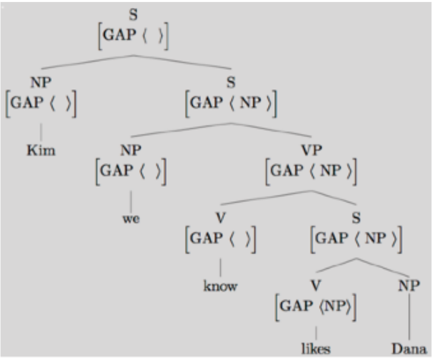
Predictive processing in human language comprehension

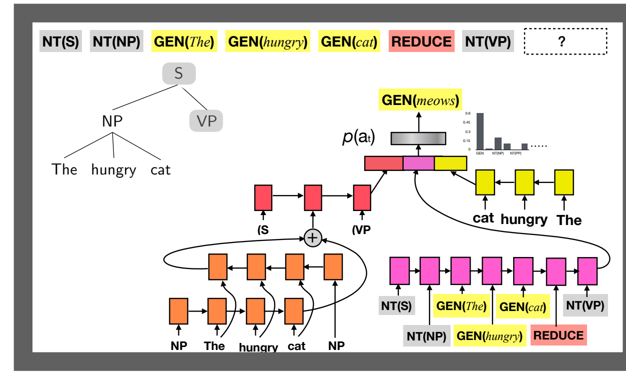
Roger Levy

9.19/9.190: Computational Psycholinguistics
November 8, 2023

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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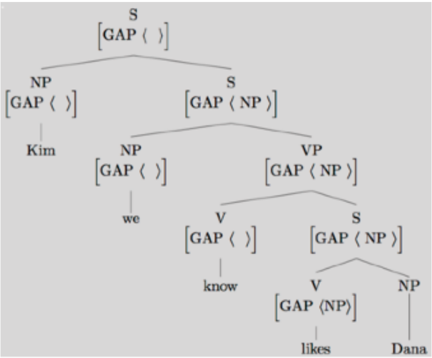

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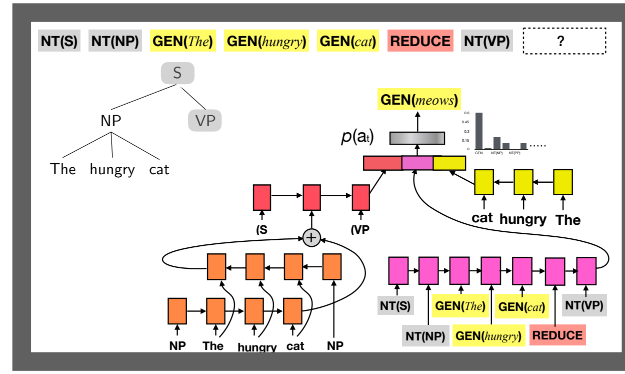

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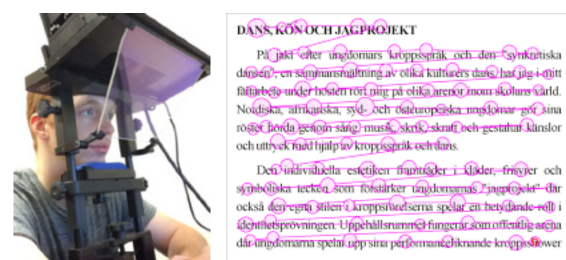
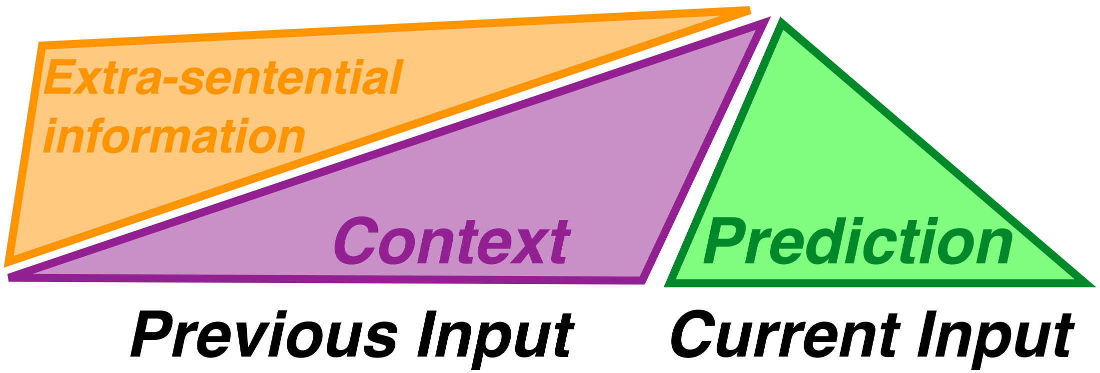


Expectations in incremental comprehension



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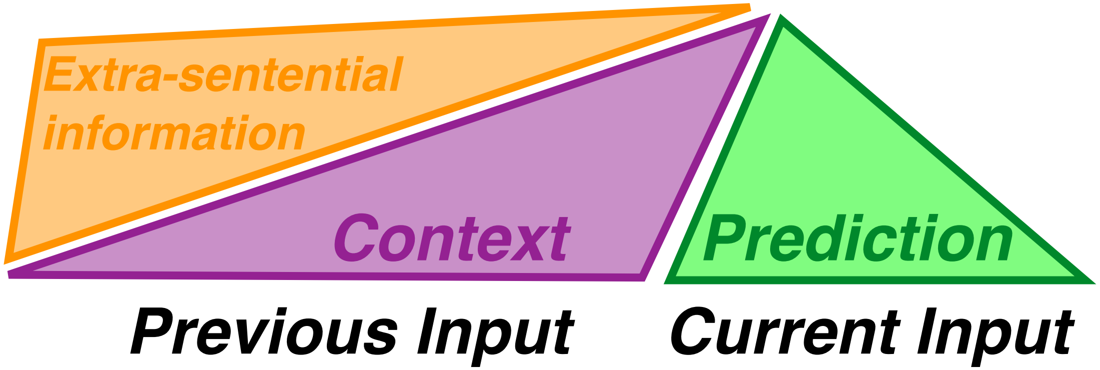
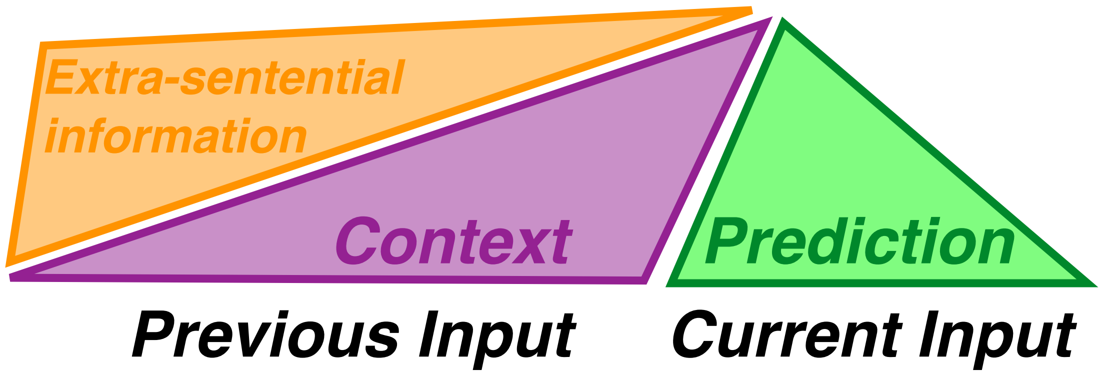


- Syntactic:

  Jamie was clearly intimidated…

Expectations in incremental comprehension



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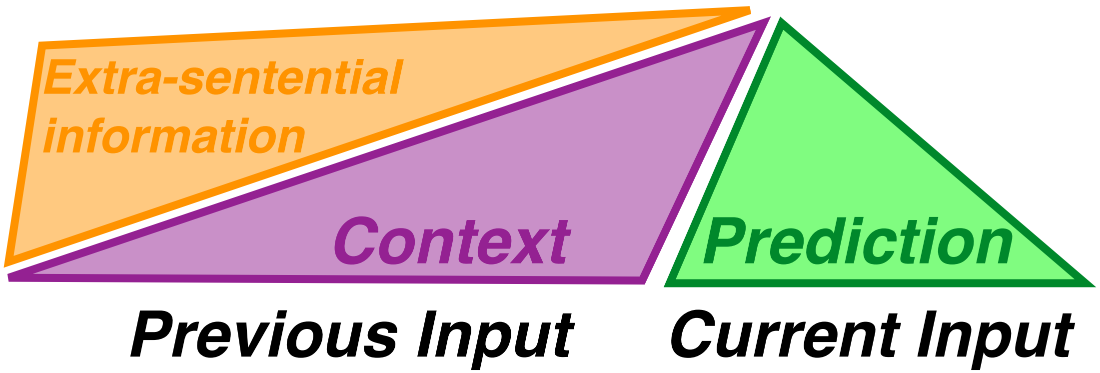

- Syntactic:

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- Phonological knowledge:

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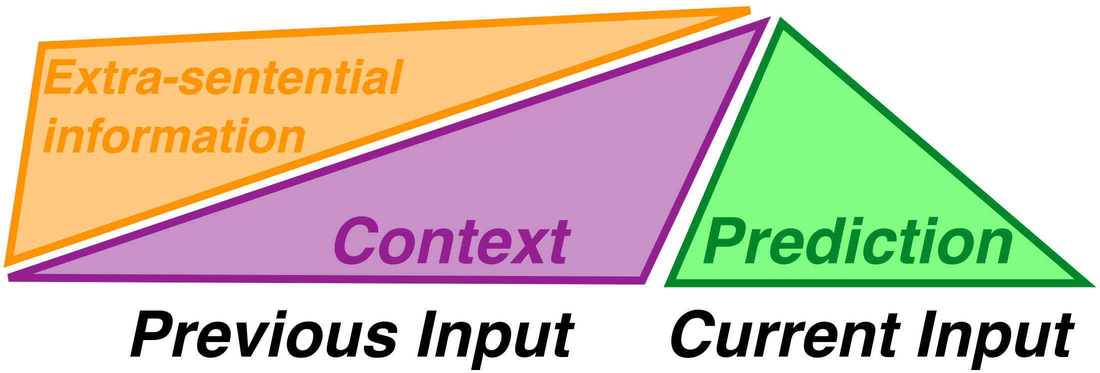

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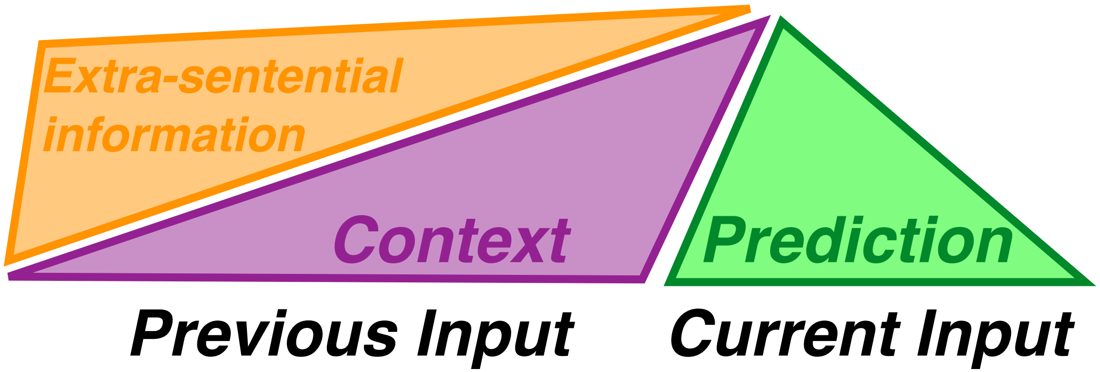

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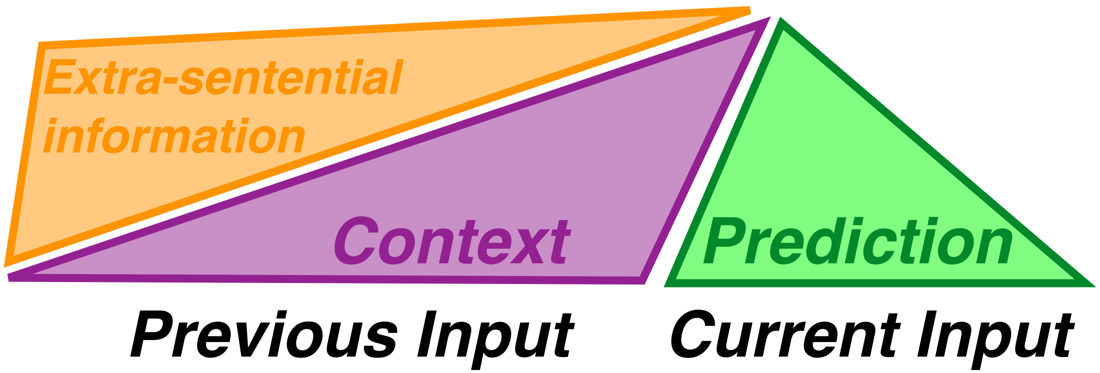

