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Modeling Task Effects in Human Reading with Neural Network-based Attention

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Abstract

Research on human reading has long documented that reading behavior shows task-specific effects, but it has been challenging to build general models predicting what reading behavior humans will show in a given task. We introduce NEAT, a computational model of the allocation of attention in human reading, based on the hypothesis that human reading optimizes a tradeoff between economy of attention and success at a task. Our model is implemented using contemporary neural network modeling techniques, and makes explicit and testable predictions about how the allocation of attention varies across different tasks. We test this in an eyetracking study comparing two versions of a reading comprehension task, finding that our model successfully accounts for reading behavior across the tasks. Our work thus provides evidence that task effects can be modeled as optimal adaptation to task demands.

1 Introduction

Explaining the cognitive processes involved in human reading poses a particularly interesting challenge for cognitive science. First, because reading is a cultural skill that is acquired through explicit instruction combined with a large amount of practice. This sets it apart from other linguistic skills such as speaking and listening, which are normally acquired earlier in life than reading and do not require explicit instruction. Often, an innate component is assumed to be part of language

Preprint of a paper accepted for publication at *Cognition*. A preliminary version of the modeling study reported in Section 5 was previously published in [Hahn and Keller \(2016\)](#). For the present article, the model has been reimplemented and all modeling experiments have been rerun and the results reanalyzed. Data and code are freely available at <https://gitlab.com/m-hahn/task-effects-neural-networks>.

acquisition; but this is not a plausible assumption for reading, as it is a recent phenomenon by evolutionary standards, dating back to around 3000–4000 BC. Reading, insofar as it is distinct from the rest of linguistic cognition, therefore must be a skill that is learnable from experience.

A second important aspect of human reading is that it is a highly task-specific process. When we read a book for entertainment, we will do so differently than when we read the same book in order to find typographical errors. For many tasks, readers employ specific information-seeking strategies. For example, to find an answer to a question in a text, they systematically search for names, dates, amounts, or whatever form the correct answer is likely to take. Reading strategy will also vary depending on whether the task is to memorize facts (perhaps for an exam), translate a text, compile a summary of book, or write a review. It is an intriguing question how the high-level cognitive requirements of such tasks are translated into low-level reading behavior, which ultimately manifests itself as a sequence of eye-movements on the words of a text.

Both the experiential nature of reading and its task specificity pose challenges for computational cognitive modeling: on the one hand, we need to develop a model that assumes only a minimum of innate knowledge and is able to learn the key properties of human reading from exposure to large amounts of text. On the other hand, our model must be amenable to explicit instruction (perhaps in the form of feedback) and has to be capable of learning different reading strategies for different tasks. In other words, we expect the model to change its eye-movement behavior depending on whether its task is to memorize information, answer a question, find typos in a text, etc.

In this article, we focus on one particular aspect of reading, viz., the allocation of attention. We assume that the allocation of attention can be studied by measuring the eye-movements that humans make as they read. These eye-movements consist of fixations and saccades: during a fixation, the eyes land on a word and remain fairly static for 200–250 ms. Saccades are the rapid jumps that occur between fixations, typically lasting 20–40 ms and spanning 7–9 characters (Rayner, 1998). Readers, however, do not simply fixate one word after another; some saccades go in reverse direction, some words are fixated more than once, and other words are skipped altogether.

We present a computational cognitive model that captures the allocation of attention during reading by modeling skipping, i.e., the process that decides which words should be fixated, and which ones should be skipped, by the reader. We will assume that a fixation strategy can be learned from large amounts of text if an explicit task is given to the reader. The task (such as text reconstruction or question answering) allows the model to infer which words are important for the task (and should be attended to), and which ones are less important (and should be skipped). Our model also includes a component which predicts how expected a word is given its context and a series of prior fixations and skips. This component allows the model to predict reading time for words in a text. Therefore, our model not only computes which words are attended to in a text, but also how much attention the fixated words receive.

When developing our model, we make the assumption that task-based reading behavior can be explained by a fundamental tradeoff: the model needs to trade off economy of attention (skipping as many words as possible, i.e., reading as fast as possible) and accuracy (making as few errors as possible in the task the reader wants to accomplish). Task-specific reading strategies emerge when the model learns the economy–accuracy tradeoff for a given task. Each task potentially requires a different tradeoff, thus occasioning task-specific differences in reading behavior.

As already mentioned, reading acquisition in humans typically involves explicit instruction. For example, at school, children may have to answer comprehension questions to determine if they have read a text correctly. We assume that our model receives a similar type of feedback in order to

enable it to learn the economy–accuracy tradeoff for a specific reading task. This feedback comes in the form of a reinforcement signal, i.e., information regarding whether the model has accurately solved the task for a given input or not. While the reinforcement signal is a type of instruction, it does not mean that we assume supervised learning, i.e., that the model is told explicitly which words to skip and to fixate, or for how long. This form of supervision would not be cognitively plausible: humans who are taught to read do receive feedback regarding whether they performed their reading task correctly or not, but they are not told whether they have fixated the right words, or spent the right amount of time on each word.

In the following, after an overview of background and related work, we will introduce the Tradeoff Hypothesis that underlies our model in more detail. Then we will present the model itself, which is implemented as an attention-based recurrent neural network that performs word prediction under uncertainty (i.e., it can decide to skip words). We derive its objective function for the baseline task of reconstructing the input text, and show how the model can be trained using reinforcement learning techniques. In Modeling Study 1, we demonstrate that our model successfully captures skipping patterns and reading times observed in a large eye-tracking corpus.

We then turn to a key prediction of our modeling approach: that eye-movement behavior should change as a function of the task a reader aims to solve. We present Experiment 1, an eye-tracking study designed to test this prediction. This experiment uses question answering as the task participants have to perform and manipulates whether they see a preview of the question they have to answer before they read the corresponding text. The results show a strong effect of task condition (preview or not) on skipping rate, reading time, and task accuracy. We also find evidence that participants adapt their reading strategy for the words that are part of the potential or actual answer to the question for a given text.

The results of Experiment 1 inform the design of an extended version of our computational model, which now performs questions answering instead of text reconstruction. In Modeling Study 2, we show that this extended model captures the reading behavior observed in Experiment 1, predicting the effect of the preview manipulation on skipping rate and task accuracy, while also correctly modeling the reading strategy effects that we found experimentally.

The article concludes with a general discussion, which summarizes our contributions, contextualizes them with respect to prior research, and addresses some of the limitations of this work.

2 Background

A significant literature exists in the domain of modeling human reading. Here, we will review work on models of eye-movement control, models of processing difficulty during language comprehension, and more generally neural approaches to cognitive modeling, with a particular focus on neural network-based attention mechanisms.

2.1 Attention in Humans and Machines

In this article, we will leverage recent developments in neural network technology to develop a cognitively plausible model of human reading that is able to process naturalistic text. More specifically, we will use a mechanism in neural networks called attention, which allows a model to dynamically focus on a restricted part of the input. Attention is also a central concept in cognitive science, where it denotes the focus of cognitive processing. In both language processing and visual processing, attention is known to be limited to a restricted area of the visual field; often it is

assumed that eye-movements indicate shifts in attention (Henderson, 2003). There is therefore an obvious conceptual link between neural network-based attention and human attention that we can exploit for model design.

In human vision, a distinction is sometimes made between overt and covert attention, where overt attention refers to the location that is behaviorally prominent a given point in time (typically the point of fixation), while covert attention refers to the current focus of cognitive processing. For example, it is possible that visual recognition occurs at a given location even though that location is not overtly attended (i.e., fixated), as Heyman, Montemayor, and Grisanzio (2017) show. Furthermore, there is evidence that viewers can classify visual scenes (i.e., perceive the gist of a scene) in the absence of overt attention (Li, VanRullen, Koch, & Perona, 2002). Findings of this sort indicate that covert and overt attention can dissociate in certain situations; however, other authors argue that overt and covert attention are so strongly related that studying them separately is not productive (see Henderson, 2003).

In the reading literature, a similar debate exists about whether the focus of cognitive processing and the overt focus of attention (the fixation point) can be dissociated. Here, the key distinction is between accounts of reading that assume strictly serial processing (one word after the other), and approaches that allow parallel processing (several words can be processed at the same time). Parallel processing implies a dissociation between covert attention (the processing of a word) and overt attention (the fixation of a word). We will discuss this in more detail in the next section.

2.2 Models of Eye-movement Control

Models of eye-movement control are designed to make detailed predictions about the pattern of fixations and saccades that occur when people read text. They typically integrate linguistic constraints (such as lexical representations) with perceptual factors (such as information about the length of a word or its visual appearance) to compute the location and the duration of eye-movements during reading. A range of computational models of eye-movement control have been developed (see Rayner & Reichle, 2010, for an overview), the most prominent of which are probably E-Z Reader (Reichle, Pollatsek, Fisher, & Rayner, 1998; Reichle, Rayner, & Pollatsek, 2003; Reichle, Warren, & McConnell, 2009) and SWIFT (Engbert, Longtin, & Kliegl, 2002; Engbert, Nuthmann, Richter, & Kliegl, 2005).

E-Z Reader assumes that eye-movements are controlled in a serial fashion: a single word is processed at any given time, and once processing of that word is finished, attention moves on to the next word. The model assumes two processing stages. The first one is the familiarity check, which takes place during lexical access up to the point when the word can be reliably identified. Once this point is reached, the saccade to the next word is programmed, and the second stage of processing, the completion of lexical access, occurs. Saccade programming itself is also subdivided into two stages: the initial labile stage, during which a saccade can still be canceled, and the non-labile stage, when the saccade has become obligatory. Another key assumption of E-Z Reader is that eye-movements target the center of words, but are subject to random over- and undershoot errors; large errors result in automatic refixations, i.e., corrective saccades towards the center of the word.

SWIFT is a parallel model of eye-movement control. This means that attention is conceptualized as a gradient that is spread across several words, and lexical access for these words happens at the same time. Another key assumption of the model is that the decision to move the eyes to the next viewing location is determined by a random timer. This timer initiates saccades at random intervals; factors such as word frequency influence saccade programming only indirectly by inhibiting the

timer. The inhibition delays when a saccade occurs, resulting in an increased fixation duration on the current word. SWIFT's assumptions about saccade programming are similar to the ones made by E-Z Reader.

More recent approaches, such as the model by [Bicknell and Levy \(2010\)](#) conceptualize reading as a Bayesian inference task. The Bicknell and Levy approach assumes a probabilistic language model which defines a prior distribution over possible word sequences. The aim of the model is to decide whether or not to move the eyes from the current position. While at a given position, it samples noisy visual input, which results in a likelihood term (the probability of the visual input given a word). By combining the prior distribution with the likelihood term, the model updates its belief about the identity of the word sequence it is reading. This updated posterior distribution is then used to decide the next reading action. [Bicknell and Levy \(2010\)](#) assume four possible actions: keep fixating the current position, initiate a backward saccade, initiate a forward saccade, or stop processing the current input. The model uses a simple control policy based on the posterior probability of the currently fixated character to decide which action to take. A distinguishing factor of this model is that it assumes realistic visual input, viz., noisy representations based on a character's eccentricity from the viewing position.

Finally, there is work in the natural language processing literature which treats eye-movement prediction as a machine learning task. More specifically, these authors train models such as logistic regression or conditional random fields on a corpus of human eye-tracking data, and then predict fixation time, skipping rate, and other eye-movement measures on an unseen test set. Unlike our goals here, the literature in this tradition (e.g., [Bestgen, 2021](#); [Hara, Kano, & Aizawa, 2012](#); [Hollenstein et al., 2021](#); [Matthies & Sogaard, 2013](#); [Nilsson & Nivre, 2009, 2010](#)) does not primarily aim to construct explanatory cognitive models, and the use of supervised training (i.e., models learn their behavior from a pre-existing training set of eye-movement data) is not psychologically realistic, as outlined in the introduction. However, machine learning-based models typically achieve good prediction accuracy, which makes them suitable for comparison with cognitive models.

The model proposed in this article does not aim to capture eye-movement control at the same level of detail as E-Z Reader, SWIFT, or the Bicknell and Levy model. We do not aim to predict where on a word a fixation will land, or which distance a saccade will span. We have no notion of reverse eye-movements or corrective saccades, and we do not model the visual input (except to a limited extent in the pre-view component of our model). Instead, our model uses an idealized, high-level notion of attention: it decides whether to fixate or skip a word, and is also able to predict reading times for fixated words (though this is merely a by-product of our model architecture, as will be explained below).

On the other hand, our approach assumes an explicit tradeoff between economy of attention and task accuracy. It shares this feature with [Bicknell and Levy \(2010\)](#), whose model trades off reading speed (a form of economy) and visual identification accuracy. Also like Bicknell and Levy, we assume that our model explicitly integrates probability distributions from a variety of sources and models decision making explicitly. We do not assume a Bayesian framework, but compute probability distributions using a more flexible neural network approach, and we capture decision making using reinforcement learning. Again like Bicknell and Levy, our approach incorporates an explicit language model, which in our case is computed using a recurrent neural network. However, whereas their model is designed specifically for optimal word recognition, our Tradeoff Hypothesis generalizes to higher-level language understanding tasks such as question answering.

Following in the footsteps of Bicknell and Levy, [Lewis, Shvartsman, and Singh \(2013\)](#) pro-

pose a model of saccade control that combines Bayesian optimization and bounded optimal control. Their model assumes an explicit speed-accuracy tradeoff which enables eye-movements to adapt to task conditions. They operationalize the tradeoff by assuming a set of predefined payoff schemes (focused on accuracy, focused on speed, or balanced). Their model is able to capture how human eye-movements in a list lexical decision task vary with the payoff scheme participants are given. The aim of our work is different from that of [Lewis et al. \(2013\)](#) in that we develop explicit computational models across several tasks and derive the tradeoff between economy of attention and task accuracy from these models through reinforcement learning, rather than having to stipulate external payoff schemes.

2.3 Models of Processing Difficulty

Model of processing difficulty are designed to predict how much processing effort is caused during sentence comprehension. Experimental studies typically find that certain words in a sentence cause increased processing effort, which empirically manifest itself as greater reading time, but also in other ways, for example slower reaction times in a go/no go task or increased ERP amplitudes. Models of processing difficulty are not designed to predict detailed eye-movement behavior; they have no notion of fixations and saccades, and do not model the visual properties of words. Often, they are tested not on naturalistic texts, but on carefully designed sentence pairs such as they are used in psycholinguistic experiments, garden path sentences being a prime example.

A prominent model of processing difficulty is surprisal, which measures the predictability of a word in context, defined as the negative logarithm of the conditional probability of the current word given the preceding words ([Hale, 2001](#); [Levy, 2008](#)). Surprisal is computed by a language model, which can take the form of a probabilistic grammar, an n-gram model, or a neural network. Like other models of processing difficulty, surprisal is designed to provide a general measure of linguistic processing effort, and cannot explain detailed eye-movement behavior during reading. Nevertheless, the surprisal of a given word can be used as a predictor of the reading time for that word, and these predictions have been shown to correlate with reading measures in eye-tracking corpora ([Demberg & Keller, 2008](#); [Frank & Bod, 2011](#); [McDonald & Shillcock, 2003a, 2003b](#); [Smith & Levy, 2013](#)).

The model proposed in this article has a surprisal component, which is implemented using a neural language model. It departs from standard surprisal by explicitly modeling which words in the input are attended to, which enables it to predict word skipping. Skipping is a particularly intriguing phenomenon in human reading: about 40% of all words in a text are skipped during reading (in the Dundee corpus, see below), without apparent detriment to understanding. In a further departure from standard surprisal, our model also models text understanding explicitly, in the form of a task the model has to perform. We experiment with two tasks: reconstructing the input text or answering questions about it. In both cases, the model needs to learn a representation of the text that enables it to perform the task in an optimal way. This optimization process is what enables us to capture how reading behavior is affected by task demands. All components of our model (surprisal, attention, task) are implemented as neural networks and trained on unannotated text.

2.4 Neural Network-based Attention

Neural networks have been used for cognitive modeling since their inception, with many of the fundamental architectures and algorithms developed decades ago by [Rumelhart and McClelland \(1986\)](#). Neural models are attractive in a cognitive context because they perform representation

learning, i.e., suitable representations for a given cognitive task emerge during training, rather than having to be pre-specified by the model designer. This provides a potential explanation for how cognitive functions are acquired based on general learning mechanisms in combination with the exposure to suitable training data.

The renaissance of neural networks in artificial intelligence was triggered by the development of new learning algorithms, more advanced network architectures, and the availability of massive amounts of data and compute. It led to breakthroughs in areas such as computer vision (Krizhevsky, Sutskever, & Hinton, 2012), speech recognition (Graves, Mohamed, & Hinton, 2013), and natural language processing (Collobert et al., 2011). Today's neural architectures and algorithms are efficient, scalable, and robust, enabling the development of models that can be trained on large, realistic datasets and achieve state-of-the-art performance on a wide range of AI tasks.

