Evaluating neural language models

Roger Levy

9.19: Computational Psycholinguistics

8 November 2021

Agenda for today

- Impressionistic assessment of the text NLMs generate
- Perplexity-based evaluation
- Targeted grammatical evaluation: subject–verb agreement
    - Left-to-right prediction paradigm
    - Psycholinguistics of subject–verb agreement
    - Evaluation on "colorless green" (*nonce*) sentences
    - Controlled stimuli
    - Ablation tests to reveal circuit-level processing in models

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1-gram	Months the my and issue of year foreign new exchange 's September were recession exchange new endorsed a acquire to six executives
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Review: perplexity-based LM evaluation

Perplexity: inverse (geometric) mean word probability

$$\textbf{PPL}(w_{1\ldots N}) = \sqrt[-N]{\prod_{i=1}^{N} P(w_i \mid w_{1\ldots i-1})}$$

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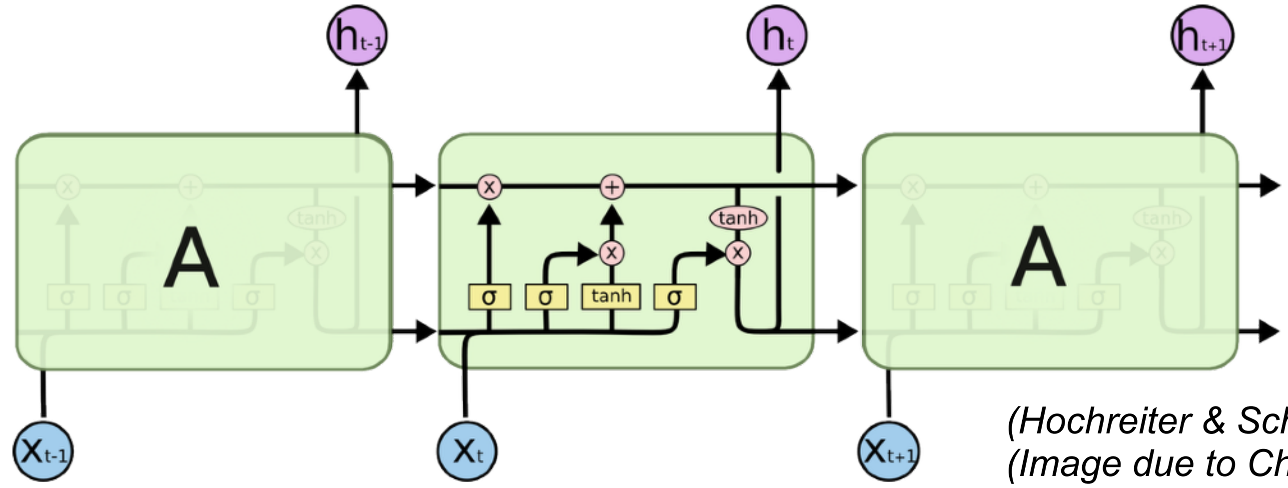
equivalently,

$$\textbf{PPL}(w_{1\ldots N}) = \exp\left[\frac{1}{N}\sum_{i=1}^{N} \log \frac{1}{P(w_i \mid w_{1\ldots i-1})}\right]$$

$$= 2^{-\frac{1}{N}\sum_{i=1}^{N} \log_2 P(w_i|w_{1\ldots i-1})}$$

(Recommended: prove the equivalence!)

Deep learning has revolutionized language modeling



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

Evaluation on "Billion word benchmark" train/dev/test:

MODEL	TEST PERPLEXITY
SIGMOID-RNN-2048 (JI ET AL., 2015A)	68.3
INTERPOLATED KN 5-GRAM, 1.1B N-GRAMS (CHELBA ET AL., 2013)	67.6
SPARSE NON-NEGATIVE MATRIX LM (SHAZEER ET AL., 2015)	52.9
RNN-1024 + MAXENT 9-GRAM FEATURES (CHELBA ET AL., 2013)	51.3
LSTM-512-512	54.1
LSTM-1024-512	48.2
LSTM-2048-512	43.7
LSTM-8192-2048 (NO DROPOUT)	37.9
LSTM-8192-2048 (50% DROPOUT)	32.2
2-LAYER LSTM-8192-1024 (BIG LSTM)	30.6
BIG LSTM+CNN INPUTS *(Jozefowicz et al., 2016)*	**30.0**

(More recent models do even better than this! Hopefully we will have a chance to look at them in a subsequent week)

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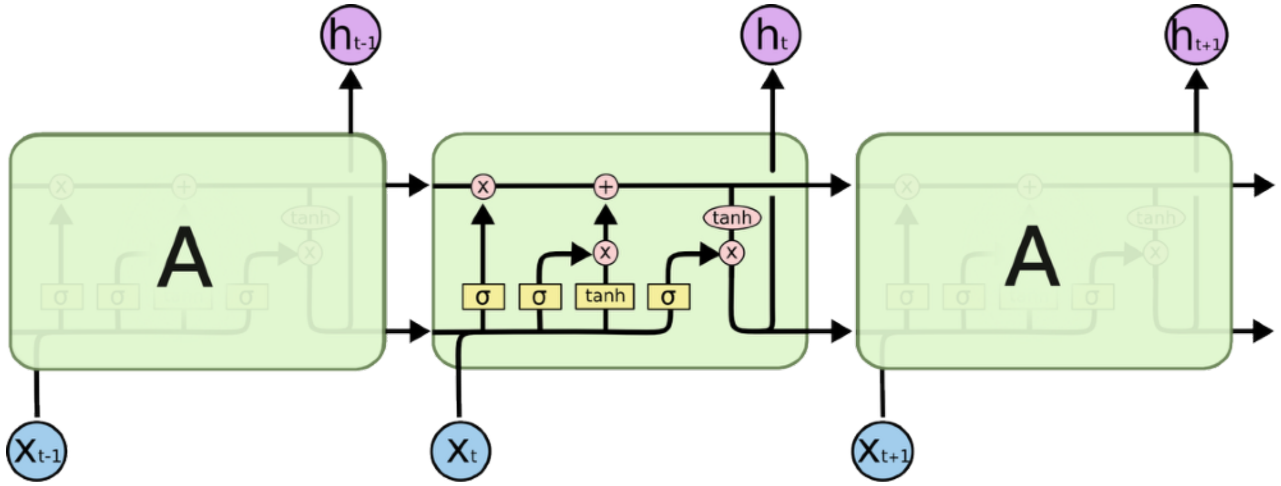

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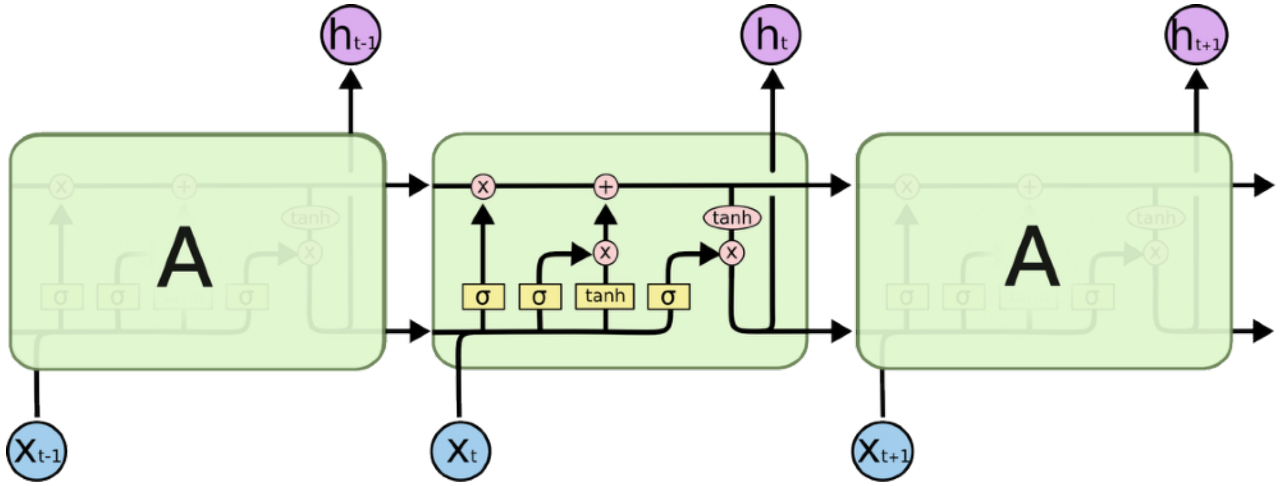

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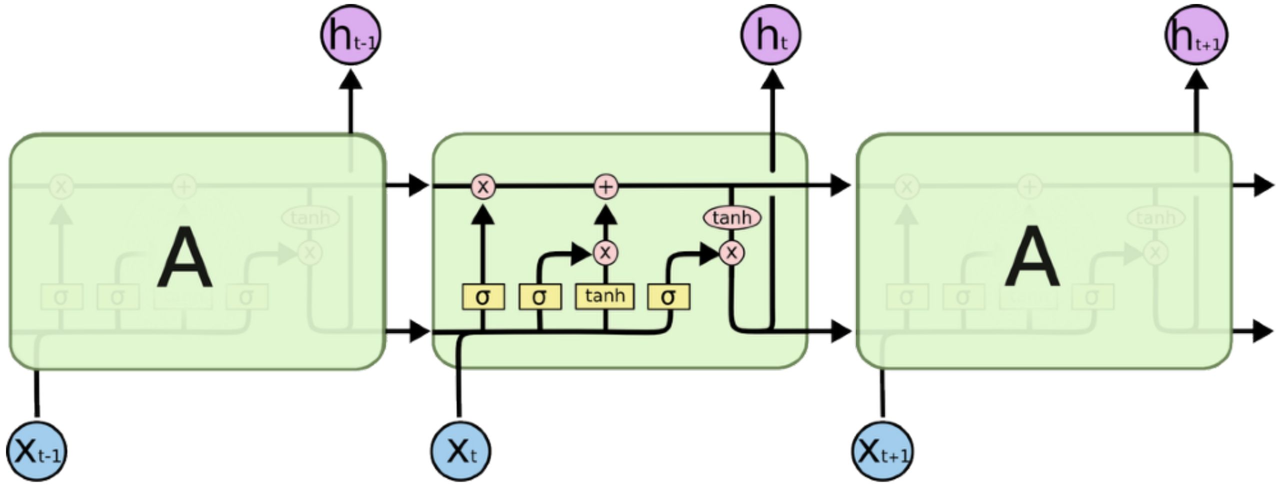

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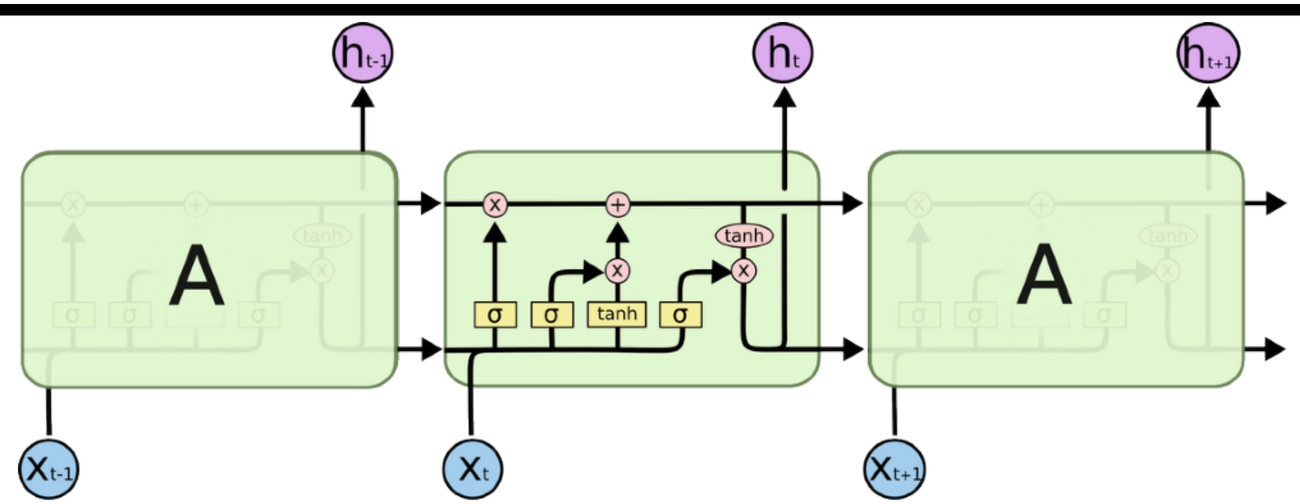

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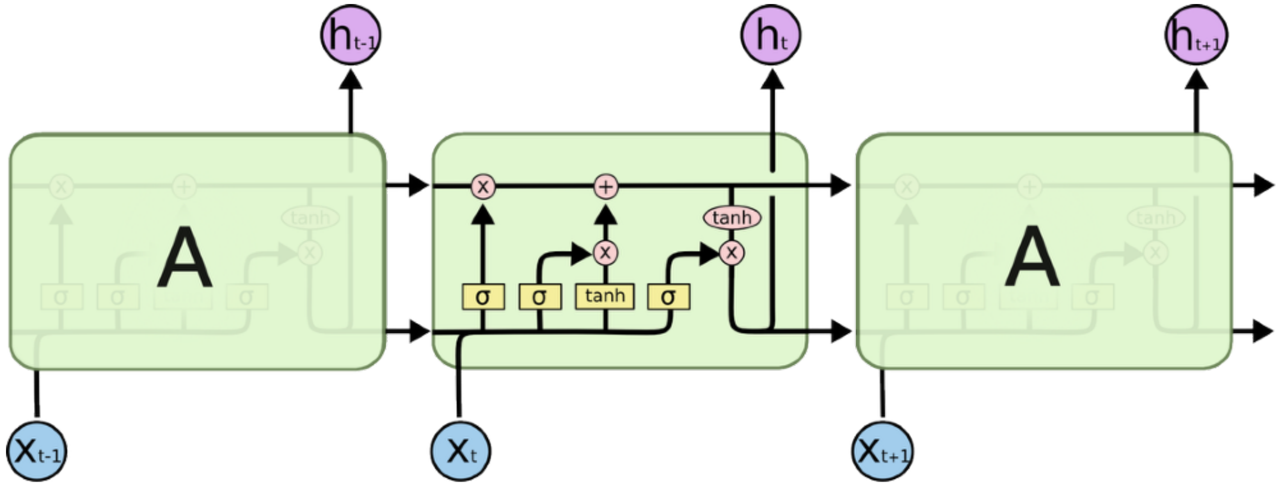

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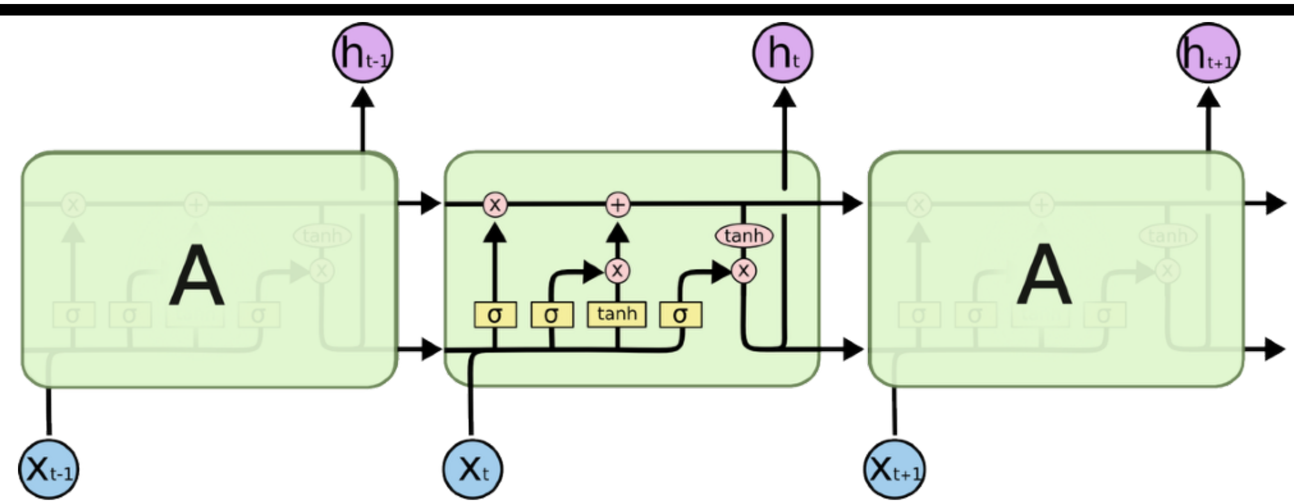

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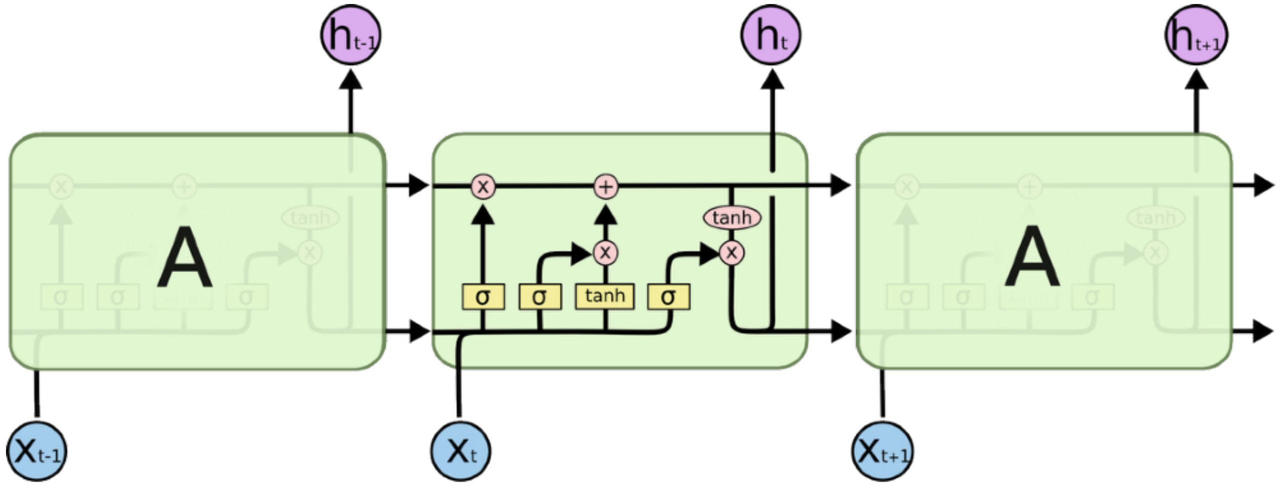

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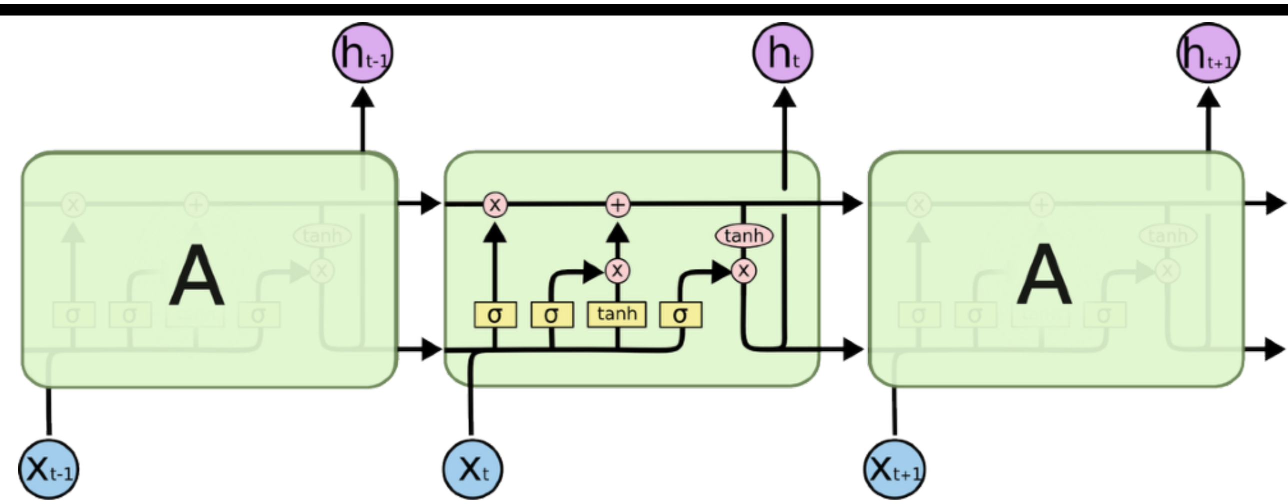

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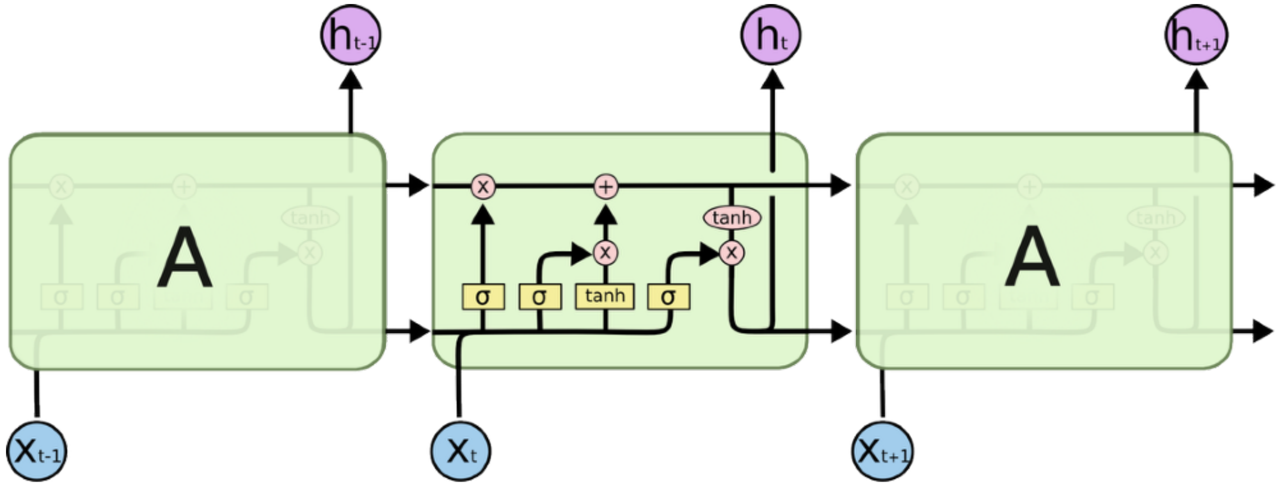

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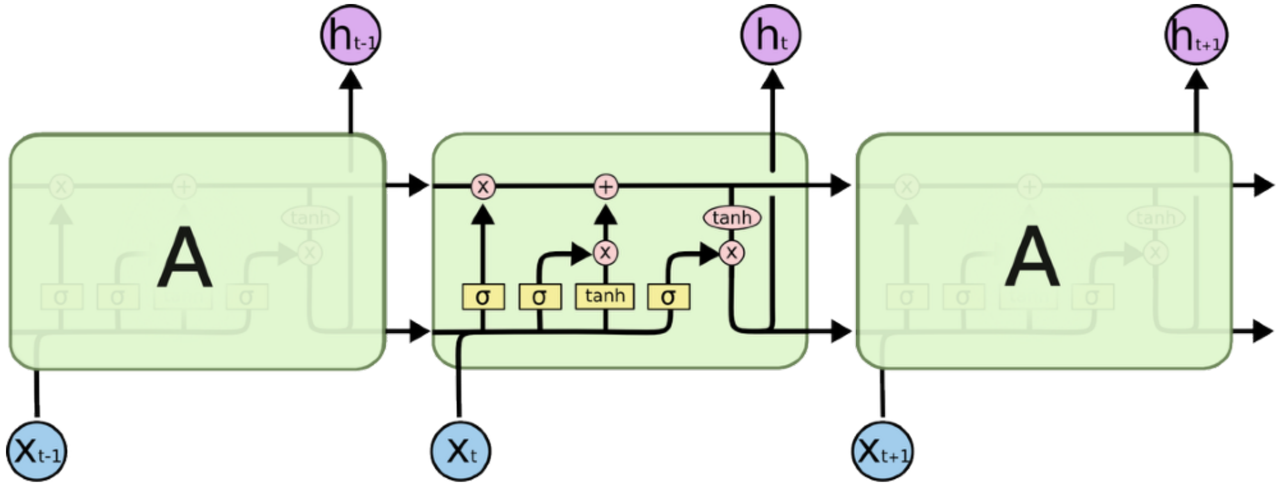

