A-maze: Easier measurement of incremental processing

Veronica Boyce

26 April 2021

Plan

Plan

- Maze task
- A-maze
- Study 1: methods comparison
- Variant of A-maze
- Study 2: test on Natural Stories Corpus

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mit computational psycholinguistics lab

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RT patterns may be phenomena that theories need to explain.

Two common methods

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Eye-tracking

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- Expensive
- Hard to analyse

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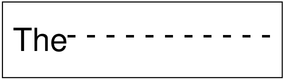
Self-paced reading



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- - - cat - - - - - - - -

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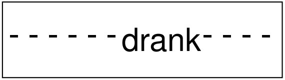

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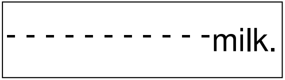

- Lots of spillover
- Messy data

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Self-paced reading

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- Lots of spillover
- Messy data

Different methods have different trade-offs

An alternative: Maze

The x-x-x

An alternative: Maze

The x-x-x

An alternative: Maze

upon dog

An alternative: Maze

upon dog

An alternative: Maze

revise chased

An alternative: Maze

revise chased

An alternative: Maze

the wish

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the wish

An alternative: Maze

mitigate. squirrel.

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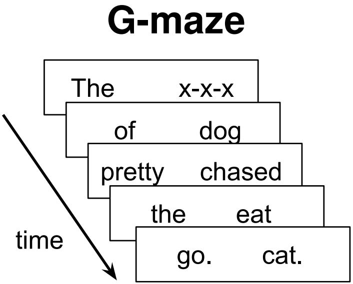
A third option: Maze



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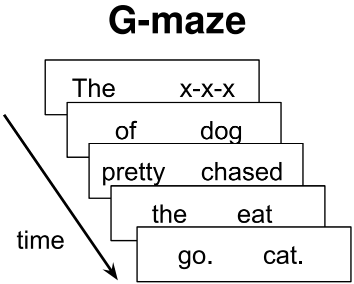

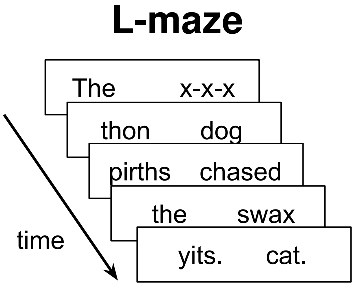

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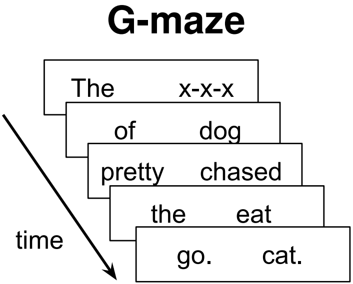

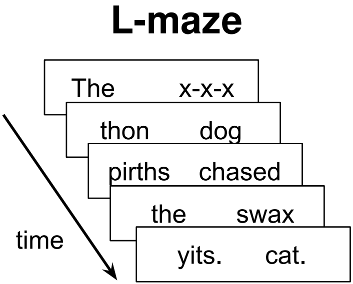

Sentence ends when a mistake is made.

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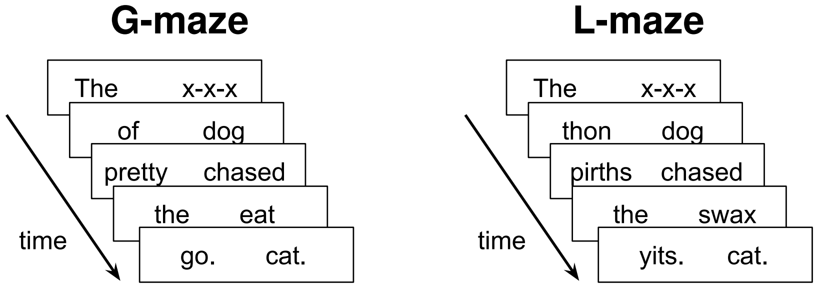

Sentence ends when a mistake is made.
Central claim: forces extremely incremental processing (no spillover)

(Forster et al. 2009; Witzel et al. 2012)

Maze Made Easy

Can we use Maze instead of web SPR?

