# A-maze: Easier measurement of incremental processing

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

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

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## Self-paced reading

- - - - - - drank - - - -

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

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- Lots of spillover
- Messy data

# A third option: Maze

# Maze Task

The x-x-x

e i

# Maze Task

The x-x-x

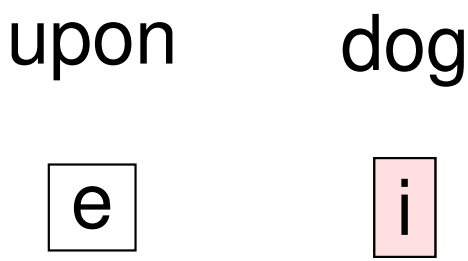
e i

# Maze Task

upon dog

e i

# Maze Task

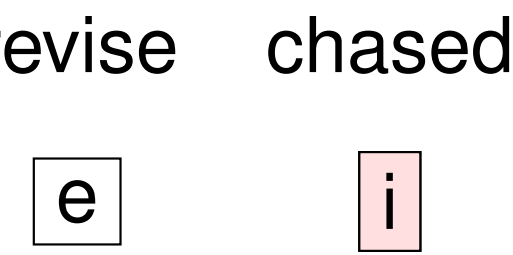


# Maze Task

revise chased

e i

# Maze Task



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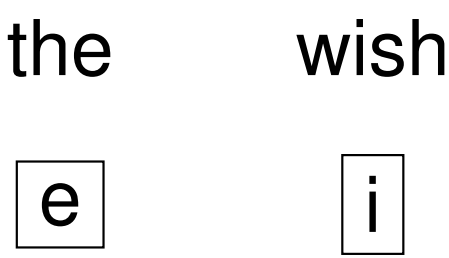

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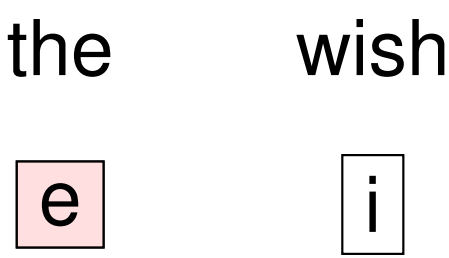

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mitigate. squirrel.

e i

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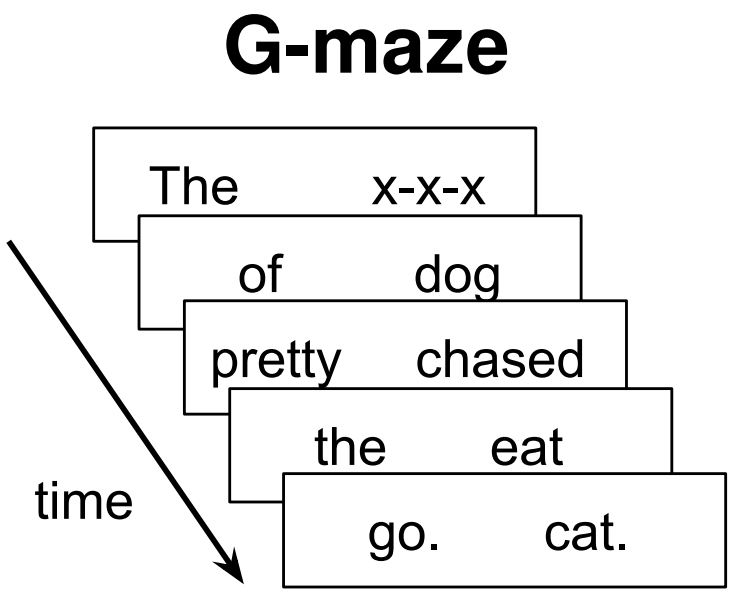
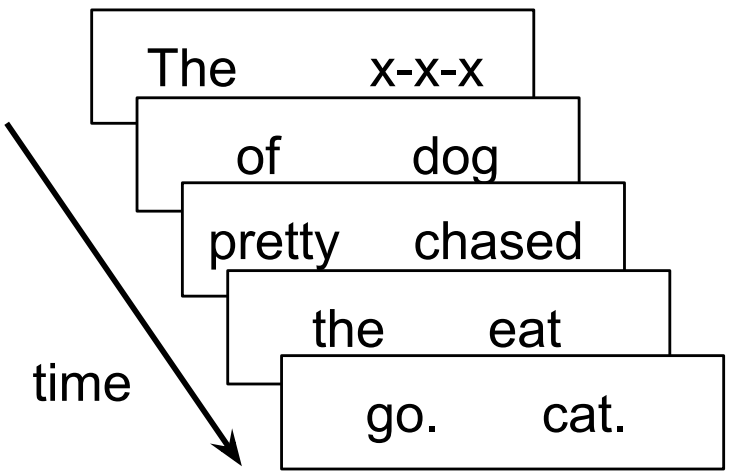
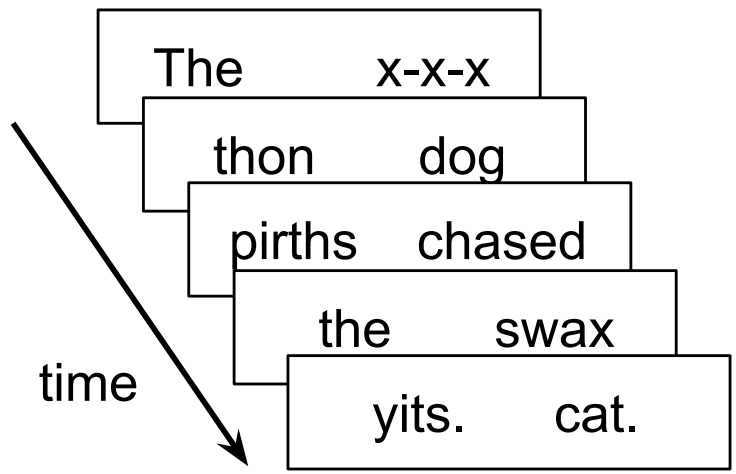


# A third option: Maze

## G-maze




## L-maze



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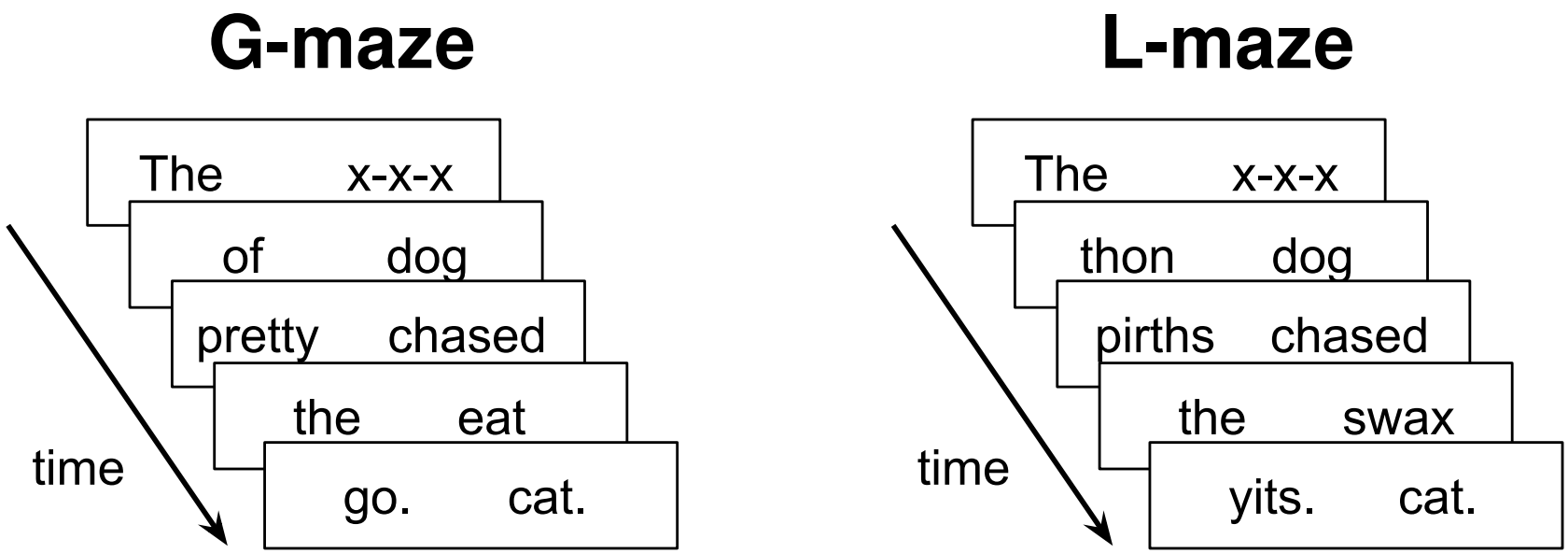


Sentence ends when a mistake is made.