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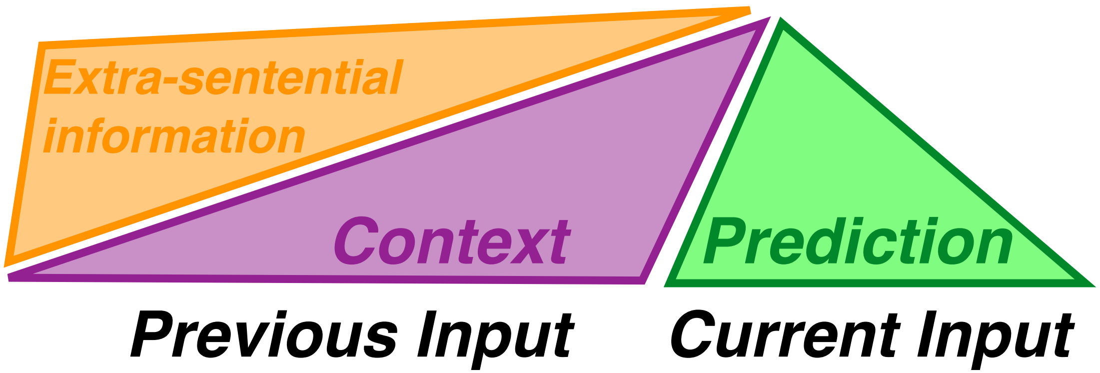

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- Semantic & situational knowledge:

  The children went outside to…

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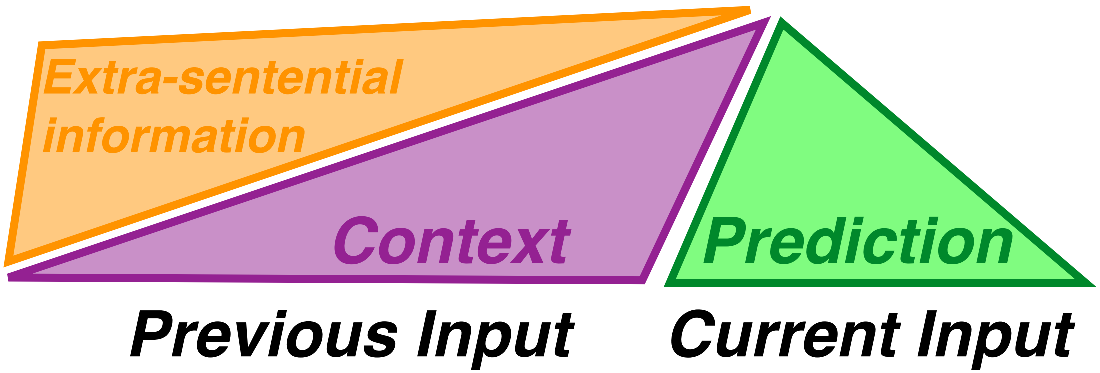

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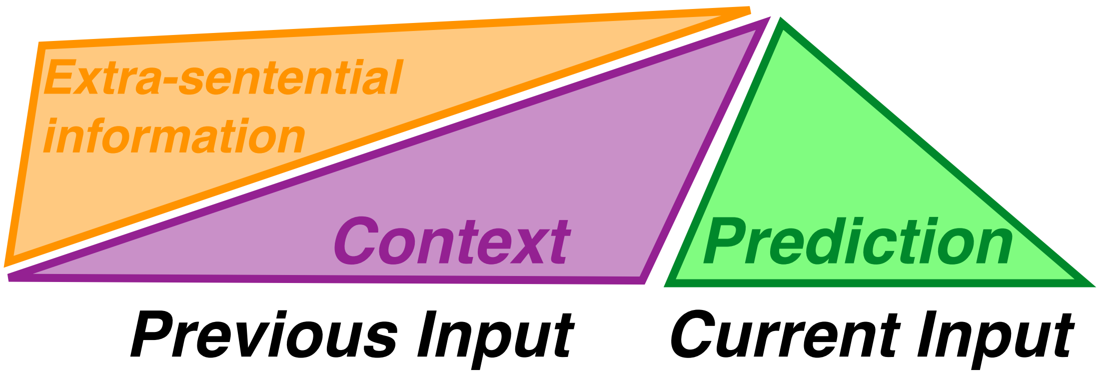

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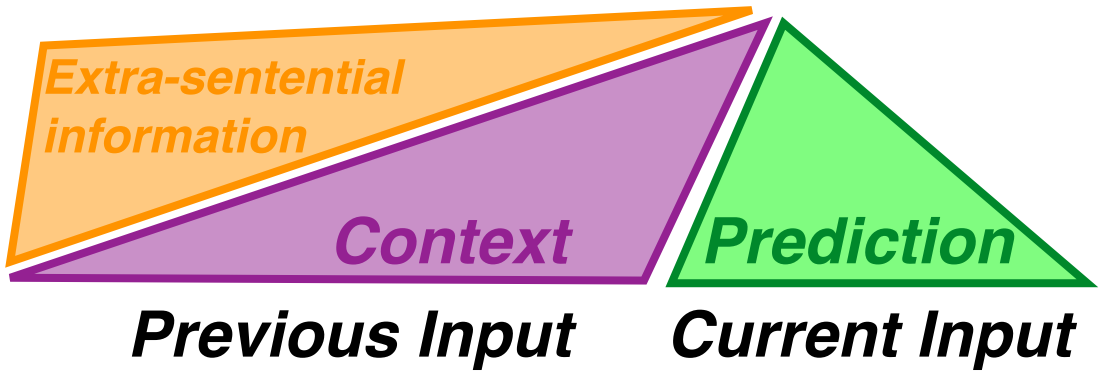

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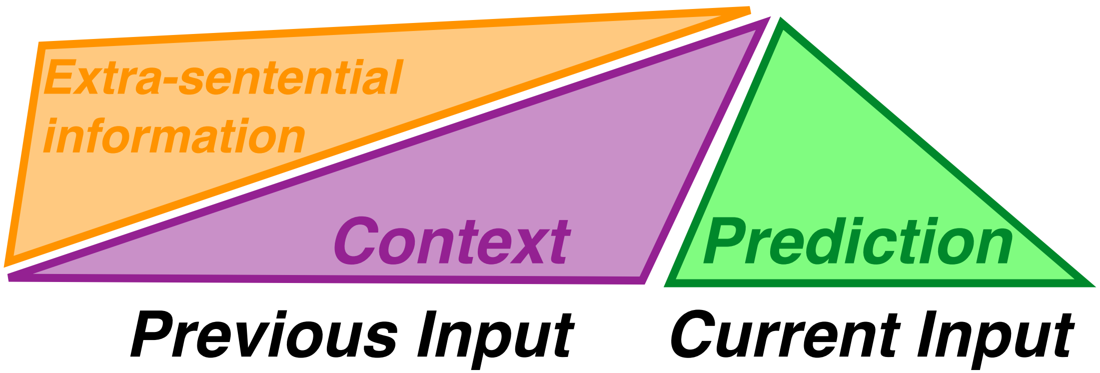

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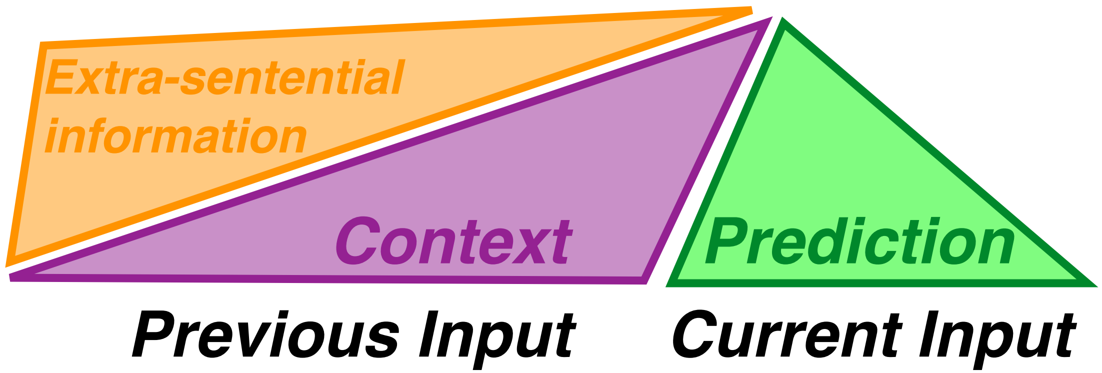
  The squirrel stored some nuts in the…~~statue~~

  tree

Expectations in incremental comprehension



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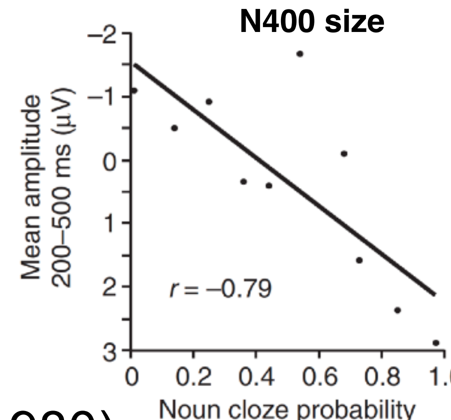
- Predictable words are:
  - read faster (Ehrlich & Rayner, 1981)
  - have distinctive EEG responses (Kutas & Hillyard 1980)



(Federmeier & Kutas, 1999)

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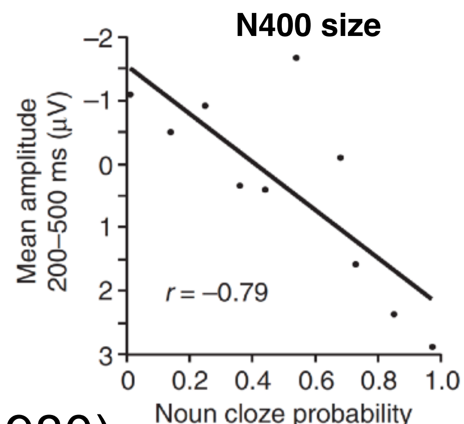


(Federmeier & Kutas, 1999)

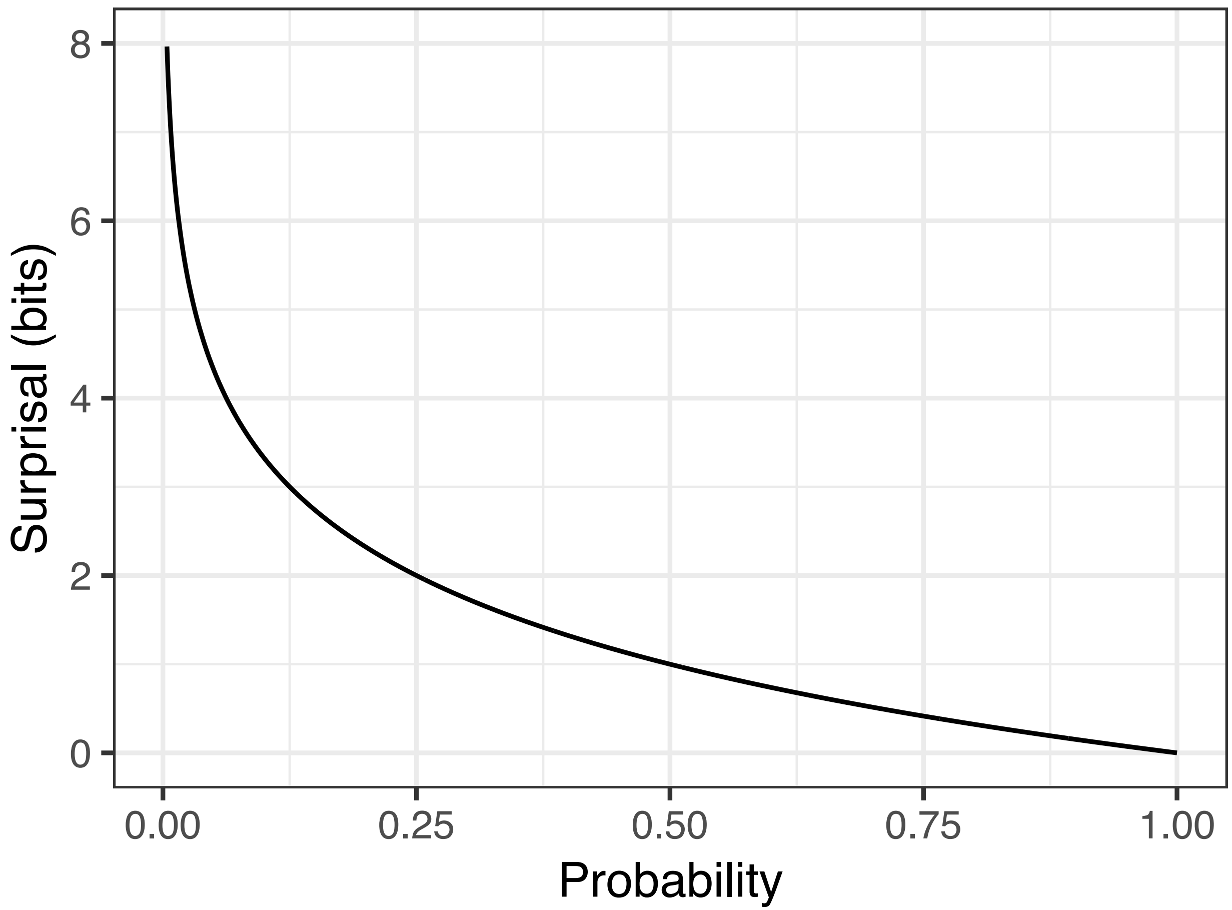
- Predictable words are:
  - read faster (Ehrlich & Rayner, 1981)
  - have distinctive EEG responses (Kutas & Hillyard 1980)
- with a language model that captures syntactic structure, we can get GRAMMATICAL EXPECTATIONS

