1   A-maze of Natural Stories: Comprehension and surprisal in the Maze task TODO title

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Abstract

TODO needs work A-maze is a new method for measuring incremental sentence processing that can localize slowdowns related to syntactic ambiguities. We adapt A-maze for use on longer passages and test it on the Natural Stories corpus. We find that people can comprehend these longer text passages during the Maze task. Moreover, the task yields useable reaction time data with word predictability effects that are linear in the surprisal of the current word, with little spillover effect from the surprisal of the previous word. This expands the types of effects that can be studied with A-maze, showing it to be a a versatile alternative to eye-tracking and self-paced reading.We find support for the localization of reading time effects during the Maze task, as well as extending the range of materials Maze is suitable for. How long it takes to read a word in a sentence is reflective of how hard it is to identify and integrate the word in the surrounding context. Techniques that slow down the reading process and localize the processing time for each word are useful to understanding the time course of language processing.

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Introduction

Sometimes we stumble in reading, where we expected a sentence to go in one direction and it did not, and then are at a parsing dead-end where we have to read a sentence again. The words that cause stumbles are the outliers on a distribution of words difficulty to read, within fluent reading, there is variation in how easy words are to read and process in their context. We're able to read many long or surprising words without noticing a problem, but these less expected words do take longer to process as we rebuild our burgeoning mental model of the sentence. Fortunately for fluent readers and unfortunately for studying language, this process of adjustment is very quick, with millisecond scale differences in reading time between words.

We don't have a thorough understanding of how the mind processes language, but we can learn something about what is going on from measuring how long it takes in different circumstances. This relies on a linking hypothesis that processing time reflects something about how much processing is going on, even if we don't know whether this is character recognition, memory retrieval, or parsing. This is enough to compare theories that predict the relative difficulty, and thus relative processing time, of two words in different contexts.

For instance, different theories about what makes object relative clauses harder to understand than subject relative clauses make different predictions about which words are the loci of the overall difficulty and slower reading times associated with object relatives (Grodner & Gibson, 2005; Staub, 2010; Traxler, Morris, & Seely, 2002). Measures of reading time can also inform theories about the time course of processing (i.e. which steps are parallel versus serial, Bartek, Lewis, Vasishth, and Smith (2011)) or the functional form of relationships between word characteristics and processing time (Smith & Levy, 2013).

Some of these theories rely on being able to attribute processing slowdowns to a particular word. Determining that object relatives are overall slower that subject relatives is easy, even an imprecise measure of reading time will determine that the same set of words in a different order took longer to read on a sentence level. However, many language processing theories make specific (and contrasting) theories about which words in a sentence should be harder to process. To adjudicate these theories, we want methods that are *localized*, where it is easy to determine which word is responsible for an observed slow-down in reading time. Ideally, a longer reading time on a word would be an indication of that word's increased difficulty, and not the lingering signal of a prior word's increased difficulty. When the signal isn't localized, advanced analysis techniques may be required to disentangle the slow-downs (Shain & Schuler, 2018).

Incremental processing methods

Behavioral methods that measure how long it takes to read each word in a sentence are referred to as incremental processing methods, and their dependent measures are called reading times or reaction times, both abbreviated RT. The two most commonly used methods are eye-tracking and self-paced reading, but both of these suffer from a lack of

localization. In eye-tracking, participants read a text on a screen naturally, while their eye-movements are recorded (Rayner, 1998). The downside of this natural reading is that people often skip short words and look ahead or look back as they read, the dynamics of which make it hard to isolate effects (Frazier & Rayner, 1982; Levy, Bicknell, Slattery, & Rayner, 2009; Rayner, Ashby, Pollatsek, & Reichle, 2004). Self-paced reading (SPR) is a more controlled process where a participant sees one word on screen at a time and presses a button to see the next word instead. Even in this method, readers may maintain ambiguities about what a word was or means until it is later resolved by context, so it may take multiple words for slowdowns to catch up with them (Koornneef & van Berkum, 2006; MacDonald, 1993). Both these methods are prone to spillover, as the time to plan motor movements like saccades or button presses is substantial compared to the time it takes to recognize a word, these movements are often initiated before a word is fully processed, so by the time any late processing difficulties occur, the reader may already be several words along.

the Maze task. An alternative method that is designed to increase localization at the expense of naturalness is the Maze task (Forster, Guerrera, & Elliot, 2009; Freedman & Forster, 1985). In the Maze task, participants see two words at a time, a correct word that continues the sentence, and a distractor which does not. Participants must choose the correct word, and their time to selection is treated as the reaction time (RT). Forster et al. (2009) introduces two versions of the Maze task: lexical L-maze where the distractors are nonce words and grammatical G-maze where the distractors are real words that don't fit with the context of the sentence so far. Theoretically, participants must fully integrate each word into the sentence in order to confidently select it; this may require mentally reparsing previous material in order to allow the integration and selection of a disambiguating word. Forster et al. (2009) call this forced incremental processing to distinguish from other incremental processing methods where words can be passively read before later committing to a parse. This idea of strong localization is supported by studies finding strongly localized effects for G-maze which is more sensitive than L-maze (Witzel, Witzel, & Forster, 2012).

The downside of G-maze is that materials are effort-intensive to construct because of the need to select infelicitious words as distractors for each spot of each sentence; this may explain why the Maze task has not been widely adopted. Boyce, Futrell, and Levy (2020) demonstrate a way to automatically generate Maze distractors by using NLP language models to find words that are high-surprisal in the context of the target sentence, and thus likely to be judged infelicitous by human readers. Boyce et al. (2020) found that materials with A-maze distractors had similar results to the hand-generated distractors from Witzel et al. (2012). A-maze outperformed L-maze and an SPR control in detecting and localizing expected slowdown effects. Sloggett, Handel, and Rysling (2020) also found that A-maze and G-maze distractors yielded similar results on a disambiguation paradigm.