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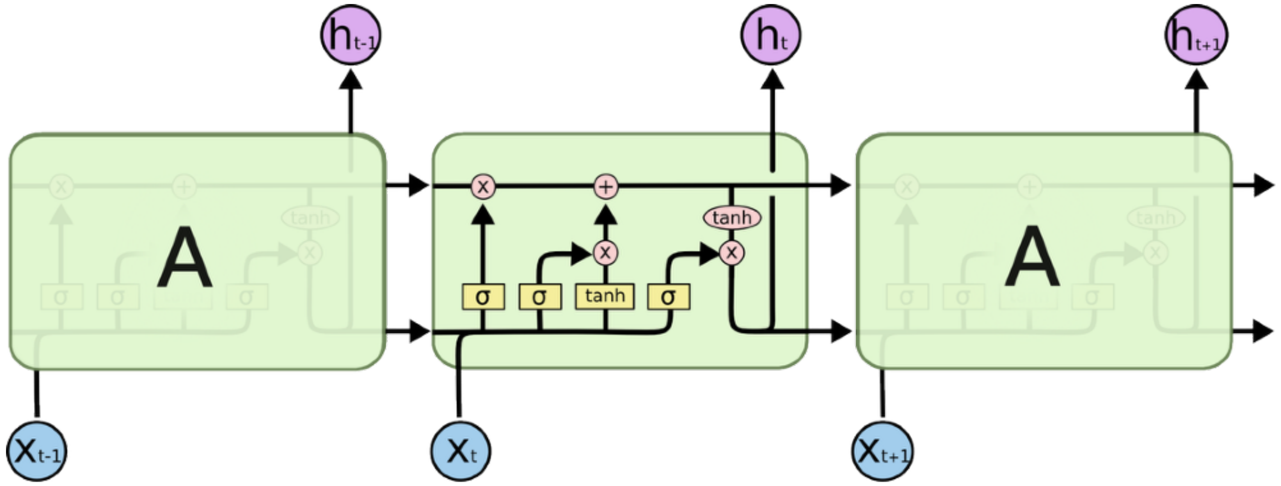

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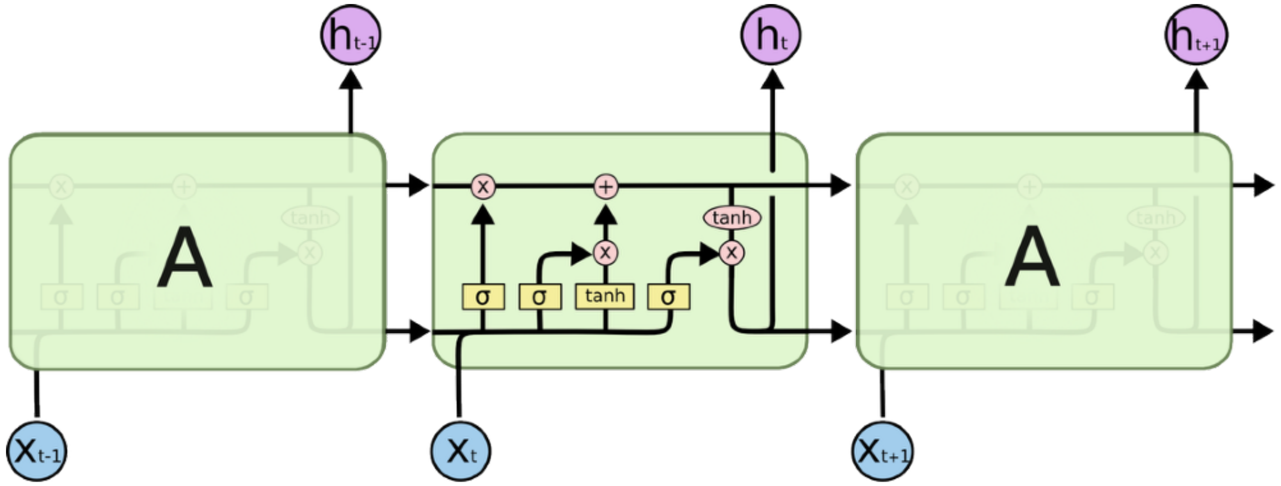

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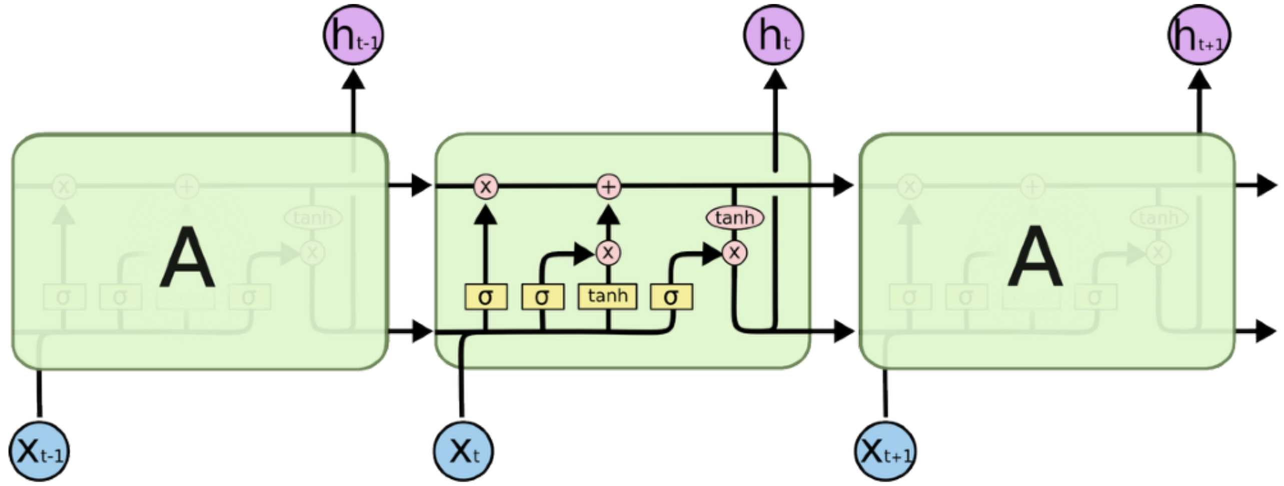

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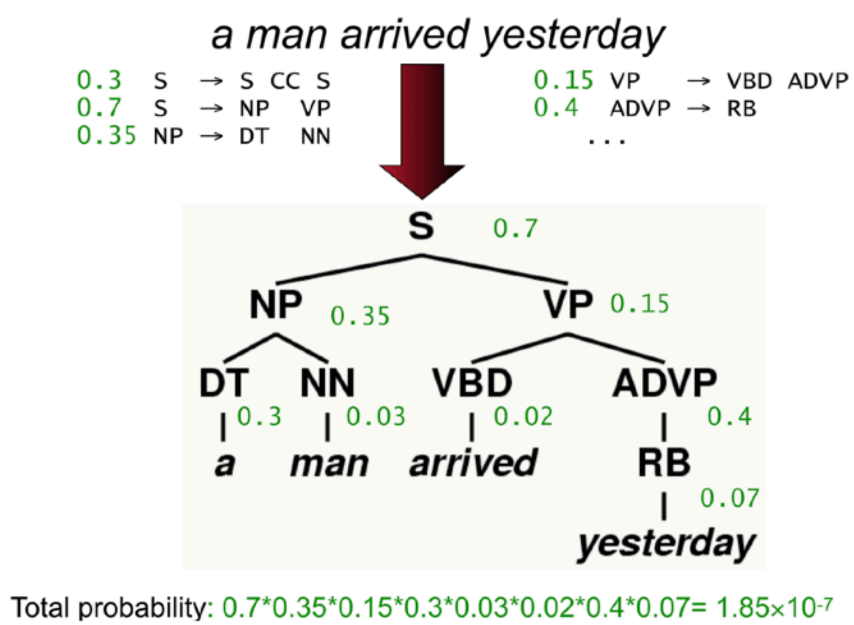

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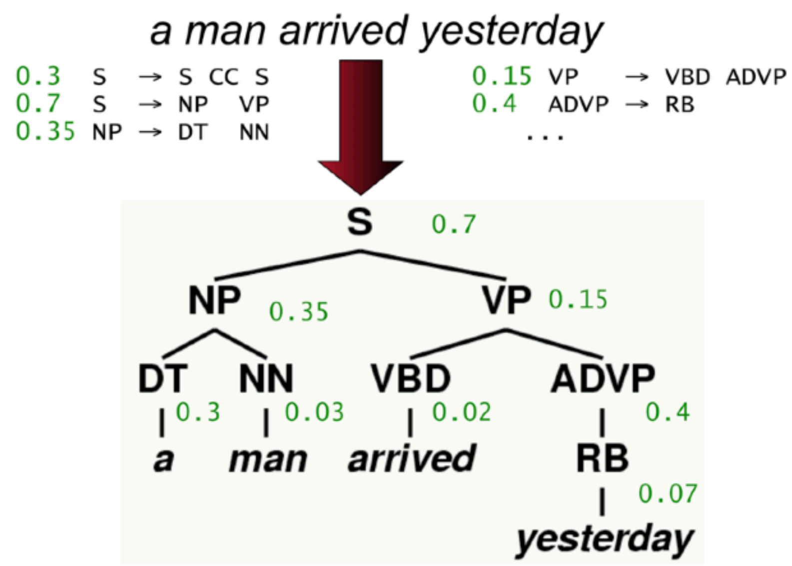

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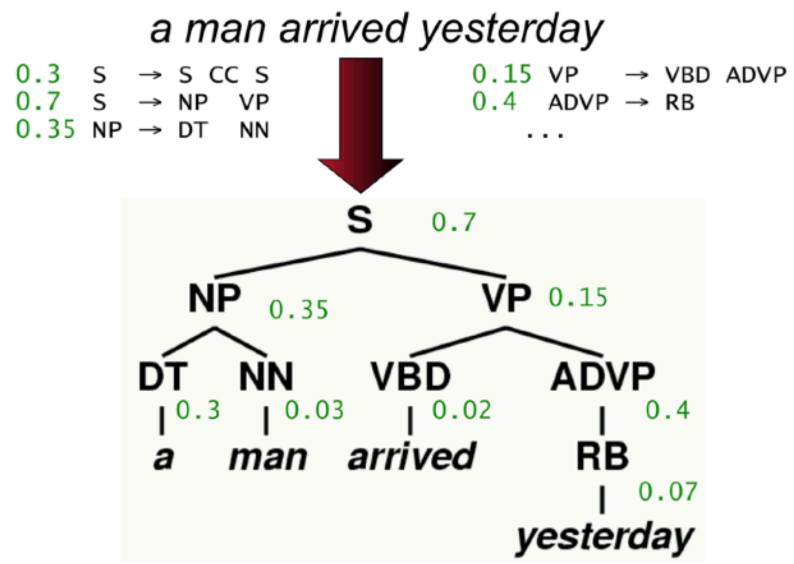

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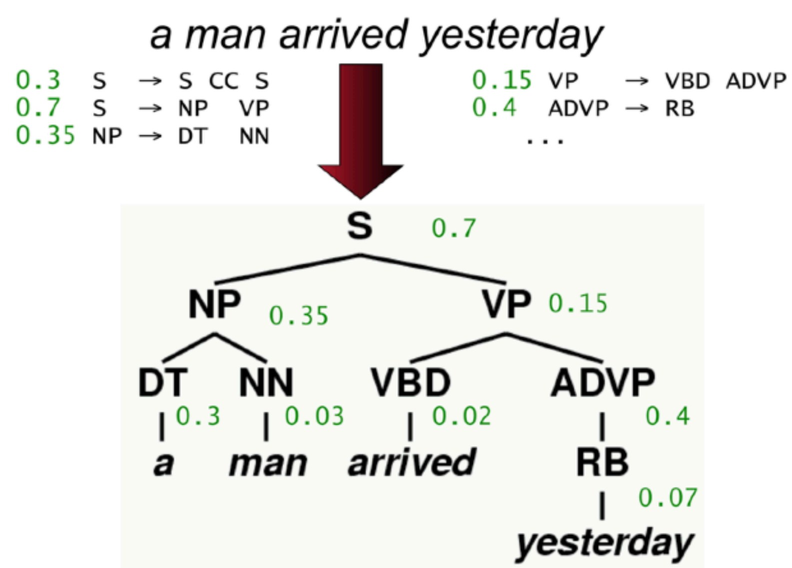

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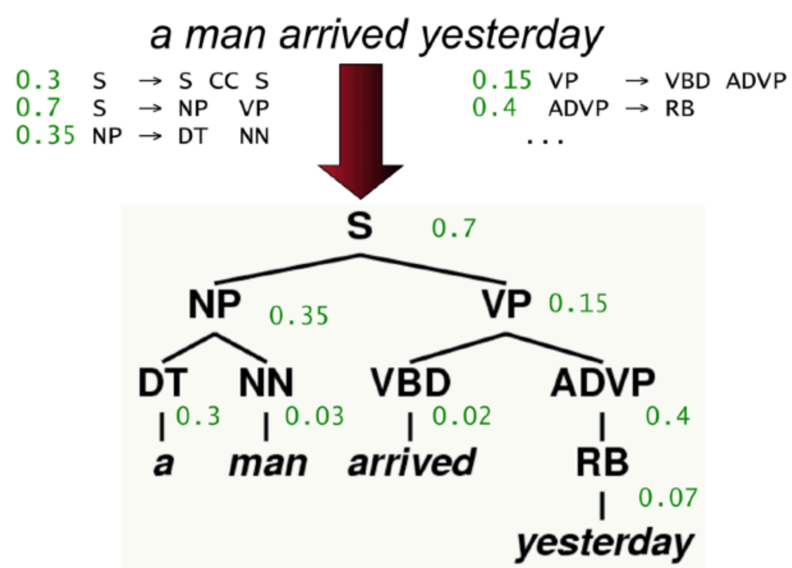

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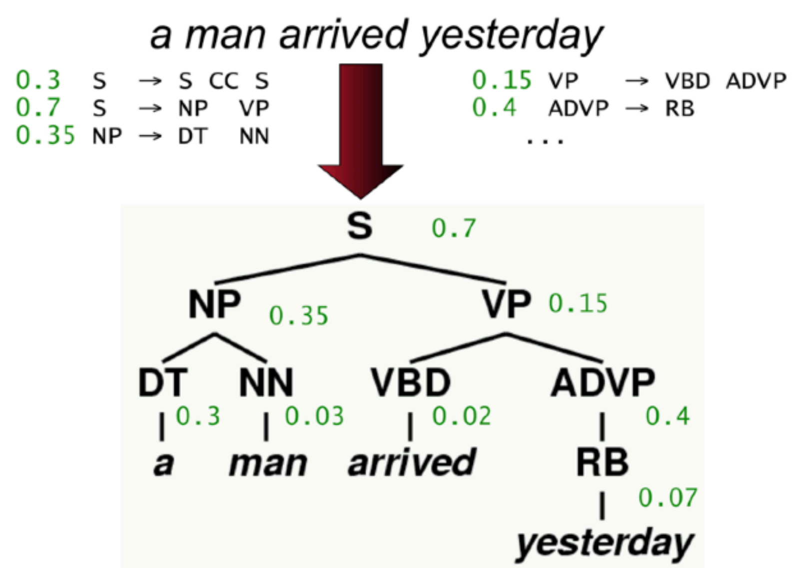

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Explainable models, explainable AI

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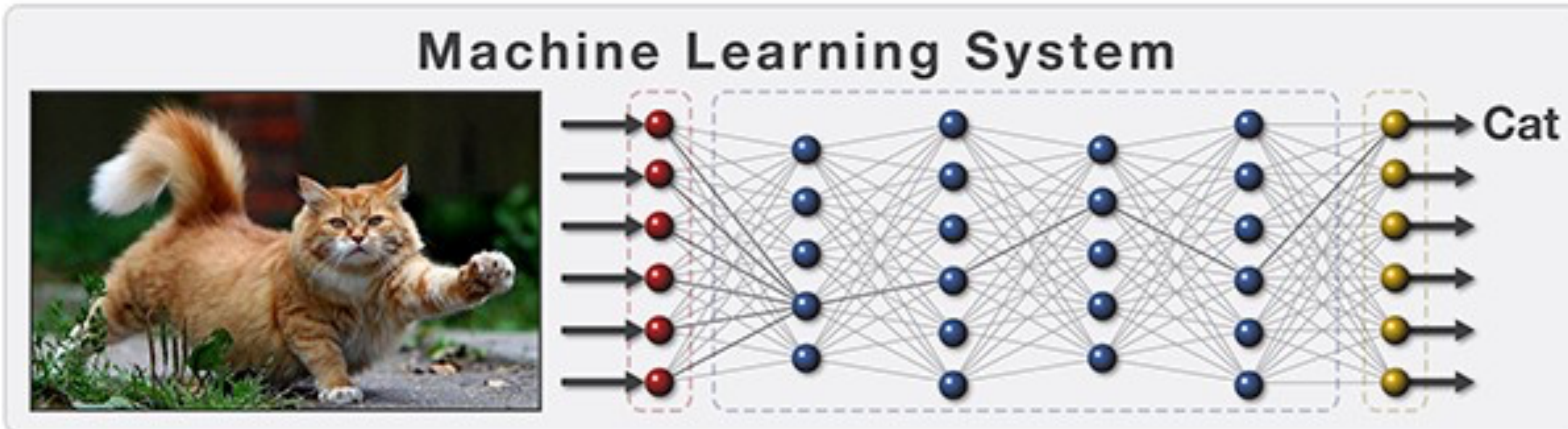
- An ideal “explainable” state-of-the-art AI system:



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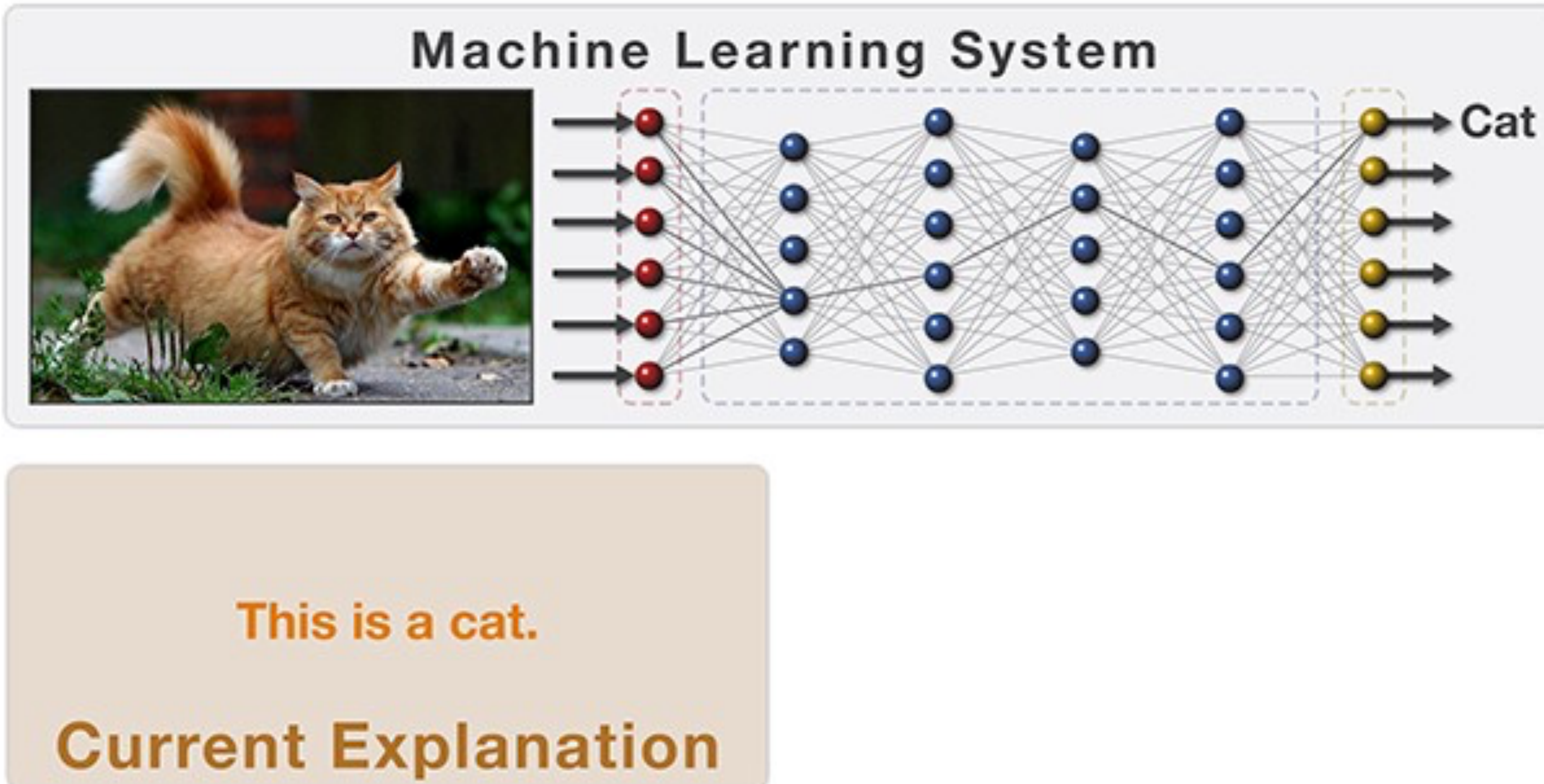

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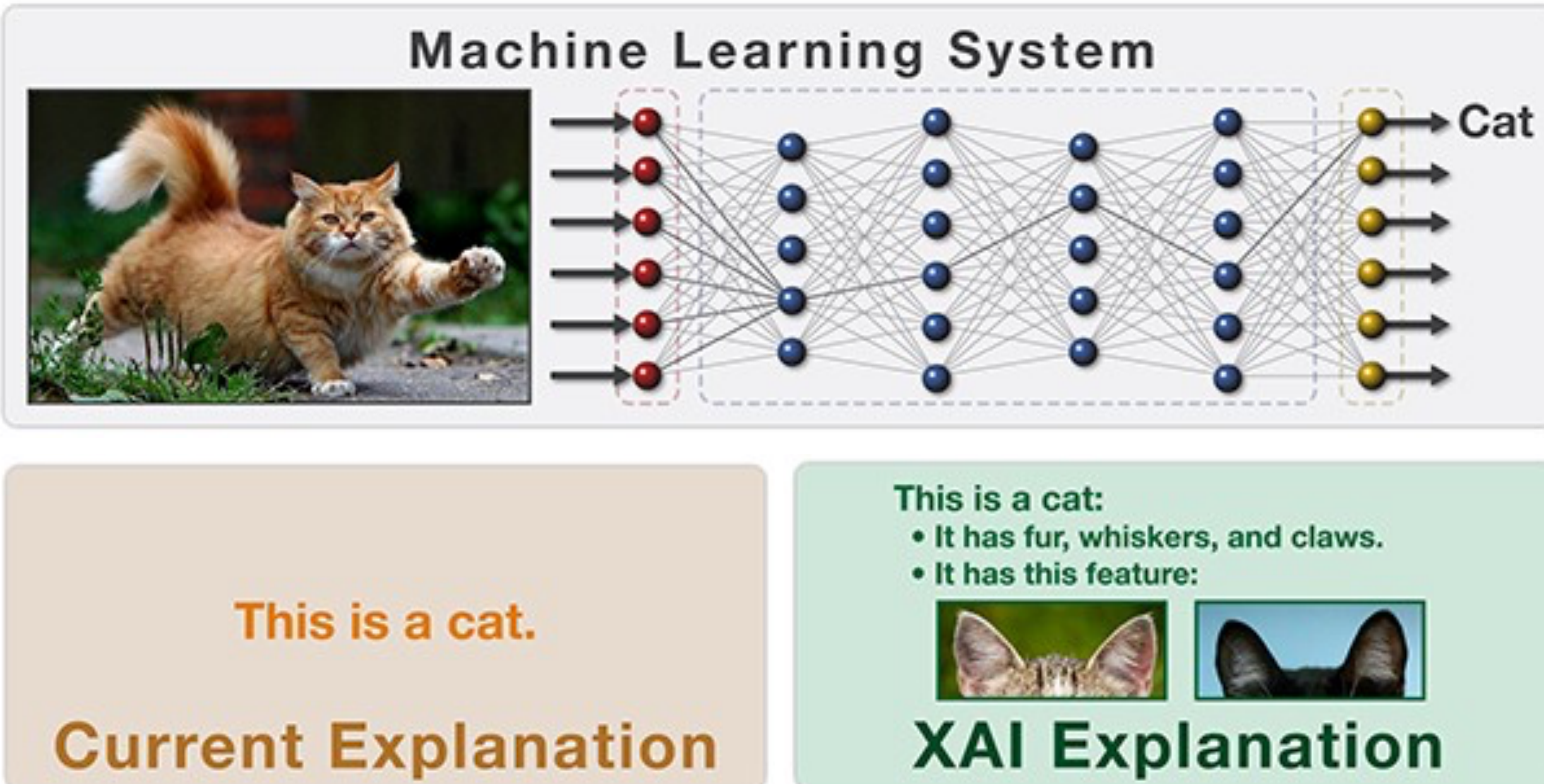

