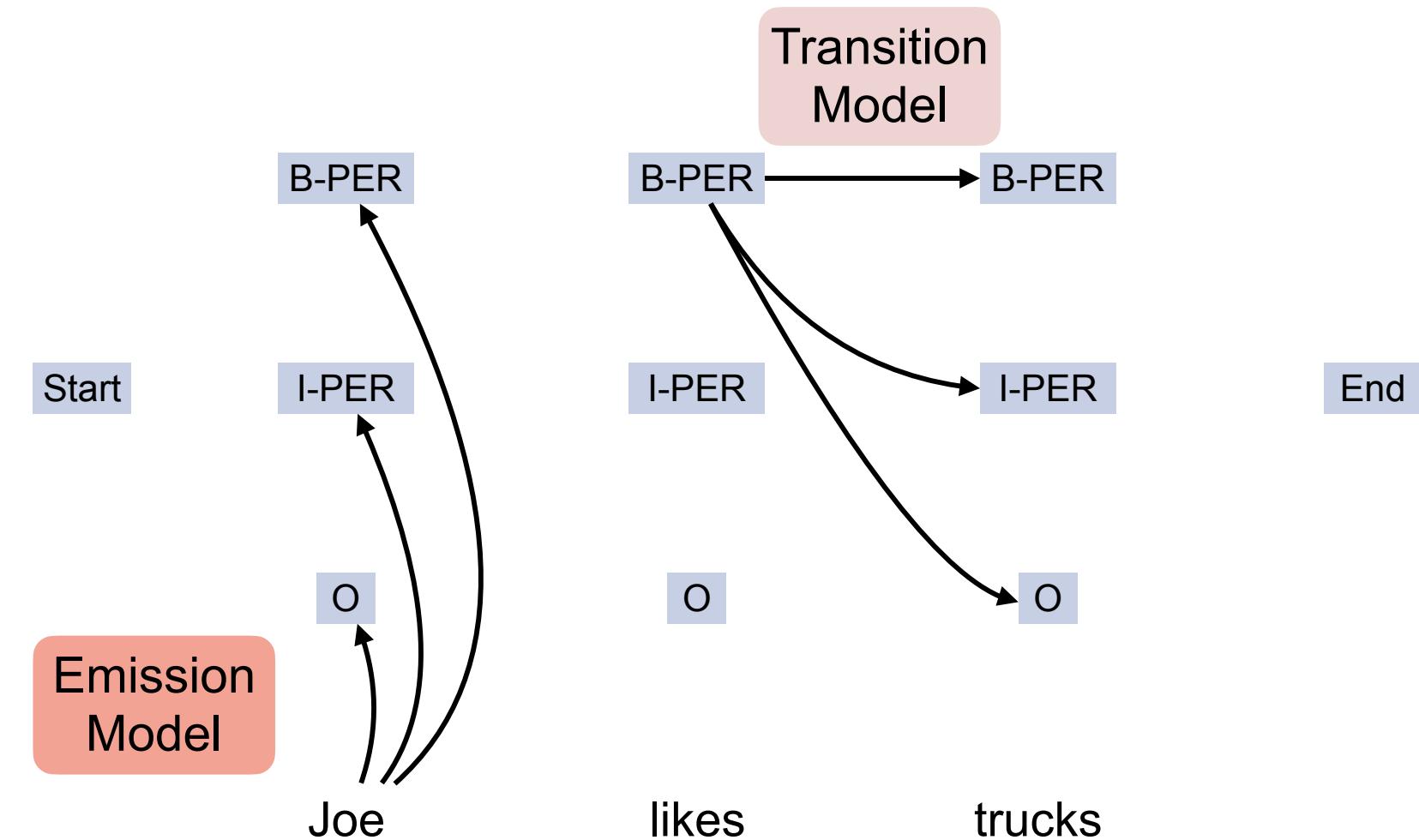


Sequence Tagging
Graph Parsing
Coreference
Workshop Preview



[menti.com 6274 6616](https://menti.com/62746616)

The two model parts from earlier correspond to parts of this grid





Sequence Tagging

Graph Parsing

Coreference

Workshop Preview

Yoh can

Read it

as output

It transition mode!

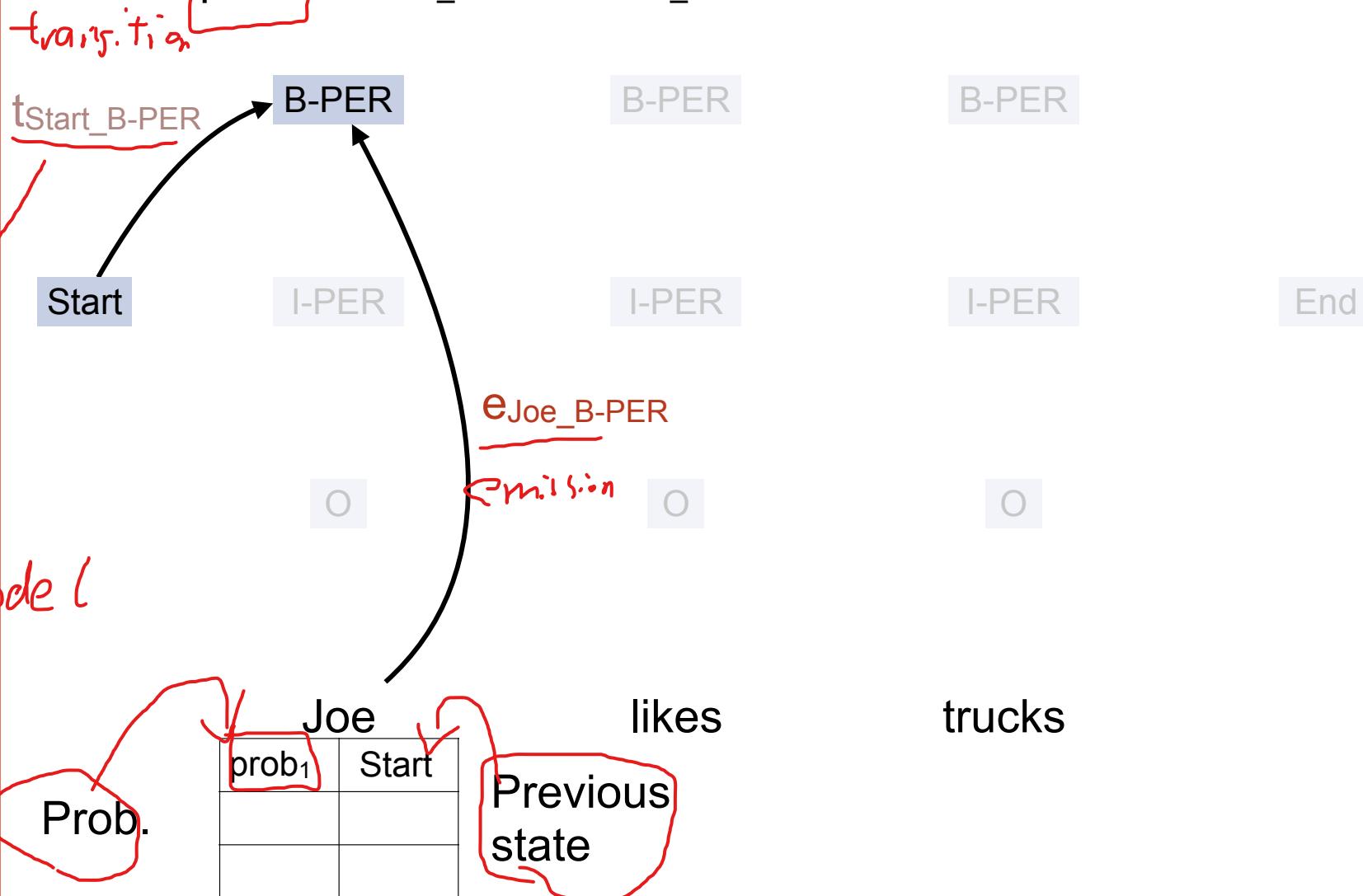


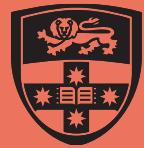
menti.com 6274 6616

We calculate intermediate scores, first for each possible start

Emission *Transition*

$$\text{prob}_1 = e_{\text{Joe_B-PER}} * t_{\text{Start_B-PER}}$$





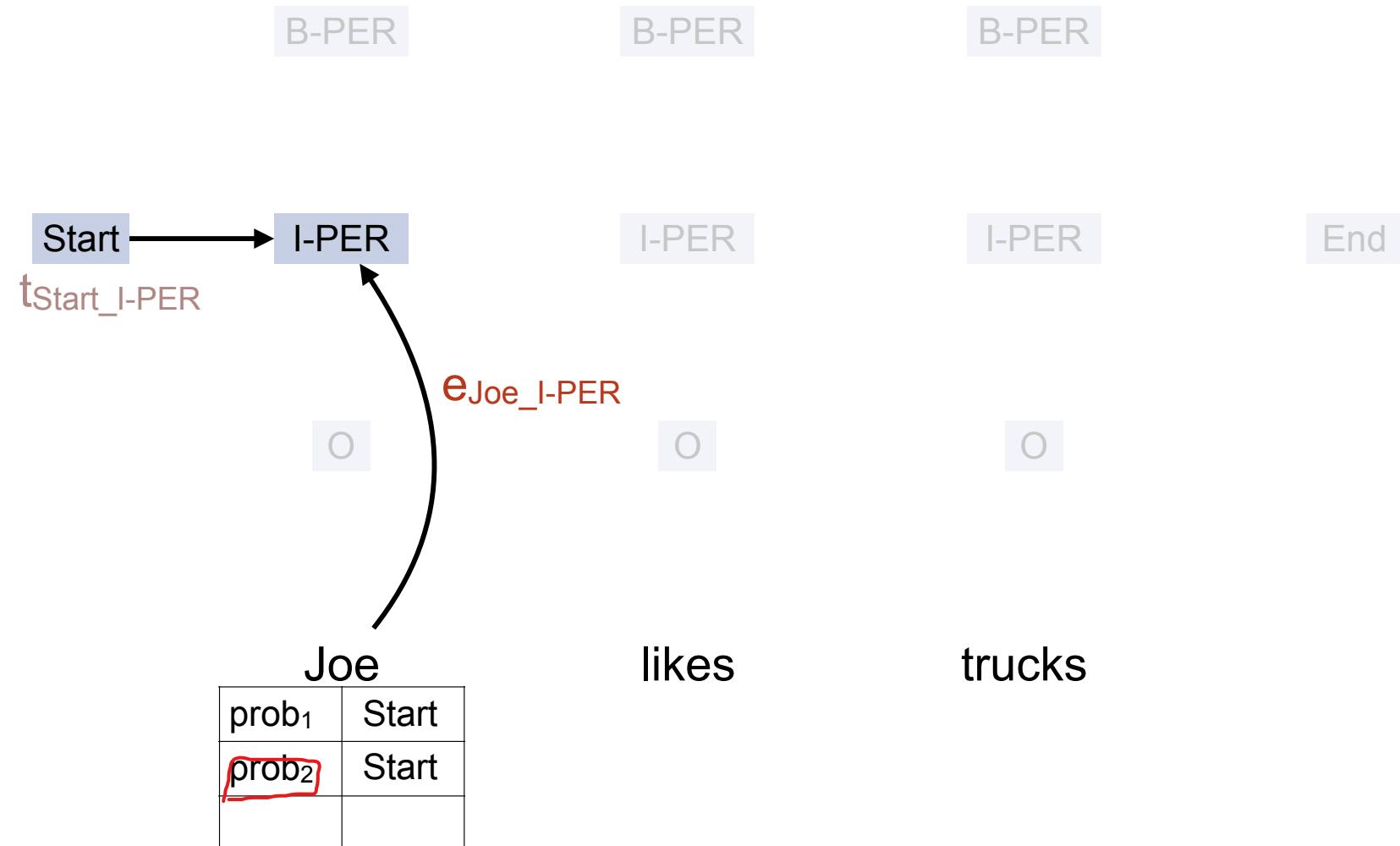
Sequence Tagging
Graph Parsing
Coreference
Workshop Preview

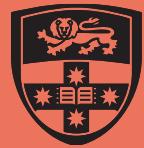


menti.com 6274 6616

We calculate intermediate scores, first for each possible start

$$\text{prob}_2 = e_{\text{Joe_I-PER}} * t_{\text{Start_I-PER}}$$





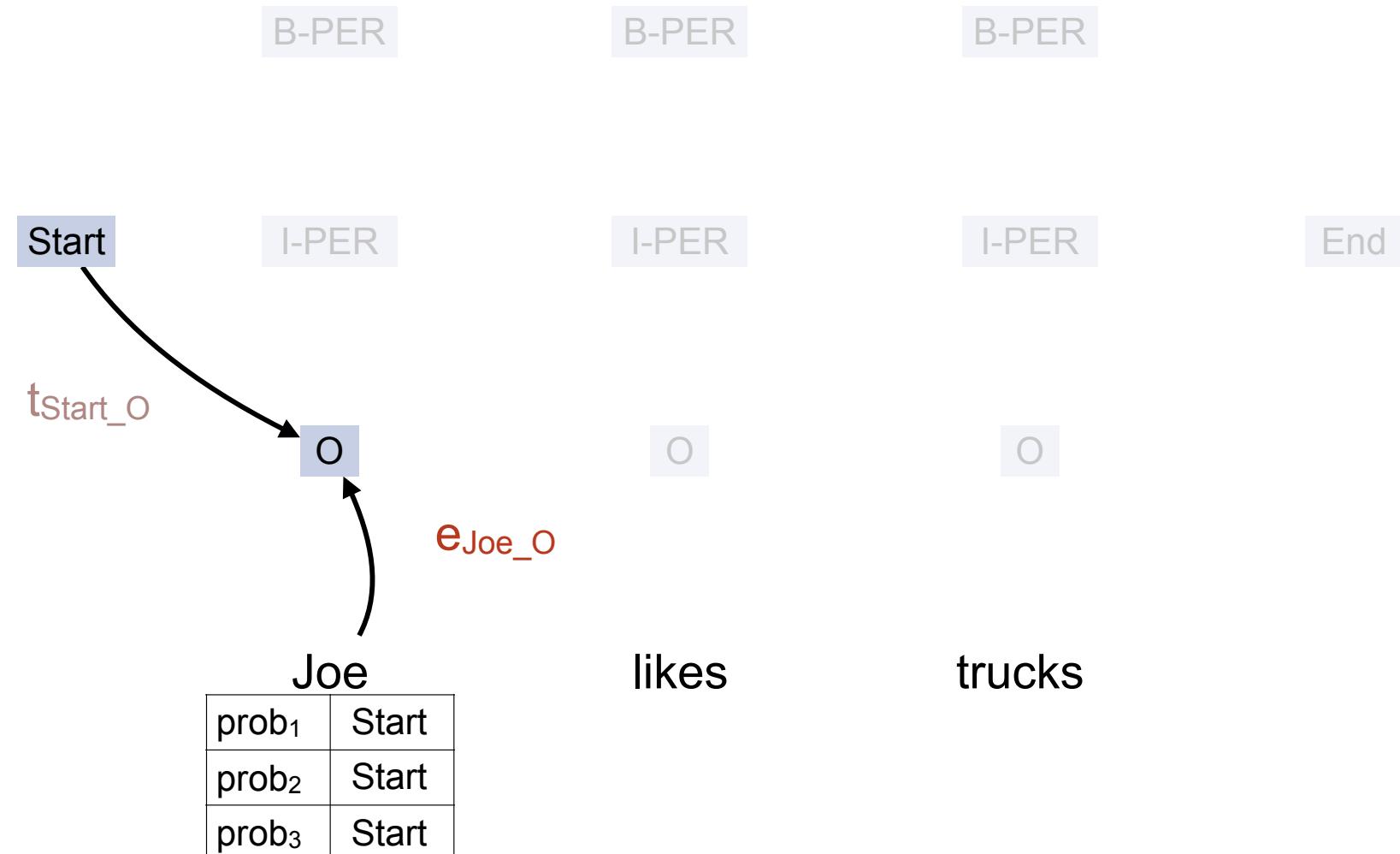
Sequence Tagging
Graph Parsing
Coreference
Workshop Preview

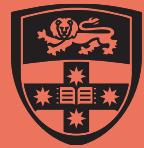


[menti.com 6274 6616](https://menti.com/62746616)

We calculate intermediate scores, first for each possible start

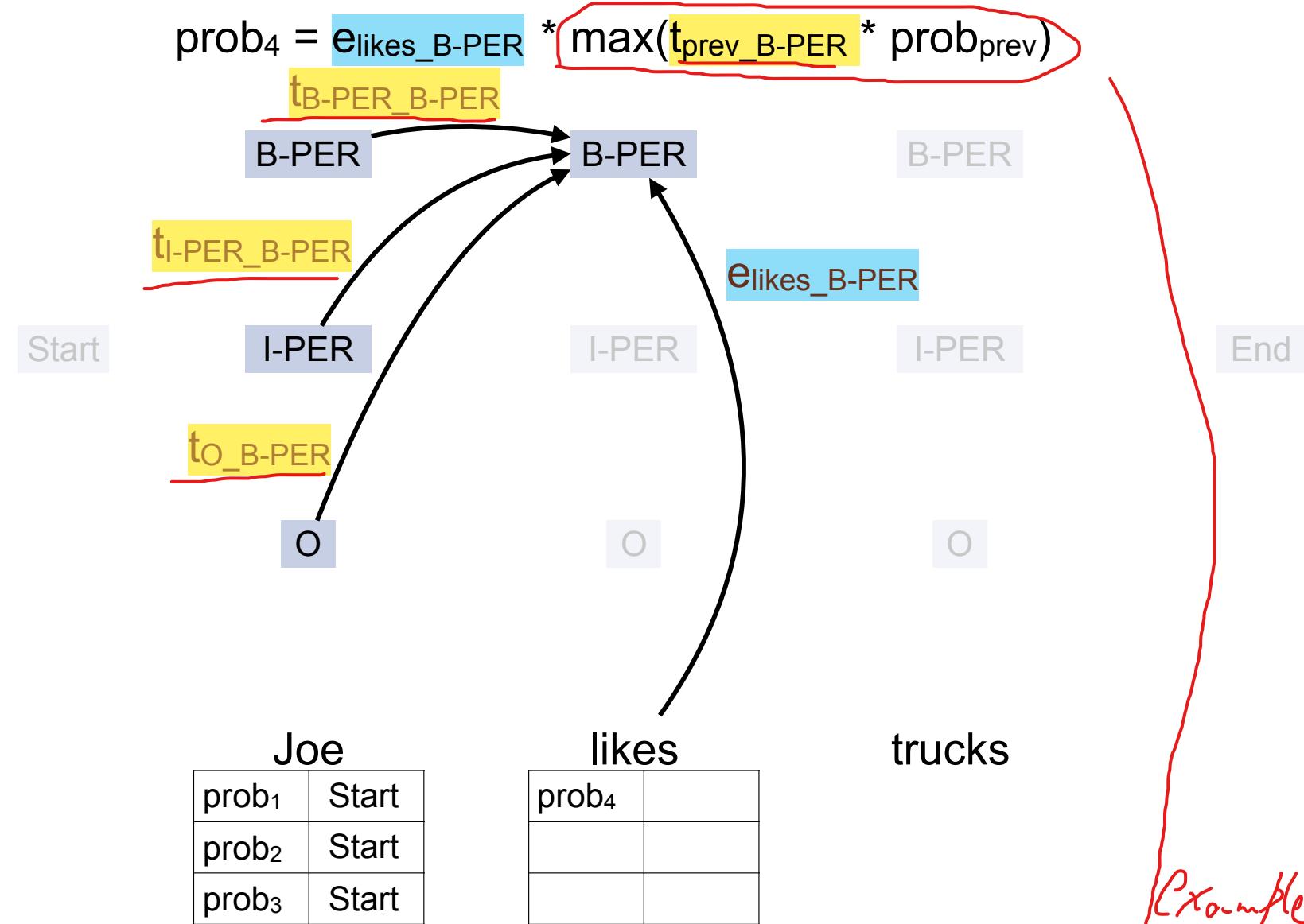
$$\text{prob}_3 = e_{\text{Joe}_O} * t_{\text{Start}_O}$$

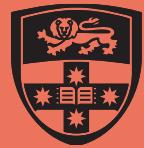




We calculate intermediate scores, then continuations, noting the best

$$\text{prob}_4 = e_{\text{likes_B-PER}} * \max(t_{\text{prev_B-PER}} * \text{prob}_{\text{prev}})$$





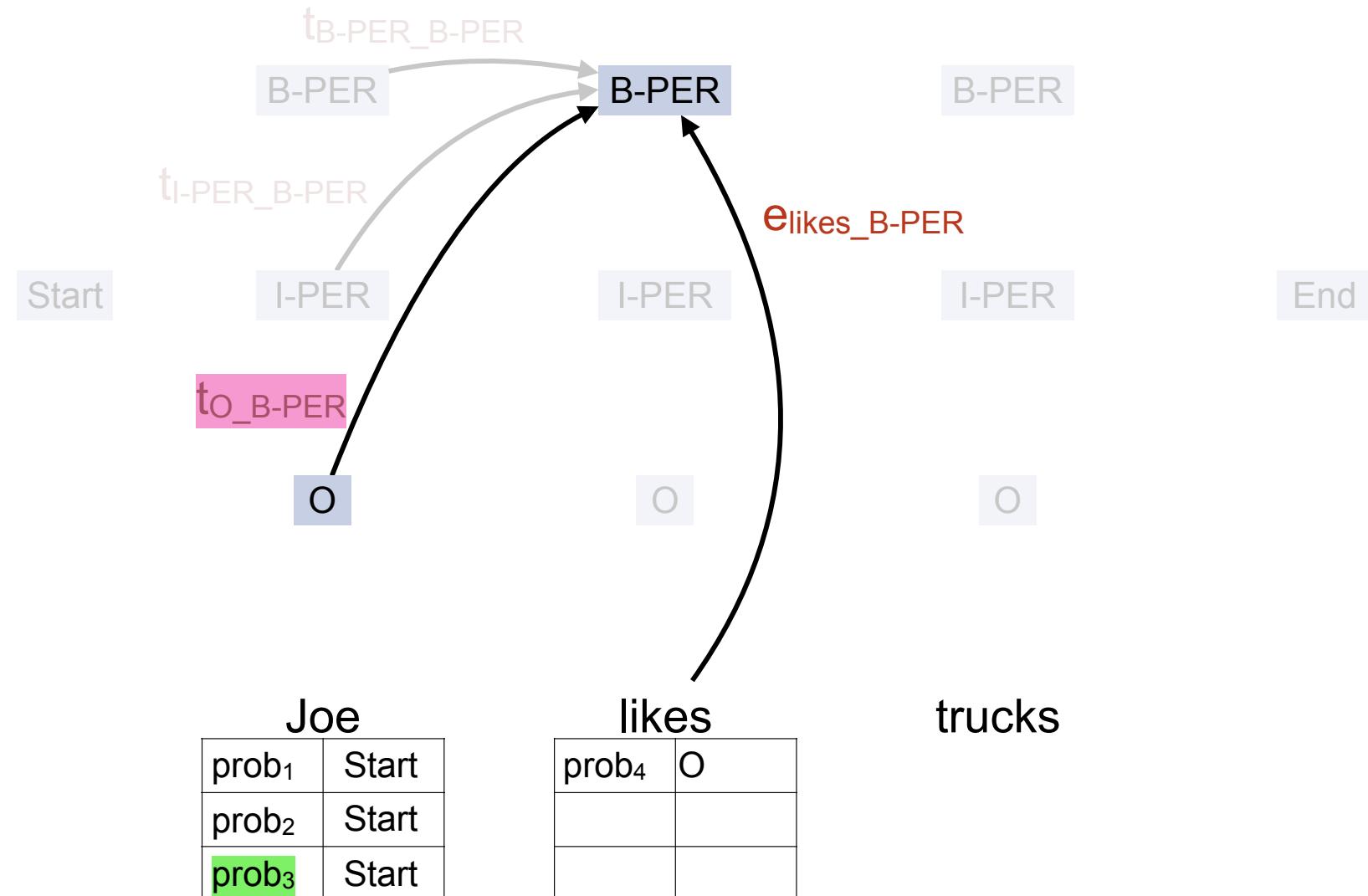
Sequence Tagging
Graph Parsing
Coreference
Workshop Preview

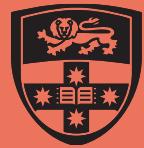


menti.com 6274 6616

We calculate intermediate scores, then continuations, noting the best

$$\text{prob}_4 = e_{\text{likes_B-PER}} * \max(t_{\text{prev_B-PER}} * \text{prob}_{\text{prev}})$$





