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

What do language models generate?

- Half of these are generated from *n*-gram models, half from an LSTM:

2-gram Last December through the way to preserve the Hudson corporation N. B. E. C. Taylor would seem to complete the major central planners one point five percent of U. S. E. has already old M. X. corporation of living on information such as more frequently fishing to keep her

LSTM Another person familiar with the diaries pointed her tonight

LSTM The state is insisting extensive sanctions against wooden emigration until I'd publish Mr. Collor 's own birth conservation control with him

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

3-gram They also point to ninety nine point six billion dollars from two hundred four oh six three percent of the rates of interest stores as Mexico and Brazil on market conditions

LSTM It has always played something so an man who asked thanks to David Smith 's case would open its Hindu jail , Brooke Wright , the president and manager of the American Express Foundation in U.S. Providence, Va.

Review: perplexity-based LM evaluation

Perplexity: inverse (geometric) mean word probability

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

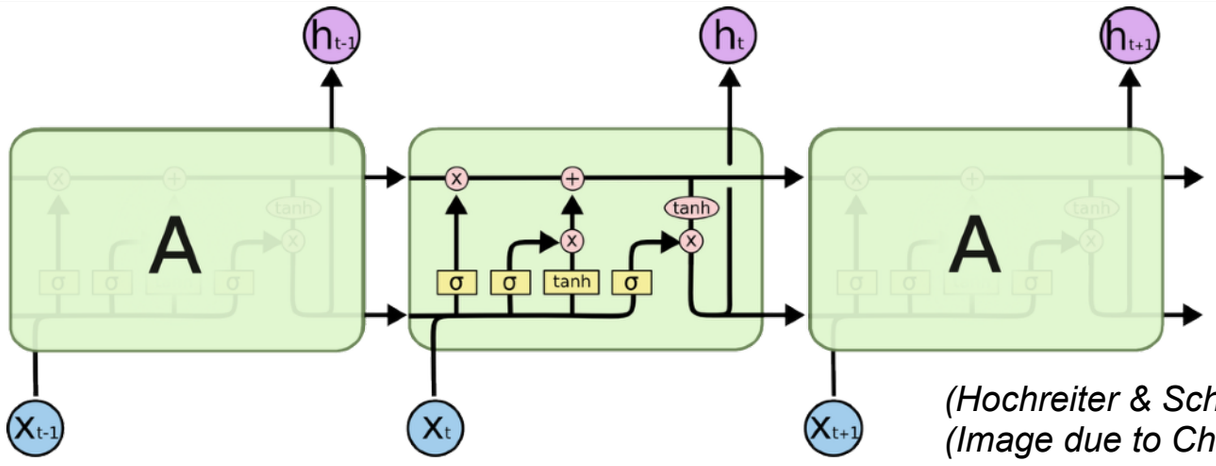
equivalently,

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

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

(Recommended: prove the equivalence!)

Deep learning has revolutionized language modeling



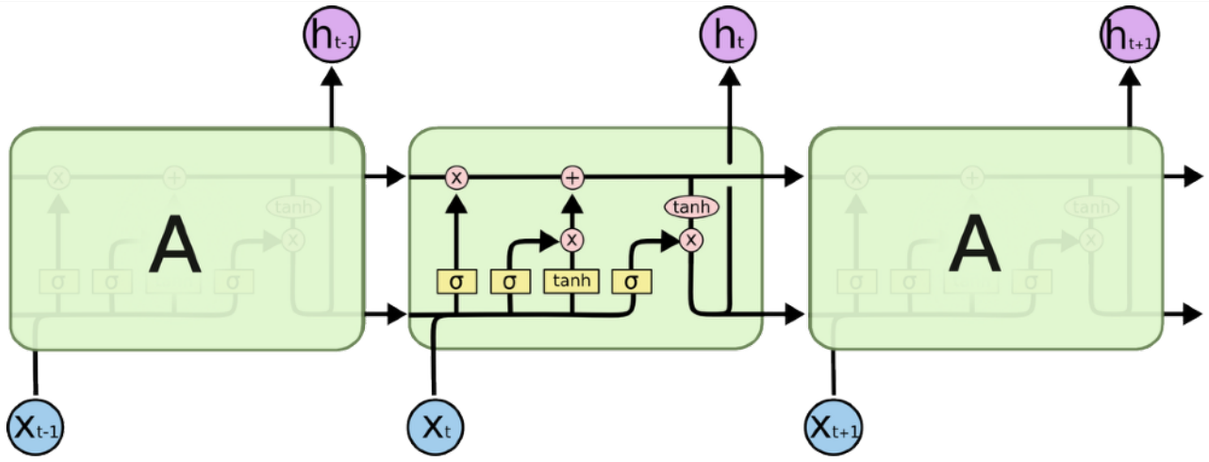
(Hochreiter & Schmidhuber, 1997)
(Image due to Christopher Olah)

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)

What have these models learned as “English”?



The girl who the newspaper.now calls his girlfriend has really been hateful . ✓

The monologue that the actor who the movie industry.likes made silent was being uploaded . ✓ (!)

The man who the car.has gazed longingly at for years . ✗

The athlete who the restaurant.would justify decided to add the main West Coast restaurants to his menu and who hadn 't upgraded from his previous suite , into a more <UNK> steakhouse in New York . ???

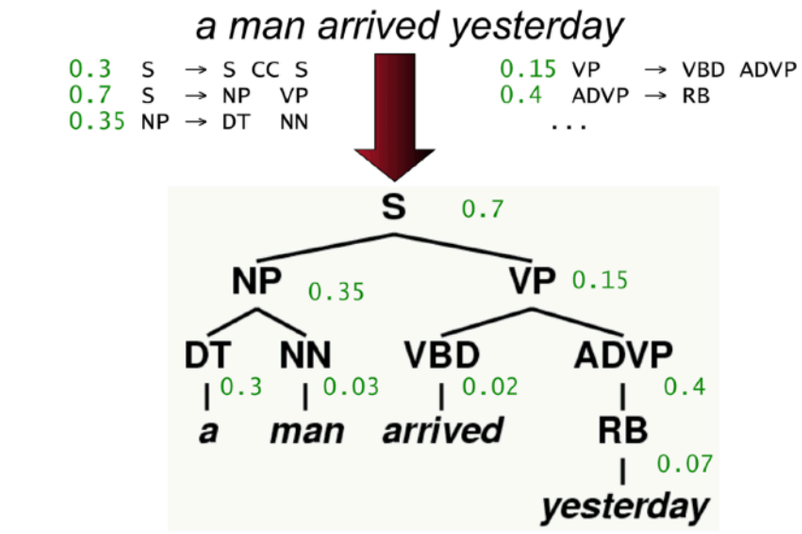
(continuations generated by model of Jozefowicz et al., 2016)

What do language models learn?

- In the case of *n-gram* models…

$$P(\texttt{\$ dogs chase cats \$}) \approx P(\texttt{\$}|\texttt{cats})P(\texttt{cats}|\texttt{chase})P(\texttt{chase}|\texttt{dogs})P(\texttt{dogs}|\texttt{\$})$$

- …and probabilistic context-free grammars…



Total probability: 0.7*0.35*0.15*0.3*0.03*0.02*0.4*0.07= 1.85×10^{-7}

- …we can reason (fairly) easily about model predictions.