Another recent variant of the Maze task is interpolated or I-maze, which uses a mix of real word distractors (generated via the A-maze process) and nonce word distractors (Vani, Wilcox, & Levy, 2021). The presence of real word distractors encourages close attention to the sentential context, while nonce words can be used as distractors where the word in the sentence is itself ungrammatical or highly unexpected. Vani et al. (2021) used I-maze to compare object- and subject- relative clauses and Wilcox, Vani, and Levy (2021) used it to

compare differences in RT for pairs of grammatical and ungrammatical sentences NLP language models predictions.

Frequency, length, and surprisal effects

One way of assessing how much a method localized RT effects is to look at how strongly properties of a word correlate with the RT of that word compared with RTs of downstream words later in the sentence. A couple of properties known to influence reading time are a word's length and overall frequency in a language, as longer and less common words take longer to process (Kliegl, Grabner, Rolfs, & Engbert, 2004). Another measure is predictability, or how expected a word is given the context, with more predictable words being read faster (Rayner et al., 2004). A word can have low predictability for a number of reasons: it could be low frequency, semantically unexpected, the start of a low-frequency syntactic construction, or a word that disambiguates prior words to the less common parse. Many targeted effects of interest are essentially looking at specific features that contribute to how predictable or unpredictable a word is. This means that how good a method is at detecting and localizing effects of predictability is a key aspect of how useful it is as measure of incremental processing. With al these factors potentially contributing to predictability, how is predictability as a whole measured? The typical method is to use language models that are trained on large corpora of language to predict what word comes next in a sentence. A variety of pre-trained models exist, that vary in their internals, but all of them will generate assessments of how predictable words are. Predictability is often represented in terms of bits of surprisal, which is the negative log probability of a word (1 bit of surprisal means a word is expected to occur half the time, 2 bits is 1/4 of the time etc). The functional form of the relationship between RTs from eye-tracking and SPR corpora and the predictability of the words is linear in terms of surprisal (Goodkind & Bicknell, 2018; Luke & Christianson, 2016; Smith & Levy, 2013; Wilcox, Gauthier, Hu, Qian, & Levy, 2020). Due to spillover effects, this linear relationship also holds between the surprisal of a previous word and the RT on the current word.

Current experiment

The Maze task has thus far only been used on constructed sentences focusing on targeted effects and not on the sorts of long naturalistic passages used to assess the relationship between RT and surprisal. We want to test whether participants can read and understand stories while doing the demanding Maze task and also whether the RT profiles from the Maze task are similar to those from other methods.

The Natural Stories corpus (Futrell et al., 2020) consists of 10 passages each roughly 1000 words long which are designed to read fluently to native speakers. At the same time, the passages contain copious punctuation, quoted speech, many proper nouns, and low frequency grammatical constructions. Taken together, these properties are a severe test of A-maze, as these features may make it harder to auto-generate appropriate distractors and require focus from participants. If participants can succeed at the Maze task on Natural Stories, we think they are likely to succeed on a wide variety of naturalistic texts. The

¹⁵³ corpus is accompanied by binary-choice comprehension questions, 6 per story, which we use
¹⁵⁴ to assess comprehension.

¹⁵⁵   We tweak the A-maze task to accomodate these longer passages and then have
¹⁵⁶ participants read the passages in the Maze. We compare our A-maze results with SPR data
¹⁵⁷ collected on this corpus by Futrell et al. (2020). We find that participants were able to read
¹⁵⁸ and understand these long passages using A-maze, and their RT profiles show a similar
¹⁵⁹ pattern to SPR but with less noise and spillover

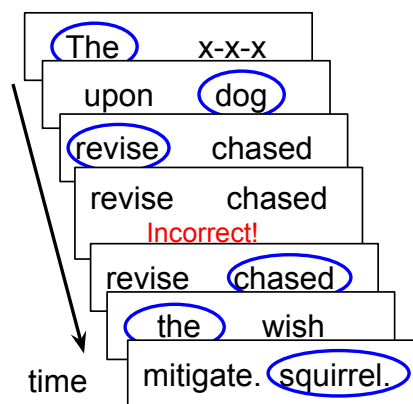¹⁶⁰   **Error-correction maze**

Figure 1. Schematic of error-correction Maze. A participant reads a sentence word by word,
choosing the correct word at each time point (selections marked in blue ovals). When they
make a mistake, an error message is displayed, so they try again and continue with the
sentence.

¹⁶¹   One of the benefits of the Maze task is that it forces incremental processing by having
¹⁶² participants make an active choice about what the next word is. But what if they choose
¹⁶³ incorrectly? In the traditional Maze paradigm, there isn't a way to handle this; a mistake
¹⁶⁴ indicates they're not understanding the sentence properly, so the sentence ends, and the
¹⁶⁵ participant moves on to the next item (Forster et al., 2009). An advantage of this is that
¹⁶⁶ participants who contribute RT data are very likely to have understand the sentence up to
¹⁶⁷ that point (it's hard to choose correctly in G-maze otherwise). This contrasts with other
¹⁶⁸ methods, where determining whether participants are paying attention usually requires
¹⁶⁹ separate comprehension check questions, that are usually not used for Maze.

¹⁷⁰   However, terminating sentences on errors means that we don't have data after a
¹⁷¹ participant makes a mistake in an item. In traditional G-maze tasks, with hand-crafted
¹⁷² distractors and attentive participants, this is a small issue. However, this data loss is much
¹⁷³ worse with A-maze materials and crowd-sourced participants (Boyce et al., 2020). The high
¹⁷⁴ errors are likely from some combination of participants guessing randomly and from
¹⁷⁵ auto-generated distractors that in fact fit the sentence; as Boyce et al. (2020) noted, some
¹⁷⁶ distractors, especially early in the sentence, were problematic and caused considerable data
¹⁷⁷ loss.

