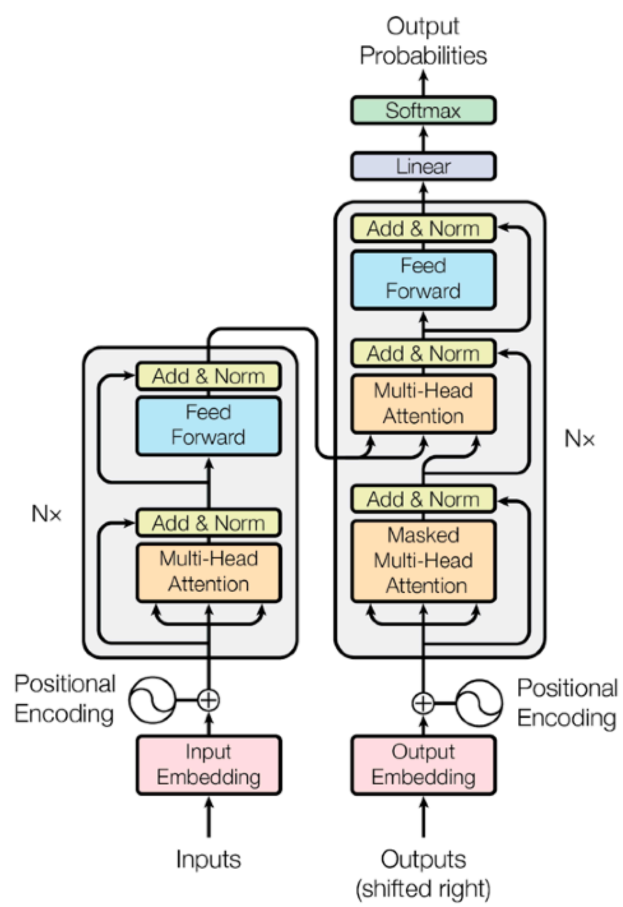
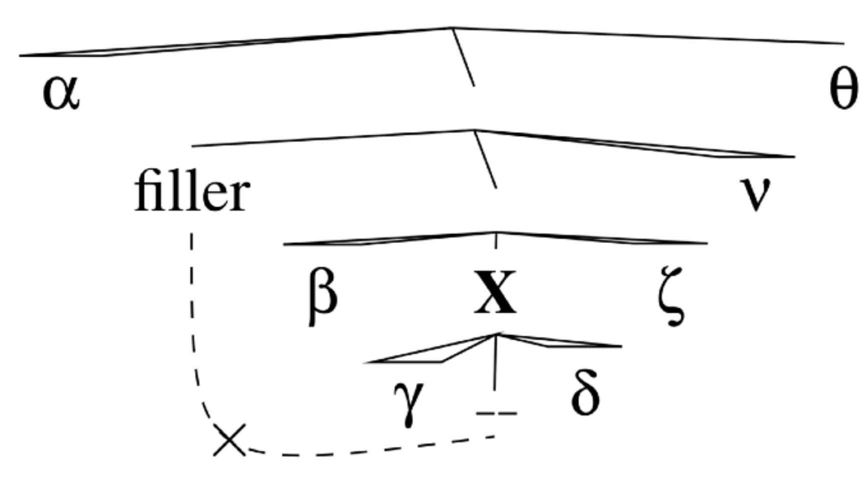
# Transformer language models, targeted syntactic evaluation, and learnability




*(Vaswani et al., 2017)*




*(Wilcox et al., 2019)*

Roger Levy

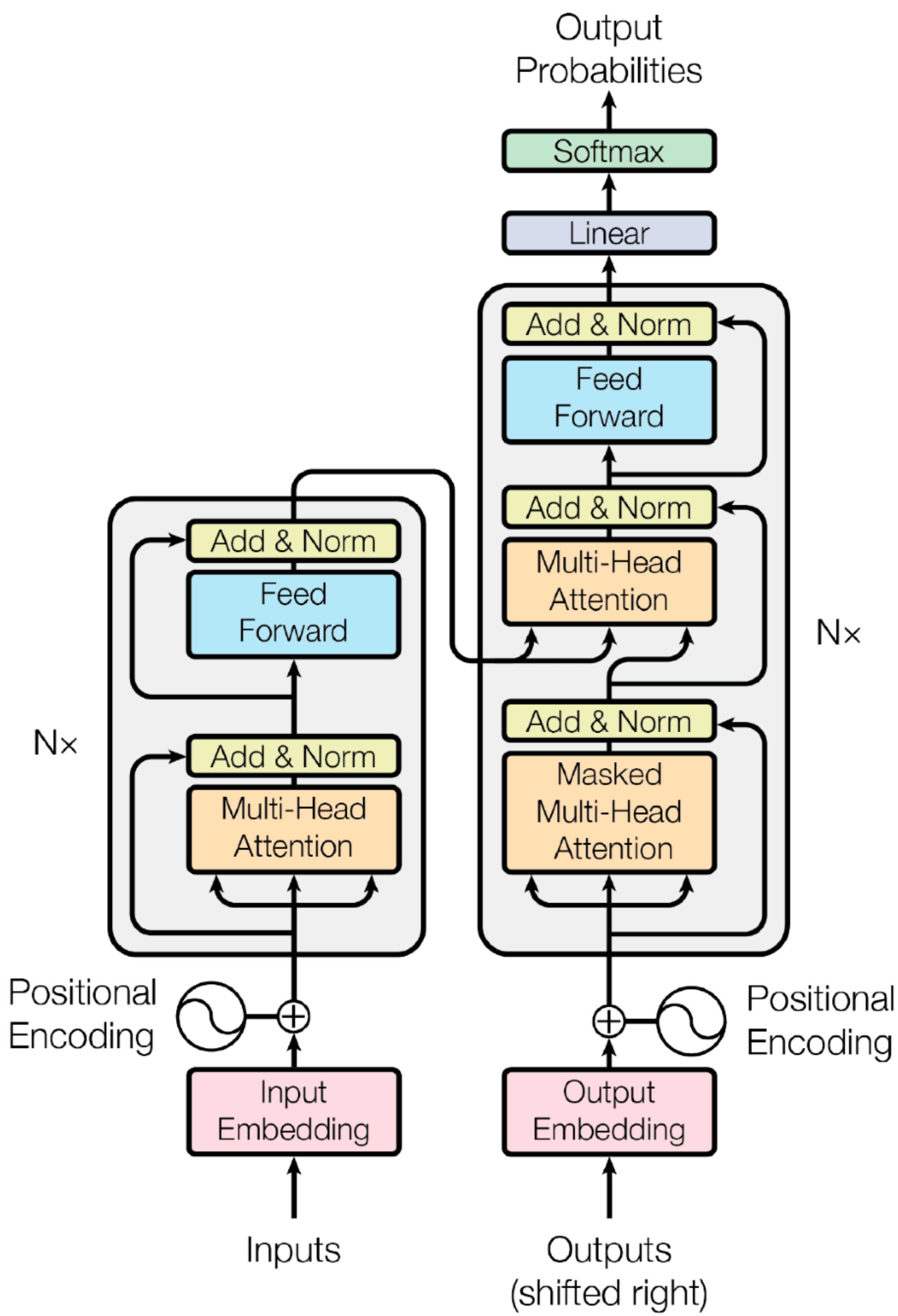
9.19: Computational Psycholinguistics

15 November 2021

# Agenda for today

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

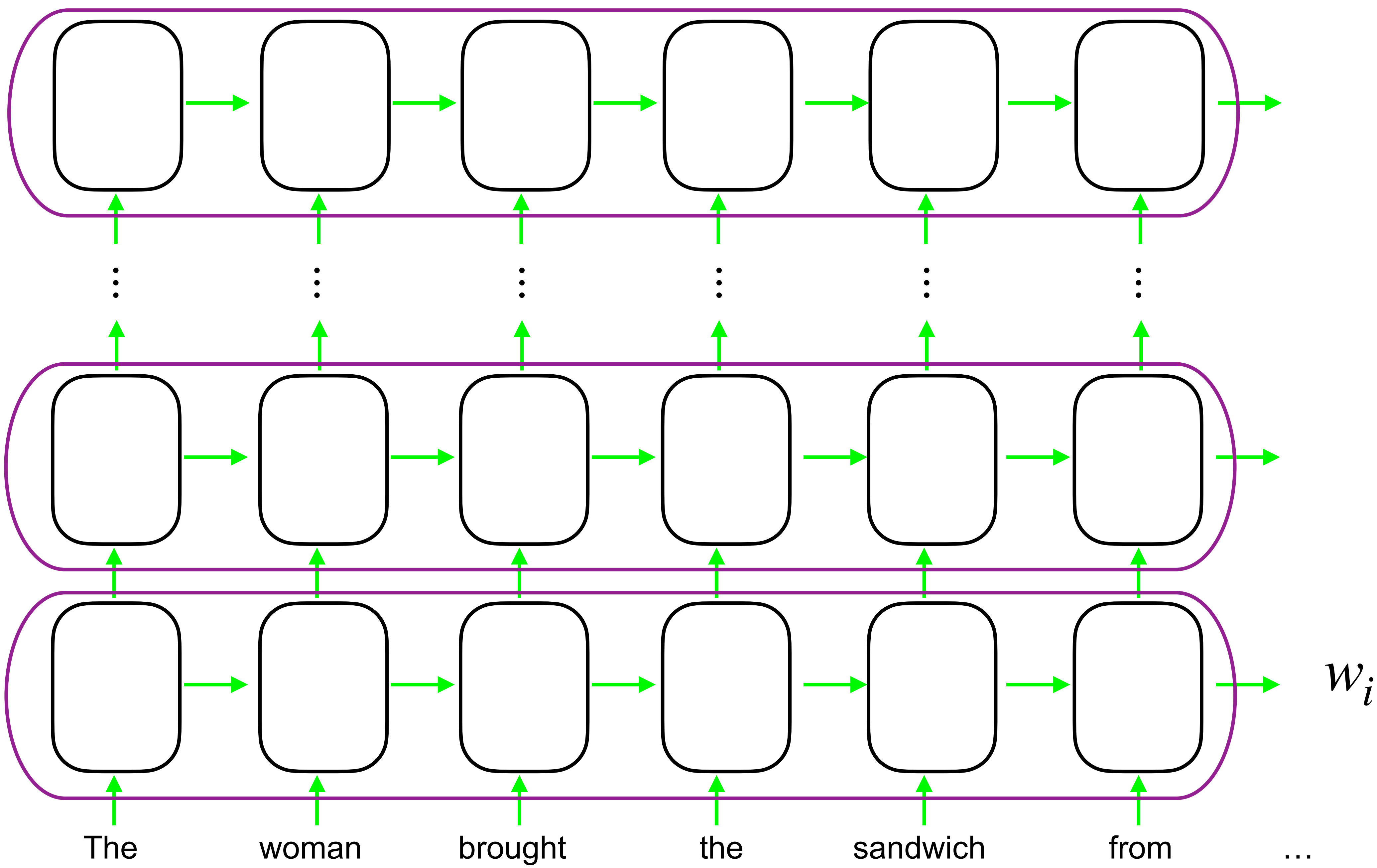
# The Transformer model




*(Vaswani et al., 2017)*

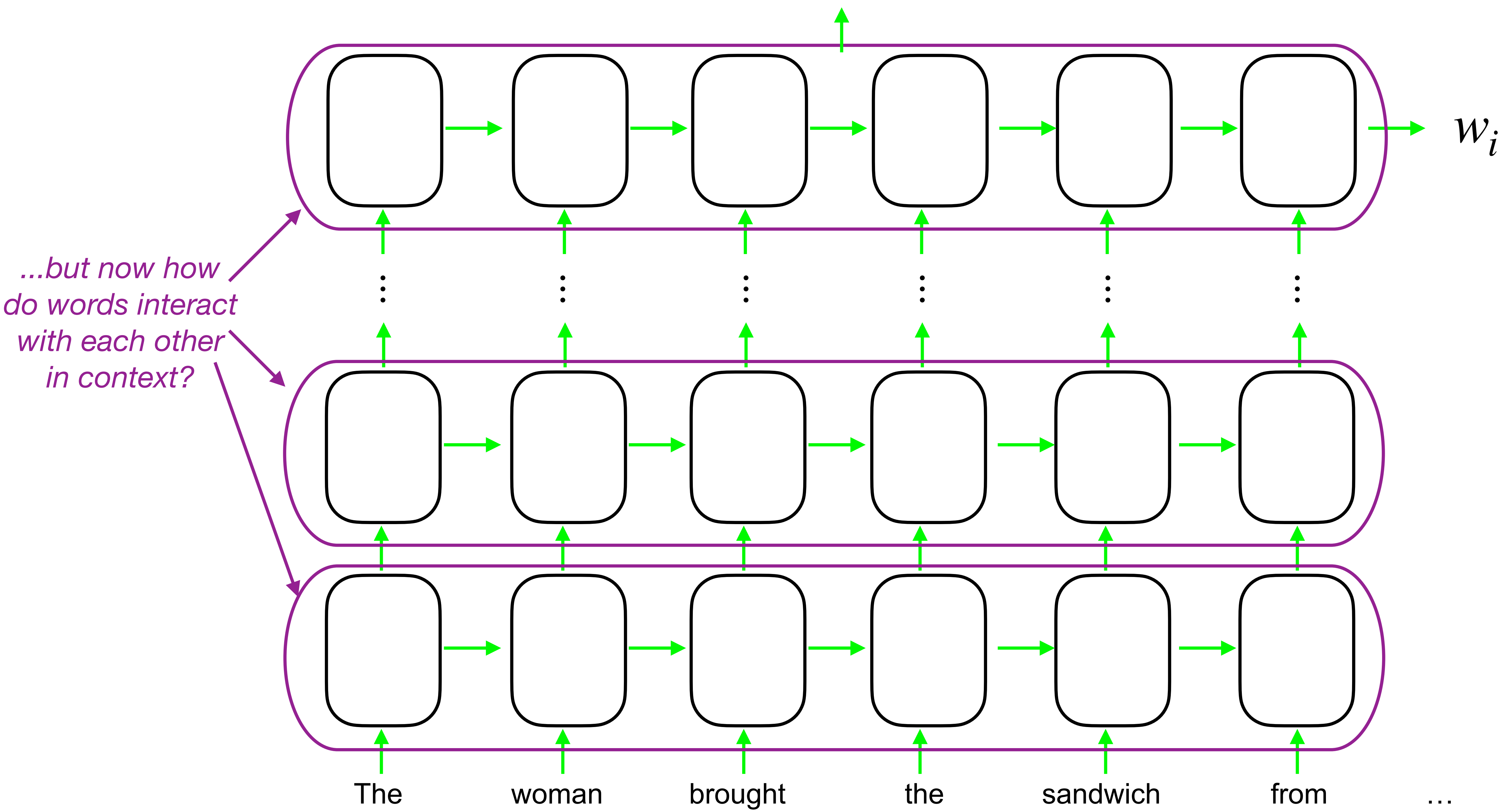
# Motivating the Transformer model

- With RNNs, a fixed-dimension model could propagate information indefinitely into the future...but it's hard!
- We can make RNNs ***deep*** by stacking them...