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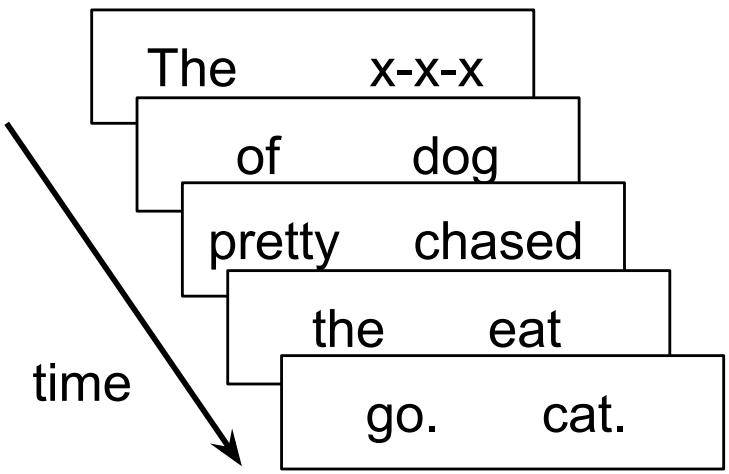


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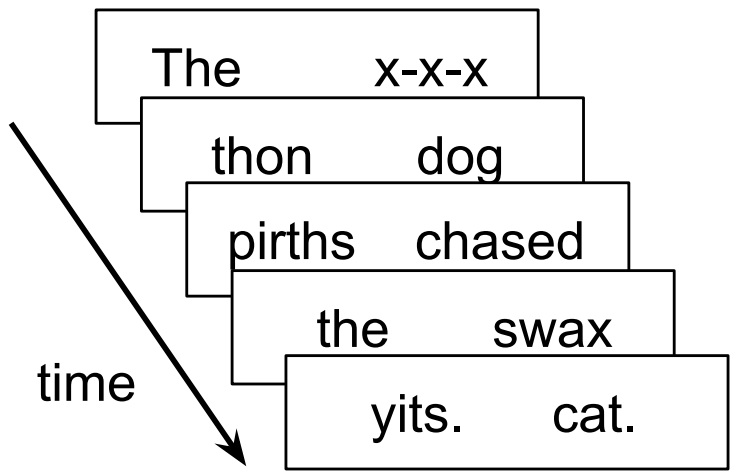


Sentence ends when a mistake is made.
Central claim: forces extremely incremental processing (no spillover)

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

# Web Implementation

Maze well suited to run on the web

- Implement in Ibex

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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.