More recently, neural networks have been augmented with attention mechanisms. Attention in this context can be understood as a distribution over the input of the network that indicates which parts of the input are important for computing the network output. A range of attention-based neural network architectures have been proposed in the literature, showing promise in both natural language processing and computer vision (e.g., Bahdanau, Cho, & Bengio, 2015; Mnih, Heess, Graves, & others, 2014). These architectures either employ soft attention or hard attention. Soft attention distributes real-valued attention values over the input and is typically trained using backpropagation. Hard attention mechanisms make discrete choices about which parts of the input to focus on, and can be trained with reinforcement learning (Mnih et al., 2014). In language processing models, soft attention can mitigate the difficulty of compressing long sequences into fixed-dimensional vectors, with applications in machine translation (Bahdanau et al., 2015) and question answering (Hermann et al., 2015). In computer vision, both types of attention can be used for selecting image regions for processing (Ba, Salakhutdinov, Grosse, & Frey, 2015; Xu et al., 2015).

When it comes to modeling word skipping, i.e., the decision whether a given word should be fixated or not, hard attention is a natural modeling choice. It mimics the binary nature of the skipping decision (rather than assuming a real-valued attention weight), and can be trained using reinforcement learning, thus avoiding a cognitively implausible supervised learning scheme.

3 The Tradeoff Hypothesis

Two observations about human reading are the starting point for our model design: its efficiency and its task adaptivity.

Despite the complexity of the reading process, experienced readers are able to process text very efficiently, at a typical rate of 200–400 words per minute (Rayner, Schotter, Masson, Potter, & Treiman, 2016). This is significantly higher than the normal speaking rate of around 150 words per minute, meaning that reading enables faster information uptake than listening at the normal rate. Reading is a cultural skill, subject to explicit teaching in school for a period of 10–14 years in most countries. This means readers have a lot of practice by the time they reach adulthood, and have honed their reading skills to the point of automaticity; the Stroop effect (Scarpina & Tagini, 2017) is often cited as evidence of such automaticity. Furthermore, the reading process is efficient in that it is able to deal with errors in the input. Even when a text contains a high rate of letter transpositions and misspellings, this does not seem to impair comprehension, and only marginally slows down reading (Hahn, Keller, Bisk, & Belinkov, 2019).

The second key observation is that humans adapt their reading strategy to the task at hand. A considerable literature exists that demonstrates how the reading task affects eye-movements,

demonstrating effects on, for instance, skipping rate, fixation duration, and saccade length. Task is also known to interact with text-related factors such as word length, word frequency, and word predictability. [Rayner and Fischer \(1996\)](#) compared normal reading with scanning transformed text (every letter is replaced with a *z*) and word search. They found shorter fixations, longer saccades, and less skipping in the normal reading condition. Also, word frequency effects were absent in the scanning and search conditions. Related to this, [Radach, Huestegge, and Reilly \(2008\)](#) compared eye-movements in reading for comprehension and in word verification, and found increased reading times, as well as larger word frequency effect in comprehension. [Greenberg, Inhoff, and Wege \(2006\)](#) compared normal reading with a letter detection task, and found longer fixations and less skipping for the letter detection, but uncovered no task differences in word class and predictability effects. In the same vein, [White, Warrington, McGowan, and Paterson \(2015\)](#) compared reading for comprehension to the task of scanning for a specific topic. In contrast to [Rayner and Fischer's \(1996\)](#) word search results, they found word frequency effects for both tasks in first fixation times, but larger effects of word frequency in later measures during reading for comprehension. When [Kaakinen and Hyönä \(2010\)](#) compared reading for comprehension and proofreading for errors, they found that the temporal and spatial properties of fixations and saccades differed for the two tasks. They also found greater word length and word frequency effects for proofreading compared to comprehension. [Schotter, Bicknell, Howard, Levy, and Rayner \(2014\)](#) replicated these results and additionally showed predictability effects in proofreading. [Kaakinen, Lehtola, and Paattilammi \(2015\)](#) compared the eye-movements of adults and children performing either a question answering or a text comprehension task, and found task effects on first-pass reading in both groups; the adults also showed a task effect on look-backs.

In summary, human reading is both very efficient and highly task adaptable. We hypothesize that readers achieve these two remarkable properties by optimizing a tradeoff between *economy* and *accuracy*. Concretely, this means that they try to read as efficiently as possible, for example by skipping as many words as they can. At the same time, their reading behavior needs to ensure that they make as few errors as possible in the task they are trying to accomplish by reading. We will call this assumption the *Tradeoff Hypothesis*. Based on this hypothesis, we expect that humans only fixate words to the extent necessary for task success, while skipping words that are not task relevant, or whose contribution to the text can be inferred from context. Crucially, the optimal economy–accuracy tradeoff depends on what the reader is trying to accomplish; it follows that there is no single reading strategy that is optimal everywhere; economy and accuracy trade off in different ways for different tasks.

As mentioned in [Section 2.2](#), the key assumption that readers make a tradeoff is shared with [Bicknell and Levy's \(2010\)](#) rational model of eye-movement control in reading. Arguably, all Bayesian models involve a tradeoff, as they assume that a prior probability distribution is combined with a likelihood function in an optimal way. Another example is [Norris's \(2006\)](#) Bayesian model of word recognition, which trades off recognition accuracy and recognition speed by combining a prior over lexical properties (such as word frequency) with a likelihood function that models noisy visual input. Also, the model of [Lewis et al. \(2013\)](#) assumes an explicit tradeoff between speed and accuracy to predict eye-movements in a list lexical decision task. They assume that information is integrated across saccades using a Bayesian update mechanism.

In order to accrue evidence for the Tradeoff Hypothesis, this article will investigate the following questions:

1. Can we use the Tradeoff Hypothesis to design a computational model that predicts quantita-

tive properties of human skipping behavior? Furthermore, can we use this model to compute a surprisal measure that correlates with human reading time, even though it only has access to the words the model fixates (rather than to all words)?

2. Does this model instantiate a key prediction of the Tradeoff Hypothesis, viz., that the optimal reading strategy depends on the task? Based on this prediction, we expect that skipping behavior changes when the reading task changes, both in humans and in our model.

To investigate these questions, we develop an architecture that combines a language model based on recurrent neural networks with an attention mechanism, two approaches that have been very successful in natural language processing and in AI more generally. We train our model on a large text corpus with an objective function that implements the Tradeoff Hypothesis. We then evaluate the model's reading behavior against human eye-tracking data, both from an existing eye-tracking corpus and from a novel eye-tracking experiment designed to study task effects. Apart from the unlabeled text used as training data and the model architecture, no further assumptions about language structure need to be made – in particular, no explicit lexical or grammatical knowledge is required, and no eye-tracking data is used at training time. We show that cognitively plausible behavior emerges as a result of devising an architecture that can solve realistic reading tasks, and training it on large amounts of unlabeled text.

4 The Neural Attention Tradeoff Model

The point of departure for our model is the Tradeoff Hypothesis introduced in the previous section: Reading optimizes a tradeoff between economy of attention and task accuracy. We make this idea explicit by proposing NEAT (NEural Attention Tradeoff), a computational model that reads text and then performs a task related to the text it has read. During reading, the network chooses which words to process and which ones to skip. During normal reading, we will assume that the task the model needs to solve is to build up a representation of the text that allows it to reconstruct the input as accurately as possible. Based on this assumption, we train the model using an objective function that minimizes the input reconstruction error while also minimizing the number of words fixated. We will drop this simplifying assumption and generalize our model to a new reading task (question answering) in Section 7.

At this point, it is important to emphasize that our assumption that text reconstruction is the default task that our model performs is clearly a simplification. We assume that during reading, the model learns a neural representation of the input text (stored in the weights of the network) that allows it to recall the input. We achieve this by training the model to reconstruct the input text as accurately as possible from its neural representation. However, by making this modeling assumption, we do not mean to imply that human readers memorize what they read verbatim; rather, it seems plausible that they construct an integrated representation of the propositions expressed in the text, as well as a mental model of the situation described, as assumed by [Kintsch \(1988\)](#). A recall of the information in the text would then be achieved by querying these integrated representations. However, given that it is not currently feasible to automatically build up Kintsch-type text representations for naturalistic text (such as the newspaper text we use), we make the simplifying assumption that the model learns a representation that can be used for input reconstruction.

To reiterate, the aim of this article is not to offer a full model of eye-movement control during reading. Rather, we want to model one particular aspect of reading, i.e., the allocation of attention

to the words in a text. Specifically, we want to capture the process that decides which words in a text are fixated and which ones are skipped when a text is read. Once we have a model of skipping, we can use that model to compute a modified version of the surprisal that only uses the words that are fixated. This in turn allows us to compute word-by-word reading times.

4.1 Architecture

Our architecture is based on the standard neural encoder-decoder architecture, which encodes a read sequence into memory representations and then decodes output from it (Cho et al., 2014; Kalchbrenner & Blunsom, 2013; Sutskever, Vinyals, & Le, 2014). We illustrate the model in Figure 1, operating on a three-word sequence $\mathbf{w} = w_1, w_2, w_3$. The basic components of NEAT are the *reader*, labeled R , and the *decoder*. Both these components are recurrent neural networks with long short-term memory (LSTM, Hochreiter & Schmidhuber, 1997) units. The recurrent reader network is expanded into time steps R_0, \dots, R_3 in the figure. It passes over the input sequence, reading one word w_i at a time, and converts the word sequence into a sequence of vectors h_0, \dots, h_3 . Each vector h_i is as a fixed-dimensional encoding of the word sequence w_1, \dots, w_i that has been read so far. The last vector h_3 (more generally h_N for a sequence of length N), which encodes the entire input sequence, is then fed into the input layer of the decoder network, which attempts to reconstruct the input sequence \mathbf{w} . The decoder is also realized as a recurrent neural network, collapsed into a single box in the figure. It models a probability distribution over word sequences w' , computing the conditional distribution $P_{Decoder}(w'_i | w'_{1..i-1}, h_N)$ over the vocabulary in the i -th step, as is common in neural language modeling (Mikolov, Karafiát, Burget, Černocký, & Khudanpur, 2010). As the decoder has access to the vector representation created by the reader network, it should be able to assign the highest probability to the word sequence \mathbf{w} that was actually read. Up to this point, the model is a standard encoder-decoder architecture designed to reconstruct an input sequence from a fixed-dimensional representation.

Secondly, we model skipping by stipulating that only some of the input words w_i are fed into the reader network R ; the other words are skipped during reading. For skipped words, R receives a special vector representation that contains no information about the input word. NEAT incorporates an *attention module* A , which at each time step during reading, decides whether the next word is shown to the reader network or not. Before fixating or skipping a word, humans obtain information about it and sometimes fully identify it using *parafoveal preview* (Gordon, Plummer, & Choi, 2013). Thus, we can assume that the choice of which words to skip takes into account a preview of the word itself. We model parafoveal preview by assuming that the attention module receives the first four characters of the input word when making its decision.

Note that the literature provides mixed evidence regarding the role of context in shaping skipping decisions. There is evidence for strong frequency effects that trump effects of contextual fit (Angele, Laishley, Rayner, & Liversedge, 2014; Angele & Rayner, 2013), but studies have also found evidence for contextual predictability effects (Balota, Pollatsek, & Rayner, 1985; Duan & Bicknell, 2020; Kliegl, Grabner, Rolfs, & Engbert, 2004; Luke & Christianson, 2016; Rayner, Slattery, Drieghe, & Liversedge, 2011). To test whether contextual information is relevant for predicting skipping with our model, we consider two versions of NEAT: In the *NoContext* version, skipping is based only on the identity of the word. In the *WithContext* version, the attention module has additionally access to the previous state h_{i-1} of the reader network, which summarizes what has been read so far. This is represented by a dashed line in Figure 1.

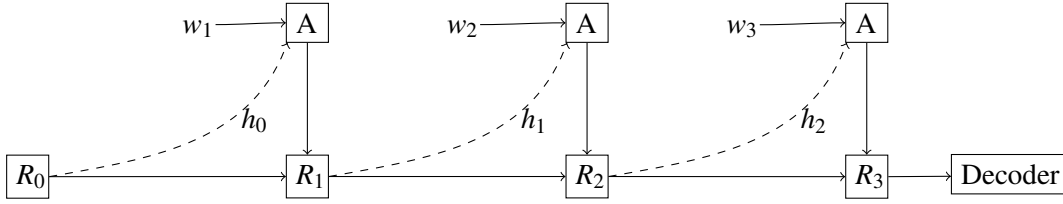


Figure 1. The architecture of the proposed NEAT model, reading a three-word input sequence w_1, w_2, w_3 . R is the reader network. A is the attention network. At each time step, the input w_i is fed into A , which then decides whether the word is read or skipped. In the *WithContext* version, the attention module additionally has access to the state h_{i-1} of the reader network, indicated by dashed lines.

If we write the decision made by A as $\omega_i \in \{0, 1\}$, where $\omega_i = 1$ means that word w_i is shown to the reader and 0 means that it is skipped, then we can write the probability of showing word w_i as:

$$P(\omega_i = 1 | \omega_{1..i-1}, \mathbf{w}) = A(w_i, h_{i-1}) \quad (1)$$

where $A(w_i, h_{i-1})$ is the output of the attention module A . We implement the attention module A as a feed-forward network, followed by taking a binary sample ω_i .

As outlined in Section 2.3, *surprisal* is a prominent model of linguistic processing difficulty that has been used to capture human reading time. Standard surprisal models assume that all words are read, and it is an interesting question whether surprisal estimates computed on noisy word sequences (where some words have been skipped) are able to predict reading time correctly.

The surprisal of an input word w_i is the negative logarithm of the conditional probability of the word given the context words $\mathbf{w}_{1..i-1}$. We estimate surprisal using a second LSTM network that at each time step computes a probability distribution P_S over the lexicon, and is trained to predict the next word given the fixated words. Using the skipping sequence $\omega_{1..i-1}$ predicted by NEAT, surprisal becomes:

$$\text{Surp}(w_i | \mathbf{w}_{1..i-1}) = -\log P_S(w_i | \mathbf{w}_{1..i-1}, \omega_{1..i-1}) \quad (2)$$

Crucially, this surprisal estimate only takes into account the words that have actually been read. We will refer to this quantity as *restricted surprisal*, as opposed to *full surprisal*, which is computed based on all prior context words, and constitutes a best possible estimate of the surprisal.

NEAT therefore computes two quantities that model important aspects of reading behavior: the fixation probability in equation (1), which predicts how likely words are to be fixated (rather than skipped), and the restricted surprisal in equation (2), which models the reading times of fixated words (in line with standard results that show that surprisal correlates with reading time, e.g., [Demberg & Keller, 2008](#)).

4.2 Objective Function

Given the network parameters θ and an input sequence of words \mathbf{w} , the network stochastically chooses a vector ω of fixation decisions according to (1) and incurs a loss $L(\omega | \mathbf{w}, \theta)$, which we take to be the negative log-probability assigned by the decoder to the correct input sequence:

$$L(\omega | \mathbf{w}, \theta) = -\frac{1}{N} \sum_{i=1}^N \log P_{\text{Decoder}}(w_i | \mathbf{w}_{1..i-1}; h_N; \theta) \quad (3)$$

where $P_{Decoder}(w_i | \mathbf{w}_{1..i-1}; h_N; \theta)$ is the probability assigned by the decoder network to the i -th input word assuming it has correctly generated the preceding words, with h_N being the vector representation created by the reader network for the entire input sequence.

To implement the Tradeoff Hypothesis, we train NEAT to solve reconstruction with a minimal number of fixations, i.e., the network minimizes the following expected loss:

$$Q(\theta) := E_{\mathbf{w}, \omega} \left[L(\omega | \mathbf{w}, \theta) + \alpha \cdot \frac{\|\omega\|_{\ell_1}}{N} \right] \quad (4)$$

where word sequences \mathbf{w} are drawn from a corpus, and ω is distributed according to $P(\omega | \mathbf{w}, \theta)$ as defined in (1). In equation (4), $\|\omega\|_{\ell_1}$ is the number of words shown to the reader, and $\alpha > 0$ is a hyperparameter, i.e., a parameter that needs to be tuned on a development set. The term $\alpha \cdot \|\omega\|_{\ell_1}$ encourages NEAT to attend to as few words as possible; the bigger α is, the higher the loss incurred when reading (as opposed to skipping) words.

Note that we make no assumption about linguistic structure – the only ingredients of NEAT are the neural architecture, the objective (4), and the corpus from which the sequences \mathbf{w} are drawn. This corpus is merely a sequence of words – NEAT is trained without linguistic annotation and without any eye-tracking data; we use eye-tracking data only for evaluating the model.

4.3 Parameter Estimation

We jointly train the parameters of the reader, decoder, and attention modules to minimize the objective function (4). We use gradient descent for the reader and decoder modules, and reinforcement learning, specifically the REINFORCE method (Williams, 1992), for the attention module A .