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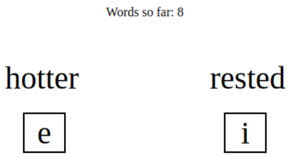

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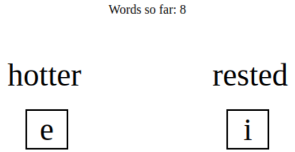


Test by replicating Witzel et al. (2012)

- Witzel et al (2012): Comparison of eye-tracking, SPR, L-maze, G-maze (all in-lab)
- Got materials and data from Witzel
- We run SPR, L-maze, and G-maze on MTurk

Materials

Relative Clause

Low: The son of the lady who politely introduced herself was popular at the party.

High: The son of the lady who politely introduced himself was popular at the party.

Adverb Clause

Low: James will fix the car he drove yesterday, but he will need some help.

High: James will fix the car he drove tomorrow, but he will need some help.

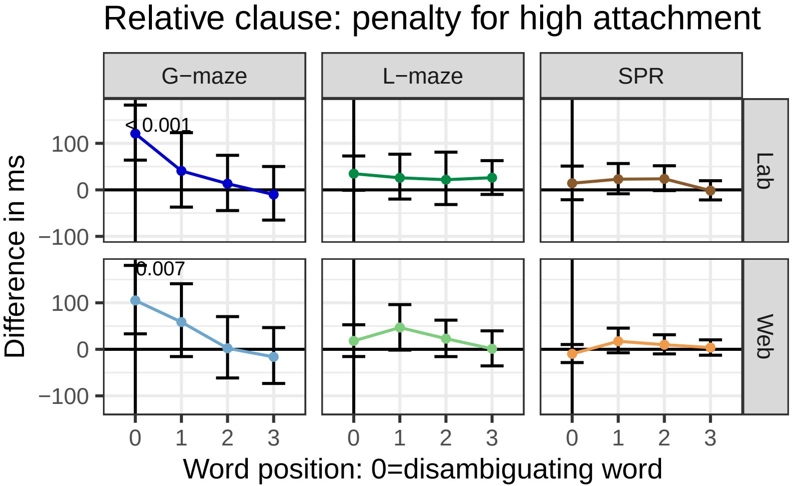
Sentence v Noun Phrase conjunction

Comma: The swimmer disappointed her coach, and her mother tried to console her.

No comma: The swimmer disappointed her coach and her mother tried to console her.

Results

The son of the lady who politely introduced herself / himself was popular at the party.



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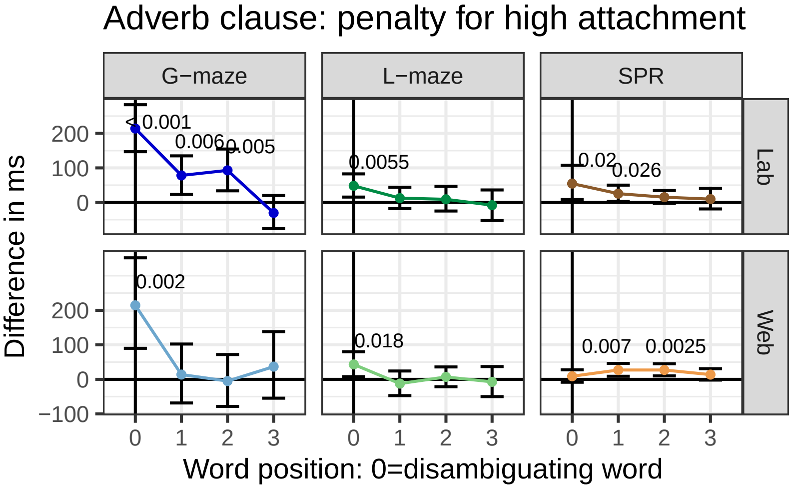