178   This situation could be improved by auto-generating better distractors or
179 hand-replacing problematic ones, but that does not solve the fundamental problem with long
180 items. Well-chosen distractors and attentive participants will reduce the error rate, but the
181 error rate will still compound over long materials. For instance, with a 1% error rate, 86% of
182 participants would complete each 15-word sentence, but only 61% would complete a 50 word
183 vignette, and 13% would complete a 200 word passage. In order to run longer materials, we
184 need something to do when participants make a mistake, other than terminate the entire
185 item.

186   To resolve this, we introduce an *error-correction* variant of Maze shown in Figure 1.
187 When a participant makes an error, we present them with an error message and wait until
188 they select the correct option, before continuing the sentence as normal. We make this
189 "error-correction" Maze available as an option in a modification of the Ibex Maze
190 implementation introduced in Boyce et al. (2020)
191 (https://github.com/vboyce/Ibex-with-Maze). The code records both the RT to the first
192 click and also the total RT until the correct answer is selected as separate values.

193   This variant of Maze expands the types of materials that can be used with Maze to
194 include arbitrarily long passages and cushions the impact of occasional problematic
195 distractors. Error-correction Maze is a change in experimental procedure, and is independent
196 of what types of distractors are used. This error-correction presentation is used here with
197 A-maze, but would also work with G-maze or I-maze.

Methods

199   We constructed A-maze distractors for the Natural Stories corpus (Futrell et al., 2020)
200 and recruited 100 crowd-sourced participants to each read a story in the Maze paradigm.

Materials

202   We took the texts of the Natural Stories corpus (Futrell et al., 2020), split them into
203 sentences, and ran the sentences through the A-maze generation process. We follow the
204 A-maze generation process outlined in Boyce et al. (2020), although we use an updated
205 version of the codebase with fixes some issues identified in that paper (code at
206 https://github.com/vboyce/Maze). Additionally, the capability to appropriately handle a
207 wider variety of punctuation (needed for this corpus) was added. We took the
208 auto-generated distractors as they were, without checking them for quality. We used the
209 original comprehension questions provided in the Natural Stories corpus. To familiarize
210 participants with the task, we wrote a short practice passage and corresponding
211 comprehension questions. See the Appendix for an except of one of the stories and its
212 corresponding comprehension questions. All materials are available at TODO NEW REPO.

Participants

214   We recruited 100 participants from Amazon Mechanical Turk, and paid each
215 participant $3.50 for roughly 20 minutes of work. We excluded data from those who did not
216 report English as their native language, leaving 95 participants.

Procedure

Participants first gave their informed consent and saw task instructions. Then they read a short practice story in the Maze paradigm and answered 2 binary-choice practice comprehension questions, before reading the main story in the A-maze task. After the story, they answered the 6 main comprehension questions, commented on their experience, answered optional demographic questions, saw an debriefing and were given a code to enter for payment. The experiment was implemented in Ibex (https://github.com/addrummond/ibex) and the experimental code is available at REPO.

Models

We conducted data processing and analyses using R (Version 4.0.3; R Core Team, 2020) and the R-packages *brms* (Version 2.14.4; Bürkner, 2017, 2018), *lme4* (Version 1.1.26; Bates, Mächler, Bolker, & Walker, 2015), *mgcv* (Version 1.8.33; Wood, 2011, 2003, 2004; Wood, N., Pya, & S"afken, 2016), *papaja* (Version 0.1.0.9997; Aust & Barth, 2020), *tidybayes* (Version 2.3.1; Kay, 2020), and *tidyverse* (Version 1.3.1; Wickham et al., 2019).

As described in the Results section, we base all models only on data from participants who choose correctly on at least 80% of the words in the Maze task.

To model the relationship between RT and word surprisal, we created a set of predictor variables of frequency, word length, and surprisals from three language models. For length, we used the length in characters excluding end punctuation. For unigram frequency, we tokenized the training data from Gulordava, Bojanowski, Grave, Linzen, and Baroni (2018) and tallied up instances. We then used the log2 frequency of the expected occurances in 1 billion words as the model predictor, so higher values indicate higher log frequencies. We got per-word surprisals for each of 4 different language models: a Kneser-Ney smoothed 5-gram, GRNN (Gulordava et al., 2018), Transformer-XL (Dai et al., 2019), and GPT-2 (Radford et al., n.d.), using lm-zoo (Gauthier, Hu, Wilcox, Qian, & Levy, 2020).

We exclude the first word of every sentence because it has a different distractor, which leaves 9782 words. Then we exclude words for which we don't have surprisal or frequency information, leaving 8489 words. We additionally exclude words that were treated as being composed of multiple tokens. This is primarily words that have punctuation, where the punctuation is treated as a separate token. While surprisals should be additive, the summing the surprisals over these parts gives unreasonable responses sometimes. For instance, in one story the word king!' is given a surprisal of 64 by GRNN (context: The other birds gave out one by one and when the eagle saw this he thought, "What is the use of flying any higher? This victory is in the bag and I am king!"). To avoid these outliers we exclude all words that a model treated as multi-token, leaving 7512 words. (While GPT-2 using byte-pair encoding that can split up words into multiple parts, excluding words it split up only excludes 30 words that were not already excluded by other models.)

For all of these predictors, we consider both the predictor at the current word as well as lagged predictors from the previous word. We excluded outlier RTs that were <100 or

256 >5000 ms (<100 is likely a recording error, >5000 is likely the participant getting
257 distracted). We exclude words where mistakes occurred or which occurred after a mistake in
258 the same sentence. We only analysed words where we had values for all predictors, which
259 means that if the previous word was unknown to a model, this word will be excluded
260 because we're missing values for a lagged predictor.

261 For generalized additive models, we centered but did not rescale the length and
262 frequency predictors, but left surprisal uncentered for interpretability. We used smooths for
263 the surprisal terms and tensor effects for the frequency by length effects and interactions. To
264 minimize the effect of repeated measures on confidence about inferred curve shapes, we
265 collapse the reading times across subjects by modelling the mean RT for each word.