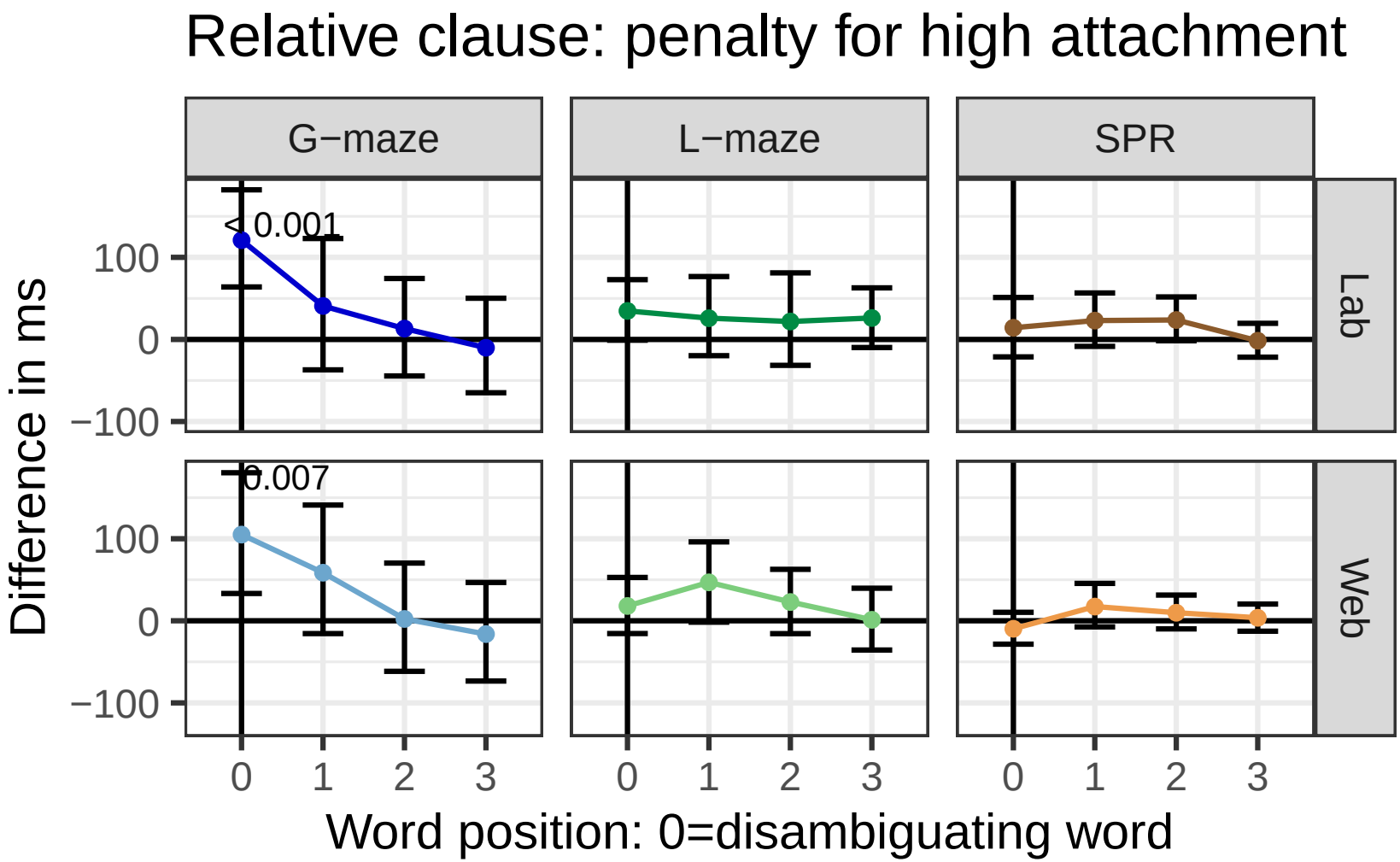
**Sentence v Noun Phrase conjunction**

*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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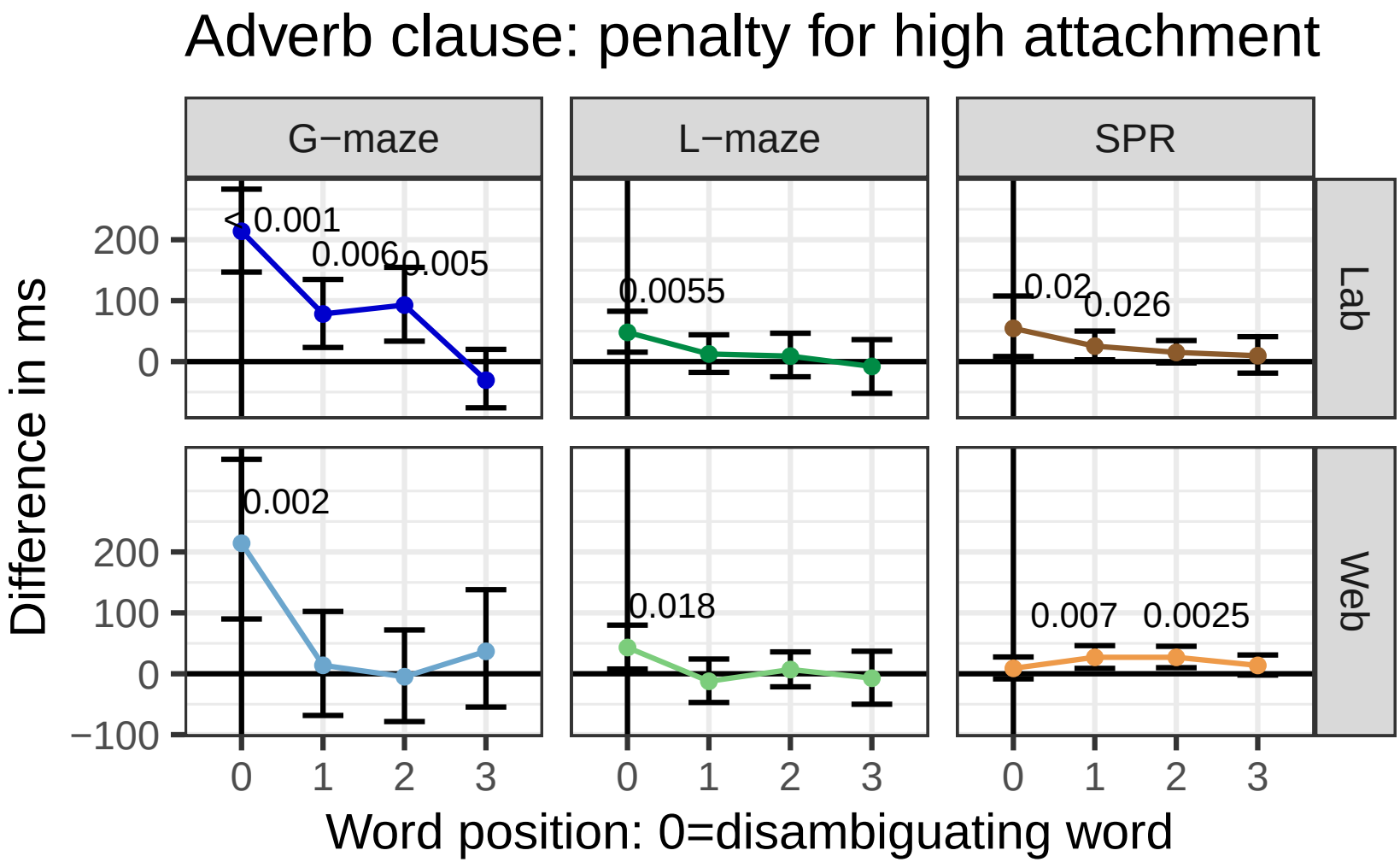

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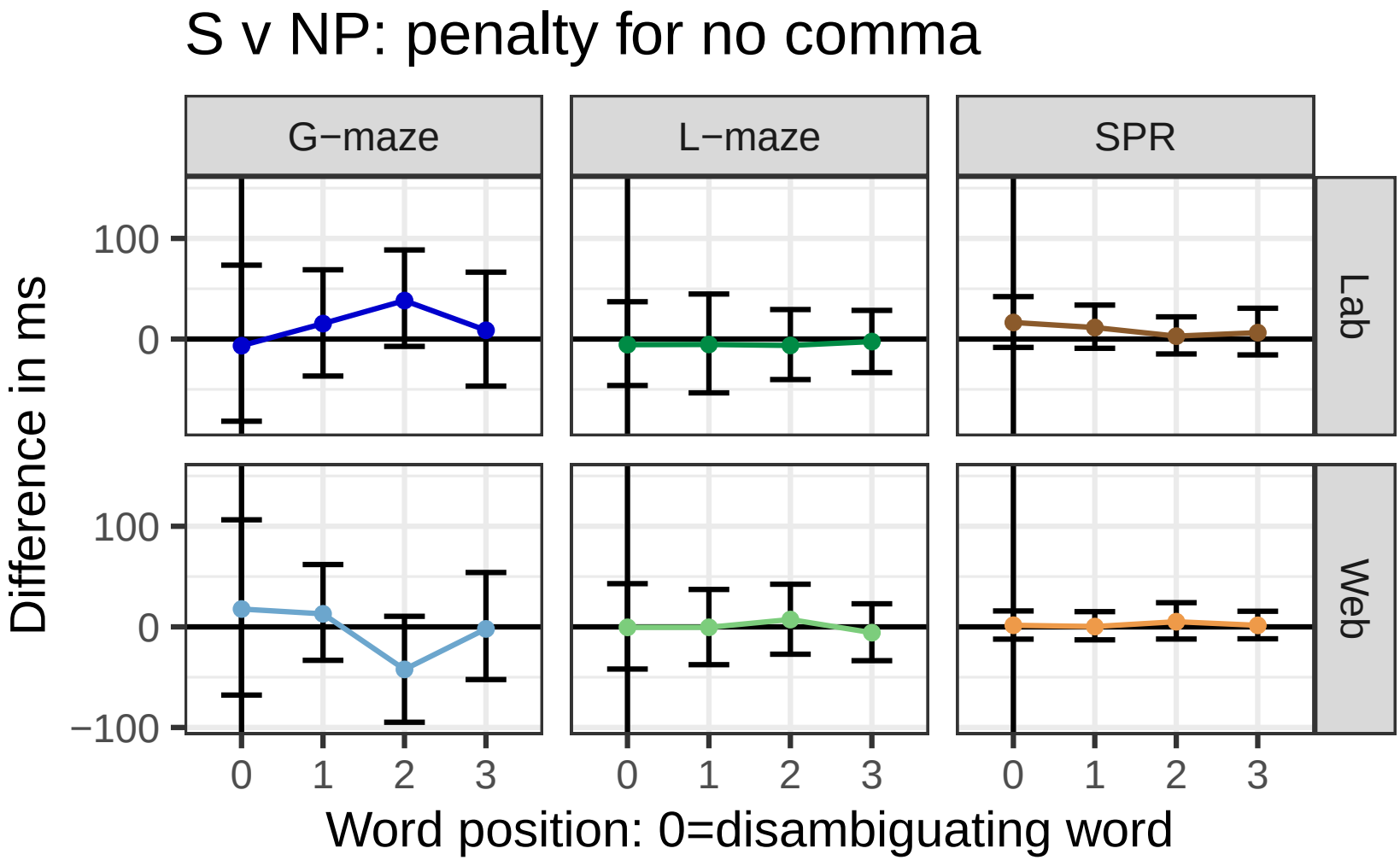

# Interim Summary

**Good news:** G-maze works well over the web (better than L-maze or SPR)

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**Bad news:** I do not want to write G-maze materials.

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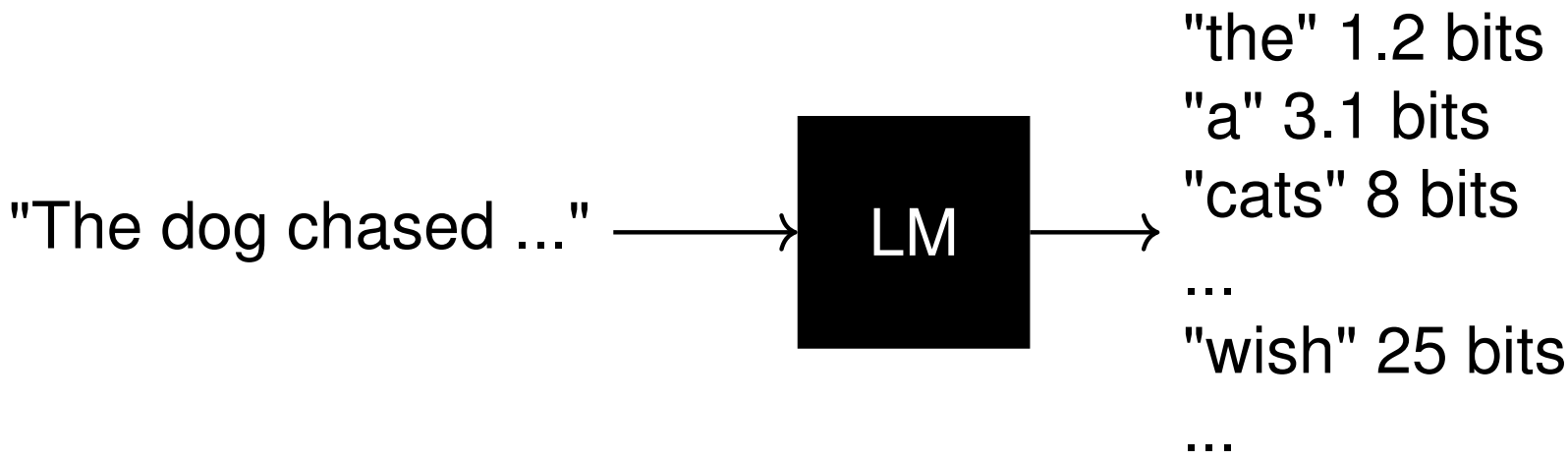