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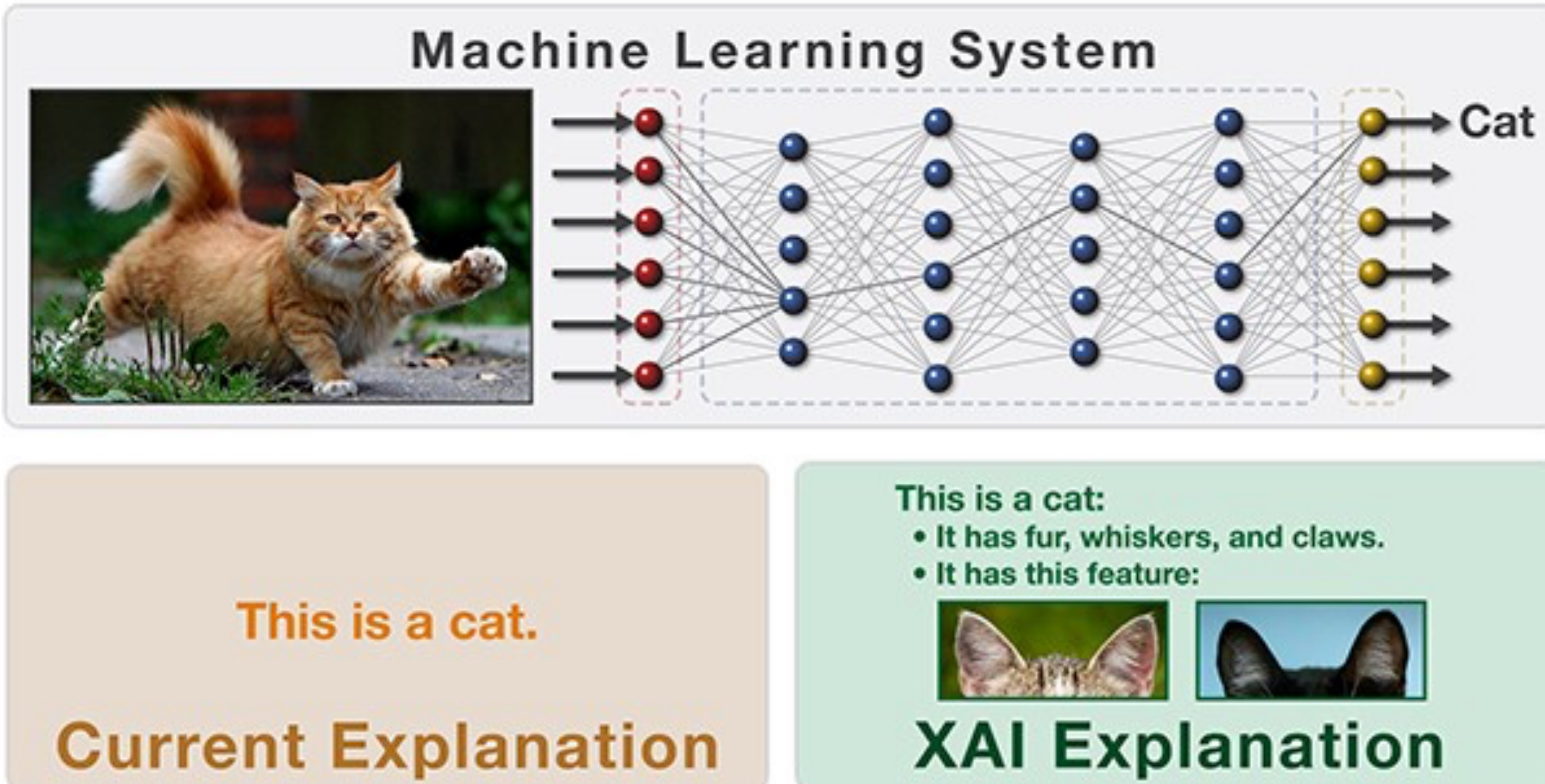

- State-of-the-art AI systems are increasingly ***opaque***, presenting challenges for explainability

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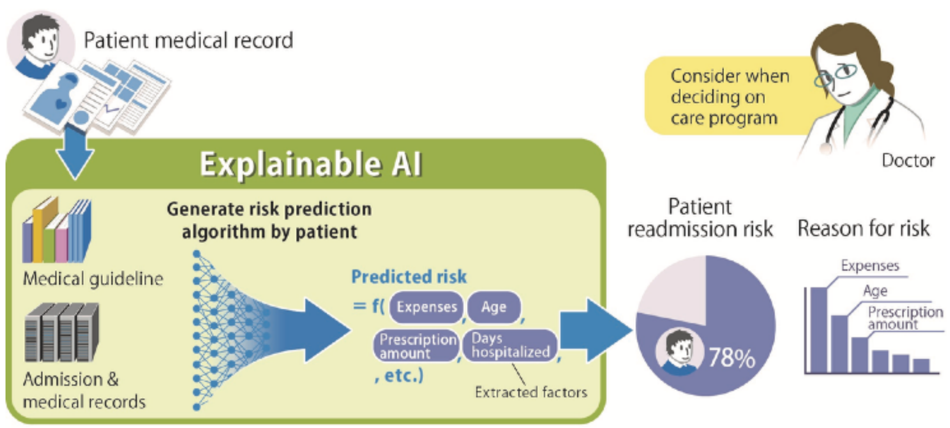
Medical decision-making



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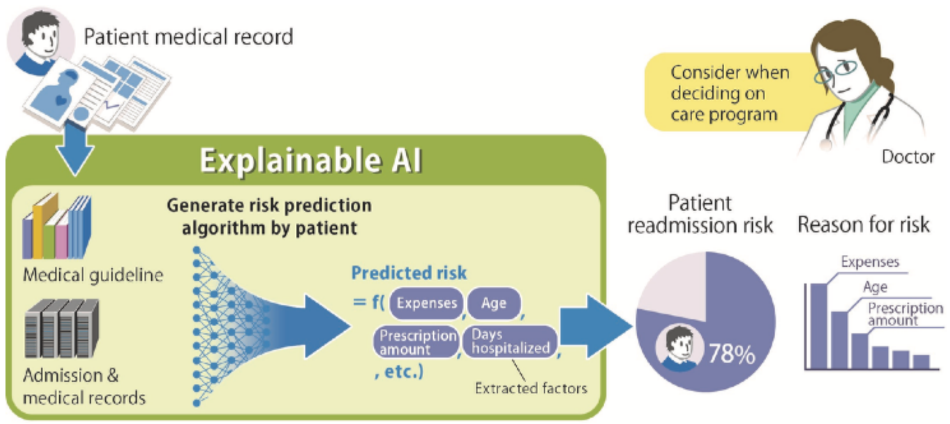

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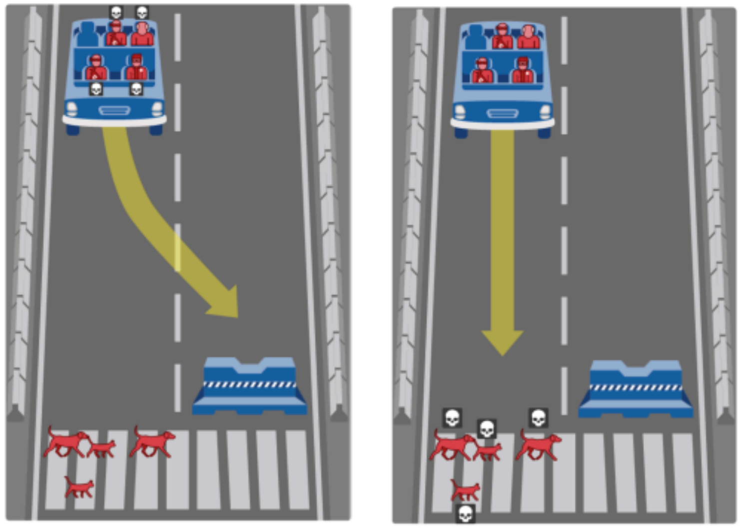
Self-driving cars



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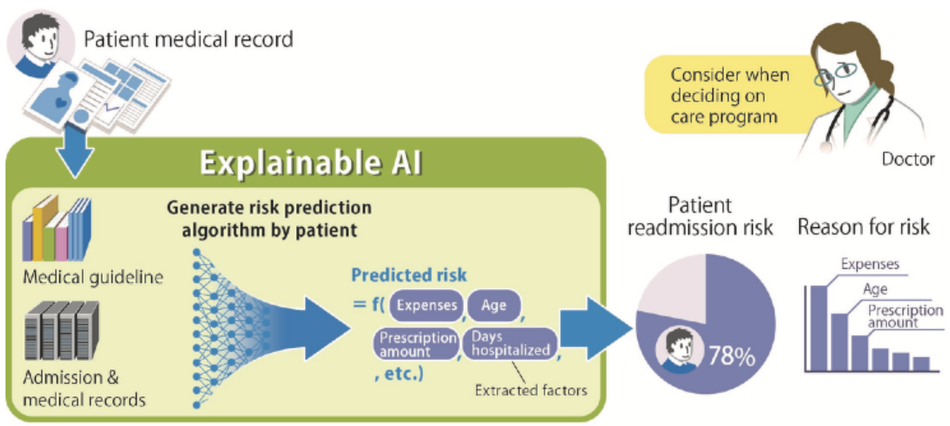

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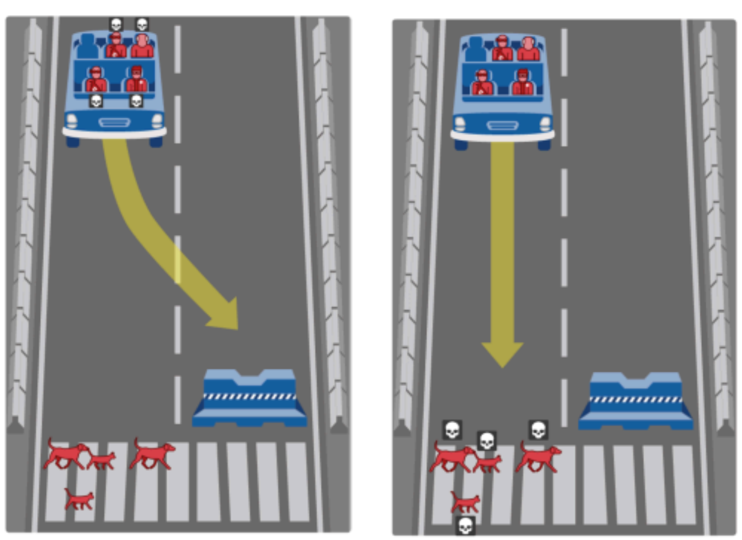

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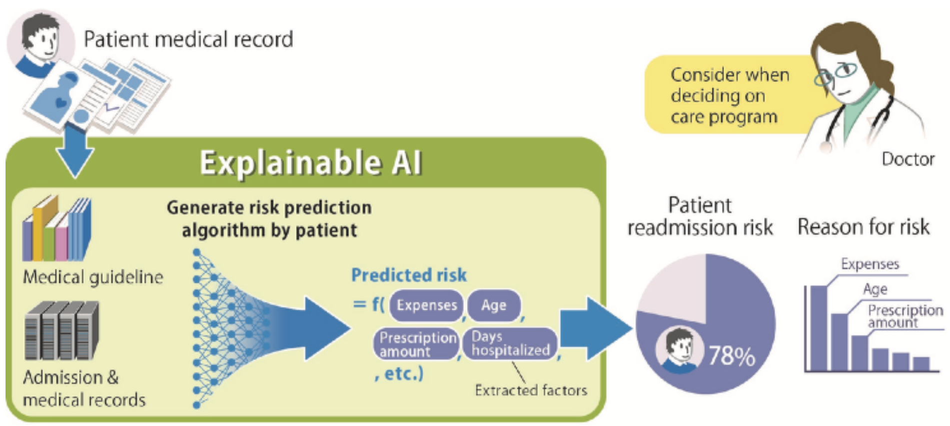

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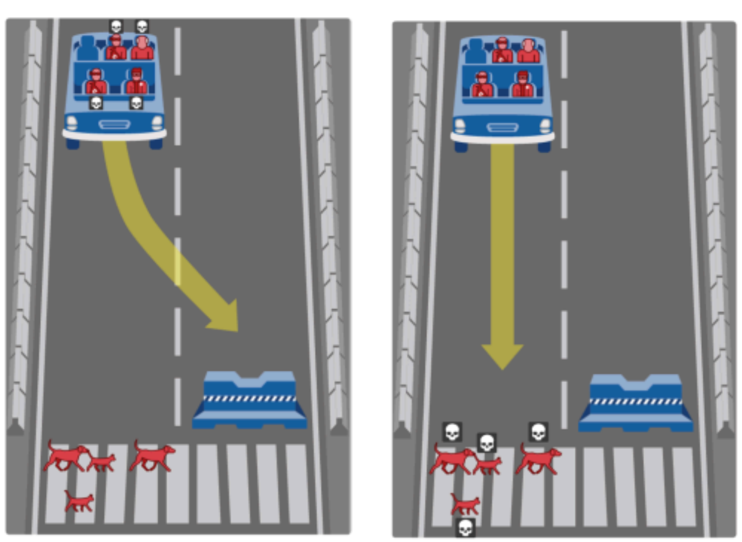

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…and more!

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Explaining is fundamentally human

“Knocking over a tower is the best part of building it!”

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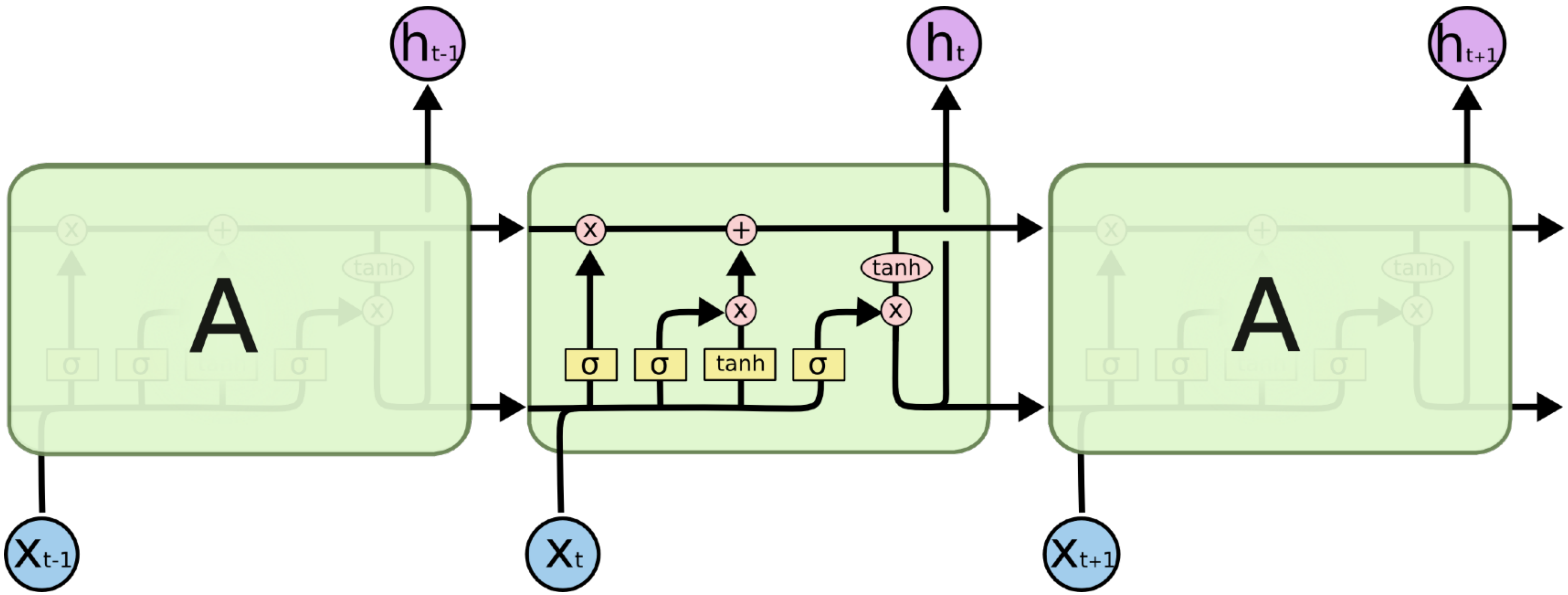
“Knocking over a tower is the best part of building it!”

“The tower was in the way of the TV set”

“I was jealous of my brother”

Understanding & explaining NLM behavior



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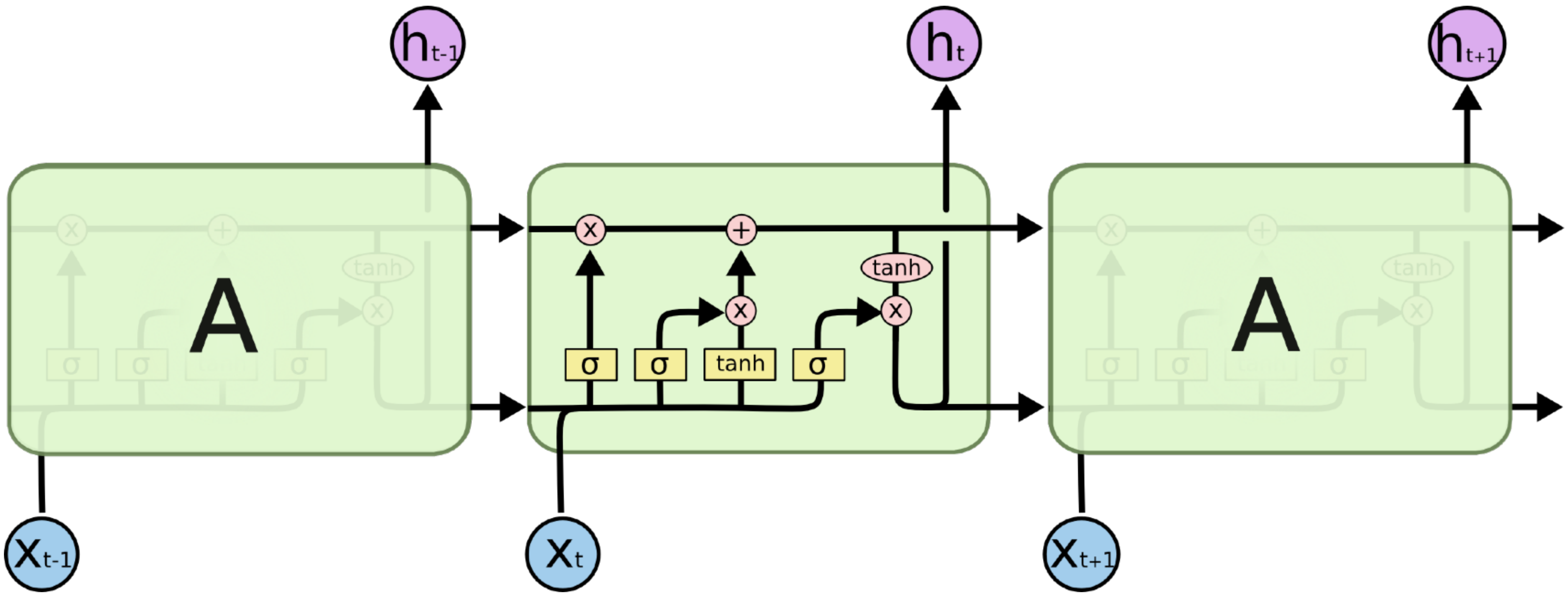

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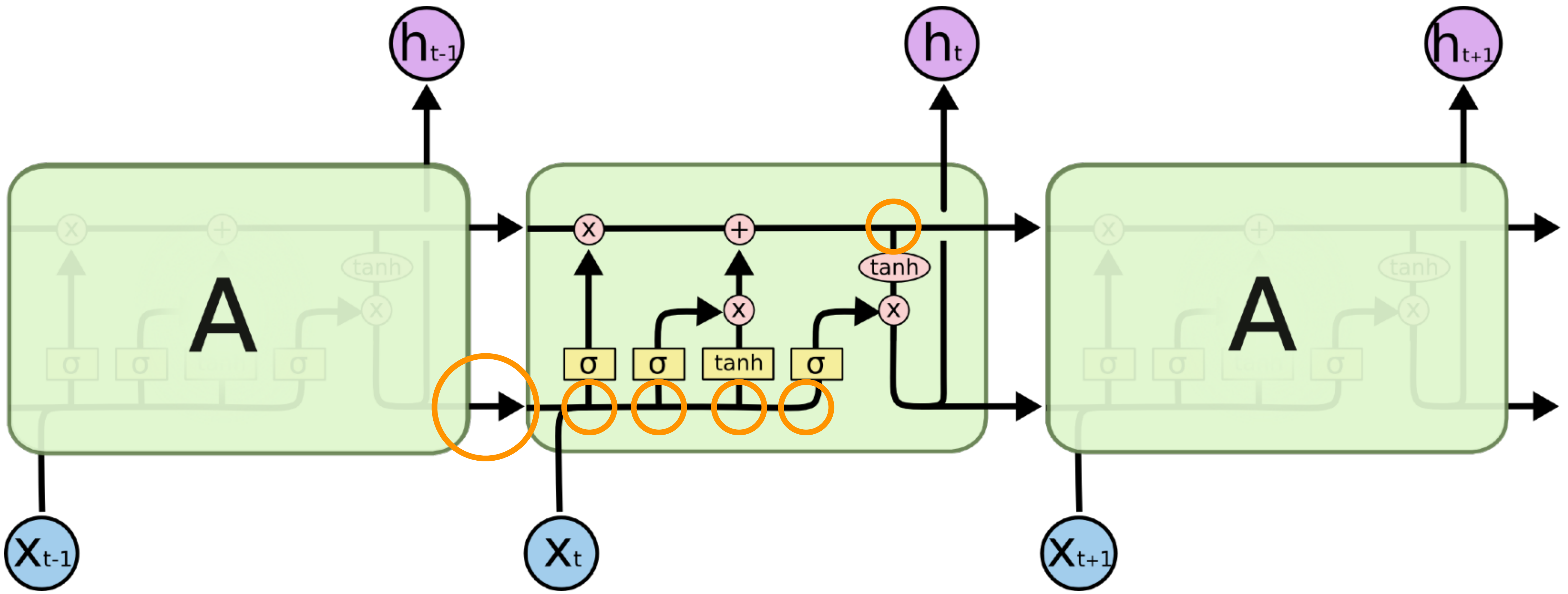

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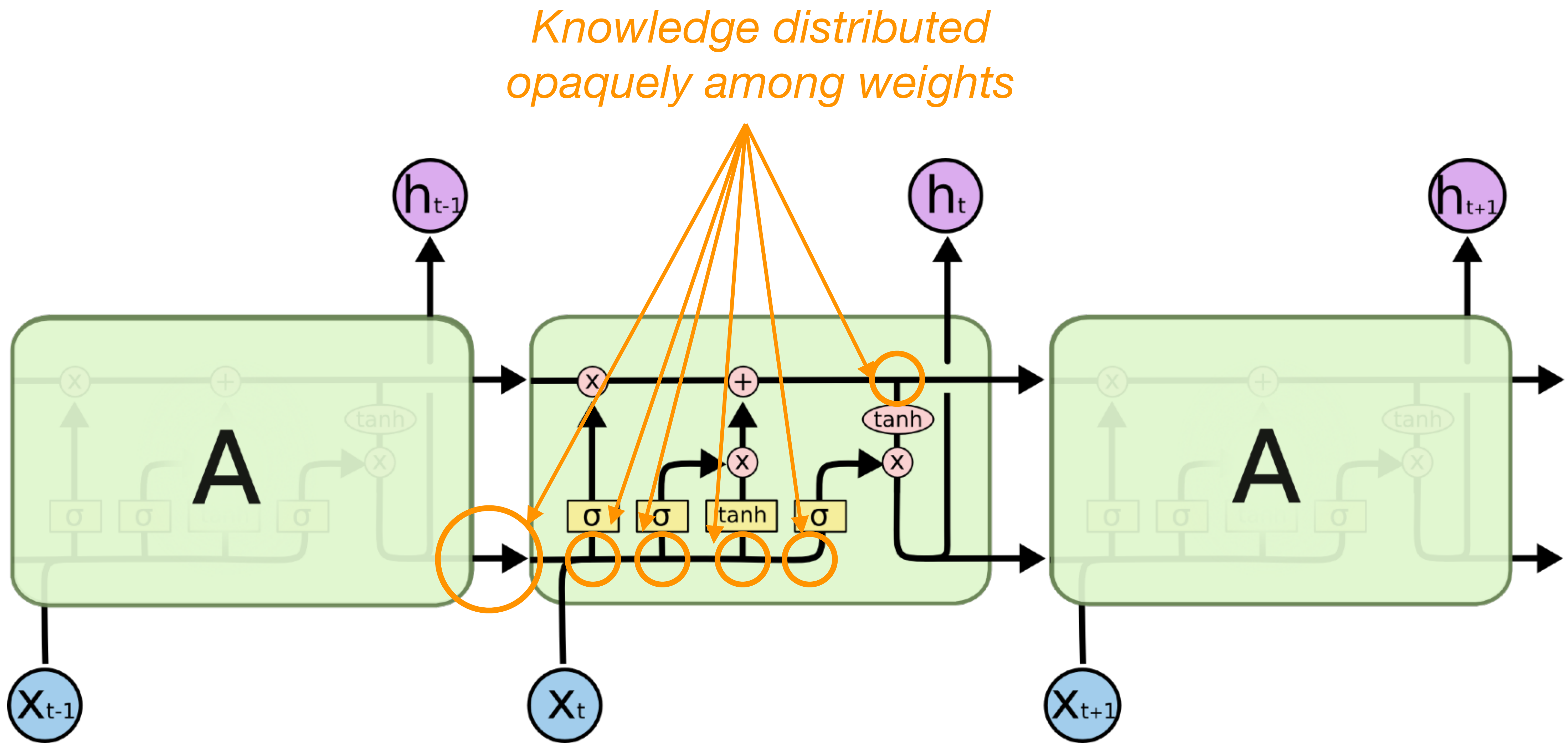