266 For linear models, we centered all predictors. We used full mixed effects, including
267 by-subject slopes and a per-word-token random intercept (Barr, Levy, Scheepers, & Tily,
268 2013). We used weak priors (normal(1000,1000) for intercept, normal(0,500) for beta and sd,
269 and lkj(1) for correlations). Models were run in brm (Bürkner, 2018).

270 For model comparison, we took by-item averaged data to aid in fast model fitting. We
271 included frequency, length, and their interaction to all models. Then we fit models with
272 either 1 or 2 sources of surprisal using lm and assessed the effect of adding the second
273 surprisal source with an anova. We used predictors for the current and past word and
274 centered all effects.

Self-paced reading comparison

276 In addition to the texts, Futrell et al. (2020) released reading time data from a SPR
277 study they ran in 2011. They recruited 181 participants from Amazon Mechanical Turk,
278 most of whom read 5 of the stories. After reading each story, each participant answered 6
279 binary-choice comprehension questions. As a comparison to our A-maze models, we run
280 similar models on the SPR corpus on Natural Stories (Futrell et al., 2020). For
281 comparability, we analyse only the first story each participant read, and, in line with Futrell
282 et al. (2020), exclude participants who got less than 5/6 of the comprehension questions
283 correct. To account for spill over effects known to exist in SPR, we analyse predictors at the
284 current word as well as the past 3 words for all models. For linear models, we centered all
285 predictors. We were unable to fit the full mixed effects model. The best model we could fit
286 had by-subject random intercept, uncorrelated by-subject random slopes for surprisal, length
287 and frequency, and a per-word-token random intercept, fit with lme4, as this structure did
288 not fit reliably in brms.

SPR-Maze correlation

290 We additionally compare how correlated the Maze and SPR results are to each other,
291 in comparison to within-Maze and within-SPR correlations. For Maze, within each story, we
292 randomly split subjects into two halves. Within each half, we calculate a per-word average
293 for each word and then a per-sentence average RT across word averages. We calculate a
294 within-Maze correlation between these two halves. To avoid differences due to dataset size,

295 we downsample the SPR data choosing a number of participants equal to the number we
296 have for Maze. We then use the same procedure on this subset as for Maze to get a
297 within-SPR correlation. For between Maze-SPR correlation, we take the average correlation
298 across each of the 4 pairs of Maze half and SPR half.
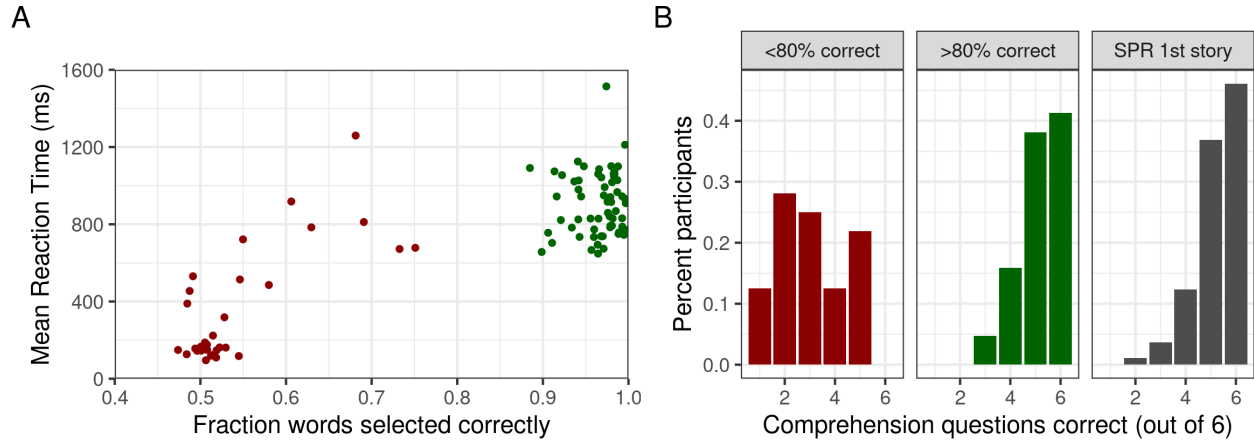
Results

Reading stories in the Maze task

Figure 2. A. Correlation between a participant's accuracy on the Maze task (fraction of words selected correctly) and their average reaction time (in ms). Many participants (marked in green) chose the correct word >80% of the time; others (in red) appear to be randomly guessing and were excluded from further analysis. B. Performance on the comprehension questions. Participants with low accuracy also performed poorly on comprehension questions; Participants with >80% task accuracy tended to do well; their performance was roughly comparable to the performance of SPR participants from Futrell et al. (2020) on their first stories.

301 Many participants completed the Maze task with a high degree of accuracy and also
302 answered the comprehension questions correctly.

303 Participant accuracy reflects both how well participants can navigate the task and
304 what quality the auto-generated distractors are. We calculated the per-word error rate for
305 each participant and graphed it against their average reaction time. (To avoid biasing the
306 average if a participant took a pause before returning to the task, RTs greater than 5 seconds
307 were excluded; this excluded 260 words, or 0.27% of trials.) As seen in Figure 2A, one cluster
308 of participants (marked in green) make relatively few errors, with some reaching 99%
309 accuracy. This confirms that the distractors were generally appropriate and shows that some
310 participants maintained focus on the task for the whole story. These careful participants
311 took around 1 second for each word selection, which is much slower than other paradigms.
312 Another cluster of participants (in red) sped through the task, seemingly clicking randomly.
313 This bimodal distribution is likely due to the mix of workers on Mechanical Turk, as we did
314 not use qualification cutoffs.