Starting with random initial values, the parameters are updated iteratively as follows. In each iteration, a text is selected from the training corpus, and a sequence of fixations and skips $\omega = \omega_1, \dots, \omega_N$ is sampled using the NEAT attention module A given the current parameter setting θ . We then compute the gradients as follows:

$$\begin{aligned} \Delta_1 &:= \left(\nabla_{\theta} \log \prod_{i=1}^N P_A(\omega_i | \omega_{1..i-1} \mathbf{w}; \theta) \right) \cdot [L(\omega | \mathbf{w}, \theta) + \alpha \cdot \|\omega\|_{\ell_1}] \\ \Delta_2 &:= \nabla_{\theta} L(\omega | \mathbf{w}, \theta) \end{aligned} \quad (5)$$

where ∇_{θ} denotes the gradient with respect to the parameters θ , using the backpropagation algorithm and update the parameters θ according to the following update rule:

$$\theta \leftarrow \theta - \gamma \cdot (\Delta_1 + \Delta_2) \quad (6)$$

where $\gamma > 0$ is the learning rate. To speed up computation, in every iteration, 64 texts are batched together, and all computations are performed in parallel on them.

This technique can be understood as a reinforcement learning method where the attention module samples actions from its current strategy and updates its parameters based on a reward that trades off accuracy and attention. The update rule in equation (6) is also an instance of stochastic gradient descent, since $\Delta_1 + \Delta_2$ is an unbiased estimator of the gradient of (4) with respect to θ (Williams, 1992). This method is widely used in the reinforcement learning literature, and commonly referred to as the policy-gradient method.

We utilize three methods for speeding up convergence of this training algorithm. First, when computing the gradient (5), we subtract from the reward signal $L(\omega|\mathbf{w}, \theta) + \alpha \cdot \|\omega\|_{\ell_1}$ a running average of its recent values on other texts, a standard approach for speeding up reinforcement learning without sacrificing the unbiasedness of the gradients (Williams, 1992). From a cognitive perspective, this corresponds to adjusting the reward signal based on the value of the loss *relative to typical values* on other texts. Second, following Xu et al. (2015), we add entropy regularization, encouraging the model to explore different reading strategies. Third, we pretrain the reading and decoder networks on input sequences where 5% of words have been skipped at random. This corresponds to collecting prior knowledge about the language before starting to optimize the reading strategy.

5 Modeling Study 1

In this study, we will evaluate our NEAT model against human eye-tracking data. In particular, we want to investigate whether NEAT, when trained to perform a generic task (reconstructing the input text), is able to simulate reading behavior as it is observed in human readers when they are not given a specific task (other than understanding the text).

NEAT predicts two quantities that can be evaluated against human reading data: Firstly, it generates vectors of skips and fixations, i.e., which words in a given input text are fixated or skipped. Secondly, it predicts surprisal values for words in context. We can evaluate model generated fixation sequences against human fixation vectors, and surprisal values against human reading time. Both can be extracted from eye-tracking corpora.

5.1 Methods

5.1.1 Model Implementation. For both the reader and the decoder networks, we choose a one-layer LSTM network with 1,024 memory cells. The attention network applies a linear transformation to word embeddings and (in the *WithContext* version) the previous reader state, and derives a probability using the logistic function:

$$P(\omega_i = 1|\omega_{1\dots i-1}, \mathbf{w}) := \sigma(u + v^T \hat{w}_i) \quad \text{NoContext} \quad (7)$$

$$P(\omega_i = 1|\omega_{1\dots i-1}, \mathbf{w}) := \sigma(u + v^T \hat{w}_i + h_{i-1}^T A \hat{w}_i) \quad \text{WithContext} \quad (8)$$

where $\hat{w}_i \in \mathbb{R}^{d_{emb}}$ is a vector encoding the preview of the word w_i (see below). The weights $v \in \mathbb{R}^{d_{emb}}$, $A \in \mathbb{R}^{d_{emb} \times 1024}$ are parameters of the model. We encoded the vectors for the preview as follows. First, for each prefix of four characters from the model’s vocabulary, we allocated 200-dimensional embedding vector that is initialized as the average of the word embeddings of all words continuing this prefix. These embedding vectors were then trained together with the other parameters of the attention network. Second, in order to make character-level information directly accessible, we represent each character in the preview prefix with a small (128-dimensional) vector trained together with the other parameters, average these, and concatenate the resulting vector with the 200-dimensional vector for the prefix, leading to an overall representation with $d_{emb} = 200 + 128$ dimensions.

The text being read is split into sequences of 50 tokens, which are used as the input sequences for NEAT, disregarding sentence boundaries. Word embeddings are shared between the reader and the attention network. The vocabulary consists of the 50,000 most frequent words from the training corpus. Words outside of this vocabulary were represented with a special out-of-vocabulary token, as is standard practice in neural sequence modeling of language; this affected 2.0% of tokens in

the training set. We trained NEAT on the training set of the DeepMind question answering corpus (Hermann et al., 2015), which consists of 90,266 articles from the CNN web site and 196,961 articles from the Daily Mail web site, containing approximately 230 million tokens (only the texts were used for this modeling study, not the questions). During training, texts were sampled from both sources in equal proportion. Training iterated through the corpus four times. For initialization, weights are drawn from the uniform distribution.

In order to determine the weight α in (4), we varied α from 0 to 3 in steps of 0.25, and chose the value ($\alpha = 3.0$) resulting in the fixation rate (63.5%) that best matched the human fixation rate on the development set (see Section 5.1.2). No eye-tracking data was used when training the model, beyond the choice of α to match human fixation rate.

5.1.2 Dataset. To evaluate the reading behavior of the trained model, we used the English section of the Dundee corpus (Kennedy & Pynte, 2005), which consists of 20 texts from *The Independent*, annotated with eye-movement data from ten English native speakers. Each native speaker read all 20 texts and answered a comprehension question after each text. We split the Dundee corpus into a development and a test set, with texts 1–3 constituting the development set. The development set consists of 78,300 tokens, and the test set of 281,911 tokens. For evaluation, we removed the datapoints removed by Demberg and Keller (2008), mainly consisting of words at the beginning or end of lines and cases of track loss. Furthermore, we removed datapoints where the word was outside of the vocabulary of the model. After preprocessing, 81.1% of tokens remained. To obtain fixation rate and reading time per token, we used the eye-tracking measures computed by Demberg and Keller (2008). The average fixation rate over all tokens was 62.1% on the development set, and 61.3% on the test set.

The development set was used to determine the human skipping rate (see Section 5.2) and to choose the model parameter α (Section 5.1.1). The model was then run on the test set to compute the results that we report in the following section.

5.2 Results and Discussion

5.2.1 Fixation Vectors. NEAT defines for each word in a sequence a probability that it will be fixated. These simulated fixation probabilities can be interpreted as defining a distribution of attention over the input sequence. Figure 2 shows heatmaps of the human and simulated fixation probabilities (*NoContext* version), respectively, for the beginning of a text from the Dundee corpus. While some differences between human and simulated fixation probabilities can be noticed, there are similarities in the general qualitative features of the two heatmaps. In particular, function words and short words are less likely to be fixated than content words and longer words in both the human and the simulated data.

In order to quantitatively assess fit to human fixation rate, we compared NEAT fixation probabilities to the following models. First, we compare to previous work on supervised models of fixation prediction on the Dundee corpus (Matthies & Sogaard, 2013; Nilsson & Nivre, 2009). Second, we considered *random attention*, which is defined by $\omega \sim \text{Binom}(n, p)$, with $p = 0.621$, the human fixation rate in the development set. This baseline corresponds to a reading strategy where words are skipped at random, so that the overall fixation rate is the same as in the development portion of the Dundee corpus. Third, we derived fixation predictions from *full surprisal*, *word frequency*, and *word length*. For this, we choose a threshold for these quantities such that the resulting fixation rate matches the human fixation rate on the development set. For example, the word frequency baseline skips all high frequency words up to a frequency threshold that ensures that the fixation rate is

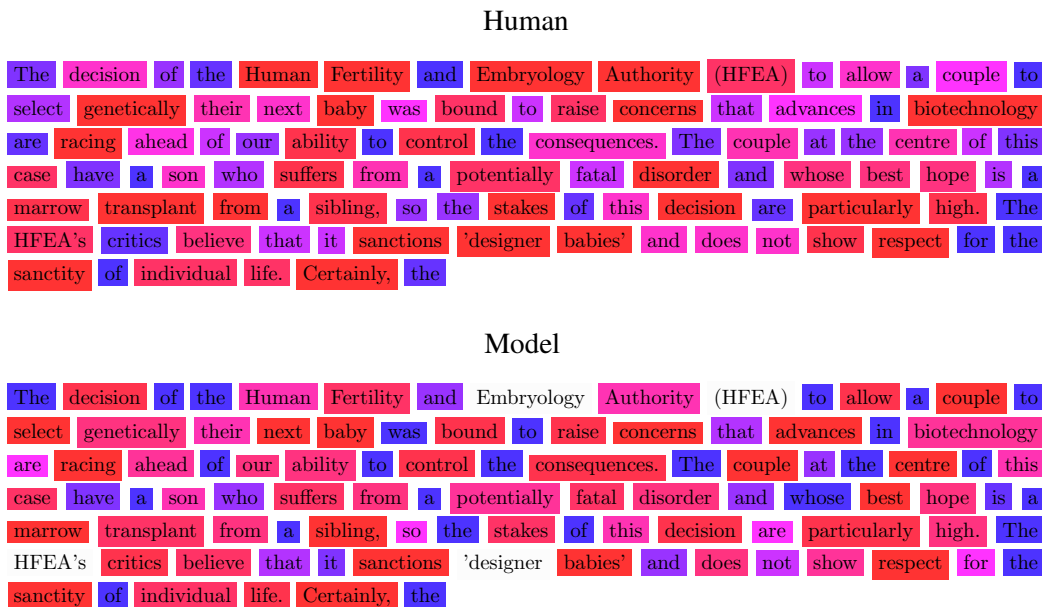


Figure 2. Top: Heatmap visualizing human fixation probabilities, as estimated from the ten readers in the Dundee corpus. In cases of track loss, we replaced the missing value with the corresponding reader’s overall fixation rate. Bottom: Heatmap showing fixation probabilities simulated by NEAT in Modeling Study 1. The color gradient denotes the fixation probability for a word, ranging from blue (low probability) to red (high probability). White background indicates that the word was excluded from the analysis because it was not part of the model’s vocabulary.

	Accuracy	F_{fix}	F_{skip}
NEAT (NoContext)	66.9	71.2	61.0
NEAT (WithContext)	66.6	71.0	60.6
Supervised Models			
Nilsson and Nivre (2009)	69.5	75.2	62.6
Matthies and Søgaard (2013)	69.9	72.3	66.1
Human Performance and Baselines			
Random Attention	51.2	58.1	41.4
Full Surprisal	61.5	66.6	54.6
Word Frequency	67.4	71.7	61.7
Word Length	69.1	72.7	64.5
Human Agreement	69.3	73.2	64.1

Table 1

Evaluation of fixation predictions against human data. To measure human agreement, we predicted the n -th reader’s fixations by taking the fixations of the $(n + 1)$ -th reader (with missing values replaced by reader average), averaging the resulting scores over the ten readers.

62.1%. Note that we need a surprisal model in order to compute the full surprisal baseline; we will return to this below. To enable meaningful comparison, we applied the same procedure to the NEAT fixation probabilities.¹

As in previous work, we report the classification accuracy (for the two classes fixation and skip), and also separate F -scores for fixation and skip prediction (F is the harmonic mean of precision and recall). We computed a separate accuracy for each human subject and averaged the results, following [Mathies and Sogaard \(2013\)](#). As lower and upper bounds, we use random attention (defined as $\omega \sim \text{Binom}(n, 0.621)$) and the agreement of the ten human readers, respectively. The results are shown in [Table 1](#). NEAT clearly outperforms random attention and shows results close to full surprisal (where we apply the same rescaling and thresholding as for NEAT). This is remarkable given that NEAT has access to only 63.5% of the words in the corpus in order to predict skipping, while full surprisal has access to all the words.

When comparing the two different versions of NEAT, we find that access to the previous context of a word does not result in improved fit; the *NoContext* model performs slightly better than the *WithContext* one.

Word frequency and word length perform well, almost reaching the performance of supervised models. This shows that the bulk of skipping behavior is already explained by word frequency and word length effects. Note, however, that NEAT is completely unsupervised, and does not know that it has to pay attention to word frequency or word length; this is something the model is needs to infer. A simple regression based on word frequency and word length would have fewer parameters than a neural network model, but it is not explanatory: it does not provide a theory of why those predictors should matter. In contrast, in NEAT, effects of these predictors are emergent properties of the Tradeoff Hypothesis.

The success of word frequency and word length is in agreement with the finding that contextual information did not improve model fit, and with prior experimental evidence indicating that frequency effects can trump contextual fit ([Angele et al., 2014](#); [Angele & Rayner, 2013](#)). While some studies have found evidence for contextual predictability effects in skipping ([Balota et al., 1985](#); [Duan & Bicknell, 2020](#); [Kliegl et al., 2004](#); [Luke & Christianson, 2016](#); [Rayner et al., 2011](#)), other work has found their role to be limited ([Heilbron, van Haren, Hagoort, & de Lange, 2021](#)). Our results suggest that context effects, as they are modeled by the *WithContext* version of NEAT, play no role for skipping in naturalistic text.

5.2.2 Reading Time. To evaluate the predictions NEAT makes for reading time, we use linear mixed effects models ([Pinheiro & Bates, 2000](#)) that include as a predictor the restricted form of surprisal derived from NEAT for the Dundee test set. The mixed models also include a set of standard baseline predictors, viz., word length, log word frequency, and the position of the word in the text. Word length and surprisal were residualized with respect to log word frequency. To keep the size of the mixed effects models manageable, we only considered binary interactions. Which interactions to include was determined by forward model selection: Starting from a model with only main effects, we iteratively added the binary interaction resulting in the greatest improvement in deviance,² until model fit did not change significantly any more according to a χ^2 test. We did this separately for all four reading measures, and then pooled the interactions, so that the final models

¹Another possibility would be to directly evaluate fixations *sampled* from NEAT, but the results would not be comparable with the other models ([Mathies & Sogaard, 2013](#); [Nilsson & Nivre, 2009](#)) – where reported results refer to their *highest probability* fixation sequences – and to the baselines, for which fixation rate is matched to the human data.

²Deviance is defined as the log likelihood of the model under consideration, multiplied by -2 .

for all measures contained the same set of interactions.

We treat participants and items as random factors. As the dependent variables, we take either first fixation duration, first pass time, total time, or fixation rate (these measures are defined in Section 6.1.4 below).

We compare NEAT surprisal against *full surprisal* as an upper bound and against *random surprisal* as a lower bound. Random surprisal is surprisal computed by a model with random attention; this allows us to assess how much surprisal degrades when only 63.5% of all words are fixated, but no information is available as to which words should be fixated. Full surprisal is the surprisal estimate computed with full attention, i.e., when our model is allowed to fixate all words.

In order to evaluate the different surprisal estimates, we compare the model fit of the three mixed effects models using deviance: higher deviance indicates greater improvement in model fit over the baseline model. For first pass, we find that the mixed model that includes NEAT surprisal reduces deviance by 413 compared to the mixed model containing only the baseline predictors. With full surprisal, we obtain a deviance difference of 499. On the other hand, the model including random surprisal achieves a lower deviance difference of 304. For the other reading time measures, the situation is similar, see Table 2 for details. (This table also contains AIC and BIC as additional measures for model comparison; these agree with the deviance results.) For fixation rate, we find that no form of surprisal has any predictive power over and above the other predictors, in line with what we found for skipping.

The reading time results in Table 2 show that restricted surprisal as computed by NEAT not only significantly predicts reading time, it also provides an improvement in model fit compared to the baseline predictors. The magnitude of this improvement in terms of deviance indicates that NEAT outperforms random surprisal. Full surprisal achieves an even greater improvement, but this is not unexpected, as full surprisal has access to all words, unlike NEAT or random surprisal, which only read to 63.5% of the words in the text, and skip the rest.³

6 Experiment 1

In Modeling Study 1 we successfully evaluated NEAT, our model of reading based on the Tradeoff Hypothesis, against a corpus of human eye-tracking data. We were able to show that human fixation sequences are predicted by NEAT's measure of fixation probability, while human reading time is predicted by its measure of restricted surprisal.

Recall that the version of NEAT used in Modeling Study 1 was based on the assumption that the task that the model needs to solve is to build up a representation of the text that allows it reconstruct the input accurately. NEAT therefore learns to reconstruct an input sequence as accurately as possible, while reading as economically as possible, i.e., fixating as few words as it can.

