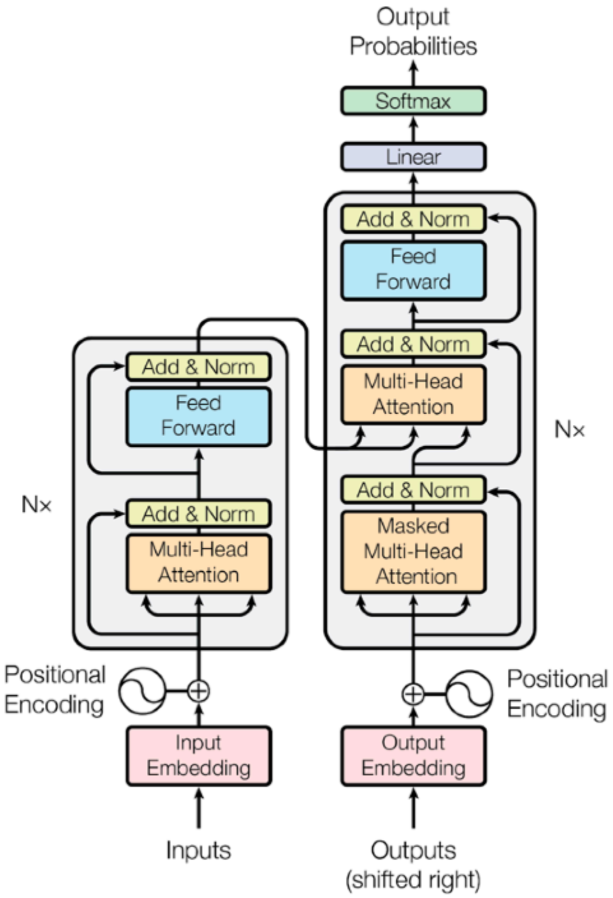
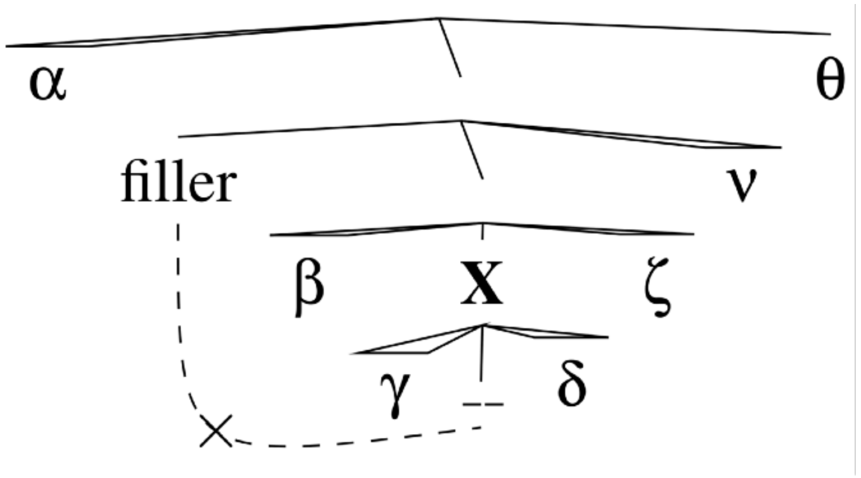
Transformer language models, targeted syntactic evaluation, and learnability



(Vaswani et al., 2017)



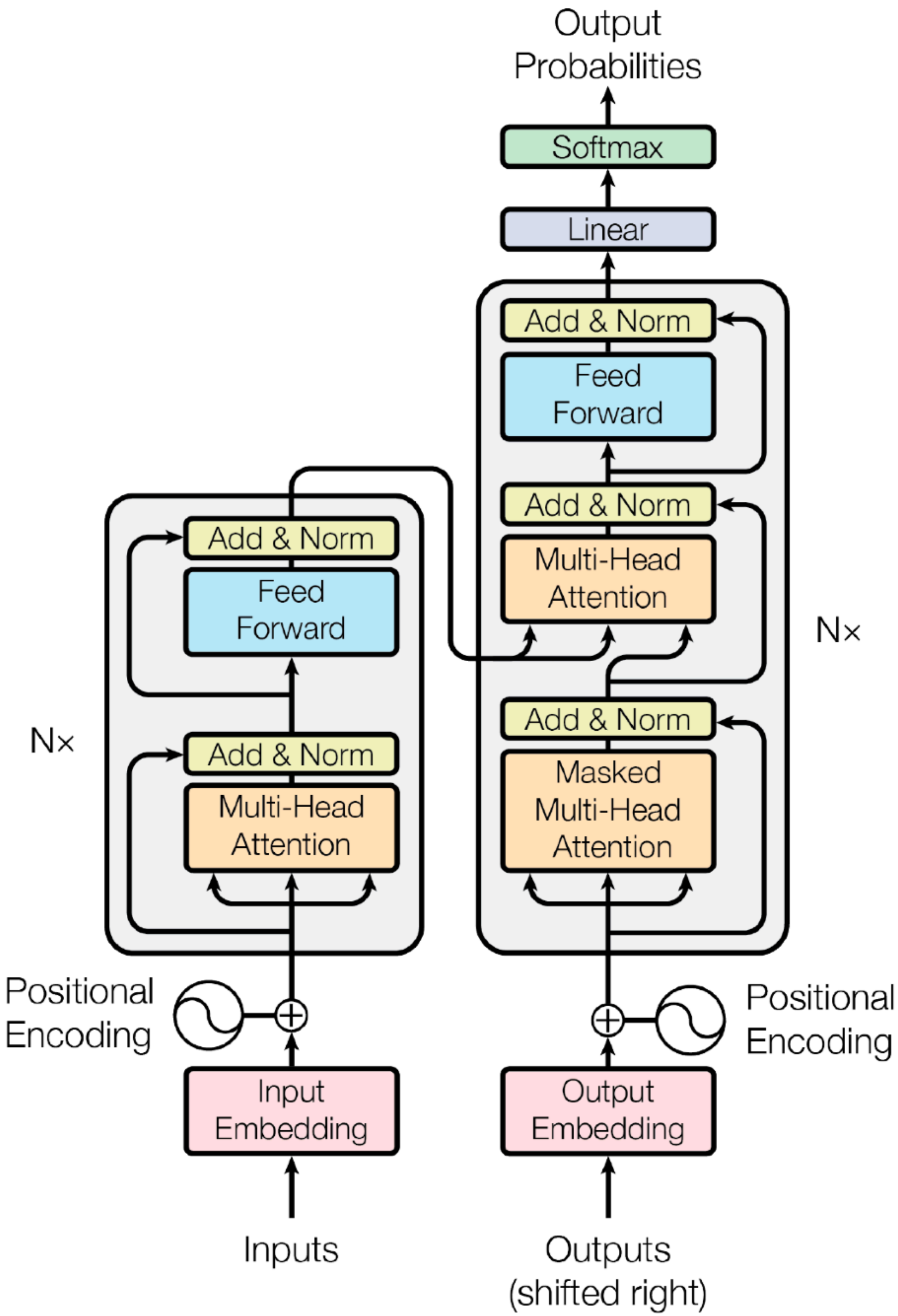
(Wilcox et al., 2019)

Roger Levy
9.19: Computational Psycholinguistics
6 November 2023

Agenda for today

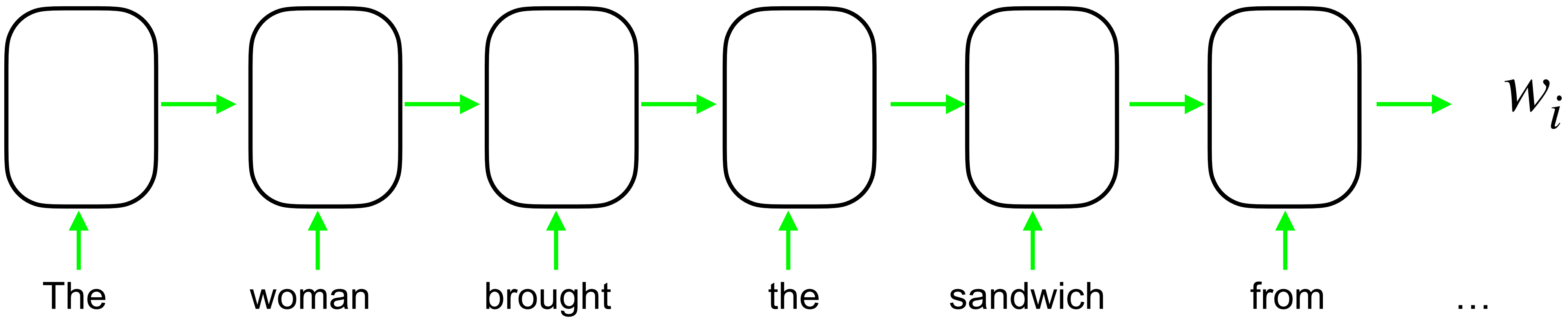
- The Transformer
- Targeted syntactic testing: filler–gap dependencies
- Learnability: syntactic **islands**

The Transformer model



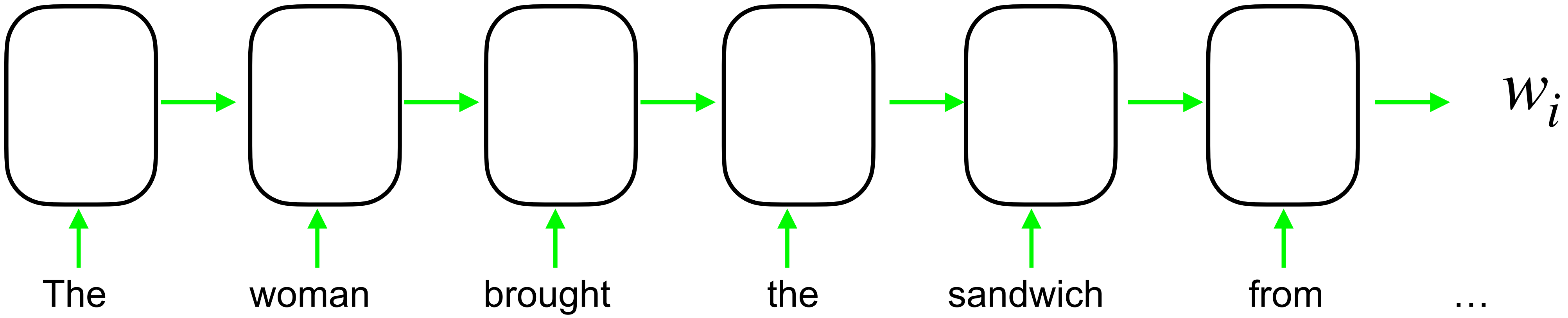
(Vaswani et al., 2017)

Motivating the Transformer model



Motivating the Transformer model

- With RNNs, a fixed-dimension model could propagate information indefinitely into the future...but it's hard!



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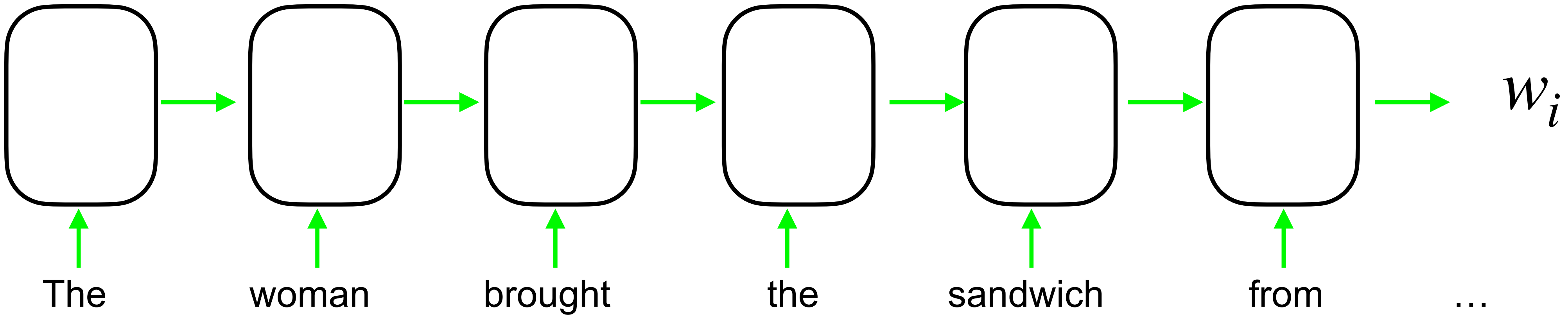

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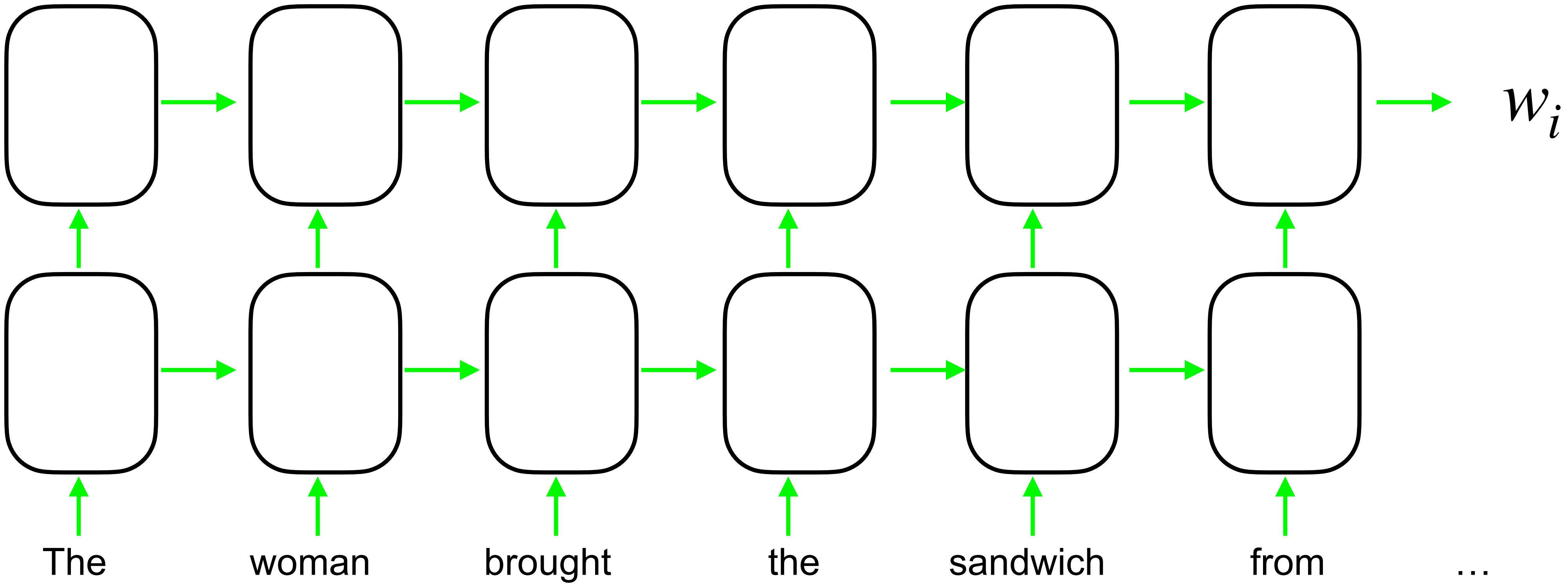

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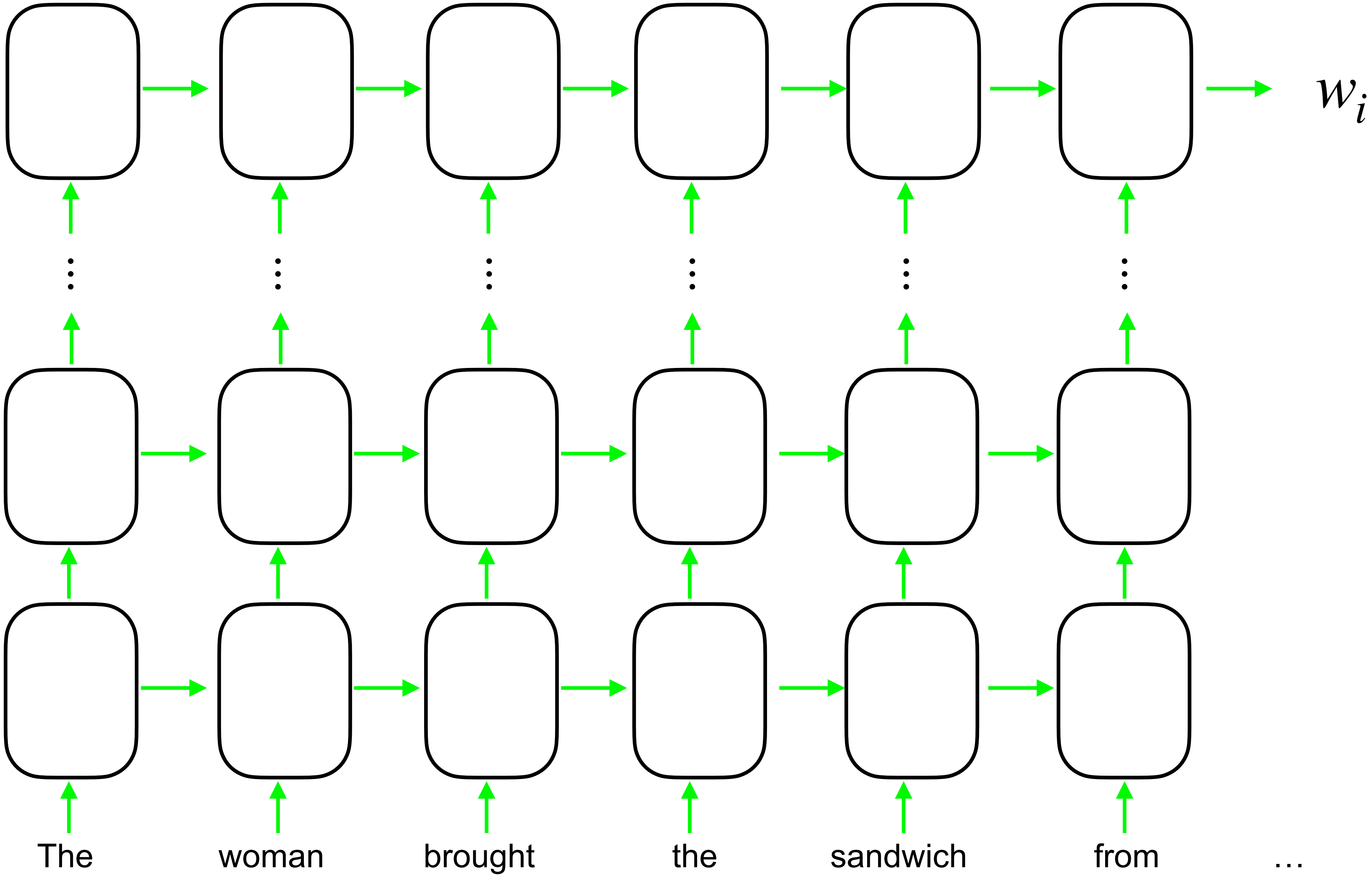

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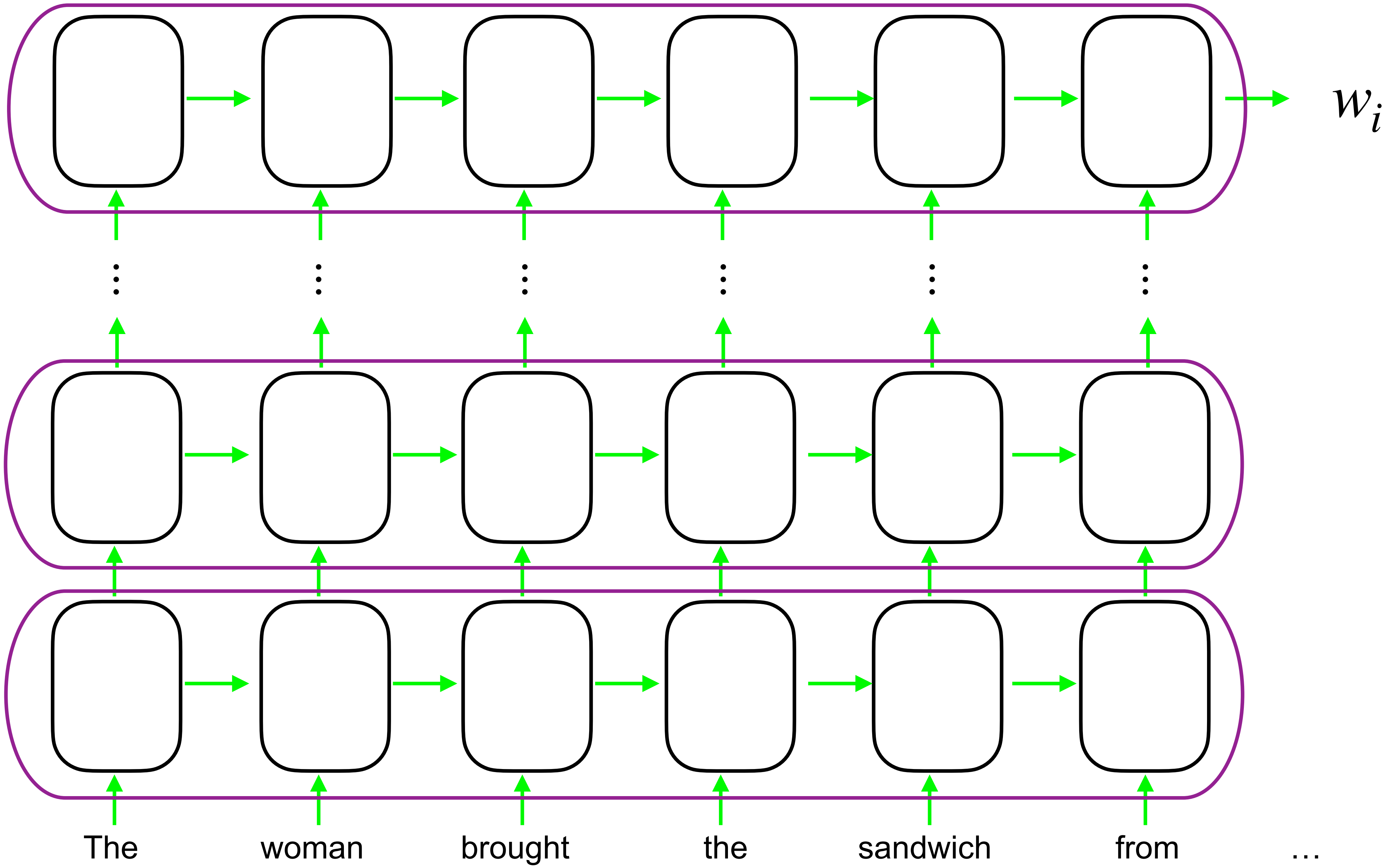

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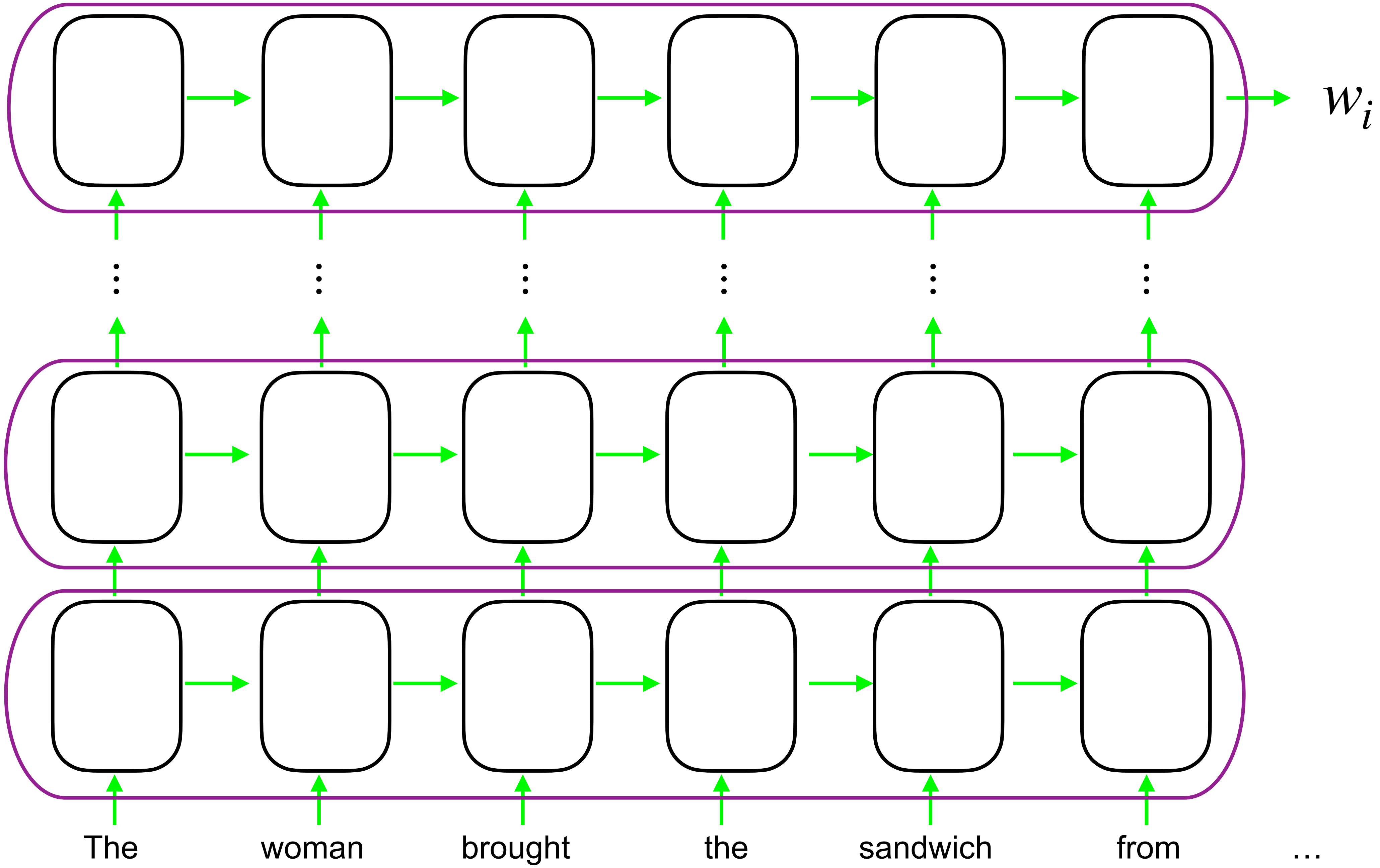
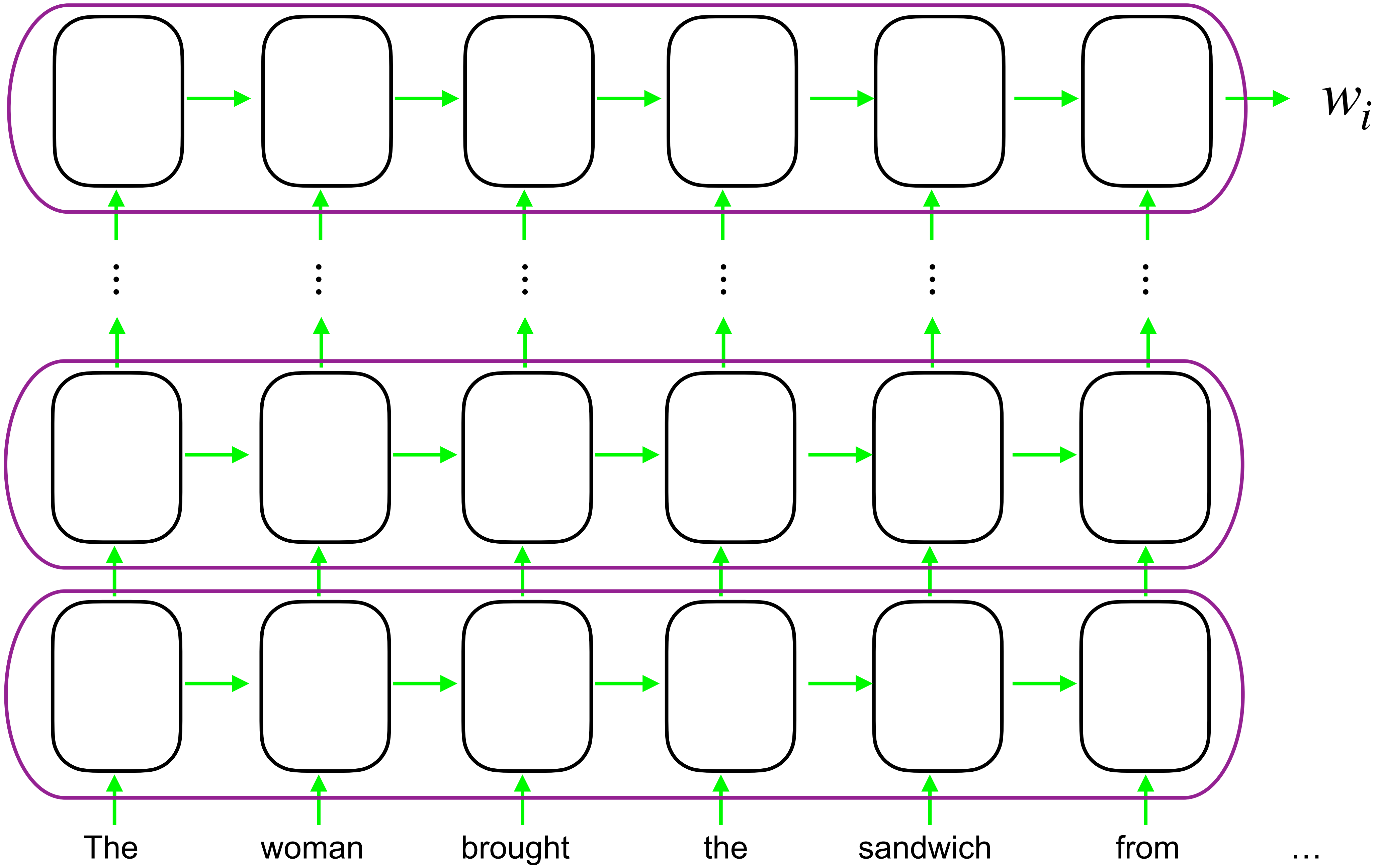


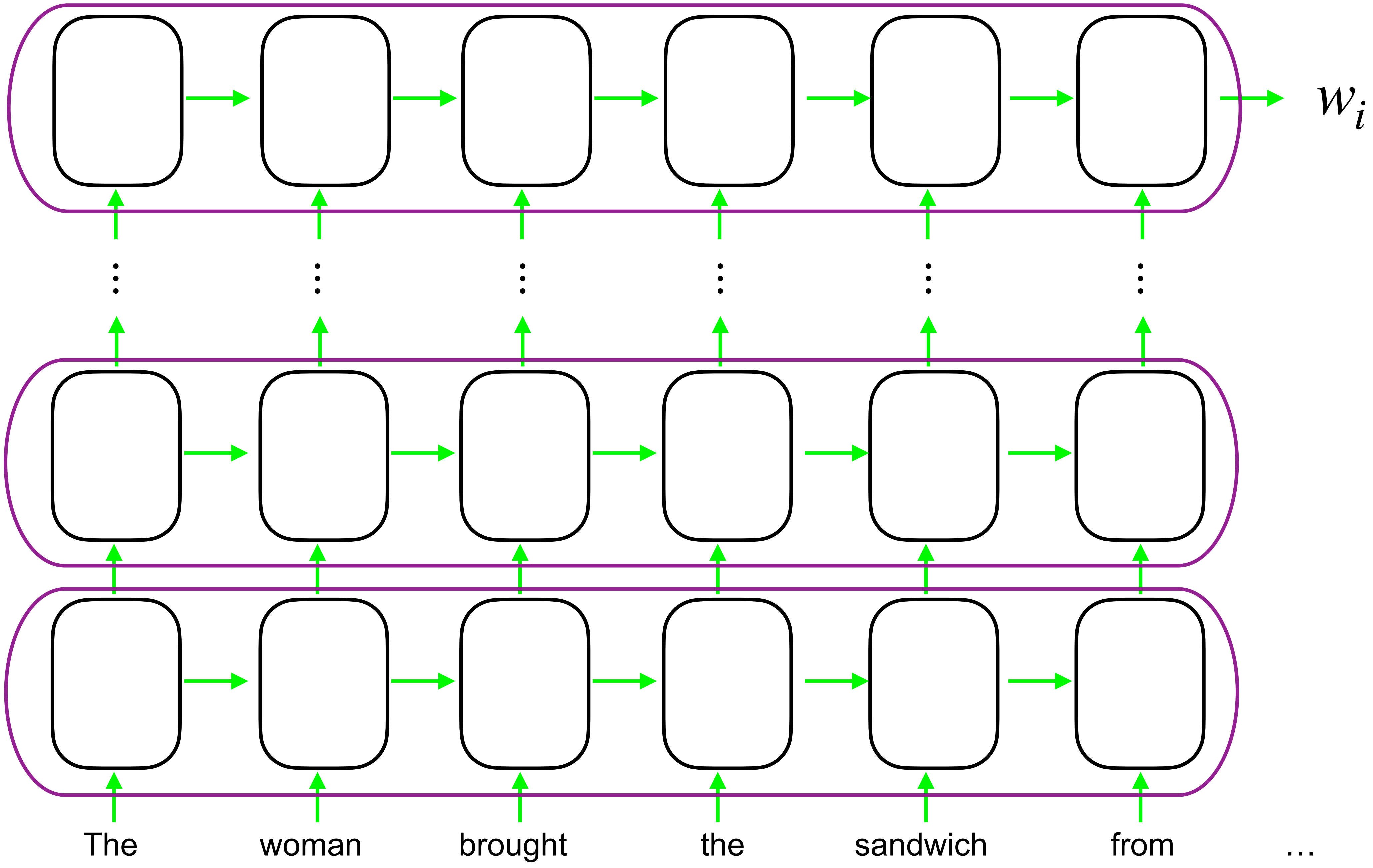
Motivating the Transformer model

- ...but input distant in the context is still far away.



Motivating the Transformer model

- ...but input distant in the context is still far away.
- Solution: make all context words equally distant from w_i!



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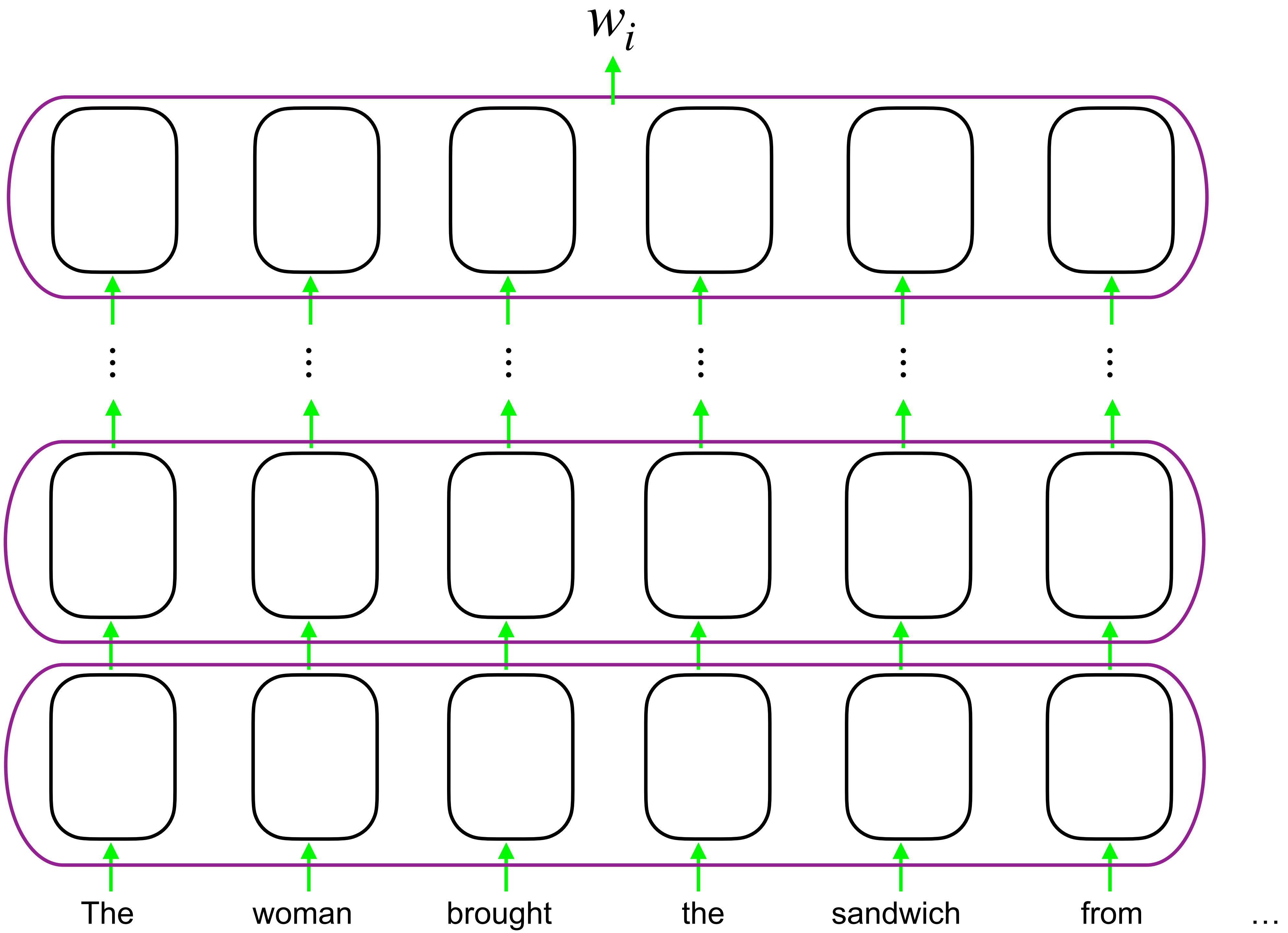

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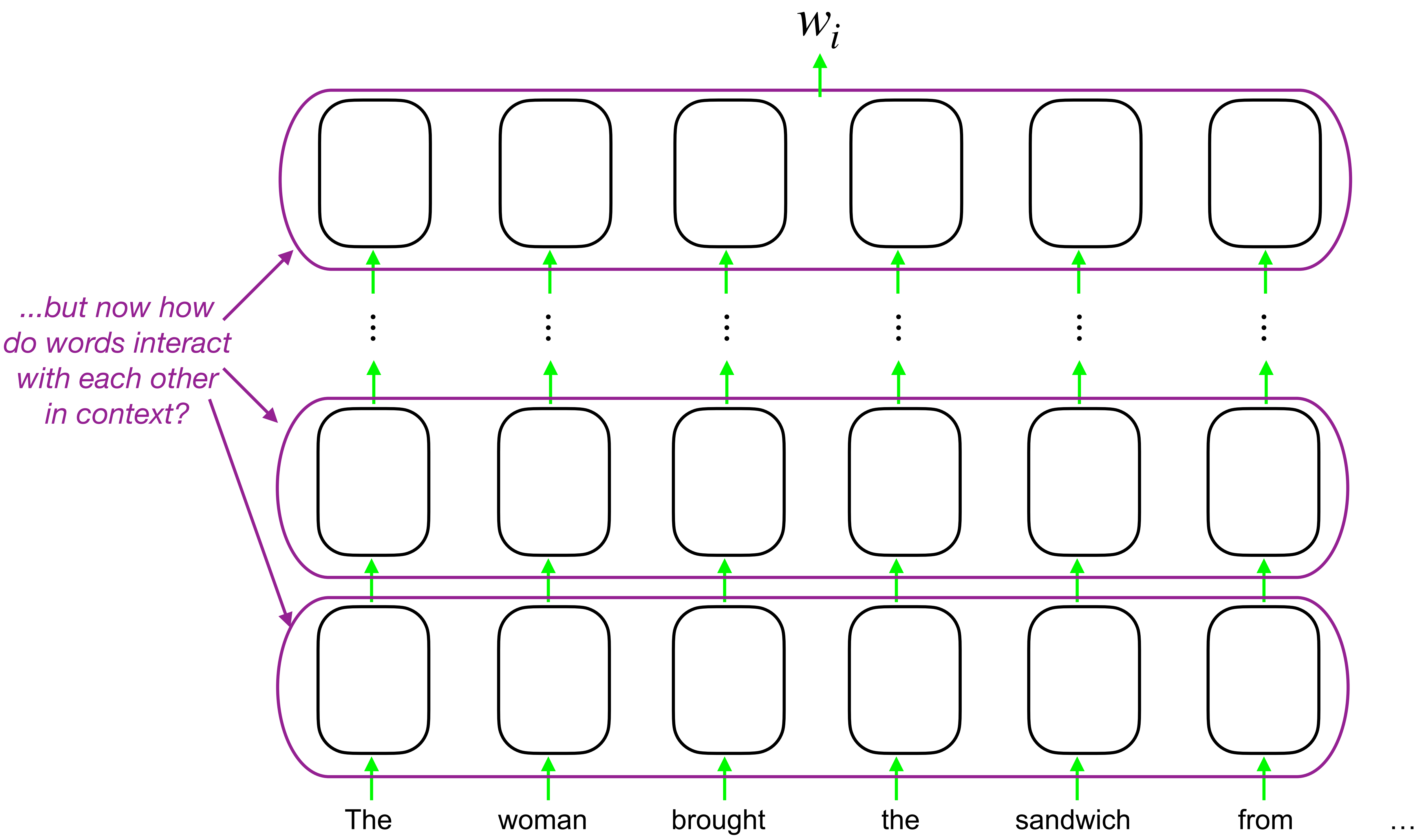


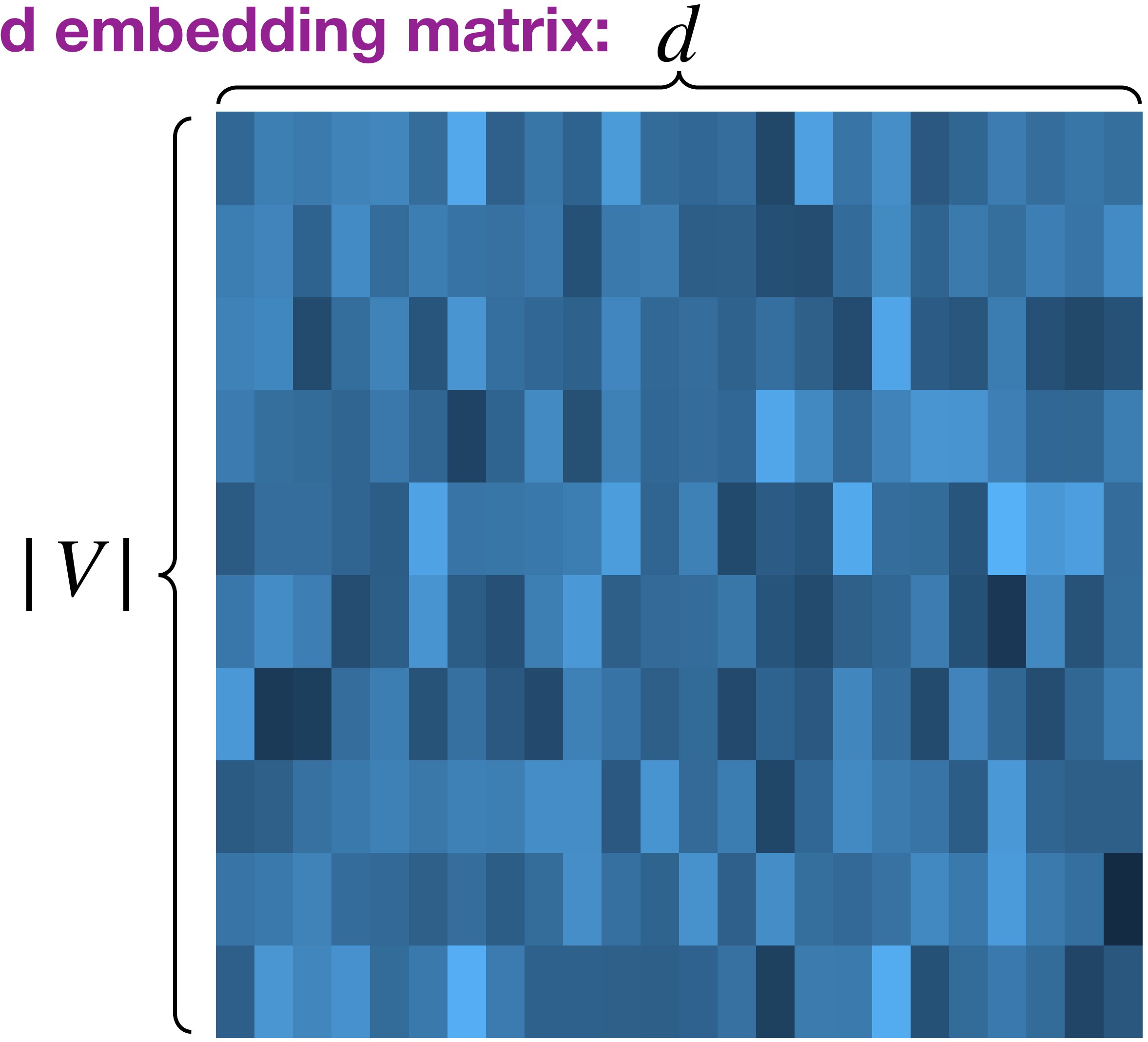
w_i
...but now how do words interact with each other in context?
The
woman
brought
the
sandwich
from
…

Input + Positional Embedding

```
the                 dog                 ate                 the                 ...
```

Input + Positional Embedding

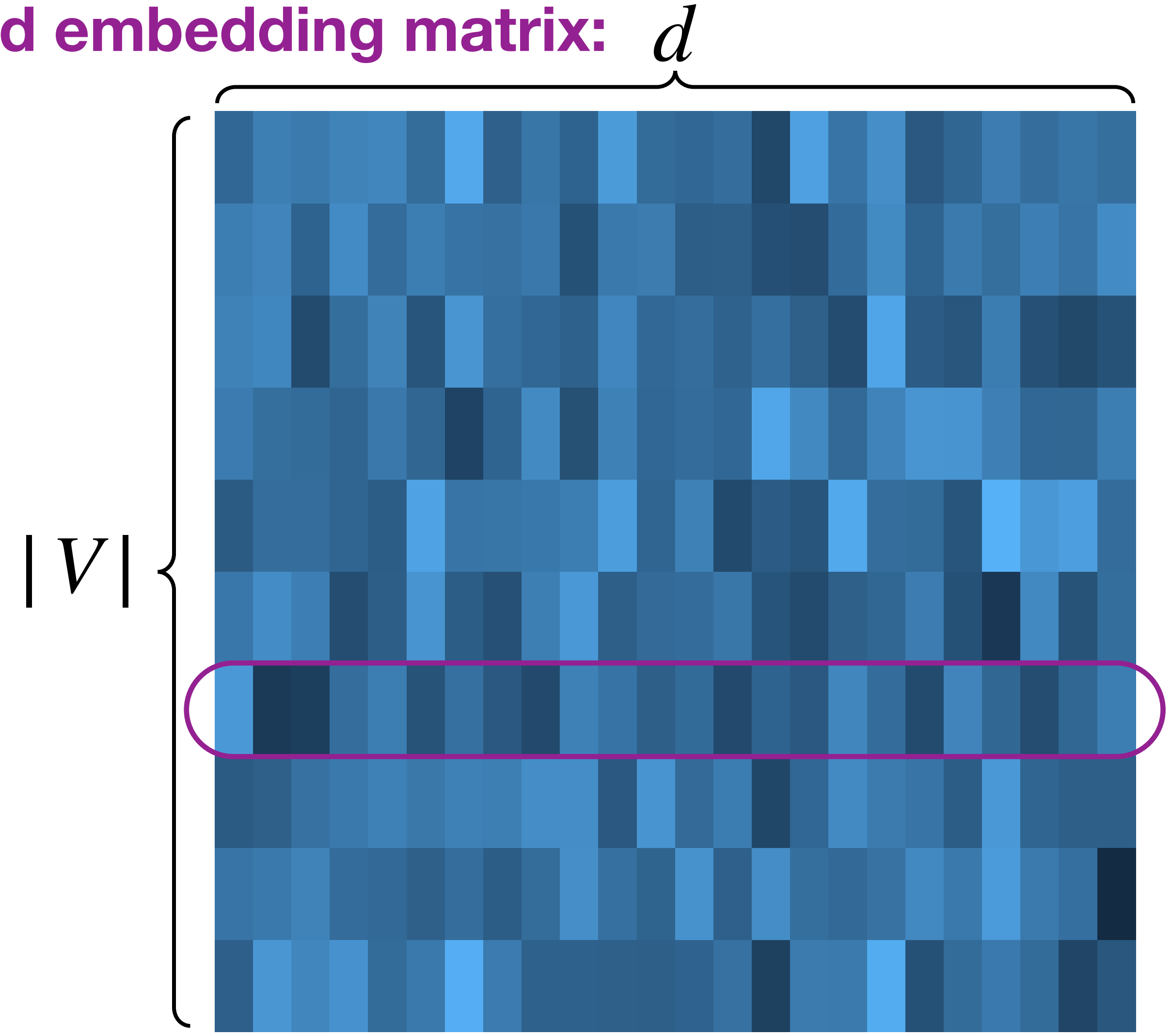
Word embedding matrix:



`the` `dog` `ate` `the` `...`

Input + Positional Embedding

Word embedding matrix:



the dog ate the ...