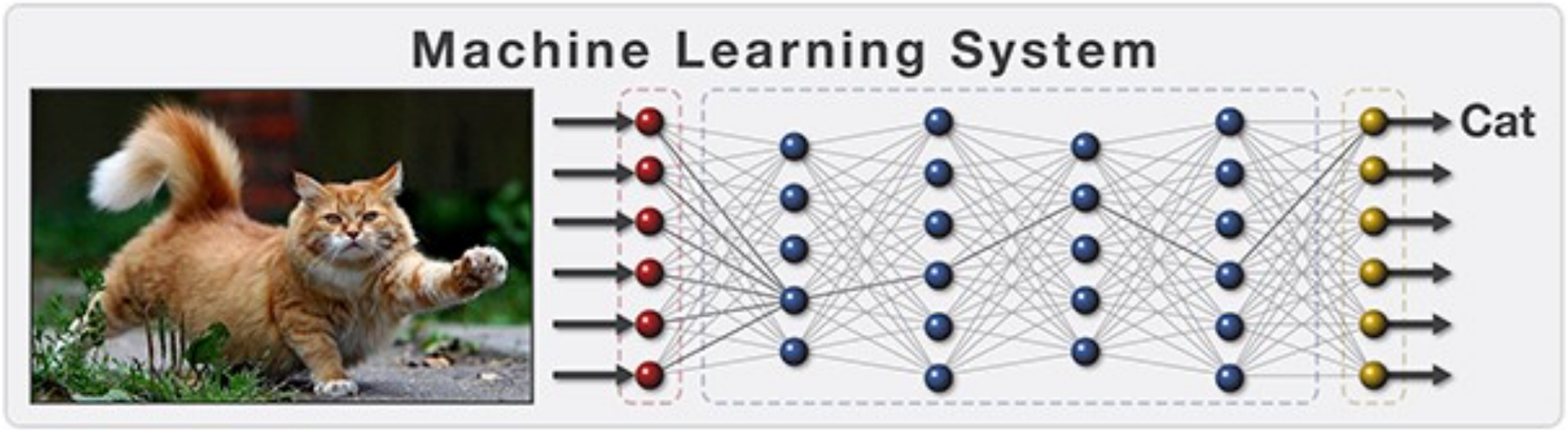
A friend of my parents… → $P_{trigram}(w|$*A friend of my parents…*$)$

A friend of my parents… → $P_{PCFG}(w|$*A friend of my parents…*$)$

- These are ***highly explainable*** probabilistic models.

Explainable models, explainable AI

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



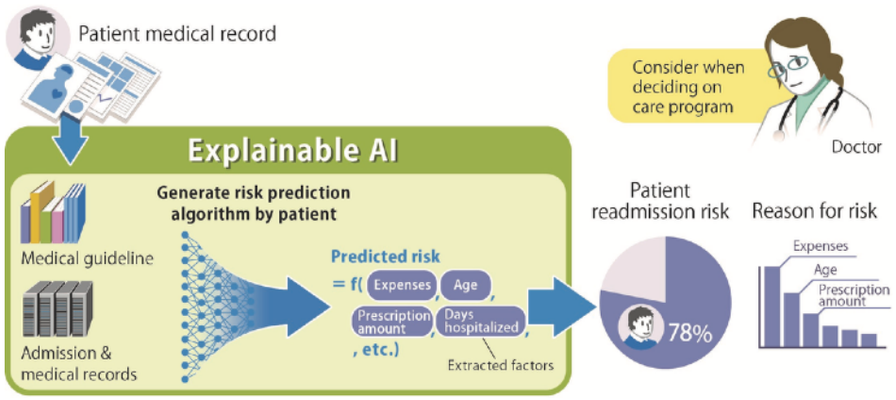
- State-of-the-art AI systems are increasingly ***opaque***, presenting challenges for explainability

Image due to Cenk Sezgin, https://cenksezgin.com/explainable-artificial-intelligence-xai-third-wave-of-ai-5879d6f40a26

Importance of explainability

- Unexplainable systems are not ***accountable***, presenting problems for:

Medical decision-making

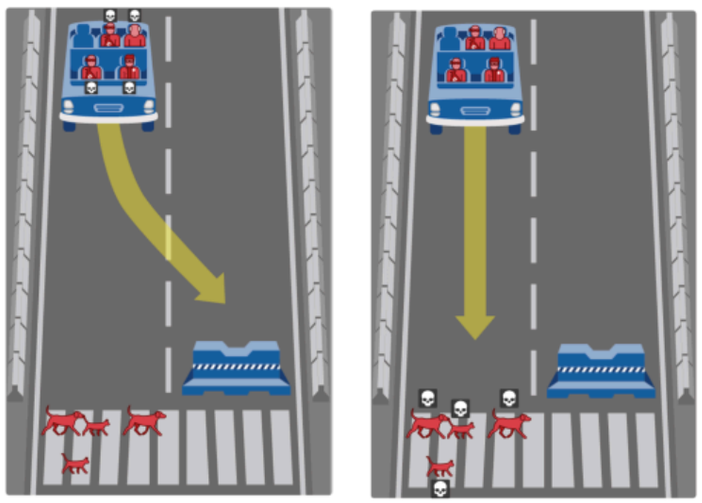


http://www.hitachi.us/sites/default/files/AI_health.jpg

Automated personnel decisions

https://www.wcn.uk/files/2016-05/making-the-most-of-automation-in-recruitment-wcn.png

Self-driving cars



http://aptgadget.com/wp-content/uploads/2016/10/what-should-the-self-driving-car-do.png

…and more!

Explaining is fundamentally human

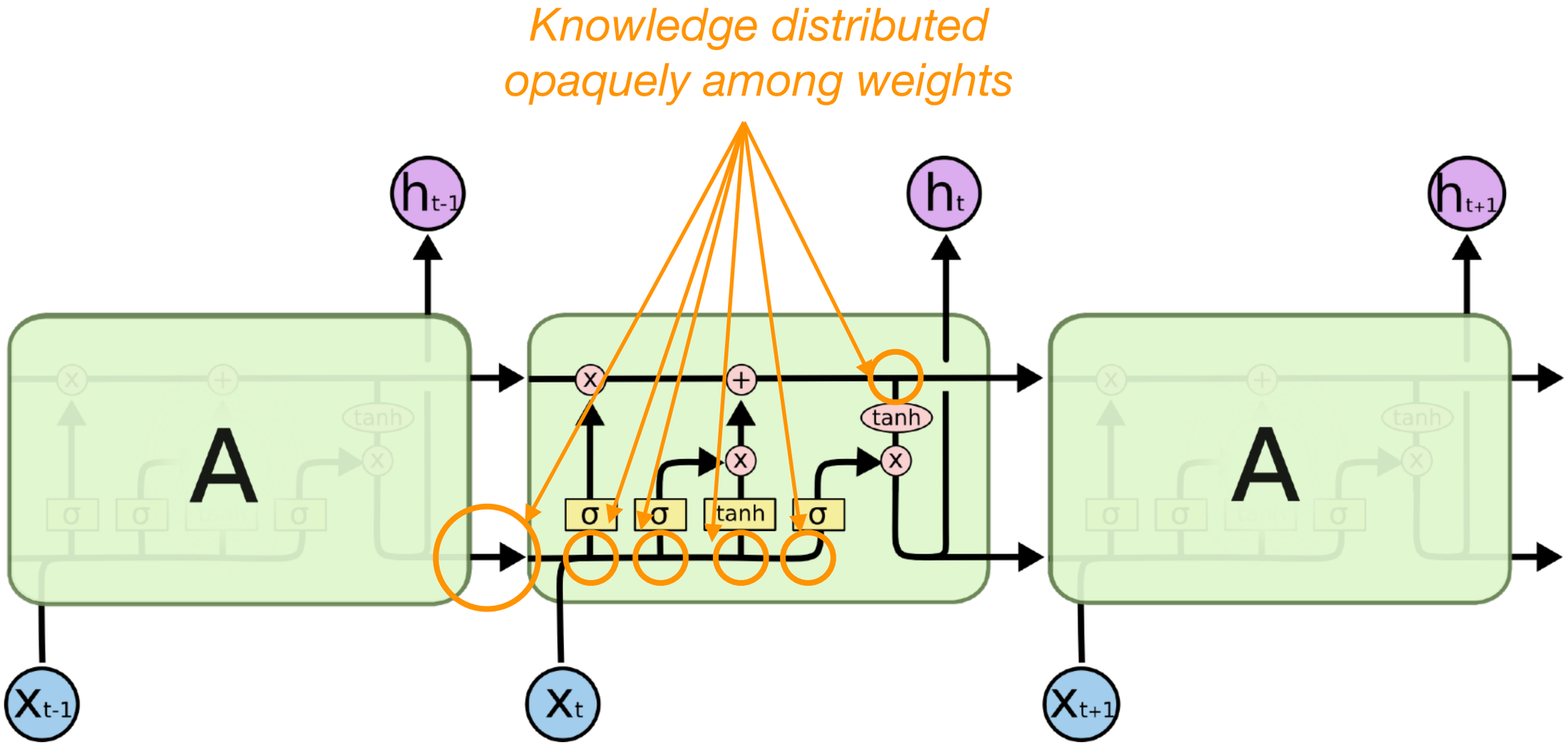
“Knocking over a tower is the best part of building it!”