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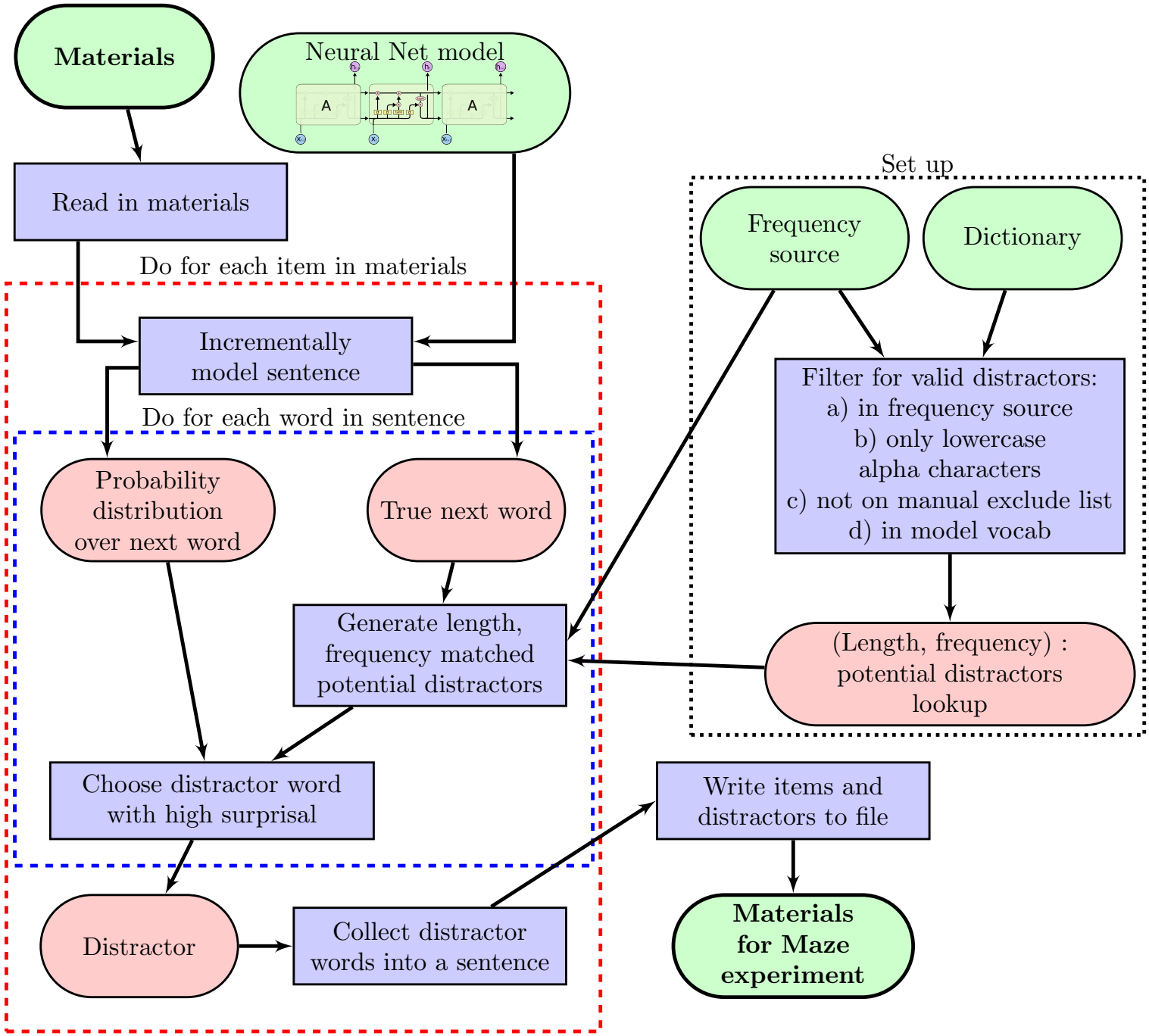
- Only consider distractors of same length, frequency as target word
- Check distractors until we find one with high surprisal


Materials
Neural Net model
A
A
Read in materials
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

# Does A-maze work?

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Test it on materials from Witzel et al. (2012)

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Try with two pre-trained LSTM models (Gulordava 2018, Jozefowicz 2016)

# Does A-maze work? Yes.

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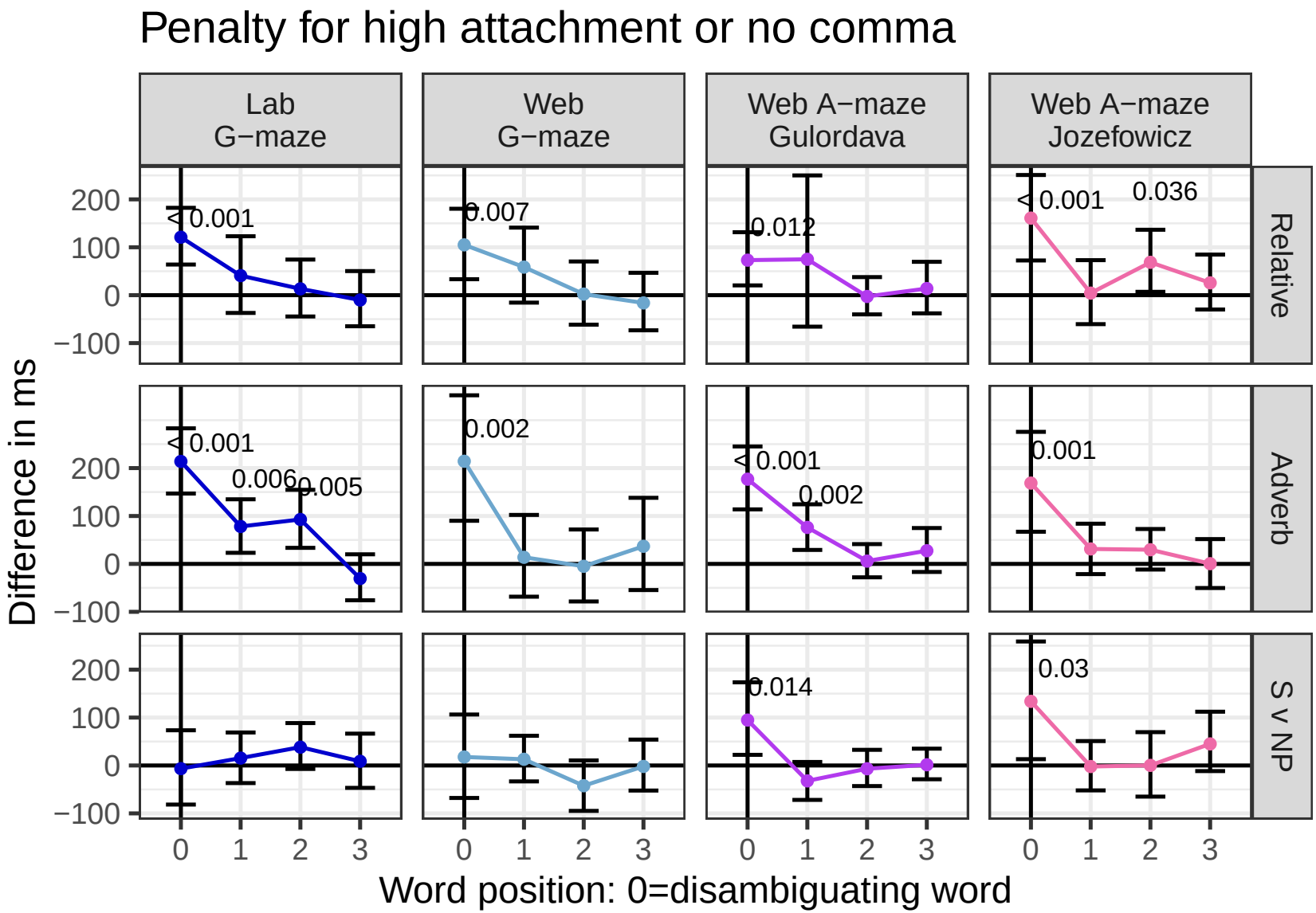