Input + Positional Embedding

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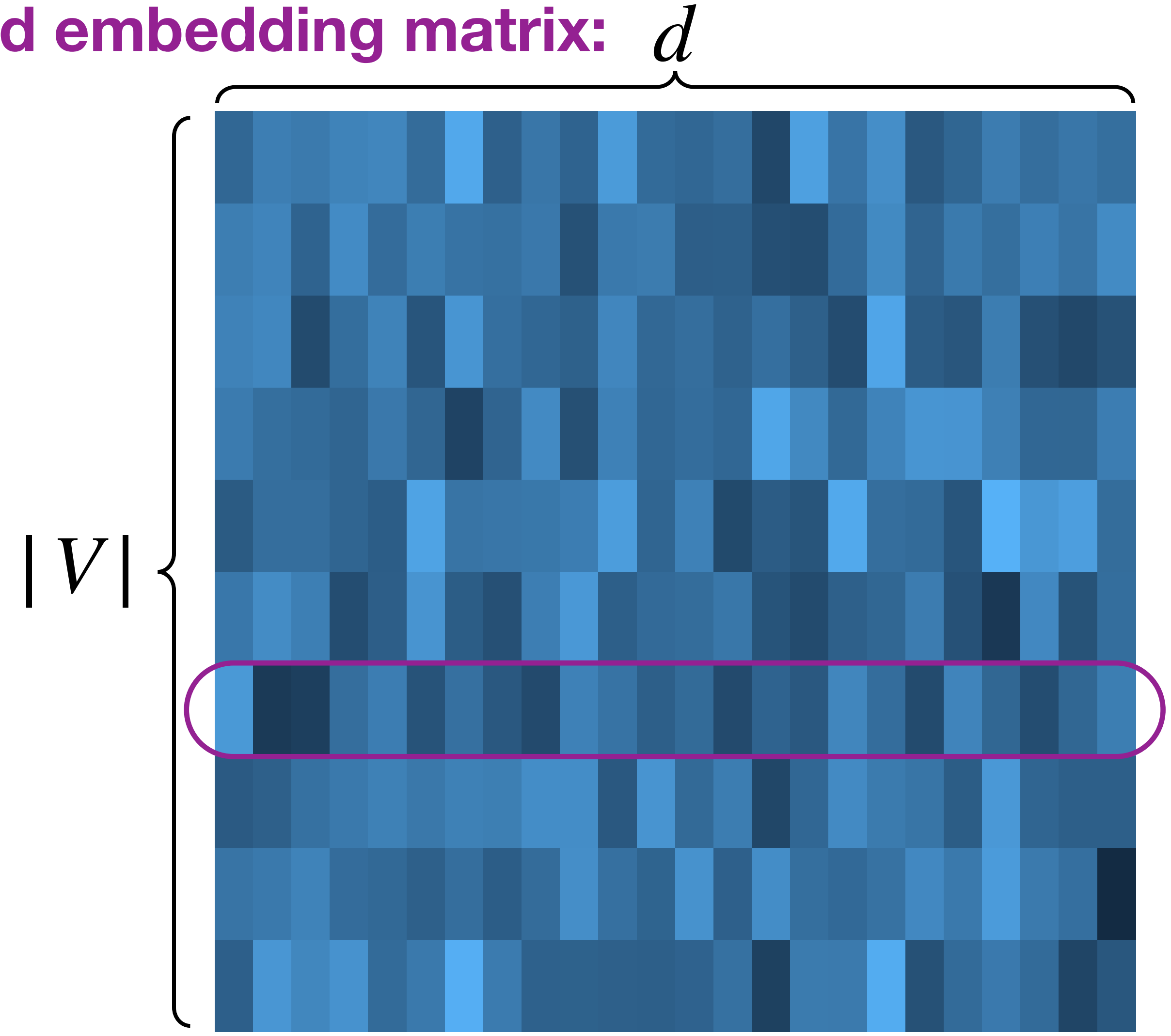

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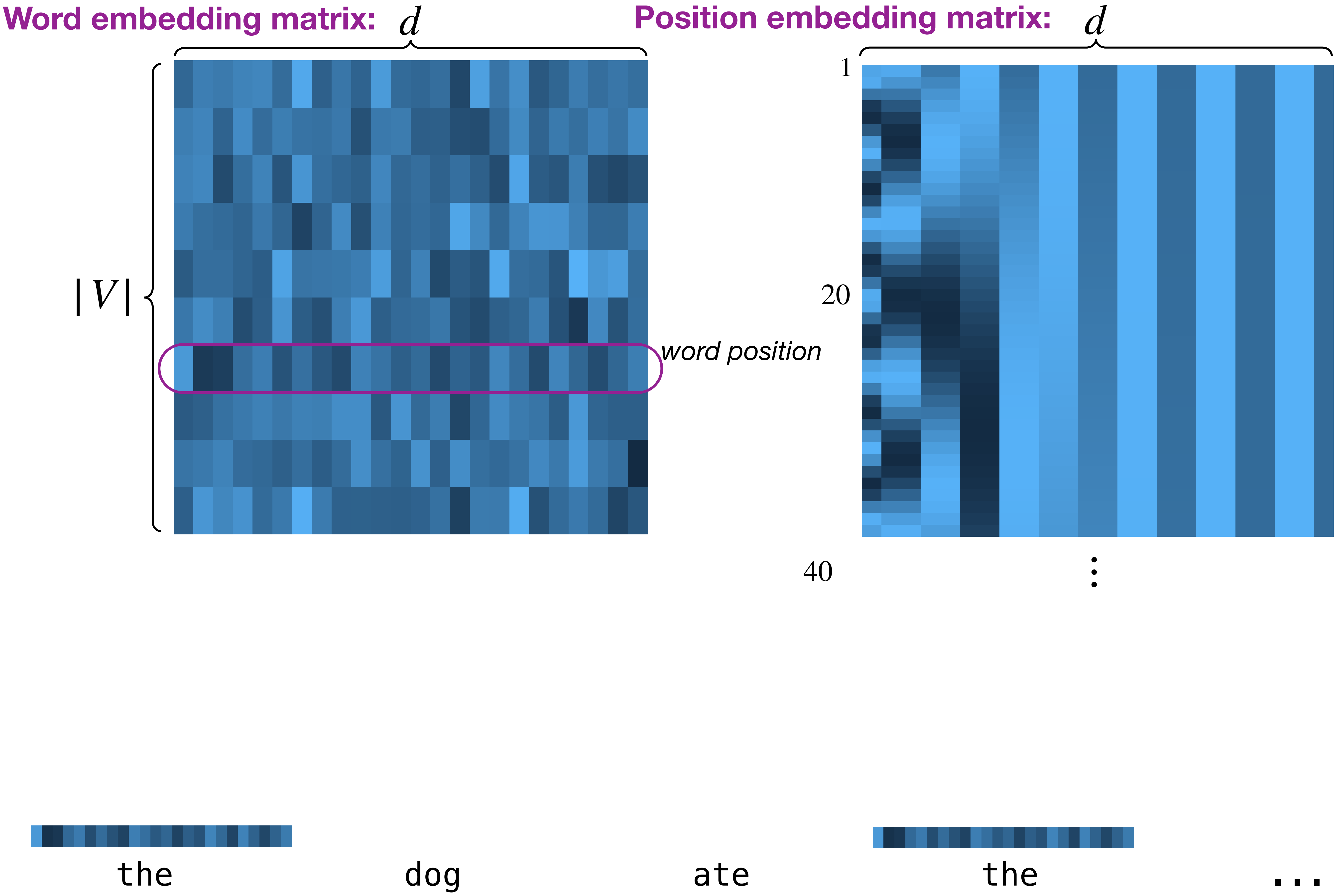
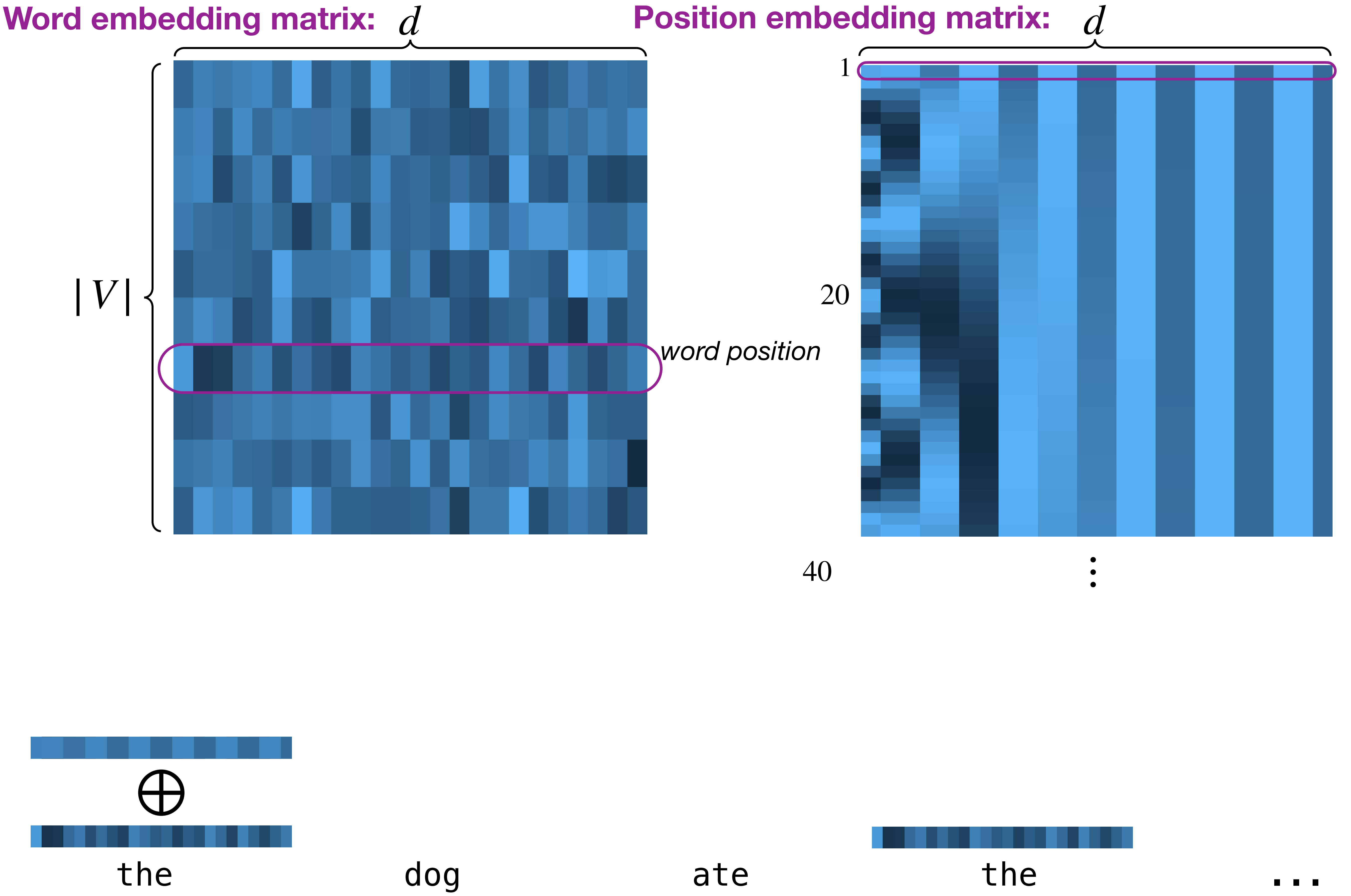


Word embedding matrix: d

Position embedding matrix: d

Input + Positional Embedding



Word embedding matrix: d

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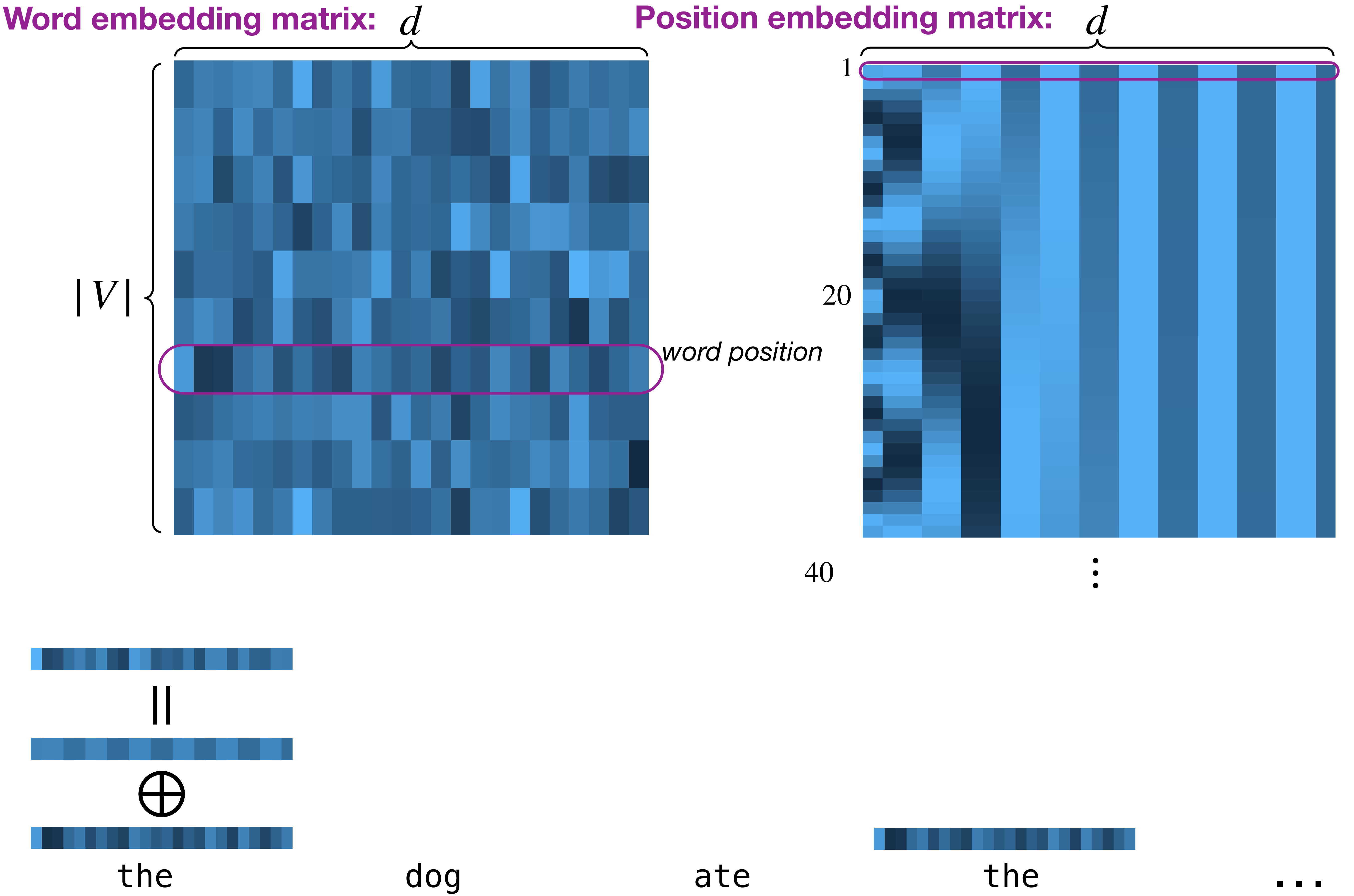


Word embedding matrix: d

$|V|$

word position

Position embedding matrix: d

1

20

40

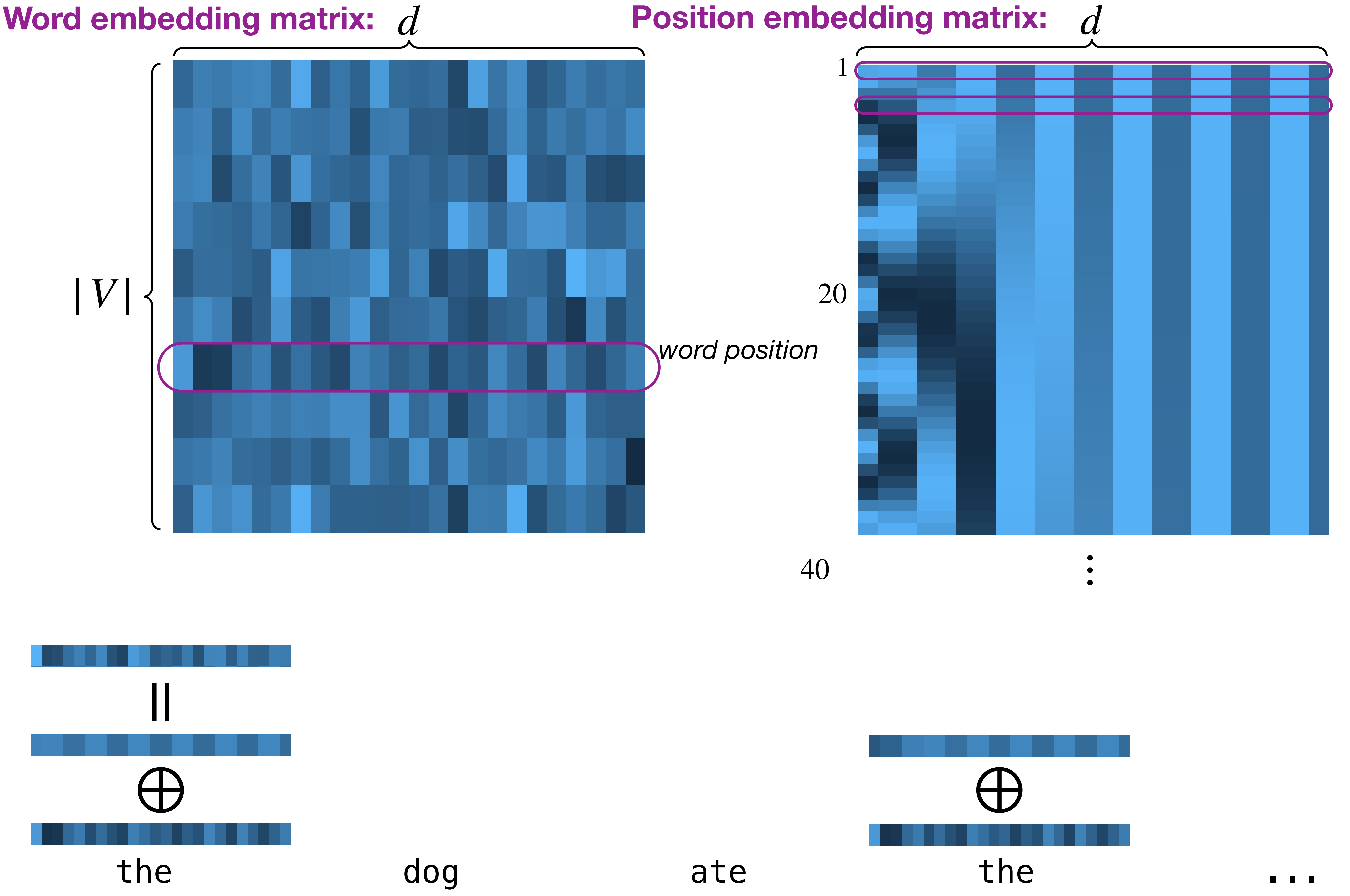
⋮

||

⊕

the dog ate the ...

Input + Positional Embedding



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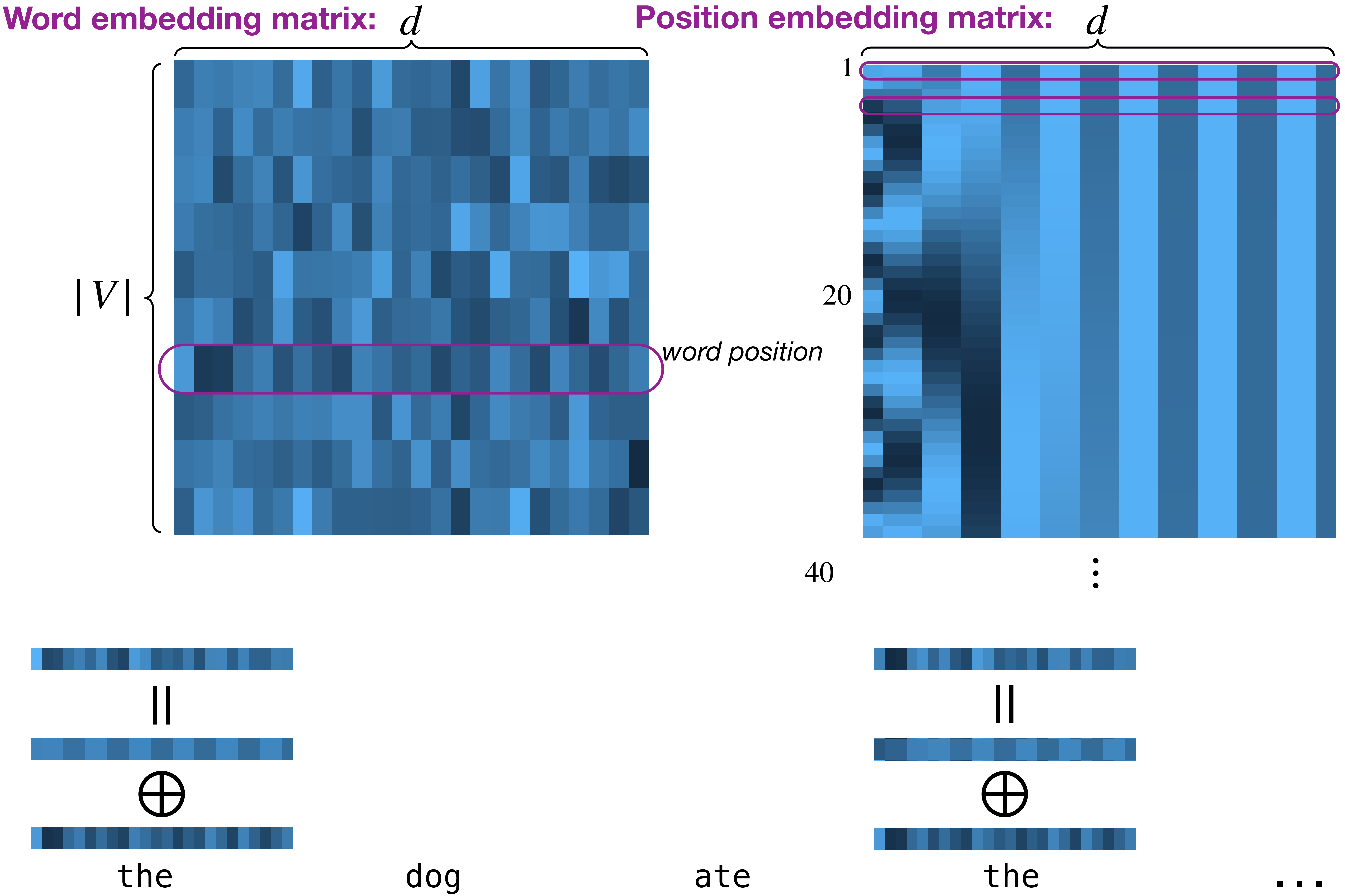
word position

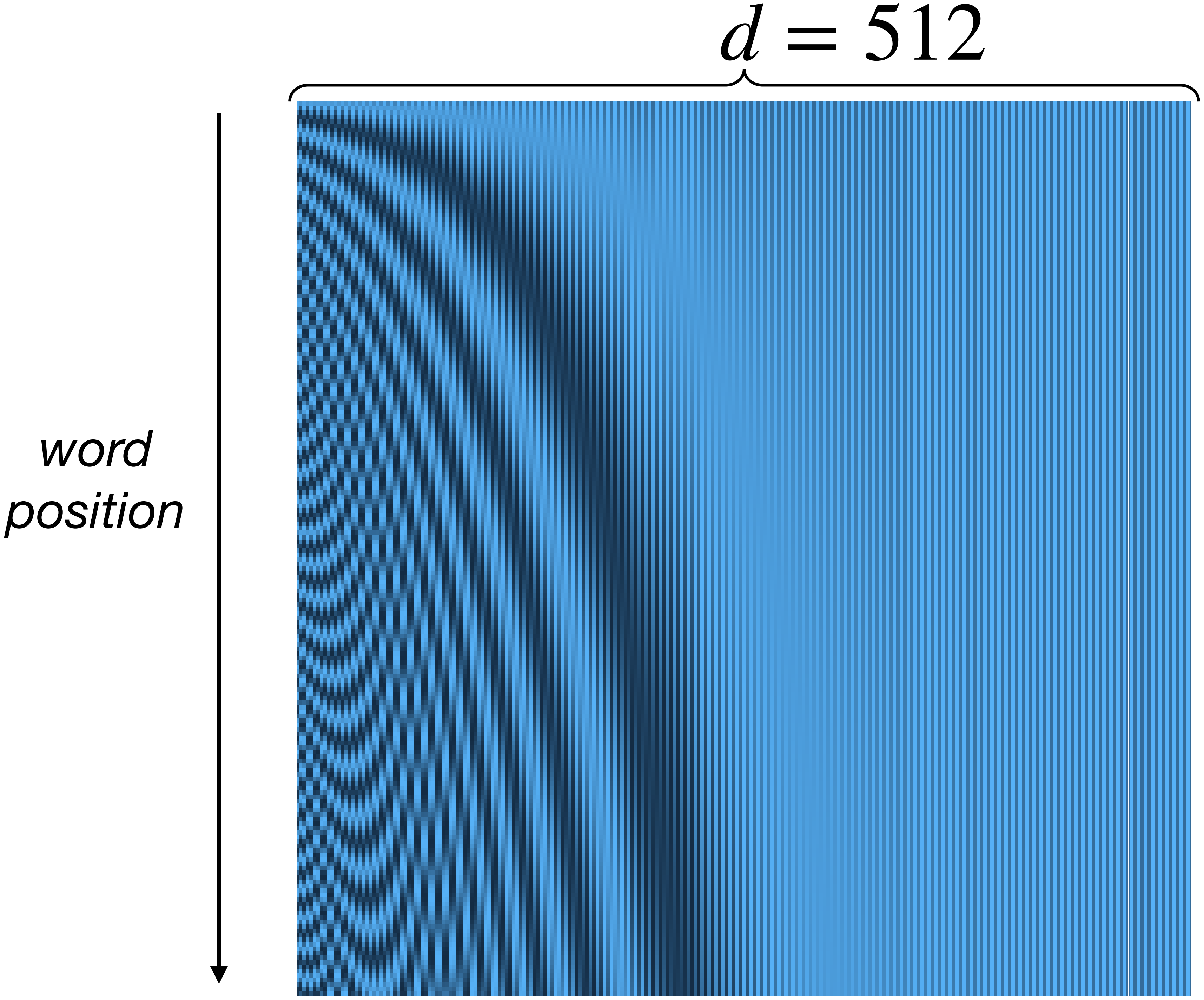
Position embedding matrix: d

Input + Positional Embedding

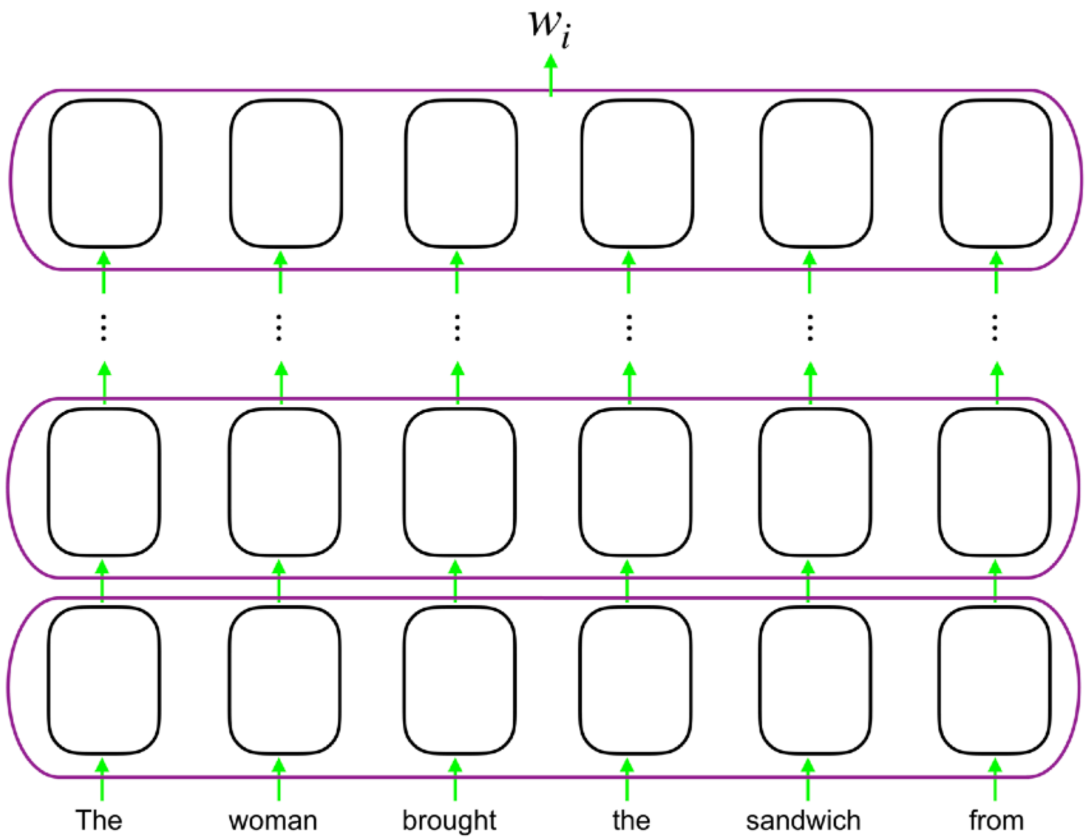


The positional embedding function

$$PE(pos, 2i) = \sin\left(\frac{pos}{10000^{\frac{2i}{d}}}\right) \qquad PE(pos, 2i+1) = \cos\left(\frac{pos}{10000^{\frac{2i}{d}}}\right)$$



The Transformer unit



(Vaswani et al., 2017)

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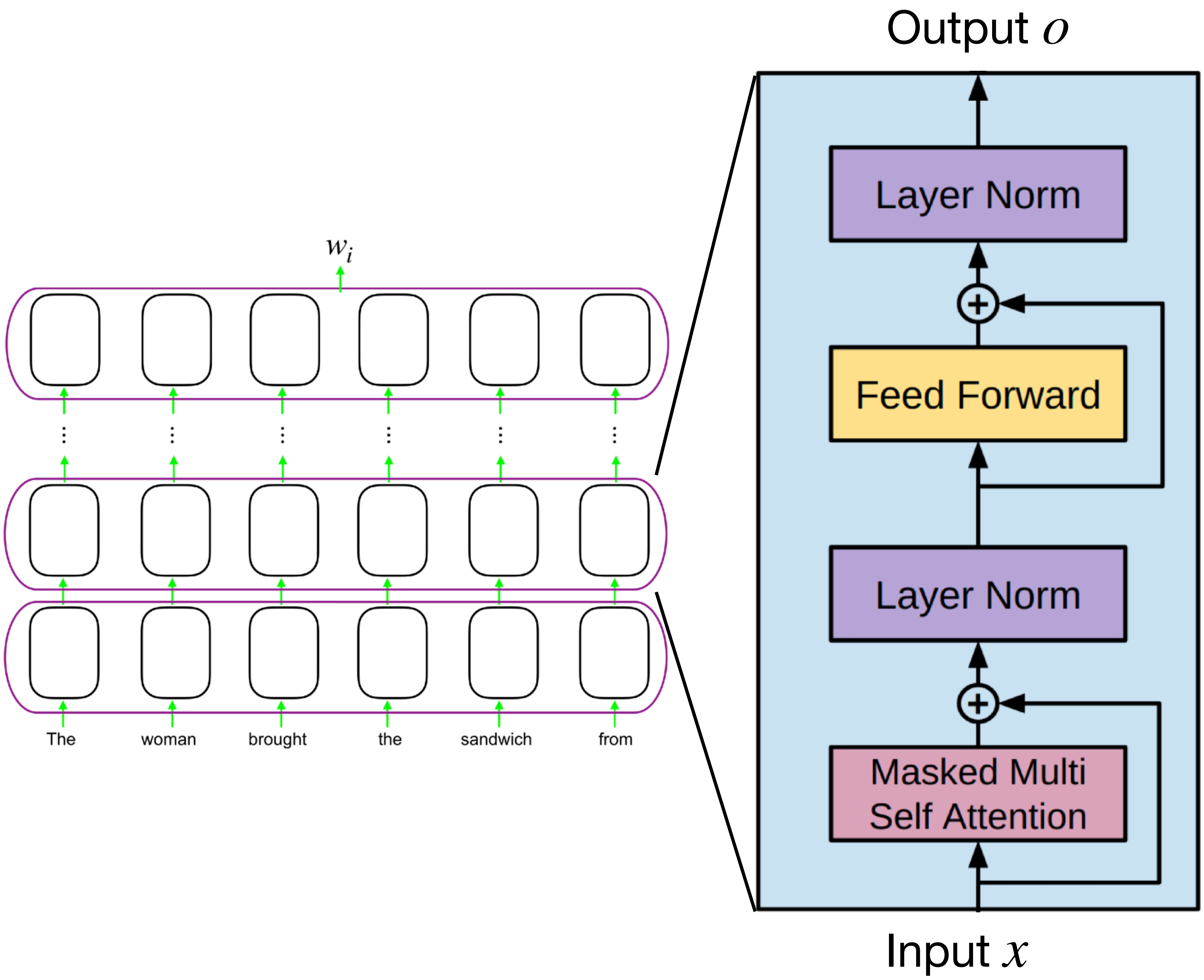

(Figure from Radford et al., 2018)

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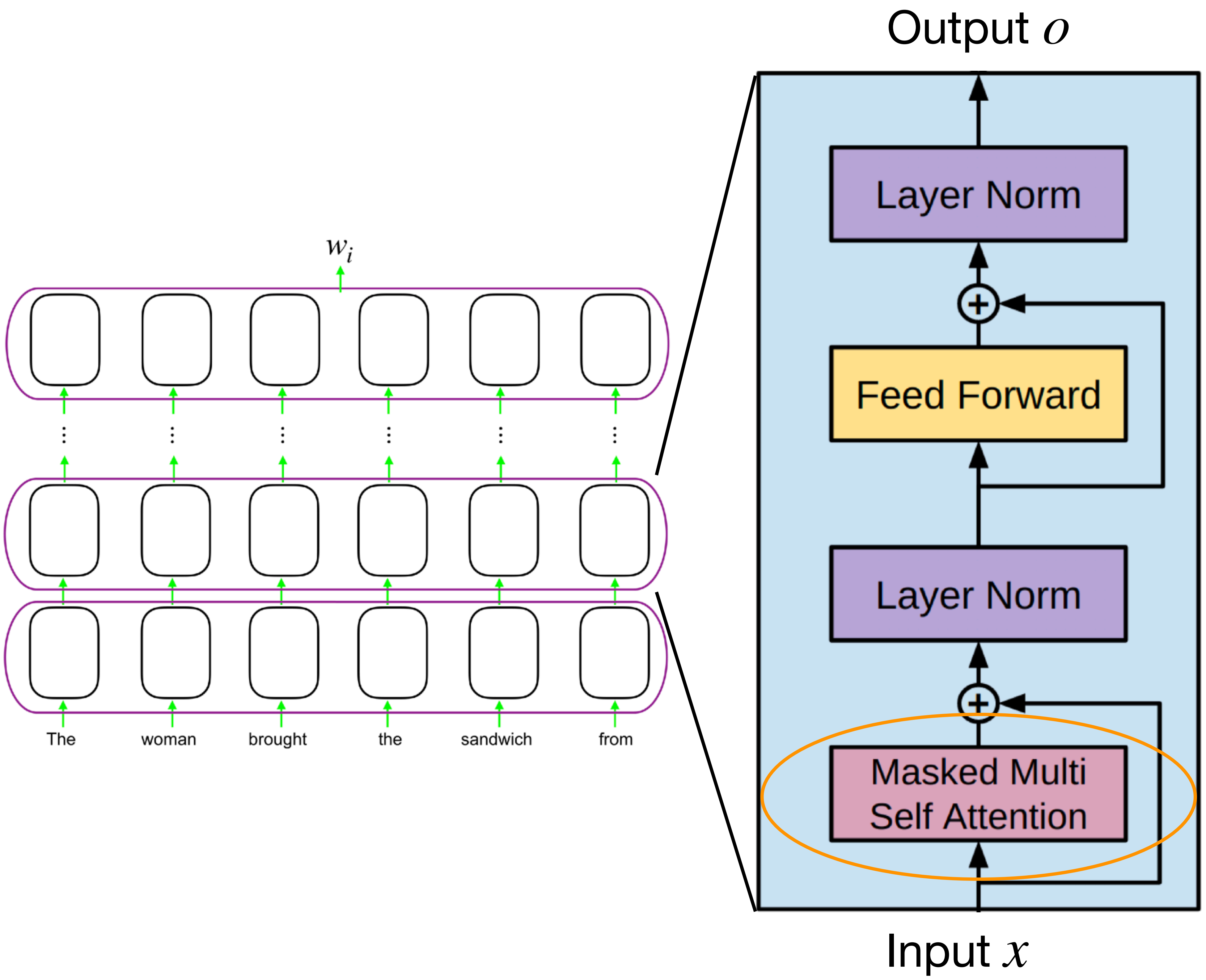

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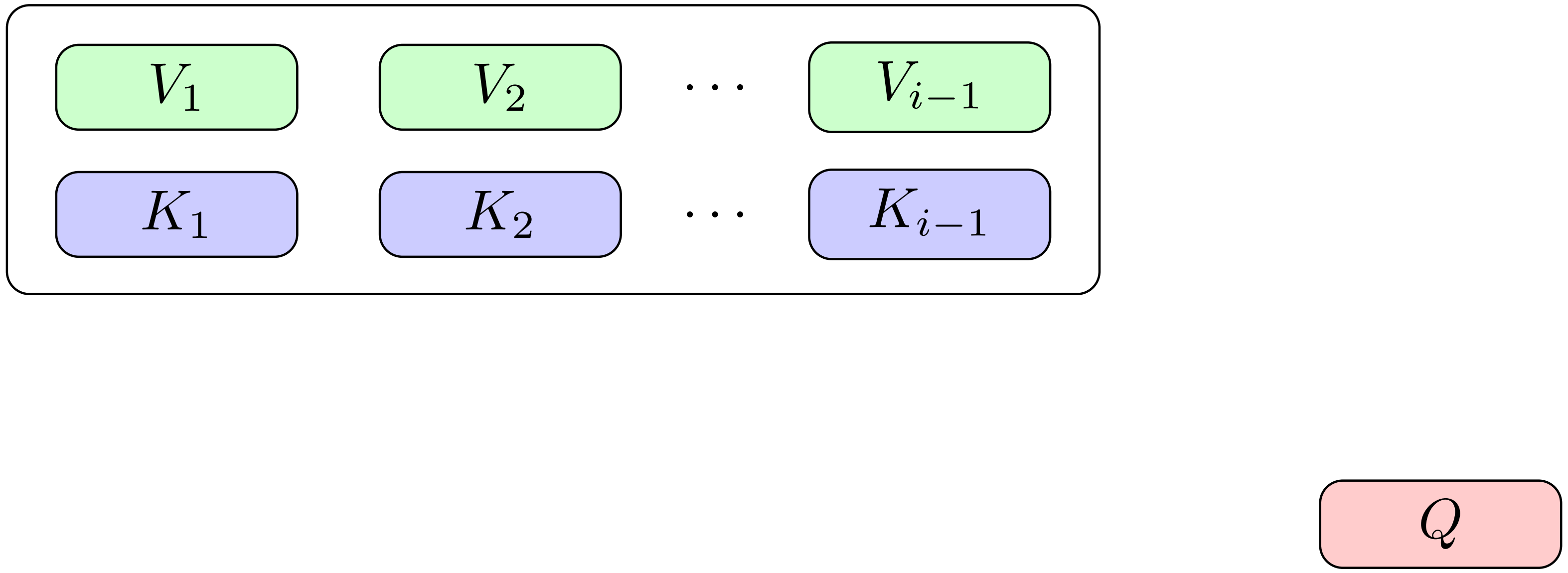
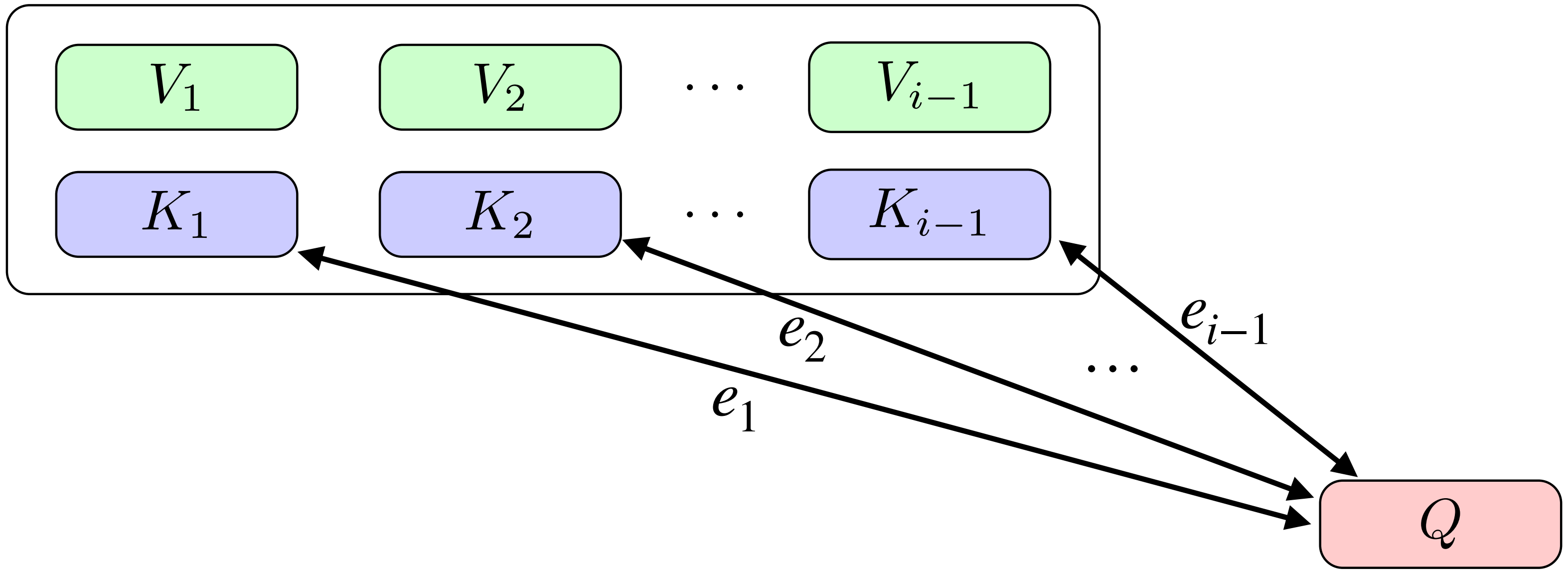
Neural Attention

***Q**uery, **K**ey, and **V**alue*



Neural Attention

Query, Key, and Value



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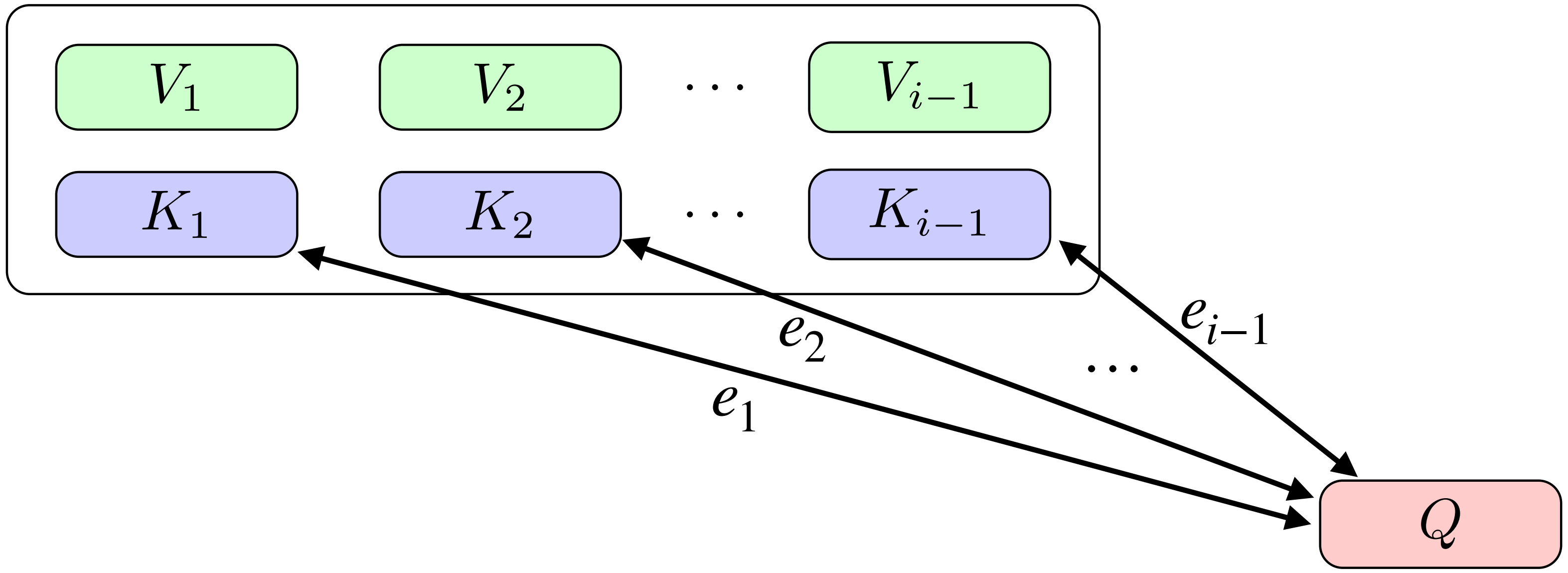


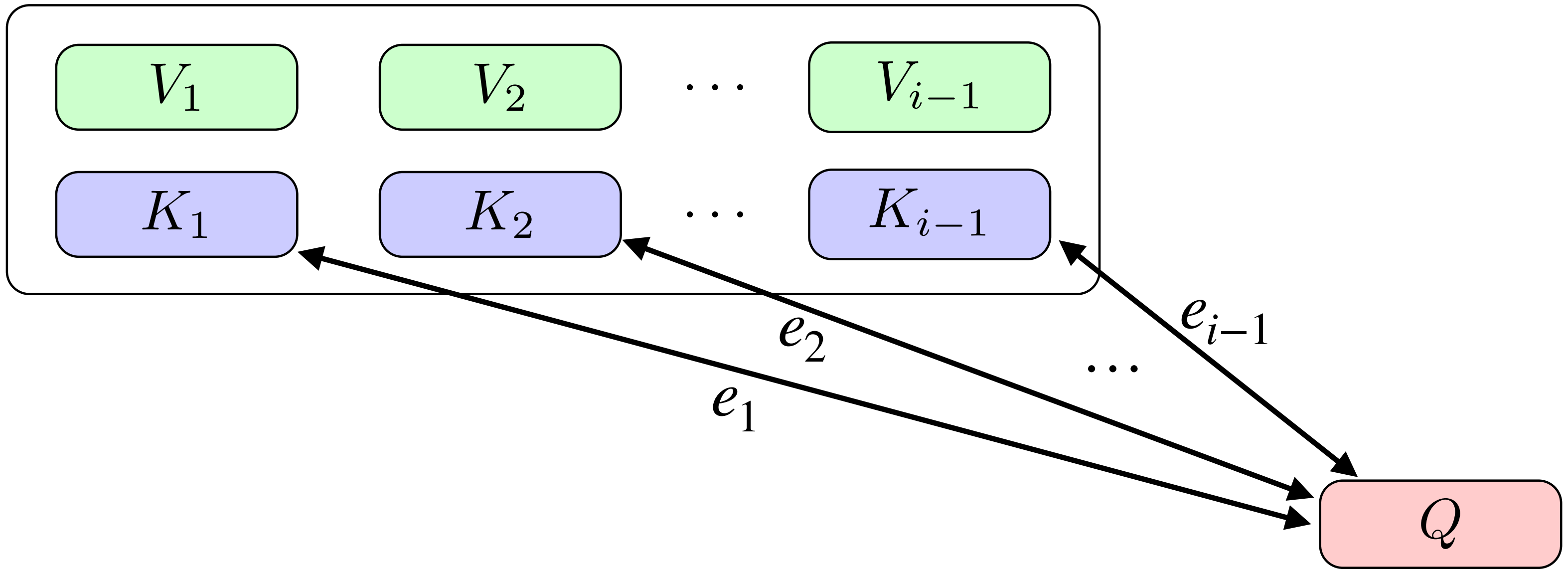
Attention function options:

$$e_j = \begin{cases} v \tanh\left[W_Q Q + W_K K_j\right] & \textbf{(Bahdanau et al., 2014)} \\ Q^T W K_j & \textbf{(Luong et al., 2015)} \\ \dfrac{Q^T K}{\sqrt{|K|}} & \textbf{(Vaswani et al., 2017)} \end{cases}$$

