Bringing together grammar and deep learning: models and targeted evaluation

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9.19: Computational Psycholinguistics

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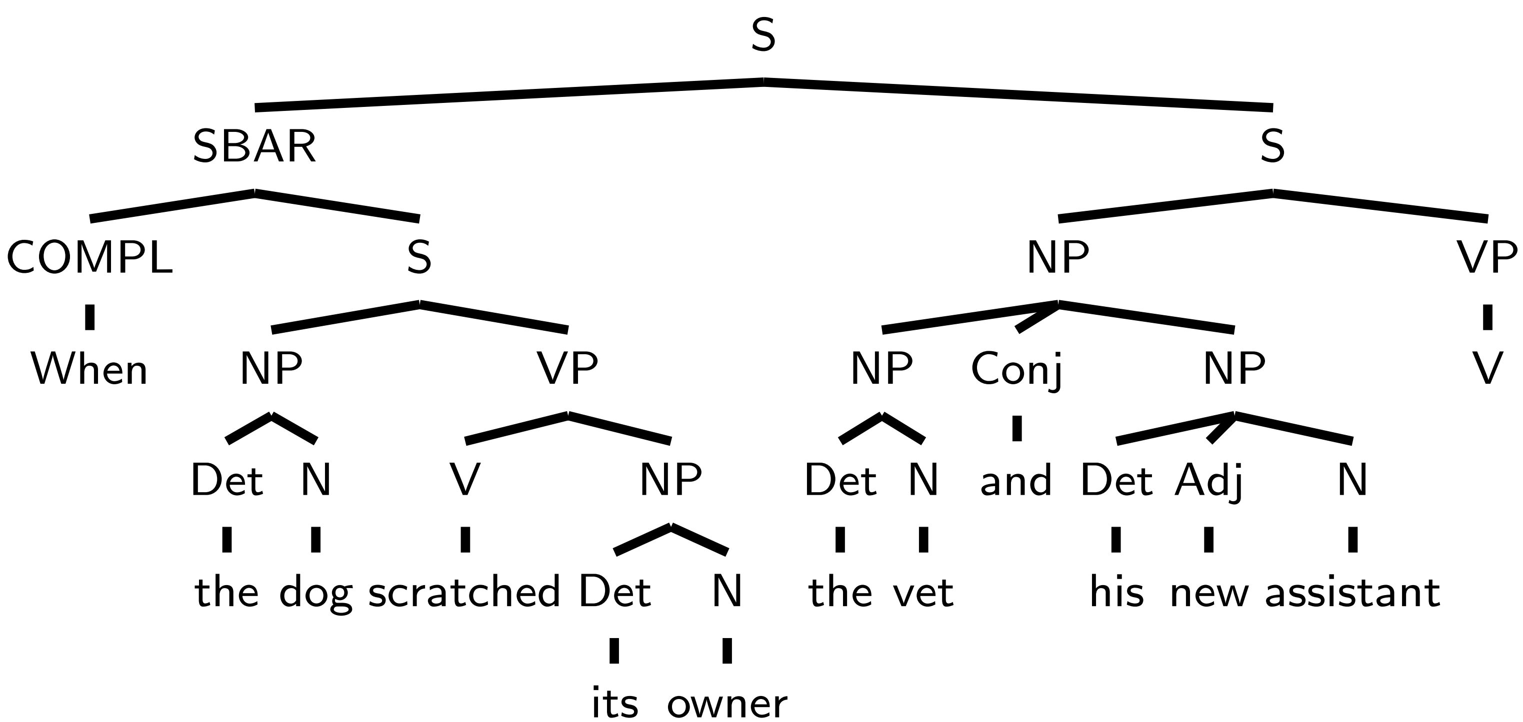
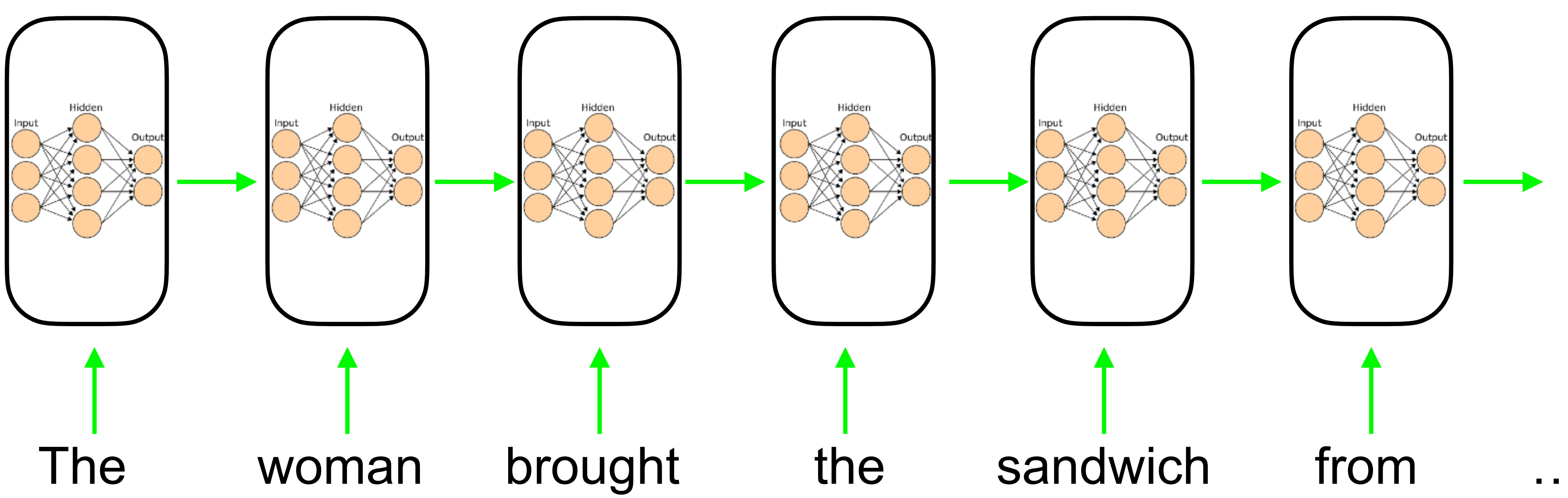
Agenda for today

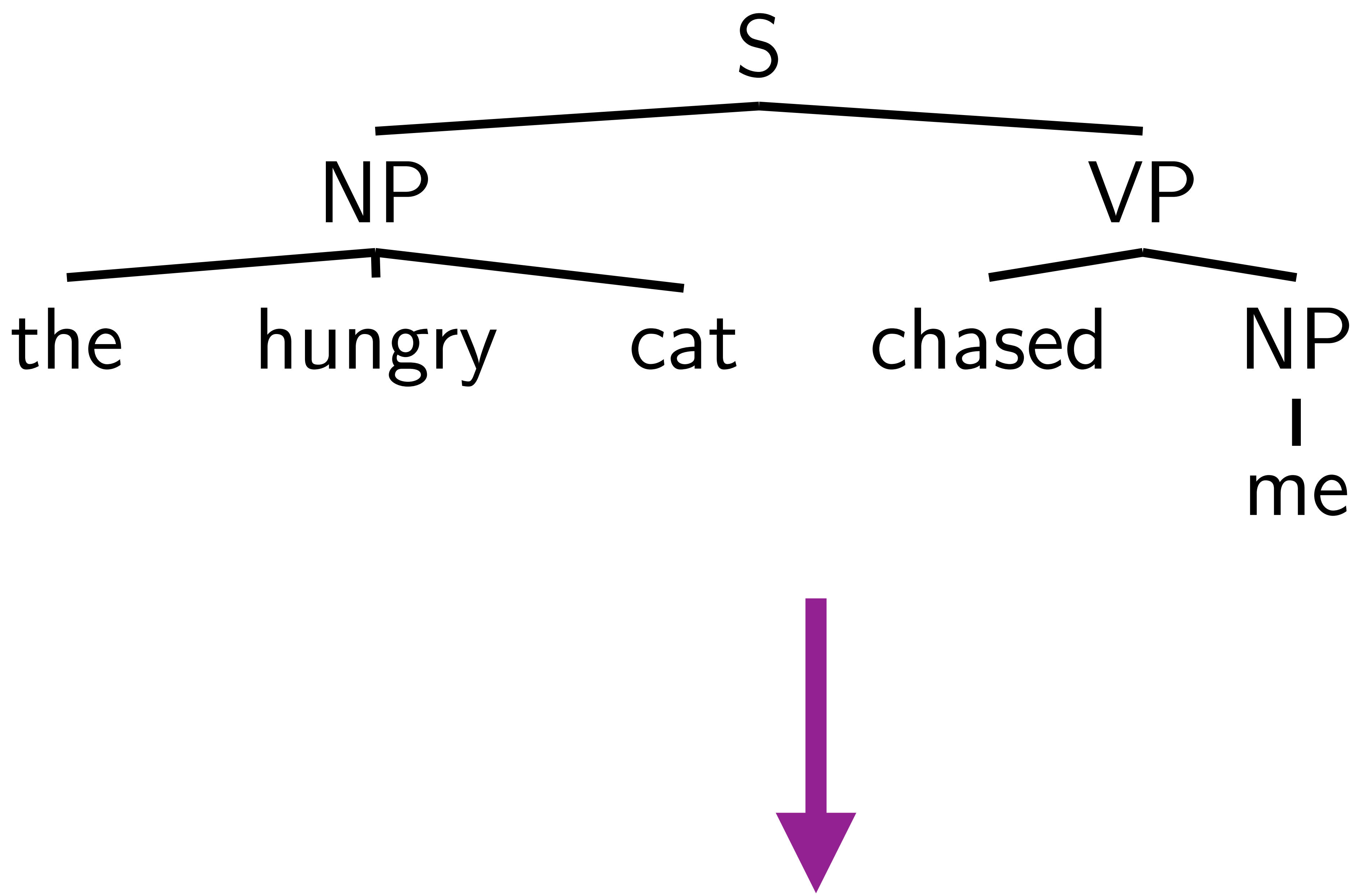
- Combining symbolic grammar and neural generalization
- Controlled tests for syntactic generalization:
  - Subordination
  - Garden-pathing

