A-maze of Natural Stories:

Texts are comprehensible using the Maze task

Veronica Boyce, Roger Levy

AMLaP 2020

Incremental processing methods

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Common ways to measure RT

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Common ways to measure RT

Eye-tracking

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Eye-tracking

Self-paced reading

The - - - - - - - - - - -

Incremental processing methods

Common ways to measure RT

Eye-tracking

Self-paced reading

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

Incremental processing methods

Common ways to measure RT

Eye-tracking

Self-paced reading

- - - - - - drank - - - -

Incremental processing methods

Common ways to measure RT

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Self-paced reading

- - - - - - - - - - -milk.

Incremental processing methods

Common ways to measure RT

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- - - - - - - - - - -milk.

Different methods have different trade-offs

An alternative: Maze

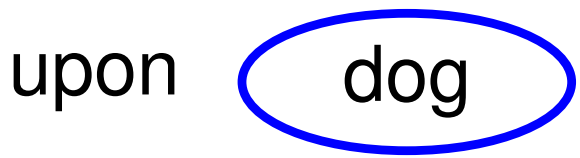
The x-x-x

An alternative: Maze

An alternative: Maze

upon dog

An alternative: Maze



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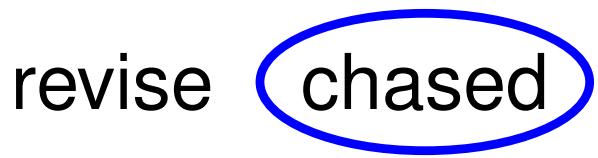

An alternative: Maze

the wish

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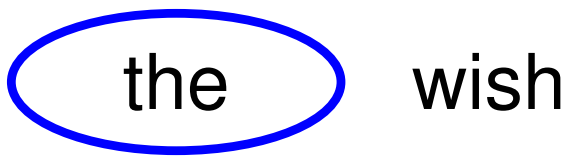

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mitigate. squirrel.

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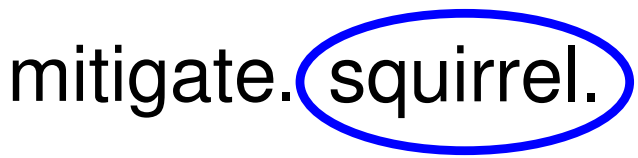
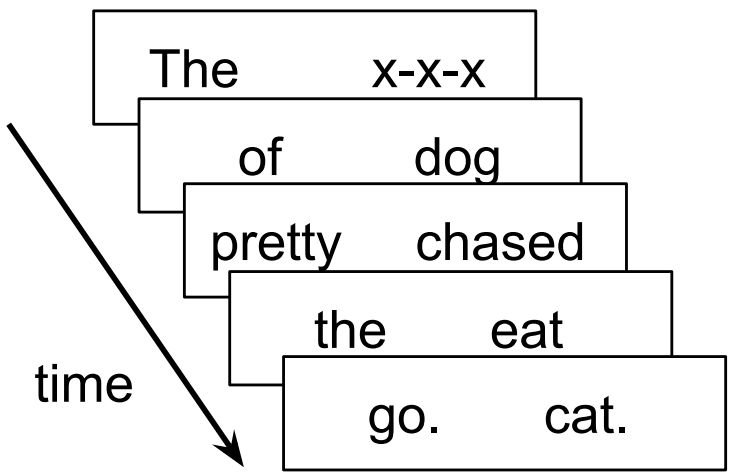


An alternative: Maze

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

G-maze

‘Grammatical’ choices



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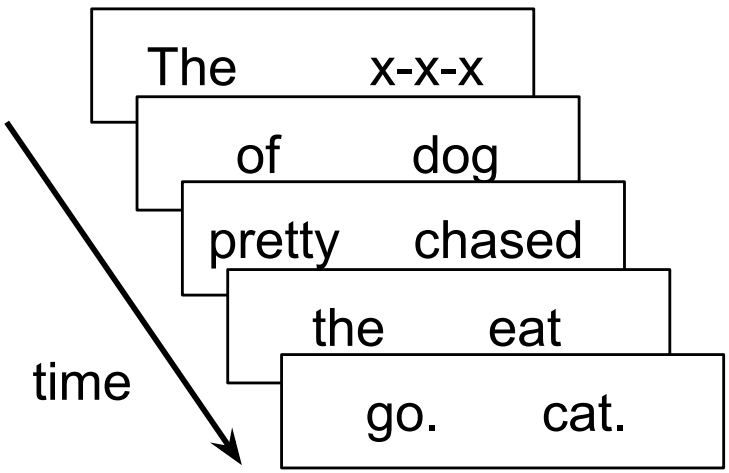
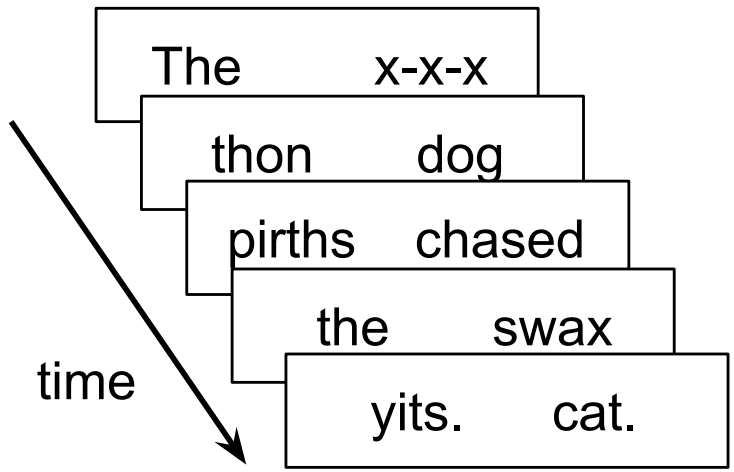