Neural Attention

Query, Key, and Value

$$\alpha_1, \ldots, \alpha_{i-1} = \textbf{softmax}(e_1, \ldots, e_{i-1})$$



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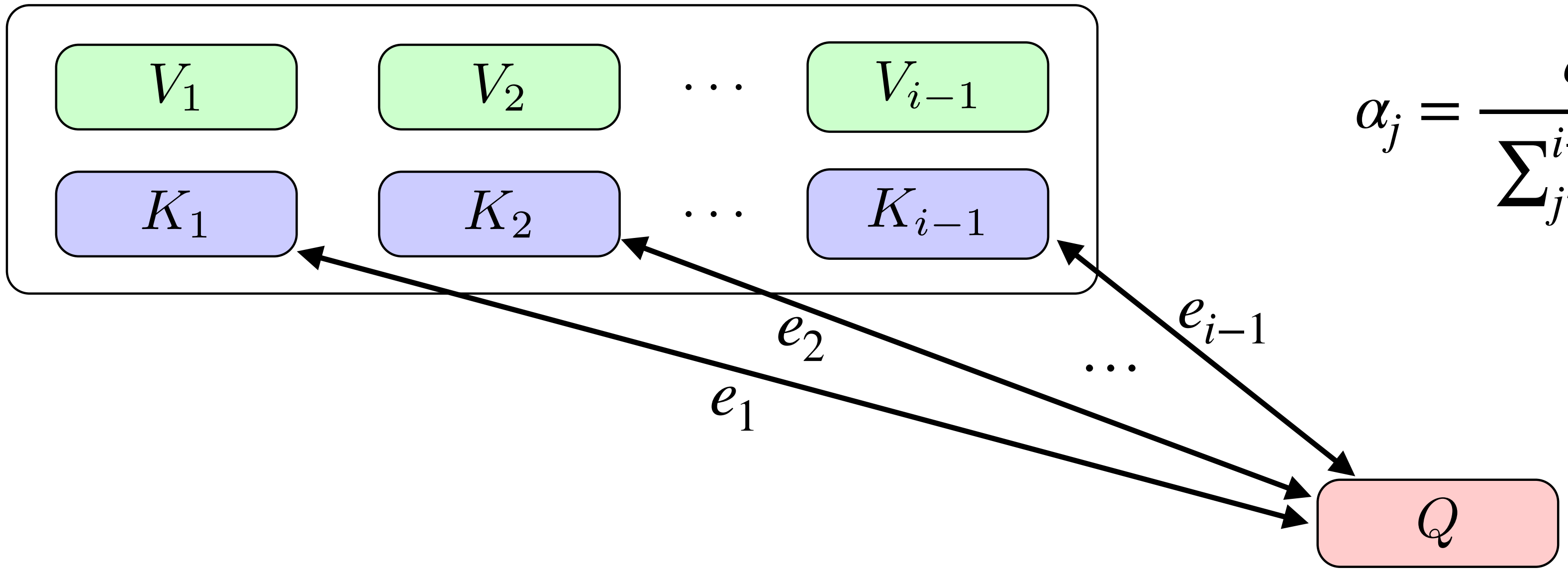

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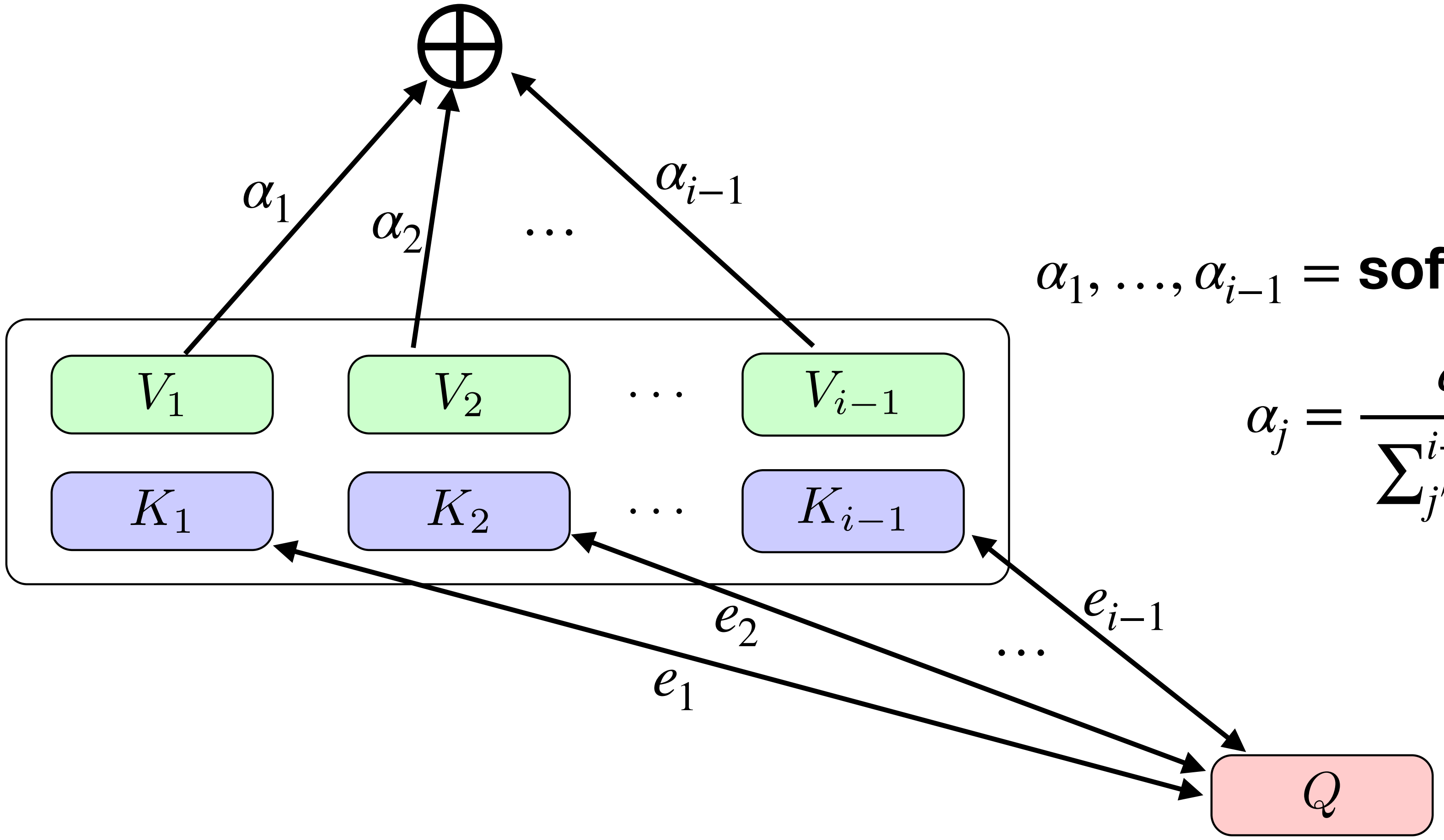

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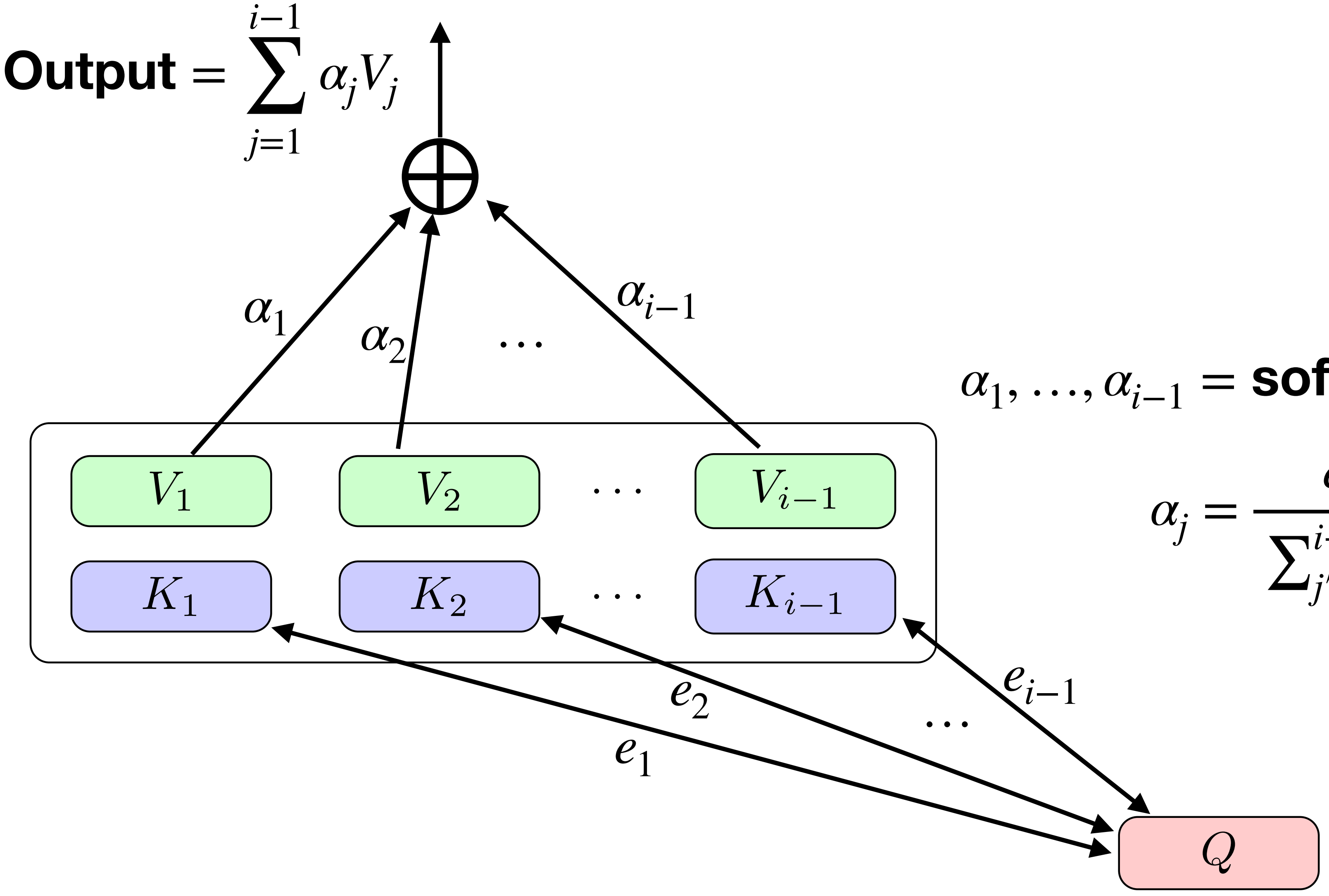
Neural Attention

Query, Key, and Value

$$\textbf{Output} = \sum_{j=1}^{i-1} \alpha_j V_j$$



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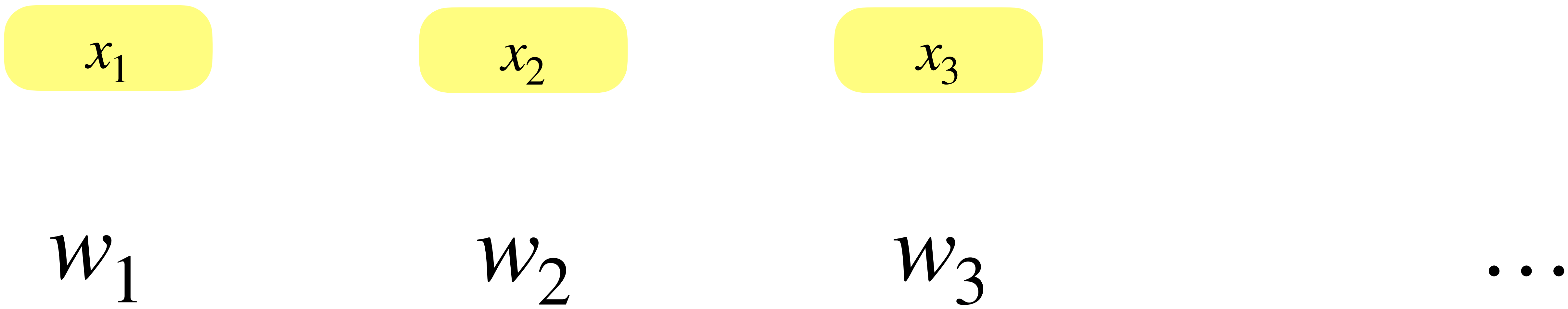
A single masked attention "head"



x_1 x_2 x_3

w_1 w_2 w_3 $\dots$

W_K, W_V, and W_Q are all learned during training

(Vaswani et al., 2017)

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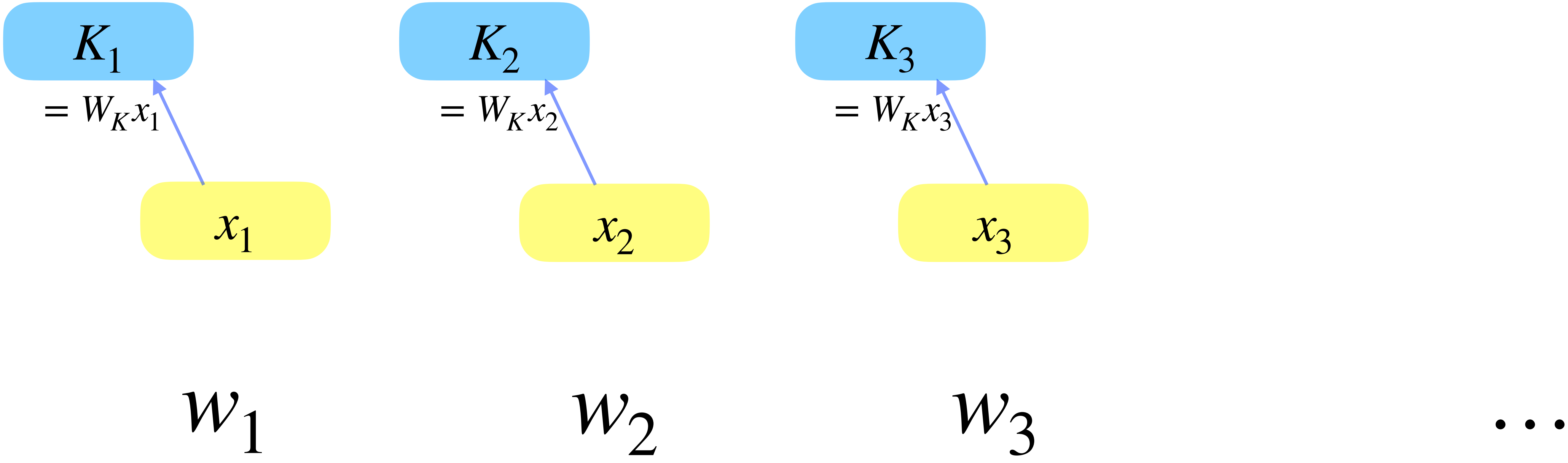

K_1 $= W_K x_1$ x_1

K_2 $= W_K x_2$ x_2

K_3 $= W_K x_3$ x_3

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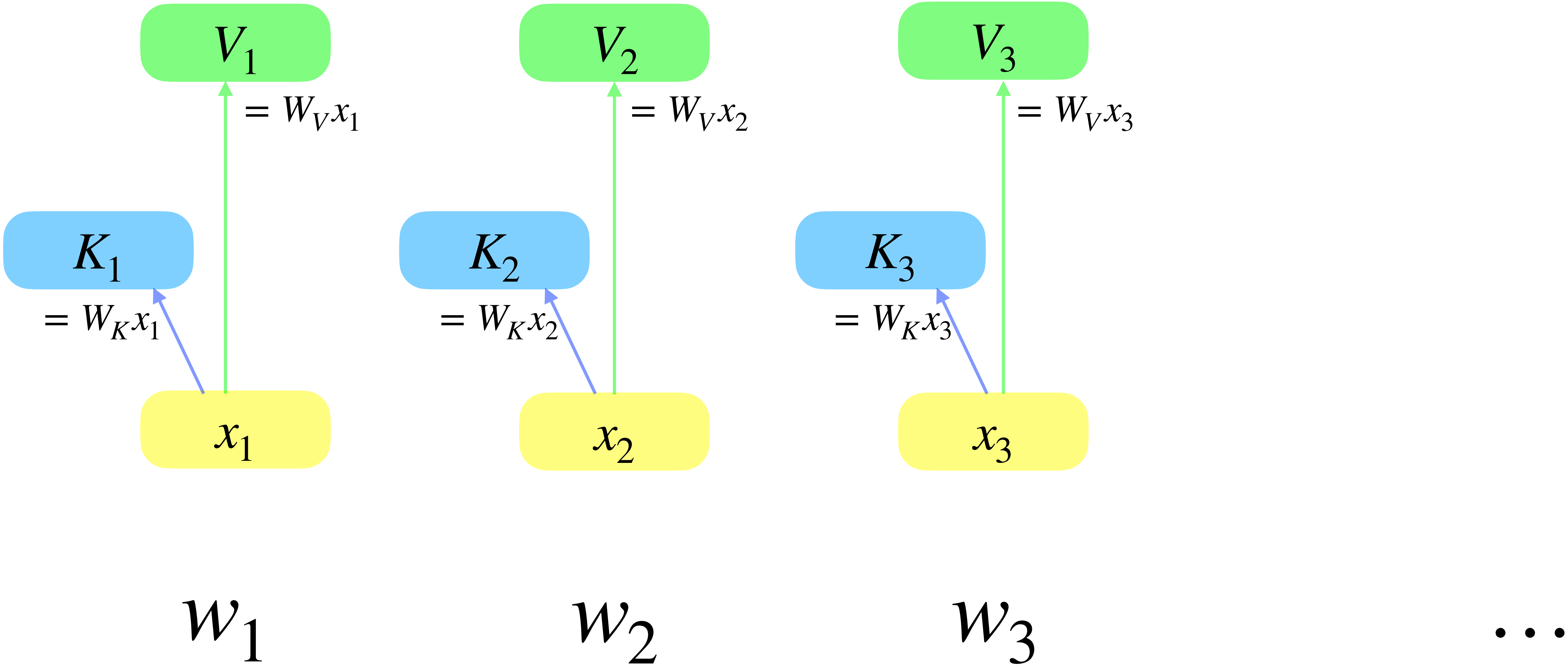

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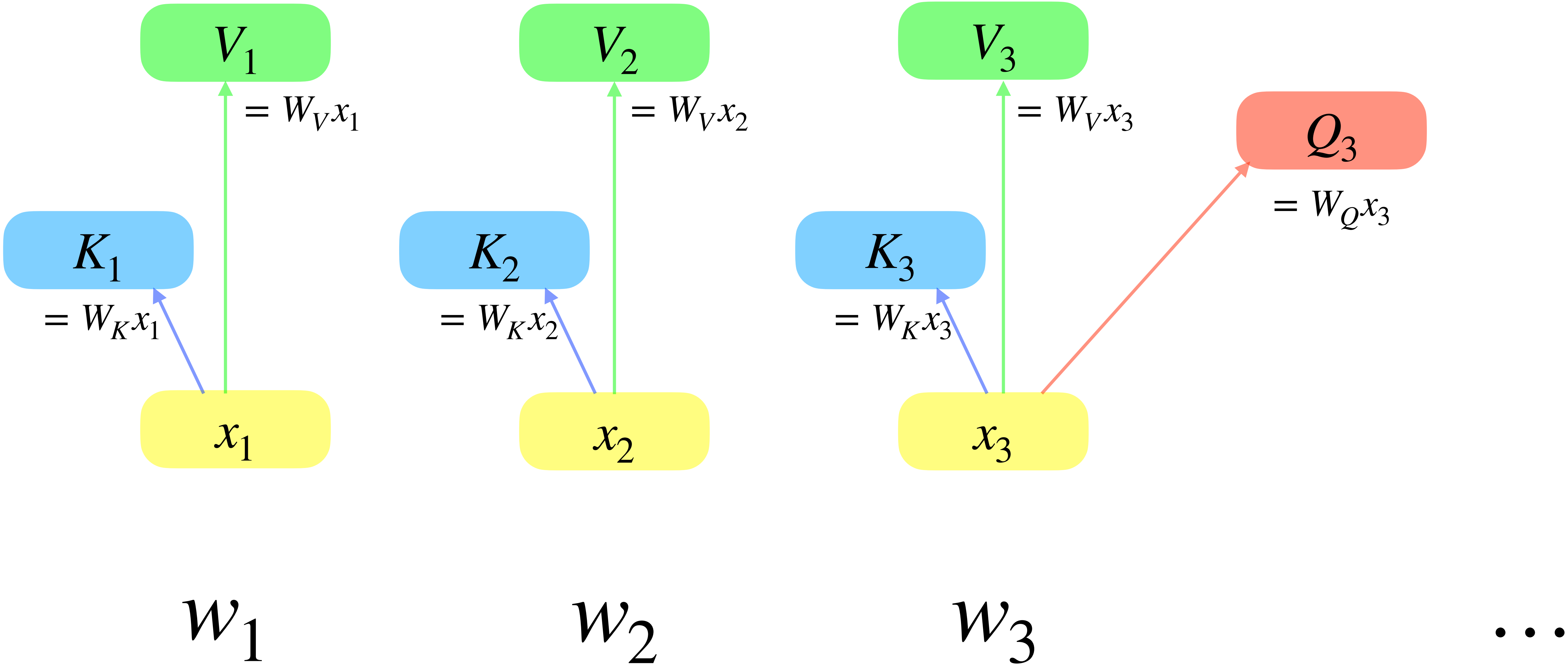

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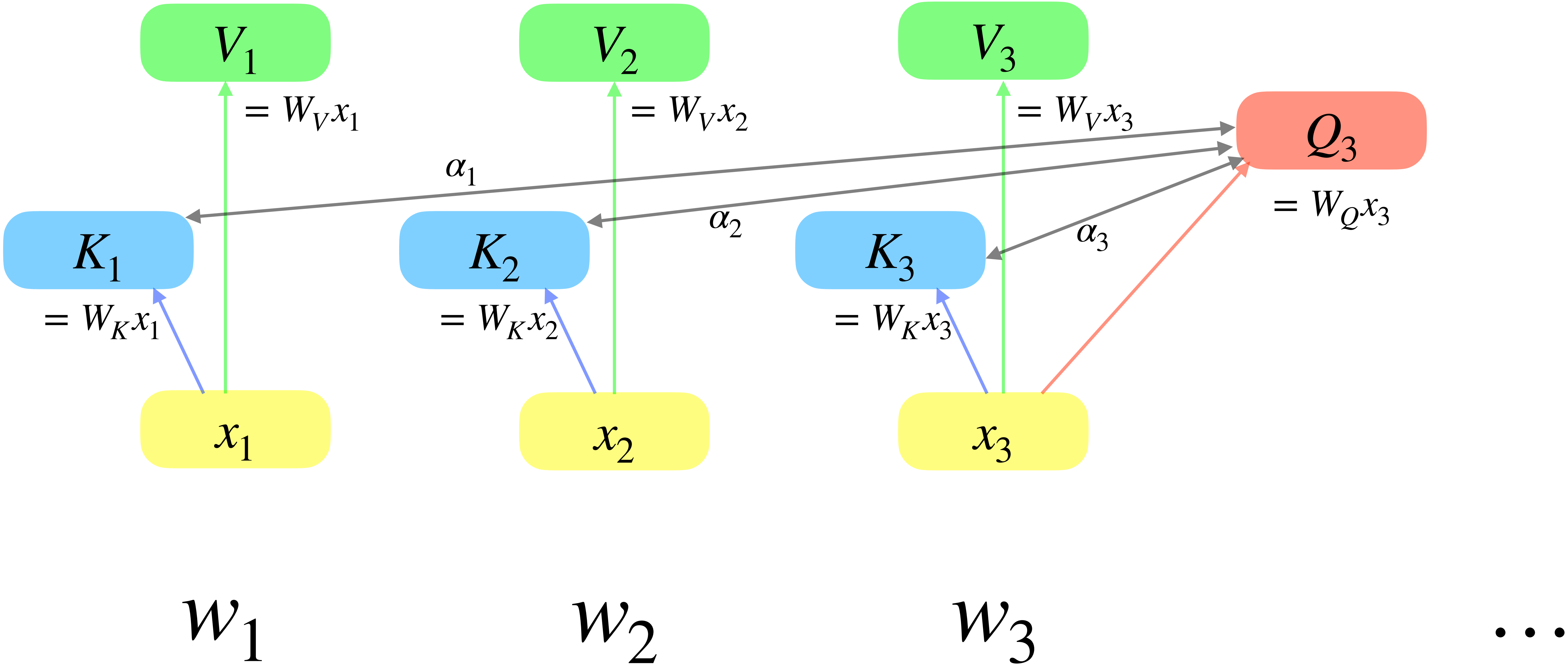

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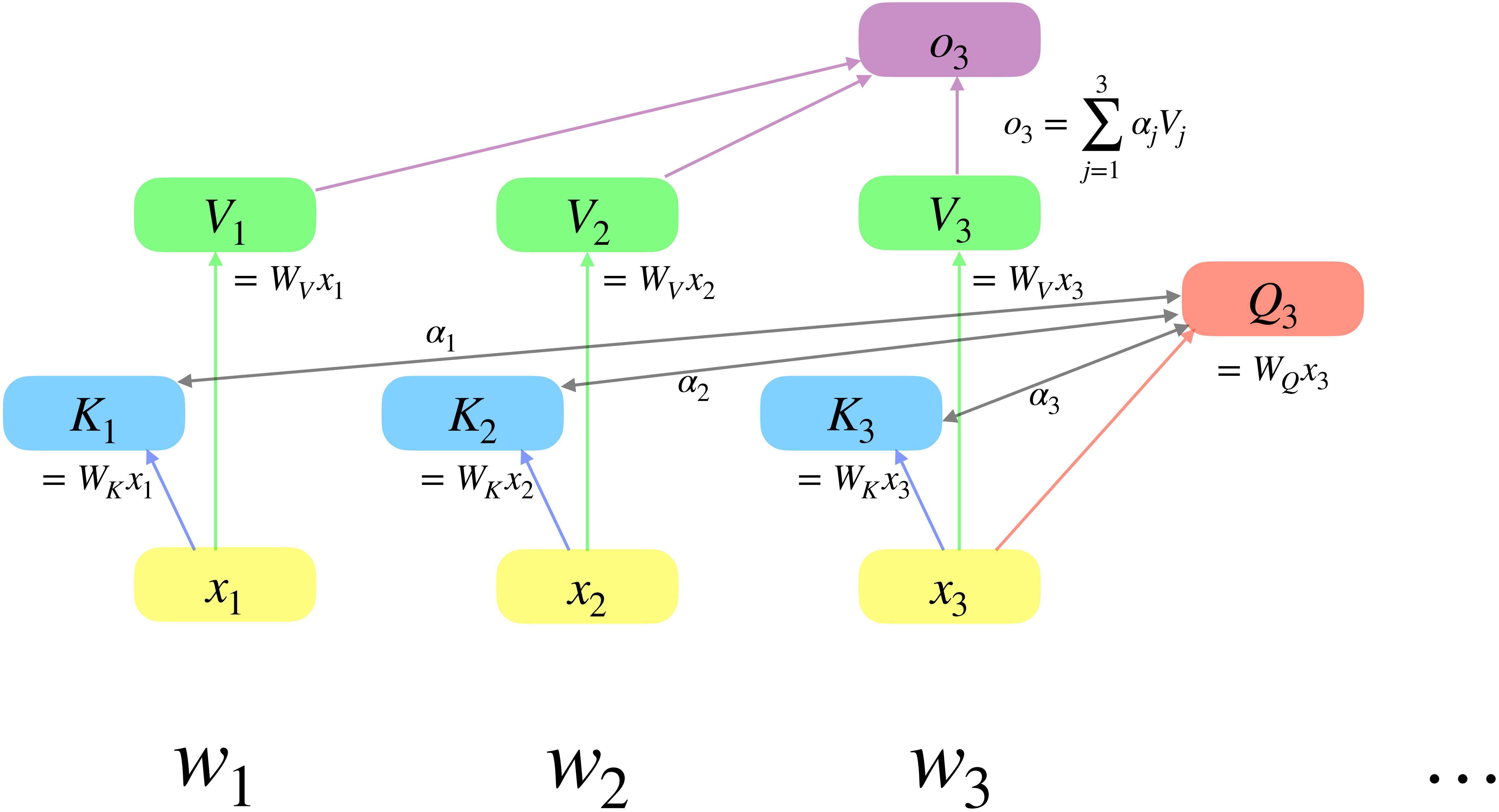

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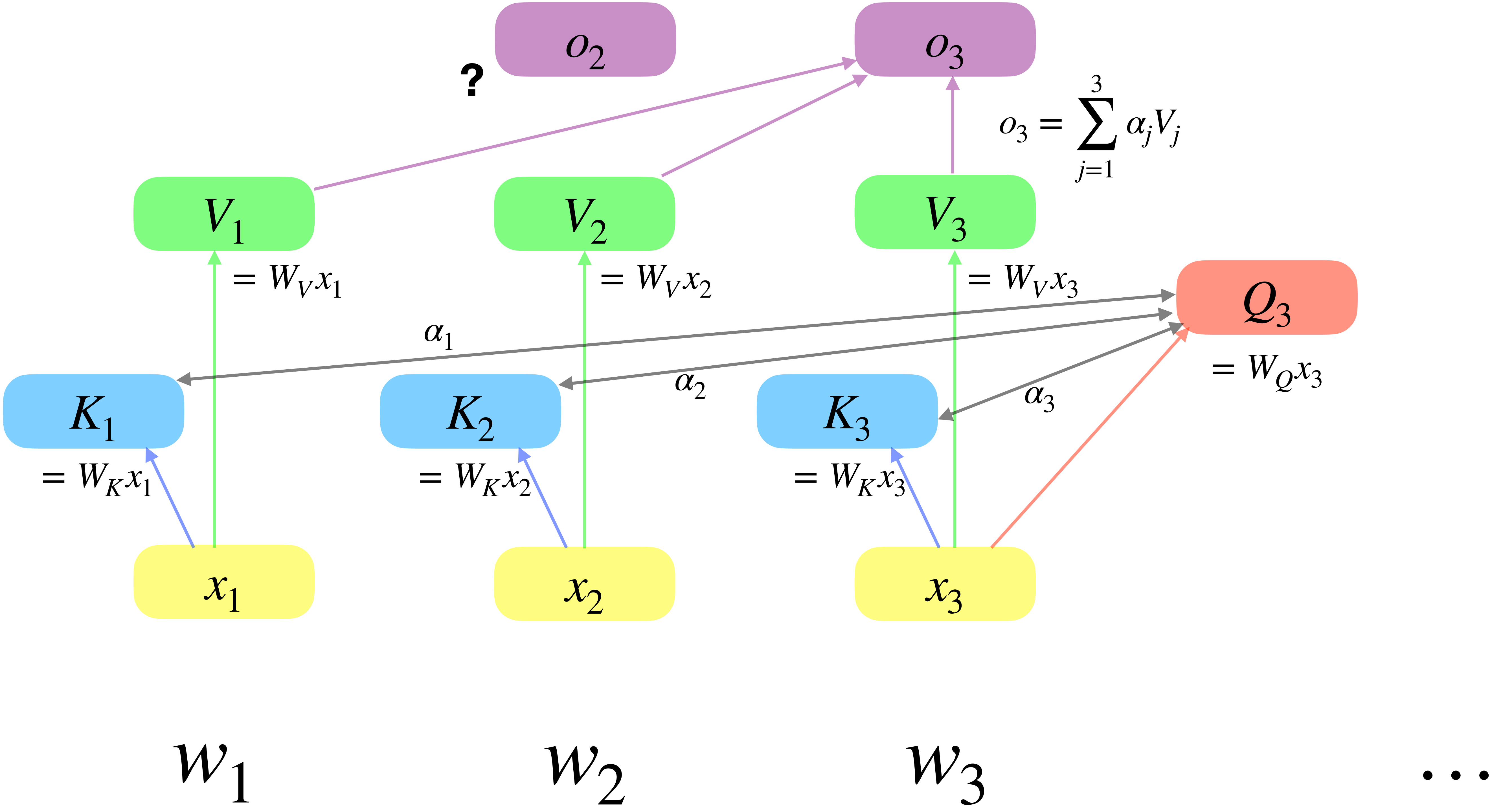
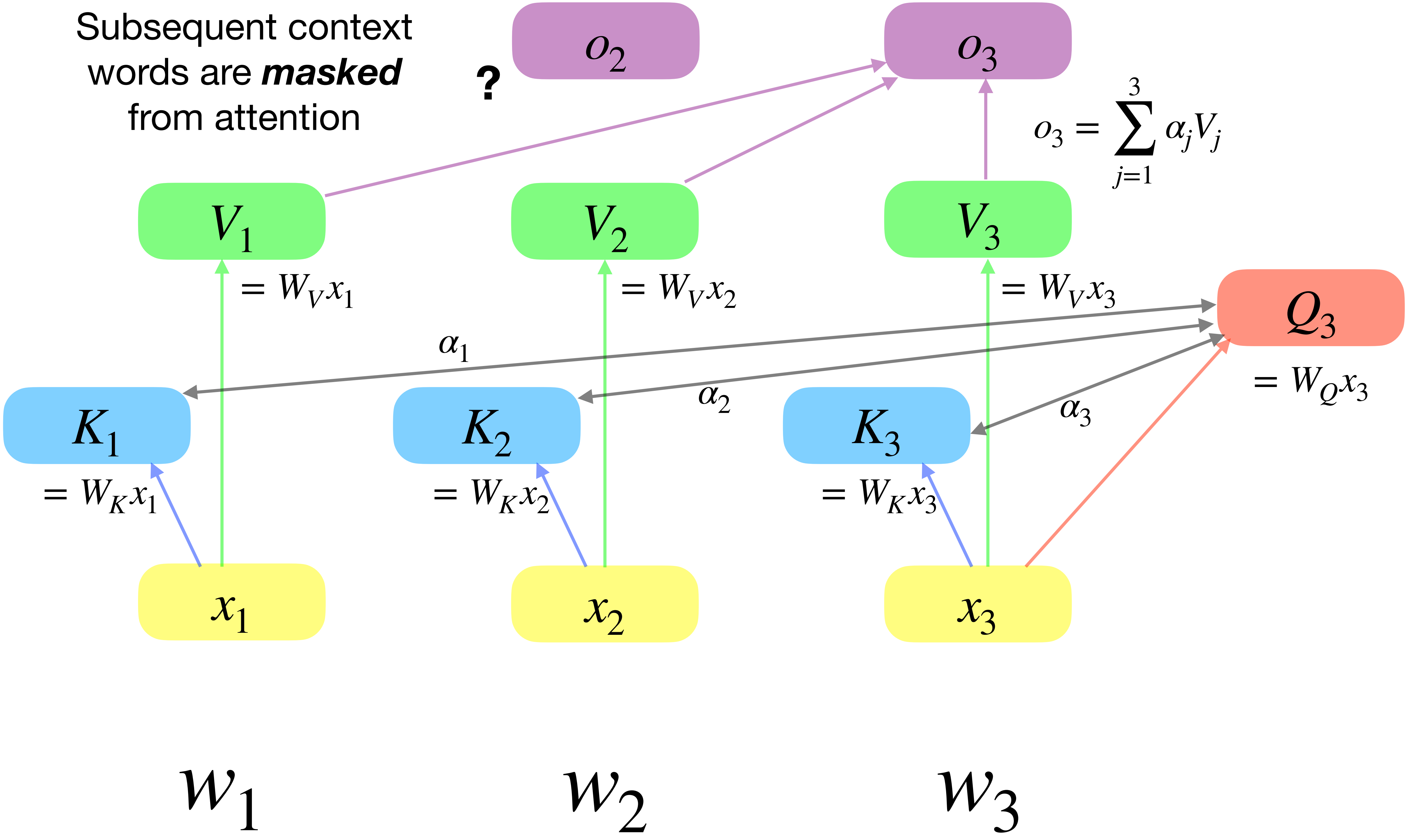


(Vaswani et al., 2017)

A single masked attention "head"

Subsequent context words are ***masked*** from attention



$\dots$

(Vaswani et al., 2017)

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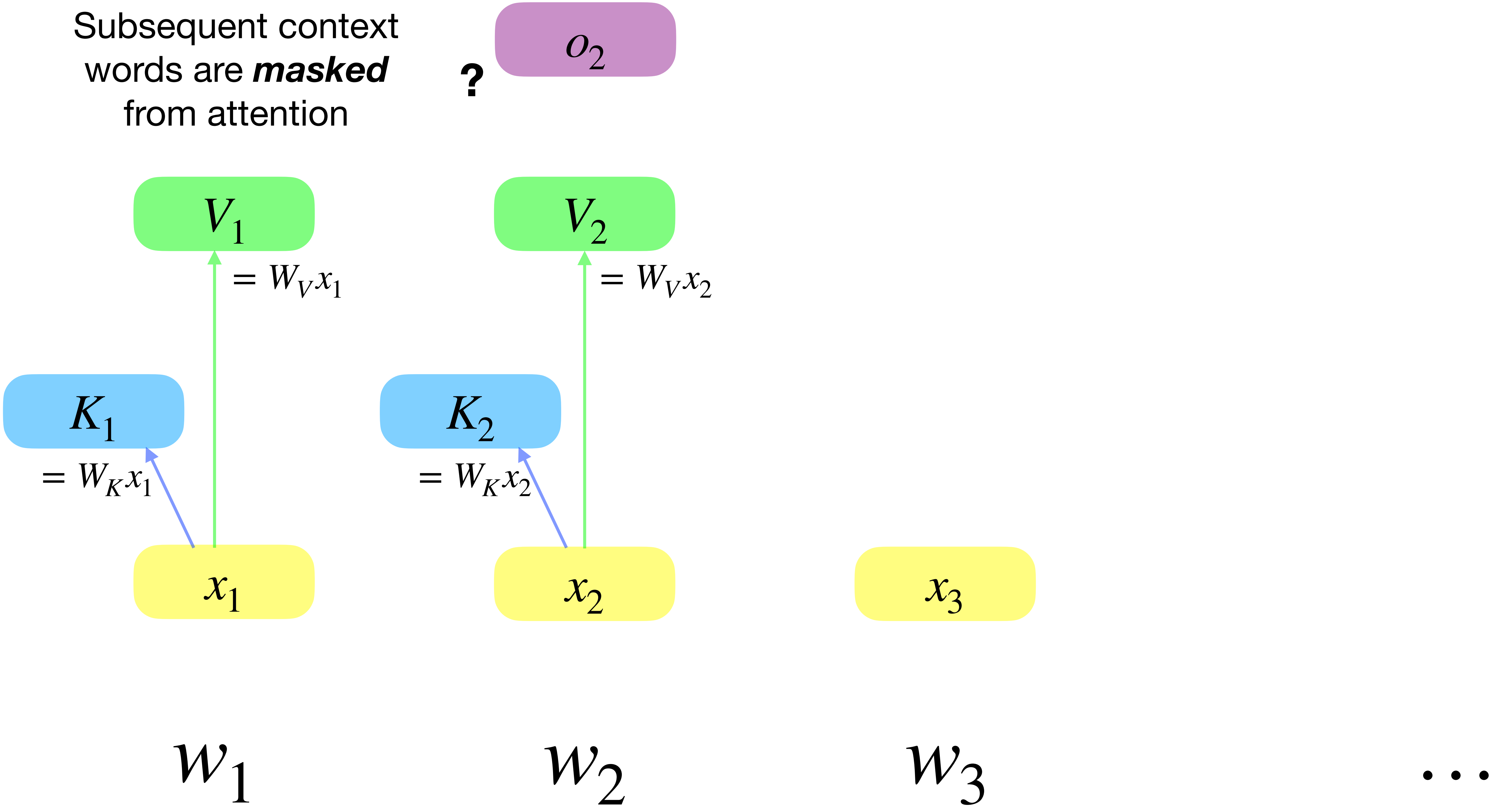

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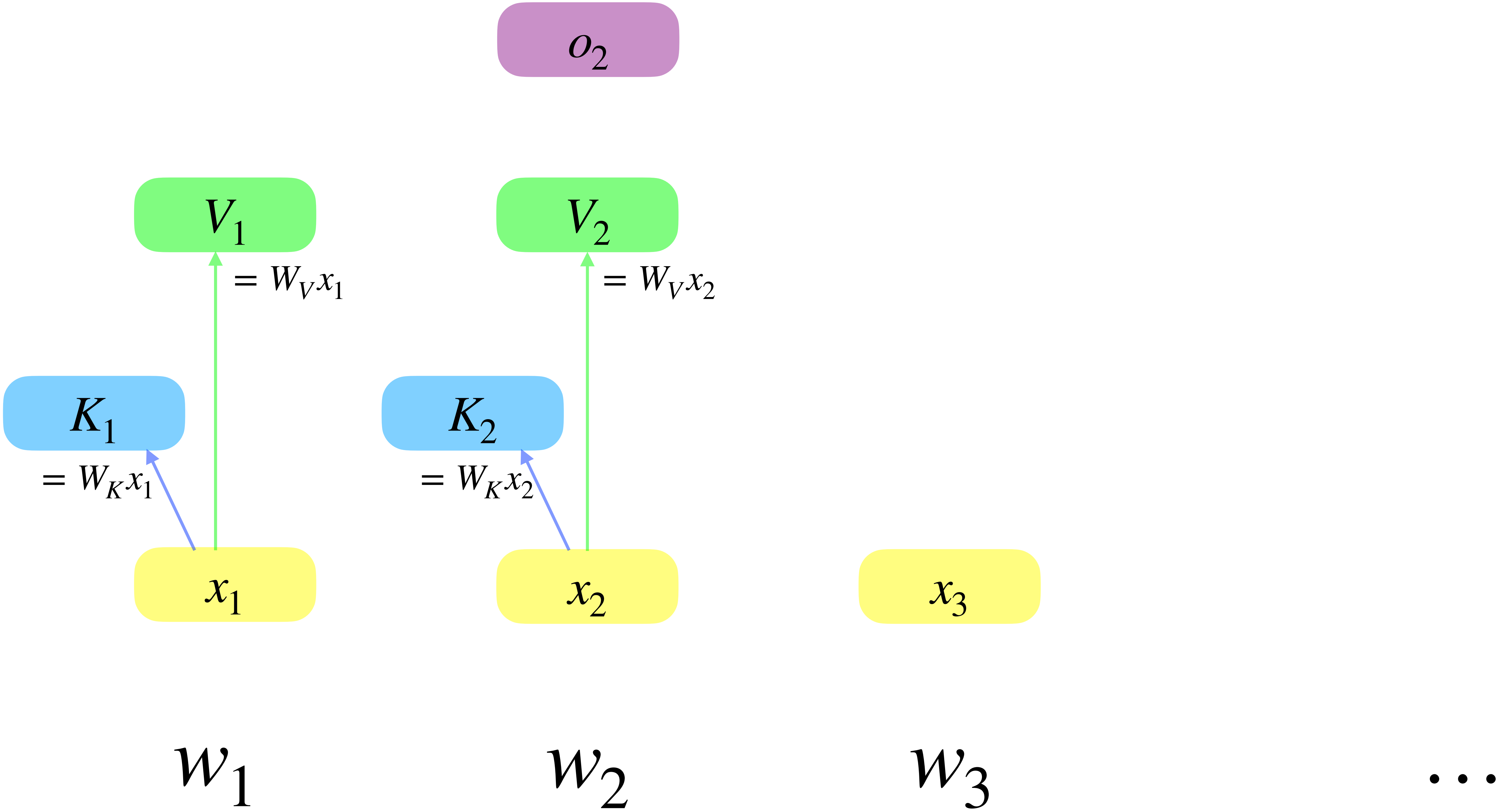

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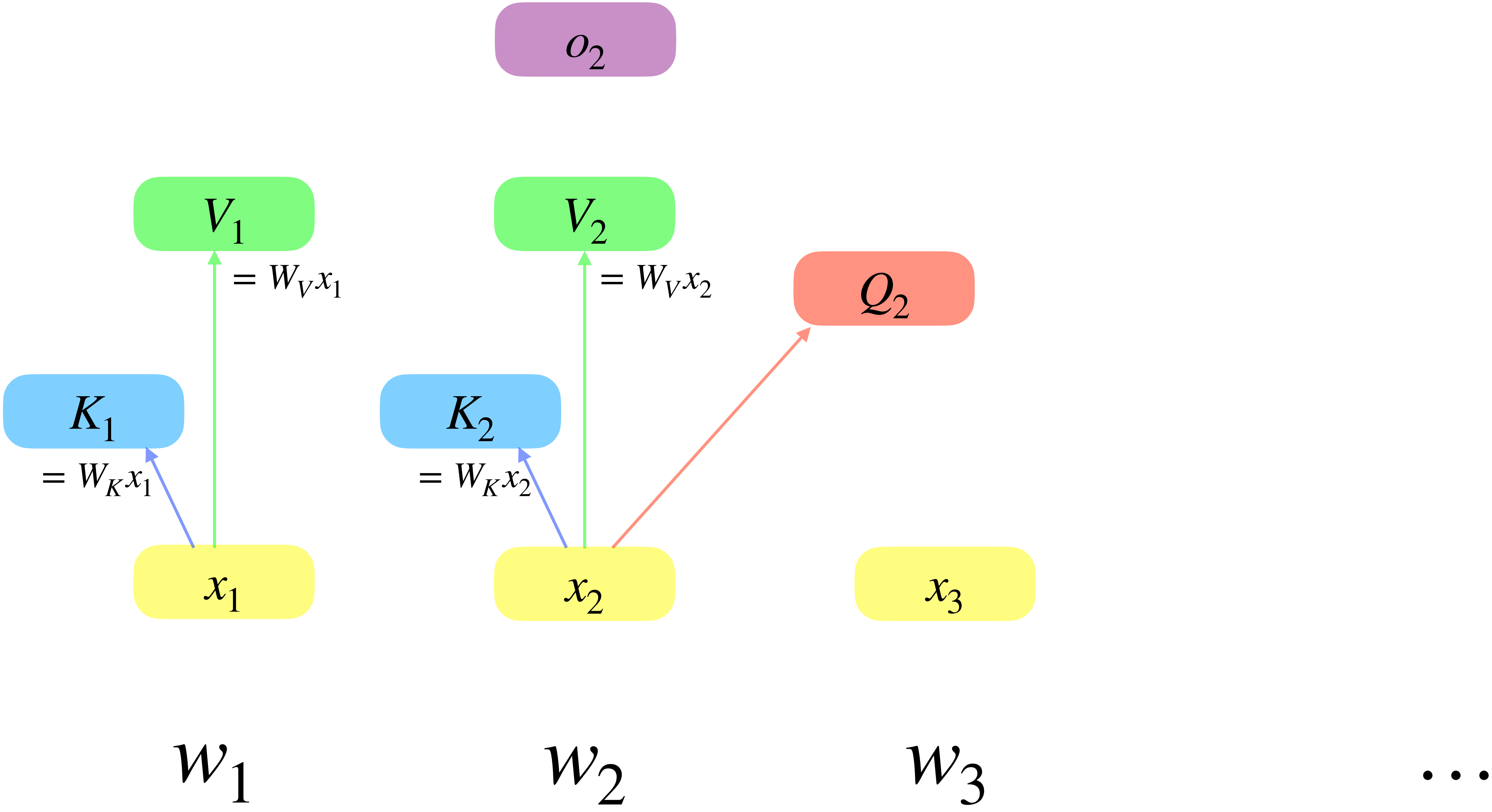