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

“I was jealous of my brother”

Understanding & explaining NLM behavior

- Remember, this is the state of the art for language models:

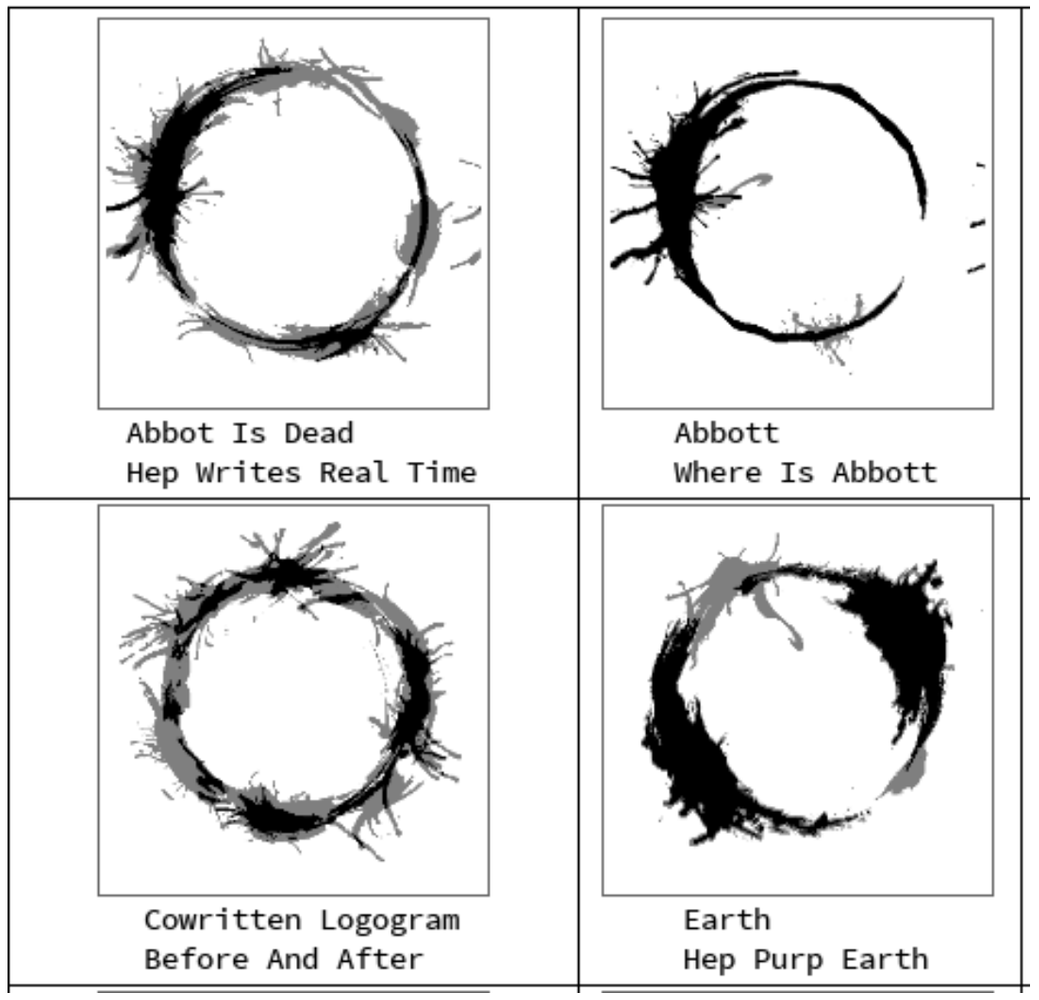


- How can we make such a system explainable?
  - Controlled tests of a model's capabilities & behaviors
  - Probing the circuitry underlying these behaviors

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

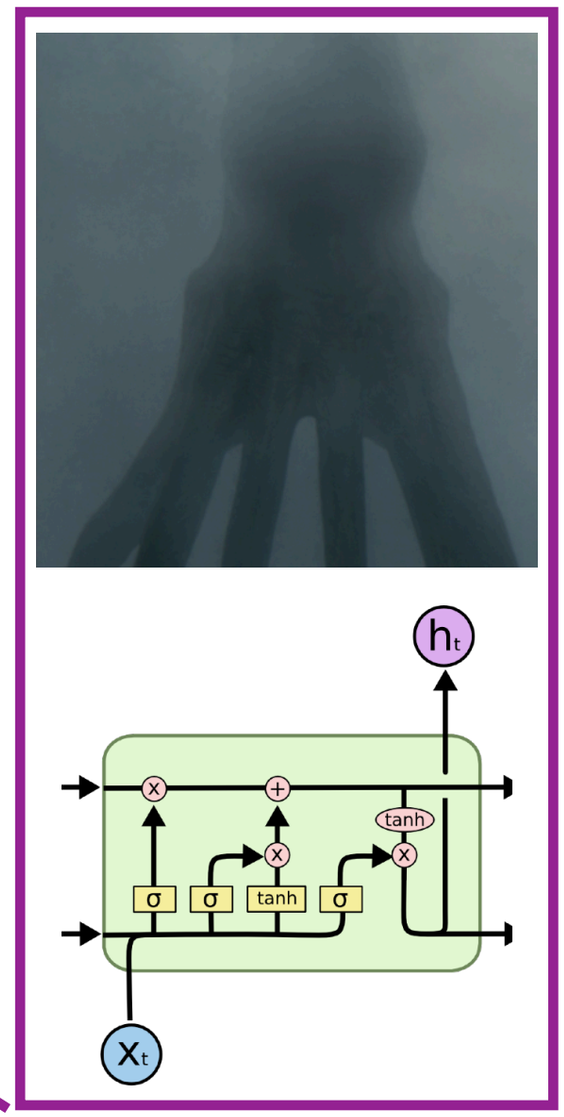
Technical question:

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!__

Explaining a model's linguistic behavior

- Let's now spend some time brainstorming how to examine a model's behavior in more detail
- Papers that have examined this more systematically:

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
{tal.linzen, emmanuel.dupoux}@ens.fr

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

Linzen et al., 2016, TACL

Colorless green recurrent networks dream hierarchically

Kristina Gulordava*
Department of Linguistics
University of Geneva
kristina.gulordava@unige.ch

Piotr Bojanowski
Facebook AI Research
Paris
bojanowski@fb.com

Edouard Grave
Facebook AI Research
New York
egrave@fb.com

Tal Linzen
Department of Cognitive Science
Johns Hopkins University
tal.linzen@jhu.edu

Marco Baroni
Facebook AI Research
Paris
mbaroni@fb.com

Gulordava et al., 2018, NAACL

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

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.