L-maze

'Lexical' choices



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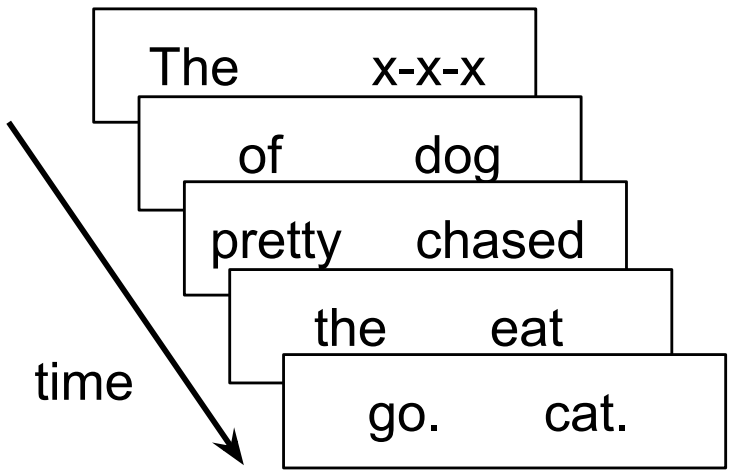

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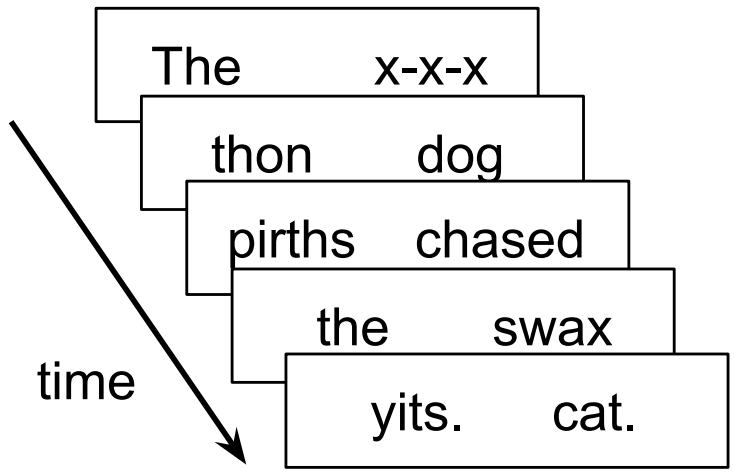

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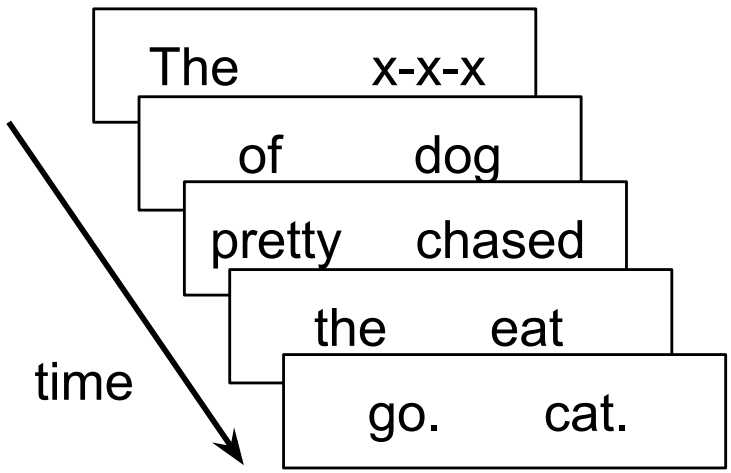

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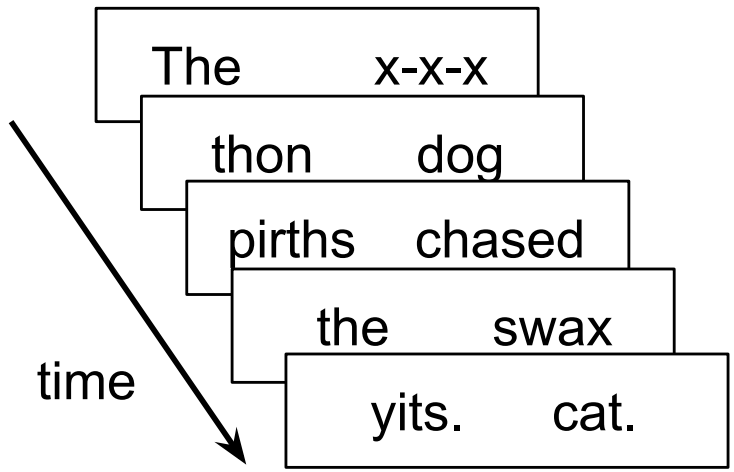

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Claim: forces incremental processing (no spillover)

Maze Made Easy

Can we use Maze instead of web SPR?