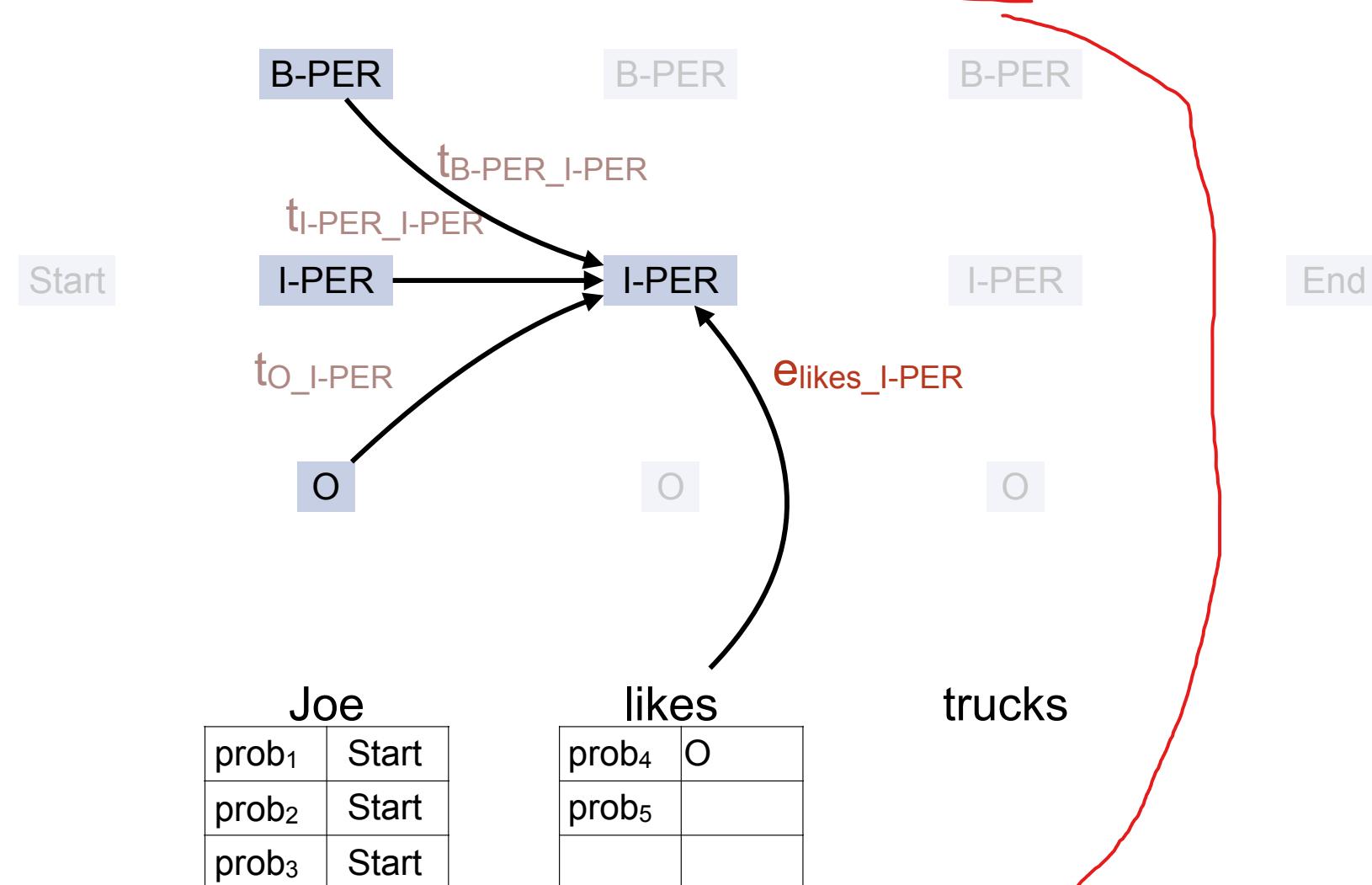
Sequence Tagging
Graph Parsing
Coreference
Workshop Preview

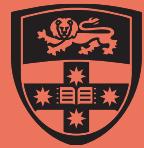


menti.com 6274 6616

We calculate intermediate scores, then continuations, noting the best

$$\text{prob}_5 = e_{\text{likes_I-PER}} * \max(t_{\text{prev_I-PER}} * \text{prob}_{\text{prev}})$$





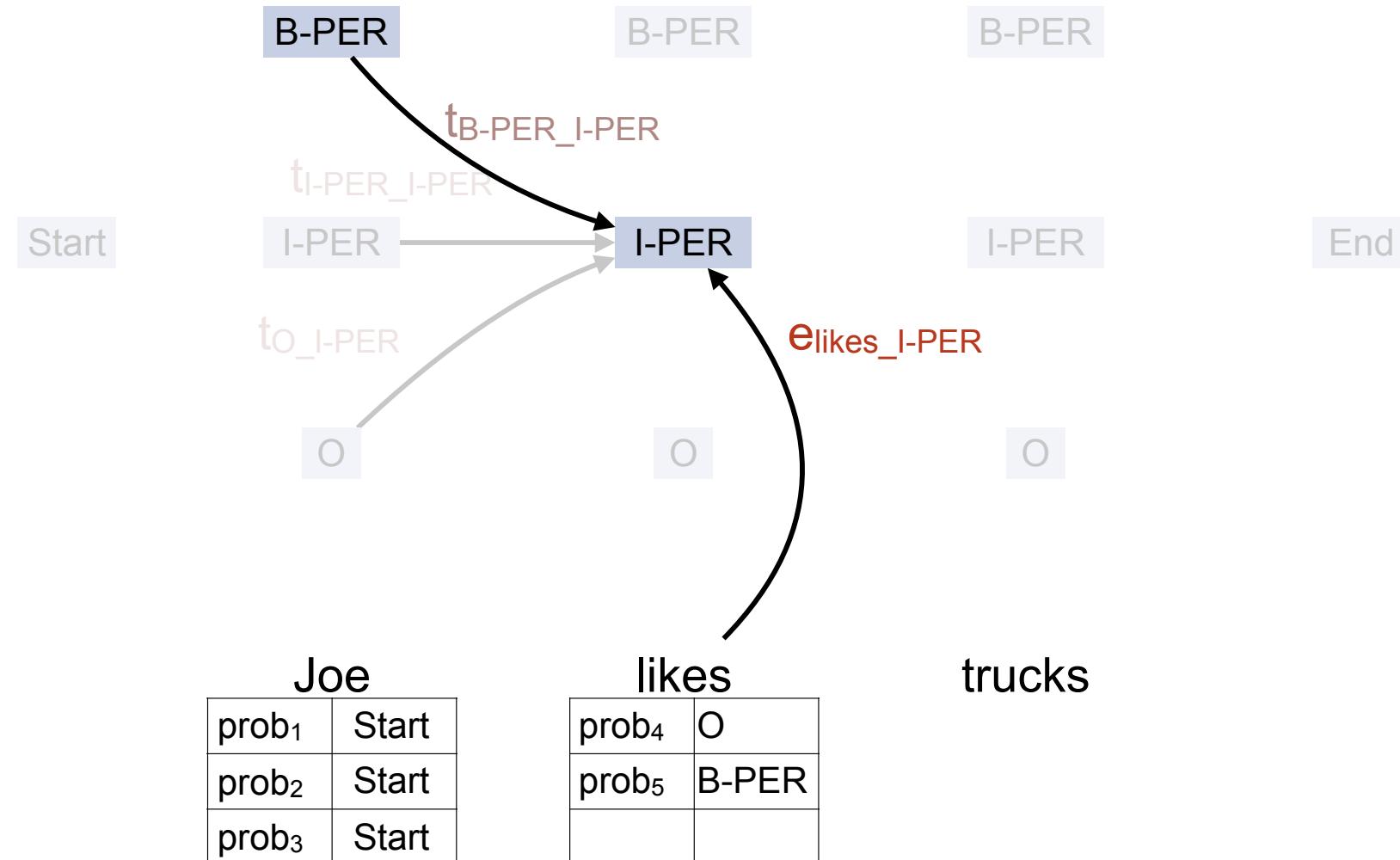
Sequence Tagging
Graph Parsing
Coreference
Workshop Preview

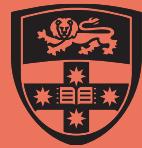


[menti.com 6274 6616](https://menti.com/62746616)

We calculate intermediate scores, then continuations, noting the best

$$\text{prob}_5 = e_{\text{likes_I-PER}} * \max(t_{\text{prev_I-PER}} * \text{prob}_{\text{prev}})$$





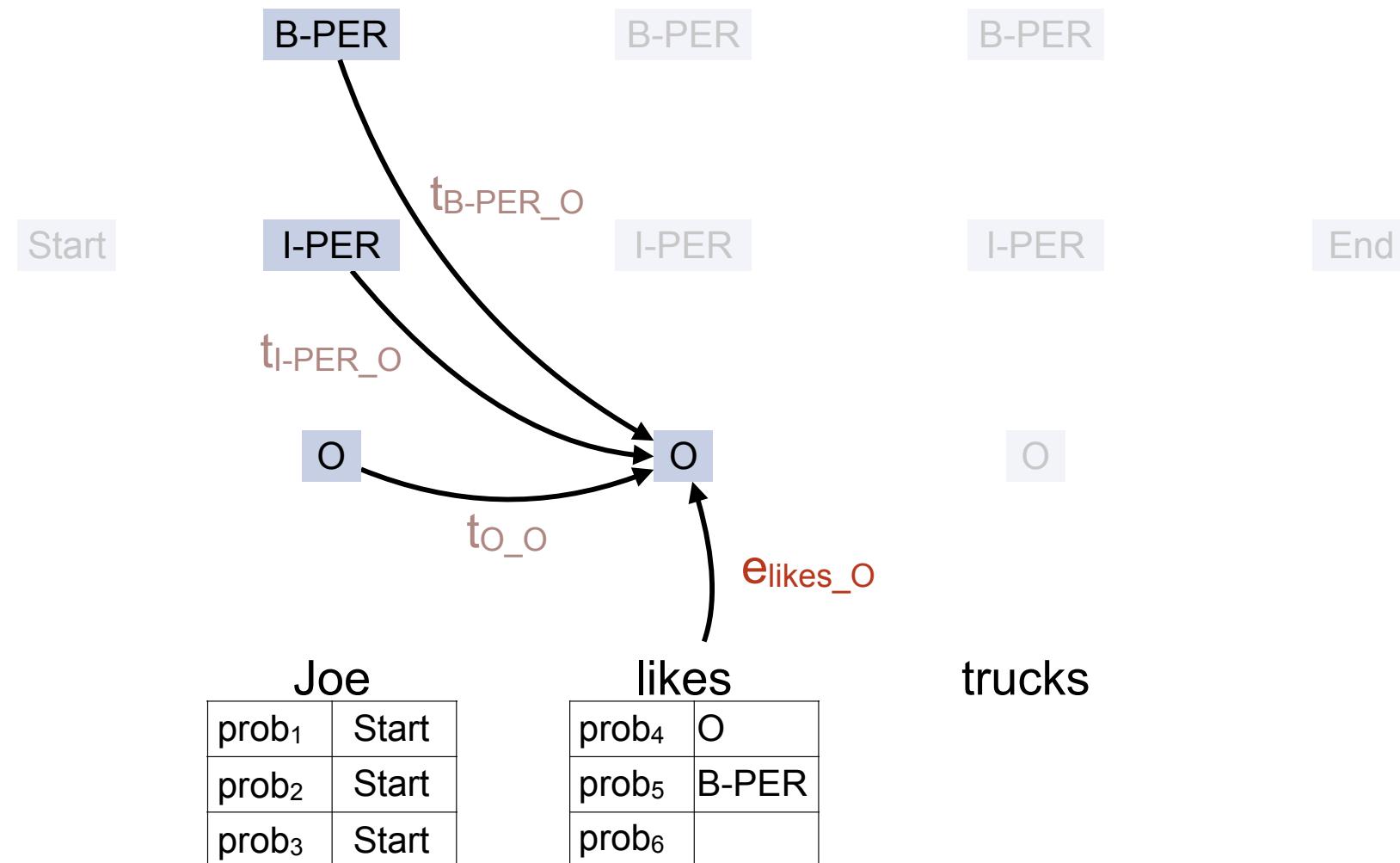
Sequence Tagging
Graph Parsing
Coreference
Workshop Preview

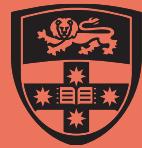


menti.com 6274 6616

We calculate intermediate scores, then continuations, noting the best

$$\text{prob}_6 = e_{\text{likes_O}} * \max(t_{\text{prev_O}} * \text{prob}_{\text{prev}})$$



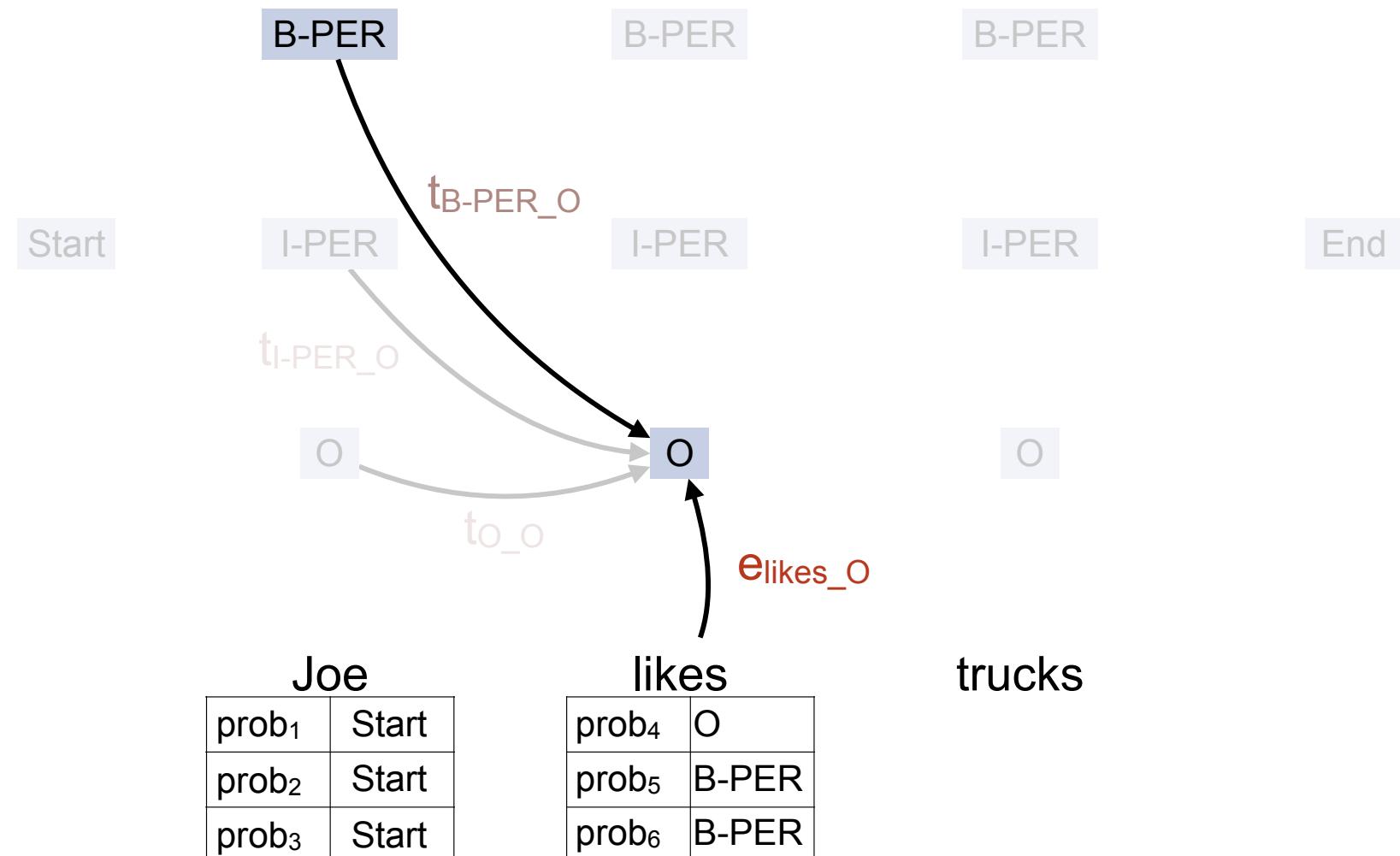


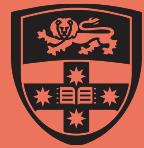
Sequence Tagging
Graph Parsing
Coreference
Workshop Preview



menti.com 6274 6616

We calculate intermediate scores, then continuations, noting the best

$$\text{prob}_6 = e_{\text{likes_O}} * \max(t_{\text{prev_O}} * \text{prob}_{\text{prev}})$$




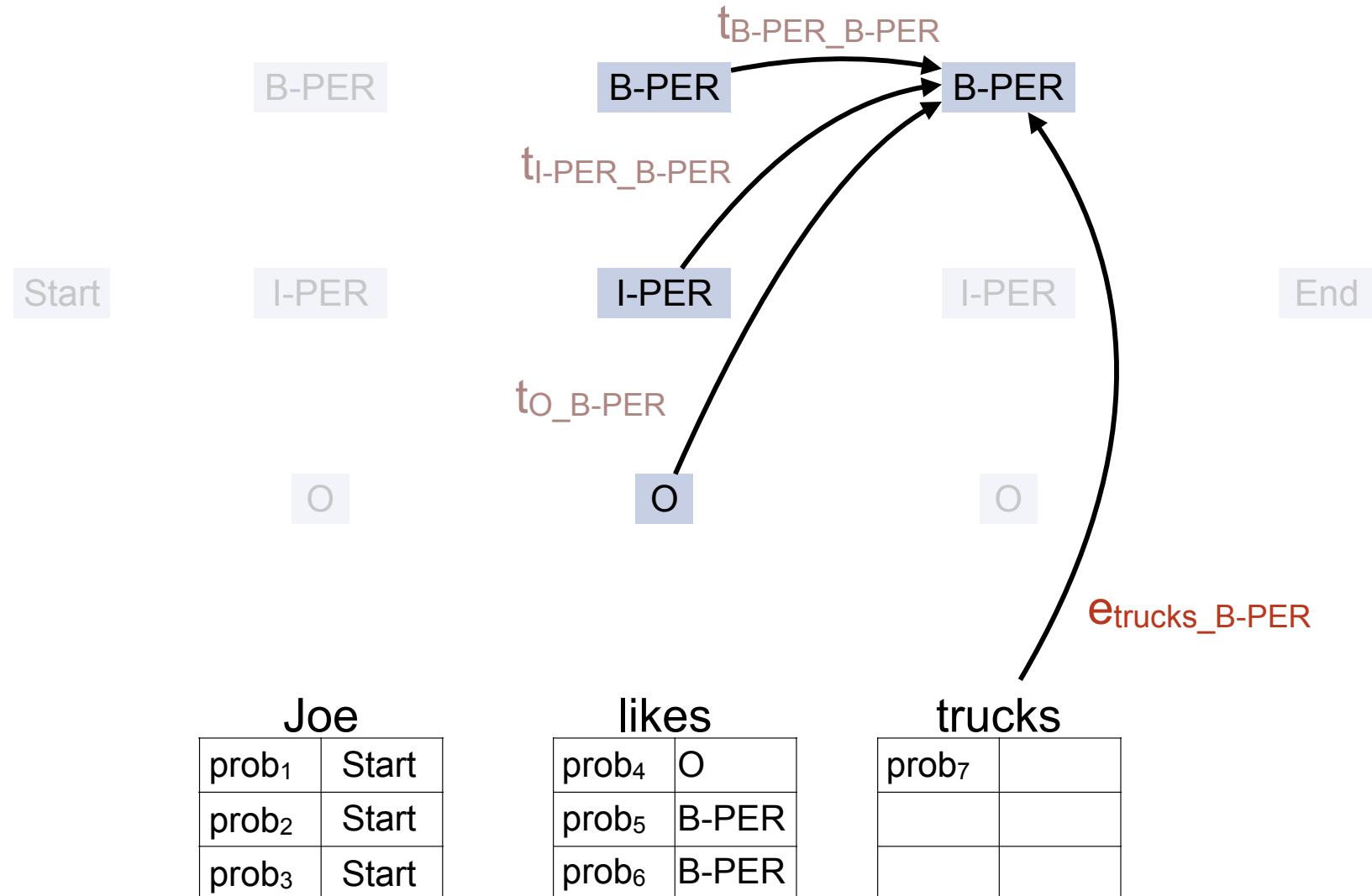
Sequence Tagging
Graph Parsing
Coreference
Workshop Preview

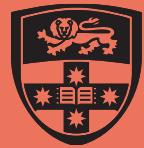


[menti.com 6274 6616](https://menti.com/62746616)

Each step only looks back one step

$$\text{prob}_7 = e_{\text{trucks_B-PER}} * \max(t_{\text{prev_B-PER}} * \text{prob}_{\text{prev}})$$





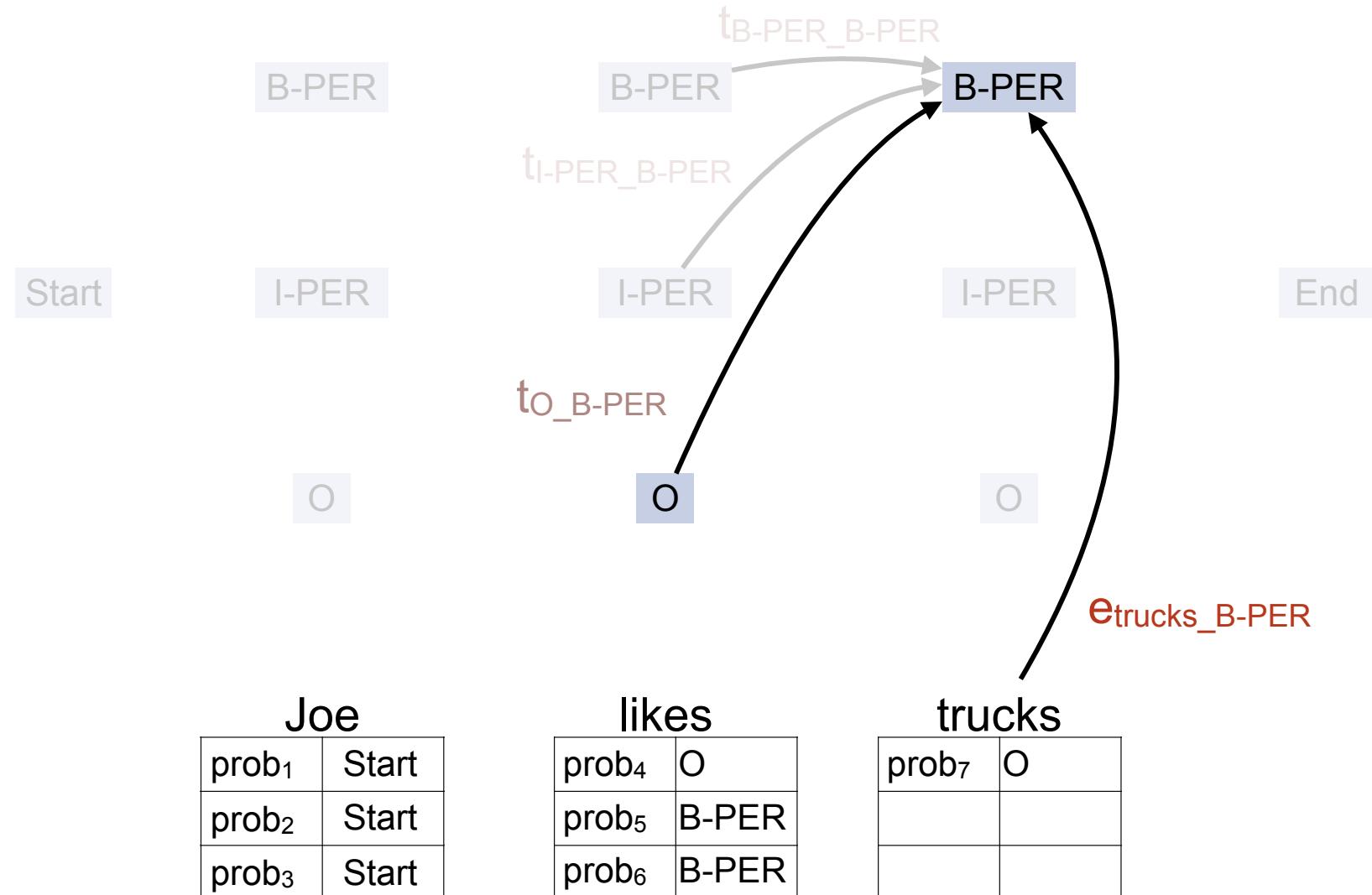
Sequence Tagging
Graph Parsing
Coreference
Workshop Preview

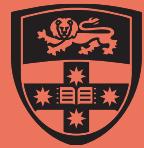


[menti.com 6274 6616](https://menti.com/62746616)

Each step only looks back one step

$$\text{prob}_7 = e_{\text{trucks_B-PER}} * \max(t_{\text{prev_B-PER}} * \text{prob}_{\text{prev}})$$





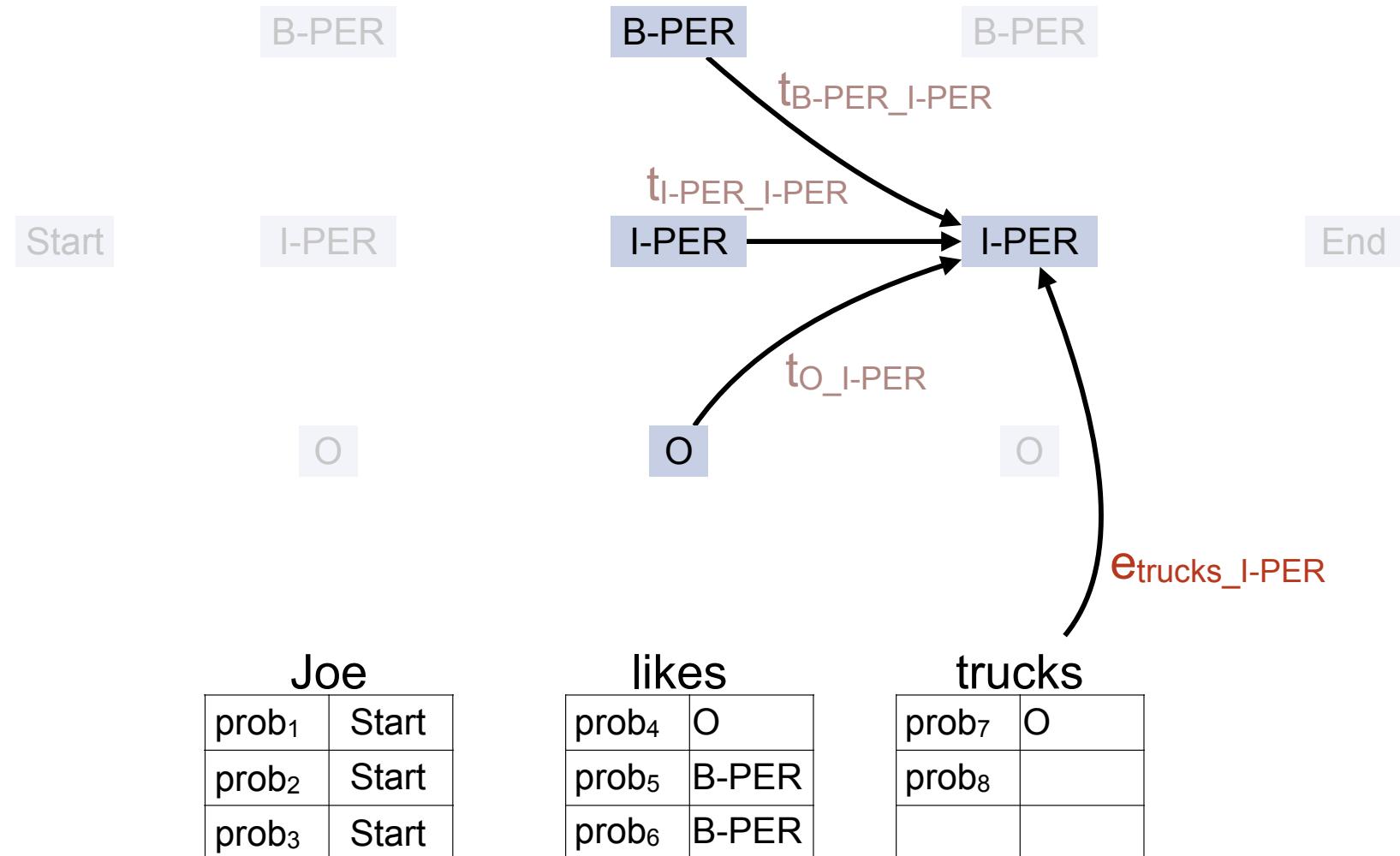
Sequence Tagging
Graph Parsing
Coreference
Workshop Preview