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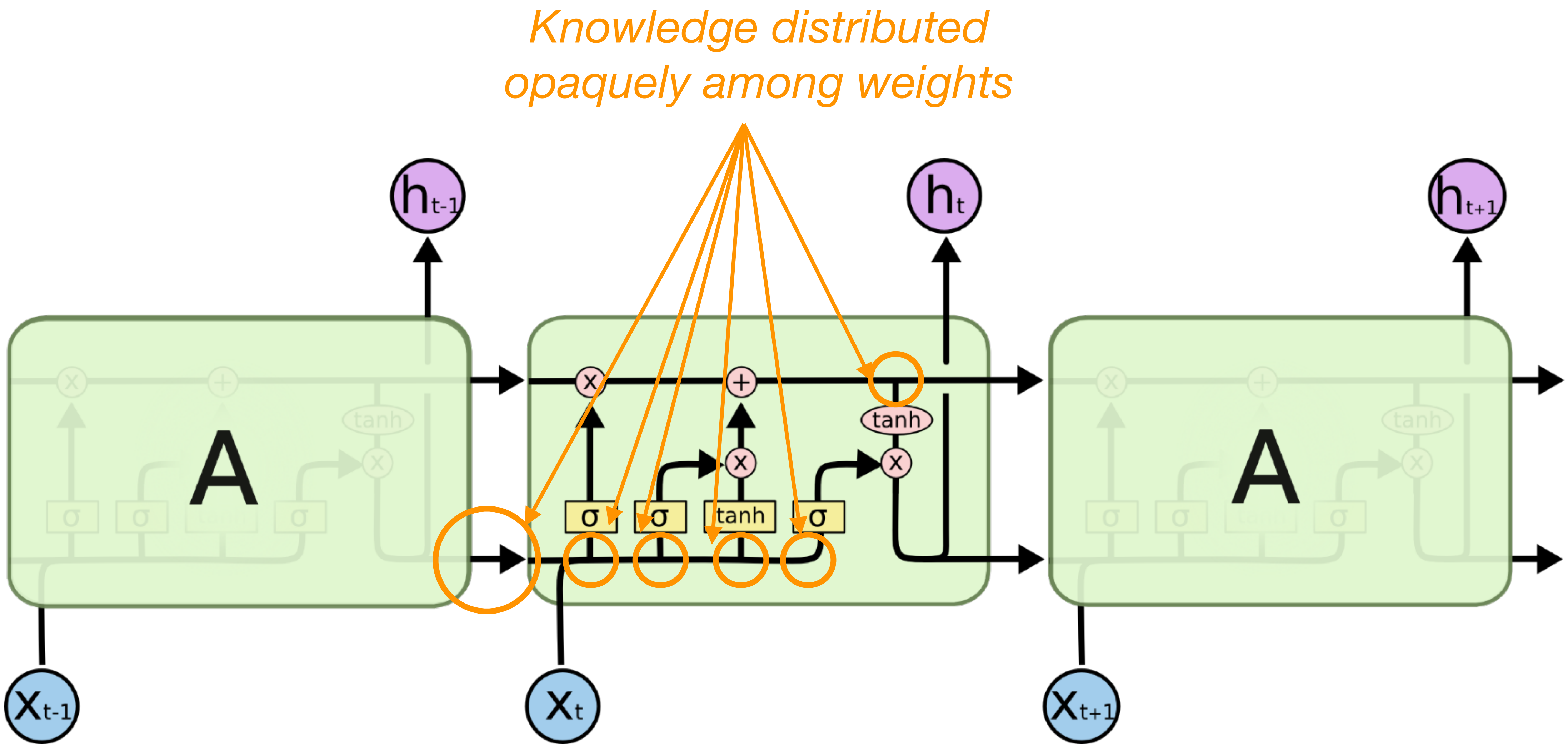

- How can we make such a system explainable?

visualization due to Christopher Olah, http://colah.github.io/posts/2015-08-Understanding-LSTMs/

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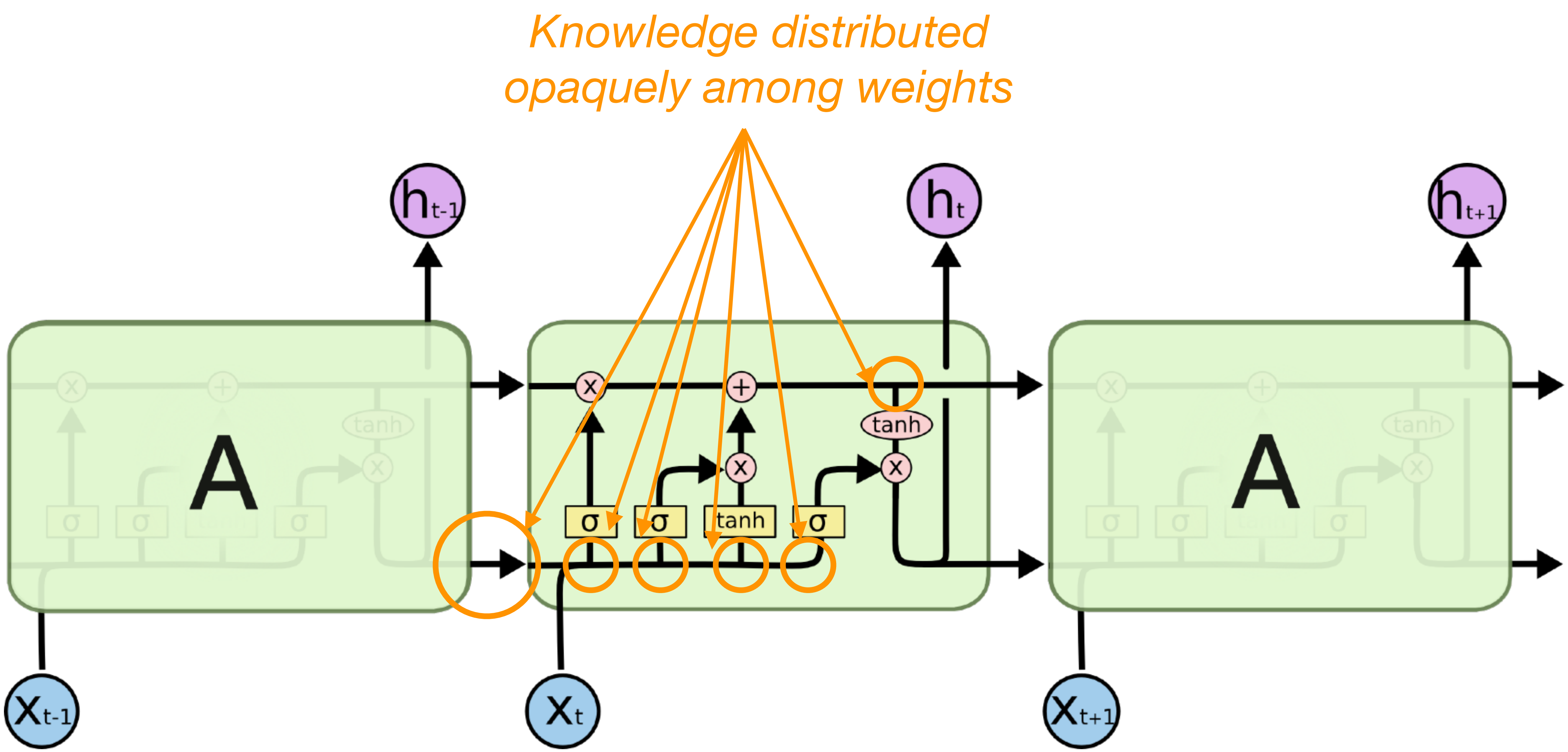

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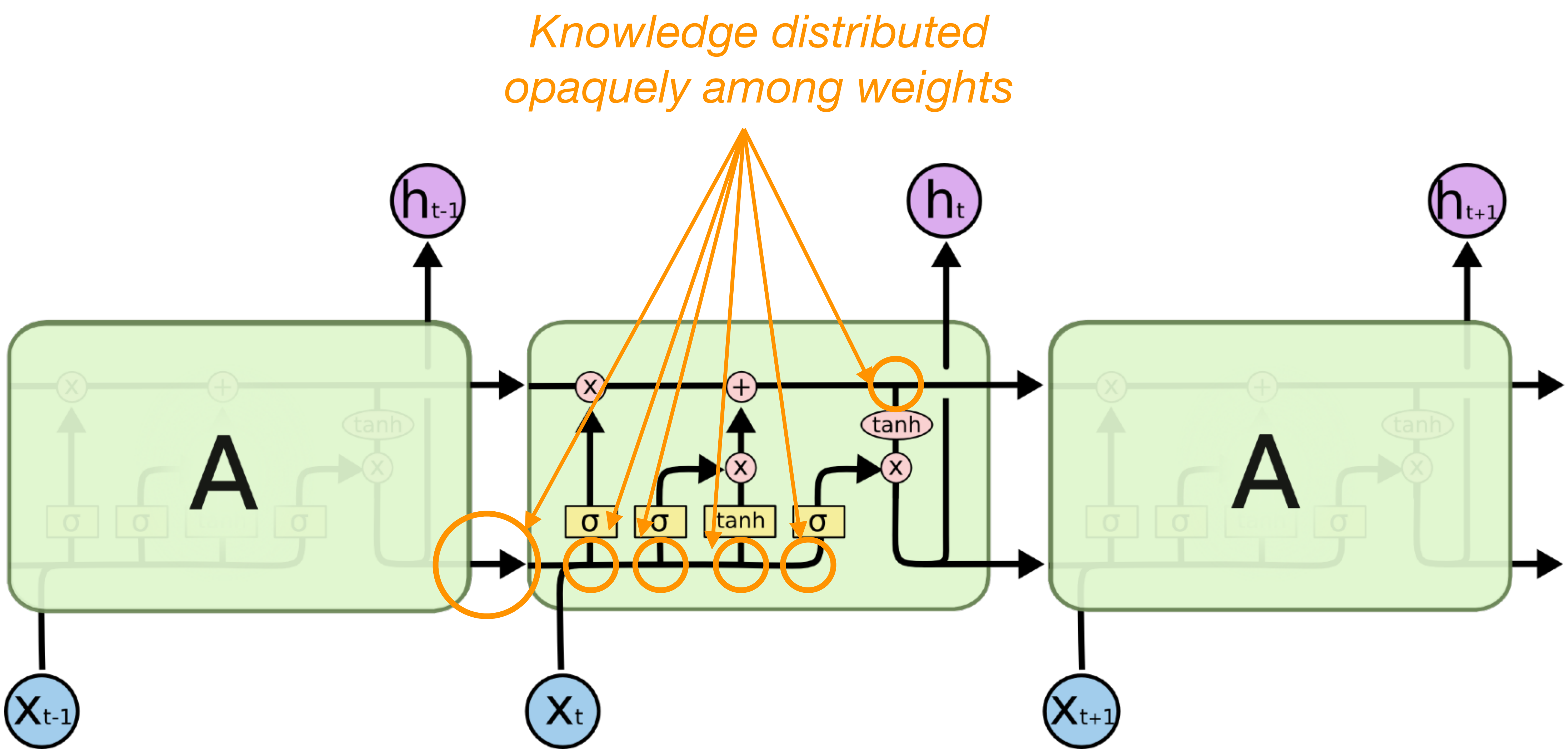
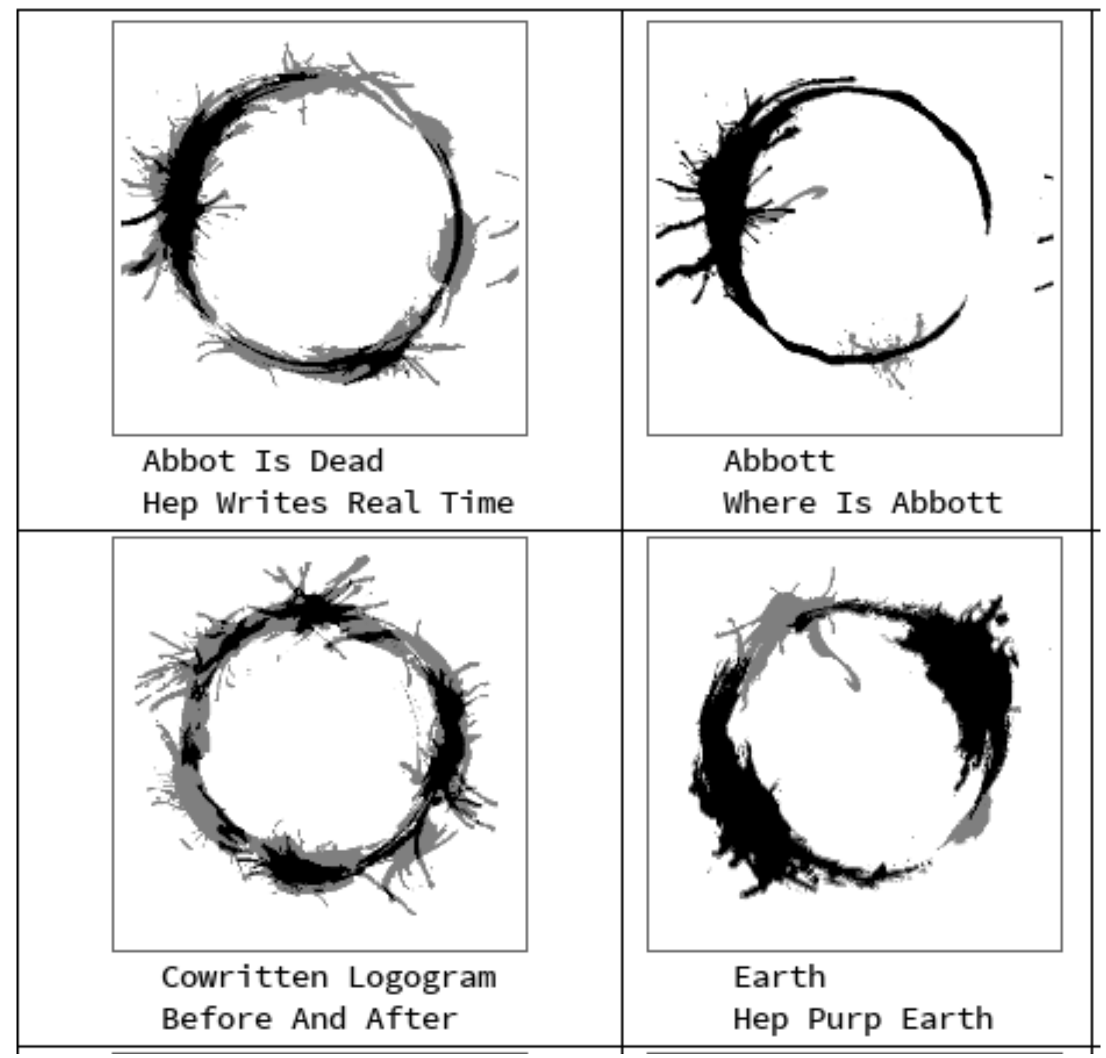


- How can we make such a system explainable?
  - Controlled tests of a model's capabilities & behaviors
  - Probing the circuitry underlying these behaviors

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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Assessing the Ability of LSTMs to Learn Syntax-Sensitive Dependencies

Tal Linzen[1,2] **Emmanuel Dupoux**[1]
LSCP[1] & IJN[2], CNRS,
EHESS and ENS, PSL Research University
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emmanuel.dupoux}@ens.fr

Yoav Goldberg
Computer Science Department
Bar Ilan University
yoav.goldberg@gmail.com

Linzen et al., 2016, TACL

Neural Language Models as Psycholinguistic Subjects: Representations of Syntactic State

Richard Futrell[1], **Ethan Wilcox**[2], **Takashi Morita**[3,4], **Peng Qian**[5], **Miguel Ballesteros**[6], and **Roger Levy**[5]

[1]Department of Language Science, UC Irvine, rfutrell@uci.edu
[2]Department of Linguistics, Harvard University, wilcoxeg@g.harvard.edu
[3]Primate Research Institute, Kyoto University, tmorita@alum.mit.edu
[4]Department of Linguistics and Philosophy, MIT
[5]Department of Brain and Cognitive Sciences, MIT, rplevy@mit.edu
[6]IBM Research, MIT-IBM Watson AI Lab, miguel.ballesteros@ibm.com

Futrell et al., 2019, NAACL

Colorless green recurrent networks dream hierarchically

Kristina Gulordava*
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Gulordava et al., 2018, NAACL

What do RNN Language Models Learn about Filler–Gap Dependencies?

Ethan Wilcox[1], **Roger Levy**[2], **Takashi Morita**[3,4], and **Richard Futrell**[5]

[1]Department of Linguistics, Harvard University, wilcoxeg@g.harvard.edu
[2]Department of Brain and Cognitive Sciences, MIT, rplevy@mit.edu
[3]Primate Research Institute, Kyoto University, tmorita@alum.mit.edu
[4]Department of Linguistics and Philosophy, MIT
[5]Department of Language Science, UC Irvine, rfutrell@uci.edu

Wilcox et al., 2018, BlackBox NLP

Subject–verb agreement

The author laughs.	*The authors laughs.
*The author laugh.	The authors laugh.

Subject–verb agreement

`The author laughs.`	`*The authors laughs.`
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Postmodification by prepositional phrase:

` The `**`author`**` of the novels `**`laughs`**`.`

`*The `**`author`**` of the novels `**`laugh`**`.`

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```
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Readers know that the **author** who wrote the novels, regardless of what people may think, **laughs** in unusual circumstances.

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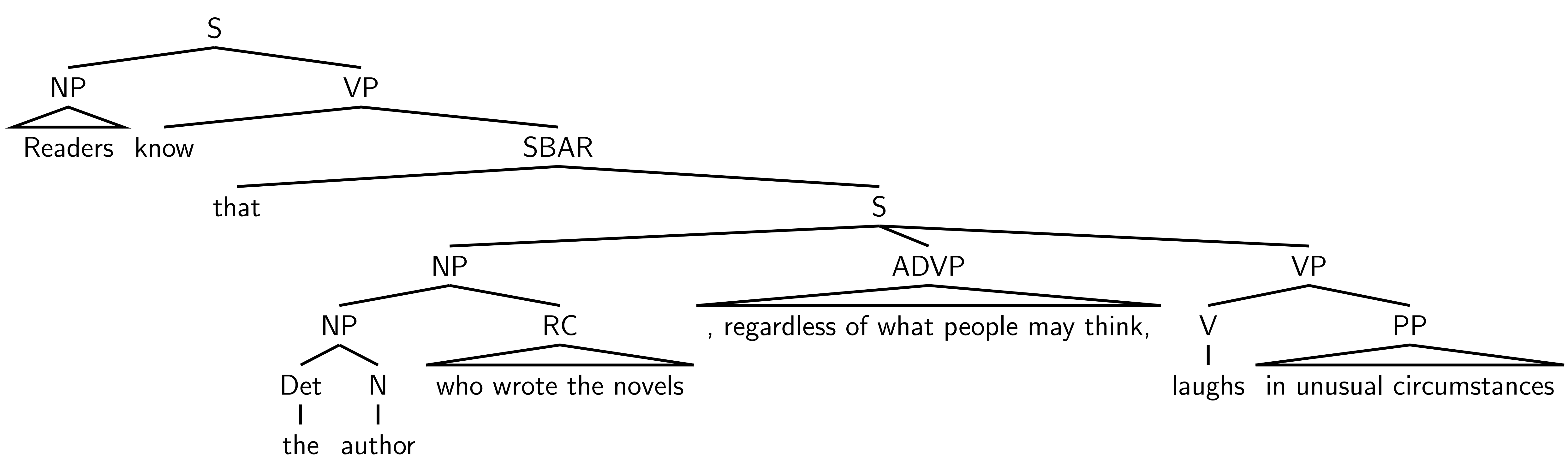

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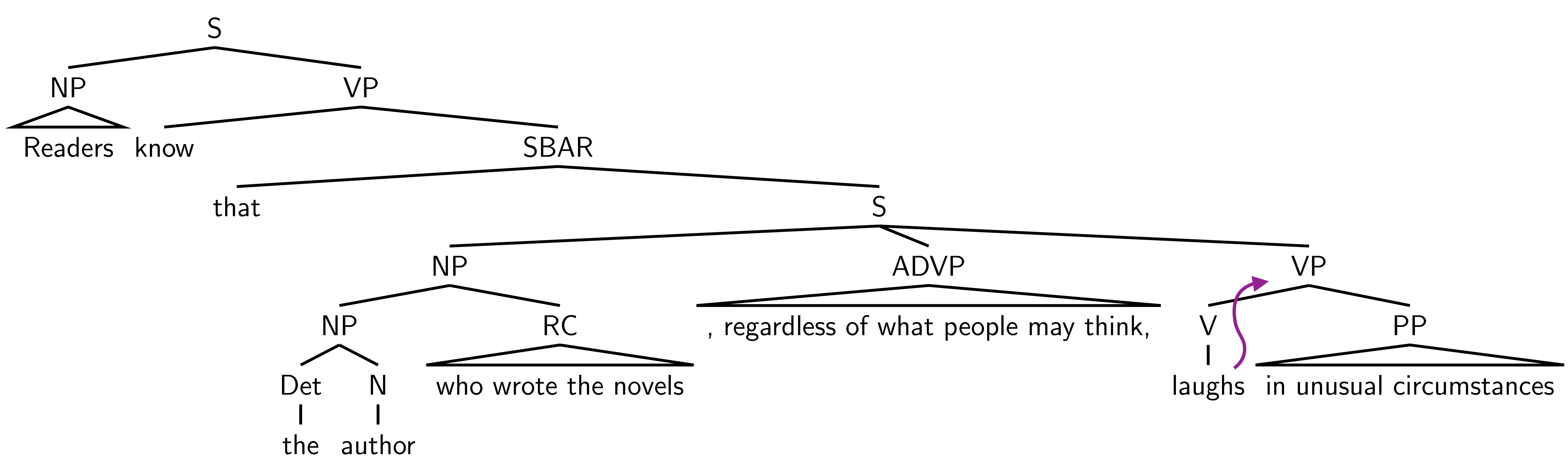

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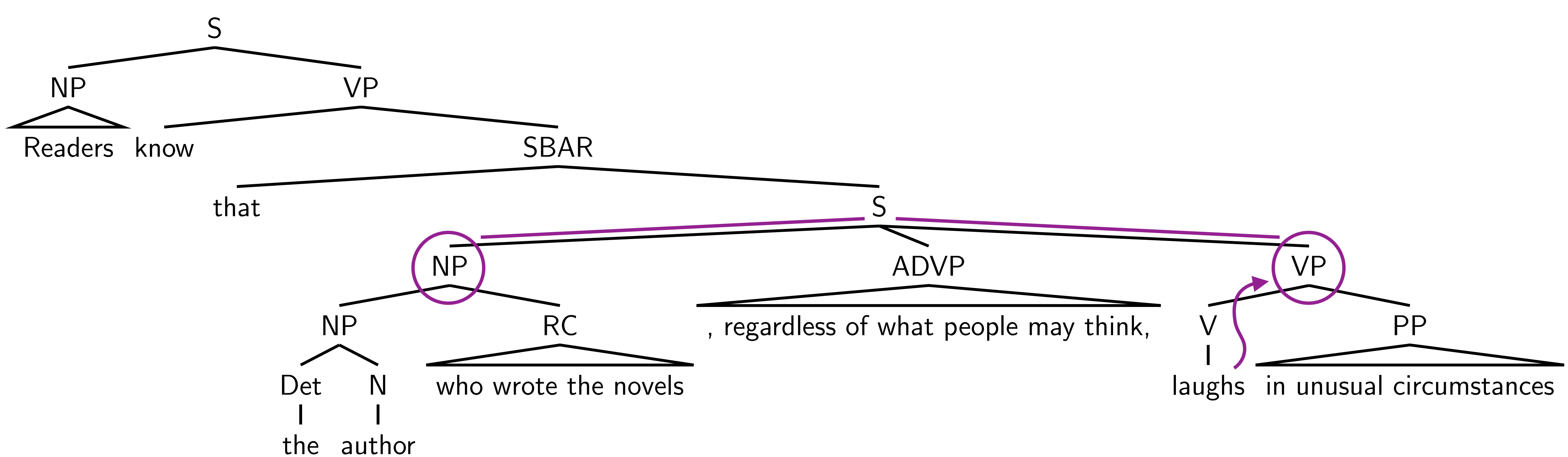