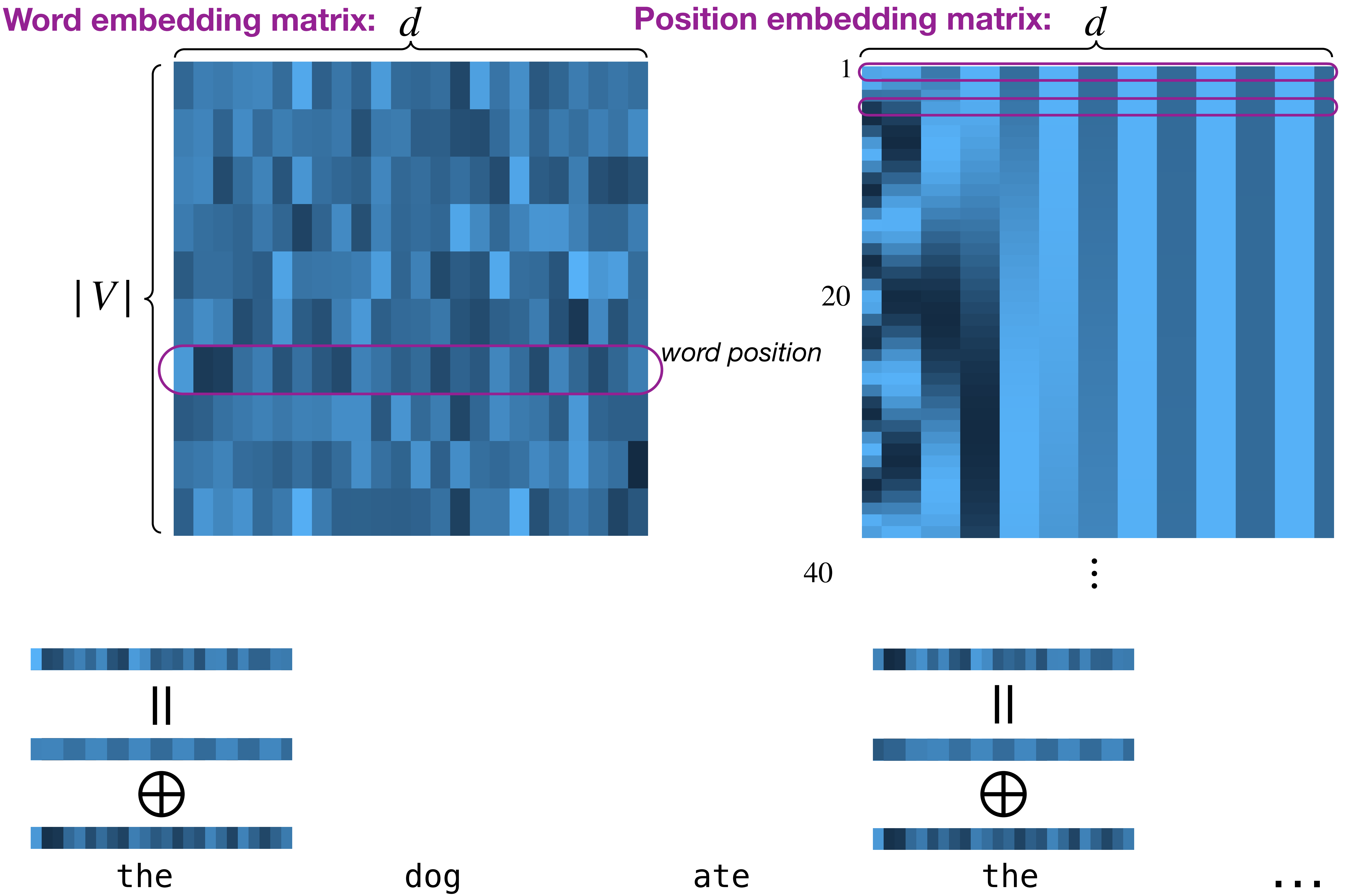


# Motivating the Transformer model

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

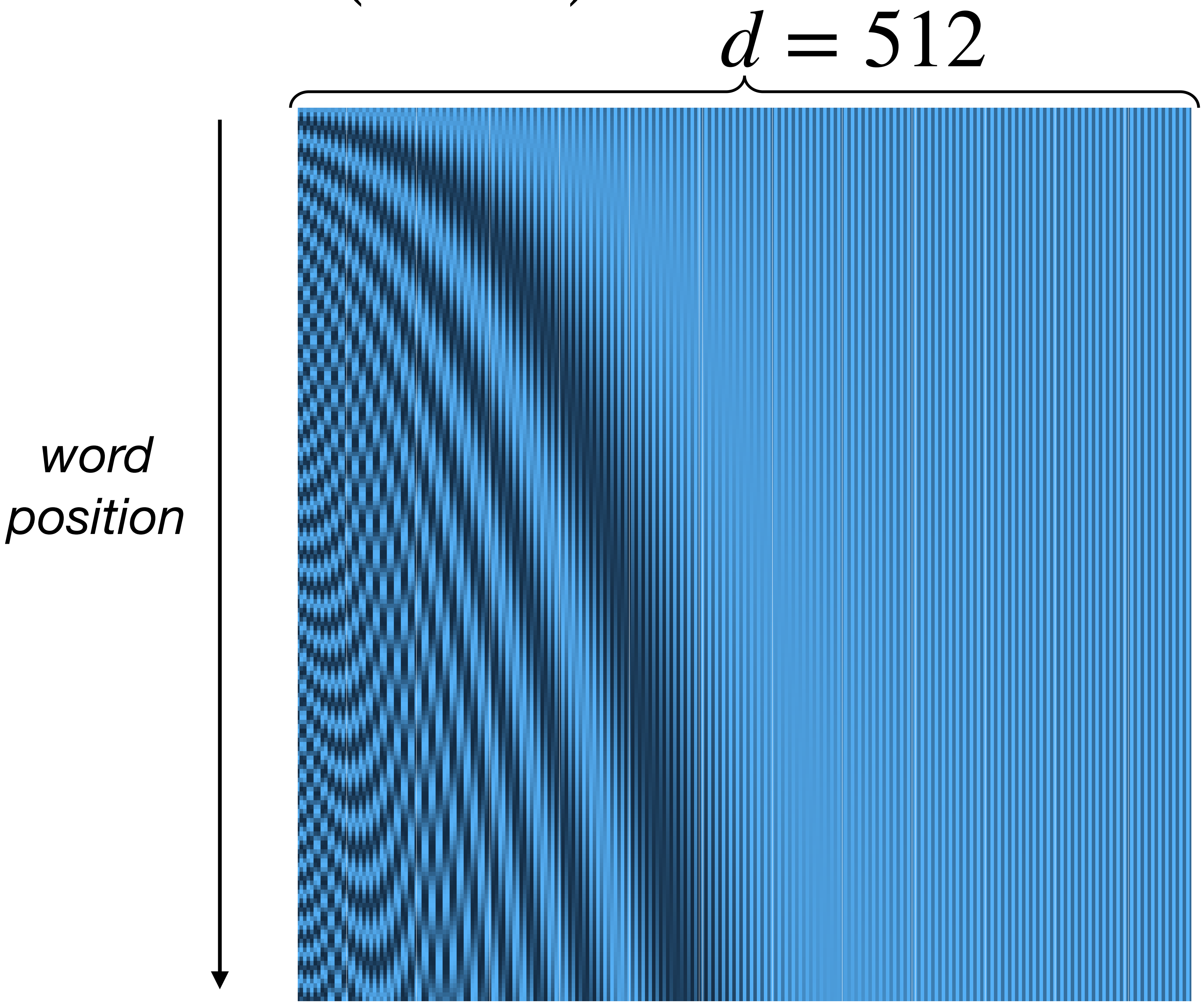


# Input + Positional Embedding

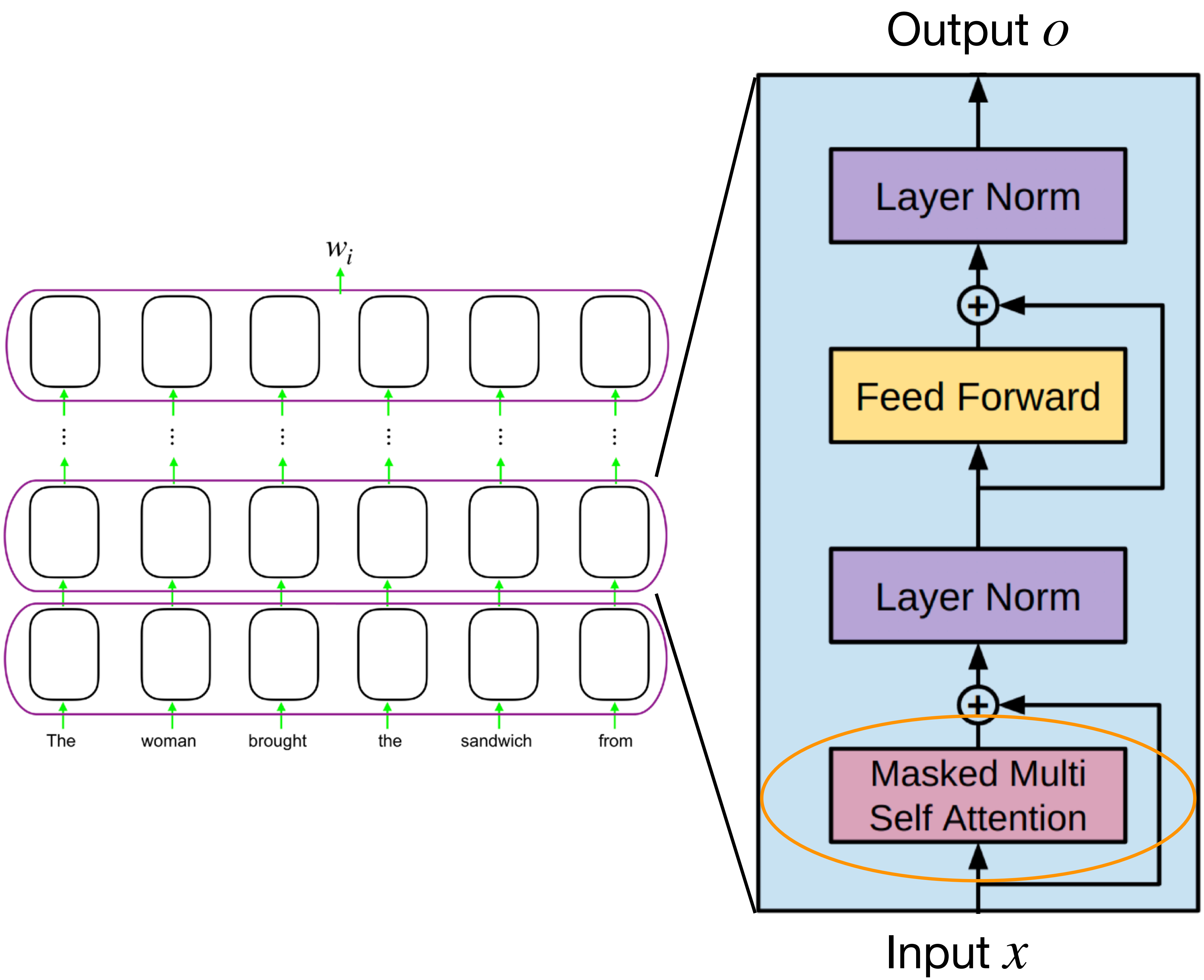


# The positional embedding function

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



# The Transformer unit



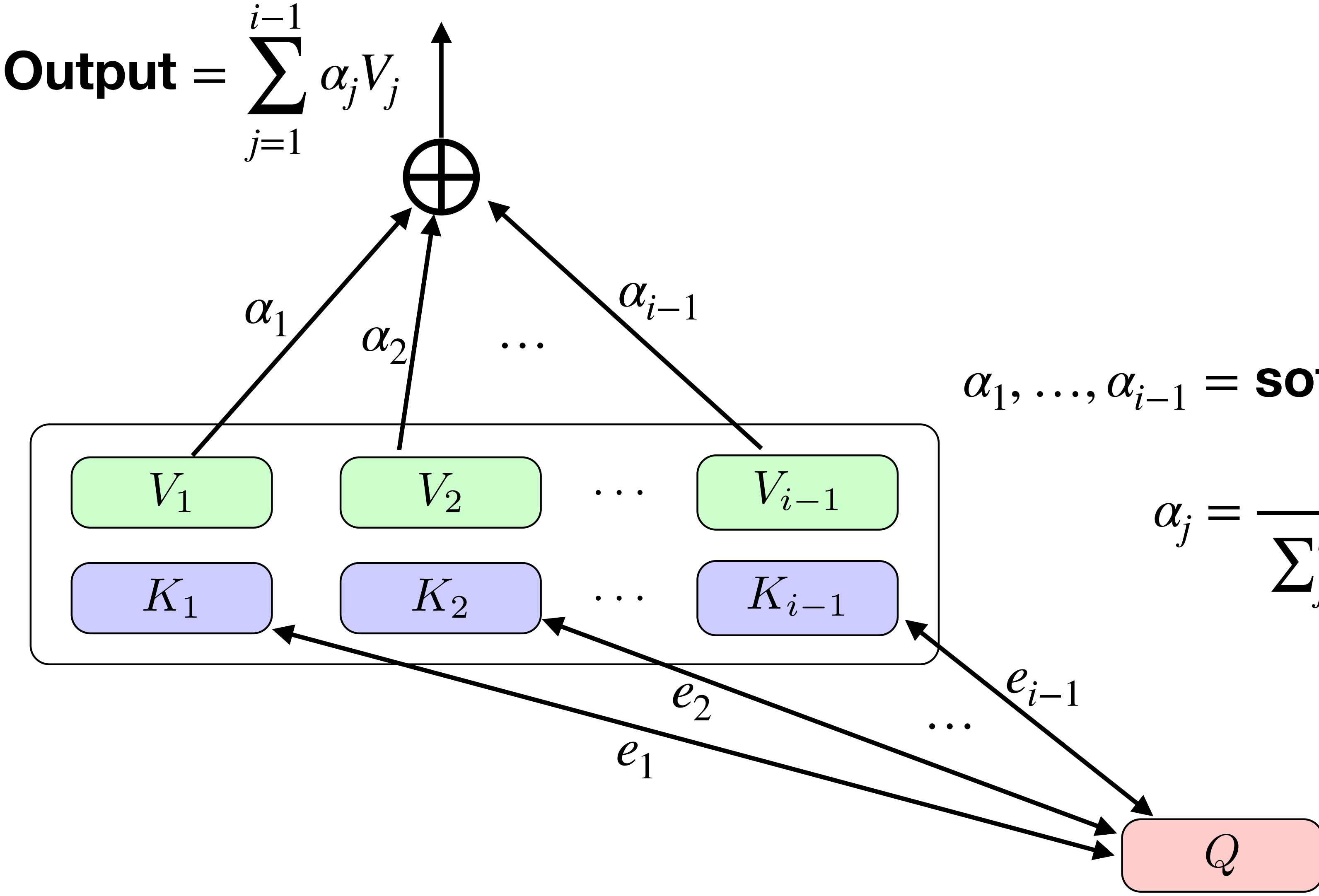

(Figure from Radford et al., 2018)

(Vaswani et al., 2017)