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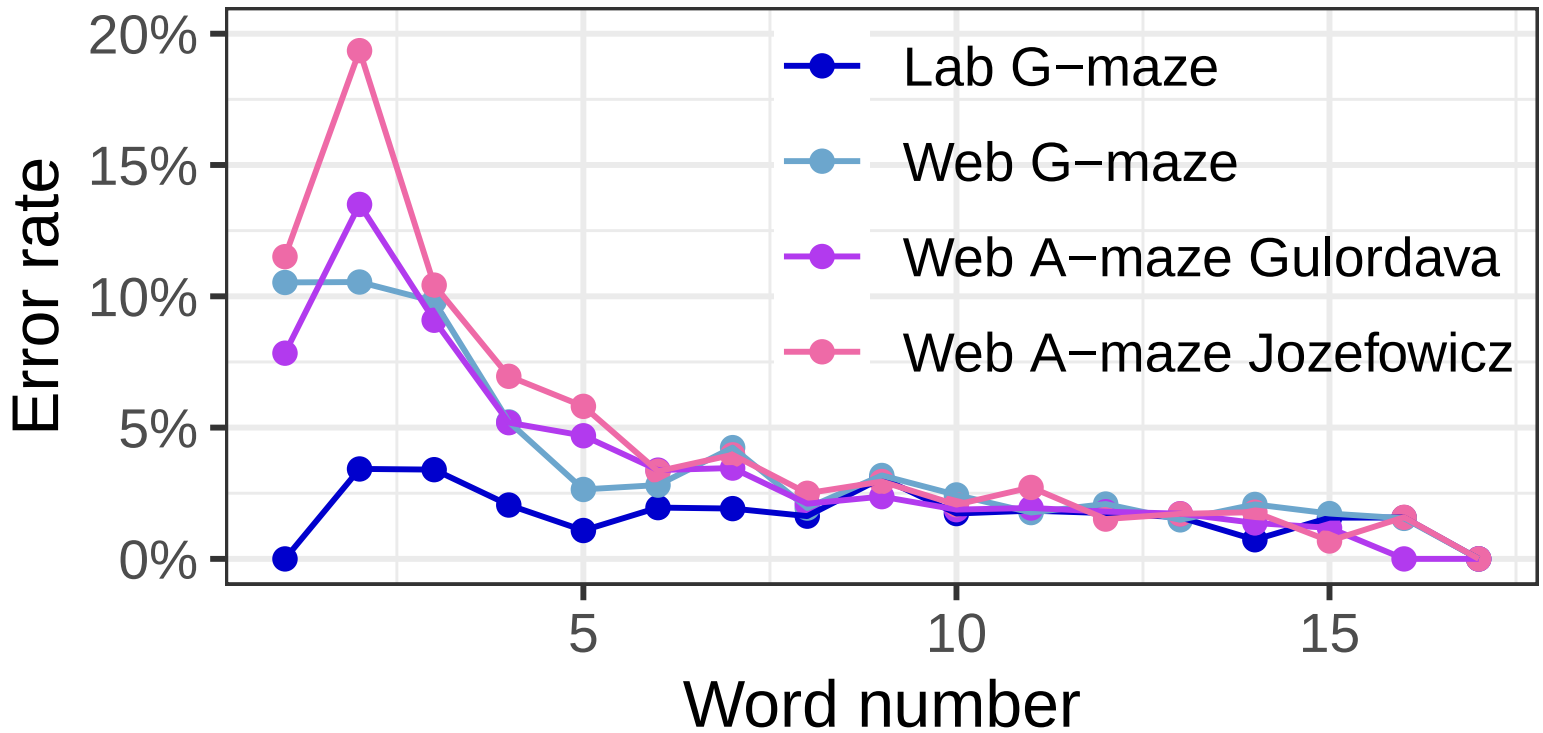

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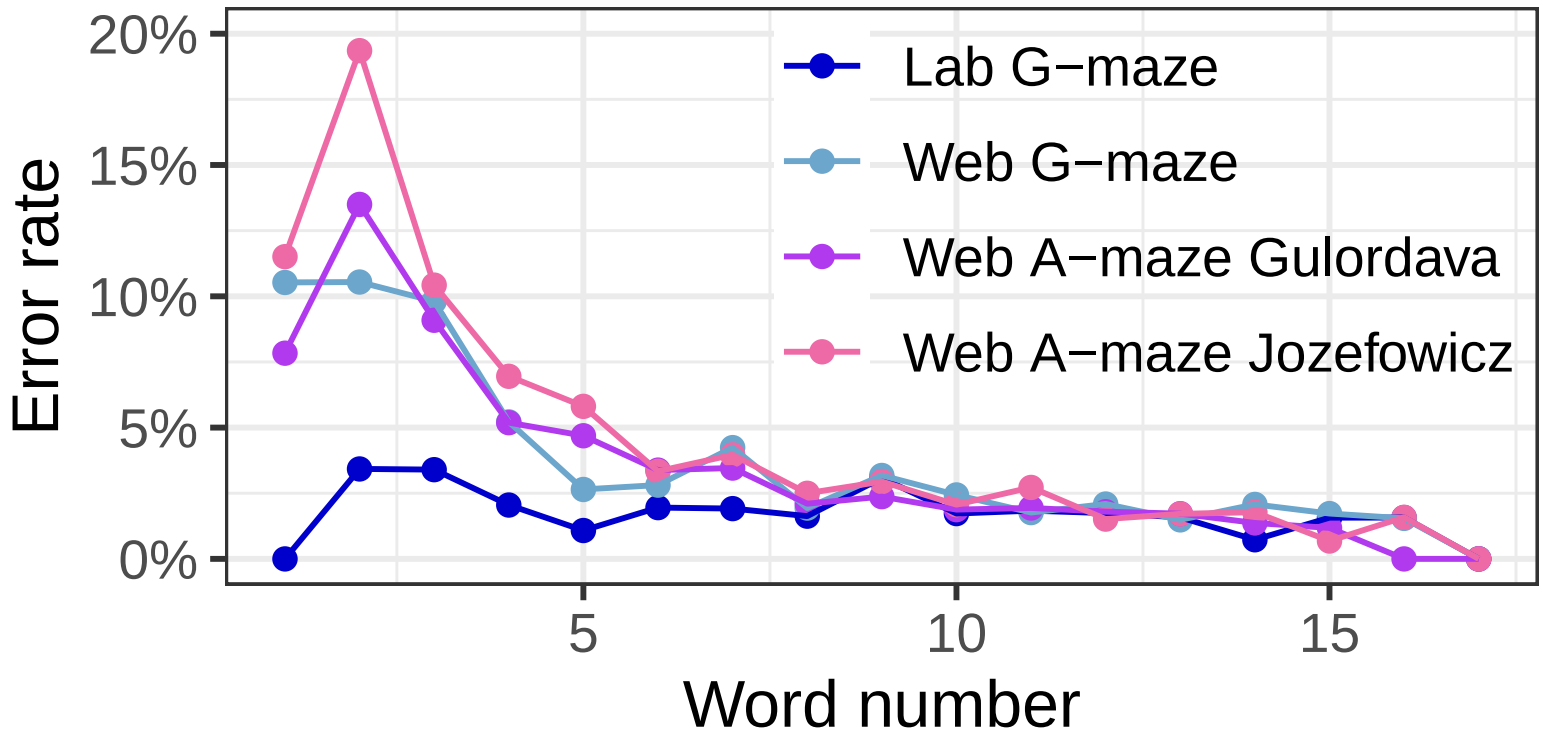


Bad participants or bad distractors?
Either way, lots of data loss.