Grammar and deep learning





Sequence representations of trees



(S (NP the hungry cat) (VP chased (NP me)))

(S (NP the hungry cat) (VP chased (NP me)))

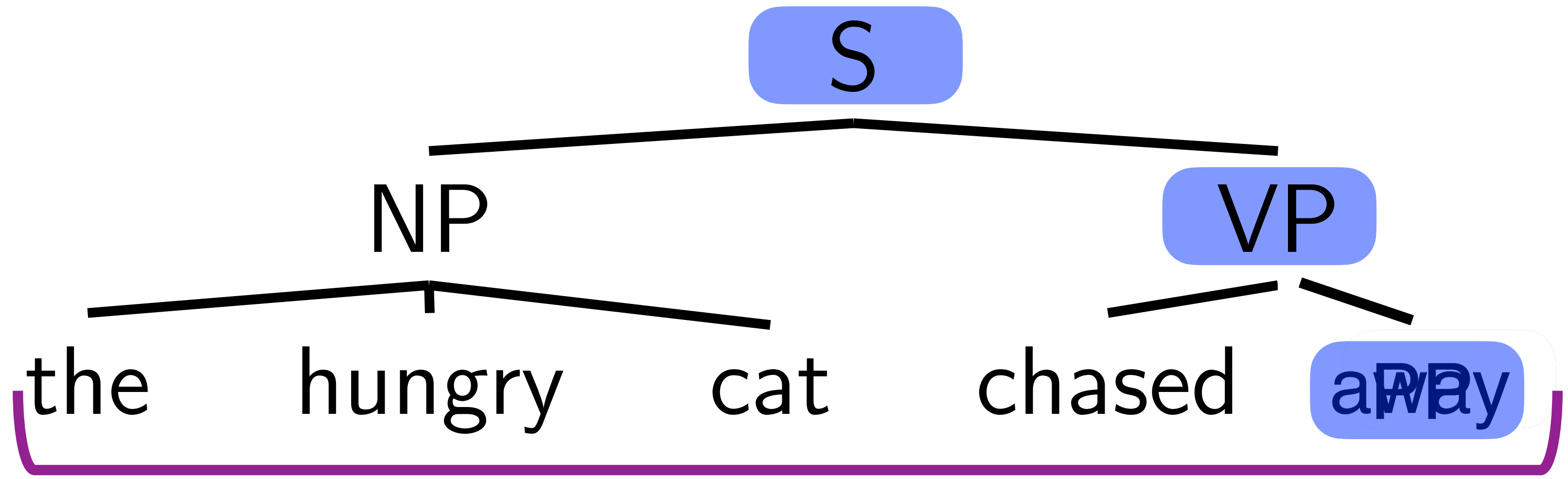
This can be seen as an *action sequence*!

Action	**Meaning**	**String gloss**
NT(X)	Push a new **open** non-terminal on top of the **stack**	**(X**
Gen(*w*)	Generate word *w* as a terminal node and put it on top of the stack (as a **closed** node)	*w*
REDUCE	Pop **closed** nodes $N_{1\ldots i-1}$ from the top of the **stack** until encountering **open** node N_i; close N_i	**)**
END	Finish parsing (iff the sole stack element is a closed S)	**n/a**

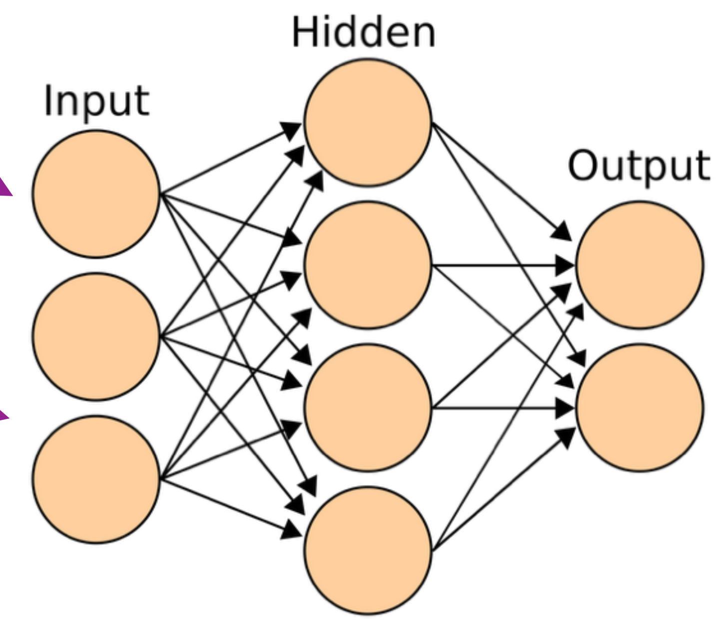
(S (NP the hungry cat) (VP chased (NP me)))

If we put a conditional probability distribution on actions, we have a probabilistic grammar!

Action	Stack
NT(S)	(S
NT(NP)	(S | (NP
Gen(the)	(S | (NP | the
Gen(hungry)	(S | (NP | the | hungry
Gen(cat)	(S | (NP | the | hungry | cat
REDUCE	(S | (NP the hungry cat)
NT(VP)	(S | (NP the hungry cat) | (VP
Gen(chased)	(S | (NP the hungry cat) | (VP | chased
NT(NP)	(S | (NP the hungry cat) | (VP | chased | (NP
Gen(me)	(S | (NP the hungry cat) | (VP | chased | (NP | me
REDUCE	(S | (NP the hungry cat) | (VP | chased | (NP me)
REDUCE	(S | (NP the hungry cat) | (VP chased (NP me))
REDUCE	(S (NP the hungry cat) (VP chased (NP me)))
END	



