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Parallel processing and sentence comprehension difficulty

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Eye fixation durations during normal reading correlate with processing difficulty, but the specific cognitive mechanisms reflected in these measures are not well understood. This study finds support in German readers' eye fixations for two distinct difficulty metrics: surprisal, which reflects the change in probabilities across syntactic analyses as new words are integrated; and retrieval, which quantifies comprehension difficulty in terms of working memory constraints. We examine the predictions of both metrics using a family of dependency parsers indexed by an upper limit on the number of candidate syntactic analyses they retain at successive words. Surprisal models all fixation measures and regression probability. By contrast, retrieval does not model any measure in serial processing. As more candidate analyses are considered in parallel at each word, retrieval can account for the same measures as surprisal. This pattern suggests an important role for ranked parallelism in theories of sentence comprehension.

Keywords: Reading; Parsing; Computer model; Corpus.

INTRODUCTION

What cognitive mechanisms are reflected in sentence comprehension difficulty? This has been a central question in psycholinguistic research,

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and the literature acknowledges two broad categories of answer. One kind of answer is predicated on resource limitations in the human sentence-processing mechanism (Clifton & Frazier, 1989; Gibson, 1991; Lewis & Vasishth, 2005; Miller & Chomsky, 1963). The other kind of answer appeals to misplaced expectations or predictions as an analysis is built (Elman, 1990; Hale, 2001; Jurafsky, 1996; Mitchell, 1995). Some recent work suggests that these two different kinds of answer may in fact explain distinct aspects of human sentence processing (Demberg & Keller, 2008; Levy, 2008). If correct, any such two-factor explanation immediately leads to the question: what are the relative contributions of the two factors, and how do they interact with common resources like memory? In this paper, we furnish an answer to this question.

Standardising on one probabilistic parsing method, we work out the predictions of both surprisal (Hale, 2001) and cue-based retrieval (Lewis & Vasishth, 2005). We use both metrics to quantify comprehension difficulty across a family of psycholinguistic models that differ only in the number of syntactic analyses they explore in parallel (Gibson & Pearlmuter, 2000; Lewis, 2000). These theoretical predictions are evaluated at a range of parallel-processing levels against fixation durations collected in a German eyetracking dataset, the Potsdam Sentence Corpus (PSC; Kliegl, Grabner, Rolfs, & Engbert, 2004). This corpus consists of 144 sentences¹ with fixation duration data from 222 readers.

The surprisal predictions that we derive account for eye fixation measures at all levels of parallel processing. The retrieval predictions that we derive account for all measures as well, but only in models that simultaneously consider multiple syntactic analyses. These contrasting outcomes illustrate how the assumed level of parallel processing can interact with different complexity metrics. While we do not claim that this demonstration identifies the specific level of parallelism in the human sentence-processing mechanism, it does argue against the view that parallelism should be thought of as orthogonal to other assumptions in psycholinguistic theory. In sentence comprehension models that derive predictions about eye-movement data, parallel processing alone can make the difference between empirical adequacy and empirical inadequacy.

Before describing the parsing model itself, we first discuss the overall methodology in the context of prior work. Subsequent sections sketch out our particular implementation of the surprisal and retrieval difficulty metrics within one shared parsing mechanism. A fuller, more technical presentation is provided in Appendix A. The main text goes on to evaluate these metrics'

¹ The PSC sentences exhibit a range of syntactic phenomena reflecting everyday language rather than tricky cases such as garden path sentences.

predictions using the PSC. The paper concludes with remarks on the implications of our findings.

METHODOLOGY AND BACKGROUND

This work poses the following research question: how helpful are notions of syntactic surprise and memory retrieval latency in accounting for German readers’ eye fixations? To address it, we pursue a corpus study methodology. While the corpus remains constant, we examine several different explanations for the observations collected in it. This set of candidate explanations reflects not only the controversy about surprisal and retrieval, but also the controversy over serial versus parallel parsing. We construct a series of comprehension models that take different theoretical positions on both of these issues. For instance, one of these parsers can handle up to 15 simultaneous analyses, and derives processing difficulty predictions using cue-based retrieval. Another model has just 1 rank—it is serial—and makes difficulty predictions via surprisal. We compute the disparity between each theory’s consequences and the PSC eye-movement data. Table 1 lays this methodology out graphically. This table highlights the research objective: to compare theories that use the same parser but vary either the complexity metric (horizontal dimension) or the degree of parallelism (vertical dimension).

The question marks are quantities that we calculate in the course of this study. They quantify the degree-of-fit for multiple linear regression models

TABLE 1
The methodology adopted in the present research

| <i>Amount of parallel processing</i> | <i>German parser</i> | | |
|--------------------------------------|-----------------------|-----------------------|-------------------------------------|
| | <i>With surprisal</i> | <i>With retrieval</i> | <i>With surprisal and retrieval</i> |
| Serial (1) | ? | ? | ? |
| Ranked parallel (5) | ? | ? | ? |
| Ranked parallel (10) | ? | ? | ? |
| Ranked parallel (15) | ? | ? | ? |
| Ranked parallel (20) | ? | ? | ? |
| Ranked parallel (25) | ? | ? | ? |
| Ranked parallel (100) | ? | ? | ? |

Holding the parser and empirical dataset constant, we systematically vary either the complexity metric (horizontal dimension) or the degree of parallelism (vertical dimension). The numbers in parentheses mark the degree of parallelism. We compute the relative quality of fit for each model against the empirical dataset to determine how well the model accounts for eye fixation measures while reading.

that include several other factors known to influence eye-movements. The degree-of-fit indexes how well such a model accounts for the same collection of observed eye-movement measures (e.g., single fixation durations, SFDs), when paired with specific predictor variables (e.g., theorised surprisal) at a given level of parallelism in parsing. These surprisal and retrieval predictions are defined in sufficient computational detail that the origins of any differences are clear. Our agenda is to juxtapose a broad range of PSC eye-movement measures against each cell's corresponding theory in an effort to discern which predictors are truly consequential in an explanation of German reading difficulty that involves syntactic parsing.

Unlike studies that consider just one parsing mechanism or just one complexity metric, the methodology we apply in this paper offers the chance to uncover relationships between controversial alternative accounts of the same data. It has the potential to find asymmetries that would not come out in a meta-analysis of surprisal or retrieval studies that themselves employ incomparable parsing mechanisms. This methodology also has the potential to find interactions between variants of the same comprehension theory. In this work, we vary the amount of memory available for parallel processing.² Because of the centrality of this background concept, the next two subsections review parallel processing and some of its implications for comprehension models. Remaining subsections take up the grammar and the parsing strategy, respectively.

The idea of parallel processing in human sentence comprehension

In this study, we examine the relative adequacy of alternative theories of human sentence processing that each assume different levels of parallel processing. But what do we mean by parallel processing? The basic idea—that people can, on some level, do more than one cognitive operation at a time while understanding sentences—is an old one. Fodor, Bever, and Garrett (1974) lay out two poles of opposition.