Postmodification by prepositional phrase:

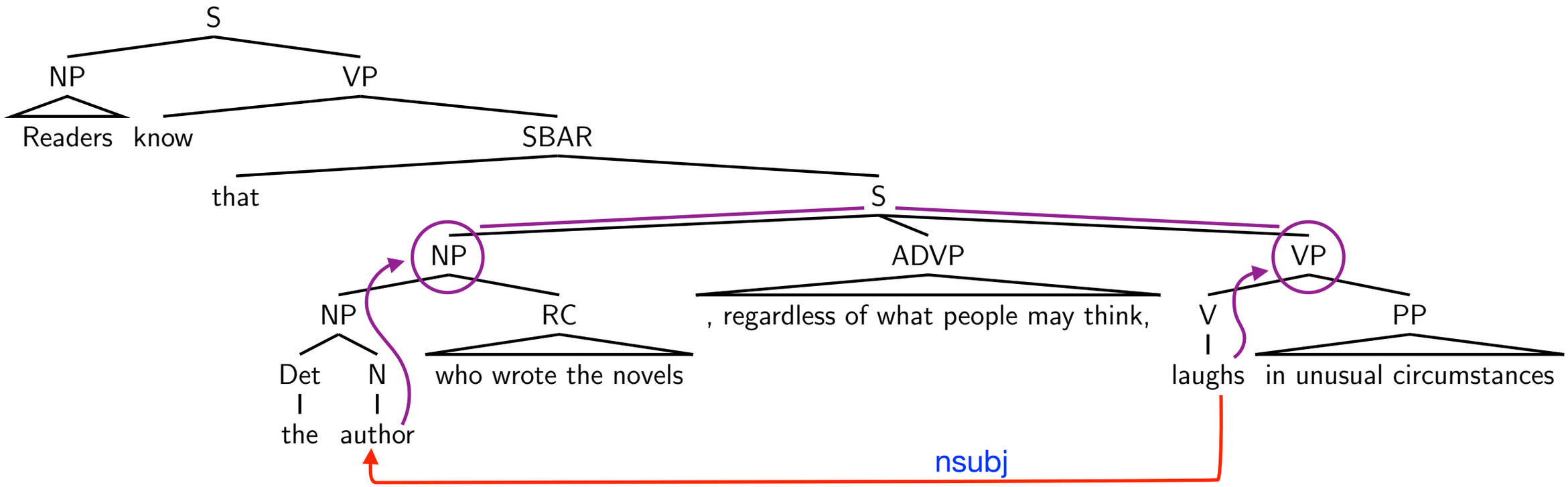
The **author** of the novels **laughs.**
*The **author** of the novels **laugh.**

"*Attractor*"

Embedding in complement clause:

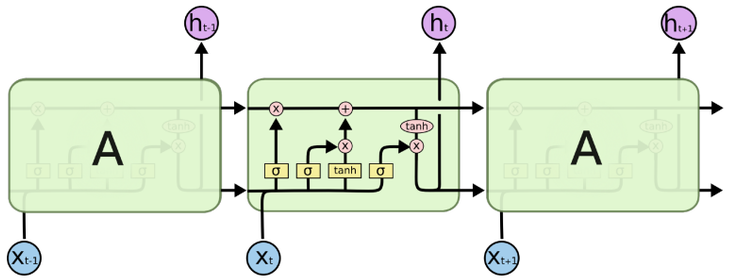
Readers know that the **author laughs.**
*Readers know that the **author laugh.**

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

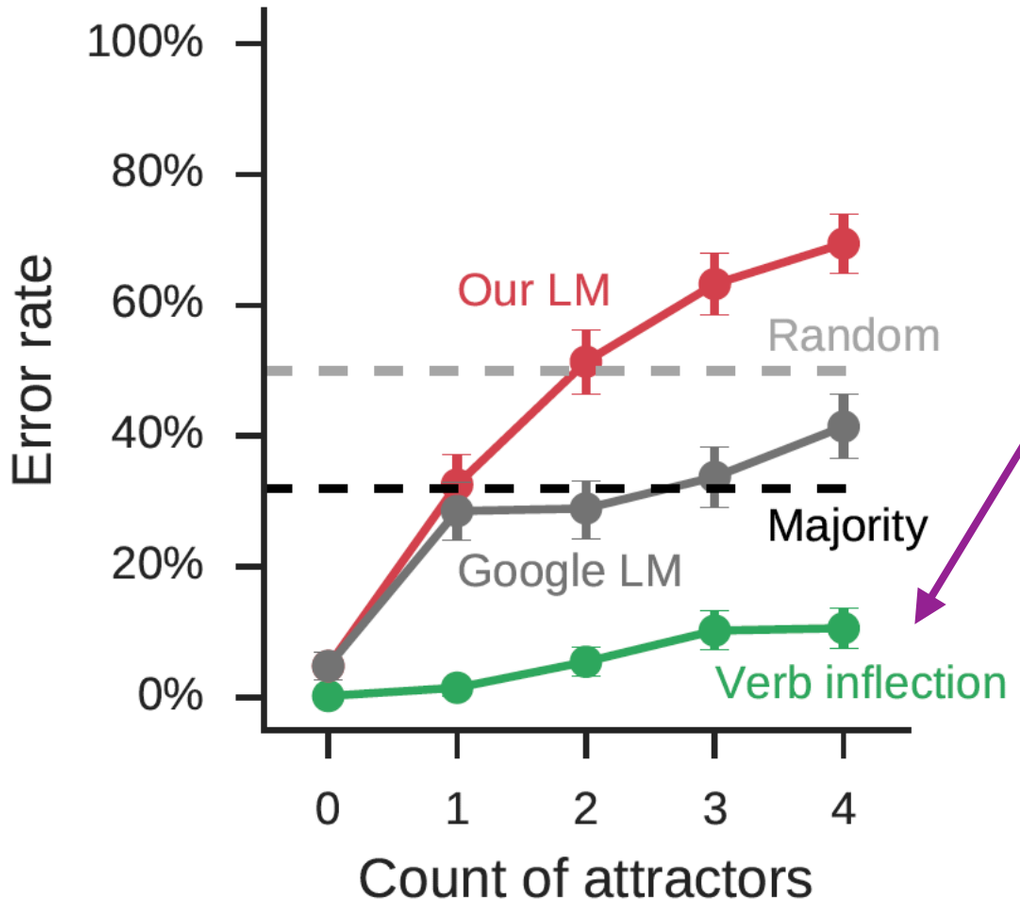


Testing NLMs on subject–verb agreement

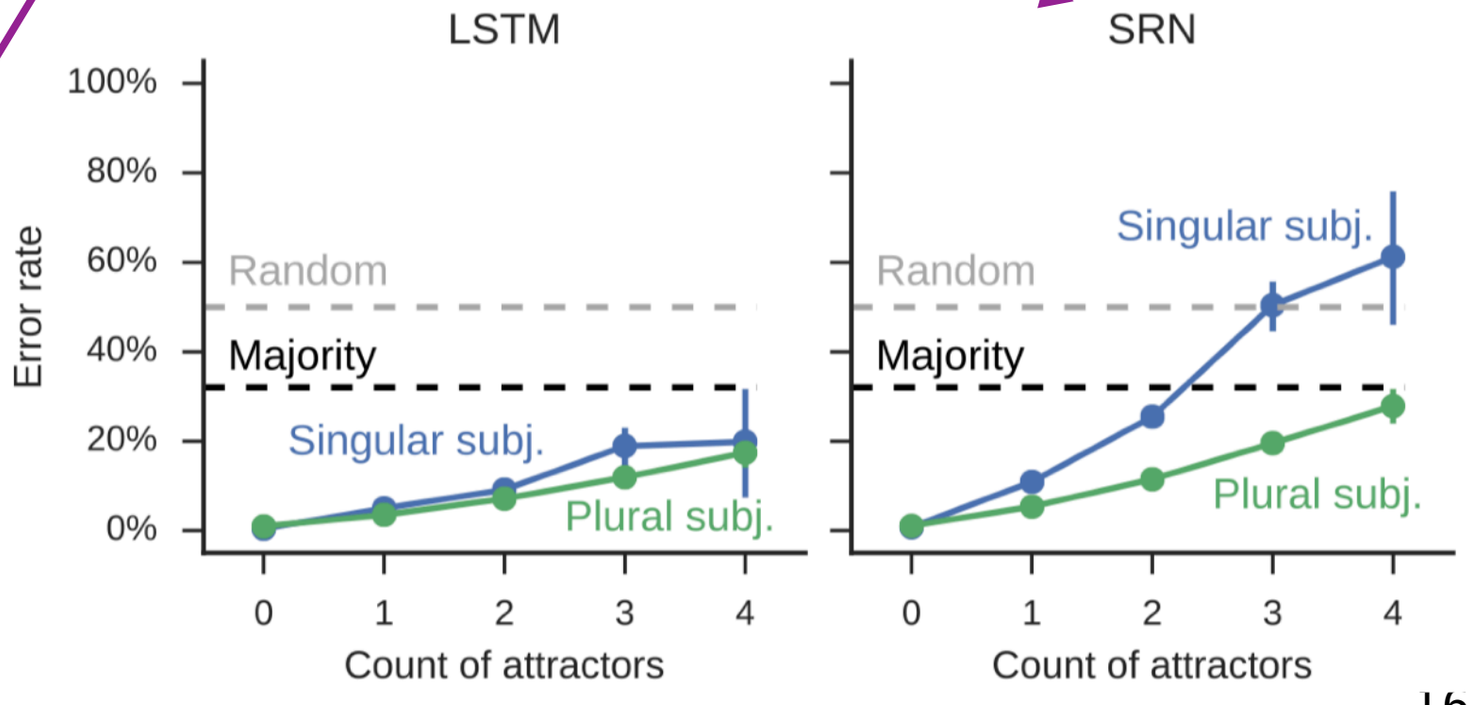
$$P(\texttt{is}|\text{Context}) \overset{?}{>} P(\texttt{are}|\text{Context})$$