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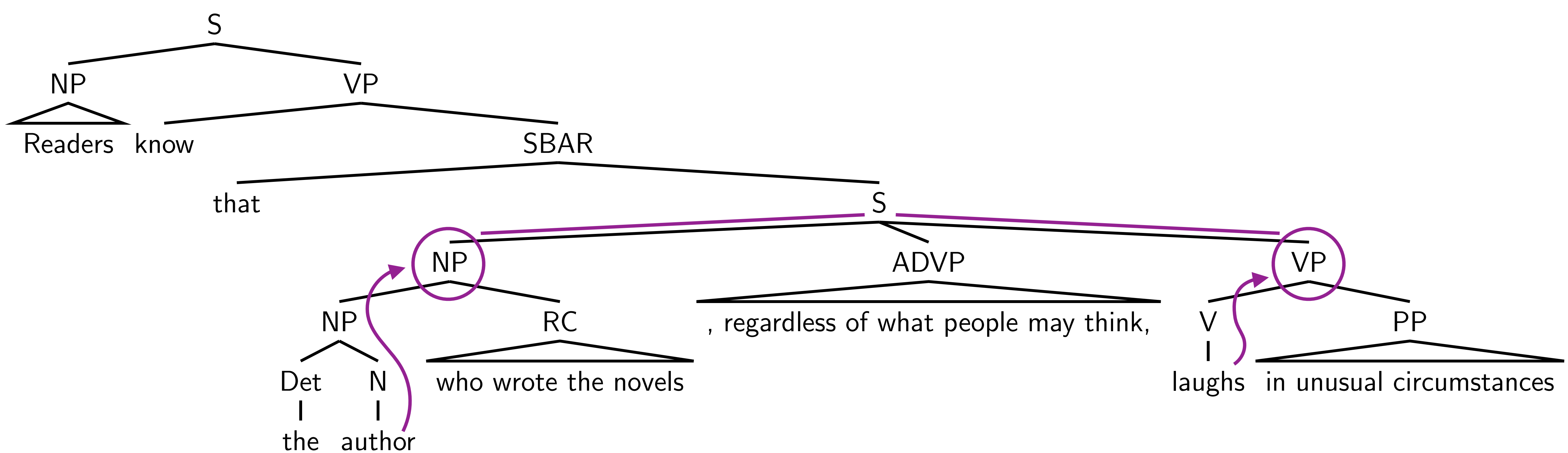

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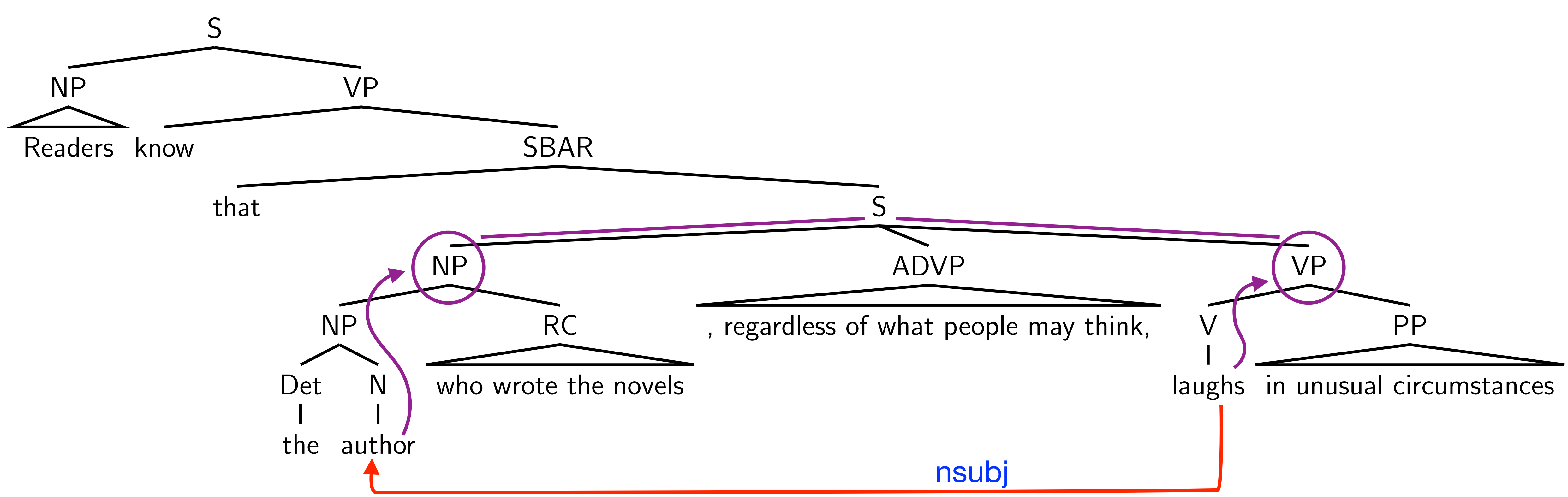