# Neural Attention

*Query, Key, and Value*

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

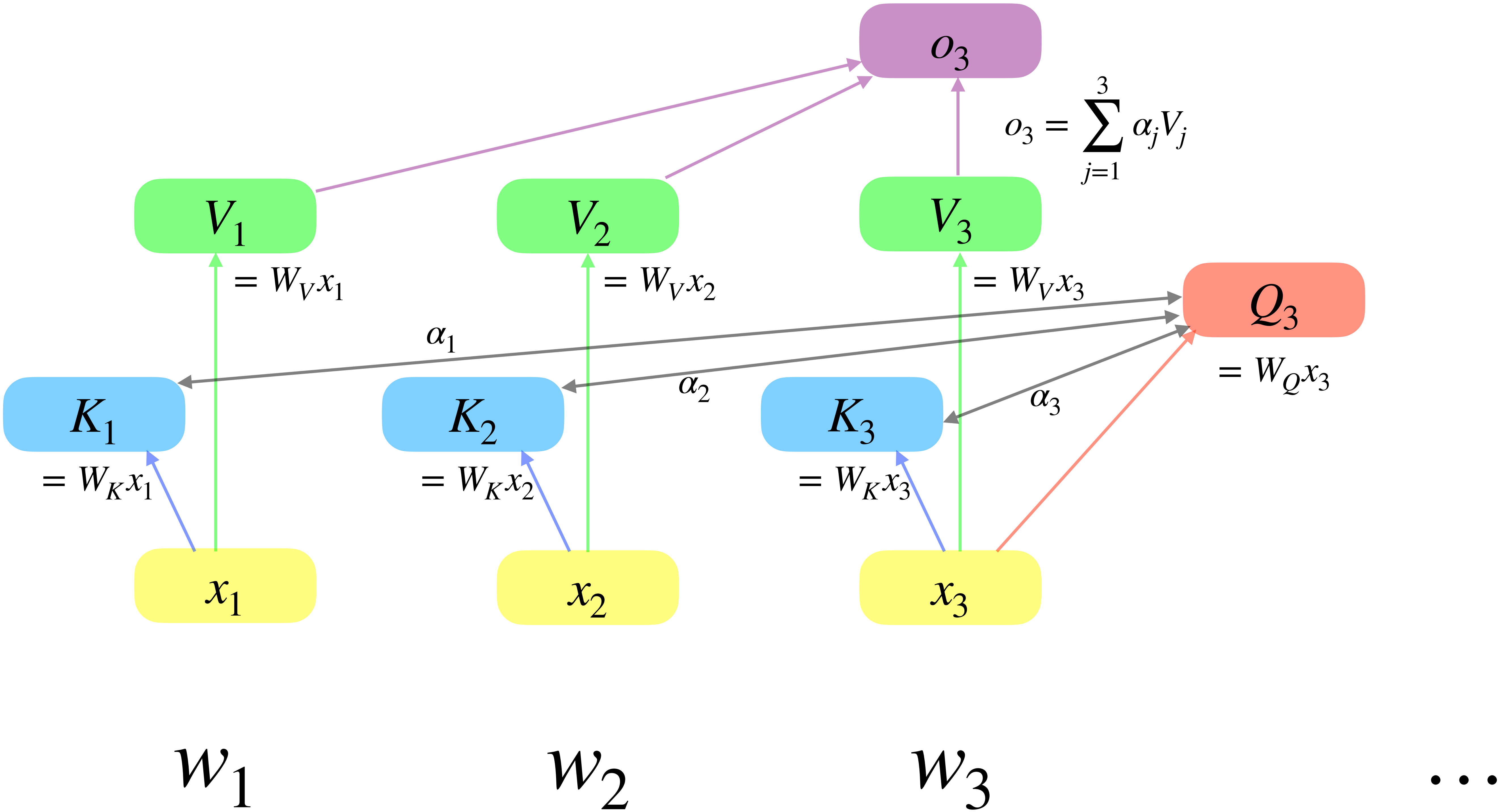



$$\alpha_1, \ldots, \alpha_{i-1} = \textbf{softmax}(e_1, \ldots, e_{i-1})$$

$$\alpha_j = \frac{e^{e_j}}{\sum_{j'=1}^{i-1} e^{e_j'}}$$

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

# A single masked attention "head"

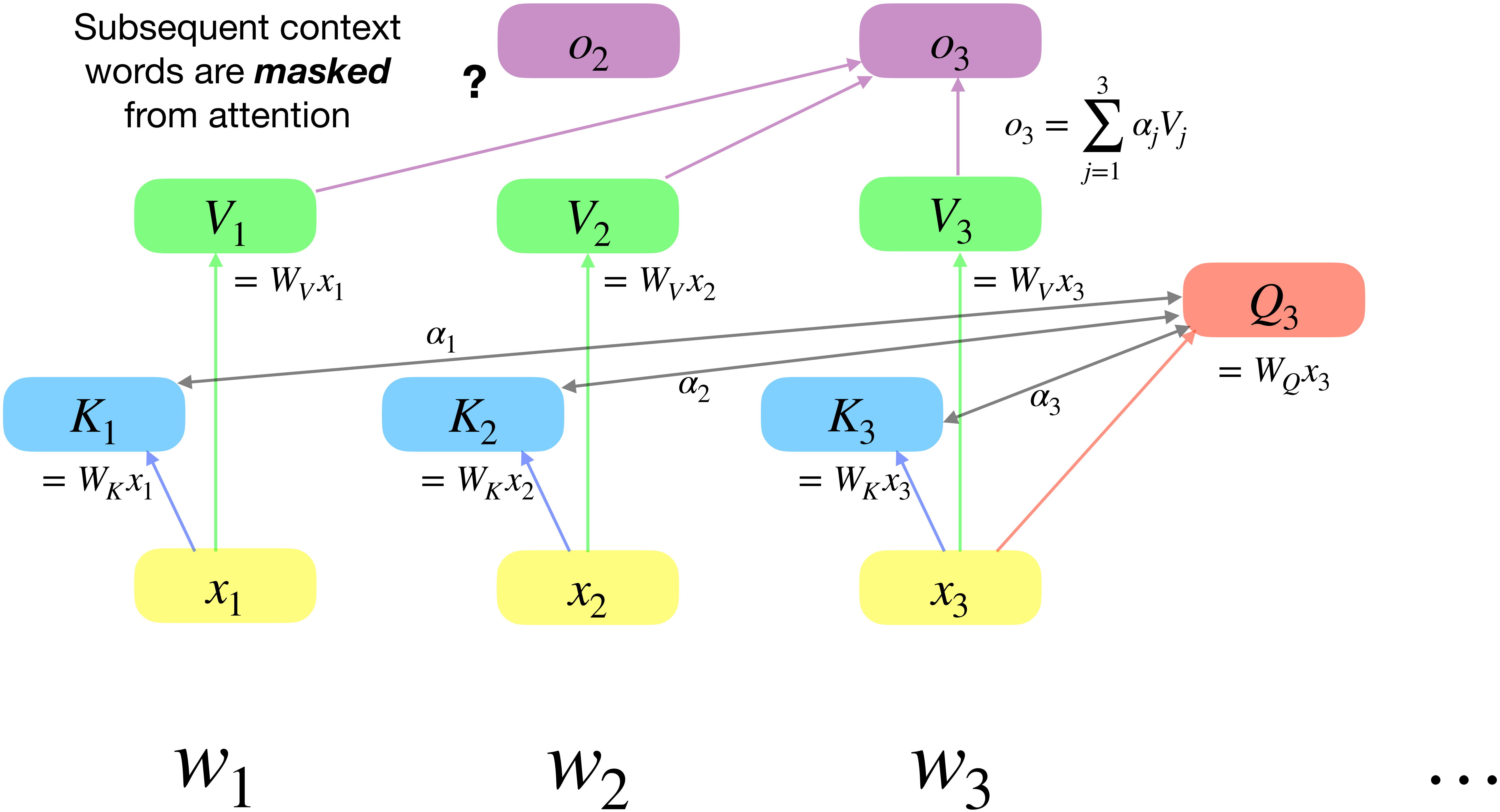



$W_K$, $W_V$, and $W_Q$ are all learned during training

*(Vaswani et al., 2017)*

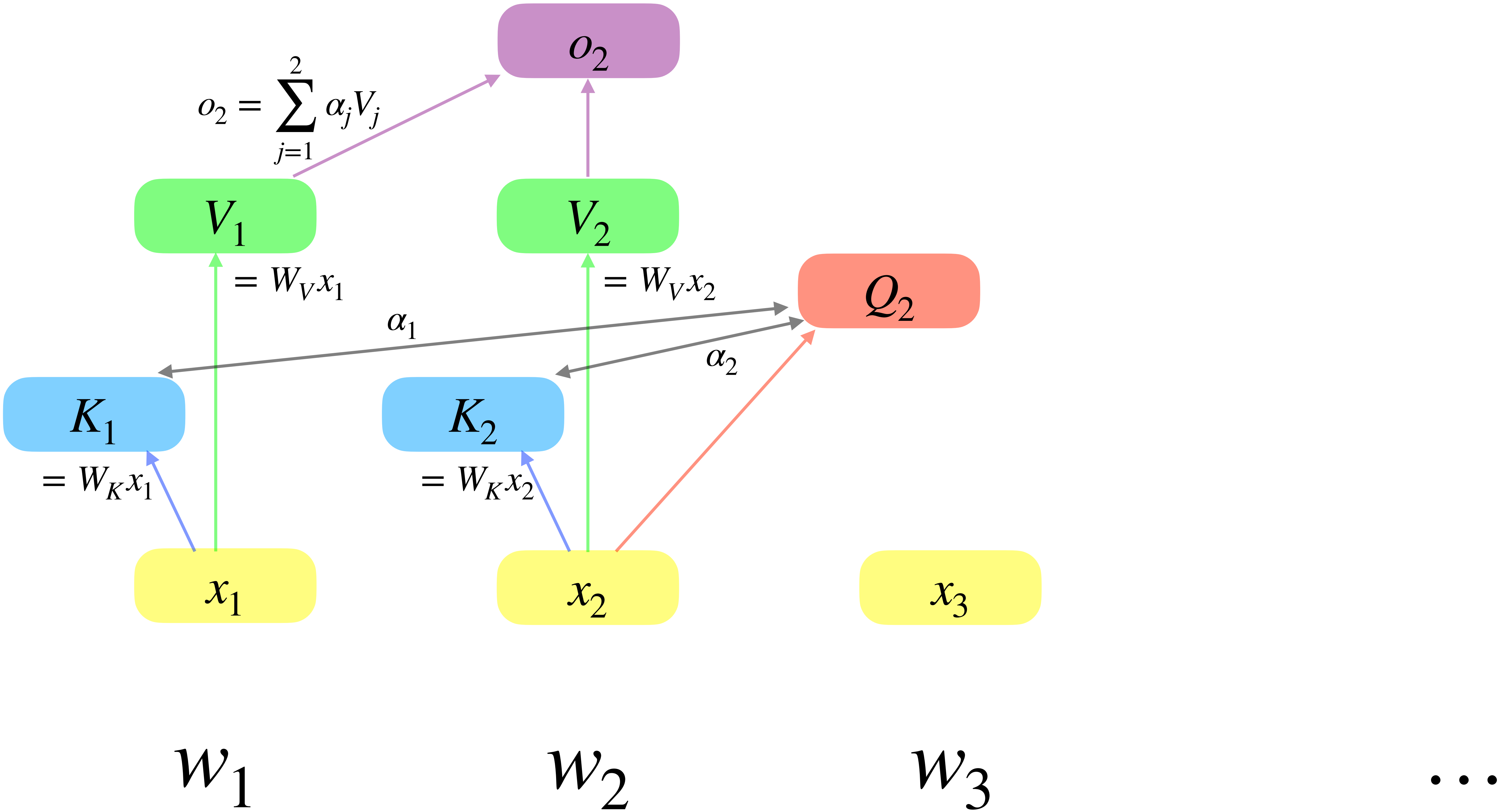
# A single masked attention "head"

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




*(Vaswani et al., 2017)*

# A single masked attention "head"

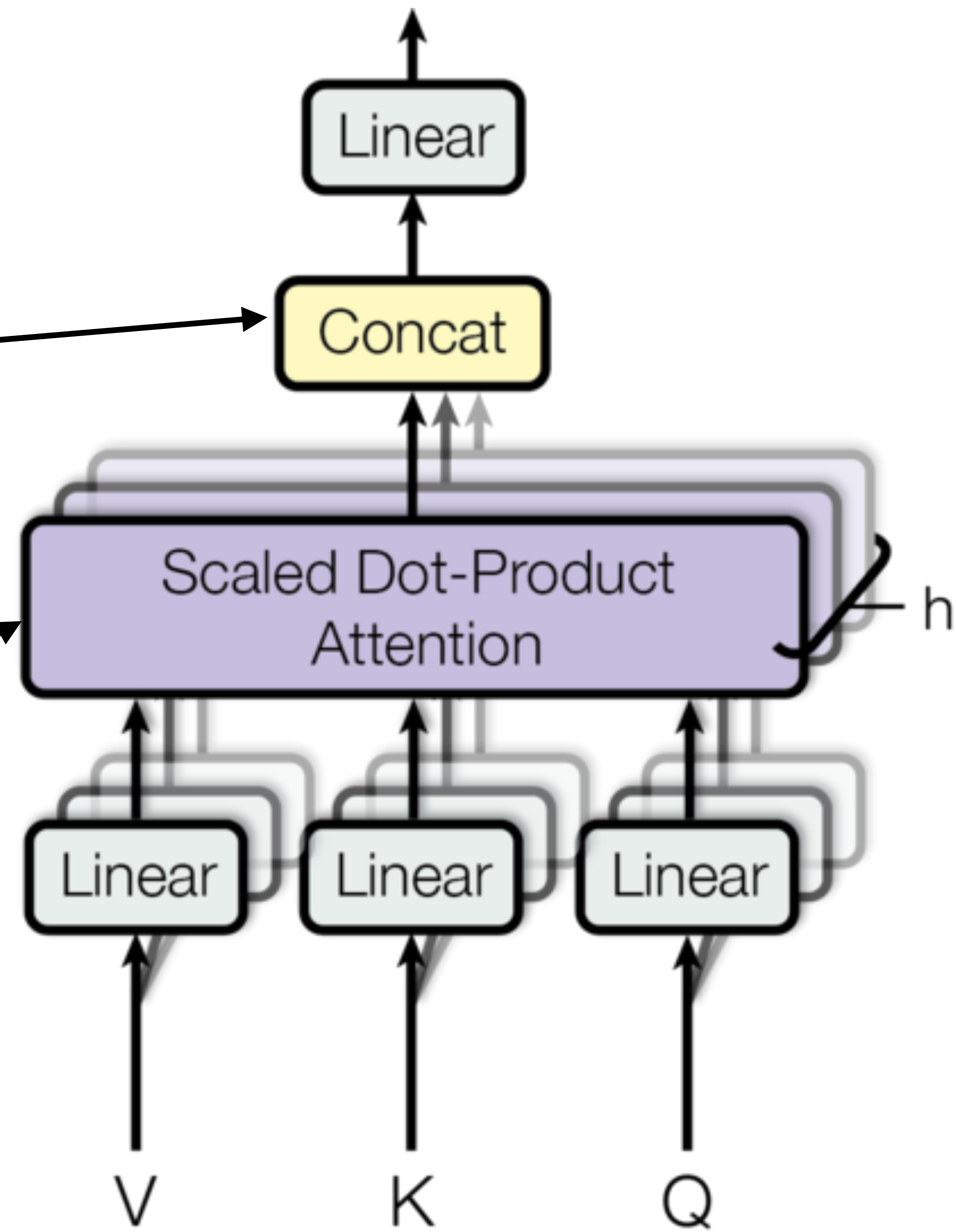



*(Vaswani et al., 2017)*

# Multi-headed attention

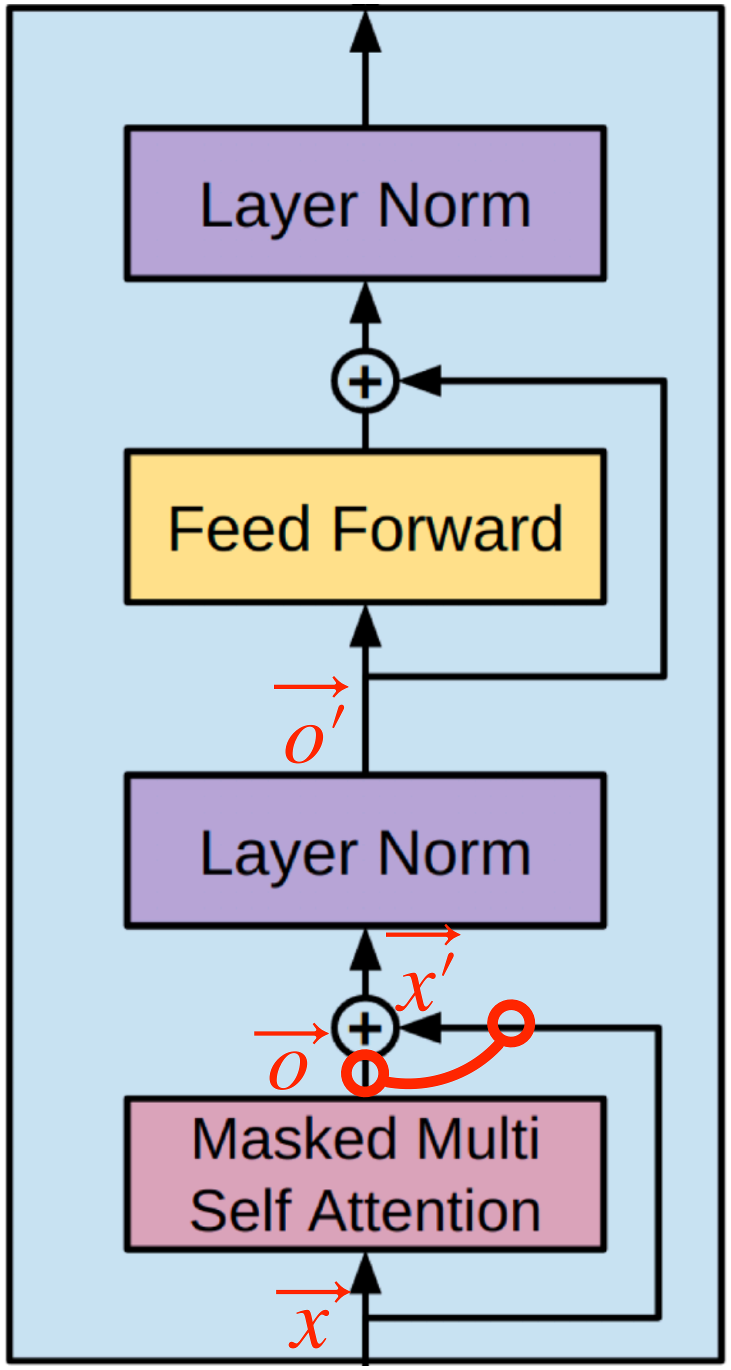
The $h$ output vectors are concatenated and then linearly transformed with learned matrix $W_O$

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




*(image from Vaswani et al., 2017)*

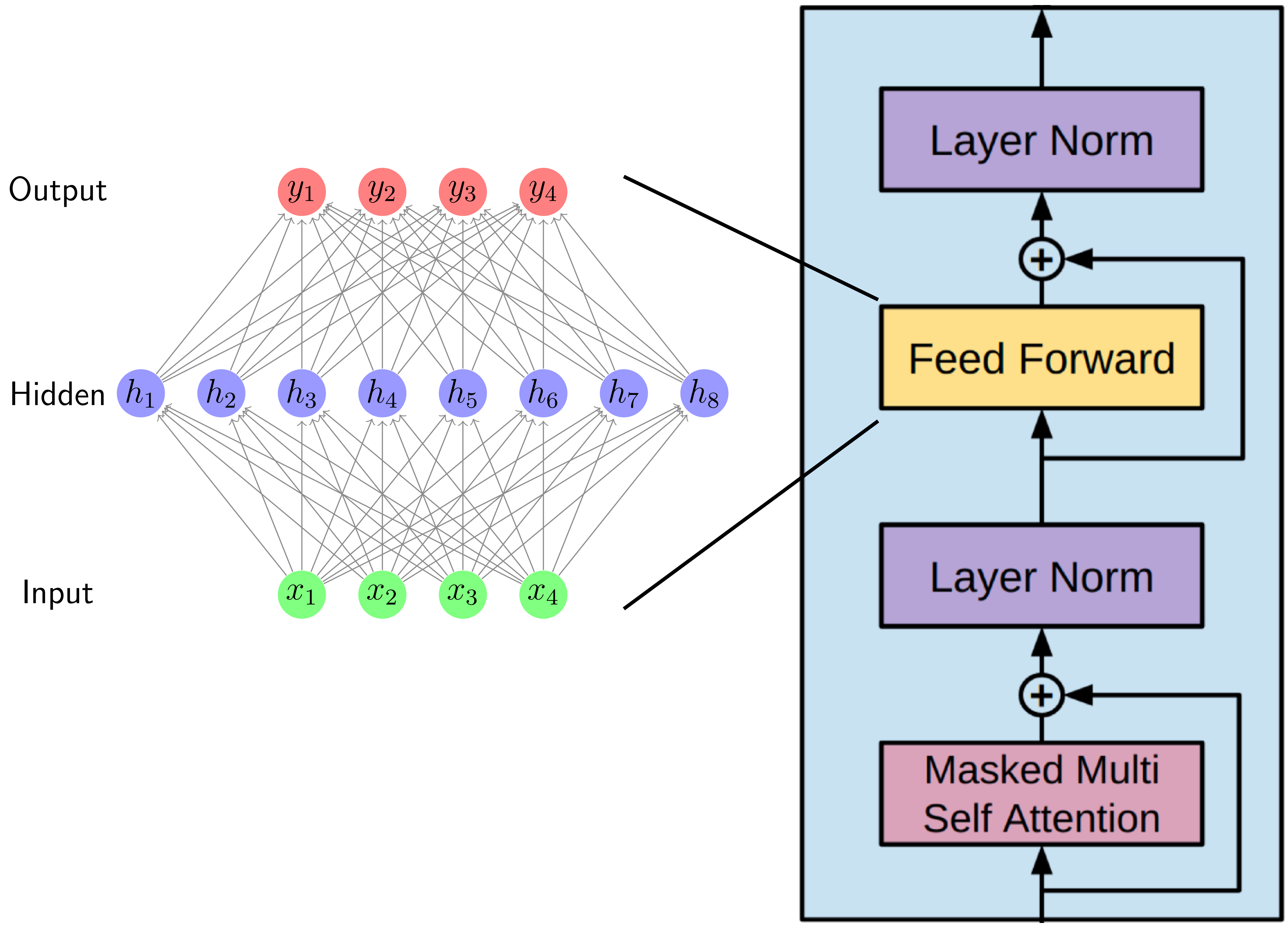
# Residual connection & layer normalization



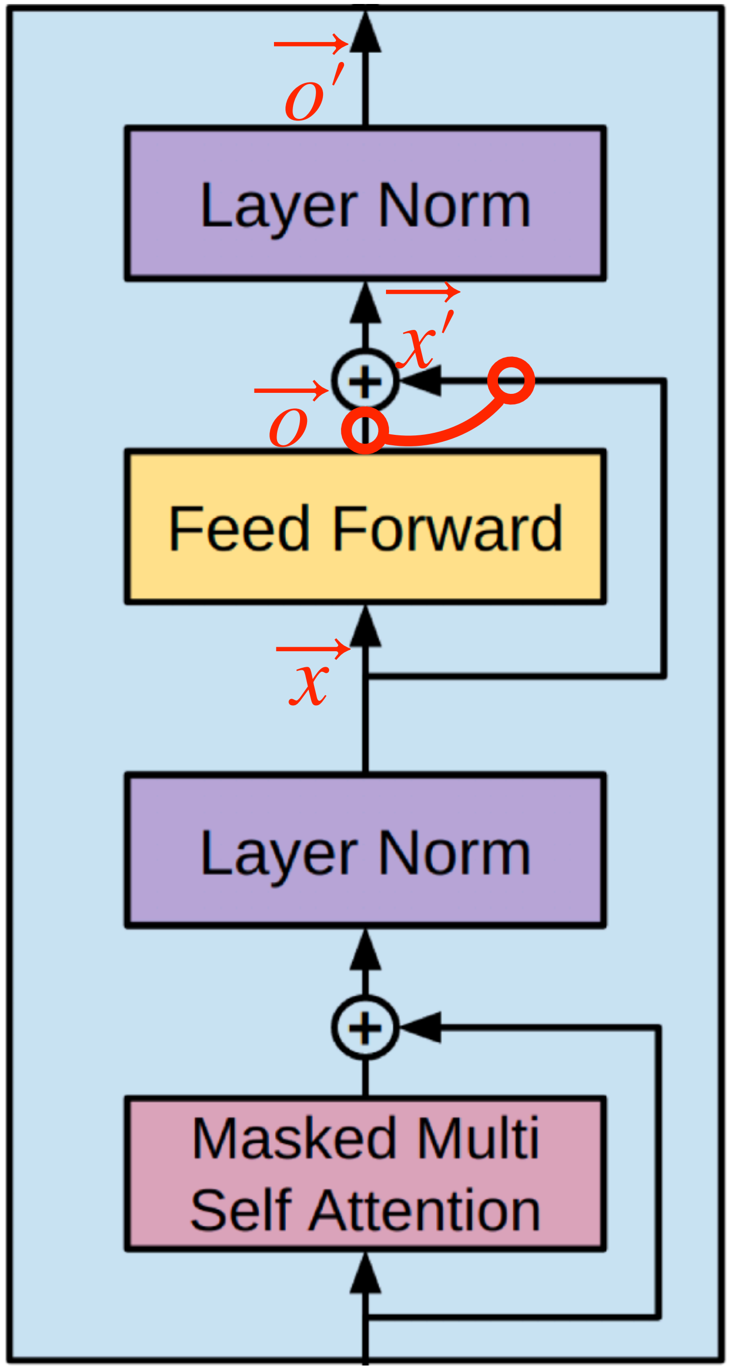

$$\vec{o}' = \frac{\vec{x}' - \textbf{Mean}(\vec{x}')}{\textbf{StdDev}(\vec{x}')}$$