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

Quantifying structure and surprise

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

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



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

Estimating probability/time curve shape

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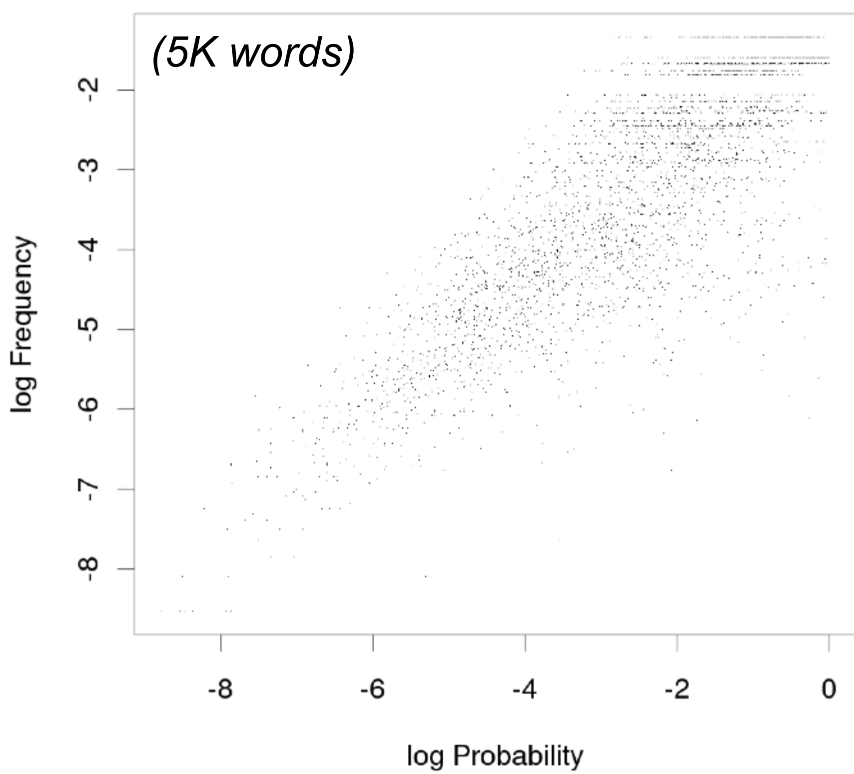
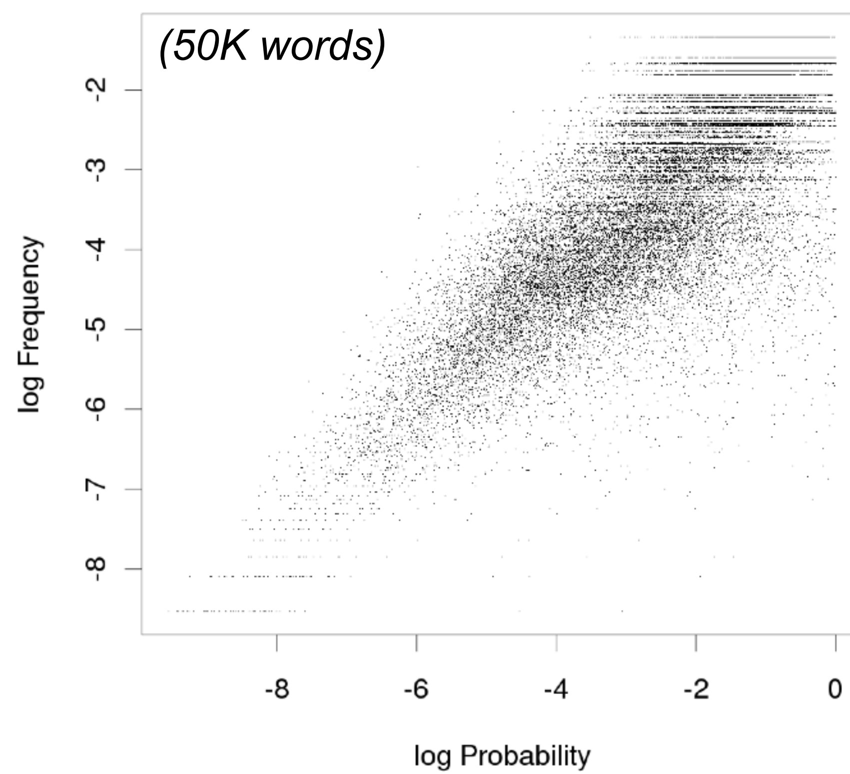
Brown data availability



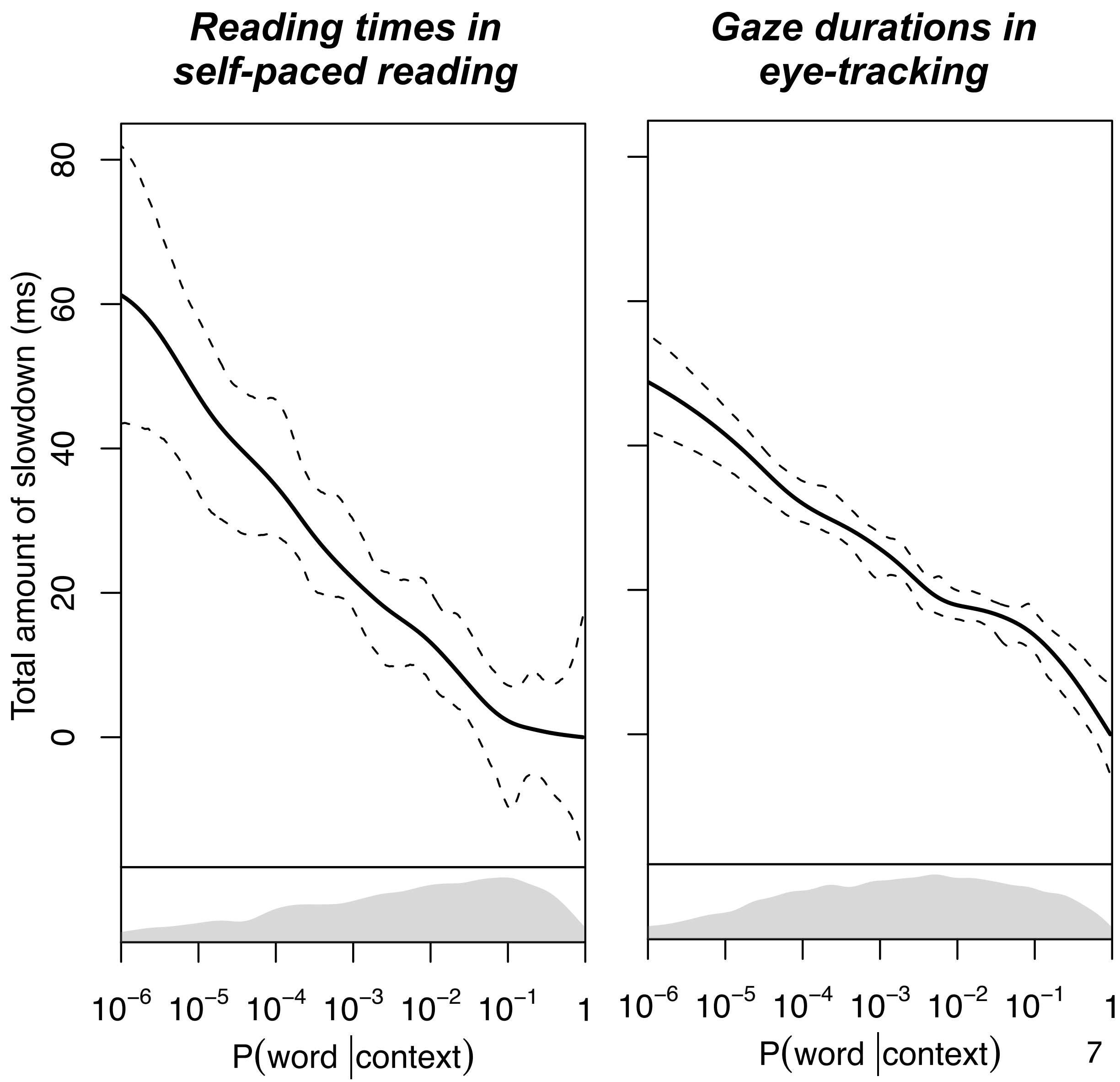
Dundee data availability



Estimating probability/time curve shape

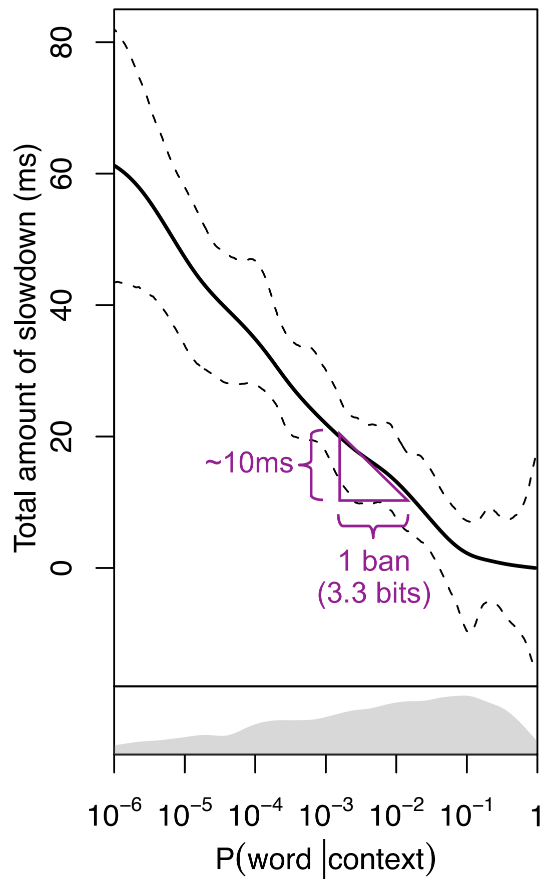
- Generalized additive model regression: total contribution of word (trigram) probability to RT near-linear over 6 orders of magnitude!

(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.

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

A model system with incrementality, structure, and surprise

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

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

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

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

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

	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.

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

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	Simple past	Past participle
bring	***brought***	***brought***
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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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F J

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of	dog
F	J

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of　　　　dog

[F]　　　　[J]

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pretty   chased

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the	eat
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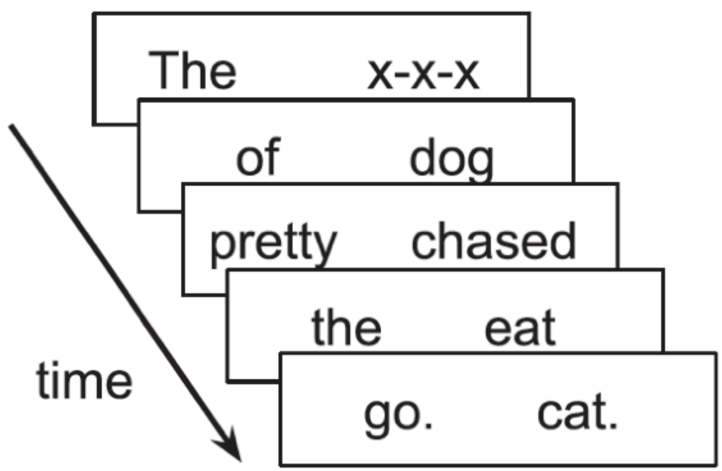

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Incrementality, structure, and surprise

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., 2021)

Incrementality, structure, and surprise

		Is the relative clause reduced?
The woman brought the sandwich from the kitchen tripped.	(red line)	+
The woman given the sandwich from the kitchen tripped.	(green line)	+
The woman who was brought the sandwich from the kitchen tripped.	(cyan line)	–
The woman who was given the sandwich from the kitchen tripped.	(purple line)	–

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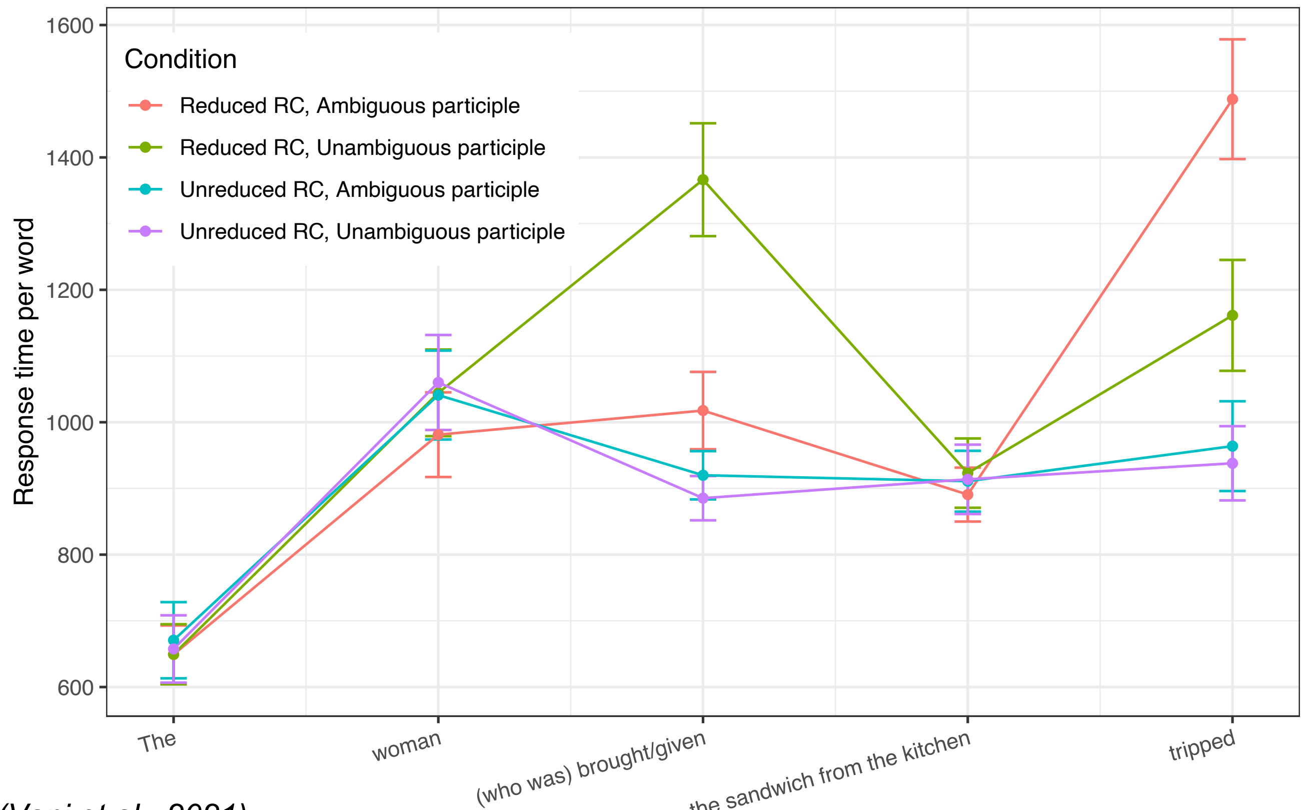