Another check is whether participants comprehended the story. We counted how many of the binary-choice comprehension questions each participant got right (out of 6). As seen in Figure 2B, most participants who were accurate on the task also did well on comprehension questions, while participants who were at chance on the Maze task were also at chance on the comprehension questions. Participants usually answered quickly (within 10 seconds), so we do not believe they were looking up the answers on the internet. We can't rule out that some participants may have been able to guess the answers without understanding the story. Nonetheless, this provides preliminary evidence that people can understand and remember details of stories they read during the Maze task. The comprehension question performance of accurate Maze participants is broadly similar to the performance of SPR participants from Futrell et al. (2020) on the first story read. Overall, 60% of Maze participants got 5 or 6 questions right (22% of low-accuracy participants and 79% of high-accuracy participants) compared to 91% of all SPR reads and 83% of 1st SPR reads. Note that these differences cannot be directly attributed to methods, as the participant populations differed. While both studies were conducted on Mturk, the quality of Mturk data has decreased from 2011 when the SPR was collected to 2020 when the A-maze was collected.

We use task performance as our exclusion metric because it is more fine-grained and only analyze data from participants with at least 80% accuracy (in the gap between high-performers and low-performers). For the SPR comparison, we follow Futrell et al. (2020)'s criteria and exclude participants who got less than 5 of the questions correct.

RT and surprisal

We fitted generalized additive models to test whether the RTs from the Maze experiment showed a linear relationship with surprisal and whether the effect was limited the current word or had spilled over from the prior word. For these models, we only included data that occurred before any mistakes in the sentence; due to limits of model vocabulary, words with punctuation and some uncommon or proper nouns were excluded.

The smooths for the current and previous words surprisals are shown in Figure 3. Note that for each of the models, high-surprisal words are rare, with much of the data for words between 0 and 15 bits of surprisal. All of the models show a roughly linear relationship between current word surprisal and RT, especially in the region with more data. All of the models show a flat relationship between previous word surprisal and RT. This is a sign of localization as the previous word's surprisal is not affecting RT, only the word's own suprisal is. The linear relationship matches that found with other methodologies.

Given that the GAM models show a roughly linear relationship, we fit mixed linear models to quantify the influence of surprisal, frequency and word length. We built linear models with surprisal, frequency, length and surprisal x length and frequency x length effects from the current and previous words as predictors. We centered, but did not rescale, the predictors.

As we can see in Table 1, we find large effects of surprisal and length, but minimal effects of frequency. These effects are larger than what is usually reported in other methods
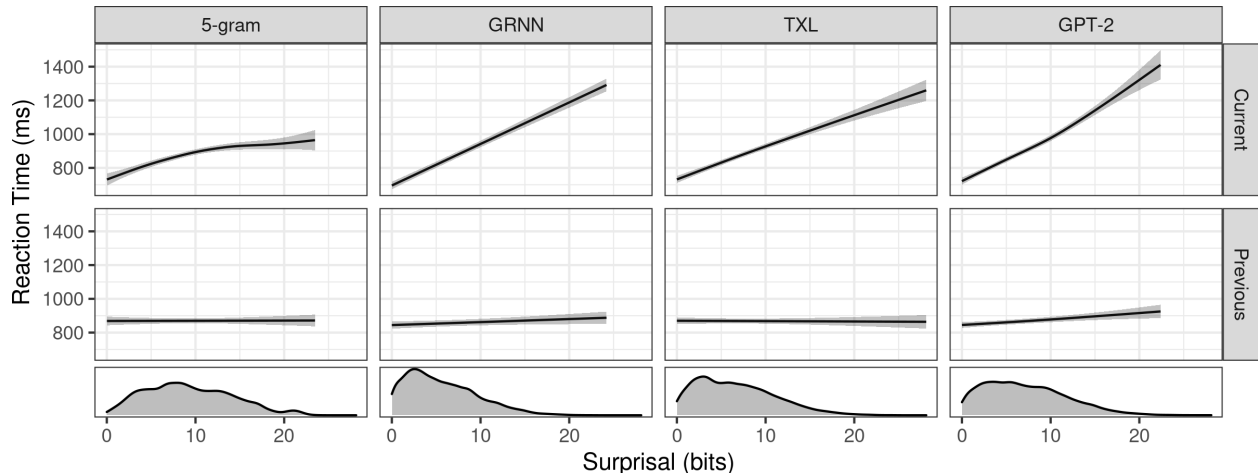
Figure 3. GAM predictions of reaction time (RT) as a function of either current word surprisal (top) or previous word surprisal (bottom). Density of data is shown along the x-axis. For each of the 4 language models used, there is a linear relationship between current word surprisal and RT (at least when there is enough data). There is no relationship between previous word surprisal and RT.

355 CITE, but this could be due to the overall slowness of the method. The lack of frequency
356 effects is somewhat surprising, but consistent with Shain (2019). Notably the coefficients for
357 the lagged terms are small relative to the effects of surprisal and length of the current word.

358   As a last analysis, we checked which of our surprisal models had the best fit using a
359 nested model comparison shown in Table 2. We assess the benefits of adding each model's
360 predictions as a second surprisal source to see which models pick up on information not
361 contained in another model. In terms of log likelihoods, GPT-2 is better than GRNN is
362 better than TXL is better than 5-gram. Model comparisons tell a similar story; GPT-2
363 provides a lot of additional predictive value over each other model, GRNN provides a lot
364 over 5-gram and TXL and a little complemetary information over GPT-2. TXL provides a
365 lot over 5-gram, and 5-gram provides little over any model.

Comparison with SPR

367   As a comparison, we ran the same types of models on the Self-Paced Reading data
368 collected by Futrell et al. (2020). As shown in Figure 4, there is a roughly linear but fairly
369 flat relationship between RT and surprisal. Note that the y-axis is fairly narrow, and so the
370 predicted effect of changes in surprisal is fairly small. This is confirmed by linear models (see
371 Table 3). Surprisal and length effects are evident for the current word, and most models
372 shows surprisal effects from the past word, but we do not see frequency effects. The effects
373 are much smaller than for A-maze, even though this model accounts for spillover effects from
374 more previous words.