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

# Feed-forward layer



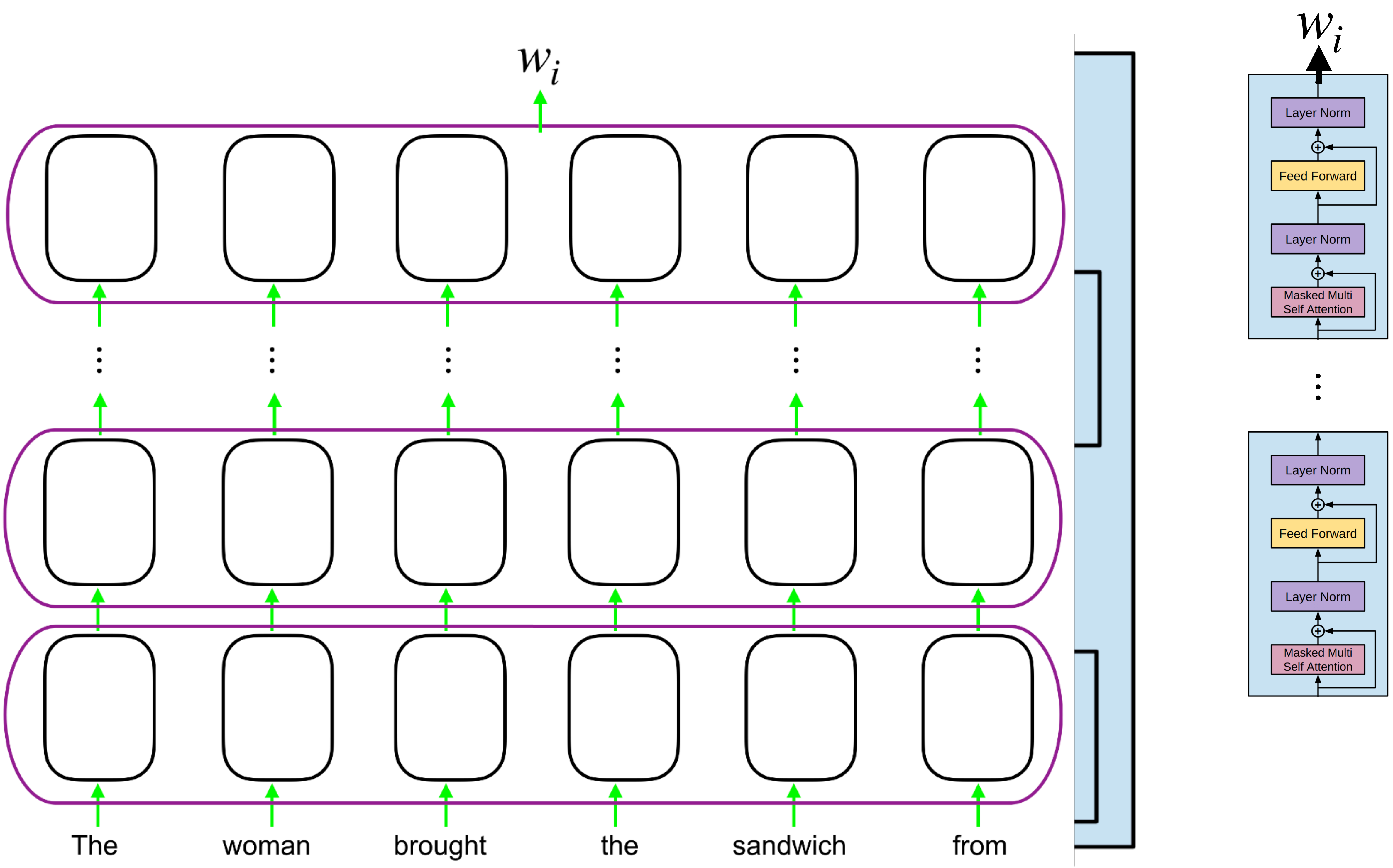
# Res. connection & layer norm. (again)




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

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

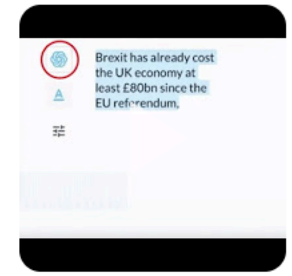
# Res. connection & layer norm. (again)



# Transformer + a huge corpus = ...?

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

The Guardian



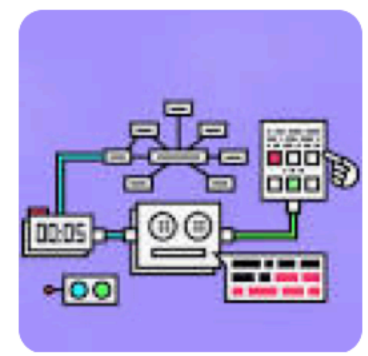

- **OpenAI text-generating tool GPT2 won't be released for fear of misuse**
  Business Insider

View Full Coverage

Feb 14, 2019

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

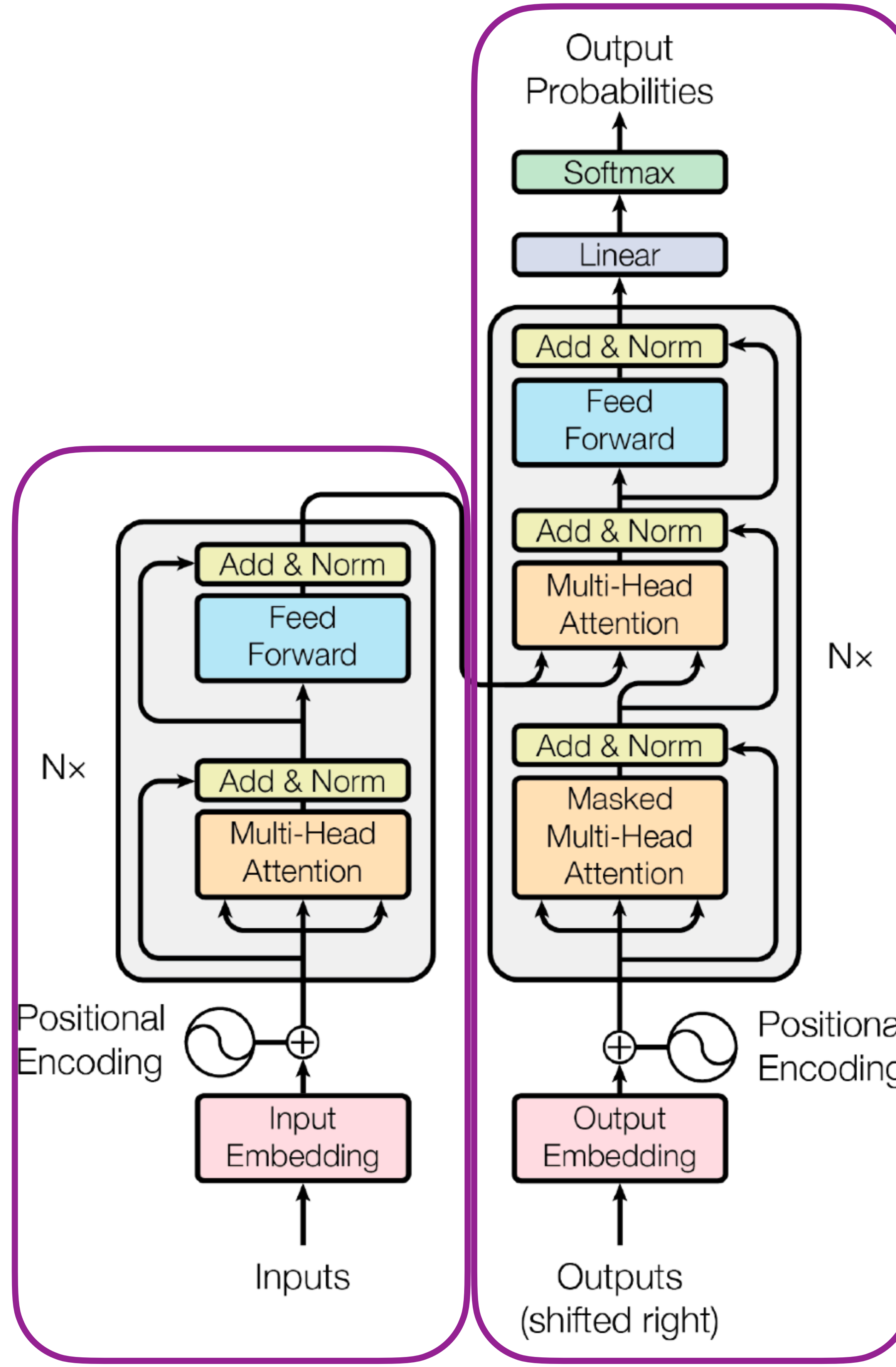
# The full Transformer model

- 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

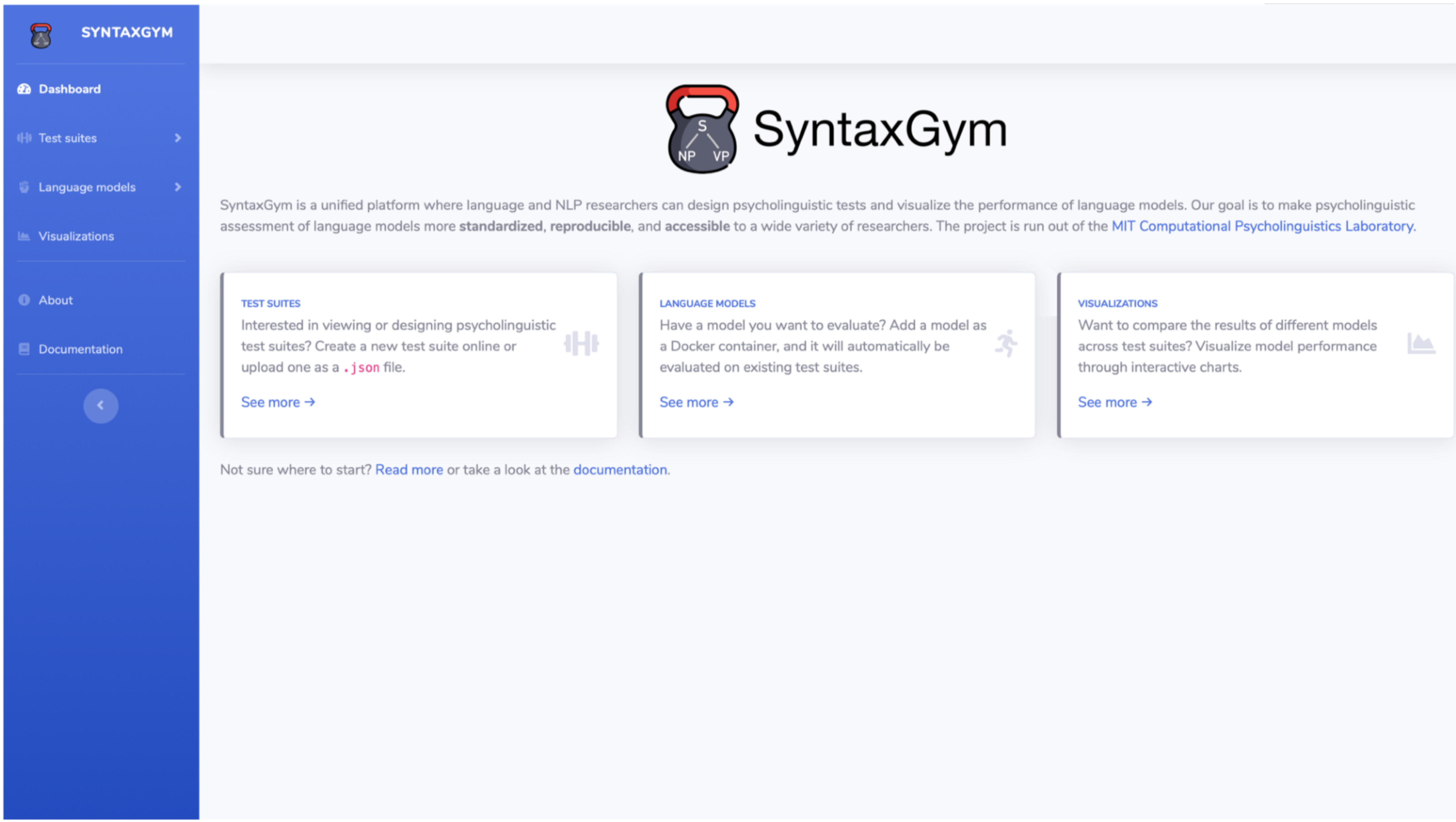
(Devlin et al., 2018)




(Vaswani et al., 2017)

# GPT-2 on targeted syntax testing

syntaxgym.org




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

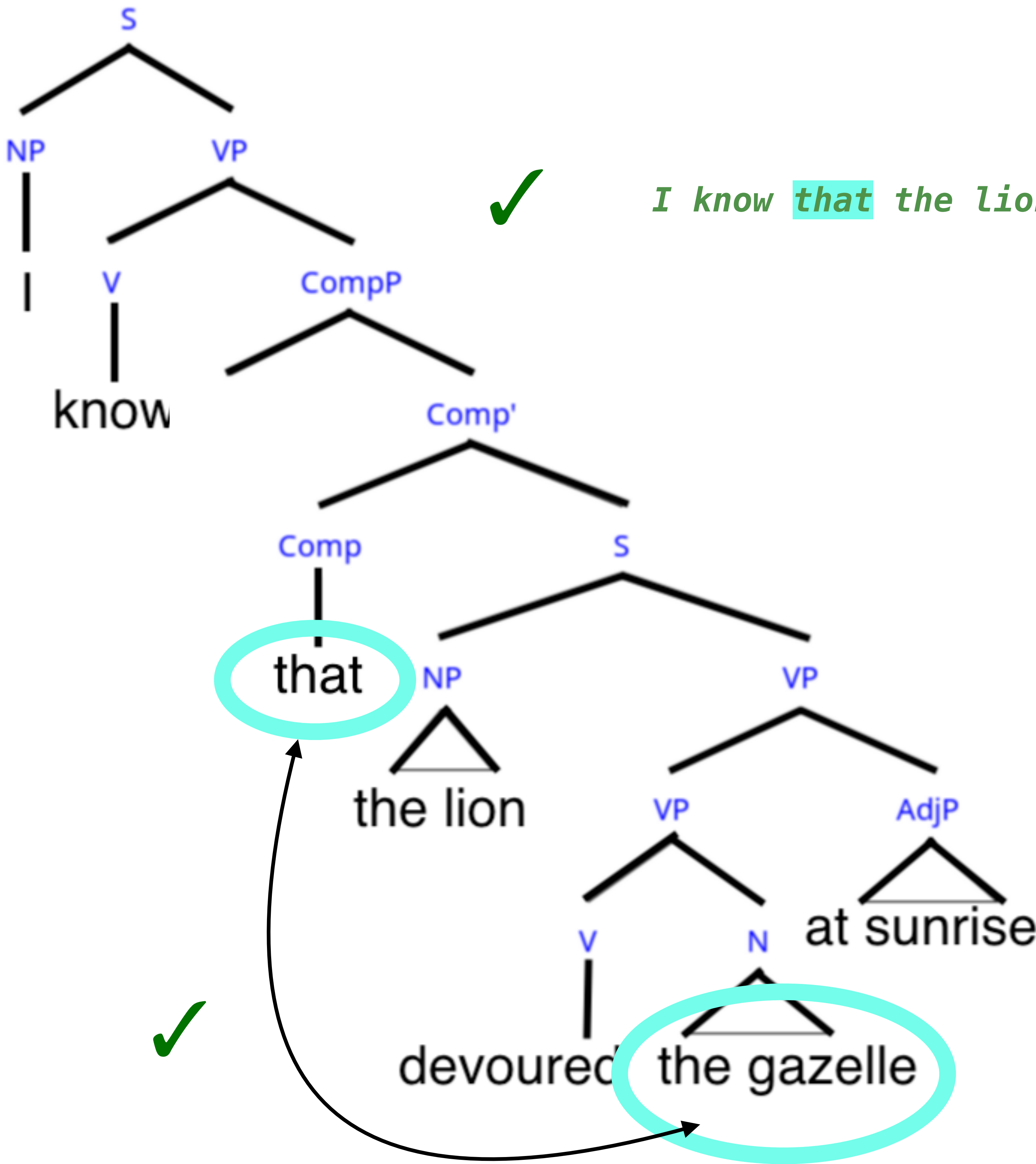
# Filler—gap dependencies

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



(Wilcox et al. 2018, Blackbox NLP)

