The Acquisition and Processing of Grammatical Structure: Insights from Deep Learning

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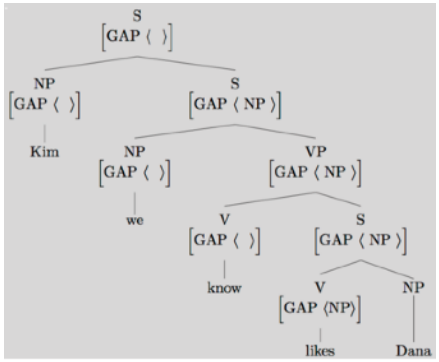
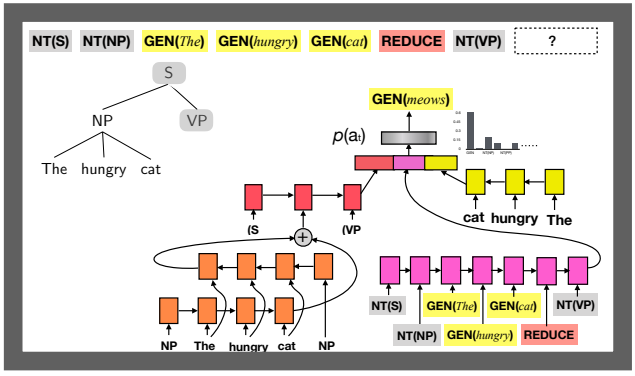
Triangulating on a model of human(-like) language



Theory of linguistic knowledge

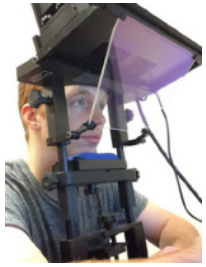


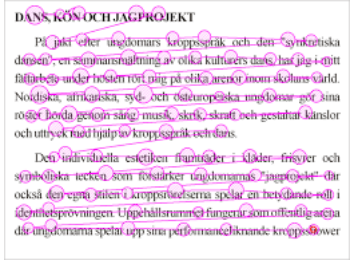
Computational Models

Human(-like) linguistic knowledge and use

Language Datasets

Psychological Experimentation





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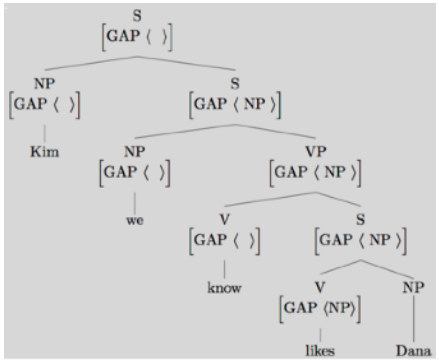

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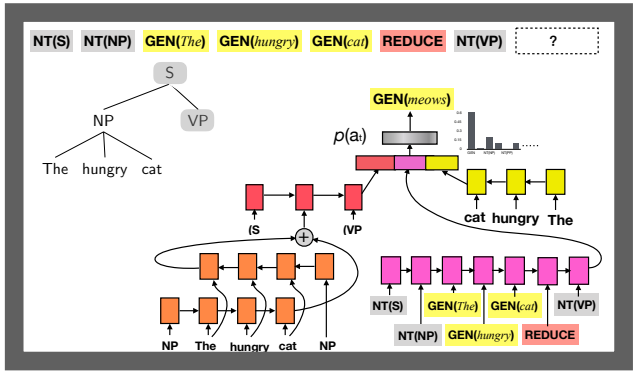

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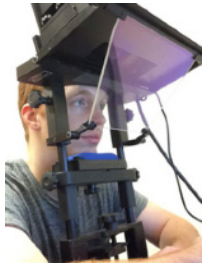
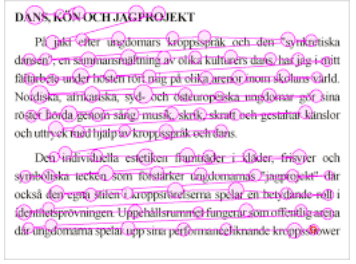
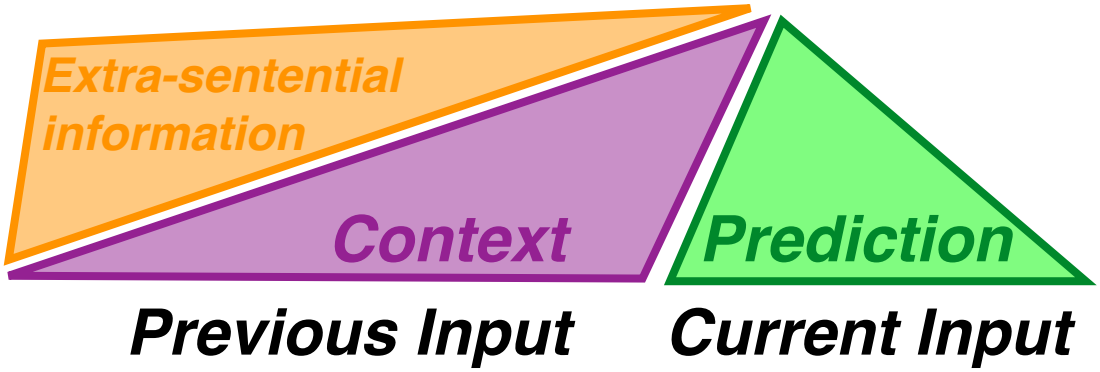




Expectations in incremental comprehension



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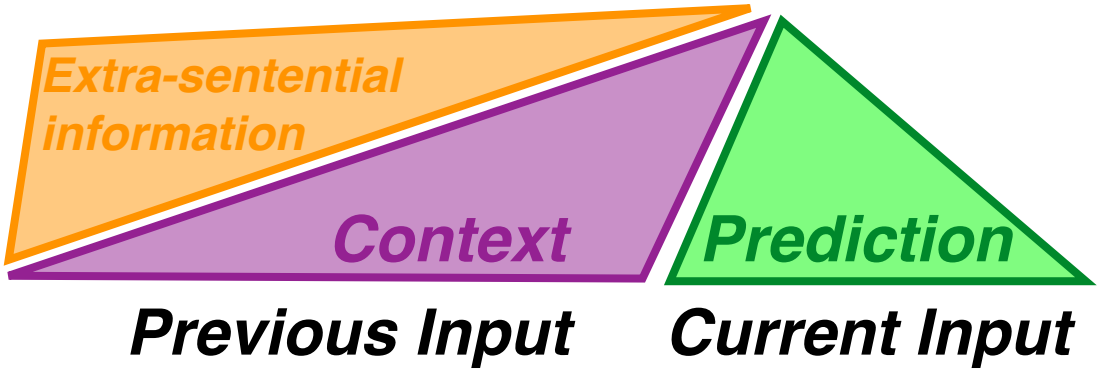

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  Jamie was clearly intimidated…

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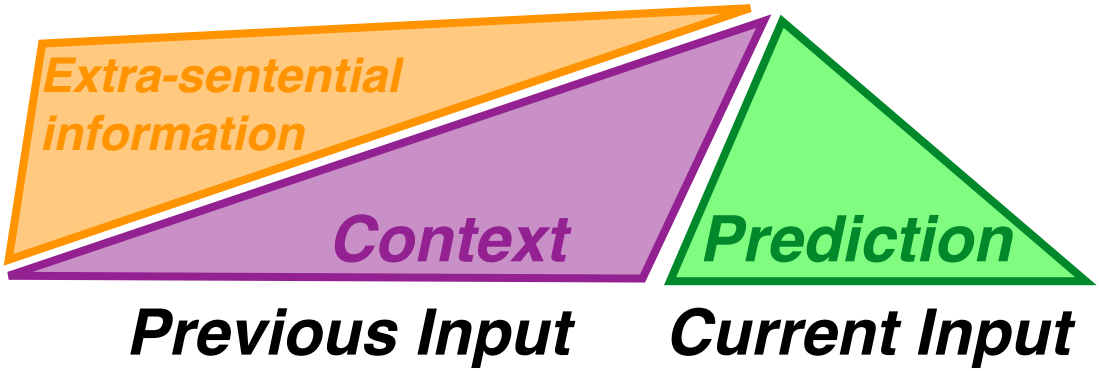

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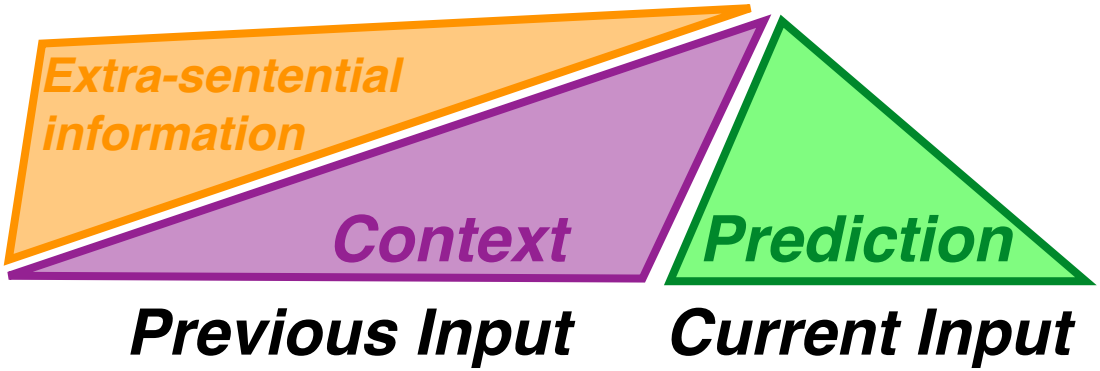

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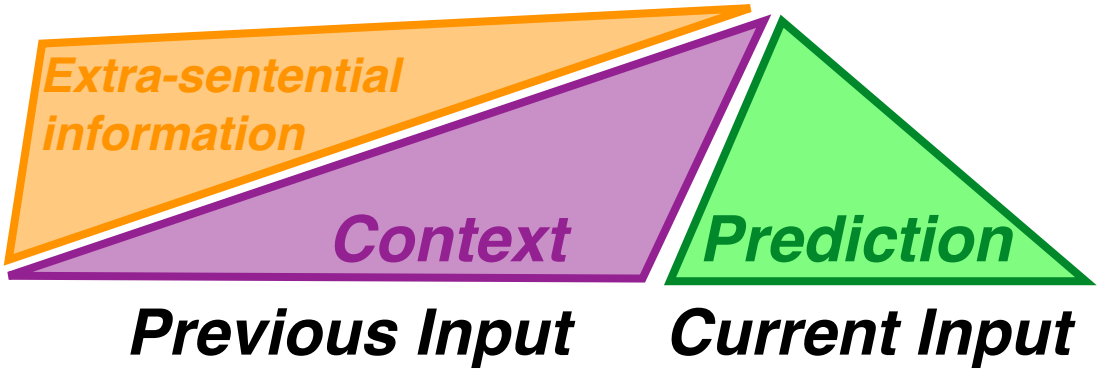

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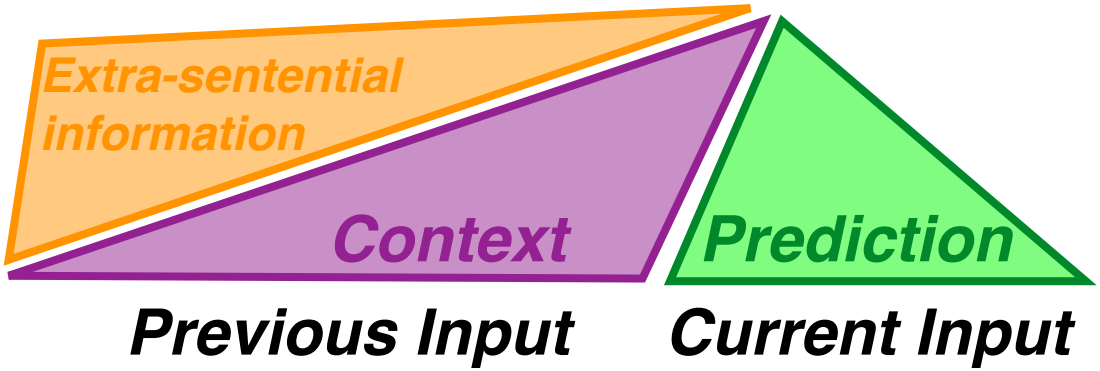

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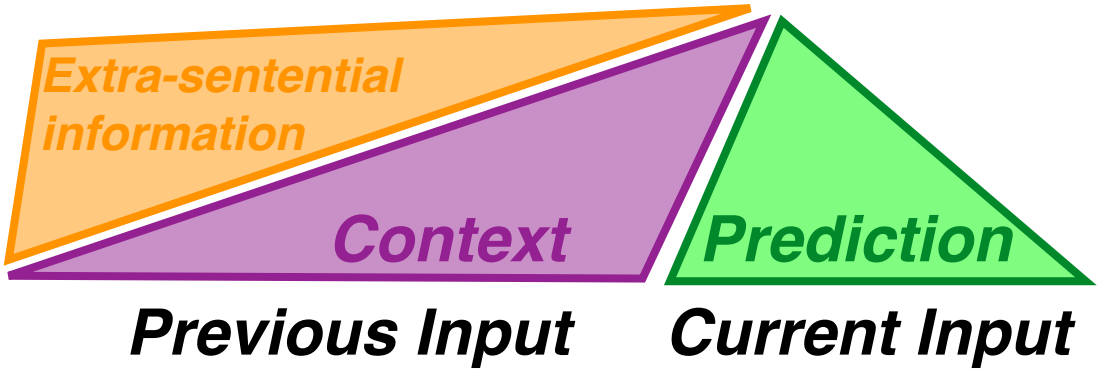

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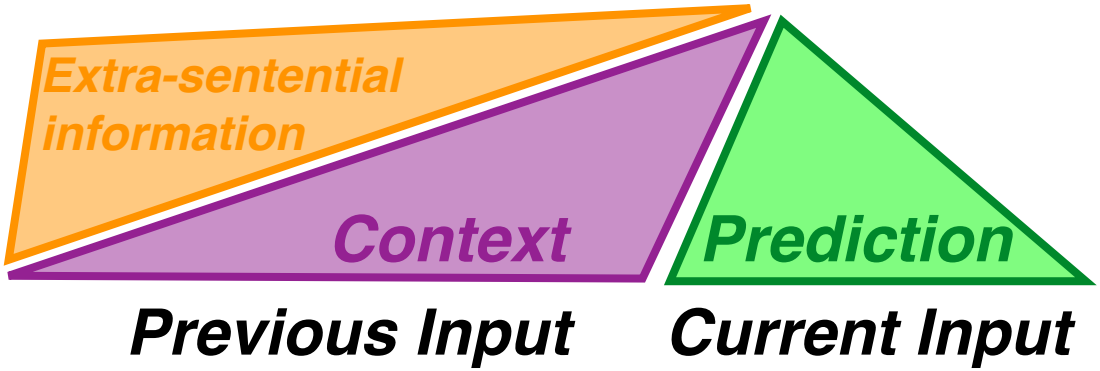

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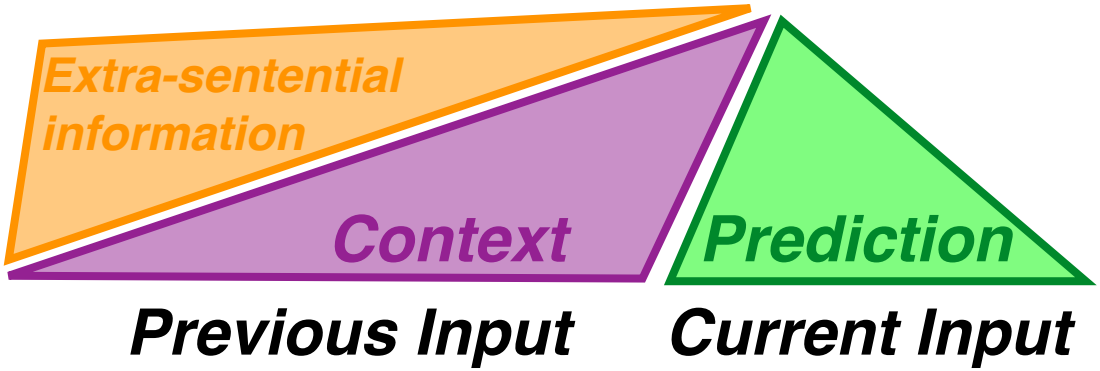

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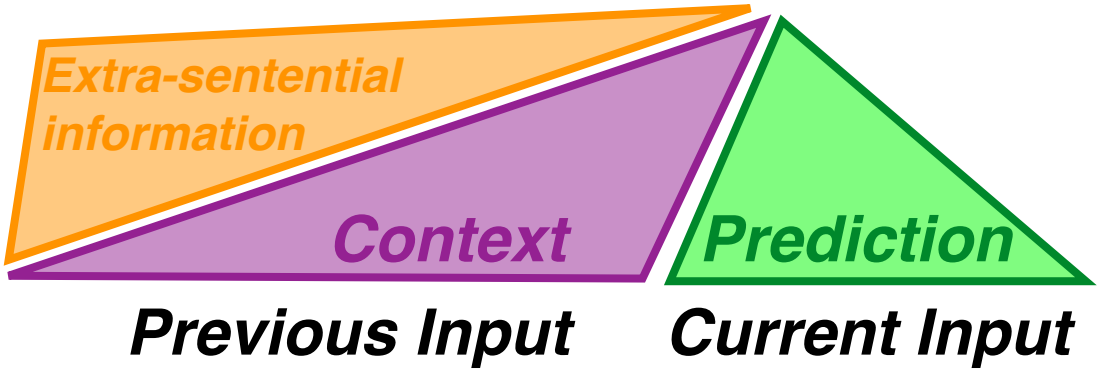

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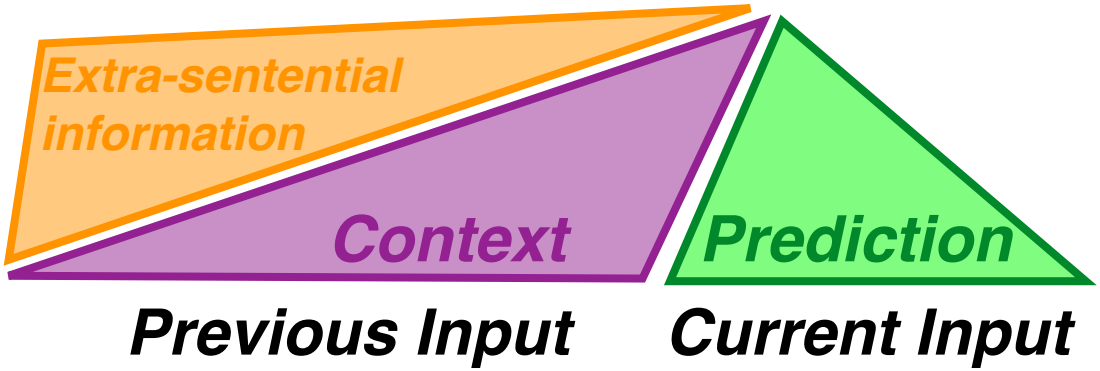

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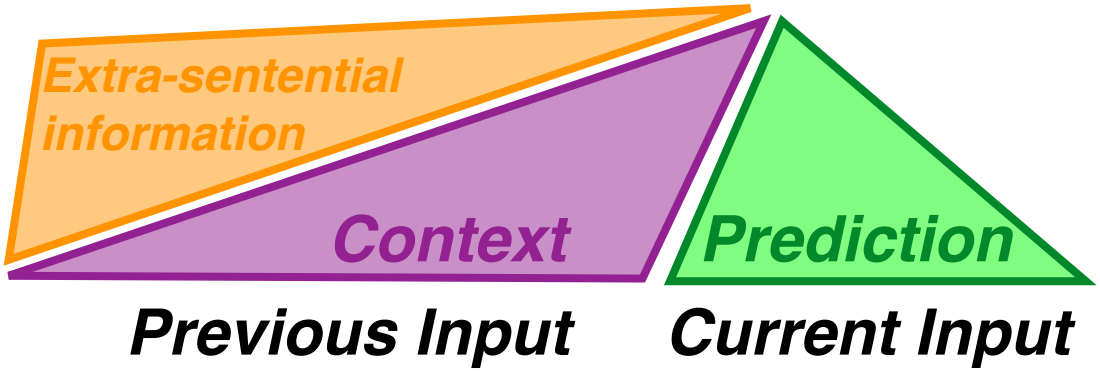

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  tree

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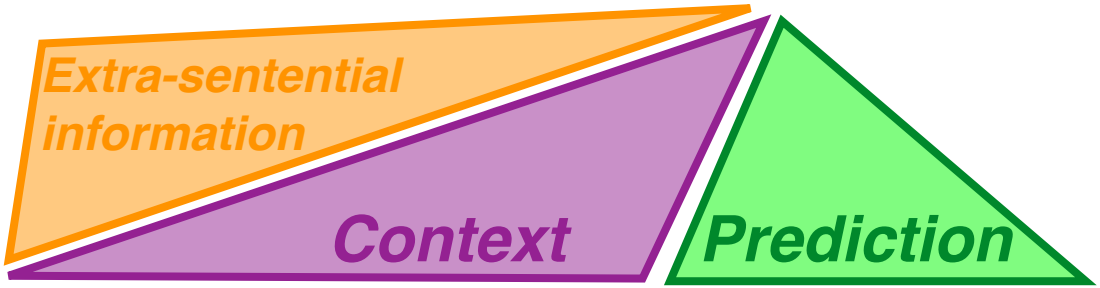

*These expectations from **diverse contextual cues** affect human language processing **extremely quickly***

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Surprisal as an index of real-time processing load

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- Let a word's difficulty be its *surprisal* given its context:

$$\text{Surprisal}(w_i) \equiv \log \frac{1}{P(w_i|\text{CONTEXT})}$$

$$\left[\approx \log \frac{1}{P(w_i|w_{1\ldots i-1})} \right]$$

(Hale, 2001, NAACL; Levy, 2008, Cognition)

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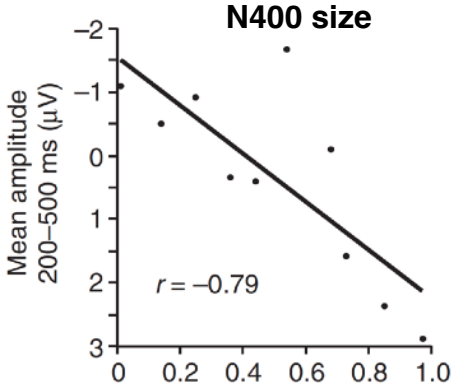
  - read faster (Ehrlich & Rayner, 1981)
  - have distinctive EEG responses (Kutas & Hillyard 1980)



(Federmeier & Kutas, 1999)

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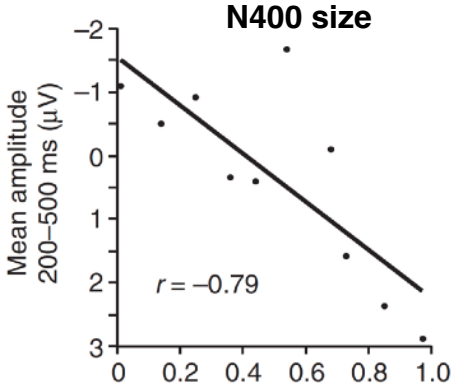


(Federmeier & Kutas, 1999)

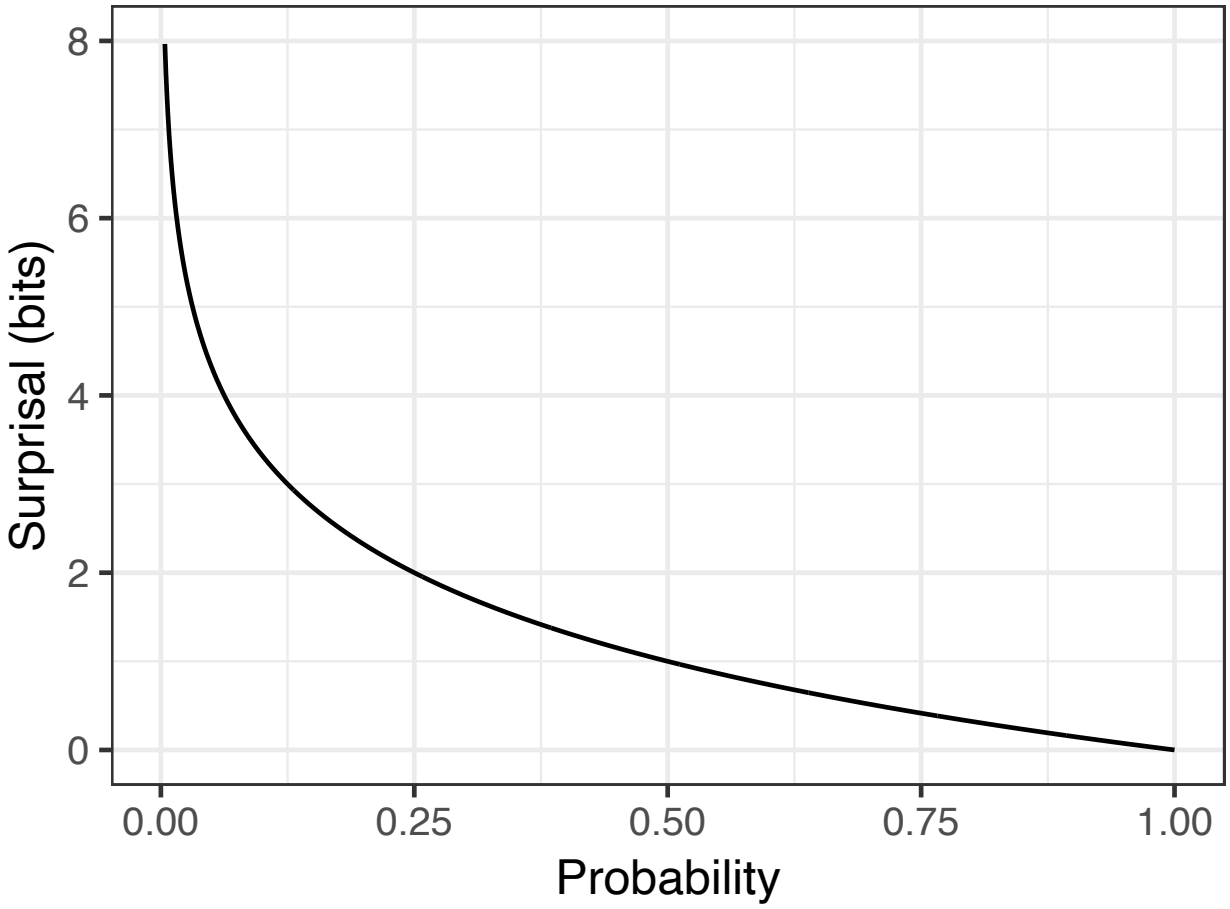
- Predictable words are:
  - read faster (Ehrlich & Rayner, 1981)
  - have distinctive EEG responses (Kutas & Hillyard 1980)
- with a language model that captures syntactic structure, we can get GRAMMATICAL EXPECTATIONS

(Hale, 2001, NAACL; Levy, 2008, Cognition)

Quantifying structure and surprise

- Hypothesis: a word's difficulty is its *surprisal* in context:

$$\text{Surprisal}(w_i) \equiv \log \frac{1}{P(w_i|\text{CONTEXT})}$$



(Shannon, 1948: a basic quantity from information theory!)