375   Similarly to the model comparison for Maze, we also conducted a model comparison on
376 the SPR data shown in Table 4. In terms of log likelihoods, we find that GPT-2 is better

Table 1
Predictions from fitted Bayesian regression models. All terms were centered, but not rescaled. Units are in ms. Surprisal is per bit, length per character, and frequency per $\log_2$ occurance per billion words. Interval is 2.5th quantile to 97.5th quantile of model draws.

Term	5-gram	TXL	GRNN	GPT-2
Intercept	876 [840.4, 910.9]	880 [842.8, 914.9]	876.8 [840.1, 911.5]	878.5 [845.6, 911.6]
Surprisal	11.1 [8.7, 13.6]	17.8 [15.3, 20.2]	22.3 [19.7, 25]	24.2 [21.5, 27]
Length	21.4 [16.6, 26.3]	20.5 [15.6, 25.4]	17.9 [13.2, 22.7]	16.2 [11.3, 21.2]
Frequency	-3.2 [-6.7, 0.5]	-0.1 [-3.2, 2.9]	1.8 [-1.1, 4.7]	-1.4 [-4.2, 1.2]
Surp x Length	-2 [-3, -0.9]	-1.4 [-2.1, -0.6]	-2.1 [-3, -1.2]	-1.8 [-2.7, -1]
Freq x Length	-1 [-2.5, 0.6]	0.1 [-1, 1.1]	-0.4 [-1.5, 0.7]	0.1 [-0.9, 1.1]
Past Surprisal	1.5 [-0.6, 3.5]	0.9 [-0.7, 2.5]	2.7 [1, 4.4]	3.5 [1.8, 5.3]
Past Length	-3.5 [-7.8, 0.7]	-3.7 [-7.7, 0.3]	-4.8 [-9, -0.8]	-5.1 [-9.2, -1.1]
Past Freq	2.5 [-0.3, 5.4]	1 [-1.3, 3.3]	1.8 [-0.4, 4]	0.7 [-1.4, 2.8]
Past Surp x Length	-0.2 [-1.1, 0.8]	-0.5 [-1.2, 0.2]	-0.9 [-1.7, -0.2]	-1.1 [-1.8, -0.4]
Past Freq x Length	-1 [-2.4, 0.4]	-1.5 [-2.5, -0.4]	-1.8 [-2.8, -0.8]	-1.7 [-2.7, -0.8]

Table 2
Results of model comparisons on Maze data. Each row shows the additional predictive value gained from adding that model to another model. F values and p values from anova tests are reported. We also report log likelihoods of models with only one surprisal source.

Model	over 5-gram	over GRNN	over TXL	over GPT-2	Log Lik	r_squared
5-gram		2 (p=0.153)	3 (p=0.035)	0 (p=0.611)	-43817	0.16
GRNN	287 (p<0.001)		113 (p<0.001)	13 (p<0.001)	-43544	0.23
TXL	174 (p<0.001)	5 (p=0.006)		2 (p=0.137)	-43650	0.2
GPT-2	394 (p<0.001)	113 (p<0.001)	213 (p<0.001)		-43445	0.25

than 5-gram is better than GRNN is better than TXL, although differences are small. Model comparisons show that GPT-2 and 5-gram models contain some value over each other model, which is less clear for TXL and GRNN. The relatively good fit of 5-gram models to SPR data compared with neural models matches results from Hu, Gauthier, Qian, Wilcox, and Levy (2020) and Wilcox et al. (2020). This contrasts with the Maze results, where the 5-gram model has the worst fit and does not provide additional predictive value to the other models.

As an overall measure of fit to data, we calculate multiple R-squared for the single surprisal source models for both A-maze and SPR. The models predict A-maze better with R-squared values ranging from 0.16 for the 5-gram model to 0.25 for GPT-2. Whereas for SPR, the R-squared values range from from 0.007 to 0.011. This suggests that the effect size differences are not due merely to the larger overall reading time for A-maze, but that instead A-maze is more sensitive to surprisal and length effects.

An additional comparison between SPR and Maze is how correlated their reading times are; that is, do the methods pick up on the same effects. If so, we would expect that the
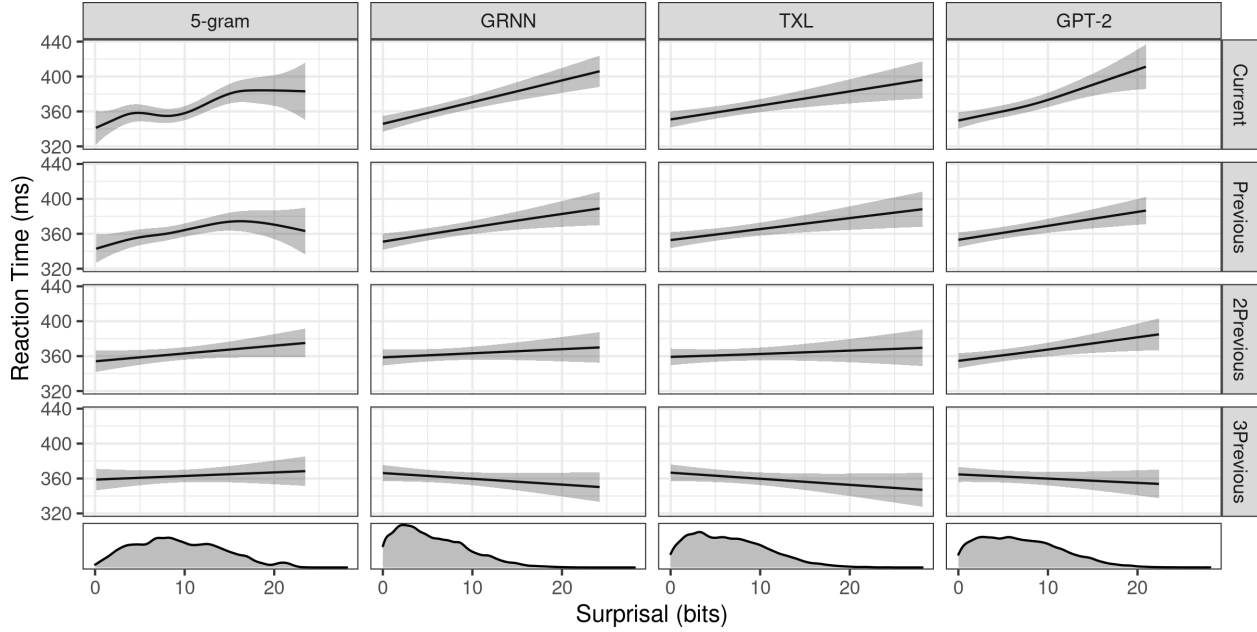
Figure 4. GAM predictions of reaction time (RT) for SPR data from Futrell et al. (2020) as a function of current word surprisal (top) or the surprisal of an earlier word, up to 3 words back. Density of data is shown along the x-axis.
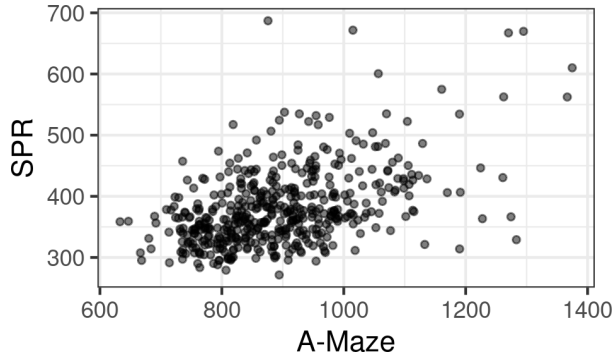