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



RNN models trained solely for the verb inflection task



(Linzen et al., 2016)

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."

https://afterdeadline.blogs.nytimes.com/2016/03/08/ugly-disagreements-4/

Psycholinguistics of subject–verb agreement

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

`The key to the cabinets...`

The key to the cabinets was on the table.

The key to the cabinets doesn't work anymore.

The key to the cabinets are rusty.

The key to the cabinets would be really helpful to have right now!

The keys to the cabinets are in my pocket.

$\frac{1}{3} = 33\,\%$ error rate

sg sg `The key to the cabinet...`

sg pl `The key to the cabinets...`

pl sg `The keys to the cabinet...`

pl pl `The keys to the cabinets...`

(Bock & Miller, 1991; Eberhard et al., 2005; Franck et al., 2002; Wagers et al., 2009; many others)

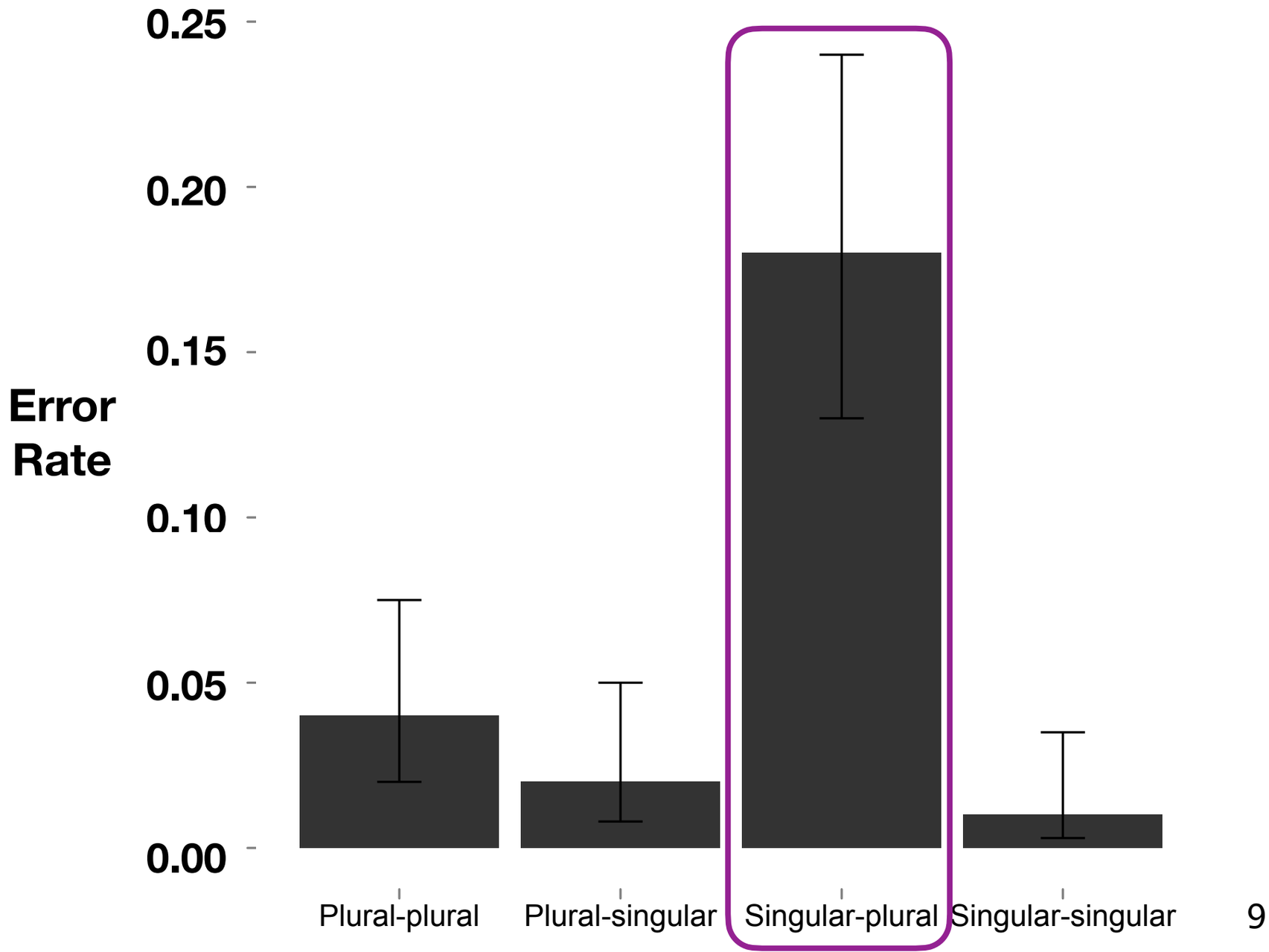
Production error rates

sg sg The key to the cabinet...

sg pl The key to the cabinets...