Estimating probability/time curve shape

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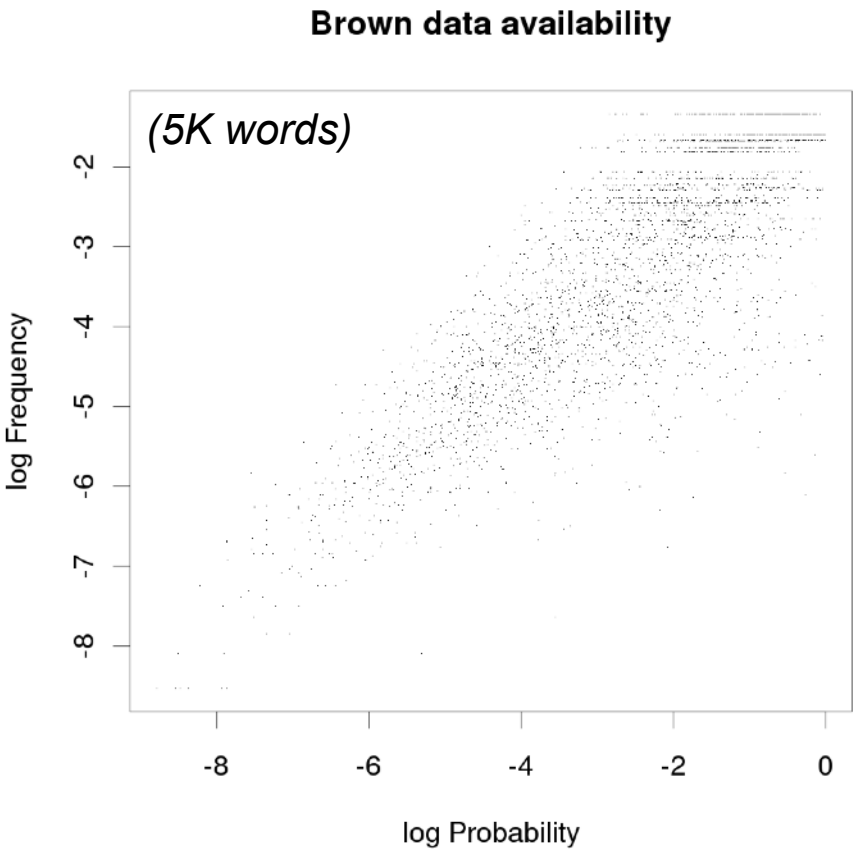
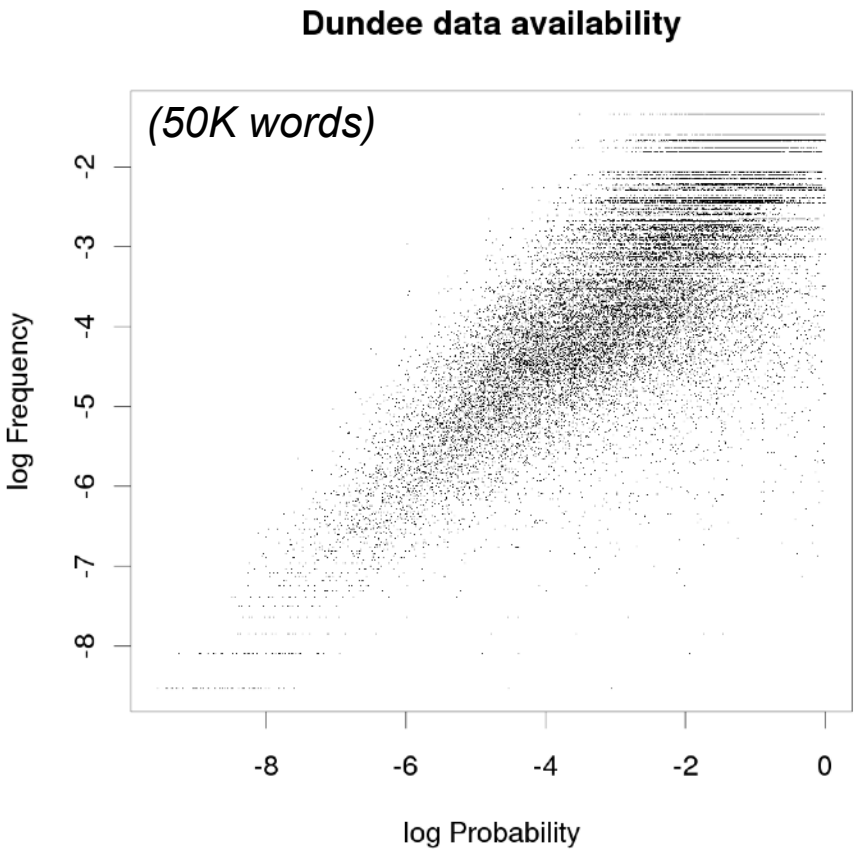
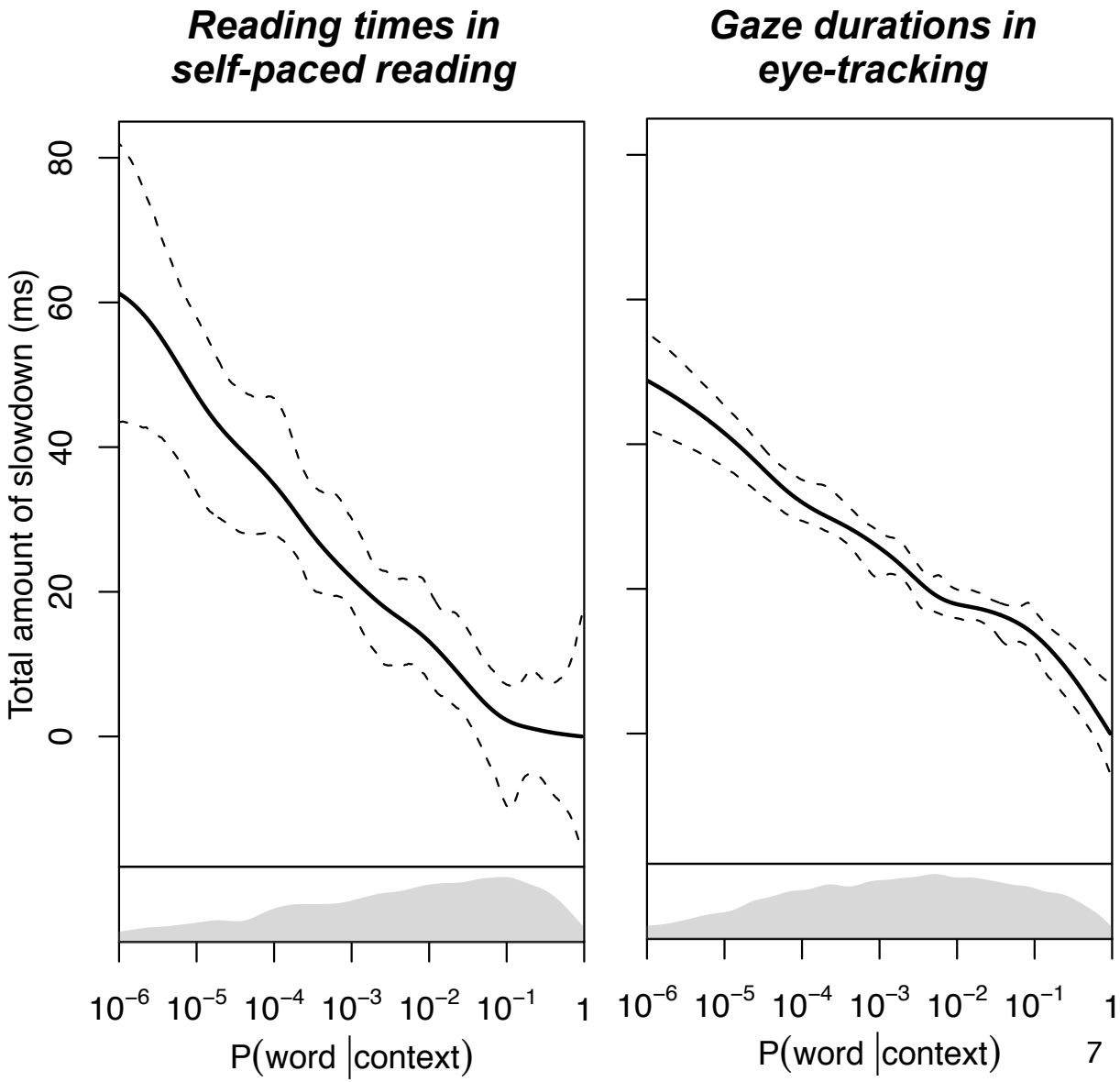




Estimating probability/time curve shape

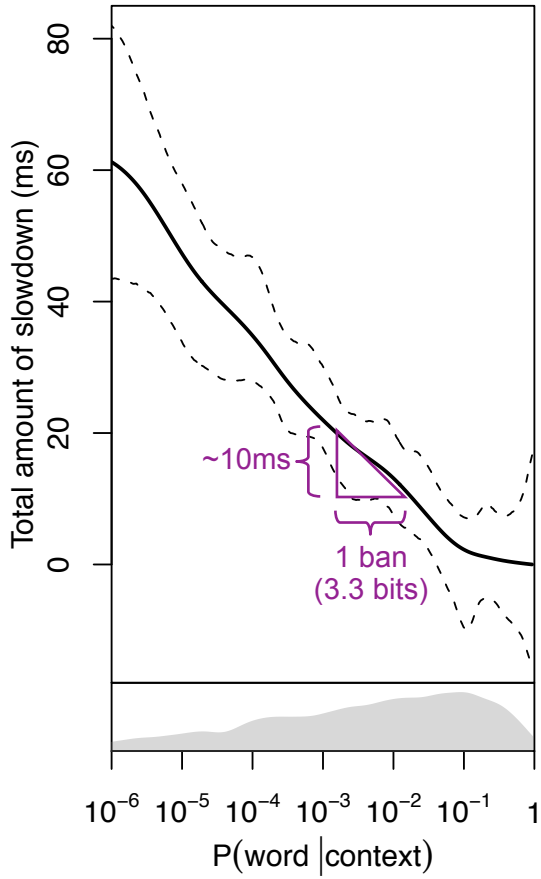
- Generalized additive model regression: total contribution of word (trigram) probability to RT near-linear over 6 orders of magnitude!

(Smith & Levy, 2013)



Take-away: how long to process a word in context?

- On average, time ***linear in the word's log-probability***
- Methodologically: reading puts control in the comprehender's hands (and eyes!), allowing us to study processing difficulty through reading time



A model system with incrementality, structure, and surprise

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The

A model system with incrementality, structure, and surprise

The woman

A model system with incrementality, structure, and surprise

The woman brought

A model system with incrementality, structure, and surprise

The woman brought the

A model system with incrementality, structure, and surprise

The woman brought the sandwich

A model system with incrementality, structure, and surprise

The woman brought the sandwich from

A model system with incrementality, structure, and surprise

The woman brought the sandwich from the

A model system with incrementality, structure, and surprise

The woman brought the sandwich from the kitchen

A model system with incrementality, structure, and surprise

The woman brought the sandwich from the kitchen tripped.

A model system with incrementality, structure, and surprise

A model system with incrementality, structure, and surprise

The woman who was given the sandwich from the kitchen tripped.

A model system with incrementality, structure, and surprise

The woman(who was given the sandwich from the kitchen)tripped.

A model system with incrementality, structure, and surprise

The woman((who was)given the sandwich from the kitchen)tripped.

A model system with incrementality, structure, and surprise

The woman(given the sandwich from the kitchen)tripped.

The woman((who was)given the sandwich from the kitchen)tripped.

A model system with incrementality, structure, and surprise

The woman((who was)brought the sandwich from the kitchen)tripped.

The woman(given the sandwich from the kitchen)tripped.

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A model system with incrementality, structure, and surprise

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	Simple past	Past participle
bring	***brought***	***brought***
give	***gave***	***given***

A model system with incrementality, structure, and surprise

The woman(brought the sandwich from the kitchen)tripped.

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Low-tech, crowd-sourceable reading

(Forster et al., 2009; Boyce et al., 2020)

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- The **maze task**

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of

F

dog

J

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F　　J

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the	eat
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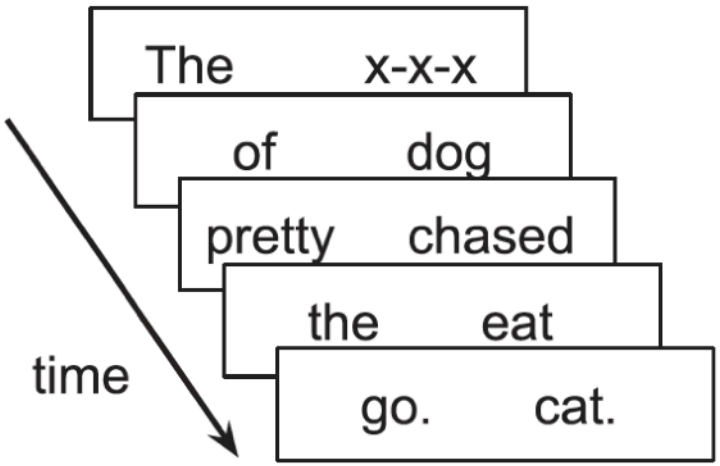

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Incrementality, structure, and surprise

The woman brought the sandwich from the kitchen tripped.

The woman given the sandwich from the kitchen tripped.

The woman who was brought the sandwich from the kitchen tripped.

The woman who was given the sandwich from the kitchen tripped.

(Vani et al., in progress)

Incrementality, structure, and surprise

	Is the relative clause reduced?
The woman brought the sandwich from the kitchen tripped.	+
The woman given the sandwich from the kitchen tripped.	+
The woman who was brought the sandwich from the kitchen tripped.	–
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(Vani et al., in progress)

Incrementality, structure, and surprise

	Is the relative clause reduced?	Is the participle part-of-speech ambiguous?
The woman brought the sandwich from the kitchen tripped.	+	+
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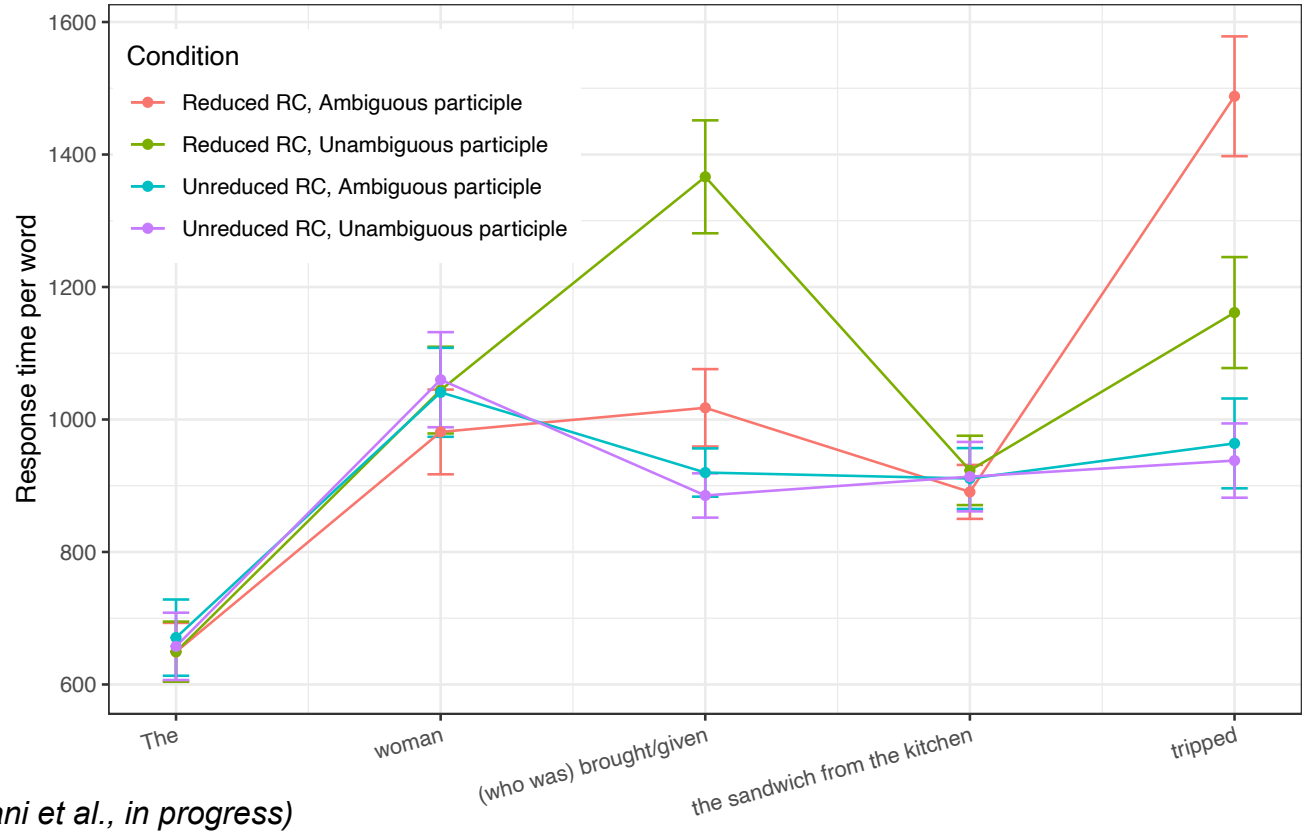

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Desiderata for human-like processing

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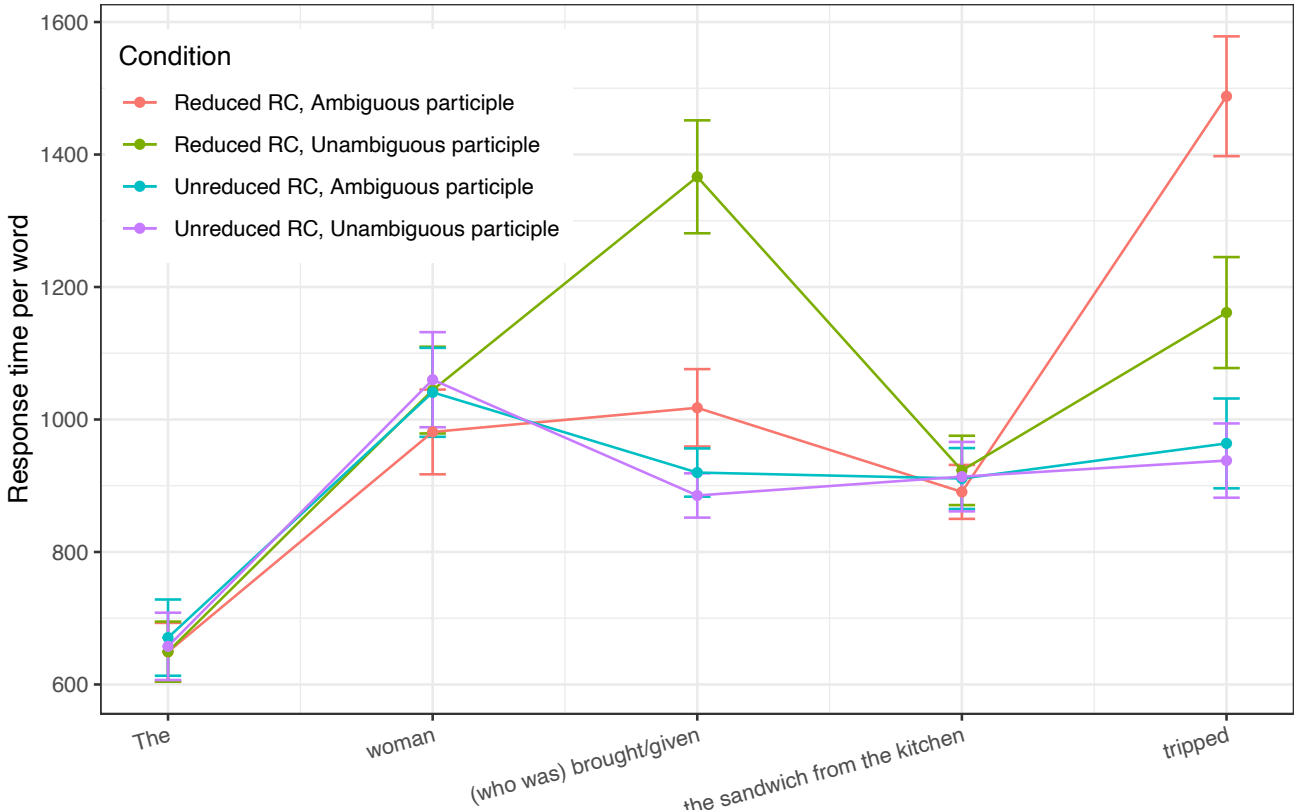
The woman given the sandwich from the kitchen tripped.	+	–
The woman who was brought the sandwich from the kitchen tripped.	–	+
The woman who was given the sandwich from the kitchen tripped.	–	–



(Futrell et al., 2019; Hu et al., 2020; Gauthier et al., 2020; Vani et al., in progress)

Desiderata for human-like processing

	Is the relative clause reduced?	Is the participle part-of-speech ambiguous?
The woman brought the sandwich from the kitchen tripped.	+	+
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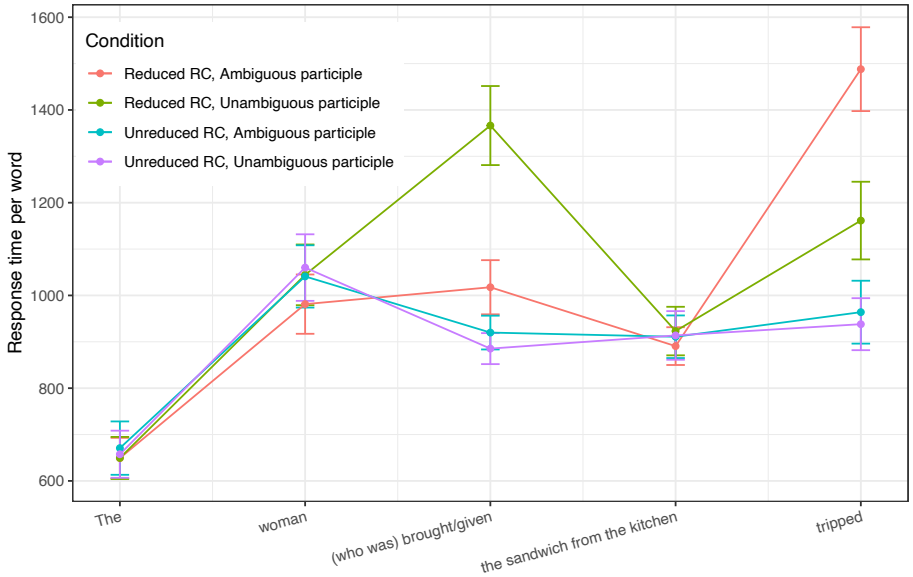

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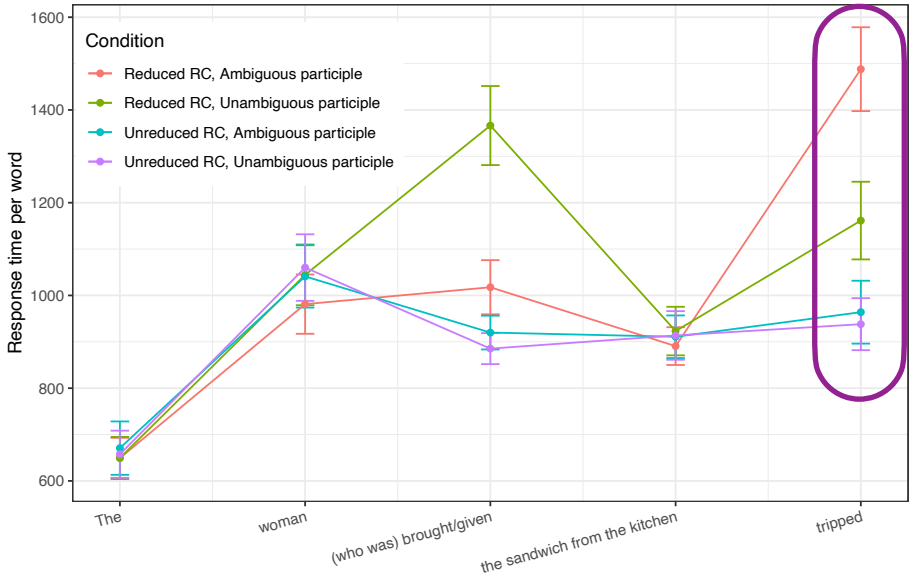

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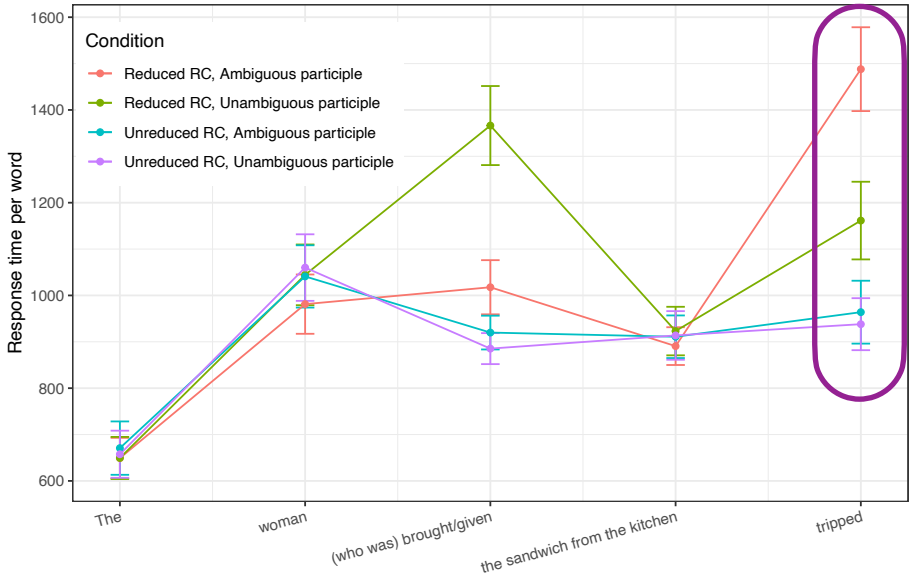

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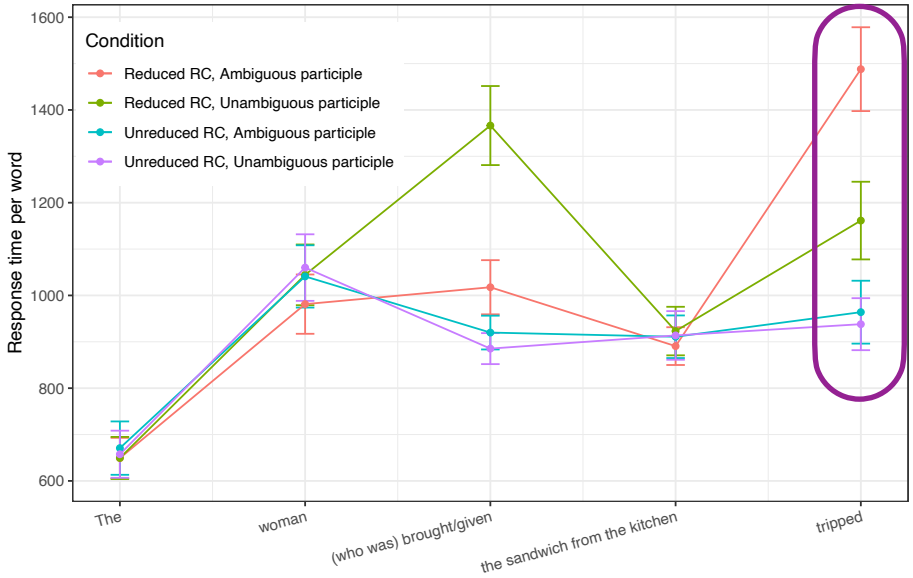

Define:

$$S(x) = \log \frac{1}{P(\text{tripped} \mid \text{Context}_x)}$$

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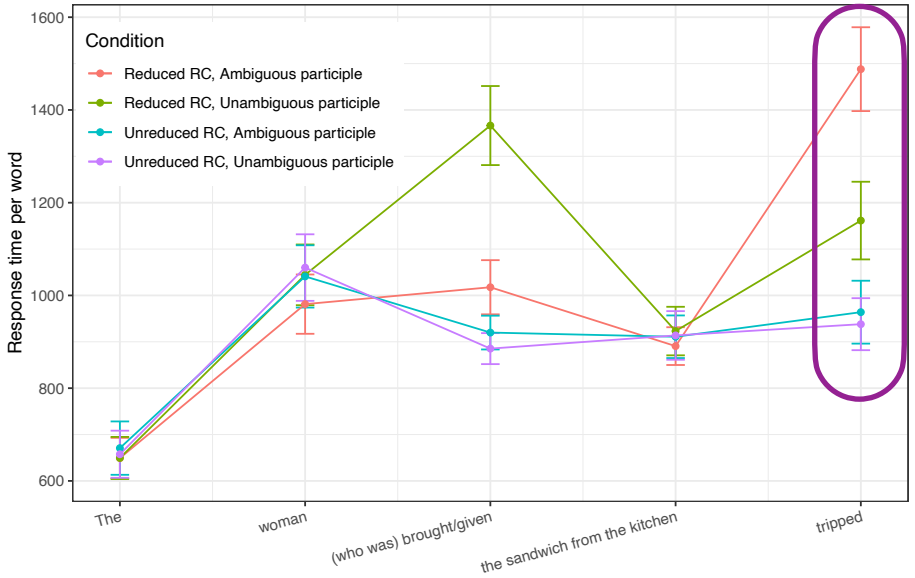

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Then we can define three criteria for "human-like" processing:

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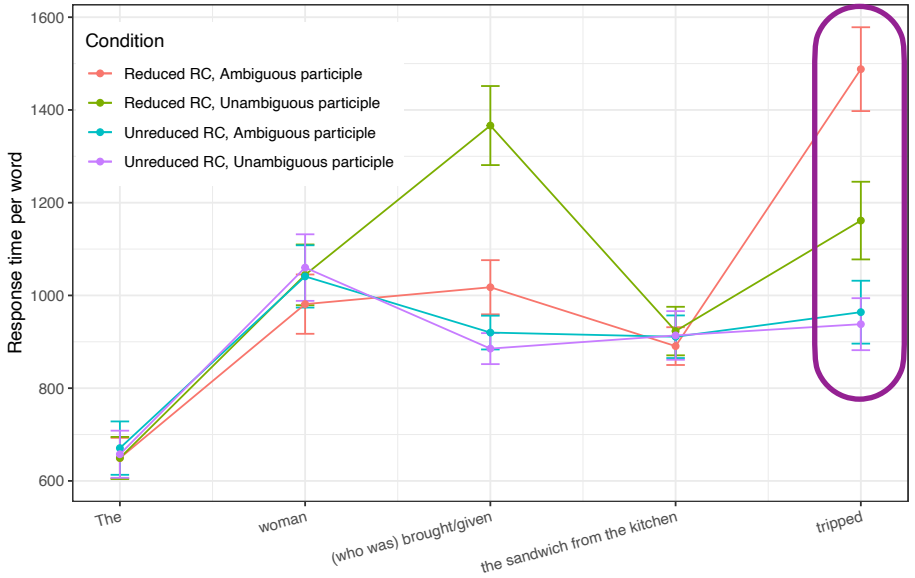

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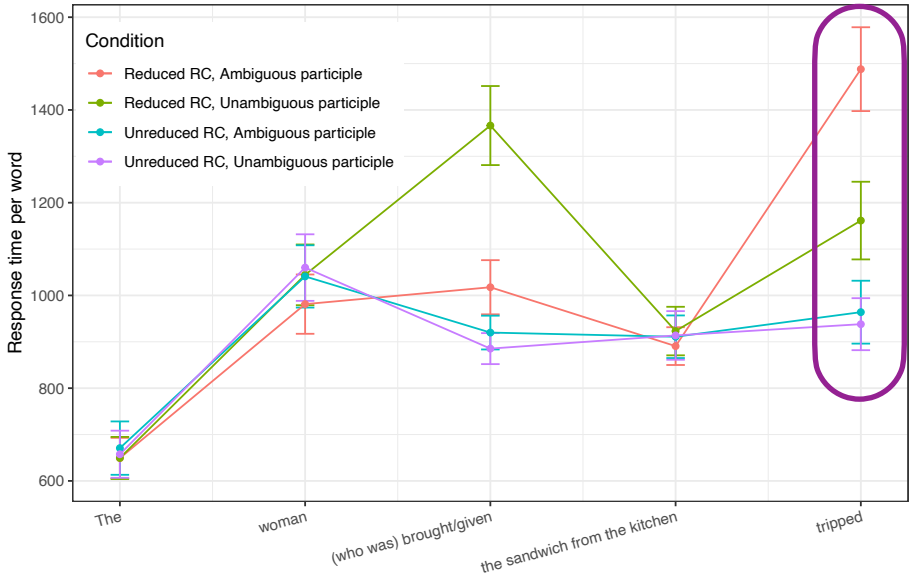