We will now turn to an important prediction that can be derived from the Tradeoff Hypothesis. If reading behavior is the consequence of a tradeoff between task accuracy and reading economy, then this predicts that the tradeoff will change when the reading task changes. More specifically, if

³Full surprisal predicts reading time better than restricted surprisal. We could hypothesize that this indicates that words that are not fixated are in fact processed in some way, rather than truly skipped. However, this would only be true if all human readers in the Dundee corpus skipped the same words. In reality, individual participants will each skip a certain proportion of words, but they don't all skip the same words. Full surprisal was trained using a model that doesn't skip any words, so it can provide the best possible prediction of reading time for every participant, no matter which words they skip. Restricted surprisal, on the other hand, is trained on a model that skips words (but not necessarily the ones skipped by any one participant), and thus provides a worse estimate of reading time for an individual participant.

	First Fixation		First Pass		Total Time	
(Intercept)	200.84	(5.73)	232.71	(7.84)	243.36	(8.34)
WordLength	3.54	(0.23)	32.82	(0.43)	35.54	(0.48)
LogWordFreq	-4.66	(0.23)	-2.99	(0.41)	-4.92	(0.45)
PositionText	-0.65	(0.18)	-2.3	(0.32)	-2.91	(0.35)
LogWordFreq:WordLength	0.37	(0.17)	-0.62	(0.32)	-1.52	(0.35)
LogWordFreq:PositionText	-0.54	(0.22)	-0.96	(0.40)	-0.31	(0.45)
WordLength:PositionText	-0.78	(0.22)	-2.94	(0.41)	-2.74	(0.46)
NEAT Surprisal	1.54	(0.08)	3.48	(0.14)	4.21	(0.15)
AIC Difference	411.0		633.0		749.0	
BIC Difference	400.0		623.0		738.0	
Deviance Difference	413.0		635.0		751.0	
Full Surprisal	1.45	(0.06)	3.2	(0.12)	4.03	(0.13)
AIC Difference	497.0		735.0		947.0	
BIC Difference	486.0		725.0		937.0	
Deviance Difference	499.0		737.0		949.0	
Random Surprisal	1.21	(0.07)	2.65	(0.13)	3.18	(0.14)
AIC Difference	302.0		439.0		513.0	
BIC Difference	292.0		429.0		503.0	
Deviance Difference	304.0		441.0		515.0	

Table 2

Linear mixed effects models for reading time measures on the Dundee corpus, with model comparisons between base model and models including different types of surprisal. For each coefficient, we show estimates and standard errors. Boldfacing indicates model coefficients that are significant predictors. All model comparisons are significant at $p < 2.2 \cdot 10^{-16}$ using a χ^2 test.

a reader is given a task that requires them to pay particular attention to certain aspects of the text, then their eye-movements will change in a way that is optimal for this task. Experimental evidence for this comes, for instance, from studies comparing proofreading and normal reading (Schotter et al., 2014), see Section 3 for details.

In the following, we will present an eye-tracking experiment that tests this prediction of the Tradeoff Hypothesis. We investigate a specific task, viz., reading a text in order to find the answer to a question, and manipulate how much readers know about the task. In one condition (No Preview), participants first read the text and then answer a question about it; in the second condition (Preview), they first see the question, then read the text, and then answer the question. In the No Preview condition, readers have no idea what the answer will look like, and their reading behavior should be similar to normal reading: they try to build up a representation of the text that is as complete as possible, as the question can be about anything they have read. In the Preview condition, on the other hand, readers know what type of information to seek, allowing them to read faster and skip more words. In the Preview condition, we also expect them to focus more on answer-relevant words (e.g., named entities), and expect to see increased reading time on these words.

6.1 Methods

6.1.1 Participants. The experimental protocol was approved the ethics committee of the School of Informatics at the University of Edinburgh. Twenty-two members of the University community took part in the experiment after giving informed consent. They were paid £10 for their participation. All participants had normal or corrected-to-normal vision and were self-reported native speakers of English.

6.1.2 Materials. Twenty newspaper texts were selected from the DeepMind question answering corpus (Hermann et al., 2015). Ten texts were taken from the CNN section of the corpus and the other ten texts from the Daily Mail section. Texts were selected so that they were comparable in length and represented a balanced selection of topics. Text lengths ranged from 149 to 805 words (mean 323 words). Two additional texts were selected as practice items. All texts were selected from the test partition, which we did not use for training any of the neural models described in this article.

For each text, a question and the correct answer were selected from the corpus. In the DeepMind corpus, questions are formulated as sentences with a blank to be completed with a named entity so that a statement implied by the text is obtained. An example is the following question for the text in Figure 3:

- (1) A random sample from a _____ store tested positive for *Listeria monocytogenes*.

Questions were selected so that the correct answer does not occur at the beginning of the text. The correct answer in this case is *Michigan*. All named entities are marked up in the DeepMind corpus, a fact that we will use for our analysis later.

For each text, three incorrect answers (distractor) were created (these are not included in the DeepMind corpus). The distractors were also named entities, chosen so that correctly answering the question would likely be impossible without reading the text. In the present example, the distractors were names of other US states.

6.1.3 Procedure. The experiment included two conditions: Preview and No Preview. In the Preview condition, participants first read the question, then they read the text, and then they saw the question again with four answer choices and had to select one answer. In the No Preview condition, the question was not presented at the beginning of the trial, only after the text had been read.

The design was between-groups, i.e., each participant took part either in the Preview or No Preview version of the experiment. There were 10 participants in the Preview group and 10 participants in the No Preview group. In both groups, participants first received written instructions (appropriate for their condition) and went through two practice trials whose data was discarded. Then, each participant read and responded to all 20 items (texts with questions and answer choices); the items were the same for all participants (modulo question preview), but were presented in a new random order for each participant. The order of the answer options was randomized for each condition, but the same answer order was used for all participants in a given condition.

The experiment was conducted in a sound-attenuated room, where the text was presented on a 24 inch LCD screen, in a Lucida Sans Typewriter font with a fontsize of 20 points, line spacing of 20 points, and x- and y-offsets of 113 points. Each trial consisted of the question preview (in the Preview condition only; without answer choices), presented on its own page. After a button press, the text was displayed; texts were between one and five pages long (mean 2.1 pages), where each

page contained up to eleven lines with about 80 characters per line. To get to the next page, and at the end of the text, participants again had to press a button. After the last page of text, the question was displayed, together with the four answer choices, on a separate page. Participants had to press one of four buttons to select an answer.

Eye-movements were recorded using an Eyelink 2000 tracker manufactured by SR Research (Ottawa, Canada). The tracker recorded the dominant eye of the participant (as established by an eye-dominance test) with a sampling rate of 2000 Hz. The participant was positioned about 60 cm away from the screen, and a head rest was used to minimize head movements. Before the experiment started, the tracker was calibrated using a nine-point calibration procedure. At the start of each trial, a fixation point was presented and drift correction was carried out. Throughout the experiment, the experimenter monitored the accuracy of the recording and carried out additional calibrations as necessary. Button presses were collected using a USB game pad.

6.1.4 Data Analysis. Drift in the vertical position of fixations was corrected automatically. For this, we used custom-made software that adjusts the vertical position of the nine calibration points, accordingly moving recorded fixations. On each trial, the software minimizes a linear combination of the squares of:

1. for each calibration point, the Euclidean distance from the recorded position;
2. the number of fixations not falling on any line of the text;
3. the number of pairs of successive fixations assigned to different lines of the text;
4. for each fixation falling within a line, the vertical distance from the center of that line;
5. for each fixation falling above the first line or below the last line, the vertical distance to the first or last line.

We selected the coefficients for these five factors manually so as to optimize the correction on a number of selected trials. The software only adjusted vertical positions; the horizontal positions of the calibration points and thus of the fixations was left unchanged.

We also pooled short, contiguous fixations as follows: fixations of less than 80 ms were incorporated into larger fixations within one character, and any remaining fixations of less than 40 ms were deleted. Readers do not extract much information during such short fixations ([Rayner & Pollatsek, 1989](#)).

For data analysis, each word in the text was defined as a region of interest. Punctuation was included in the region of the word it followed or preceded without intervening whitespace. If a word was preceded by a whitespace, then the space was included in the region for that word.

We report data for the following eye-movement measures in the critical and spill-over regions. *First fixation duration* is the duration of the first fixation in a region, provided that there was no earlier fixation on material beyond the region. *First pass time* (often called gaze duration for single-word regions) consists of the sum of fixation durations beginning with this first fixation in the region until the first saccade out of the region, either to the left or to the right. *Total time* consists of the sum of the durations of all fixation in the region, regardless of when these fixations occur. *Fixation rate* measures the proportion of subjects who fixated (rather than skipped) the region on first-pass reading.

	No Preview	Preview	No Preview, before answer	No Preview, after answer	Preview, before answer	Preview, after answer
First fixation	214.1	194.1	215	213.6	193.2	194.7
First pass	257.3	213.2	259.6	256	213.2	213.3
Total time	317.6	262.5	329.8	310.3	266.5	259.9
Fixation rate	0.52	0.32	0.51	0.52	0.32	0.32
Accuracy	70%	89%				

Table 3

Left: mean fixation rate, reading time, and question accuracies by conditions in our reading experiment. Right: the same measures separately for words that occur before and after the correct answer in the text.

For first fixation duration and first pass time, no trials in which the region is skipped on first-pass reading (i.e., when first fixation duration is zero) were included in the analysis. For total time, only trials with a non-zero total time were included in the analysis.

6.2 Results

6.2.1 Tradeoff between Accuracy and Economy. Table 3 shows descriptive statistics for the reading time measures first fixation duration, first pass time, and total time. We also report fixation rate, i.e., the proportion of words that were fixated rather than skipped.

While the fixation rate was 0.52 in the No Preview condition, it dropped to 0.32 in the preview condition. Similarly, all reading time measures were substantially lower in the Preview condition: we observe a 20 ms reduction in first fixation duration, and reductions of 44 ms and 55 ms in first pass duration and total time, respectively. (We statistically analyze these differences using mixed effects models below.) Note also that fixation rate was substantially lower than in the Dundee corpus.

It is possible this result is simply due to the participants in the Preview condition being strategic: once they have found the answer in the text, they only read the rest of the text superficially, or even skip it completely. This would result in reduced overall reading time and fixation rate when averaging across the text as a whole. The right half of Table 3 presents reading time and fixation rate for the Preview condition separately for the words in the text that occur before and after the answer. The measures in both cases are indistinguishable (except for a small reduction in total time). This is evidence that participants read all of the text in the same way, and do not adopt a special strategy once they have found the answer.

Turning now to question answering accuracy, we found an accuracy of 70% in the No Preview condition, rising to 89% in the Preview condition. This difference was significant ($\beta = 2.05$, $SE = 0.69$, $p = 0.0027$) in a logistic mixed effects model with text and participant as random effects and condition as fixed effect, and the appropriate random intercepts and slopes (i.e., a by-text slope for condition). The question accuracies show that participants were reading the texts attentively, performing substantially above chance (25% accuracy) in both conditions, despite the low fixations rate observed in this experiment.

A sample visualization of skipping behavior in the two conditions is shown in Figure 3. Overall fixation rate is higher in the No Preview condition (top) than in the Preview condition (bottom). In the No Preview condition, most content words were fixated at least by some participants, and

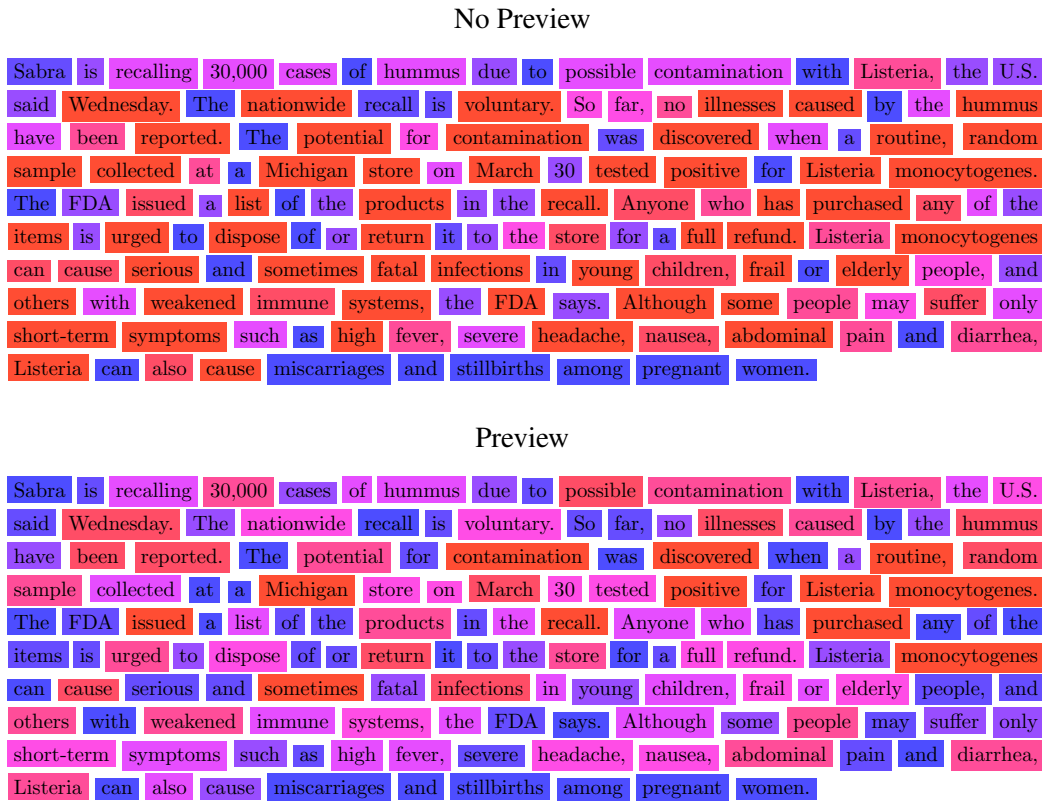


Figure 3. Heatmap visualizing human fixation probabilities in Experiment 1, averaged over all participants per condition. Top: No Preview, bottom: Preview. The color gradient denotes the fixation probability for a word, ranging from blue (0.0) to red (1.0). The question was *A random sample from a _____ store tested positive for Listeria monocytogenes.* The correct answer was *Michigan*, which occurs in the fourth line of the text.

longer words were fixated by most participants. This contrasts with the Preview condition, where only a few words have high fixation rate, including the correct answer (*Michigan*, in the fourth line of the text).

Based on this observation, we wanted to test whether spending more time reading the answers in the text enables participants to answer the questions more accurately. We therefore built a logistic mixed effects model predicting whether a question was answered correctly based on (1) condition (Preview or No Preview), and (2) total time spent on all the occurrences of the correct answer in the text, centered and scaled to unit variance. The model included text and participant as random effects, and the appropriate random slopes (i.e., by-text slope for condition, and by-text and by-participant slopes for total time). We conducted a Bayesian logistic analysis using *brms* (Bürkner, 2017), as frequentist models were numerically unstable. Reading time was a significant predictor ($\beta = 1.22$, $SE = 0.3434$, $95\% CrI = [0.39, 2.22]$), with higher reading time increasing the probability of answering correctly. The main effect of condition was also significant ($\beta = 2.00$, $SE = 0.74$, $95\% CrI = [0.70, 3.67]$). There was an interaction, such that the effect of reading time was stronger in the Preview condition ($\beta = 1.81$, $SE = 0.98$, $95\% CrI = [0.04, 3.90]$).

	First Fixation	First Pass	Total Time	Fixation Rate
(Intercept)	201.60 (4.71)	227.17 (6.84)	276.30 (7.61)	-0.35 (0.16)
Task	20.09 (9.40)	48.53 (13.62)	67.52 (15.10)	0.98 (0.31)
IsCorrectAnswer	-2.31 (3.79)	-27.84 (10.49)	8.21(16.81)	0.21 (0.13)
IsNamedEntity	-2.73 (1.42)	-10.14 (2.86)	4.96 (4.38)	0.05 (0.06)
WordLength	0.40 (0.24)	8.11 (0.38)	13.87 (0.58)	0.29 (0.01)
LogWordFreq	-6.30 (0.52)	-7.28 (0.28)	-40.84 (1.26)	-0.65 (0.04)
PositionText	0.74 (0.45)	-1.10 (0.76)	-9.87 (1.15)	0.02 (0.1)
Surprisal	1.27 (0.19)	1.43 (0.30)	3.39 (0.45)	0.01 (0.01)
IsCorrectAnswer:Surprisal		-5.20 (1.98)	-16.07 (3.03)	
IsCorrectAnswer:WordLength			18.58 (4.56)	
IsNamedEntity:Surprisal		-1.96 (0.68)	-3.62 (1.01)	0.02 (0.01)
IsNamedEntity:WordLength			6.27 (1.53)	
LogWordFreq:IsCorrectAnswer		-12.69 (2.48)	-96.79 (12.30)	
LogWordFreq:IsNamedEntity		-6.53 (0.76)	-44.01 (3.61)	0.21 (0.05)
LogWordFreq:Surprisal	0.52 (0.21)			
LogWordFreq:WordLength	1.06 (0.23)			0.05 (0.01)
LogWordFreq:PositionText		0.81 (0.25)	6.11 (1.24)	
PositionText:IsCorrectAnswer		-31.76 (8.89)	-115.03 (14.20)	
PositionText:IsNamedEntity			-18.97 (3.52)	
Surprisal:WordLength	0.17 (0.08)	0.34 (0.13)		
Task:IsCorrectAnswer	-12.97 (5.84)		-186.23 (12.06)	-0.31 (0.16)
Task:IsNamedEntity				-0.19 (0.09)
Task:LogWordFreq		-4.28 (0.39)	-18.46 (1.52)	-0.14 (0.07)
Task:Surprisal				-0.02 (0.01)
Task:WordLength	-0.89 (0.35)	4.11 (0.55)	5.11 (0.73)	0.04 (0.03)
Task:PositionText				0.06 (0.08)

Table 4

Mixed effects models for the data from Experiment 1. Task is coded as -0.5 (Preview) vs. +0.5 (No Preview). Binary interactions were identified automatically using forward model selection, as described in the text. For first fixation, first pass and total time, we report the estimated coefficient and its standard error as obtained using linear mixed effects models. For fixation rate, the dependent variable is binary (word fixated or not), so we fitted Bayesian logistic mixed effects models and report the estimated coefficient and its posterior standard deviation. Effects were interpreted as significant when $|t| > 2$ (reading time) or the posterior probability that the coefficient has the opposite sign was < 0.05 (fixation rate). Continuous predictors were centered and scaled to have unit standard deviation.