Figure 5. Correlation between SPR and Maze data. RTs were averaged across participants per word and then averaged together within each sentence. RTs in ms.

sentences that take longer to read in one method also take longer in the other. We calculate the average RT at the sentence level (see Methods for details). The correlation between Maze and SPR is 0.26, compared to 0.23 within SPR and 0.37 within Maze. See Figure 5 for a visual comparison of overall Maze versus SPR RTs.

Discussion

We introduced a tweak to the paradigm for displaying Maze tasks that makes it useable for multi-sentence materials. In this error-correction Maze paradigm, participants read all the words because they can correct their mistakes and move on. We tested this method on the Natural Stories corpus, showing that, despite the oddness of the task,

Table 3
Predictions from fitted regression models for SPR data. All terms were centered, but not rescaled. Units are in ms. Surprisal is per bit, length per character, and frequency per log_2 occurance per billion words. Uncertainty interval is +/- 1.97 standard error.

Term	5-gram	TXL	GRNN	GPT-2
Intercept	361.6 [344.5, 378.6]	363.9 [346.9, 380.9]	363.8 [346.8, 380.8]	363.9 [346.9, 380
Surprisal	1.1 [0.2, 2.1]	1.1 [0.3, 1.9]	1.8 [1, 2.7]	1.1 [0.3, 1.9]
Length	2.1 [0, 4.2]	2.2 [0.1, 4.2]	2 [-0.1, 4]	2.2 [0.1, 4.2]
Frequency	1.4 [0, 2.8]	1.2 [0.1, 2.4]	1.6 [0.5, 2.8]	1.2 [0.1, 2.4]
Surp x Length	-0.2 [-0.6, 0.3]	0.1 [-0.3, 0.4]	-0.2 [-0.6, 0.1]	0.1 [-0.3, 0.4]
Freq x Length	-0.4 [-1, 0.2]	-0.2 [-0.7, 0.3]	-0.4 [-0.9, 0.1]	-0.2 [-0.7, 0.3]
Past Surprisal	1 [0.1, 1.9]	0.7 [0, 1.5]	0.9 [0.1, 1.7]	0.7 [0, 1.5]
Past Length	0.1 [-2, 2.1]	0.1 [-1.9, 2.1]	-0.1 [-2.1, 1.9]	0.1 [-1.9, 2.1]
Past Freq	1.5 [0.2, 2.9]	1.1 [0, 2.2]	1.1 [0, 2.2]	1.1 [0, 2.2]
Past Surp x Length	-0.1 [-0.5, 0.3]	0.2 [-0.2, 0.5]	0 [-0.4, 0.3]	0.2 [-0.2, 0.5]
Past Freq x Length	-0.2 [-0.8, 0.5]	0.1 [-0.4, 0.6]	-0.1 [-0.6, 0.4]	0.1 [-0.4, 0.6]
2Past Surprisal	0.6 [-0.4, 1.5]	-0.2 [-1, 0.6]	0 [-0.8, 0.8]	-0.2 [-1, 0.6]
2Past Length	2.2 [0.3, 4.2]	2.1 [0.2, 4]	2.1 [0.2, 4]	2.1 [0.2, 4]
2Past Freq	1.5 [0.2, 2.8]	0.7 [-0.5, 1.8]	0.8 [-0.3, 1.9]	0.7 [-0.5, 1.8]
2Past Surp x Length	-0.3 [-0.7, 0.2]	0 [-0.3, 0.4]	-0.3 [-0.6, 0.1]	0 [-0.3, 0.4]
2Past Freq x Length	-0.3 [-1, 0.3]	0 [-0.5, 0.4]	-0.3 [-0.7, 0.2]	0 [-0.5, 0.4]
3Past Surprisal	-0.3 [-1.3, 0.6]	-0.9 [-1.7, -0.2]	-1 [-1.8, -0.2]	-0.9 [-1.7, -0.2]
3Past Length	1.1 [-0.9, 3]	0.8 [-1.1, 2.7]	1.1 [-0.9, 3]	0.8 [-1.1, 2.7]
3Past Freq	0.4 [-1, 1.7]	0 [-1.2, 1.1]	0 [-1.1, 1.1]	0 [-1.2, 1.1]
3Past Surp x Length	-0.5 [-0.9, 0]	-0.1 [-0.4, 0.3]	-0.3 [-0.6, 0.1]	-0.1 [-0.4, 0.3]
3Past Freq x Length	-0.4 [-1.1, 0.2]	-0.1 [-0.6, 0.4]	-0.2 [-0.7, 0.3]	-0.1 [-0.6, 0.4]

participants can read and understand a 1000 word story in this method. We additionally showed that the RTs generated in the Maze task show a linear relationship between the RT of a word and it's surprisal, but no relationship with the surprisal of the previous word. This provides additional evidence for the argument that the Maze task forces very incremental processing (Forster et al., 2009).