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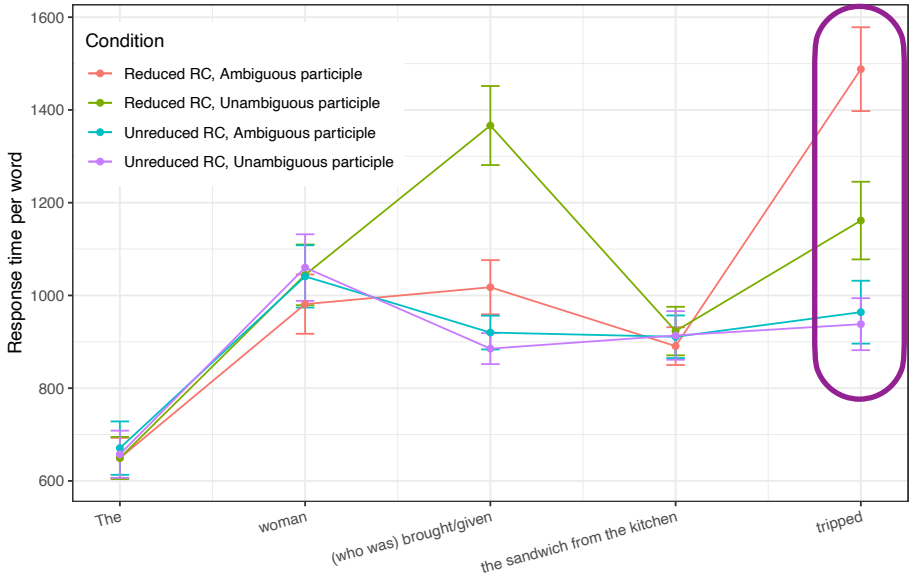

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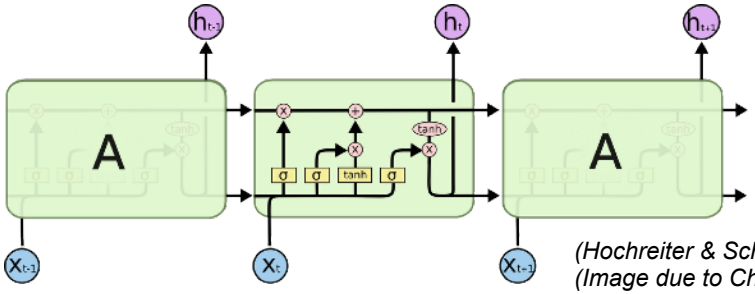
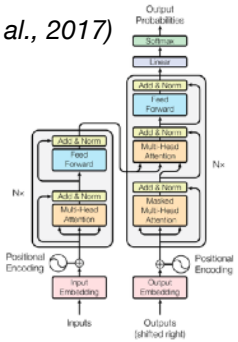
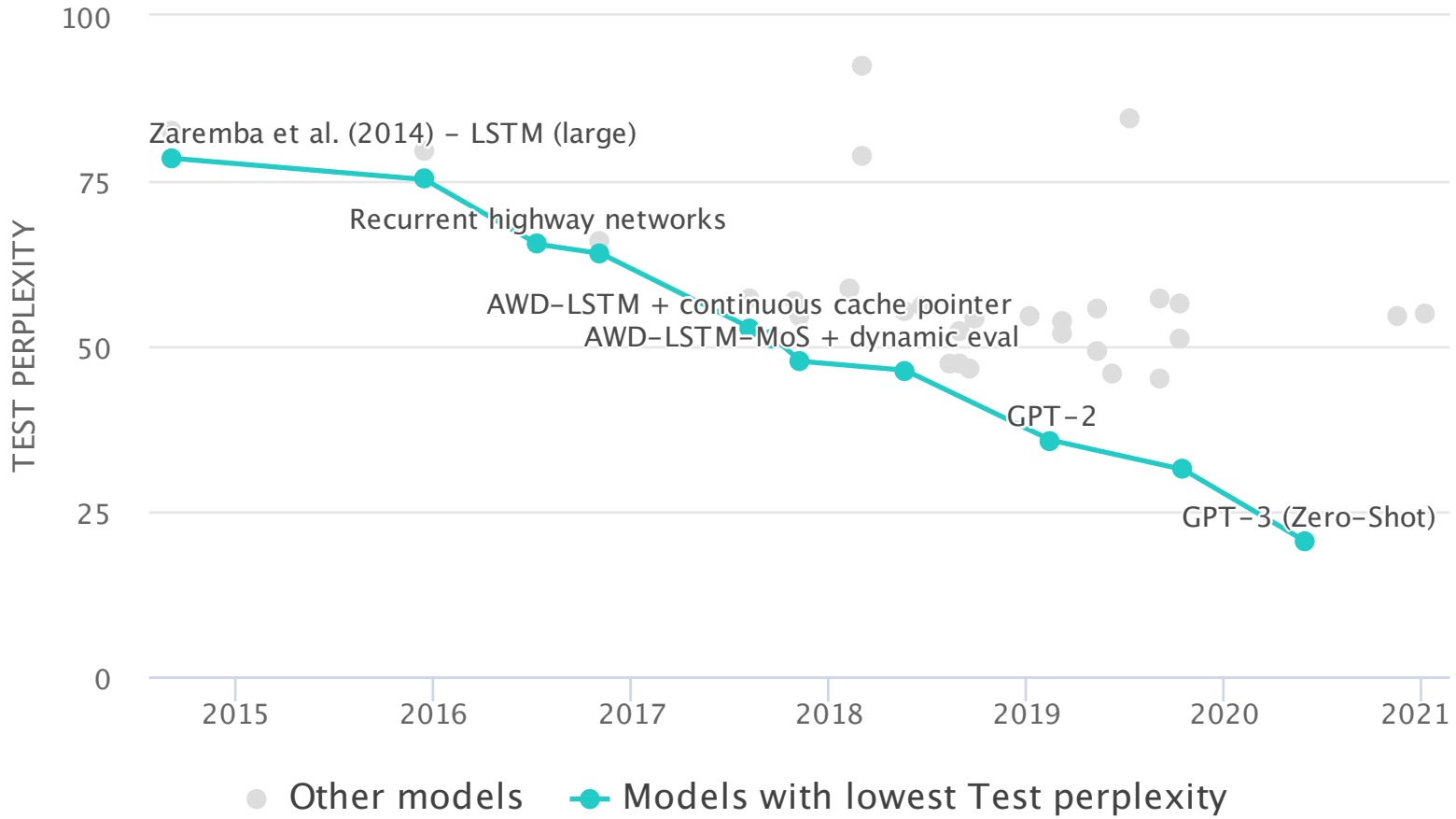
Deep learning has revolutionized language modeling



(Hochreiter & Schmidhuber, 1997)
(Image due to Christopher Olah)

(Vaswani et al., 2017)





https://paperswithcode.com/sota/language-modelling-on-penn-treebank-word

What have these models learned as “English”?

(continuations generated by model of Jozefowicz et al., 2016)

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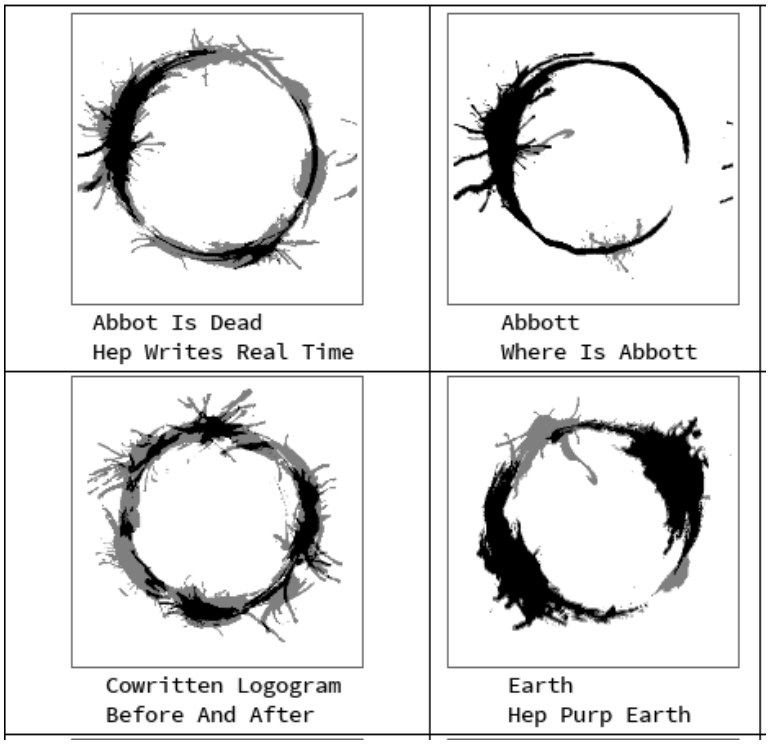
Technical question:

What generalizations are these models learning?



Theoretical question:

How well would positive* input data alone deliver the right linguistic generalizations to a generic flexible learner without strong hierarchical bias?

******No negative evidence!***

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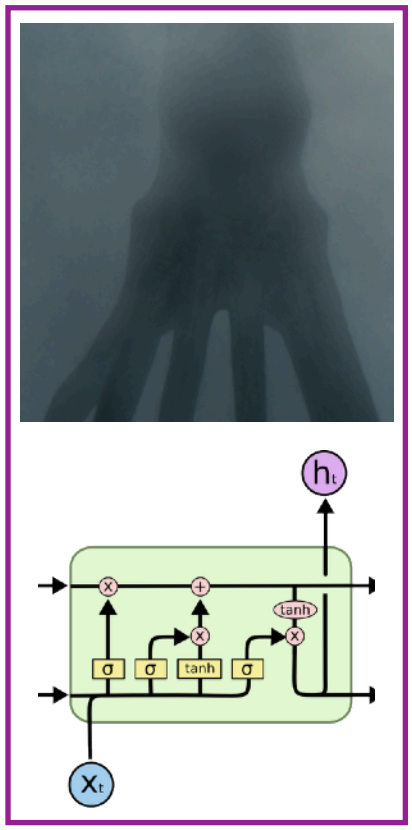

***No negative evidence!**

Focus: *grammatical generalizations*

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- Languages vary dramatically across the world in structure

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English:
I bought the bed

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English:	Japanese:		
I bought the bed	beddo	-o	ka-tta
	(pro) bed	-ACC	buy-PAST

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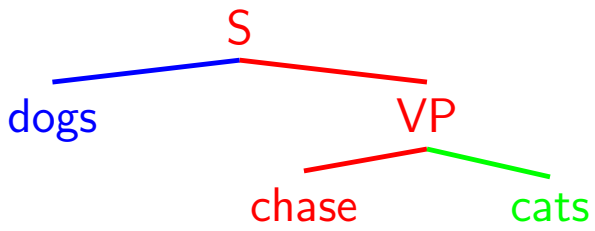

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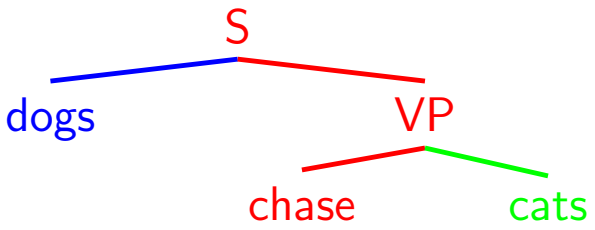

Idiosyncrasy:

$[\![\text{kick the bucket}]\!]$

$\neq$

$[\![\text{kick}]\!](\iota(\lambda x.[\![bucket]\!](x)))$

Focus: *grammatical generalizations*

INFORMATION AND CONTROL 10, 447–474 (1967)

Language Identification in the Limit

E MARK GOLD*

The RAND Corporation

Language learnability has been investigated. This refers to the following situation: A class of possible languages is specified, together with a method of presenting information to the learner about an unknown language, which is to be chosen from the class. The question is now asked, "Is the information sufficient to determine which of the possible languages is the unknown language?" Many definitions of learnability are possible, but only the following is considered here: Time is quantized and has a finite starting time. At each time the learner receives a unit of information and is to make a guess as to the identity of the unknown language on the basis of the information received so far. This process continues forever. The class of languages will be considered *learnable* with respect to the specified method of information presentation if there is an algorithm that the learner can use to make his guesses, the algorithm having the following property: Given any language of the class, there is some finite time after which the guesses will all be the same and they will be correct.

Linguistic Inquiry Volume 10 Number 4 (Fall, 1979) 533–581.

C. L. Baker

Syntactic Theory and the Projection Problem*

0. Introduction

One of the most basic concerns in the writings of Noam Chomsky, beginning in *Syntactic Structures* and extending through his recent work, has been to draw attention to the profundity of one of the central psychological problems posed by the phenomenon of first language acquisition.[1] Following Peters (1972), I will refer to this problem as the "projection problem". Reduced to essentials, solving the projection problem involves finding a satisfactory answer to the following question: What is the functional relation that exists between an arbitrary human being's early linguistic experience (his "primary linguistic data") and his resulting adult intuitions?[2] A solution to this problem requires a body of hypotheses that would make it possible to deduce the full range of adult intuitions in advance, given only a suitable record of the early experience. Applied to

Linguistic Nativism and the Poverty of the Stimulus

Alexander Clark and Shalom Lappin

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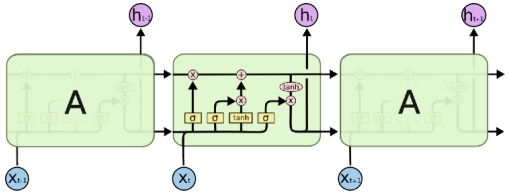
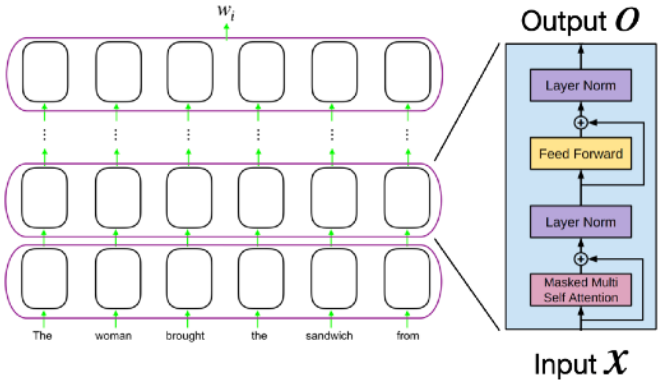
Language models tested

Model	Architecture	Training Data	Data size (tokens)	Reference
JRNN	LSTM	Web text	~800,000,000	Jozefowicz et al. (2016)
GRNN	LSTM	Wikipedia	~90,000,000	Gulordava et al. (2018)
GPT-2	Transformer	Web text	~8,000,000,000	Radford et al. (2019)
GPT-3	Transformer	Web text	~40,000,000,000	Brown et al. (2020)
RNNG	Syntax+LSTM	Penn Treebank	~1,000,000	Dyer et al. (2016)
tinylstm	LSTM	Penn Treebank	~1,000,000	
n-gram	5-gram model	British Nat'l Corpus	~100,000,000	

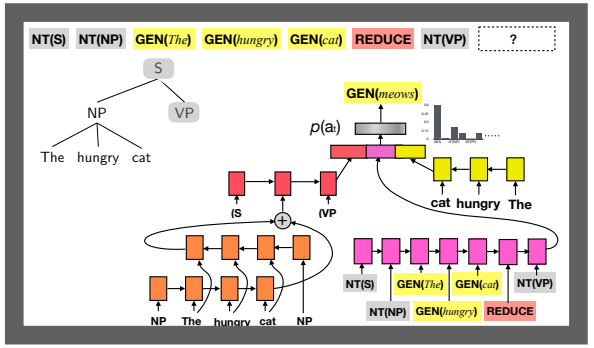
Long Short-Term Memory (LSTM) Network



Transformer decoder



Recurrent Neural Network Grammar



Language models tested

*~human **childhood** of linguistic experience*

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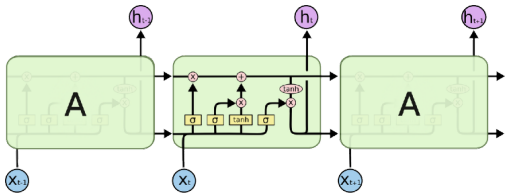

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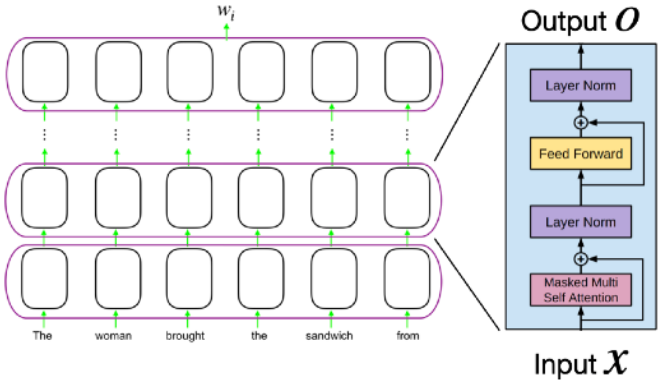

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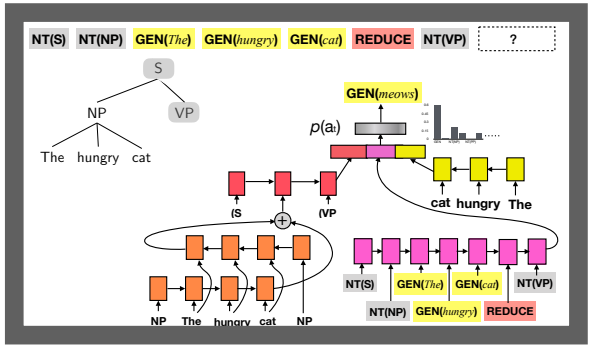


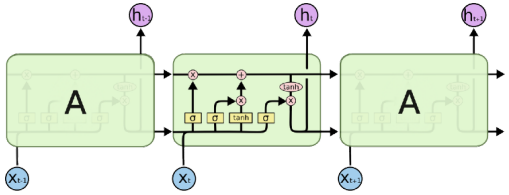
Language models tested

*~human **lifetime** of linguistic experience*

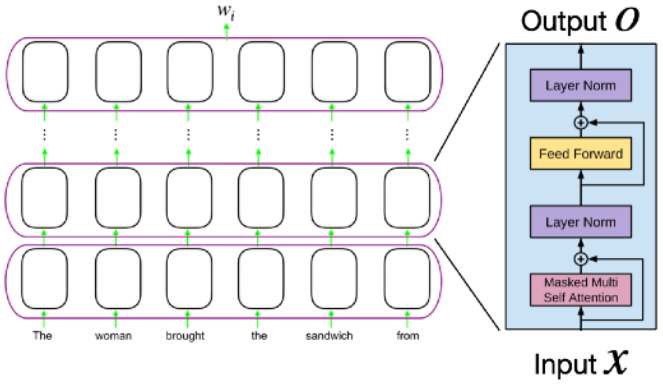
*~human **childhood** of linguistic experience*

Model	Architecture	Training Data	Data size (tokens)	Reference
JRNN	LSTM	Web text	~800,000,000	Jozefowicz et al. (2016)
GRNN	LSTM	Wikipedia	~90,000,000	Gulordava et al. (2018)
GPT-2	Transformer	Web text	~8,000,000,000	Radford et al. (2019)
GPT-3	Transformer	Web text	~40,000,000,000	Brown et al. (2020)
RNNG	Syntax+LSTM	Penn Treebank	~1,000,000	Dyer et al. (2016)
tinylstm	LSTM	Penn Treebank	~1,000,000	
n-gram	5-gram model	British Nat'l Corpus	~100,000,000	

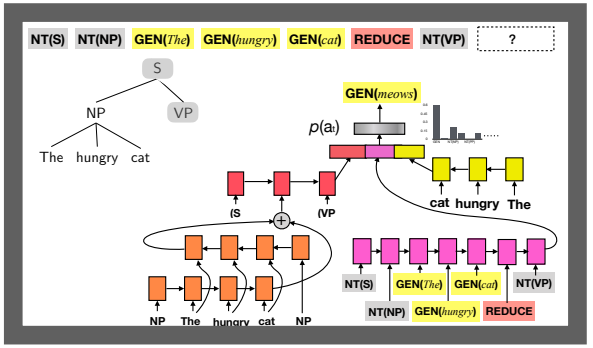
Long Short-Term Memory (LSTM) Network



Transformer decoder



Recurrent Neural Network Grammar



Simplest syntactic hierarchy: subordination

(Futrell, Wilcox, Morita, Qian, Ballesteros, & Levy, NAACL 2019)

Simplest syntactic hierarchy: subordination

The doctor studied the textbook .

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The doctor studied the textbook
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Context | Completion

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$$-\log P(\text{Completion}|\text{Context})$$

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"No-matrix" variants
(No subsequent matrix clause)

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Surprisal difference (should be *positive*)

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Surprisal difference (should be *negative*)

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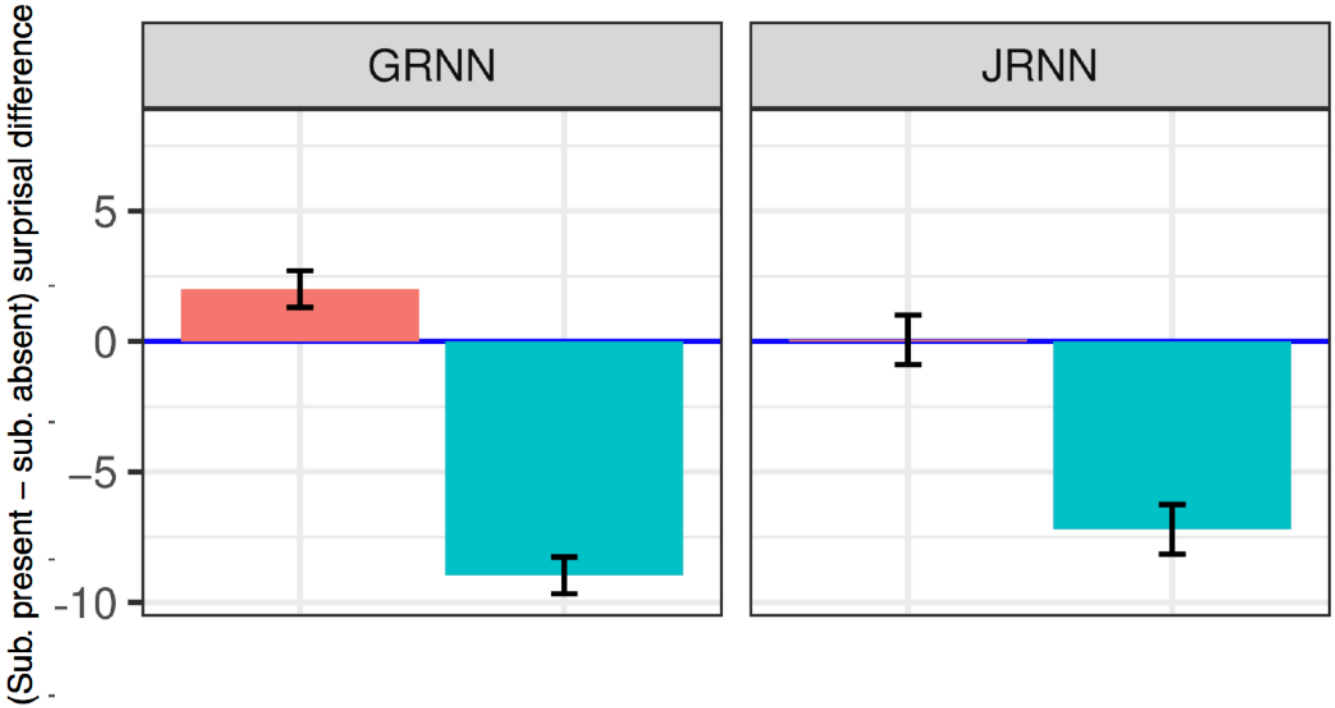
Effects of Subordinate Clauses



(Futrell, Wilcox, Morita, Qian, Ballesteros, & Levy, NAACL 2019)

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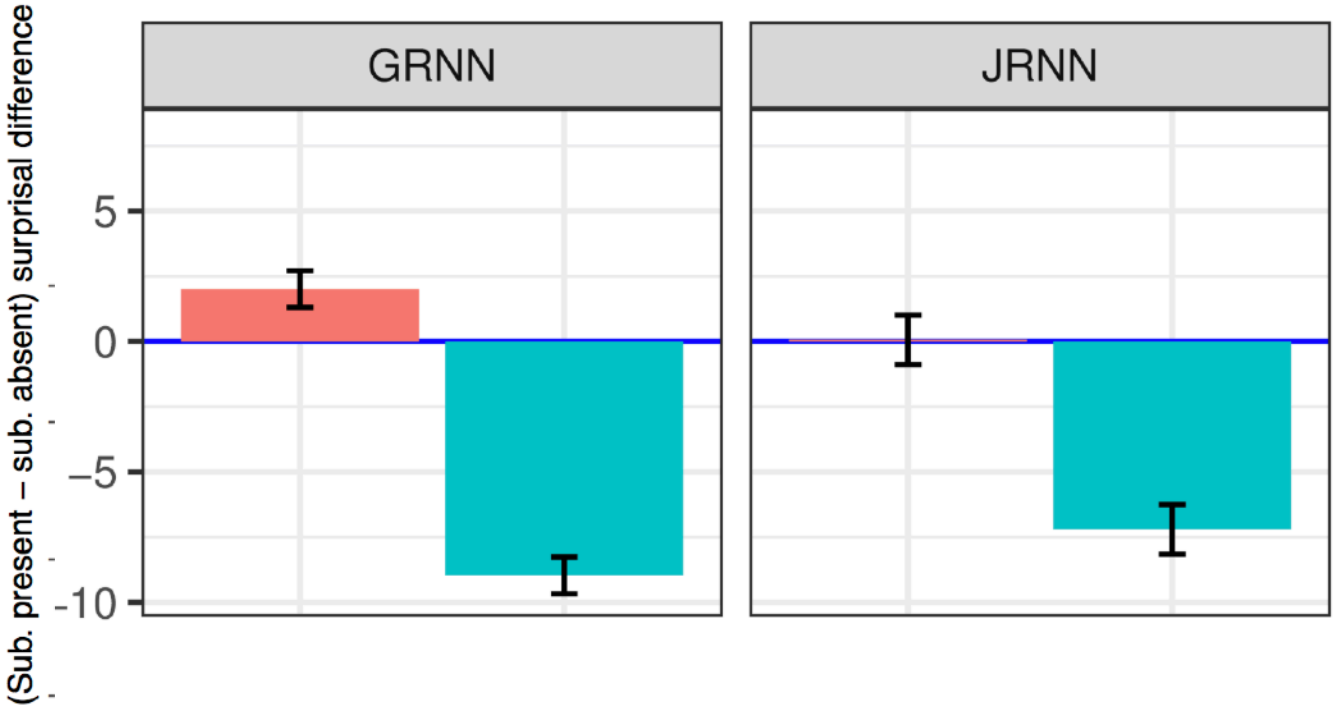

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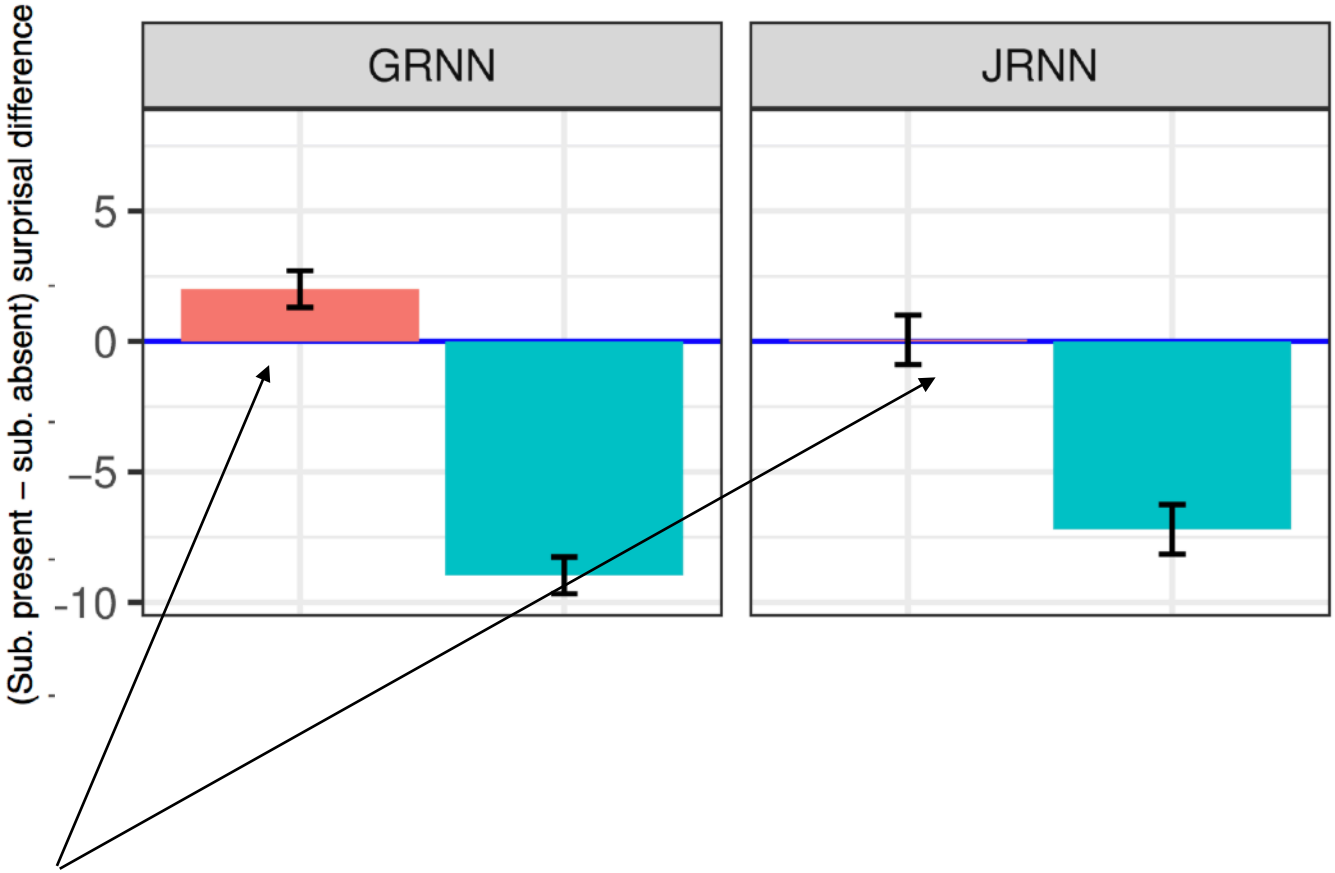