There are, patently, two broad theoretical options. On the one hand, one might imagine that the perceptual system is a parallel processor in the sense that given

² The amount of parallel processing available in each of the candidate theories reflects human memory in a limited and idealised way. Systems that can keep track of more alternative syntactic analyses have more “memory” in this idealised sense than systems constrained to fewer, but nothing else can be said. In this idealisation, syntactic alternatives are not affected by similarity to each other, or by experience gained during prior discourse. This lack of detail should not be misconstrued as a rejection of established findings regarding human memory. On the contrary, we look forward to more realistic models that cast off these simplifications.

a portion of a sentence which has n possible linguistic structures, each of the n structures is computed and “carried” in short-term storage. If a disambiguating item is encountered, all but one of the n analyses are rejected, with the residual analysis being the one which is stored. If no disambiguating material is encountered, all n analyses are retained, and the sentence is represented as ambiguous in n ways.

Alternatively, one might suppose that the system is a serial processor in the sense that given a portion of a sentence which has n possible linguistic structures, only one of the n structures is computed. This structure is accepted as the correct analysis unless disambiguating material incompatible with it is encountered. If such material is encountered, then the processor must go back to the ambiguous material and compute a different analysis.

There are obviously a variety of modifications and blends of these two proposals that one might consider. (p. 362)

At the time that Fodor and colleagues were writing, parallel processing was under study. Lackner and Garrett (1973) found support for parallelism in a dichotic listening task, and Cowper’s (1976) model availed itself of up to three “tracks” in accounting for performance phenomena across several languages.

But it was the serial parsing idea that was prominently realised in computational cognitive models during the 1970s. For instance, Kaplan (1972) used Augmented Transition Networks (ATNs) to deduce a variety of detailed predictions about relative clauses which were upheld in experimental work by himself and others (Wanner & Maratsos, 1978). The ATNs that Kaplan considered are serial processors: they pursue one linguistic structure at a time and backtrack when they reach an impasse. By the 1980s researchers like Gorrell (1989) and Kurtzman (1984) began to reconsider parsing models with parallel processing as an alternative to other serial-processing proposals like the Sausage Machine (Frazier & Fodor, 1978) and Parsifal (Marcus, 1980). Gibson (1991) developed the idea of “ranked parallel” approaches. It became *de rigueur* during the 1990s to interpret new experimental results from the vantage point of ranked parallel as well as serial processing. Around this same time, parallel processing also surfaced as an essential element in many connectionist models of language processing (MacDonald, Pearlmutter, & Seidenberg, 1994; McClelland & Kawamoto, 1986; McClelland, St. John, & Taraban, 1989). This is natural, because parallel processing is a fundamental assumption of the PDP school of connectionist modelling (Rumelhart, McClelland, & PDP Research Group, 1986). Spivey and Tanenhaus (1998), for instance, embrace parallel processing in a passage where they characterise the processing models for which they intend to offer an explicit connectionist implementation.

Specific models differ in their details, but as a class they share two common features: (a) multiple constraints are combined to compute alternative interpretations in parallel and (b) the alternatives compete with one another during processing. (p. 1522)

By the end of the 1990s, members of the scientific community could be divided according to their stance on parallel processing. It was widely acknowledged as a fundamental issue in the cognitive science of language. A variety of experimental studies grappled with it, but none proved decisive. Lack of progress on this question was perhaps unsurprising, given that the sentence comprehension theories widely known in psycholinguistics at the time were not well-formalised.

The idea of parallelism in broad-coverage parsing

With the advent of statistical natural language processing (NLP) in the 1990s, another way of addressing the serial/parallel question started to emerge. Following Jurafsky's (1996, §2.1) declaration that "the underlying architecture of the human language interpretation mechanism is parallel," researchers like Roark and Johnson (1999) began to adapt probabilistic parser designs from natural language engineering to serve as cognitive models of human comprehension. These designs typically used parallel processing for efficiency. But T. Brants and Crocker (2000) found that, with the right ranking factors, parallel processing was nearly unnecessary—the same level of parsing performance could be maintained at a degree of parallelism so low as to be almost serial. Indeed, Lewis (1993) demonstrated that a fundamentally serial cognitive architecture like SOAR (Rosenbloom, Laird, & Newell, 1993) was in fact compatible with a large subset of the available comprehension data. The theoretical innovations of the 1990s allowed for a re-consideration of the same parallelism question on a larger scale.

Broad-coverage approaches borrow from NLP the imperative to cover a wide range of language structures. Researchers such as Crocker and Brants (2000) enjoined psycholinguists to consider garden-variety language, not just garden-path sentences. This new generation of sentence-processing models abandoned hand-crafted grammars in favour of parsing methods that could be relied upon to work with large corpora. Under these conditions, Fodor et al.'s (1974) notion of syntactically "incompatible" material becomes useless: because broad-coverage parsers must be robust, nothing can be ruled out for certain. Instead, the relative ranking of their "*n* possible linguistic structures" takes centre stage.

Broad-coverage models of human sentence comprehension typically impose fine-grained preferences on the analyses that they consider in parallel, preferences that go beyond the pursue-vs.-abandon distinction. It

is standard to codify these preferences using probability. Despite widespread availability of these techniques, the implications of parallel processing for sentence comprehension theories have so far not been studied in a way that is simultaneously empirical and computationally explicit. We strive to do exactly that in this research, building on assumptions about grammar and parsing that are laid out in the next two subsections.

Dependency grammar

Even older than the question “how many alternative readings does the parser maintain?” is the question “what is the right theory of sentence structure?” The profusion of syntactic theories is a familiar problem for sentence-processing researchers. It often seems that when a grammar-based hypothesis fails to find support in the results of a behavioural experiment, its proponents quickly offer a modified version. These proponents suggest that their new proposal is the same in spirit, yet compatible in detail with whatever results cast doubt on the old theory. The really central claims of a particular syntactic theory, as regards sentence comprehension, can be difficult to pin down.

To cope with this problem, in this research we step back and work with a simplified formalism called dependency grammar that stands in for a consensus view of syntax. Dependency grammar as a distinct linguistic tradition traces its intellectual lineage back to Hays (1964) and Tesnière (1959), and continues to develop in more recent work such as Hudson (2007) and Mel’čuk (1988). Its foundational concept—that words depend on other words—is adopted, explicitly or implicitly, in virtually every modern syntactic theory. An example structural description in dependency grammar is given in Figure 1.

The arcs in Figure 1 emanate from words in the role of *head* to other words that are said to be their *dependents*. The symbols underneath the words are part-of-speech tags: NNP stands for proper noun, VBD for verb, and ADV for adverb. Heads are said to “govern” their dependents. In typical dependency grammars, a head may have multiple dependents but not the other way around.

This kind of asymmetric word-to-word relationship figures in many well-known approaches to grammar. For instance, in Head-Driven Phrase Structure Grammar, a word’s ARG-ST list constrains its possible dependents (Pollard & Sag, 1994). In Minimalist Grammars based on the notion of Bare Phrase Structure (Chomsky, 1995), words bear selectional features that cause them to enter dependency relationships in the course of a derivation. In Tree-Adjoining Grammars, words figure in elementary trees whose substitution nodes set up an asymmetric relationship with other words in other elementary trees (R. Frank, 2002; Kroch & Joshi, 1985).

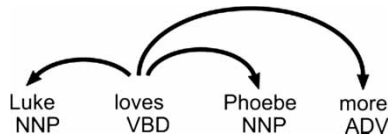


Figure 1. A dependency graph identifies heads and dependents in a sentence.