# Filler—gap dependencies



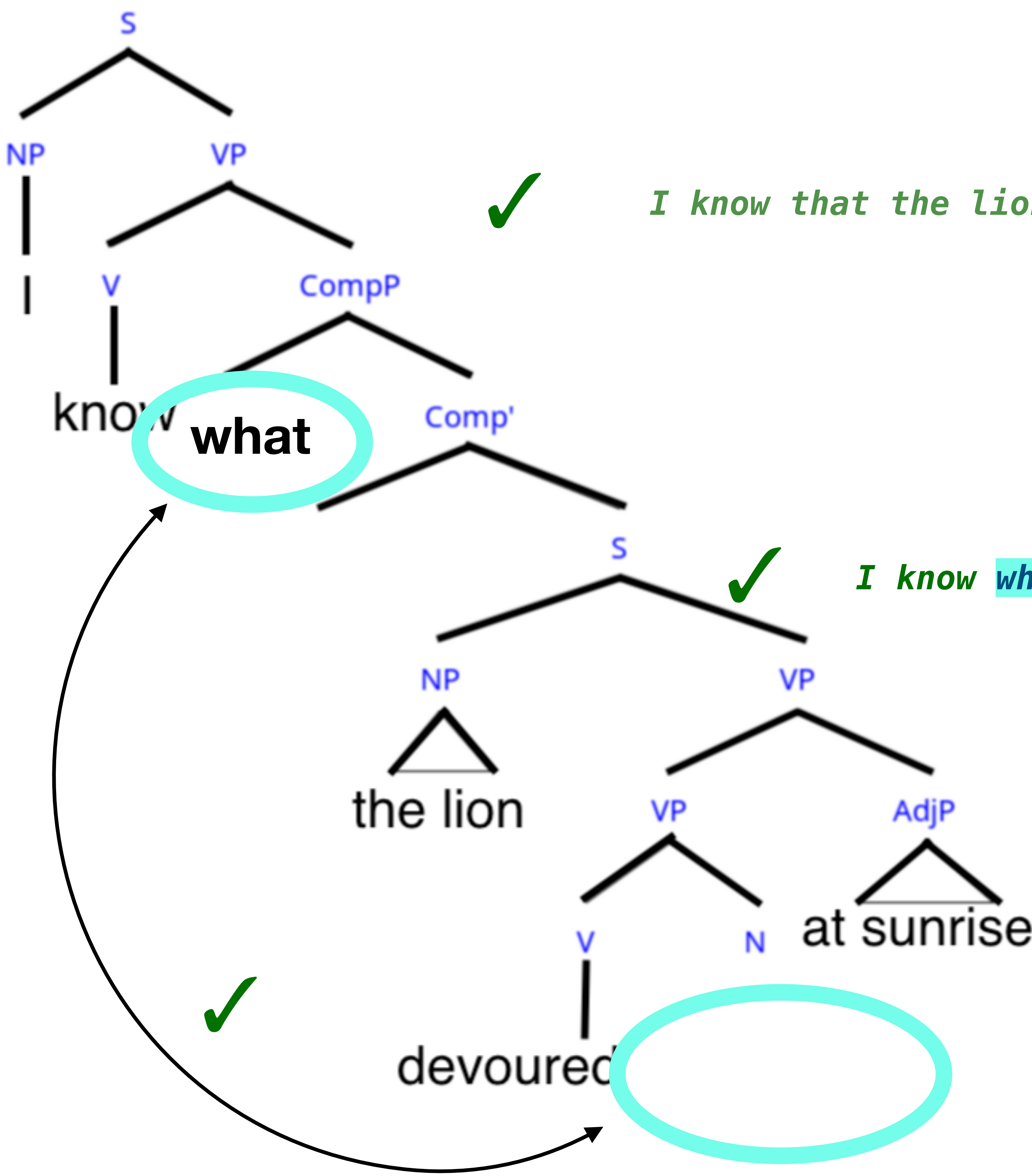

✓ *I know that the lion devoured the gazelle at sunrise.*

**-FILLER**
**-GAP**



*(Wilcox et al. 2018, Blackbox NLP)*

# Filler—gap dependencies




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

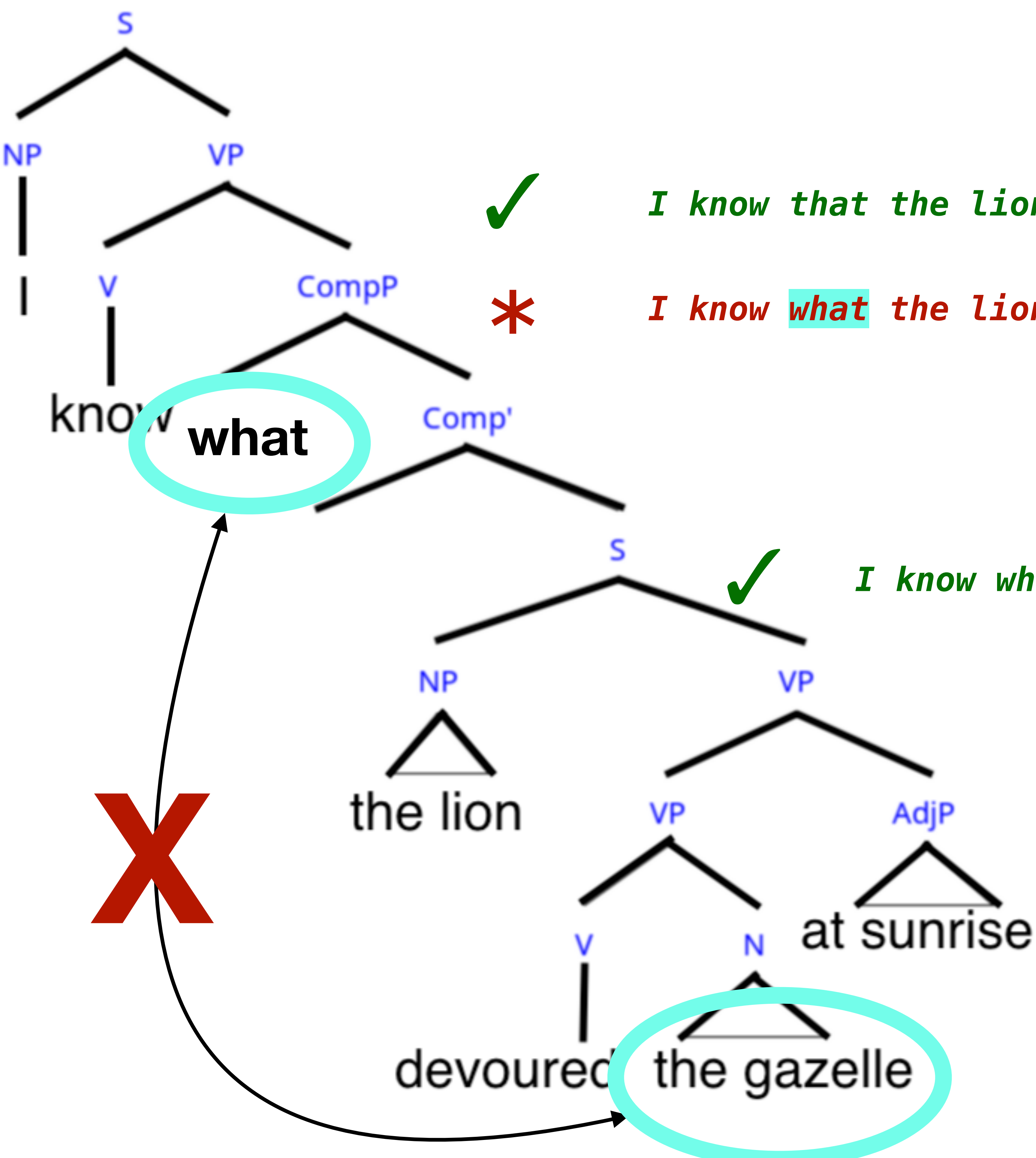
*I know what the lion devoured ___ at sunrise.*

**+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.*

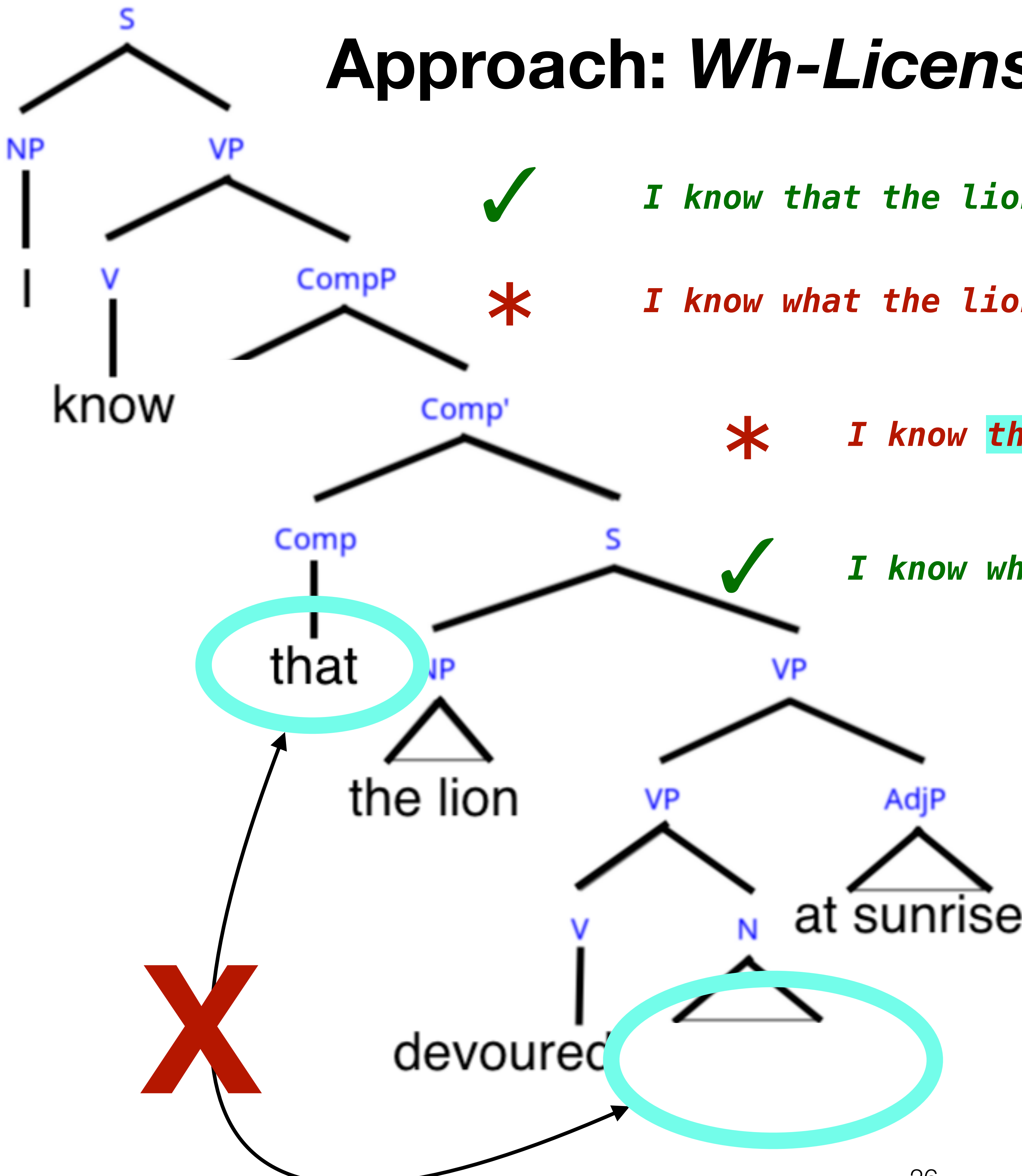
**+FILLER**
**–GAP**



(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**



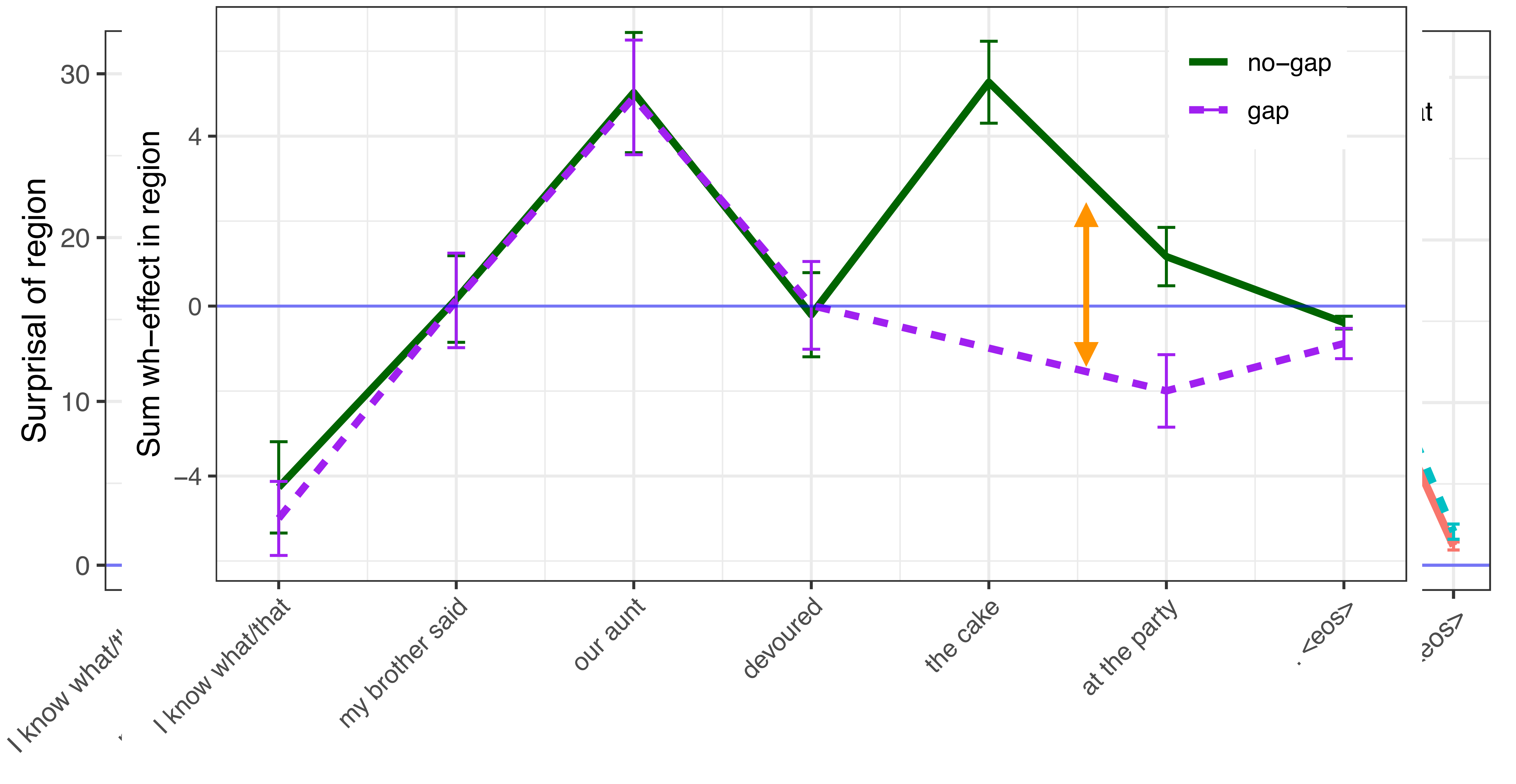
(Wilcox et al. 2018, Blackbox NLP)

✓ *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 ________ at the party.*

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



# Unboundedness of *wh*-dependencies

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

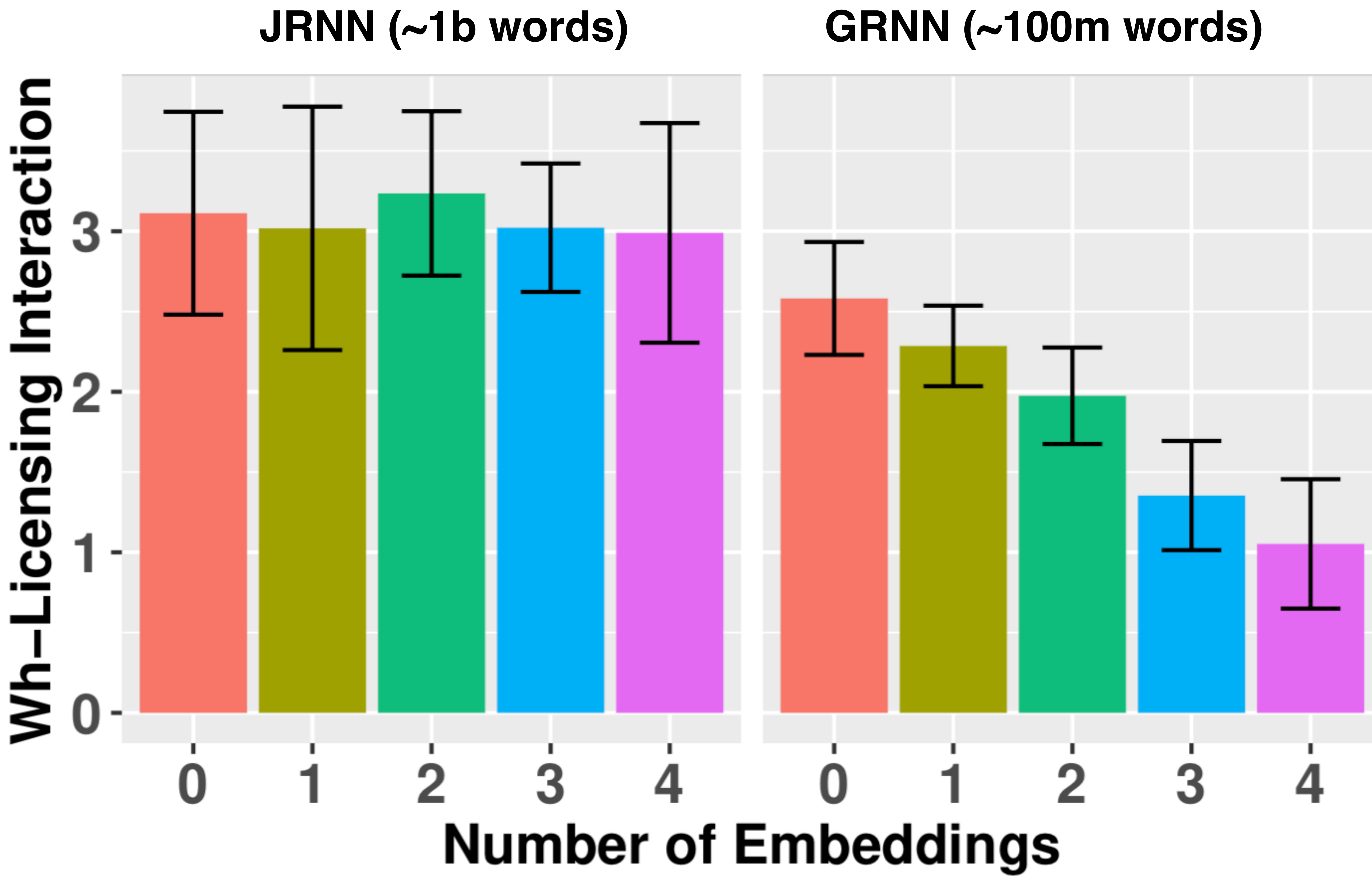
**1** *I know what our mother said that your friend gave __ to Mary last weekend.*