No-matrix penalty

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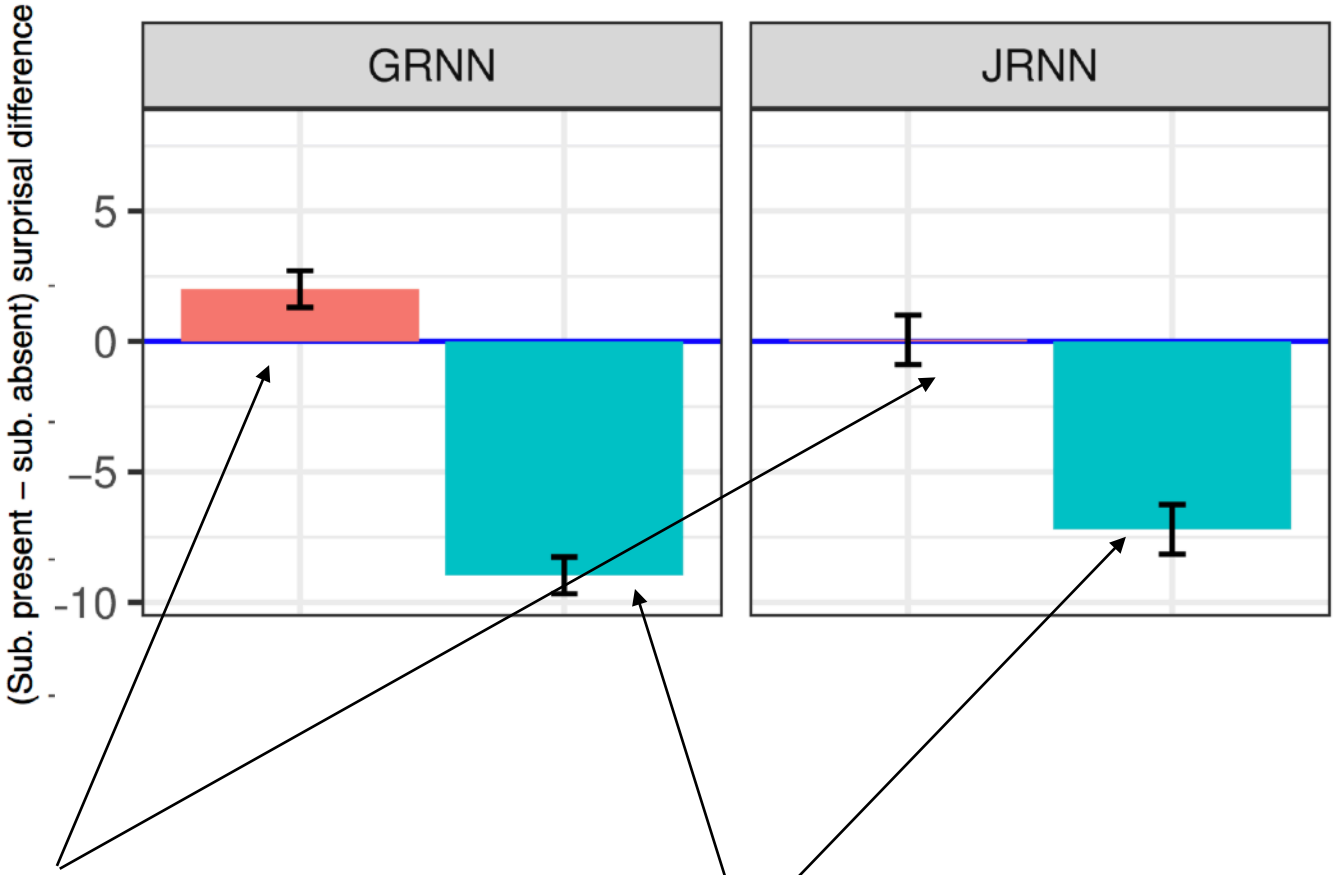
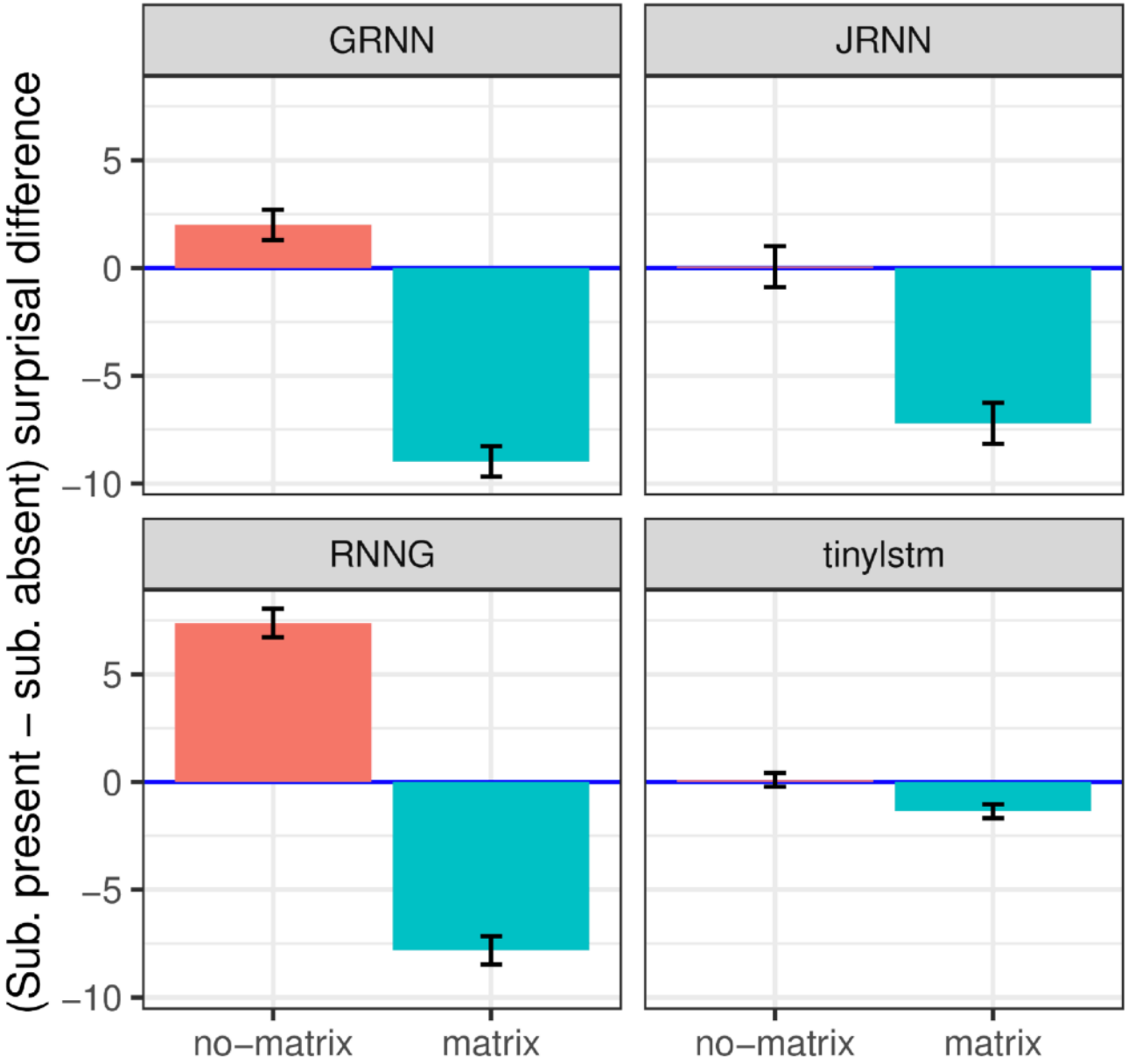


No-matrix penalty

Matrix licensing

(Futrell, Wilcox, Morita, Qian, Ballesteros, & Levy, NAACL 2019)

Subordination: results



(Futrell, Wilcox, Morita, Qian, Ballesteros, & Levy, NAACL 2019)

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

(Wilcox et al., 2018; in prep)

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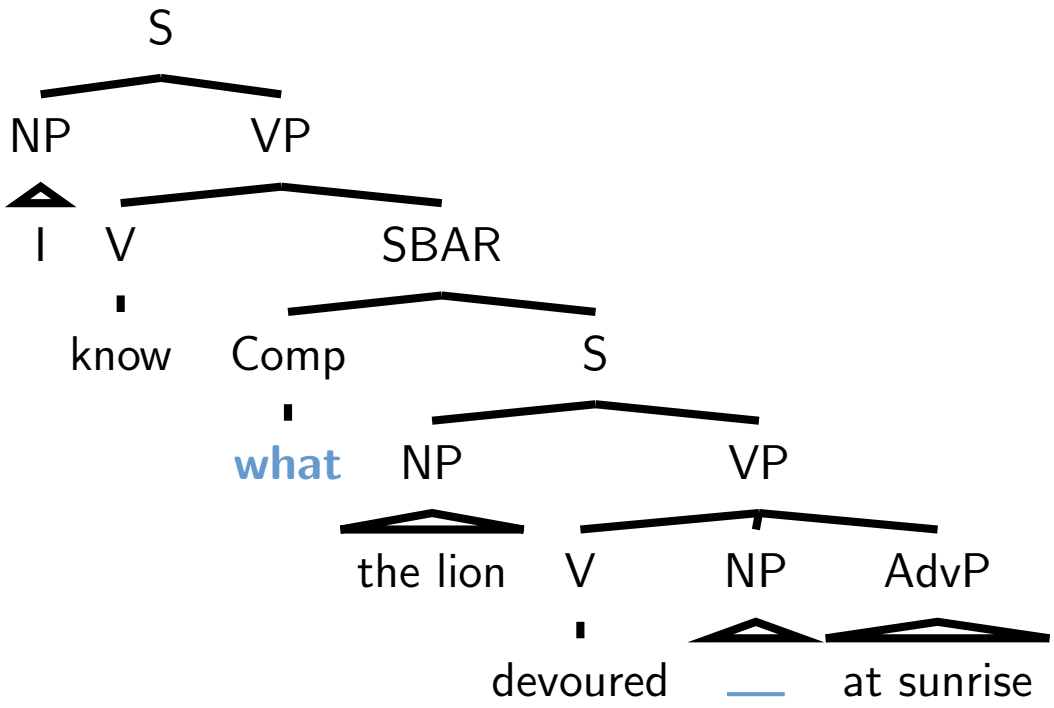

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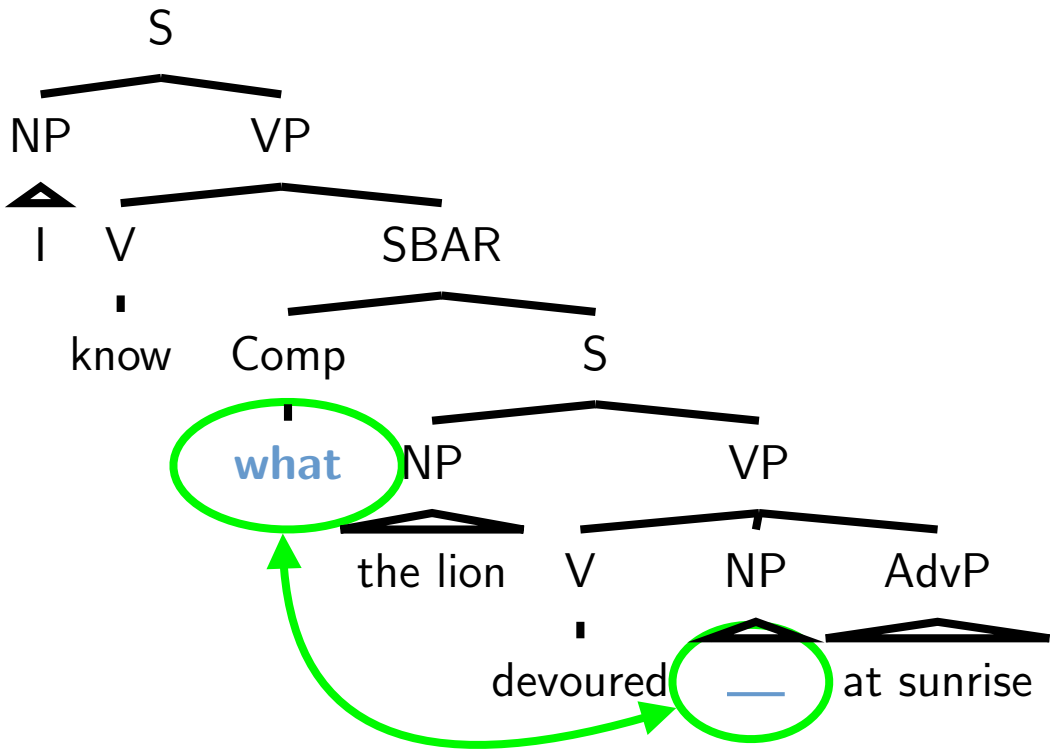

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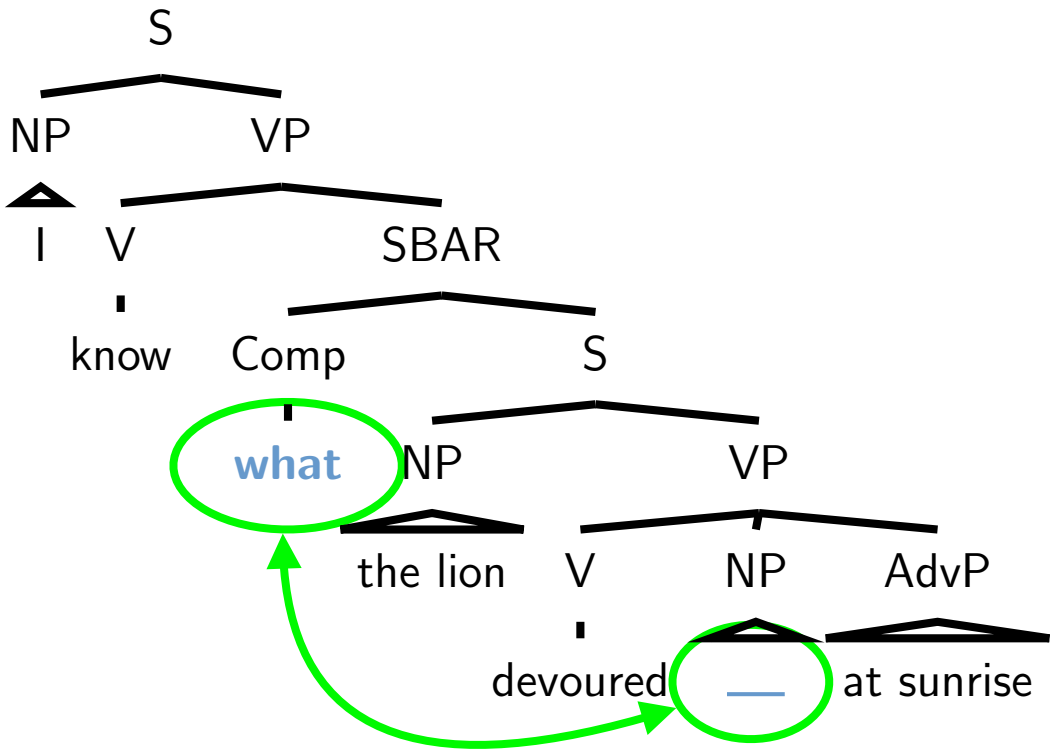

+FILLER
+GAP

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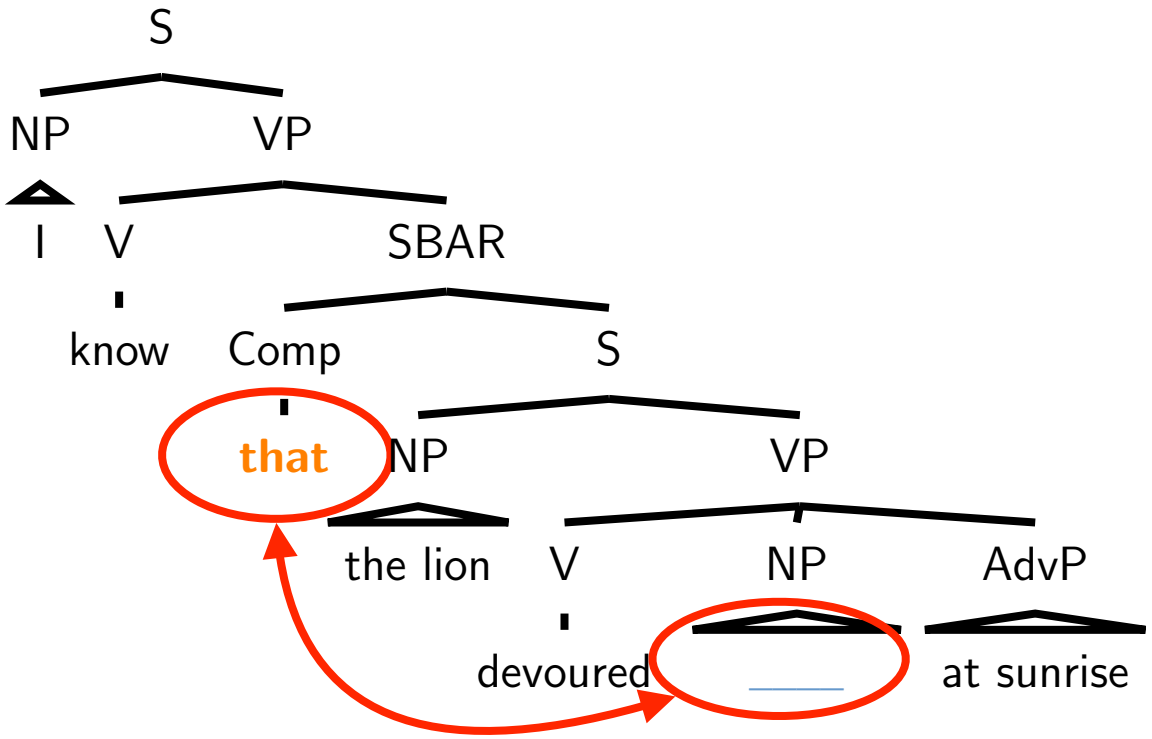

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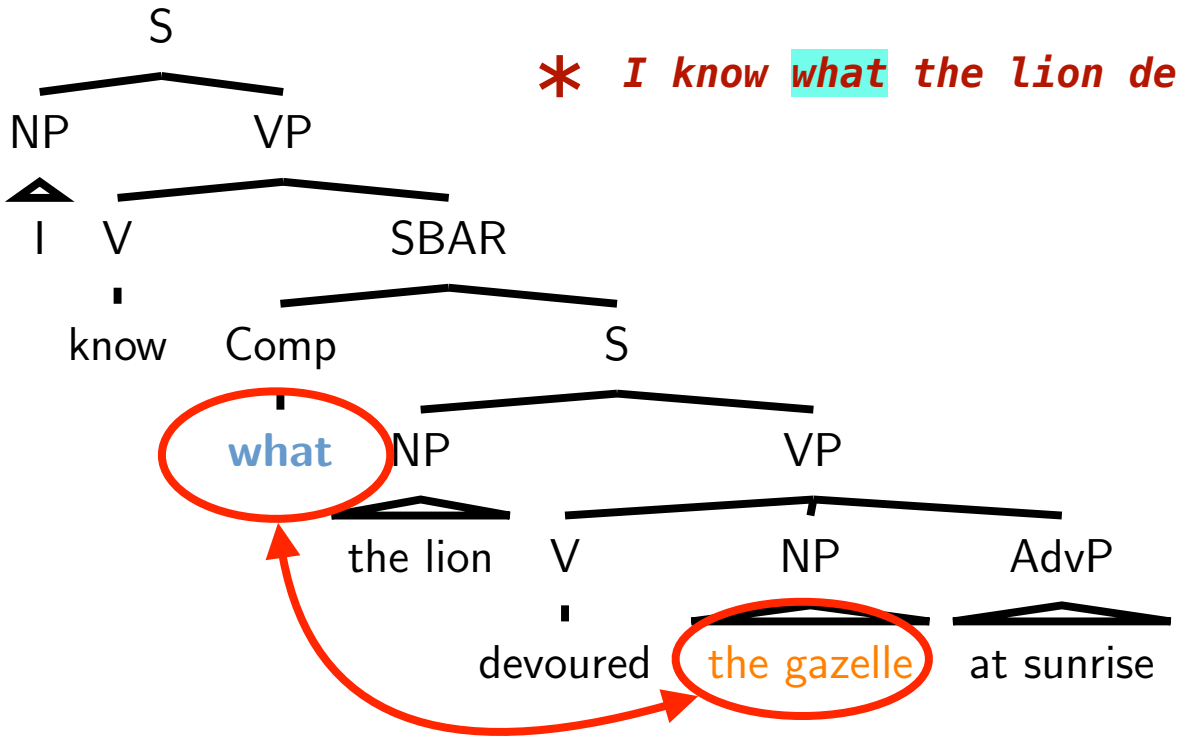

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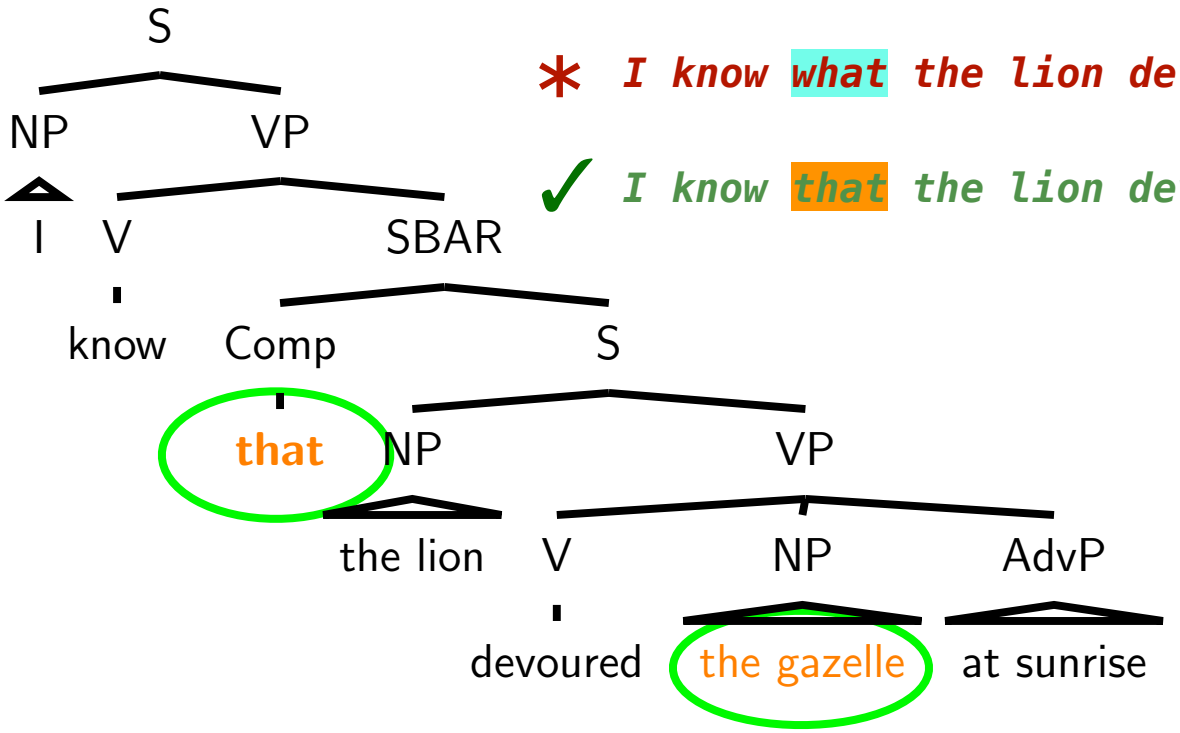

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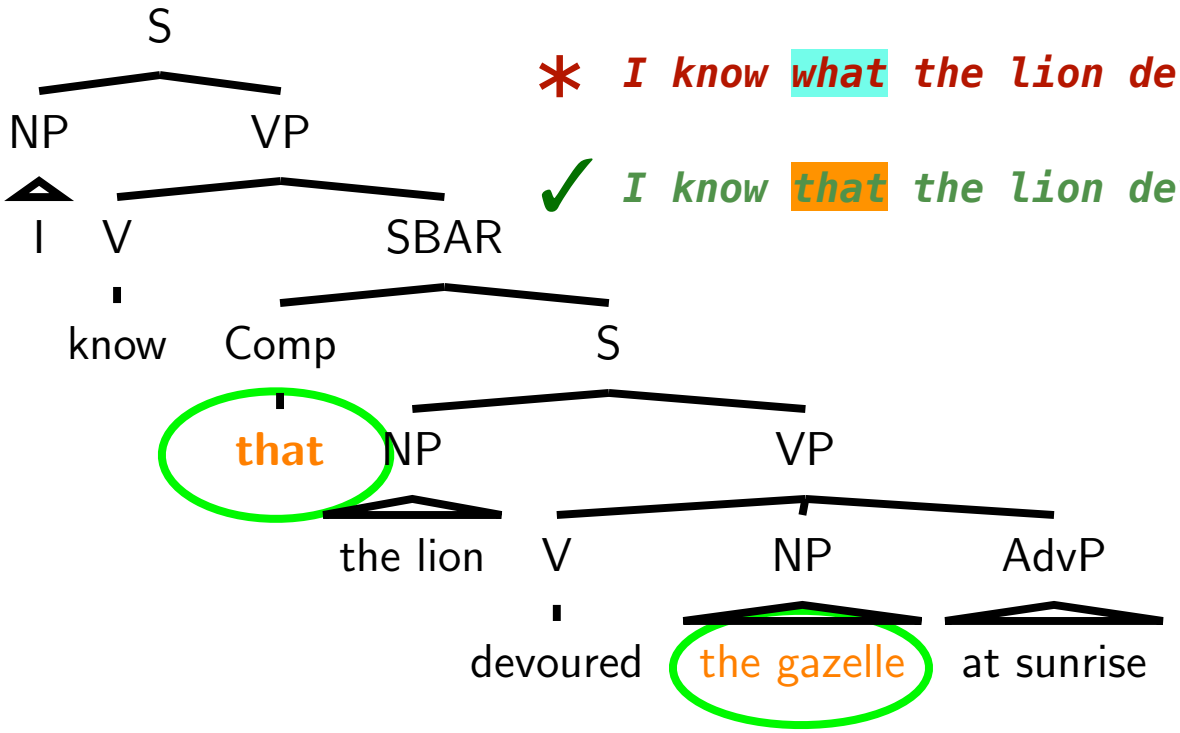

–FILLER
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Filler–gap dependencies *are a signature, theoretically central feature of natural language grammar*

(Wilcox et al., 2018; in prep)

✓ *I know that ... the CEO showed the slides to the guests after lunch.*

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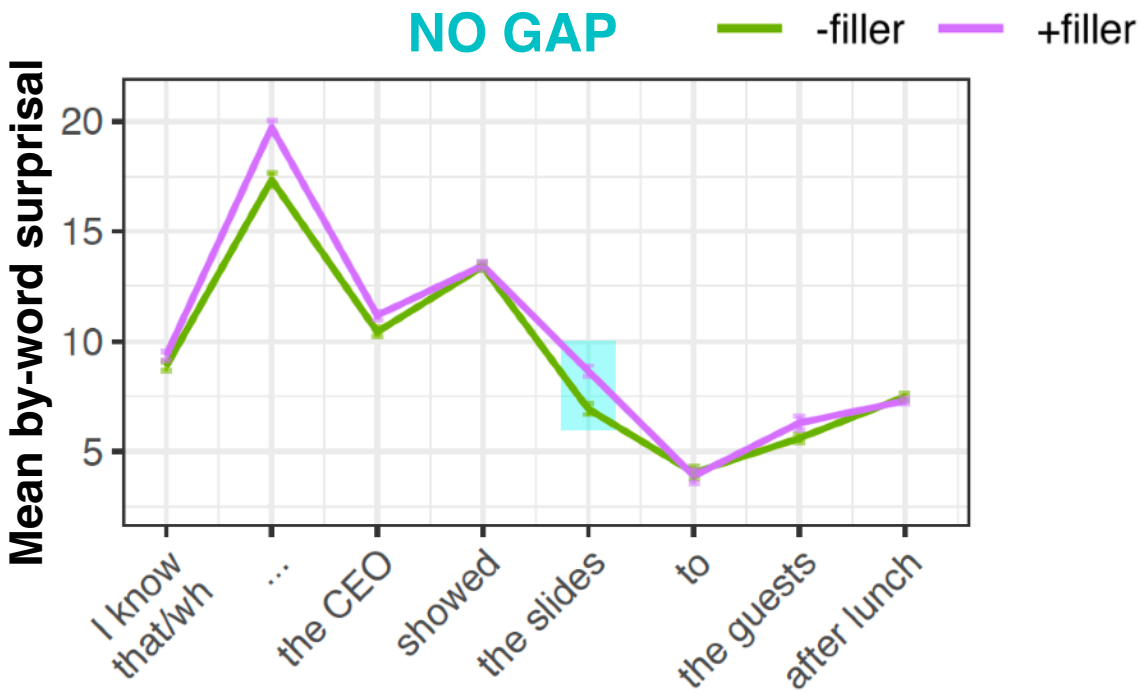