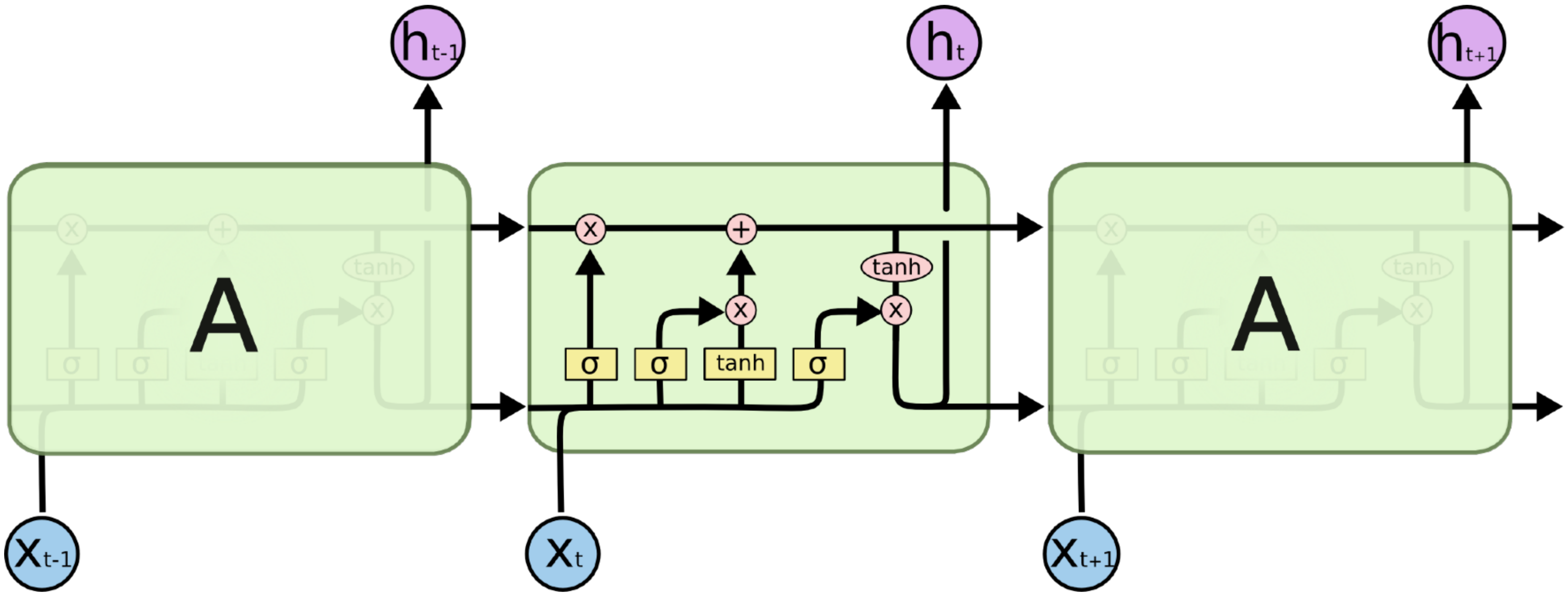
Action	Stack
NT(S)	(S
NT(NP)	(S | (NP
Gen(the)	(S | (NP | the
Gen(hungry)	(S | (NP | the | hungry
Gen(cat)	(S | (NP | the | hungry | cat
REDUCE	(S | (NP the hungry cat)
NT(VP)	(S | (NP the hungry cat) | (VP
Gen(chased)	(S | (NP the hungry cat) | (VP | chased
???	



Gen(away) REDUCE NT(PP) NT(NP)

Knowledge characterization: P(action|context)

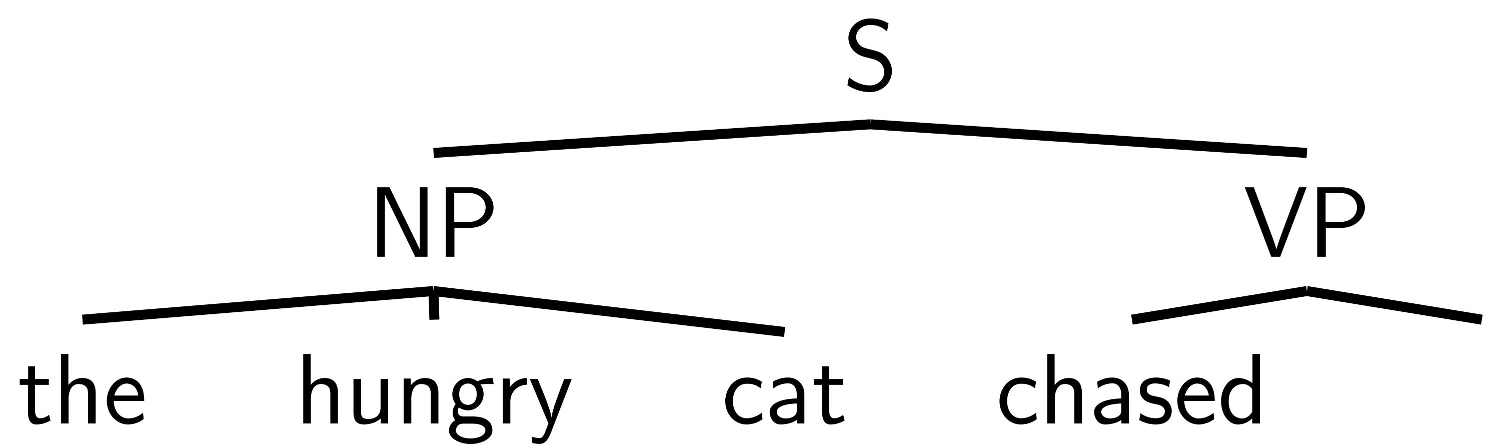
Our friend the LSTM



(image due to Chris Olah)

Some options for neural generalization

- Option 1: run RNN over words as normal for language modeling, but predict tree-generation actions



Action	Stack
NT(S)	(S
NT(NP)	(S | (NP
Gen(the)	(S | (NP | the
Gen(hungry)	(S | (NP | the | hungry
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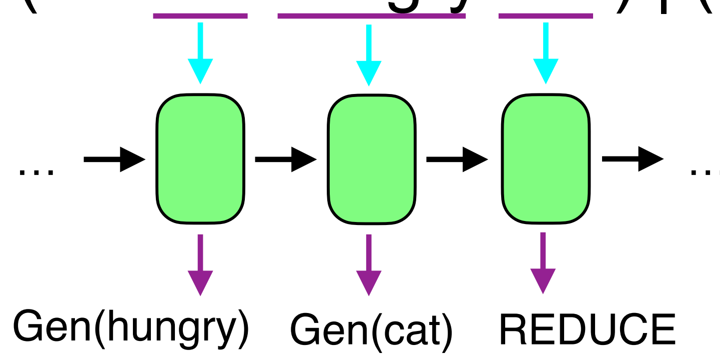
REDUCE	(S | (NP the hungry cat)
NT(VP)	(S | (NP the hungry cat) | (VP
Gen(chased)	(S | (NP the hungry cat) | (VP | chased

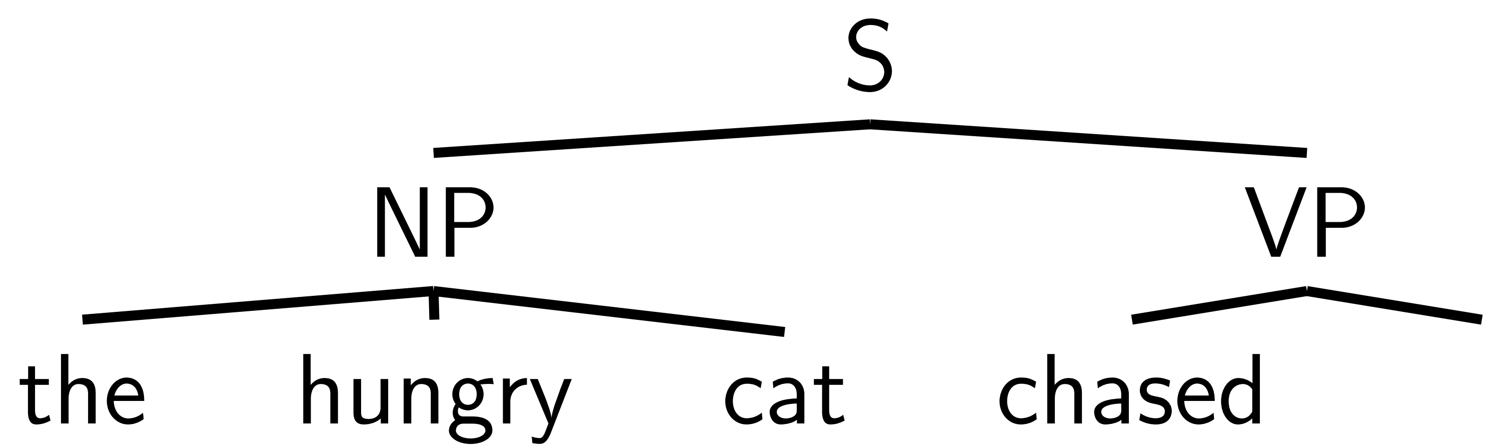


This will not work well at all—why???