**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

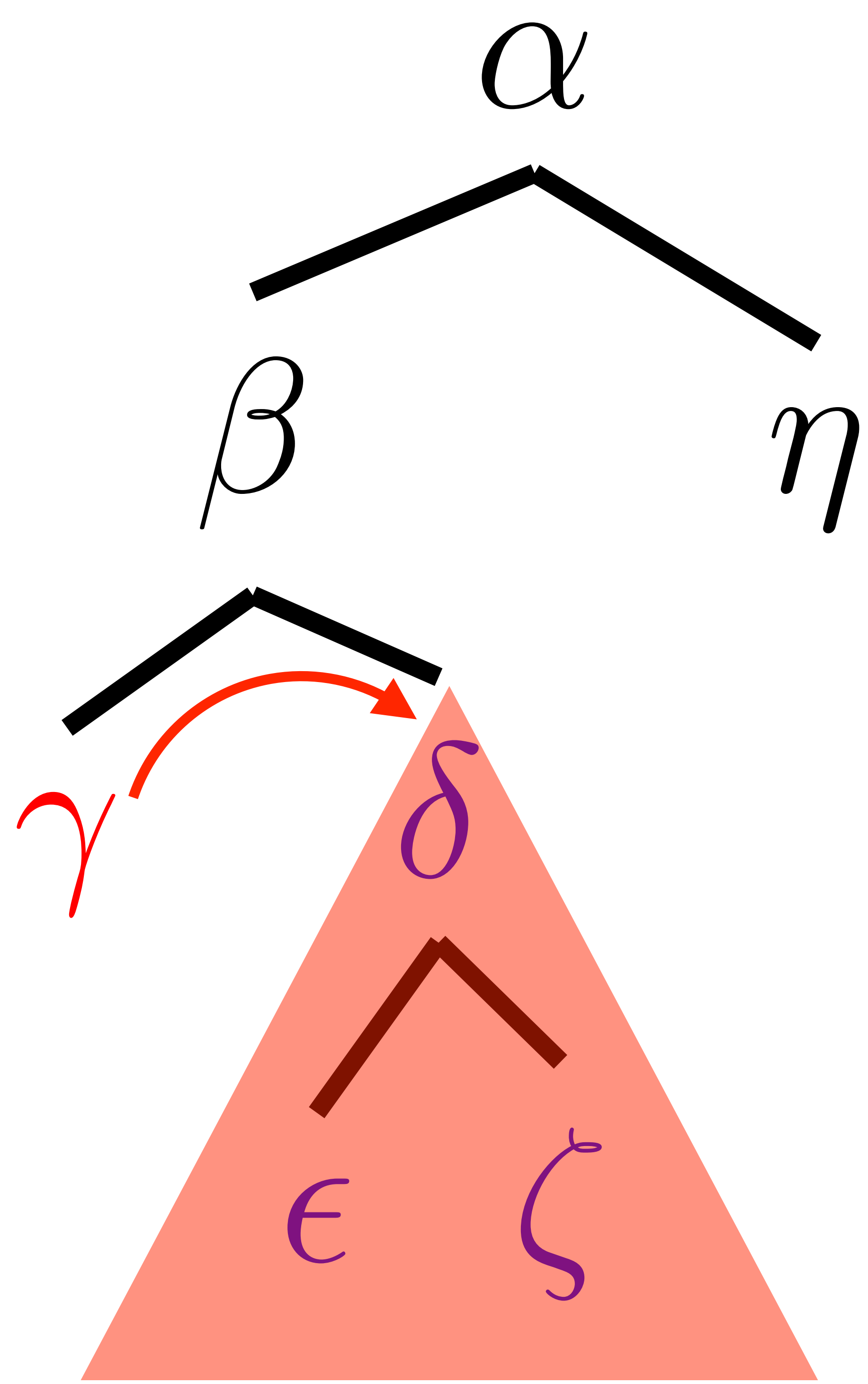


# Potential concern #1

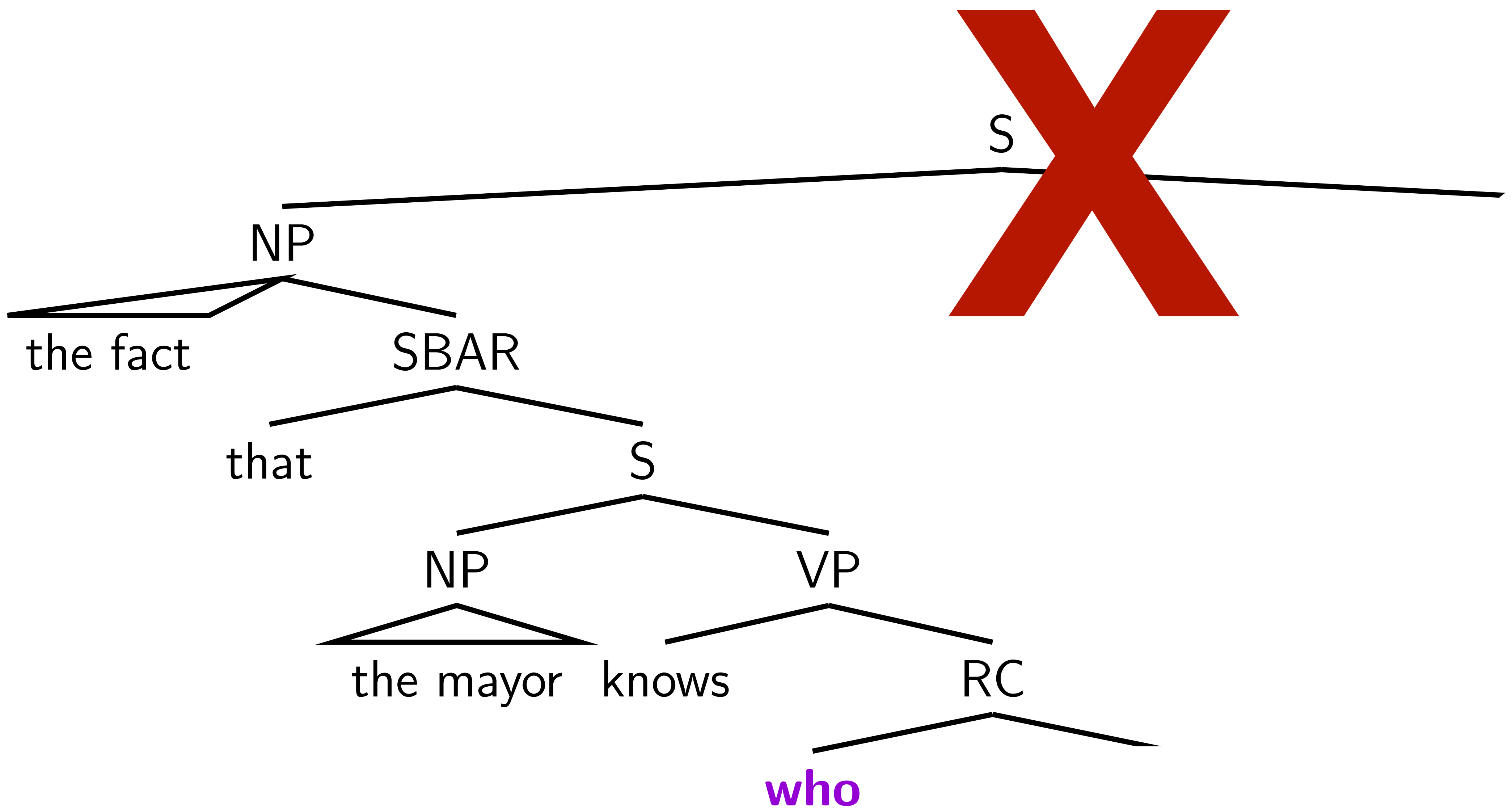
Couldn't the models be learning a ***linear*** dependency between filler and gap, not a ***hierarchical*** dependency?

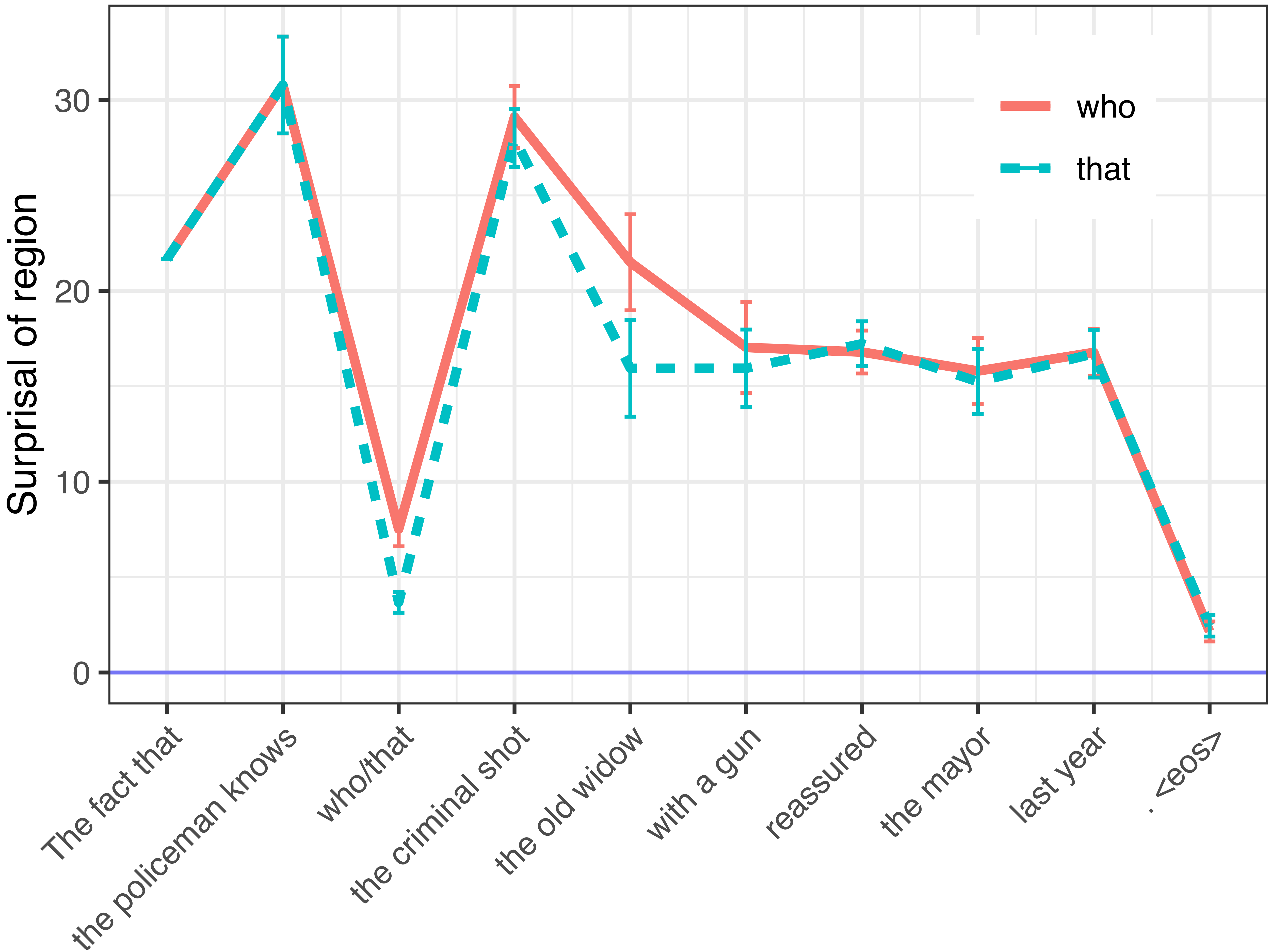
# Syntactic Hierarchy

- A filler must be appropriately “above” its gap

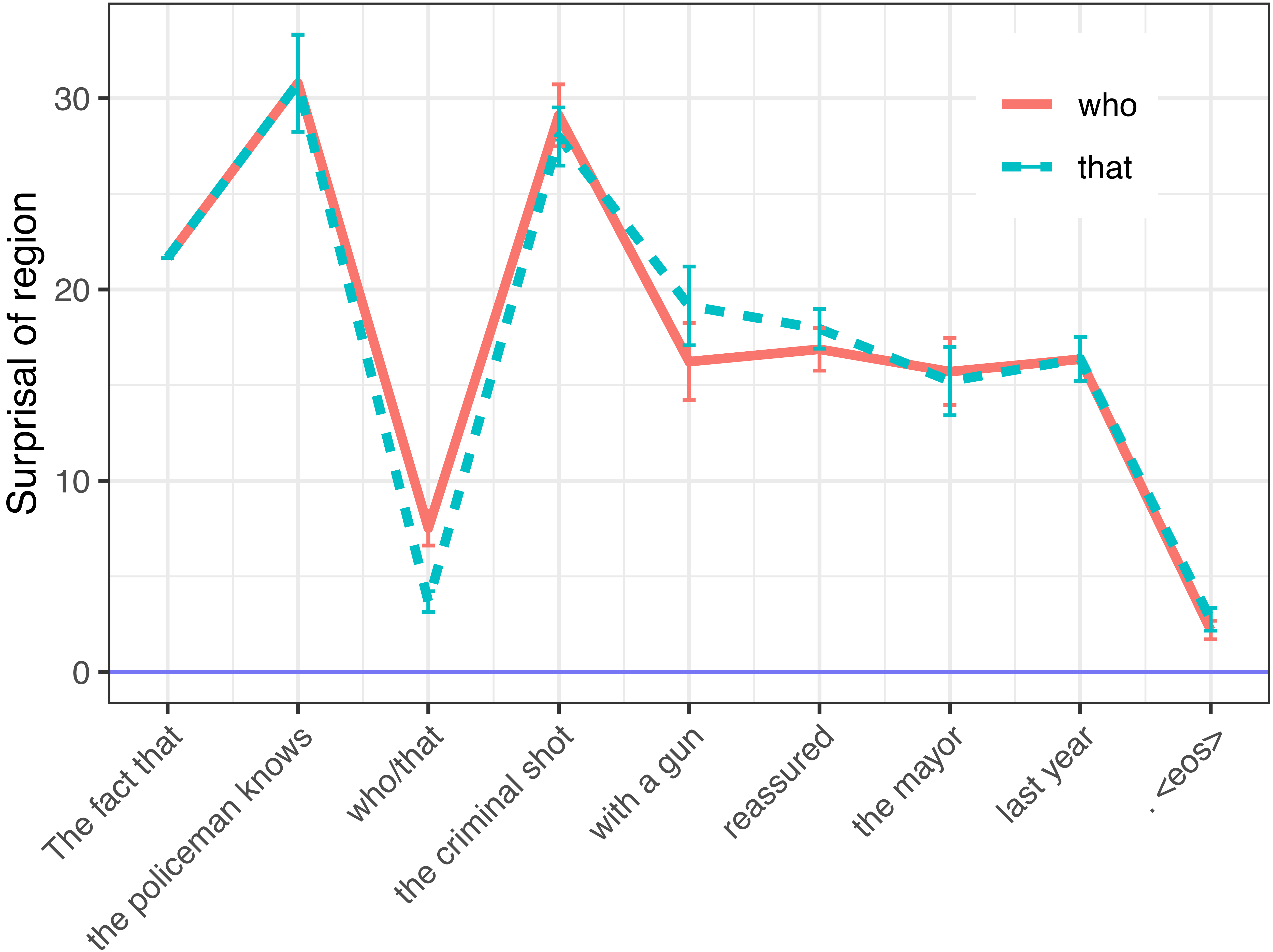



(Wilcox et al., 2019, CogSci)

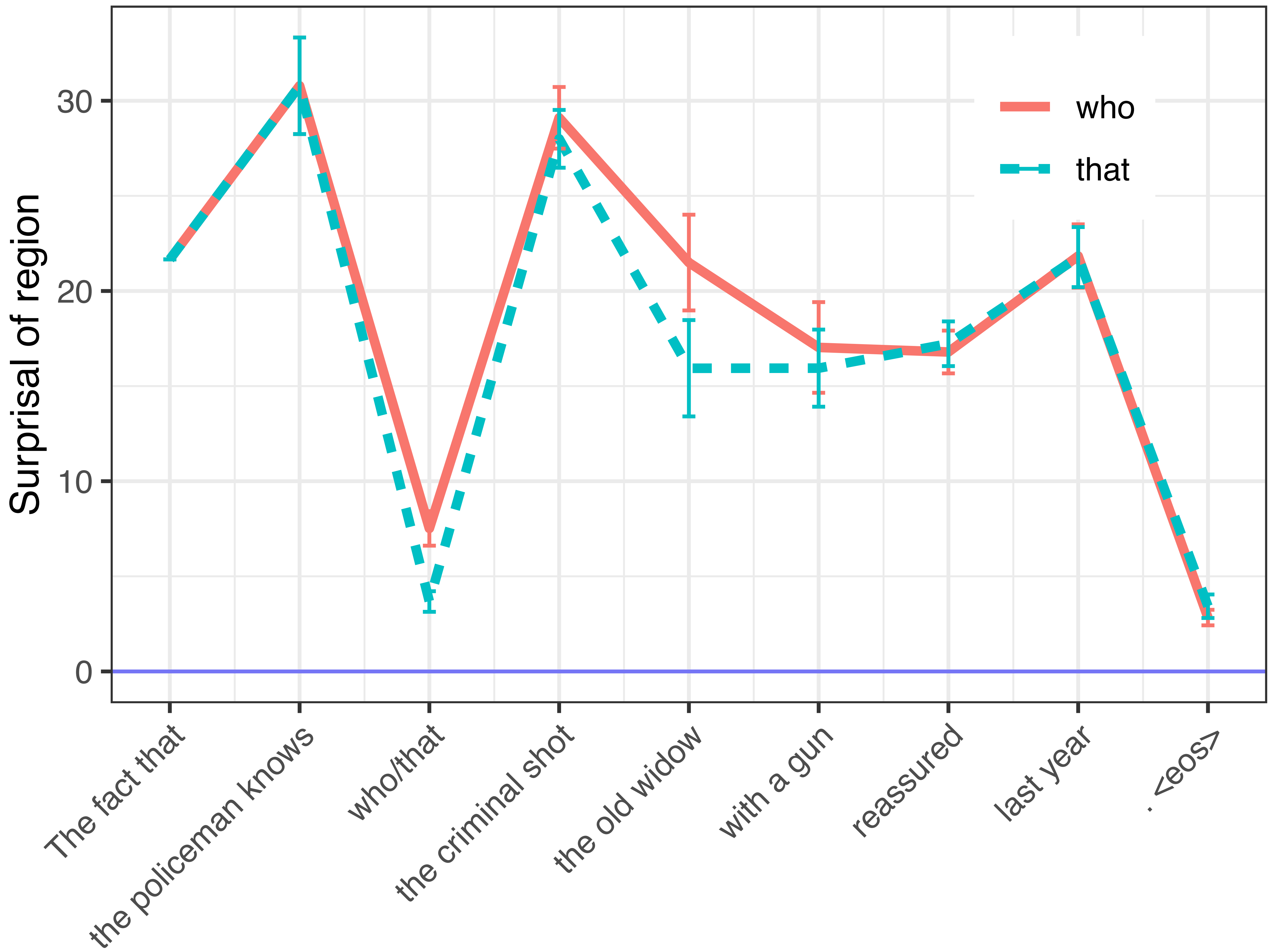

S
NP
the fact
SBAR
that
S
NP
VP
the mayor
knows
RC
who

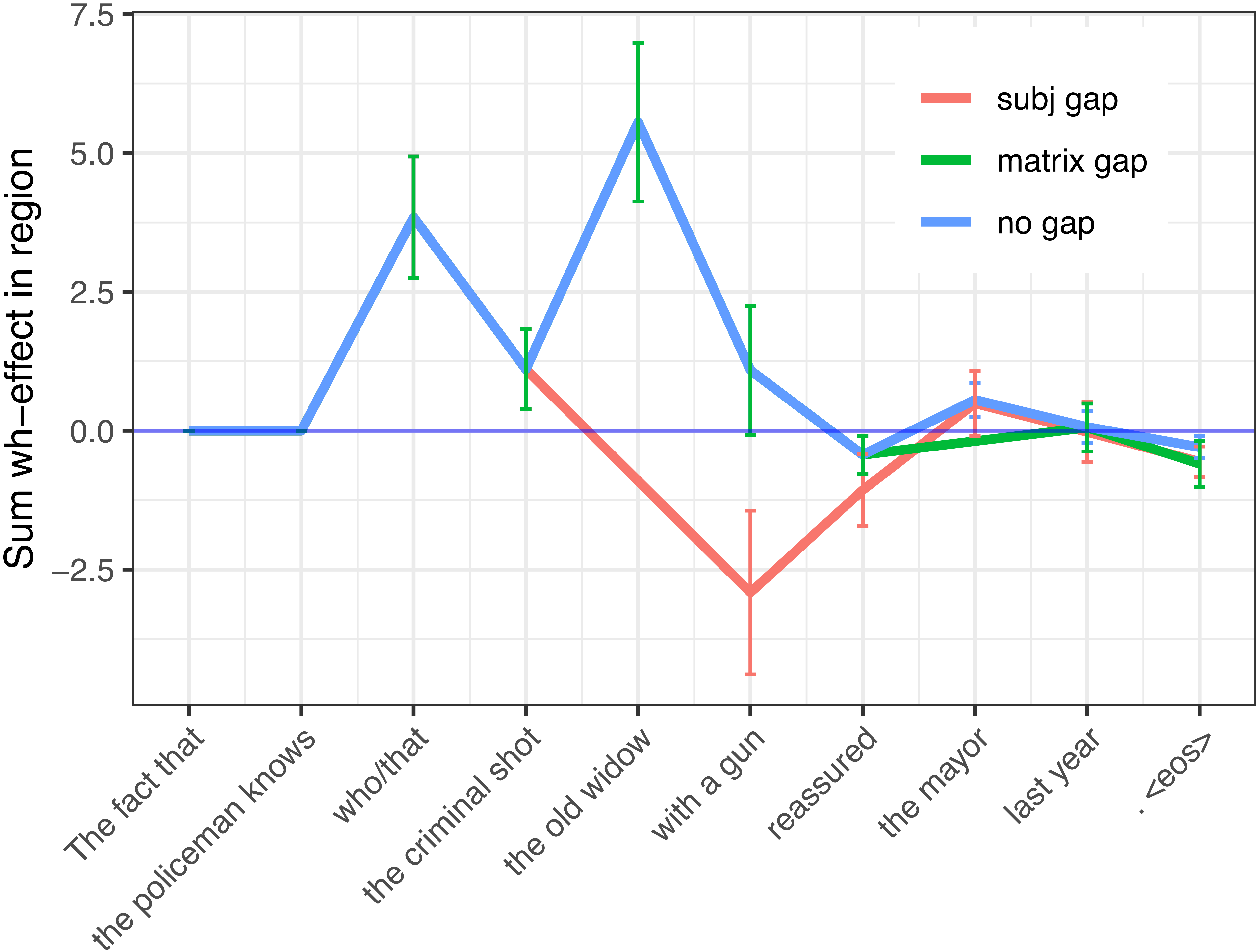


Surprisal of region
0
10
20
30
who
that
The fact that
the policeman knows
who/that
the criminal shot
the old widow
with a gun
reassured
the mayor
last year
. <eos>