# 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% |

# Potential improvements

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- Could search for optimal thresholds.
- Could manually check and fix distractors.

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- Just don't terminate on mistakes.
- Instead have participant correct mistake and continue.

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# Maze with Error Correction

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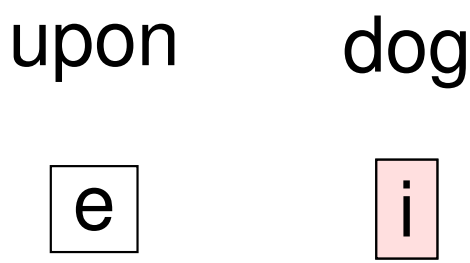

# Maze with Error Correction

revise chased

e i

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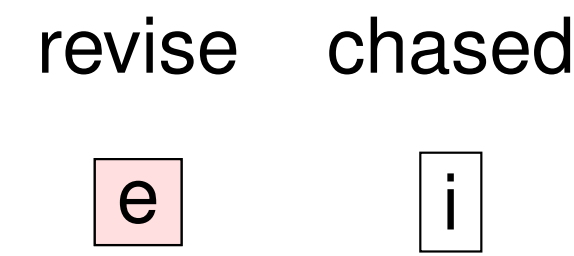

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Incorrect. Please try again.

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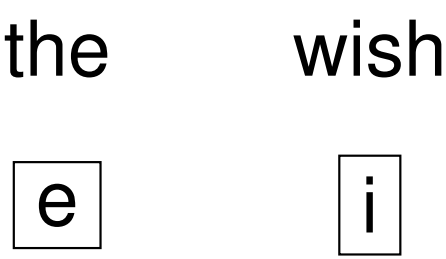

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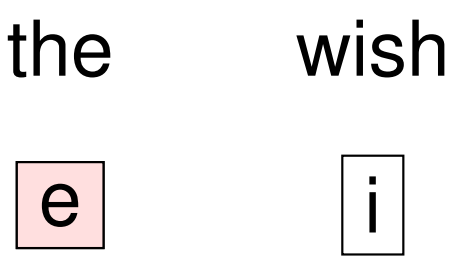

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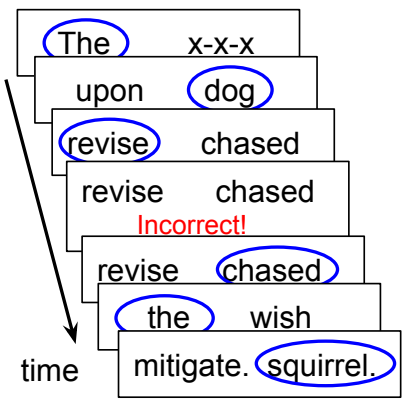

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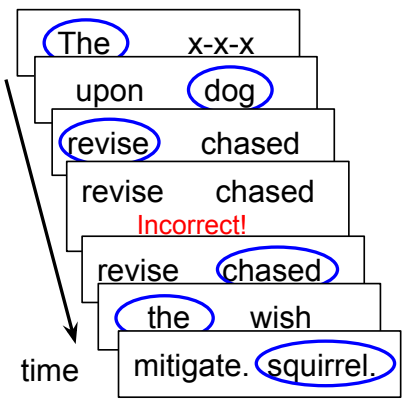


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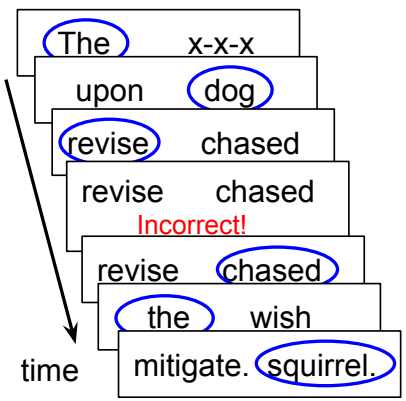


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- Have all the data

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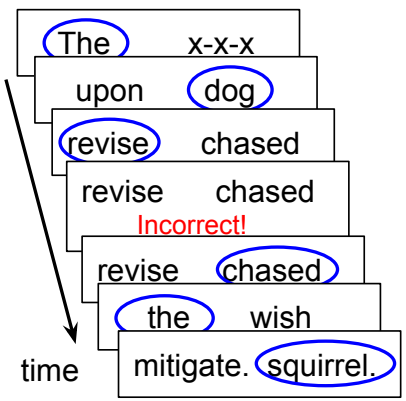


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- Have all the data
- Identify bad participants v bad distractors

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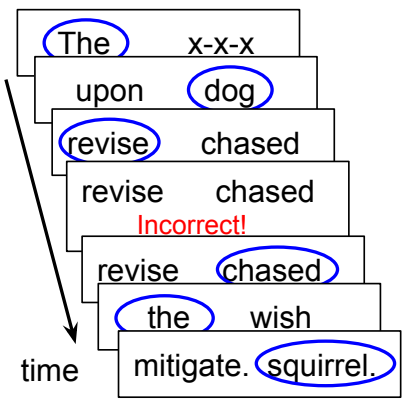


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- Have all the data
- Identify bad participants v bad distractors

Side effect: Can now run multi-sentence items!

# Natural Stories

Natural stories corpus (Futrell et al. 2017)

- 10 stories, each about 1000 words
- Some unusual constructions, but read fluently
- 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

# Experiment Plan

Experiment questions:

- Will people do this task?
- Can participants comprehend the stories?

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Checks on RT data

- Check if RT is linear in surprisal (Smith & Levy 2013)
- Check for known effects of word length, frequency
- Check for spillover effects

# Participant accuracy

100 participants each read 1 story

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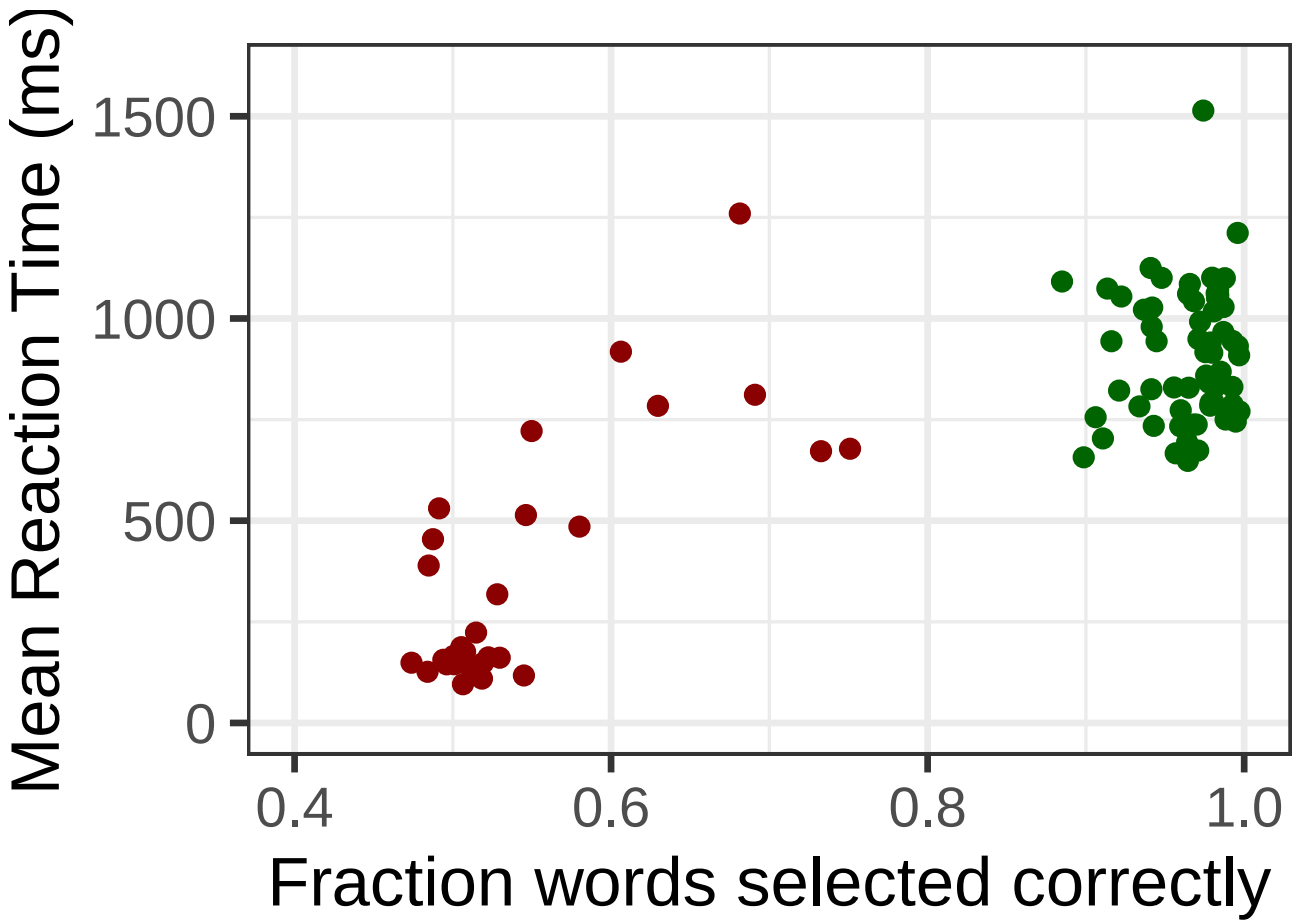