Some options for neural generalization

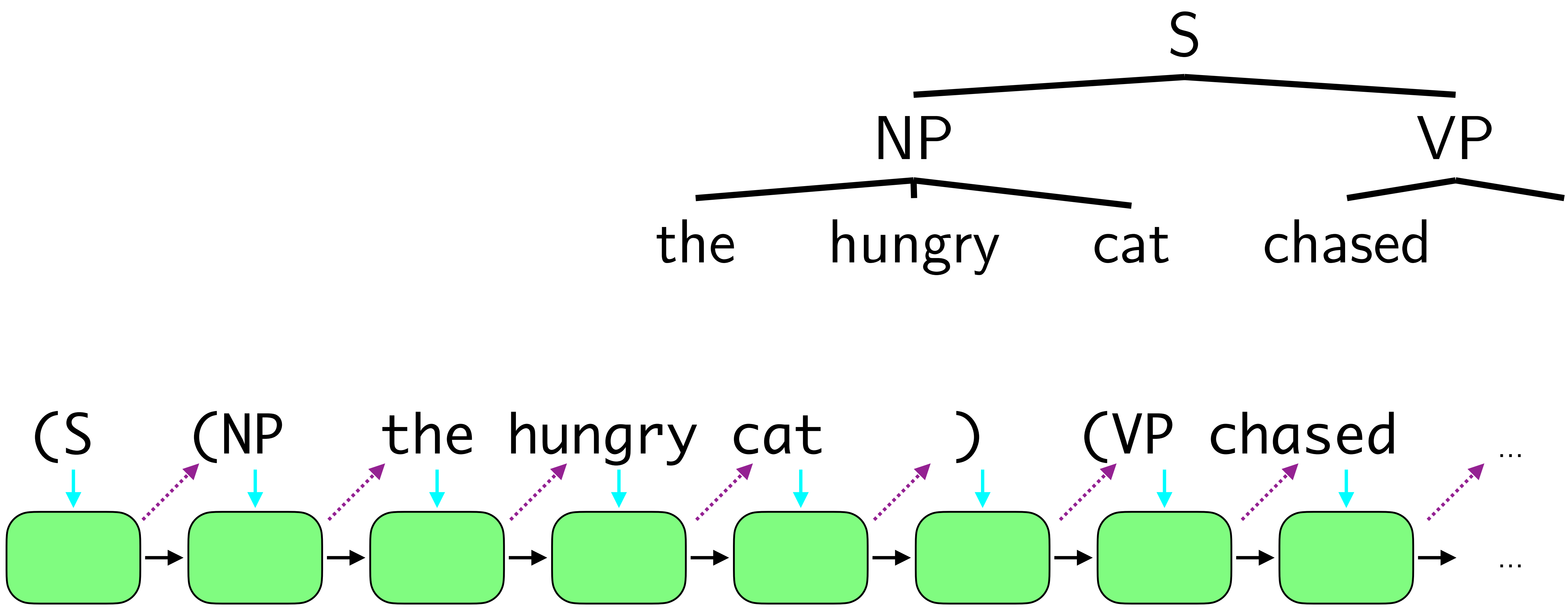
- Option 2: run RNN over *tree-generation actions*

Action	Stack
NT(S)	(S
NT(NP)	(S | (NP
Gen(the)	(S | (NP | the
Gen(hungry)	(S | (NP | the | hungry
Gen(cat)	(S | (NP | the | hungry | cat
REDUCE	(S | (NP the hungry cat)
NT(VP)	(S | (NP the hungry cat) | (VP
Gen(chased)	(S | (NP the hungry cat) | (VP | chased



Some options for neural generalization

- Option 2: run RNN over *tree generation actions*



(Choe & Charniak, 2016)

An inferential challenge

`(S (NP I ) (VP saw      the`	*I saw the child*
`(S (NP I ) (VP saw (NP (NP the`	*I saw the child's dog*
`(S (NP I ) (VP saw (S (NP the`	*I saw the child leave*
`(S (NP I ) (VP saw (S (NP (NP the`	*I saw the child's dog leave*
`(S (NP I ) (VP saw (SBAR (NP the`	*I saw the child left*
`(S (NP I ) (VP saw (SBAR (NP (NP the`	*I saw the child's dog left*

There is a potentially unbounded number of tree-generation operations just to get to the next word!

Inference using beam search

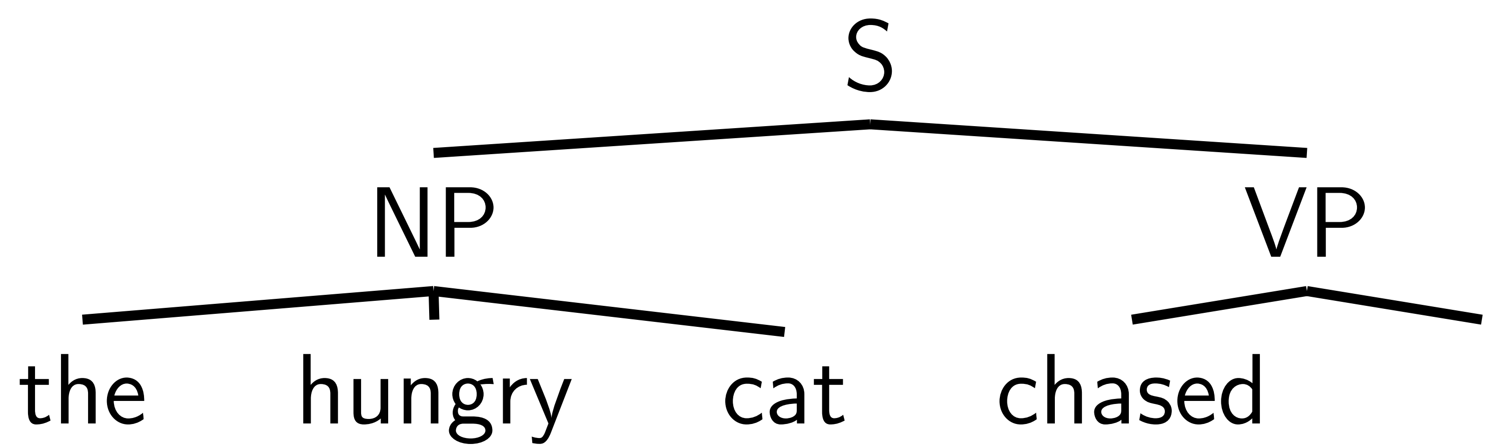
Context C	Action Sequences A	$\log P(A \mid C)$	Rank on beam
(S (NP I) (VP saw	(NP the	-5.1	1
(S (NP I) (VP saw	(NP (NP the	-6.3	4
(S (NP I) (VP saw	(S (NP the	-5.8	2
(S (NP I) (VP saw	(S (NP (NP the	-7.2	✘
(S (NP I) (VP saw	(SBAR (NP the	-6.2	3
(S (NP I) (VP saw	(SBAR (NP (NP the	-7.8	✘

A "word-synchronous" beam, beam size=4

(Stern et al., 2017)