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

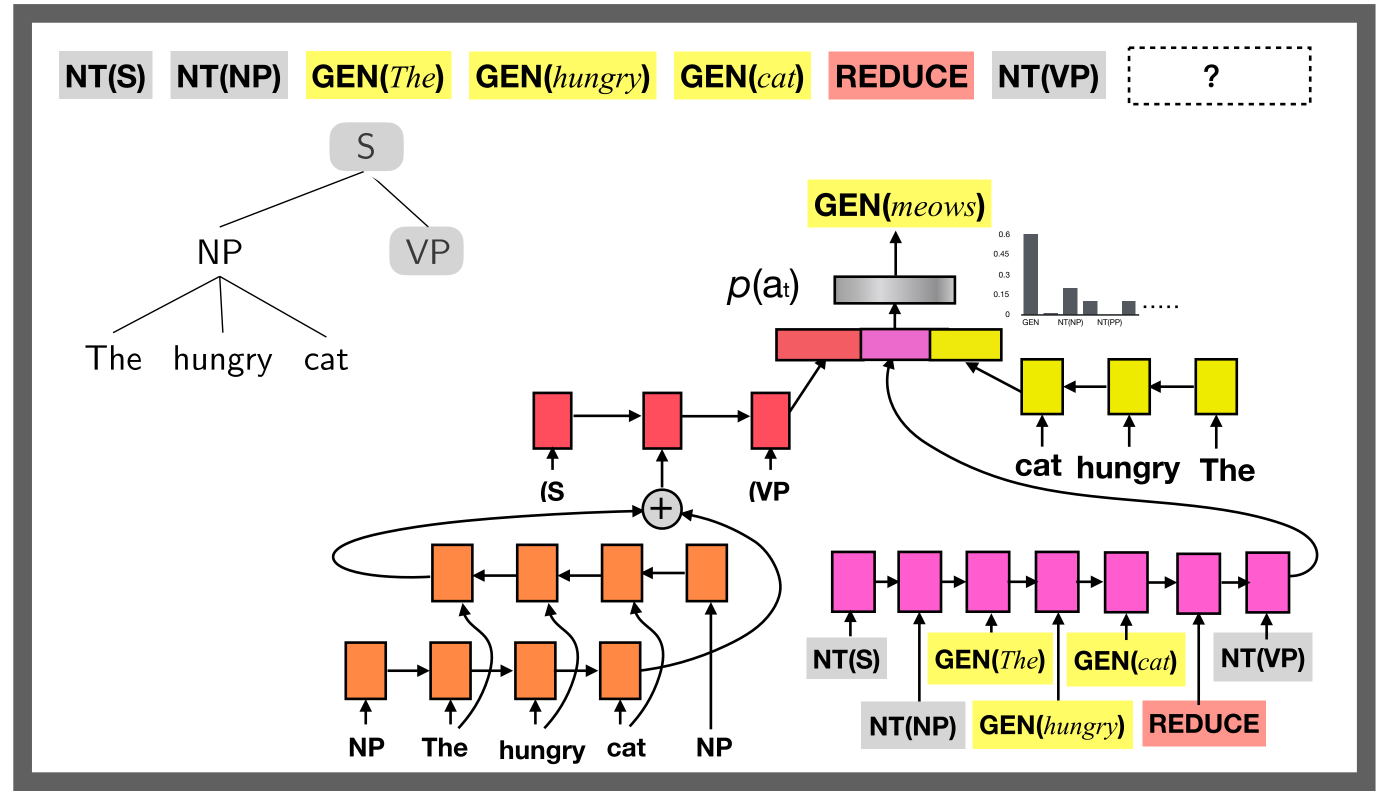
Couldn't the models be learning a ***linear*** dependency between filler and gap, not a ***hierarchical*** dependency?

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

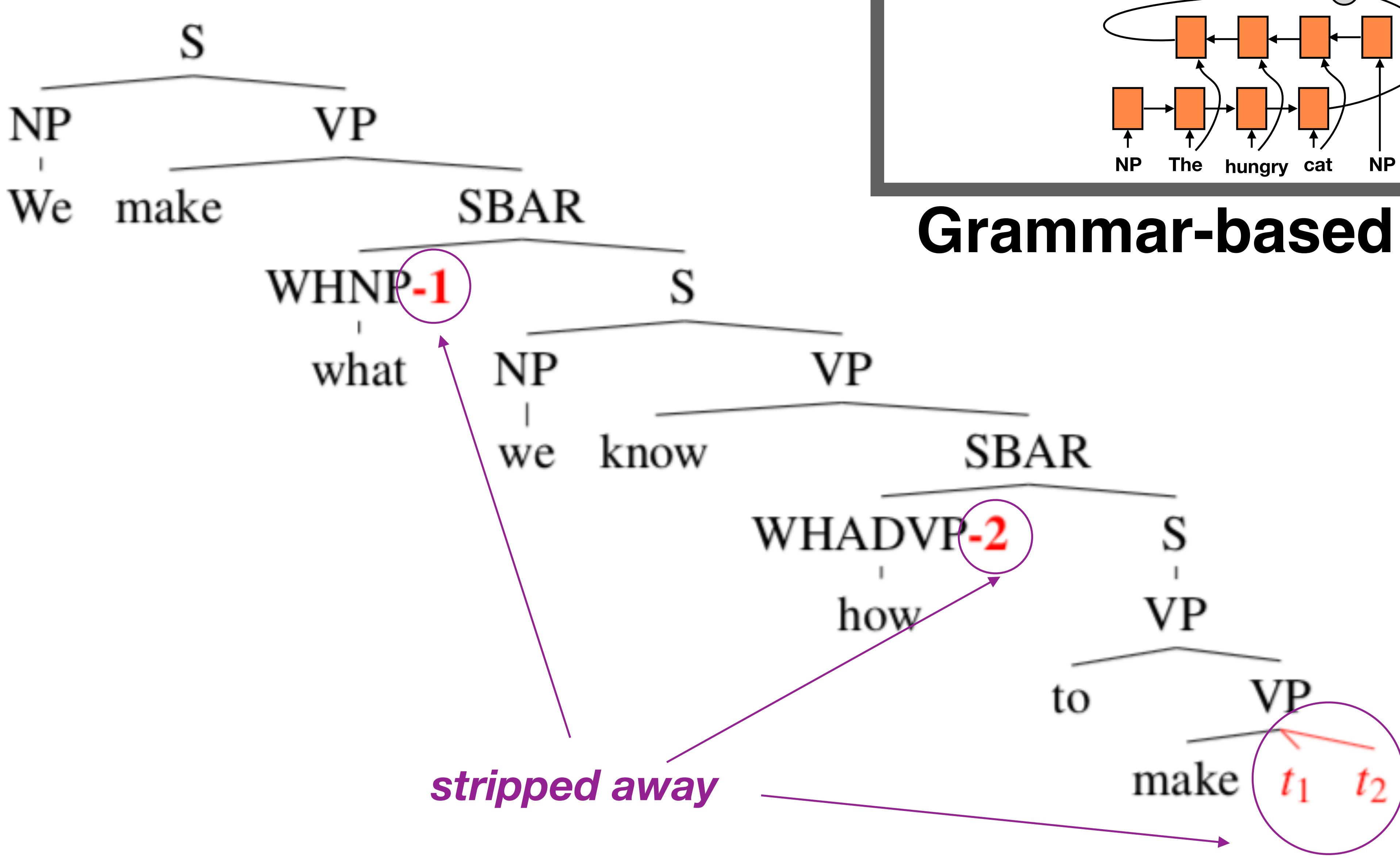
Couldn't the models be learning a ***linear*** dependency between filler and gap, not a ***hierarchical*** dependency?

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

# Does syntactic supervision help?



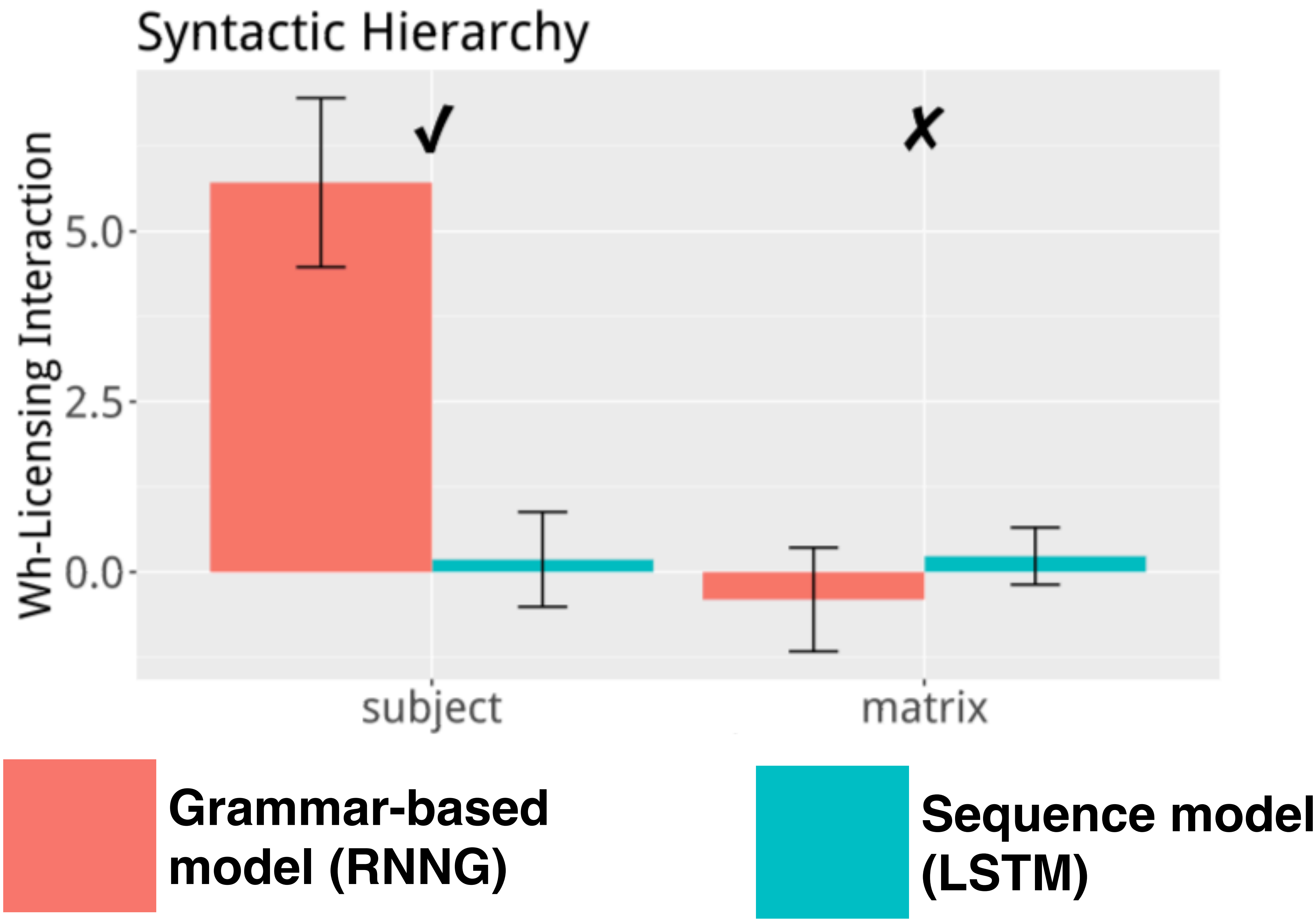

**Grammar-based model (RNNG)**




(Wilcox et al., 2019, NAACL)

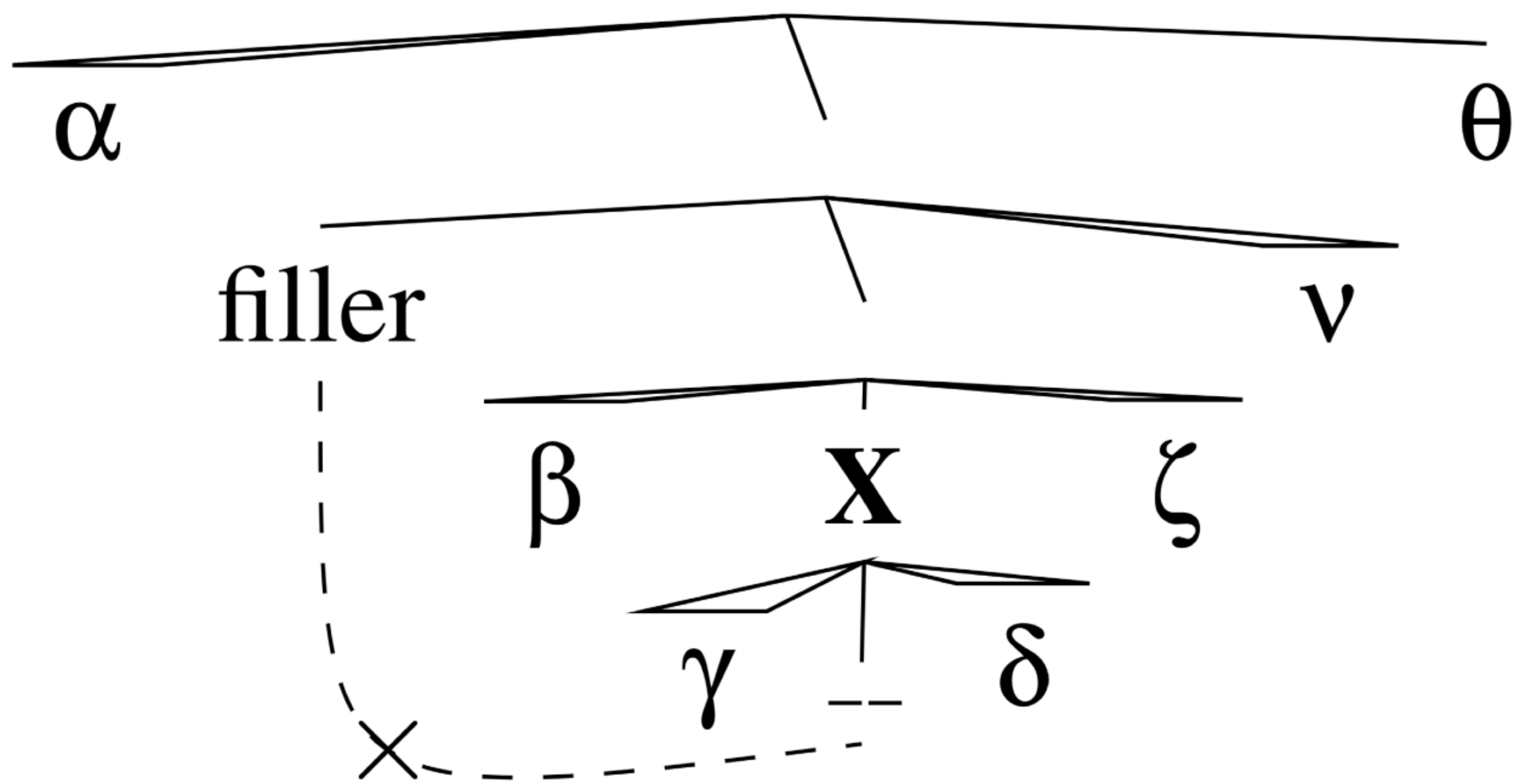
# Syntactic supervision helps a lot!

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



# Syntactic island constraints

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




- 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]

Do the RNNs learn this?