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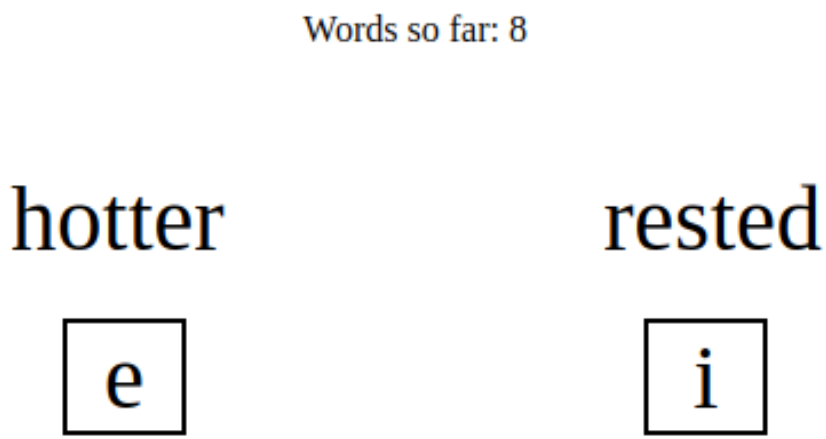

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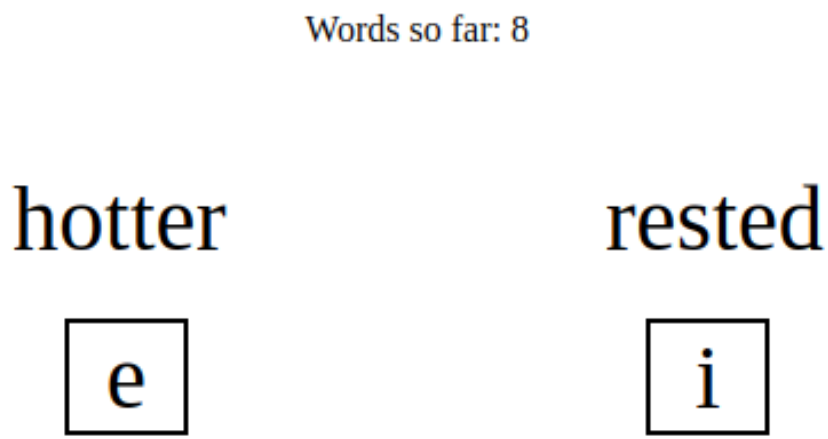

Replicated Witzel et al. (2012) results (Boyce et al. 2020)

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

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Can we use Neural Language Models?

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

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Run items through LM, choose high surprisal words as distractors

Does it work?

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Yes, at least well enough.

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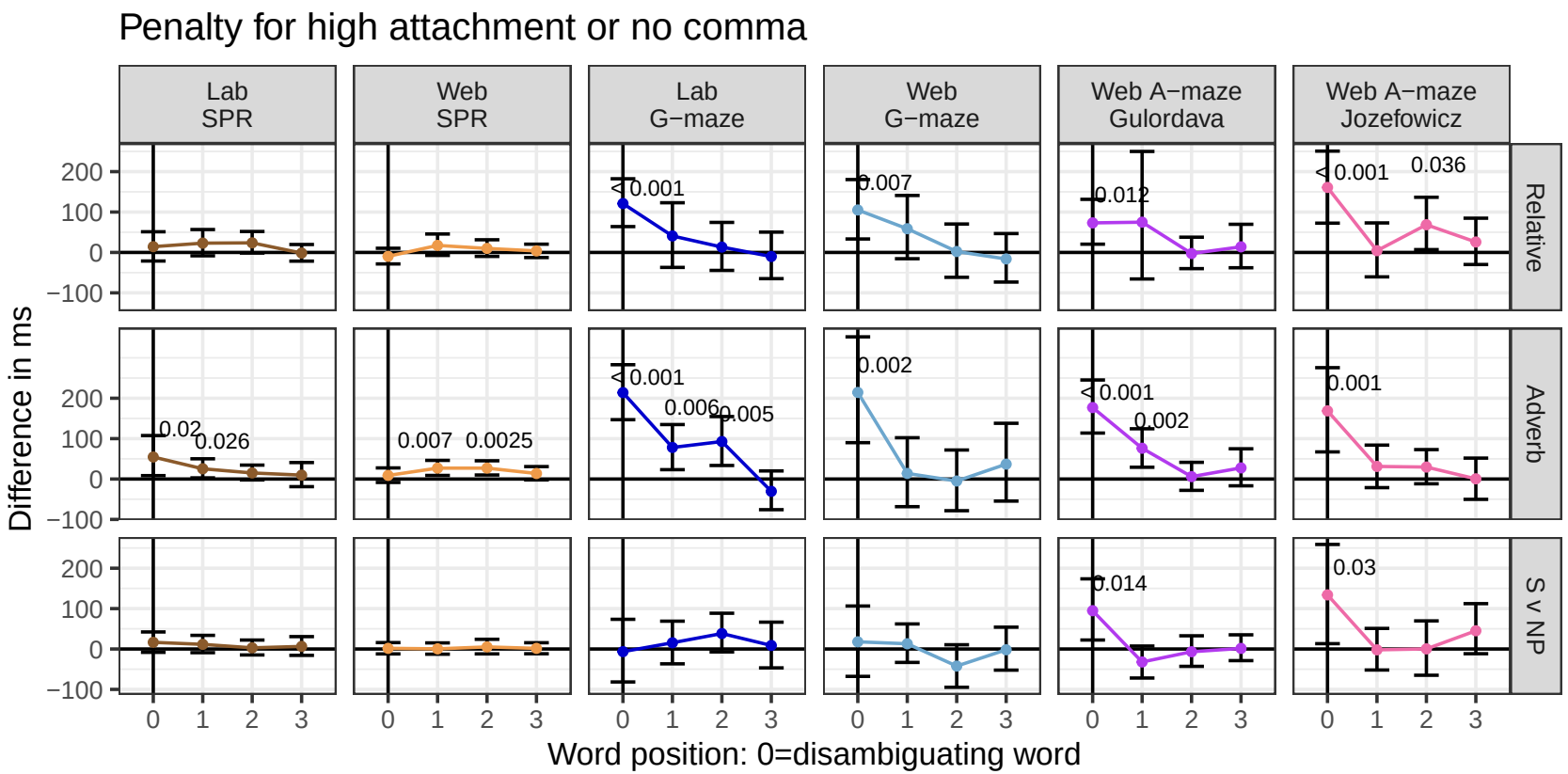