Some options for neural generalization

- Option 3: run RNN over *stack elements*

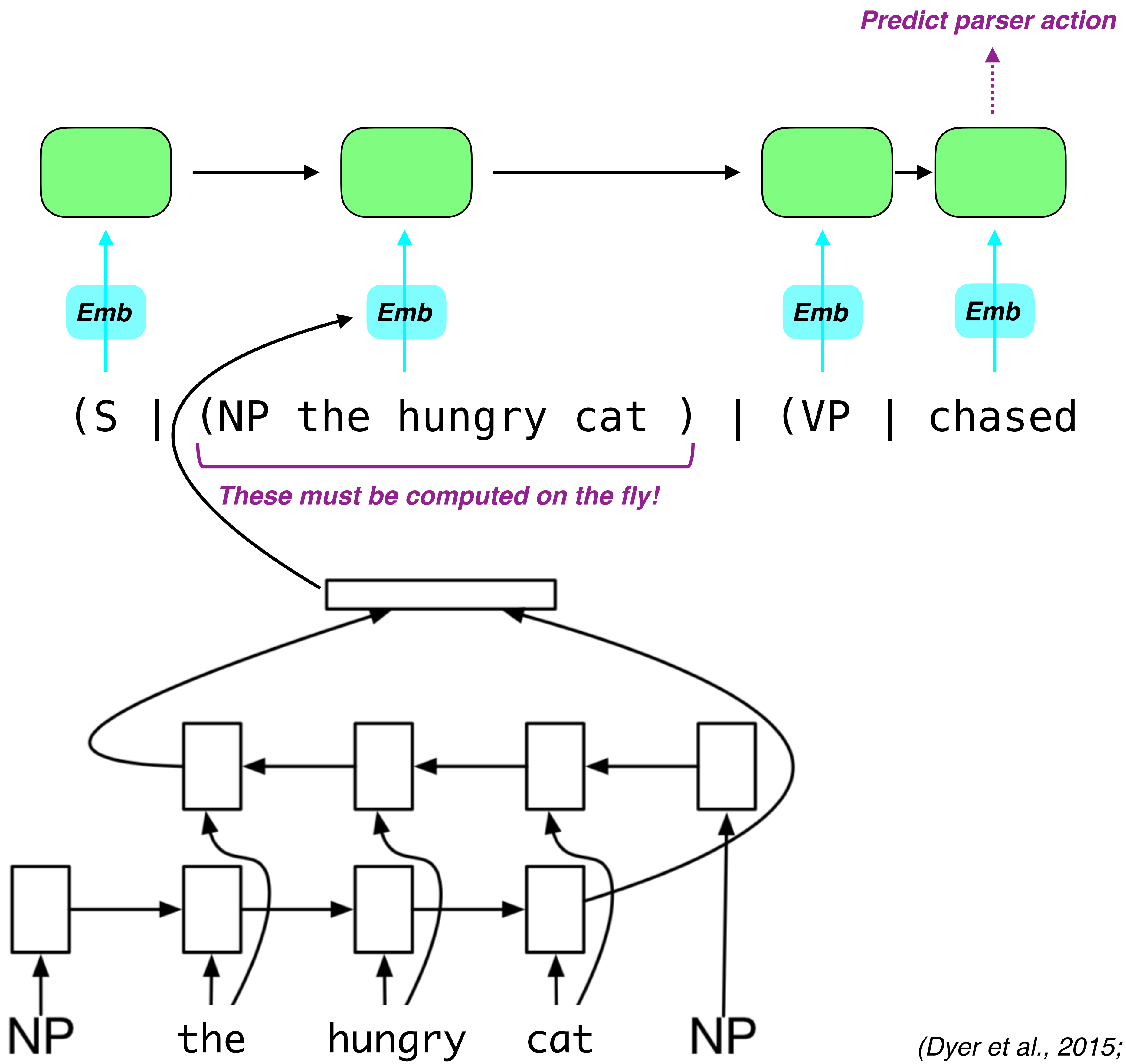


Action	Stack
NT(S)	(S
NT(NP)	(S | (NP
Gen(the)	(S | (NP | the
Gen(hungry)	(S | (NP | the | hungry
Gen(cat)	(S | (NP | the | hungry | cat
REDUCE	(S | (NP the hungry cat)
NT(VP)	(S | (NP the hungry cat) | (VP
Gen(chased)	(S | (NP the hungry cat) | (VP | chased

Generalize from the stack!

…but how???

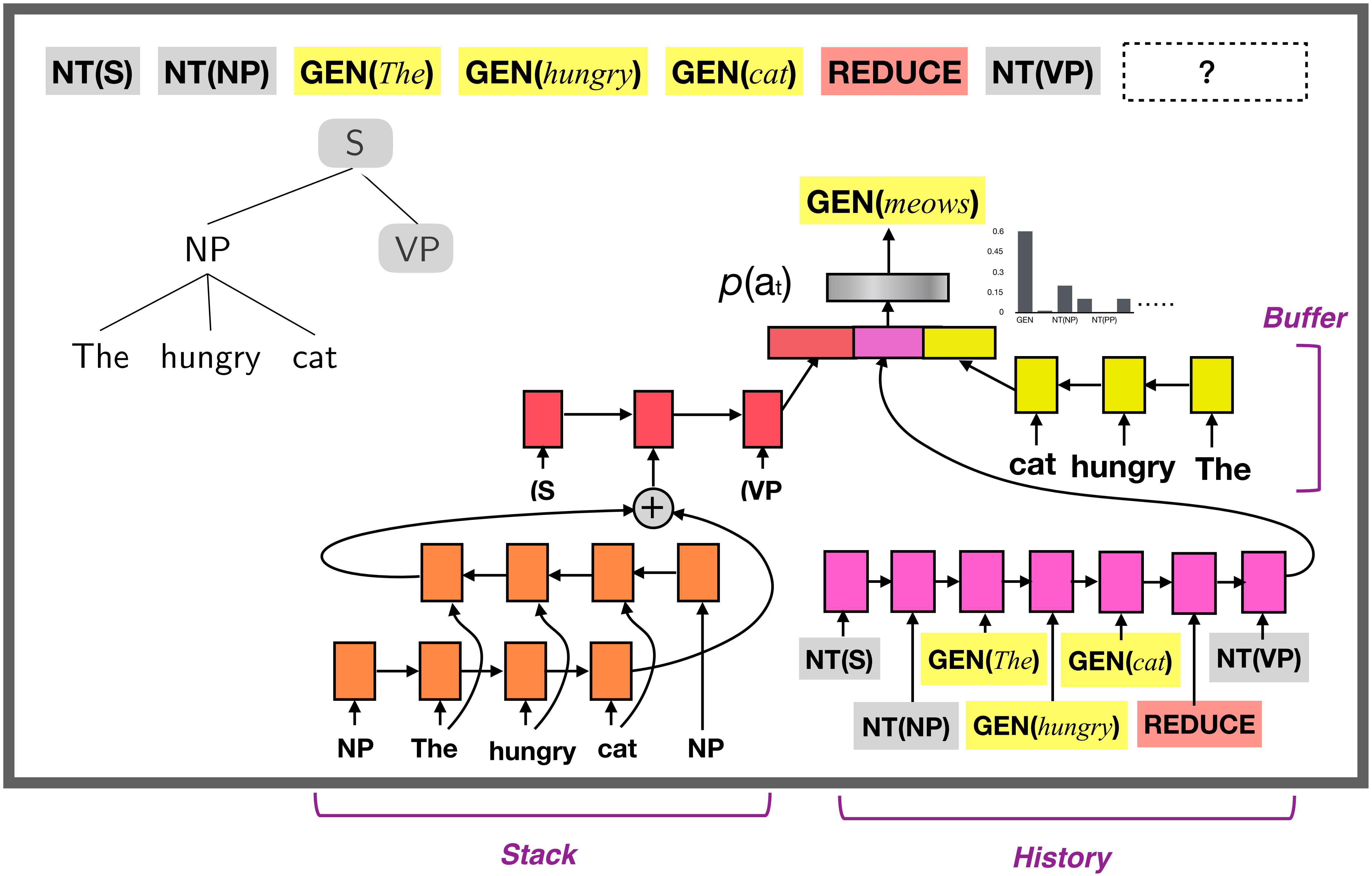
A challenge for generalization



(Dyer et al., 2015; Dyer et al., 2016)

Neural generalization from *all three* sources

Recurrent Neural Network Grammars (RNNGs)



(Dyer et al., 2016; Kuncoro et al., 2017)

NN Language Models Tested

Model	Architecture	Training data	Data size (tokens)	Reference
JRNN	LSTM	One Billion Word	$\sim$ 800 million	Jozefowicz et al. (2016)
GRNN	LSTM	Wikipedia	$\sim$ 90 million	Gulordava et al. (2018)
RNNG	RNN Grammar	Penn Treebank	$\sim$ 1 million	Dyer et al. (2016)
TinyLSTM	LSTM	Penn Treebank	$\sim$ 1 million	—

- LSTMs have no explicit syntactic state representations.
- RNN Grammars do, but it is not always clear how they use them in making predictions.