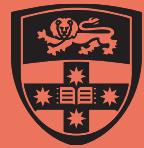


[menti.com 6274 6616](https://menti.com/62746616)

Each step only looks back one step

$$\text{prob}_8 = e_{\text{trucks_I-PER}} * \max(t_{\text{prev_I-PER}} * \text{prob}_{\text{prev}})$$





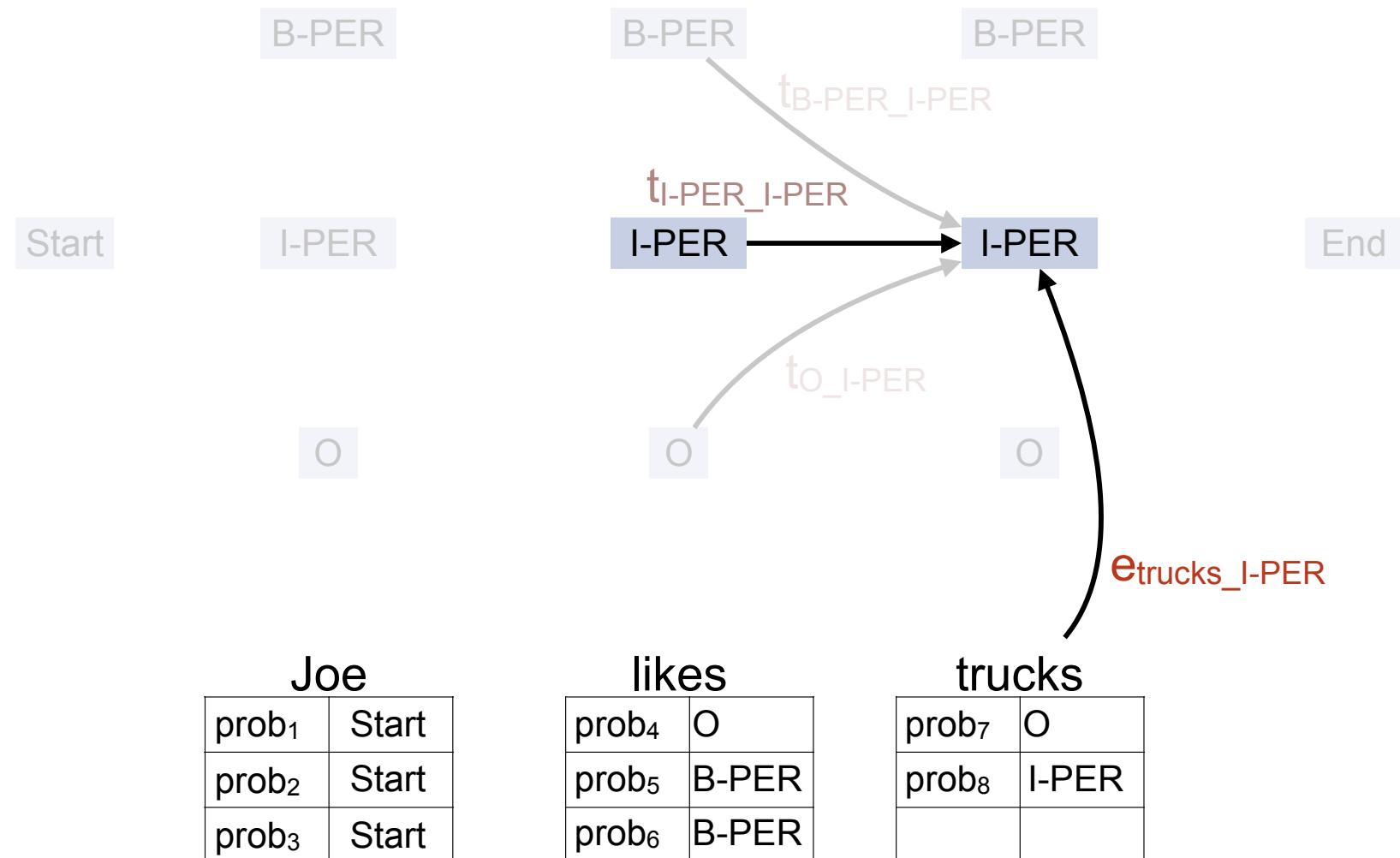
Sequence Tagging
Graph Parsing
Coreference
Workshop Preview



menti.com 6274 6616

Each step only looks back one step

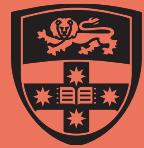
$$\text{prob}_8 = e_{\text{trucks_I-PER}} * \max(t_{\text{prev_I-PER}} * \text{prob}_{\text{prev}})$$



prob ₁	Start
prob ₂	Start
prob ₃	Start

prob ₄	O
prob ₅	B-PER
prob ₆	B-PER

prob ₇	O
prob ₈	I-PER



Sequence Tagging

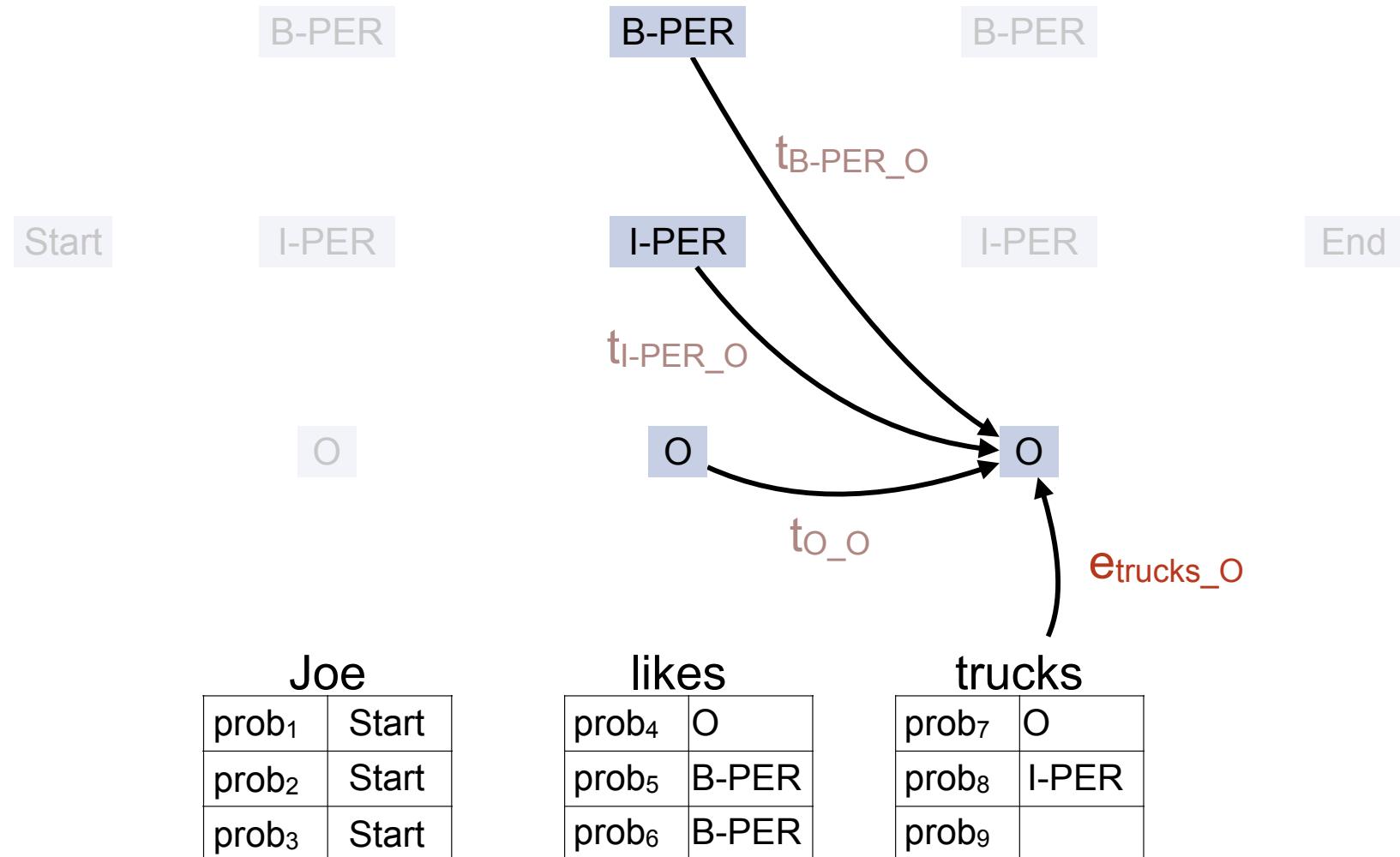
Graph Parsing
Coreference
Workshop Preview

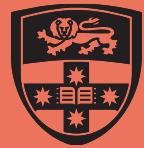


menti.com 6274 6616

Each step only looks back one step

$$\text{prob}_9 = e_{\text{trucks_I-PER}} * \max(t_{\text{prev_I-PER}} * \text{prob}_{\text{prev}})$$





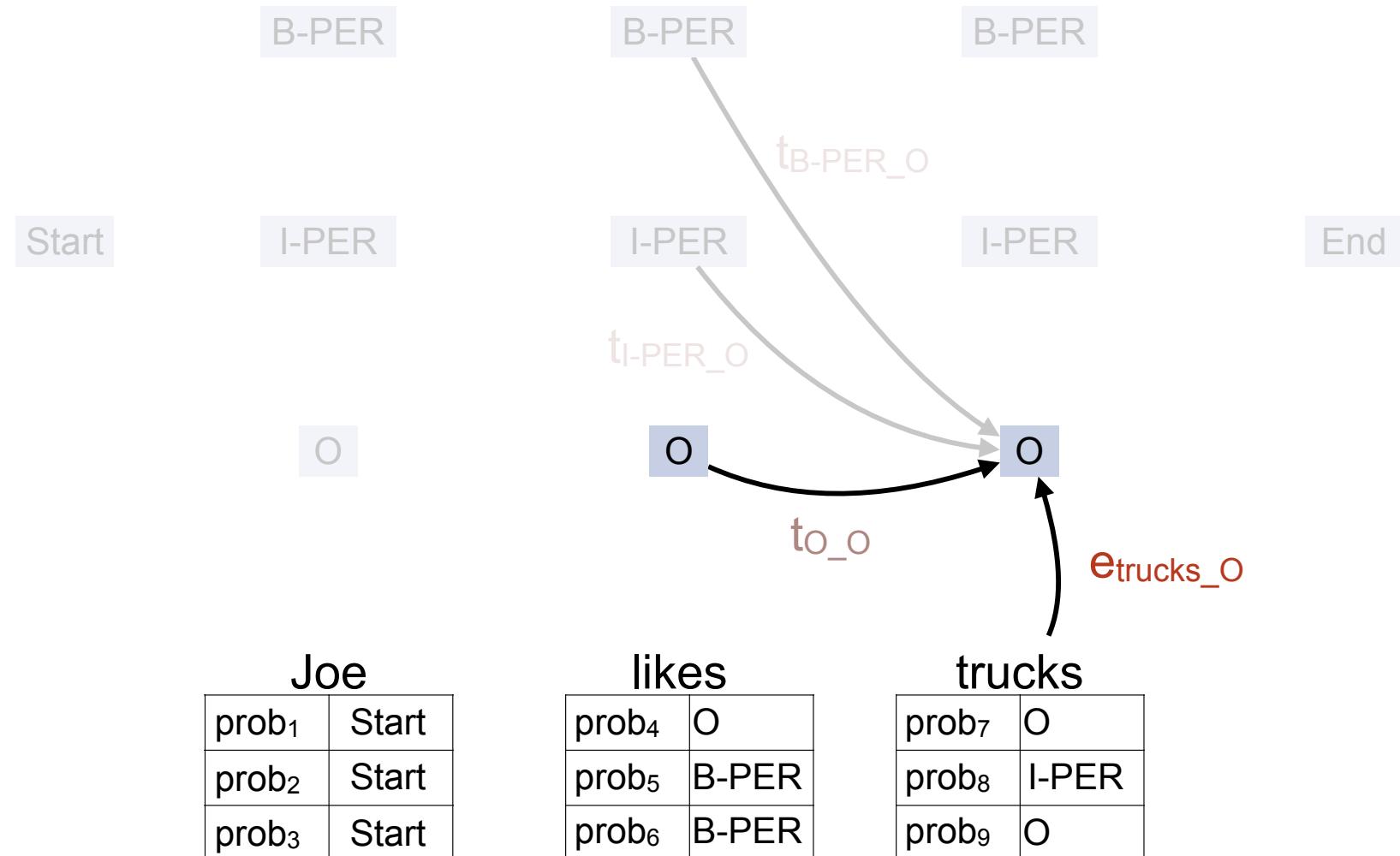
Sequence Tagging
Graph Parsing
Coreference
Workshop Preview

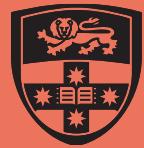


[menti.com 6274 6616](https://menti.com/62746616)

Each step only looks back one step

$$\text{prob}_9 = e_{\text{trucks_I-PER}} * \max(t_{\text{prev_I-PER}} * \text{prob}_{\text{prev}})$$





Sequence Tagging
Graph Parsing
Coreference
Workshop Preview

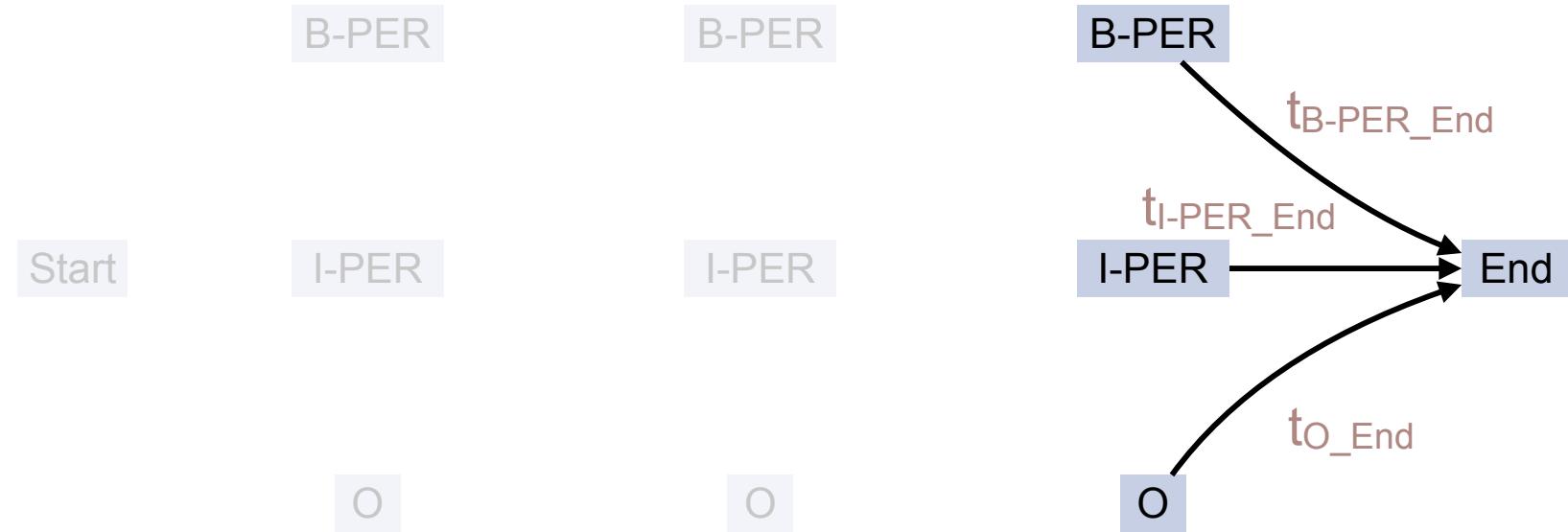


menti.com 6274 6616

Each step only looks back one step

Ending

$$\text{prob}_{10} = \max(t_{\text{prev_End}} * \text{prob}_{\text{prev}})$$



prob ₁	Start
prob ₂	Start
prob ₃	Start

prob ₄	O
prob ₅	B-PER
prob ₆	B-PER

prob ₇	O	prob ₁₀
prob ₈	I-PER	
prob ₉	O	



Each step only looks back one step

$$\text{prob}_{10} = \max(t_{\text{prev_End}} * \text{prob}_{\text{prev}})$$

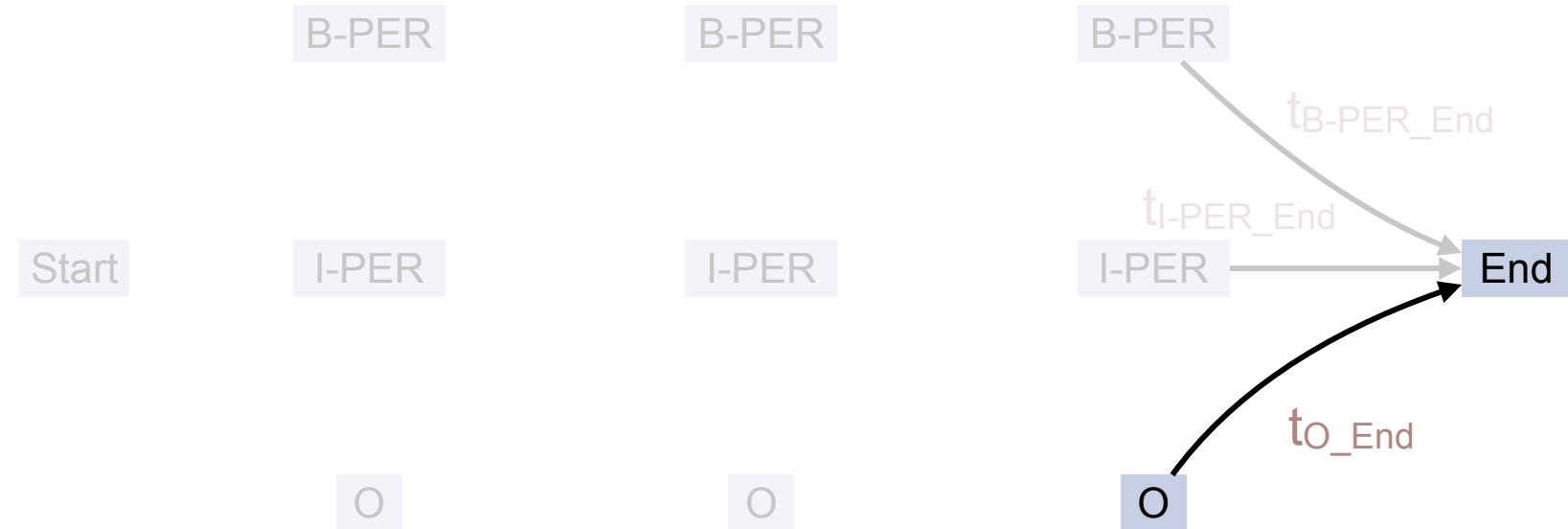
Example

Sequence Tagging

Graph Parsing

Coreference

Workshop Preview



[menti.com 6274 6616](https://menti.com/62746616)

prob ₁	Start
prob ₂	Start
prob ₃	Start

Joe

prob ₄	O
prob ₅	B-PER
prob ₆	B-PER

likes

prob ₇	O
prob ₈	I-PER
prob ₉	O

trucks

prob₁₀ | O

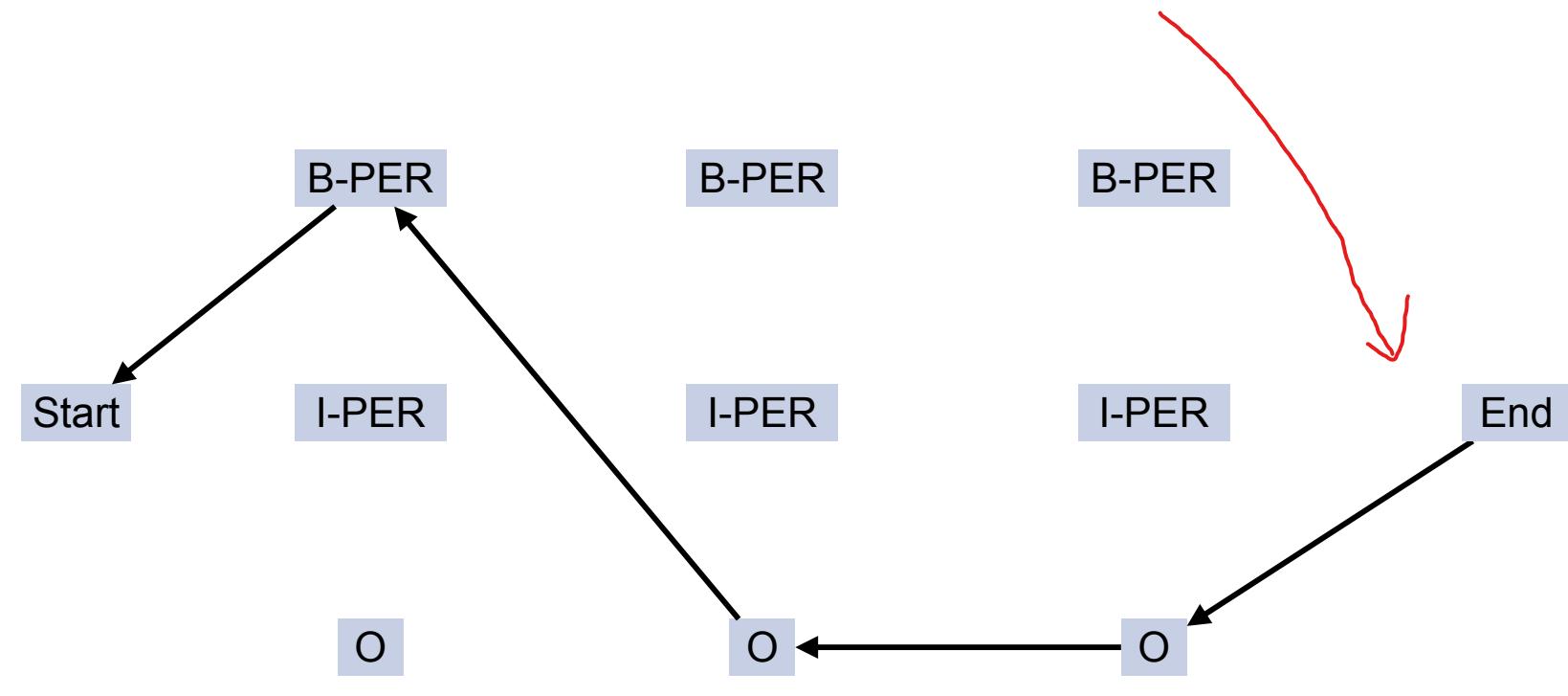


Sequence Tagging
Graph Parsing
Coreference
Workshop Preview



[menti.com 6274 6616](https://menti.com/62746616)

To get the path, follow the references backwards to the start



prob ₁	Start
prob ₂	Start
prob ₃	Start

Joe

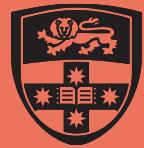
prob ₄	O
prob ₅	B-PER
prob ₆	B-PER

likes

prob ₇	O
prob ₈	I-PER
prob ₉	O

trucks

prob₁₀ | O

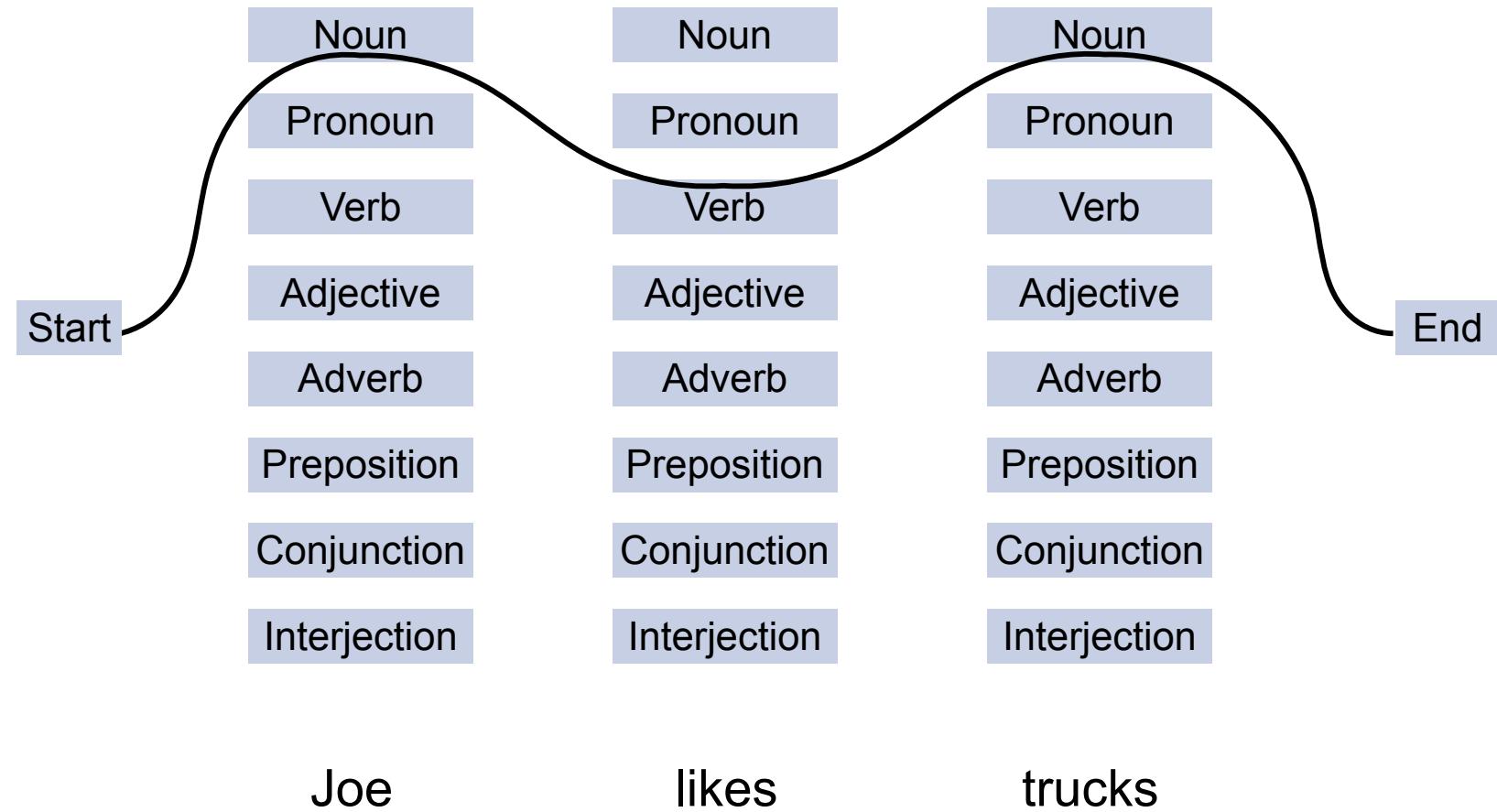


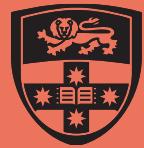
Sequence Tagging
Graph Parsing
Coreference
Workshop Preview