6.2.2 Mixed Effects Analyses. In order to more comprehensively analyze the effect of our experimental manipulation on eye-tracking measures, we fitted a series of mixed effects models to the data. We include not only task (Preview or No Preview, coded as -0.5 and $+0.5$, respectively) as a fixed factor in our models, but also the following word-based factors, which allow us to analyze in more detail how the question-answering task influences reading strategy:

1. **LogWordFreq:** log-transformed word frequency, computed from the training set of the DeepMind corpus (230 million words of newstext);
2. **WordLength:** length of the word in characters, residualized with respect to log word frequency (see SI Appendix, Section 3);
3. **PositionText:** the position of the word in the text, counted from the first word of the text;
4. **Surprisal:** $-\log P(w_n|w_{1...n-1})$ computed using a recurrent neural network language model trained on the training set of the DeepMind corpus. This was residualized with respect to log word frequency (see SI Appendix, Section 3). After residualizing, we set surprisal to zero for those words that are outside of the vocabulary of the neural language model (2.8% of tokens), as it does not compute meaningful surprisal estimates for those.
5. **IsNamedEntity:** whether the word is part of a named entity (i.e., a potential answer), coded as -0.5 for no and $+0.5$ for yes.
6. **IsCorrectAnswer:** whether the word is part of the correct answer to the question for this text, again coded as -0.5 for no and $+0.5$ for yes, and then residualized with respect to IsNamedEntity (only named entities can belong to the correct answer).

For first fixation, first pass, and total time, we fitted mixed effects models using the R package `lme4` (Bates, Mächler, Bolker, & Walker, 2015). These models included random intercepts for participants and items and their outputs are shown in Table 4. Models with random slopes did not converge when using `lme4`. We therefore also built Bayesian linear mixed effects models with all appropriate random slopes using `brms` (Bürkner, 2017), both for reading times and for log-transformed reading time; the results of these models broadly agree with the non-Bayesian models, and are given in SI Appendix, Section 2.

For fixation rate, the dependent variable was binary (word fixated or skipped). We found that fitting logistic mixed models with `lme4` gave unstable results, so we fitted Bayesian logistic mixed effects models with participants and items as random effects and all appropriate random slopes using `brms`. The fitted model for fixation rate is also shown in Table 4. See SI Appendix, Section 2 for details.

For first fixation, first pass, and total time, only fixated words were included in the analysis. All predictors were centered. Continuous predictors were scaled to unit standard deviation, and categorical predictors had a difference of one between their two levels. The coefficient of a predictor in these models can therefore be interpreted as the change in milliseconds per standard deviation of the predictor (continuous), or the change (in milliseconds) induced by going from one level to the other (categorical predictors). In order to select which binary interactions to include in the models, we conducted forward model selection with a χ^2 test as described in Section 5.2.2. We removed the first token of each text from analysis.

6.2.3 Task-independent Effects. We will first discuss the main effect found in our mixed effects analysis, see the first section of Table 4. The results show main effects of log word frequency (all measures) and word length (first pass, total time, fixation rate), indicating that infrequent words and long words are read more slowly and are more likely to be fixated, independent of task. There is also a significant effect of named entity status on first pass. Words that are part of a named entity (i.e., a potential answer) are read faster in this measure. We also observe a main effect of whether a word is part of the correct answer (decreased first pass time) and of text position: words later in the text have lower total time. There is also a significant main effect of surprisal on all reading time measures: more surprising words are read more slowly. This is consistent with previous work on surprisal in reading time corpora (Demberg & Keller, 2008). There is no effect of surprisal on fixation rate.

We now turn to interactions that do not involve task, which are given in the second section of Table 4. We find an interaction of word length and word frequency in first fixation and fixation rate, which is a standard reading time effect. We also observe that the position of a word in the text interacts with its frequency (in first pass and total time), which is again a standard reading time effect. There are negative interactions of text position with named entity status (total time) and answer status (first pass and total time), which indicates that named entities are read faster later in the text, presumably because a named entity is less likely to be the correct answer later in the text, as the answer has already been encountered by then.

We also find four interactions involving surprisal. There is a positive interaction of surprisal and word length in first fixation and first pass, indicating that surprisal has a bigger effect on longer words than on shorter words. An interaction between log word frequency and surprisal is found in first fixation. There are also interactions of surprisal and named entity status, and between surprisal and answer status. Words that belong to named entities are less affected by surprisal than other words in the reading time measures, but more than other words in fixation rate. Relatedly, we find interactions between answer status and log word frequency (first pass and total time), and between answer status and word length (total time), showing that frequency and length effects are stronger on the correct answer than on other words.

We also find interactions of named entity status with log word frequency (first pass, total time, and fixation rate). This indicates that the effect of log word frequency is more pronounced on named entities in reading time, and less pronounced in fixation rate.

6.2.4 Task-dependent Effects. As predicted by the Tradeoff Hypothesis, we find a significant main effect of task in all measures: first fixation, first pass, total time, and fixation rate are all higher in the No Preview condition, confirming the observations we made based on the descriptive statistics in Table 3.

We now turn to the third section of Table 4, which shows interactions involving task. As explained in Section 6, we expect readers in the Preview condition to focus more on answer-relevant words (e.g., named entities), which means we should see increased reading time on these words. We visualize the significant interactions in Figures 4–7.

The results show a significant negative interaction between task and word frequency in first pass, total time, and fixation rate (see Figure 4). This means that the word frequency effect is less pronounced in the Preview condition. We observe a similar effect for word length (see Figure 5): the positive interaction of task and word length in first pass and total time indicates that word length has a weaker effect on reading time in the Preview condition; though there is a negative interaction in first fixation. We hypothesize that when readers have preview of the question, they adopt a strategy

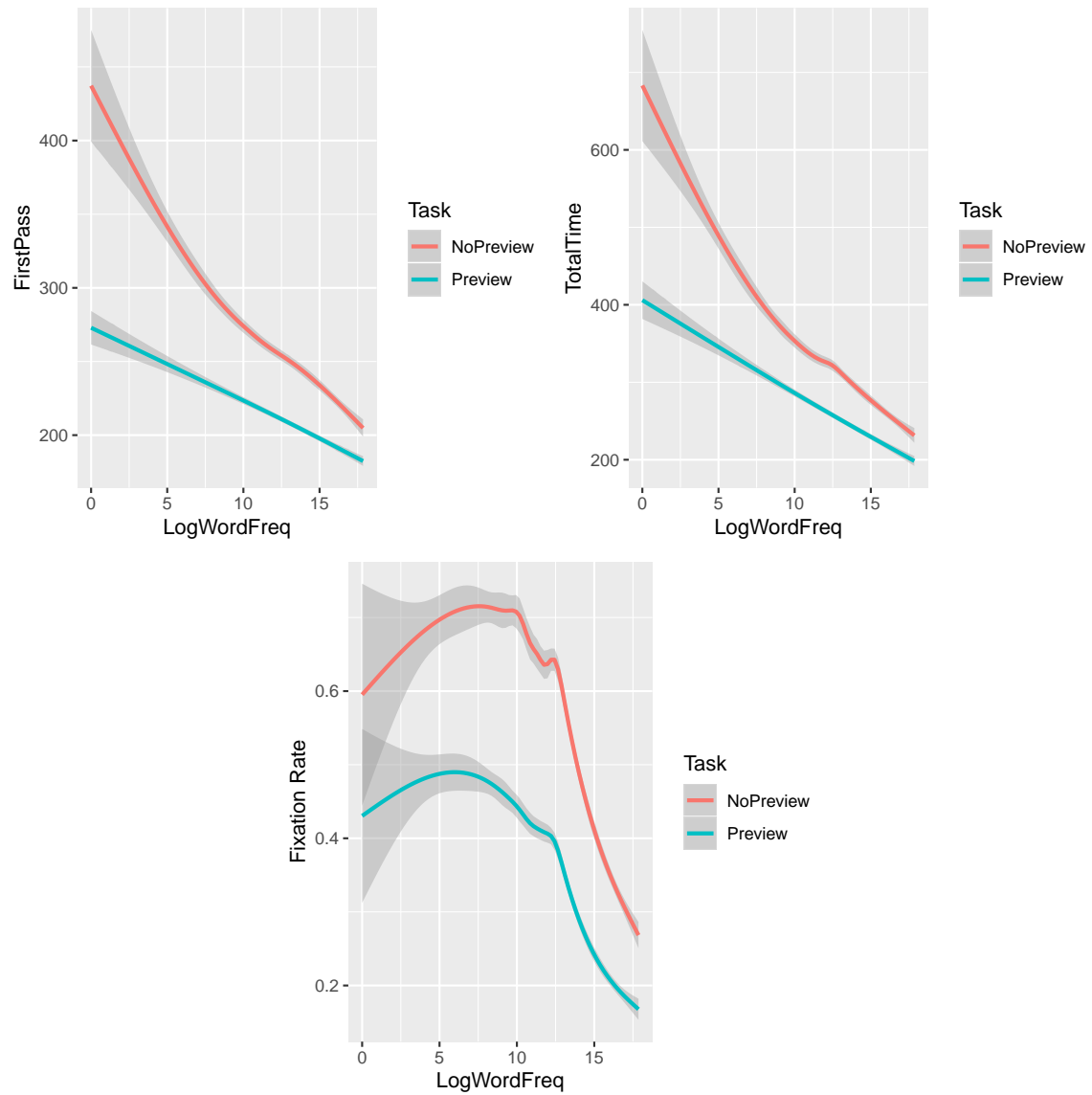


Figure 4. Interaction between task and log word frequency in first pass duration, total time and fixation rate. We show GAM-smoothed means with 95% confidence intervals.

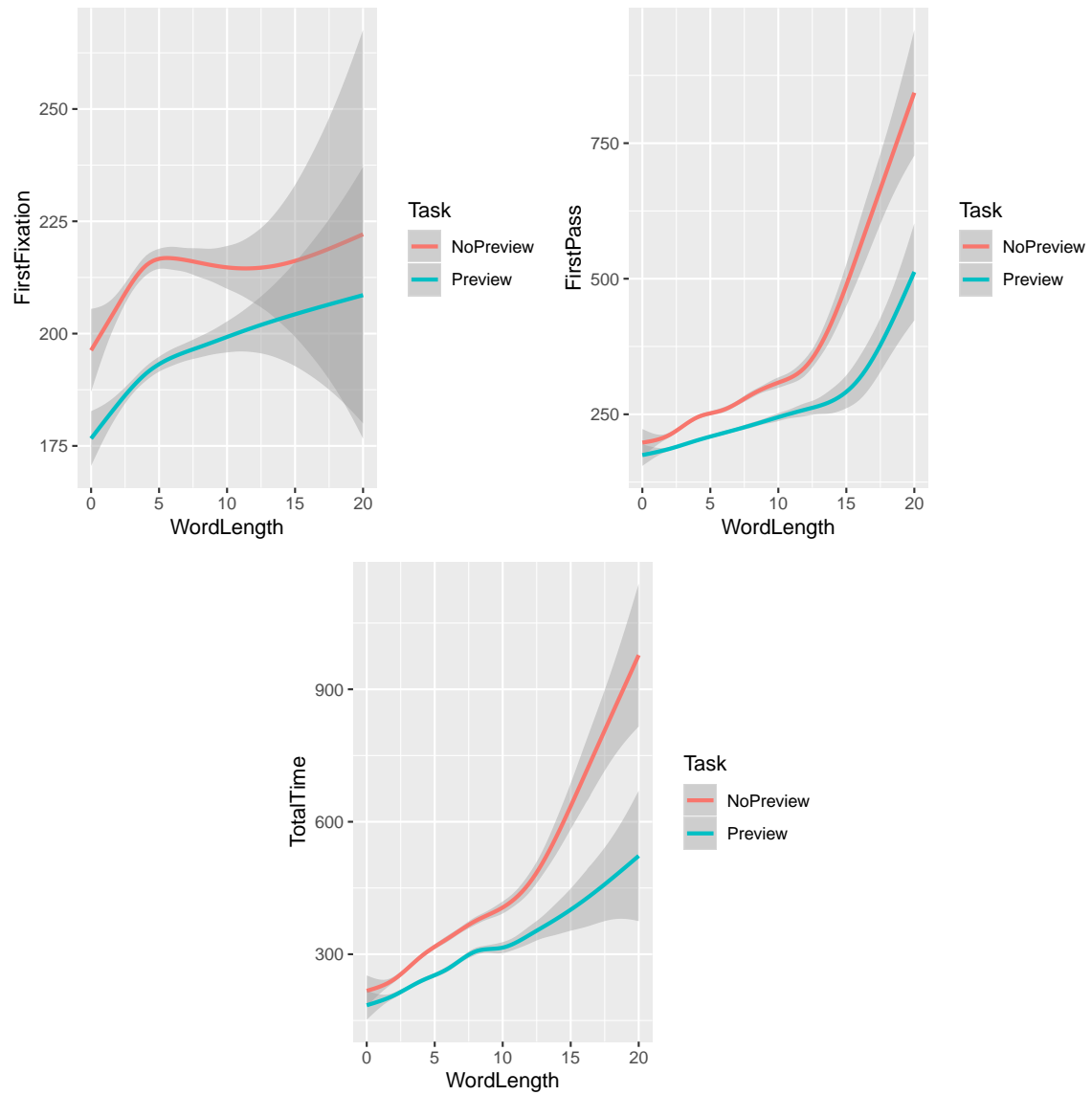


Figure 5. Interaction between task and word length in first fixation duration, first pass duration and total time. We show GAM-smoothed means with 95% confidence intervals.

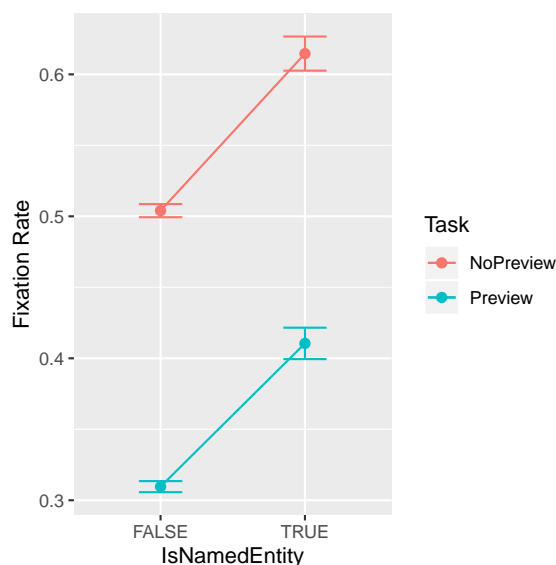


Figure 6. Interaction between task and named entity status in fixation rate.

in which the allocation of attention (i.e., the reading time) depends more heavily on information extracted from the question, and is less reliant on low-level factors such as word frequency and word length.

We also find a negative interaction of task and named entity status in fixation rate (see Figure 6). This indicates that the overall task effect on fixation rate is reduced for named entities, potentially because readers focus more on such highly answer-relevant words in the Preview condition.

Finally, we observe an interaction between task and IsCorrectAnswer in first fixation, total time, and fixation rate (see Figure 7). This is a large effect: words occurring in the correct answer are read for an extra 186 ms in the Preview condition. Again, this provides clear evidence of a task effect. Readers modify their reading strategy when they have access to information about the question: their main goal is to find the answer in the text, and if they have found words that could belong to the answer, they want to make sure of this, and spend a extra time reading these words.

6.3 Discussion

We found clear differences in reading time, fixation rate, and accuracy between the two experimental conditions. In the Preview condition, participants read faster and skipped more, but achieved a higher accuracy, compared to the No Preview condition. This is consistent with our hypothesis that task has an effect on reading behavior: the presence of the question at the start of a trial changes the task from a normal reading task to an information-seeking task. This in turn changes the economy–accuracy tradeoff (as predicted by NEAT): even with reduced reading time and increased skipping rate (more economical reading), readers achieve increased accuracy.