Each of these approaches brings its own inventory of additional concepts and notation to the structural analysis of sentences. For instance, Figure 1 could be enriched by noting that **Phoebe**'s dependency on the word **loves** is a case of direct-objecthood, whereas the dependency with **more** is a kind of modification. In the hope that our results might speak to a common core of attachment decisions implicated by a wide variety of syntactic theories, we avoid decorating our dependency arcs with additional labels in this work. Such an enrichment would be a natural follow-up project, however, for those seeking to tease apart the perceptual implications of different syntactic theories.

Incremental parsing

The results reported in this paper are set against one final swath of background, one that has to do with the design space of incremental parsers. While a parser's task is to recover structural descriptions from sequences of words, an *incremental* parser is additionally subject to the requirement that it work through its input words from left to right, just as a human would. We have adopted, in this project, the straightforward view of incremental parsing as a process of repeatedly adding³ to partial structural descriptions of sentence-initial fragments (Barton & Berwick, 1985; Marcus, Hindle, & Fleck, 1983; Weinberg, 1993).

The essential point is that ambiguity sets up difficult decisions about what to add. We view particular ways of extending a dependency graph as *operators* in the sense of Newell and Simon (1972). This is illustrated in Figure 2, where the operator names are written inside the large rightward-pointing arrows. Operators are actions in a problem space that take an incremental parser into a new state. In this overview of conceptual background, we leave the notion of state intentionally vague. We note, however, that at a minimum, states must include information about the dependency arcs that have been drawn by earlier operators.

³ This monotonic view fits a large class of parsing algorithms, but excludes "repair" or reanalysis operations like snip or tree lowering that change sentence structures in ways other than adding to them (Buch-Kromann, 2001; Lewis, 1993; Sturt & Crocker, 1996).

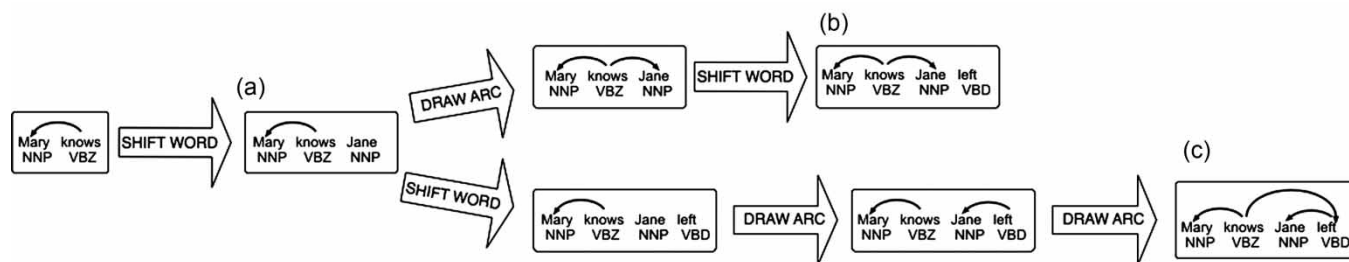


Figure 2. Partial syntactic analyses occupy states in the problem space.

As in other cognitive problem spaces, an incremental parser may not be able to determine locally which operator leads to a successful analysis. This is the familiar notion of garden-pathing, where local decisions lead to errors in the global parse. Parallel processing represents a way to hedge bets about which pathway will ultimately work out. If enough memory is available, all states can be retained, and exhaustive search can be relied upon to find the best path. On the other hand, if only a limited amount of memory is available, difficult choices need to be made about which states are kept and which are discarded.⁴ A parallel parser exploring the space depicted in Figure 2 might be said to be in the *disjunction* of states (b) or (c) at the word **left**. With broad-coverage grammars, these disjunctions can get very wide very quickly. Long sentences can lead to states with many possible successors if a parser has to consider many potential attachment sites. To put it another way, if the grammar doesn't rule out enough attachment possibilities, the problem space that the parser must navigate can have a high *branching factor*. Figure 2's miniature problem space has a branching factor of two: from the state marked (a), two different successor states can be reached depending on whether the DRAW-ARC operator or the SHIFT-WORD operator is chosen.

A major research goal within computational psycholinguistics is to find human-like parse ranking schemes that push the scores of reasonable and ridiculous analyses far apart. In this work, we adopt a simple regime where the score of a state is the product of the conditional probabilities of all the *operator applications*, or transitions between states, that it took to arrive at that state. These probabilities are based on simulated "experiences" reading German newspaper text (S. Brants et al., 2004). We train our parsers on 70,602 sentences from the *Frankfurter Rundschau*.⁵ The probability model itself reflects the truism that people's sentence comprehension is largely determined by words they have already heard, as opposed to those they have yet to hear.

The simple model that we use in this paper is neither complete in the sense of being guaranteed to visit all states, nor is it a language model in the technical sense of defining a distribution on an infinite class of word sequences. We impose these limitations in an effort to define a more psychologically realistic hypothesis. Curtailing the idealisations inherent in

⁴ This picture is, in practice, complicated by the fact that significant economies can be gained by sharing the representation of parser states that overlap in some way. In this paper, we do not address the cognitive implications of structure-sharing.

⁵ The sentences come from full articles sampled from all domains in the *Frankfurter Rundschau* except regional and sports news. These domains are excluded because they contain fewer complete sentences (S. Brants et al., 2004). Further details are reported in Appendix A and largely follow Nivre (2006).

earlier work (Hale, 2001), we view the computational limits of this parser as bounds on rationality (Gigerenzer, Todd, & the ABC Research Group, 1999; Simon, 1955). By focusing on the parsing process as opposed to the language definition, and by introducing a parametric memory limit, we attempt to move towards a model that corresponds to the way human parsing does work — rather than the way it ought to work.

Having outlined the methodology and a few points of background, the next section sketches out this particular study's implementation of the surprisal and retrieval complexity metrics in a common parsing mechanism.

A SYSTEMATIC COLLECTION OF COMPREHENSION-DIFFICULTY THEORIES

As indicated in Table 1, our goal is to compare the predictions made by alternative theories of sentence comprehension difficulty against the fixed set of observations collected in the PSC. To ensure that these comparisons are interpretable, we consider just one basic parsing mechanism. We vary both the amount of memory available for parallel processing as well as the way in which we interpret the parser's internal states as making psychological difficulty predictions. This interpretation is known as the *complexity metric*. A complexity metric is not itself a theory of sentence processing, but rather an auxiliary hypothesis that, in combination with a parsing mechanism, can be used to draw difficulty predictions for given sentences. The parsing mechanism outlines how the sentence is understood; the complexity metric identifies which parts of this process are cognitively taxing. In this section, we describe a parsing mechanism and two complexity metrics. We refer to the same German example throughout to show how difficulty predictions follow on each metric.

A parallel-processing variant of Nivre's dependency parser

The incremental parsing mechanism applied in this paper uses operators defined by Nivre (2004). Rather than just one DRAW-ARC action, Nivre distinguishes between operators that draw left-pointing arcs and operators that draw right-pointing arcs. Building on the work of Covington (2001), Nivre also includes an operator called REDUCE. This operator allows the parser to rule out words as potential attachment sites to the left. REDUCE can lessen the branching factor in problem subspaces by eliminating attachment possibilities. The dual of REDUCE is SHIFT, which brings new words under consideration for eventual casting in the role of head or dependent. These four operators are summarised informally in Table 2. Appendix A provides additional details.