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Desiderata for human-like processing

	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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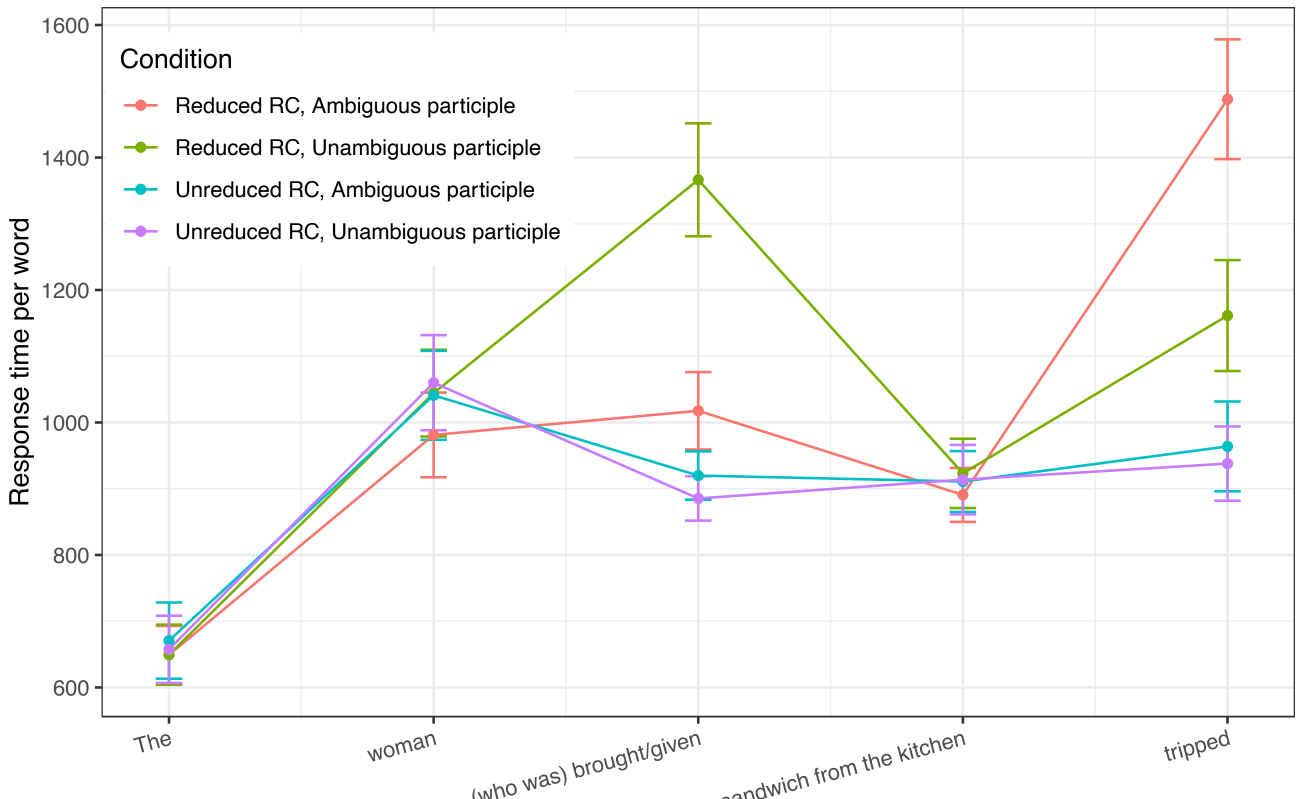

(Futrell et al., 2019; Hu et al., 2020; Gauthier et al., 2020; Vani et al., 2021)

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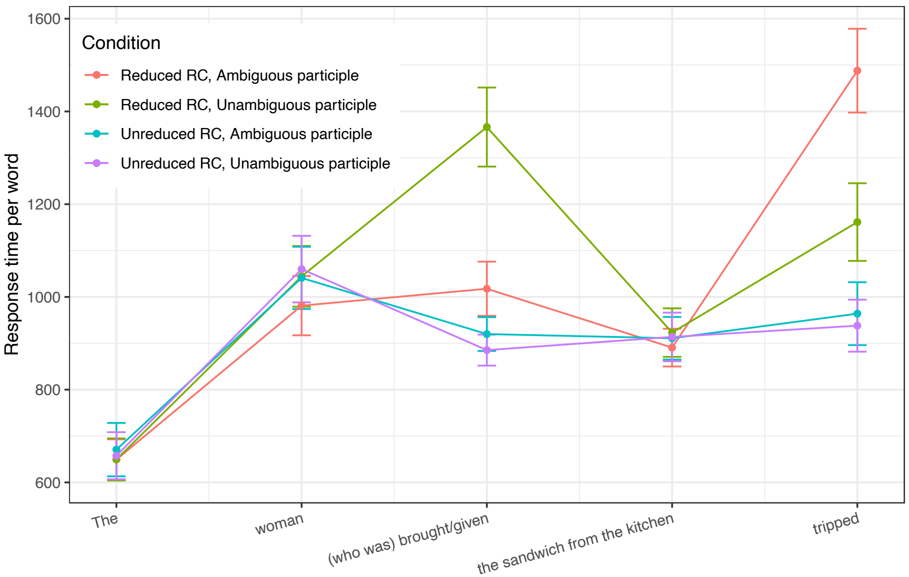

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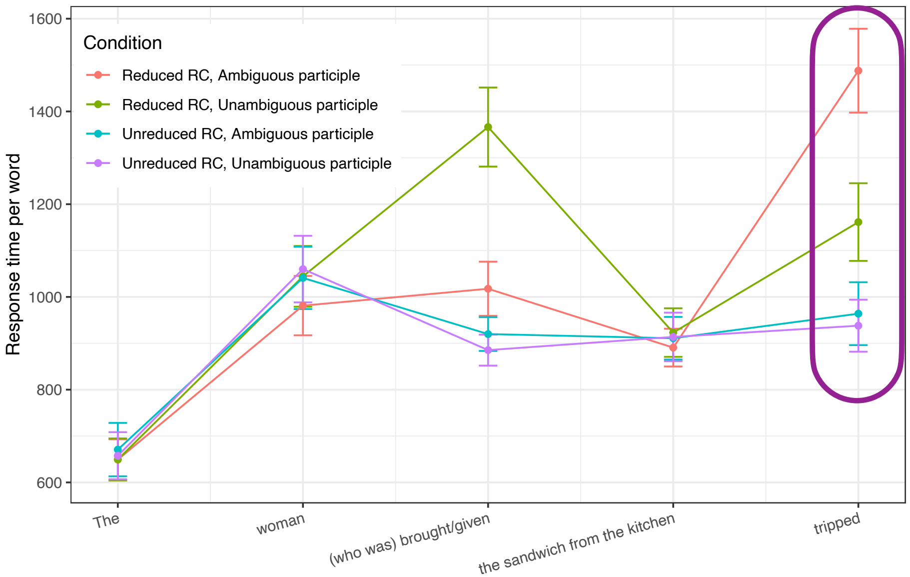

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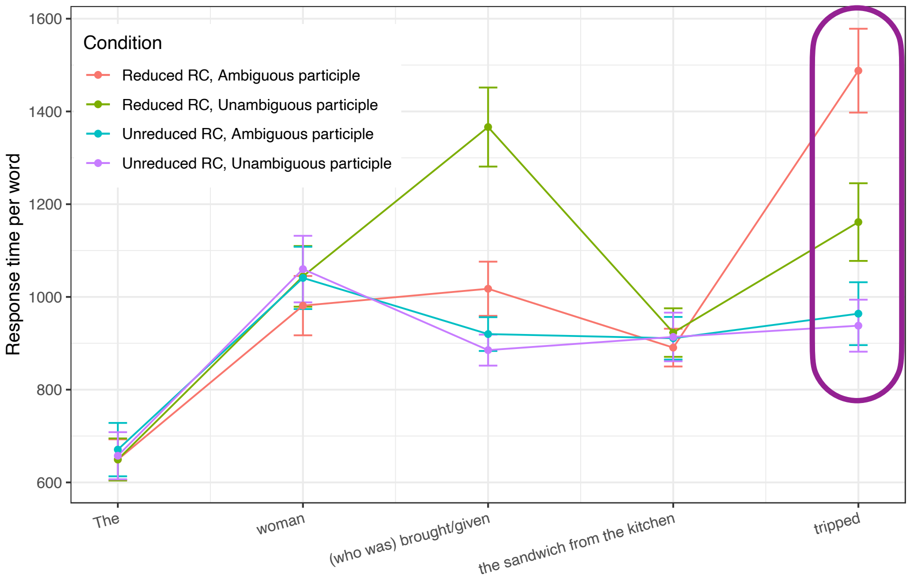
The woman brought the sandwich from the kitchen tripped.	a	+	+
The woman given the sandwich from the kitchen tripped.	b	+	–
The woman who was brought the sandwich from the kitchen tripped.	c	–	+
The woman who was given the sandwich from the kitchen tripped.	d	–	–



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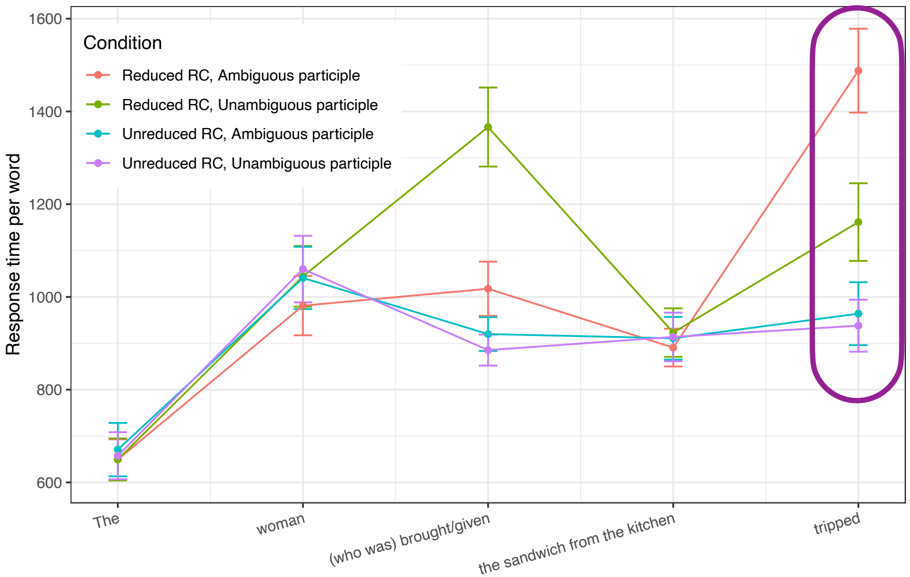


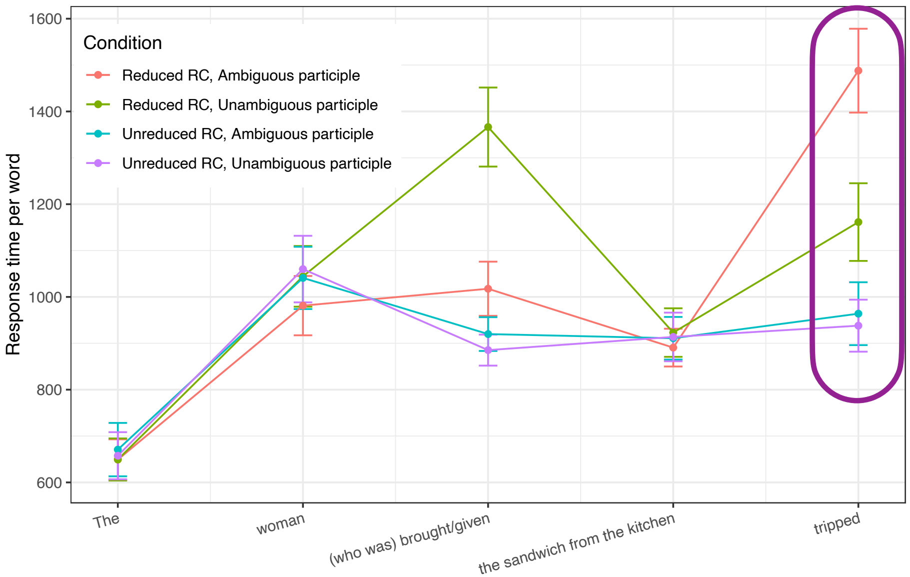
Define:

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

(Futrell et al., 2019; Hu et al., 2020; Gauthier et al., 2020; Vani et al., 2021)

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.	a	+	+
The woman given the sandwich from the kitchen tripped.	b	+	–
The woman who was brought the sandwich from the kitchen tripped.	c	–	+
The woman who was given the sandwich from the kitchen tripped.	d	–	–



Define:

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

(Futrell et al., 2019; Hu et al., 2020; Gauthier et al., 2020; Vani et al., 2021)

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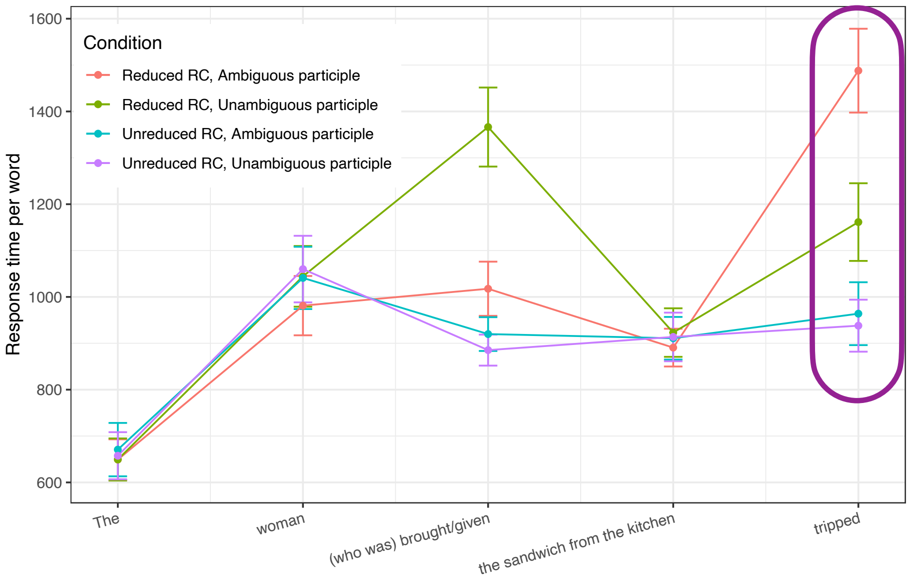

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Then we can define three criteria for "human-like" processing:

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

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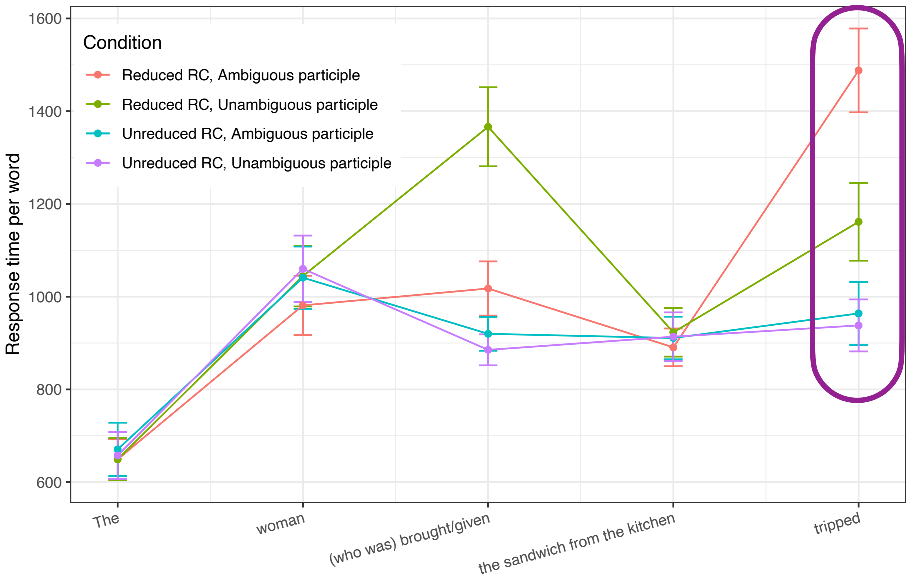

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(ii) $S(a) > S(c)$

(Futrell et al., 2019; Hu et al., 2020; Gauthier et al., 2020; Vani et al., 2021)

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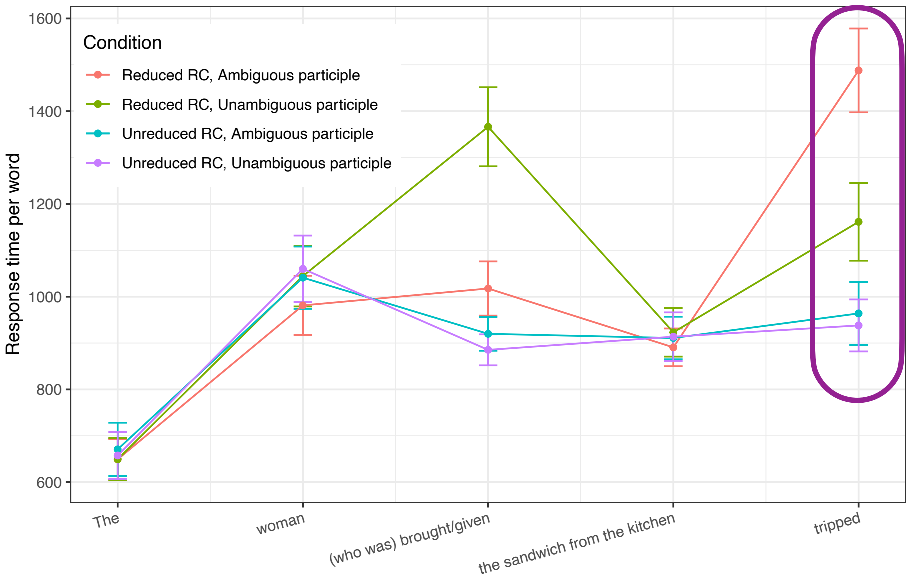


Define:

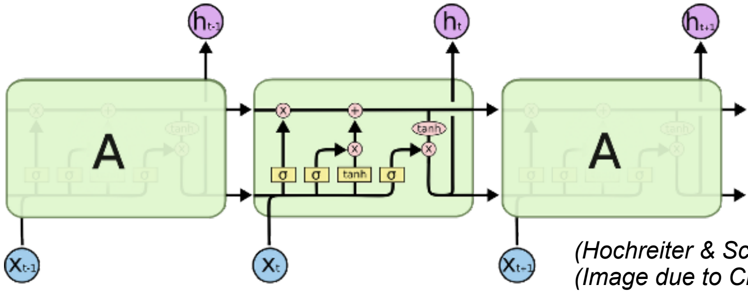
$$S(x) = \log \frac{1}{P(\text{tripped} \mid \text{Context}_x)}$$

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

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

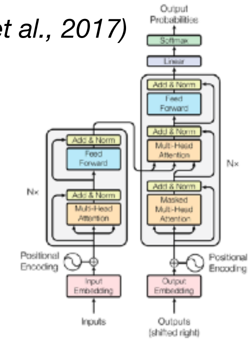
(Futrell et al., 2019; Hu et al., 2020; Gauthier et al., 2020; Vani et al., 2021)

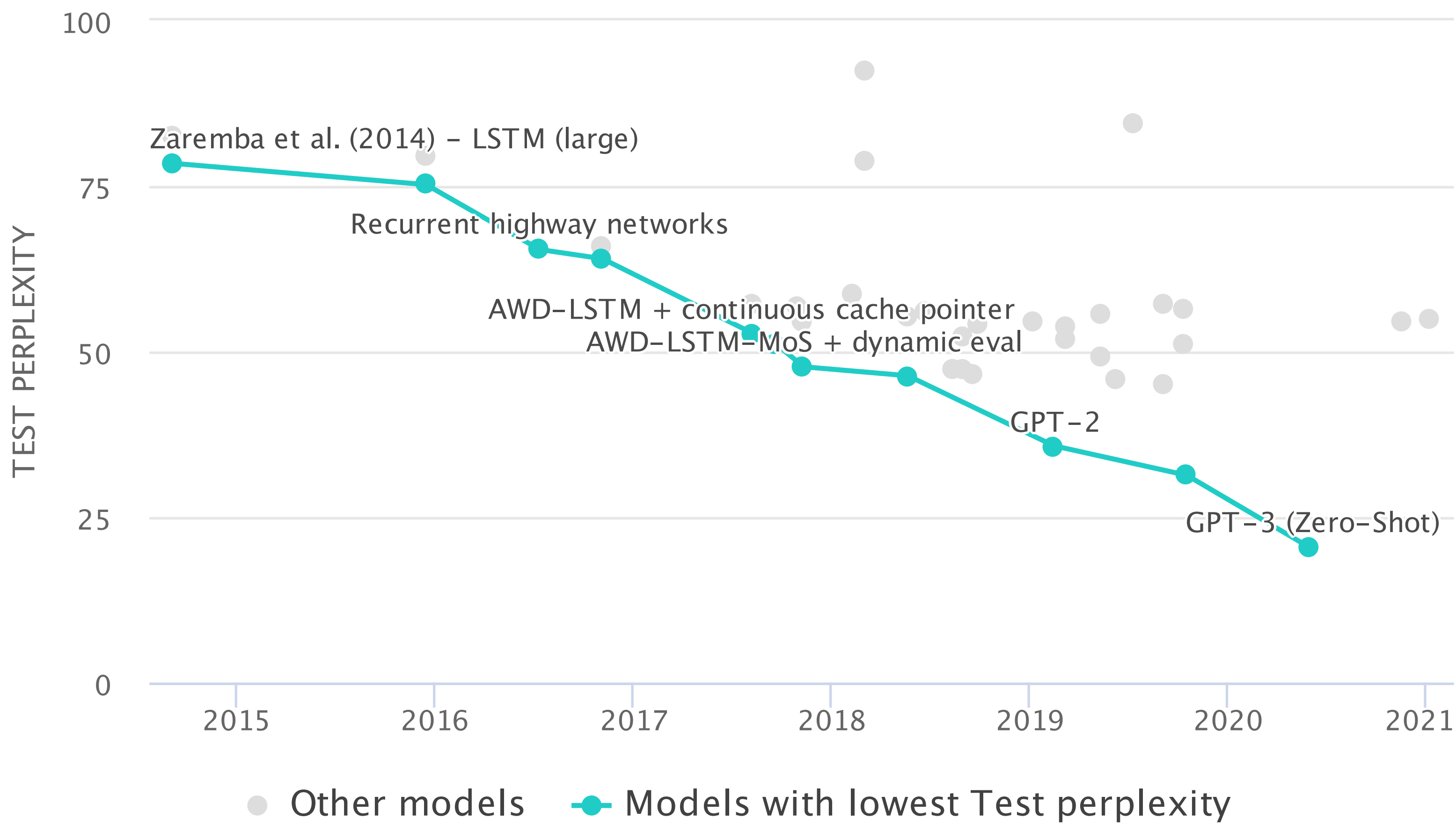
Deep learning has revolutionized language modeling



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

(Vaswani et al., 2017)