(Matches well-known human reading-time patterns: Stowe, 1986)

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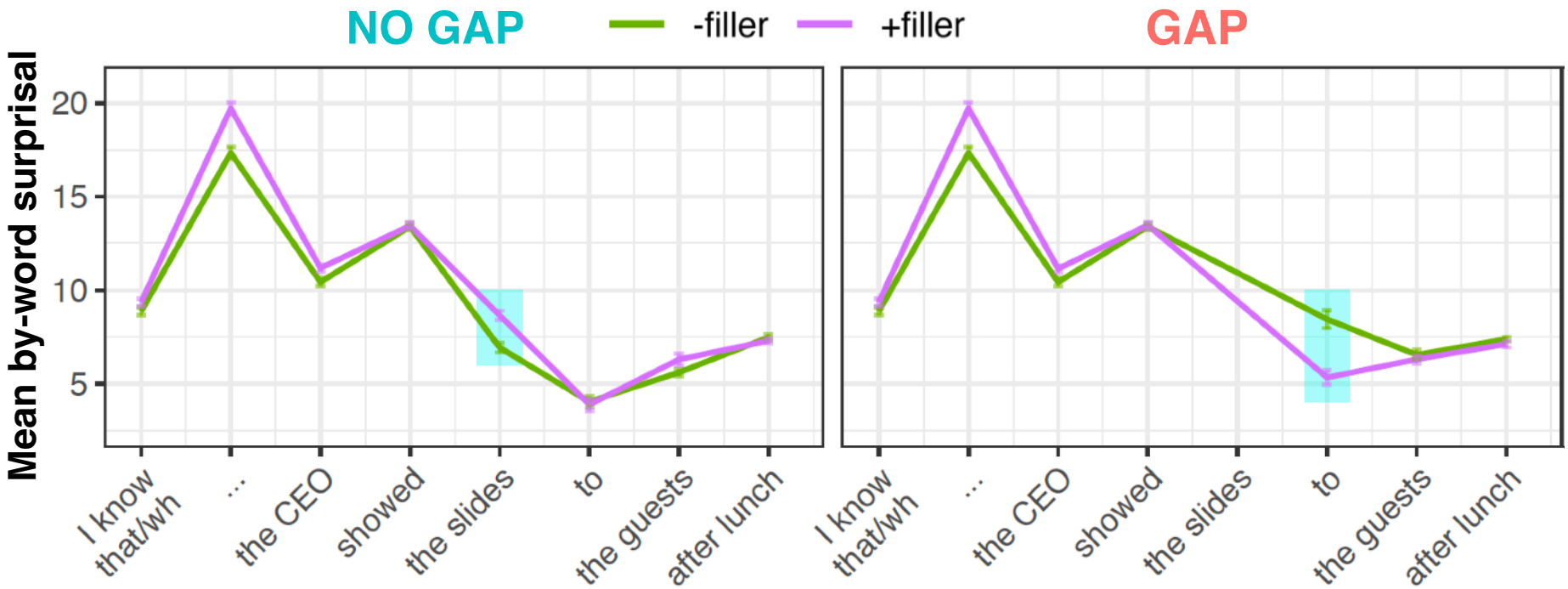

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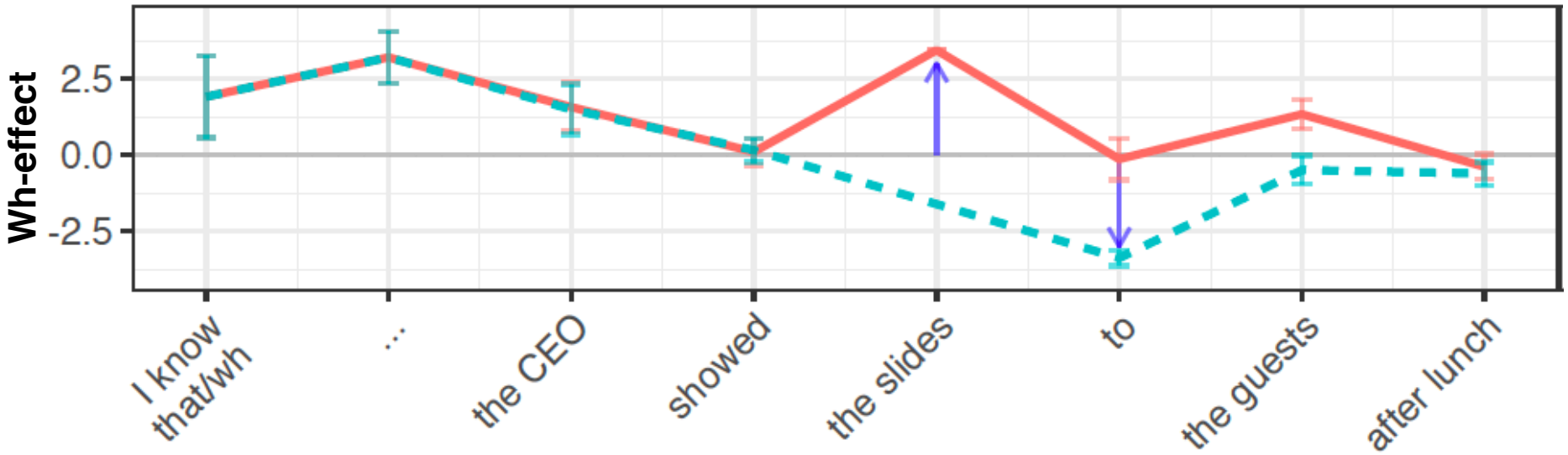

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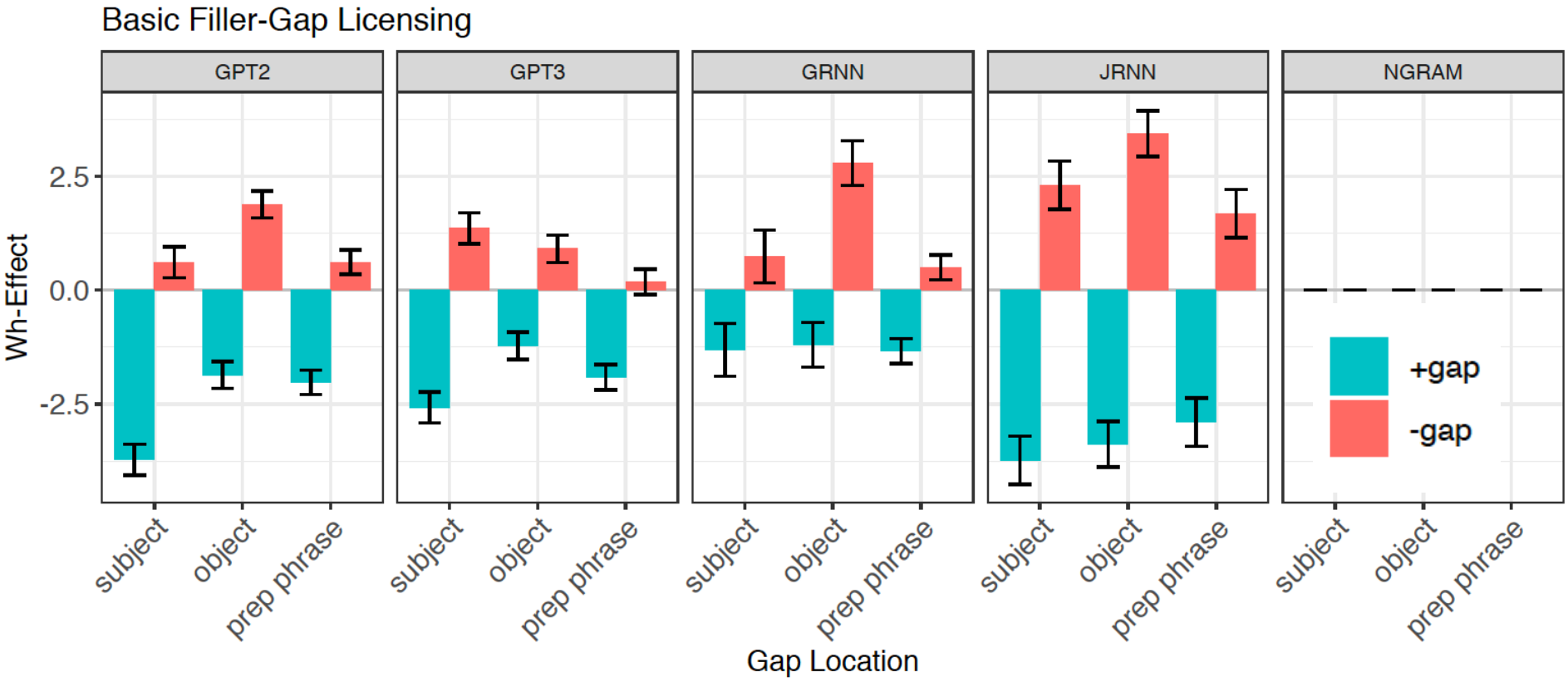
Flexibility of filler–gap dependencies



(Wilcox et al., 2018, in prep)

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

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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

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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.*

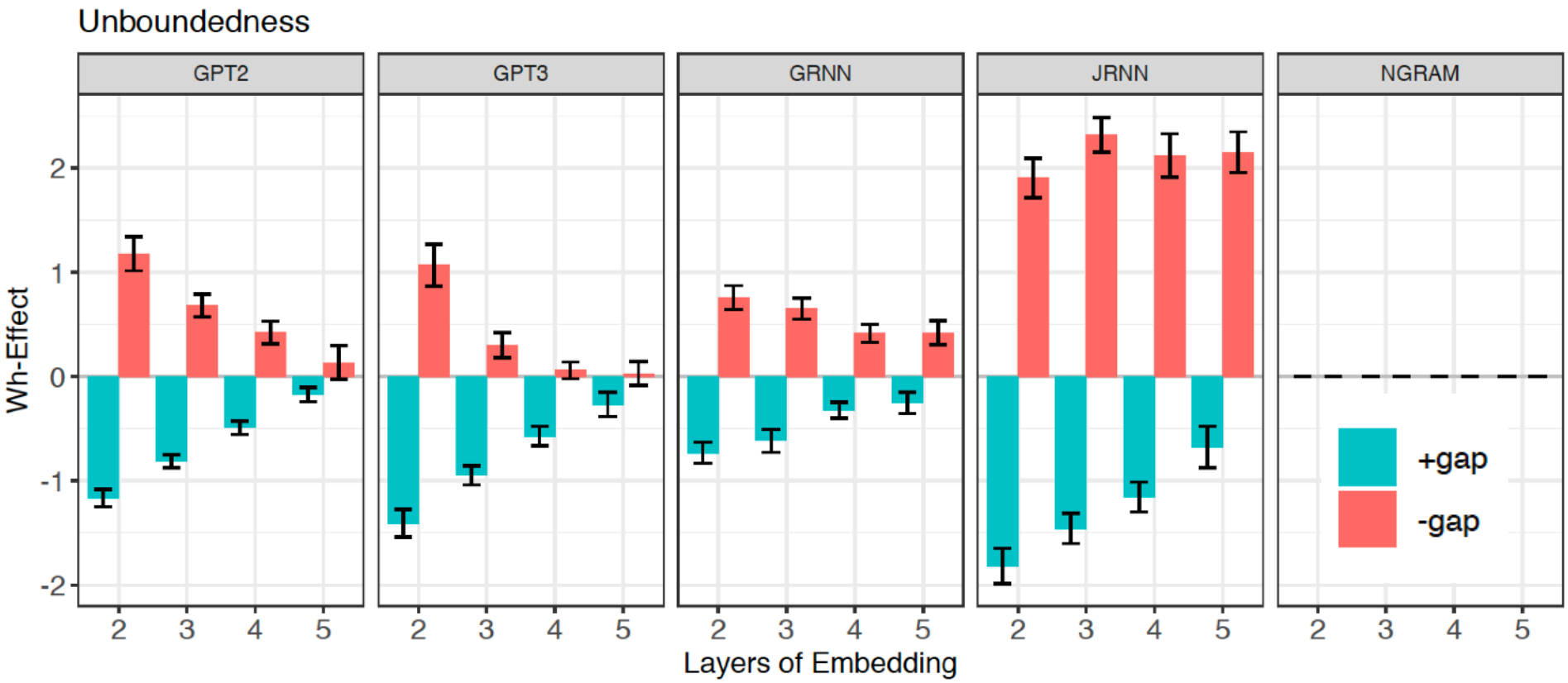
2 *I know what our mother said that her friend remarked that your friend gave __ to Mary last weekend.*

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 of filler–gap dependency

- For object gaps:



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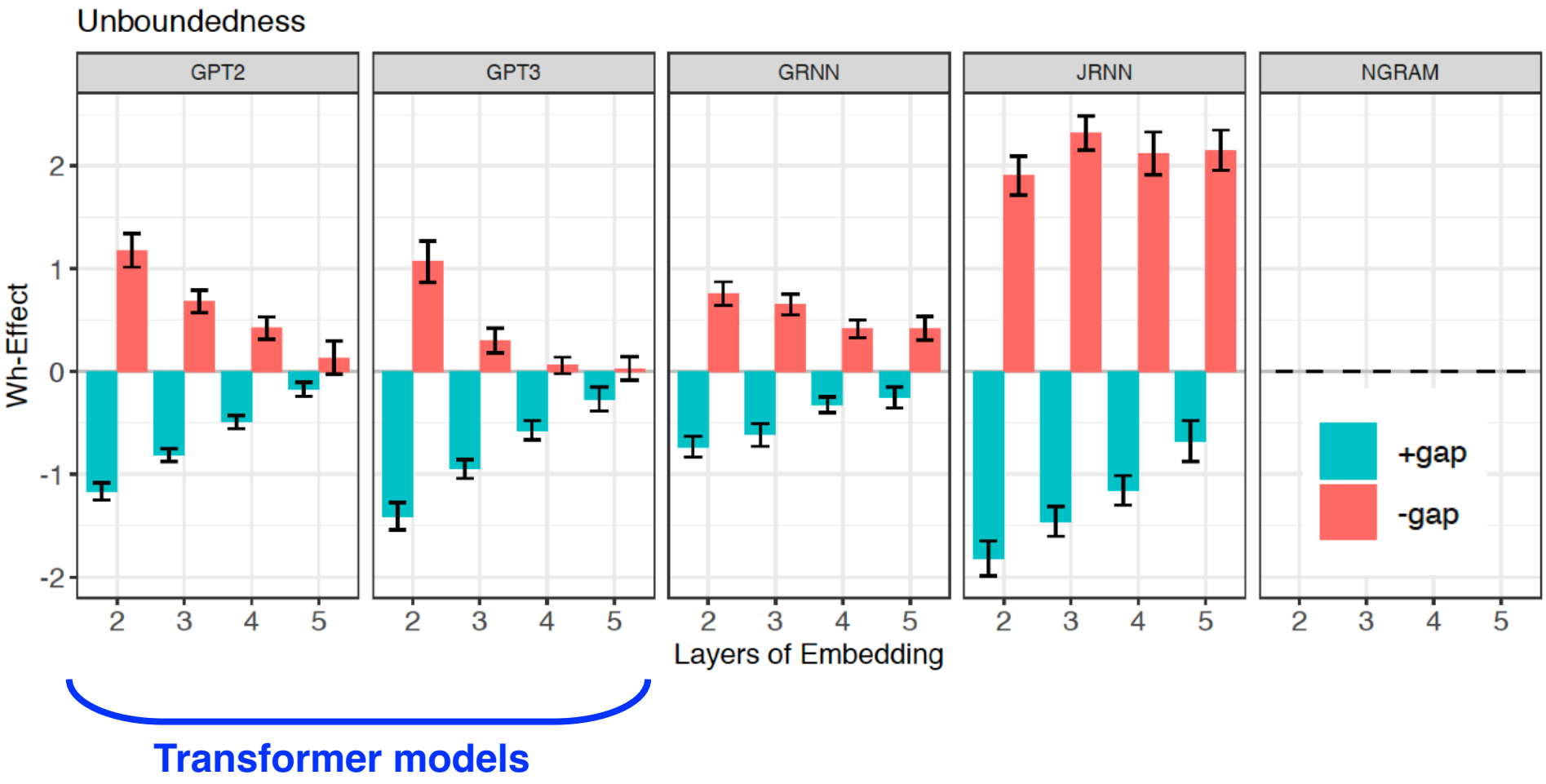

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Unboundedness of filler–gap dependency

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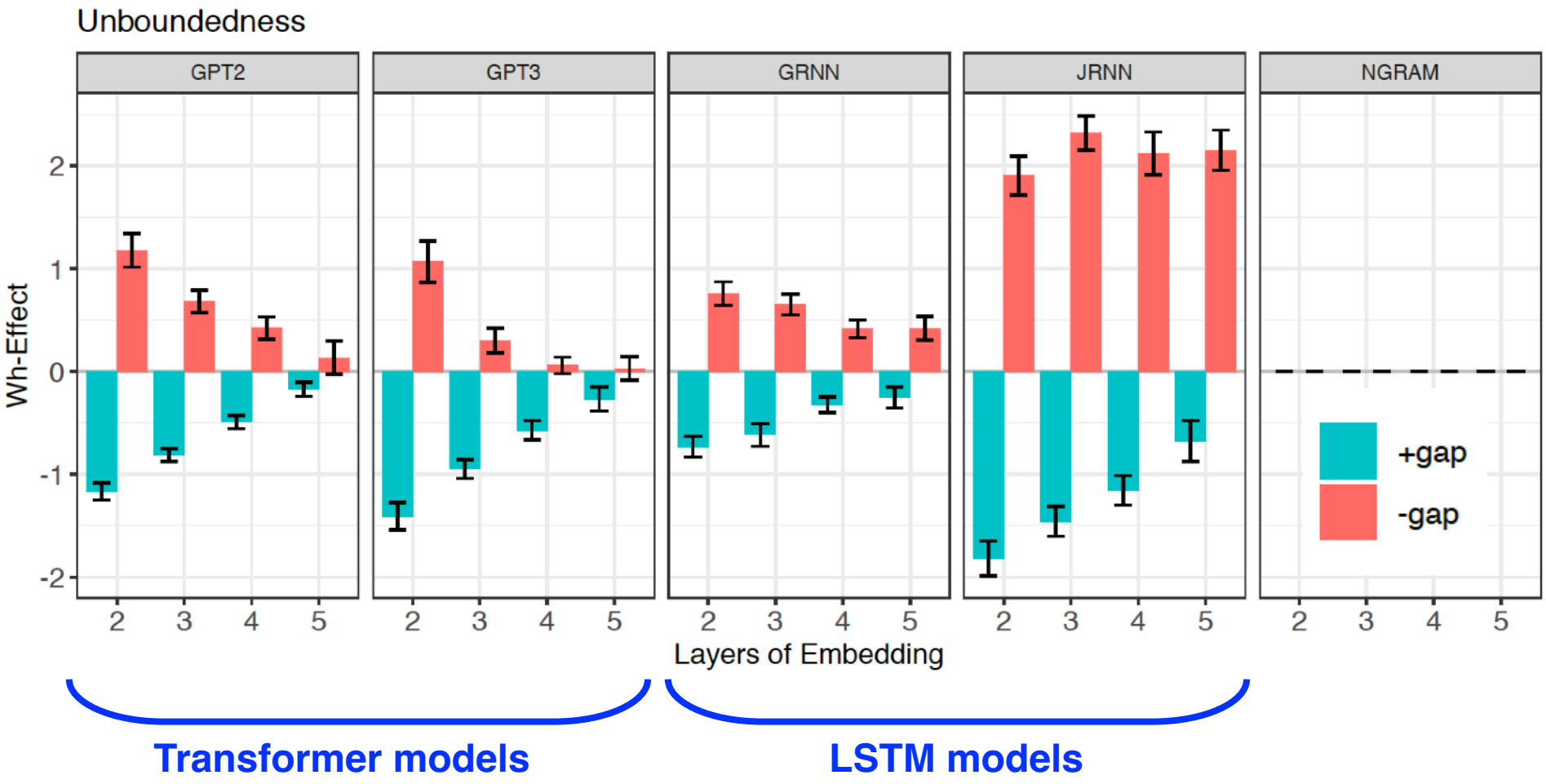


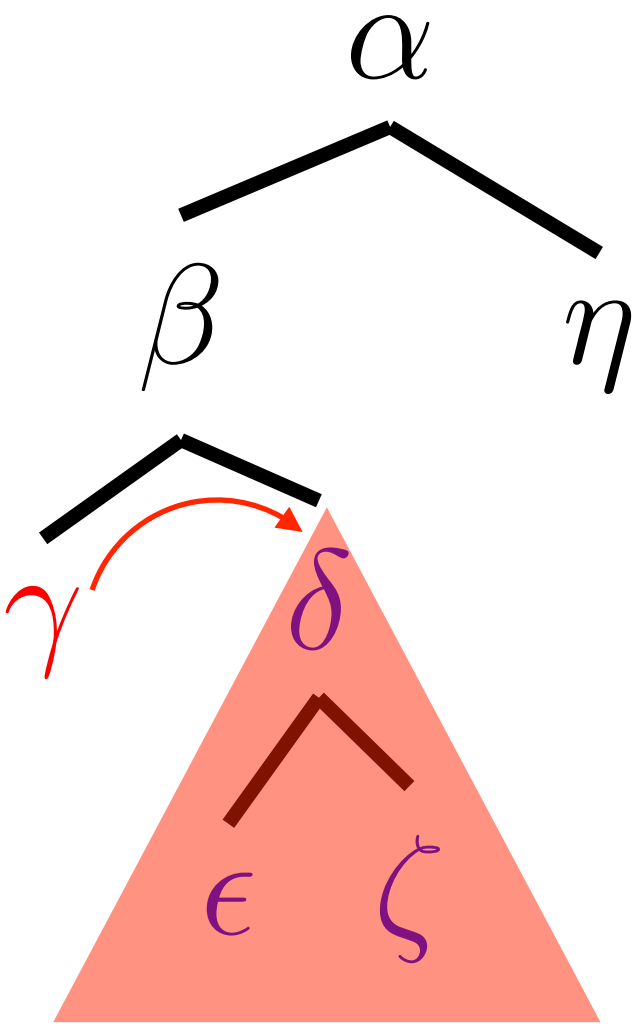
(Wilcox et al., in prep)

Potential concern #1

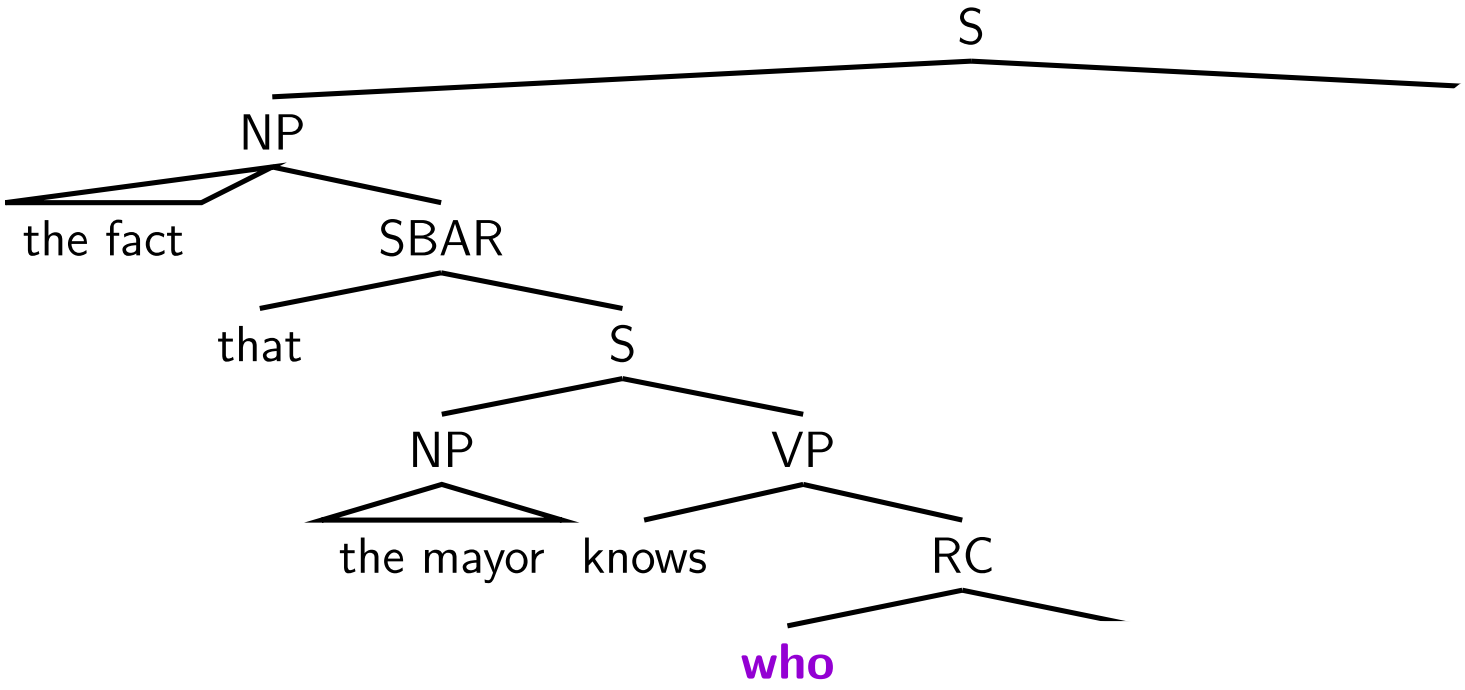
Couldn't the models be learning a ***linear*** dependency between filler and gap, not a ***hierarchical*** dependency?

Syntactic Hierarchy

- A filler must be appropriately "above" its gap



(Wilcox et al., 2019; in prep)



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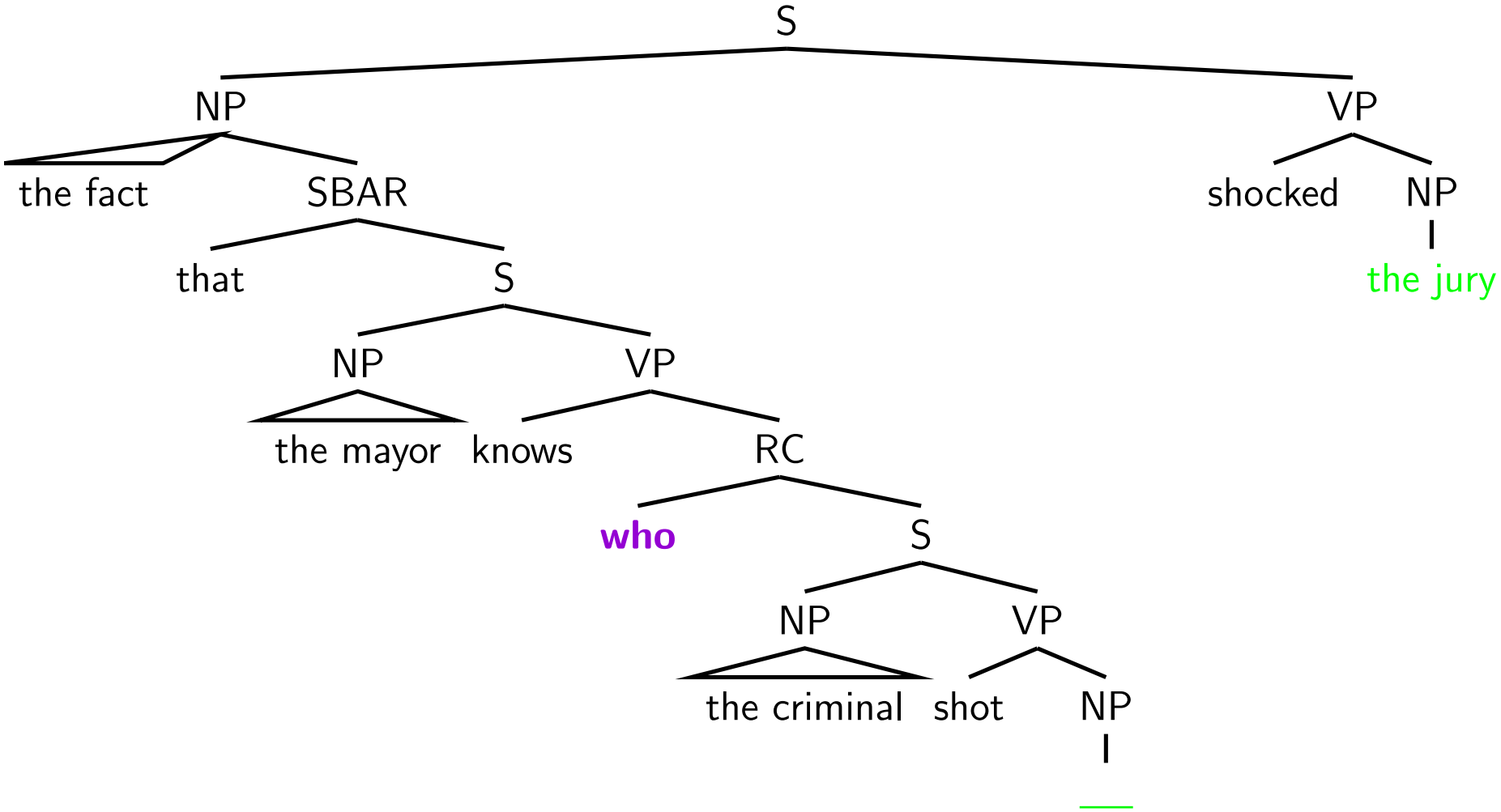