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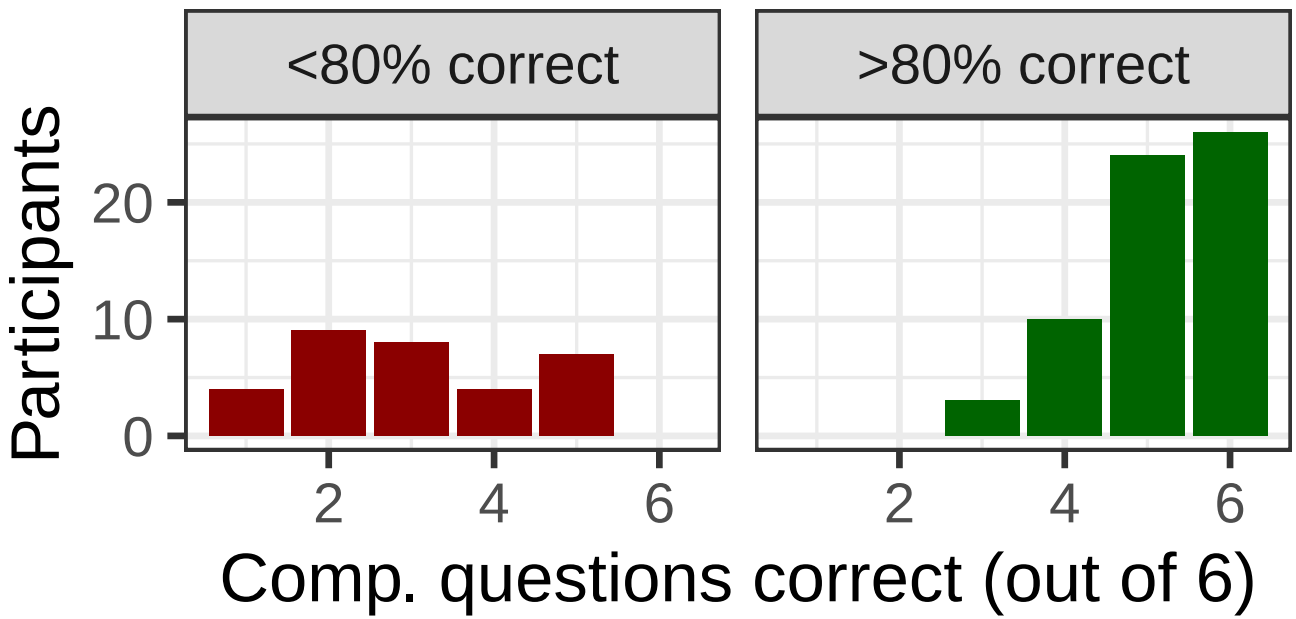

# Surprisal Effects

Use 3 LMs to estimate surprisal: smoothed 5-gram, Gulordava RNN, Transformer-XL (Gulordava et al. 2018, Dai et al. 2019)

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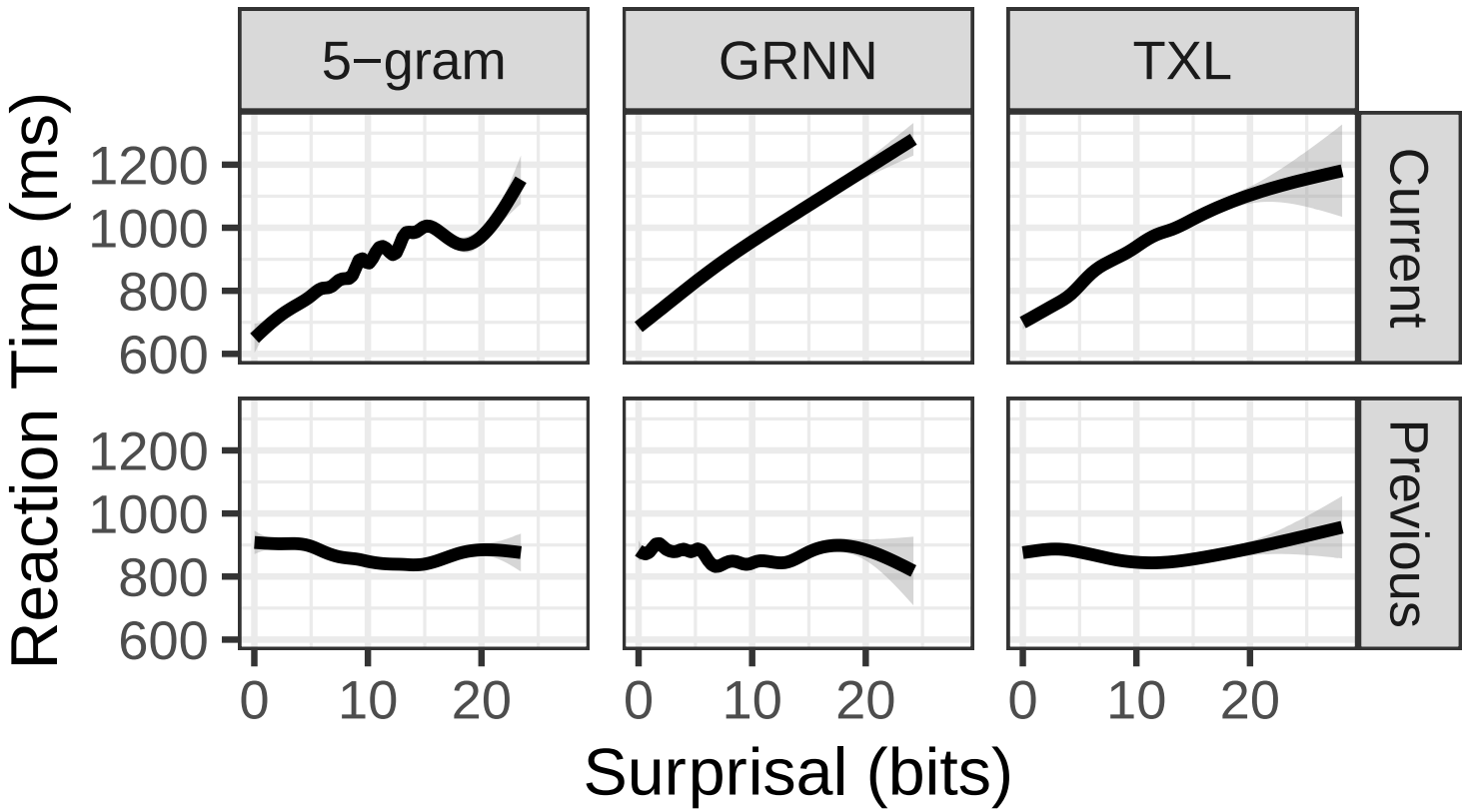
Fit GAMs on pre-error data.