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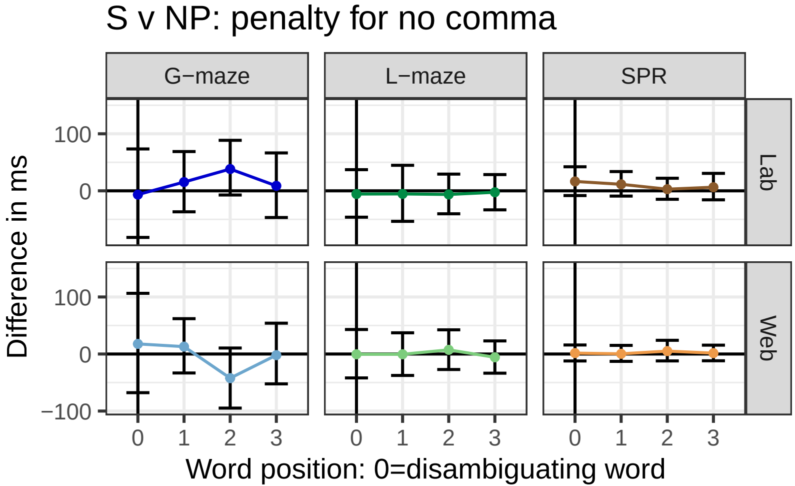

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Goal: Find a word that can't continue a partial sentence

- Ex. *The dog chased*

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Can we use Neural Language Models?

Meanwhile in Natural Language Processing

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Language models (LMs)

- Trained on large corpora to predict the next word
- Given a partial sentence, return probabilities of the next word

Surprisal: negative log probability

- 2 bits of surprisal = 1/4
- 10 bits of surprisal $\approx$ 1/1000
- +1 surprisal = half as likely

"The dog chased ..." $\longrightarrow$ LM $\longrightarrow$

"the" 1.2 bits
"a" 3.1 bits
"cats" 8 bits
...
"wish" 25 bits
...

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Use high surprisal according to LM as a proxy for bad in context

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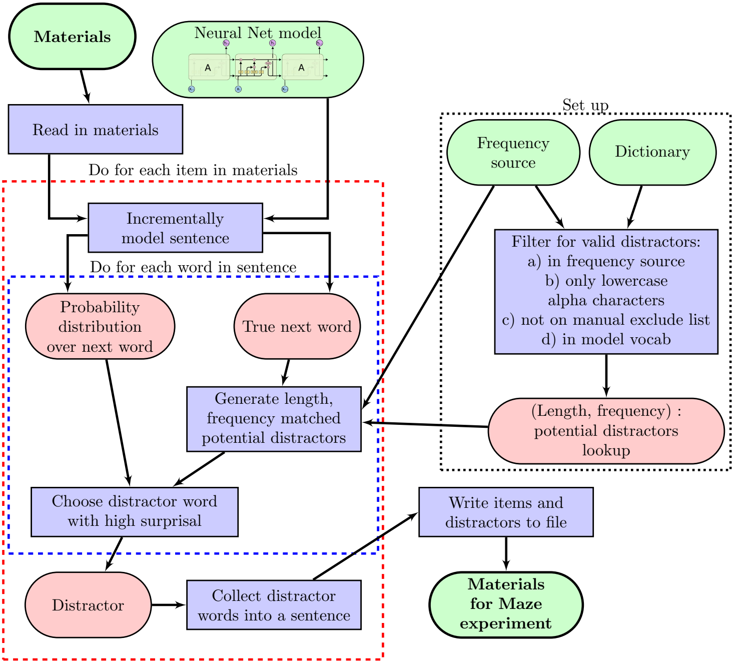
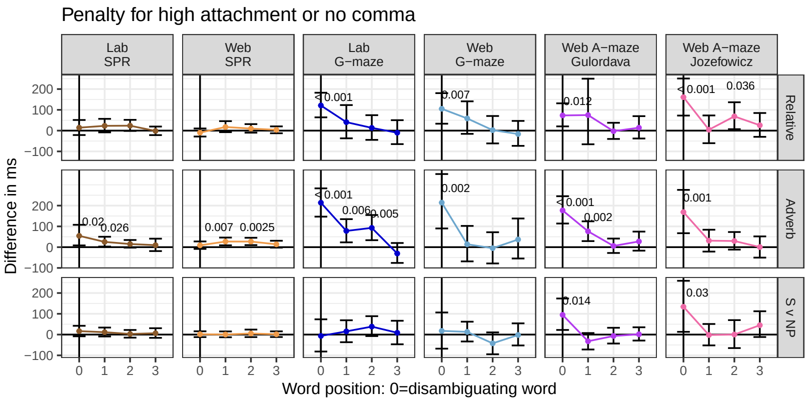
- At each position, choose a high surprisal word