Actually the potential applicability and value is much broader, for any question where nailing down the locus on incremental processing difficulty is important, little spillover is very valuable.

This extreme incrementality makes the Maze task a good target for any question that requires precisely determining the locus of incremental processing difficulty and thus benefits from the lack of spillover. It shows broadly the same effects as other methods; however the differences in scale of suprisal effects and the lack of frequency effects detected here are a reason to explore more. Comparisons between different processing on the same materials could be useful for identifying how task demands influence language processing (ex. Bartek

Table 4

Results of model comparisons on SPR data. Each row shows the additional predictive value gained from adding that model to another model. F values and p values from anova tests are reported. We also report log likelihoods of models with only one surprisal source.

Model	over 5-gram	over GRNN	over TXL	over GPT-2	Log Lik	r_squared
5-gram		3 (p=0.032)	4 (p=0.001)	3 (p=0.033)	-51798	0.007
GRNN	7 (p<0.001)		6 (p<0.001)	2 (p=0.153)	-51790	0.009
TXL	3 (p=0.010)	0 (p=0.910)		1 (p=0.462)	-51801	0.007
GPT-2	10 (p<0.001)	5 (p<0.001)	10 (p<0.001)		-51783	0.011

⁴¹⁴ et al., 2011).

⁴¹⁵ While the error-correction paradigm is crucial to running long materials, it also
⁴¹⁶ provides some benefits even on shorter materials when using A-maze with variable
⁴¹⁷ participant populations. The error-correction compensates for some of the shortcomings of
⁴¹⁸ A-maze identified in Boyce et al. (2020); poor distractors might still cause participants to
⁴¹⁹ make unavoidable mistakes, but they will still see the rest of the sentence, which may reduce
⁴²⁰ frustration. One questions that remains is whether this post-mistake data is useable, which
⁴²¹ depends on whether RTs from a few words after a mistake show any differences from RTs
⁴²² before any mistakes. Whether post-mistake data is high-quality and trustworthy enough to
⁴²³ be included in analyses is a hard-to-assess question of potential interest.

⁴²⁴ Even if post-mistake data is not analysed, it can be used to distinguish between errors
⁴²⁵ due to inattentive participants or merely specific bad distractors early in the sentence.
⁴²⁶ Researchers can calculate a per-word error rate for each participant; high per-word error
⁴²⁷ rates are consistent with guessing, low error rates with errors clustered early the sentence are
⁴²⁸ consistent with poor distractors. This per-word error rate metric measures participants task
⁴²⁹ accuracy and provides a convenient and clear-cut way of controlling data quality after the
⁴³⁰ fact.

⁴³¹ Error-correction Maze also starts to reduce perverse incentives from the desire to
⁴³² complete the task quickly. With traditional Maze, clicking randomly will likely lead to a
⁴³³ mistake, which will cause a participant to skip ahead to the next sentence. With
⁴³⁴ error-correction Maze, randomly jamming buttons takes more effort, but is still faster than
⁴³⁵ doing the task. In discussing this work, we received the suggestion that one way to
⁴³⁶ disincentivize random clicking is to add a pause when a participant makes a mistake, forcing
⁴³⁷ them to wait some short period of time (ex 500ms or 1 sec) before being able to correct their
⁴³⁸ mistake. This seems like a promising improvement that could be worth implementing and
⁴³⁹ testing.

⁴⁴⁰ Between the distractor auto-generation process introduced in Boyce et al. (2020) and
⁴⁴¹ the error-correction paradigm introduced here, the Maze paradigm is now easy to use on a
⁴⁴² wide range of materials. The ease of use, large effects, and forced incrementality make Maze
⁴⁴³ a good complement to existing incremental processing methods. We encourage researchers to

444   consider Maze as an option for doing incremental processing work.

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Appendix

571 The beginning of one of the stories. This is the first 200 words of a 1000 word story.

572 Tulip mania was a period in the Dutch Golden Age during which contract prices for
573 bulbs of the recently introduced tulip reached extraordinarily high levels and then suddenly
574 collapsed. At the peak of tulip mania in February sixteen thirty-seven, tulip contracts sold
575 for more than ten times the annual income of a skilled craftsman. It is generally considered
576 the first recorded economic bubble. The tulip, introduced to Europe in the mid sixteenth
577 century from the Ottoman Empire, became very popular in the United Provinces, which we
578 now know as the Netherlands. Tulip cultivation in the United Provinces is generally thought
579 to have started in earnest around fifteen ninety-three, after the Flemish botanist Charles de
580 l'Ecluse had taken up a post at the University of Leiden and established a botanical garden,
581 which is famous as one of the oldest in the world. There, he planted his collection of tulip
582 bulbs that the Emperor's ambassador sent to him from Turkey, which were able to tolerate
583 the harsher conditions of the northern climate. It was shortly thereafter that the tulips
584 began to grow in popularity. The flower rapidly became a coveted luxury item and a status
585 symbol, and a profusion of varieties followed.

586   The first 2 out of the 6 comprehension questions.

587   When did tulip mania reach its peak? 1630's, 1730's

588   From which country did tulips come to Europe? Turkey, Egypt