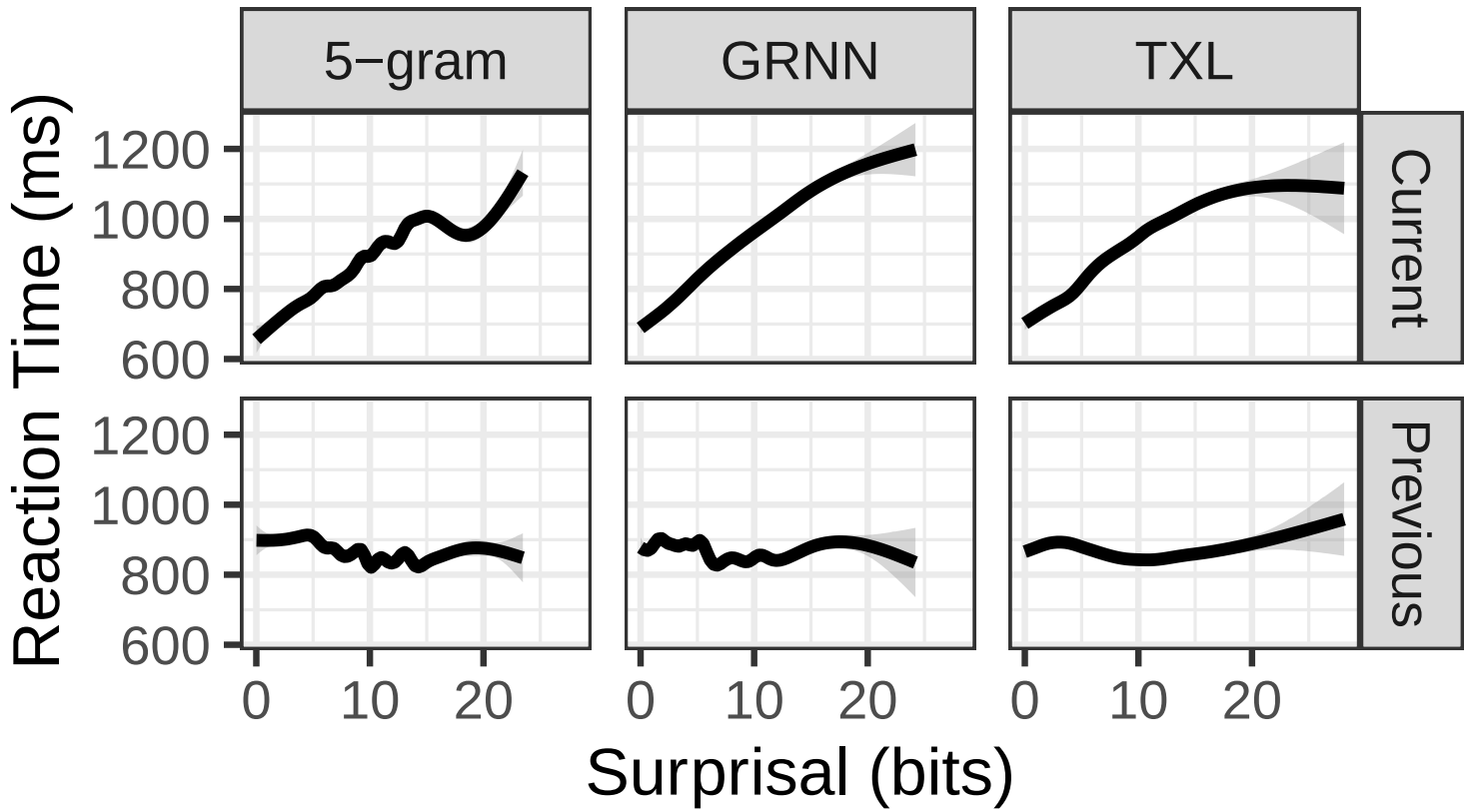
- Limit to single-token words.
- Fit to both current and past word surprisal.

# Surprisal Effects



# What about post-mistake data?

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



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- People will read in the Maze task for 15-20 minutes
- It's possible to comprehend during Maze
- Distractors are generally good enough
- Find expected RT patterns
- Very little spillover

# Use A-maze!

Easy to use!

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- Runs on command line

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Easy to use!

- Runs on command line
- Match distractors across minimal pair sentences
- Customize surprisal thresholds, vocabulary lists
- Can output pre-formatted for Ibex

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Contribute to A-maze:

- Written in Python 3

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Contribute to A-maze:

- 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
- Sample task: syntaxgym.org:666
- Paper: psyarxiv.com/b7nqd/

# Matching distractors

If unspecified: Match by position

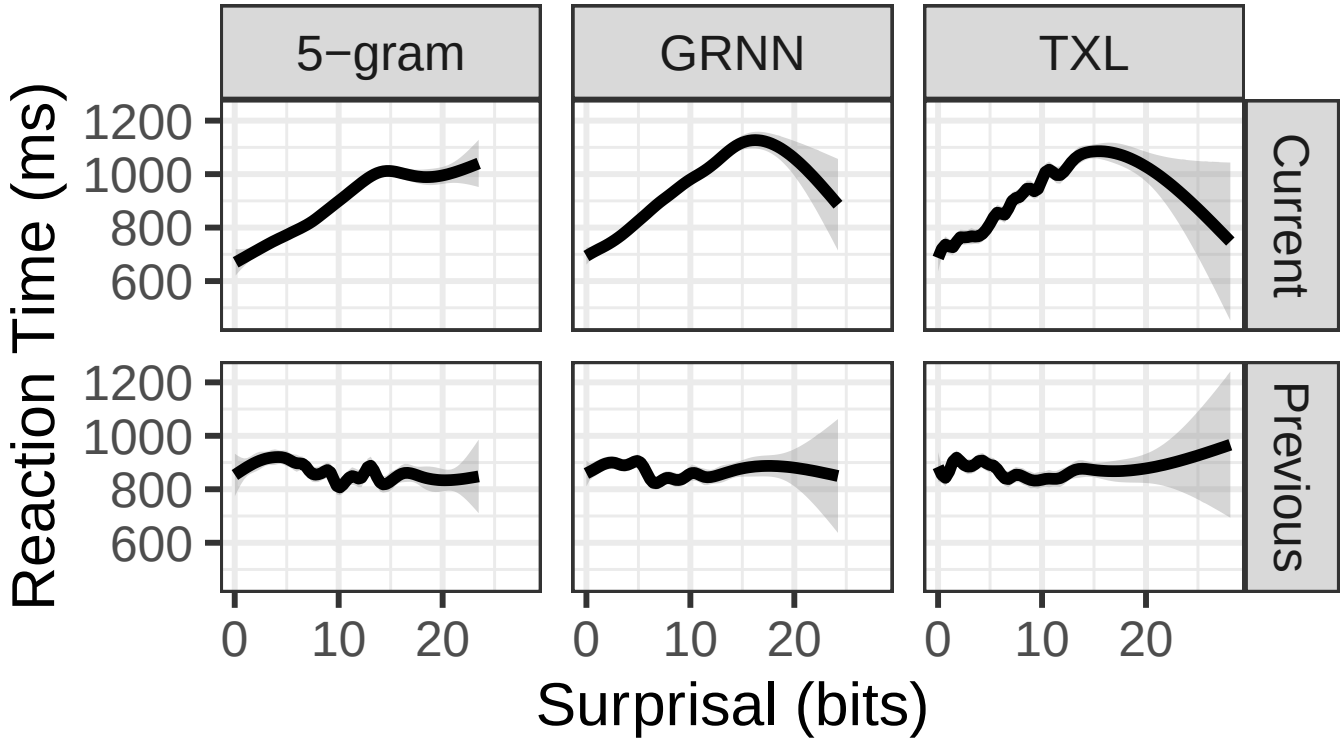
- The son of the lady who politely introduced herself / himself was popular at the party.

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

# Post-mistake only

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



# 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] |