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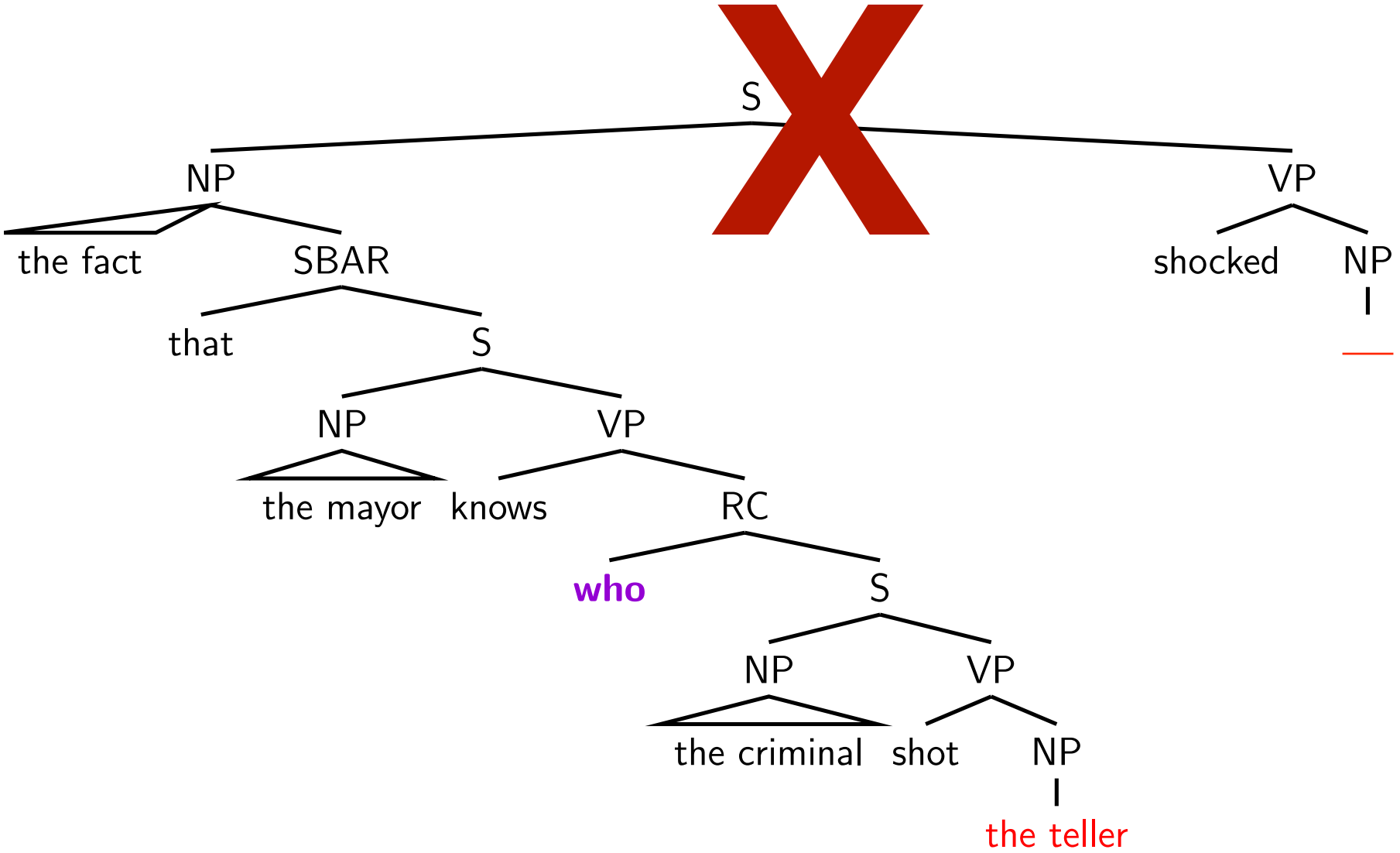


(Wilcox et al., 2019; in prep)

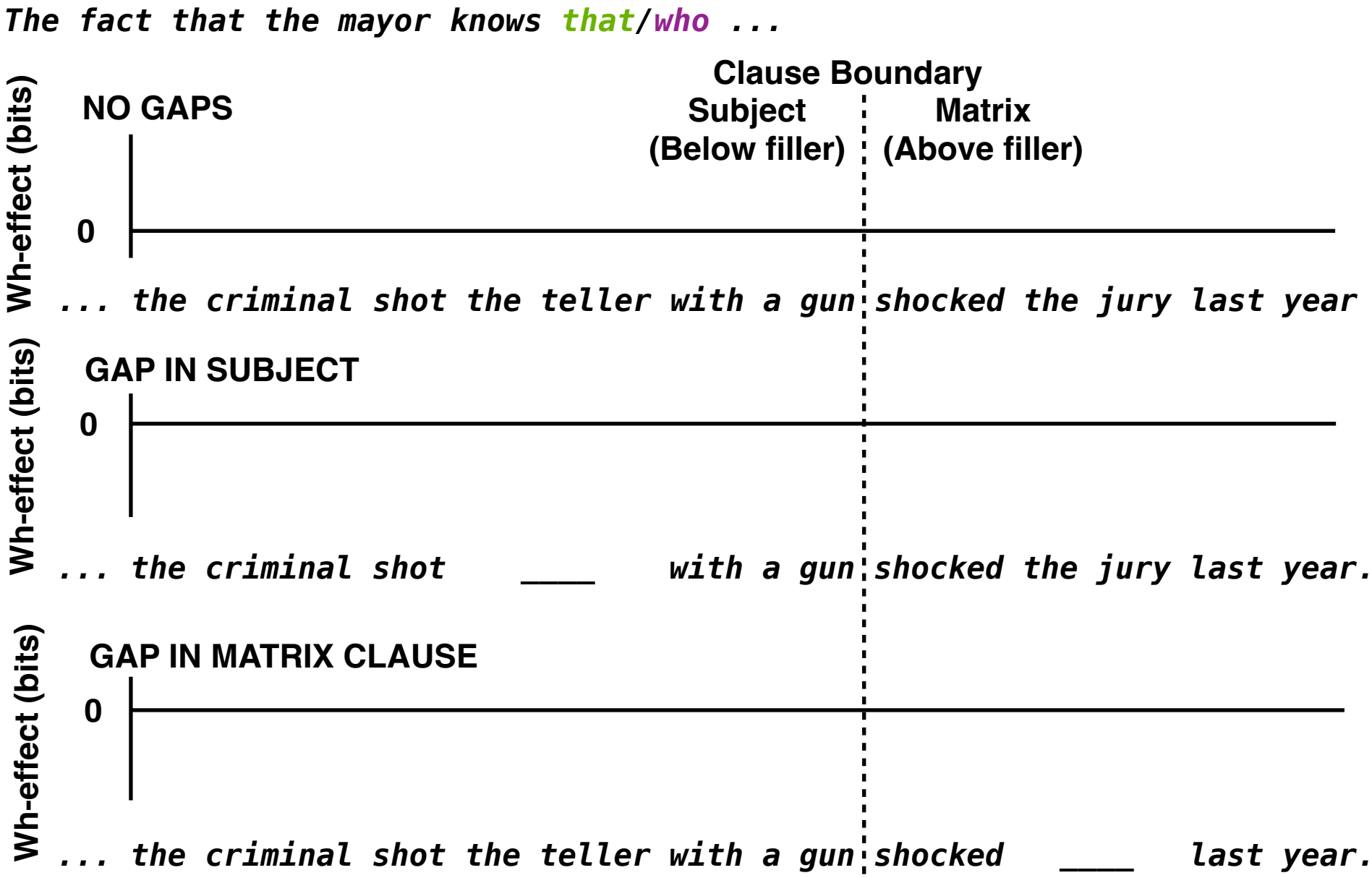
Predictions for human-like processing

The fact that the mayor knows that/who ...

	Clause Boundary: Subject (Below filler)	Clause Boundary: Matrix (Above filler)
NO GAPS		
	... the criminal shot the teller with a gun	*shocked the jury last year*
GAP IN SUBJECT		
	... the criminal shot ____ with a gun	*shocked the jury last year.*
GAP IN MATRIX CLAUSE		
	... the criminal shot the teller with a gun	*shocked ____ last year.*

(Wilcox et al., 2019; in prep)

Predictions for human-like processing



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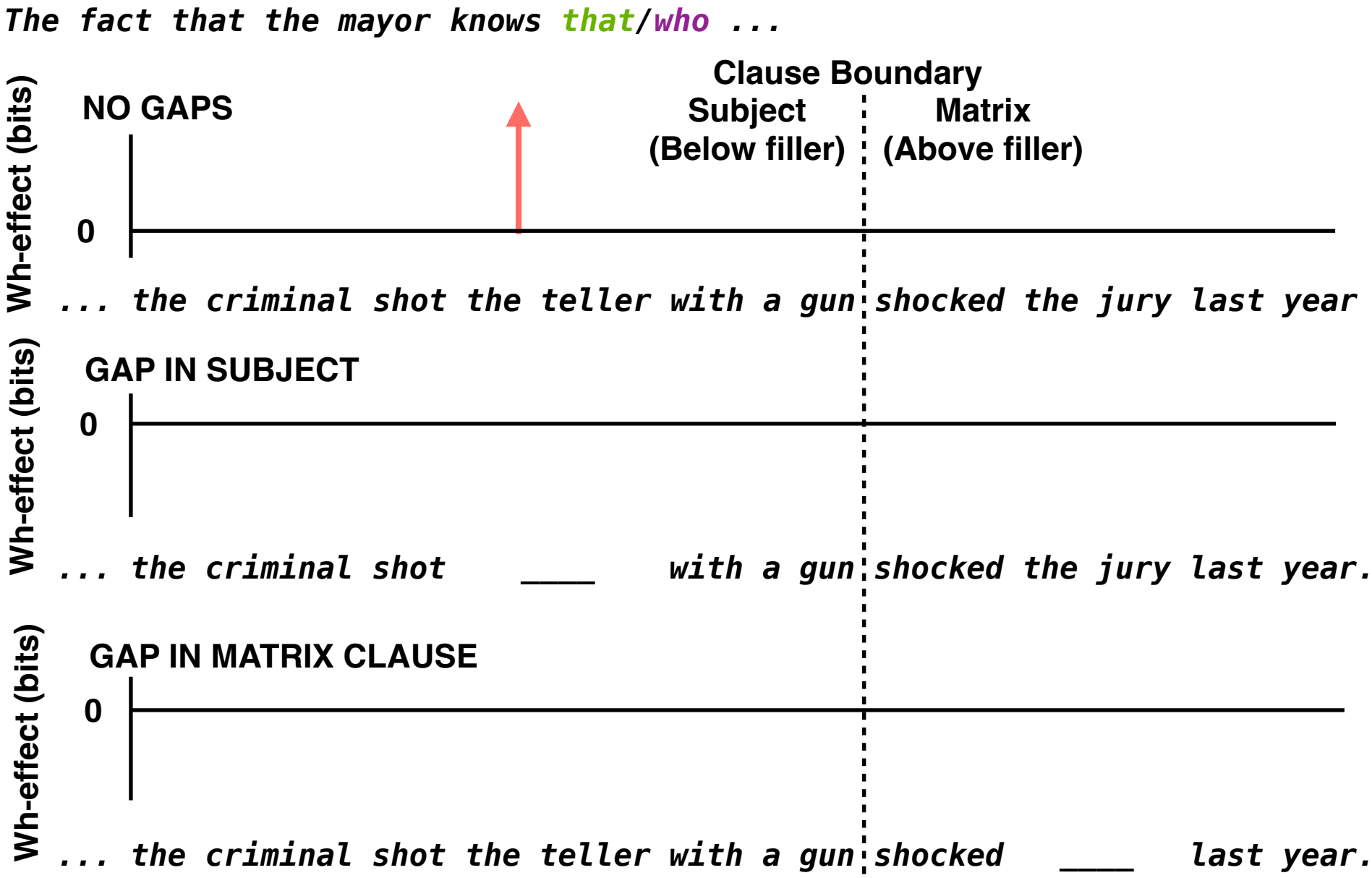
Predictions for human-like processing



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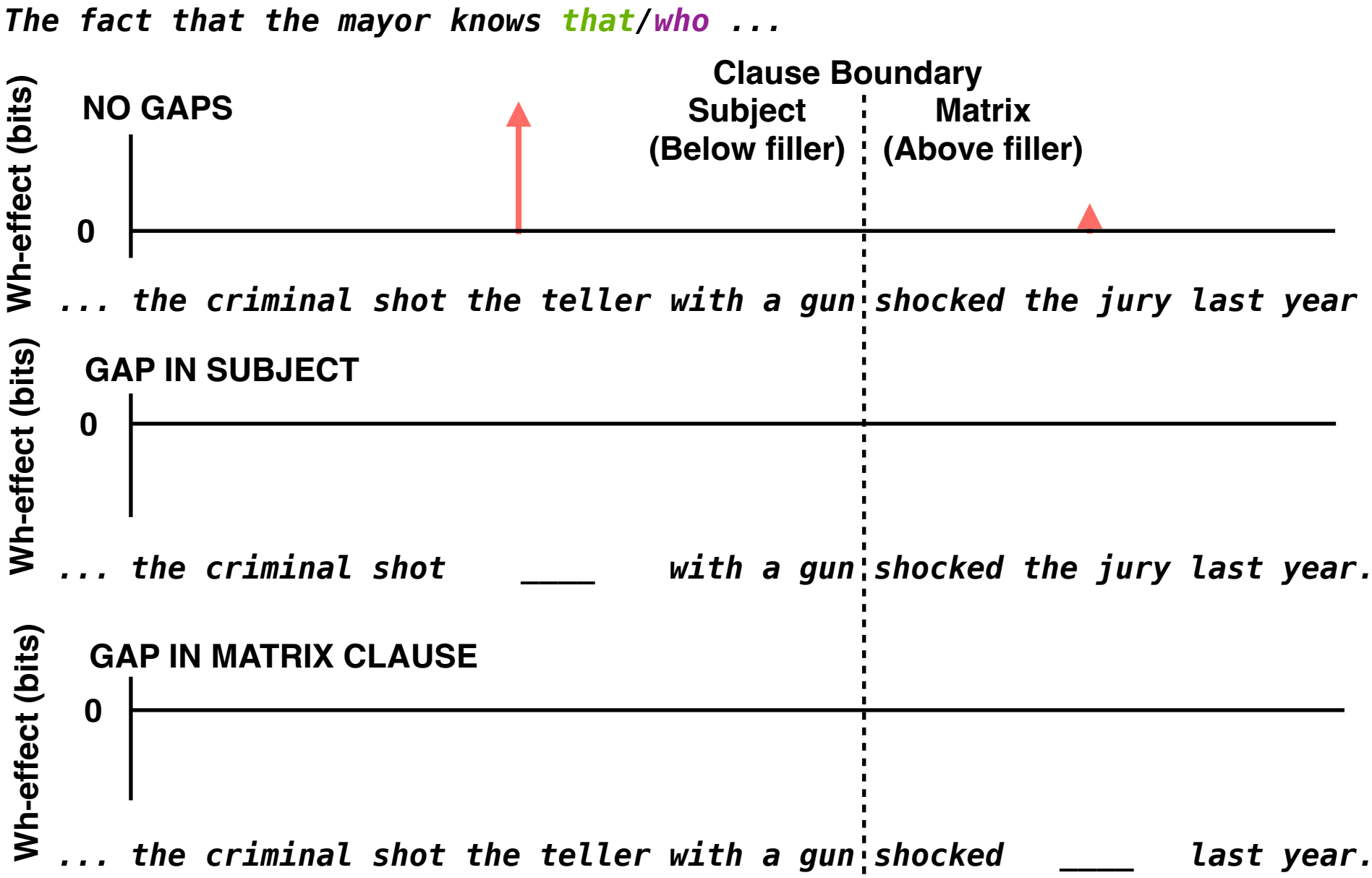
Predictions for human-like processing



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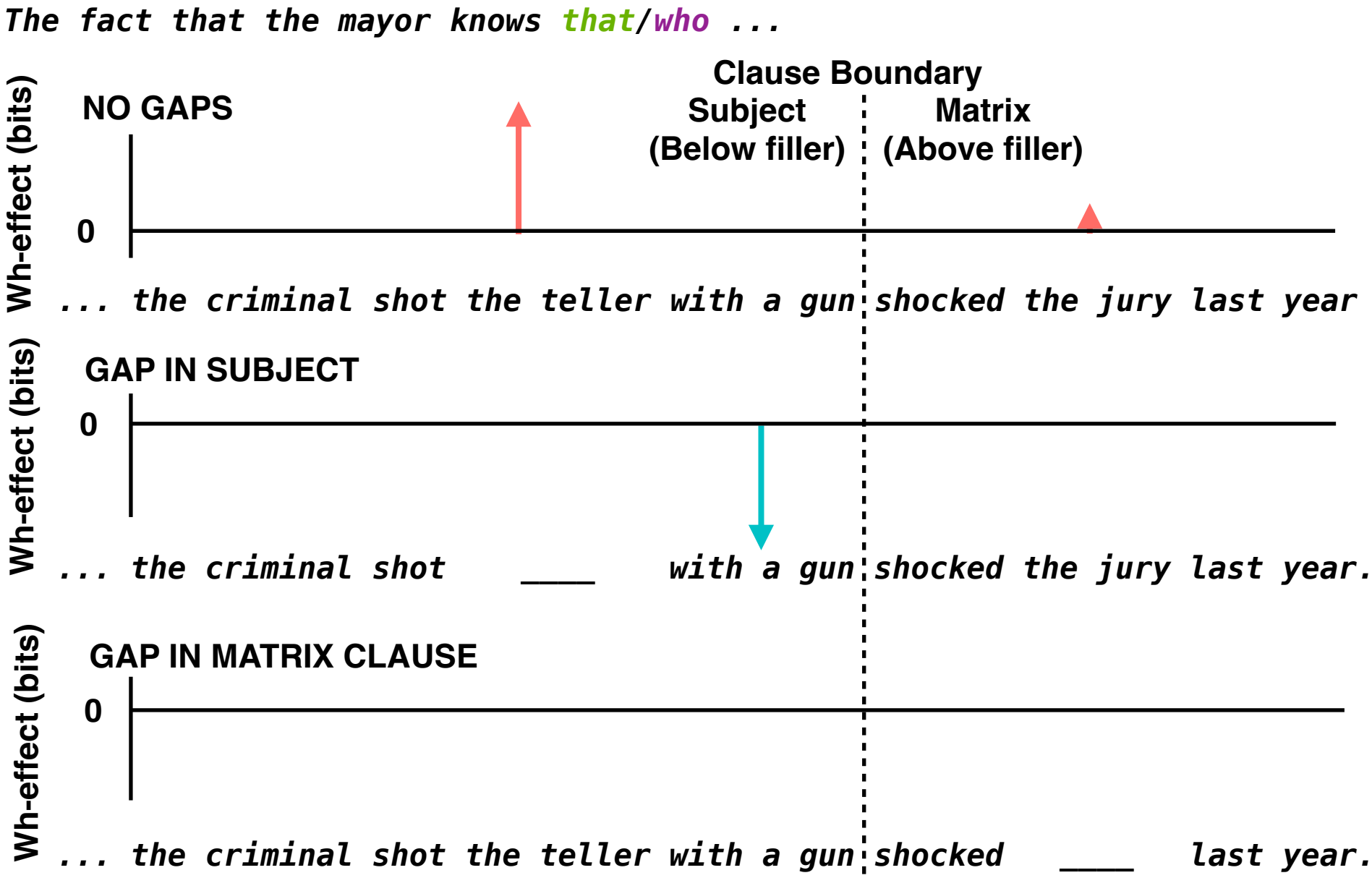
Predictions for human-like processing



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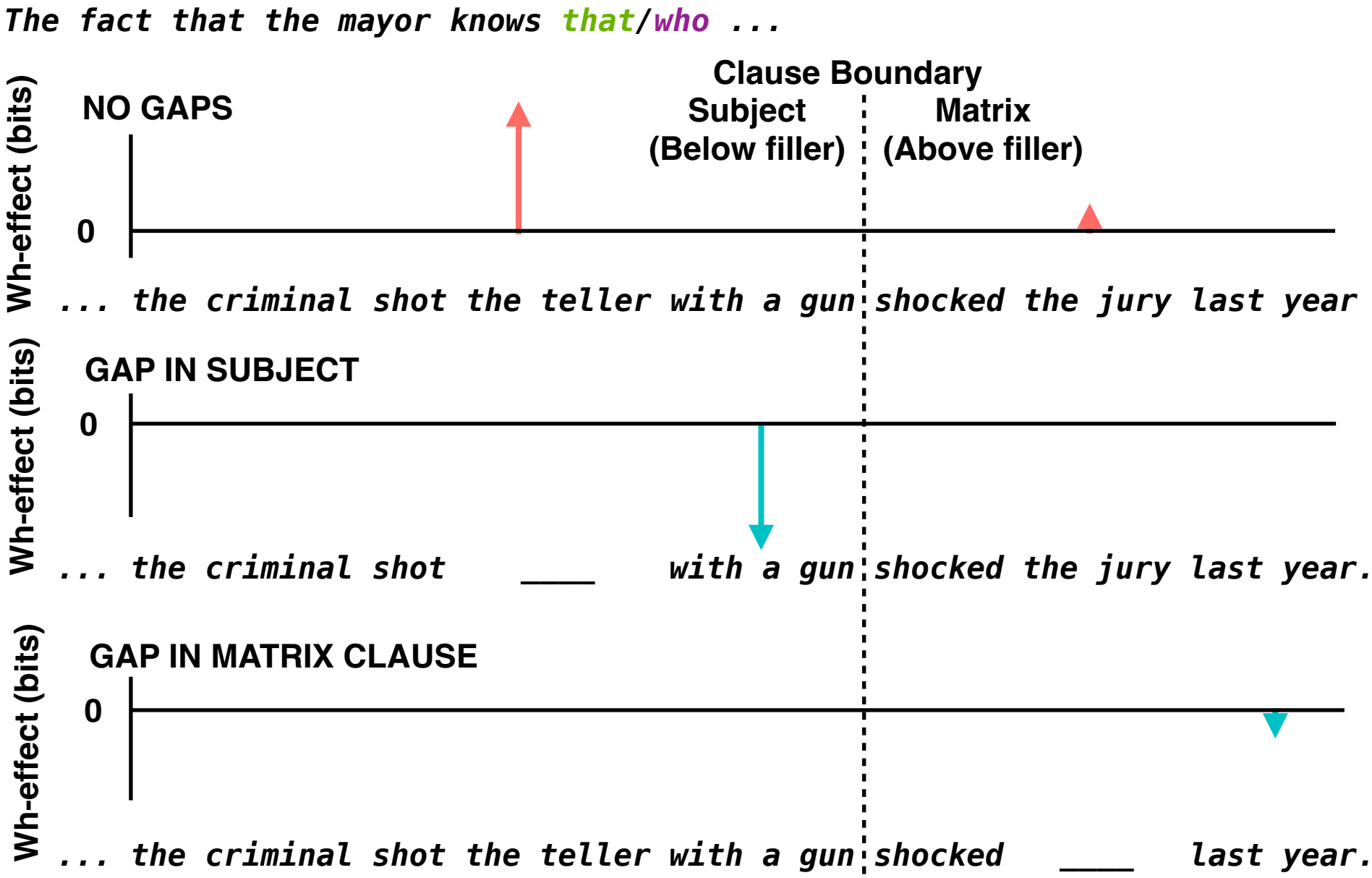

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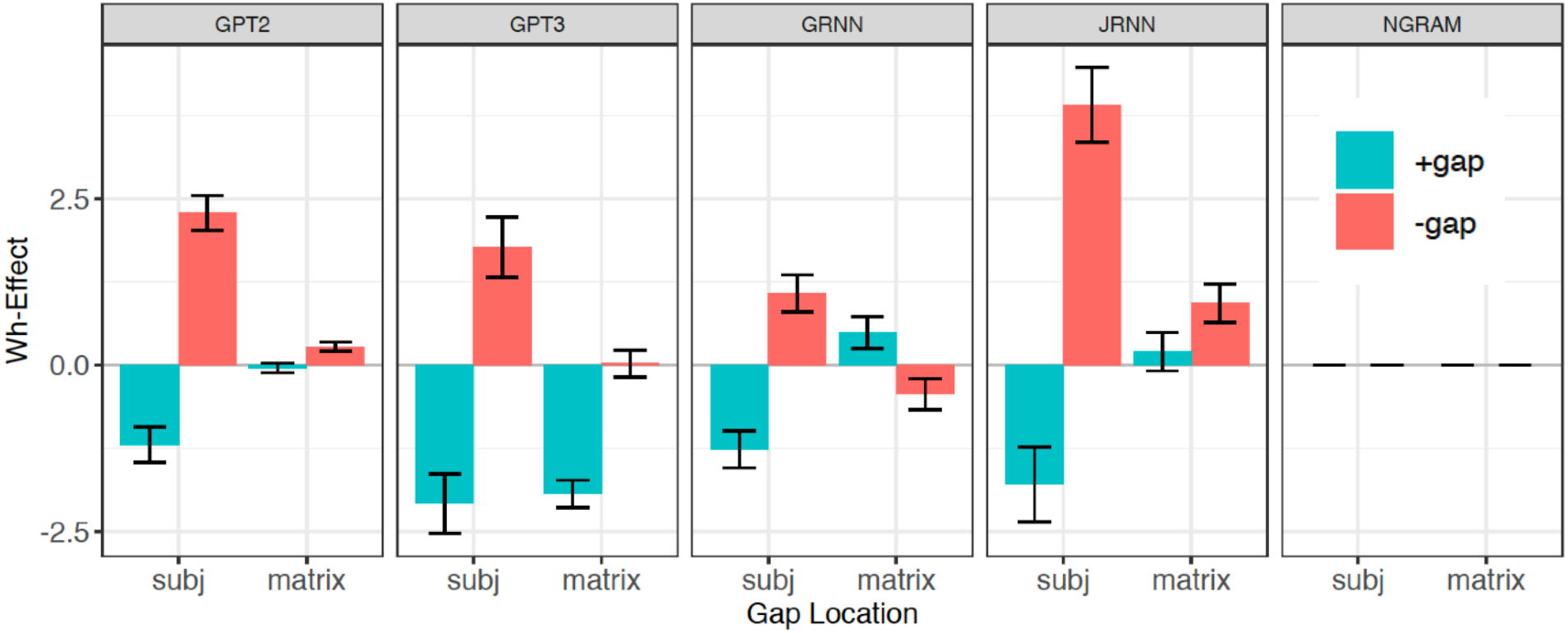
Sensitivity to syntactic hierarchy

- For object gaps:



(Wilcox et al., in prep)

Potential concern #1

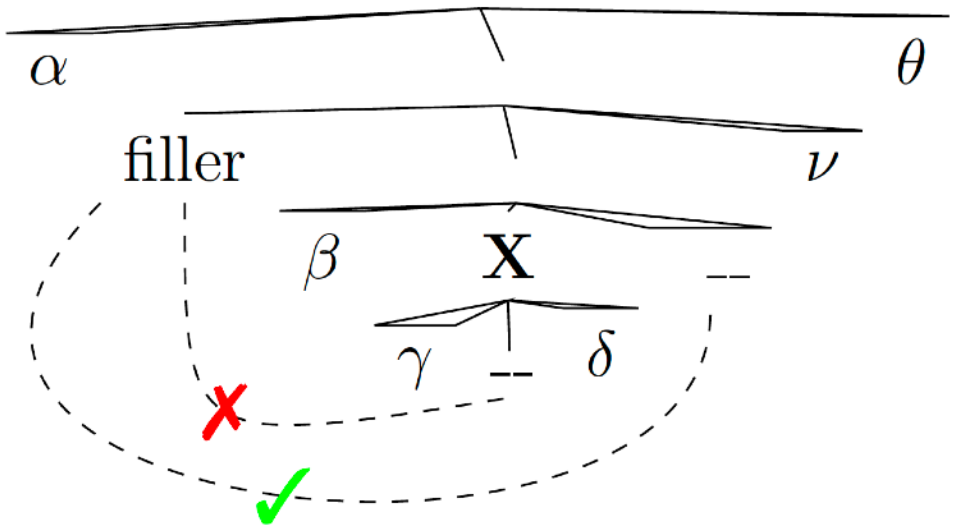
Couldn't the models be learning a ***linear*** dependency between filler and gap, not a ***hierarchical*** dependency?

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 deep-learning models trained on enough data are sensitive to syntactic hierarchy for *wh*-dependency

Syntactic island constraints

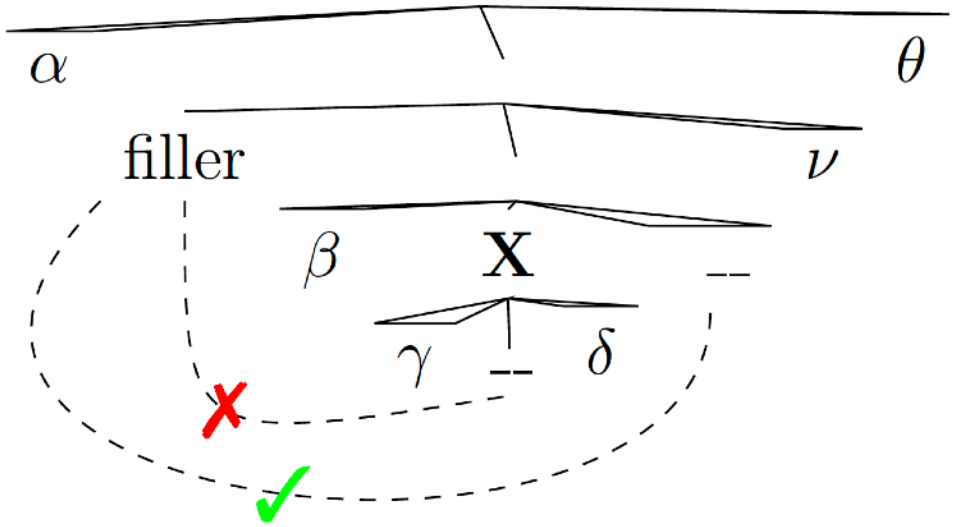


(Phillips, 2013; see also Pearl & Sprouse, 2013)

(Wilcox et al., 2018; in prep)

Syntactic island constraints

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



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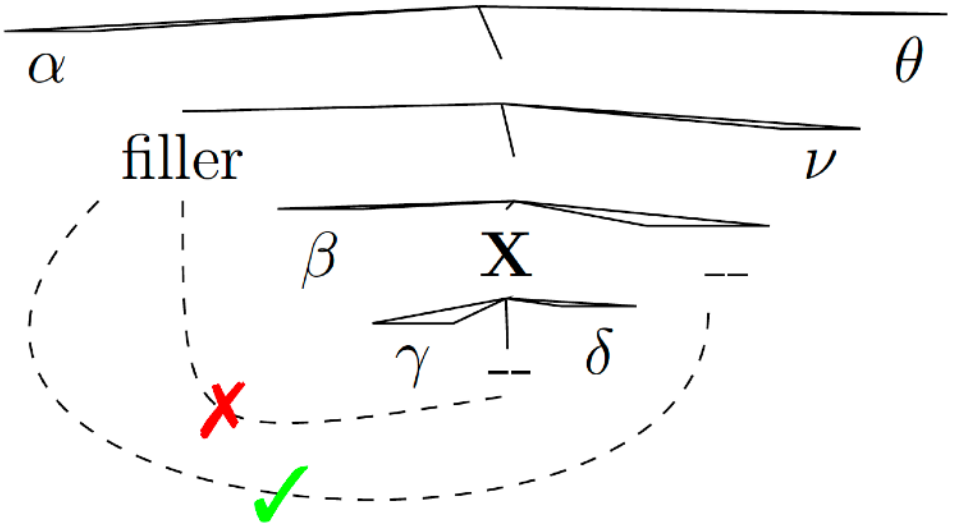

- "Island effects have long been regarded as strong motivation for domain-specific innate constraints on human language...likely to be difficult to observe in the input that children must learn from."