[menti.com 6274 6616](https://menti.com/62746616)

We can apply the same idea to POS tagging





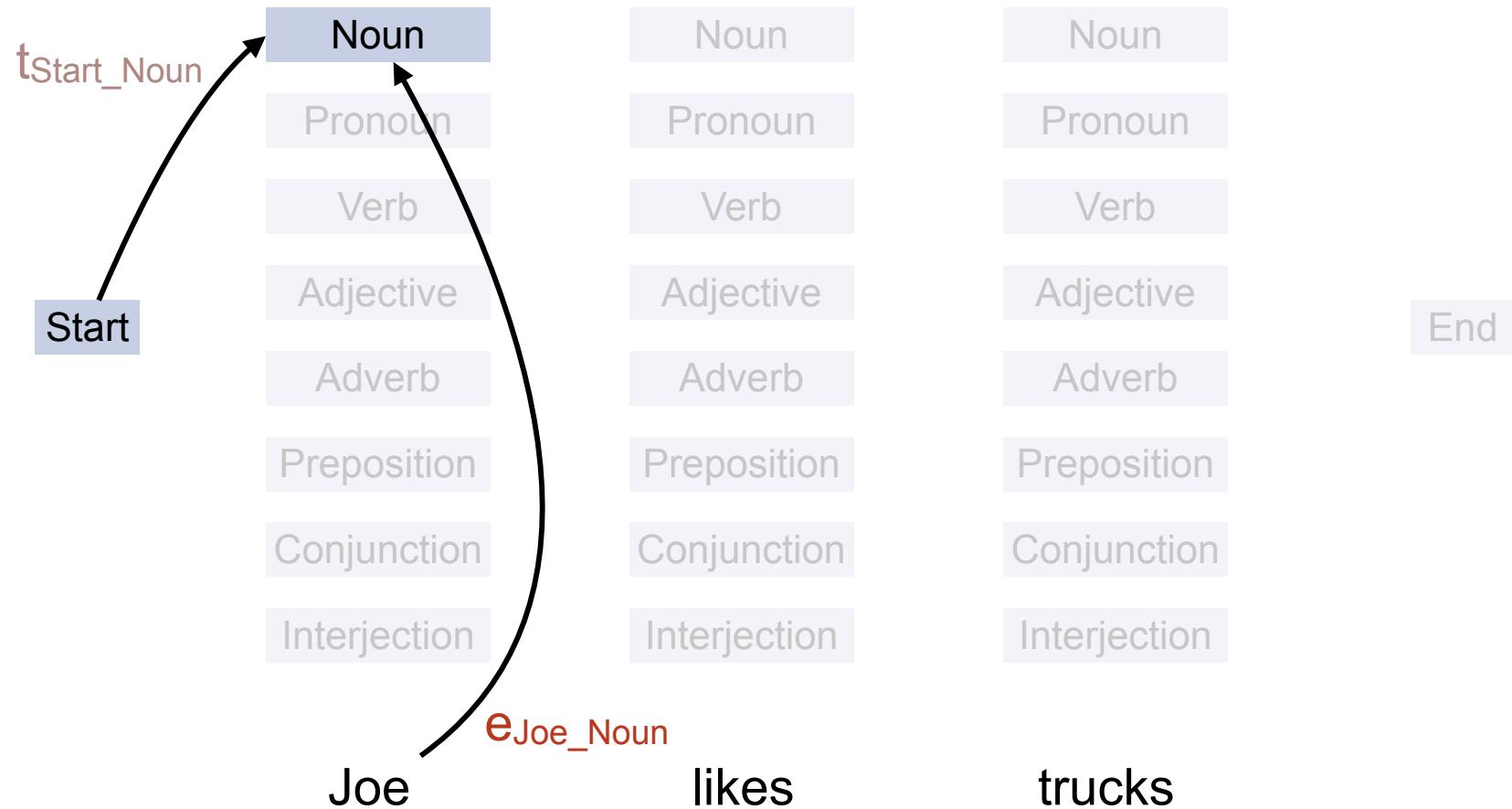
Sequence Tagging
Graph Parsing
Coreference
Workshop Preview

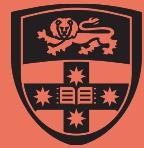


[menti.com 6274 6616](https://menti.com/62746616)

We can apply the same idea to POS tagging

One move
Example





Sequence Tagging

Graph Parsing

Coreference

Workshop Preview



menti.com 6274 6616

Forward

Pseudocode for the algorithm to calculate scores and previous labels

Create storage for best option for each (position, label) pair

For each position in input:

 For each label:

 Best score = -infinity

 Best previous = None

 For each previous_label:

 Score = previous_label's prob *
 prob(label | input and
 previous label)

 If score is better than best:

 Update best

 Save best score and best previous for this (position, label) pair

Called the
Viterbi algorithm

(note, also need to account for start and end)



Pseudocode for the algorithm to get the path
path back

Sequence Tagging

Graph Parsing

Coreference

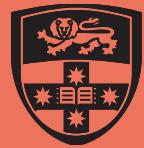
Workshop Preview

```
Path = []
Current label = End
For position from end of sequence to start:
    Current label = Best for this position and
                    the current label
    Append current label to Path
```

Reverse path



[menti.com 6274 6616](https://menti.com/62746616)



Sequence Tagging

Graph Parsing

Coreference

Workshop Preview



[menti.com 6274 6616](https://menti.com/62746616)

Time complexity is $O(|words| * |labels|^2)$



$|words|$ steps

In each step, consider $|labels|$

For each option, consider $|labels|$ previous options

similar to Perception

ex. barkprob



COMP 4446 / 5046
Lecture 5, 2025

Learn by comparing the final output with the true answer

Sequence Tagging

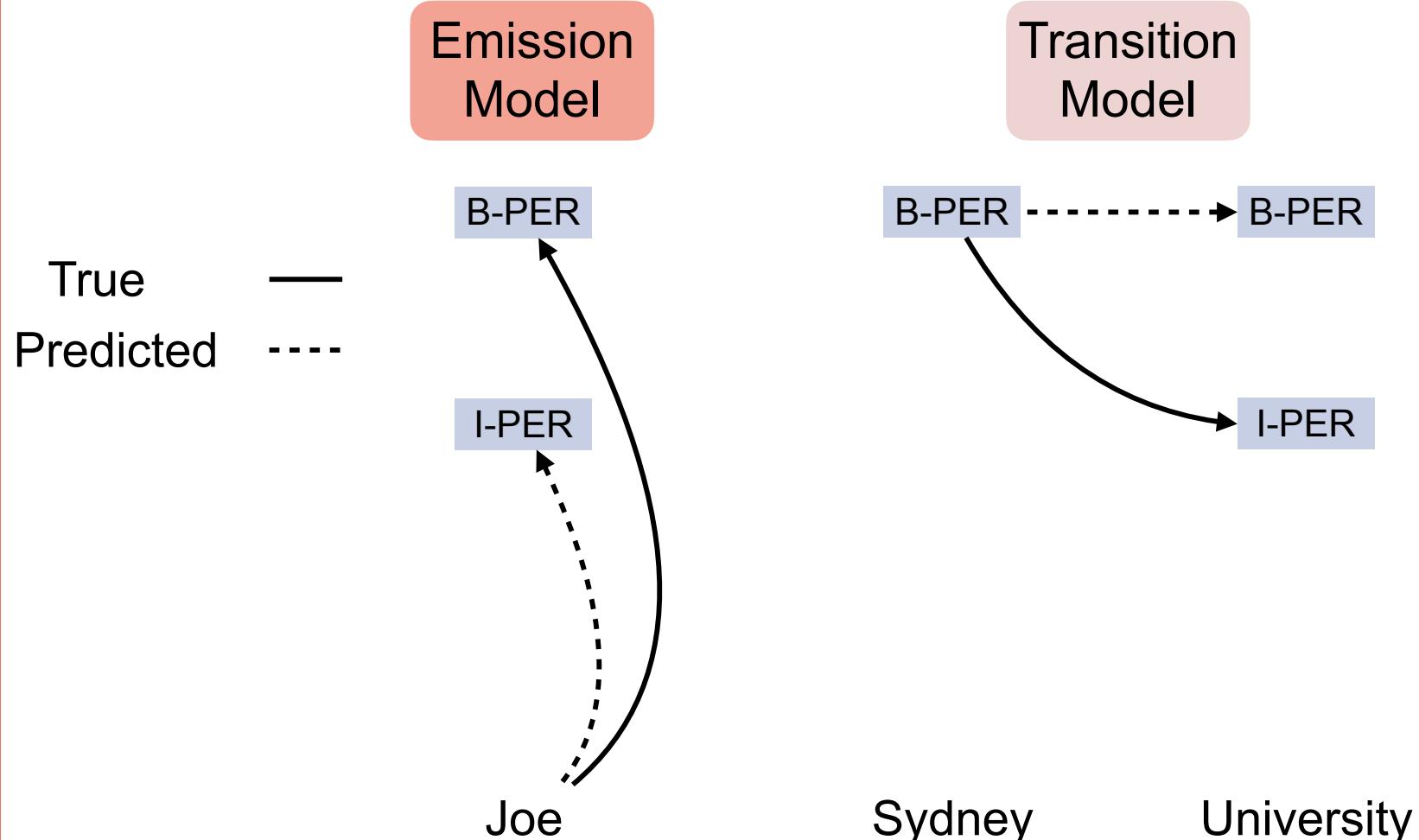
Graph Parsing

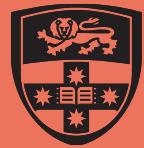
Coreference

Workshop Preview



menti.com 6274 6616





Sequence Tagging

Graph Parsing

Coreference

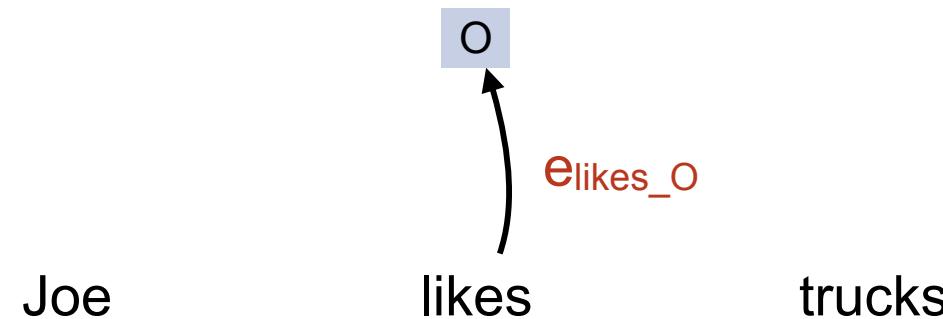
Workshop Preview

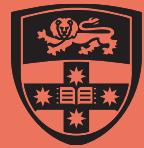


[menti.com 6274 6616](https://menti.com/62746616)

The model can use all of the input, and the previous label

Emission Model





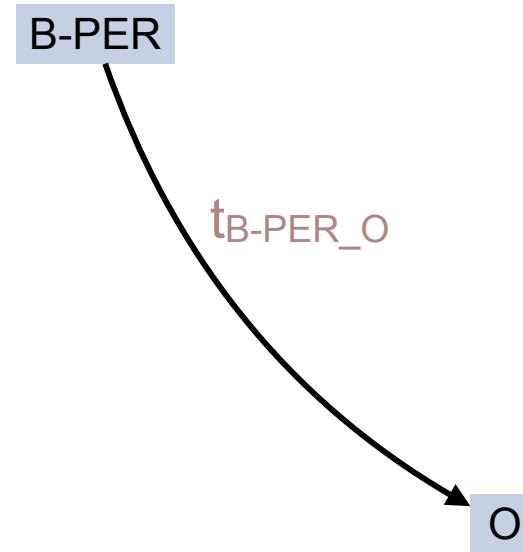
Sequence Tagging
Graph Parsing
Coreference
Workshop Preview



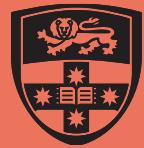
[menti.com 6274 6616](https://menti.com/62746616)

The model can use all of the input, and the previous label

Transition Model



Joe likes trucks



Sequence Tagging
Graph Parsing
Coreference
Workshop Preview

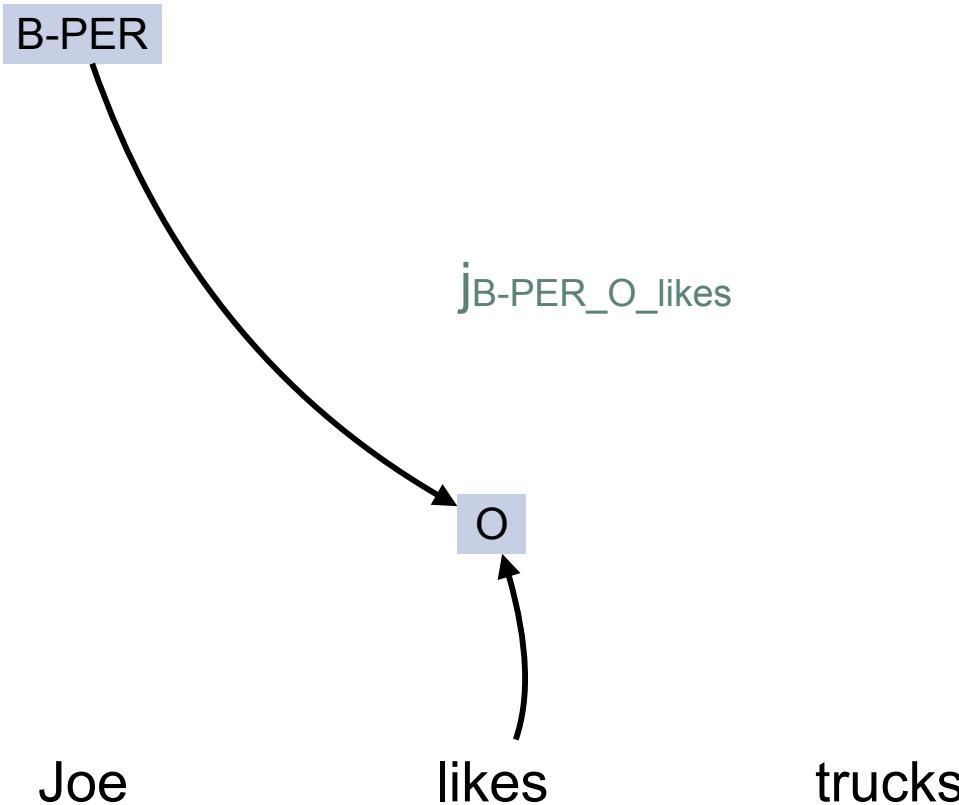


[menti.com 6274 6616](https://menti.com/62746616)

We can also define a model that does both scores at once

Joint
Model

$$\text{score}_{\text{current}} = \max(j_{\text{prev_label_word}} * \text{score}_{\text{prev}})$$





Sequence Tagging

Graph Parsing

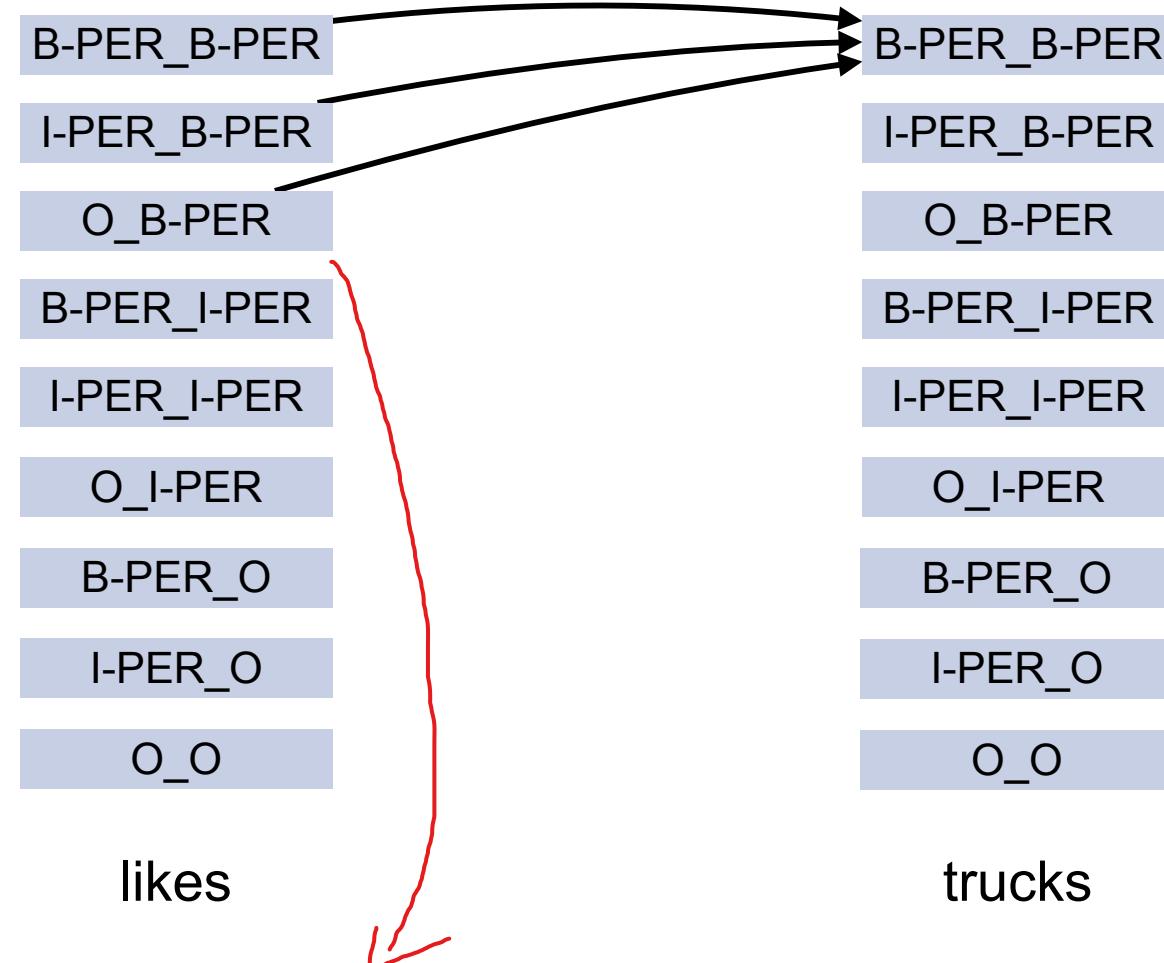
Coreference

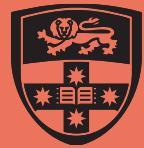
Workshop Preview



[menti.com 6274 6616](https://menti.com/62746616)

If we are willing to increase complexity, we can use more label context





Sequence Tagging

Graph Parsing

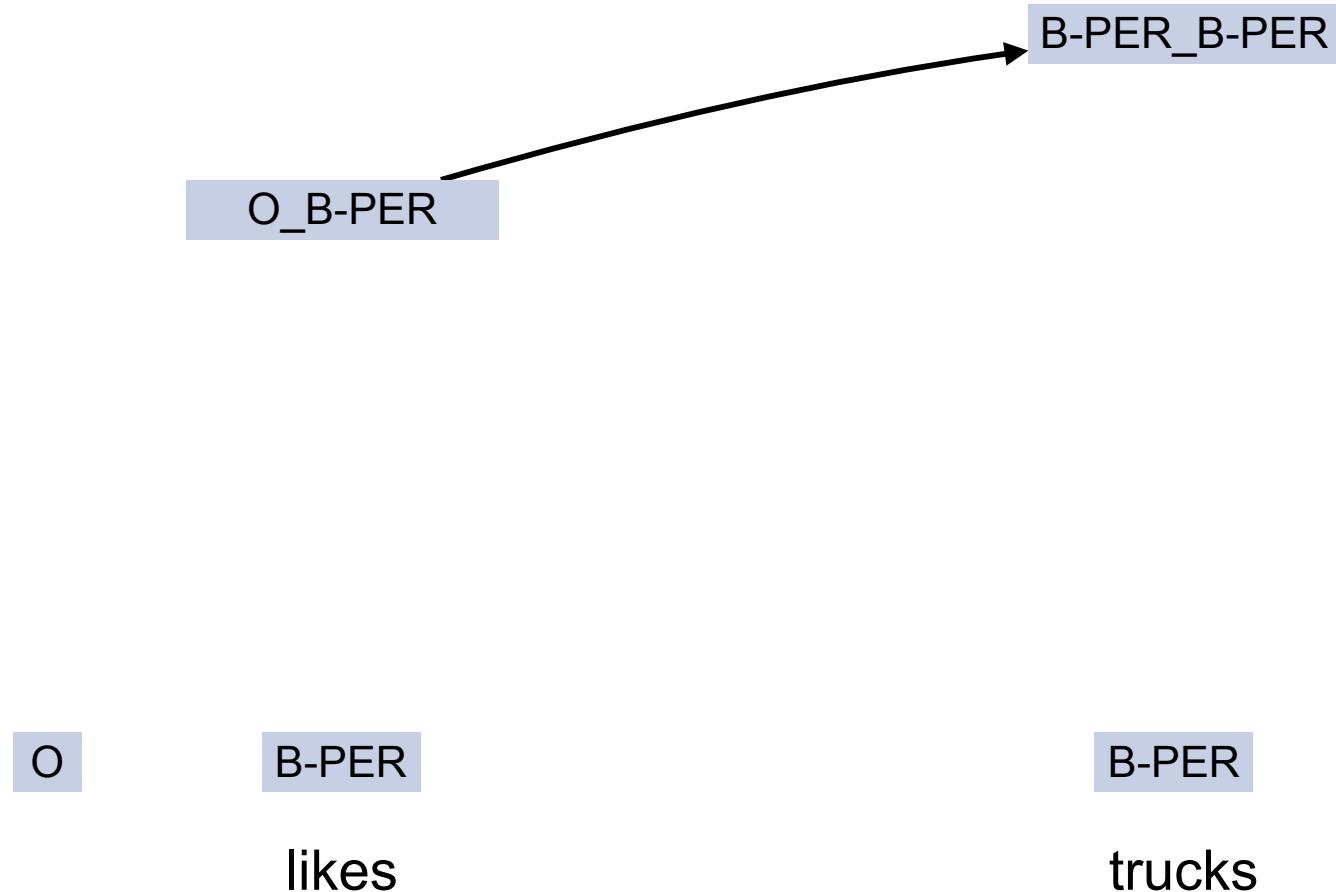
Coreference

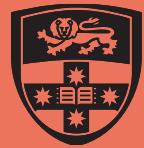
Workshop Preview



[menti.com 6274 6616](https://menti.com/62746616)

If we are willing to increase complexity, we can use more label context





Sequence Tagging

Graph Parsing

Coreference

Workshop Preview



[menti.com 6274 6616](https://menti.com/62746616)

Now, time complexity is $O(|\text{words}| * |\text{labels}|^3)$

Joe, likes, trucks

$|\text{words}|$ steps

B-PER_B-PER

I-PER_B-PER

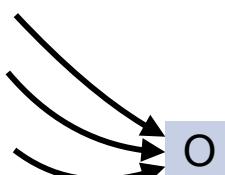
O_B-PER

...