Testing NLMs on subject–verb agreement

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 The key to the cabinets is on the table.
*The key to the cabinets are on the table.
```

(*Linzen et al., 2016*)

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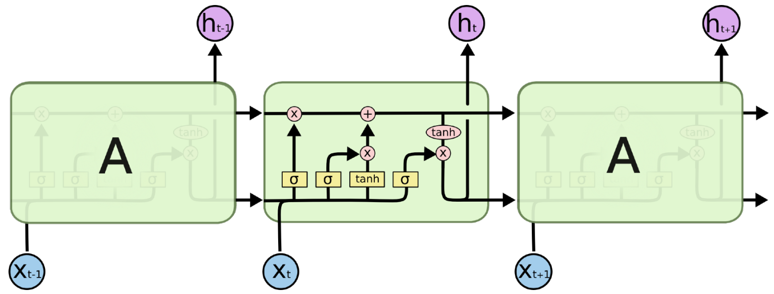


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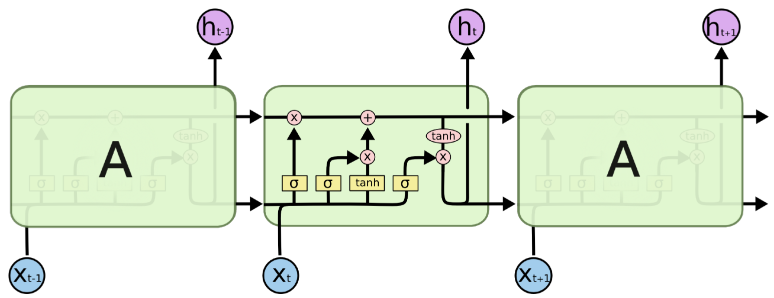


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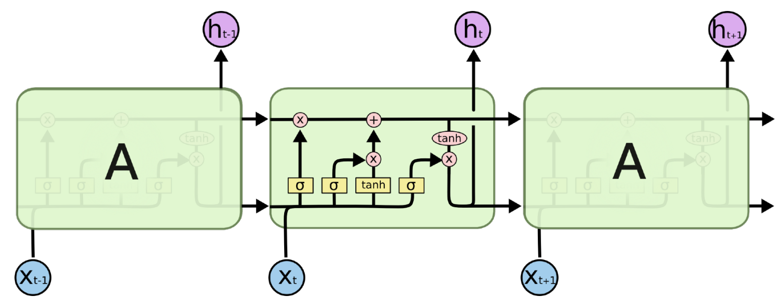


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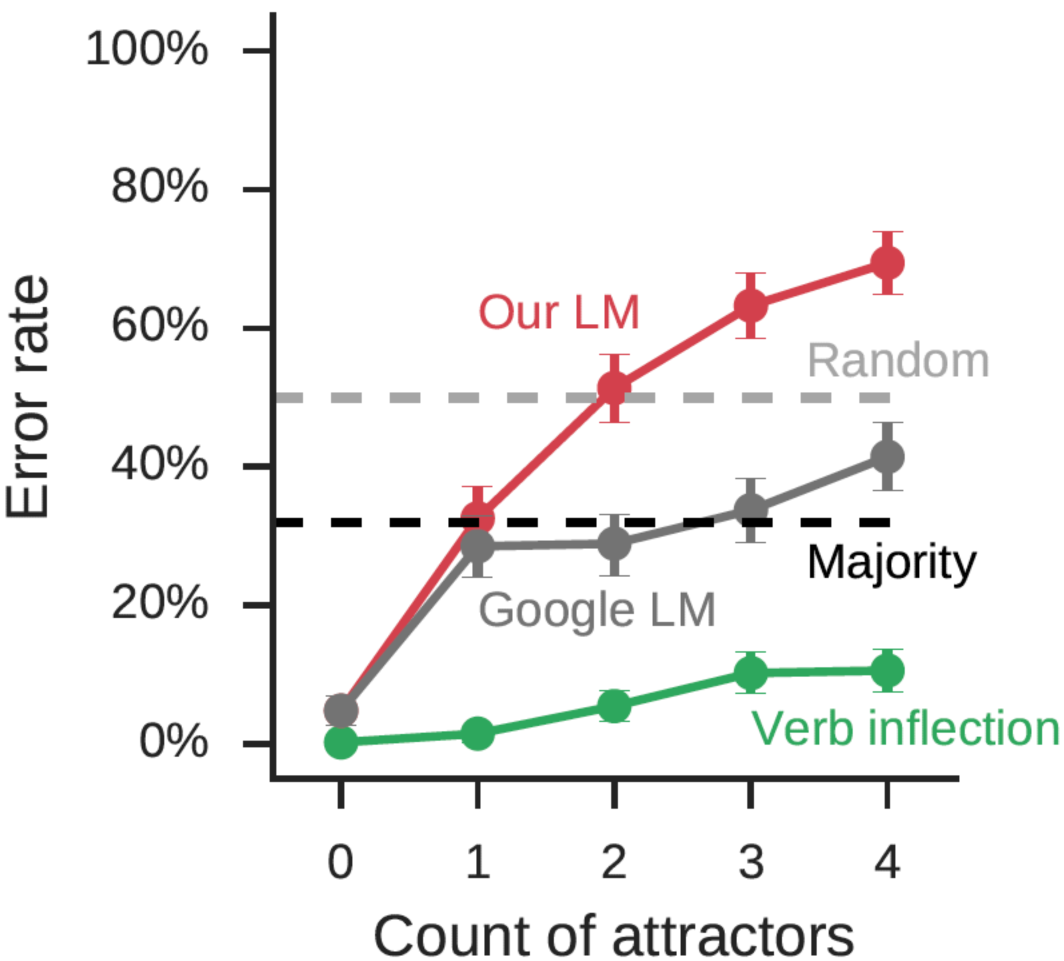

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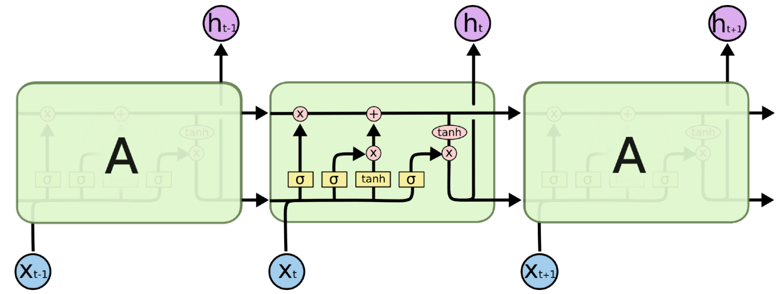


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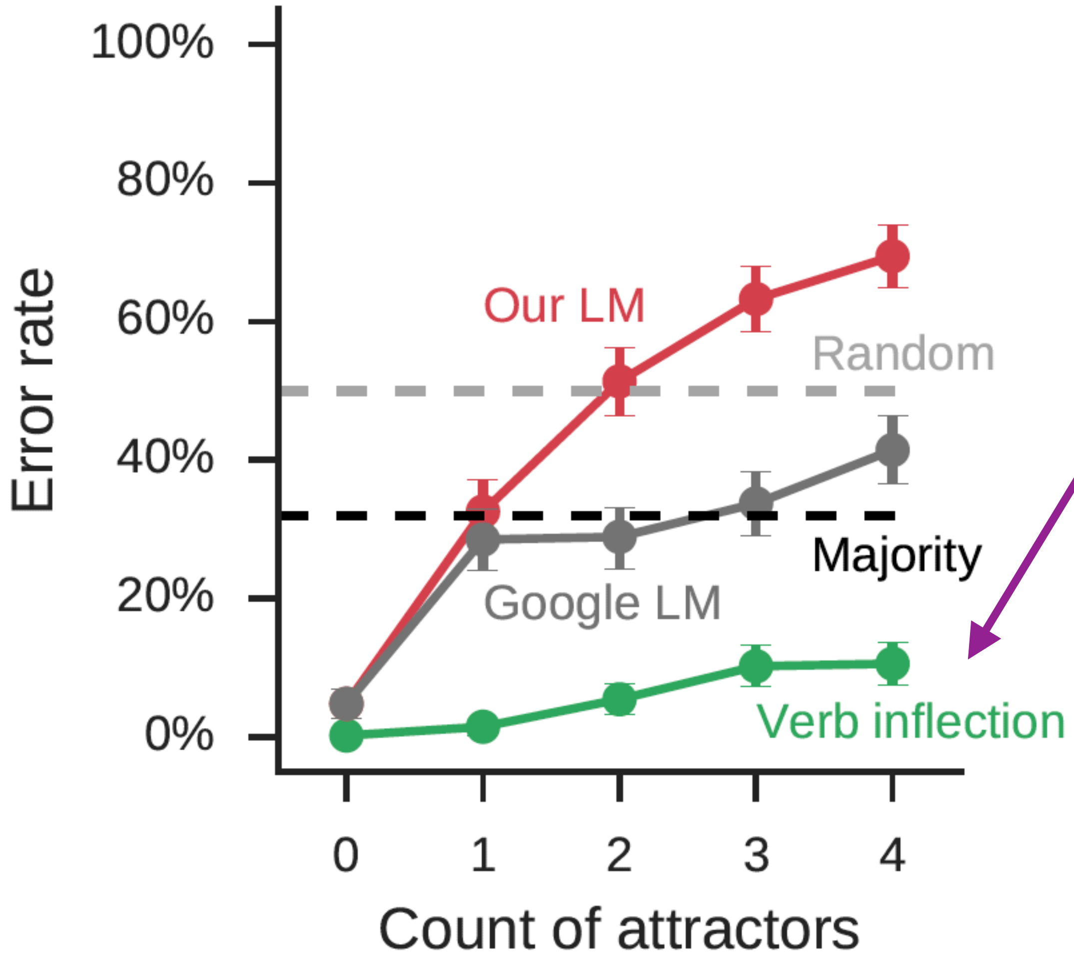

RNN models trained solely for the verb inflection task

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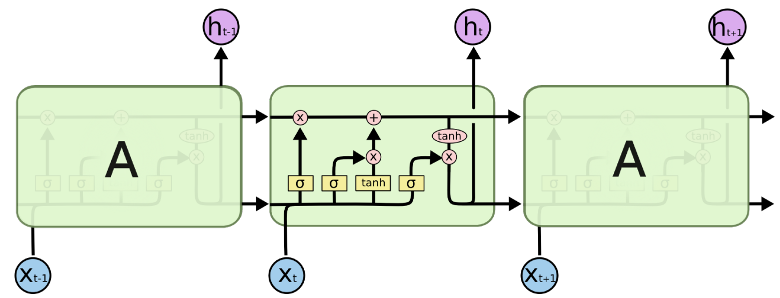


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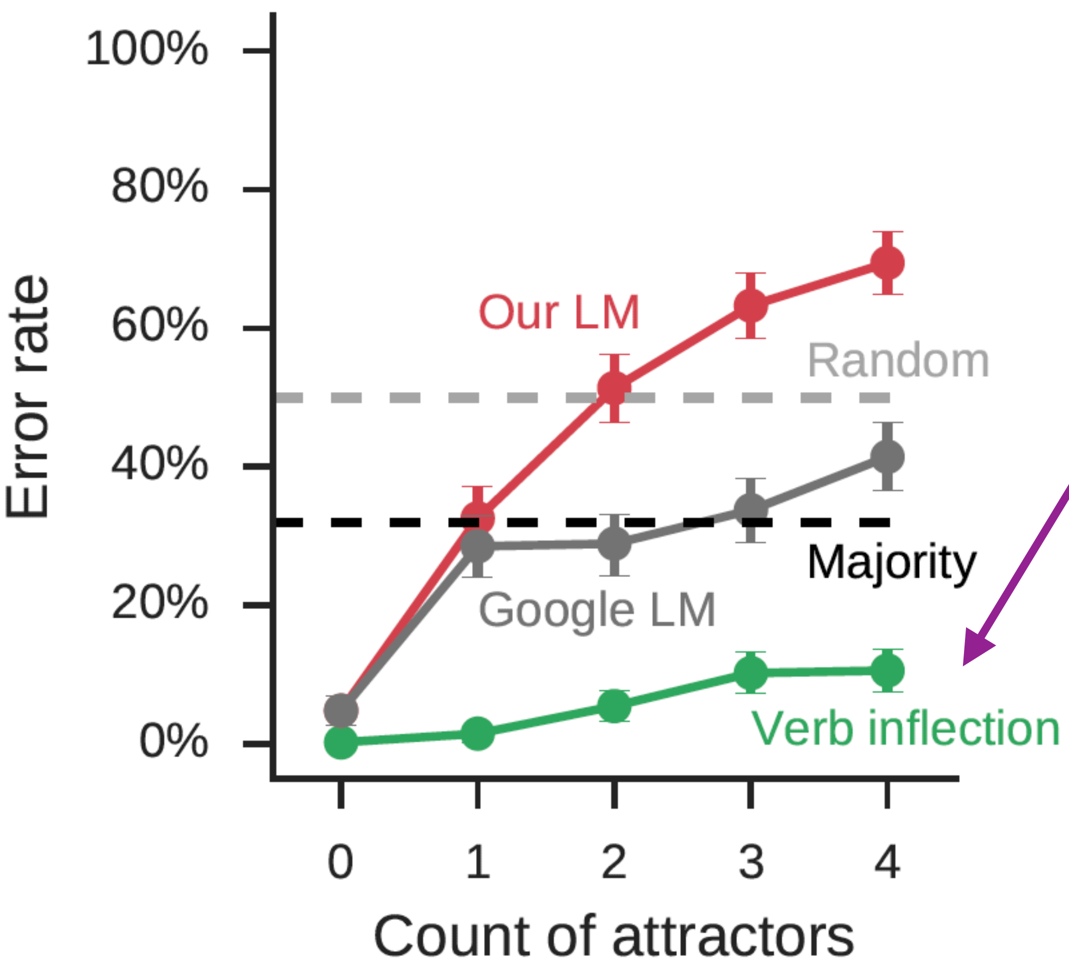

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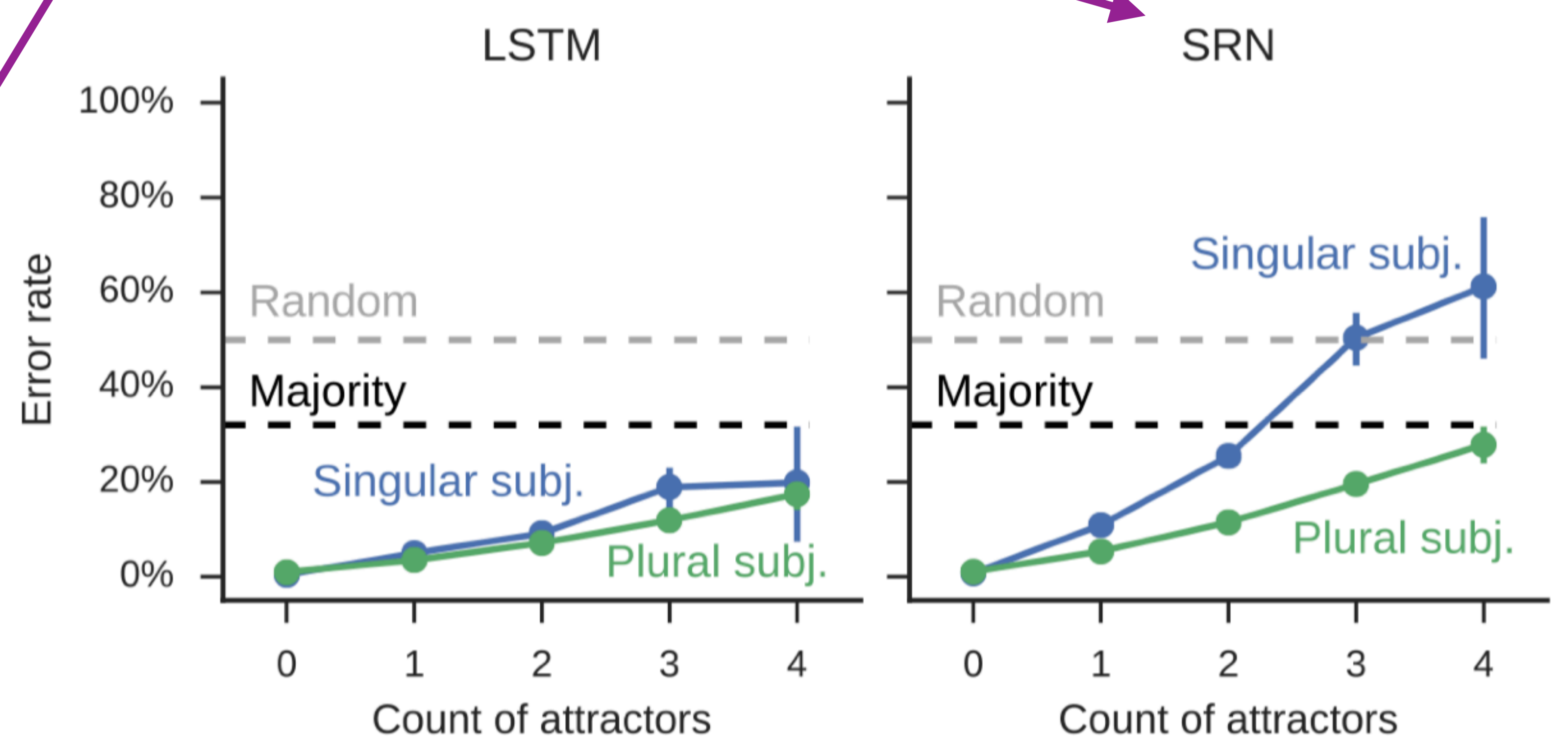

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Psycholinguistics of agreement production

- Subject–verb agreement is one of the most common "errorful" human language production behaviors in English

After Deadline

New York Times Blog

Ugly Disagreements

BY PHILIP B. CORBETT MARCH 8, 2016 8:00 AM 49

…

__The push__ by Mr. Xi's to assert state control over the markets and the economy __go__ against the philosophy of China's early reformers under Deng Xiaoping, the paramount leader who sought to give more space to the market.

As frequently happens, the phrase between the subject and verb threw us off. Most often, as here, a singular subject is followed by a plural noun, and we are misled into using a plural verb. Make it "the push … goes." (Also, there's no need for the possessive "Xi's.")

…

Her __criticism__ of "medieval" punishments in Saudi Arabia and of Israeli violence against Palestinians __have led__ to diplomatic breaches — and __have prompted__ Ms. Wallstrom to be compared to Mr. Palme.

And yet again! Despite the intervening phrases, the subject is "criticism," so make it "has led" and "has prompted."

Psycholinguistics of subject–verb agreement

- In human language production, agreement performance typically studied with a *preamble completion task:*

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The key to the cabinets...
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(Bock & Miller, 1991; Eberhard et al., 2005; Franck et al., 2002; Wagers et al., 2009; many others)

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Production error rates

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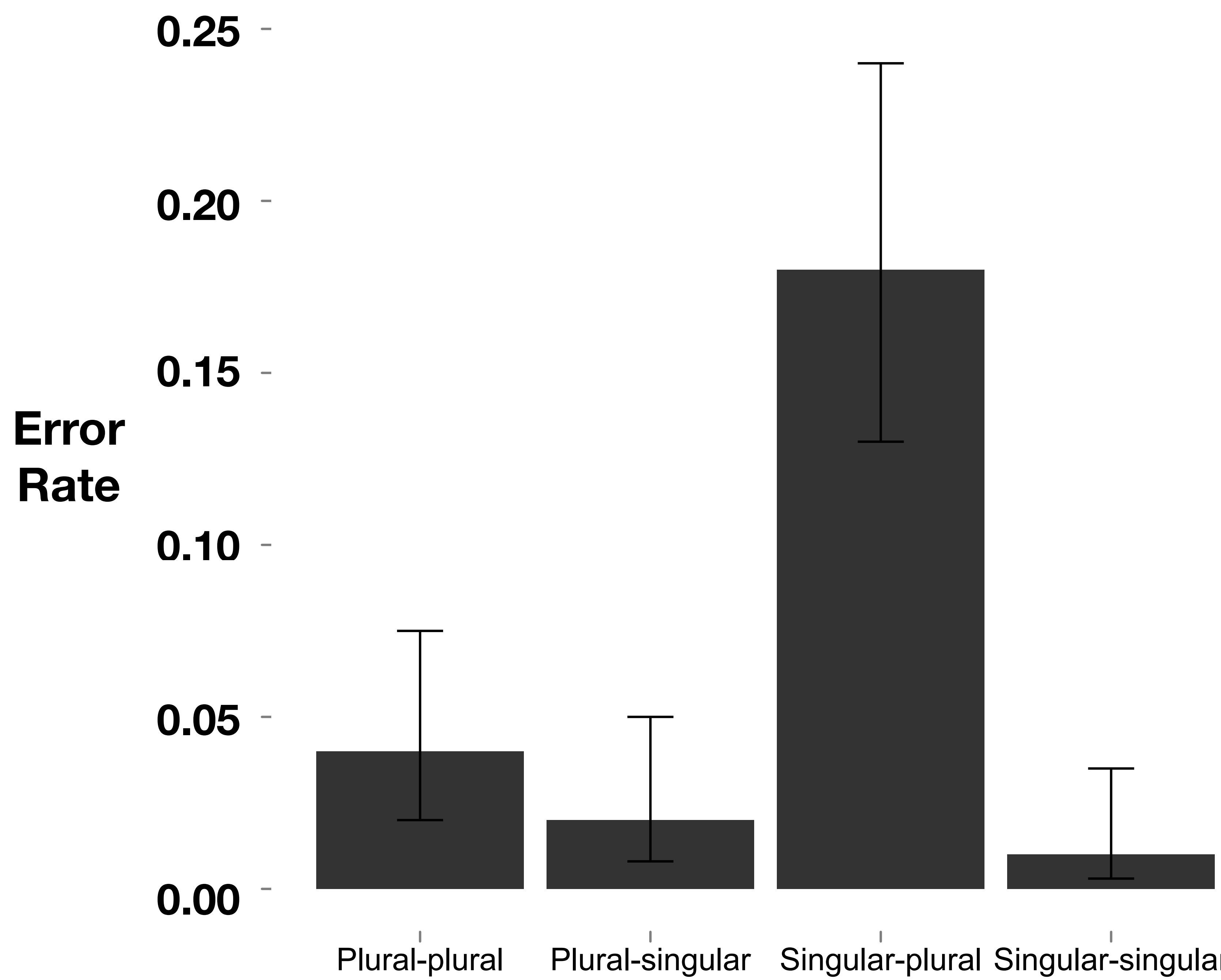

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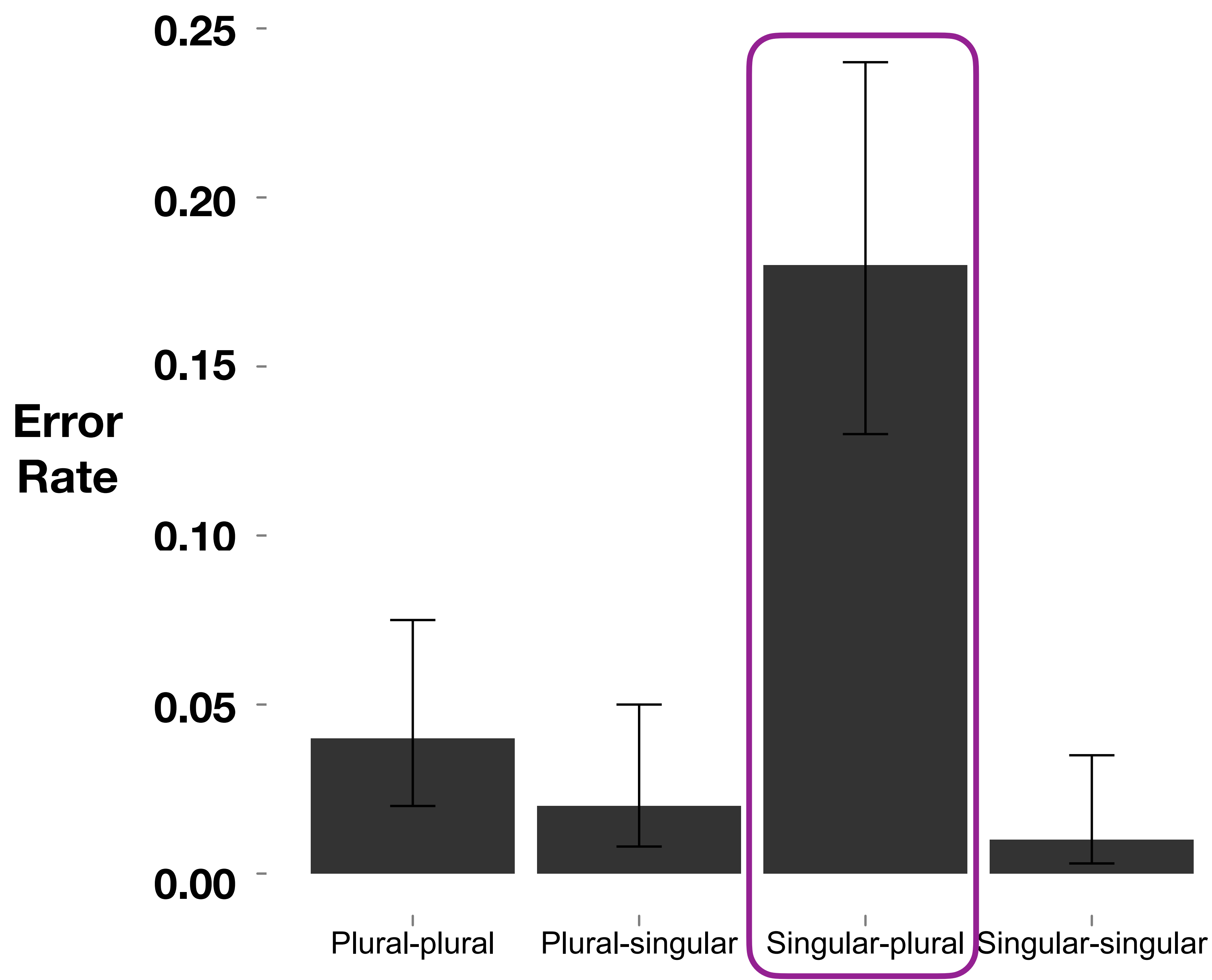

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Comprehension of agreement errors

The musician (SG) who the reviewer praise so highly will probably win ...

(Wagers et al., 2009)

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The musician (SG) / musicians (PL) who the reviewer praise so highly will probably win ...

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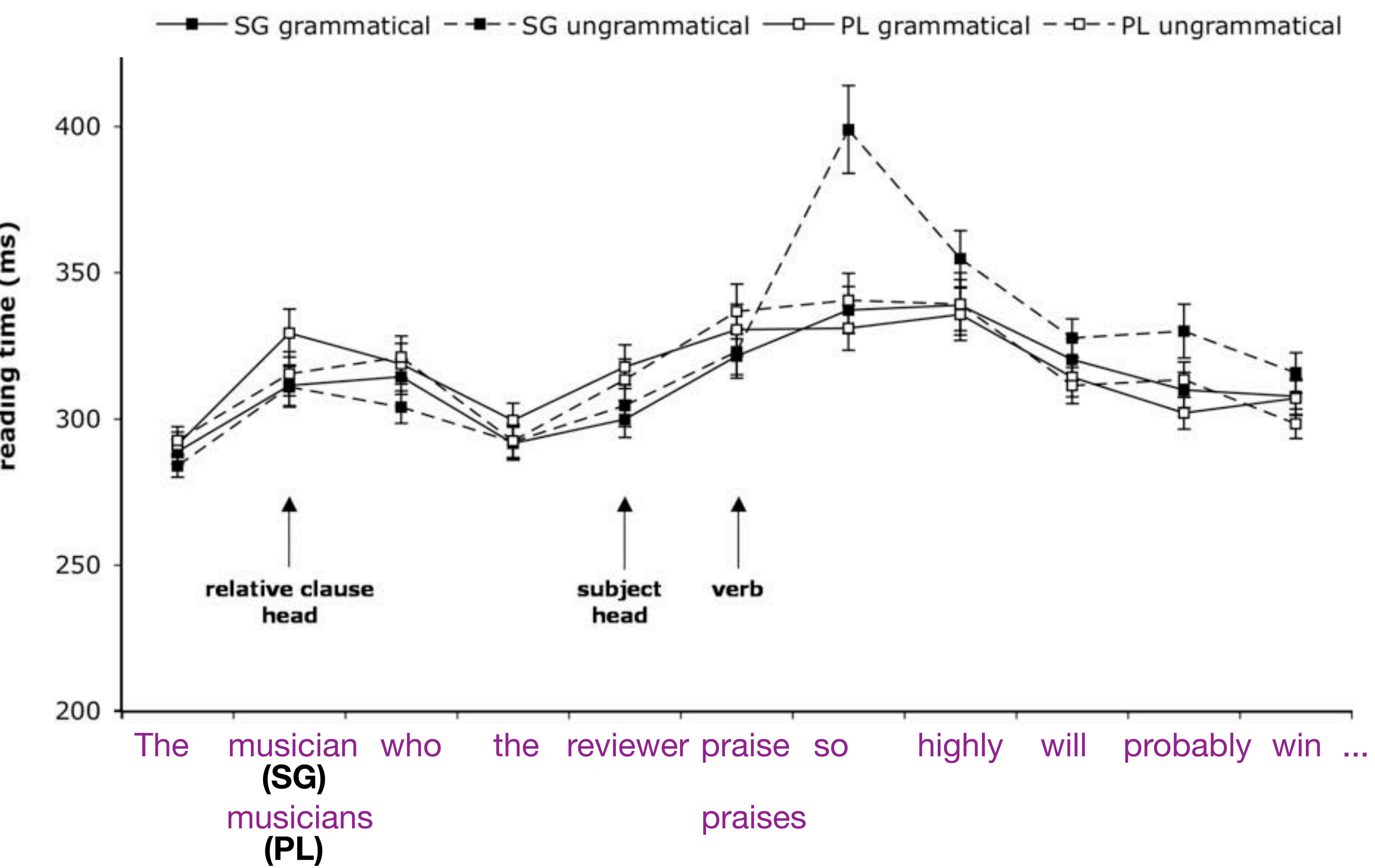

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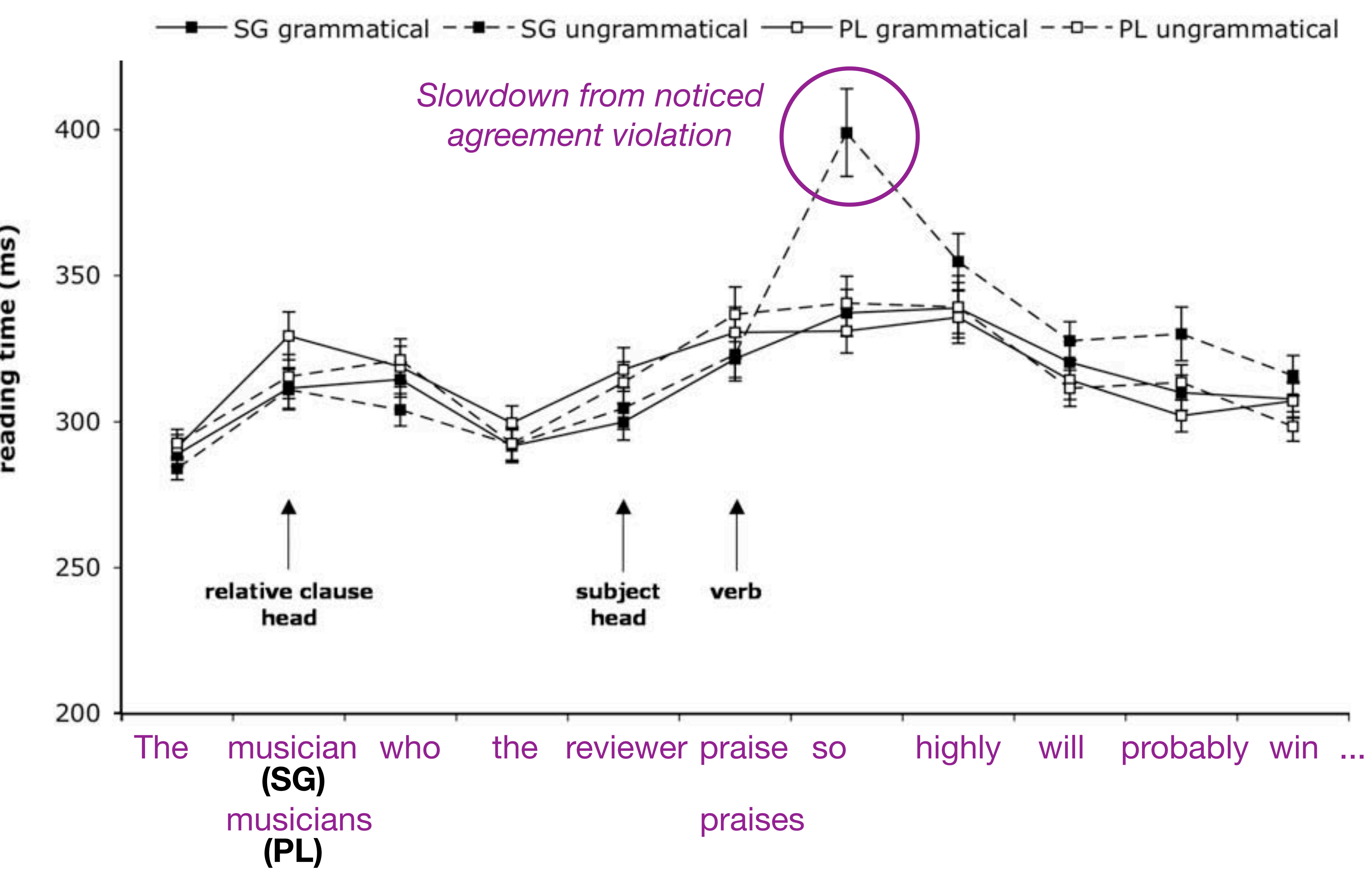

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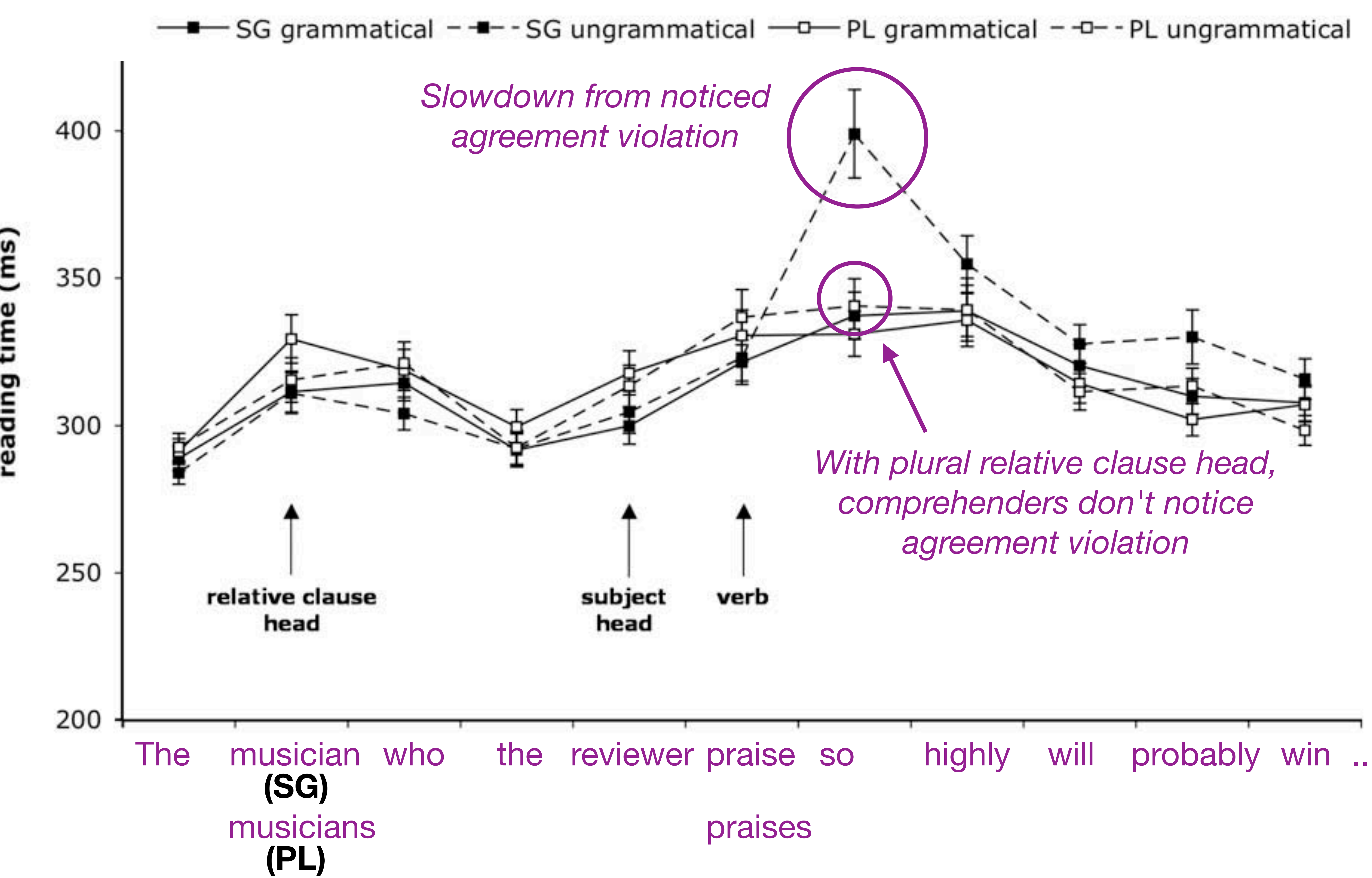

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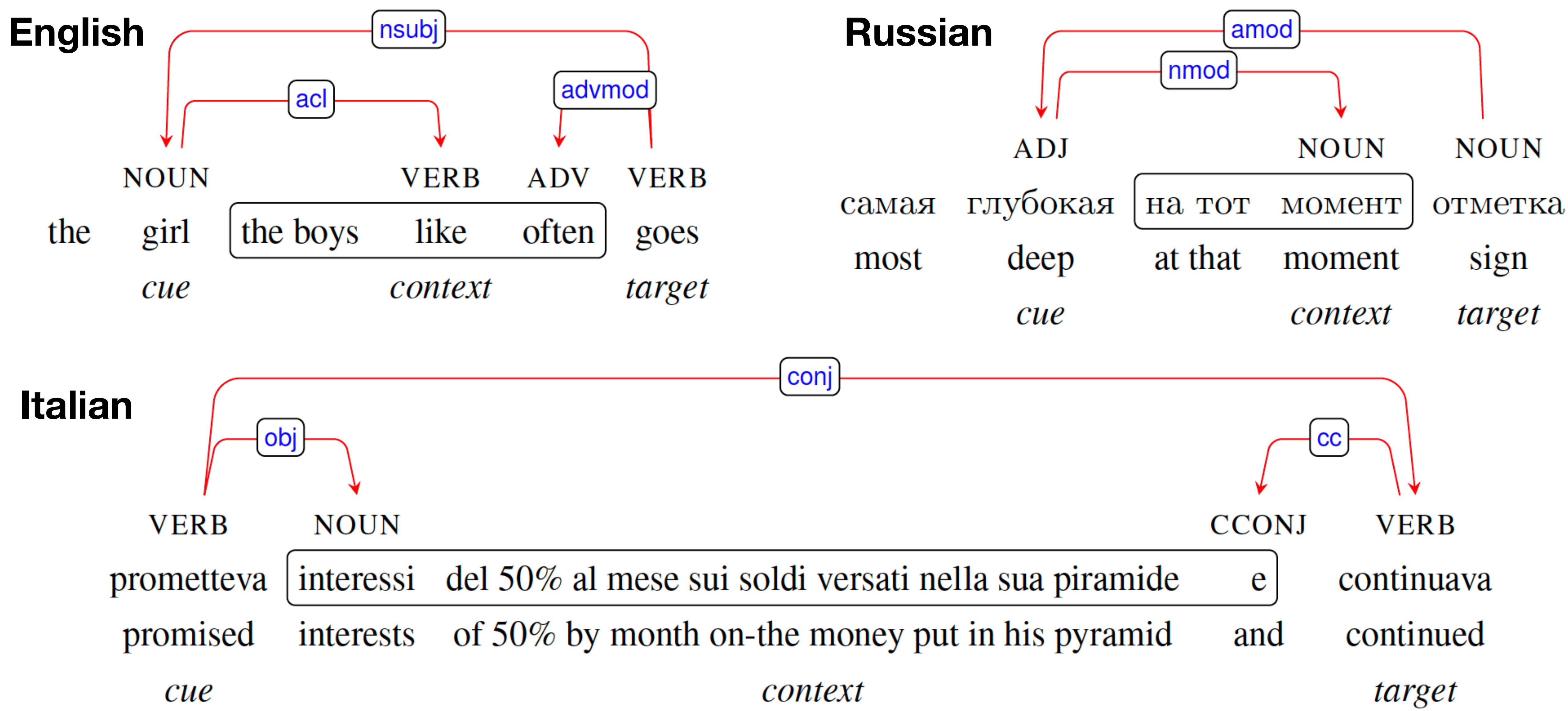
Corpus-based long-distance agreement benchmark



Hebrew (not shown)

(Gulordava et al., 2018)

Real and "artificial" examples

Original to "colorless green" (*nonce*) sentence conversion by part-of-speech-preserving content-word substitution:

It **presents** the **case** for **marriage** **equality** and **states**...

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↓ ↓ ↓ ↓ ↓

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Original

```
I guess the questions on which I should like your steer      is|are
The main thing people do there                               is|are
The first thing you notice when you arrive on location is
that the waiting line literally goes out the door and        spill|spills
Please let me know if you have any questions or              need|needs
```

"Colorless green" (*nonce*)