TABLE 2
Informal description of Nivre parser actions

| | |
|--------|---|
| LEFT | The next word becomes the governor of the closest attachment site |
| RIGHT | The next word becomes a dependent of the closest attachment site and becomes itself a potential attachment site |
| SHIFT | The next word becomes a potential attachment site; no arcs are drawn |
| REDUCE | Rule out closest attachment site |

Our implementation deploys these operators in a probabilistic, incremental dependency parser for part-of-speech tag sequences.⁶ We impose no categorical matching requirements on the system. By contrast, in an explicitly grammar-based parser, if a dependency arc fails to be licensed by a rule, then states incorporating that arc are not considered. In our probabilistic Nivre implementation, all conceivable attachments, even those that are ungrammatical, are possible; we leave it to the system of ranking preferences to determine which is best.

To deploy the Nivre operators in a parallel parser, we apply a standard technique from artificial intelligence (AI) called local beam search (Russell & Norvig, 2003, p. 115). The “beam” in local beam search names the collection of states that are still in play at any given word. Local beam search subsumes the idea of ranked parallel parsing in the sense that it is defined on states rather than analyses. States incorporate more information than just a partial dependency graph. For instance, states may include, as a result of REDUCE, information disqualifying certain words from ever serving as attachment points.

We use the symbol k to identify the maximum number of states that a local beam search procedure can handle at any particular iteration. Since each state contains just one (partial) dependency analysis, this number is the same as what Fodor et al. (1974) refer to as n . However, in what follows, we stick to the AI notation to avoid confusion with the standard psychological notion of number-of-participants. For local beam search to have beam-width k means that, out of all the successor states reachable by any operator from any parent state in the previous beam, only the top k best states will survive in the next iteration of search. This use of a fixed parameter to control parallelism contrasts with that of Roark (2004) and Roark, Bachrach, Cardenas, and Pallier (2009). Roark uses a self-adjusting beam defined in terms of his probability model. Under this arrangement, the degree of parallel processing can go up or down depending on how focused the ranking preferences are in a particular state. Our method permits the sentence-processing theorist to vary one without disturbing the other.

⁶ Demberg and Keller (2008) and S. Frank (2009) call their work at this level of analysis “unlexicalised surprisal.”

Perhaps the clearest way to think about parallel processing in this context is to view the beam of alternative states as a kind of “macrostate”. From word-to-word, the incremental parser occupies a particular macrostate composed of up to k microstates. Each new iteration of local beam search considers all possible successor states attainable via the Nivre operators in Table 2. But only the highest-scoring k states out of these candidate successors are included in the next macrostate. The theoretical challenge is to somehow aggregate aspects of the microstates into difficulty predictions that faithfully index the computational work going on in the transition from macrostate to macrostate. The following subsections describe two different ways of doing this.

Surprisal

Attneave (1959, p. 6) introduced the term “surprisal” to cognitive science as part of a wave of interest in information-processing and information theory during the late 1950s and early 1960s. A surprisal is the logarithm of the reciprocal of a probability. By an elementary law of logarithms, this is equivalent to the negative log of the probability itself. This mathematical definition, discussed further in Appendix C, codifies the commonsense idea that low-probability events are surprising. The logarithmic aspect of the formulation follows Hartley (1928). Hale (2001) revived surprisal as part of a way to predict sentence-processing difficulty at a word. He used Stolcke’s Earley algorithm to work out the total probability of all parser states reachable before a word, denoted α_{i-1} as well as after the word, denoted α_i (Earley, 1970; Stolcke, 1995). The ratio of these two values is the transition probability at the i th word of a sentence. The negative logarithm—the surprisal—of this transition probability indexes how “surprising” the transition itself is, compared to other transitions a parser might have been forced to go through. This method makes it possible, at least with small grammars, to calculate the total probability of all reachable parser states at intermediate points within a sentence.⁷ We shall refer to this as the “ideal” prefix probability because it reflects all possible ways of parsing the first i words or the *prefix* of length i . The summation implied by the phrase “total probability” is explicitly written out below in Definition 1.

$$\alpha_i = \sum_{\substack{t \text{ is a sequence of parser operations} \\ \text{that successfully analyses up to position } i}} \text{Prob}(t) \quad (1)$$

⁷ The feasibility of calculating ideal prefix probabilities is underwritten by the fact that the Earley parser is a chart parser that aggressively shares the substructure of derivations. See Footnote 4.

The notation Prob refers to the score associated with a parser state. In this paper, $\text{Prob}(t)$ is the product of the probabilities of all the operators in the sequence $t = t_0, t_1, t_2, \dots, t_m$ where $m \geq i$. Given a definition of α , the surprisal associated with a transition between positions $i-1$ and i would then be as in Definition 2.

$$\text{surprisal}(i) = -\log_2 \left(\frac{\alpha_i}{\alpha_i - 1} \right) \quad (2)$$

Any modelling based on Definition 2 proceeds from the idealisation that all possible syntactic analyses of the prefix string may influence difficulty at the next word. The definition expresses this idealisation by the variable t in Definition 1 being universally quantified: the summation is over all sequences of operator applications—a set of size 4^m . This assumption is only reasonable in the context of small grammar fragments. From the perspective of broad-coverage grammars, the number of possible analyses becomes truly daunting. Most of these are linguistically implausible readings that no human would ever consider as part of a natural interpretation of an initial sentence fragment.⁸ To our taste, detailed consideration of all of these improbable analyses suggests a kind of omnipotence upon which modern psycholinguistics has, at the very least, cast some doubt. In the spirit of bounded rationality, we instead use Definition 3 in this paper as a more realistic substitute for Definition 1.

$$\alpha_i^k = \sum_{\substack{t \text{ is a sequence of parser operations} \\ \text{that successfully analyses up to position } i \\ \text{and arrives at one of the top } k \text{ states}}} \text{Prob}(t) \quad (3)$$

The superscripted k in α_i^k is exactly as described above in the explanation of local beam search. Surprisal, when calculated using α^k as defined in Equation (3) for some parallelism level k reflects just those parser states that are actually visited by the local beam search procedure. The variable t ranges over just those sequences of operations that managed to remain in the top k , the entire way out to position i . Surprisal at a word is still defined on macrostates as in Hale (2001), but in this bounded-rationality formulation, there is a limit (k) on

⁸ While it is a truism in computational linguistics that broad-coverage grammars license many implausible analyses, the notion of “bad syntactic analysis” is as slippery as the notion “good syntactic analysis”. Absent some independent yardstick of linguistic quality—perhaps a panel of human judges or a formal grammar of German—all that can be said is that an analysis found by a parser either matches the human-supplied annotation or it does not. Indeed, in incremental parsing, analyses may be postulated that would have been linguistically reasonable if only the sentence had ended some other way. At this time, no appropriate yardstick of this kind exists for the prefix strings of PSC sentences. We thus forgo systematic linguistic assessment of these transient structures in this work.

the number of microstates that a macrostate may contain.⁹ One might identify the quantity $-\log(\alpha_i^k/\alpha_{i-1}^k)$ as “realistic surprisal”. It is a surprisal, but it is a surprisal derived from a less-idealised parsing model that incorporates local beam search.

Surprisal: a worked example

To see how surprisal works, consider the words **goss** and **Kapitaen** in Figure 3. As indicated in the thermometers below the words, surprisal is lower at the verb **goss** than it is at the noun **Kapitaen**.