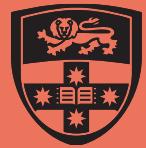
likes

In each step, consider
 $|\text{labels}| * |\text{labels}|$

difference



For each option, consider
 $|\text{labels}|$ previous options



Sequence Tagging

Graph Parsing

Coreference

Workshop Preview



[menti.com 6274 6616](https://menti.com/62746616)

We can apply this method to a variety of models

Linear models (e.g., CRF)

Feedforward Networks

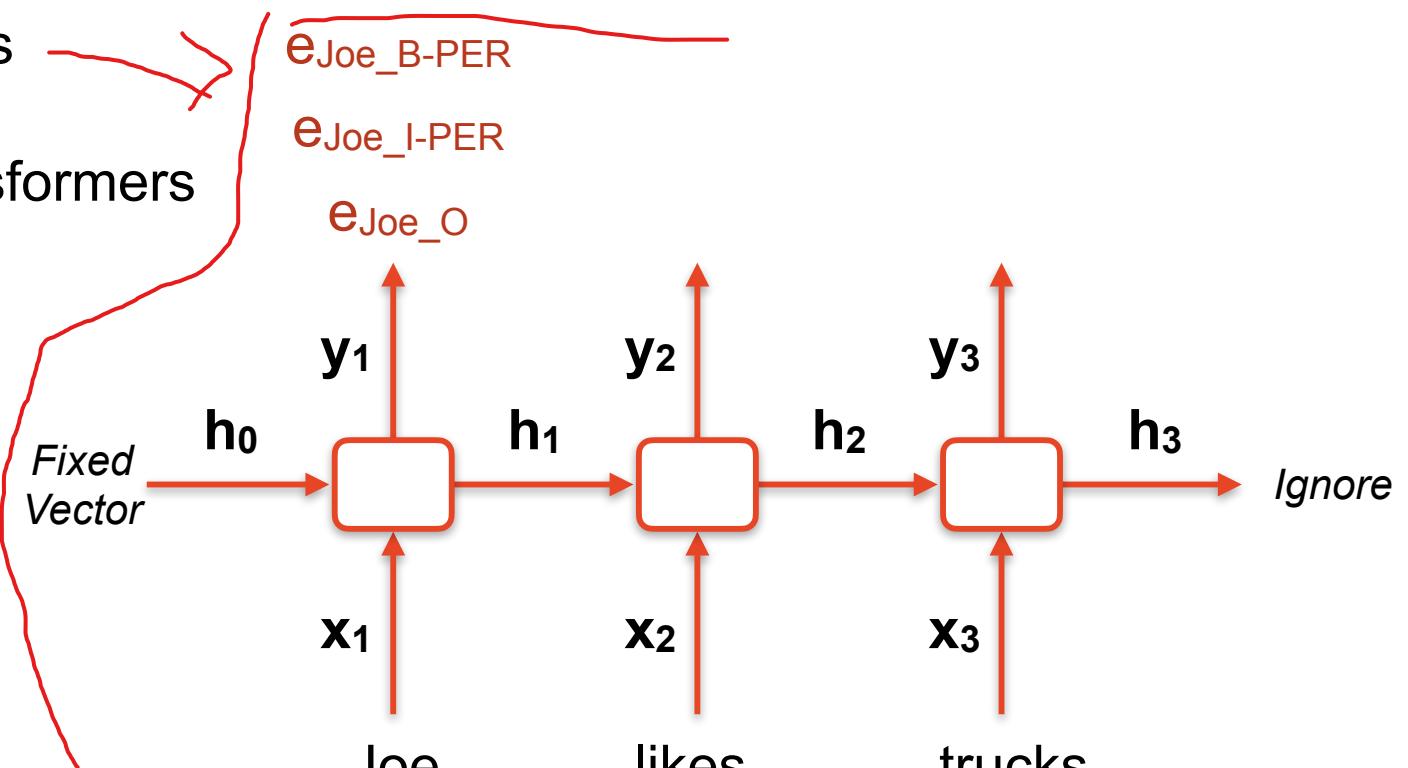
RNNs

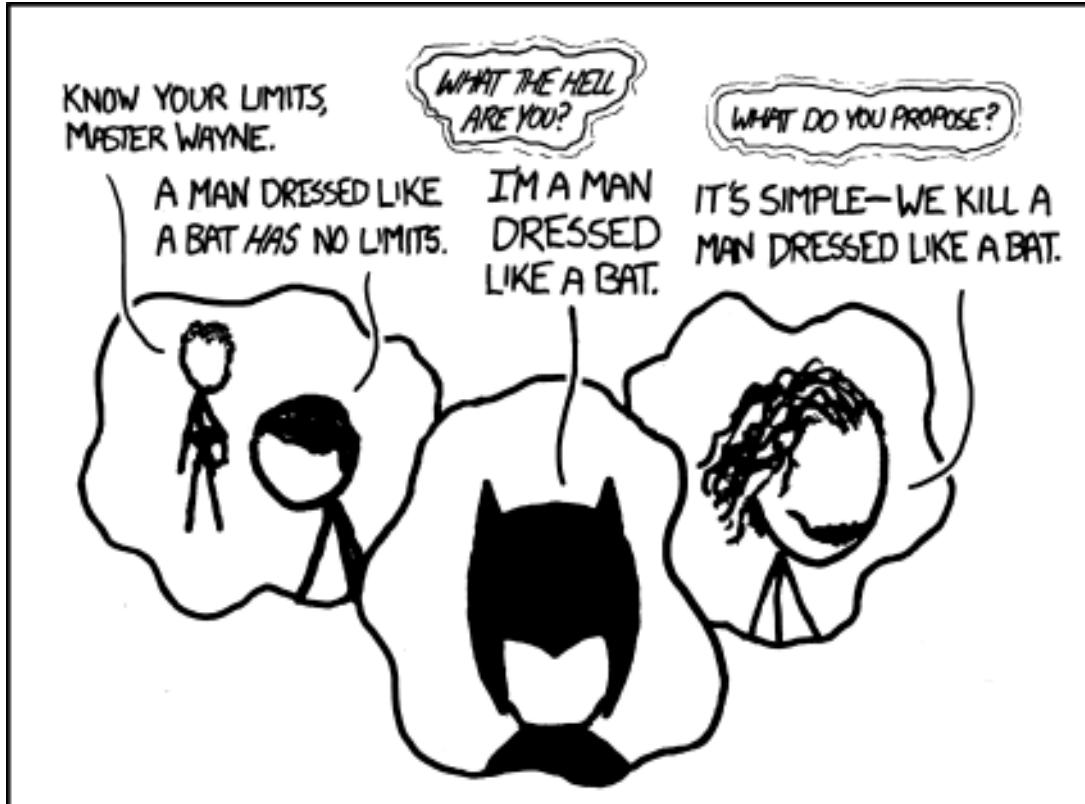
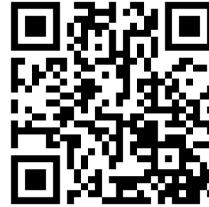
Transformers

$e_{\text{Joe_B-PER}}$

$e_{\text{Joe_I-PER}}$

$e_{\text{Joe_O}}$





MY HOBBY:

WHENEVER ANYONE SAYS "BATMAN", I MENTALLY
REPLACE IT WITH "A MAN DRESSED LIKE A BAT."

Batman

[I'm really worried Christopher Nolan will kill a man dressed like a bat in his next movie. (The man will be dressed like a bat, I mean. Christopher Nolan won't be, probably.)]

Source: <https://xkcd.com/1004/>



COMP 4446 / 5046
Lecture 5, 2025

Sequence Tagging
Graph Parsing
Coreference
Workshop Preview



[menti.com 6274 6616](https://menti.com/62746616)

Graph Parsing



Syntactic parsing can resolve ambiguities

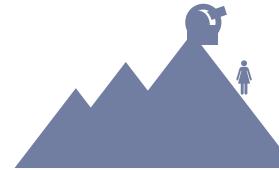


I saw the person on the hill with a telescope

3 *Meanings*



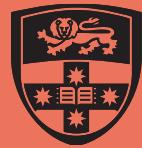
I saw the person on the hill with a telescope



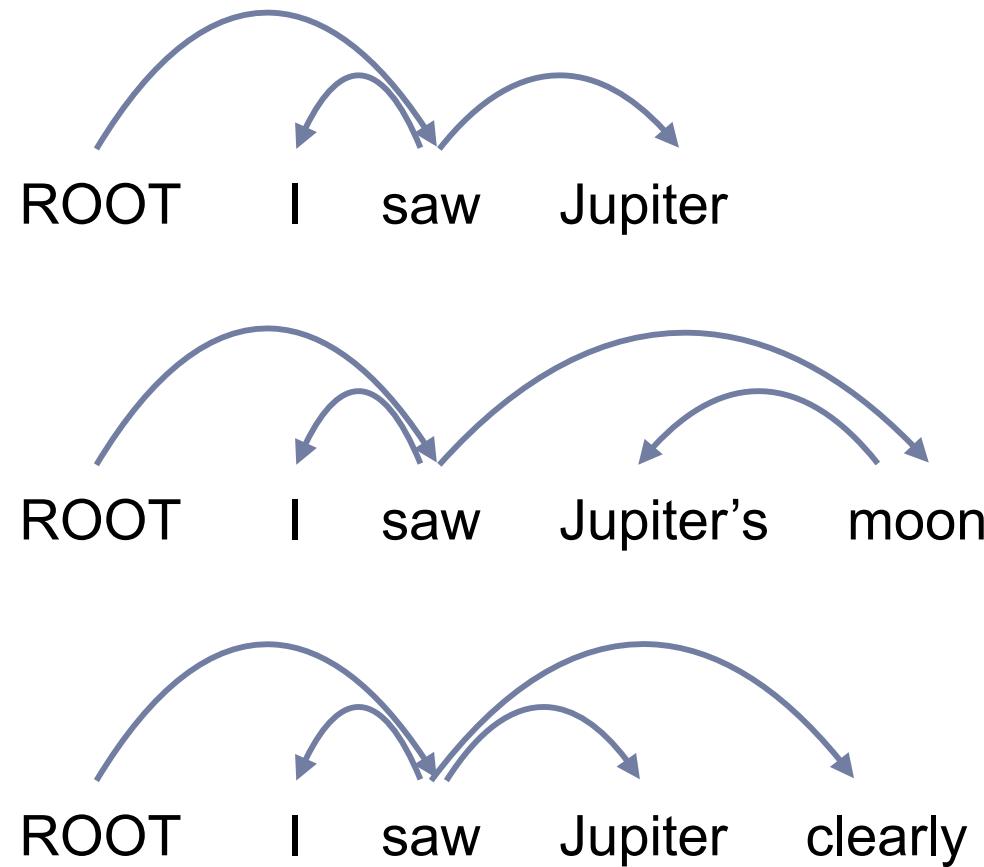
I saw the person on the hill with a telescope

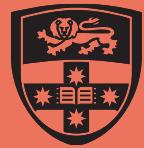


I saw the person on the hill with a telescope

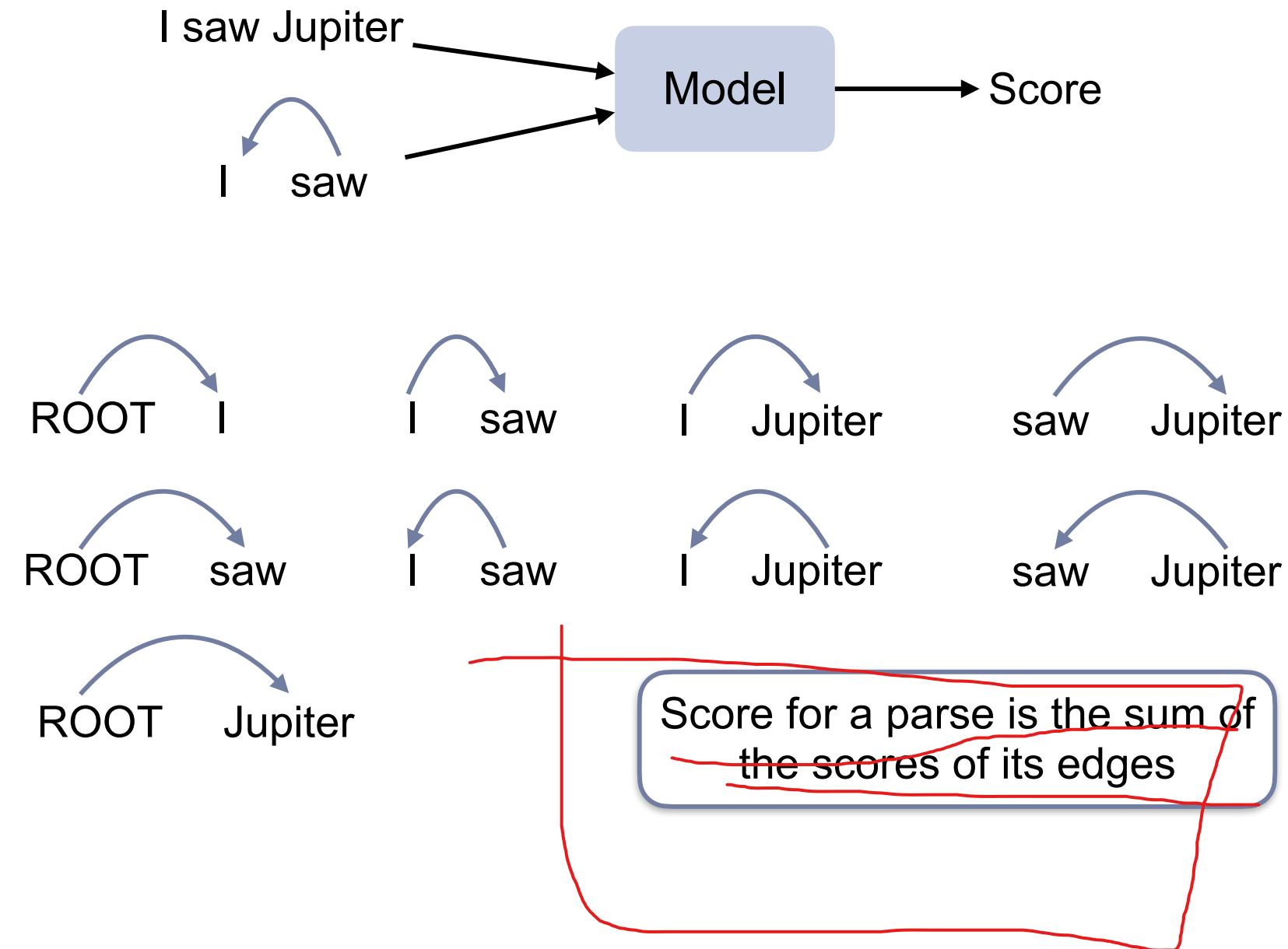


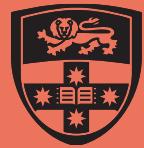
Arcs / Edges / Dependencies go from a head to a dependent





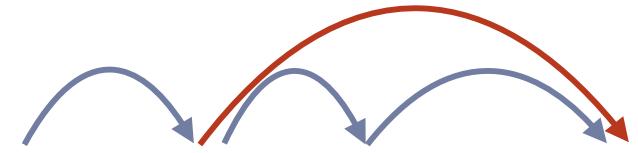
We'll use an arc model to score options



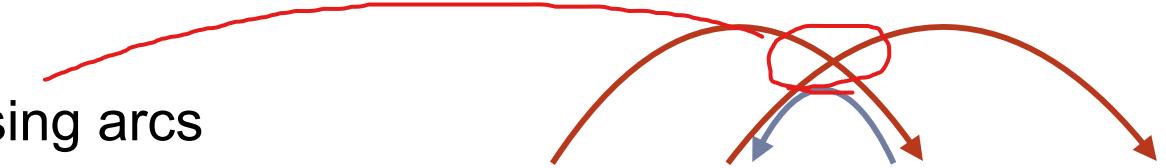


Requirements for our inference method

1. Produce a tree



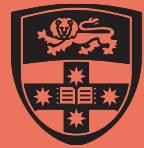
2. No crossing arcs



3. A single root



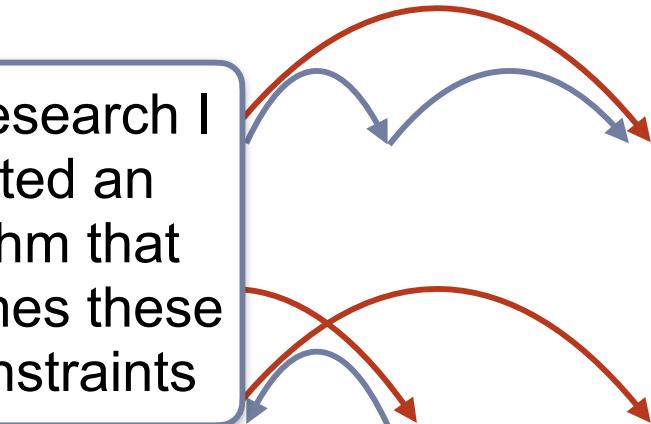
4. The tree has the highest score of all possible trees

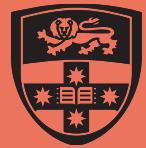


Requirements for our inference method

1. Produce a tree
2. No crossing arcs
3. A single root
4. The tree has the highest score of all possible trees

In my research I invented an algorithm that overcomes these two constraints





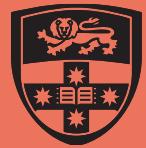
Sequence Tagging
Graph Parsing
Coreference
Workshop Preview



[menti.com 6274 6616](https://menti.com/62746616)

Many inference methods - today we see **dynamic programming**

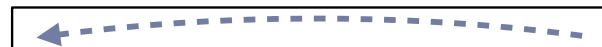
in ~~the room for my~~
~~my~~ class



~~Box meaning in rest pages~~

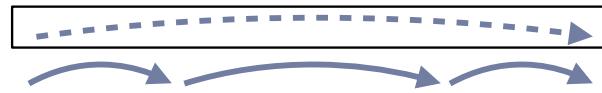
Our inference algorithm is defined by **items** and rules

Item



Represents

A structure with an indirect path from *class* to *in*



A structure with an indirect path from *in* to *class*



A structure with an **arc** from *class* to *in*



A structure with an **arc** from *in* to *class*

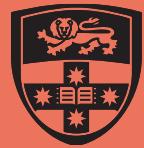


A structure with no link between *in* and *class*

in

...

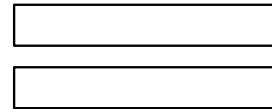
class



combine
Our inference algorithm is defined by items and **rules**

Adding
Arcs

Item



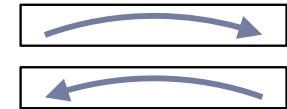
+

Arc



=

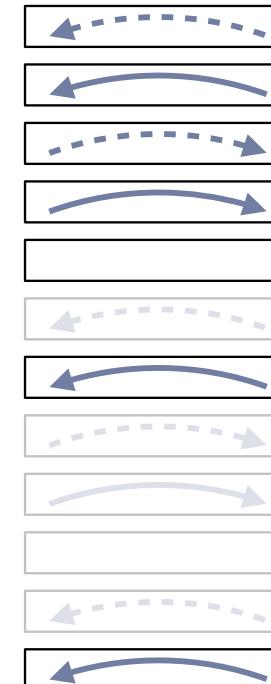
Result



*include
by set*

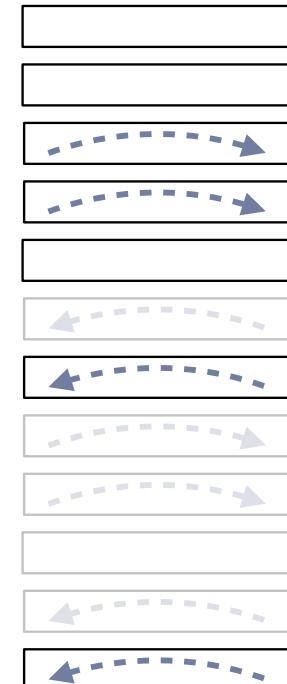
width = 1
Combining
Items

Left *Combine* Right

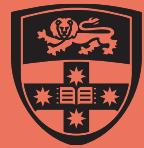


=

Result



Example



Sequence Tagging
Graph Parsing
Coreference
Workshop Preview

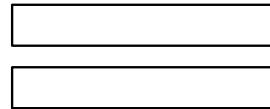


menti.com 6274 6616

Our inference algorithm is defined by items and **rules**

Adding
Arcs

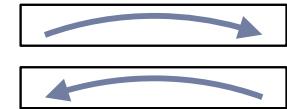
Item



Arc



Result

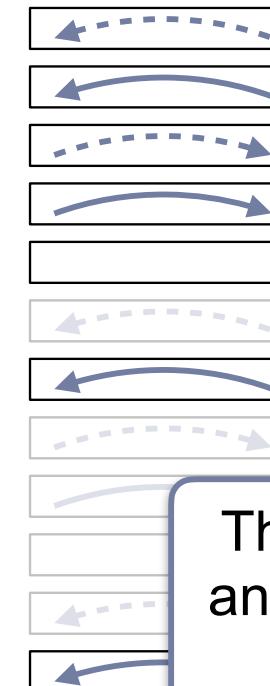


Combining
Items

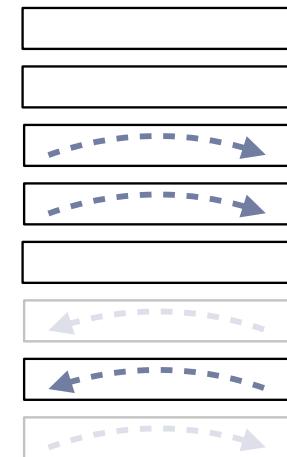
Left



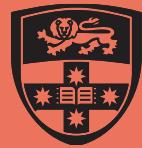
Right



Result



This subset of rules gives
an algorithm that is *sound*,
complete and *unique*

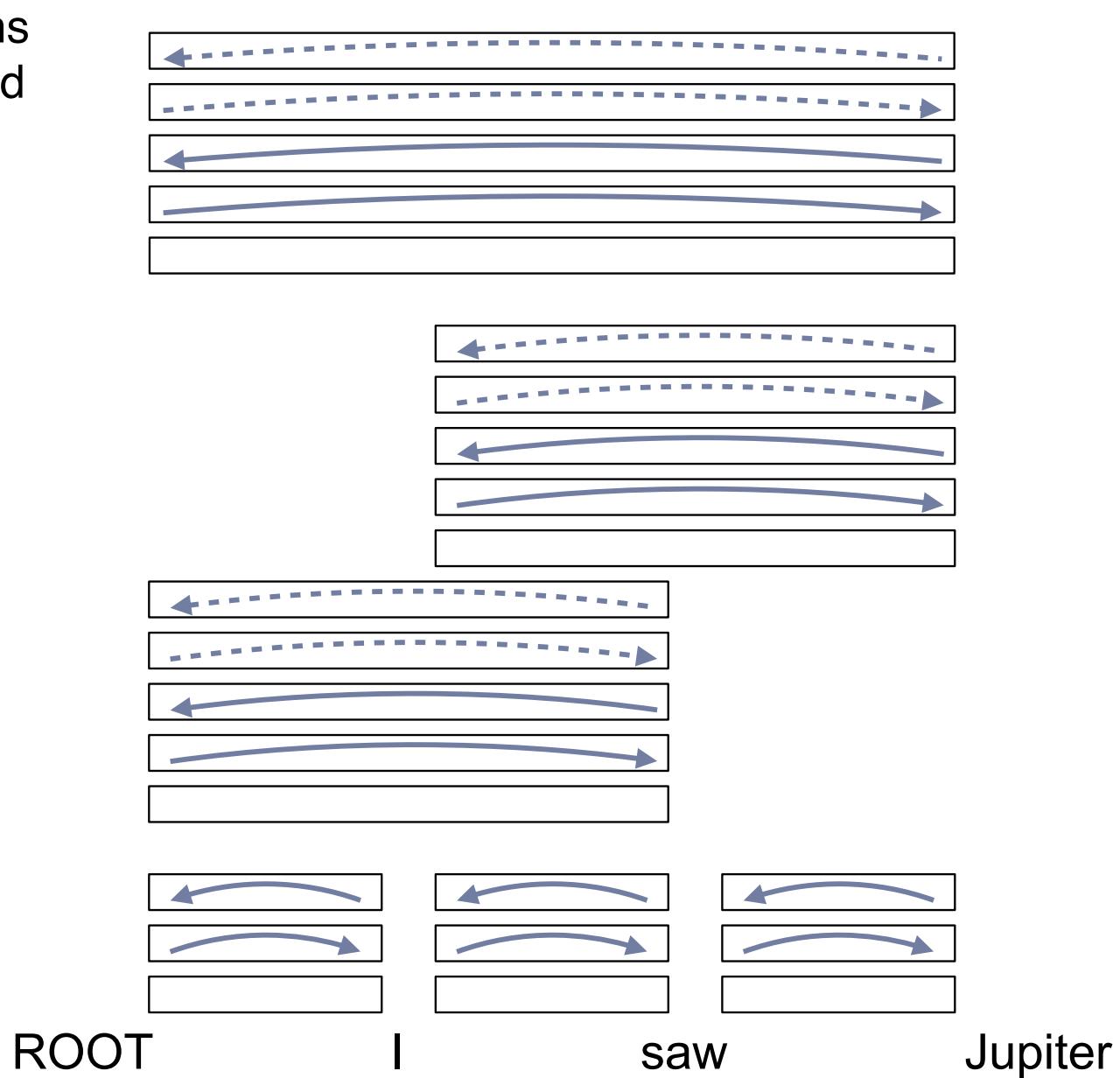


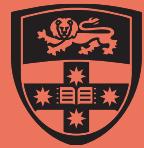
Sequence Tagging
Graph Parsing
Coreference
Workshop Preview



[menti.com 6274 6616](https://menti.com/62746616)

We use the items and rules to build up the parse



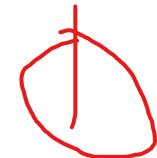


Sequence Tagging
Graph Parsing
Coreference
Workshop Preview



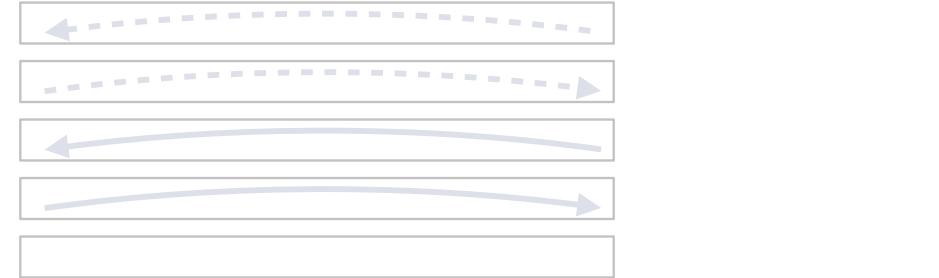
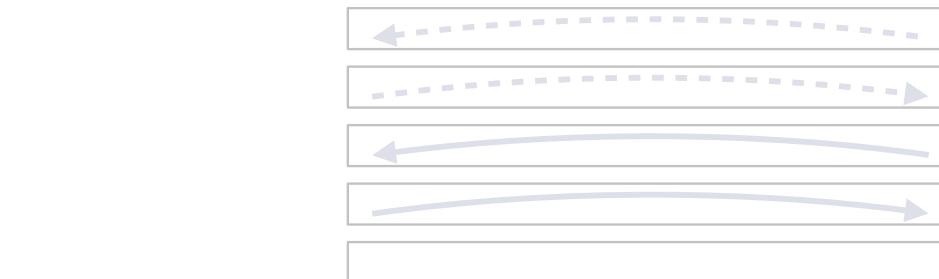
[menti.com 6274 6616](https://menti.com/62746616)

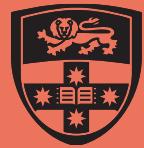
We use the items and rules to build up the parse



Create starting items

ROOT | saw Jupiter



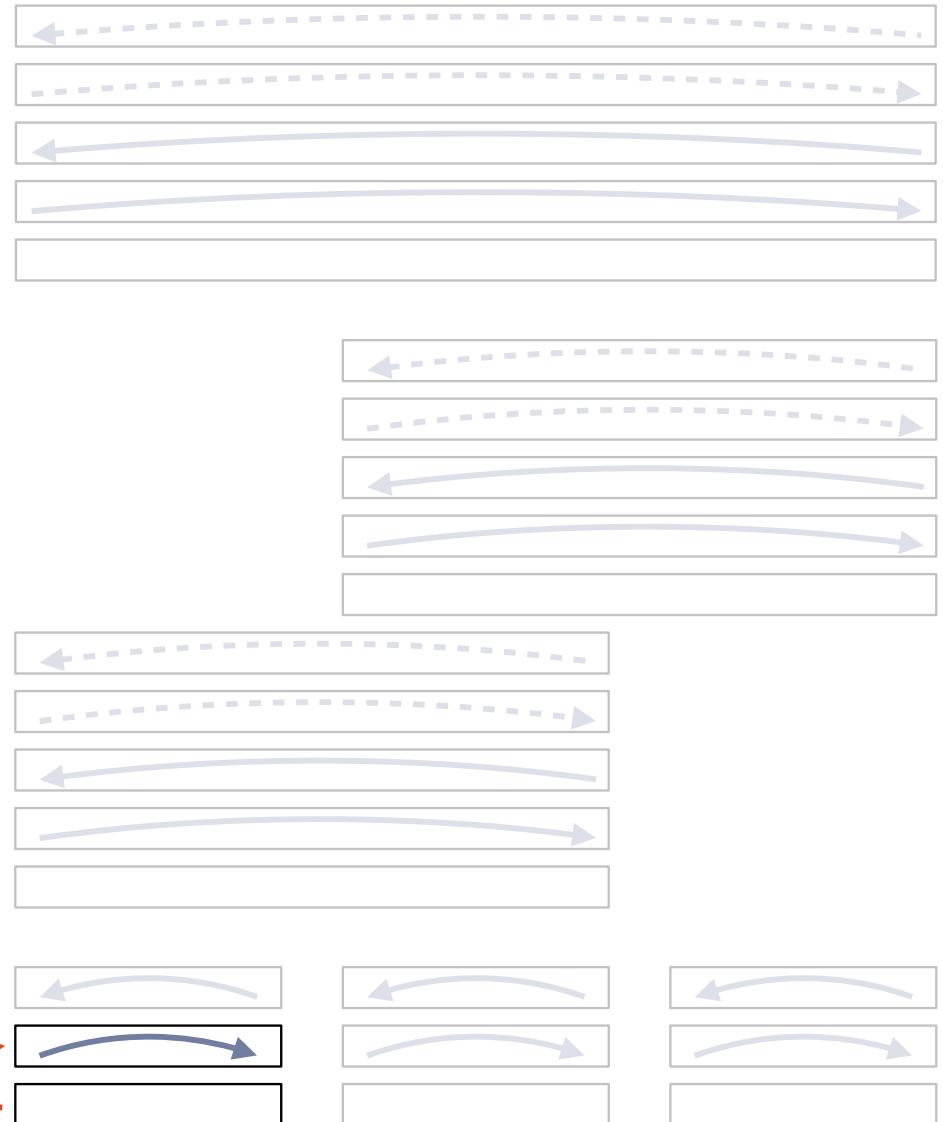


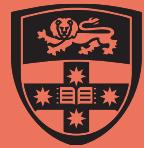
We use the items and rules to build up the parse

Z!