```
the ecological wines we believe in our night                 assume|assumes
You assume the picketing and                                 seek|seeks
The sauce to recruit in pastor                               advise|advises
Can you expire that the ground we are happening              produce|produces
```

(Gulordava et al., 2018)

Real and "artificial" examples

Original to "colorless green" (*nonce*) sentence conversion by part-of-speech-preserving content-word substitution:

`It` **`presents`** `the` **`case`** `for` **`marriage equality`** `and` **`states`**`...`

↓ ↓ ↓ ↓ ↓

`It` **`stays`** `the` **`shuttle`** `for` **`honesty insurance`** `and` **`finds`**`...`

Original

`I guess the questions on which I should like your steer`	`is|are`
`The main thing people do there`	`is|are`
`The first thing you notice when you arrive on location is that the waiting line literally goes out the door and`	`spill|spills`
`Please let me know if you have any questions or`	`need|needs`

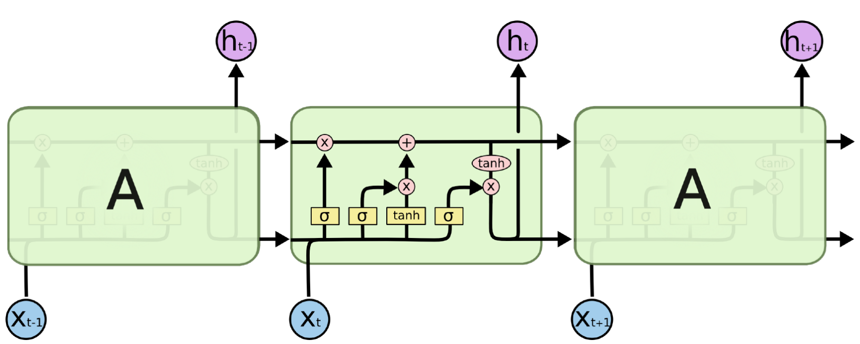
"Colorless green" (*nonce*)

`the ecological wines we believe in our night`	`assume|assumes`
`You assume the picketing and`	`seek|seeks`
`The sauce to recruit in pastor`	`advise|advises`
`Can you expire that the ground we are happening`	`produce|produces`

(Gulordava et al., 2018)

Human and LSTM performance

90m words per language



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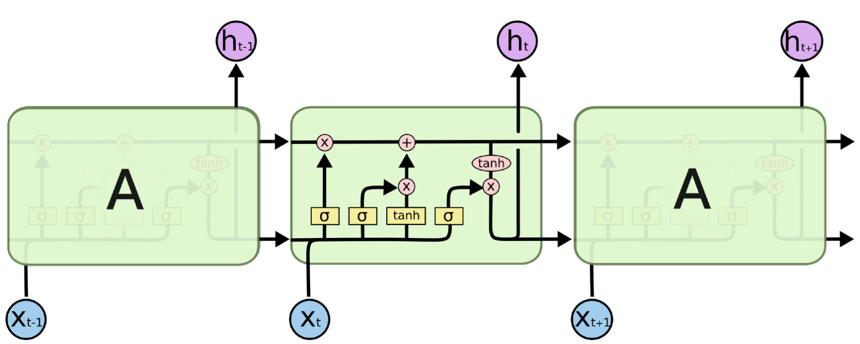

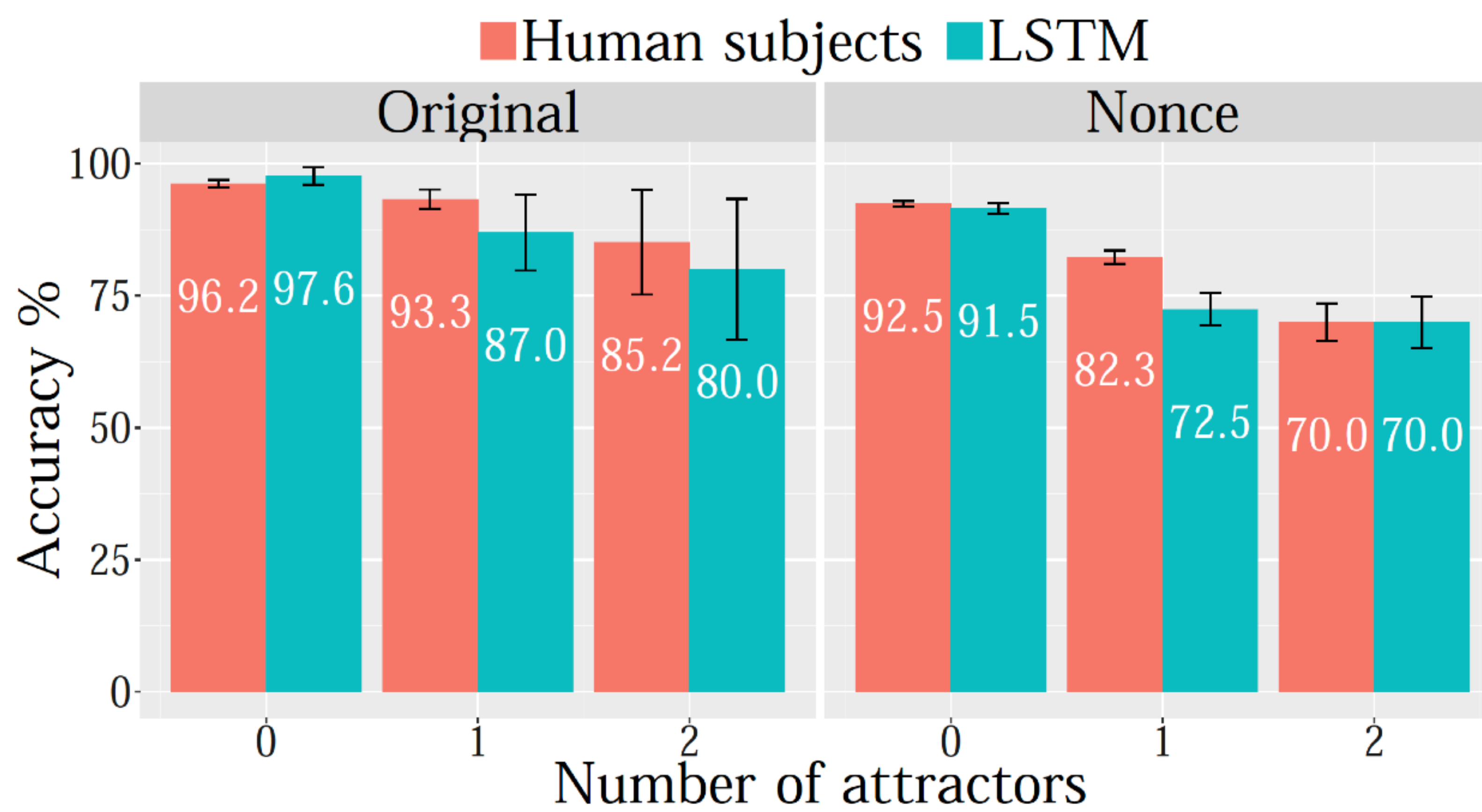

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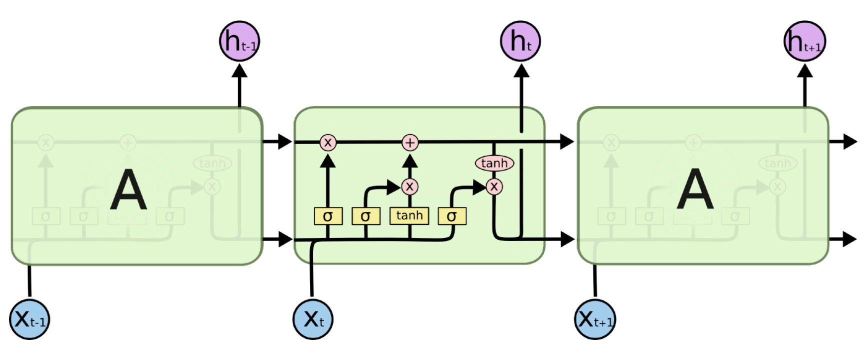

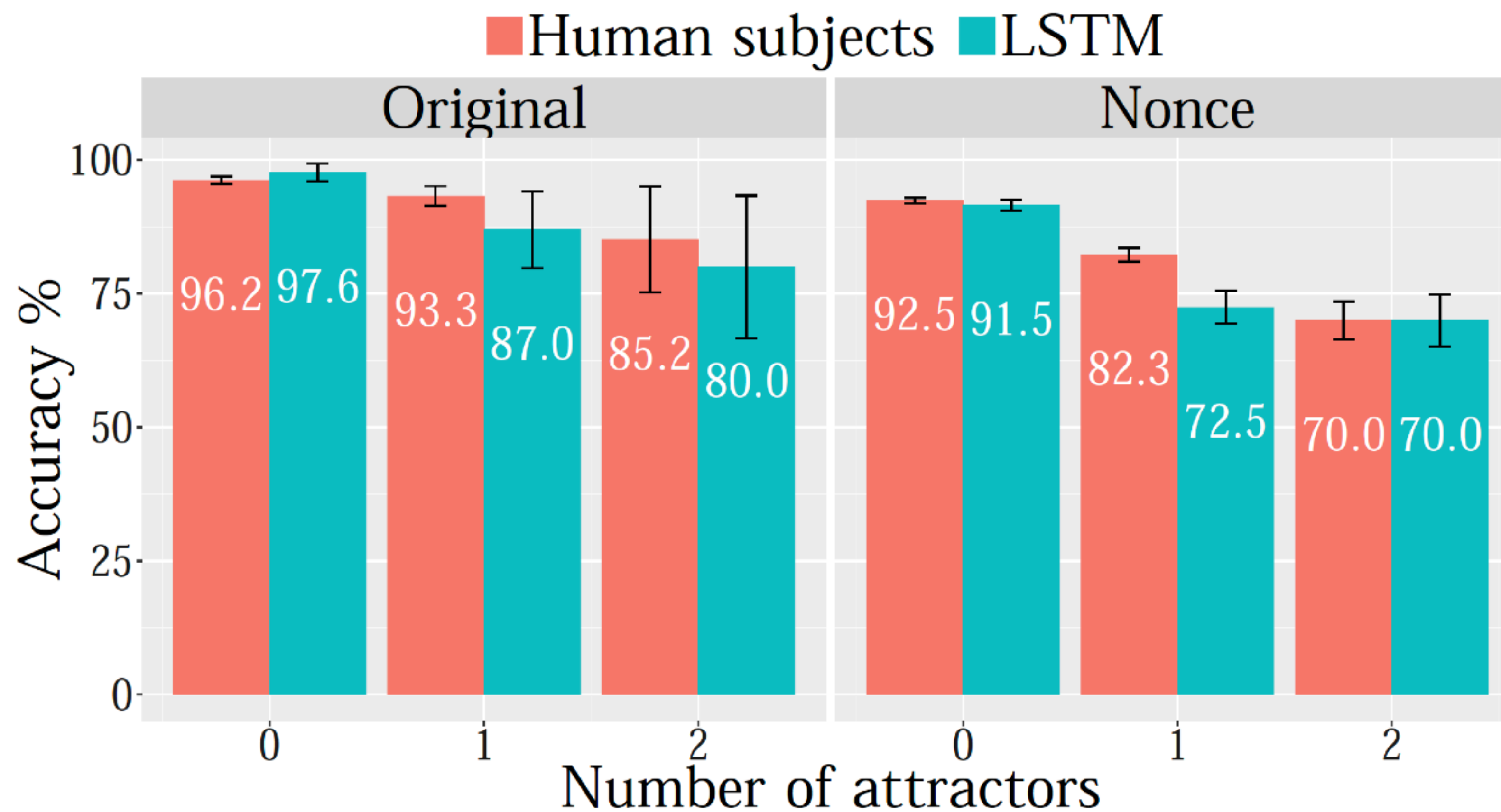

Construction	#original	Original Subjects	Original LSTM	Nonce Subjects	Nonce LSTM
DET [AdjP] NOUN	14	98.7	$98.6_{\pm 3.2}$	98.1	$91.7_{\pm 0.4}$
NOUN [RelC / PartP] clitic VERB	6	93.1	$100_{\pm 0.0}$	95.4	$97.8_{\pm 0.8}$
NOUN [RelC / PartP] VERB	27	97.0	$93.3_{\pm 4.1}$	92.3	$92.5_{\pm 2.1}$
ADJ [conjoined ADJs] ADJ	13	98.5	$100_{\pm 0.0}$	98.0	$98.1_{\pm 1.1}$
NOUN [AdjP] relpron VERB	10	95.9	$98.0_{\pm 4.5}$	89.5	$84.0_{\pm 3.3}$
NOUN [PP] ADVERB ADJ	13	91.5	$98.5_{\pm 3.4}$	79.4	$76.9_{\pm 1.4}$
NOUN [PP] VERB (participial)	18	87.1	$77.8_{\pm 3.9}$	73.4	$71.1_{\pm 3.3}$
VERB [NP] CONJ VERB	18	94.0	$83.3_{\pm 10.4}$	86.8	$78.5_{\pm 1.7}$
(Micro) average		94.5	$92.1_{\pm 1.6}$	88.4	$85.5_{\pm 0.7}$

Table 3: Subject and LSTM accuracy on the Italian test set, by construction and averaged.

Targeted syntactic evaluation

(Marvin & Linzen, 2018)

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- Frequency *in naturalistic usage* is important for understanding our linguistic environment & for applications

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Across PP	`The farmer near the parents` **`smiles`**
Across Subject RC	`The officers that love the skater` **`smile`**
Across Coordination	`The senator smiles and` **`laughs`**