It is comparatively unsurprising that a verb should follow a noun in a German sentence. Indeed, these surprisal values reflect distributional regularities in the newspaper text on which the parser was trained (see Appendix A for details). However, this relationship is not direct. Rather, it is mediated by the unseen syntactic structure that the parser recovers. The surprisal values used in this paper follow from the choice of particular operations used to build the syntactic analysis. Table 3 shows the operations used to build the analysis depicted in Figure 3.

Figure 4 depicts the numerical ingredients of this “realistic” surprisal complexity metric in a $k=3$ parser operating on our running example sentence from Figure 3. The boxes indicate the states the parser visits, with states vertically ordered by their probability. The input sentence is laid out horizontally across the page, with grey lines signifying transitions between words.

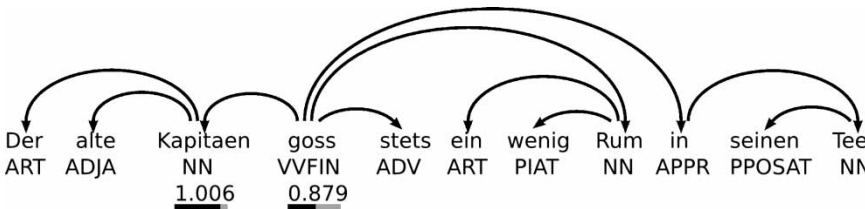


Figure 3. Surprisal is a word-by-word complexity metric.

⁹ This memory limit k plays an important role in the parsing mechanisms we consider in this paper. As the main text indicates, we do not impose any hard constraints on possible parser actions. Rather, all knowledge of German is encoded as parsing preferences. It is the memory limit’s thresholding action on the probability model, rather than any a priori grammar, that eliminates analyses from the beam. At $k=\infty$, in an exhaustive parser where such filtering is “turned off”, the forward probabilities α would all be the same and surprisal would be identically zero on all words. This limiting behaviour reflects the particular formulation of the Nivre parser (see Appendix C). Parsers that do employ an a priori generative grammar, as in Demberg and Keller (2008) or Hale (2001), could still derive nonzero surprisal values even at this limit.

TABLE 3
Parser state trajectory for the sentence depicted in
Figure 3

| | |
|-----|--------------------------------|
| 1. | Shift ART |
| 2. | Shift ADJA |
| 3. | Left NN \leftarrow ADJA |
| 4. | Left NN \leftarrow ART |
| 5. | Shift NN |
| 6. | Left VVFIN \leftarrow NN |
| 7. | Shift VVFIN |
| 8. | Right VVFIN \rightarrow ADV |
| 9. | Shift ART |
| 10. | Shift PIAT |
| 11. | Left NN \leftarrow PIAT |
| 12. | Left NN \leftarrow ART |
| 13. | Reduce ADV |
| 14. | Right VVFIN \rightarrow NN |
| 15. | Reduce NN |
| 16. | Right VVFIN \rightarrow APPR |
| 17. | Shift PPOSAT |
| 18. | Left NN \leftarrow PPOSAT |
| 19. | Right APPR \rightarrow NN |
| 20. | Reduce NN |
| 21. | Reduce APPR |
| 22. | Reduce VVFIN |

The numbers inside the state boxes indicate the precise height of the box; they are sometimes called *forward* probabilities. These forward probabilities do no more than record the product of operator-application probabilities on paths that lead to this state. These operator-application probabilities are given as numerical annotations on the lines connecting the state boxes. The heavy line is the path corresponding to the operator sequence in Table 3. Relatively low surprisal at **goss** restates the fact that the negative log ratio of α_{goss}^3 and $\alpha_{\text{Kapitaen}}^3$ on this probability model is small. We say that the surprisal of the word in that position is 0.879 bits. Surprisal is greater at the noun **Kapitaen** because the total probability of the parser actions required to extend the previous best-states to cover that word is comparatively low (recall that surprisal is a negative logarithm of a probability). This compulsion to transit low-probability states is indexed by greater surprisal at **Kapitaen** compared to **goss**.

A bigram or trigram model could also capture the fact that a noun is likely to follow an adjective. However, surprisal in a dependency parser can reflect very long-distance dependencies like the seven-word span in Figure 5 (See Appendix E for discussion on the distribution of dependency lengths in

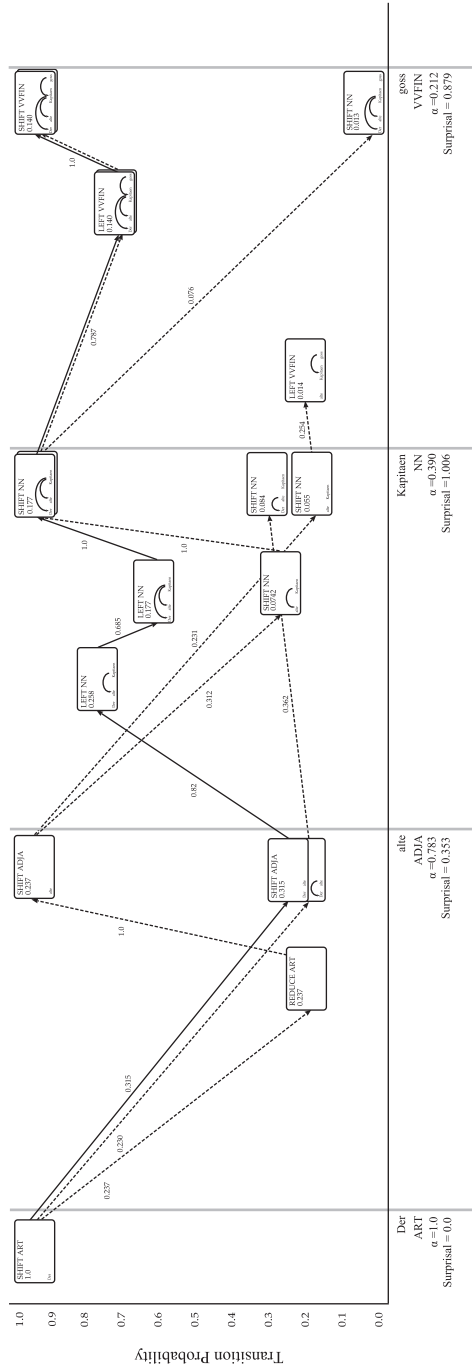


Figure 4. Sketch of surprisal calculation for a $k=3$ parser.

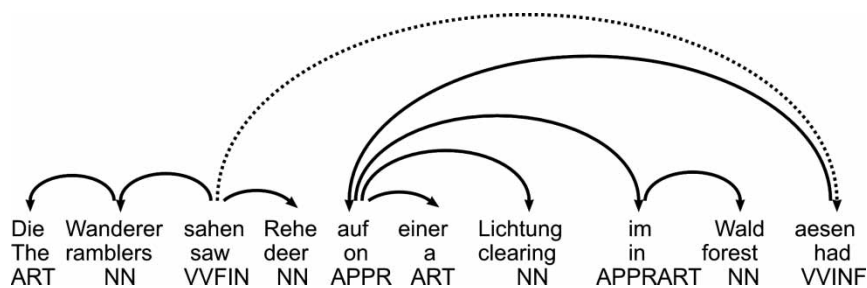


Figure 5. The longest dependency in the PSC.

the PSC). This ability stands in contrast with Markov models, which are subject to a finite length limit (Park & Brew, 2006).