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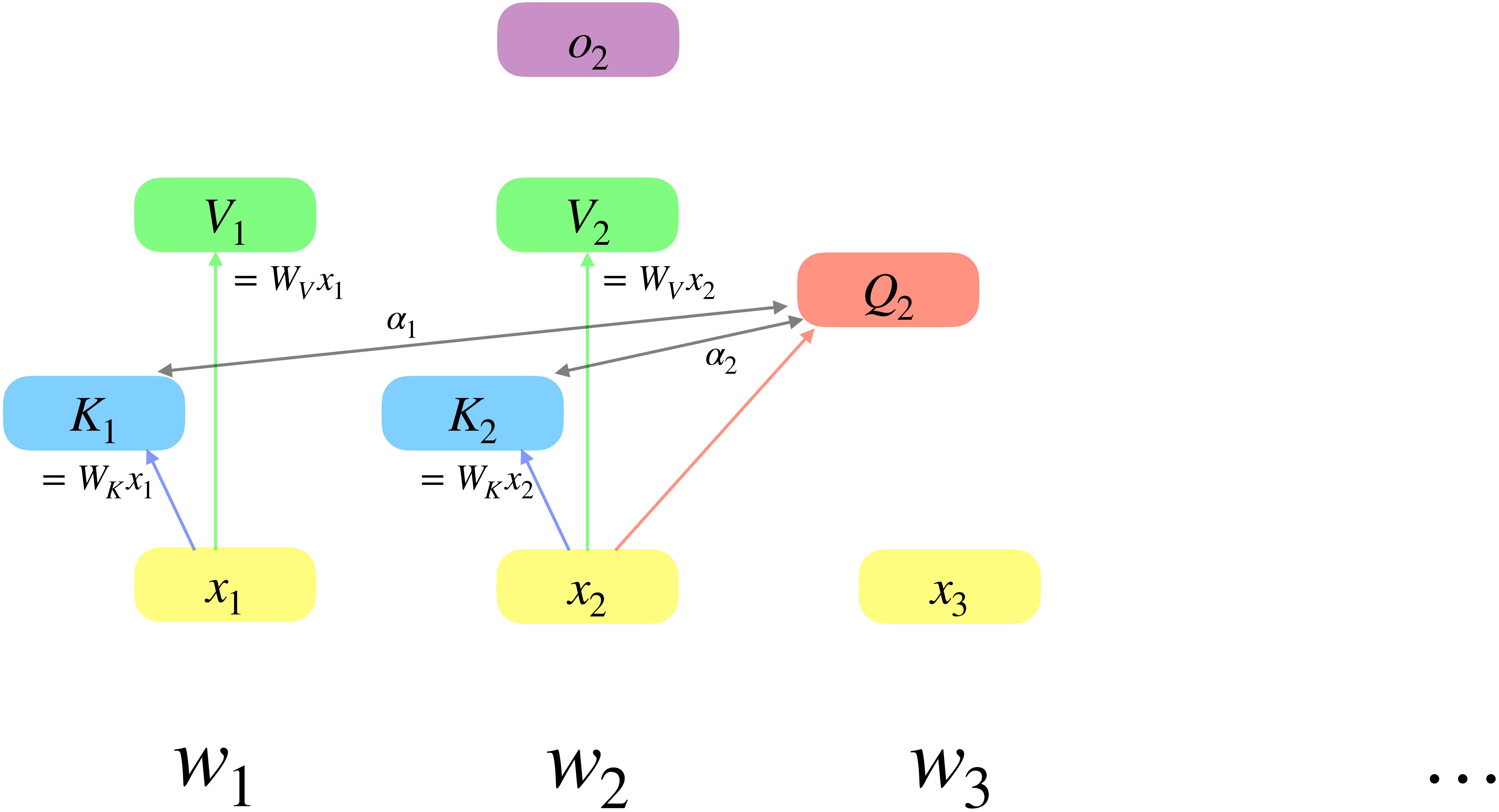

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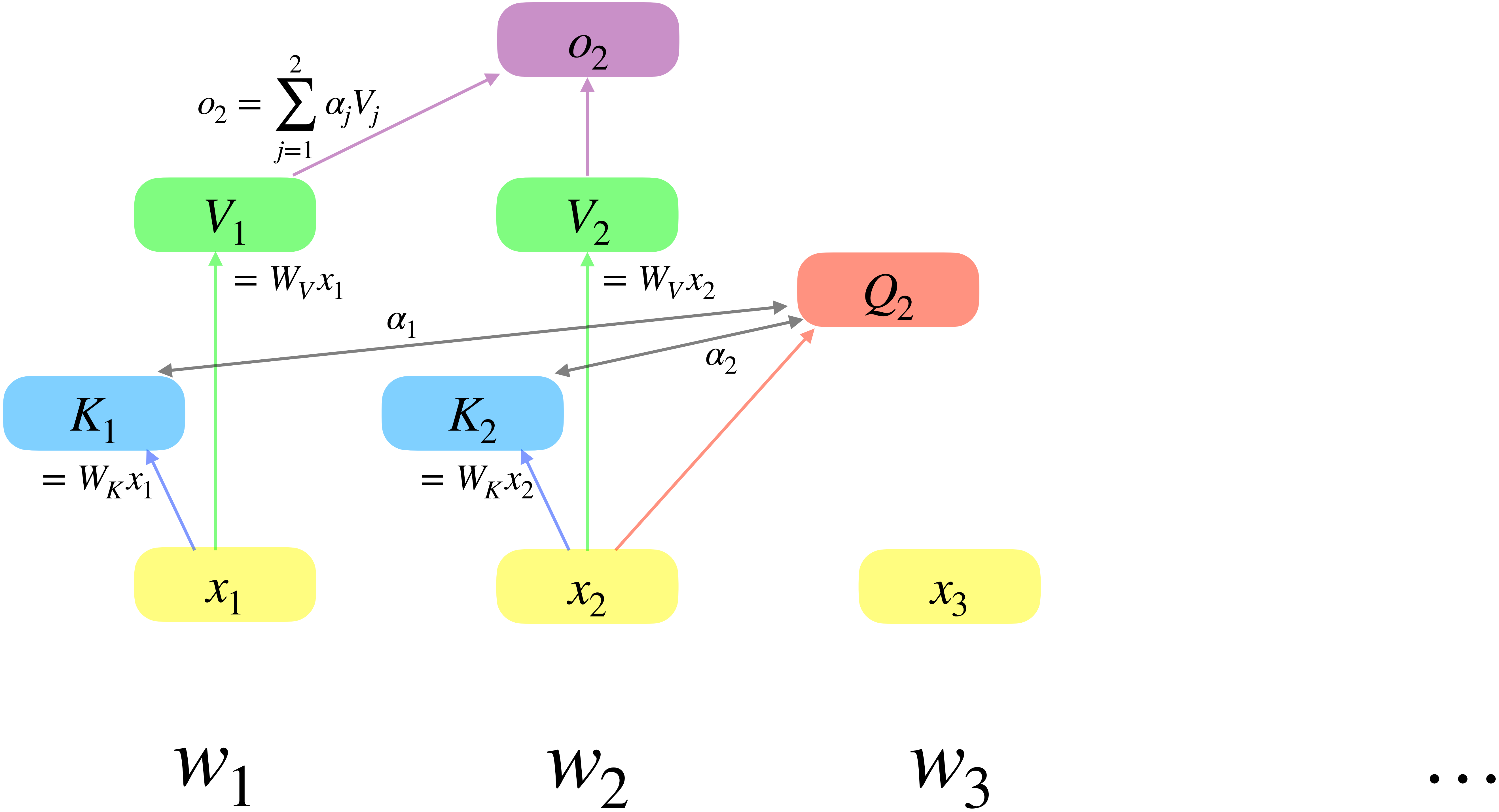
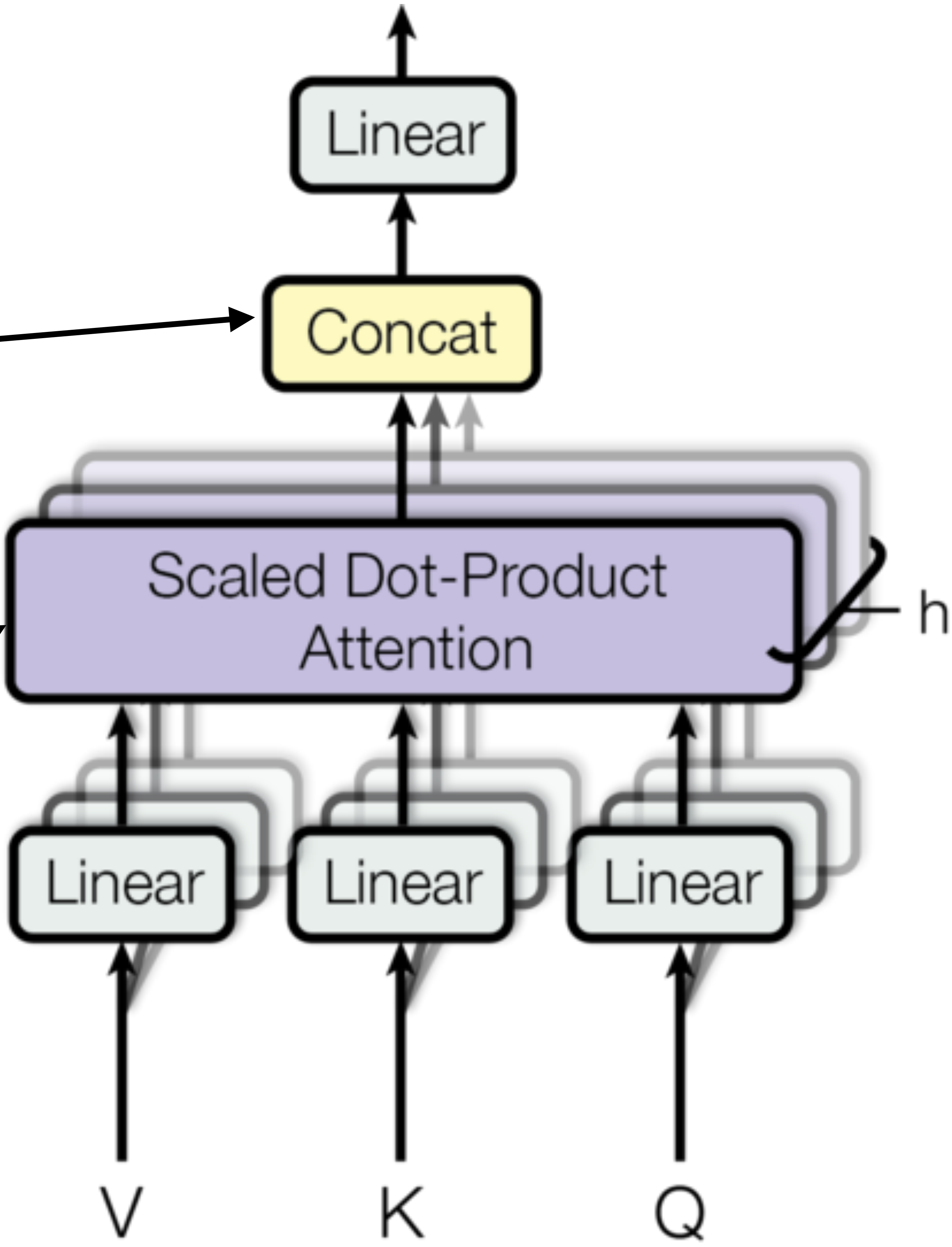


(Vaswani et al., 2017)

Multi-headed attention

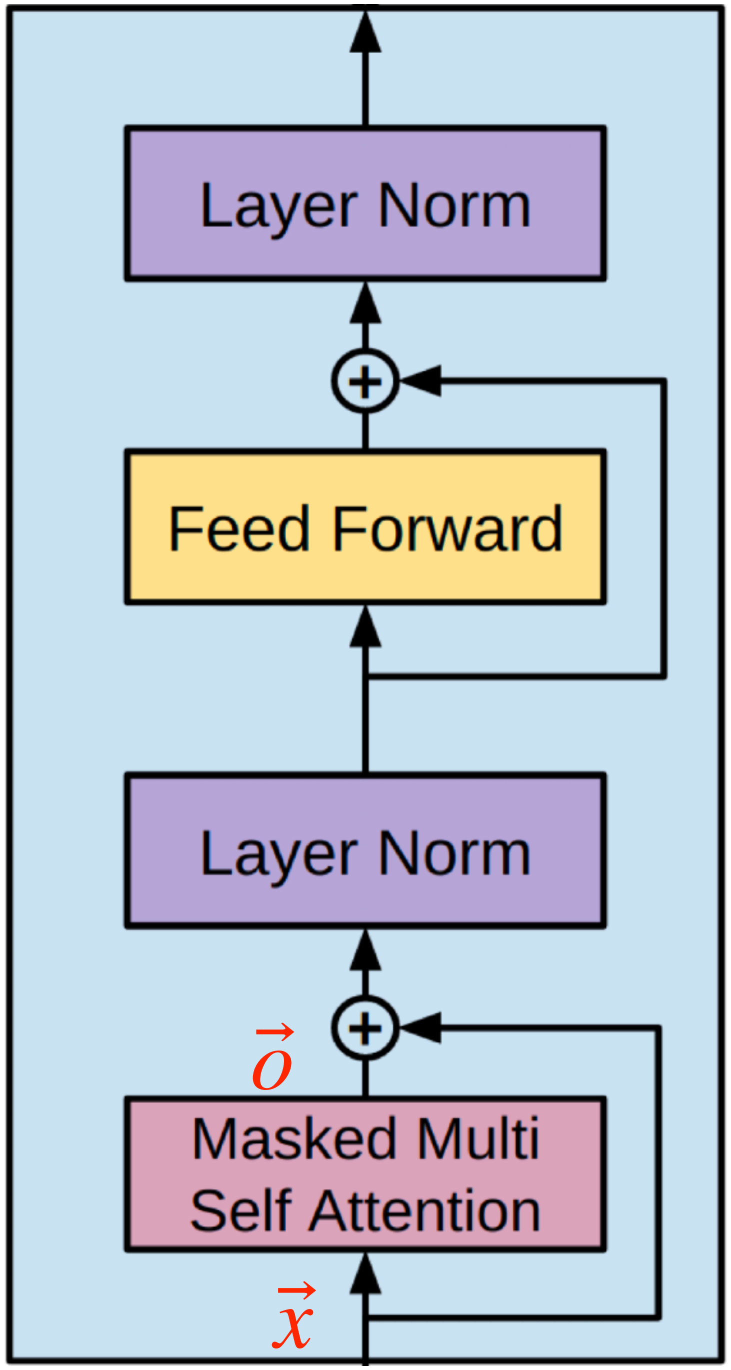
The h output vectors are concatenated and then linearly transformed with learned matrix W_O



h heads, each with its own W_K, W_V, W_Q matrices

(image from Vaswani et al., 2017)

Residual connection & layer normalization



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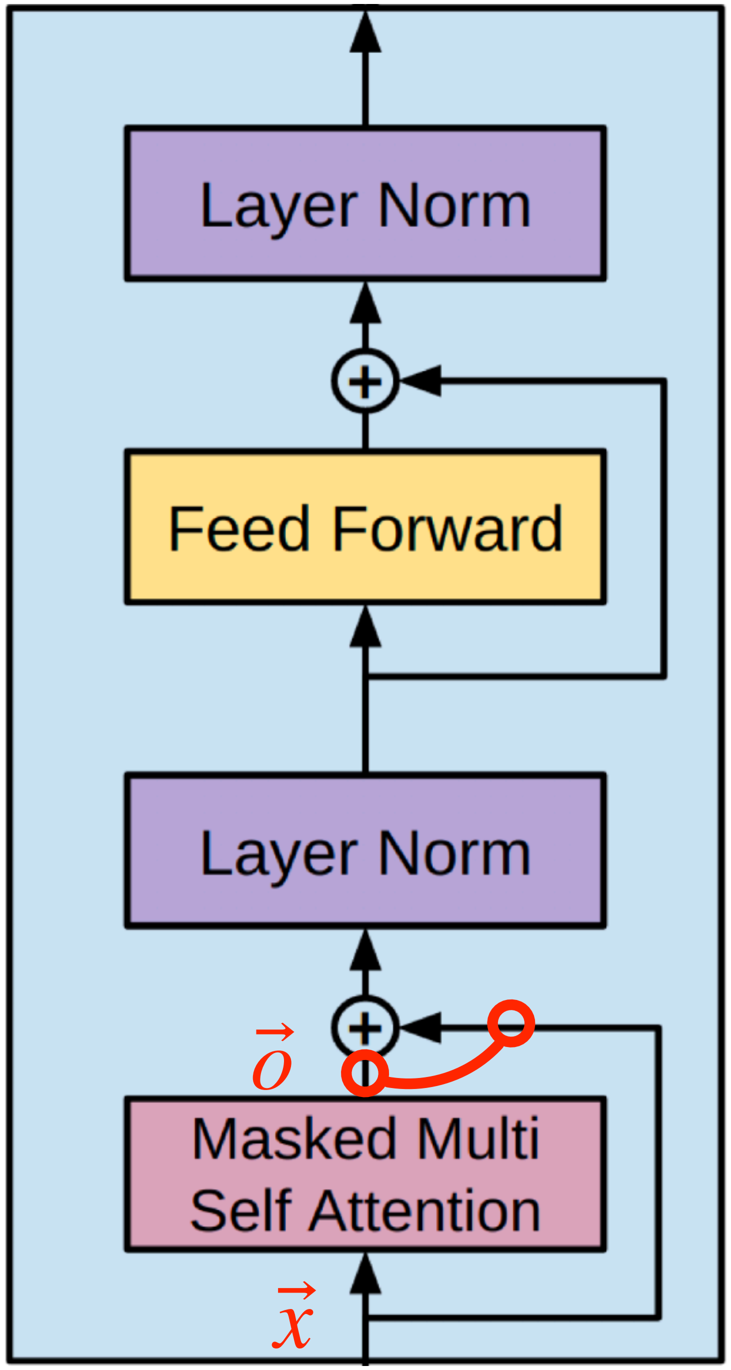

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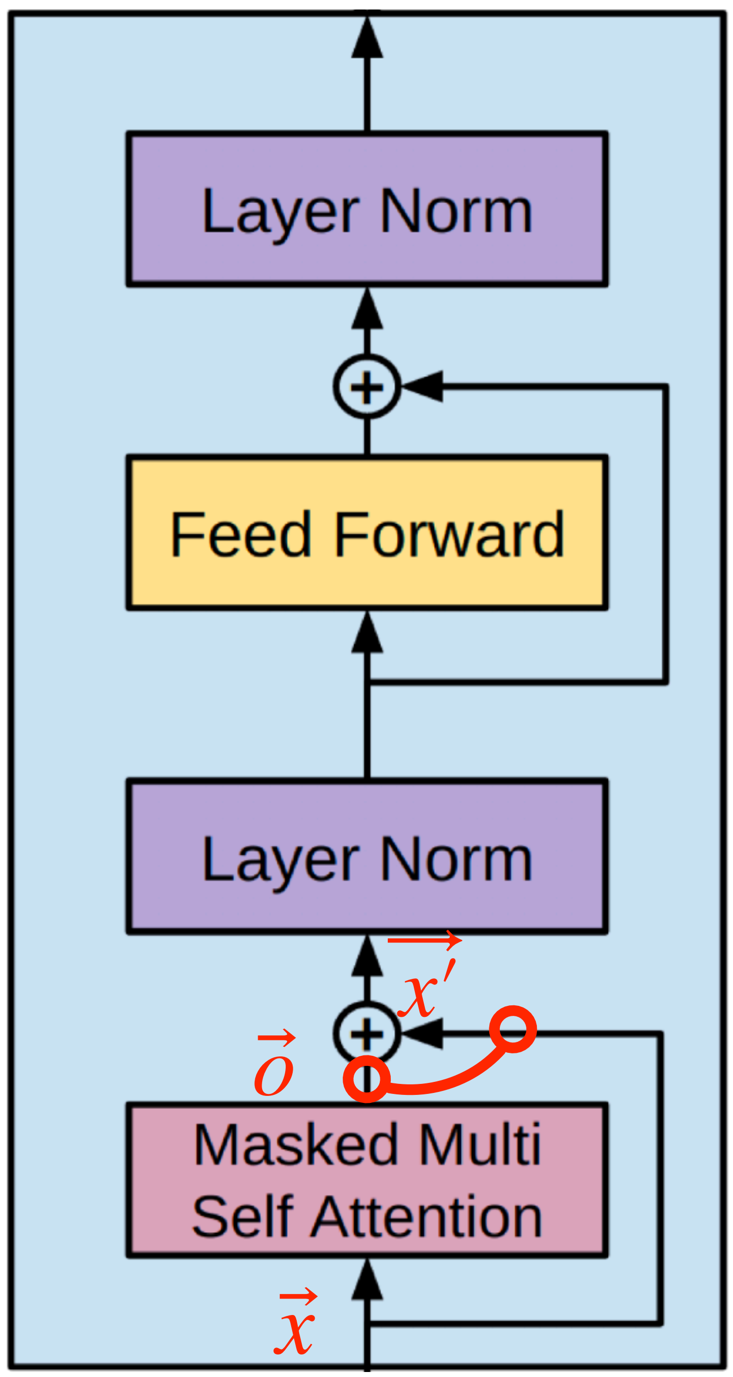
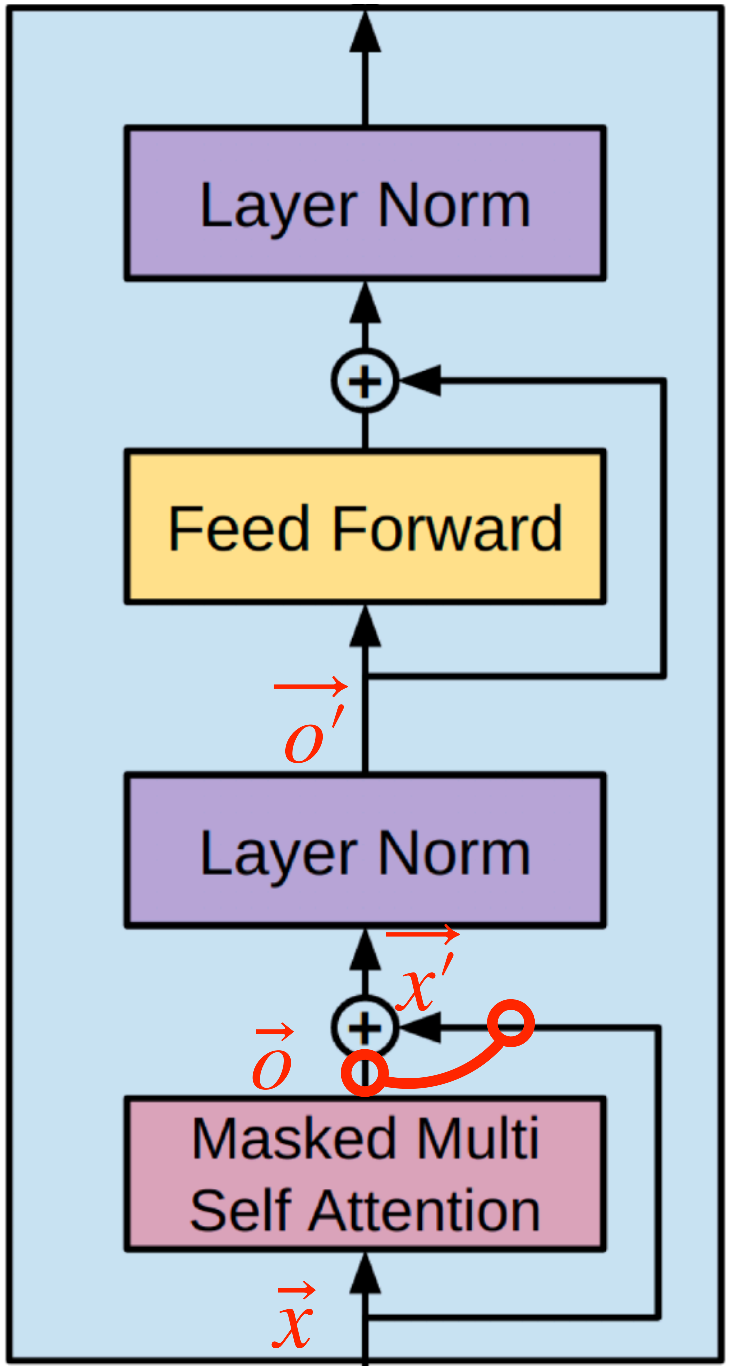


$$\vec{x'} = \vec{x} + \vec{o}$$

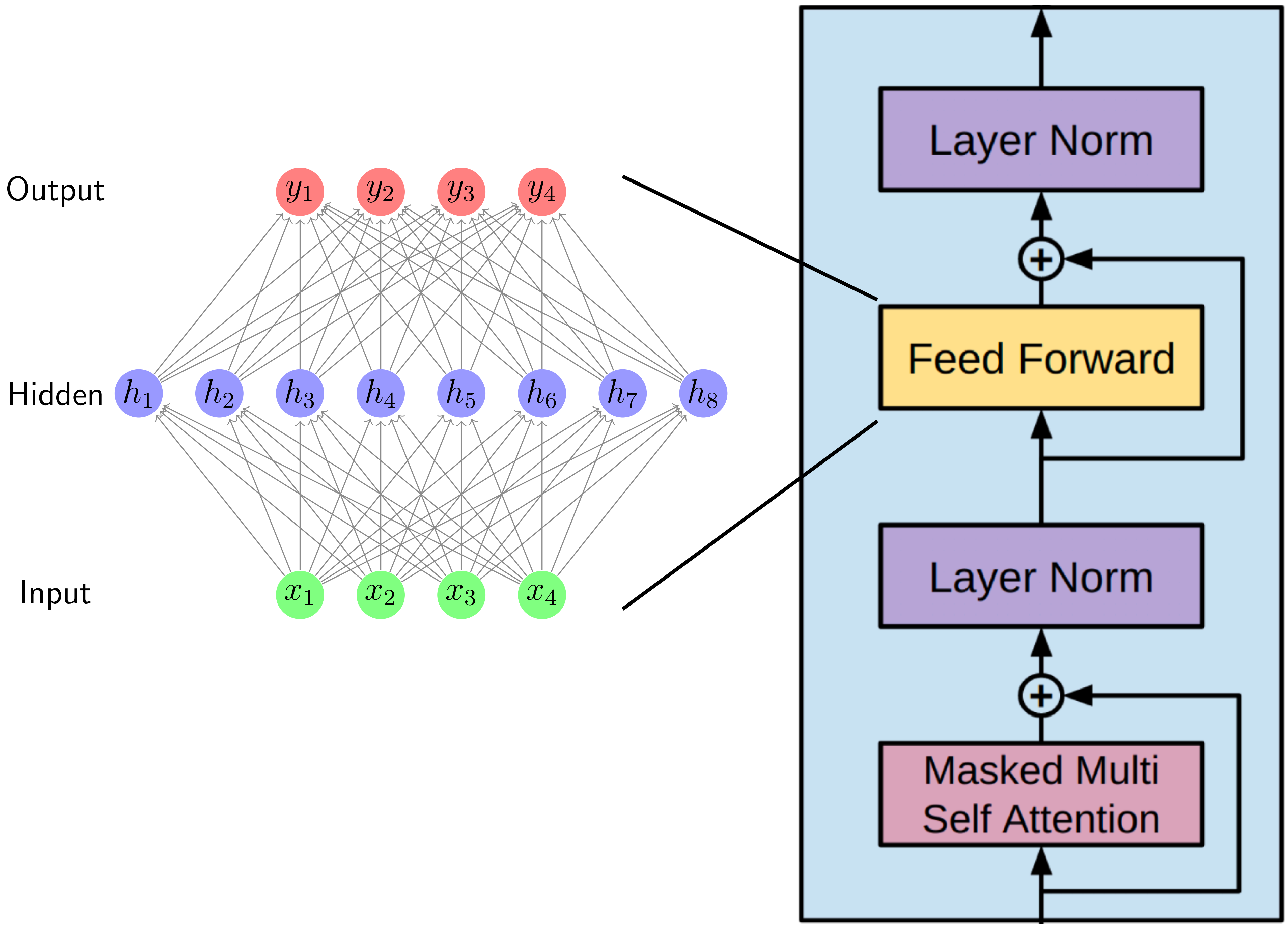
Residual connection & layer normalization



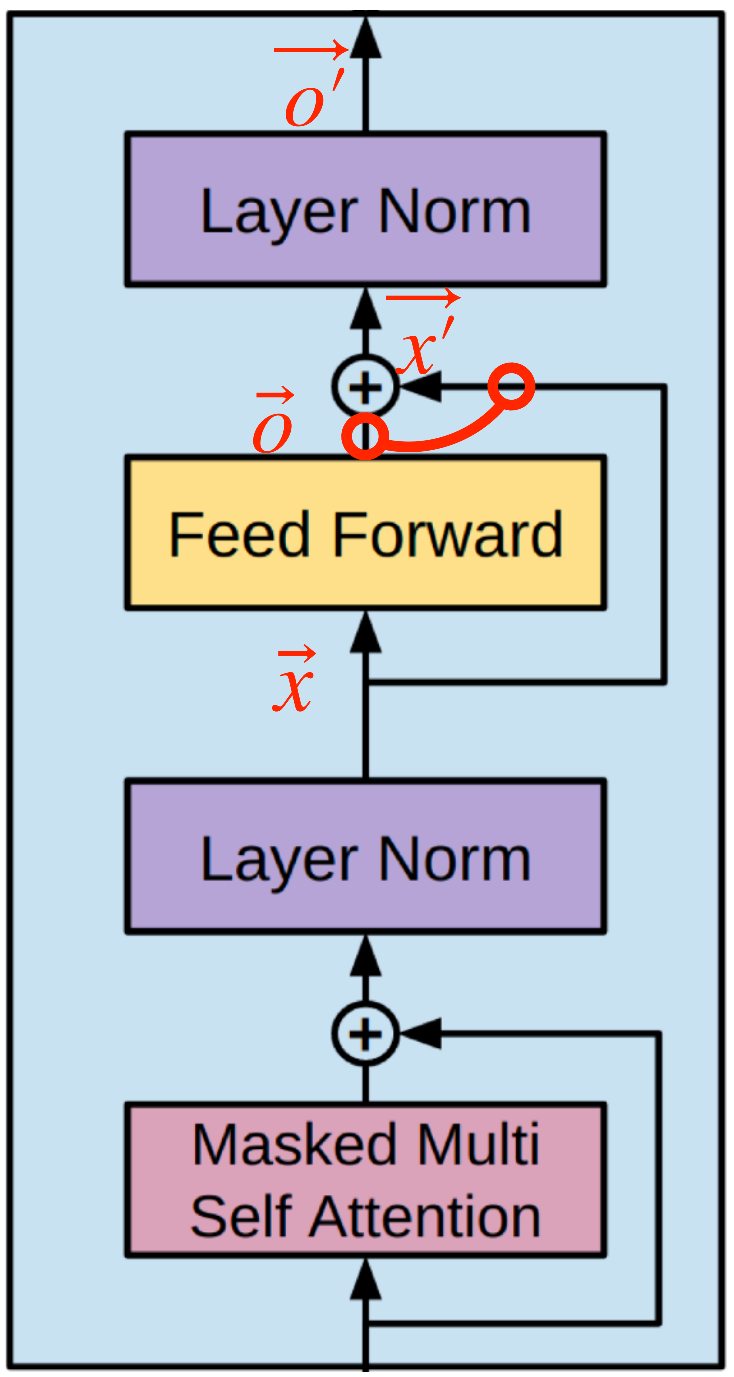
$$\overrightarrow{o'} = \frac{\overrightarrow{x'} - \textbf{Mean}(\overrightarrow{x'})}{\textbf{StdDev}(\overrightarrow{x'})}$$

$$\overrightarrow{x'} = \vec{x} + \vec{o}$$

Feed-forward layer



Res. connection & layer norm. (again)



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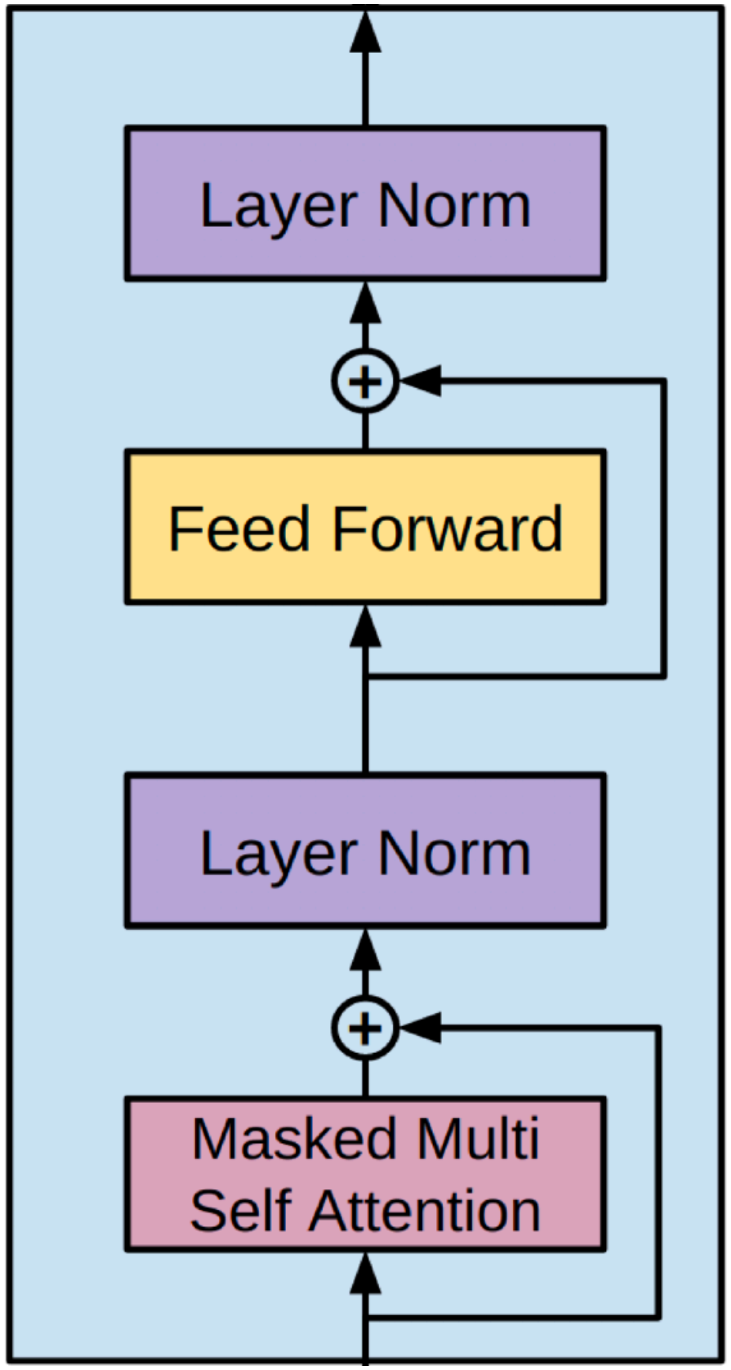
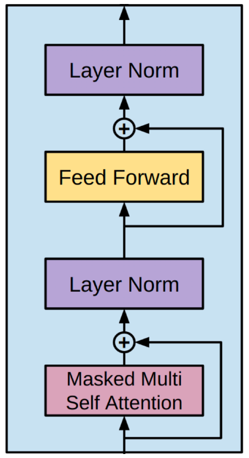
$$\overrightarrow{x'} = \vec{x} + \vec{o}$$

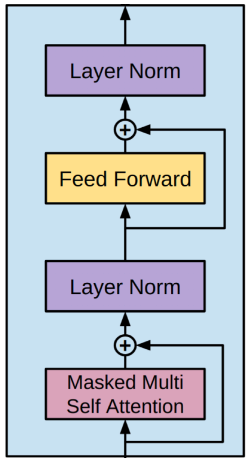
Res. connection & layer norm. (again)

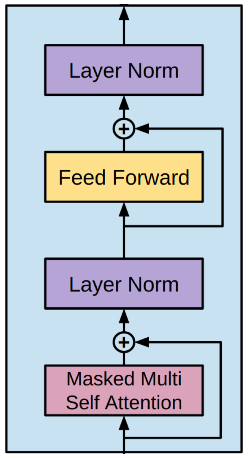


Res. connection & layer norm. (again)

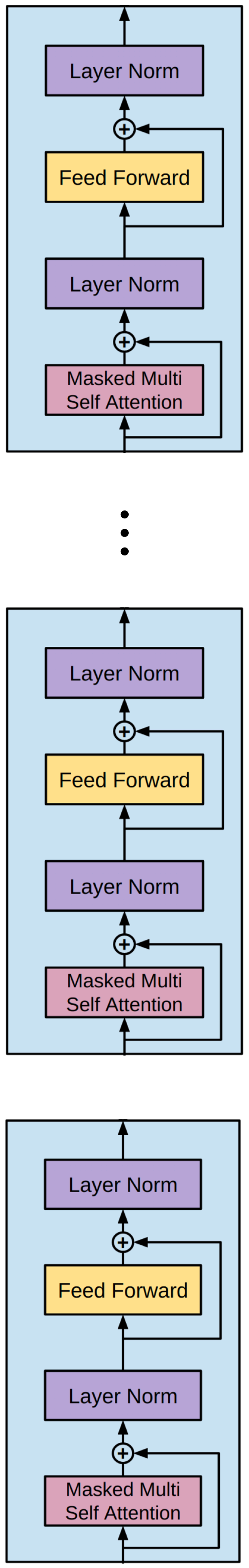


Res. connection & layer norm. (again)

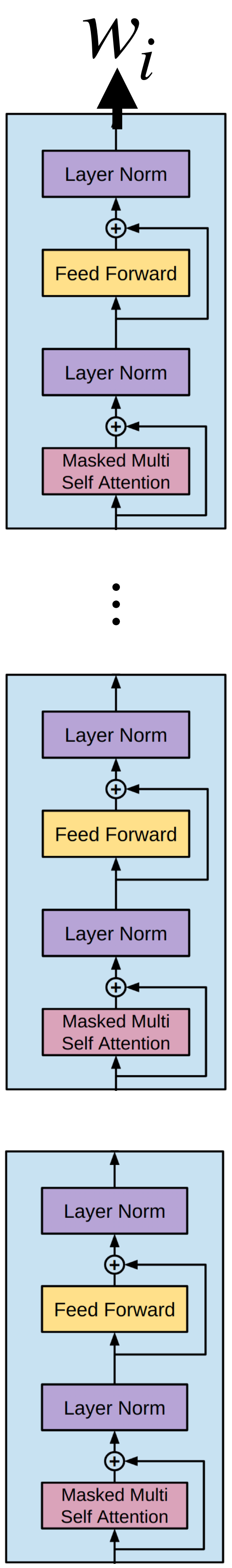




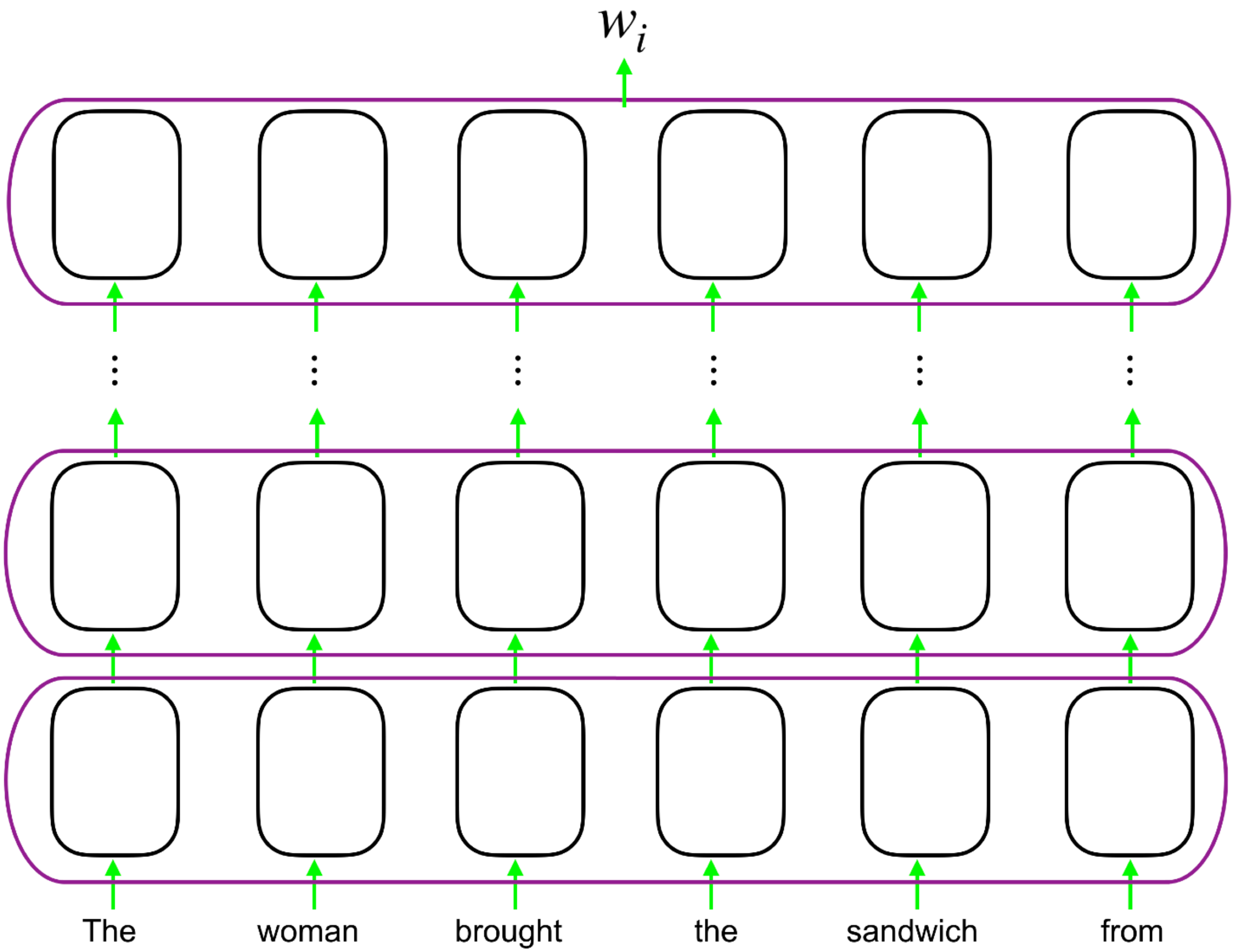
Res. connection & layer norm. (again)

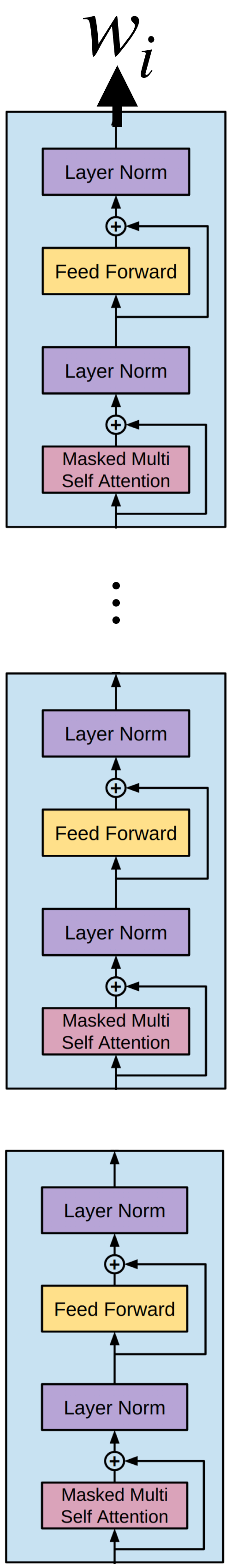


Res. connection & layer norm. (again)

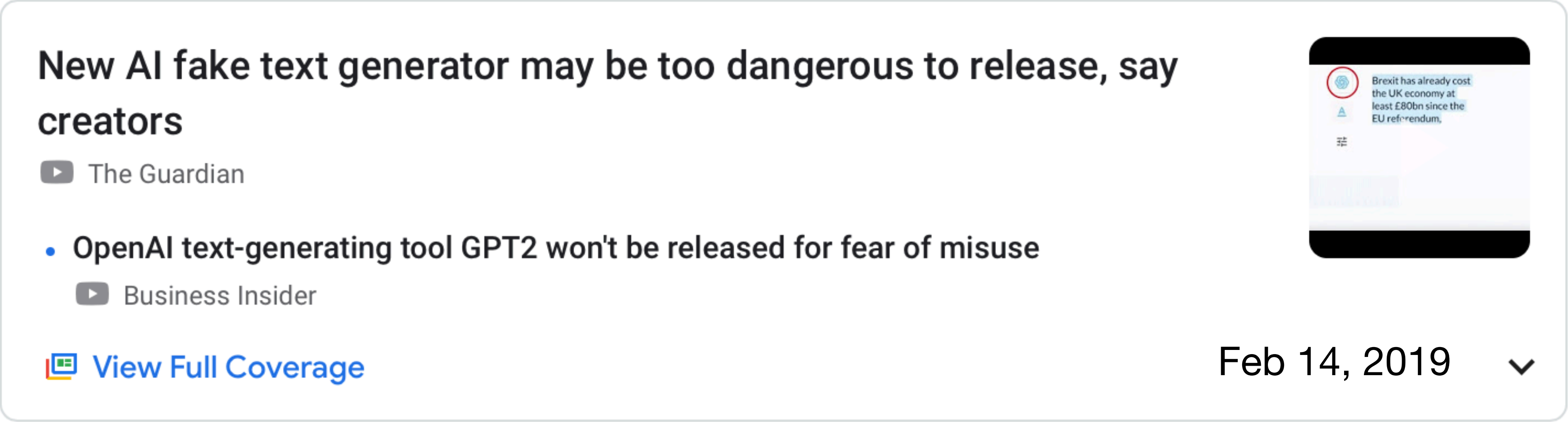


Res. connection & layer norm. (again)





Transformer + a huge corpus = ...?



New AI fake text generator may be too dangerous to release, say creators

The Guardian

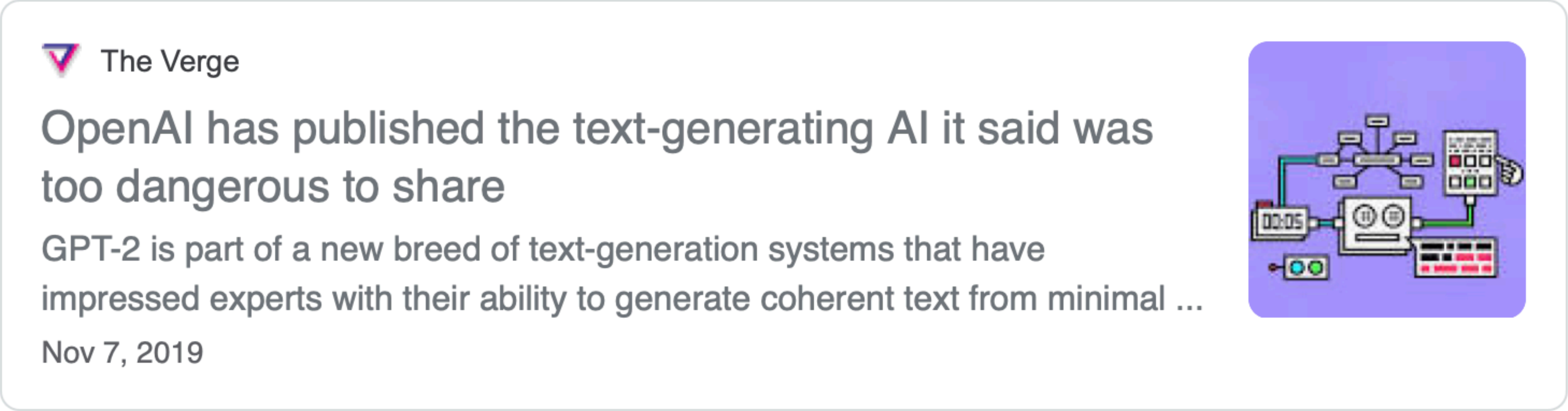
- OpenAI text-generating tool GPT2 won't be released for fear of misuse

  Business Insider

View Full Coverage

Feb 14, 2019

Brexit has already cost the UK economy at least £80bn since the EU referendum.



The Verge

OpenAI has published the text-generating AI it said was too dangerous to share

GPT-2 is part of a new breed of text-generation systems that have impressed experts with their ability to generate coherent text from minimal ...