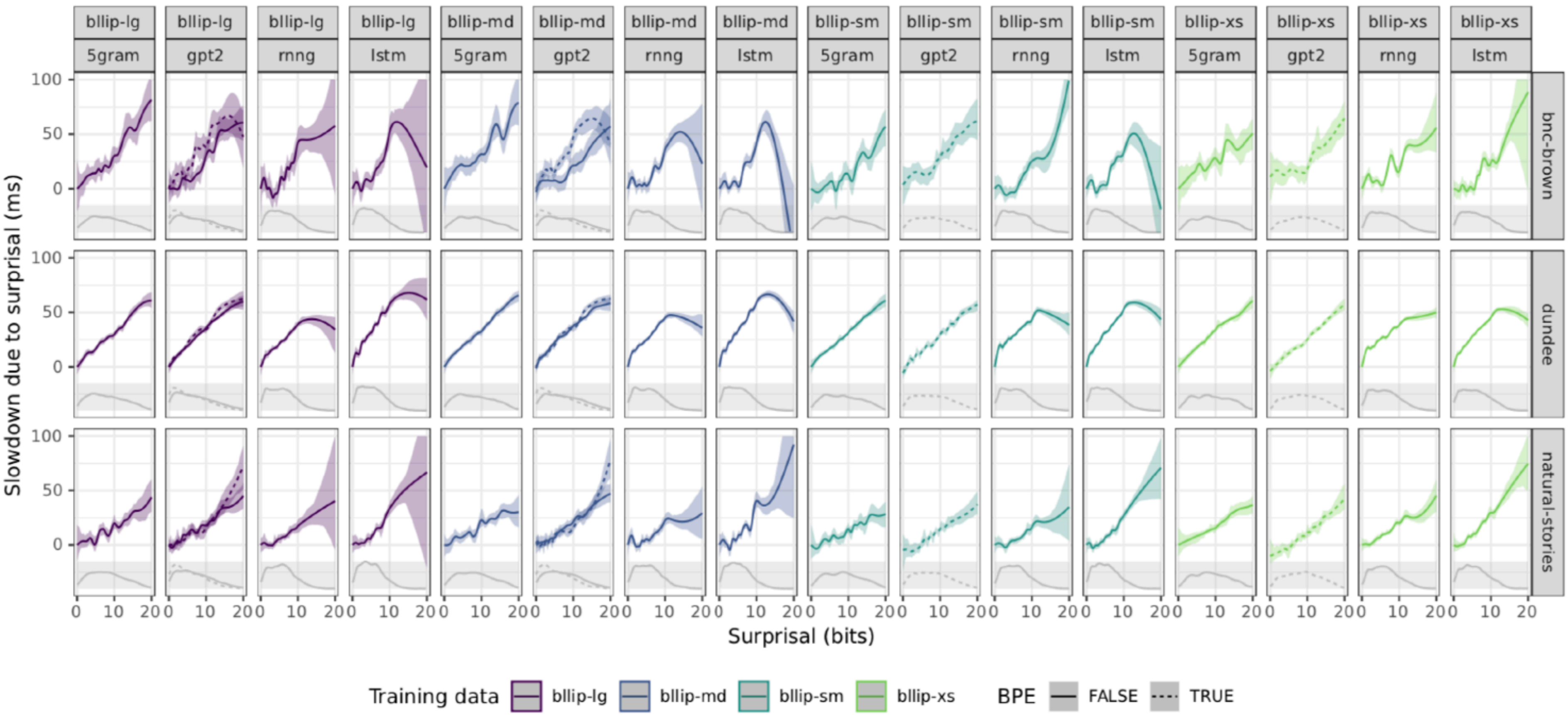




https://paperswithcode.com/sota/language-modelling-on-penn-treebank-word

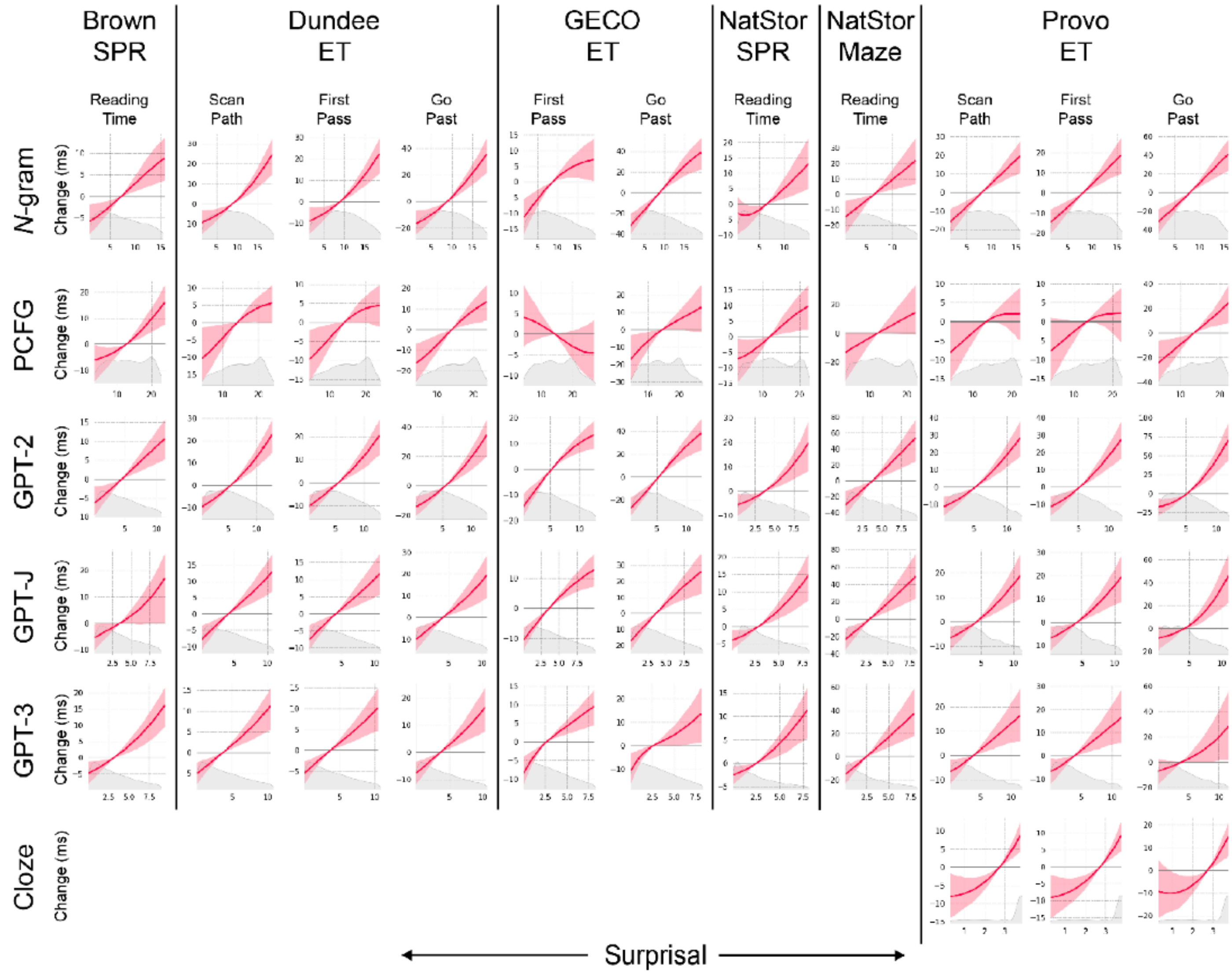
Quantitative calibration to human processing

- The surprisal–RT relationship in naturalistic reading:



(Wilcox et al., 2020)

Quantitative calibration to human processing



(Shain et al., 2022)

Brain signatures of predictive processing

EEG

(Creator: Tim Sheerman-Case, CC-BY)

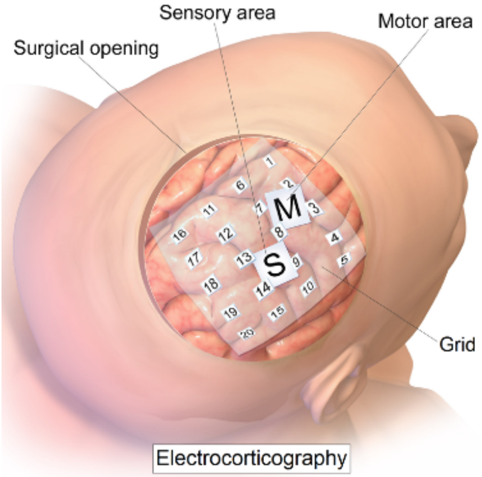
MEG

(Creator: J.M Eddings Jr, CC-BY-NC)

fMRI

(NIH Image Gallery, public domain)

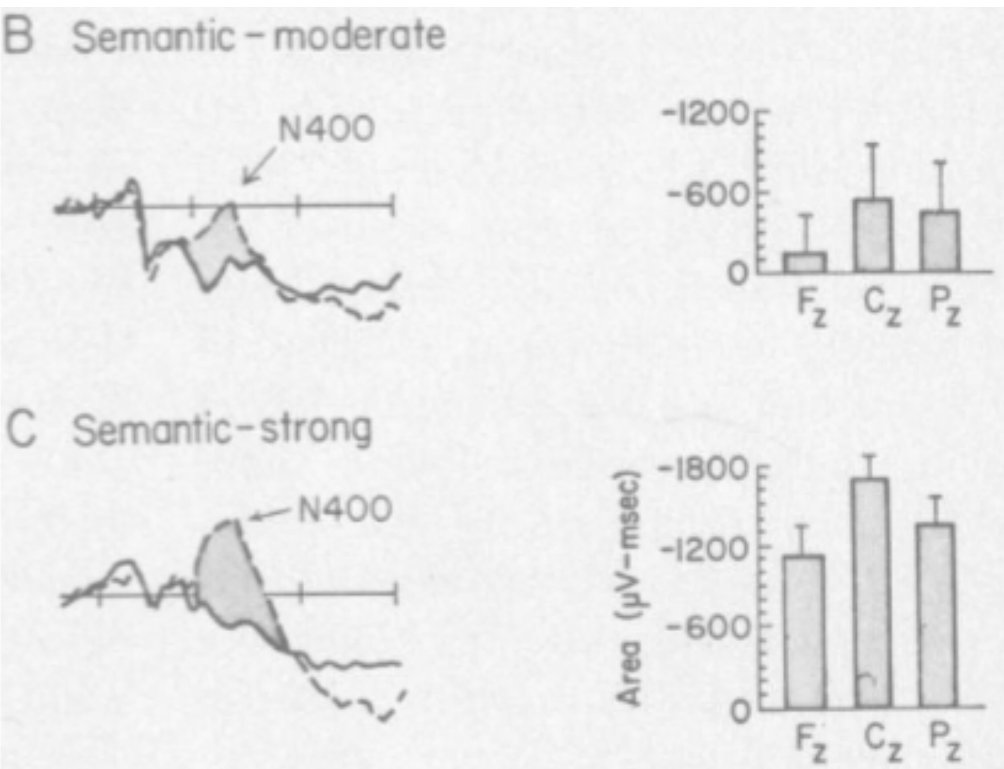
ECoG

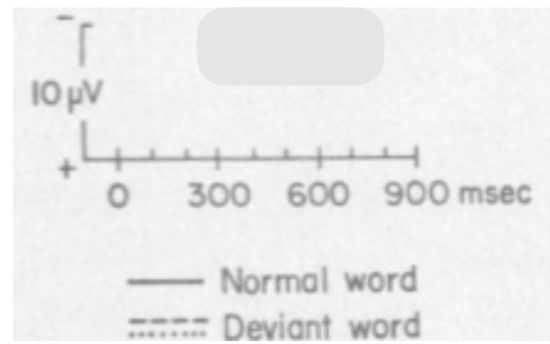


https://commons.wikimedia.org/wiki/File:Intracranial_electrode_grid_for_electrocorticography.png

The N400 in language comprehension

- Differing degrees of semantic congruity:
  - He took a sip from the *drink*. (normal)
  - He took a sip from the *waterfall*. (moderate incongruity)
  - He took a sip from the *transmitter*. (strong incongruity)





(Kutas & Hillyard, 1980, 1984)

Word probability effects in the brain

(Original data: Federmeier et al., 2007; analysis: Szewczyk & Federmeier, 2022)

Word probability effects in the brain

Joy was too frightened to...

(Original data: Federmeier et al., 2007; analysis: Szewczyk & Federmeier, 2022)

Word probability effects in the brain

Joy was too frightened to... ***look***

(Original data: Federmeier et al., 2007; analysis: Szewczyk & Federmeier, 2022)

Word probability effects in the brain

Joy was too frightened to... ***look*** ***move***

(Original data: Federmeier et al., 2007; analysis: Szewczyk & Federmeier, 2022)

Word probability effects in the brain

Joy was too frightened to... ***look*** ***move***

He brought her a pearl necklace for her...

(Original data: Federmeier et al., 2007; analysis: Szewczyk & Federmeier, 2022)

Word probability effects in the brain

Joy was too frightened to... ***look*** ***move***

He brought her a pearl necklace for her... ***collection***

(Original data: Federmeier et al., 2007; analysis: Szewczyk & Federmeier, 2022)

Word probability effects in the brain

Joy was too frightened to... ***look*** ***move***

He brought her a pearl necklace for her... ***collection*** ***birthday***

(Original data: Federmeier et al., 2007; analysis: Szewczyk & Federmeier, 2022)

Word probability effects in the brain

Weakly constraining *Joy was too frightened to...* ***look*** ***move***

He brought her a pearl necklace for her... ***collection*** ***birthday***

(Original data: Federmeier et al., 2007; analysis: Szewczyk & Federmeier, 2022)

Word probability effects in the brain

Weakly constraining *Joy was too frightened to...* ***look*** ***move***

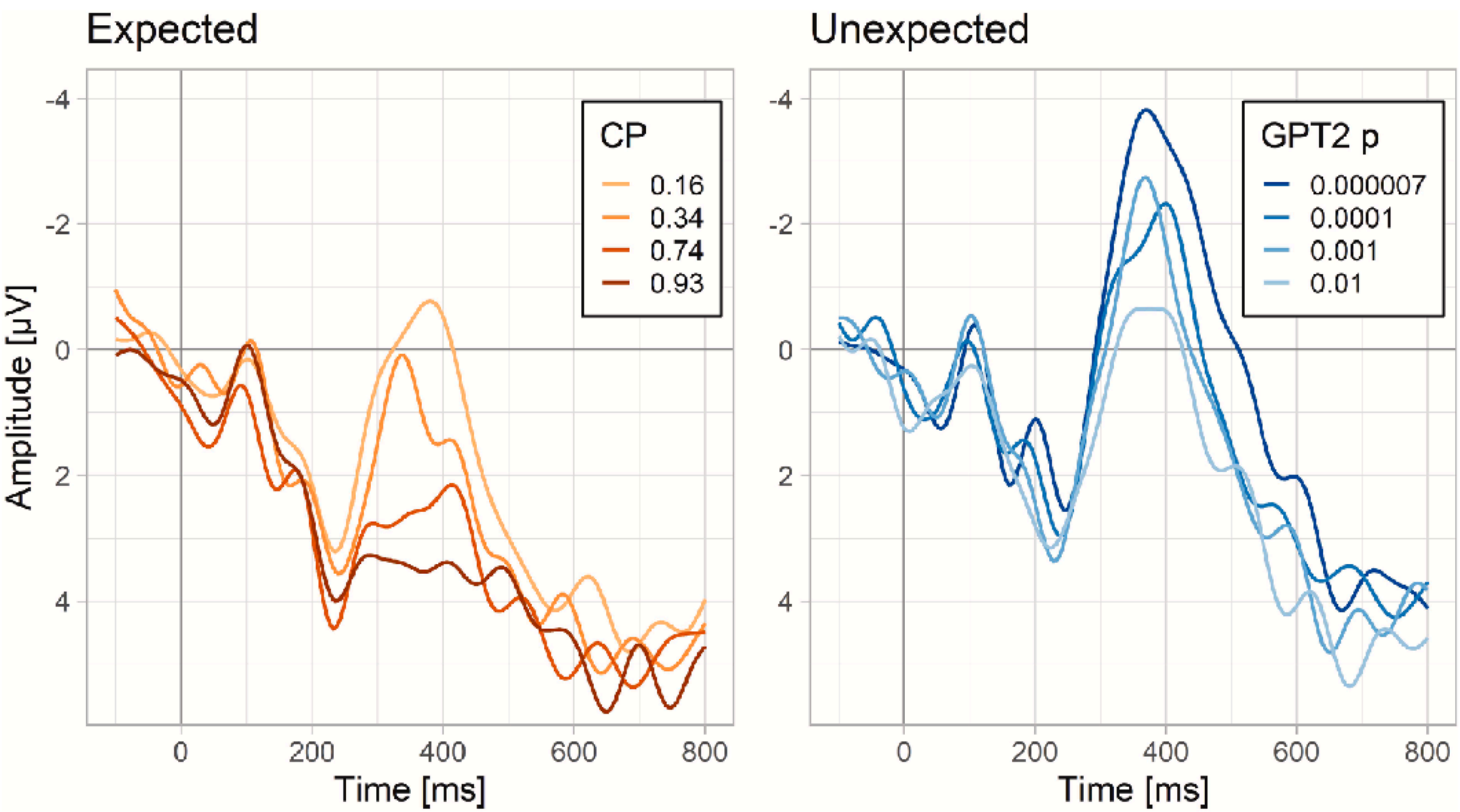
Strongly constraining *He brought her a pearl necklace for her...* ***collection*** ***birthday***