Surprisal imposes comparatively few requirements at the implementation level. It has been combined with a variety of language-analysis devices including the Simple Recurrent Network (S. Frank, 2009). Surprisal is also agnostic about the degree of parallelism. This differs from the Tuning Hypothesis, which is serial (Mitchell, 1994, 1995). In subsequent sections, we leverage this generality to examine different theories of comprehension difficulty that all share the surprisal complexity metric but make different commitments as regards parallel parsing.

Retrieval

The temporal nature of speech suggests that sentence understanding requires a comprehending person to remember properties of earlier words. As each new word is heard, linguistic structures associated with earlier words need to be *retrieved* to perceive the meaningful content of the sentence. Does such “remembering” employ the same working memory as the rest of cognition? The cue-based retrieval theory of Lewis and Vasishth (2005) (henceforth, LV05) holds that it does, integrating an account of sentence-processing difficulty into a general theory of cognitive architecture, Adaptive Control of Thought—Rational (ACT-R) (Anderson, 2005; Anderson & Lebiere, 1998). In this work, we re-formalise a subset of key theoretical ideas from LV05 in the dependency parsing system described above.

Absent some degree of familiarity with ACT-R itself, these theoretical choices may appear arbitrary. But they constitute a zero-parameter model. By zero-parameter model, we mean that the same ACT-R assumptions that have been repeatedly applied to different domains of cognition over the years also seem to apply in accounting for sentence comprehension difficulty. Success in the domain of sentence comprehension strengthens the overall case for ACT-R as a general theory of cognition.

Adaptive Control of Thought—Rational (ACT-R)

ACT-R represents the latest in a series of cognitive architectures developed over the past 30 years by Anderson (1976, 1983, 1990). Each of these theories is different, but there are identifiable themes that have persisted throughout Anderson's work. The most fundamental theme is that computational modelling of human cognition is not premature. Rather than being simply an equivalent calculation or an abstract description of what cognitive agents do, Anderson's cognitive architectures have all been intended as detailed, practical theories of what is actually going on in the minds of real people engaged in tasks that require intelligence. Although pursuit of this goal has led Anderson and his colleagues to develop computer simulation programs that are consistent with the theories, the programs themselves are not the theories. They do, however, make it much easier to work out the consequences of more complete theoretical proposals.

Another theme running through Anderson's work is the distinction between procedural and declarative knowledge. This distinction is reified in ACT-R, which has both a declarative memory for "facts" and a procedural memory for things that the model "knows how to do". Each sort of knowledge is particular to a domain. In a cognitive model of arithmetic, a fact might represent the knowledge that 12 times 7 is 84, whereas in a sentence-processing model, a fact might encode the belief that a particular noun–adjective combination forms a phrase. In ACT-R, individual declarative memory elements are known as *chunks*. Each one has an activation level that determines the latency and accuracy with which it can be retrieved. Chunks are to be contrasted with pieces of procedural knowledge. Anderson's work adopts the idea of a production system from Newell and Simon (1972). A production is an association between two states of mind.¹⁰ If a production *applies*, a thinker transits from the old state-of-mind to the new state-of-mind defined in the production. ACT-R countenances exactly one state of mind at any given instant. To put it another way, "the production system comprises the central bottleneck" (Anderson, 2005, p. 315).

Sentence processing as memory retrieval

LV05 argue not only that ACT-R is an appropriate medium in which to express parsing models, but indeed that its specific theoretical commitments make sense of several outstanding puzzles in the field of human sentence comprehension. As a step towards a complete cognitive model of sentence comprehension, LV05 define a production system that incrementally builds

¹⁰ A production's ability to refer to intermediate states of mind differentiates it from the classic notion of an association between overt stimulus and overt response. This aspect renders production systems "cognitive" as opposed to merely behavioural models.

syntactic structure in declarative memory. These structures respect X-bar theory, an approach that incorporates ideas from dependency grammar quite directly (Kornai & Pullum, 1990). Because these syntactic structures are built using procedural knowledge in ACT-R, the model is a serial parser. To postulate, as LV05 do, that the developing syntactic structures are held in declarative memory, is to hypothesise that these are subject to the same activation dynamics as in other cognitive domains. Individual productions in the LV05 production system access declarative memory to attach new pieces of sentence structure. LV05 show that the pattern of retrieval latencies derived from these memory accesses, under standard ACT-R assumptions, derives human reading time patterns across a range of English constructions that includes centre-embedding, garden-path sentences, and relative clauses.

The ACT-R chunk-activation dynamics thus play a key role in LV05's activation-based sentence-processing model. These dynamics give rise to two effects, decay and similarity-based interference (SBI). Decay and SBI also appear in memory tasks with nonlinguistic stimuli (Anderson et al., 2004). The idea of decay is that words heard farther back are more difficult to retrieve for attachments; this idea is realised in work by Just and Carpenter (1992, p. 133) and in abstract form by Chomsky (1965, pp. 13–14) as well as Gibson and colleagues (Gibson, 1998, p. 11; 2000; Grodner & Gibson, 2005; Warren & Gibson, 2002).¹¹ The idea of SBI, spelled out explicitly in the context of sentence processing by Lewis (1993, 1996), is that earlier words can act as distractors if they happen to match along certain cues, like plural number, accusative case, or animacy. Such distractors make sentence comprehension harder at points where an earlier word must be retrieved (Van Dyke & McElree, 2006). Both of these effects are widespread (Hofmeister, 2007; Lewis & Nakayama, 2001; Logačev & Vasishth, in press; Van Dyke, 2007; Van Dyke & Lewis, 2003; Van Dyke & McElree, 2006; Vasishth & Lewis, 2006).

We adapt the ACT-R theory of memory-element activation dynamics applied in LV05 to the broad-coverage dependency parsing system discussed above. In this broad-coverage setting, we leave hand-crafting of the grammar behind (cf. Patil, Vasishth, & Kliegl, 2009). But we retain ACT-R's power-law of activation decay. We also retain LV05's interpretation of parser actions as productions that cause retrievals. Specifically, we interpret the LEFT and

¹¹ It may be worth noting some differences between the two most recent variants of the decay idea. Both the DLT and LV05's activation-based theory predict that recency decreases difficulty. However, the DLT does not include any notion of interference. Moreover, LV05's activation theory, but not the DLT, acknowledges the possibility of re-activation. Such re-activation can account for cases where increased head-dependent distance facilitates comprehension (Hofmeister, 2009; Shafer, Engelmann, Logačev, Vasishth, & Srinivasan, 2009; Vasishth & Lewis, 2006).

RIGHT operators as causing a retrieval of the word at the left end of the newly drawn dependency arc. The latency of these retrievals, as a function of the ACT-R declarative memory chunk dynamics, is the key determinant of the difficulty prediction that we deduce on this complexity metric.

Similarity-based interference (SBI) and the fan effect

One of the phenomena that the ACT-R declarative memory theory is designed to derive is called the fan or “min” effect (Anderson, 1976, p. 276). Anderson (1974) finds that, in a memory test, participants’ verification responses about a remembered entity grow slower as more propositions come to be associated with that entity. For instance, in Figure 6, a hippie would be remembered in a memory chunk to which three properties are linked. It has a fan of 3.

As a subject links more properties to the same entity, pushing the fan value up, it takes longer and longer to verify probe propositions in a set that was previously learned to criterion. The standard ACT-R memory dynamics in the LV05 model derive this behaviour. In LV05, “fan” reflects not only a panoply of linguistic factors including morphological features like tense and number, but also tree-geometric connections to other nodes in a developing phrase structure.