Apply arc creation rules

ROOT | saw Jupiter





We use the items and rules to build up the parse

I - living

2.2

Apply arc creation rules

ROOT | I saw Jupiter



We use the items and rules to build up the parse

Hiding
B

Apply combination rules

ROOT | saw Jupiter



We use the items and rules to build up the parse

Keep the higher scoring of this pair and the other pair

Apply combination rules

ROOT | I saw Jupiter



Sequence Tagging
Graph Parsing
Coreference
Workshop Preview

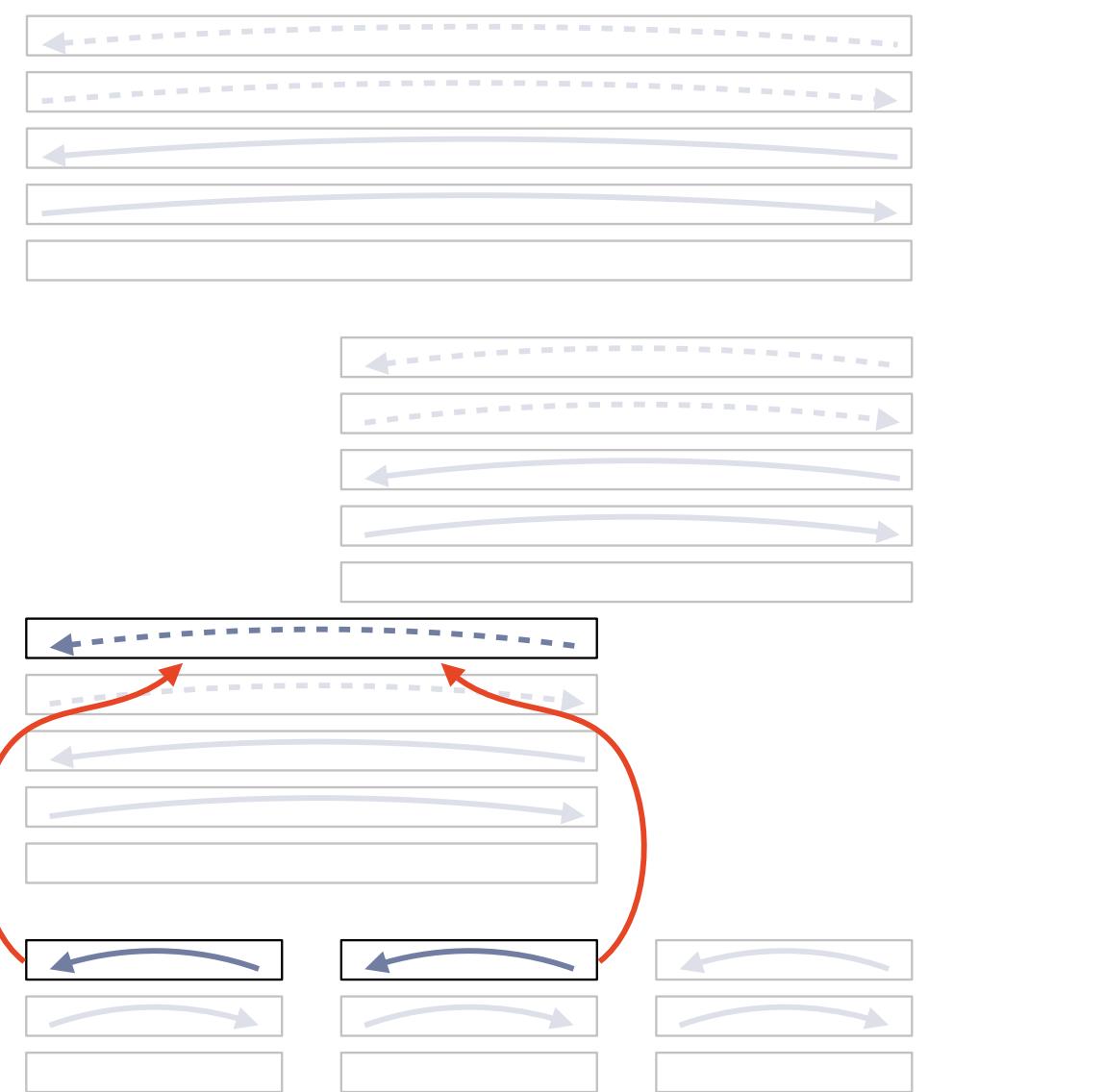


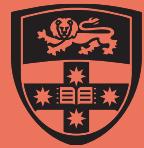
[menti.com 6274 6616](https://menti.com/62746616)

Apply
combination
rules

We use the items
and rules to build
up the parse

ROOT | saw Jupiter





We use the items and rules to build up the parse

Apply arc creation rules

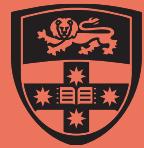
ROOT | saw Jupiter



We use the items and rules to build up the parse

Apply combination rules

ROOT | saw Jupiter



We use the items and rules to build up the parse

Apply combination rules

ROOT

|

saw

Jupiter



We use the items and rules to build up the parse

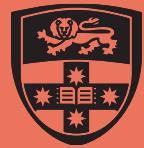
Apply combination rules

ROOT

|

saw

Jupiter



We use the items and rules to build up the parse

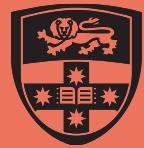
Apply combination rules

ROOT

|

saw

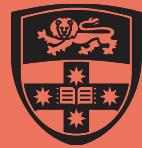
Jupiter



We use the items and rules to build up the parse

Apply combination rules

ROOT | saw Jupiter

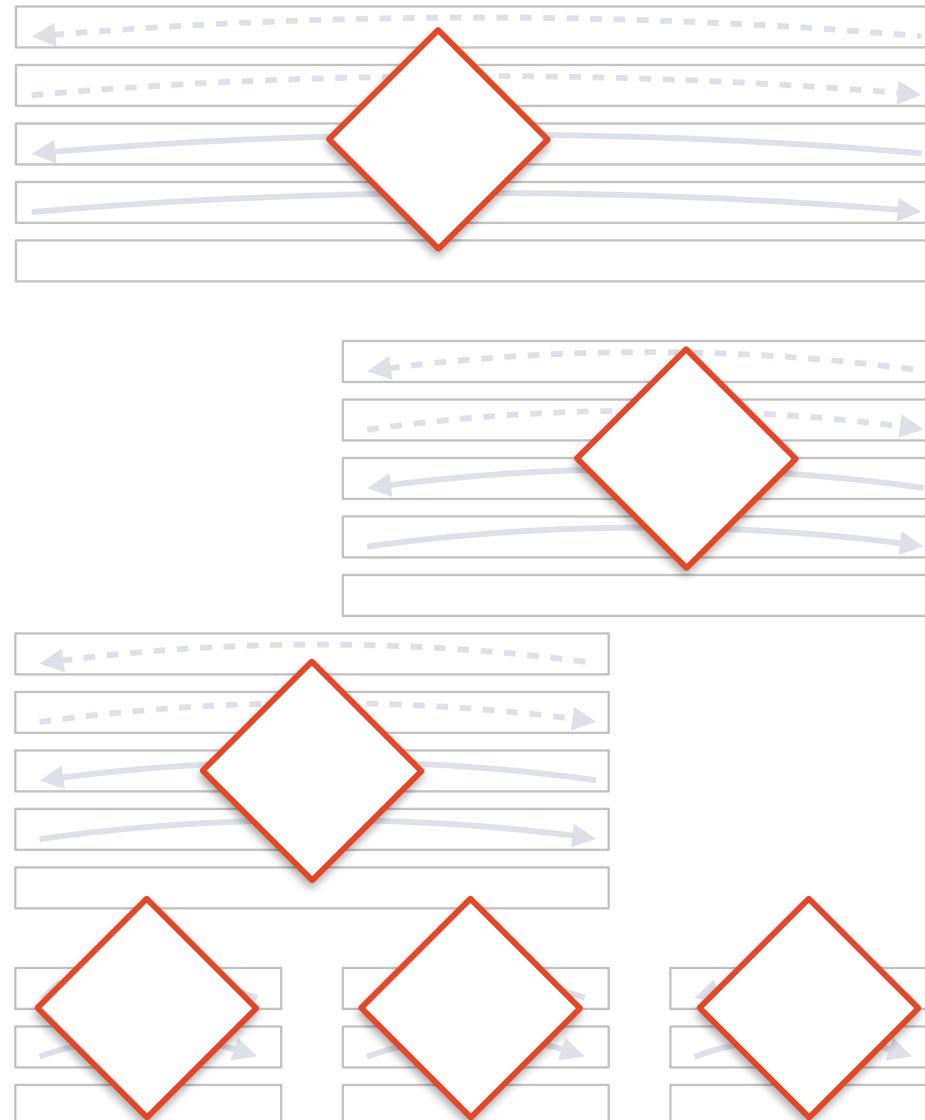


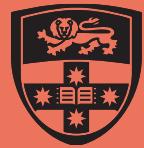
Sequence Tagging
Graph Parsing
Coreference
Workshop Preview



[menti.com 6274 6616](https://menti.com/62746616)

General idea: Consider each way to form each item, store the best and how you got it





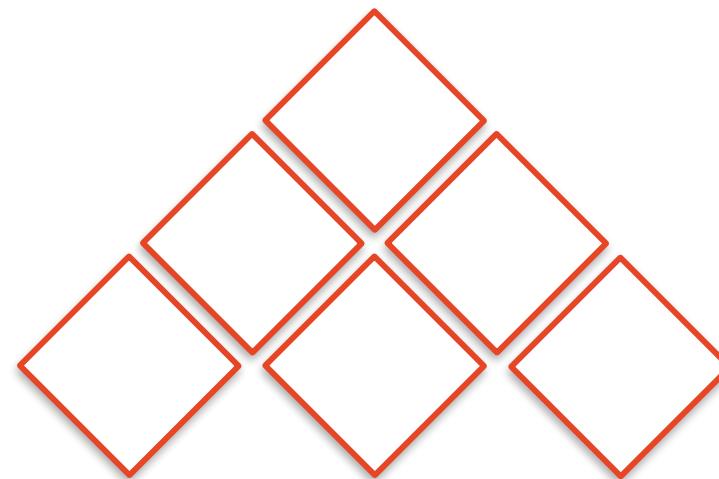
COMP 4446 / 5046
Lecture 5, 2025

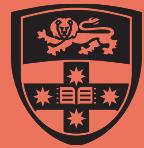
Sequence Tagging
Graph Parsing
Coreference
Workshop Preview



[menti.com 6274 6616](https://menti.com/62746616)

General idea: Consider each way to form each item, store the best and how you got it





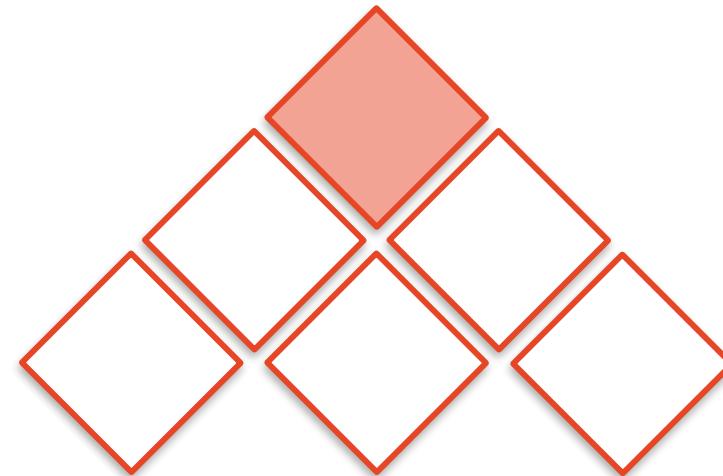
COMP 4446 / 5046
Lecture 5, 2025

Sequence Tagging
Graph Parsing
Coreference
Workshop Preview



[menti.com 6274 6616](https://menti.com/62746616)

General idea: Consider each way to form each item, store the best and how you got it





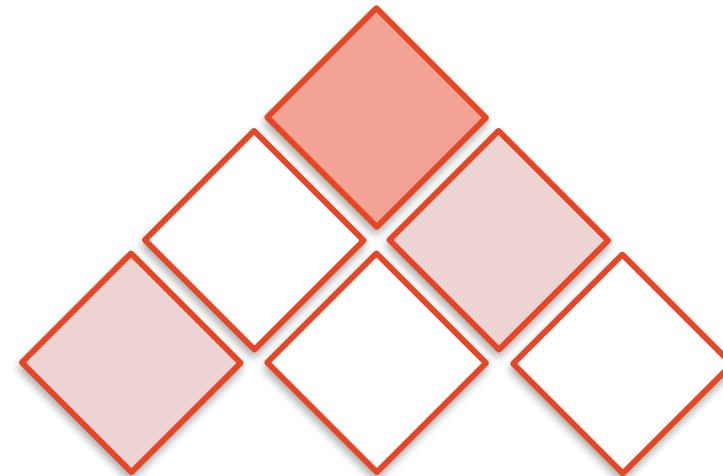
COMP 4446 / 5046
Lecture 5, 2025

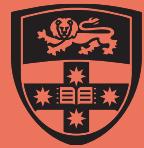
Sequence Tagging
Graph Parsing
Coreference
Workshop Preview



[menti.com 6274 6616](https://menti.com/62746616)

General idea: Consider each way to form each item, store the best and how you got it





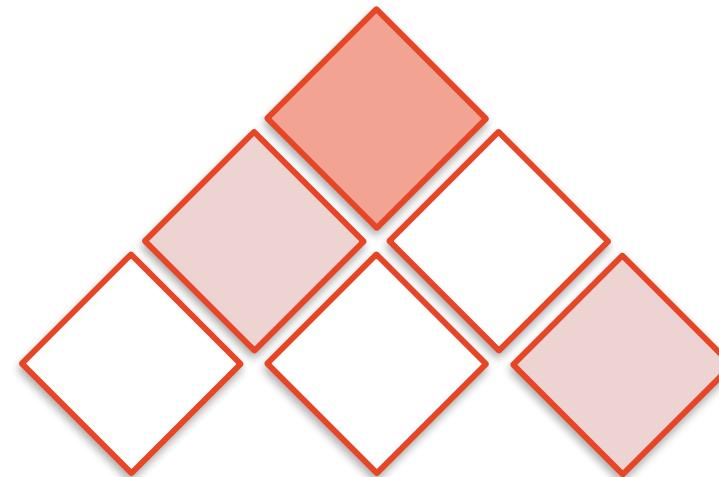
COMP 4446 / 5046
Lecture 5, 2025

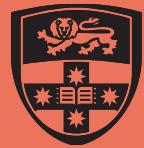
Sequence Tagging
Graph Parsing
Coreference
Workshop Preview



[menti.com 6274 6616](https://menti.com/62746616)

General idea: Consider each way to form each item, store the best and how you got it





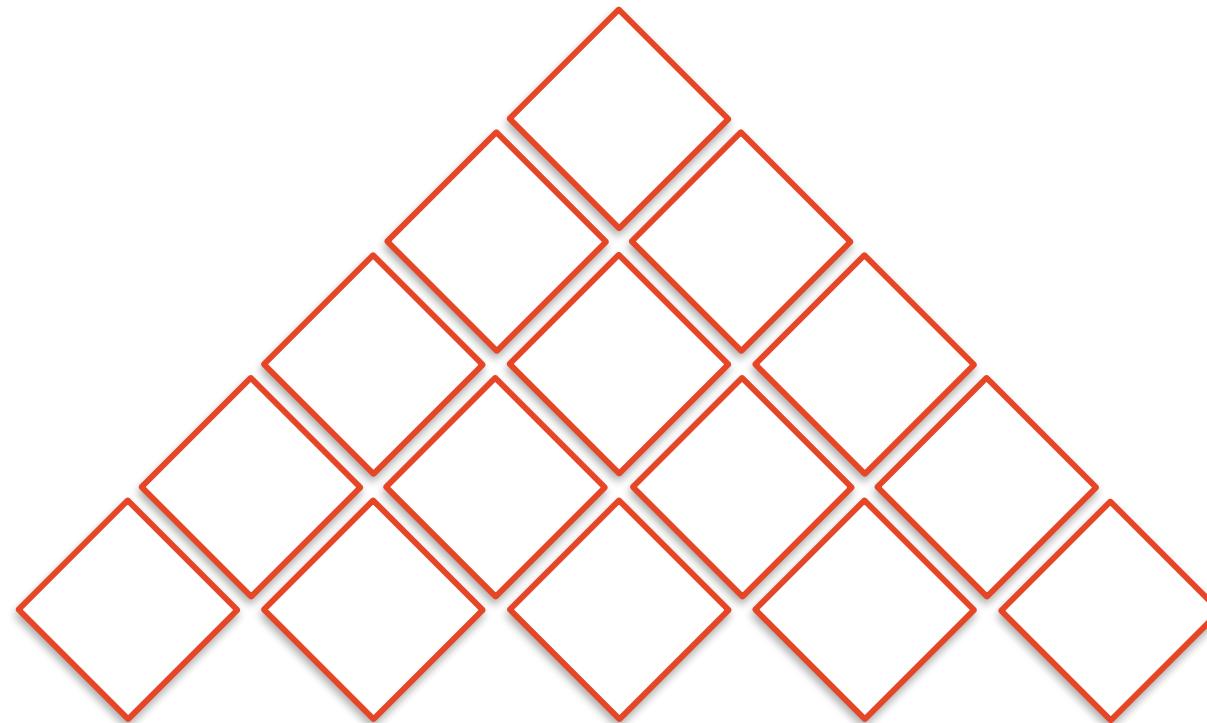
COMP 4446 / 5046
Lecture 5, 2025

Sequence Tagging
Graph Parsing
Coreference
Workshop Preview



[menti.com 6274 6616](https://menti.com/62746616)

General idea: Consider each way to form each item, store the best and how you got it





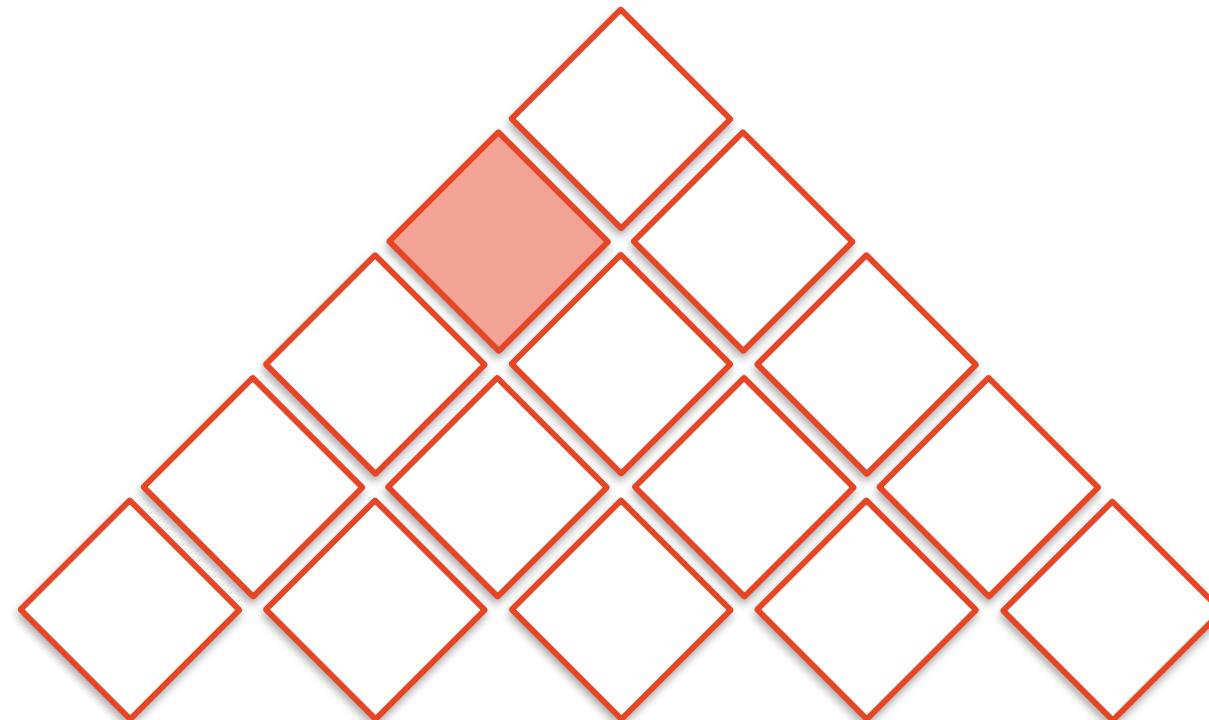
COMP 4446 / 5046
Lecture 5, 2025

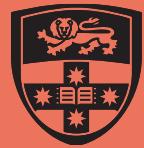
Sequence Tagging
Graph Parsing
Coreference
Workshop Preview



[menti.com 6274 6616](https://menti.com/62746616)

General idea: Consider each way to form each item, store the best and how you got it





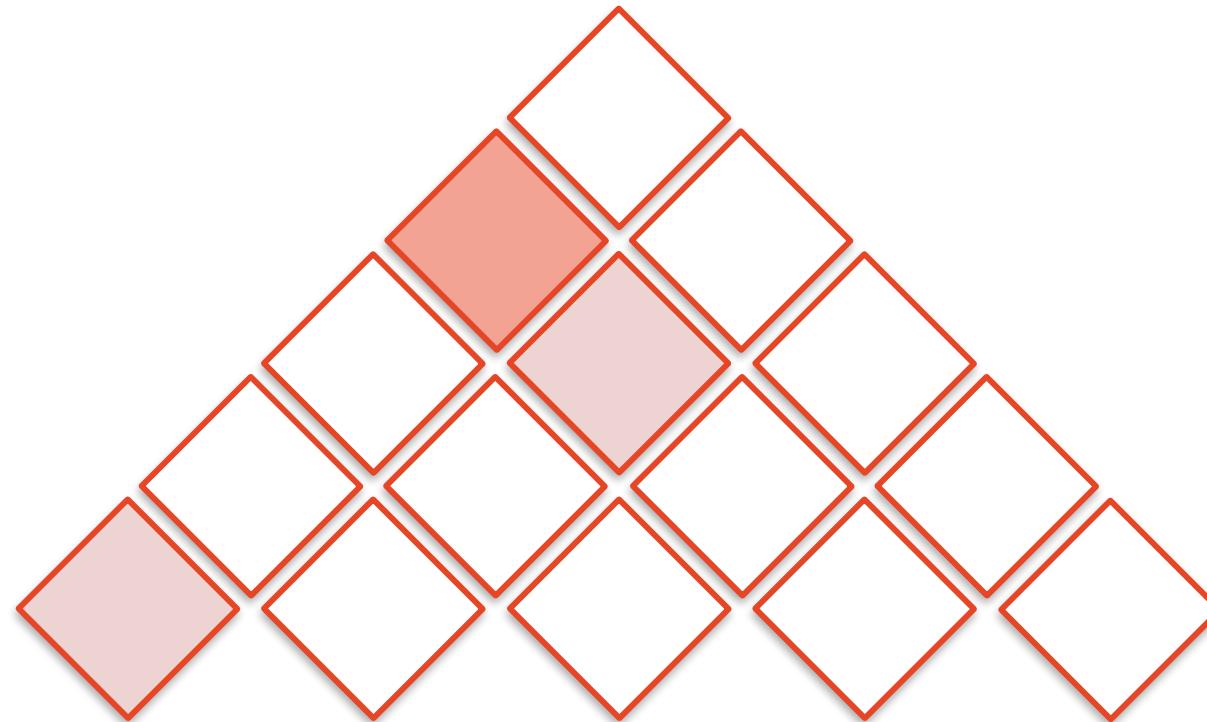
COMP 4446 / 5046
Lecture 5, 2025

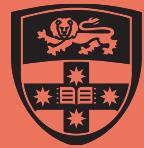
Sequence Tagging
Graph Parsing
Coreference
Workshop Preview



[menti.com 6274 6616](https://menti.com/62746616)

General idea: Consider each way to form each item, store the best and how you got it