In addition to the main effect of task, we also found main effects of word frequency, word length, text position, and surprisal, which are well known from the reading time literature (e.g., Demberg & Keller, 2008). Furthermore, we found words that are parts of named entities, particularly

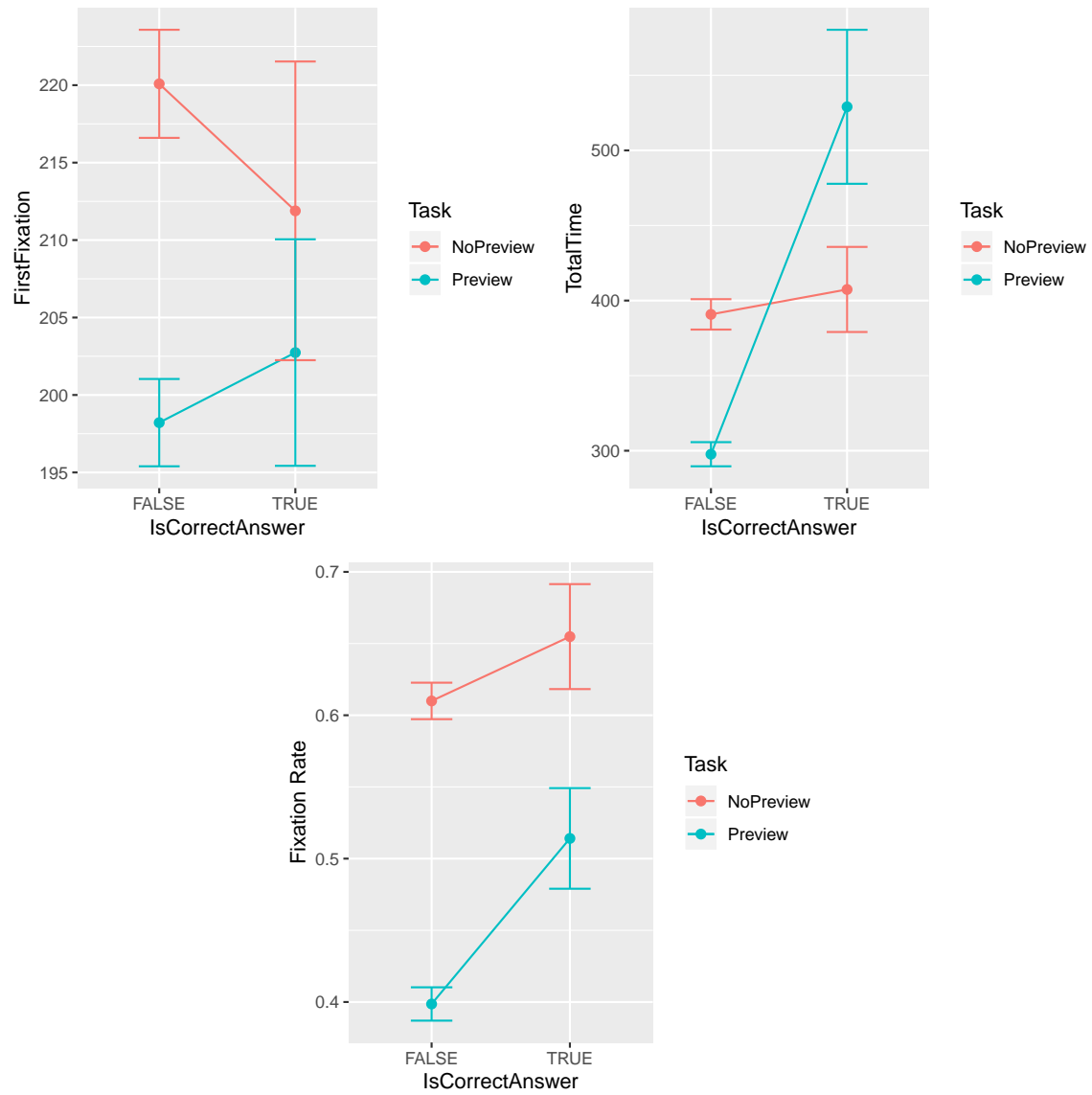


Figure 7. Interaction between task and answer status in first fixation duration, total time and fixation rate. We only show datapoints belonging to named entities, as answer status is only relevant for those.

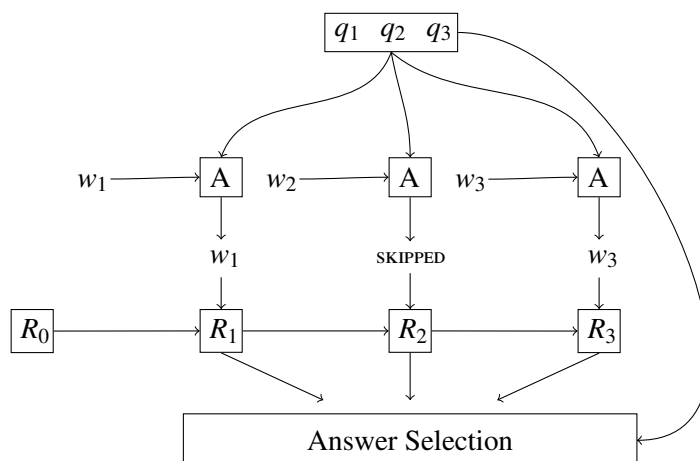


Figure 8. Architecture of the NEAT question answering model as applied to a text $w_1w_2w_3$ together with a question $q_1q_2q_3$.

those that are part of the correct answer, are read faster in first pass reading.

Finally, we uncovered a set of interactions between task (Preview or No Preview) and word frequency, word length, named entity status, and correct answer status. Across reading measures, effects of frequency and length were reduced in the Preview condition. As participants already know what kind of information to look for, their reading is affected more by the question, and less by low-level properties such as frequency. In the Preview condition, they also spend more time reading words that occur in the answer, potentially in order to make sure that they have indeed found the right answer. Again, this provides evidence for task effects, i.e., a change in reading strategy depending on whether participants perform a task that is similar to standard reading (No Preview), or an information seeking task (Preview).

Overall, this experiment demonstrated that reading behavior is finely attuned to the reading task at hand. For instance, in the particular task we evaluated, named entities play a crucial role, and we found reading behavior that is adapted to this fact. The challenge now is to devise a computational model that is able to capture both the main effects and the complex pattern of interactions we observed in the human reading data collected in this experiment.

7 Modeling Task Effects in NEAT

In the version introduced in Section 4, the NEAT model assumes the following default task: during normal reading, the reader tries to build up a representation of the text that enables them to later recall it as accurately as possible. The cognitive tradeoff that readers face is therefore one between skipping as many words as possible (economy) and reconstructing the input as well as possible (accuracy). In NEAT, this is implemented by combining a reader module (which predicts the next word) with an attention module (which decides whether to fixate the next word or not), and a task module (which tries to reconstruct the input based on the text representation computed by the reader).

The Tradeoff Hypothesis predicts that the model's behavior should change if the reading task changes and necessitates a different tradeoff between task accuracy and reading economy. The

results from the eye-tracking experiment reported in Section 6 confirm this prediction. We gave readers a question answering task and manipulated whether they had access to the question before they read the text or not (Preview or No Preview). The results clearly show that preview has an effect on reading strategy, affecting both reading times and skipping behavior. The NEAT model should be able to capture this finding if we assume a different task module, viz., one that performs question answering rather than input reconstruction. In this section, we introduce a modified version of NEAT that has this property and evaluate it against the eye-tracking data from Experiment 1.

7.1 Architecture

The architecture of our revised version of NEAT is diagrammed in Figure 8. For illustrative purposes, we assume the input text consists only of the words w_1, w_2, w_3 . As further input, the model now receives a question, consisting of the words q_1, q_2, q_3 in our example. Like in the previous version of NEAT, the reader module is a recurrent neural network which reads the text in linear order and creates a memory representation, recording a vector of neural activations at each word. These vectors are denoted as R_0, R_1, R_2, R_3 in Figure 8.

As before, the attention module A decides for each input word w_i whether to read or skip that word. If w_i it is read, then it is shown to the reader and incorporated into its memory representation. If it is skipped, then the reader is only shown a placeholder symbol indicating that a word was skipped.

In the Preview condition, the attention module A has access to the question q_1, q_2, q_3 when making decisions about fixations and skips. In Figure 8, this is marked by connections going from the question to the attention module. In the No Preview condition, these connections are absent, and the attention module A has no access to the question while it is reading the input text.

The representations created by the reader are passed to the task module, which is a neural network which matches the memory representation with the question and attempts to select the correct answer. At this point, the question is available to the model, independently of whether it is in the Preview or No Preview condition.

The reader module and the task module can be trained using supervised learning on the basis of a corpus of texts with questions and answers, with the objective of maximizing question answering accuracy. As before, the attention module is trained using reinforcement learning, but now a question answering task rather than a reconstruction task provides the reinforcement signal: during training, the module generates fixation decisions, and passes the fixated words on to the reader. The parameters of the attention module are then updated to upweight decisions that led to correct answers, and downweight decisions that did not.

The reader module remains unchanged from our original version of NEAT as introduced in Section 4 (but the hidden layer is smaller, containing 128 memory cells only). However, changes are necessary to the attention and task modules, which we will describe in the following sections.

7.1.1 Attention Module. Our new version of NEAT is based on the *NoContext* version of the original NEAT model. As in Modeling Study 1, we compute fixation probabilities a_i of a word w_i by applying a linear transformation followed by the logistic function, but unlike before, attention decisions are now conditioned on task-specific features. We use the following model (compare to Equation 7 from Modeling Study 1):

$$a_i := \sigma(u + v^T \hat{w}_i + X_i^T A \hat{w}_i) \quad (9)$$

As in Equation 7, $\hat{w}_i \in \mathbb{R}^{100}$ is a word embedding representing w_i , and $u \in \mathbb{R}$, $v \in \mathbb{R}^{100}$ are weight vectors.

The innovation compared to Equation 7 is the addition of the third term $X_i^T A \hat{w}_i$, which encodes task-specific information. $X_i \in \mathbb{R}^3$ is a feature vector encoding the condition and, in the Preview condition, also whether the token occurs in the question, detailed below. The weight $A \in \mathbb{R}^{3 \times 100}$ is a parameter of the model.

We build a single model that can simulate both experimental conditions. This way, the model can share parameters across conditions, but we have to add some additional parameters indicating differences between the conditions. Building separate versions of the model for the two experimental condition would double the number of parameters, making the model less parsimonious. It would also generate two sets of results that are not directly comparable, making it hard to evaluate whether the model shows the interactions we observed experimentally in the eye-tracking data reported in Section 6 (especially the interactions with task, which theoretically the most relevant).

The key to using a single model for both conditions is the feature vector X_i , which encodes the following: (a) the experimental condition (-0.5 for Preview, $+0.5$ for No Preview), (b) whether the word occurs in the question, and (c) an exponentially decaying running average of (b) over all fixated preceding tokens.

Crucially, the question feature (b) (as well as feature (c) derived from it) is only available in the Preview condition, and zeroed out in the No Preview condition. This means that the attention module only has information about the question in the Preview condition. In the No Preview condition, the attention score a_i has to be calculated without taking the question into account.

Feature (c) encodes the relevance of prior context to the question, and represents a simple form of recurrence. The decay factor for feature (c) is a parameter of the model, learned together with u, v, A . Feature (b) is centered and scaled to $[-0.5, +0.5]$ using the mean and range of the feature values estimated from the training corpus.

7.1.2 Task Module. Compared to Modeling Study 1, the most extensive changes are necessary in the task module. The task module of this version of NEAT performs answer selection (recall that participants perform a multiple-choice task in which they need to identify the correct answer among a set of three distractors).

On a high level, similar to Modeling Study 1, the task module collects the information gathered from the fixated words into a vector representation, from which it then computes an answer. For the precise technical implementation of the module, we build on methods from the recent natural language processing literature. Specifically, we build on the Attentive Reader model for textual question answering described by [Hermann et al. \(2015\)](#), with some simplifications suggested by [Chen, Bolton, and Manning \(2016\)](#). The input to the answer selection module consists of the fixated words, and the neural activations h_i computed by the reader module for each word w_i . Crucially, skipped words are not provided to the task module, and cannot be taken into account when answering the question.

The task model first assembles all words read by the reader module using a bidirectional LSTM (BiLSTM), a standard neural network model for aggregating information from long sequences, consisting of two recurrent networks that aggregate the input in forward and backward direction. For the forward component, we use the activations h_i created by the reader; the backward component similarly creates a vector $r_i \in \mathbb{R}^{128}$ of neural activations for each token w_i .

Similarly, the question is summarized by a BiLSTM networks, again with 128 memory cells each. Their final states are concatenated to obtain a vector representation $r \in \mathbb{R}^{256}$ for the question.

After that, for each token w_i in the text, a number b_i is computed as:

$$b_i = \exp\left(r^T B[h_i, w_i]\right) \quad (10)$$

where $B \in \mathbb{R}^{256 \times 256}$ is a weight matrix and $[h_i, r_i] \in \mathbb{R}^{256}$ is the concatenation of the vectors h_i and r_i . The value of b_i can be interpreted as encoding the relevance of token w_i to answering the question.

After that, the hidden states are averaged weighted with b_i to create a final vector representation as:

$$s := \frac{\sum_{i=1}^N b_i [h_i, r_i]}{\sum_{j=1}^N b_j} \quad (11)$$

This representation, computed based both on the text and on the question, is then used to choose the answer. For this, a probability distribution over the set of named entities is computed according to:

$$t := \text{softmax}(C \cdot s) \quad (12)$$

where C is a matrix, and $\text{softmax}(x)_i := \frac{\exp(x_i)}{\sum_j \exp(x_j)}$ is an operation turning arbitrary vectors into probability vectors. The resulting t is a vector of probabilities, indexed by the set of named entities occurring in the text, numbered in the order of appearance. In order to indicate the indexing of named entities to the reader model, we allocate an embedding vector for every index up to the maximal number of named entities (e_1, e_2, \dots, e_{600}), trained as model parameters, and add the relevant index embedding vector to the word embeddings when feeding it into the reader module. The probability vector in (12) indicates how likely a given named entity is to be the correct answer to the question, given the text.⁴

A question is counted as answered correctly if the named entity corresponding to the correct answer is assigned a higher probability than any other named entity in the probability vector t . Our model has to choose among all named entities occurring in the text, not just among the answer and the three distractors. This means the task is considerably harder for our model than for the participants in our eye-tracking study (a random baseline would perform at $< 10\%$ accuracy on most texts). We note that it would technically possible to train the model to select from only four entities, but this would make the task almost trivial for the model, because it could easily check which one of the entities occurs in the text.

7.2 Objective Function

As in Modeling Study 1, we formalize the Tradeoff Hypothesis in terms of an objective function weighting task success and the fraction of fixated words. However, task success is now defined not in terms of reconstructing the input, but in terms of correctly answering questions.

⁴It is important to note that the distractors (i.e., the incorrect answer choices) that are part of the task differ between the version of the task that participants perform, and the version of the task that the model performs. Unfortunately, this is unavoidable for practical reasons. For participants, we have to use distractors that are similar to the correct answer (e.g., if the correct answer is Michigan, then the distractors are also US states, see the example in Figure 3). This is because using named entities from the text will make the task too easy. For the text in Figure 3, this would result in a list of answers such as: Sabra, FDA, Michigan, March (these are all named entities in the text). For a human participant, it is obvious that Michigan is the correct answer. For the model, the situation is reversed: the model essentially has perfect memory, so it is trivial for it to determine that Michigan has appeared in the text, but other US states have not. On the other hand, for the model it is difficult to figure out which of the named entities in the text is a valid answer to the question it is asked. Therefore, non-answer named entities from the text are appropriate distractors for the model.

For a text t and a question q with correct answer a , drawn from the corpus, NEAT stochastically chooses a fixation vector $\omega \sim P_A(\omega|T, t, q; \theta)$, where $T \in \{\text{Preview}, \text{NoPreview}\}$ is the experimental condition. Here, θ denotes a setting for the parameters of the attention module. The fixated words in the text, together with the question, are passed to the answer selection module. Success on question answering is formalized as the surprisal of the correct answer a :

$$L(a|\omega, t, q, T, \theta) := -\log P(a|\omega, t, q, T, \theta) \quad (13)$$

This term quantifies the loss on the question answering task and should be *minimized*.

As in the original NEAT model, we trade off task success and the fraction of fixated words with a factor $\alpha > 0$. We average over (a) the two conditions, (b) the texts and questions from the training corpus, (c) the fixation vectors ω generated by NEAT, to obtain the following loss function:

$$Q(\theta) := \frac{1}{2} \sum_{T \in \{\text{Preview}, \text{NoPreview}\}} \mathbb{E}_{(t,q,a)} \mathbb{E}_{\omega} \left[L(a|\omega, t, q, T, \theta) + \alpha \cdot \frac{\|\omega\|_{\ell_1}}{N} \right] \quad (14)$$

Compared to Equation 4 in Modeling Study 1, the differences are that (1) loss is averaged across both conditions, and (2) task success is defined in terms of the probability assigned to the correct answer, not reconstruction of the input.