This paper’s adaptation of LV05 to broad-coverage and parallel parsing is much simpler. It derives the fan effect from just one cue: a word’s part of speech. We theorise that retrievals are delayed by a factor reflecting the presence of other words sharing the same grammatical category that have come earlier in the input sentence. This principle applies to all words, regardless of their attachment status, thus implementing a simplified version of SBI. The motivation for reducing the cues to part-of-speech is merely a matter of convenience: if more detailed information were available for each word to be processed (e.g., case and animacy information), these cues could be deployed in the calculation of interference costs. Our adaptation should therefore be seen as a simplifying assumption which could in principle be extended.

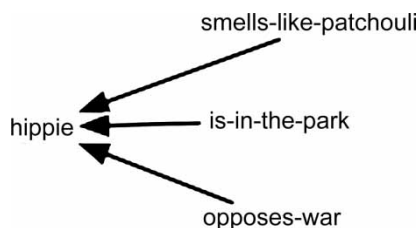


Figure 6. A fact in memory to which other facts are connected.

Retrieval: a worked example

To see how retrieval works, consider the first few words, **Der**, **alte** and **Kapitaen** of our running example. The problem states explored by a $k=3$ parser are arranged by predicted difficulty in Figure 7. This figure is analogous to the earlier Figure 3, but note that the vertical axis is predicted duration in milliseconds, rather than predicted surprisal in bits. Times accumulate for parser actions associated with a single word, but are reset between words.

Figure 8 shows the time course of events postulated in the model for the top three analyses at **Kapitaen**. All times are cumulative except for Action Time, which is specific to each word's parsing time. The first two words are handled with the SHIFT operator, and each takes a constant amount of time. For the top analysis (1), the LEFT operator applies twice to attach the article **Der** and the adjective **alte** as dependents of **Kapitaen**; these are Steps 3 and 4, respectively from Table 3. The retrieval of **Der** takes longer than the retrieval of **alte** because its memory chunk's activation has decayed ever so slightly. For the remaining two analyses in the diagram, the parse time for **Kapitaen** is shorter because fewer words are retrieved.

The durations in Figure 8 reflect the time it takes to parse each word. For larger beam-widths, we take the maximum retrieval time for any analysis in the beam. Selecting max as the mode of combination means that the predictions reflect difficulty associated with the worst-case analysis in the beam.¹²

The equations defining the ACT-R memory chunk dynamics are provided in Appendix B. Aside from our assumptions about the scale of constant durations of Nivre operators, the particular formulation of retrieval given above follows directly from principles of ACT-R. The numerical constants in Equations (8–11) of Appendix B are kept at the default ACT-R values used in previous sentence comprehension models like LV05 as well as in other domains. This implementation of retrieval is thus a zero-parameter model in the sense that no ACT-R parameters are estimated.

Examining both surprisal and retrieval in the same incremental parser states facilitates a fine-grained analysis of the differences between the two complexity metrics. The next sections compare the predictions of the two metrics to fixation durations recorded in the PSC.

¹² An anonymous reviewer brings up the wide variety of alternatives to this “max” mode of combination. Another attractive mode of combination would weight the retrieval times by the probability of the operator application that causes the retrieval. At high parallelism levels, under this “nondeterministic serial” arrangement, retrievals that would have been long in duration are weighted by smaller and smaller probabilities. Thus, we expect that only the retrievals occurring in the highest-probability analysis will have much effect on the overall prediction. This arrangement makes it harder to examine the role of ranked parallelism in human sentence processing and for this reason, we decided not to pursue it in the work reported here. However, we believe it holds considerable interest for the development of serial parsing theories.

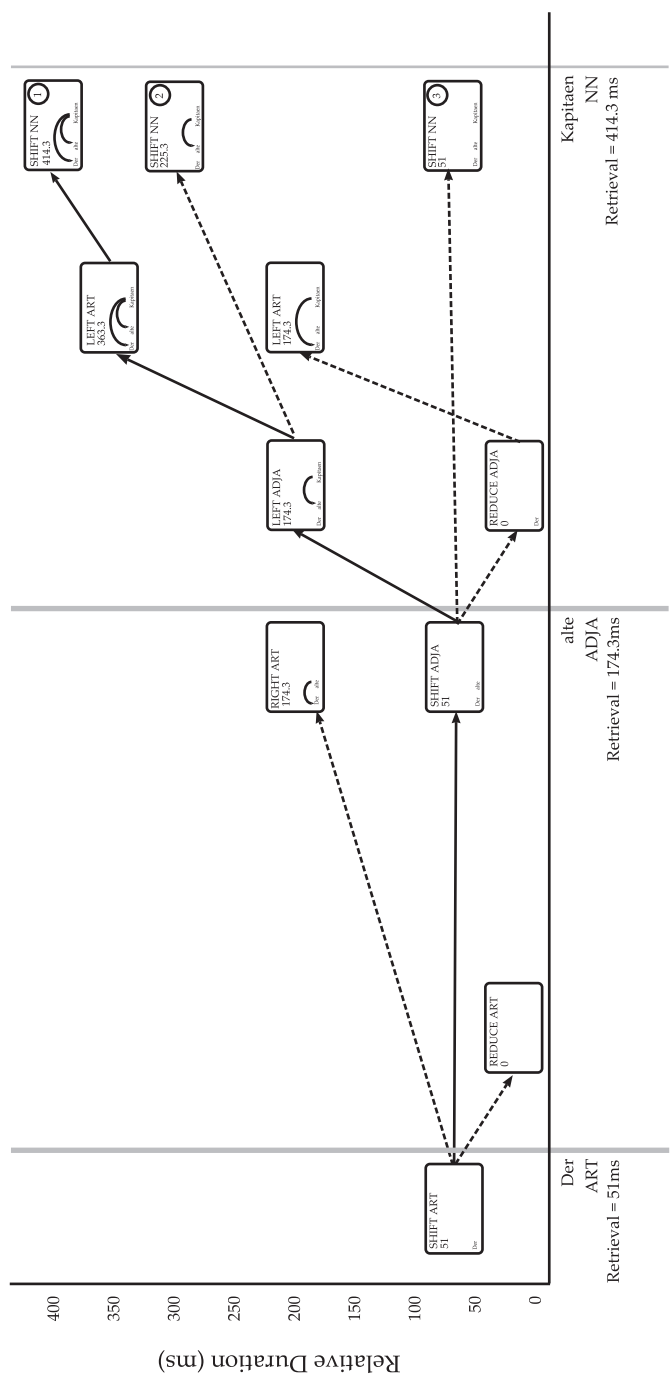


Figure 7. Sketch of retrieval times for a $k=3$ parser.


```

READING: "Der" at 0.
0.051: SHIFT "Der".
*****
Action Time for "Der": 0.051
*****
READING: "alte" at 0.051
0.102: SHIFT "alte".
*****
Action Time for "alte": 0.051
*****
READING: "Kapitaen" at 0.102
0.152: Decide to attach "alte" as dependent.
0.2263: Retrieve "alte".
0.2763: LEFT-ARC with "alte".
0.3263: Decide to attach "Der" as dependent.
0.4153: Retrieve "Der".
0.4653: LEFT-ARC with "Der".
0.5163: SHIFT "Kapitaen".
*****
Action Time for "Kapitaen": 0.4143
*****
READING: "goss" at 0.5163...
(a) Trace of 1.