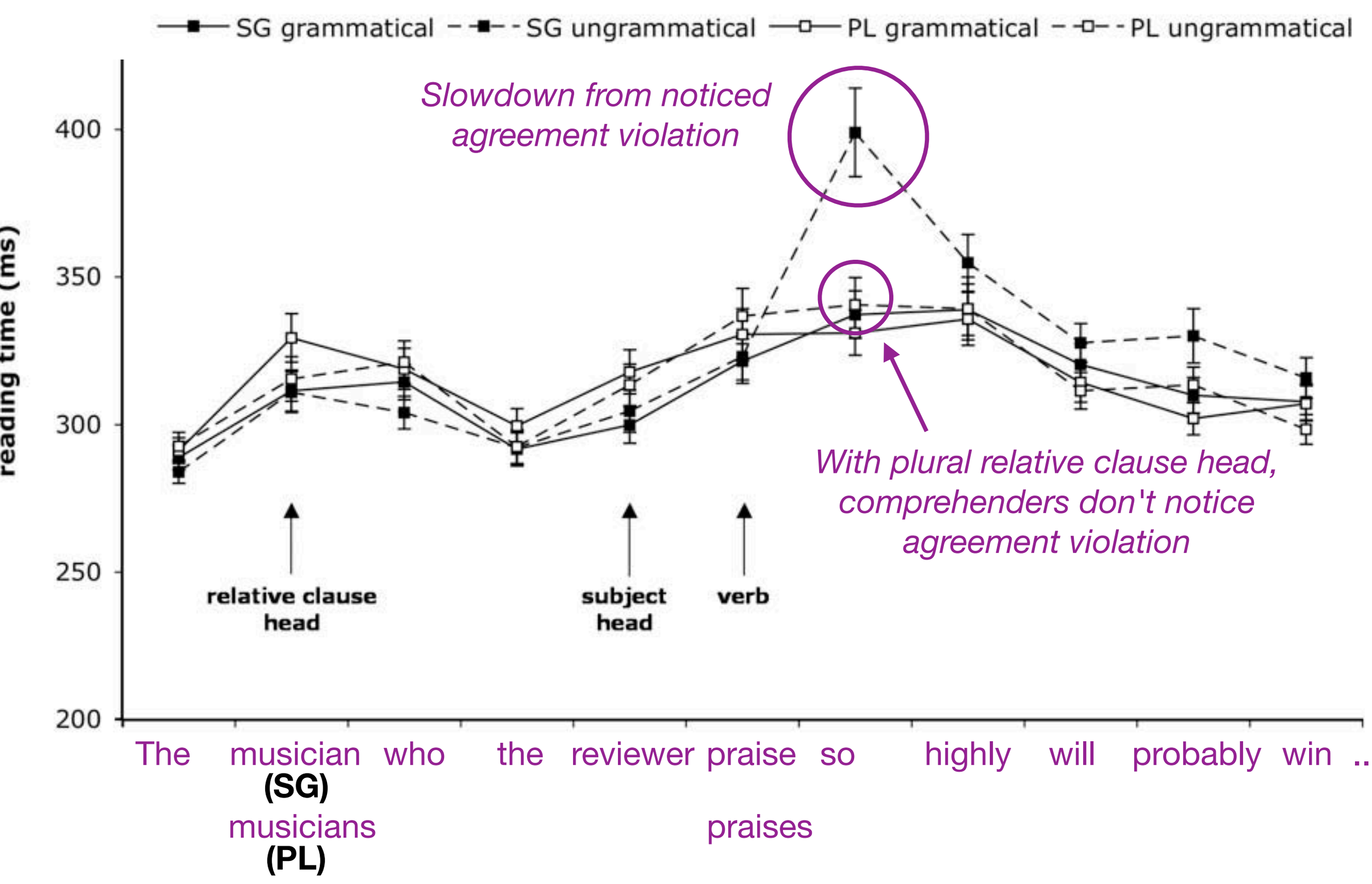
pl sg The keys to the cabinet...

pl pl The keys to the cabinets...



(Bock & Miller, 1991; data from Bergen & Gibson, unpublished)

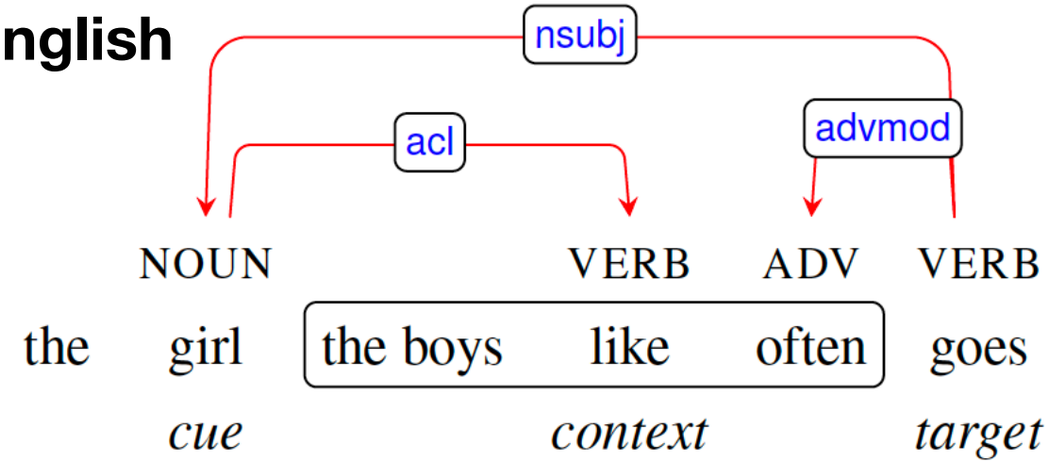
Comprehension of agreement errors



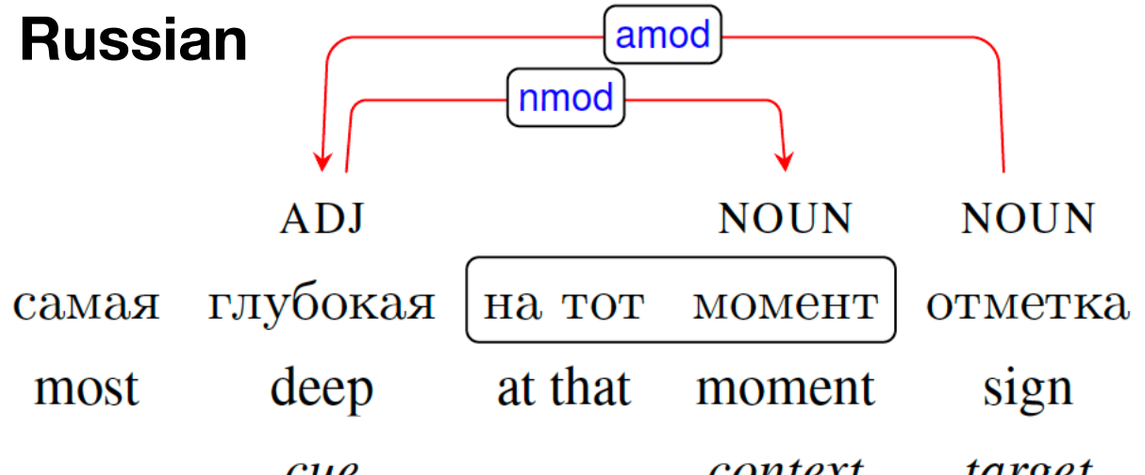
(Wagers et al., 2009)