Simplest syntactic hierarchy: subordination

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

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

Context | **Completion**

✓ *The doctor studied the textbook* | *.*

✗ *As the doctor studied the textbook .*

Surprisal difference (should be *positive*)

"Matrix" variants
(There is a subsequent matrix clause)

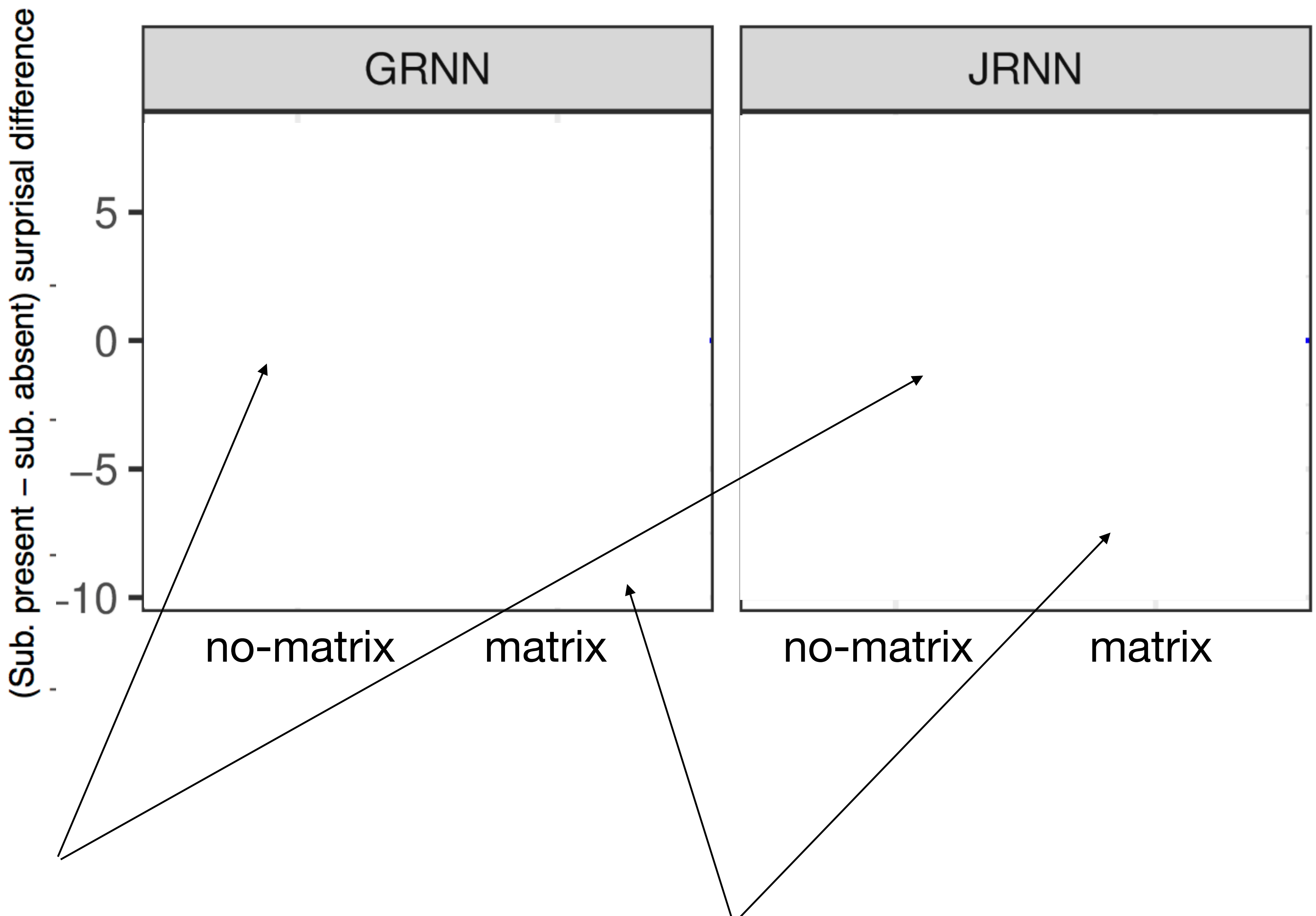
? *The doctor studied the textbook*
, the nurse walked into the office .

✓ *As the doctor studied the textbook*
, the nurse walked into the office .

Surprisal difference (should be *negative*)

(Futrell et al. 2019, NAACL)

Effects of Subordinate Clauses

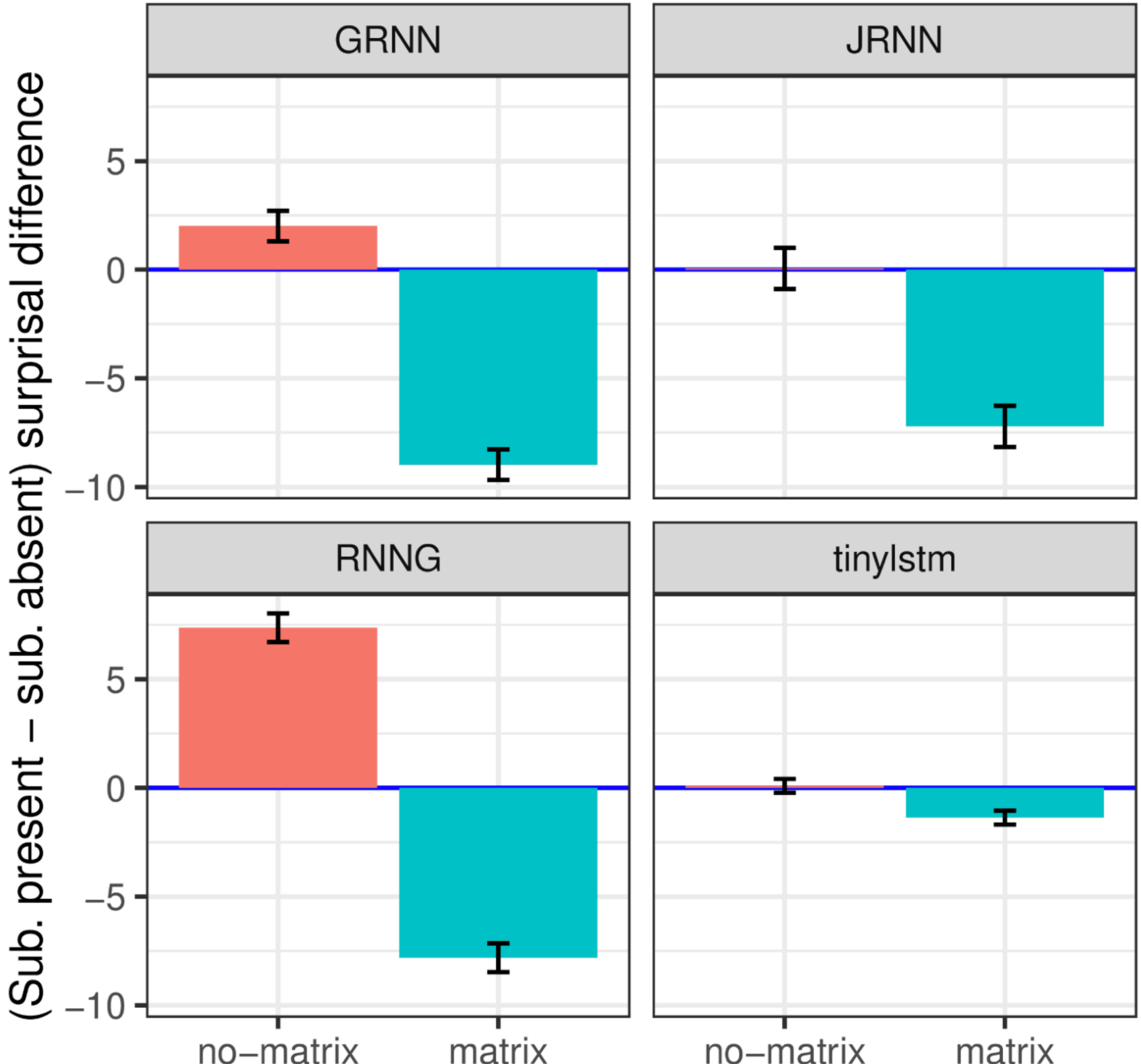


No-matrix penalty

Matrix licensing

(Futrell et al. 2019, NAACL)

Subordination: results



(Futrell et al. 2019, NAACL)

Subordination: summary

- All models learned *something* about the contingency between initial subordinator & need for a second clause
- Explicit representation of grammatical structure substantially sharpened that contingency

(Futrell et al. 2018, ArXiv; Futrell et al. 2019, NAACL)

Garden-pathing

(a) [transitive, −comma]

When the dog scratched the vet with his new assistant removed the muzzle.

difficulty here

(b) [transitive, +comma]

When the dog scratched, the vet with his new assistant removed the muzzle.

easier

(c) [intransitive, −comma]

When the dog arrived the vet with his new assistant removed the muzzle.

(d) [intransitive, +comma]

When the dog arrived, the vet with his new assistant removed the muzzle.