Nov 7, 2019

Write With Transformer

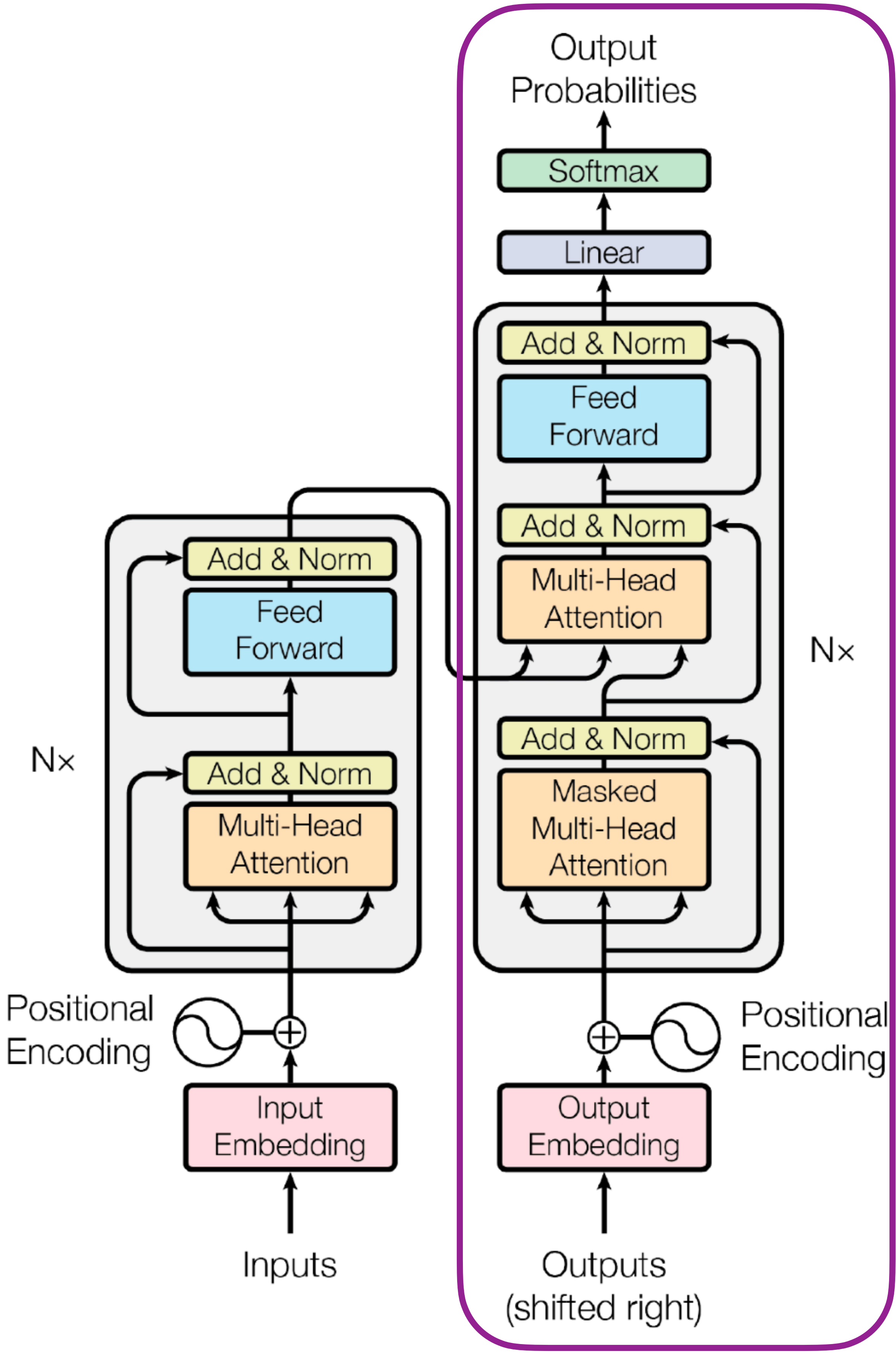
transformer.huggingface.co

Giant language model testing room: `http://gltr.io/dist/index.html`

Papers to read to understand GPT-2

- Radford et al. (2019): the GPT-2 paper itself
- Radford et al. (2018): the GPT architecture, mostly shared by GPT-2
- Liu et al. (2018): the Transformer decoder
- Vaswani et al. (2017): the original Transformer paper
- Ba et al. (2016): layer normalization

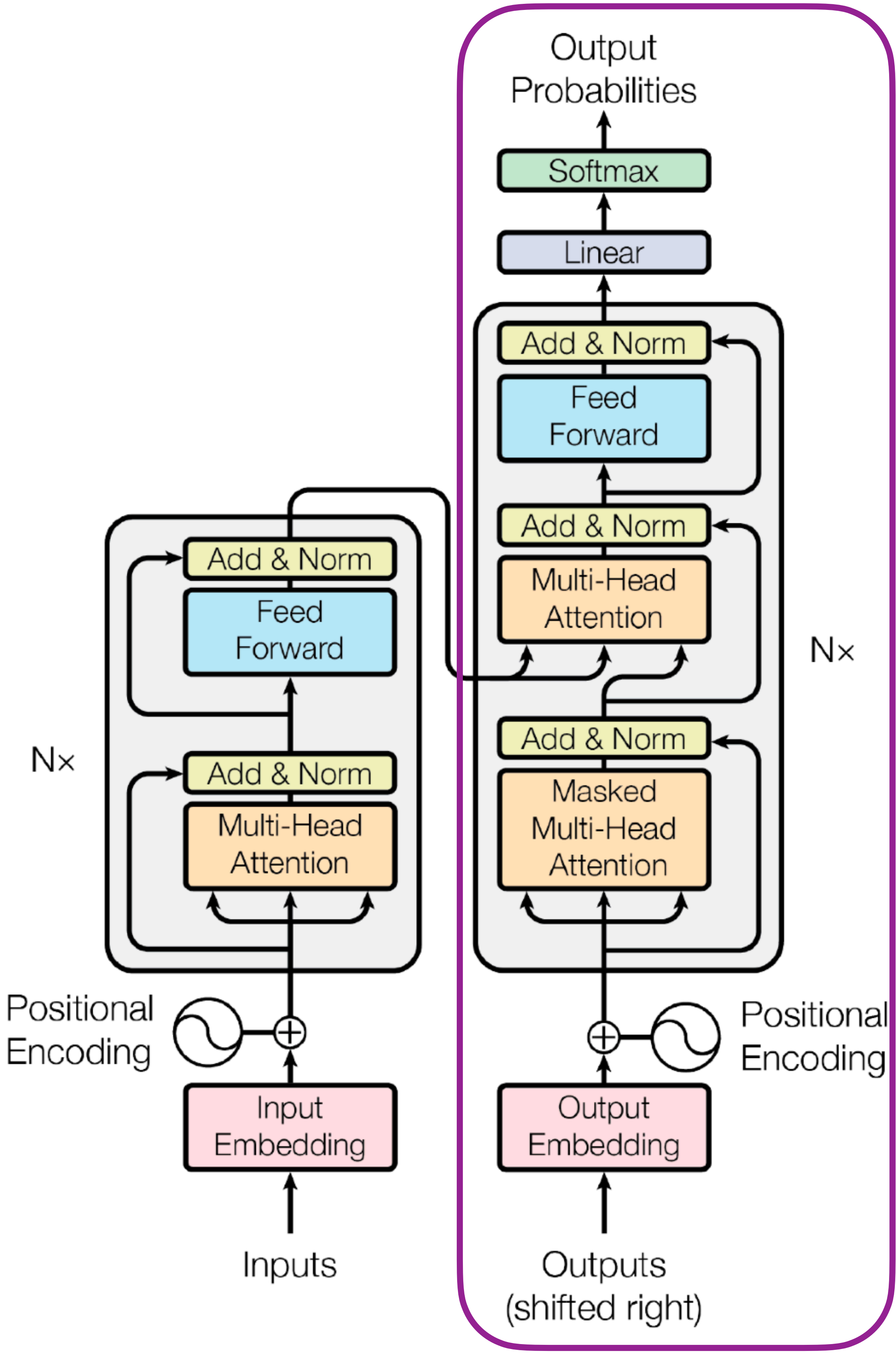
The full Transformer model



(Vaswani et al., 2017)

The full Transformer model

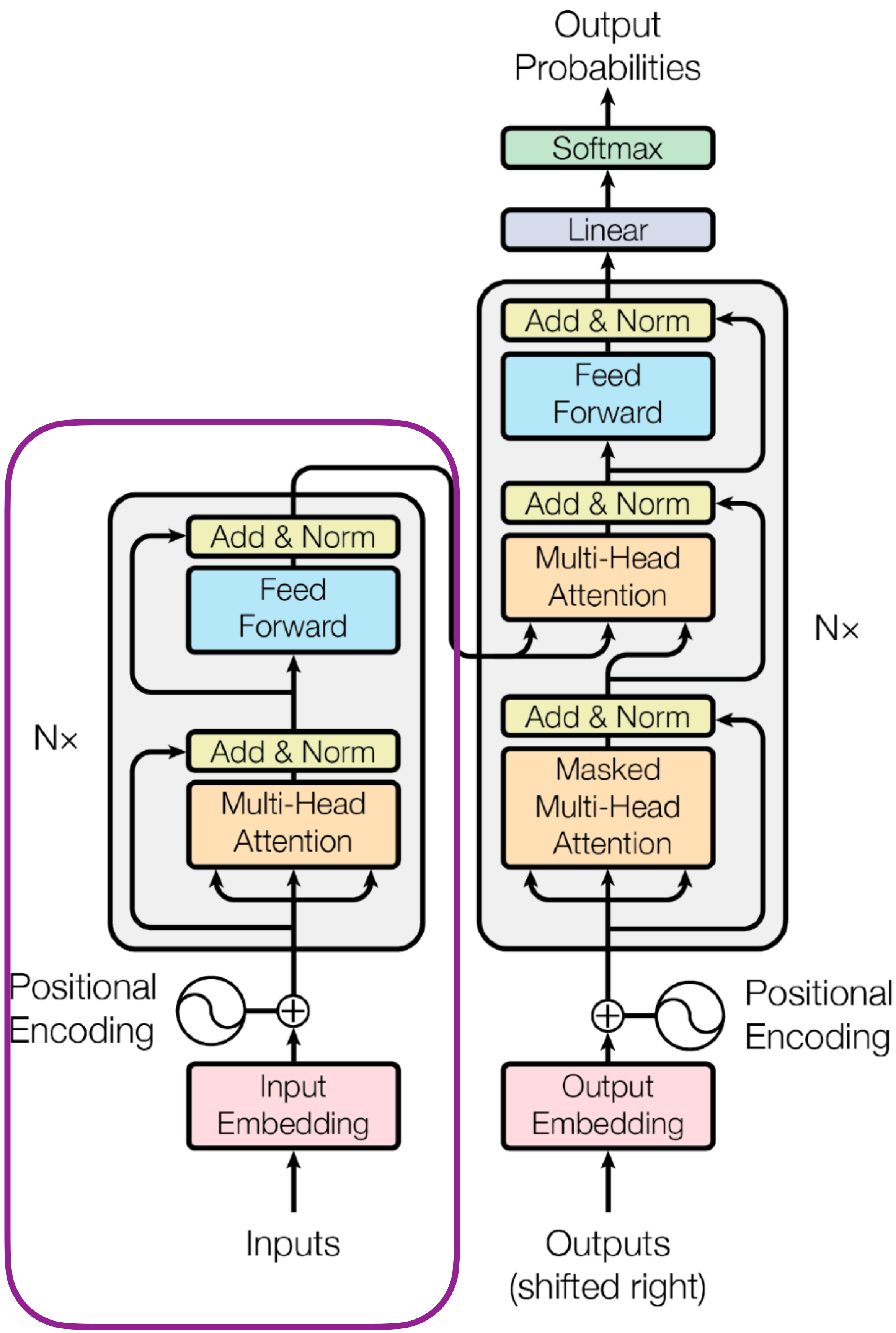
- In ML/NLP, the model we just studied is called the ***Transformer decoder***



(Vaswani et al., 2017)

The full Transformer model

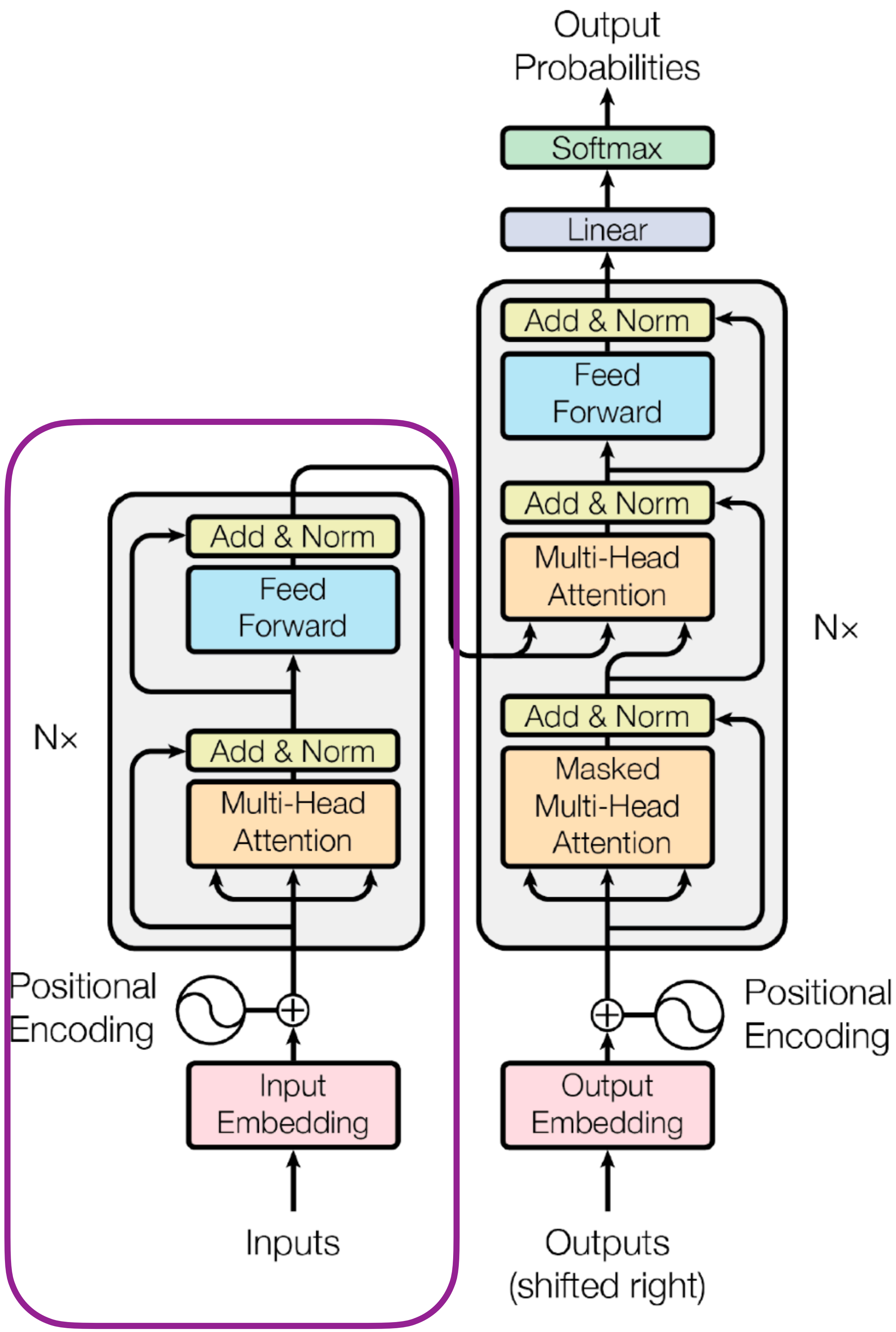
- In ML/NLP, the model we just studied is called the ***Transformer decoder***
- Sometimes, the Transformer is conditioned on a string that doesn't itself get predicted—this is called the ***encoder***



(Vaswani et al., 2017)

The full Transformer model

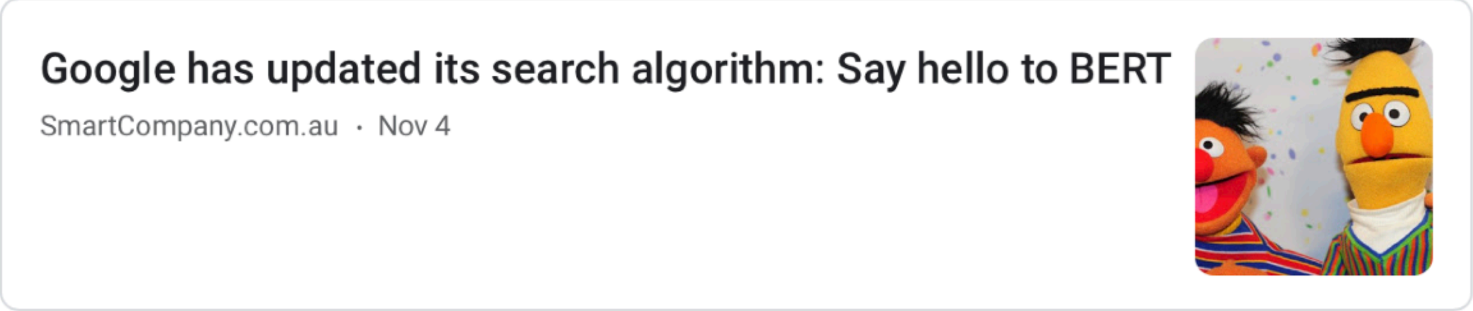
- In ML/NLP, the model we just studied is called the ***Transformer decoder***
- Sometimes, the Transformer is conditioned on a string that doesn't itself get predicted—this is called the ***encoder***
- Only difference: in encoder, attention is over the ***entire string***, not just words to the left



(Vaswani et al., 2017)

The full Transformer model

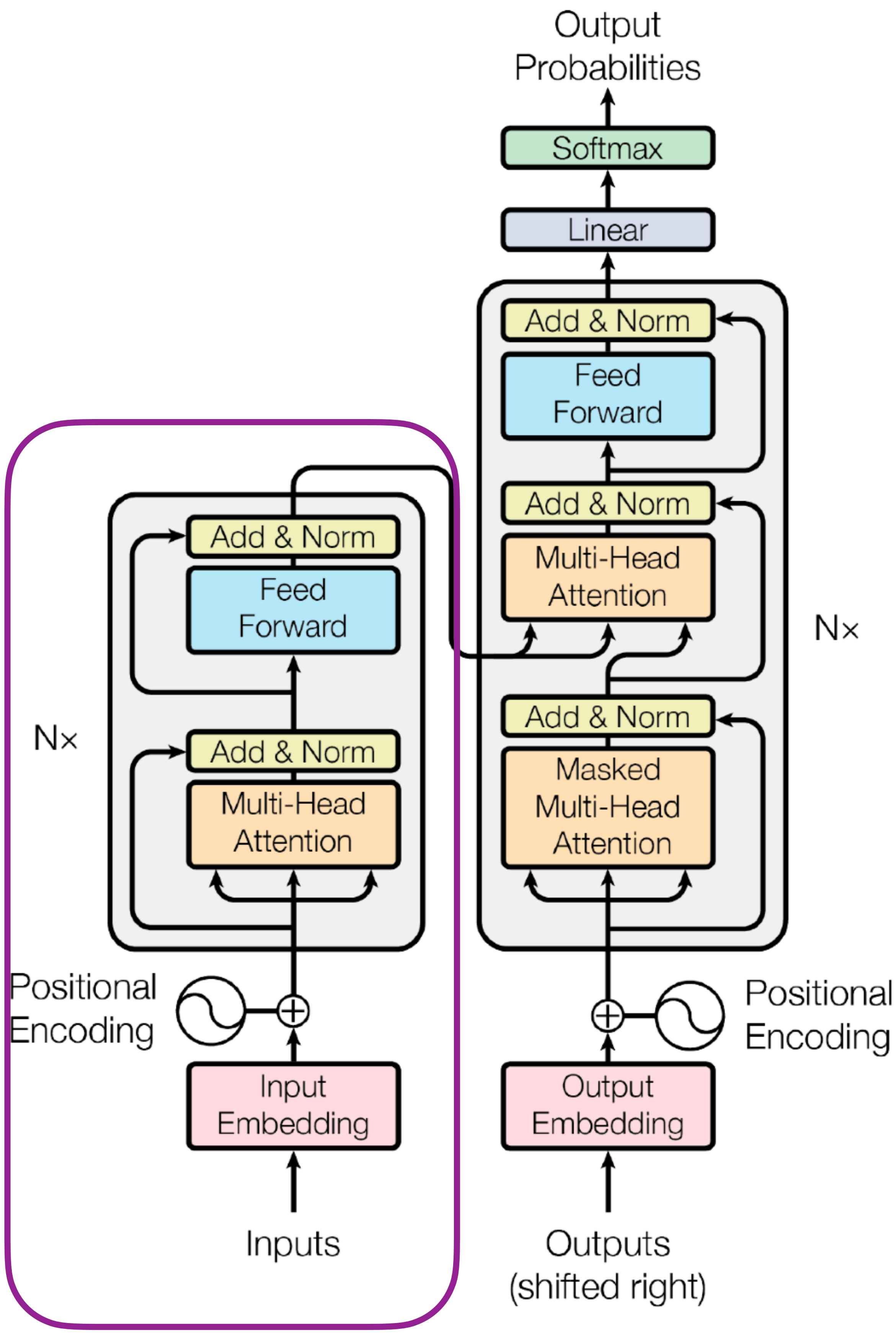
- In ML/NLP, the model we just studied is called the ***Transformer decoder***
- Sometimes, the Transformer is conditioned on a string that doesn't itself get predicted—this is called the ***encoder***
- Only difference: in encoder, attention is over the ***entire string***, not just words to the left
- BERT = Transformer encoder!



Google has updated its search algorithm: Say hello to BERT

SmartCompany.com.au · Nov 4

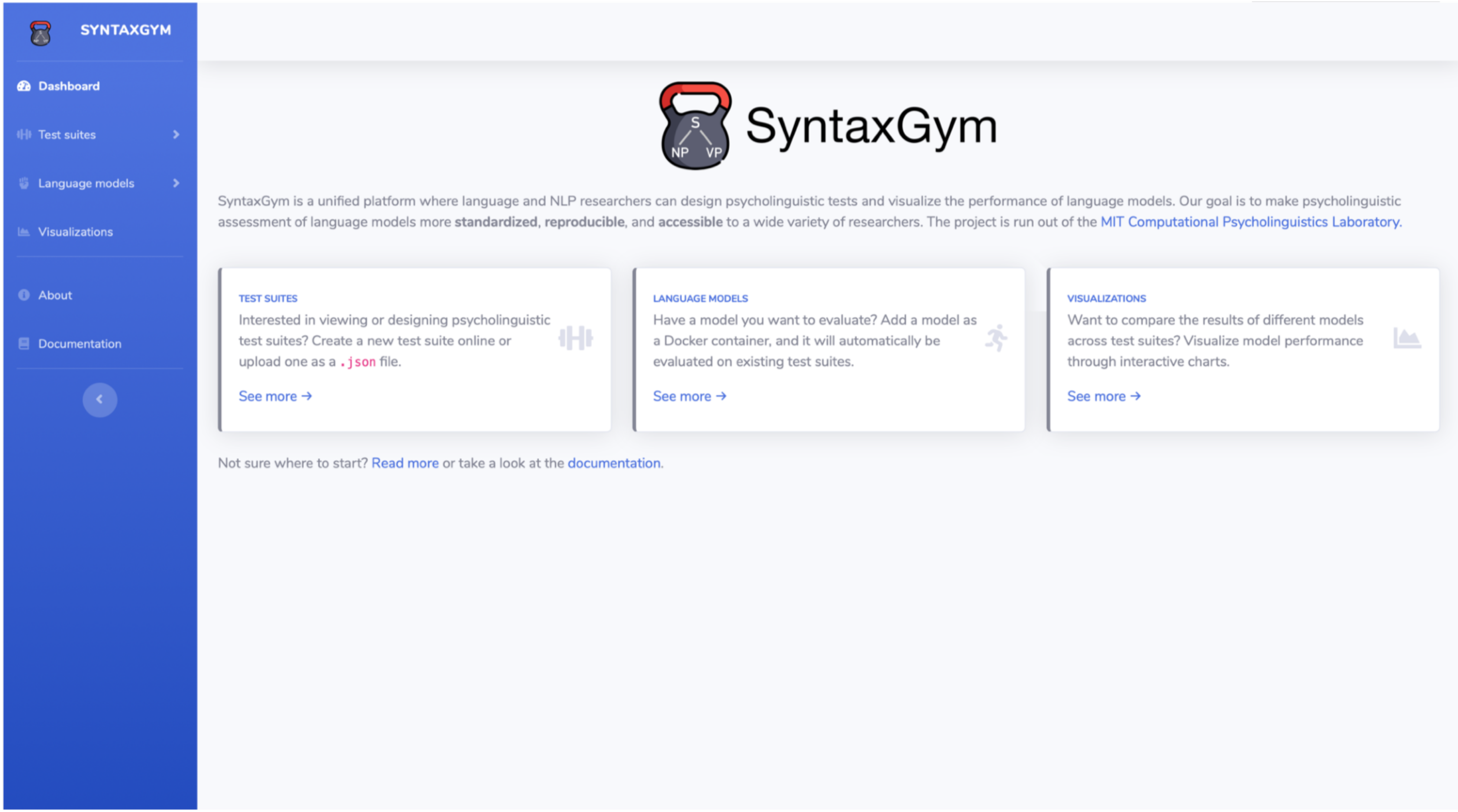
(Devlin et al., 2018)



(Vaswani et al., 2017)

GPT-2 on targeted syntax testing

syntaxgym.org



SyntaxGym is a unified platform where language and NLP researchers can design psycholinguistic tests and visualize the performance of language models. Our goal is to make psycholinguistic assessment of language models more **standardized**, **reproducible**, and **accessible** to a wide variety of researchers. The project is run out of the MIT Computational Psycholinguistics Laboratory.

TEST SUITES
Interested in viewing or designing psycholinguistic test suites? Create a new test suite online or upload one as a `.json` file.
See more →

LANGUAGE MODELS
Have a model you want to evaluate? Add a model as a Docker container, and it will automatically be evaluated on existing test suites.
See more →

VISUALIZATIONS
Want to compare the results of different models across test suites? Visualize model performance through interactive charts.
See more →

Not sure where to start? Read more or take a look at the documentation.

(Gauthier et al., 2020; Hu et al., 2020)

Filler—gap dependencies

✓ `I know that the lion devoured the gazelle at sunrise.`

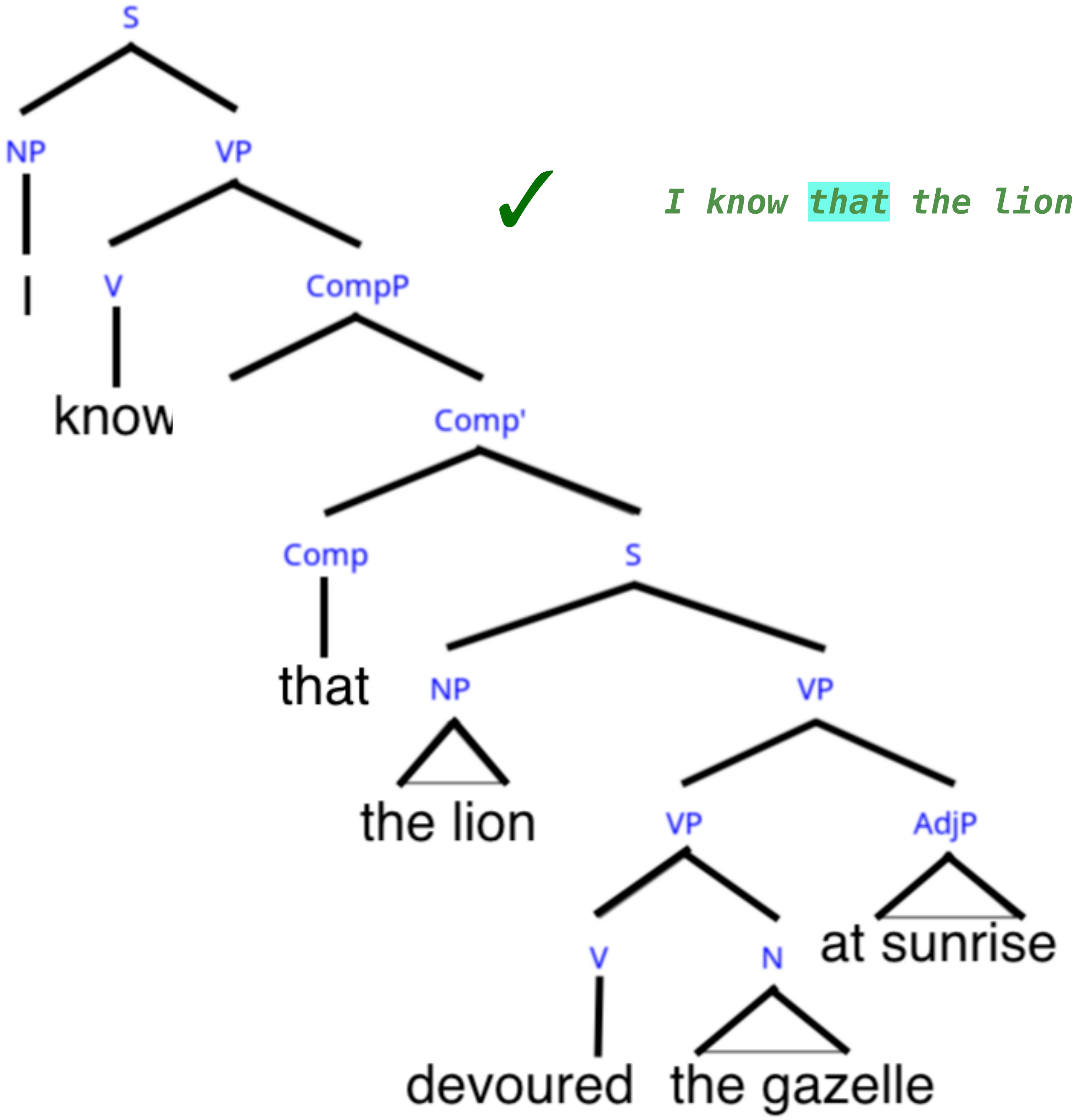
(Wilcox et al. 2018, Blackbox NLP)

Filler—gap dependencies

✓ *I know that the lion devoured the gazelle at sunrise.*

(Wilcox et al. 2018, Blackbox NLP)

Filler—gap dependencies

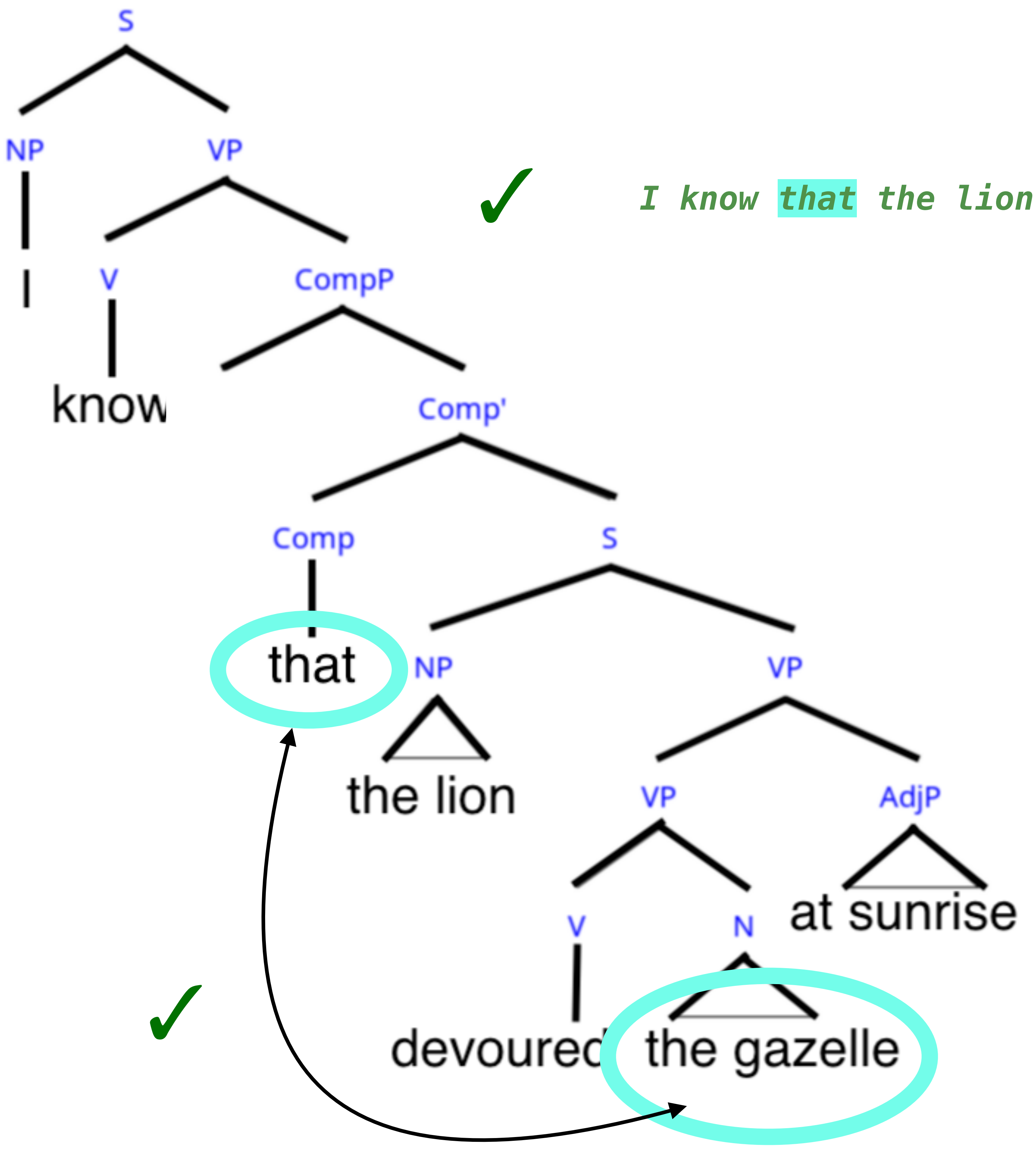


✓ *I know that the lion devoured the gazelle at sunrise.*

(Wilcox et al. 2018, Blackbox NLP)

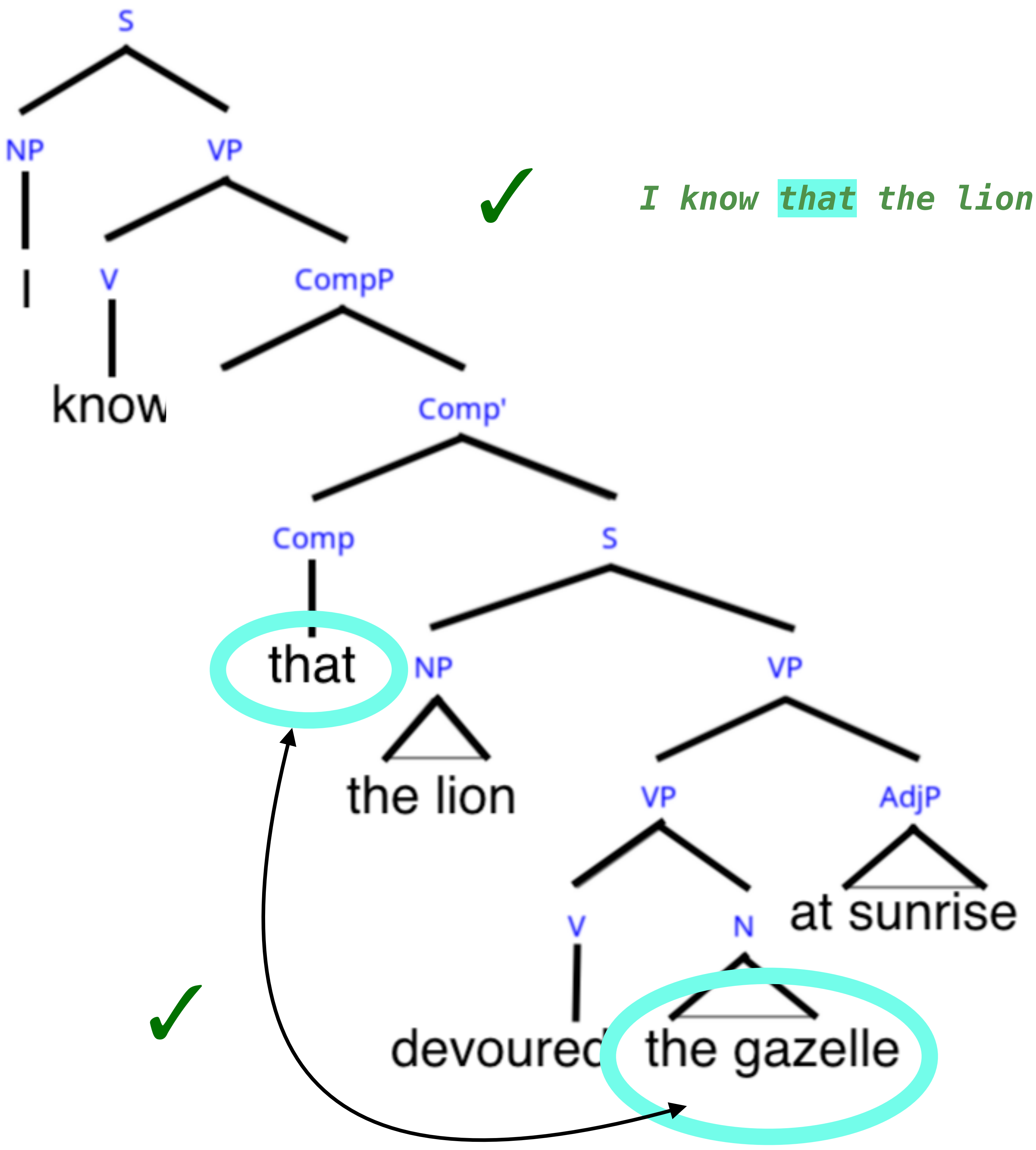
Filler—gap dependencies

✓ *I know **that** the lion devoured **the gazelle** at sunrise.*



(Wilcox et al. 2018, Blackbox NLP)

Filler—gap dependencies

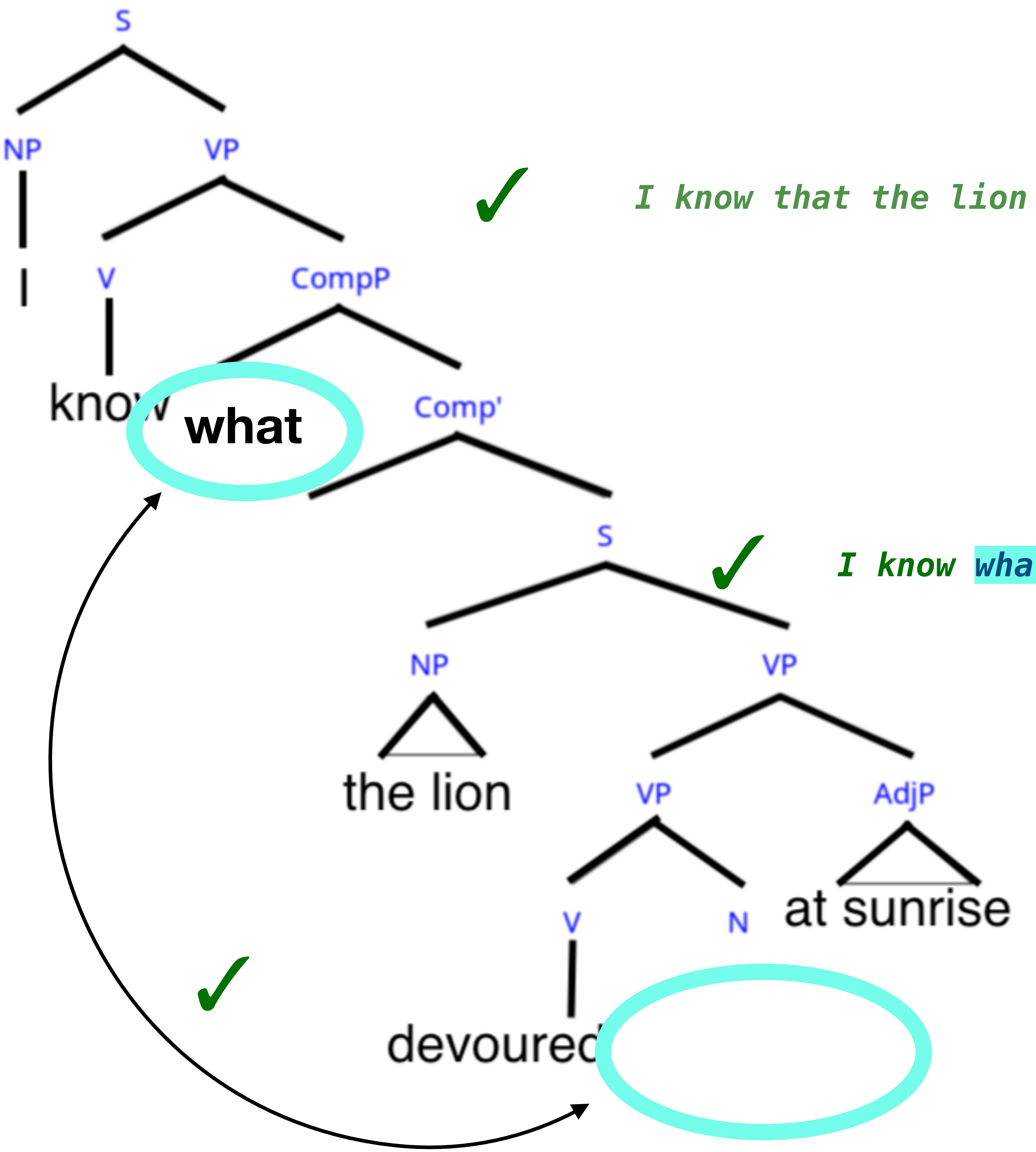


✓ *I know that the lion devoured the gazelle at sunrise.*

-FILLER
-GAP

(Wilcox et al. 2018, Blackbox NLP)

Filler—gap dependencies



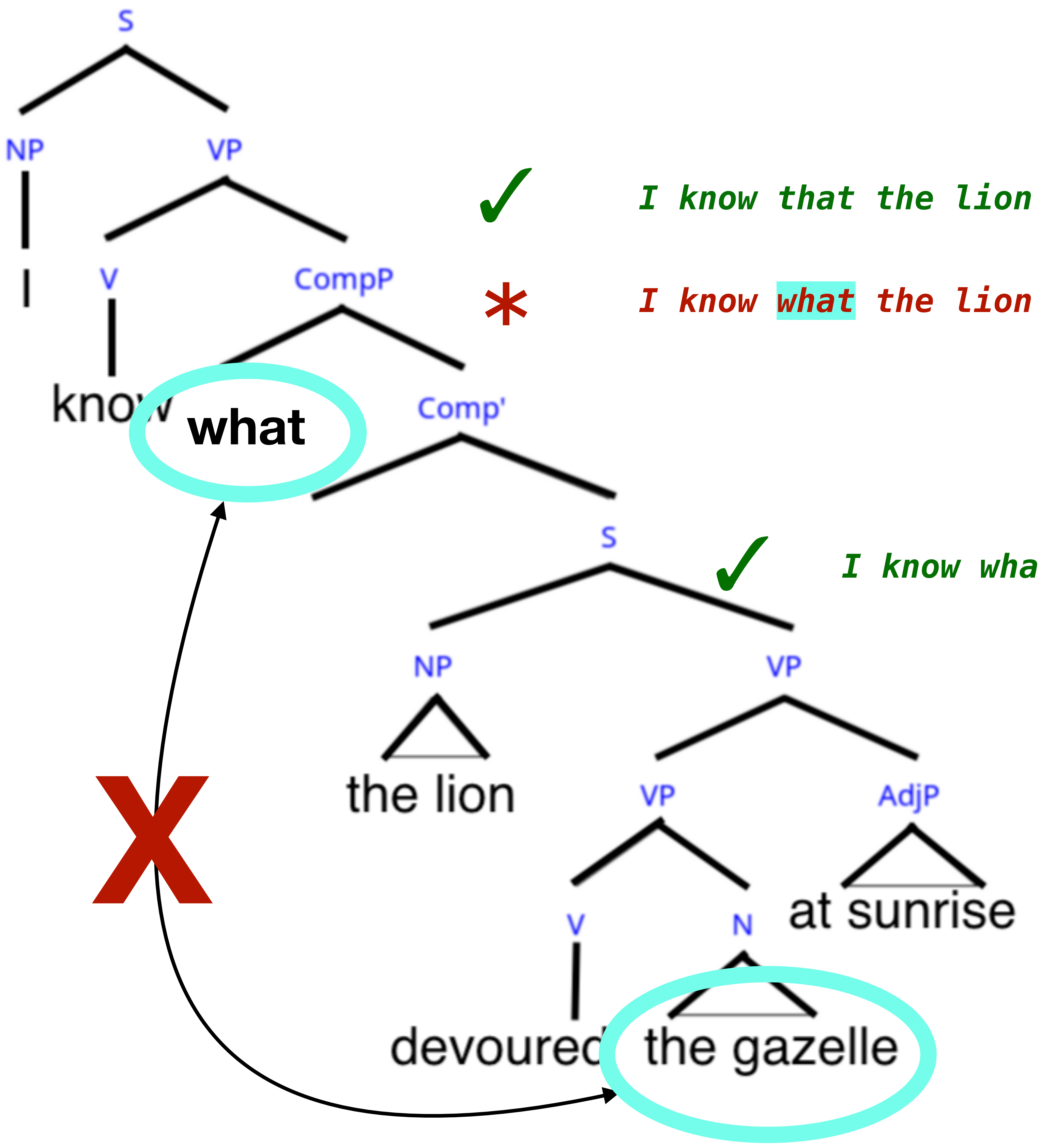
✓ *I know that the lion devoured the gazelle at sunrise.*

✓ *I know **what** the lion devoured ___ at sunrise.*

+FILLER
+GAP

(Wilcox et al. 2018, Blackbox NLP)

Filler—gap dependencies



✓ *I know that the lion devoured the gazelle at sunrise.*

* *I know what the lion devoured the gazelle at sunrise.*

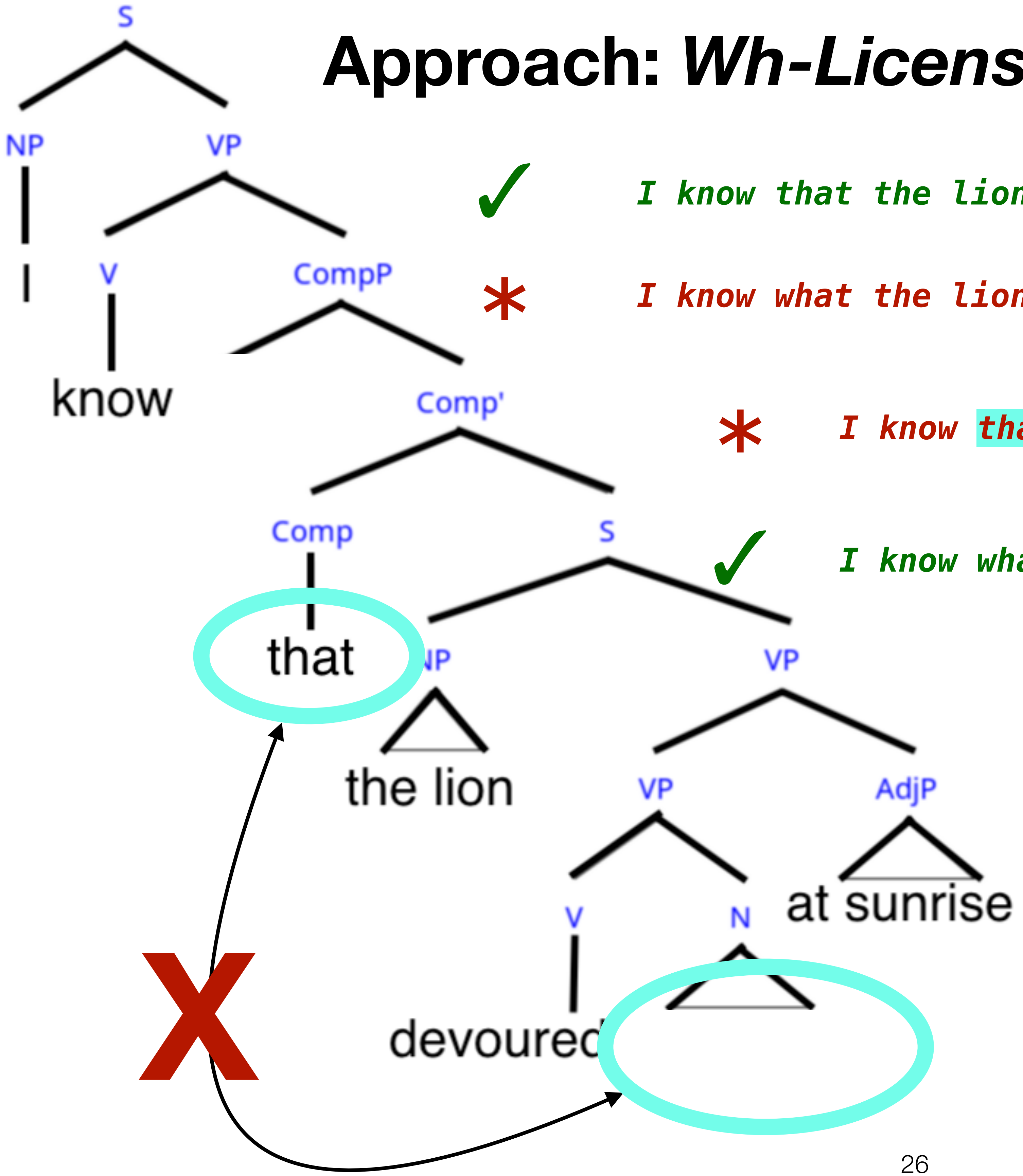
✓ *I know what the lion devoured ___ at sunrise.*

+FILLER
–GAP

(Wilcox et al. 2018, Blackbox NLP)