Corpus-based long-distance agreement benchmark

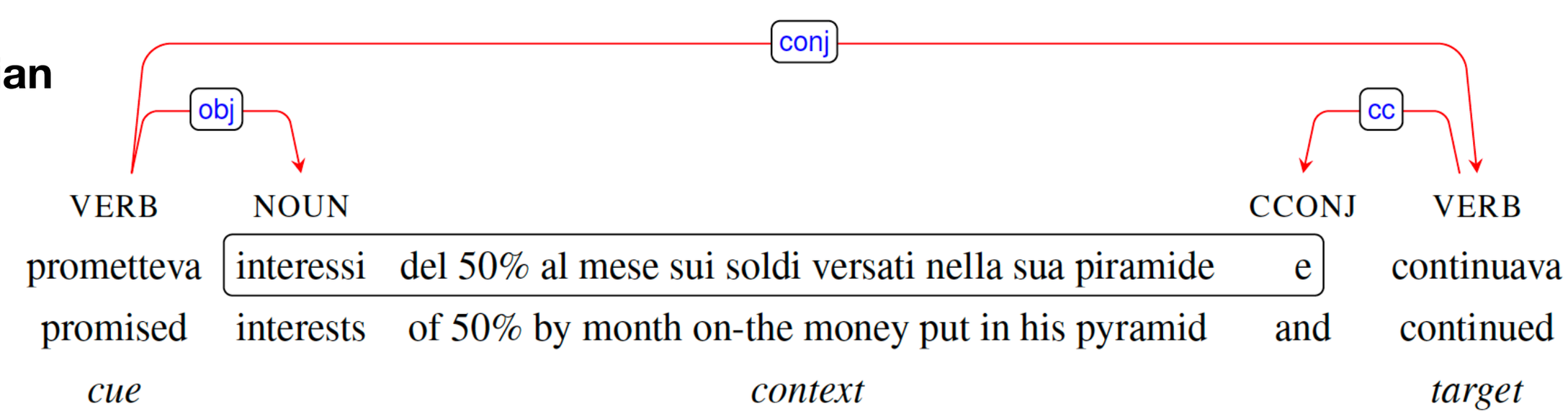
English



Russian



Italian

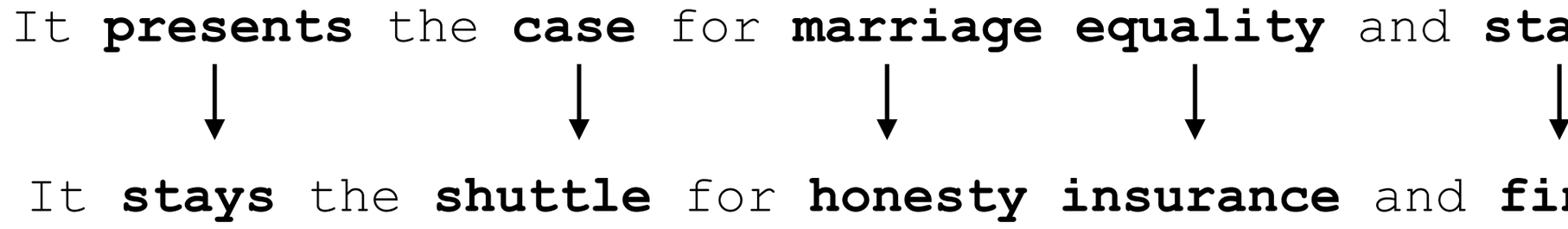


Hebrew (not shown)

(Gulordava et al., 2018)

Real and "artificial" examples

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



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

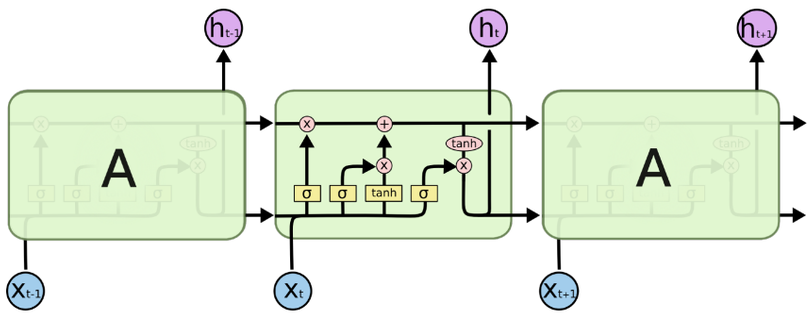
The sauce to recruit in pastor advise|advises

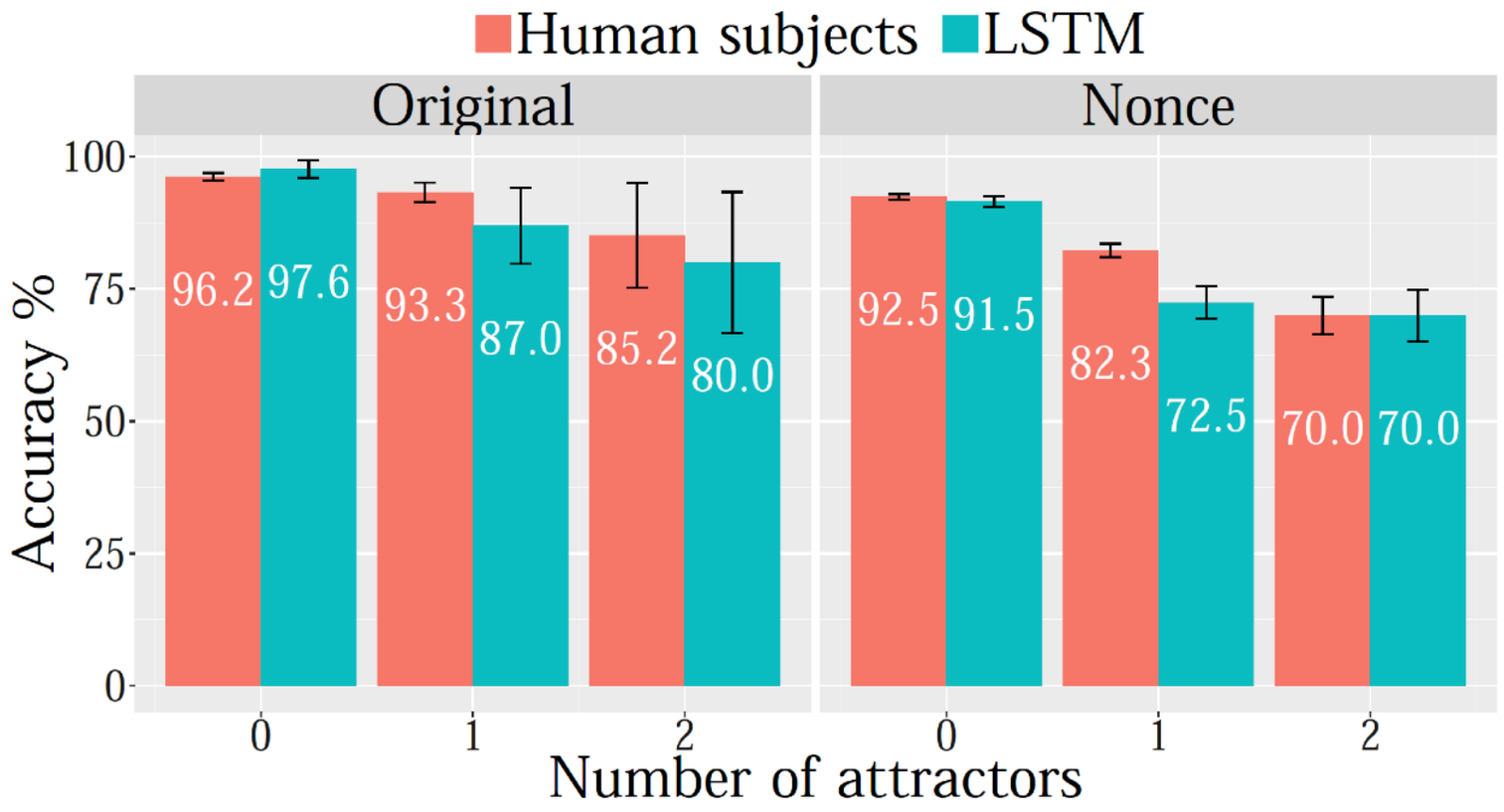
Can you expire that the ground we are happening produce|produces

(Gulordava et al., 2018)

Human and LSTM performance

90m words per language





Construction	#original	Original		Nonce	
		Subjects	LSTM	Subjects	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