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Long items

Want to run multi-sentence items.

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- Treat whole story as a unit: Few participants make it to the end.
- 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

Maze with Error Correction

upon dog

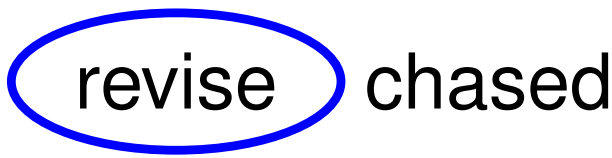
Maze with Error Correction

upon

Maze with Error Correction

revise chased

Maze with Error Correction



Maze with Error Correction

revise chased

Incorrect. Please try again.

Maze with Error Correction

revise chased

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Maze with Error Correction

the wish

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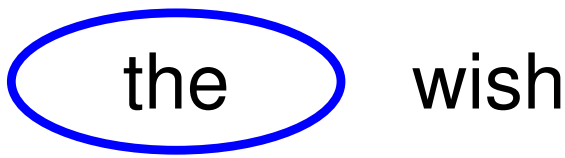

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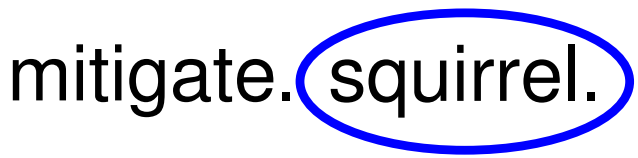

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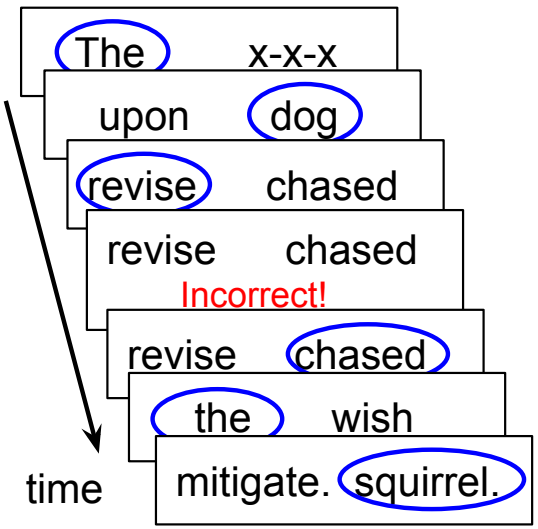

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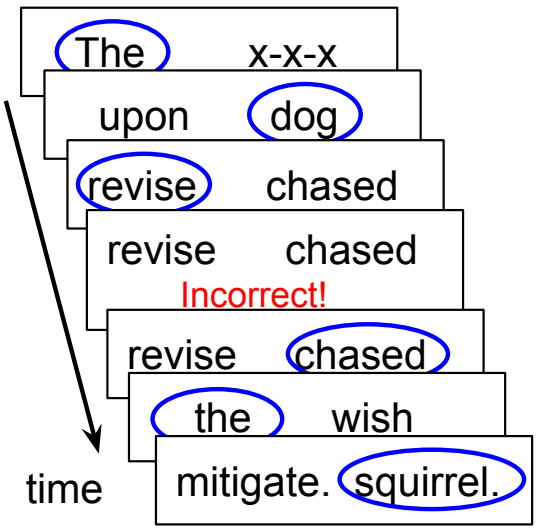

- Can be toggled in Ibex Maze

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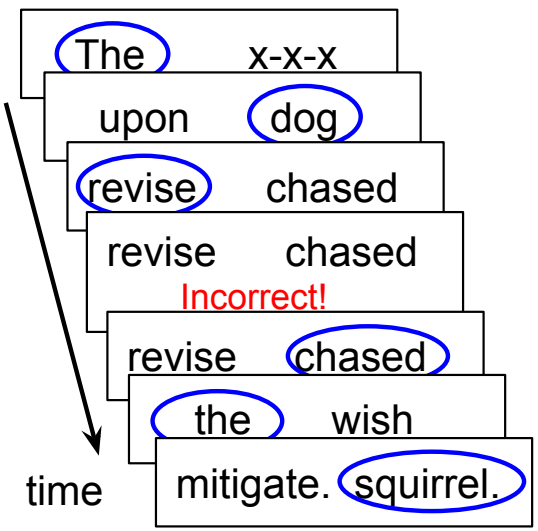
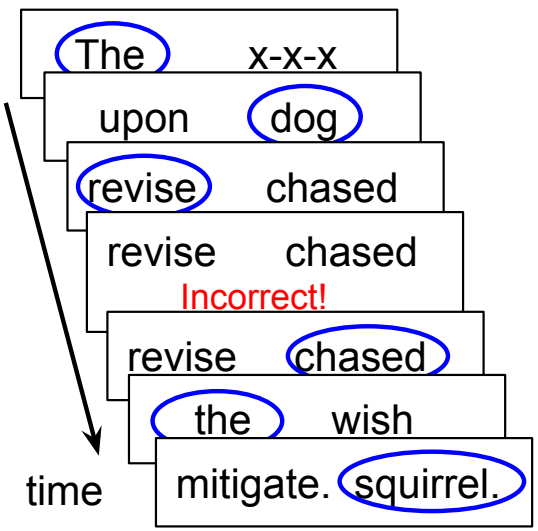