We apply the same parameter estimation techniques as in Modeling Study 1 (see Section 4.3), jointly training the reader module, task module, and attention module with a combination of gradient descent and reinforcement learning, to minimize the loss function (14).

8 Modeling Study 2

The aim of this modeling study is to test if the revised version of NEAT that we developed in the previous section is able to correctly account for the eye-tracking data of the task-based reading experiment that we presented in Section 6. If NEAT is able to capture the task variation attested in the experimental data, then this will provide evidence for the Tradeoff Hypothesis that NEAT is based on, and for our prediction that reading strategy is crucially influenced by the task readers have to perform.

8.1 Methods

8.1.1 Model Implementation. The reader module is implemented as an LSTM, in the same way as in the original version of NEAT (see Section 5.1), except that we now use a smaller hidden layer with only 128 memory cells. Hermann et al. (2015) and Chen et al. (2016) showed that this lower dimensionality is sufficient for the question answering task. Furthermore, the length of the texts prohibits the use of larger layers due to memory limitations.

Following Chen et al. (2016), the reader module uses pre-trained word embeddings from GloVe (Pennington, Socher, & Manning, 2014), which we continue training with the reader module. The parameters in θ are initialized randomly using the method described by Glorot and Bengio (2010).

To choose α in (14), we ran the following procedure. We first estimated parameters for each α from 0 to 2 in steps of size 0.2. We then selected the α that resulted in an overall fixation rate closest to the human fixation rate. This way we arrived at $\alpha = 1.0$. The reinforcement learning algorithm stochastically explores the action space and running it multiple times may result in different

strategies (Islam, Henderson, Gomrokchi, & Precup, 2017); this challenge is more pronounced in this second version of NEAT since behavior depends on the task. In order to estimate the variance introduced by this, we ran the optimization algorithm 35 times to create 35 parameter settings for A for $\alpha = 1.0$.

The only ingredients of our model are a corpus of texts with questions and answers, the neural architecture, and the objective function in (14), combined with standard optimization techniques for neural networks. The reading strategies are optimized on the basis of success in answering question. As in Modeling Study 1, no grammar, lexical knowledge, eye-tracking corpus, or other labeled data are required to train our model. Only one parameter, the scalar α in (14), has to be adjusted to human eye-tracking data; all other parameters are chosen to optimize (14).

8.1.2 Dataset. We trained our model on the training section of the DeepMind question answering corpus (Hermann et al., 2015), using the same corpus pre-processing as the original authors. This results in 1,259,748 text–question–answer triples. On each pass through the training data, we downsampled the larger subcorpus (Daily Mail) so that an equal number of triples were sampled from the two sources (CNN and Daily Mail). We clipped long texts after 500 tokens due to memory constraints.

We evaluated all model runs on the validation partition of the DeepMind corpus, where we downsampled the larger subcorpus as in training, resulting in 7,848 text–question pairs. For comparison, we also ran the task module with all words fixated, which corresponds to the original question-answering setup of Hermann et al. (2015). We note that Hermann et al. (2015) represented named entities using anonymized identifiers (e.g., “@entity7” instead of “London”). We reinserted named entities into the text as ordinary (capitalized) tokens; this makes the task harder for machine learning models, but matches the input available to the human participants.

8.2 Results

8.2.1 Tradeoff between Accuracy and Economy. When all words are fixated, the task module of NEAT achieves a question answering accuracy of 65.5% – similar to the accuracy of 66.1% reported for the original model by Hermann et al. (2015) on the same dataset, averaged across the CNN and Daily Mail sections. As noted above, Hermann et al. (2015) evaluated on an artificially modified task where named entities were anonymized, which we found makes the task easier for machine learning models.

When we consider NEAT as a whole, i.e., including the reading module and the attention module that skips words, we observe average fixation rates of 51% (SD 2.6%) in the No Preview condition, and 44% (SD 1.5%) in the Preview condition. NEAT therefore captures the qualitative characteristics of the human data (see Table 3): the human fixation rate is 0.50 in the No Preview condition, and 0.34 (slightly lower than predicted by the model) in the Preview condition, close to what the model predicts.

Turning to question accuracy, we find that NEAT’s accuracy is 56% (SD 1.0%) in the No Preview condition, and 60% (SD 1.5%) in the Preview condition. The model therefore shows the same qualitative effect as in the human data: accuracy increases in the Preview condition, even though fixation rate goes down. Nevertheless, the model falls short of human accuracy (which was 70% in the Preview condition and 89% in the No Preview condition). However, the model has to choose between all named entities appearing in the text, rather than just selecting one out of four. That means the random baseline for human participants is 25%, and for the model it is < 10%, i.e., the absolute accuracies are not directly comparable (see Section 7.1.2).

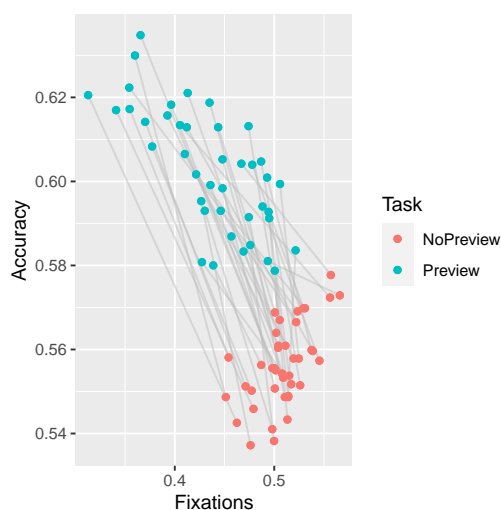


Figure 9. Accuracy and economy in the two task conditions, at the selected tradeoff parameter ($\alpha = 1.0$). Each pair of points linked by a gray line represents one run in the two task conditions. Across runs, the model tends to achieve higher accuracy and lower fixation rate in the Preview condition, when compared to the No Preview condition. Numbers were computed on the validation partition of the DeepMind corpus (7,848 text–question pairs). See SI Appendix, Figure 3, for results across values of the tradeoff parameter α .

In Figure 9, we plot accuracy as a function of fixation rate. All models achieve higher accuracies with lower fixation rate in the Preview condition.

For comparison, we also ran the question answering model with random fixations at the same rate of 0.51 as in the No Preview condition. In this setting, accuracy on question answering drops to 27%, which indicates that NEAT learns a skipping strategy which is clearly much better than random even in the No Preview condition.

Figure 10 shows heatmaps visualizing NEAT fixation probabilities for the same text as in Figure 3 (which displays human fixation probabilities). This plot confirms that the overall fixation rate is higher in the No Preview condition. In both conditions, long words and content words are more likely to be fixated. In the Preview condition, reading appears to be more targeted: Fixations are concentrated on the sentence containing the answer *Michigan* in the fourth line. The phrase *tested positive for Listeria monocytogenes*, which appears in the question, shows higher fixation rate in the Preview condition than in the No Preview condition. In other areas of the text, content words have decreased fixation probabilities relative to the No Preview condition.

8.2.2 Mixed Effects Analyses. We ran each of the model parameterizations generated by the 35 training runs at $\alpha = 1.0$ on the same texts as used in Experiment 1.

Then we built a logistic mixed effects model with NEAT fixation rate as the dependent variable. The random effects structure and the priors were the same as when analyzing human fixation rate in Experiment 1 (see SI Appendix, Section 2). Our mixed effects model includes model runs as a random effect; it plays a role analogous to the random effect of participants in a mixed effects model of experimental data.

As fixed factors, our mixed effects model included those that were also used to analyze the

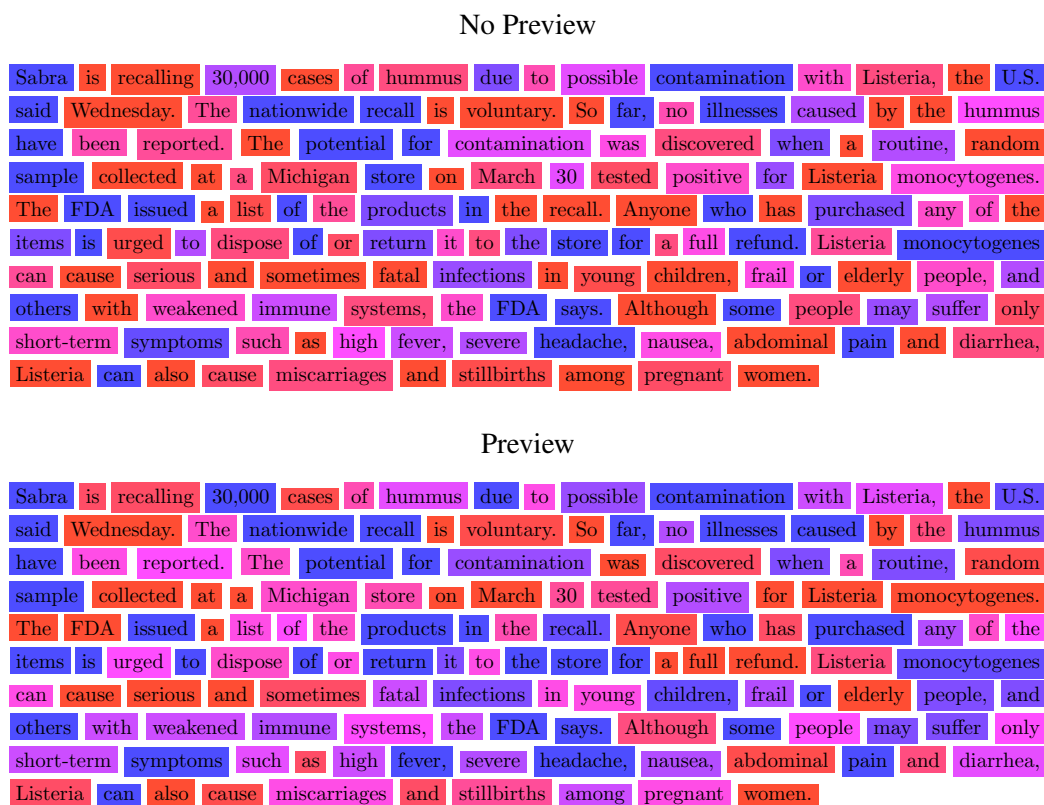


Figure 10. Heatmap visualizing NEAT fixation probabilities in Modeling Study 2, averaged over 35 model runs. Top: No Preview, bottom: Preview. The color gradient denotes the fixation probability predicted by NEAT for the word in a given condition, ranging from blue (< 0.3) to red (1.0). The question and answer for this text are the same as in Figure 3; the correct answer is the word *Michigan* in the fourth line. See SI Appendix, Figure 2 for a visualization of the difference between the two tasks.

eye-tracking data from Experiment 1 (see Section 6.1). We built the final mixed model using forward selection to include significant binary interactions into the model, in the same way as for the eye-tracking data.⁵

8.2.3 Task-independent Effects. The result of the mixed effects analysis for NEAT fixation rate is given in Table 5. We will compare the significance and the sign of the coefficients in our analysis of human fixation rate in Table 4.

We observe a significant, negative main effect of log word frequency and a significant, positive effect of word length on NEAT fixation rate. Both of these correspond to the effects found in human fixation rate. Furthermore, we observe a positive main effect of named entity status: words that are part of named entities are more likely to be fixated by NEAT. This effect makes sense in terms of task adaptation: all the answers are named entities (in both the Preview and the No Preview

⁵In Modeling Study 1, we used NEAT surprisal to predict human reading times. An analysis of this type doesn't make sense for Modeling Study 2, as the human reading data (see Table 4) did not show an interaction of surprisal and task, neither in the reading times nor in fixation rate. We therefore expect NEAT surprisal to be unaffected by task and instead analyze whether human fixation rate effects correspond to model fixation rate effects.

	NEAT Fixation Rate	
(Intercept)	-0.19	(0.04)
Task	0.25	(0.04)
IsCorrectAnswer	-0.20	(0.13)
IsNamedEntity	1.68	(0.10)
WordLength	0.15	(0.01)
LogWordFreq	-0.23	(0.01)
PositionText	0.02	(0.02)
Surprisal	0.01	(0.00)
LogWordFreq:IsNamedEntity	0.17	(0.01)
LogWordFreq:WordLength	0.02	(0.00)
Task:IsNamedEntity	-0.33	(0.05)
Task:LogWordFreq	-0.03	(0.01)

Table 5

Logistic mixed effects model for fixation rate predicted by NEAT, with item and model run ($N = 35$) as random effects. Task was coded as -0.5 (Preview) vs. $+0.5$ (No Preview). Binary interactions were identified automatically using forward model selection, as described in the text. For each predictor, we give the coefficient and the standard deviation. Effects were interpreted as significant when the posterior probability that the coefficient has the opposite sign was < 0.05 .

condition), so fixating them more than normal words enables the model to perform more accurate question answering. However, the effect of named entity status is not found in human fixation rate (though there is an `IsNamedEntity:Surprisal` interaction in human fixation rate which is not present in NEAT fixation rate). NEAT shows no significant main effects of whether a word is part of the correct answer, its position in the text, or its surprisal; these effects are not present in human fixation rate either.

Turning now to the interactions, NEAT exhibits a significant interaction of log word frequency and whether a word is part of a named entity. We also find that log word frequency interacts with word length. Both interactions are present in the human fixation rate data. Human fixation rate also shows an interaction of named entity status and surprisal, which NEAT is not able to capture.

8.2.4 Task-dependent Effects. We will now discuss main effect and interactions involving the factor task, i.e., effects that depend on the reading task (Preview or No Preview). Again, we compare the modeling results in Table 5 with the human fixation data in Table 4.

As we saw when discussing the descriptive statistics, NEAT fixation rate in the No Preview condition is higher than in the Preview condition. This is confirmed by a significant positive main effect of task in human fixation rate in Table 5.

We also observe a significant negative interaction between task and log word frequency. This effect is illustrated in Figure 11. The human data shows the same significant negative interaction in fixation rate. The explanation for this interaction is that NEAT is less guided by word frequency in its fixation decision when it knows which words to fixate, viz., in the Preview condition, where it has read the question and knows what the answer should look like. There furthermore is an interaction of task with named entity status, illustrated in Figure 12. An effect of the same sign is also found in human fixation rate. This shows that NEAT is more likely to skip words that are part of named

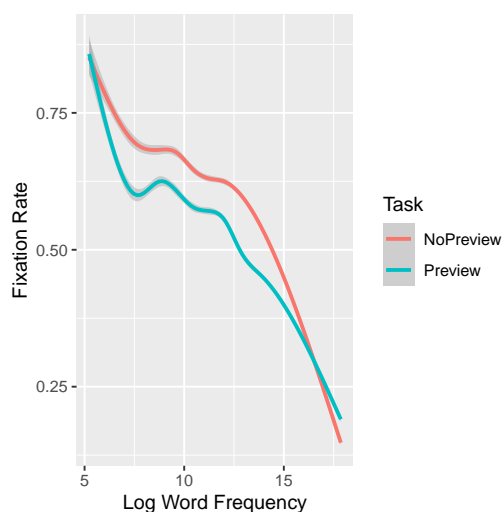


Figure 11. Model fixation rate by log word frequency by task condition. We show GAM fits with 95% confidence intervals. Compare Figure 4 for corresponding human data from Experiment 1. See SI Appendix, Figure 4 for corresponding results including out-of-vocabulary tokens.

entities in the Preview condition than in the No Preview condition. This is an adaptive strategy, as in this condition, the model knows what type of named entity it is looking for (as it has seen the question), which allows it to spend less time on named entities overall.

Human fixation rate shows an interaction of task and whether a word is part of the correct answer or not. This interaction is not present in NEAT fixation rate; we will return to this in the discussion below. The interactions Task:Surprisal, Task:WordLength are not significant in both the human fixation rate and model fixation rate.

8.3 Discussion

In this modeling study, we qualitatively evaluated the fixation probabilities predicted by a new version of the NEAT reading model which performs question answering. We conducted a mixed model analysis on NEAT fixation rate and found that the effects mirrored the effects found in human fixation rate in the eye-tracking experiment reported in Section 6. The results show that NEAT reading behavior and human reading behavior are qualitatively similar: Crucially, we found the same main effect of task, i.e., preview affects fixation rate in the same way in the model and in the human data. And we found that the experimental interactions between task and word frequency and task and named entity status were also replicated by the model.

One experimental effect that we failed to replicate was the interaction of task and whether a word is part of the correct answer or not. This interaction was present in human fixation rate and there was an extraordinarily large effect in total time, but the interaction was not significant in NEAT fixation rate. A possible explanation for the large effect in total time is that human readers exhibit a checking behavior in the preview condition when they read a word that is part of the correct answer: in this condition, they know what the answer should look like, so they re-read it once they have encountered it in the text. This way they make sure that they have really found the answer. Our model has no way of modeling regressions (as it's a model of skipping only).