Inside Object RC	`The farmer that the parents` **`love`** `swims`
⋮	⋮

(Marvin & Linzen, 2018)

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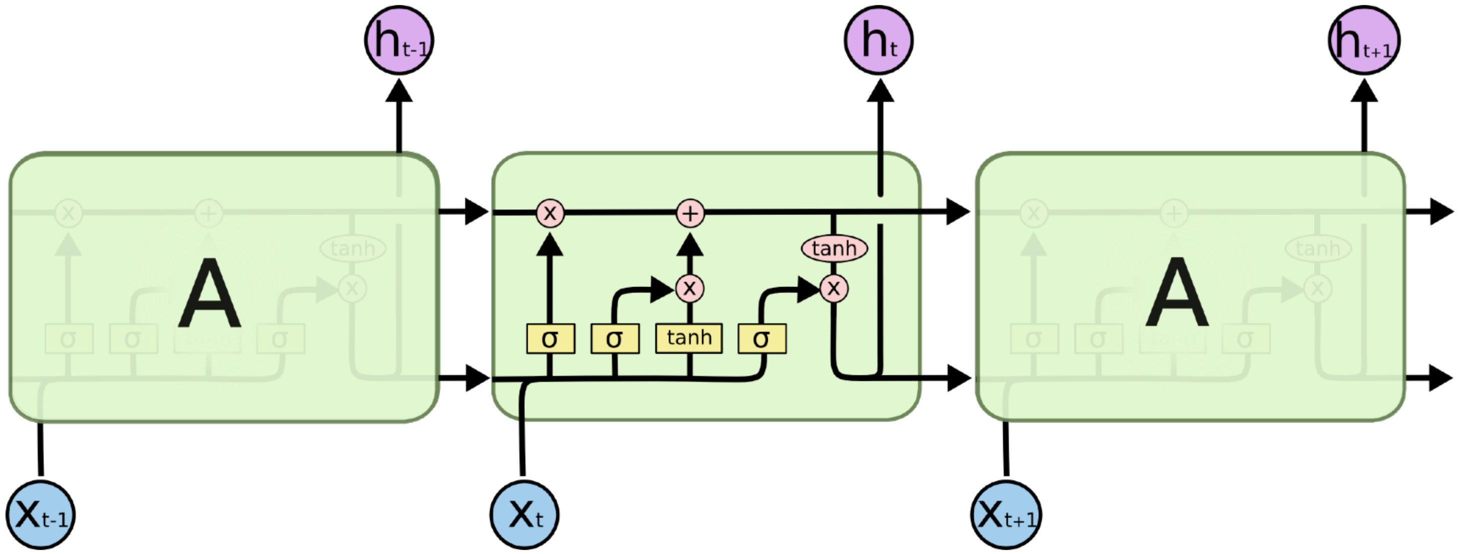
⋮	⋮

	RNN	*n*-gram	Humans
SUBJECT-VERB AGREEMENT:			
Simple	0.94	0.79	0.96
In a sentential complement	0.99	0.79	0.93
Short VP coordination	0.90	0.51	0.94
Long VP coordination	0.61	0.50	0.82
Across a prepositional phrase	0.57	0.50	0.85
Across a subject relative clause	0.56	0.50	0.88
Across an object relative clause	0.50	0.50	0.85
Across an object relative (no *that*)	0.52	0.50	0.82
In an object relative clause	0.84	0.50	0.78
In an object relative (no *that*)	0.71	0.50	0.79

(Marvin & Linzen, 2018)

LSTM learned circuitry for S–V agreement



(Lakretz et al., 2019)

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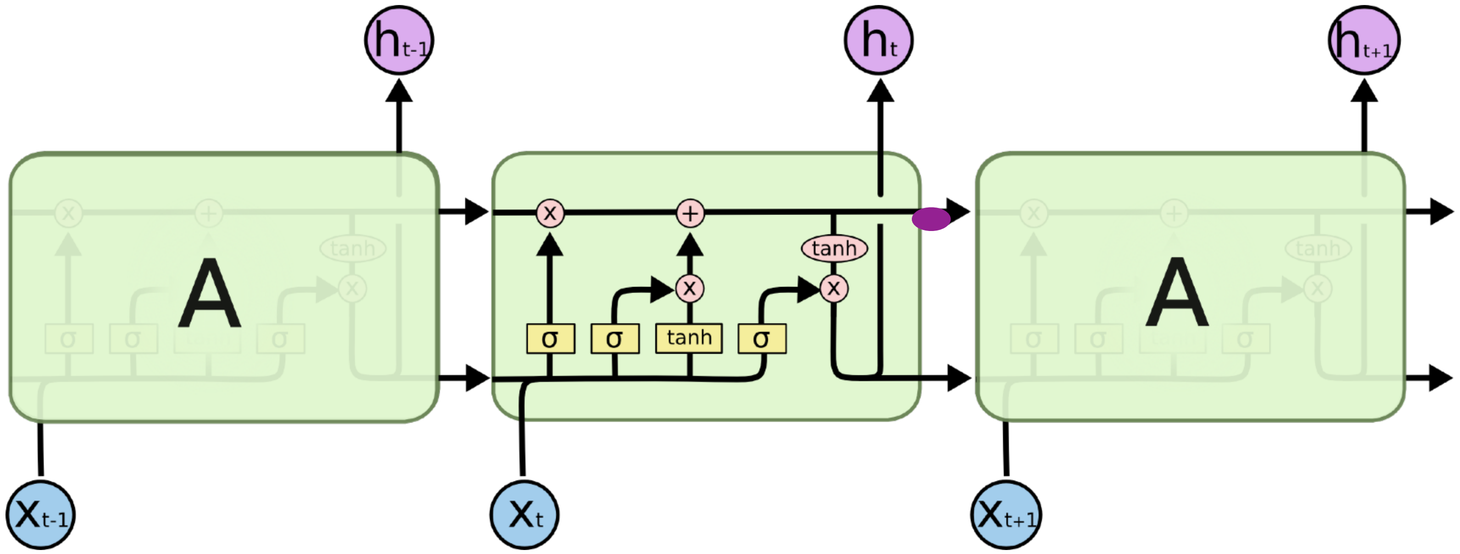

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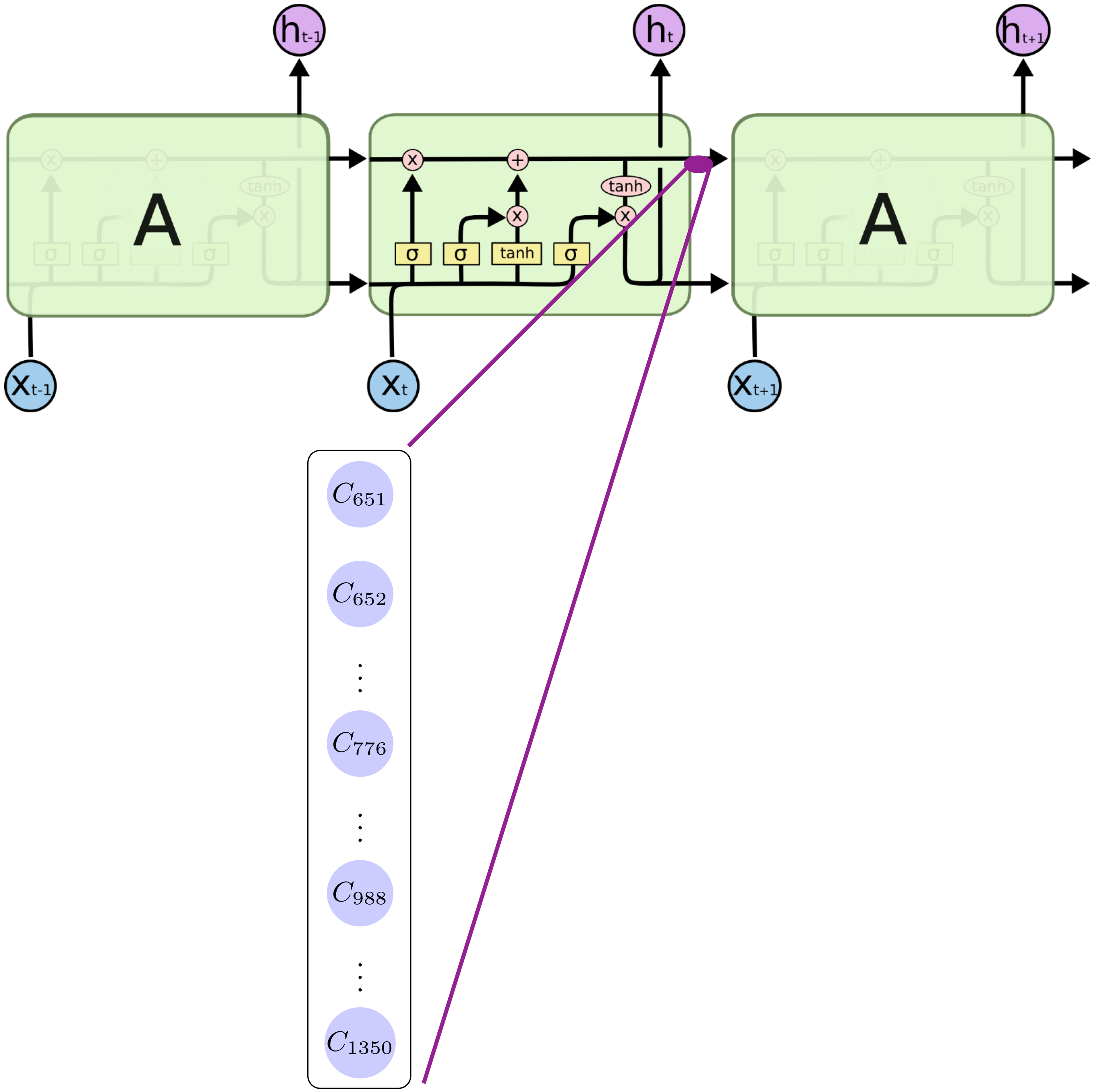

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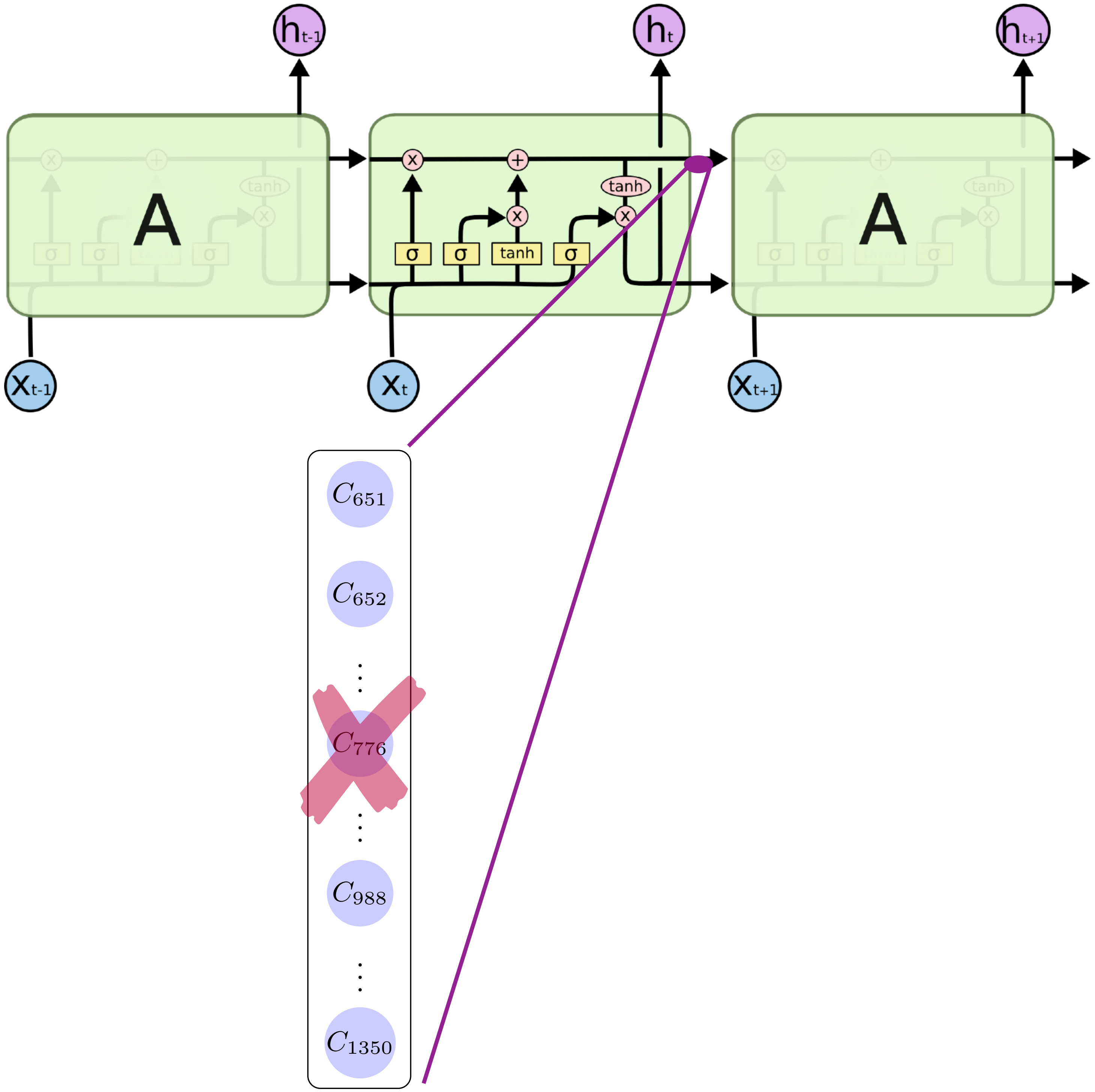

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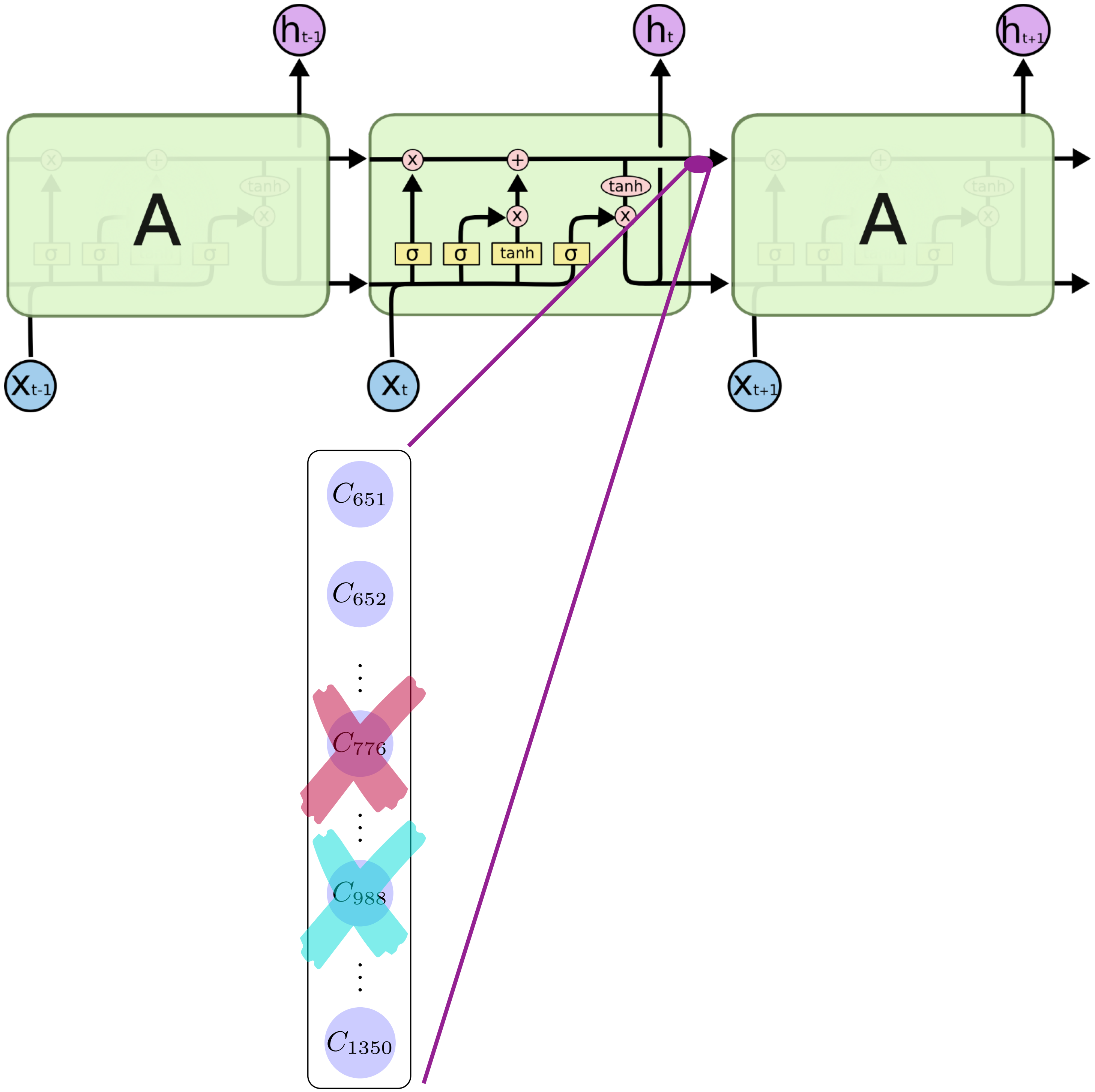

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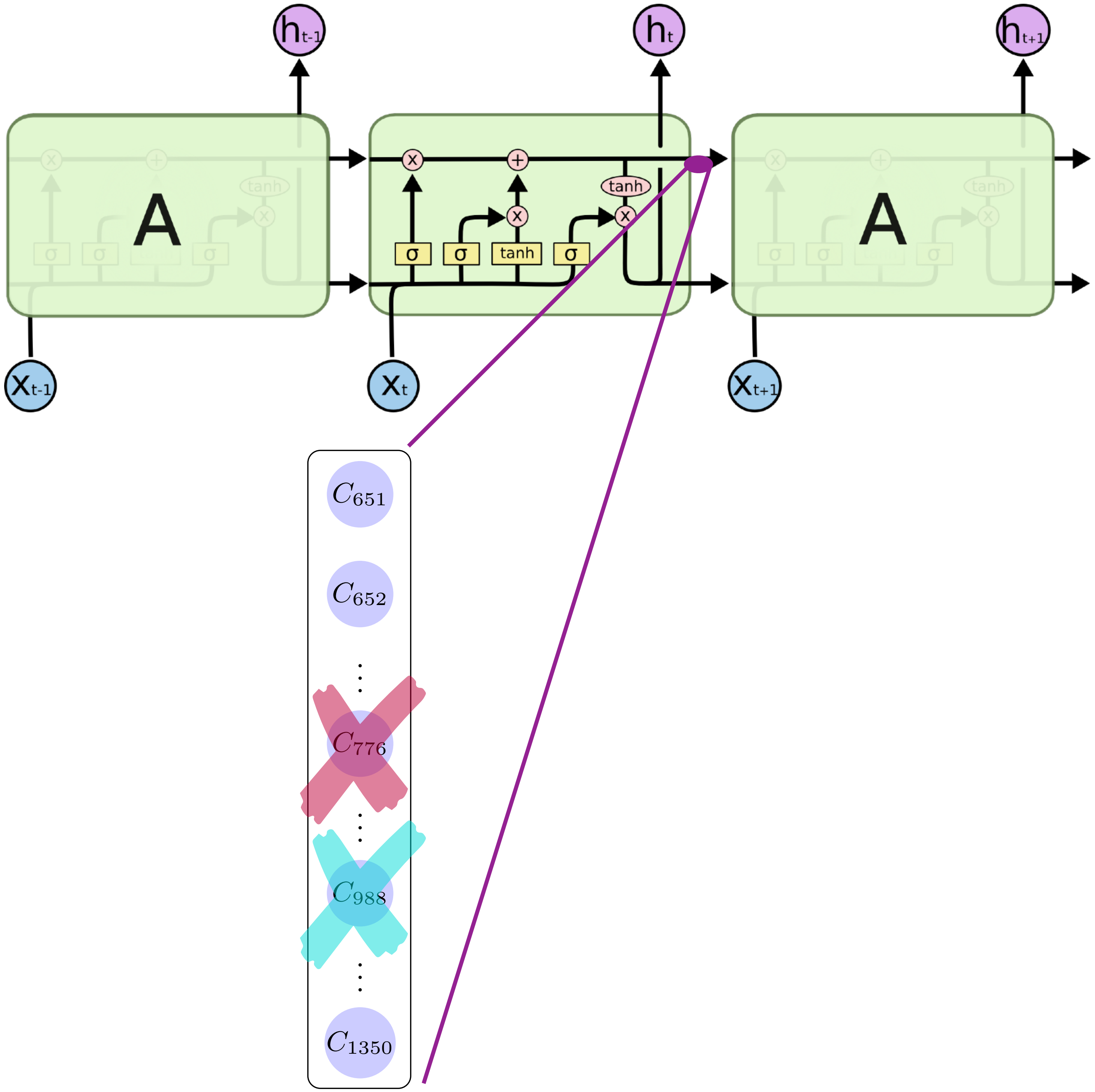

NA task	C	Ablated 776	Ablated 988	Full
Simple	S	-	-	100
Adv	S	-	-	100
2Adv	S	-	-	99.9
CoAdv	S	-	82	98.7
namePP	SS	-	-	99.3
nounPP	SS	-	-	99.2
nounPP	SP	-	54.2	87.2
nounPPAdv	SS	-	-	99.5
nounPPAdv	SP	-	54.0	91.2
Simple	P	-	-	100
Adv	P	-	-	99.6
2Adv	P	-	-	99.3
CoAdv	P	79.2	-	99.3
namePP	PS	39.9	-	68.9
nounPP	PS	48.0	-	92.0
nounPP	PP	78.3	-	99.0
nounPPAdv	PS	63.7	-	99.2
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(Lakretz et al., 2019)

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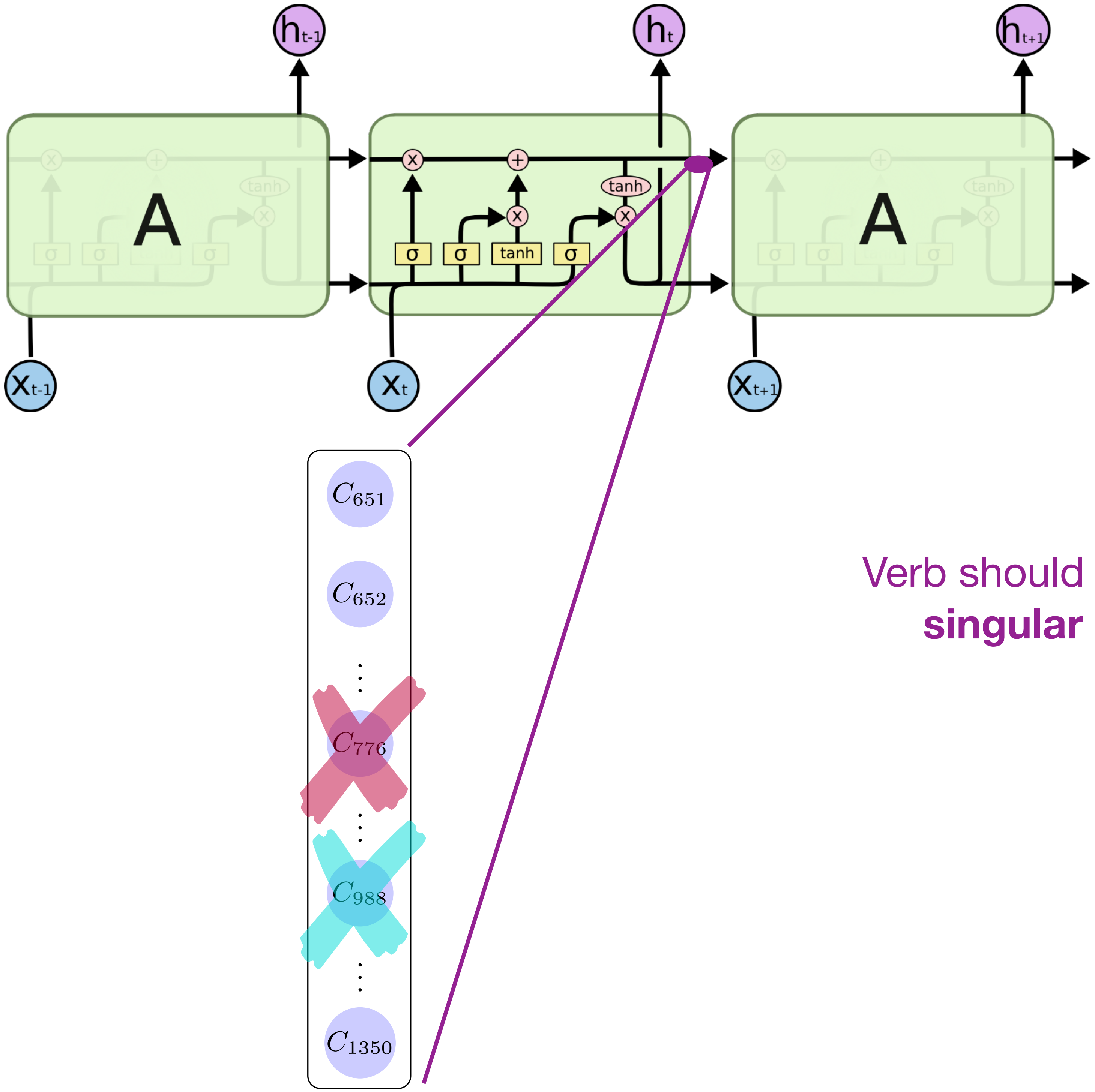

Verb should be **singular**

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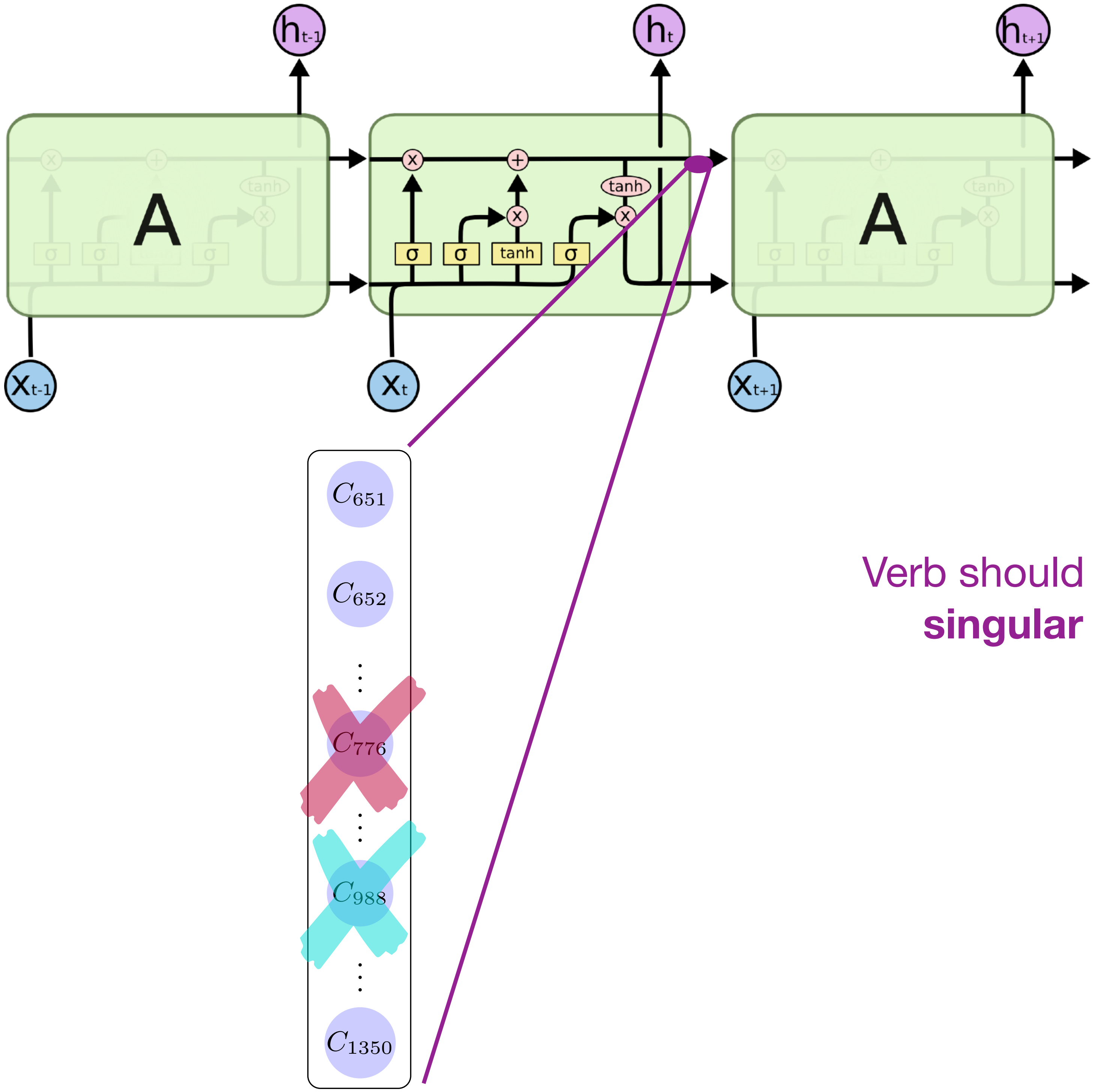

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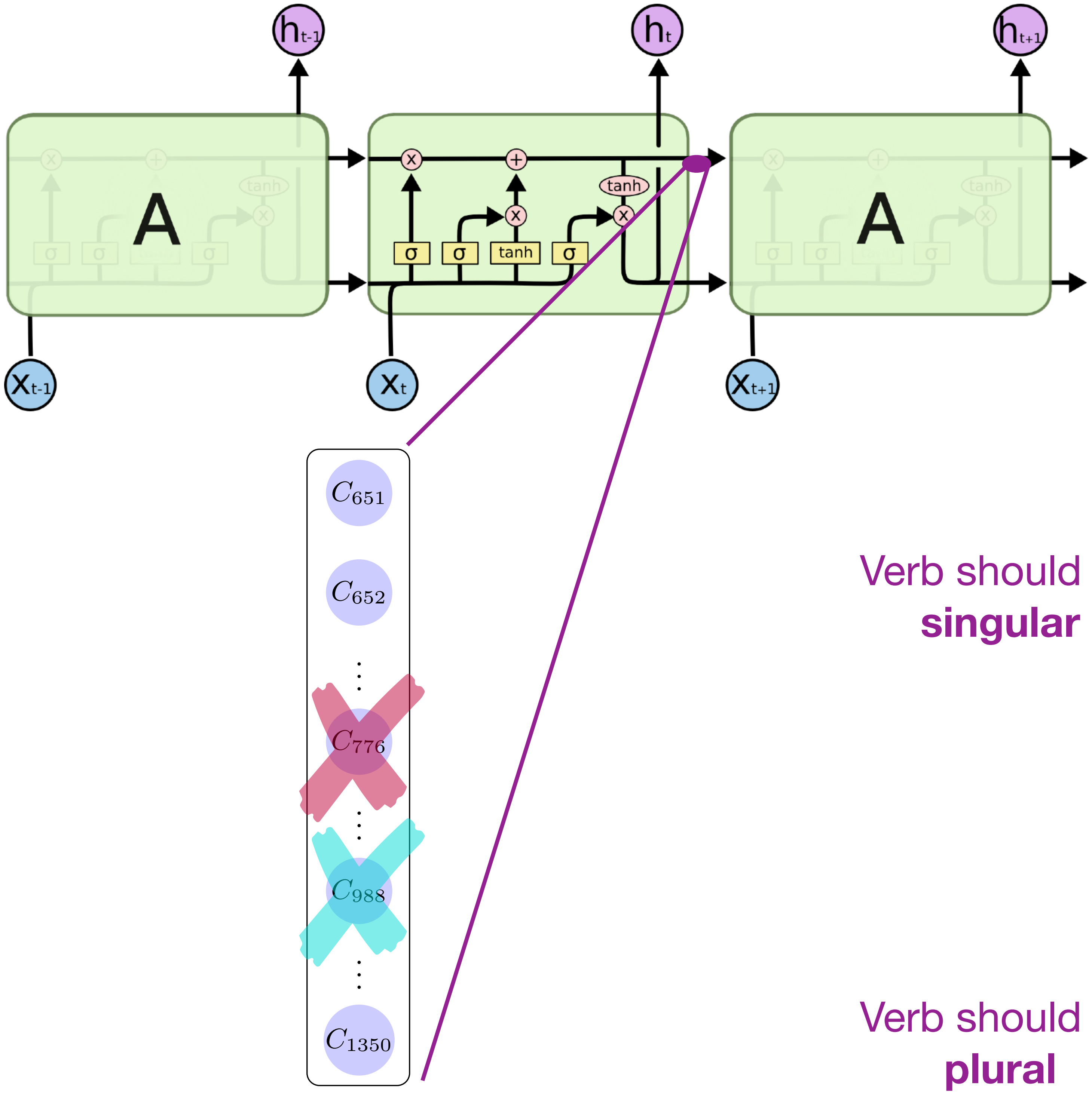

Verb should be **singular**

Verb should be **plural**

NA task	C	Ablated 776	Ablated 988	Full
Simple	S	-	-	100
Adv	S	-	-	100
2Adv	S	-	-	99.9
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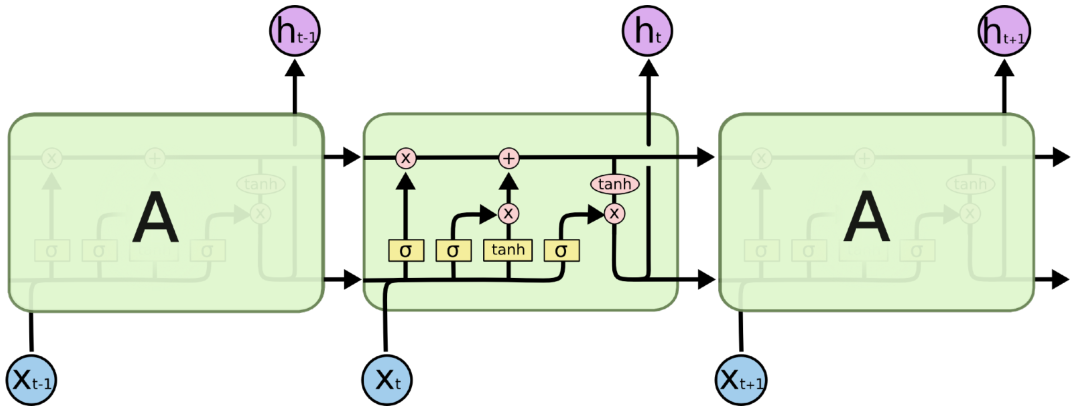

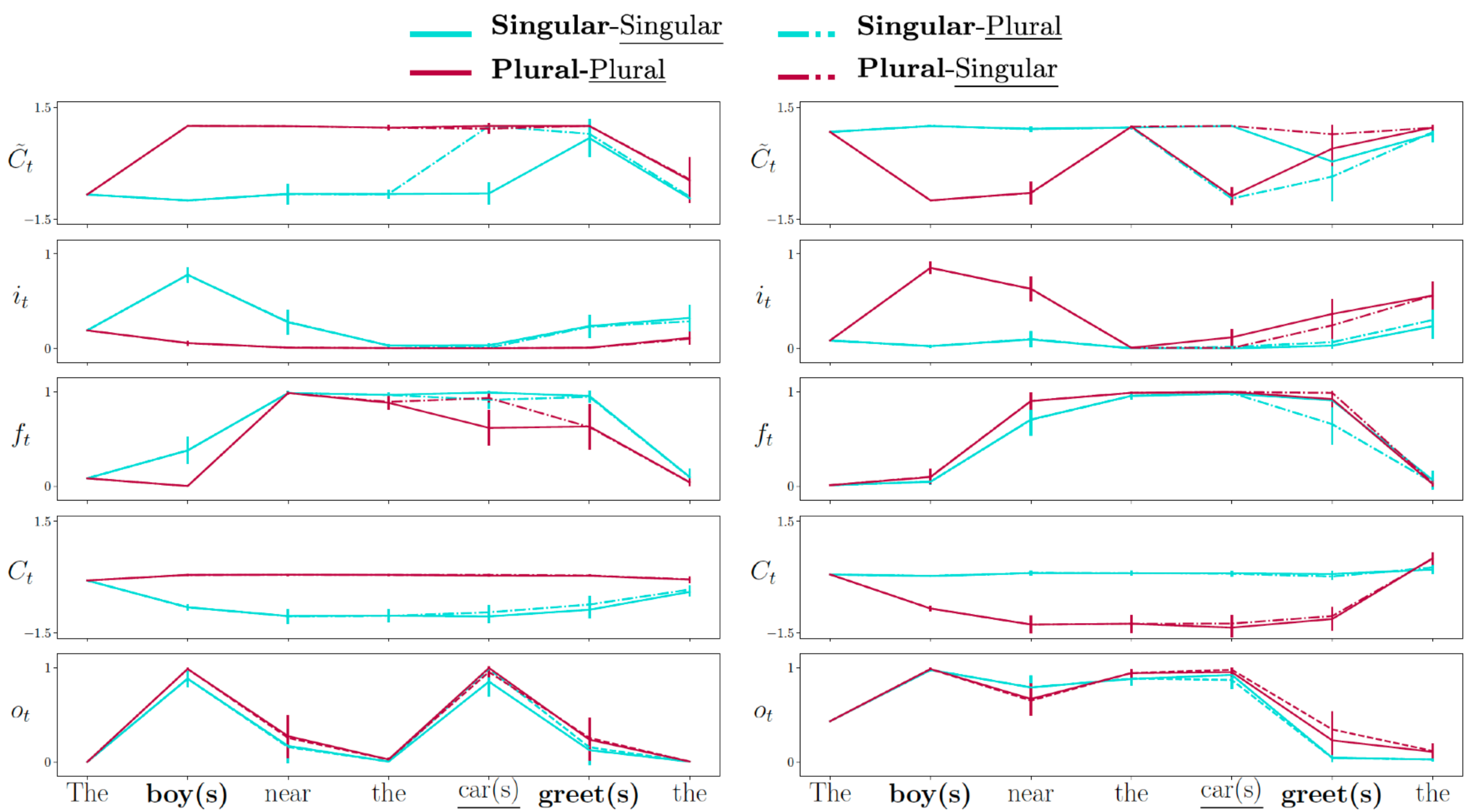

(a) 988 (singular)

(b) 776 (plural)

What we covered today

- Impressionistic assessment of language model text
- Perplexity-based evaluation
- Targeted grammatical evaluation: subject–verb agreement
  - Left-to-right prediction paradigm
  - Psycholinguistics of subject–verb agreeement
  - Evaluation on "colorless green" (*nonce*) sentences
  - Controlled stimuli
  - Ablation tests to reveal circuit-level processing in models

Next time: more targeted evaluation of neural language models' grammatical capabilities, and implications for learnability of natural language grammar

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