- Can be toggled in Ibex Maze
- Long materials feasible

Maze with Error Correction



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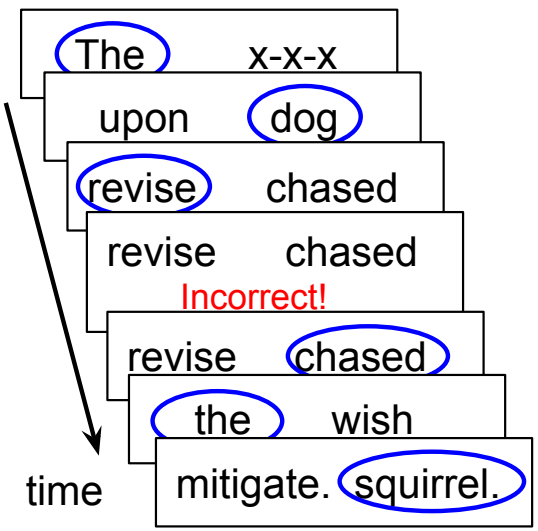
Maze with Error Correction



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

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- Work for multi-sentence items ✓ ?

Current experiment

Various open questions to address

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- Will people read long texts in Maze?

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- 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. [...]

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Q: When did tulip mania reach its peak?

A: 1630's 1730's

Participant accuracy

100 participants from MTurk each read 1 story (20 minutes)

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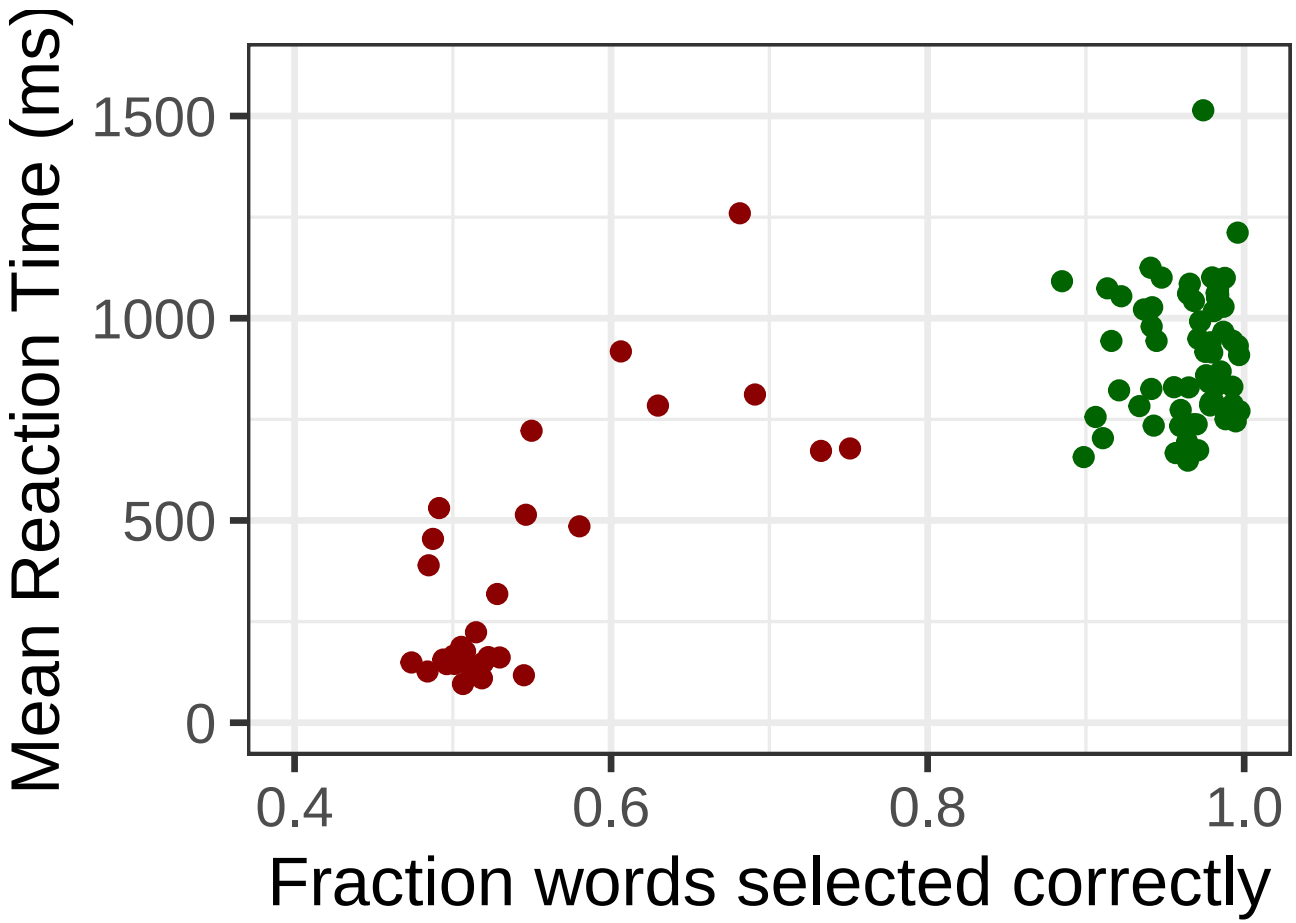