Filler—gap dependencies

Approach: *Wh-Licensing Interaction*



✓ *I know that the lion devoured the gazelle at sunrise.*

* *I know what the lion devoured the gazelle at sunrise.*

* *I know that the lion devoured ___ at sunrise.*

✓ *I know what the lion devoured ___ at sunrise.*

–FILLER
+GAP

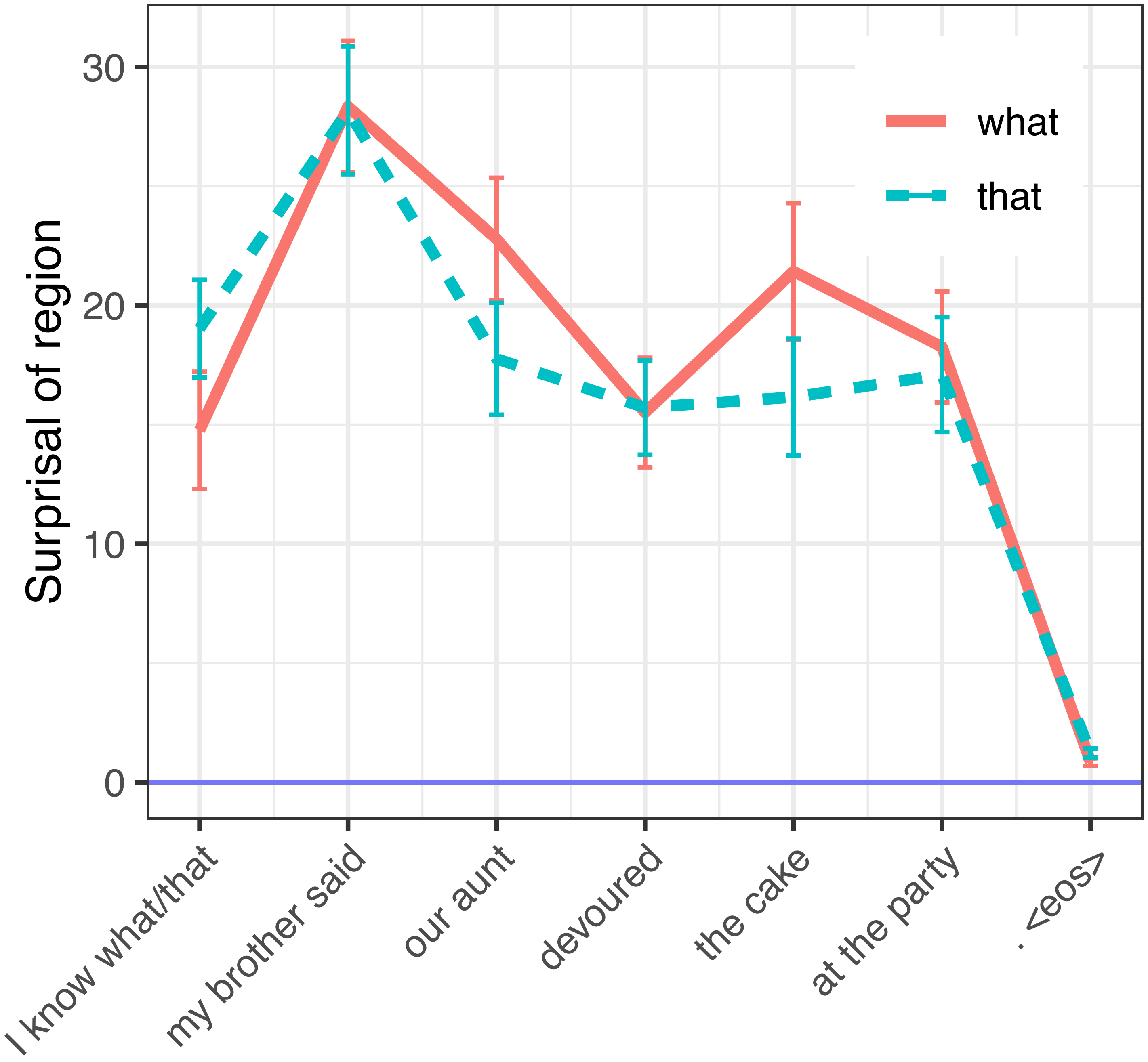
(Wilcox et al. 2018, Blackbox NLP)

✓ *I know that my brother said our aunt devoured the cake at the party.*

* *I know what my brother said our aunt devoured the cake at the party.*

✓ *I know that my brother said our aunt devoured the cake at the party.*

* *I know what my brother said our aunt devoured the cake at the party.*

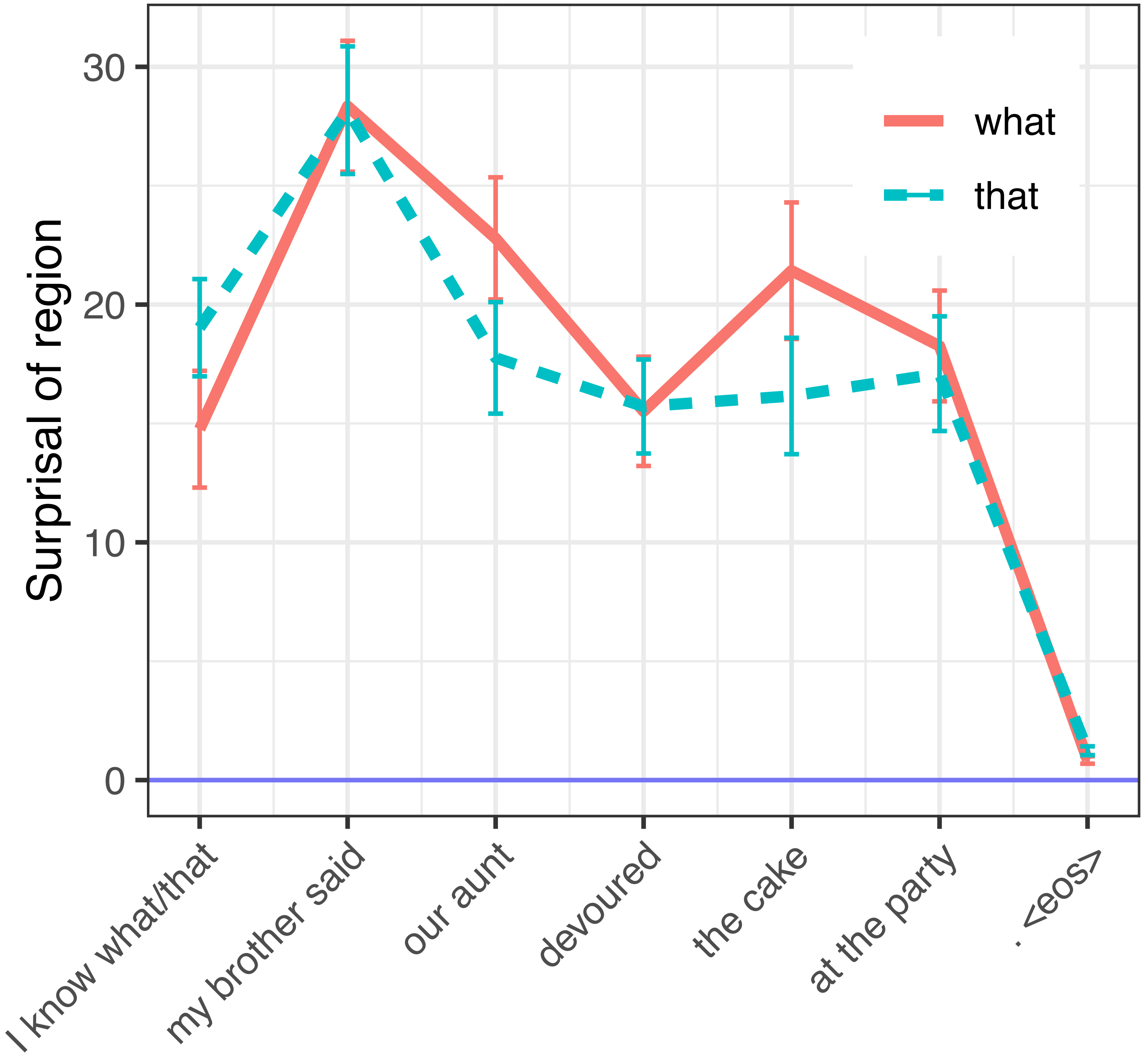


✓ *I know that my brother said our aunt devoured the cake at the party.*

* *I know what my brother said our aunt devoured the cake at the party.*

* *I know that my brother said our aunt devoured ________ at the party.*

✓ *I know what my brother said our aunt devoured ________ at the party.*

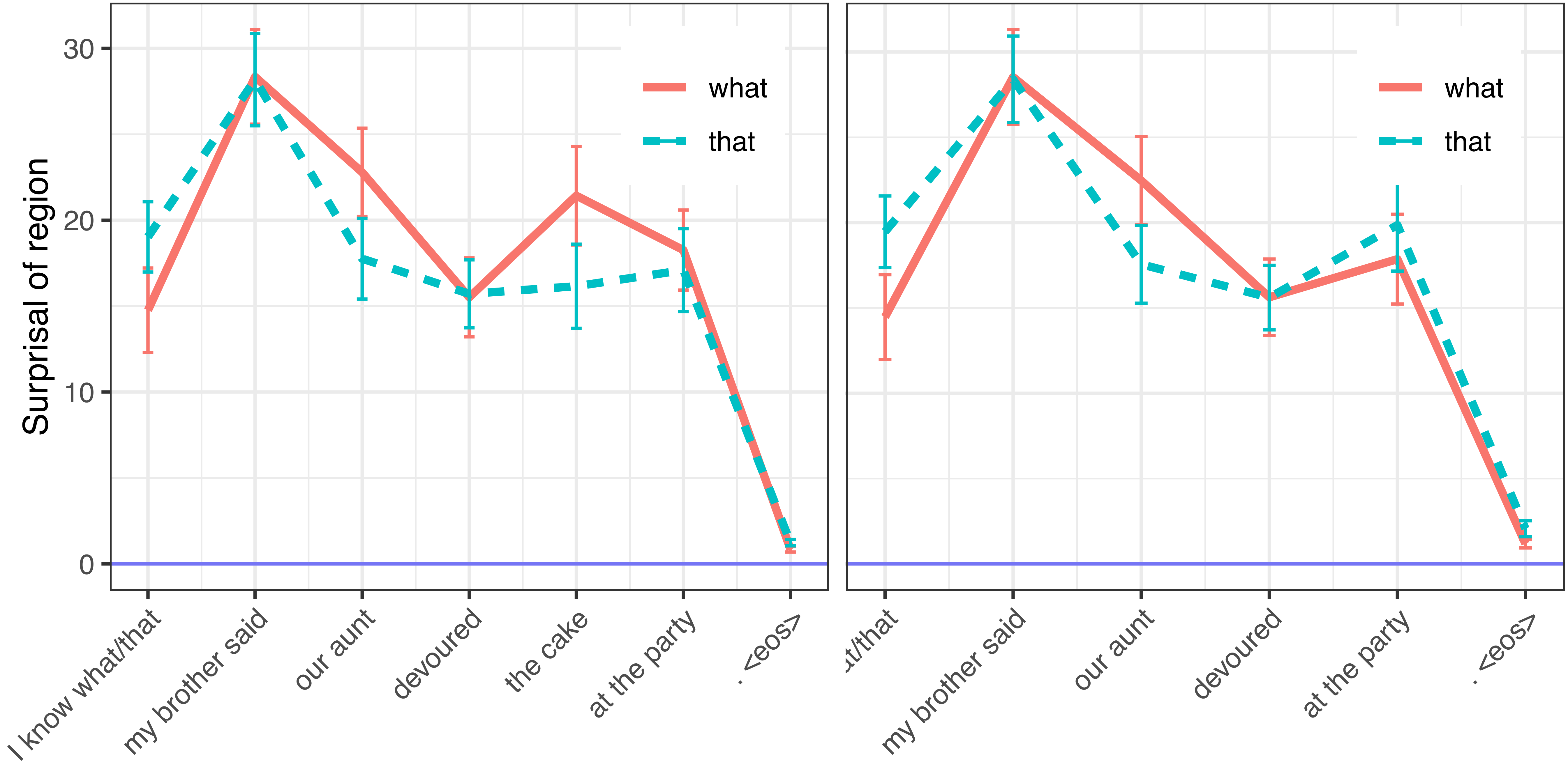


✓ I know that my brother said our aunt devoured the cake at the party.

∗ I know what my brother said our aunt devoured the cake at the party.

∗ I know that my brother said our aunt devoured ________ at the party.

✓ I know what my brother said our aunt devoured ________ at the party.

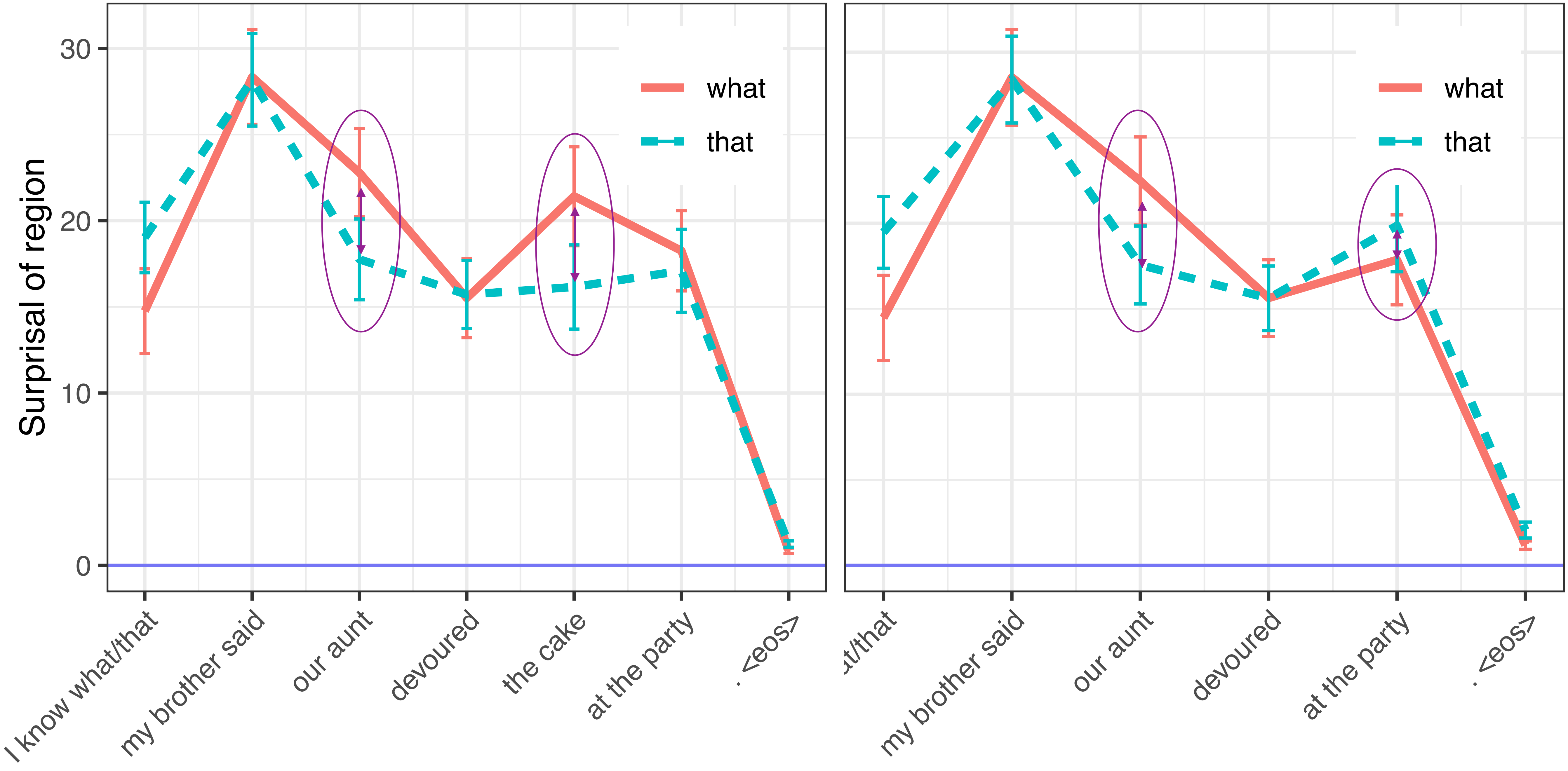


✓ *I know that my brother said our aunt devoured the cake at the party.*

* *I know what my brother said our aunt devoured the cake at the party.*

* *I know that my brother said our aunt devoured ________ at the party.*

✓ *I know what my brother said our aunt devoured ________ at the party.*

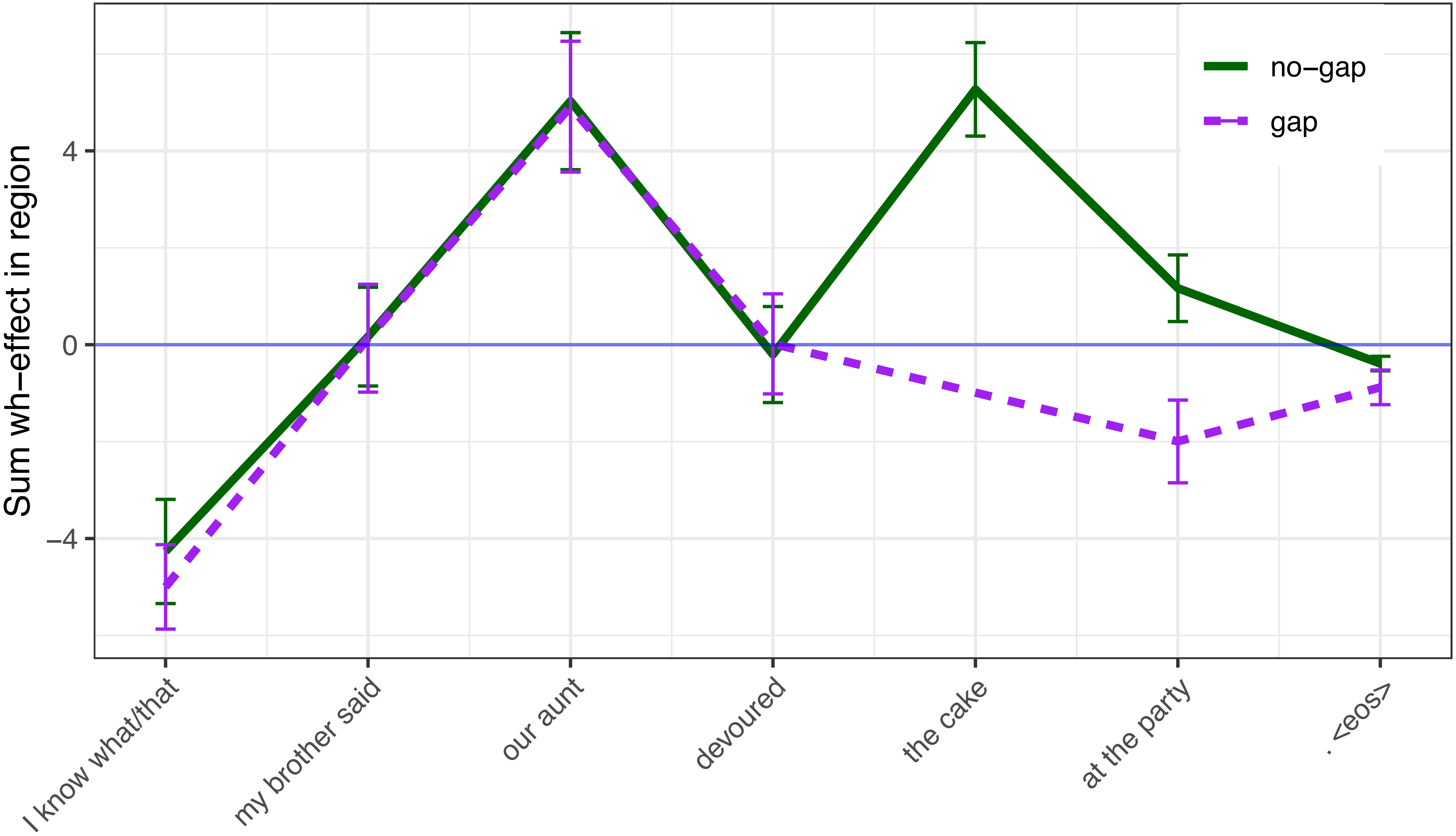


✓ *I know that my brother said our aunt devoured the cake at the party.*

* *I know what my brother said our aunt devoured the cake at the party.*

* *I know that my brother said our aunt devoured ________ at the party.*

✓ *I know what my brother said our aunt devoured ________ at the party.*

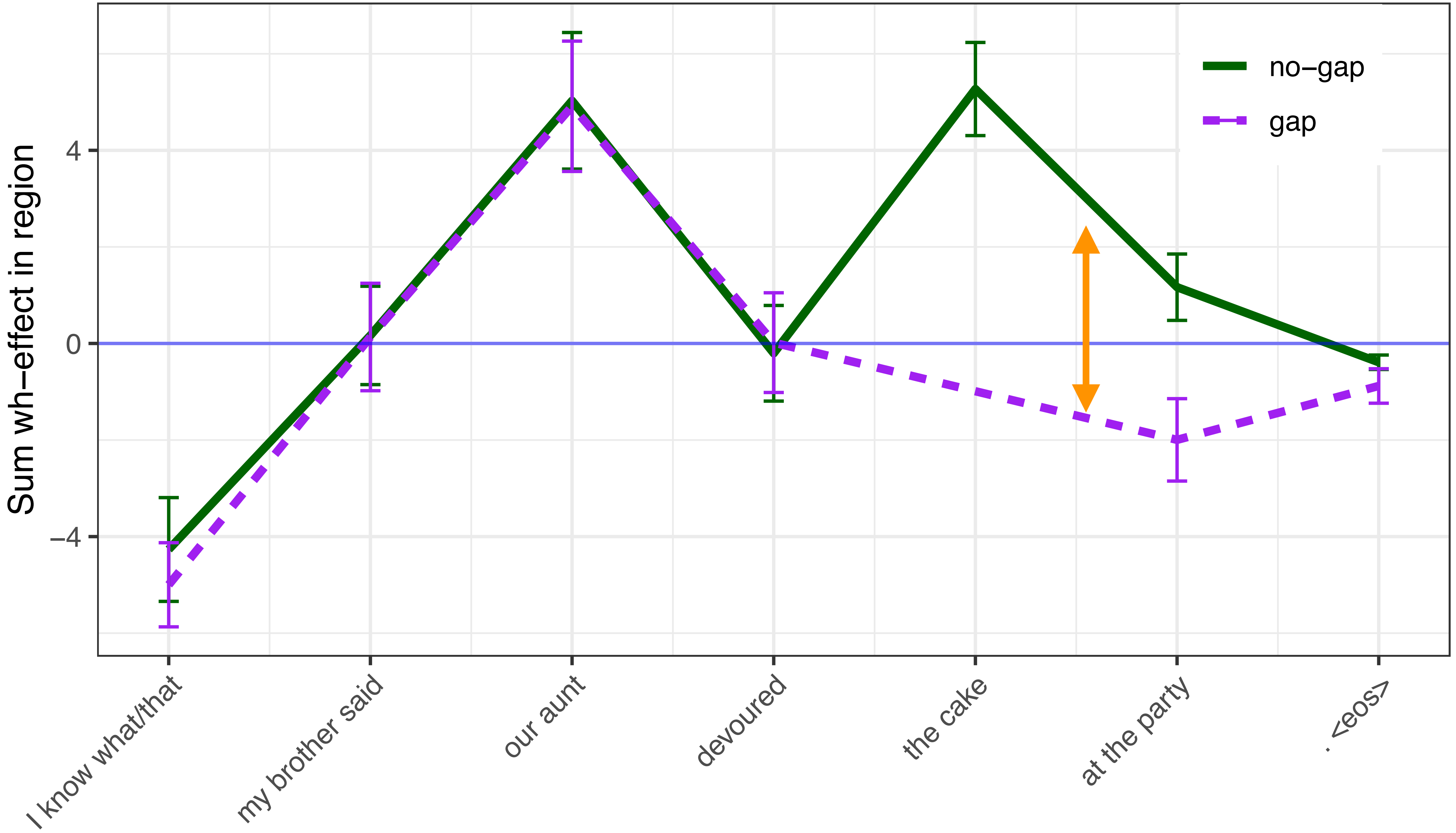


✓ *I know that my brother said our aunt devoured the cake at the party.*

* *I know what my brother said our aunt devoured the cake at the party.*

* *I know that my brother said our aunt devoured ________ at the party.*

✓ *I know what my brother said our aunt devoured ________ at the party.*



Unboundedness of *wh*-dependencies

I know what our mother gave __ to Mary last weekend.

Unboundedness of *wh*-dependencies

I know what our mother gave __ to Mary last weekend.

I know what our mother said that your friend gave __ to Mary last weekend.

Unboundedness of *wh*-dependencies

0 *I know what our mother gave __ to Mary last weekend.*

1 *I know what our mother said that your friend gave __ to Mary last weekend.*

Unboundedness of *wh*-dependencies

0 I know what our mother gave __ to Mary last weekend.

1 I know what our mother said that your friend gave __ to Mary last weekend.

2 I know what our mother said that her friend remarked that your friend gave __ to Mary last weekend.

Unboundedness of *wh*-dependencies

0 *I know what our mother gave __ to Mary last weekend.*

1 *I know what our mother said that your friend gave __ to Mary last weekend.*

2 *I know what our mother said that her friend remarked that your friend gave __ to Mary last weekend.*

3 *I know what our mother said that her friend remarked that the park attendant wondered that your friend gave __ to Mary last weekend.*

Unboundedness of *wh*-dependencies

0 *I know what our mother gave __ to Mary last weekend.*

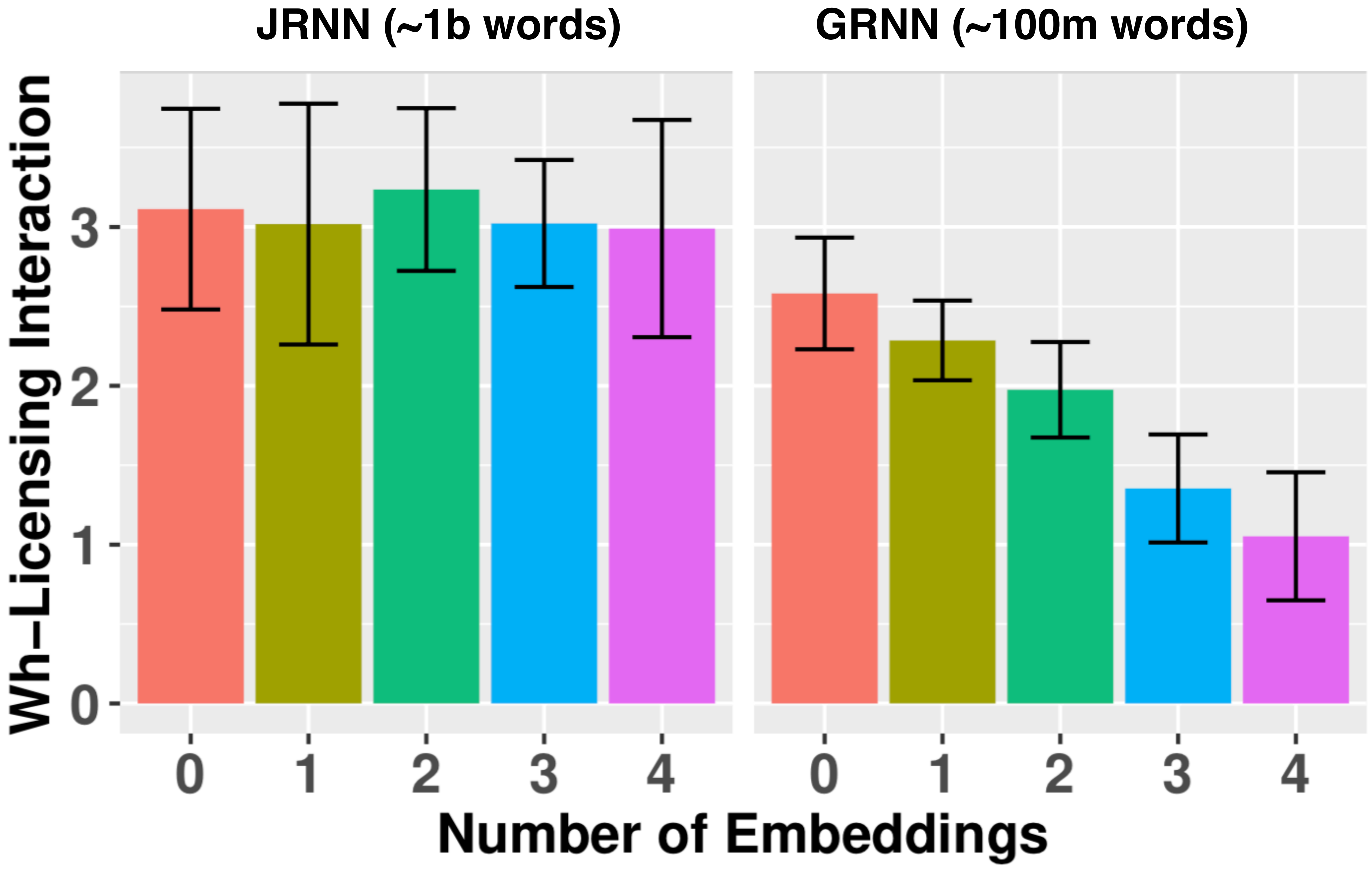
1 *I know what our mother said that your friend gave __ to Mary last weekend.*

2 *I know what our mother said that her friend remarked that your friend gave __ to Mary last weekend.*

3 *I know what our mother said that her friend remarked that the park attendant wondered that your friend gave __ to Mary last weekend.*

4 *I know what our mother said that her friend remarked that the park attendant wondered that the people stated that your friend gave __ to Mary last weekend.*

Unboundedness: Object Gap

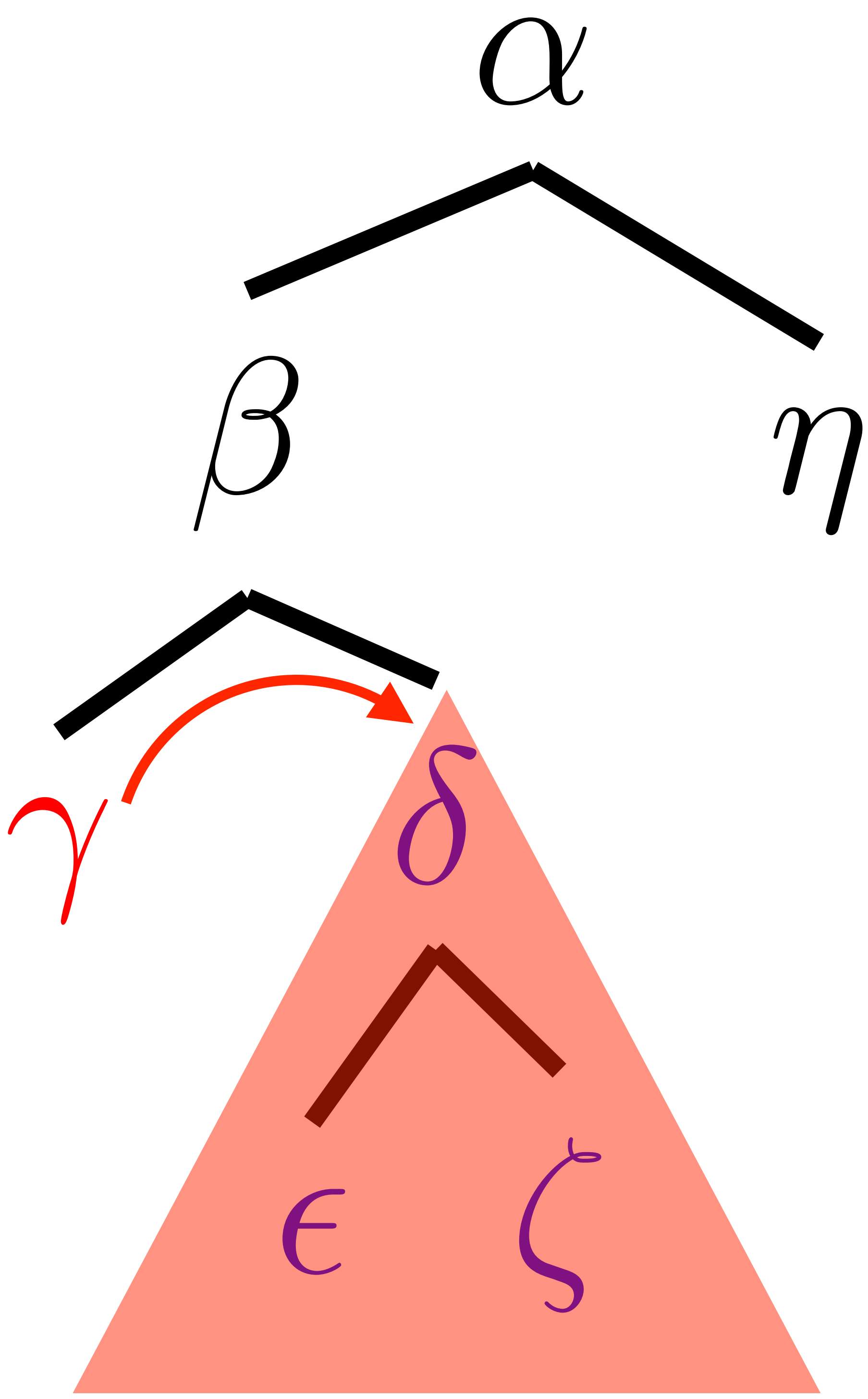


Potential concern #1

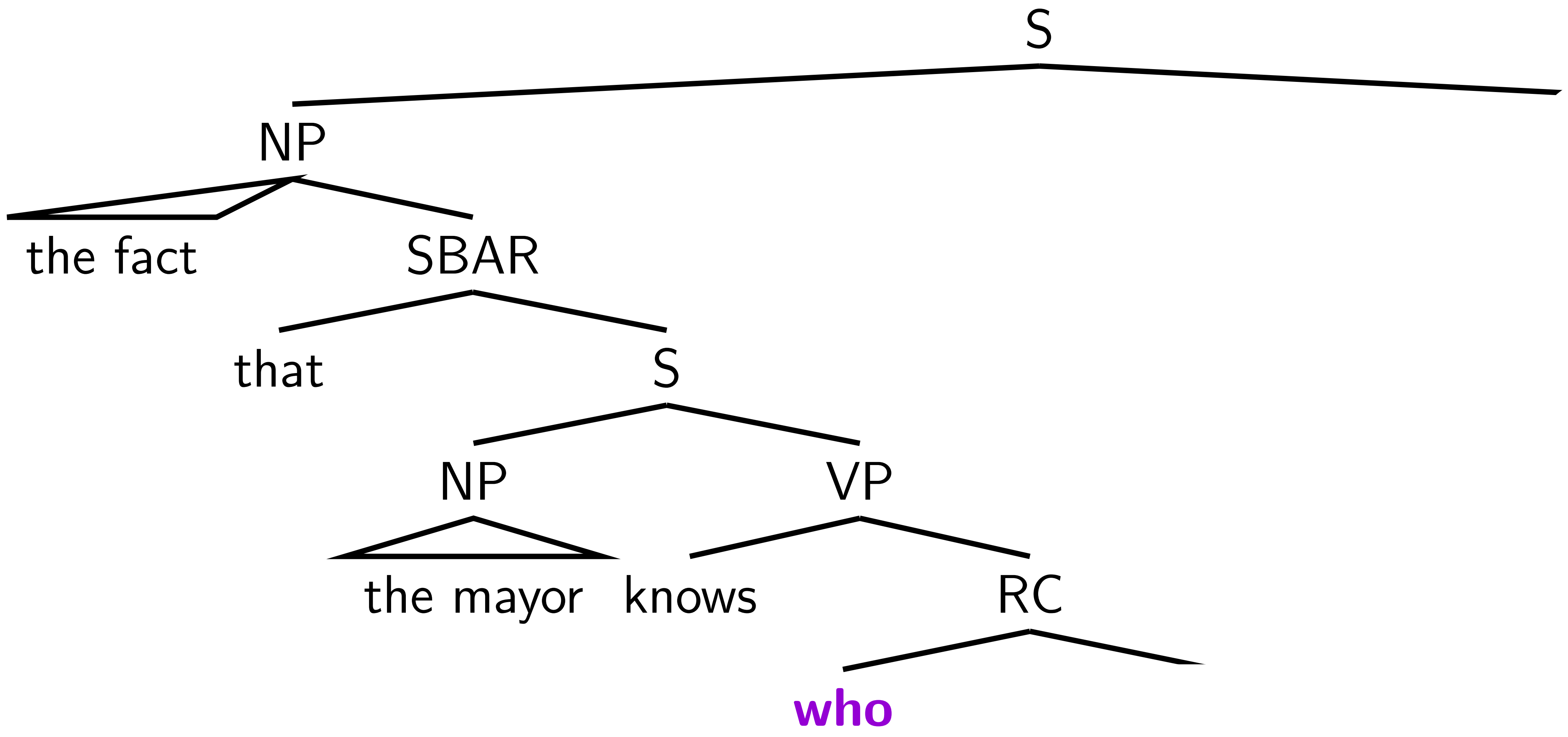
Couldn’t the models be learning a ***linear*** dependency between filler and gap, not a ***hierarchical*** dependency?

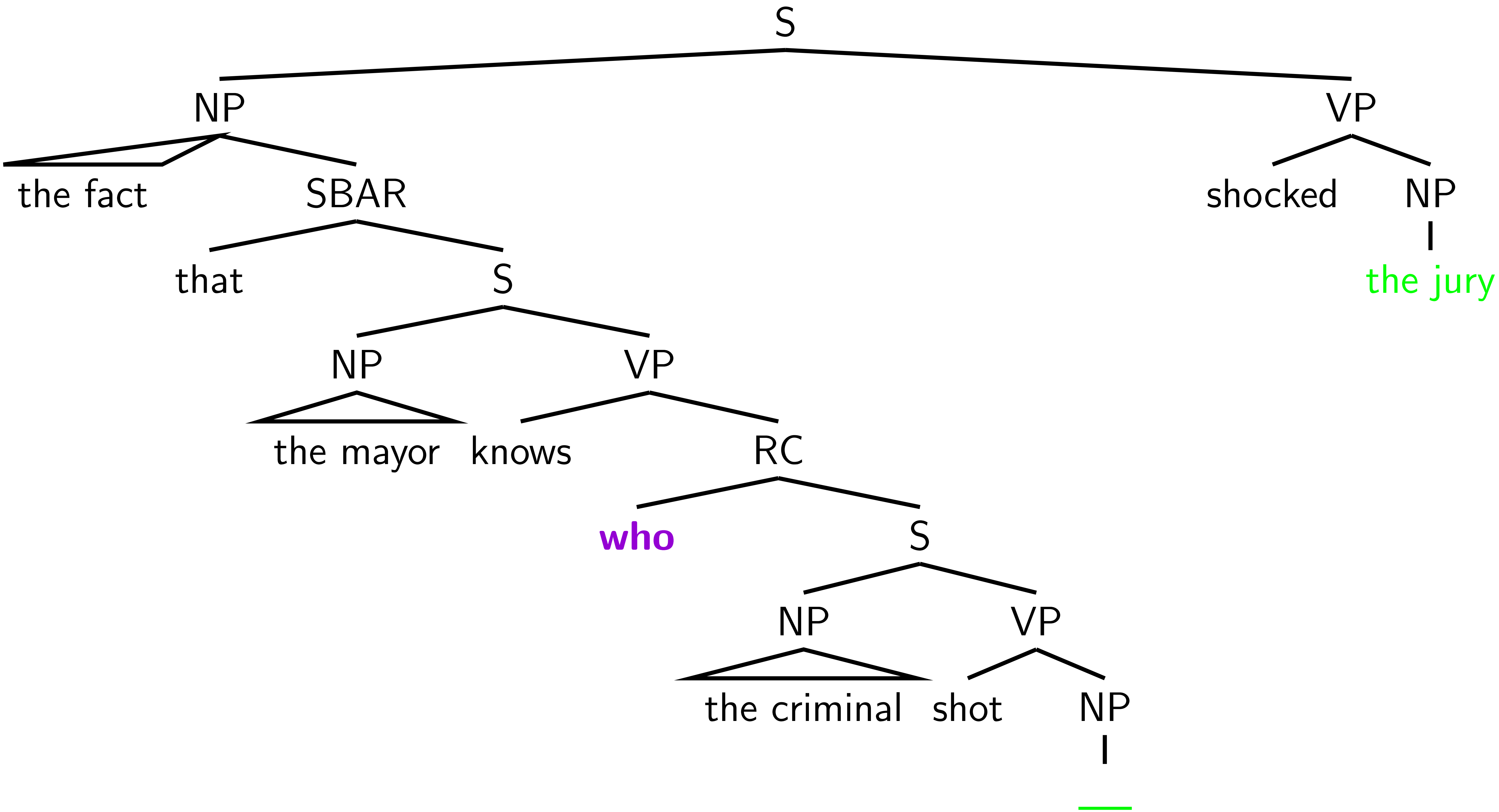
Syntactic Hierarchy

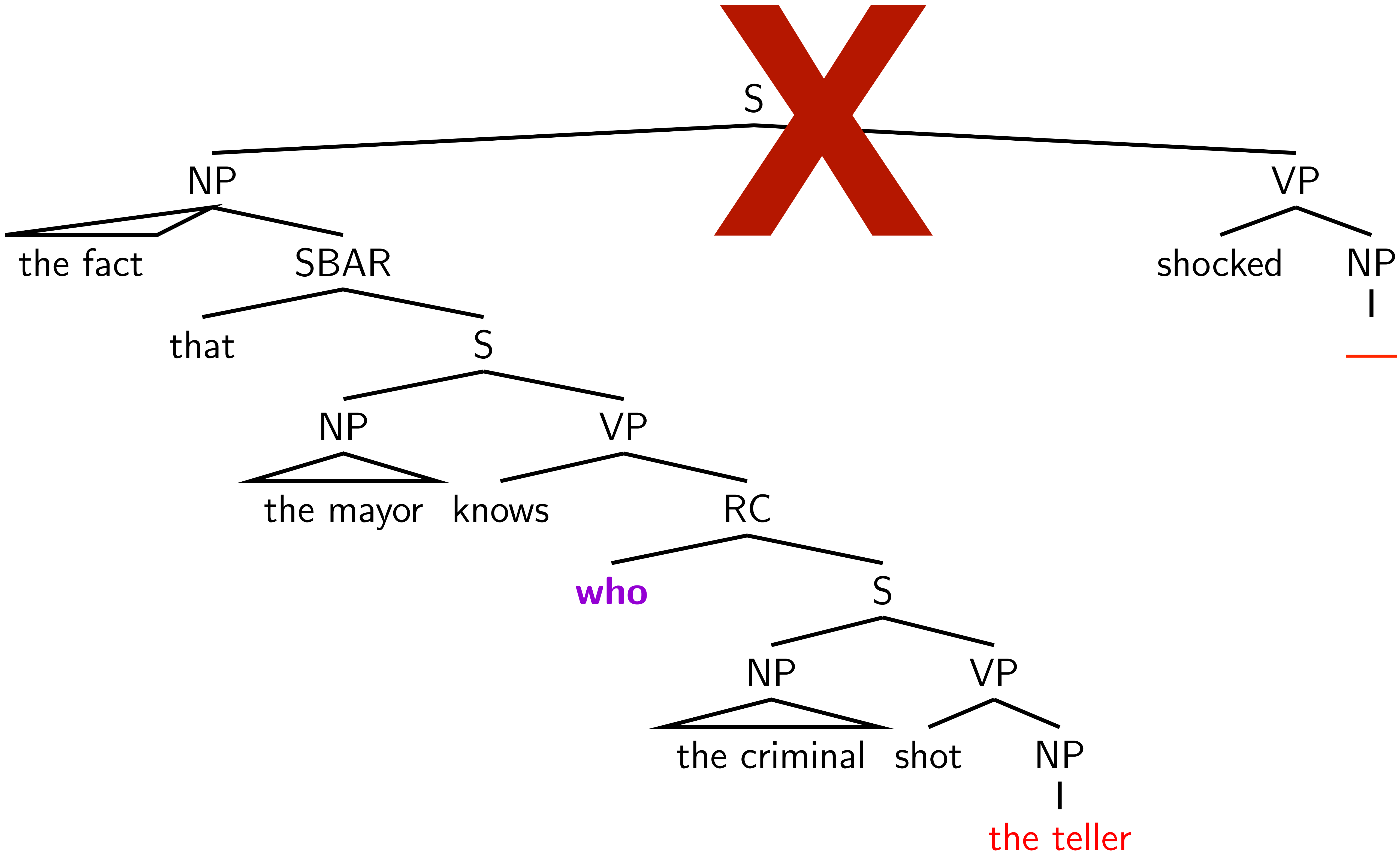
- A filler must be appropriately "above" its gap

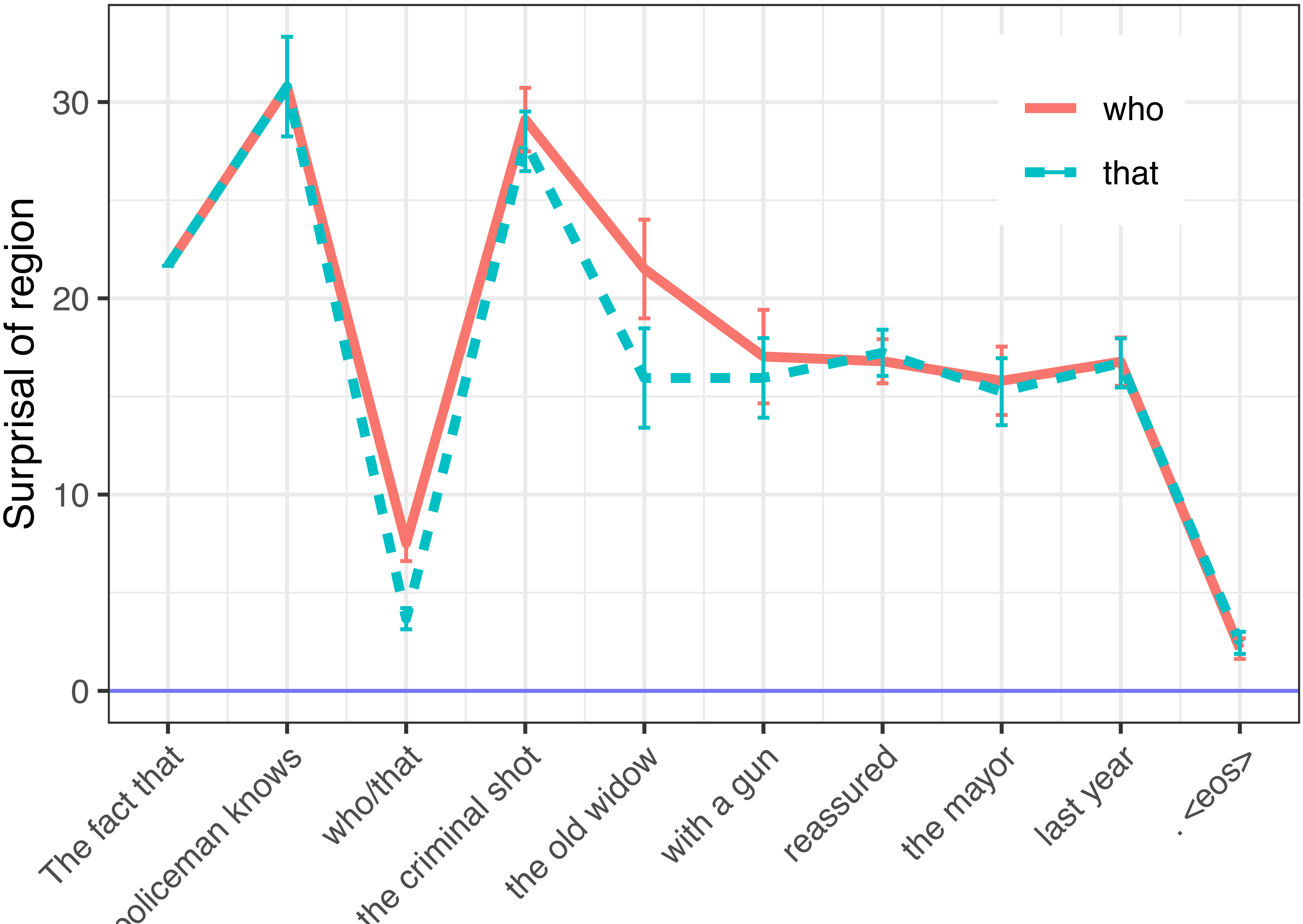


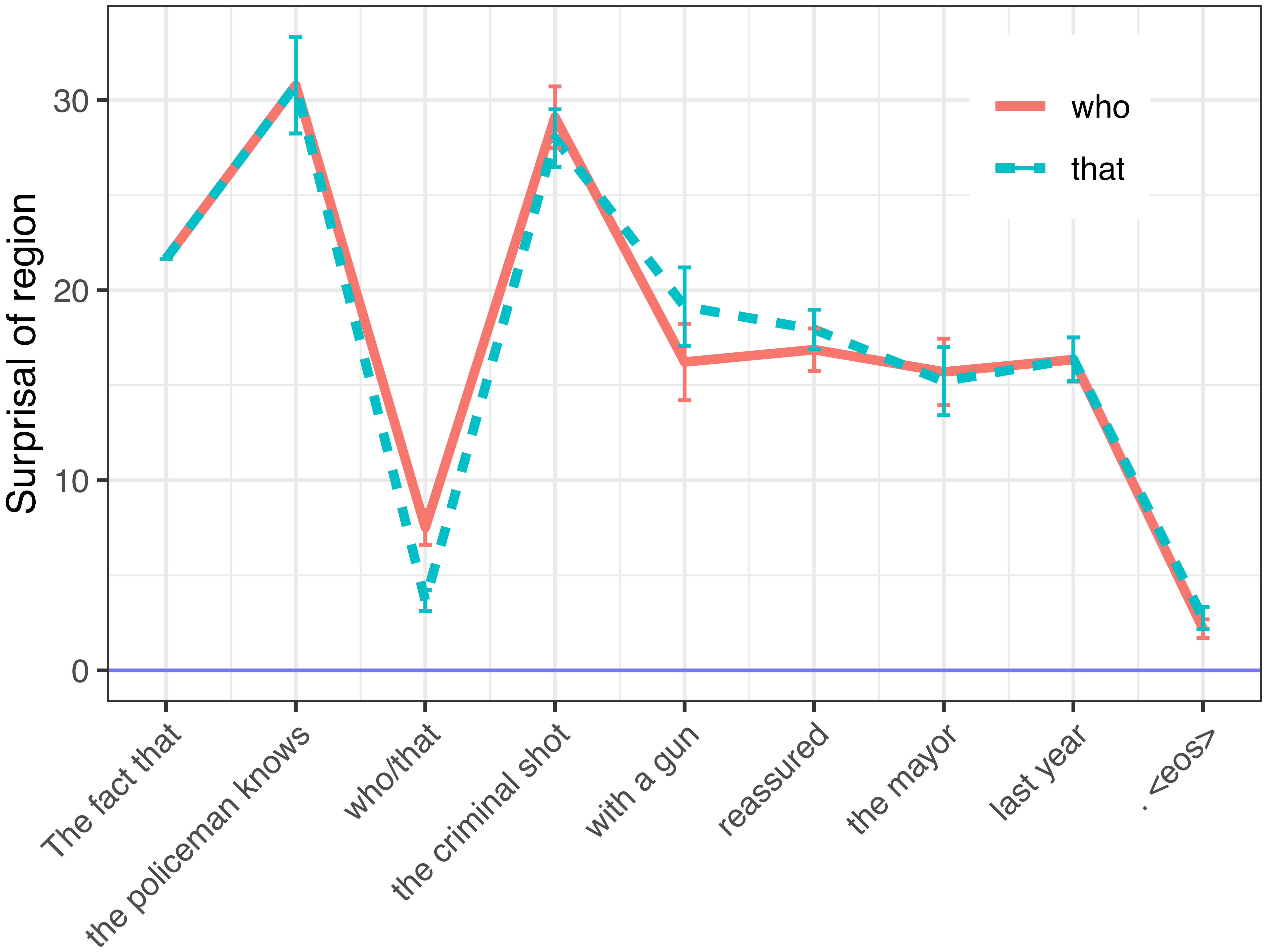
(Wilcox et al., 2019, CogSci)