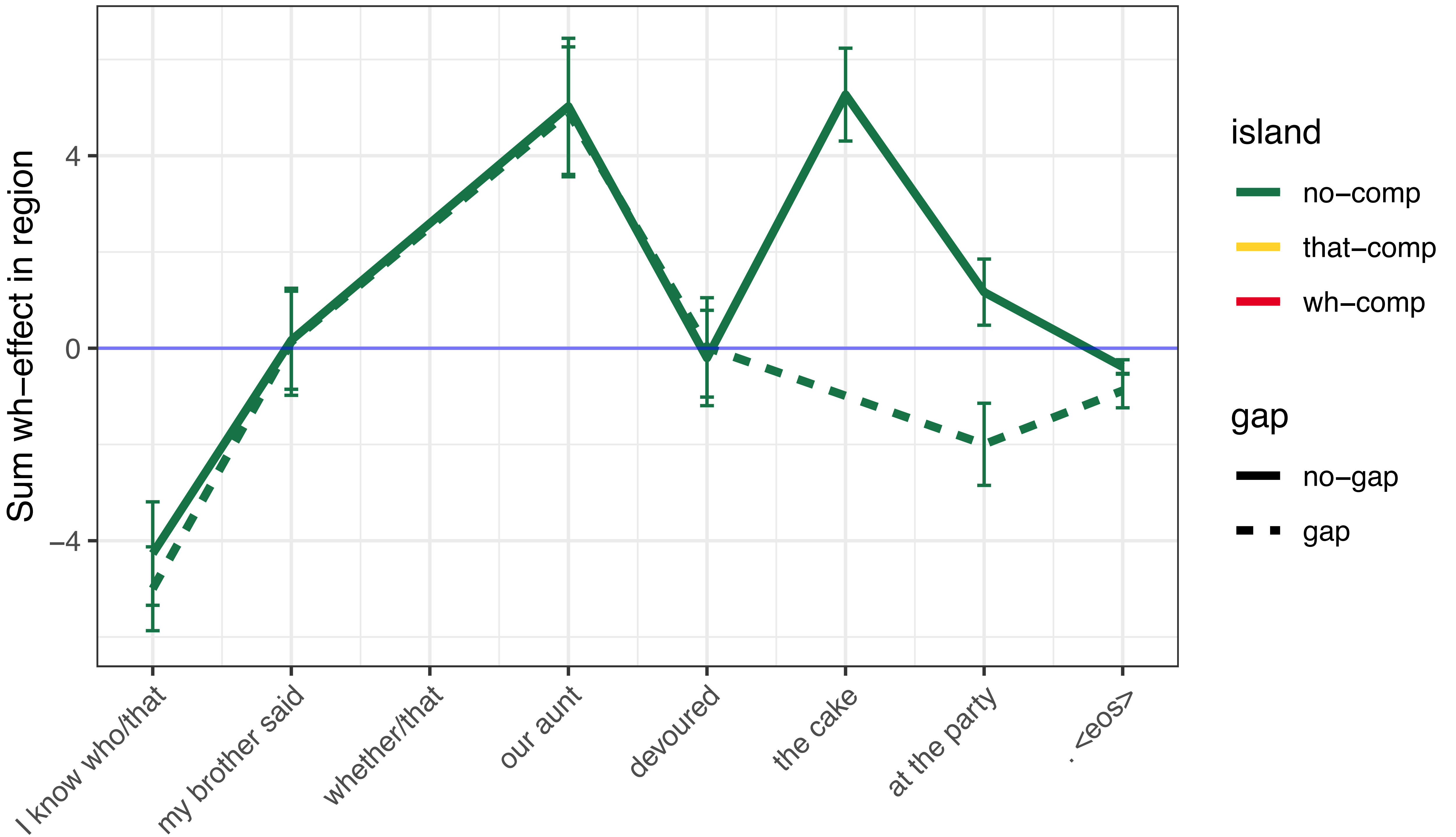
*(Wilcox et al., 2018, BlackBox)*

✓ *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.*

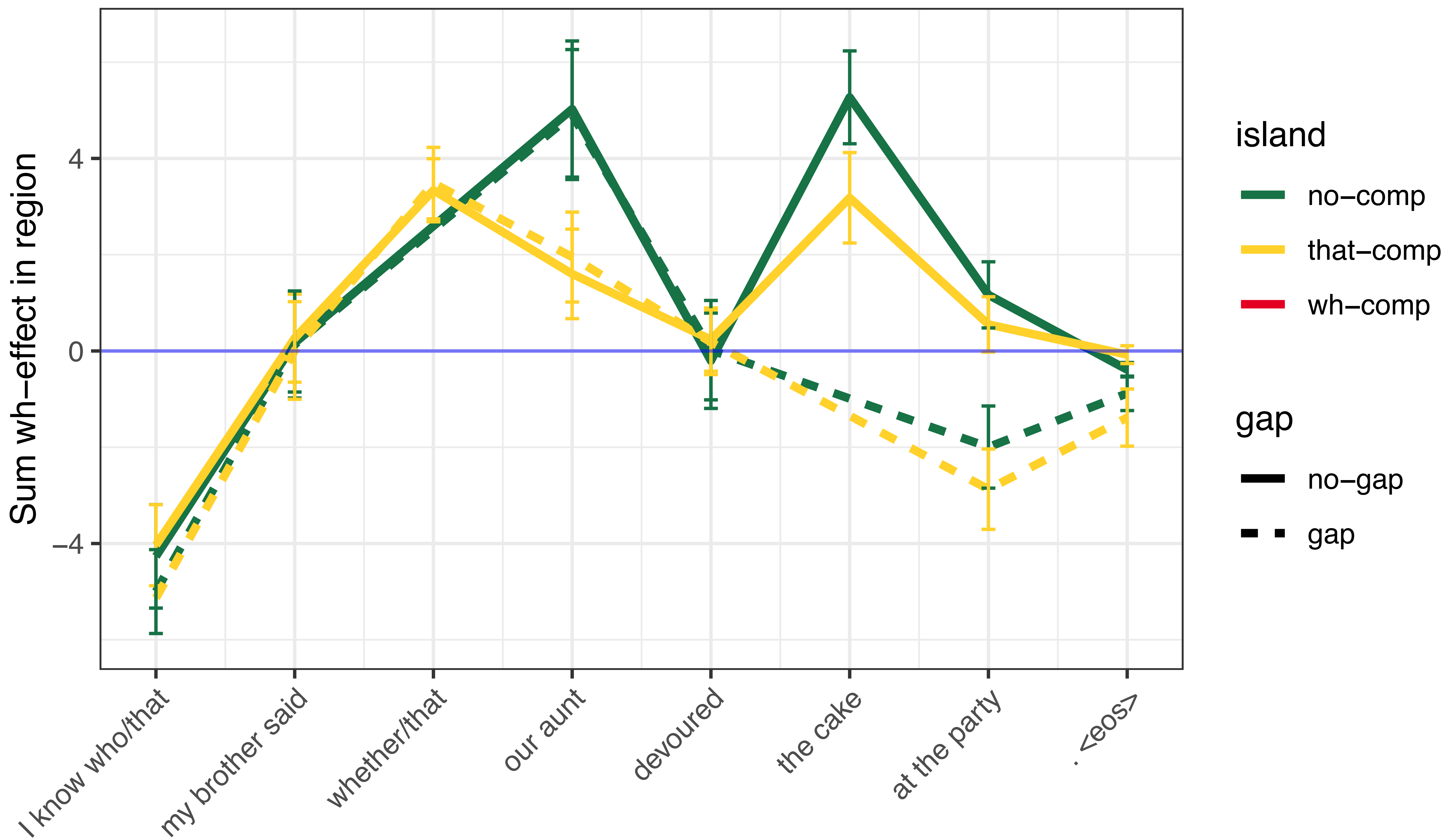


✓ *I know that my brother said **that** our aunt devoured the cake at the party.*

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

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

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

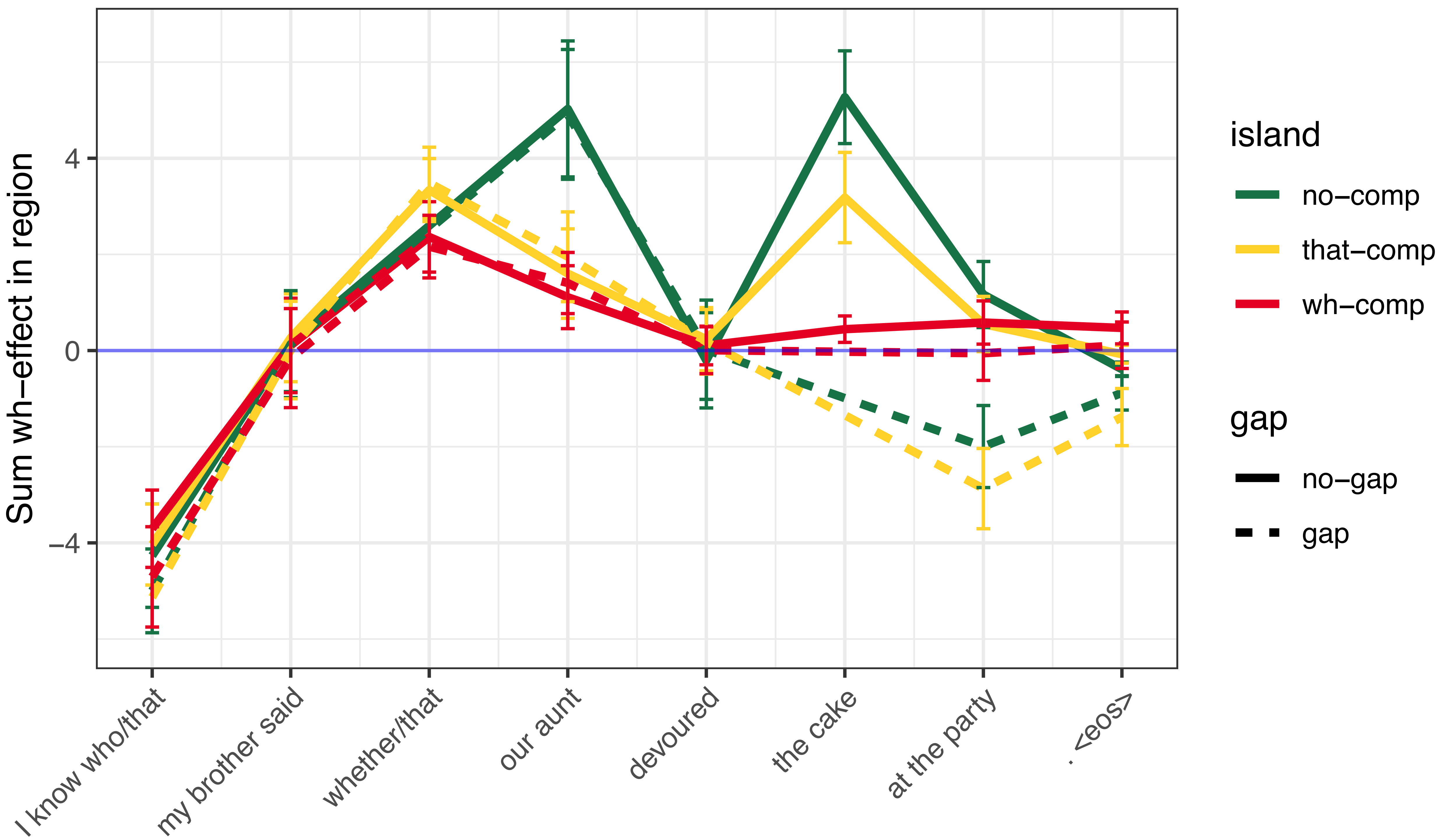


* *I know that my brother said* ***whether*** *our aunt devoured the cake at the party.*

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

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

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



# Potential concern #2

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

# Gendered-pronoun Expectation Control

- Worry: Can the models thread **any** expectation into islands?
- Test with expectation for **gendered pronouns** set up by **culturally or morphologically gendered subjects**.

**Gender Expectation Effect (#-✓ should be *positive)***

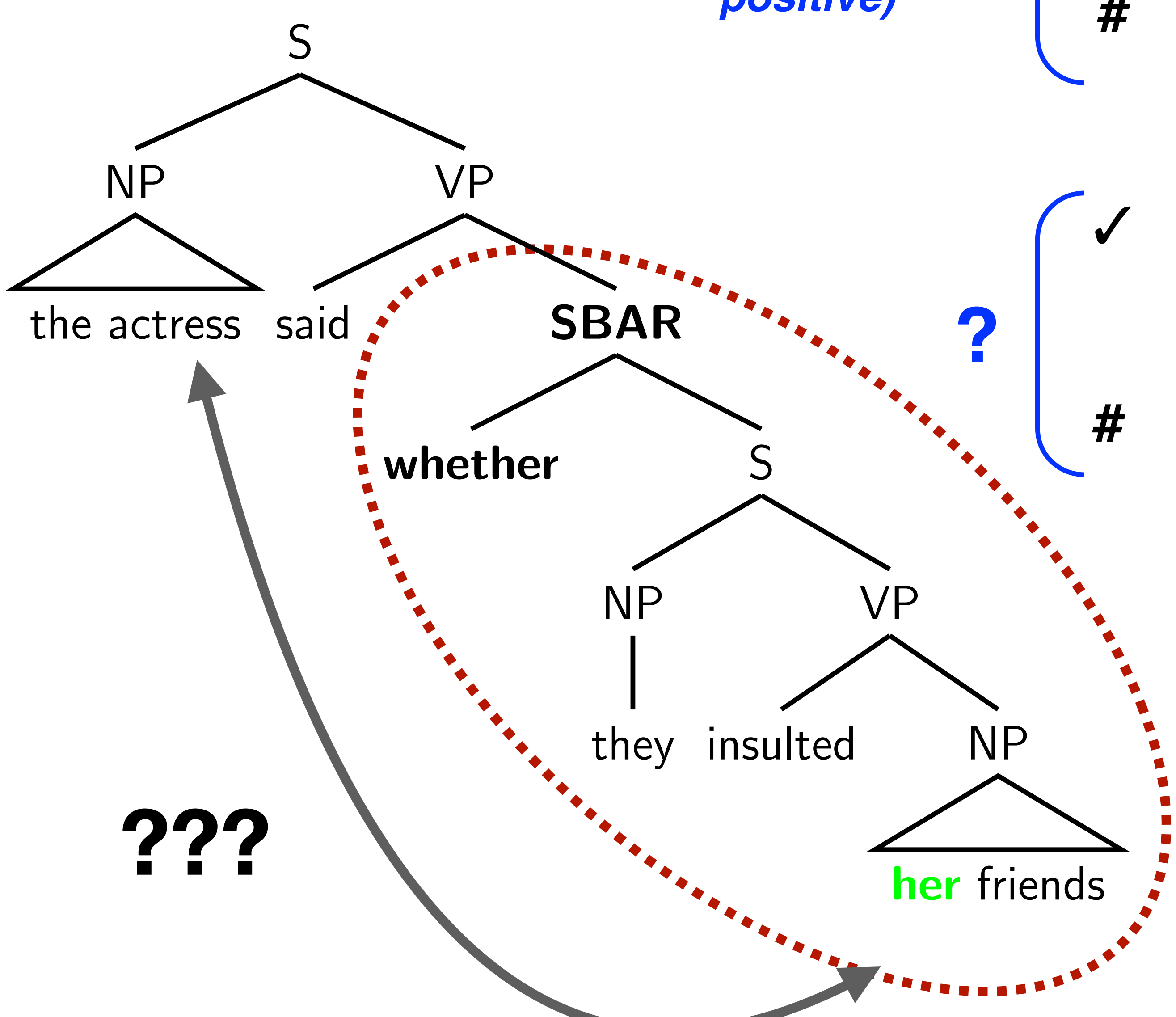
✓ *The actress said that they insulted* **her** *friends.*
**[CONTROL, MATCH]**

\# *The actress said that they insulted* **his** *friends.*
**[CONTROL, MISMATCH]**

**?**

✓ *The actress said whether they insulted* **her** *friends.*
**[ISLAND, MATCH]**

\# *The actress said whether they insulted* **his** *friends.*
**[ISLAND, MISMATCH]**




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

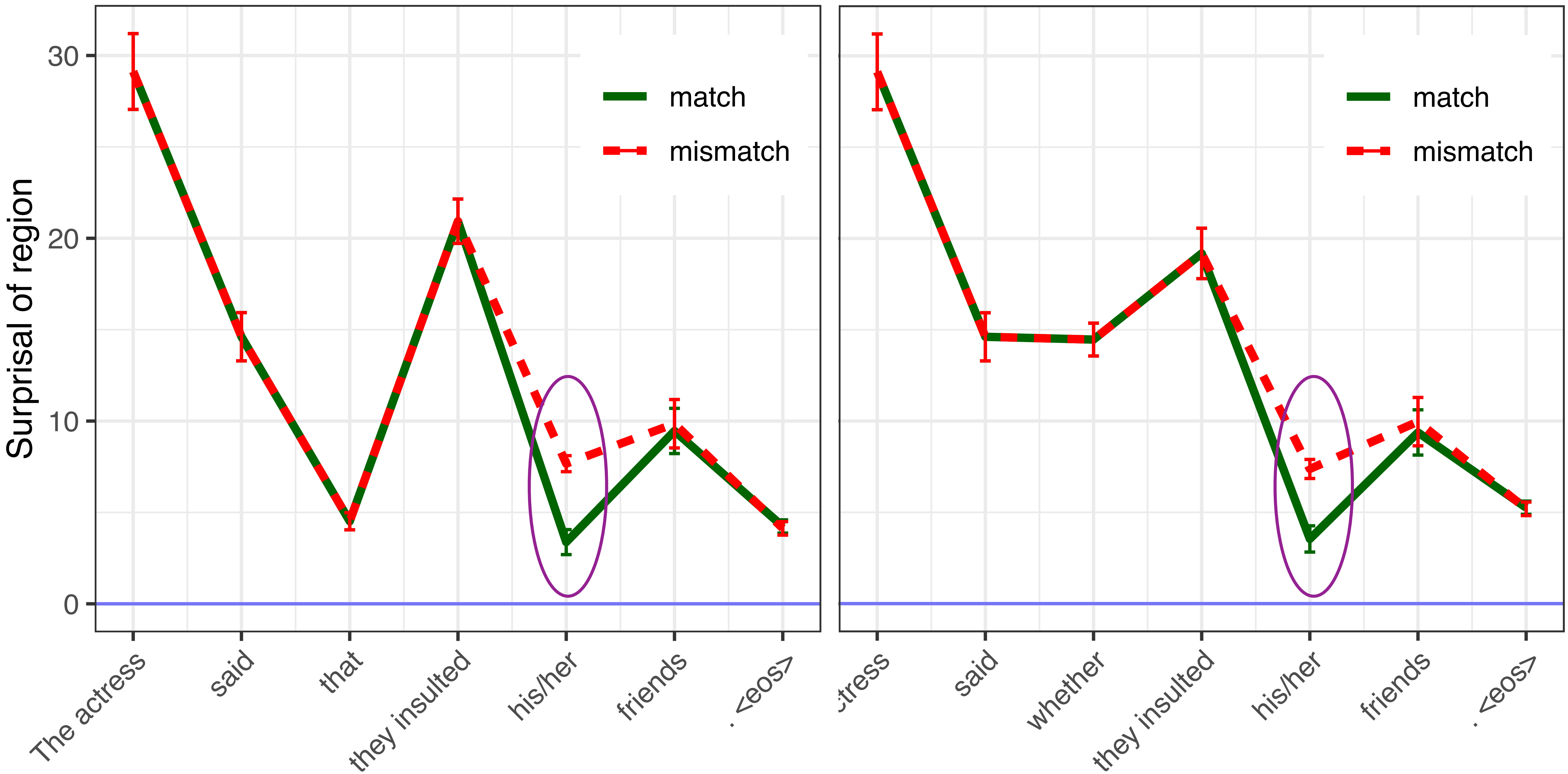
*(Wilcox et al., 2019, CogSci)*

***The actress said that they insulted her friends.***

***The actress said that they insulted his friends.***

***The actress said whether they insulted her friends.***

***The actress said whether they insulted his friends.***



# Potential concern #2

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

# 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

# References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