Want quality control on distractors

- Restrict to a list of possible distractors
- Only consider distractors of same length, frequency as target word
- Check distractors until we find one with high surprisal


Materials
Neural Net model
A
A
Read in materials
Do for each item in materials
Incrementally model sentence
Do for each word in sentence
Probability distribution over next word
True next word
Generate length, frequency matched potential distractors
Choose distractor word with high surprisal
Distractor
Collect distractor words into a sentence
Set up
Frequency source
Dictionary
Filter for valid distractors:
a) in frequency source
b) only lowercase alpha characters
c) not on manual exclude list
d) in model vocab
(Length, frequency) : potential distractors lookup
Write items and distractors to file
Materials for Maze experiment

Does it work?



Error bars: 95% CI

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- Sloggett et al (2020) also found A-maze results comparable with G-maze

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Want to run multi-sentence items.

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- Treat each sentence as a unit: Some participants miss key context.

What if after an error, participants corrected errors and the sentence continued?

Maze with Error Correction

The x-x-x

Maze with Error Correction

The x-x-x

Maze with Error Correction

upon dog

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upon dog

Maze with Error Correction

revise chased

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Incorrect. Please try again.

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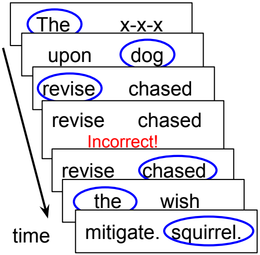
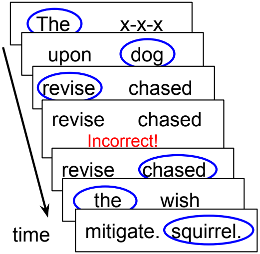


Maze with Error Correction



- Can be toggled in Ibex Maze

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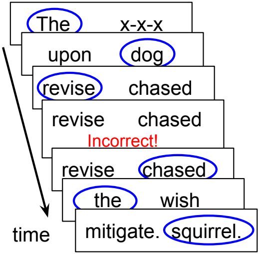
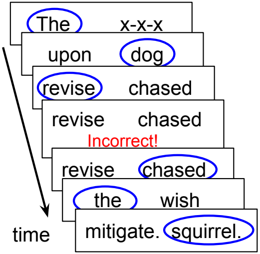


- Can be toggled in Ibex Maze
- Long materials feasible

Maze with Error Correction



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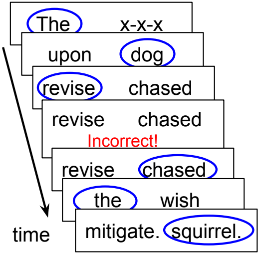
Maze with Error Correction



- Can be toggled in Ibex Maze
- Long materials feasible
- Have all the data
- Compensates for bad distractors

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- Will they comprehend what they read?
- Does error correction Maze work?
- Do we get predictability effects?

Natural Stories

Natural stories corpus (Futrell et al. 2017)

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- 10 stories, each about 1000 words

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- 10 stories, each about 1000 words
- 6 comprehension questions per story

Natural Stories

Tulip mania was a period in the Dutch Golden Age during which contract prices for bulbs of the recently introduced tulip reached extraordinarily high levels and then suddenly collapsed. At the peak of tulip mania in February sixteen thirty-seven, tulip contracts sold for more than ten times the annual income of a skilled craftsman. It is generally considered the first recorded economic bubble. [...]

Q: When did tulip mania reach its peak?

A: 1630's 1730's

Participant accuracy

100 participants each read 1 story

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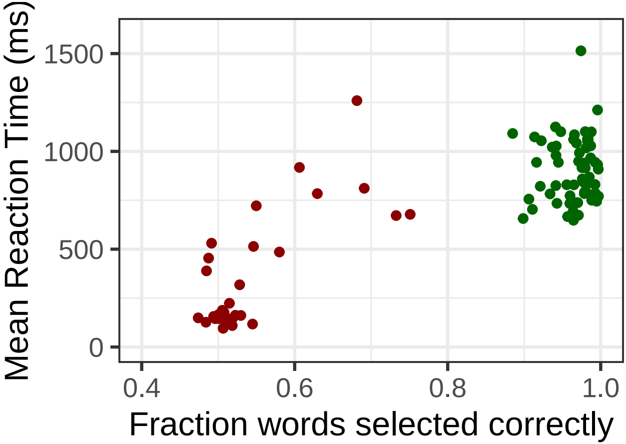