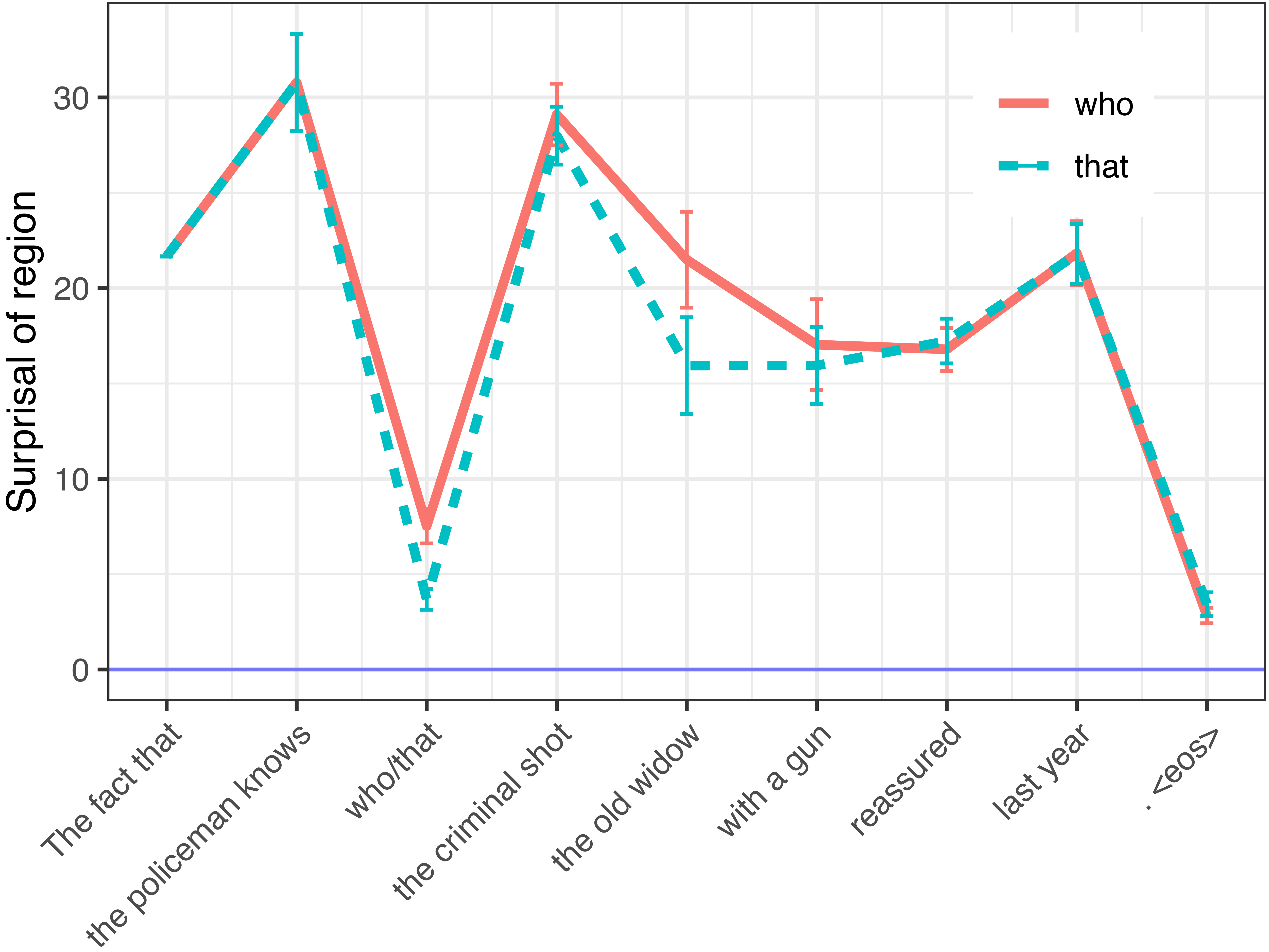

S
NP
the fact
SBAR
that
S
NP
VP
the mayor
knows
RC
who

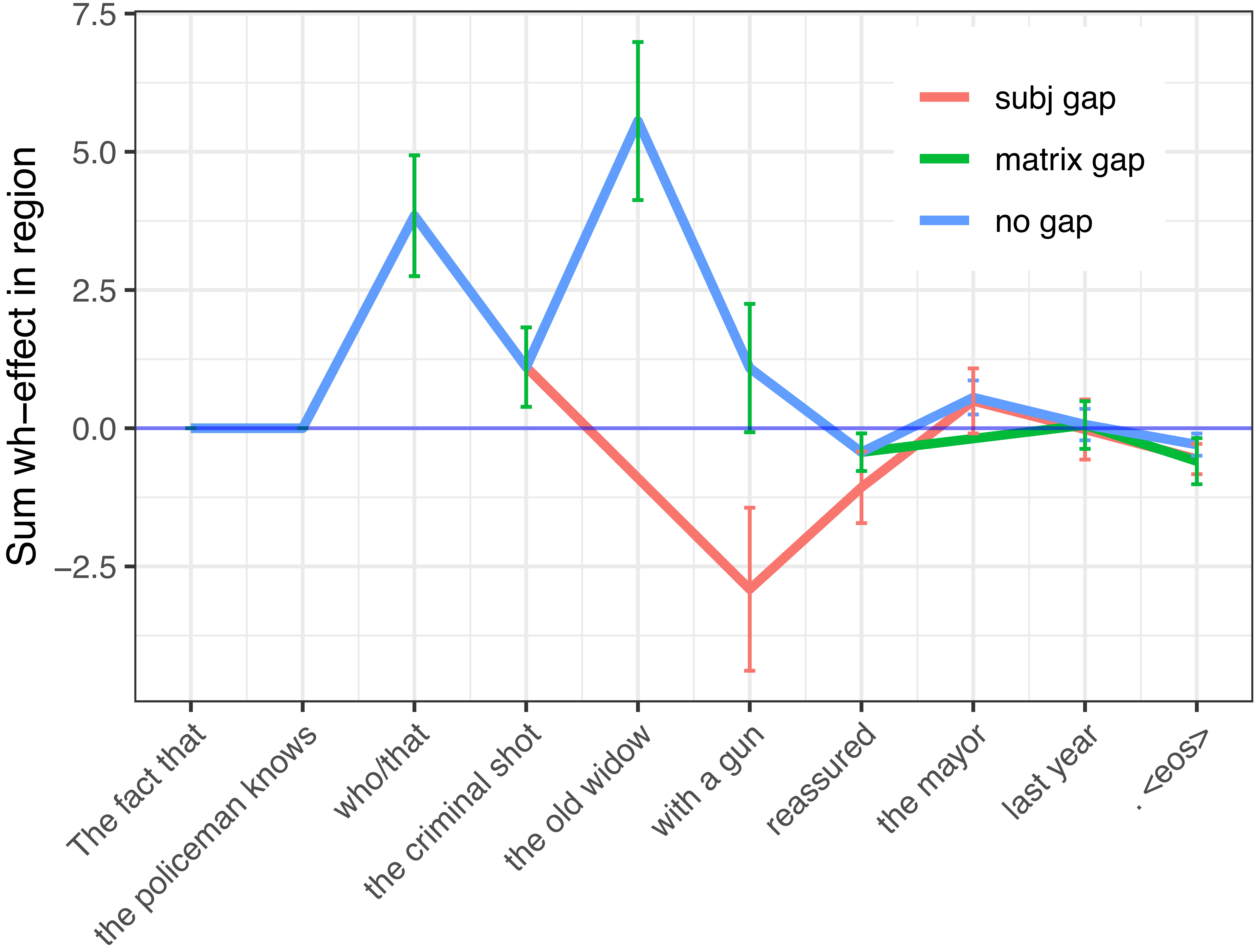

S
NP
VP
the fact
SBAR
shocked
NP
that
S
the jury
NP
VP
the mayor
knows
RC
who
S
NP
VP
the criminal
shot
NP
—


S
NP
the fact
SBAR
that
S
NP
the mayor
VP
knows
RC
who
S
NP
the criminal
VP
shot
NP
the teller
VP
shocked
NP
—


Surprisal of region
0
10
20
30
who
that
The fact that
the policeman knows
who/that
the criminal shot
the old widow
with a gun
reassured
the mayor
last year
. <eos>


Surprisal of region
0
10
20
30
who
that
The fact that
the policeman knows
who/that
the criminal shot
with a gun
reassured
the mayor
last year
. <eos>


Surprisal of region
0
10
20
30
who
that
The fact that
the policeman knows
who/that
the criminal shot
the old widow
with a gun
reassured
last year
. <eos>


Sum wh−effect in region
7.5
5.0
2.5
0.0
−2.5
subj gap
matrix gap
no gap
The fact that
the policeman knows
who/that
the criminal shot
the old widow
with a gun
reassured
the mayor
last year
. <eos>

Potential concern #1

Couldn’t the models be learning a ***linear*** dependency between filler and gap, not a ***hierarchical*** dependency?

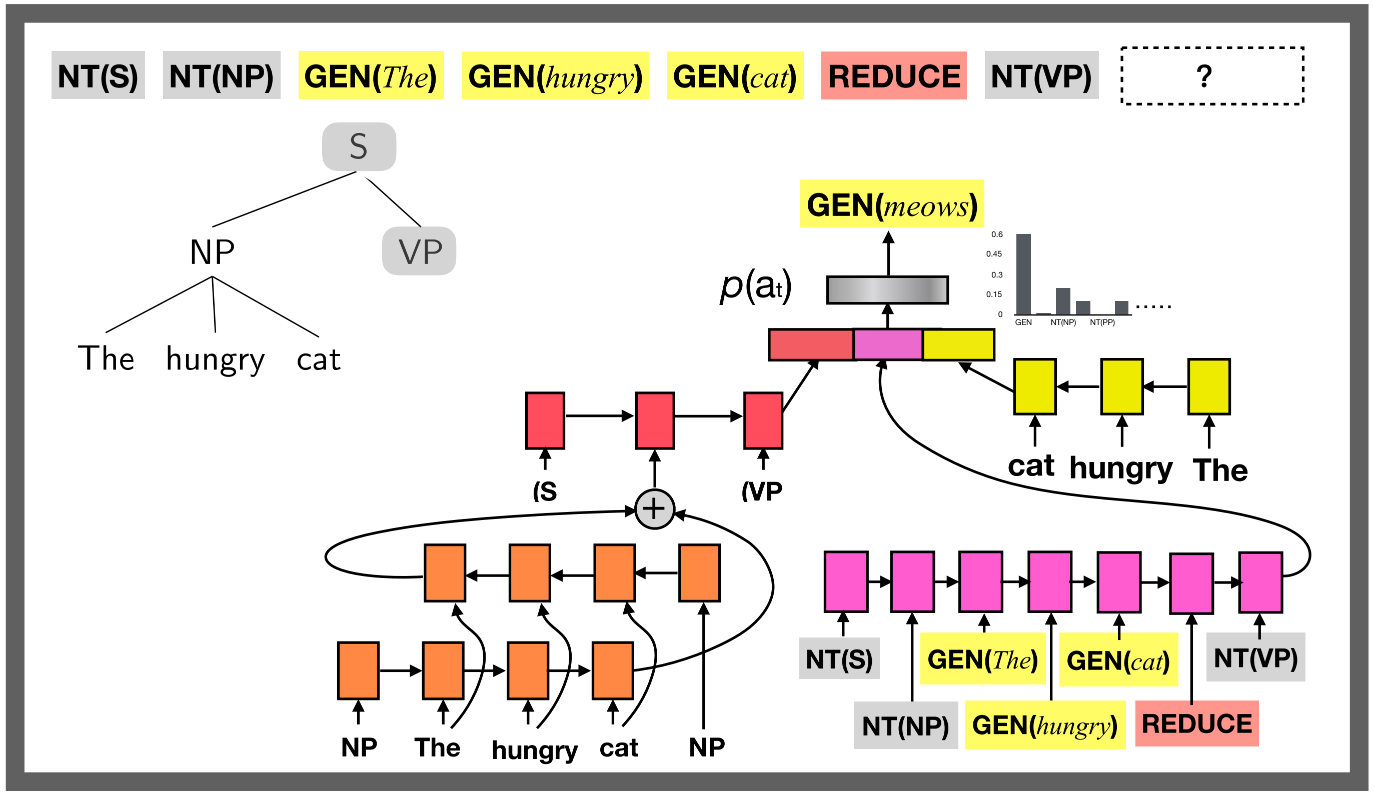
Potential concern #1 — ***addressed***

✗

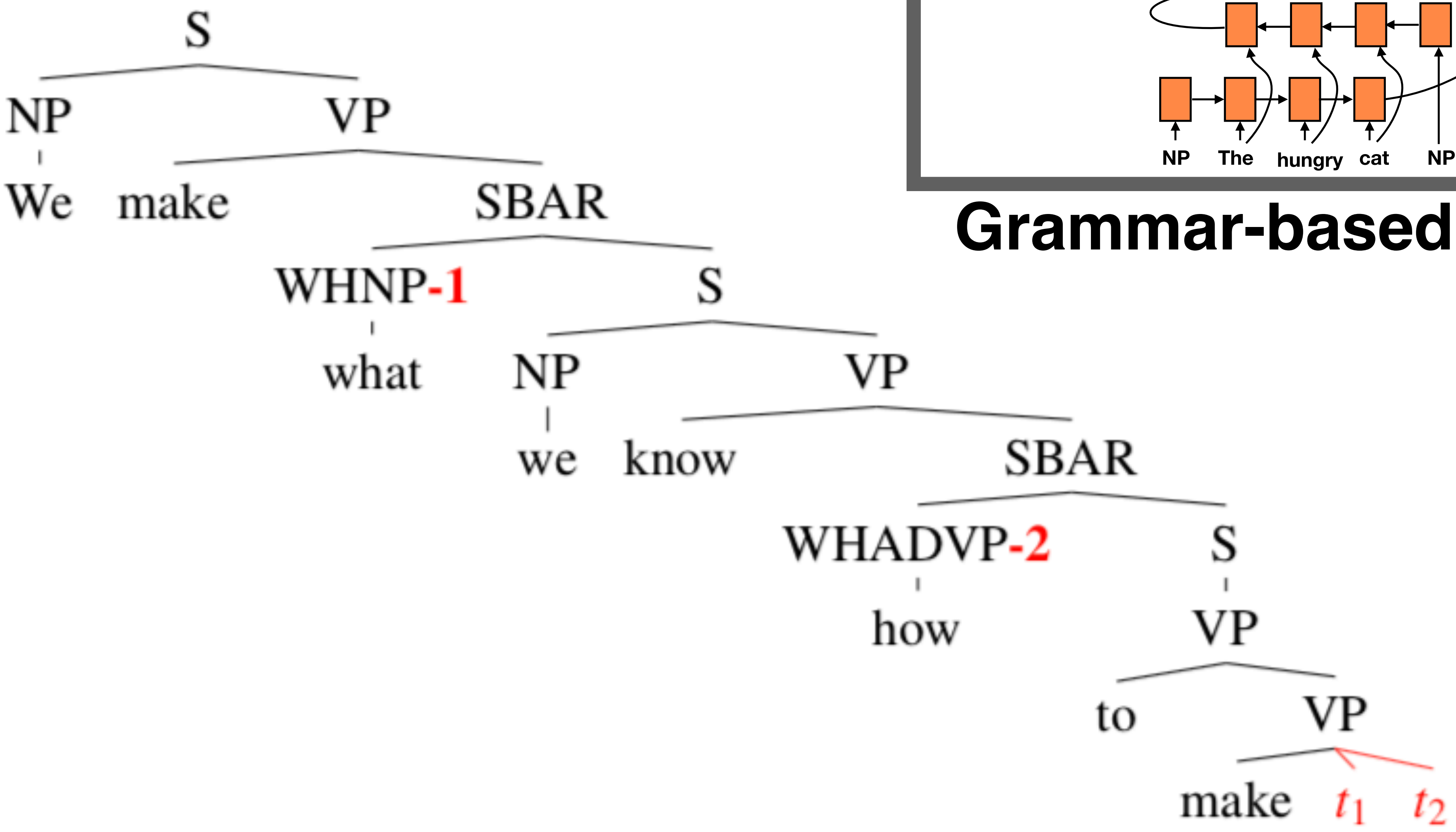
Couldn’t the models be learning a ***linear*** dependency between filler and gap, not a ***hierarchical*** dependency?

Our results suggest that RNN models trained on enough data are sensitive to syntactic hierarchy for *wh*-dependency

Does syntactic supervision help?

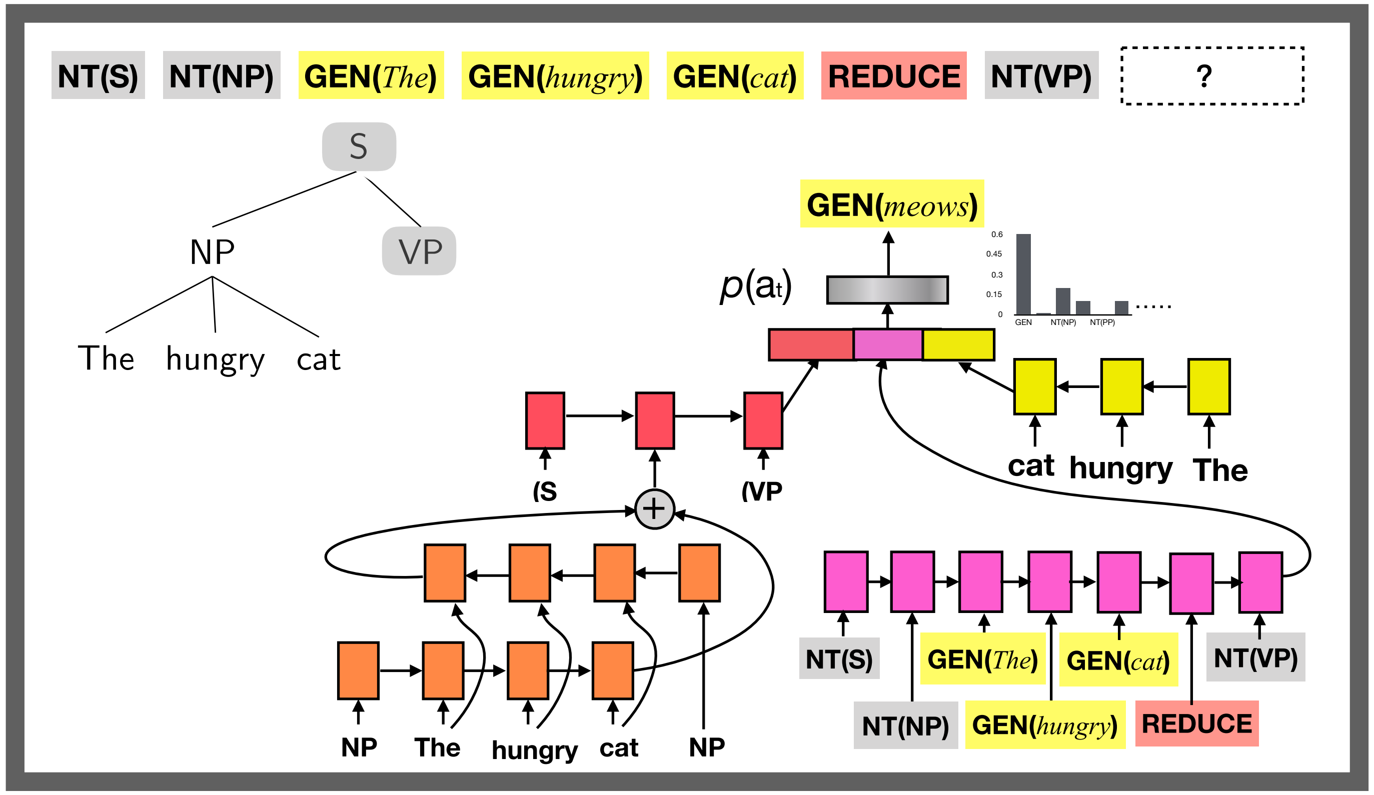

NT(S) NT(NP) GEN(*The*) GEN(*hungry*) GEN(*cat*) REDUCE NT(VP) ?
S
NP
VP
The hungry cat
GEN(*meows*)
$p(a_t)$
(S
(VP
cat hungry The
NP The hungry cat NP
NT(S) GEN(*The*) GEN(*cat*) NT(VP)
NT(NP) GEN(*hungry*) REDUCE

Grammar-based model (RNNG)

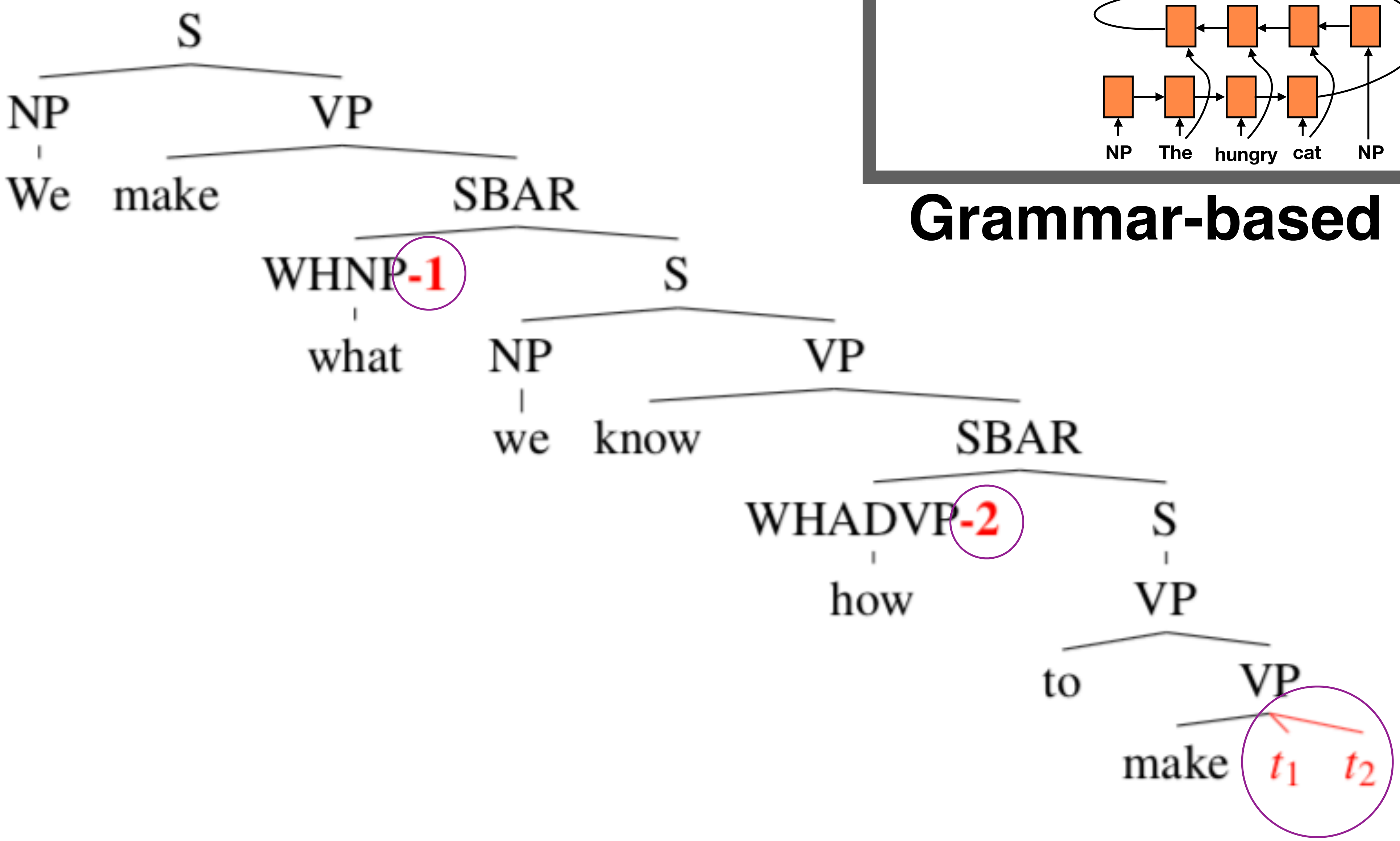


(Wilcox et al., 2019, NAACL)

Does syntactic supervision help?

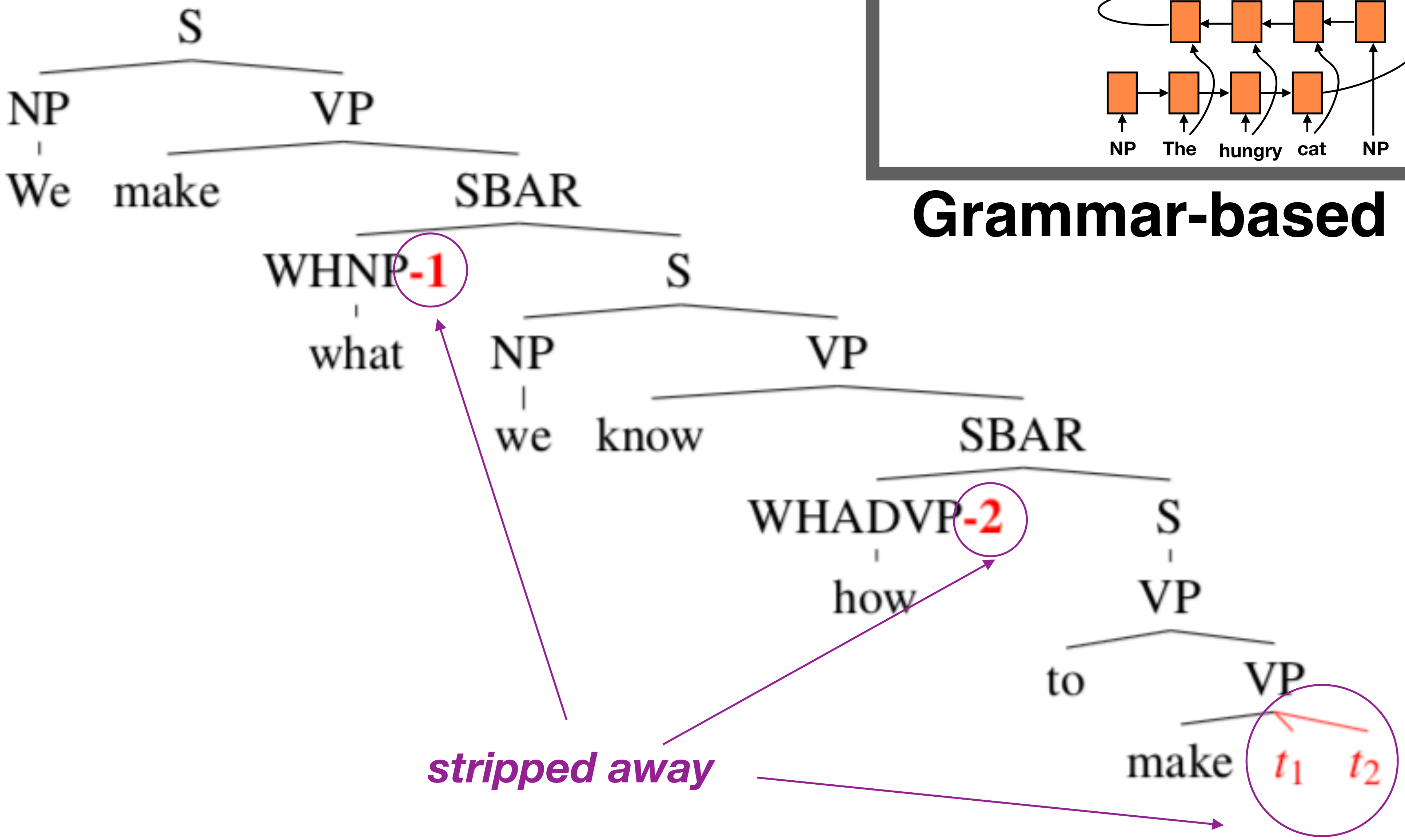


Grammar-based model (RNNG)

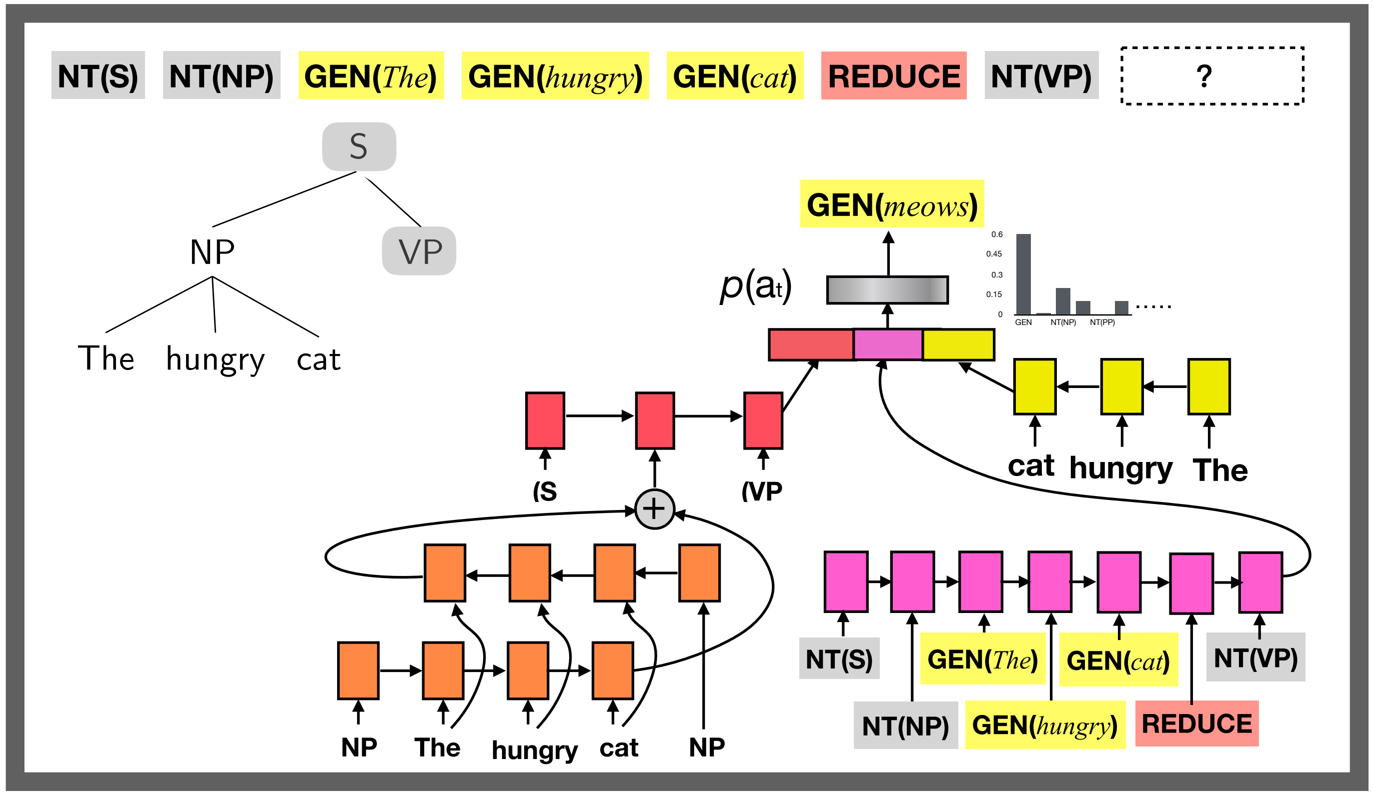


(Wilcox et al., 2019, NAACL)

Does syntactic supervision help?



stripped away

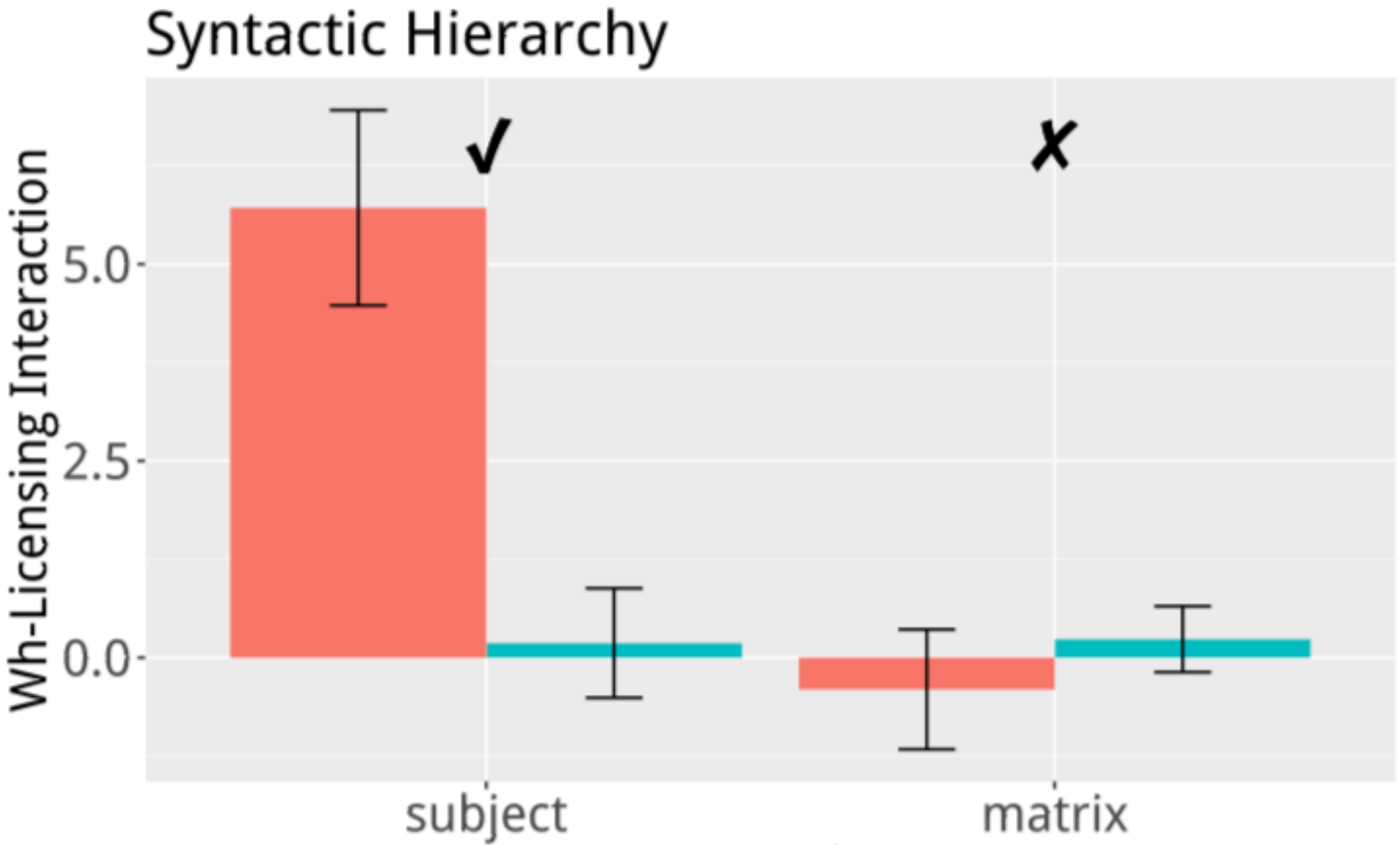


Grammar-based model (RNNG)

(Wilcox et al., 2019, NAACL)

Syntactic supervision helps a lot!

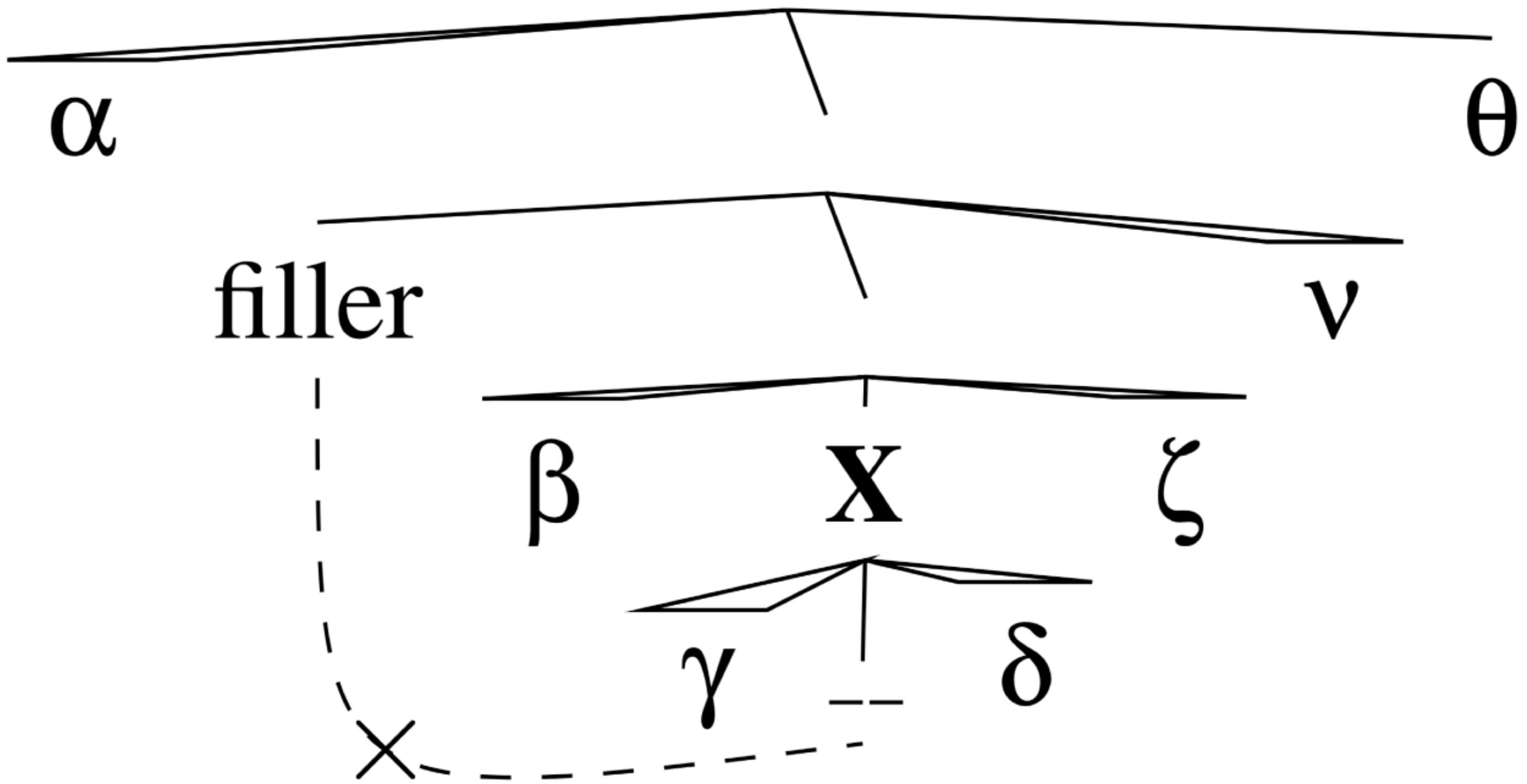
- With small-dataset training (1m words):



🟥 **Grammar-based model (RNNG)**

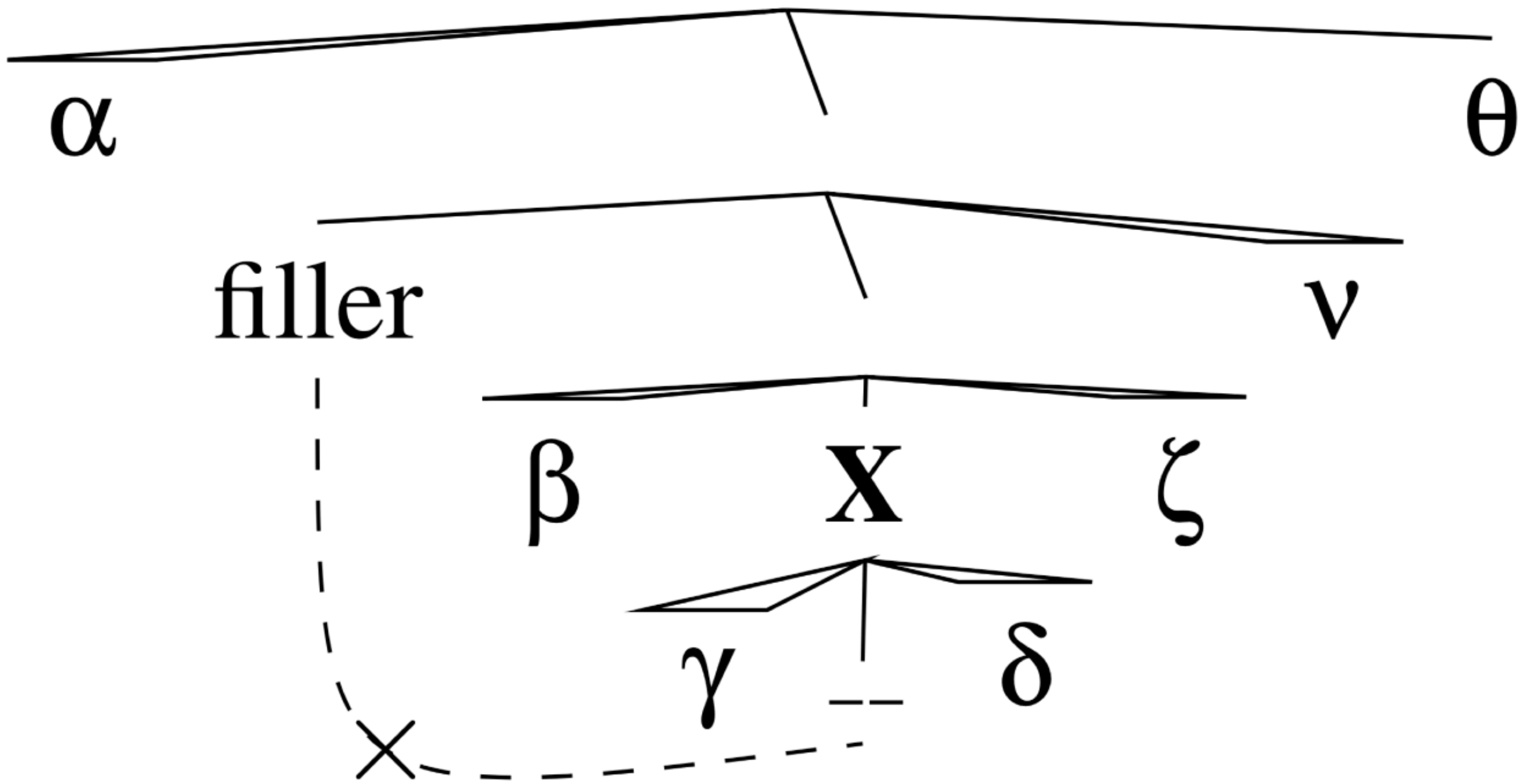
🟦 **Sequence model (LSTM)**

Syntactic island constraints



Syntactic island constraints

- Some types of phrases are ***islands***: filler–gap dependencies cannot link from outside to inside of them



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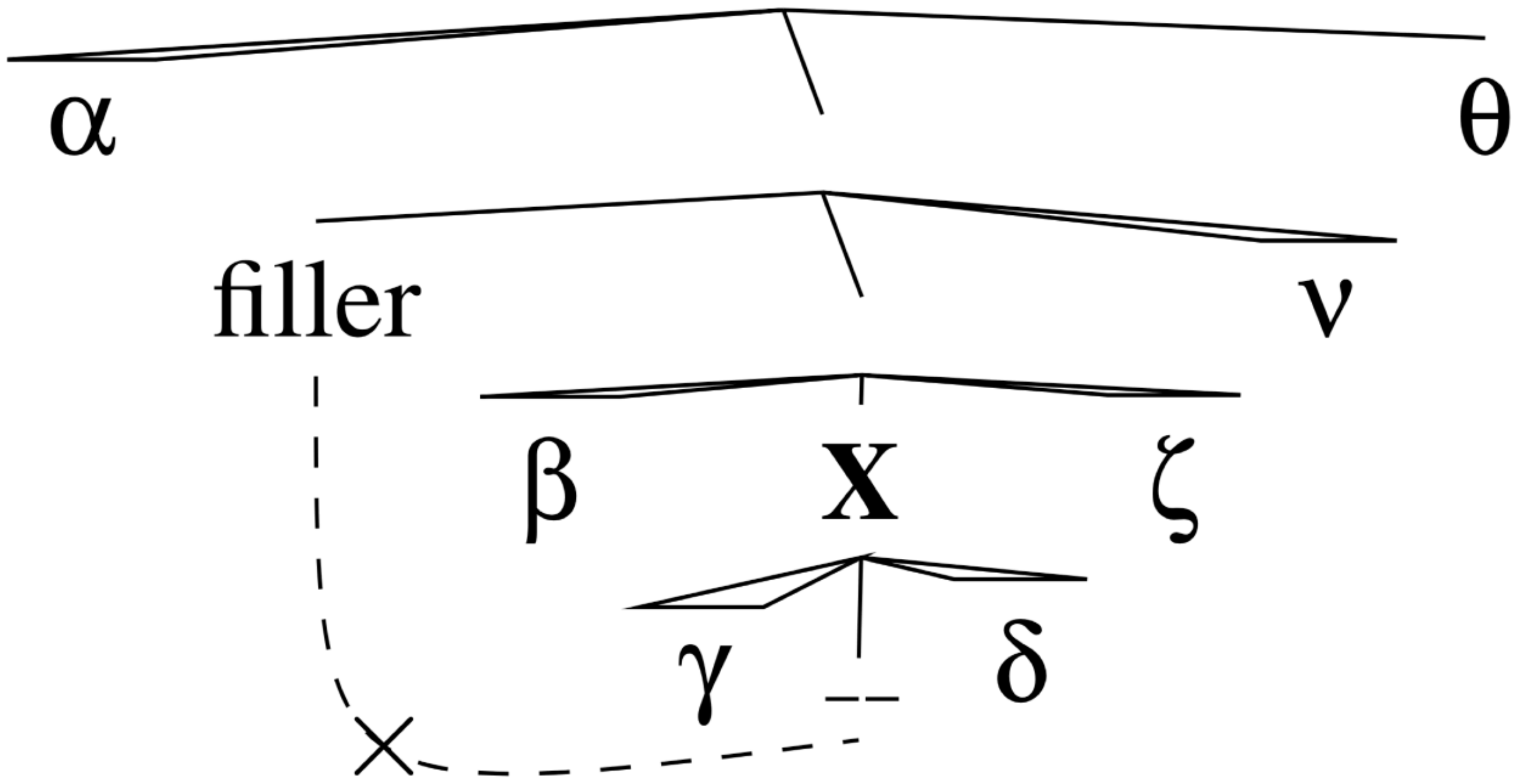

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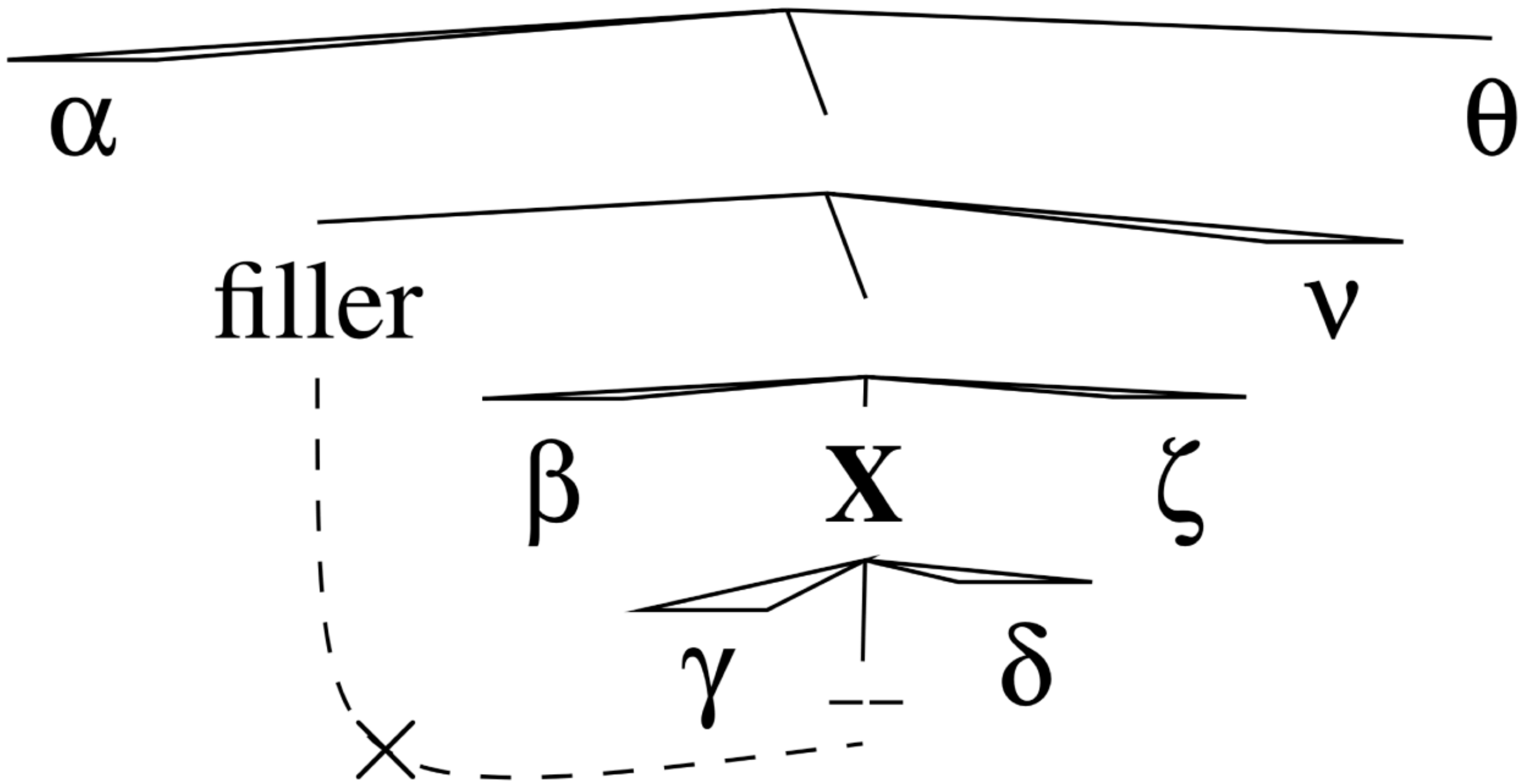

- Islands are prominent in learnability debates: they'd require learning from negative evidence, and are rare structures
- We take a language model to have learned an island constraint if it *fails* to propagate filler-generated expectations for gaps into phrases that should be islands

Syntactic islands

***Wh*-complementizers** block filler—gap dependencies:

I know what Alex said…

…your friend devoured __ at the party.
[null complementizer]

(Wilcox et al., 2018, BlackBox)

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Do the RNNs learn this?