(Original data: Federmeier et al., 2007; analysis: Szewczyk & Federmeier, 2022)

Word probability effects in the brain

Weakly constraining *Joy was too frightened to...* ***look*** ***move***

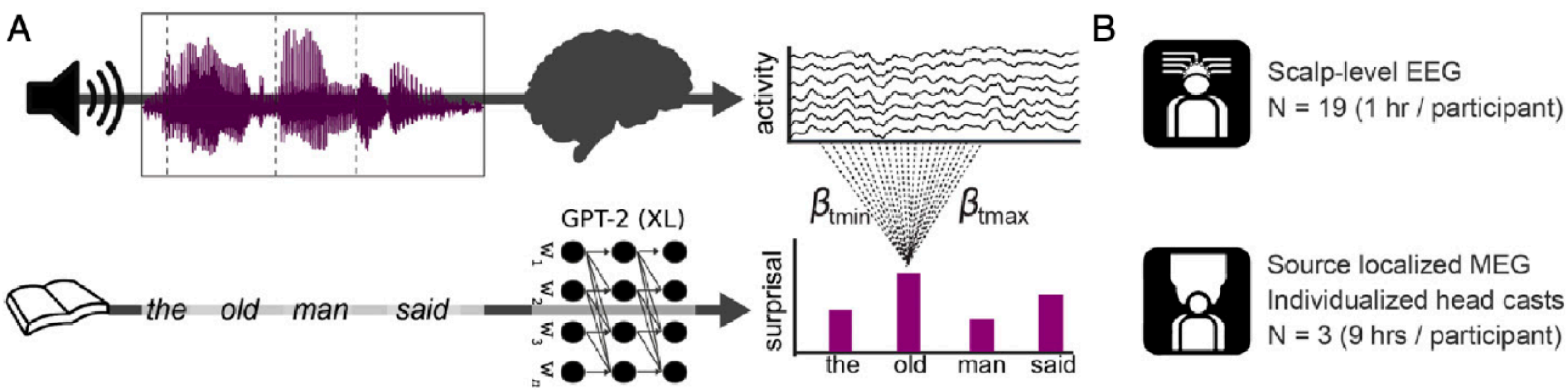
Strongly constraining *He brought her a pearl necklace for her...* ***collection*** ***birthday***



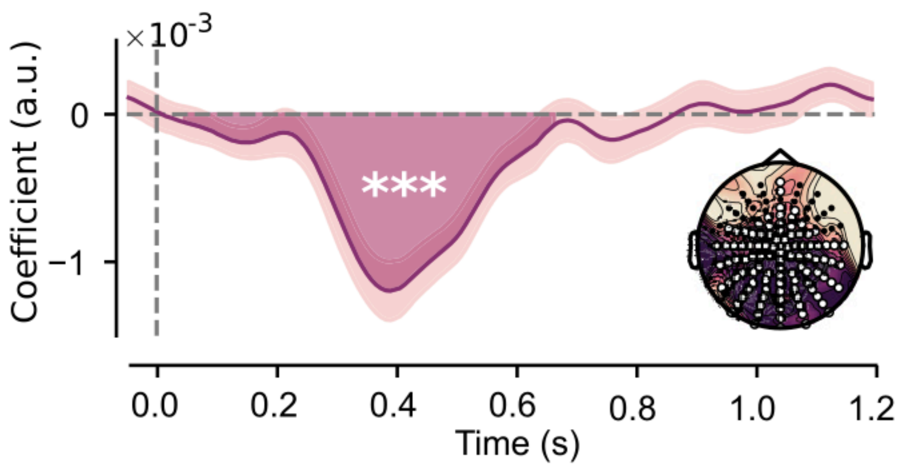
(Original data: Federmeier et al., 2007; analysis: Szewczyk & Federmeier, 2022)

Surprisal effects in audiobook listening

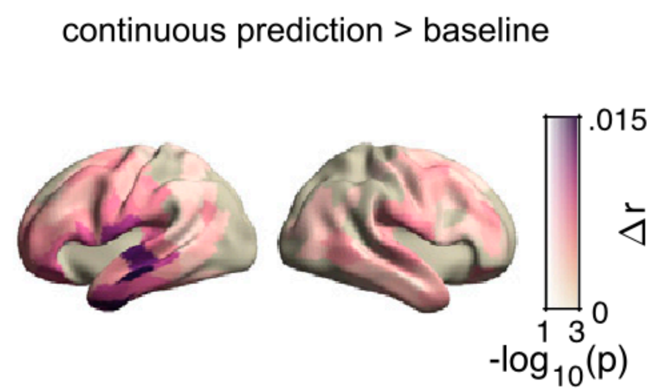
- Analytic framework:



EEG results (temporal)

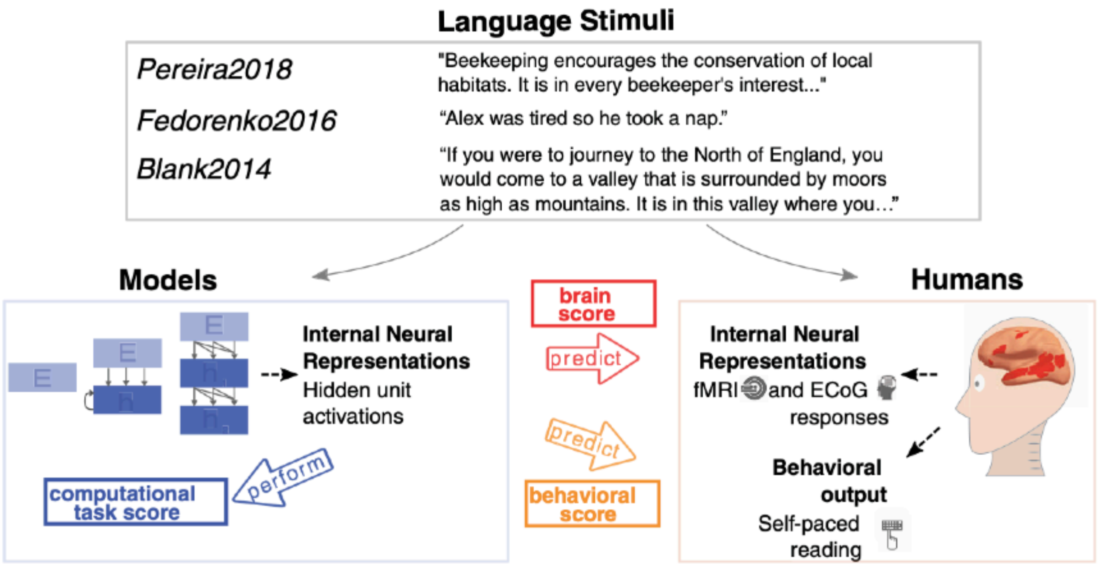


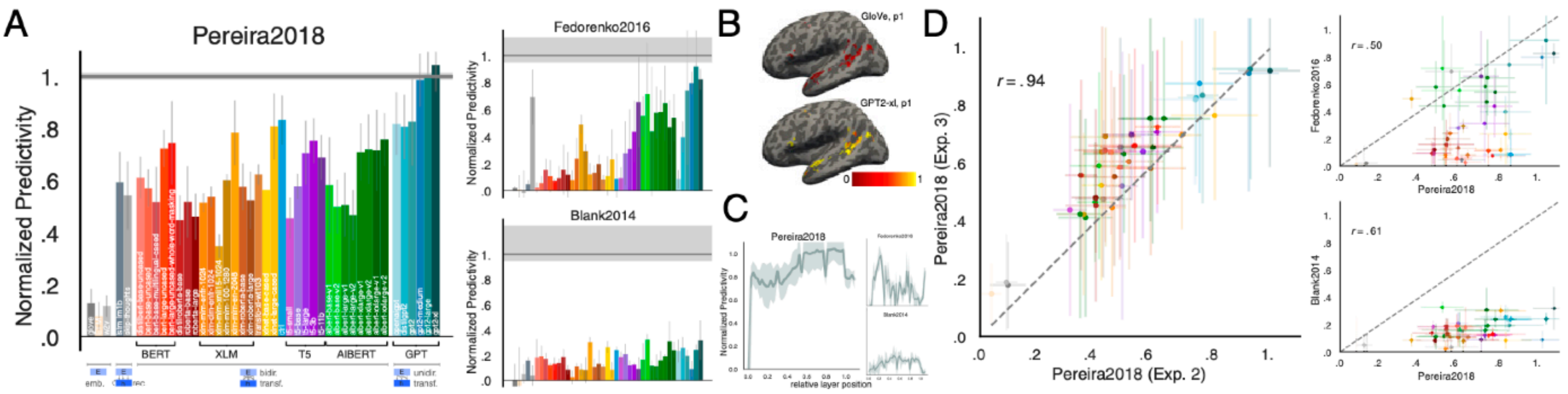
MEG results (temporal)



(Heilbron et al., 2022)

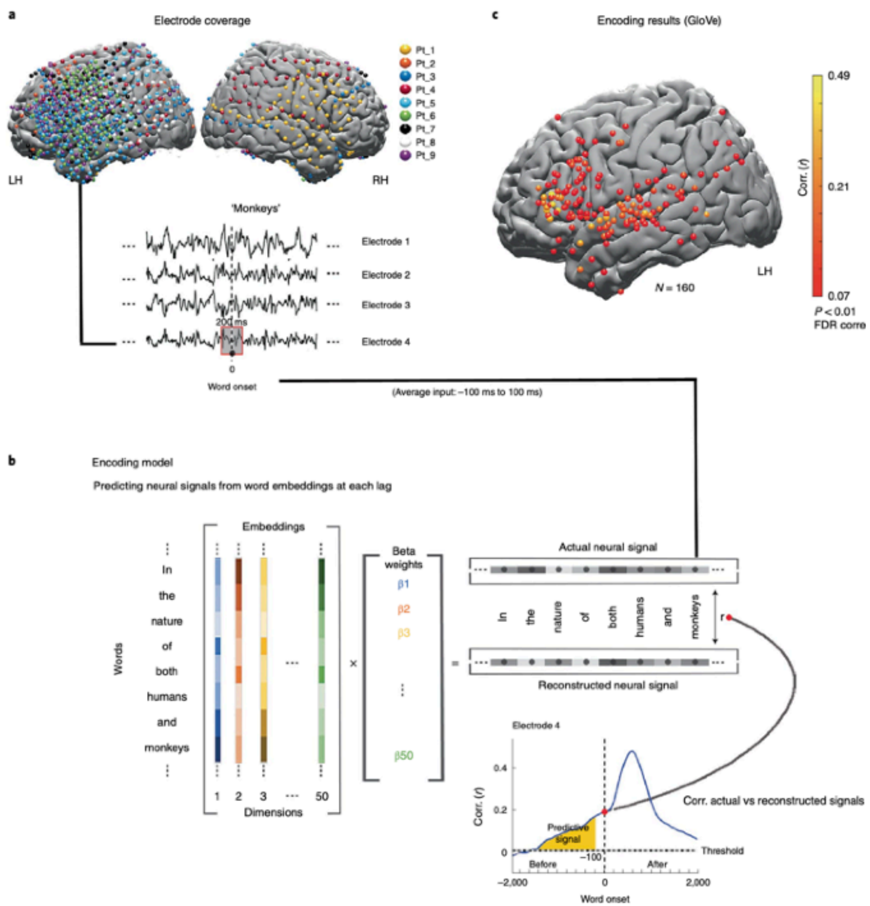
Aligning neural network embeddings to brain responses