Comprehension questions

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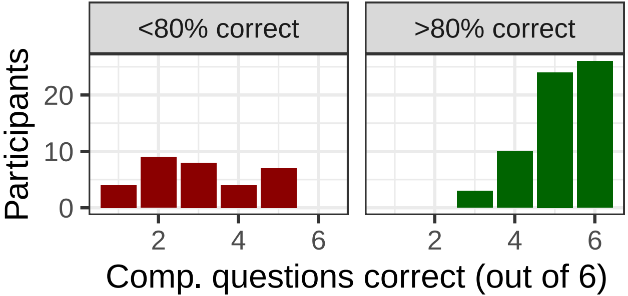

Surprisal Effects

Is RT linear in terms of surprisal?

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Estimate surprisal from 3 models:

- smoothed 5-gram
- LSTM-RNN (Gulordava et al. 2018)
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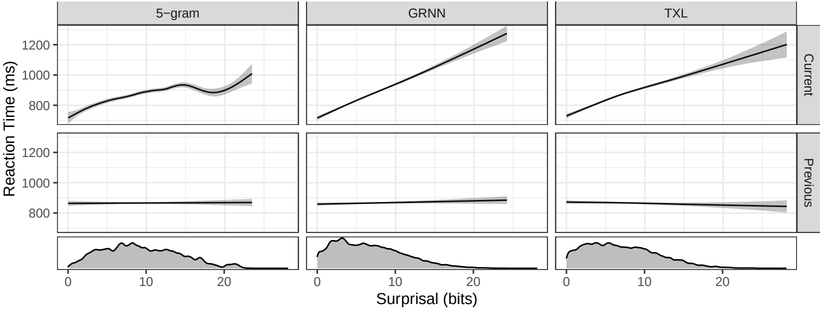
Fit GAMs

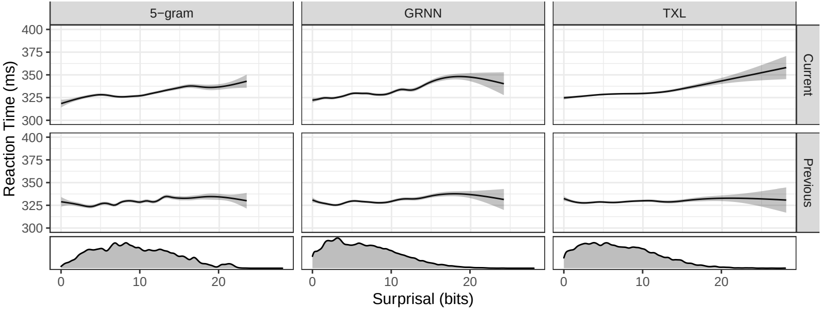
- Fit to both current and past word surprisal
- Include frequency, length as predictors

Surprisal Effects



SPR comparison

Using SPR data collected by Futrell et al. (2017)



Surprisal Effects

Linear Models

Surprisal Effects

Linear Models

	5-gram	GRNN	TXL
Intercept	**865.3**	**871.1**	**870.8**
Surprisal	**11.7**	**23.7**	**18.5**
Frequency	-2.9	2.9	0.4
Length	**20.5**	**18.5**	**21.4**
Surprisal:Length	**-2.0**	**-1.8**	**-1.4**
Freq:Length	-1.0	-0.1	0.2
Past Surprisal	1.6	**2.7**	0.8
Past Freq	2.6	1.9	1.2
Past Length	**-4.8**	**-6.6**	**-5.2**
Past Surp:Length	-0.2	**-0.9**	-0.6
Past Freq:Length	-1.0	**-1.8**	**-1.5**

Surprisal in bits, Length in characters,
Frequency in log_2 occurrences/billion words

Surprisal Effects

Takeaways:

- Minimal frequency effects (consistent with Shain 2019)
- Large effects of Length, Surprisal
- Very little spillover

Summary

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- People will read in the Maze task for 15-20 minutes

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Consider A-maze!