(Wilcox et al., 2018, BlackBox)

✓ `I know that my brother said our aunt devoured the cake at the party.`

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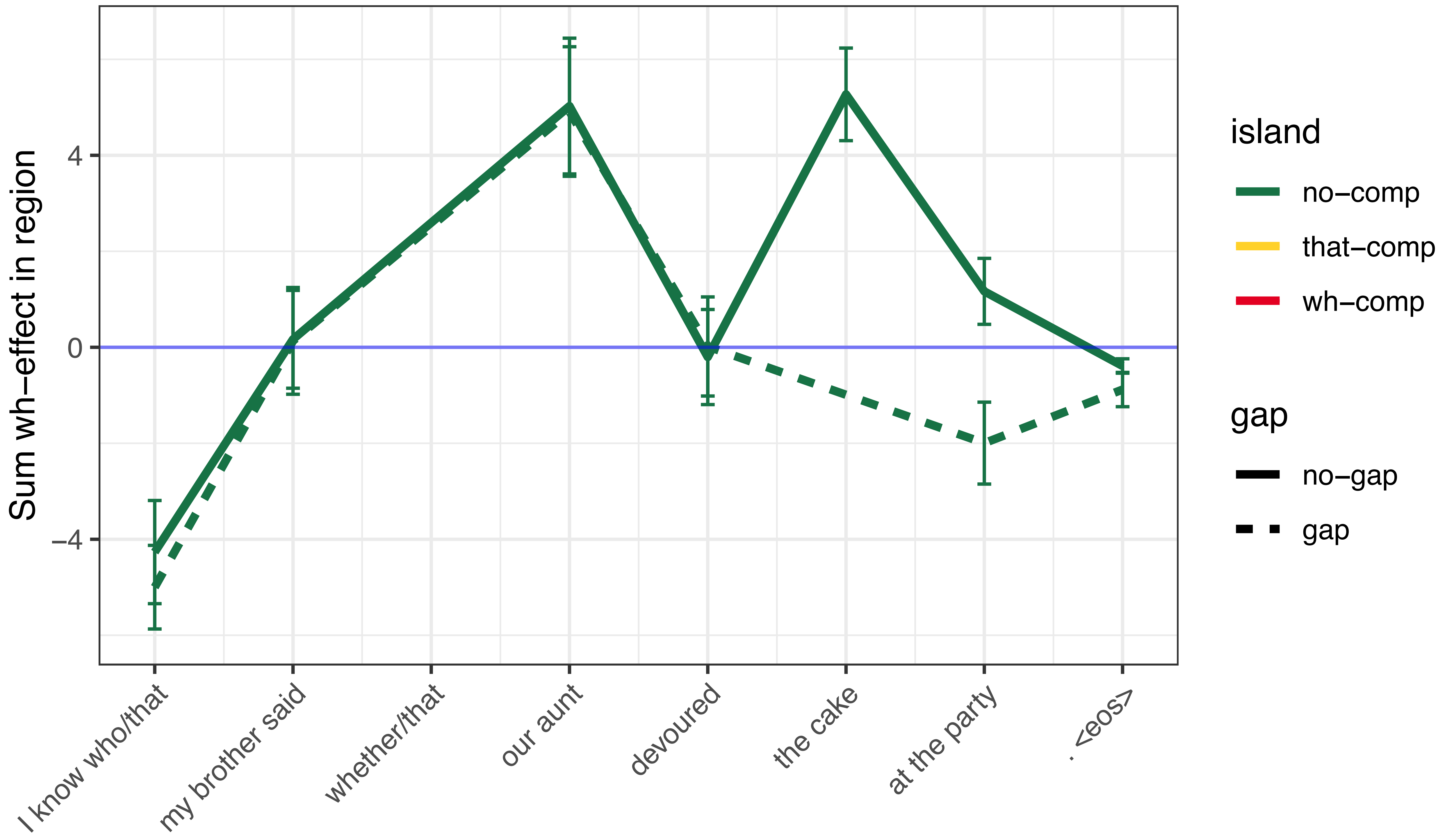

✓ *I know that my brother said* ***that*** *our aunt devoured the cake at the party.*

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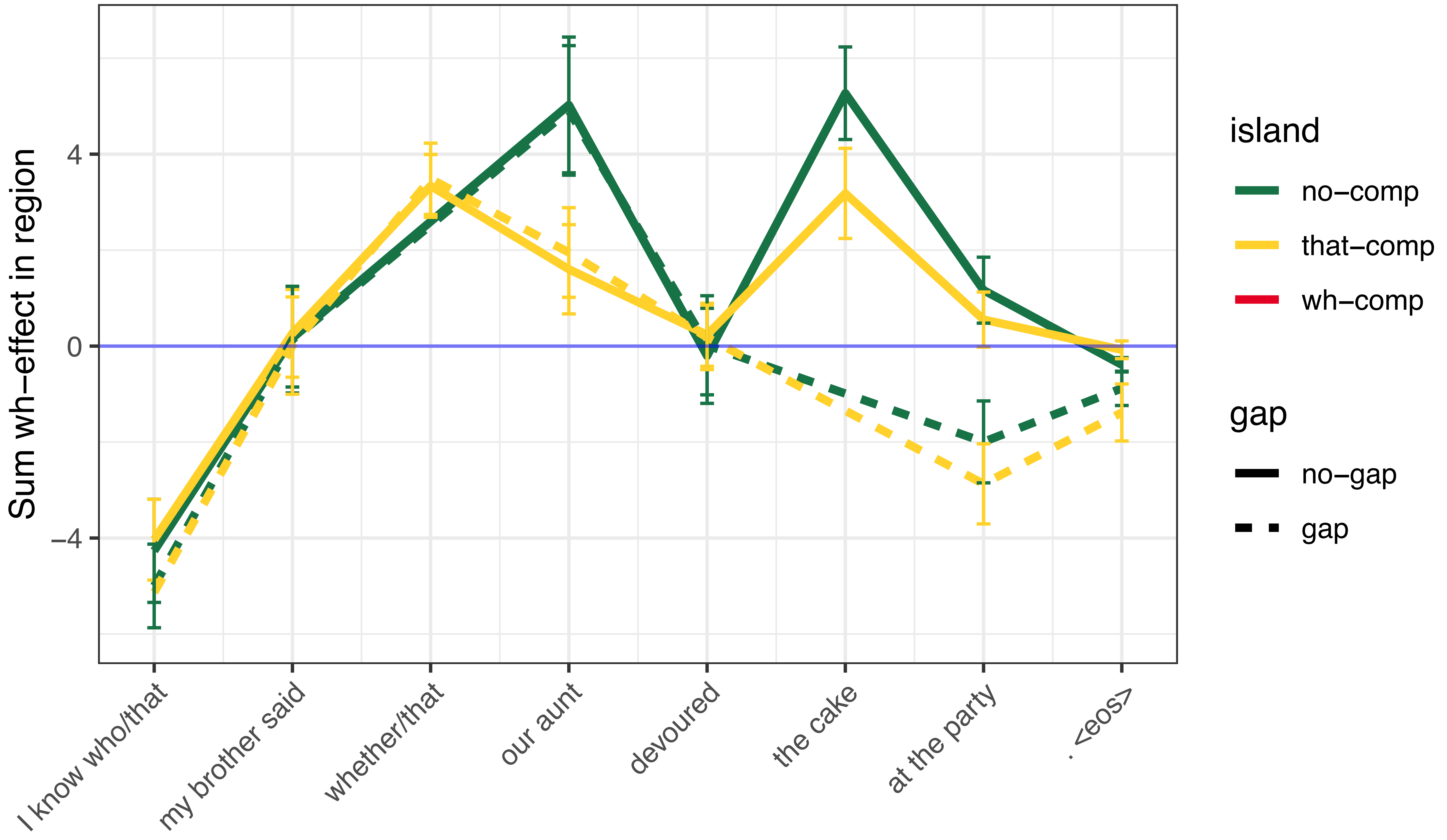

* I know that my brother said **whether** our aunt devoured the cake at the party.

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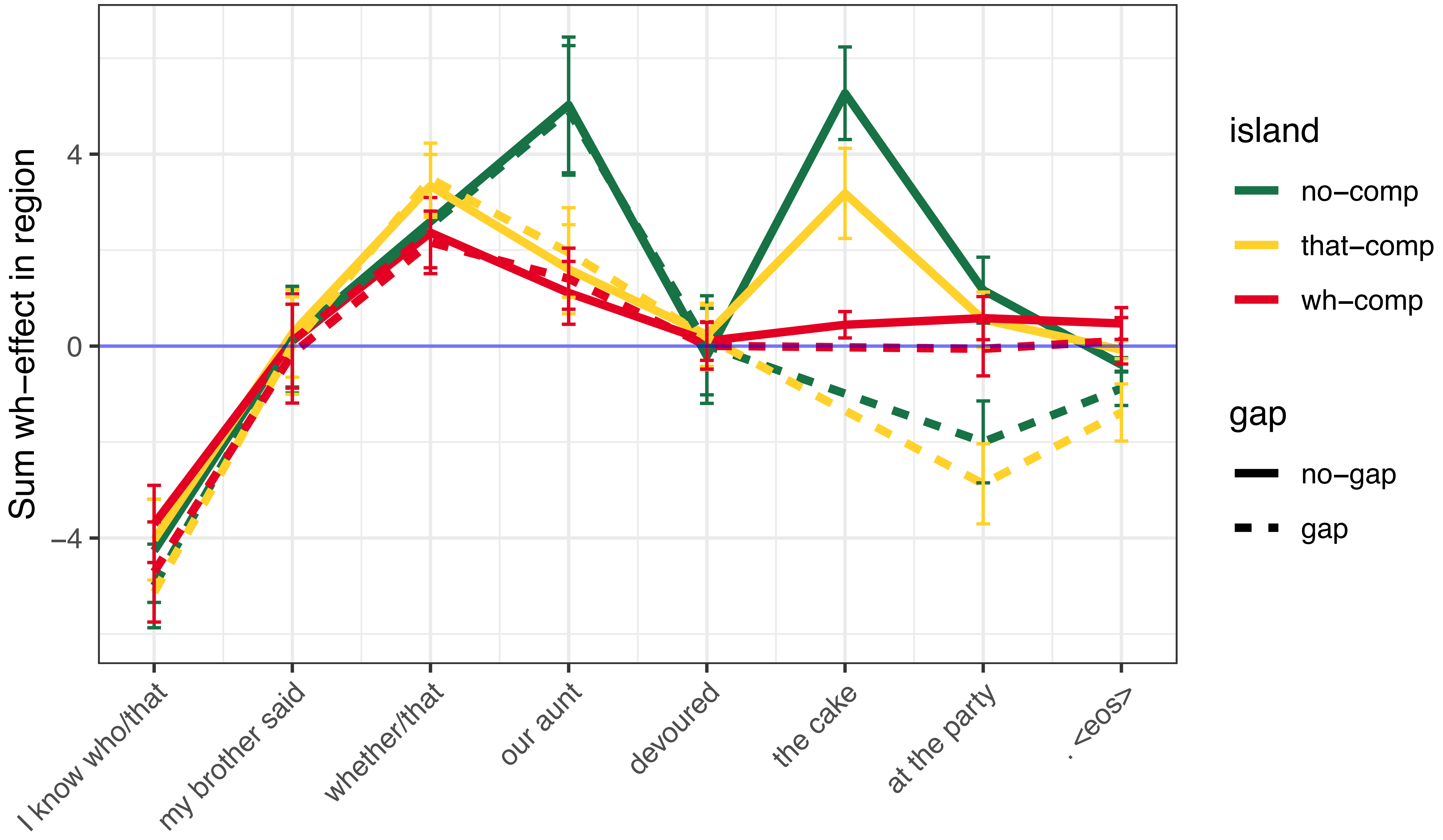

Potential concern #2

Could RNNs have difficulty threading ***any*** type of expectation into a syntactic island?

Gendered-pronoun Expectation Control

(Wilcox et al., 2019, CogSci)

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- Worry: Can the models thread **any** expectation into islands?

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✓ *The actress said that they insulted* **her** *friends.* **[CONTROL, MATCH]**

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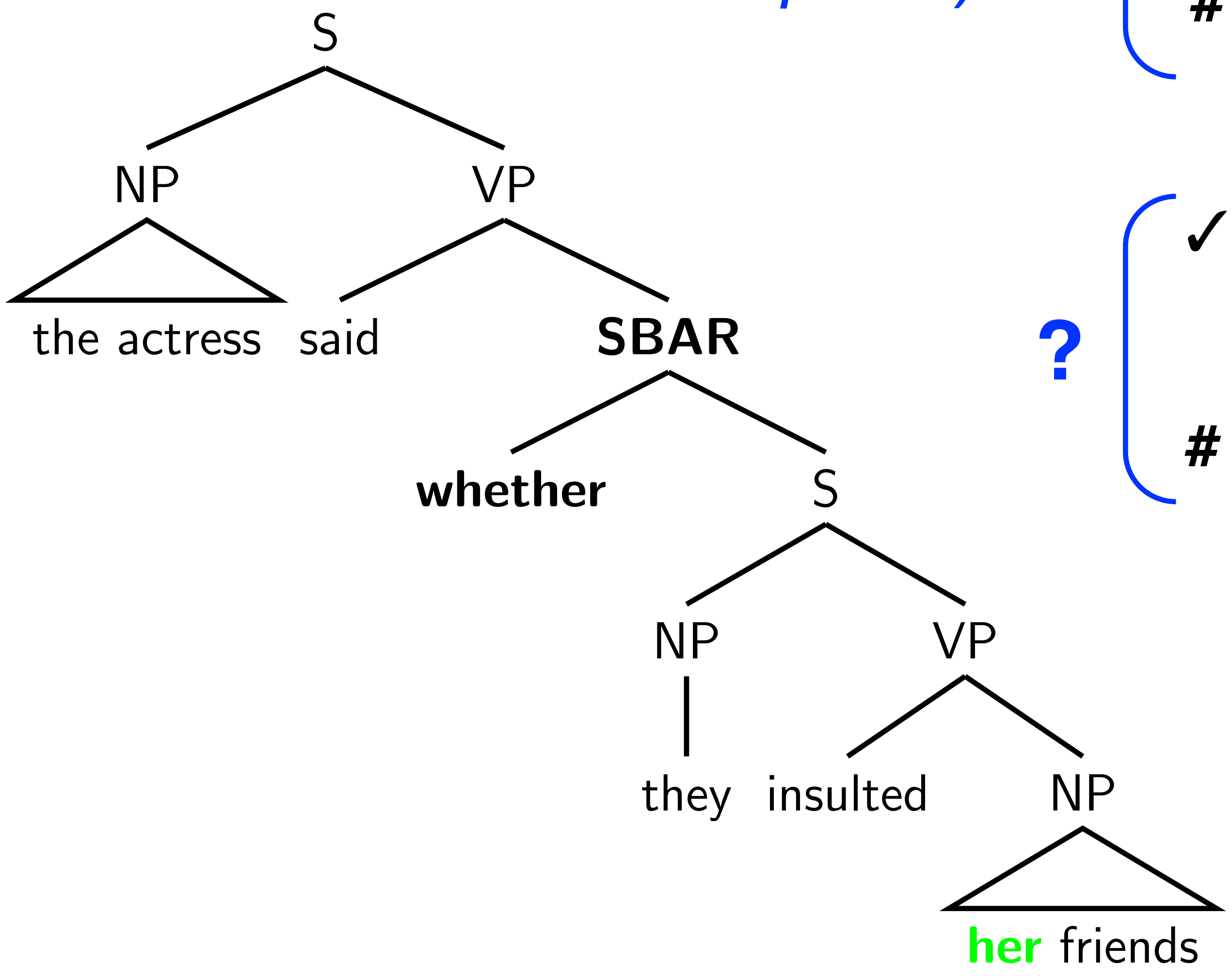

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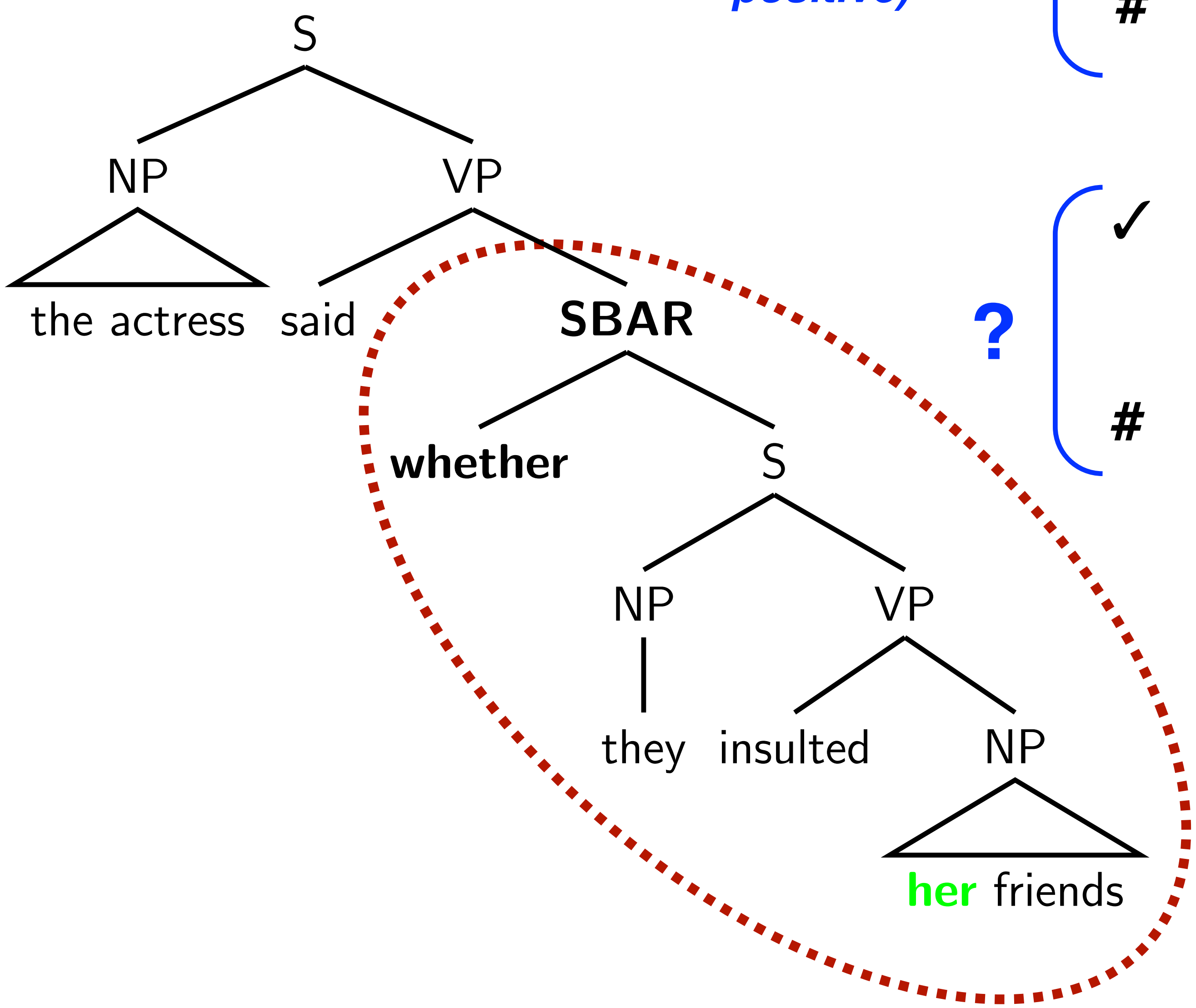

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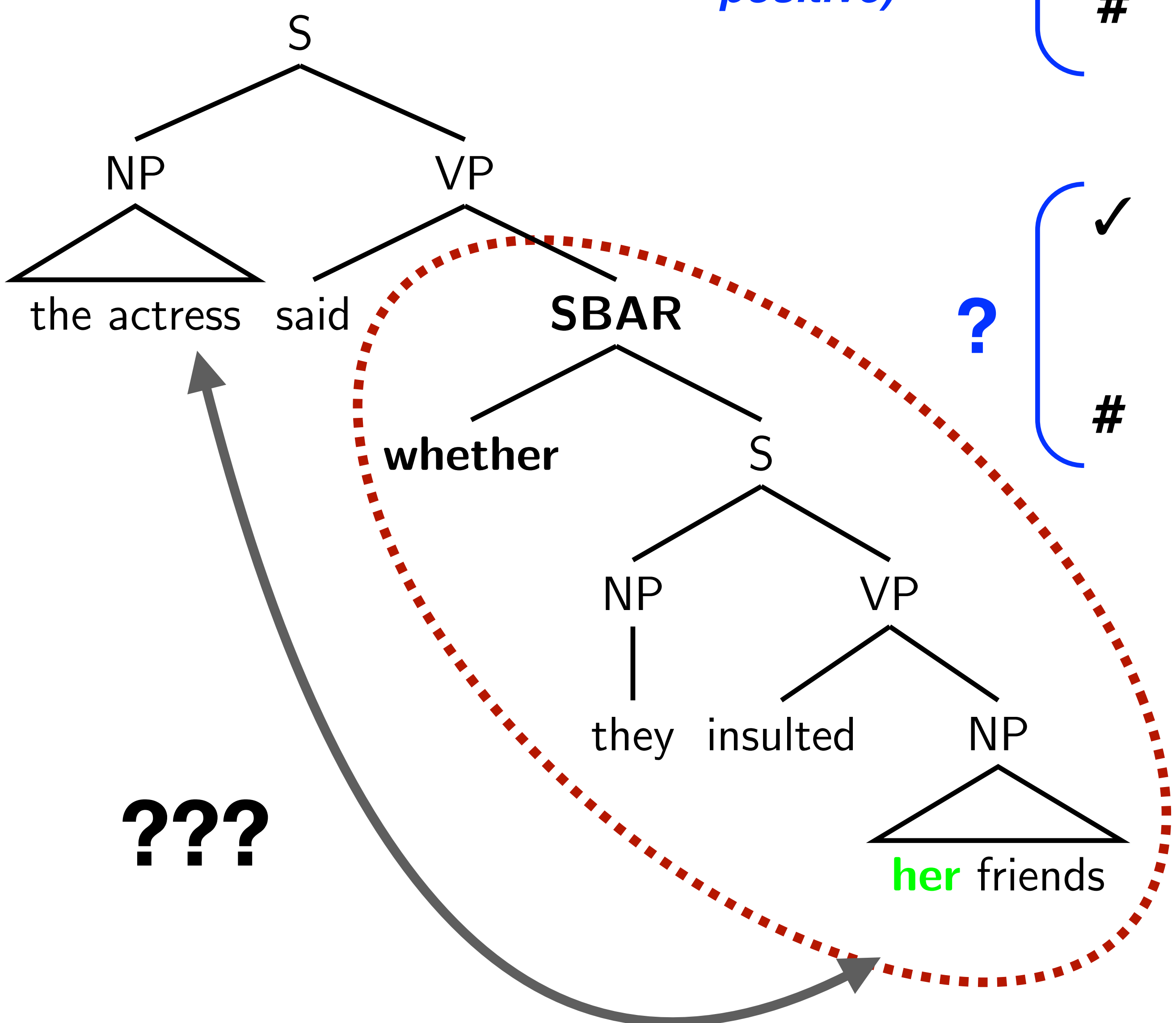

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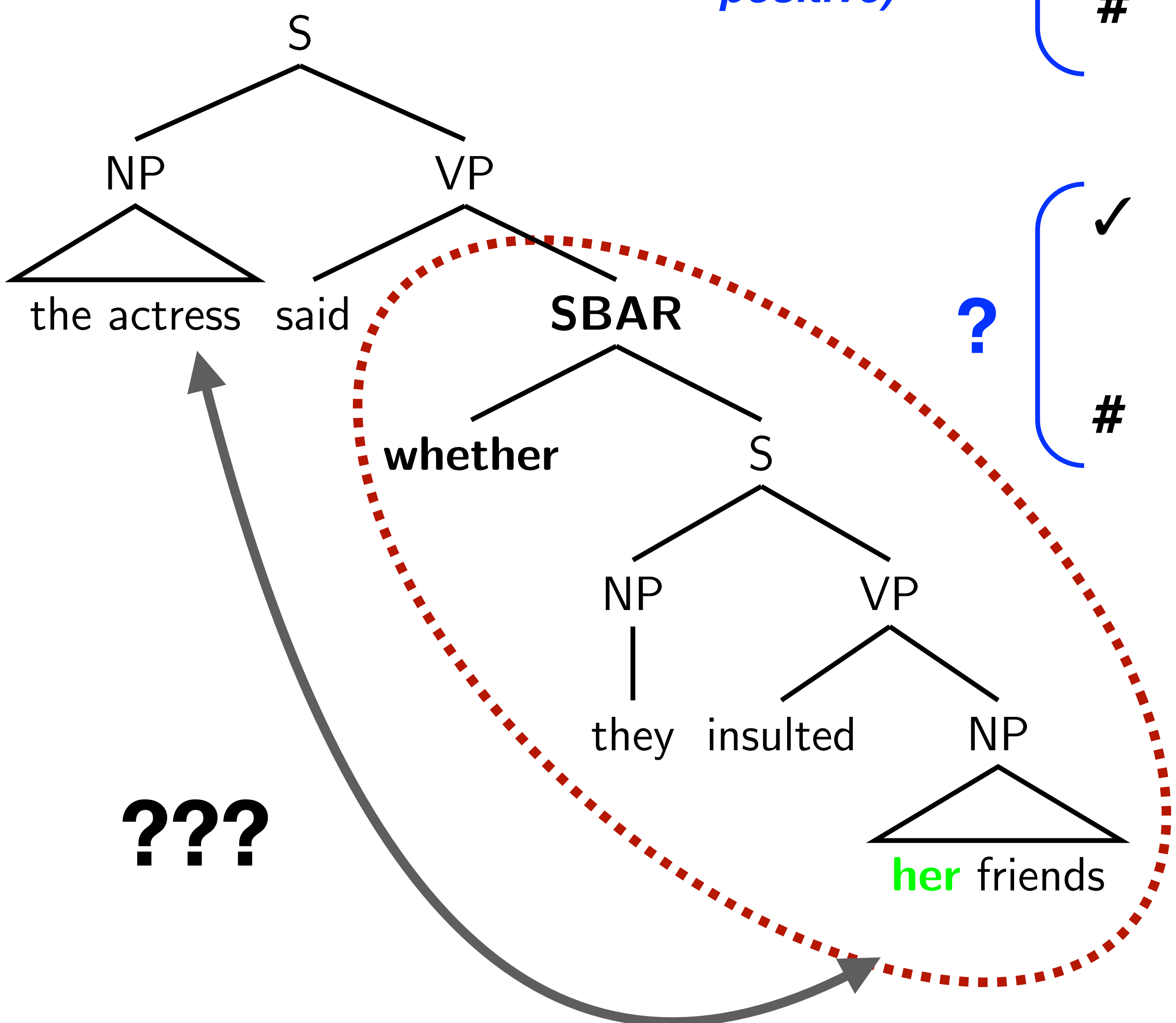

If models can thread gender expectation into islands, the gender expectation effect should **look the same in islands as in the control conditions.**

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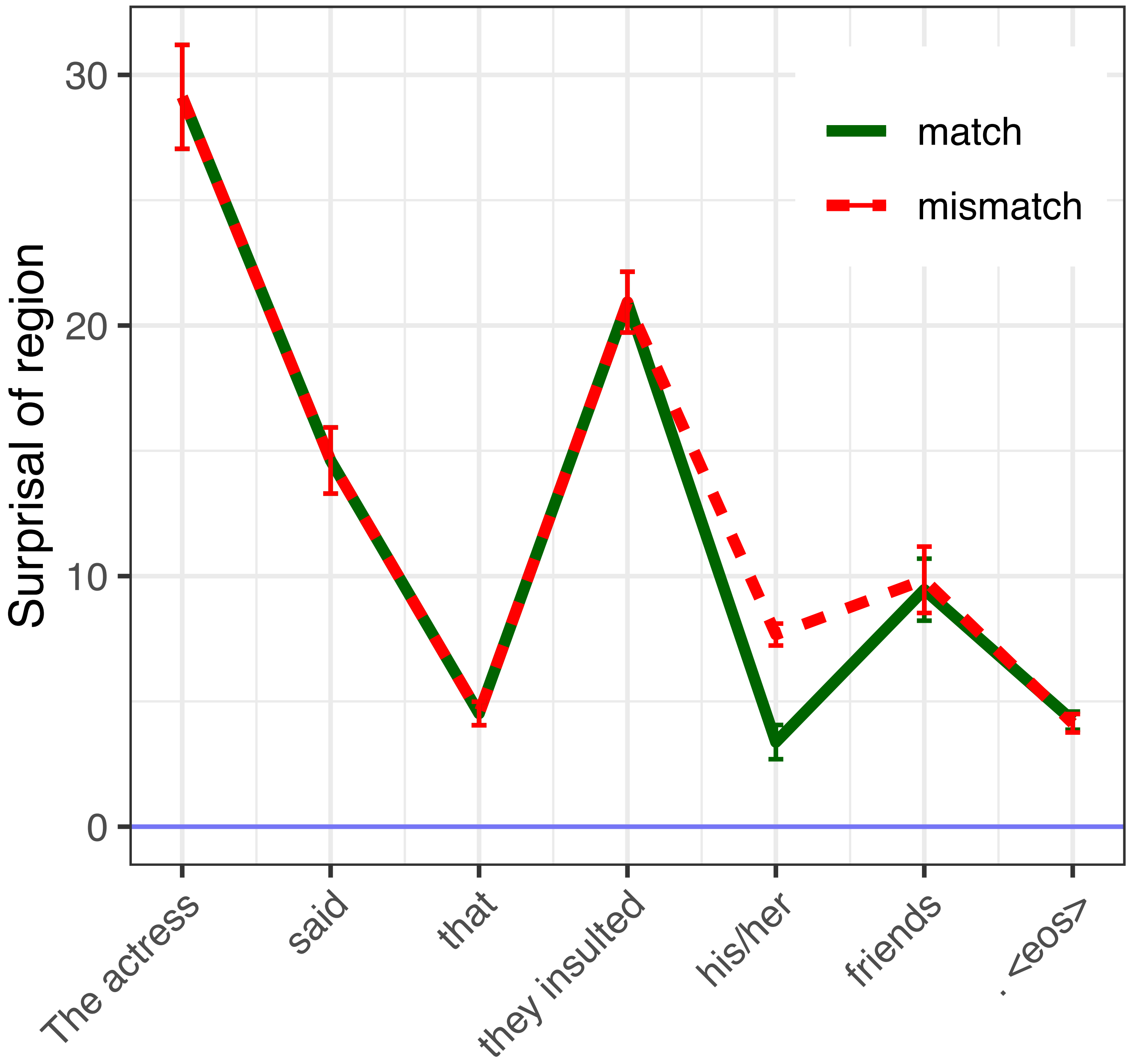

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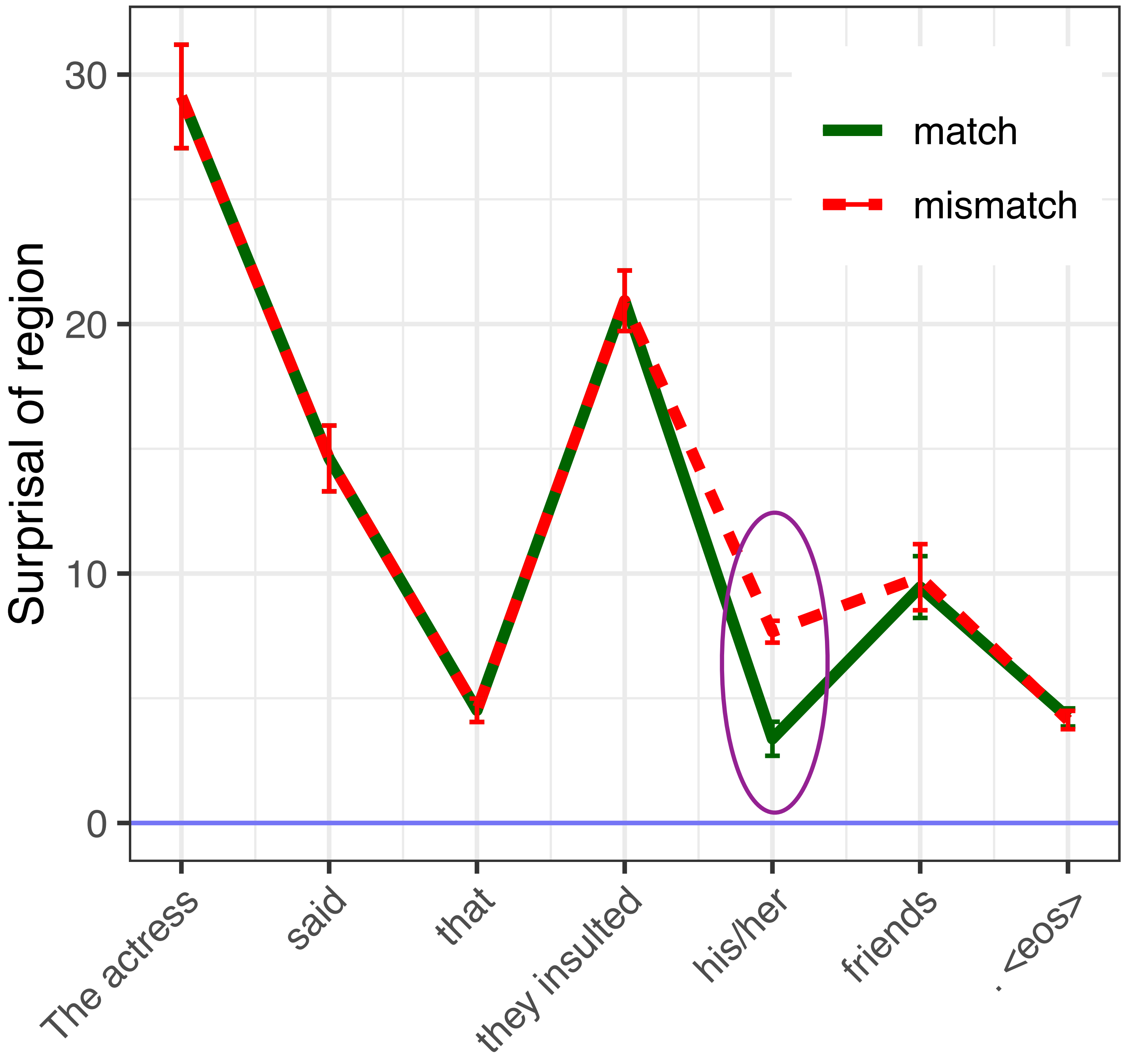

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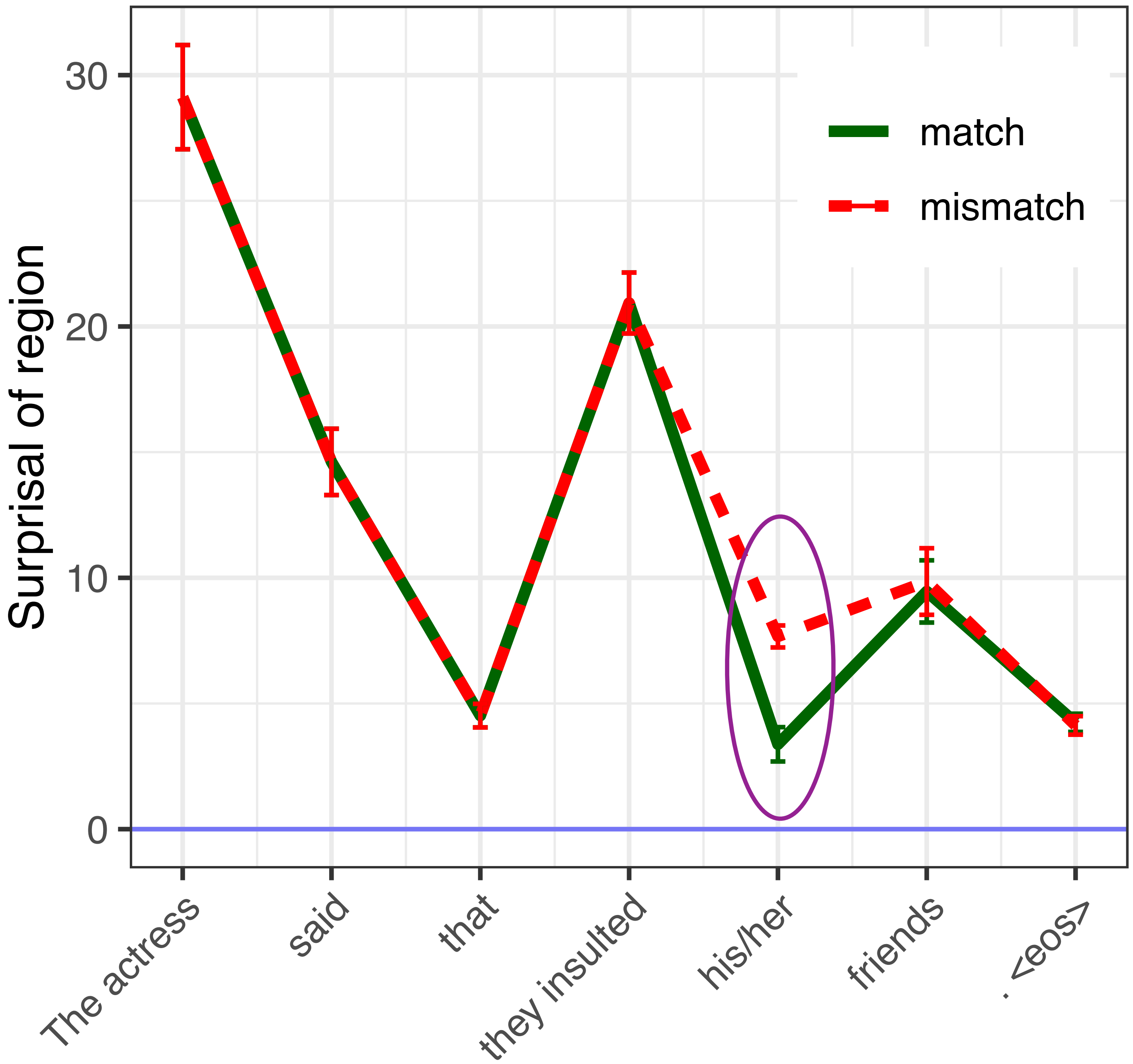

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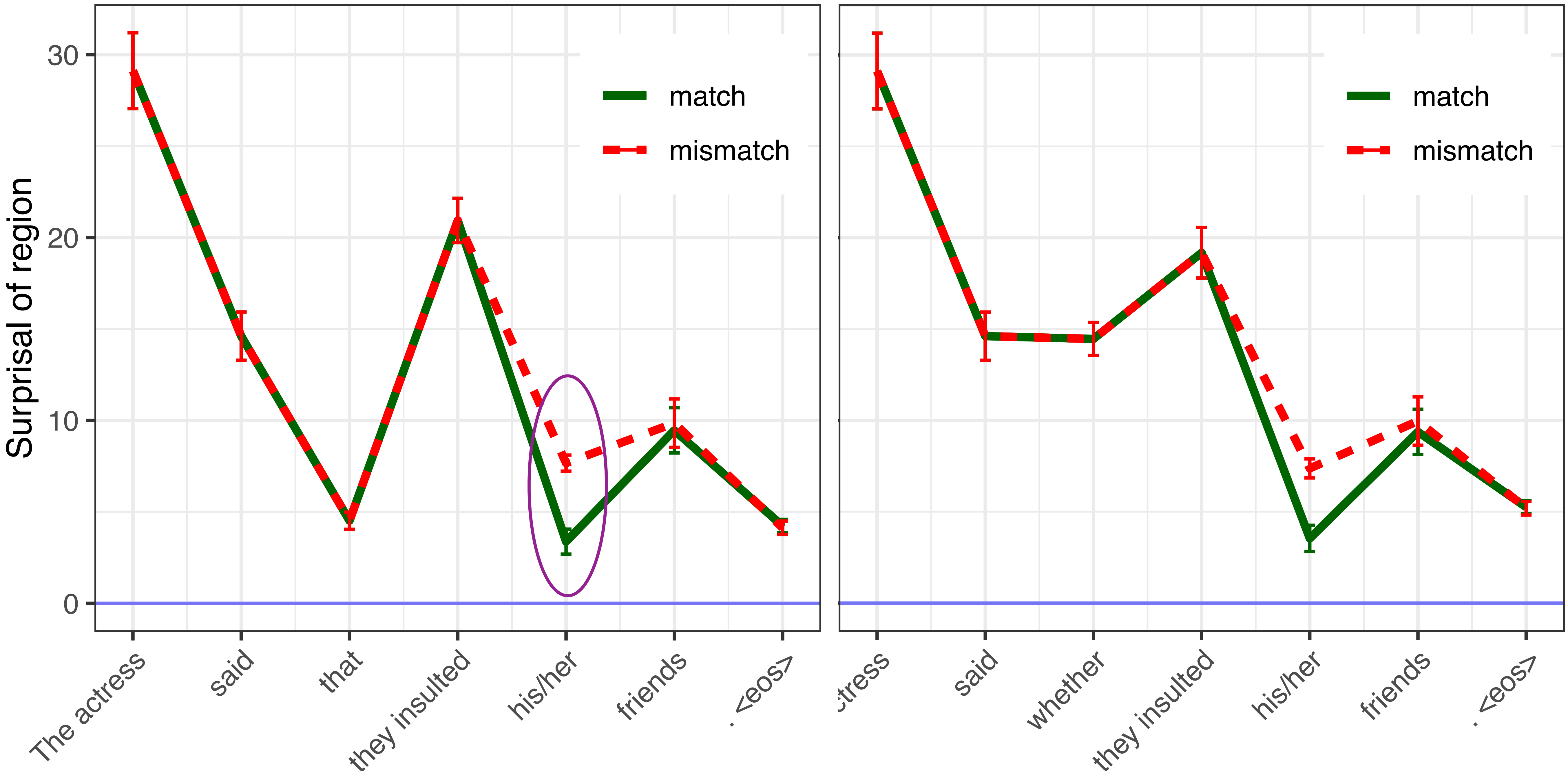

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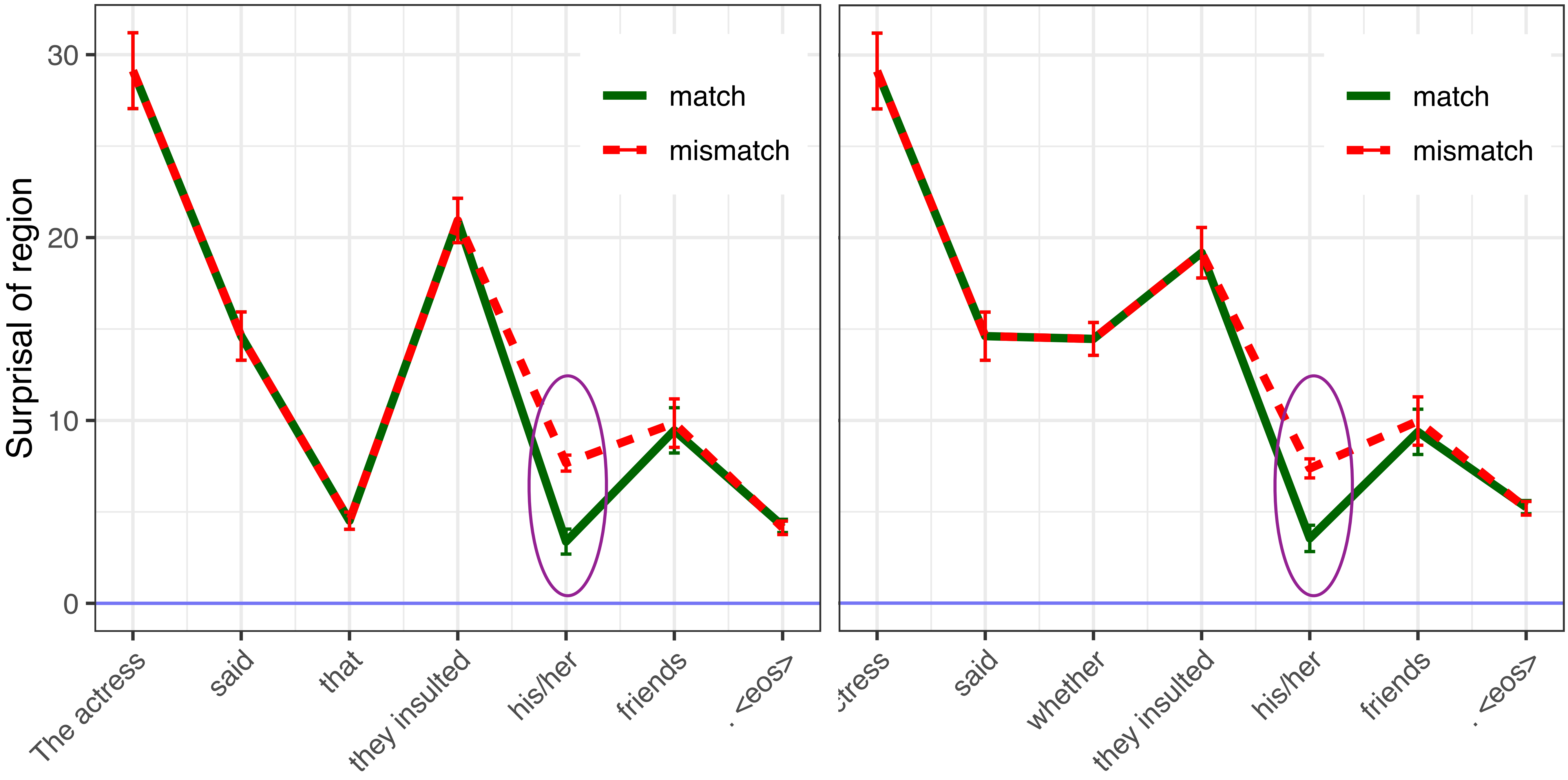

Potential concern #2

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Potential concern #2 — ***addressed***

~~Could RNNs have difficulty threading ***any*** type of expectation into a syntactic island?~~

RNN models that learn island constraints still propagate pronoun gender expectations into islands

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