(Phillips, 2013; see also Pearl & Sprouse, 2013)

(Wilcox et al., 2018; in prep)

Syntactic islands

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

I know what Alex said…

✓ *…your friend devoured __ at the party.*
[no complementizer]

(Wilcox et al., 2018; in prep)

Syntactic islands

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I know what Alex said…

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(✓) ***…that*** *your friend devoured __ at the party.*
[*that* complementizer]

(Wilcox et al., 2018; in prep)

Syntactic islands

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I know what Alex said…

✓ *…your friend devoured __ at the party.*
[no complementizer]

(✓) ***…that** your friend devoured __ at the party.*
[*that* complementizer]

* ***…whether** your friend devoured __ at the party.*
[*wh*-complementizer]

(Wilcox et al., 2018; in prep)

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

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

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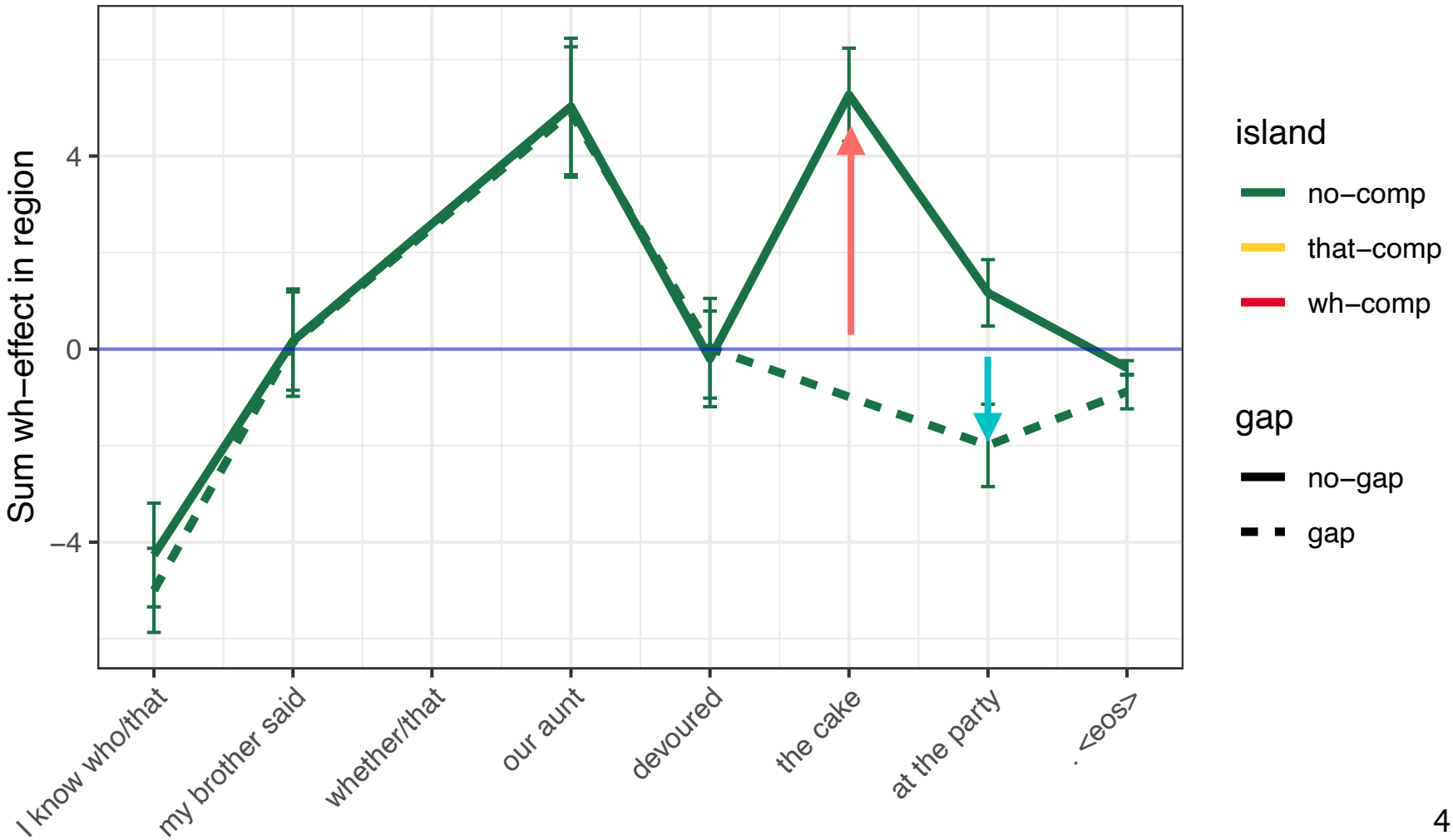

✓ *I know that my brother said that our aunt devoured the cake at the party.*

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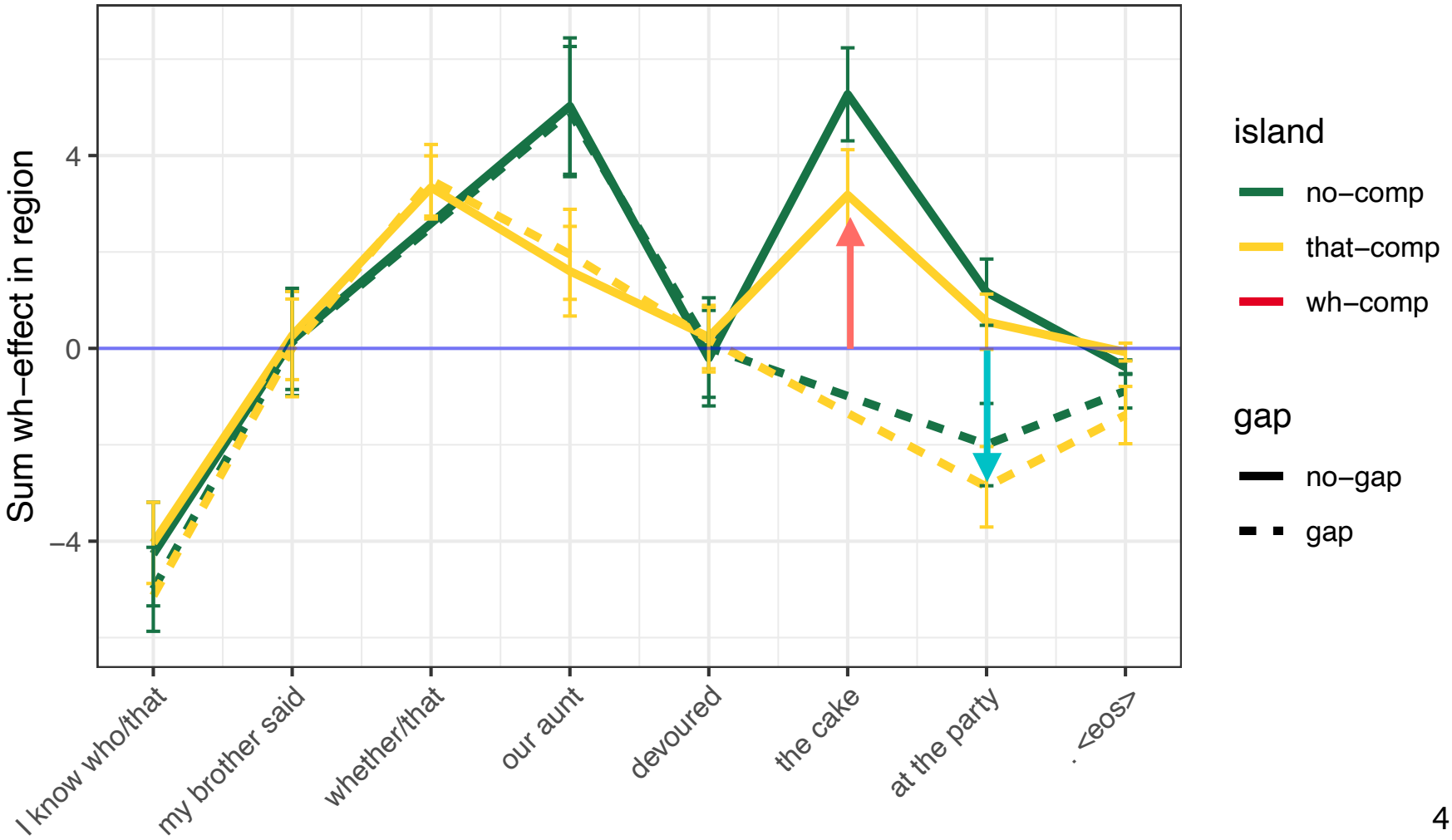

✓ *I know that my brother said **whether** our aunt devoured the cake at the party.*

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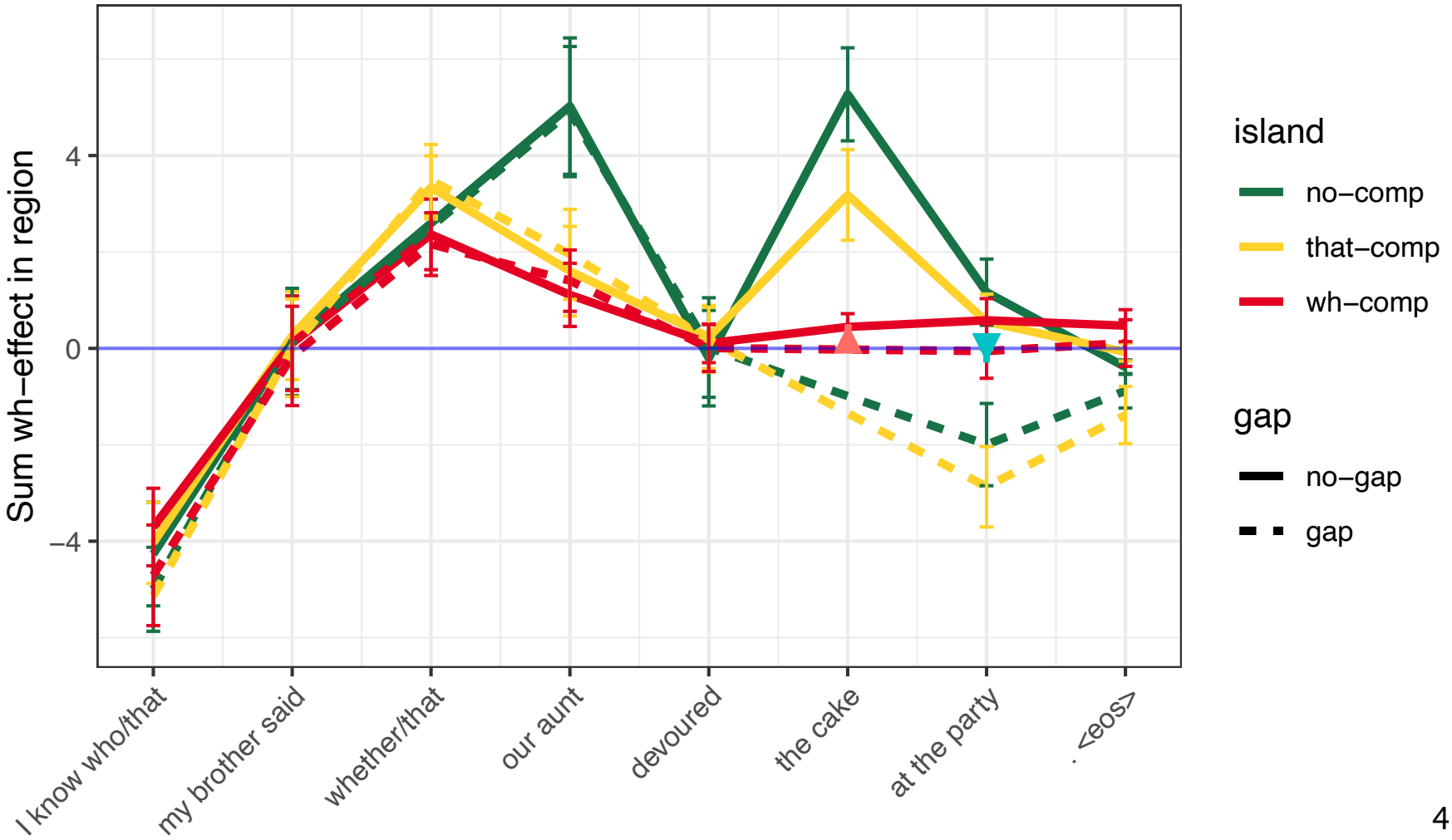
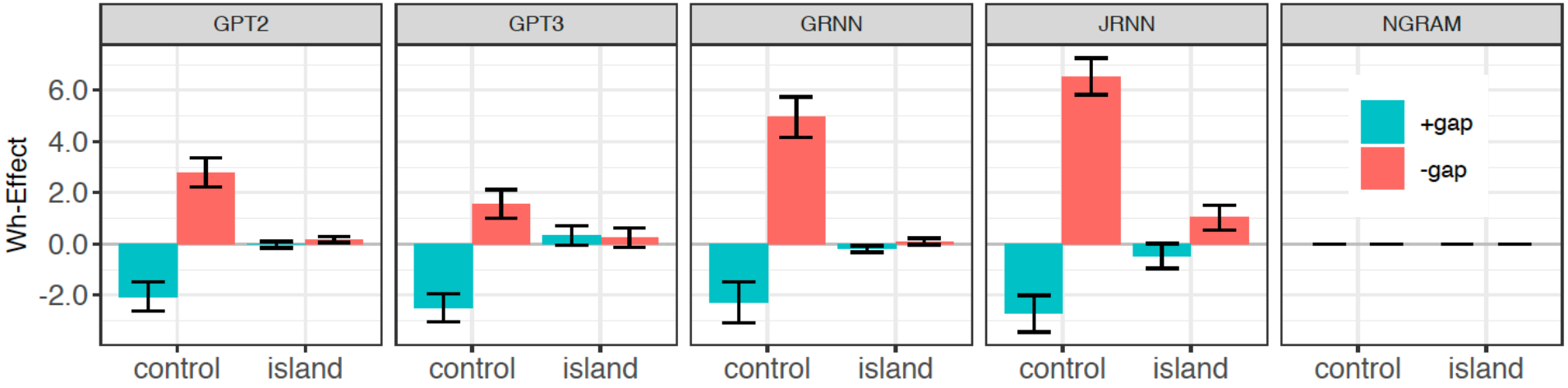


Results for **WH-islands**



(Wilcox et al., in prep)

Potential concern #2

Could deep-learning models have difficulty threading ***any*** type of expectation into a syntactic island?

Gendered-pronoun Expectation Control

(Wilcox et al., 2019; in prep)

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**.

(Wilcox et al., 2019; in prep)

Gendered-pronoun Expectation Control

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

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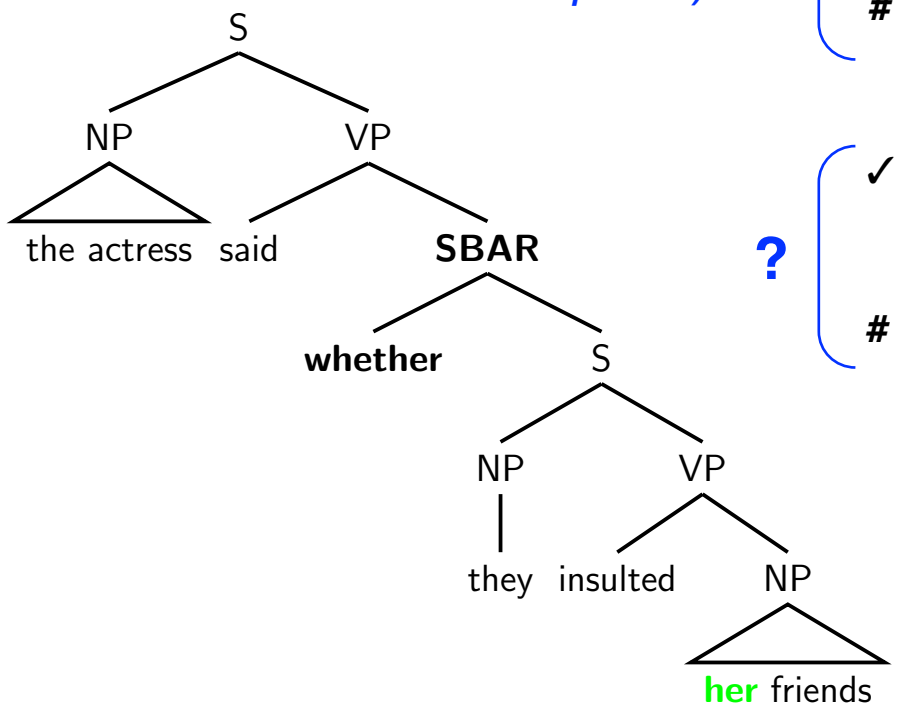

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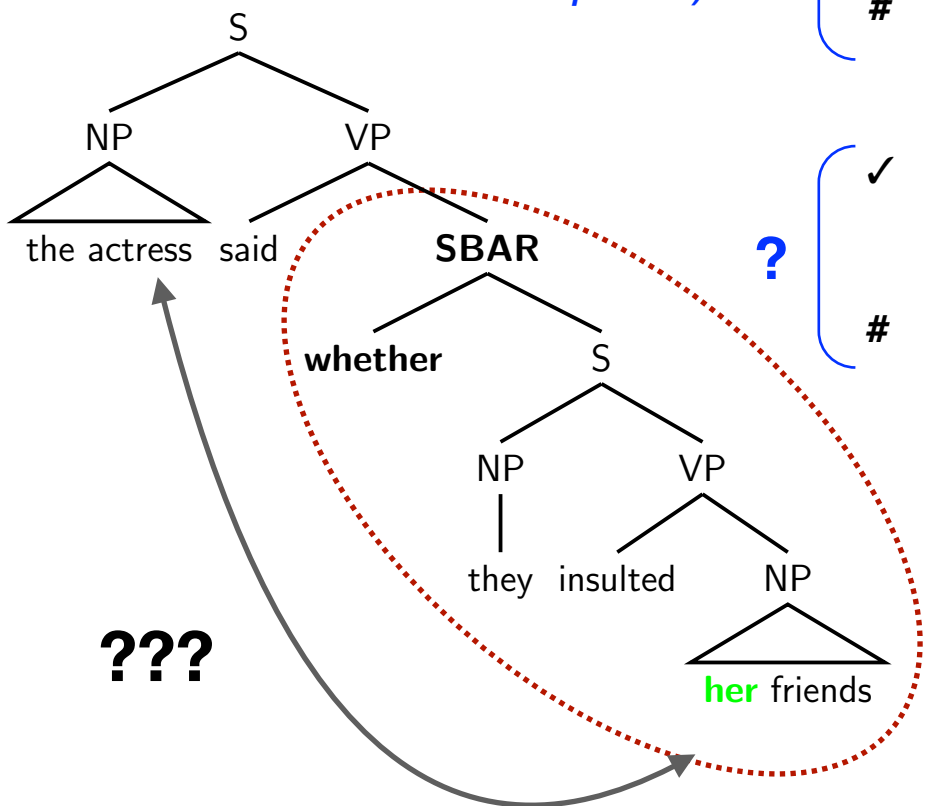

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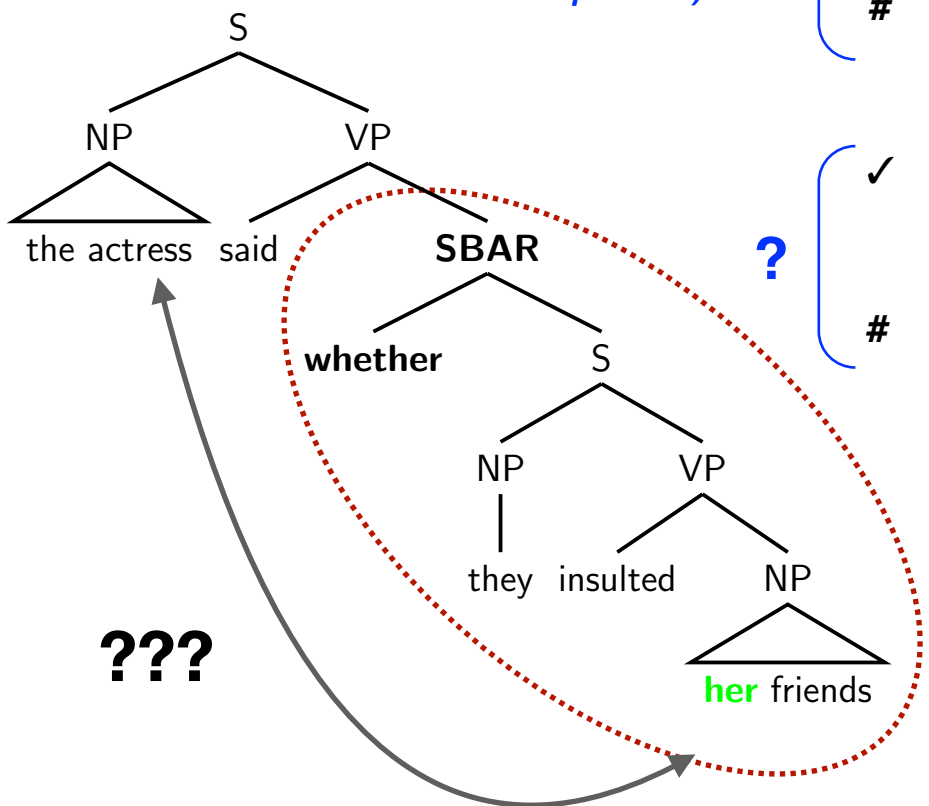

If models can thread gender expectation into islands, the gender expectation effect should **look the same in islands as in the control conditions.**

(Wilcox et al., 2019; in prep)

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

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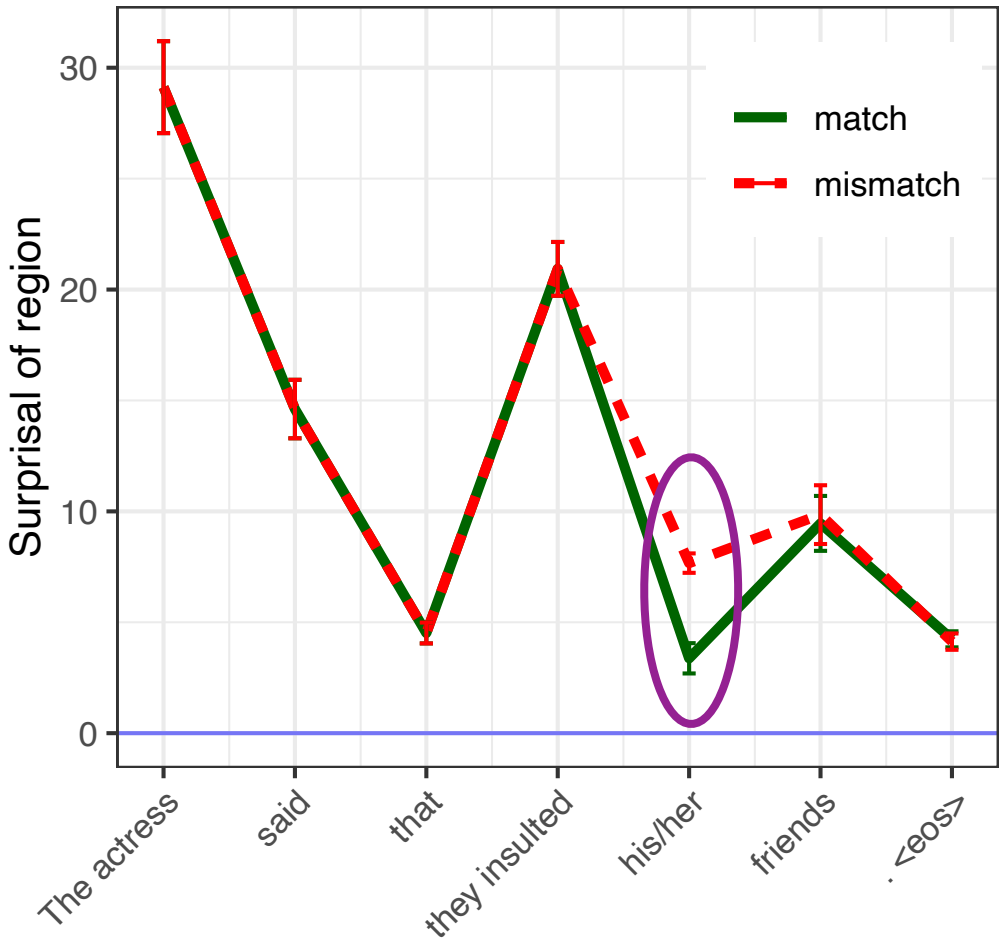

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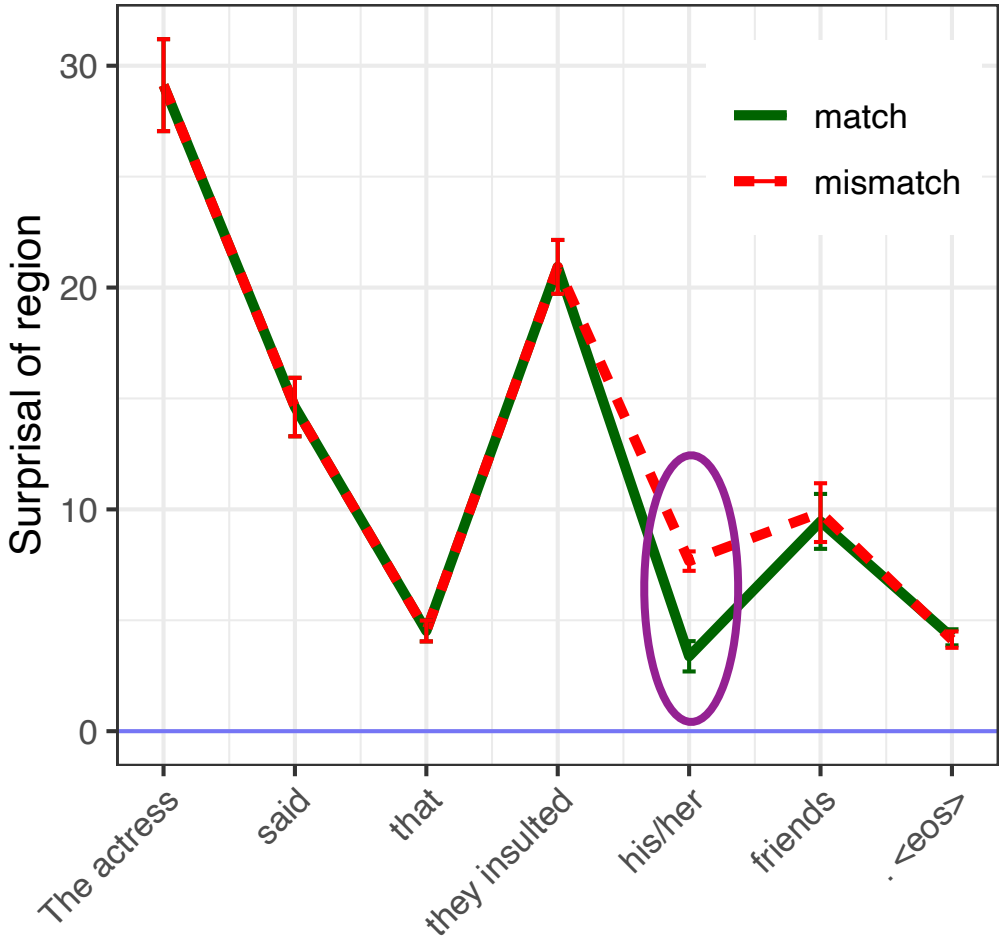