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Adapt A-maze to your projects:

- Written in Python 3
- Interface with other language models
- Add more frequency sources
- Extend to non-English languages

Documentation: vboyce.github.io/Maze

with links to the following:

- A-maze code: github.com/vboyce/Maze
- Web-maze code: github.com/vboyce/Ibex-with-Maze
- Exp 1 Paper: psyarxiv.com/b7nqd/

Matching distractors

If unspecified: Match by position

- The son of the lady who politely introduced herself / himself was popular at the party.

Can specify labels for each word to pair (within item)

- The cat who the dog scared hid in a box.
  pre-1 pre-2 who art noun verb main-verb post-1
  post-2 post-3
- The dog who scared the cat sniffed around the couch.
  pre-1 pre-2 who verb art noun main-verb post-1
  post-2 post-3

Regression coefficients

	5-gram			GRNN			TXL	
	Est	CI	*p*	Est	CI	*p*	Est	CI
Intercept	865.3	[829.9, 902.9]	0.00	871.1	[837.9, 905.3]	0.00	870.8	[832.5, 907.8]
Surprisal	11.7	[9.3, 14.1]	0.00	23.7	[21, 26.5]	0.00	18.5	[16.1, 21.1]
Frequency	-2.9	[-6.3, 0.5]	0.10	2.9	[-0.2, 6]	0.06	0.4	[-2.7, 3.5]
Length	20.5	[15.4, 25.6]	0.00	18.5	[13.3, 23.7]	0.00	21.4	[16.2, 26.6]
Surprisal:Length	-2.0	[-3, -1]	0.00	-1.8	[-2.7, -0.9]	0.00	-1.4	[-2.2, -0.6]
Freq:Length	-1.0	[-2.5, 0.4]	0.16	-0.1	[-1.2, 1]	0.82	0.2	[-0.9, 1.2]
Past Surprisal	1.6	[-0.5, 3.6]	0.14	2.7	[0.8, 4.5]	0.00	0.8	[-0.9, 2.5]
Past Freq	2.6	[-0.1, 5.4]	0.06	1.9	[-0.2, 4.2]	0.08	1.2	[-1.1, 3.6]
Past Length	-4.8	[-9, -0.1]	0.04	-6.6	[-10.9, -2.1]	0.00	-5.2	[-9.3, -0.7]
Past Surp:Length	-0.2	[-1.2, 0.8]	0.72	-0.9	[-1.7, -0.2]	0.01	-0.6	[-1.3, 0.2]
Past Freq:Length	-1.0	[-2.3, 0.3]	0.15	-1.8	[-2.9, -0.8]	0.00	-1.5	[-2.6, -0.5]

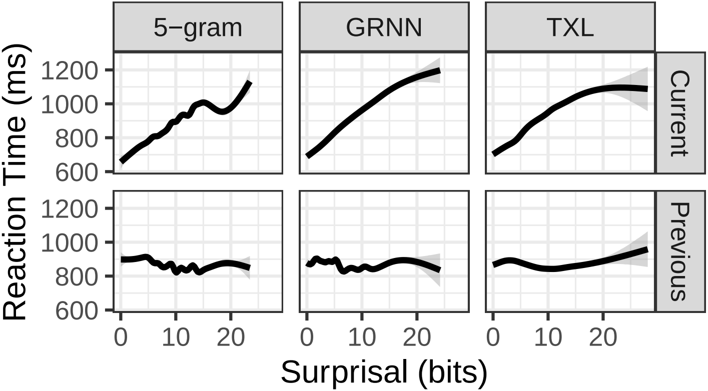
Caveats

Definitely some bad distractors

Prefix	Correct	Distractor	Error Rate
Gulordava			
The	niece	cooks	44%
The swimmer	disappointed	propositions	30%
The	semester	steroids	29%
Jozefowicz			
The	husband	authors	46%
Jim	listened	survived	43%
The	uncle	roads	42%
The	knight	saints	40%

What about post-mistake data?

Exclude data from mistakes or the two words after a mistake.



Why such large effects?

Bayesian Reader (Norris 2006): Look at words long enough to ID with some threshold of certainty
Possible mechanisms for difference:

- Higher threshold
- Fewer available resources for processing
- Presence of second word