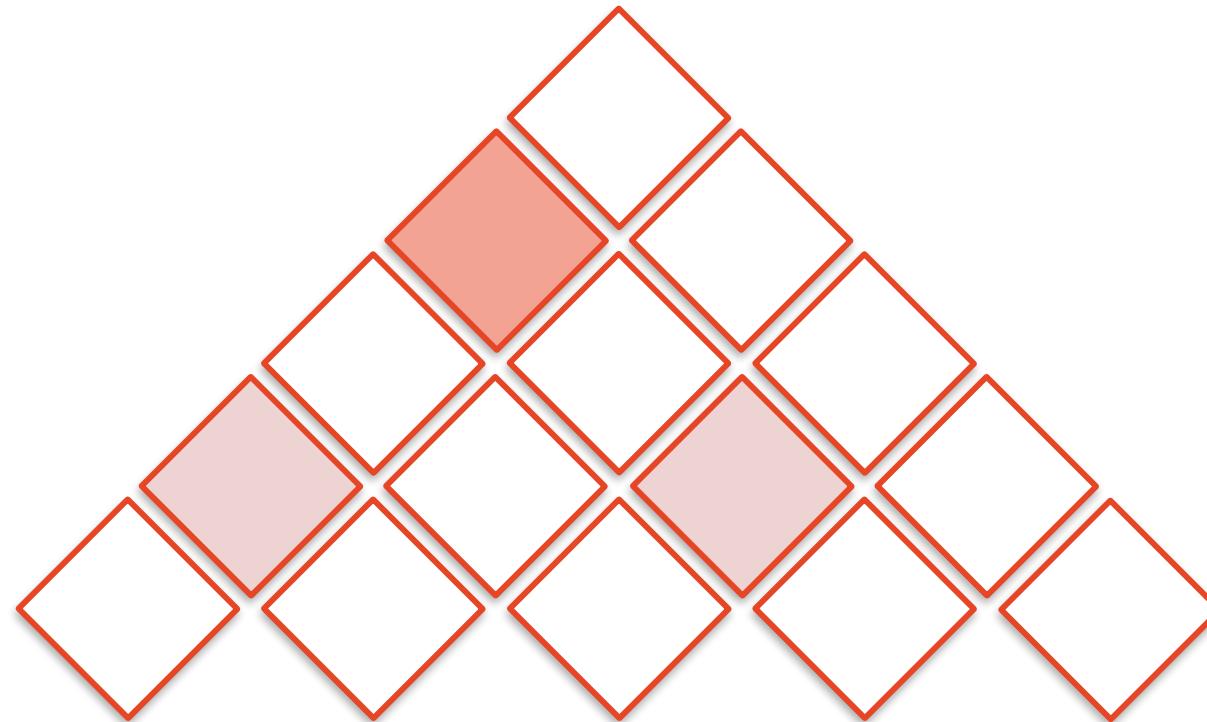
COMP 4446 / 5046
Lecture 5, 2025

Sequence Tagging
Graph Parsing
Coreference
Workshop Preview



[menti.com 6274 6616](https://menti.com/62746616)

General idea: Consider each way to form each item, store the best and how you got it



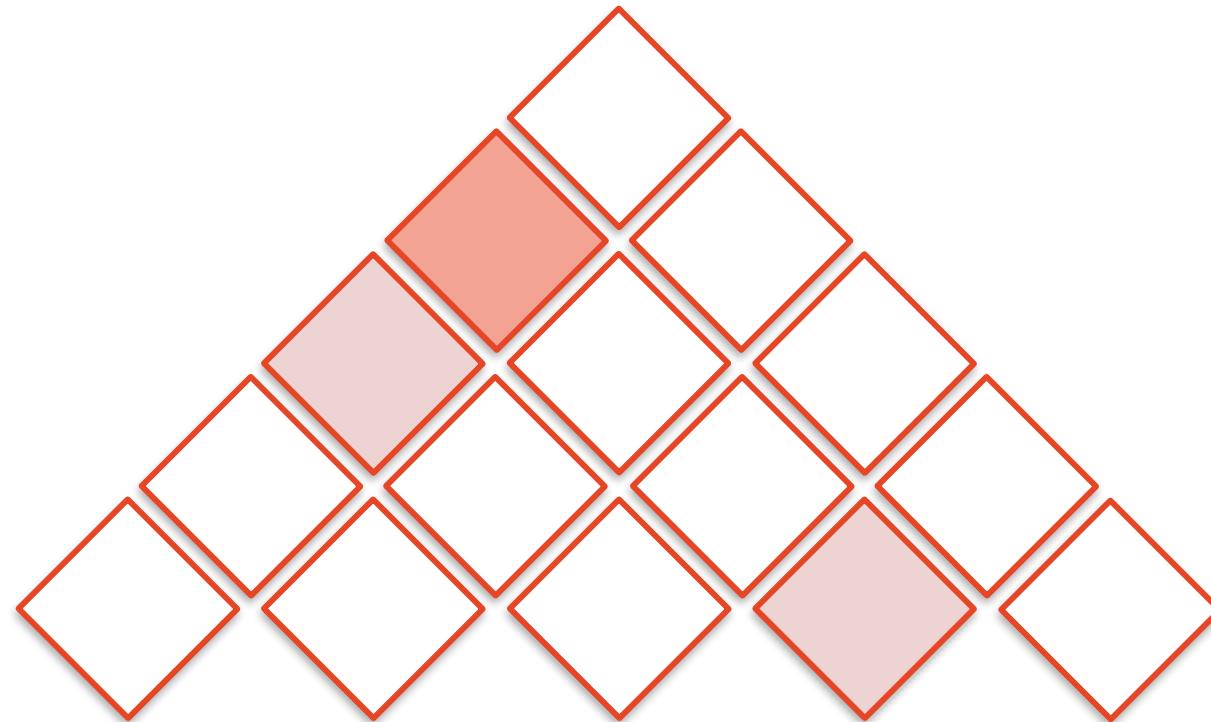


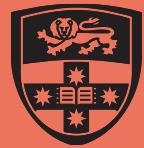
Sequence Tagging
Graph Parsing
Coreference
Workshop Preview



[menti.com 6274 6616](https://menti.com/62746616)

General idea: Consider each way to form each item, store the best and how you got it



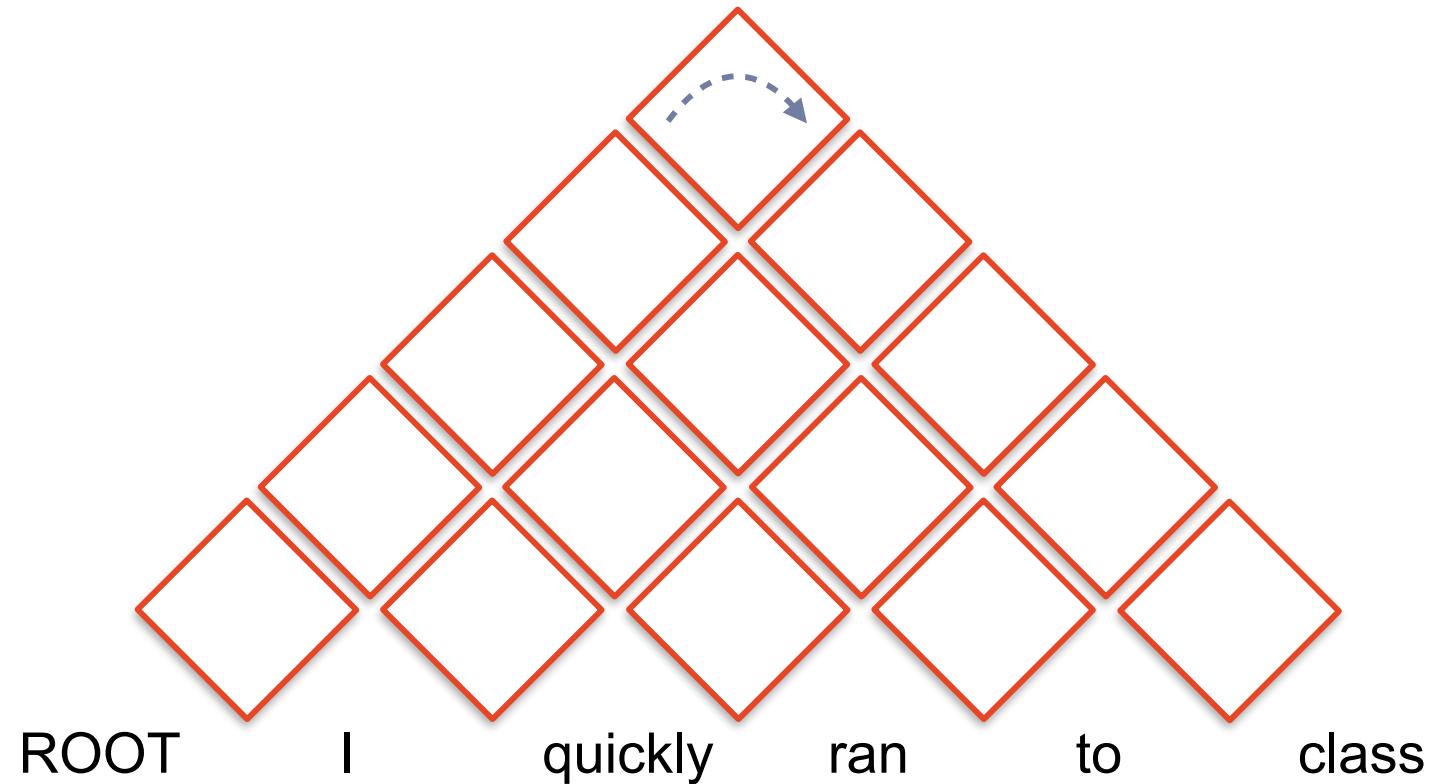


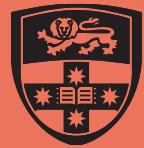
Sequence Tagging
Graph Parsing
Coreference
Workshop Preview



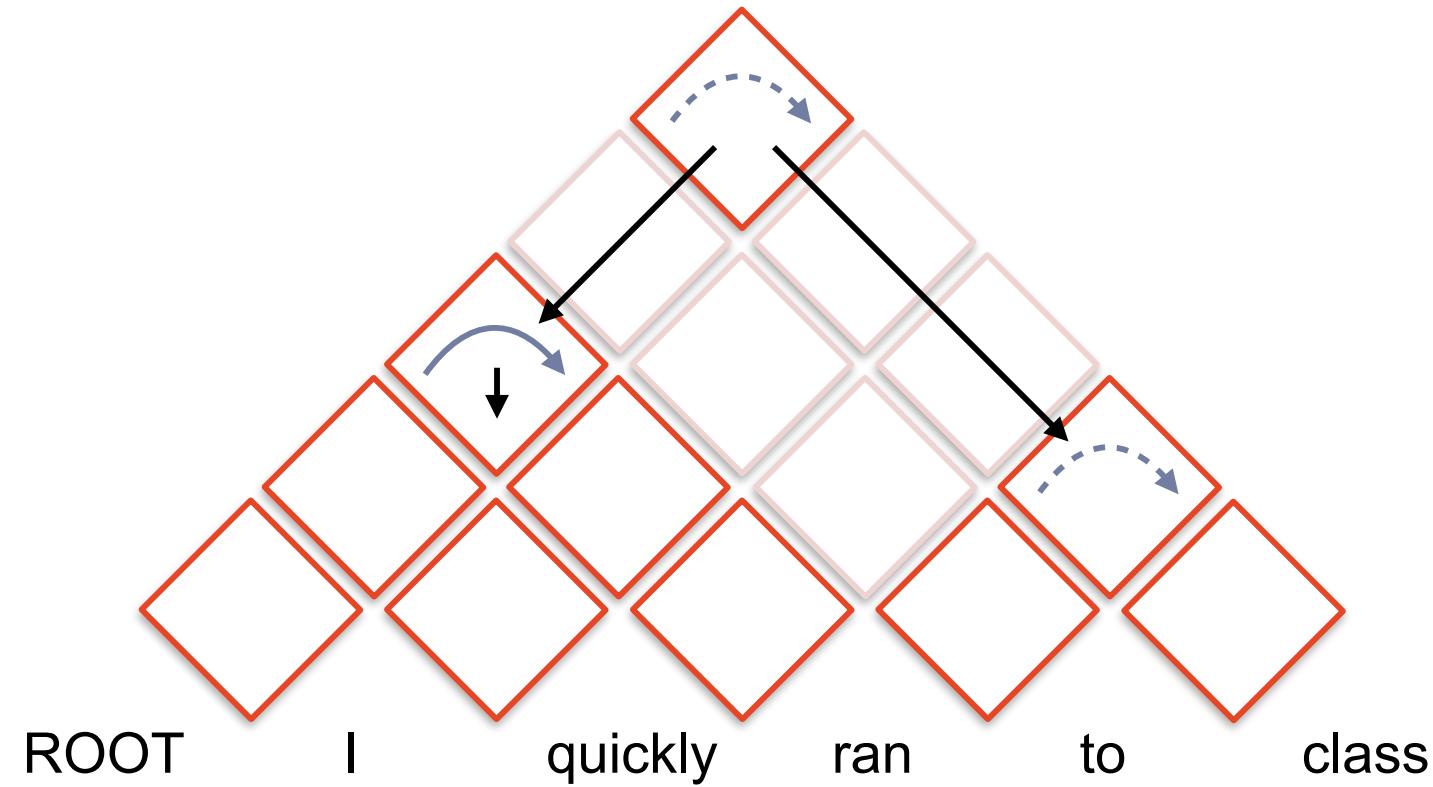
[menti.com 6274 6616](https://menti.com/62746616)

At the end, start at the top and work downwards to get the parse



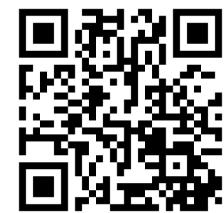


At the end, start at the top and work downwards to get the parse



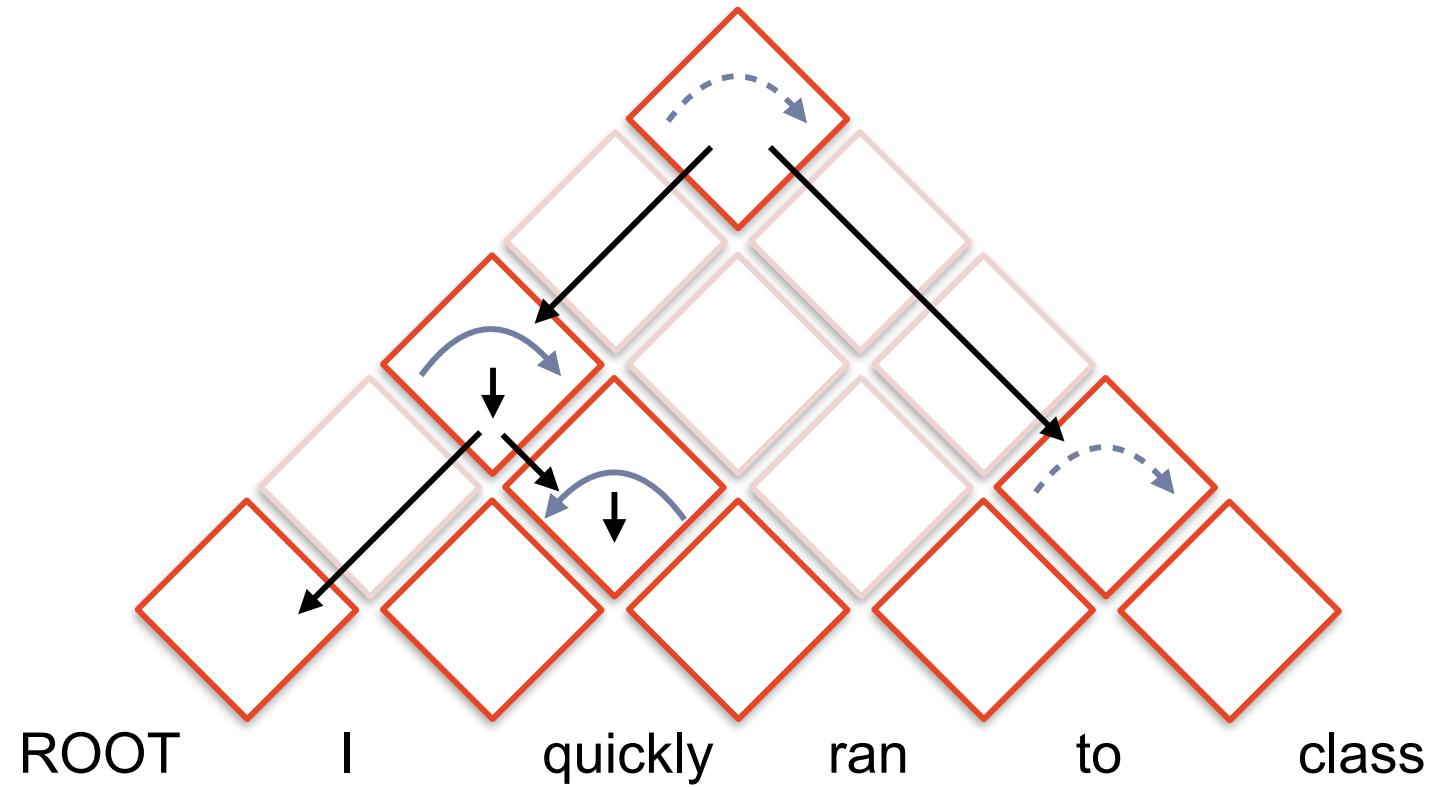


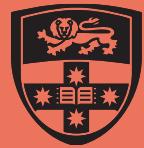
Sequence Tagging
Graph Parsing
Coreference
Workshop Preview



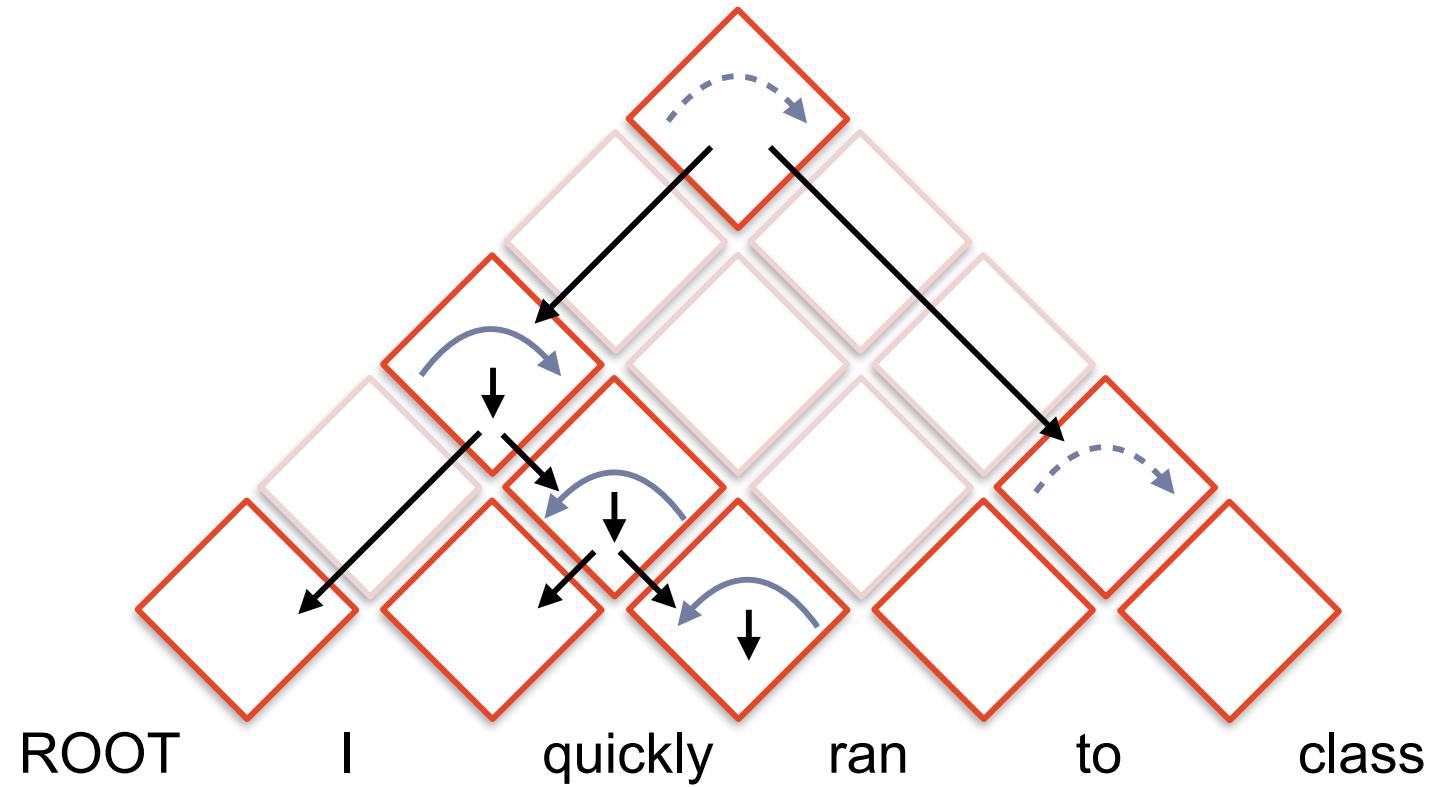
[menti.com 6274 6616](https://menti.com/62746616)

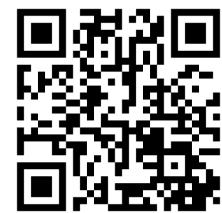
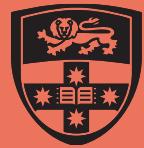
At the end, start at the top and work downwards to get the parse



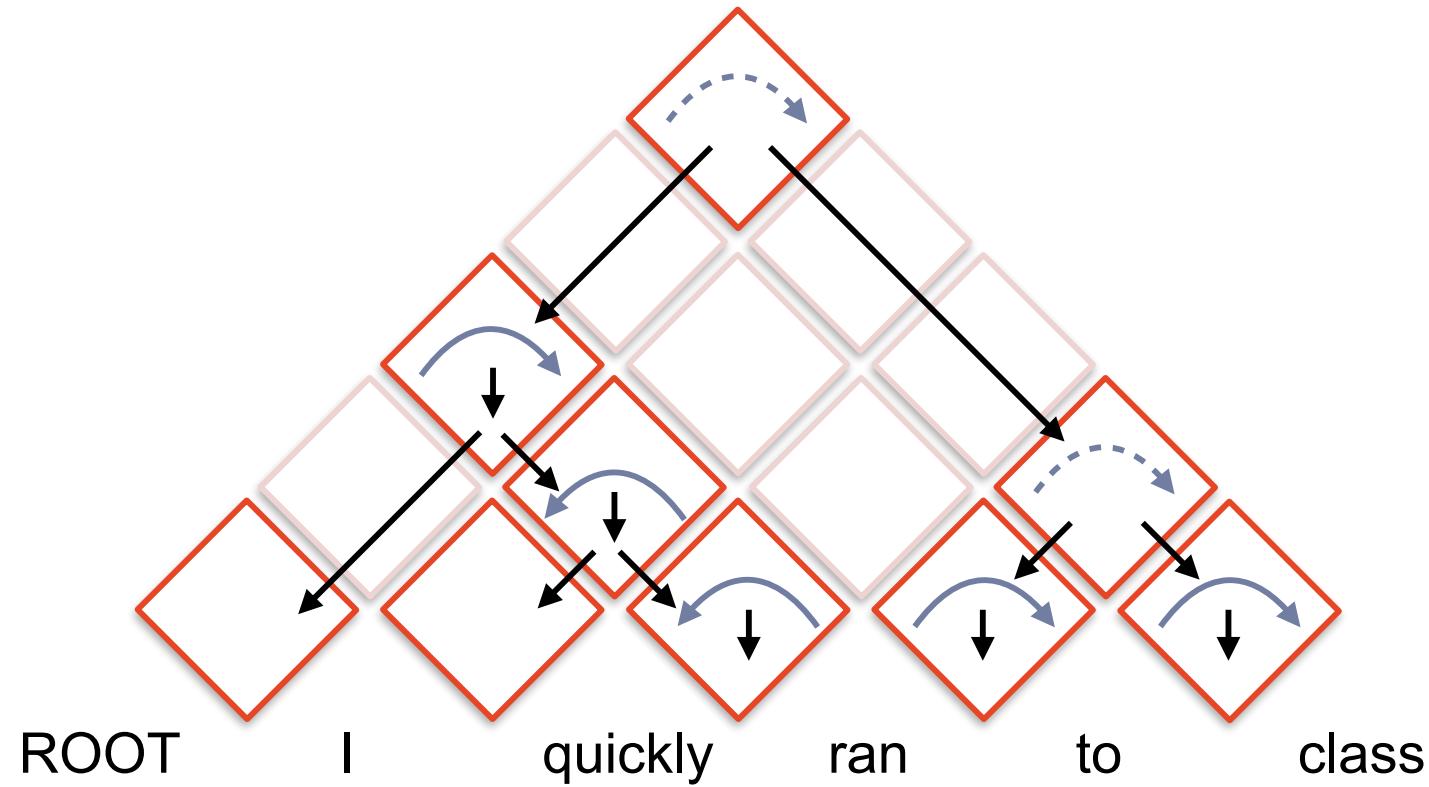


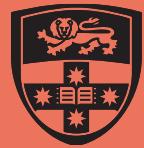
At the end, start at the top and work downwards to get the parse