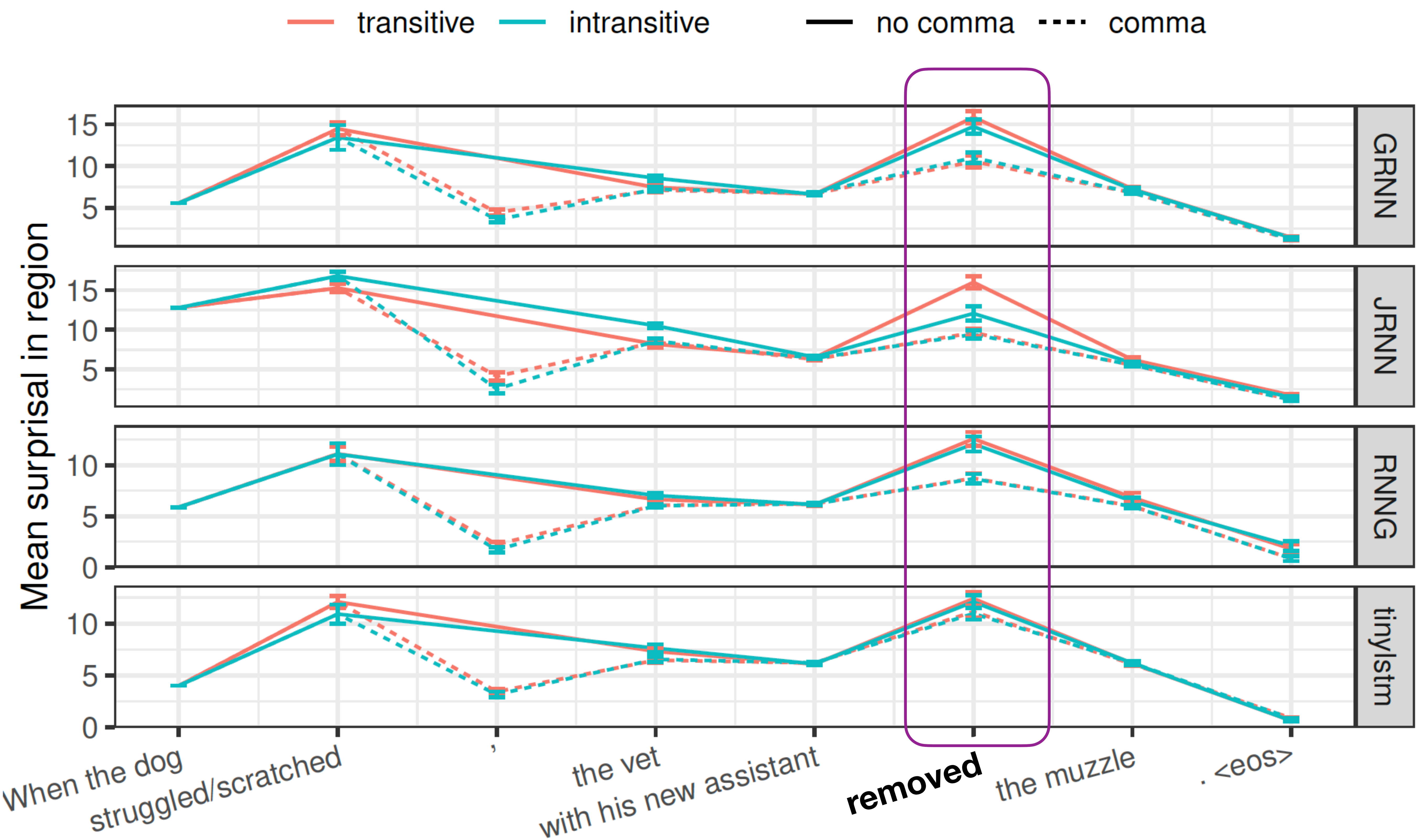
$$S(x) = -\log P(\text{removed} \mid \text{Context of version } x)$$

(i) $S(a) > S(b)$

(ii) $S(a) - S(b) > S(c) - S(d)$

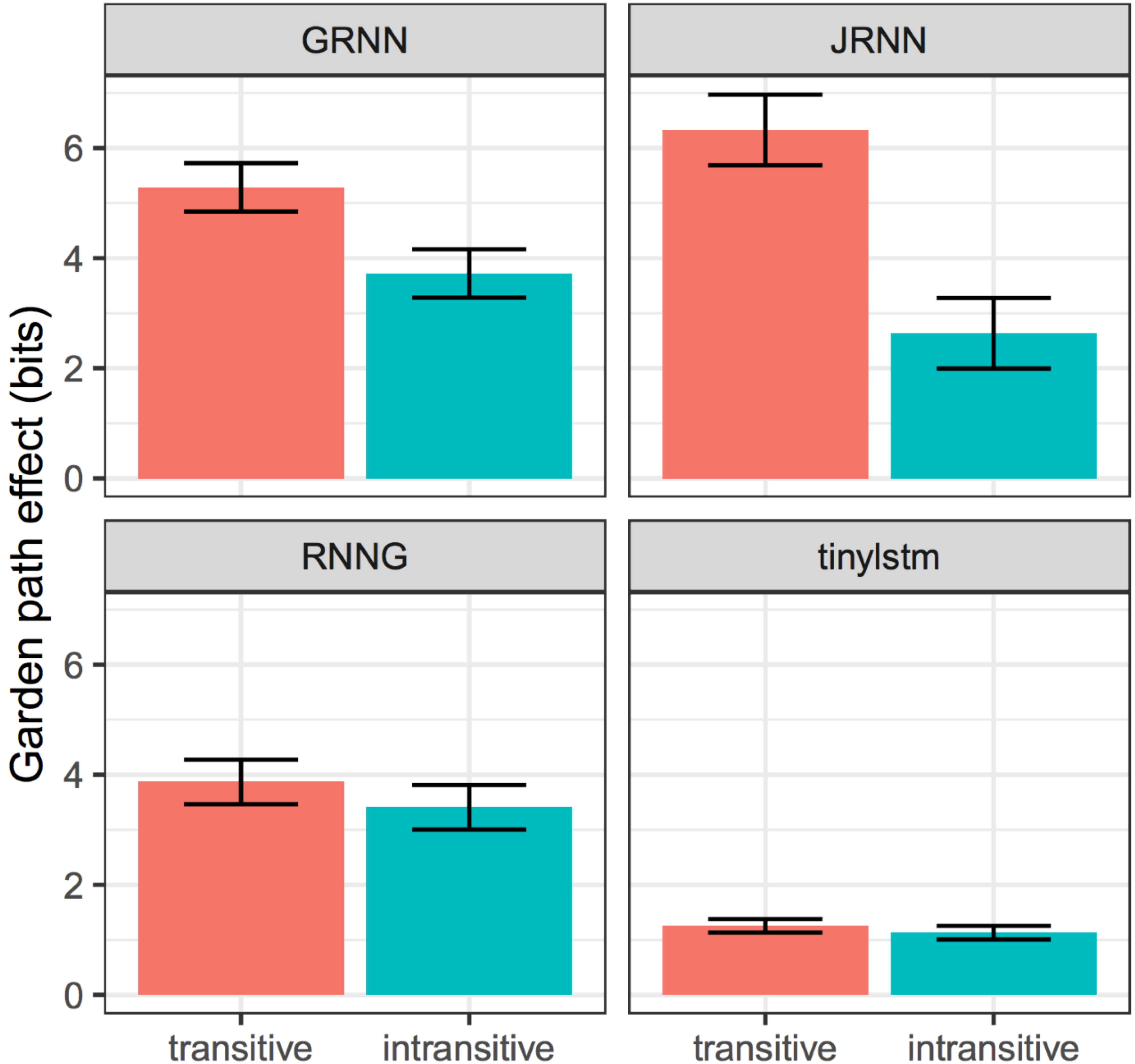
(Frazier & Rayner, 1982; Adams et al., 1998; Mitchell, 1987; van Gompel & Pickering, 2001; Staub, 2007)

Region-by-region surprisal profiles



(Futrell et al. 2019, NAACL)

NP/Z Garden Path Results



(Futrell et al. 2019, NAACL)

NP/Z Garden Paths: Degradation Over Time

(a) [short, −comma] As the author studying Babylon in ancient times wrote the book **grew**.

(b) [short, +comma] As the author studying Babylon in ancient times wrote, the book **grew**.