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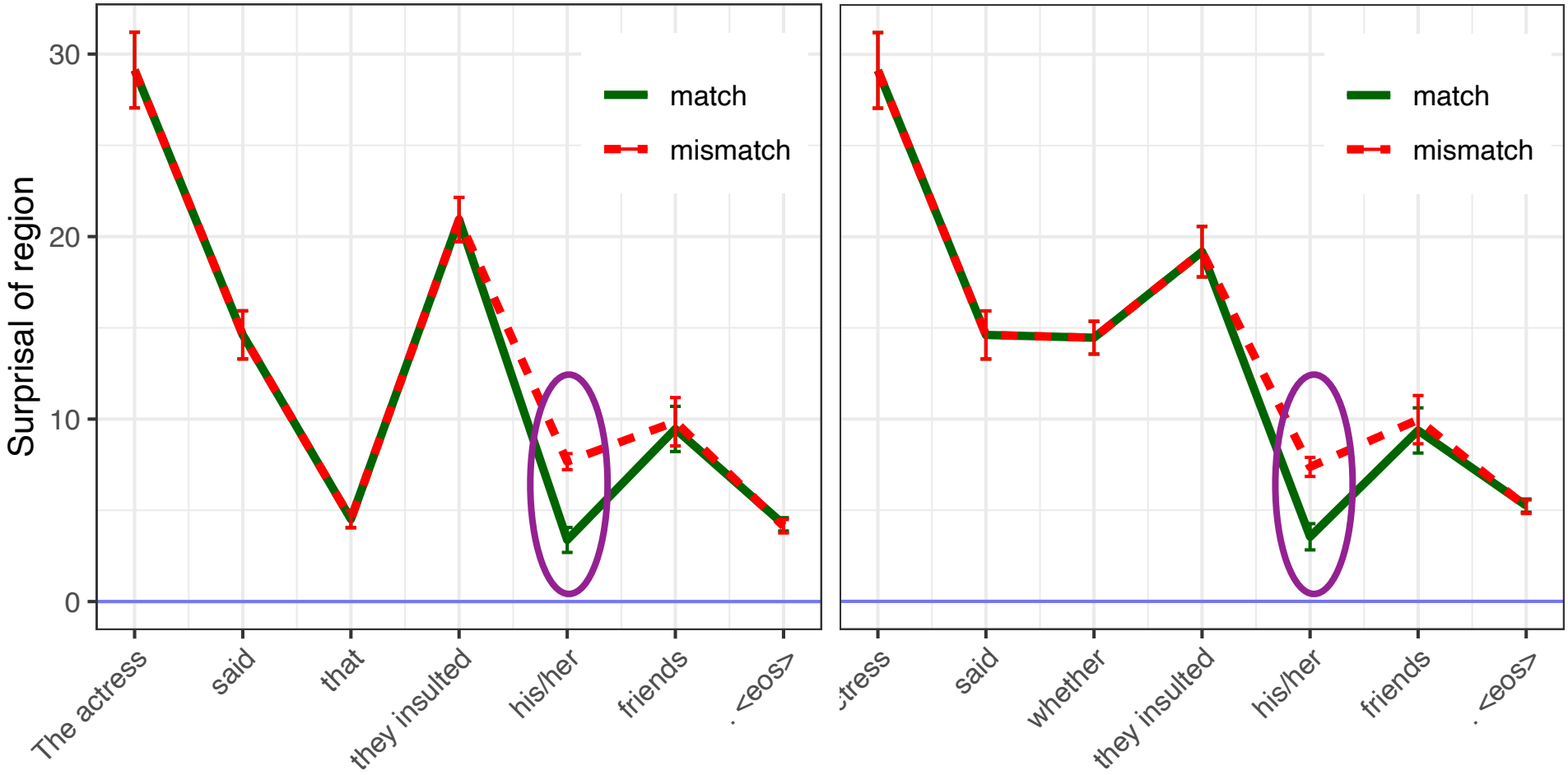
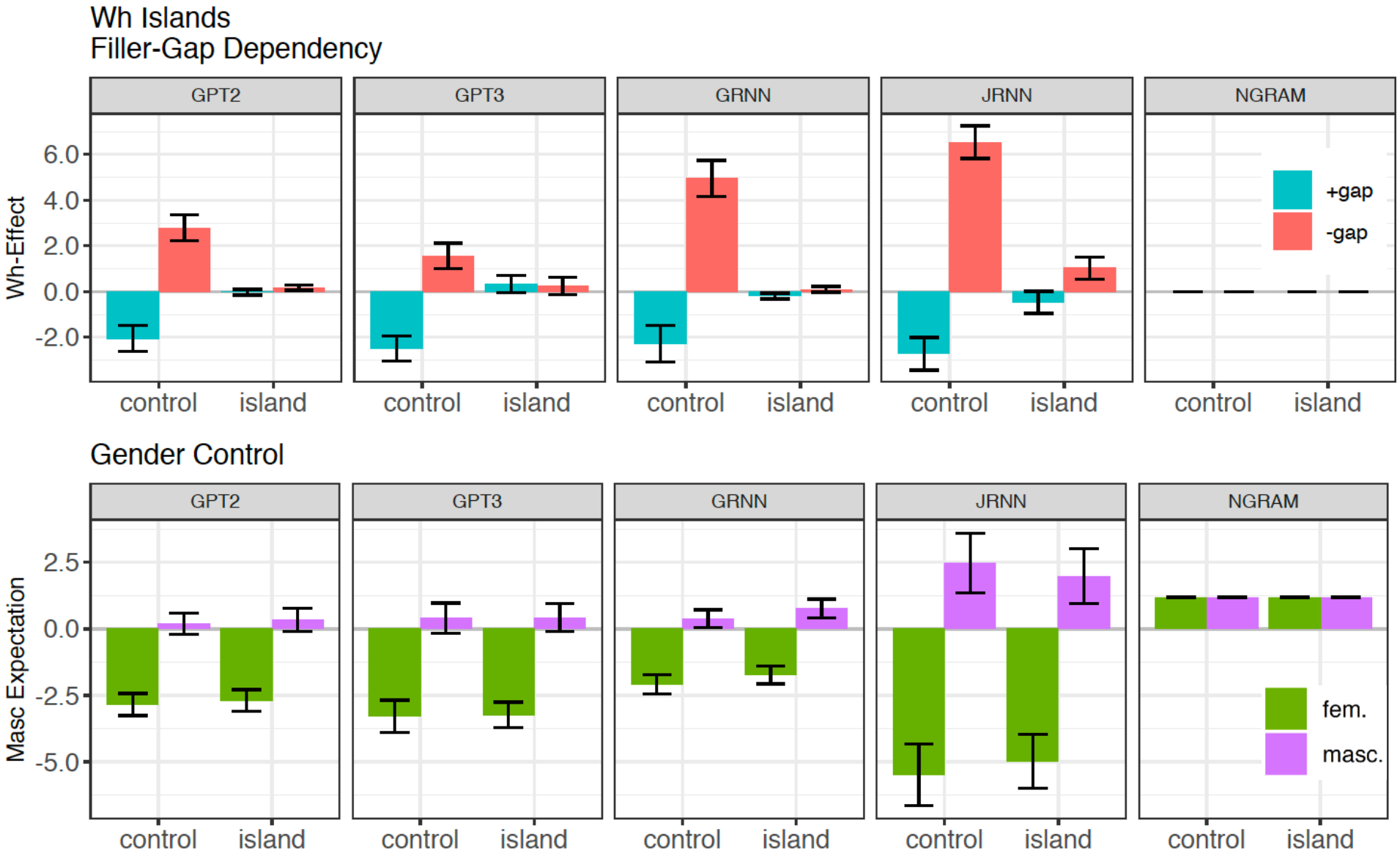


Filler–gap vs. gender expectations in WH-islands



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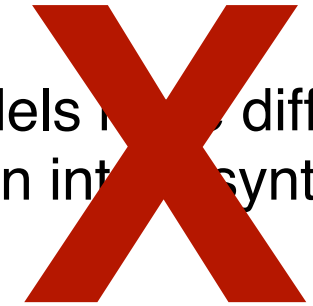
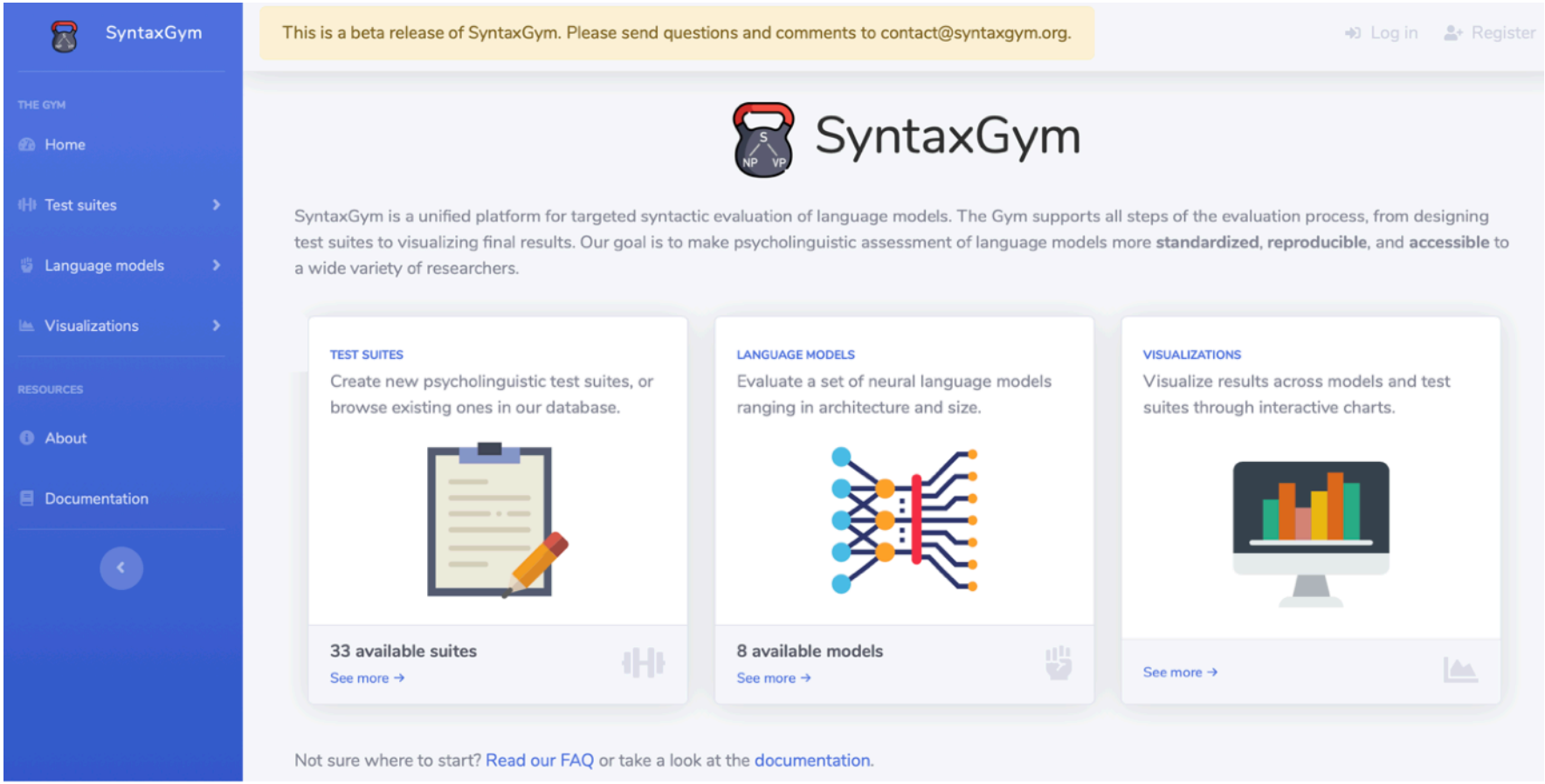


Deep-learning models that learn island constraints still propagate pronoun gender expectations into islands

Psycholinguistic tests of AI language models

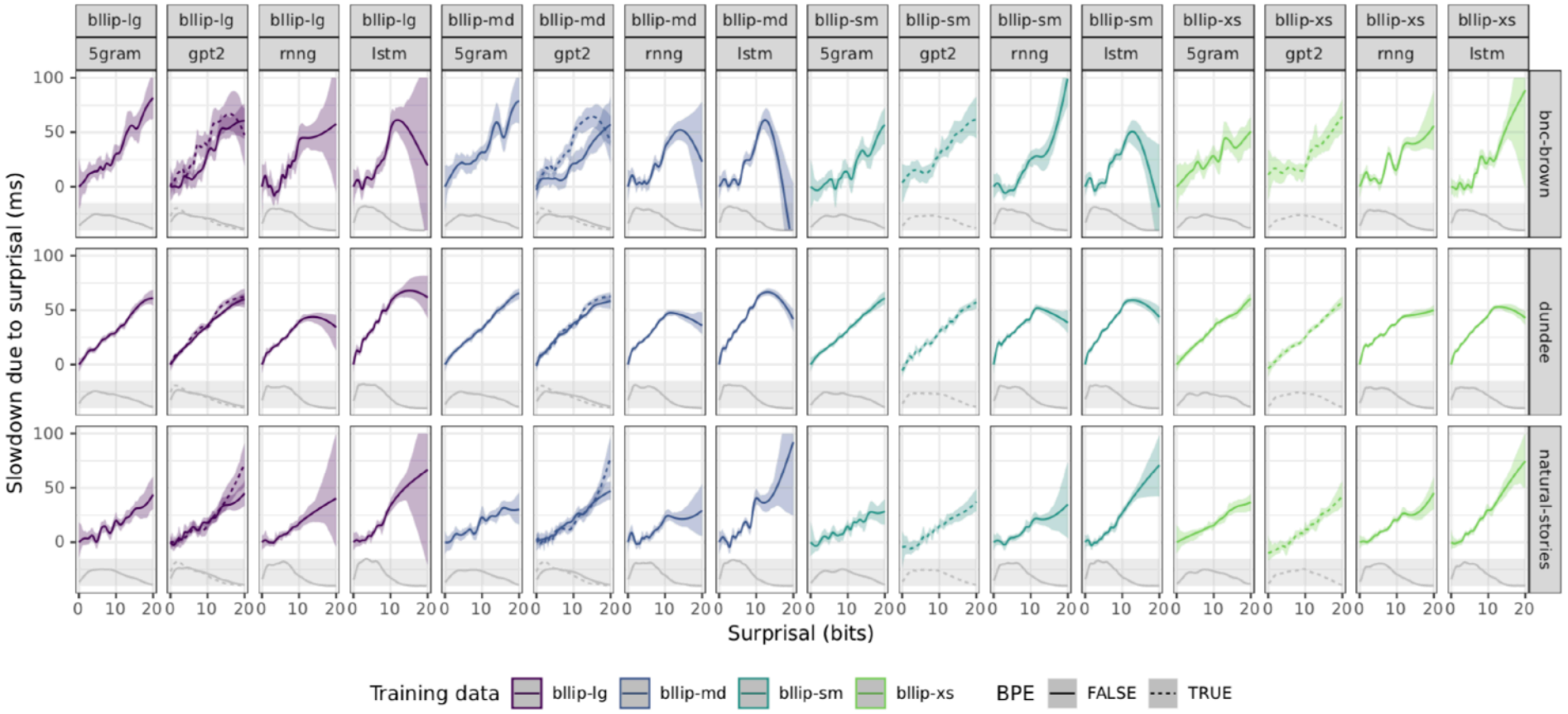


http://syntaxgym.org

(Gauthier et al., 2020)

Quantitative calibration to human processing

- The surprisal–RT relationship in naturalistic reading:



(Wilcox et al., 2020)

Low-tech, crowd-sourceable reading

(Forster et al., 2009; Boyce et al., 2020)

Low-tech, crowd-sourceable reading

- The **maze task**

(Forster et al., 2009; Boyce et al., 2020)

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- The **maze task**
- Choose the string that fits given the preceding context

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F J

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The x-x-x

F J

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of

F

dog

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pirty	chased
F	J

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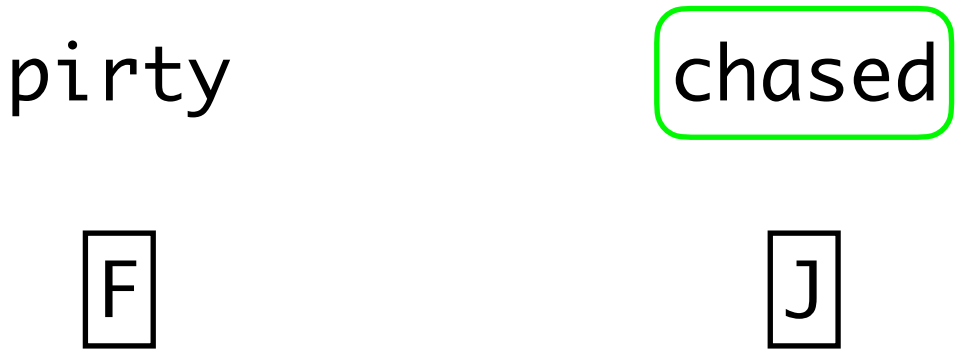

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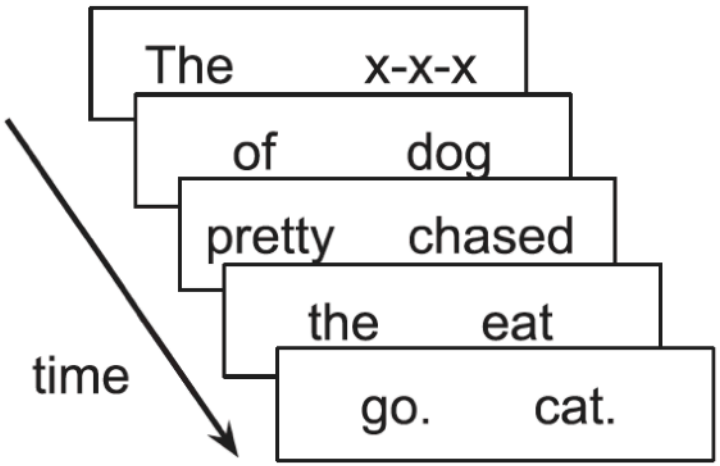
the eat

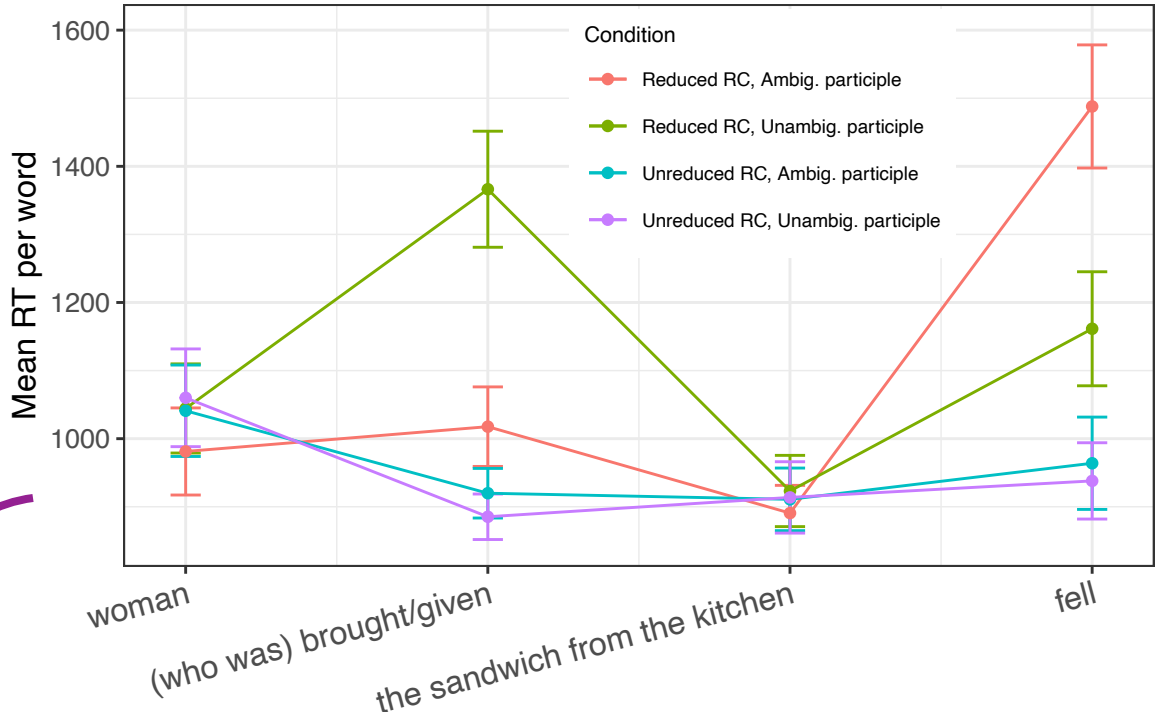
F J



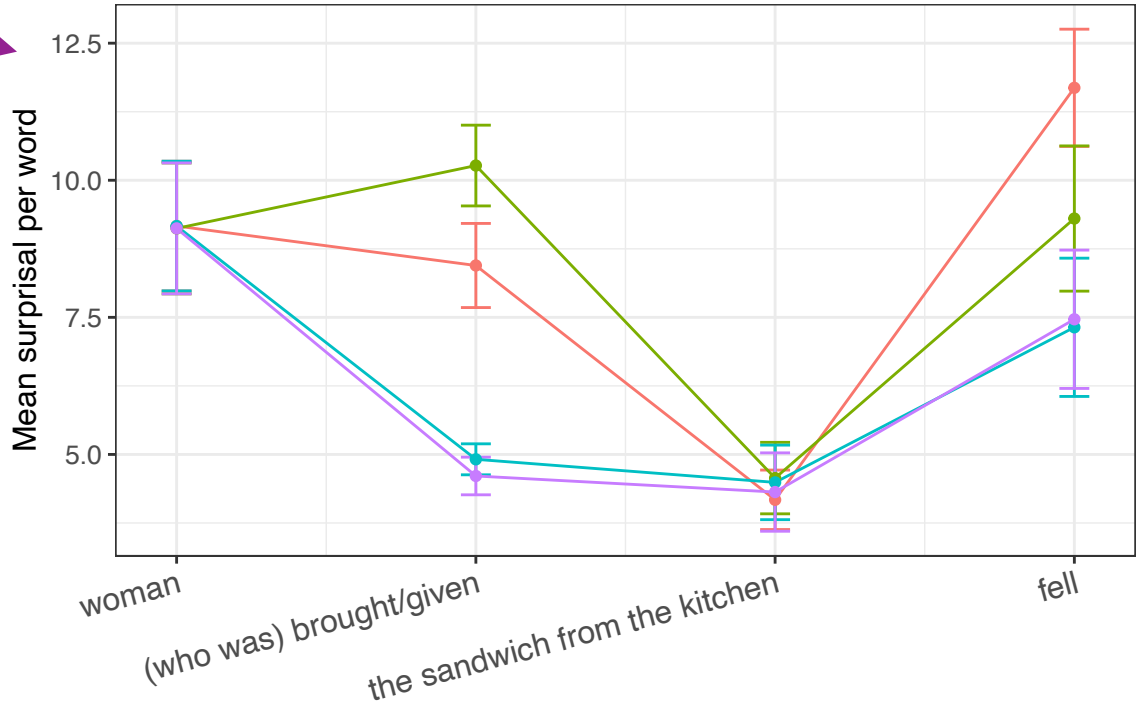
(Forster et al., 2009; Boyce et al., 2020)

Human reaction times

*Pooling many controlled experiments, regress human RTs against model surprisal and examine **residual***



GPT-2 Surprisal



(Wilcox et al., 2021; see also van Schijndel & Linzen, 2020)

✓ *I know that ... the CEO showed the slides to the guests after lunch.*

✳ *I know what ... the CEO showed the slides to the guests after lunch.*

✳ *I know that ... the CEO showed _____ to the guests after lunch.*

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(Wilcox et al., 2021)

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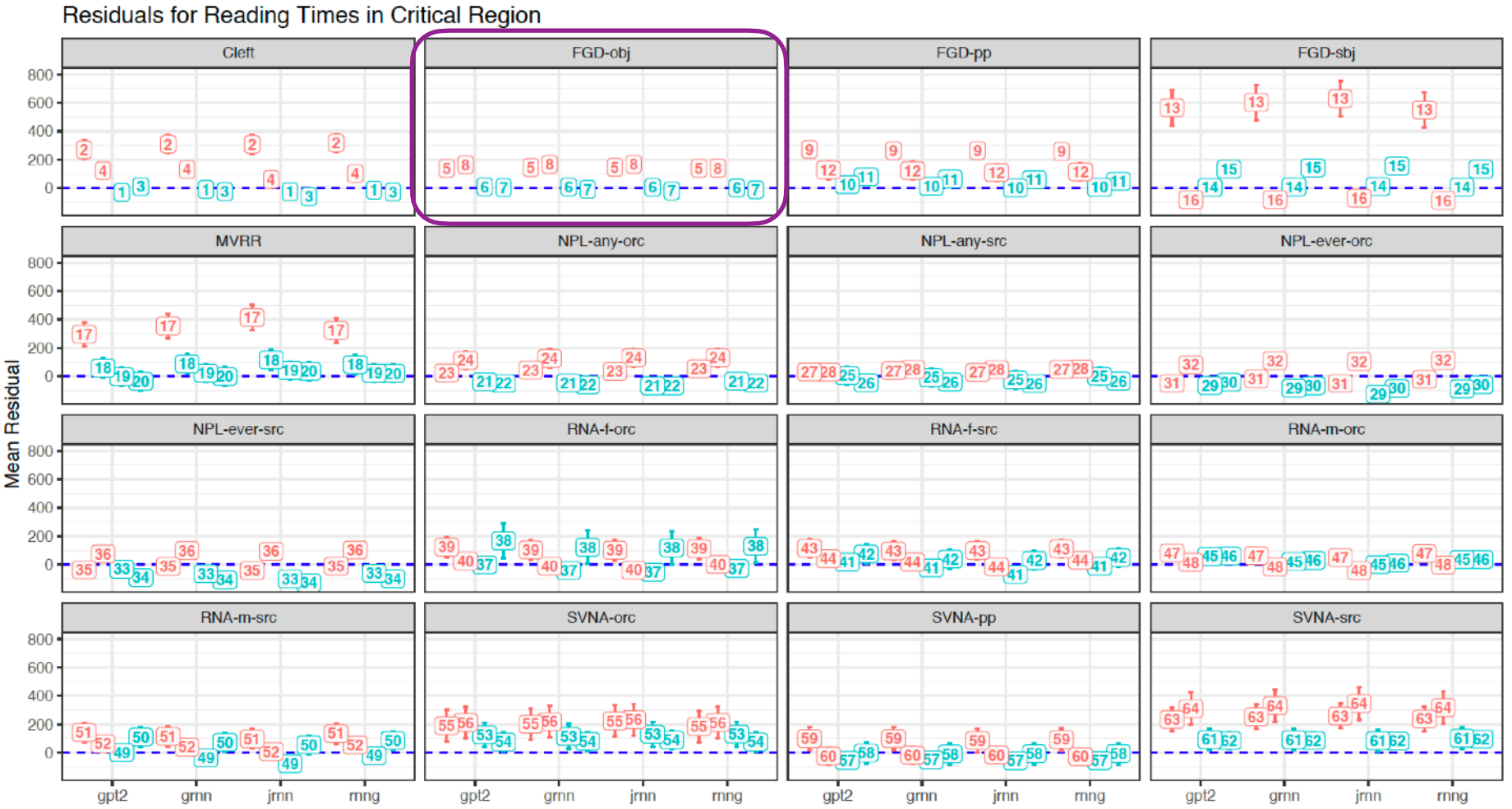


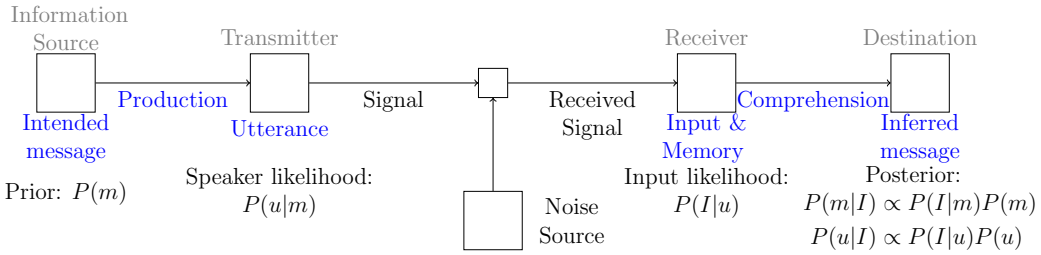
(Wilcox et al., 2021)

Summary: what I have argued today

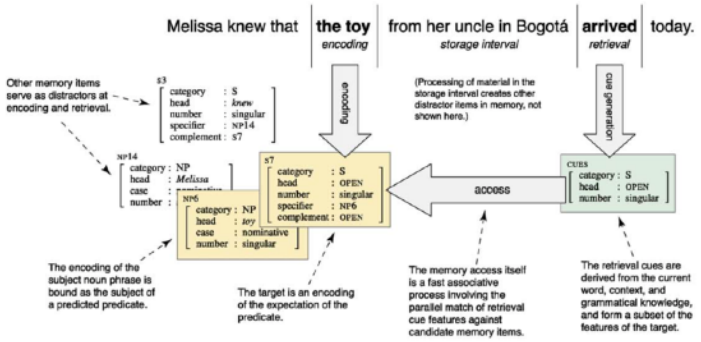
- Standard deep-learning models **learn remarkably subtle features of human grammar** from a **childhood's worth of linguistic input** (no real-world grounding needed!)
- However, these models' predictions are **not quantitatively aligned with human comprehension behavior when expectations about grammatical structure are violated**
- Deep-learning models offer **insights into learnability** and **a powerful scientific tool for expectation estimation,** but **not a theoretical account** of human language representation and processing

Other ingredients for theory of human language comprehension

- Noisy-channel mechanisms for error detection & robustness (Levy 2008, Gibson et al., 2013, Futrell et al., 2020)

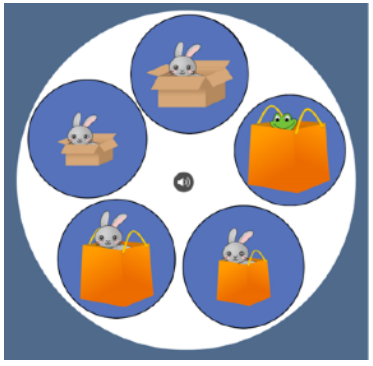


- Limitations on fidelity of memory representations & access (Lewis et al., 2006)



- Incremental semantic representations evaluable in context (Jacobson 1999, Aparicio et al. in prep)

Click on the rabbit in the big...



Mary loves and John hates...

λx[LOVE(x)(mary) ∧HATE(x)(john)]

Acknowledgments

- **Collaborators**: Miguel Ballesteros, Veronica Boyce, Richard Futrell, Jon Gauthier, Jennifer Hu, Takashi Morita, Peng Qian, Pranali Vani, Ethan Wilcox
- **Funders:** National Science Foundation, MIT–IBM AI Research Lab, MIT Quest for Intelligence, Google, Elemental Cognition
- The **MIT Computational Psycholinguistics Laboratory**

Thank you for listening!

http://syntaxgym.org

http://cpl.mit.edu

http://www.mit.edu/~rplevy

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