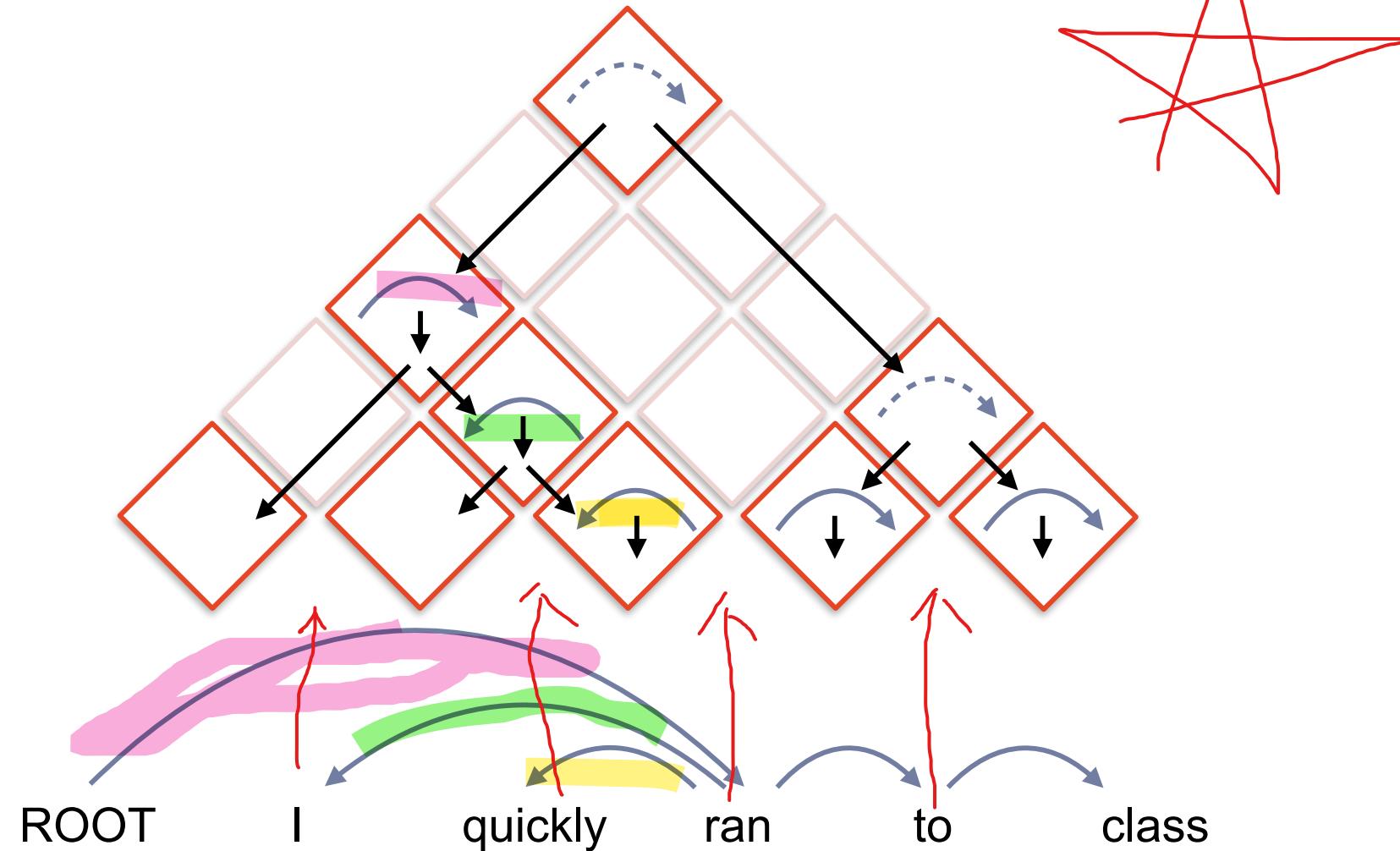


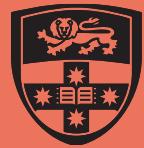
At the end, start at the top and work downwards to get the parse





At the end, start at the top and work downwards to get the parse





Algorithm in pseudocode

Called the **CKY algorithm**
.or CYK algorithm

Create storage for best options for each span and item type

Insert initial items

For each possible span length

For each possible span start

For each possible item type

Best = None

For each possible split point

For each rule

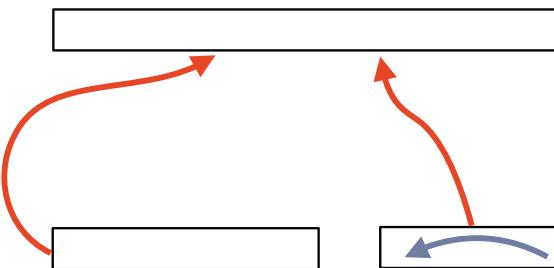
Get the score for this combination and update best

Record the best

Get the scores for adding an arc to the empty items and record them

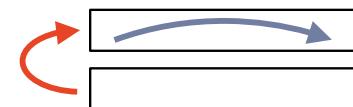


Time complexity is $O(\underbrace{|\text{rules}_{\text{comb}}| |\text{words}|^3 + |\text{rules}_{\text{arc}}| |\text{words}|^2}_{})$



Combinations:
Each start point
Each length
Each split point
Each rule

$O(|\text{words}|)$
 $O(|\text{words}|)$
 $O(|\text{words}|)$
 $O(|\text{rules}_{\text{comb}}|)$

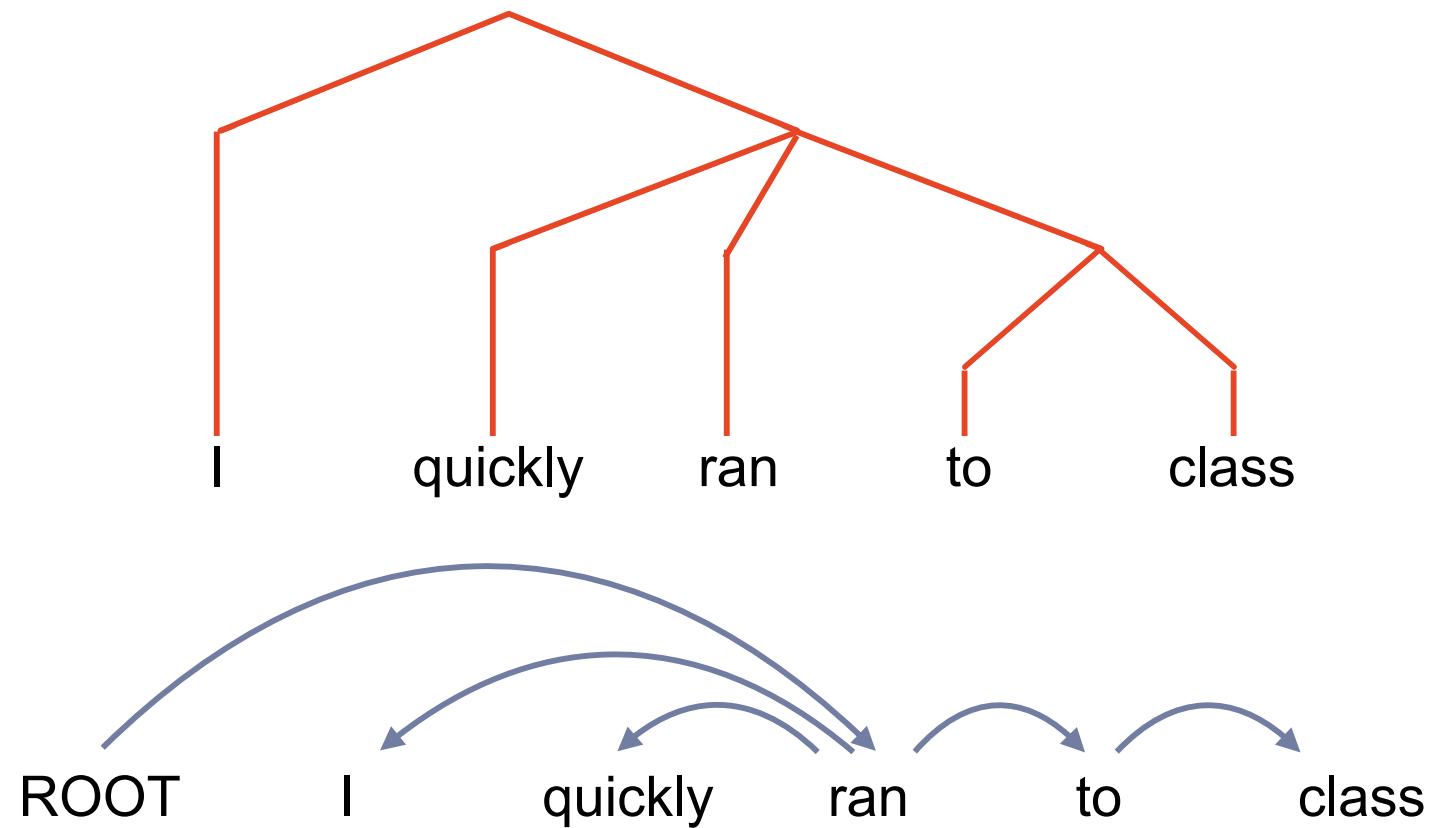


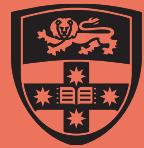
Arc creation:
Each start point
Each length
Each rule

$O(|\text{words}|)$
 $O(|\text{words}|)$
 $O(|\text{rules}_{\text{arc}}|)$

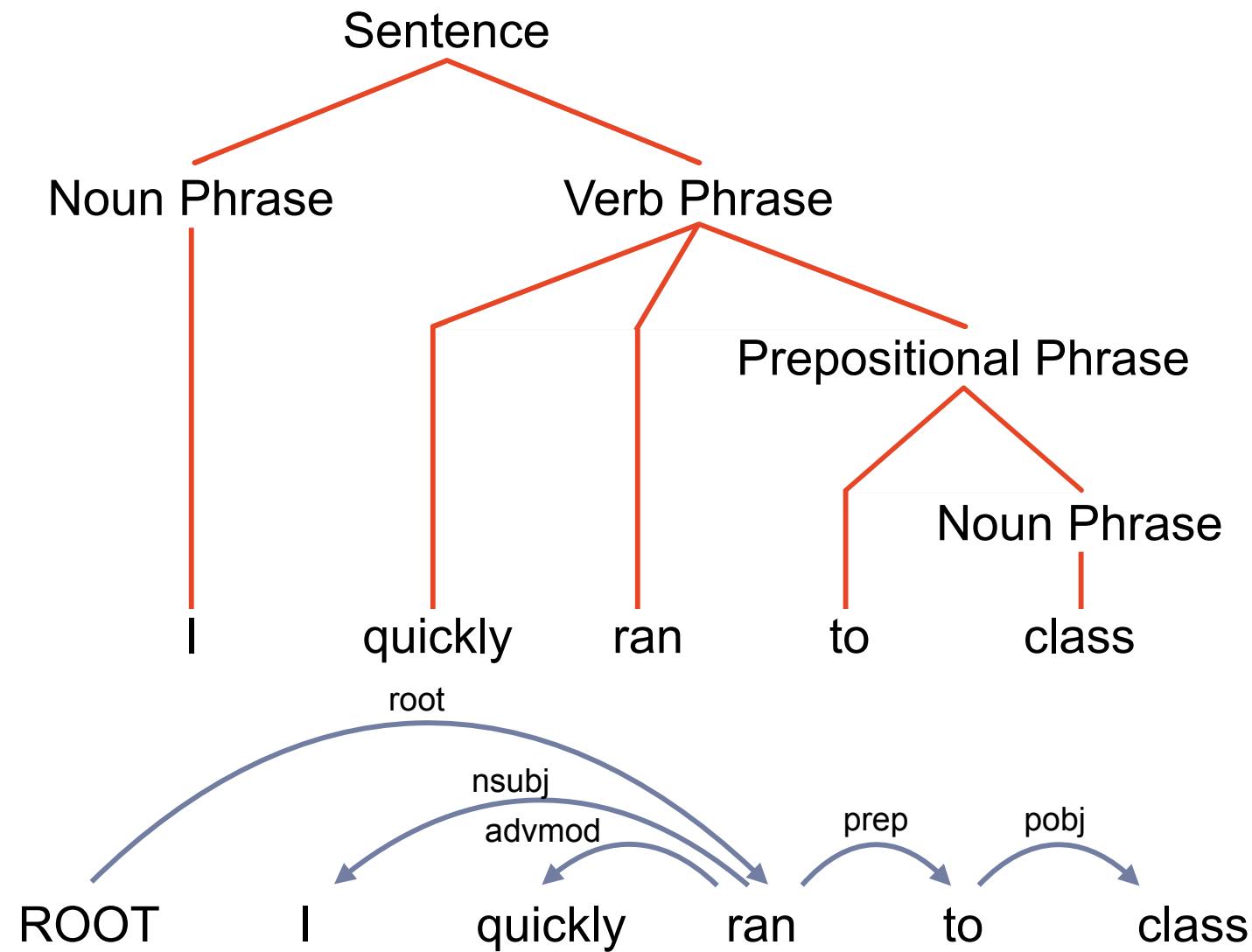


Dependencies are one representation, constituency parses are another





Dependencies are one representation, constituency parses are another





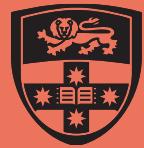
Why is this still relevant in the age of LLMs?

Usage

1. Occasionally, this is what you need

The screenshot shows the SHeLL Editor interface. At the top, there's a toolbar with buttons for H1, H2, H3, bold, italic, underline, and alignment. Below the toolbar, a status bar displays: Characters: 0 | Words: 0 | Unique Words: 0 | Sentences: 0 | Paragraphs: 0. To the right of the status bar are 'Full Text Editor' and 'Text Preparation' tabs, along with 'IMPORT' and 'EXPORT' buttons. A message at the bottom left says 'Welcome to the SHeLL Editor. Start typing here...'. On the right side, there are several sections: 'Complex Language' (0 words or phrases with alternatives in our thesaurus, 0 uncommon words, 0 instances of acronyms), 'Passive Voice' (0 uses of passive voice), and other sections like 'Text complexity: N/A' and '7 OF 12 FEATURES ACTIVE'. At the bottom right, there are 'About' and 'Privacy' links.

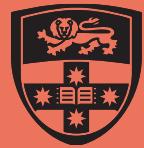
Run parser, check for *nsubjpass* edge



Why is this still relevant in the age of LLMs?

2. You can use parsing as part of a system

We propose a new representation and algorithm for a class of graph structures that is flexible enough to cover almost all treebank structures, while still admitting efficient learning and inference



Why is this still relevant in the age of LLMs?

2. You can use parsing as part of a system

We propose a new representation and algorithm for a class of graph structures that is flexible enough to cover almost all treebank structures, while still admitting efficient learning and inference.

Limit parts of text to query LLM with based on the parse, e.g., don't cut in the middle of an arc



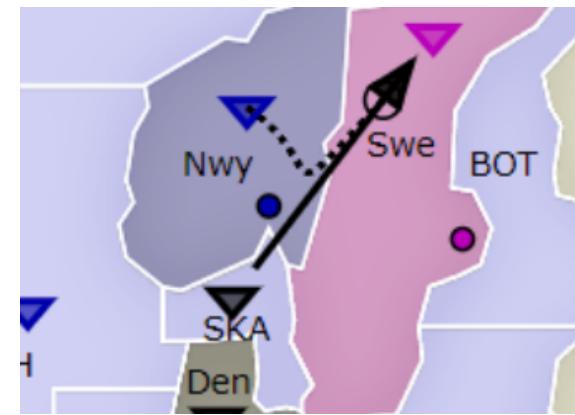
Sequence Tagging
Graph Parsing
Coreference
Workshop Preview



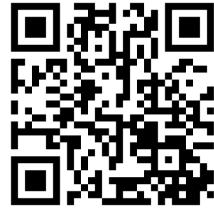
[menti.com 6274 6616](https://menti.com/62746616)

Why is this still relevant in the age of LLMs?

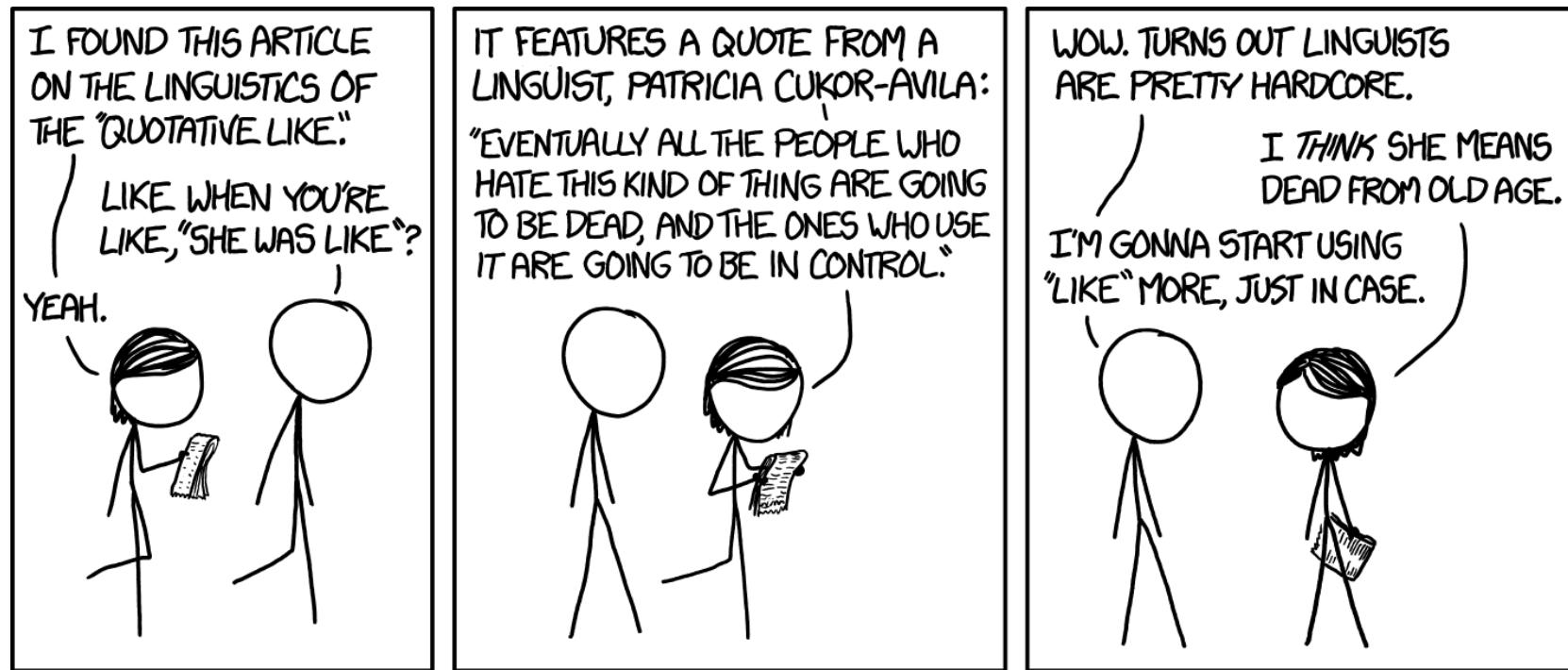
3. LLMs are still bad at some things



AMR = Abstract Meaning Representation
(another type of parsing, focused on semantics rather than syntax)



Quotative Like



[God was like, “Let there be light,” and there was light.]

Source: <https://xkcd.com/1483/>



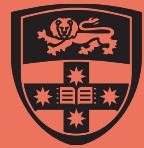
COMP 4446 / 5046
Lecture 5, 2025

Sequence Tagging
Graph Parsing
Coreference
Workshop Preview

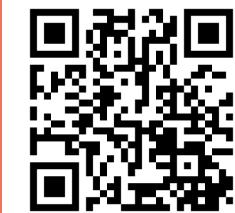


[menti.com 6274 6616](https://menti.com/62746616)

Coreference



Sequence Tagging
Graph Parsing
Coreference
Workshop Preview



[menti.com 6274 6616](https://menti.com/62746616)

References are when entities are mentioned in text

Victoria Chen, CFO of Megabucks Banking, saw her pay jump to \$2.3 million, as the 38-year-old became the company's president. It is widely known that she came to Megabucks from rival Lotsabucks.

Example text is from the J+M textbook, chapter 23



Coreference is identifying which mentions refer to the same entity

Victoria Chen

Megabucks Banking

Lotsabucks

her pay

Victoria Chen, CFO of Megabucks

Banking, saw her pay jump to \$2.3

million, as the 38-year-old became

the company's president. It is widely

known that she came to Megabucks

from rival Lotsabucks.



Entity Linking / Wikification is a related task that links each entity to an external knowledge base

Victoria Chen

Megabucks Banking

Lotsabucks

her pay



Victoria Chen, CFO of Megabucks

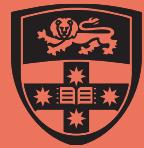
Banking, saw her pay jump to \$2.3

million, as the 38-year-old became

the company's president. It is widely

known that she came to Megabucks

from rival Lotsabucks.



The search space is huge!

Possible references:

$|words| * |words|$

Possible sets:

All ways to cluster
all references

Victoria Chen, CFO of Megabucks

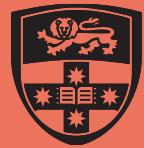
Banking, saw her pay jump to \$2.3

million, as the 38-year-old became

the company's president. It is widely

known that she came to Megabucks

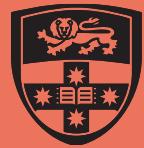
from rival Lotsabucks.



First idea for simplification: do mention detection and filtering first

Possible references:
 $|\text{words}| * |\text{words}|$

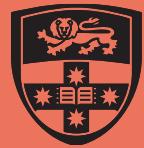
Victoria
Victoria Chen
Victoria Chen ,
Victoria Chen , CFO
Victoria Chen , CFO of
Victoria Chen , CFO of Megabucks
Victoria Chen , CFO of Megabucks Banking
Victoria Chen , CFO of Megabucks Banking ,
Victoria Chen , CFO of Megabucks Banking , saw
Victoria Chen , CFO of Megabucks Banking , saw her



First idea for simplification: do mention detection and filtering first

Possible references:
 $|\text{words}| * |\text{words}|$

Victoria
Victoria Chen
~~Victoria Chen~~,
Victoria Chen , CFO
~~Victoria Chen , CFO of~~
~~Victoria Chen , CFO of Megabucks~~
~~Victoria Chen , CFO of Megabucks Banking~~
~~Victoria Chen , CFO of Megabucks Banking ,~~
~~Victoria Chen , CFO of Megabucks Banking , saw~~
~~Victoria Chen , CFO of Megabucks Banking , saw her~~



Second idea for simplification: Link pairs of mentions

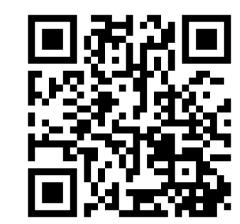
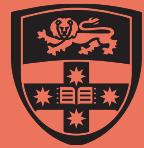
Just find the best previous mention for this mention to be coreferent with

Victoria Chen, CFO of Megabucks

The diagram illustrates coreference resolution in a sentence. It features several horizontal lines of varying colors (red, blue, brown) underlining specific words or phrases. Arrows point from the underlined words to their corresponding mentions above them. The sentence is: "Banking, saw her pay jump to \$2.3 million, as the 38-year-old became the company's president. It is widely known that she came to Megabucks from rival Lotsabucks." The underlined words and their links are: 'Victoria Chen' (red line) points to 'she' (brown line); 'Megabucks' (blue line) points to 'Megabucks' (red line); 'the company's' (brown line) points to 'the company's' (red line); 'she' (brown line) points to 'she' (brown line); and 'Megabucks' (red line) points to 'Megabucks' (blue line).

Banking, saw her pay jump to \$2.3 million, as the 38-year-old became the company's president. It is widely known that she came to Megabucks

from rival Lotsabucks.



Second idea for simplification: Link pairs of mentions

Just find the best previous mention for this mention to be coreferent with

Victoria Chen, CFO of Megabucks

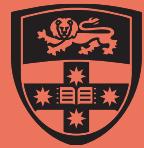
Banking, saw her pay jump to \$2.3

million, as the 38-year-old became

the company's president. It is widely

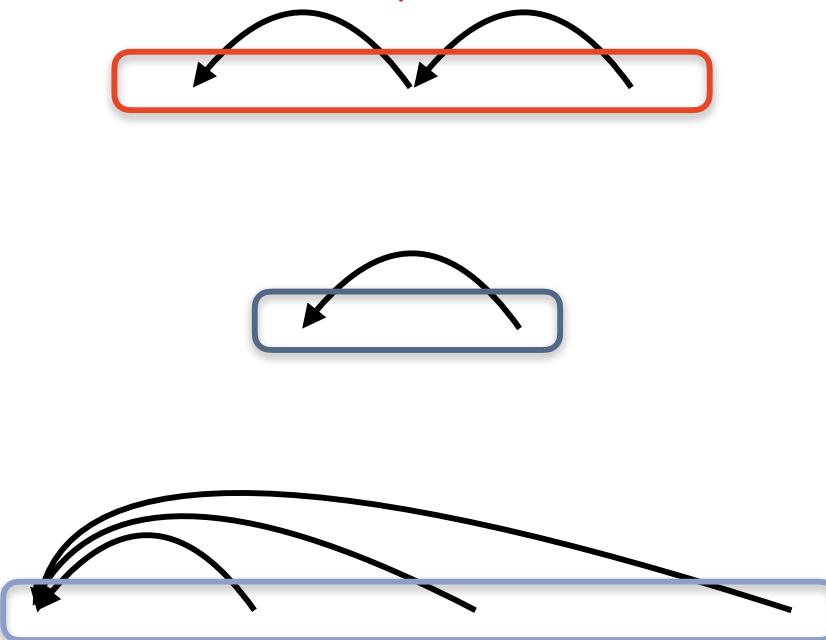
known that she came to Megabucks

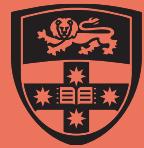
from rival Lotsabucks.



Third idea for simplification: Find the transitive closure

Clusters are separate i.e. no arrow toward other cluster





Sequence Tagging
Graph Parsing
Coreference
Workshop Preview



[menti.com 6274 6616](https://menti.com/62746616)

But what about fancy inference algorithms?

Why we not always use
LLM

Sometimes the simple idea **does** work!



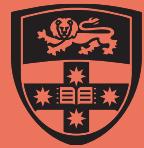
COMP 4446 / 5046
Lecture 5, 2025

Sequence Tagging
Graph Parsing
Coreference
Workshop Preview



[menti.com 6274 6616](https://menti.com/62746616)

Workshop Preview



COMP 4446 / 5046
Lecture 5, 2025

Sequence Tagging
Graph Parsing
Coreference
Workshop Preview



[menti.com 6274 6616](https://menti.com/62746616)

Workshop preview - Keras and Tensorflow

Pre-Work

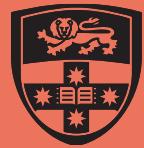
Confirm you can run the notebook
on your own machine / a web
service!

Read the initial sections

In Workshop

LSTM variations

GPT-2 text generation



COMP 4446 / 5046
Lecture 5, 2025

Sequence Tagging
Graph Parsing
Coreference
Workshop Preview



menti.com 6274 6616

Muddy Card

Open shortly, closes at 7:05pm

[https://saipll.shinyapps.io/
student-interface/](https://saipll.shinyapps.io/student-interface/)



If you do not wish to participate in the study, use
the Ed form instead

Go to Ed → Lessons → Muddy Cards Lecture 5