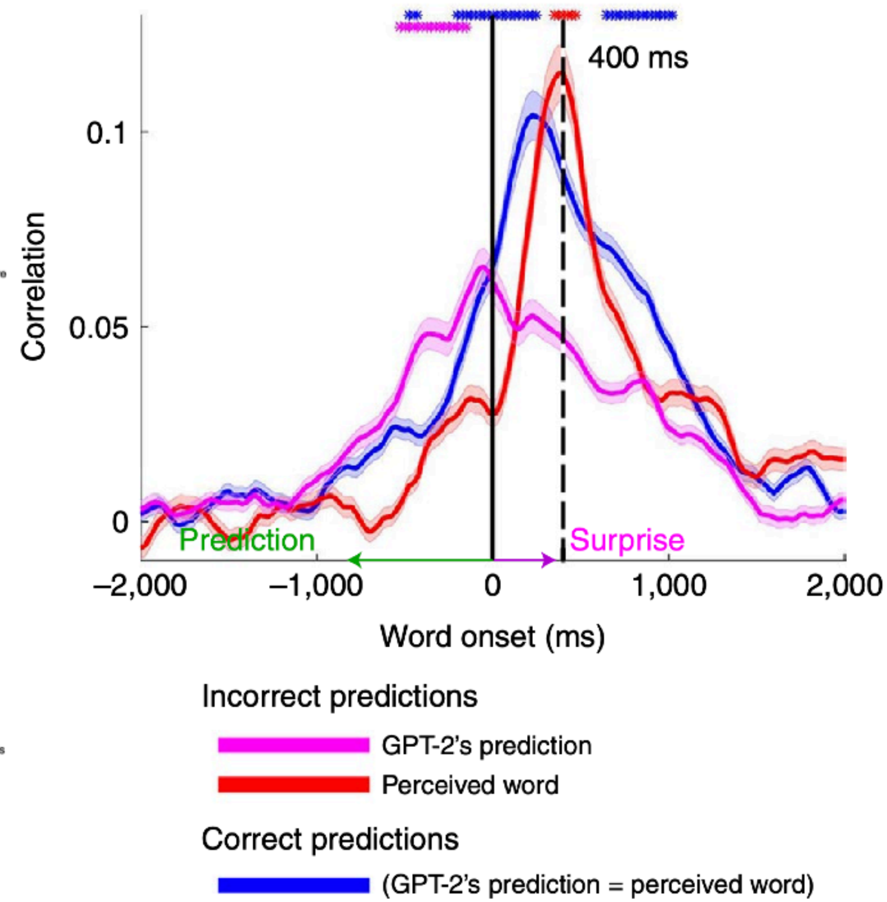




(Schrimpf et al., 2021)

Prediction versus surprise in ECoG

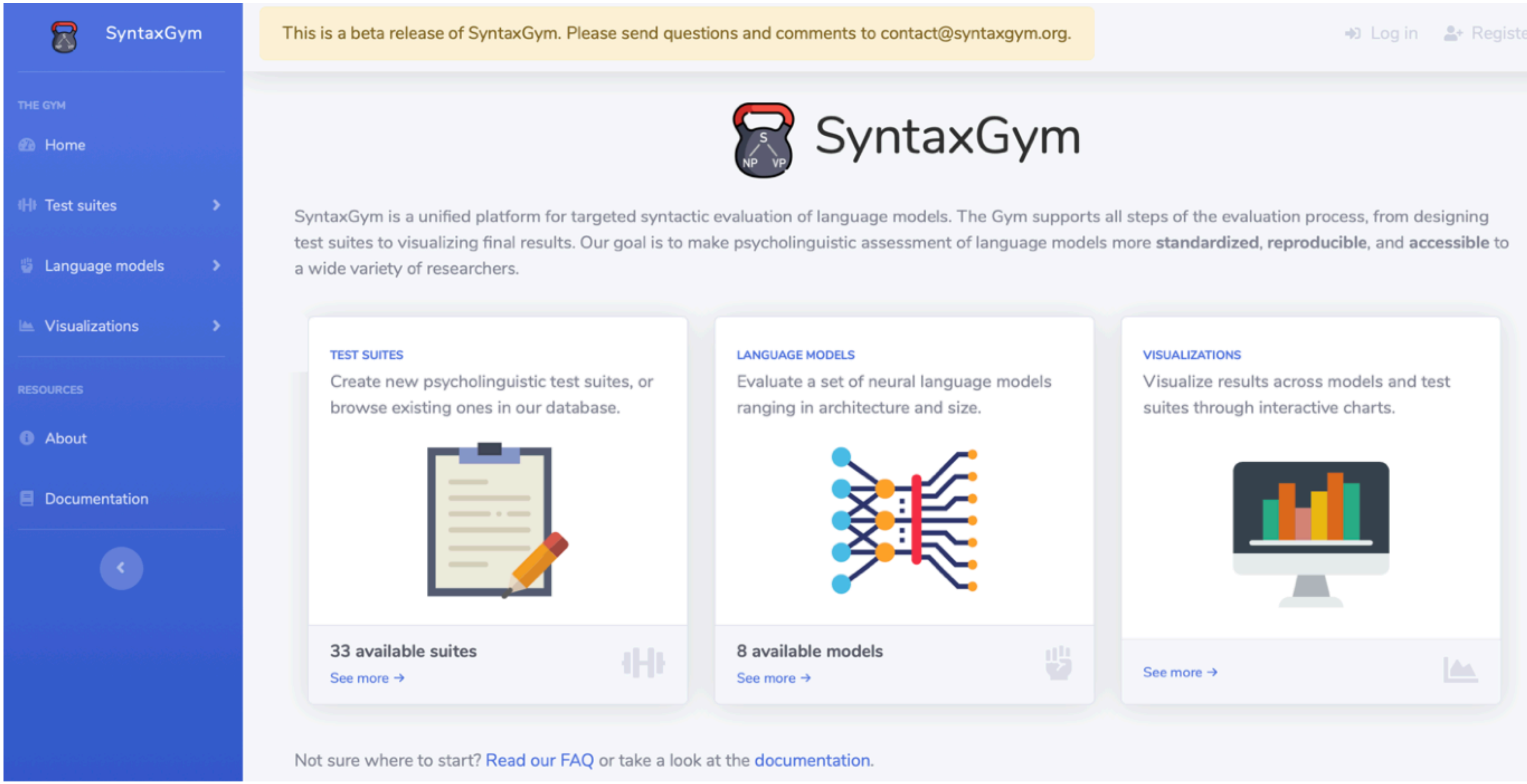




(Goldstein et al., 2022)

In-class exercise: explore GPT-2 word predictions

Psycholinguistic tests of AI language models



http://syntaxgym.org

(Gauthier et al., 2020)

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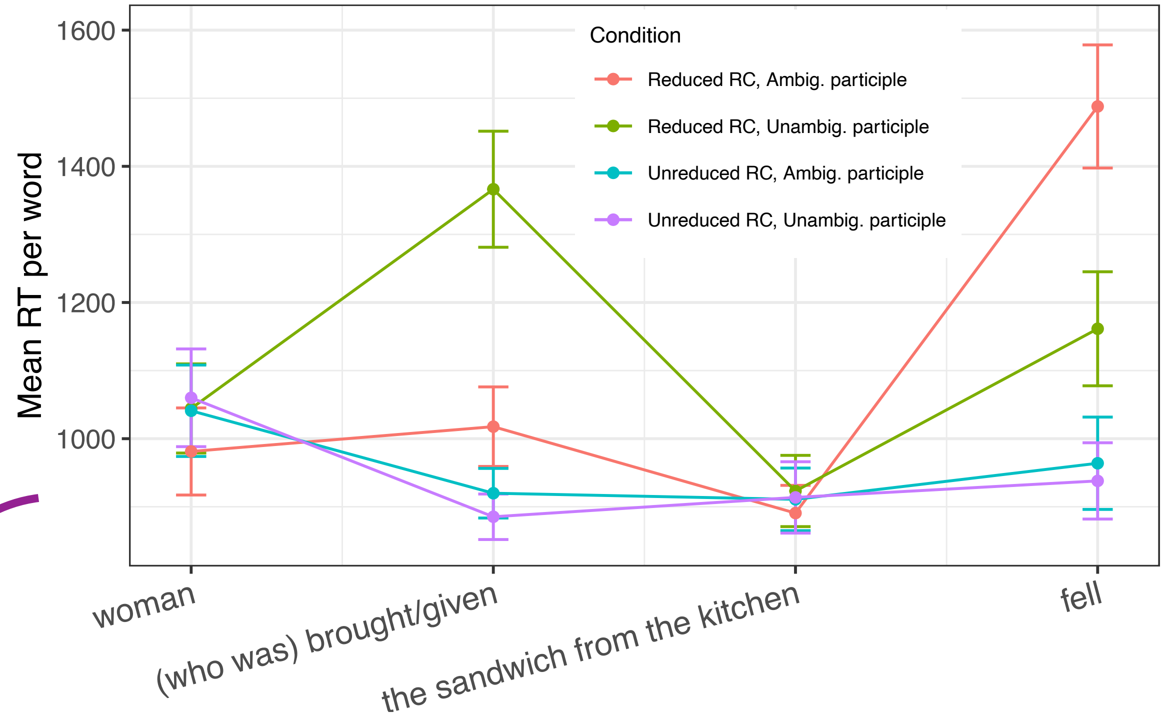
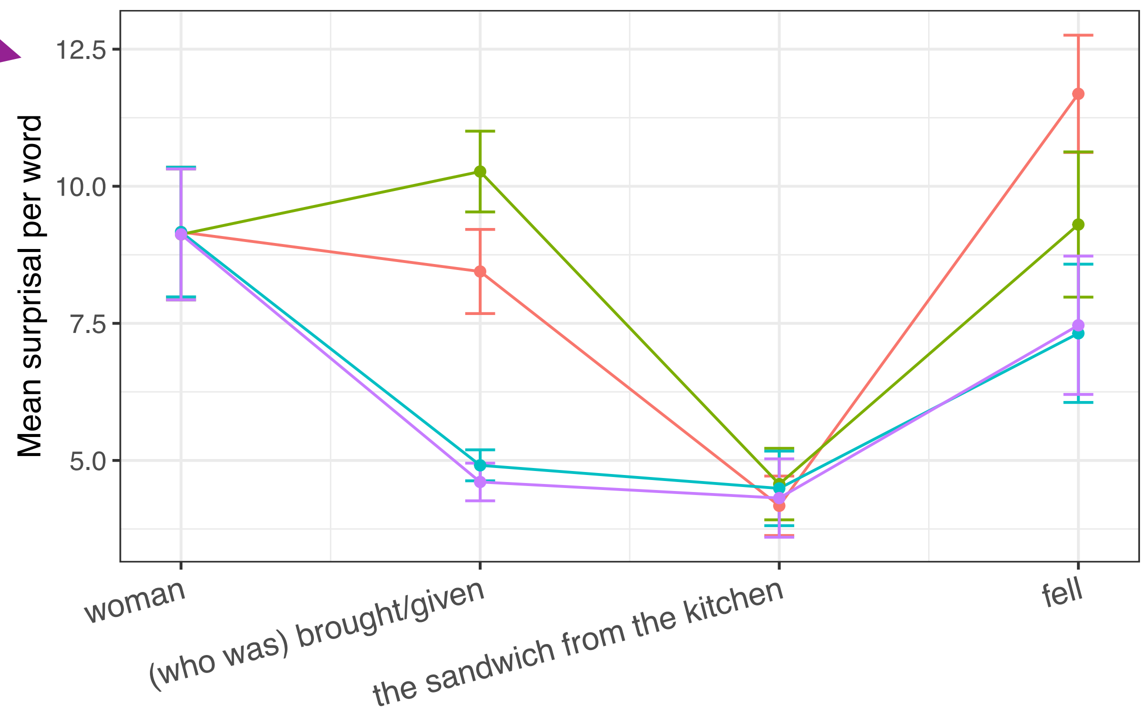
Human reaction times



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

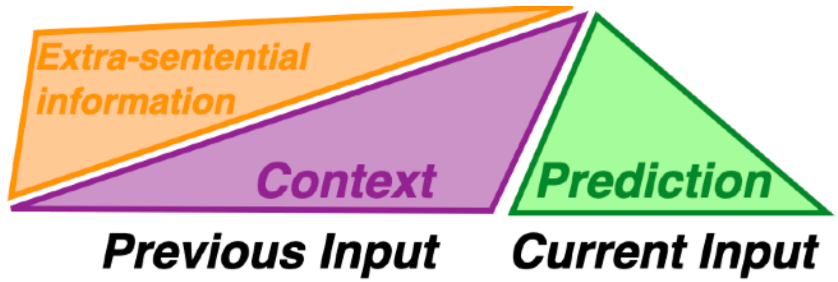
GPT-2 Surprisal



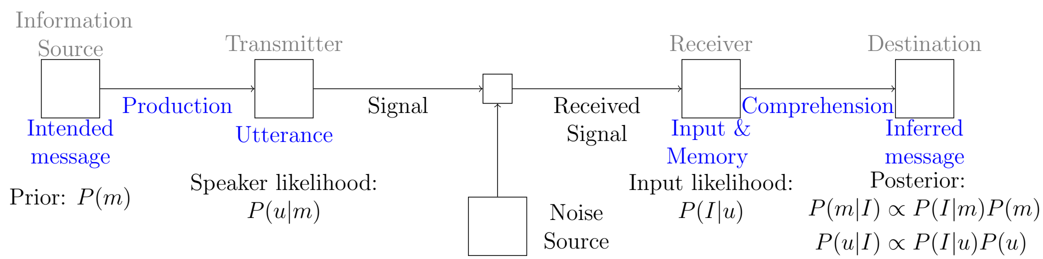
(Wilcox et al., 2021; see also van Schijndel & Linzen, 2021)

Ingredients for theory of human language comprehension

- Ubiquitous expectation-based inference, including prediction/surprisal



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



- **And of course:** 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)]