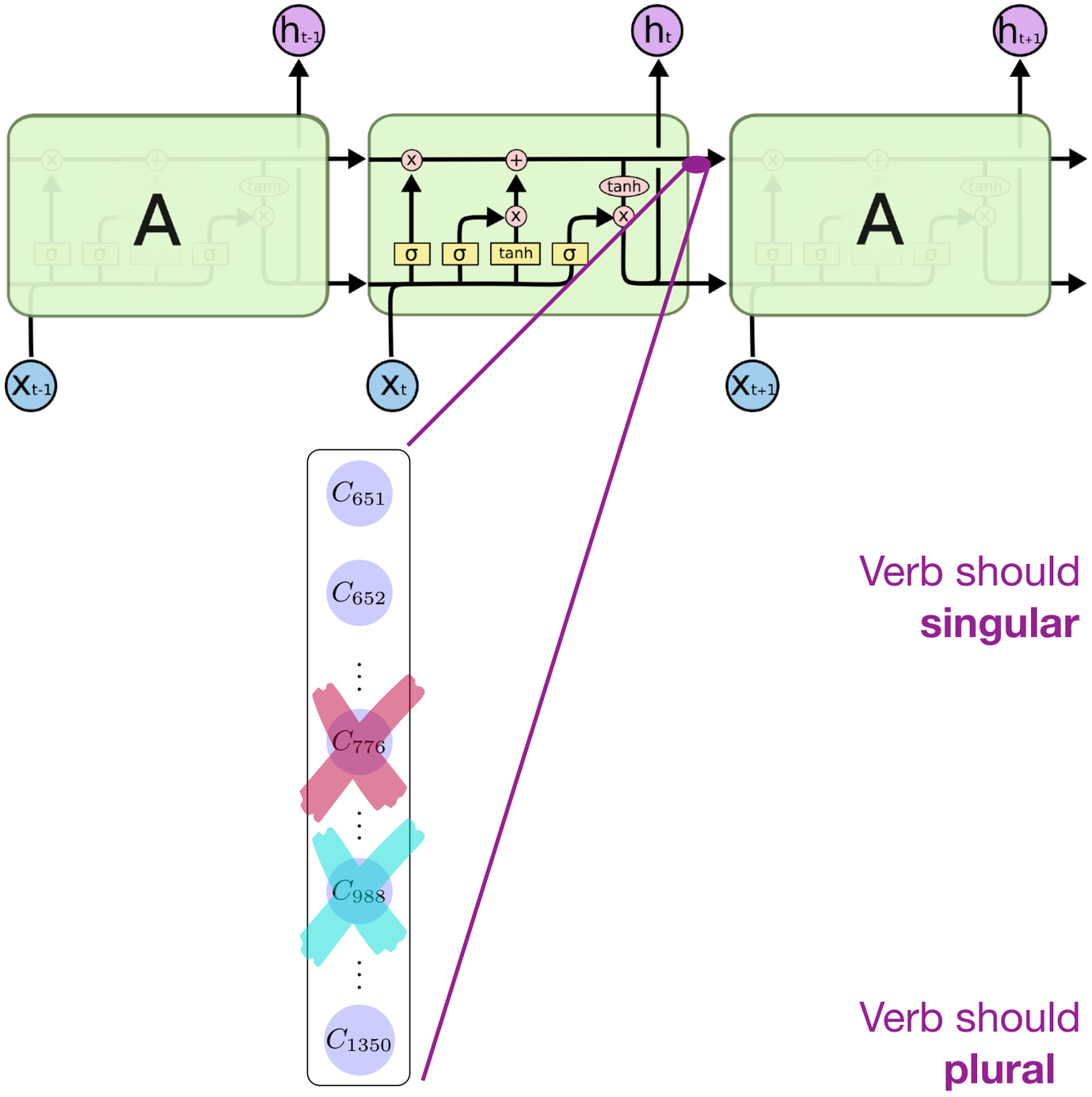
- Frequency *in naturalistic usage* is important for understanding our linguistic environment & for applications
- But targeted evaluation, where *we choose the stimuli*, may reveal more to us about a system

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`
⋮	⋮

	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



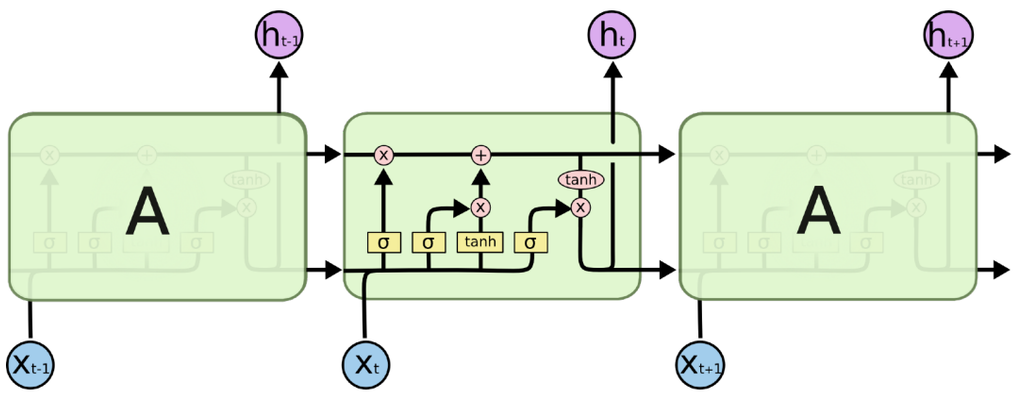
Verb should be **singular**

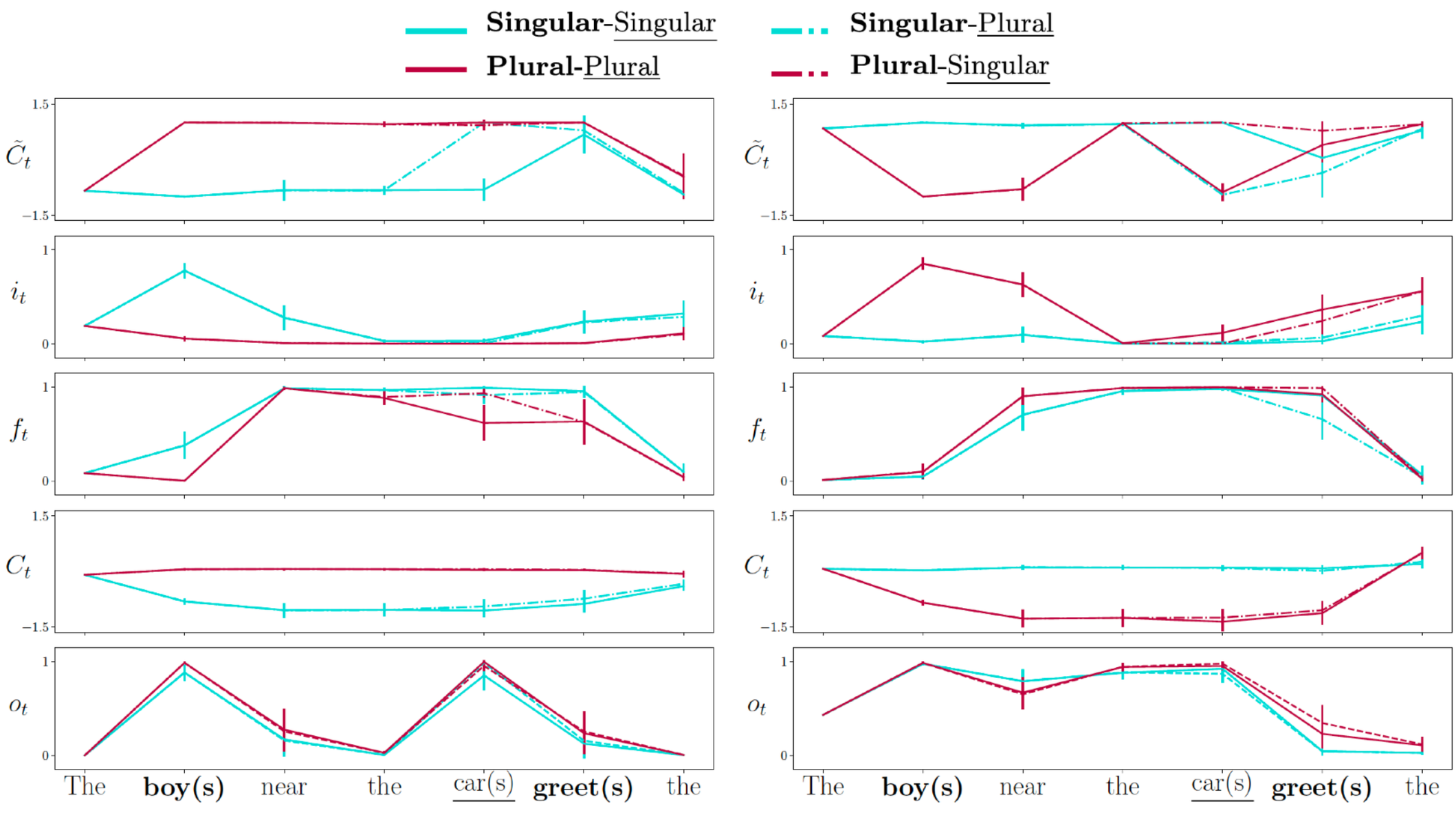
Verb should be **plural**

NA task	C	Ablated		Full
		776	988	
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
nounPPAdv	PP	-	-	99.8

(Lakretz et al., 2019)

LSTM learned circuitry for S–V agreement





(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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