Comprehension questions

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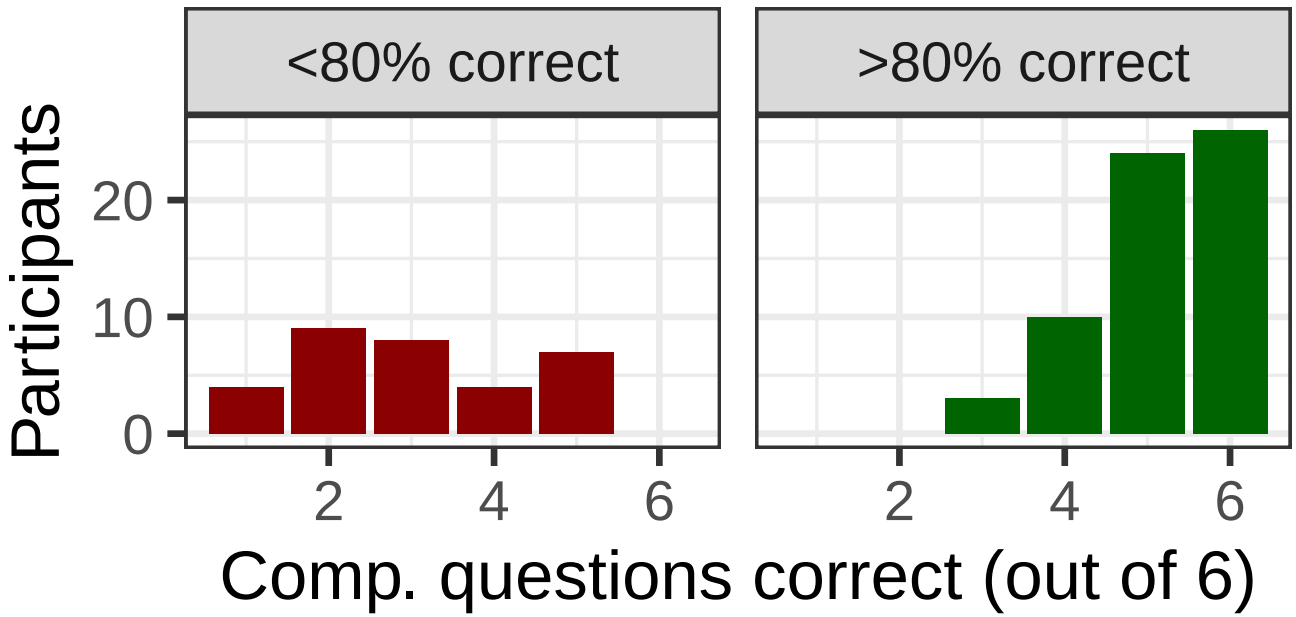

Surprisal Effects

Is RT linear in terms of surprisal?

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Estimate surprisal from 3 models:

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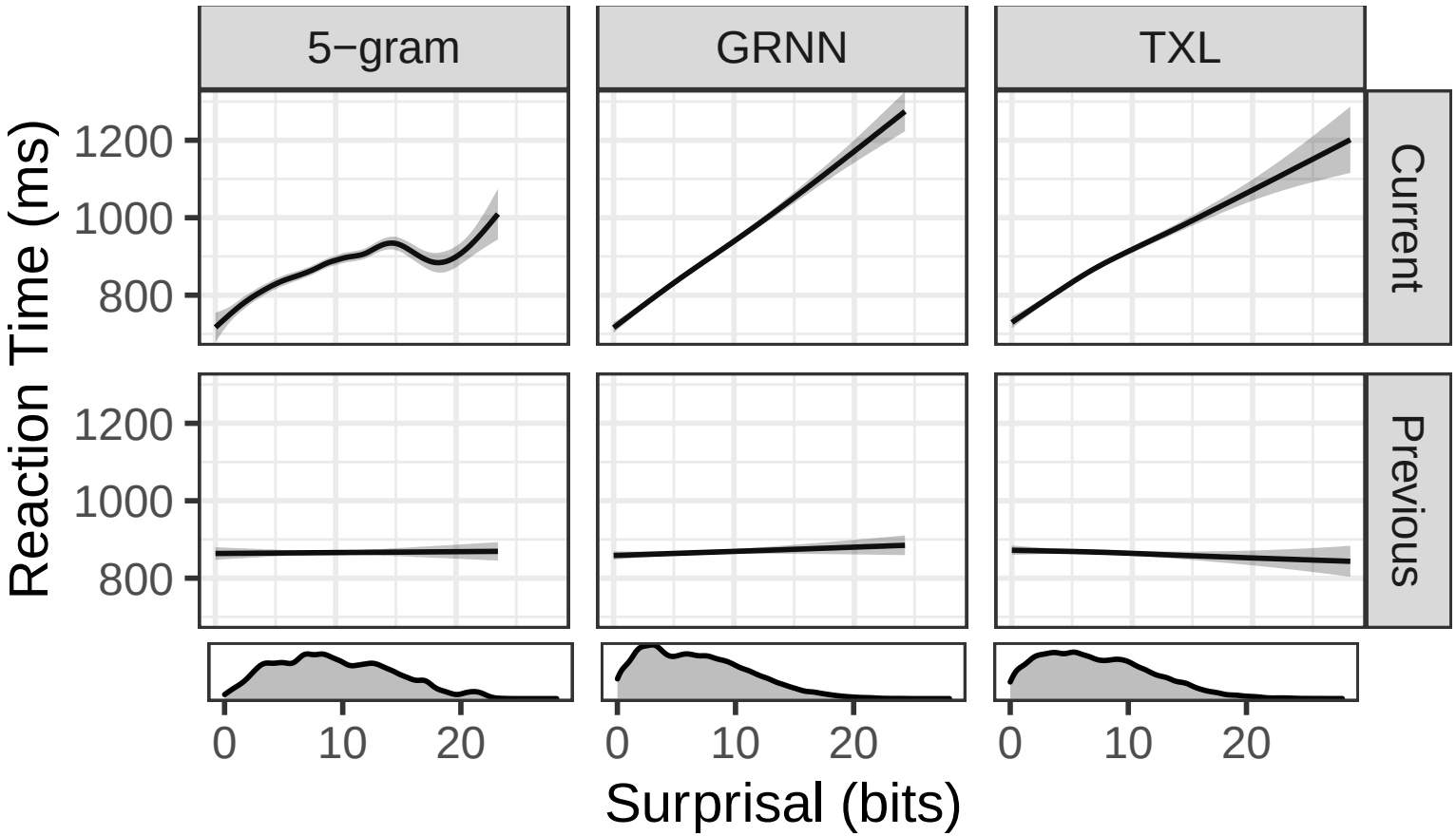
Fit GAMs

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

Surprisal Effects



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:

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- Minimal frequency effects (consistent with Shain 2019)

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Model comparison: GRNN is best, but TXL complementary

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Bayesian reader framework: Look at words long enough to ID with some threshold of certainty

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- Fewer available resources for processing

Why such large effects?

Bayesian reader framework: 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

Conclusion

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Consider A-maze!

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- Documentation: vboyce.github.io/Maze

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Natural Stories A-maze:

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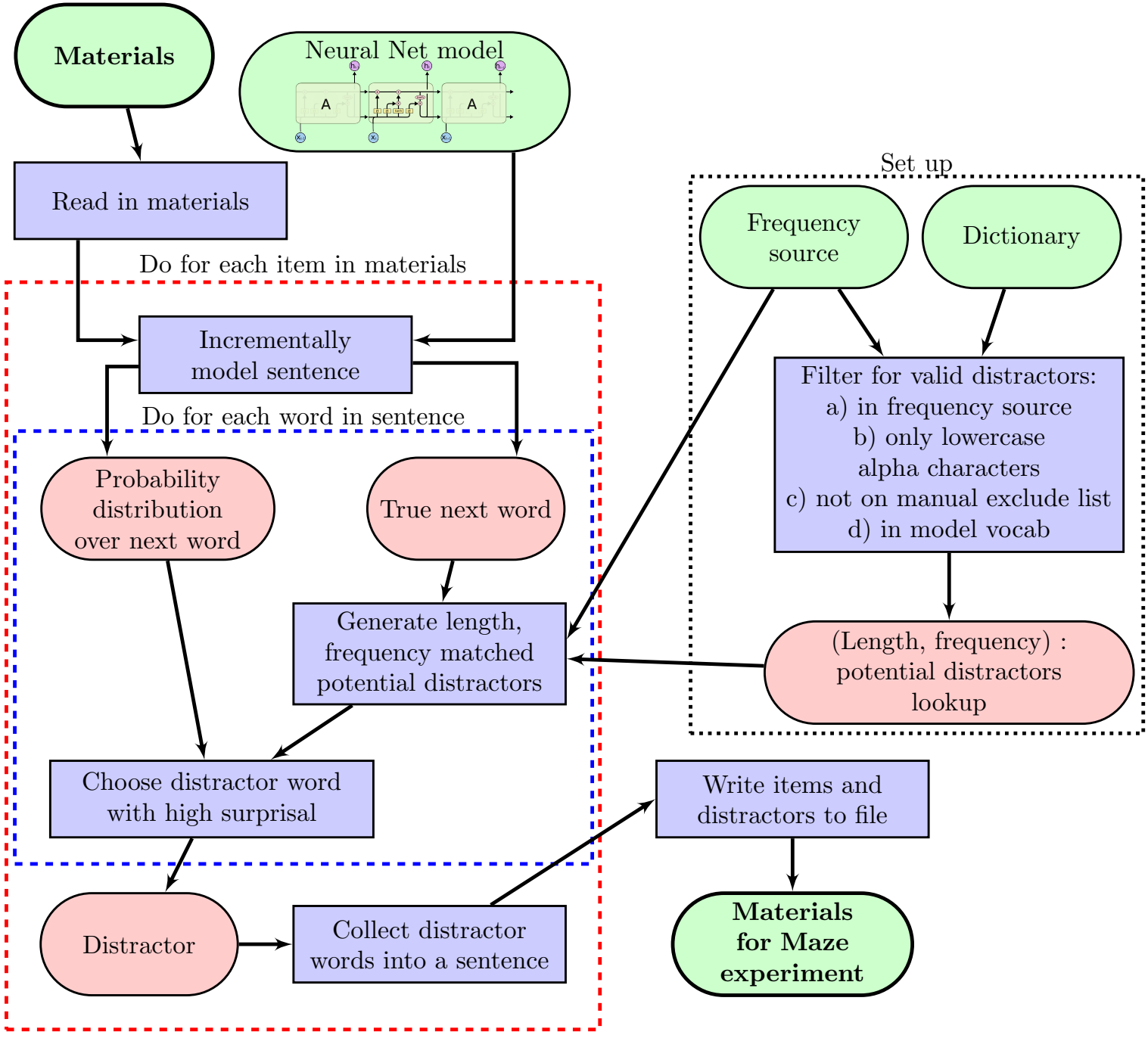
Natural Stories A-maze:

- Participants comprehend what they read
- Find linear, large surprisal effects


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

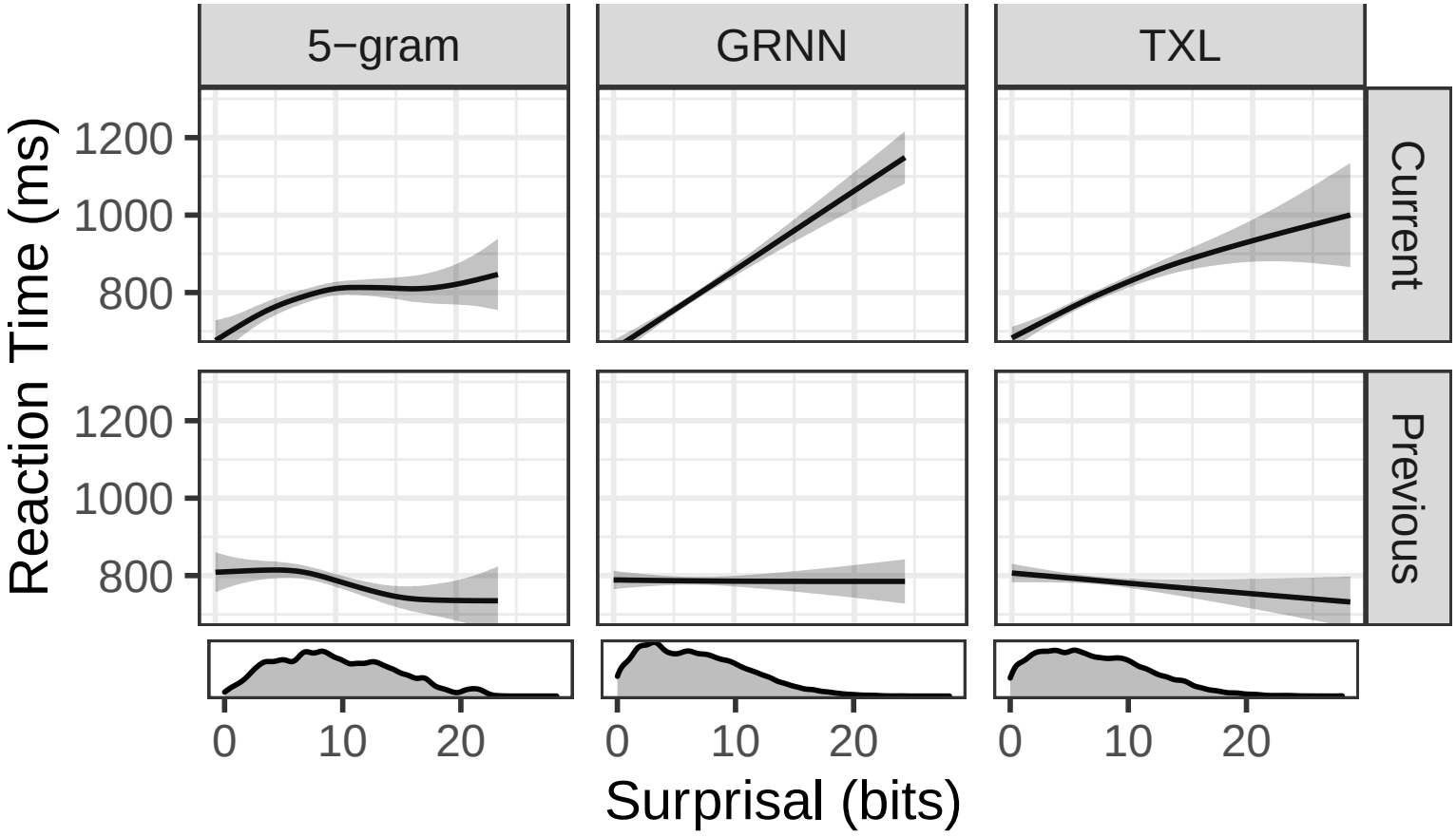
Caveats

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%

Surprisal Effects

GAM if we only exclude mistakes (all participants, post-mistake data)



Links

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
- Sample task: syntaxgym.org:666
- 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