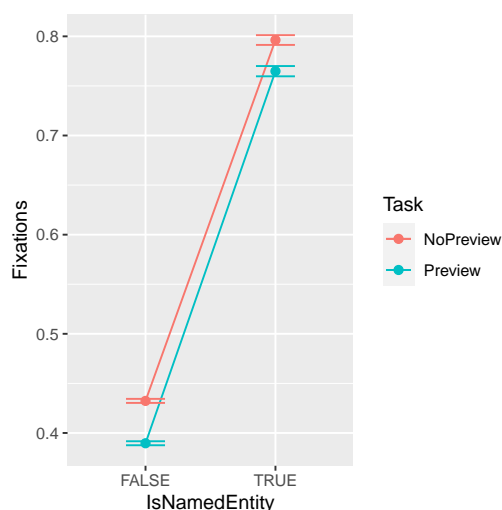


Figure 12. Model fixation rate by named entity status by task condition. Error bars indicate 95% confidence intervals. Compare Figure 6 for corresponding human data from Experiment 1.

9 General Discussion

In this article, we proposed NEAT, a neural network model of the allocation of attention during human reading. NEAT is designed to capture skipping, i.e., the process that decides which words in a text should be fixated, and which ones should be skipped during reading. NEAT is able to learn skipping strategies from large amounts of text when given an explicit reading task, such as reconstructing the input or answering questions about the text. The model is guided by the Tradeoff Hypothesis: a successful reader trades off economy of attention (skipping as many words as possible, i.e., reading as fast as possible) and accuracy (making as few errors as possible in the task the reader is trying to accomplish). The Tradeoff Hypothesis predicts that task-specific reading strategies emerge when the economy–accuracy tradeoff is optimized for a given task.

In Modeling Study 1, we implemented NEAT as a neural encoder-decoder architecture with a hard attention mechanism and showed how the model can be trained using reinforcement learning to optimize an objective function that directly implements the Tradeoff Hypothesis. An evaluation on the Dundee eye-tracking corpus showed that NEAT predicts human fixation patterns through its measure of fixation probability, and human reading time through its measure of restricted surprisal.

A key prediction follows from the Tradeoff Hypothesis: reading behavior is task-specific, as the tradeoff between economy and accuracy can differ from task to task. Experiment 1 tested this prediction in an eye-tracking experiment on newspaper text: In the No Preview condition, participants read the text and then answered a question about it. In the Preview condition, they first saw the question, then read the text, and then answered the question. In the Preview condition, participants read faster and skipped more, but achieved higher answer accuracy compared to the No Preview condition. Participants were also sensitive to the task relevance of words: In the No Preview condition, they spent more time reading words that were part of named entities (which are potential answers); in the Preview condition, they instead spent more time on words that were part of the answer (checking that they have found the answer). This provides evidence that reading strategy depends on whether participants perform a task that is similar to standard reading (No Preview), or

an information seeking task (Preview).

The aim of Modeling Study 2 was to design and evaluate a computational model that captures the reading behavior observed in Experiment 1. We achieved this by developing a modified version of NEAT which incorporated a task module that performs question answering. We analyzed the skipping behavior of the revised model and found that it predicted both the main effect of task condition and the interactions of task with word frequency and named entity status observed in Experiment 1. This indicates that NEAT is able to develop task-based reading strategies that mimic those found in human readers.

Taken together, our modeling studies showed that NEAT successfully captures human skipping behavior during the reading of text. In particular, the model is able to change its reading strategy to accomplish a particular task, in line with what humans do in task-based reading. Crucially, the behavior of our model emerged when we combined a neural network architecture that is designed to accomplish a key aspect of reading behavior, viz., deciding whether a word should be fixated or not, with a task-based objective, such as reconstructing the content of a text, or answering a question about the text. There was no need to explicitly include task-relevant features (such as word frequency or named entity status) into the model. Our model learns to pay attention to such features when trained on a large collection of texts (and question-answer pairs in Modeling Study 2), using only general optimization strategies such as reinforcement learning and backpropagation of errors.

9.1 Limitations

In future work, we aim to address some key limitations of our model. An important aspect of reading is that it in fact operates not on the word level, but on the character level. Human readers target their fixations at a specific character within the word, and then process information within a 7–9 character window. Depending on where they land on a word, a human reader may gain only a partial view of the word they are fixating, or they may be able to view some characters of an upcoming word. NEAT, which treats words as fixed-length word embeddings, is not able to capture landing position or preview effects. This is something that could be remedied by switching from word embeddings to character embeddings, an approach that has been very successful in the natural language processing literature (e.g., [Kim, Jernite, Sontag, & Rush, 2016](#)), and by modeling surprisal on the level of character input ([Hahn et al., 2019](#)).

More generally, our model only describes skipping of words (and computes skipping-based surprisal). Real eye-movements during reading are substantially more complex: a word can be fixated more than once in first-pass reading, or the word can be refixated once it has been left, either in a forward saccade or in a regression. Punctuation marks, phrase and sentence boundaries influence eye-movements, and so do end of lines, which necessitate specific return sweeps. Sometimes reading difficulty spills over to the next word, and causes increased reading time there. All of these phenomena should be captured by a comprehensive model of human reading. The coverage of our model could be extended by incorporating features of models that provide accounts at the level of saccade programming, such as E-Z Reader ([Reichle et al., 1998, 2003, 2009](#)) and SWIFT ([Engbert et al., 2002, 2005](#)).

9.2 Relation to other Models of Reading

Our model focuses on the allocation of attention and how it is influenced by the task, whereas models such as E-Z Reader ([Reichle et al., 1998, 2003, 2009](#)), SWIFT ([Engbert et al., 2002, 2005](#)),

and OBI Reader (Snell, van Leipsig, Grainger, & Meeter, 2018) provide accounts of the programming and execution of saccades at the character level. Our model does not aim to capture reading at the same level of detail as those models. It does not explicitly model saccades at the character level, nor provide a detailed account of word length and word frequency effects. It is also unable to capture regressions (reverse eye-movements).

Another difference between our model and E-Z Reader and SWIFT is that NEAT comes with an unsupervised learning method. We only have to specify how the reader trades off economy and accuracy, represented by the factor α in equation (4). We do not need to fit any model parameters directly on eye-tracking data. Through the use of reinforcement learning, NEAT relies on a cognitively plausible learning method that can discover efficient reading strategies based on how successful they are for a given task.

It is conceivable that aspects of NEAT can be integrated into existing models of eye-movement control. For example E-Z Reader assumes a component that carries out a familiarity check on the word currently being processed. The duration of this check is modulated by the word's frequency and its predicability within the sentence. In E-Z Reader, frequency and predicability (cloze probability) are pre-specified constants. NEAT on the other hand, assumes that predicability that is learned from experience (e.g., by training the model on a text corpus). It may therefore be possible to augment E-Z Reader with a NEAT-style model of predictability (which would also naturally incorporate corpus frequency).

Alternatively, NEAT could be extended to model reading at the level of eye-movement control. For instance, if we enhance NEAT with a character-level language model, then it is able to predict on which character a fixation will land. This approach has been successfully implemented by Yan, Hahn, and Keller (2022), who show that even though it is trained only on unannotated text, their version of NEAT provides fit to human fixation positions competitive with E-Z Reader. Besides modeling input at the level of characters, Bicknell and Levy (2010) also suggest a way of capturing realistic visual input including uncertainty. This could be integrated into our model by conditioning the attention module A on noisy visual input. More ambitiously, future work might develop neurally-parameterized models of eye-movement control at the level of detail of SWIFT or E-Z Reader, and embed them within NEAT in place of A , in order to account for how reading behavior is influenced by everything from low-level oculomotor control to high-level task effects (as investigated in this paper).

Our proposed Tradeoff Hypothesis follows a tradition of modeling reading as rational behavior. Prior rational models have focused on word identification, finding optimal solutions to identifying the words in a sentence in the minimum number of saccades and/or the minimum amount of time (Bicknell & Levy, 2010; Legge, Hooven, Klitz, Mansfield, & Tjan, 2002; Legge, Klitz, & Tjan, 1997; Lewis et al., 2013; Norris, 2006; Reichle & Laurent, 2006). Several models (Bicknell & Levy, 2010; Legge et al., 2002; Lewis et al., 2013; Norris, 2006) define policies that aim to minimize uncertainty about the current word before moving to the next word (or make a regression). The models of Reichle and Laurent (2006) and Lewis et al. (2013) are particularly related to ours in that they optimize policies for rewards that explicitly trade off economy with accuracy (on word identification, Reichle & Laurent, 2006, or lexical decision, Lewis et al., 2013). Beyond language, models of visual behavior based on reinforcement learning have been proposed in other domains (e.g., Acharya, Chen, Myers, Lewis, & Howes, 2017; Butko & Movellan, 2008; Hayhoe & Ballard, 2014; Nuñez-Varela & Wyatt, 2013; Sprague, Ballard, & Robinson, 2007), using both policy-gradient methods like in our model (Butko & Movellan, 2008) and Q-Learning algorithms

(Acharya et al., 2017; Nuñez-Varela & Wyatt, 2013; Sprague et al., 2007).

Compared to earlier rational models of reading, NEAT innovates in two main respects: On a technical level, while these earlier models assumed restricted state spaces with manually constructed features, and a closely delimited input domain of word lists, the combination of reinforcement learning with neural network modeling enables NEAT to be applied to real-world text data, without providing the model with information about what features (e.g., word frequency) to pay attention to. On a theoretical level, NEAT expands the domain of rational modeling of reading to language understanding tasks beyond word identification, providing a theoretically motivated account of task effects in high-level tasks such as question answering.

Of particular relevance to ours is the model of Bicknell and Levy (2010). Compared to this model, NEAT offers advances in several respects. On the theoretical level, NEAT gives an account of task-dependent reading: Whereas Bicknell and Levy (2010) focused on word identification, NEAT provides a general theory of task-specific reading behavior, including a plausible learning algorithm based on reinforcement learning. On a technical level, thanks to the use of contemporary neural network modeling, NEAT is scalable to arbitrary input and high-level language understanding tasks with little task-specific adaptation to the model. Similar arguments apply to the related model proposed by Lewis et al. (2013), which assumes a fixed task and a predefined set of payoff schemes to model tradeoff between speed and accuracy. Also, this model is only developed and tested for a list lexical decision task. It is not clear how this approach can capture effects across tasks, or where no explicit payoff is given.

As described in Section 2.2, there is also a line of work treating the prediction of eye-tracking measures as a supervised learning problem. One aim of this literature is to improve natural language processing systems by making their attention patterns similar to human attention patterns using supervised learning (Barrett, Bingel, Hollenstein, Rei, & Søggaard, 2018; Barrett & Hollenstein, 2020). Most closely related to our work, Malmaud, Levy, and Berzak (2020) and Sood, Tannert, Frassinelli, Bulling, and Vu (2020) collected eye-tracking data in reading comprehension, and showed improvements in the accuracy of automated question answering by training models to predict human reading measures (Malmaud et al., 2020; Sood, Tannert, Mueller, & Bulling, 2020). A recent machine learning-based approach that treats eye-movement prediction as an unsupervised learning task is presented by Yang, van den Bosch, and Frank (2022). These authors are able to show that text segmentation algorithms are predictive of fixation locations.

Besides fixation probabilities, NEAT computes a version of surprisal based on the fixated words only. It has some resemblance to Lossy Context Surprisal (Futrell, Gibson, & Levy, 2020). However, the two notions are conceptually distinct, because Lossy-Context Surprisal assumes that the relevant limitations arise in memory representations and memory retrieval, whereas NEAT surprisal models limitations that arise from the reading process.

9.3 Theoretical Import and Relation to Speed-Accuracy Tradeoff

Speed-accuracy tradeoffs are common in human decision making (see Heitz 2014, for an overview), so assuming that they also explain the task adaptiveness of human reading may seem self-evident. However, none of the work reviewed in Section 3 conceptualizes task effects in reading in terms of a speed-accuracy tradeoff. Instead, a large number of unrelated theoretical concepts are assumed: Rayner and Fischer (1996) and Radach et al. (2008) compare normal reading, scanning, and word verification and infer the existence of different “modes” of eye-movement control, which they attribute to top-down influences on semi-autonomous cognitive modules. Greenberg et

al. (2006) study letter detection tasks during reading and attribute task effects to differences in word class processing. White et al. (2015) also study scanning and normal reading, and attribute task differences in post-lexical integration (i.e., the formation of a coherent text representation). Studying proofreading vs. reading for comprehension, Kaakinen and Hyönä (2010) explain task differences in terms of variations in perceptual span. Schotter et al. (2014) also study proofreading and present a more elaborate theoretical framework, which assumes five component processes central in normal reading: wordhood assessment, form validation, content access, integration, and word-context validation. They hypothesize that different types of proofreading emphasize specific component processes, thus explaining task differences. Kaakinen et al. (2015) compare reading for question answering with reading for comprehension and attribute task difference to divergent memory representations being constructed for different tasks.

The ambition of our work is to offer a unified idea that can bring together this diverse set of theoretical assumptions. We conjecture that the task effects found in the experimental literature can be explained by a tradeoff between economy of attention and task accuracy, provided we have a model of attention selection and a task model, and we combine these with a suitable optimization scheme. In this article, we showed that the NEAT model in conjunction with reinforcement learning can achieve this for a small number of example tasks (text reconstruction; question answering with and without preview). Our results therefore provide a case study that can serve as a first step towards the unification of existing diverse explanations for task effects in reading.

It is also important to point out that the speed-accuracy tradeoff literature, while conceptually similar to our approach, differs in an important aspect: It typically assumes a single task and manipulates task payoff to obtain a tradeoff between speed and accuracy for that task (e.g., Lewis et al., 2013). Our work, in contrast, shows that we can predict difference in reading behavior across tasks if we assume a realistic computational model of the tasks themselves. We can then derive the payoff (the reward in our reinforcement learning setup) from the model, rather than having to pre-specify it externally. This highlights the theoretical import of the work: given the right learning mechanism and enough data (e.g., texts, question-answer pairs), we can learn the tradeoff between economy and accuracy, without having to specify external payoffs. (Such external payoff are not a realistic assumption in naturalistic reading, they are typically found in a lab setting only.)

In more general terms, our model offers not only a simulation of reading behavior, it does so by assuming a cognitively plausible architecture together with learning mechanism that uses realistic input (real text), while also respecting developmental constraints (e.g., we do not assume that eye-movement data are available during learning). This contrasts with previous models of eye-movement control such as E-Z Reader and SWIFT which presuppose that certain factors (e.g., word frequency, word length, predictability) affect reading behavior. Our model shows that these factors do not need to be stipulated: Not only can their influence be learned from raw text, but the model also learns how they interact with task factors.

9.4 Relation to Task Effects in the Literature

Our results in Experiment 1 add to the literature on task effects in human reading behavior (see Section 3 for a review). We found strong main effects of the task manipulation in both reading time and fixation rate, with faster reading when a question preview was available. Main effects of task manipulations have been observed in many of the prior studies on task effects. Most closely related to our results, it has been found that manipulating the type or difficulty of questions changes reading measures, such that harder questions lead to higher reading time and more fixations (Radach

et al., 2008; Weiss, Kretzschmar, Schlesewsky, Bornkessel-Schlesewsky, & Staub, 2018; Wotschack & Kliegl, 2013).

We also found interactions of the task manipulations and other predictors. Effects of word frequency and word length were reduced in the NoPreview condition. Task-dependent modulation of frequency effects has also been reported in previous studies (Kaakinen & Hyönä, 2010; Radach et al., 2008; Schotter et al., 2014; Wotschack & Kliegl, 2013). While some task manipulations have been shown to also interact with predictability (Schotter et al., 2014; Wotschack & Kliegl, 2013), surprisal and condition did not interact in our Experiment 1.

We further found interactions with predictors specific to the task, namely IsCorrectAnswer and IsNamedEntity. In agreement with this finding, Malmaud et al. (2020) showed – in an experiment building on our Experiment 1 – increased reading time in regions critical for answering a question when a preview of the question was available, analogous to the interaction between condition and IsCorrectAnswer we found in Experiment 1.

10 Conclusions

We introduced NEAT, a model of the allocation of attention in human reading. NEAT is implemented using neural network-based attention, and is trained using reinforcement learning to trade off economy of attention with task accuracy. We showed that NEAT predicts human fixation patterns and readings times on the Dundee Corpus. A key prediction of NEAT is that the allocation of attention should adapt to the task. We tested this in an eye-tracking experiment, finding that reading behavior in a reading comprehension task differed depending on the availability of a preview of the questions that readers had to answer. We showed that the experimentally attested task differences were predicted by a version of NEAT trained for question answering, lending support to the Tradeoff Hypothesis. Taken together, our results support NEAT as a model of attention in human reading, and suggest more generally that task effects in human reading reflect efficient adaptations to the properties of tasks.

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