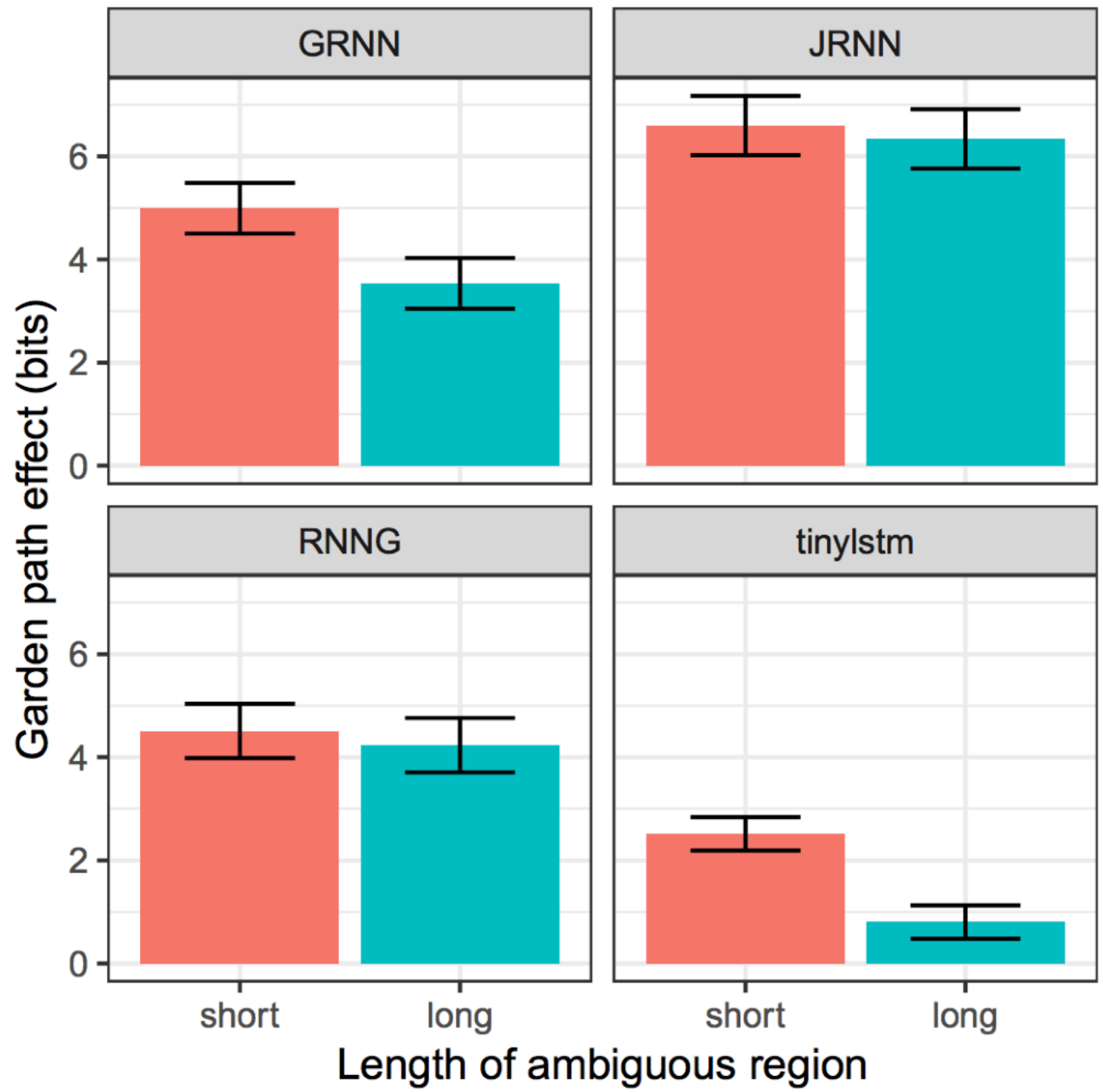
(c) [long, −comma] As the author wrote the book studying Babylon in ancient times **grew**.

(d) [long, +comma] As the author wrote, the book studying Babylon in ancient times **grew**.

(Warner & Glass, 1987; Ferreira & Henderson, 1991; Tabor & Hutchins, 2004; Levy et al., 2009)

Prediction:

$$S(a) - S(b) \approx S(c) - S(d) > 0$$



(Futrell et al. 2019, NAACL)

"Digging in" in human NP/Z garden-pathing

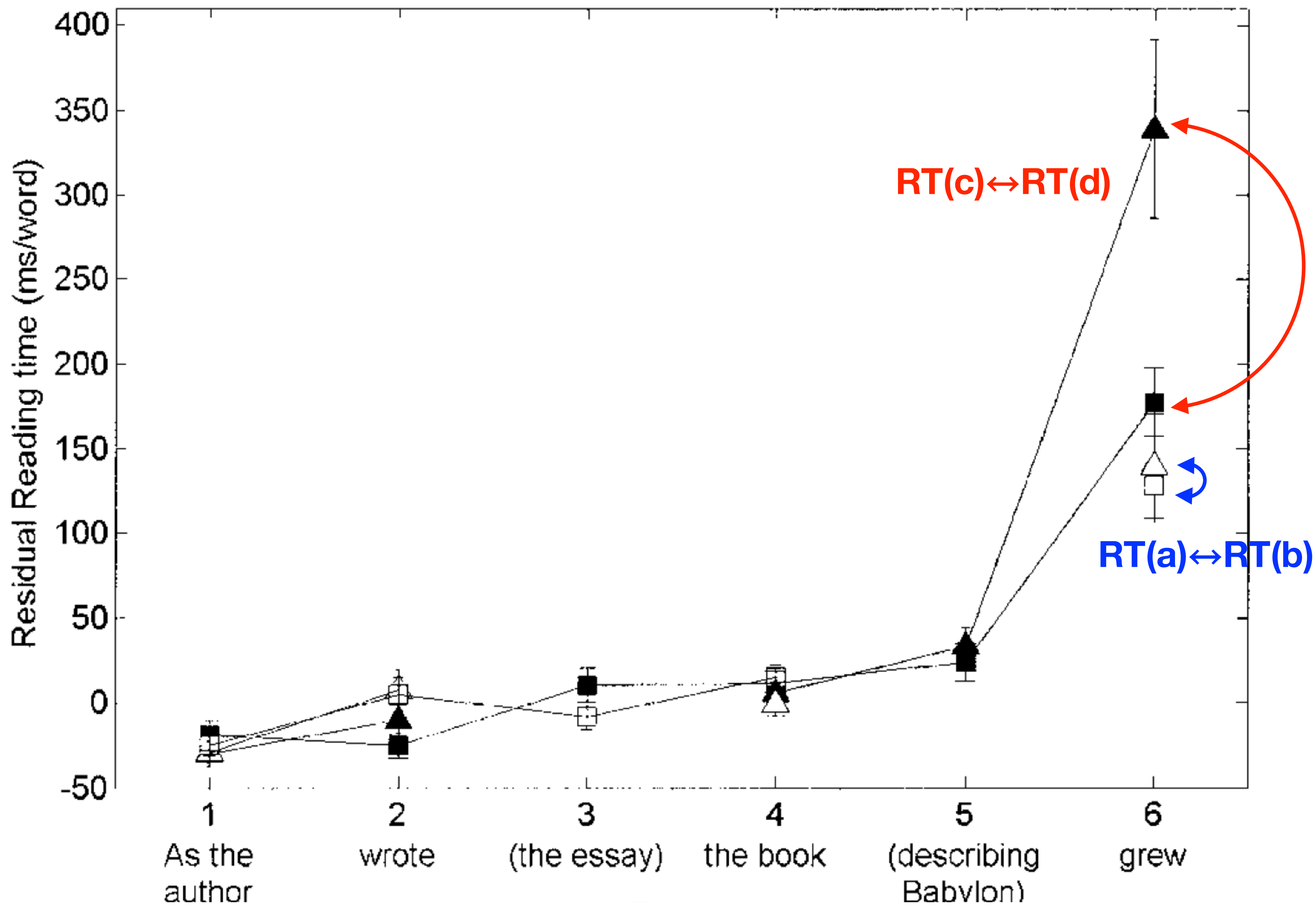
△(a) [short, −object] As the author wrote <u>the book</u> **grew.**

□(b) [short, +object] As the author wrote the essay <u>the book</u> **grew.**

▲(c) [long, −object] As the author wrote <u>the book describing Babylon</u> **grew.**

■(d) [long, +object] As the author wrote the essay <u>the book describing Babylon</u> **grew.**

Surprisal in neural language models doesn't capture the human "digging-in" effect



(Tabor & Hutchins, 2004)

NP/Z garden pathing: summary

- All models show evidence of a syntactic garden path that can be blocked by a comma
- Only models with larger amounts of data show verb transitivity-based garden-path modulation
- Not all models robustly maintain syntactic state-like distinctions over long stretches of intervening material
  - Explicit grammatical representations seem to help with this

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