```

```

READING: "Der" at 0.
0.051: SHIFT "Der".
*****
Action Time for "Der": 0.051
*****
READING: "alte" at 0.051
0.102: SHIFT "alte".
*****
Action Time for "alte": 0.051
*****
READING: "Kapitaen" at 0.102
0.152: Decide to attach "alte" as dependent.
0.2263: Retrieve "alte".
0.2763: LEFT-ARC with "alte".
0.3273: SHIFT "Kapitaen".
*****
Action Time for "Kapitaen": 0.2253
*****
READING: "goss" at 0.3273...

```

(b) Trace of 2.

```

READING: "Der" at 0.
0.051: SHIFT "Der".
*****
Action Time for "Der": 0.051
*****
READING: "alte" at 0.051
0.102: SHIFT "alte".
*****
Action Time for "alte": 0.051
*****
READING: "Kapitaen" at 0.102
0.152: SHIFT "Kapitaen".
*****
Action Time for "Kapitaen": 0.51
*****
READING: "goss" at 0.152...

```

(c) Trace of 3.

Figure 8. A partial trace of the parser's calculation for the top three parses at Kapitaen, in seconds.

FIXATION DURATIONS IN THE POTSDAM SENTENCE CORPUS

This section examines how surprisal and retrieval predict eye fixations for the Potsdam Sentence Corpus (PSC). The first section describes the PSC data, followed by a discussion of how our approach relates to eye-movement control models. We then detail the methods, results, and implications of this study.

Data

Reading involves an alternation of fixations and saccades that move words into the centre of the visual field. In the PSC, fixations between saccades last mostly between 150 and 300 ms, with a mean SFD of 206 ms (Kliegl, Nuthmann, & Engbert, 2006). The eyes do not solely move forward from word-to-word in a left-to-right fashion with single fixations (40%), but they also skip (21%) or refixate (13%) words, or regress back to a previous word of the sentence (8%). These eye-movements are correlated with many indicators of local processing difficulty, such as unigram frequency, bigram frequency, predictability,¹³ and length of the fixated word. The direction of effects is generally compatible with intuitive notions of processing difficulty: short, frequent, and predictable words are more frequently skipped, less frequently refixated, and have shorter fixation durations when they are fixated in comparison with long, rare, and unpredictable words. Longer fixation durations immediately before highly predictable words constitute a notable exception to this general pattern.

First-pass regression probability and various fixation measures are often characterised as “early” and “late” measures, with an implied mapping to “early” and “late” stages of cognitive processing. Early processing stages refer to the subprocesses of word identification comprising extraction of visual, orthographic, and phonological features subserving lexical access. Late stages refer to the difficulty of syntactic, semantic, and discourse integration. However, Clifton, Staub, and Rayner (2007) advocate caution in drawing such a simple relation between “early” and “late” measures and early versus late stages of cognitive processing. As they put it,

The terms “early” and “late” may be misleading, if they are taken to line up directly with first-stage vs. second-stage processes that are assumed in some models of sentence comprehension (Frazier, 1987; Rayner, Carlson, & Frazier, 1983). Nonetheless, careful examination of when effects appear may be able to shed some light on the underlying processes. Effects that appear only in the “late” measures are in fact unlikely to directly reflect first-stage processes; effects that appear in the “early” measures may reflect processes that occur in the initial stages of sentence processing, at least if the measures have enough temporal resolving power to discriminate among distinct, fast-acting, processes. (Clifton et al., 2007, p. 349)

We follow Clifton et al. (2007) in characterising dependent measures as “early” and “late” without committing to a simple mapping between early and late

¹³ Predictability in this sense refers to difficulty a human participant has guessing a word given its left context. Predictability can be estimated using variants of the Cloze procedure (Taylor, 1953).

stage processes. Indeed, the results to be presented below confirm the cautionary message of the above quote. The analyses we present in subsequent sections do not support a simple mapping of measures to parsing stages.¹⁴

Table 4 defines the dependent measures—four fixation measures along with first-pass regression probability—that are considered in this study. The early measures take into account first-pass data, whereas the late measures encompass both first and subsequent passes.

Relation to eye-movement control models

In his review, Rayner (1998) highlights how, in recent years, the link between fixation durations and the oculomotor, perceptual, and cognitive processes that drive them has been enhanced considerably by mathematical models of eye-movement control. The two most prominent cognitive processing models, E-Z Reader (Pollatsek, Reichle, & Rayner, 2006; Reichle, Pollatsek, Fisher, & Rayner, 1998) and SWIFT (Engbert, Nuthmann, Richter, & Kliegl, 2005; Kliegl et al., 2004) predict fixation durations as a function of word frequency and length. They also account for fixation positions in words. However, the role of parsing actions in eye-movement control is yet to be investigated; work by Reichle, Warren, and McConnell (2009) is the first major attempt in this direction. One reason for the absence of a parsing theory in eye-movement control models is that until quite recently large-scale

TABLE 4
The four fixation measures and one regression probability modeled in this study

Early measures

Single fixation duration (SFD)

The amount of time a word is fixated in first pass if it is only fixated once.

First fixation duration (FFD)

The amount of time a word is fixated during the first fixation in first pass.

Regression probability (REG)

Likelihood of regressing to a previous word during the first pass.

Late measures

Regression path duration (RPD)

The sum of all reading times at a word and all words to its left, starting from the first fixation in the word until the first fixation past the region.

Total reading time (TRT)

The sum of all fixation durations at a word, including first pass and re-reading.

¹⁴ Note that early and late measures are also compromised by being derived from overlapping sets of data (i.e., SFDs are a subset of first-pass gaze durations, and gaze durations are a subset of total reading time or TRT). This positive dependency will tend to diminish any differential effects between early and late measures.

computational models of parsing cost were unavailable. This situation has recently changed. The work of Boston, Hale, Patil, Kliegl, and Vasishth (2008), Demberg and Keller (2008), Hale (2001), and Levy (2008) makes it possible to consider, for arbitrary sentences, the role of parsing costs in co-determining fixation durations and eye-movement patterns in conjunction with eye-movement control. Although investigating this relationship is by no means going to be trivial or straightforward, the development of large-scale parsing models is an important step in this direction.

In this study, we extend the above-mentioned large-scale investigations of surprisal by testing the predictions of both surprisal and retrieval on a German eyetracking dataset. Both factors are predicted to help in modelling the fixation data, but, because they make different claims about the source of human processing difficulty, they could model different sources of difficulty in the data.

Method

The PSC provides the data for this study. As mentioned above, the dataset consists of 144 individual German sentences (1138 words) read by 222 native German speakers. When first and last words are removed to reduce start-up and wrap-up effects, fixations for the 850 remaining words are available for each of the five measures in Table 4. We do not consider fixations with durations of less than 50 ms. The dataset is further restricted to just those words where a retrieval is postulated, since retrieval does not make any interesting prediction on words where no attachment occurs.¹⁵ The cardinality of this set varies with beam-width, from 668 words at $k = 1$ to 841 words at $k \geq 6$. The occurrence of regressions is binomially coded, with 1 indicating a regression occurred during first pass, and 0 that a regression did not occur.

The surprisal and retrieval predictions follow from parser runs at a systematic selection of beamwidths, schematically indicated in Table 1. The beamwidths are $k = 1, 5, 10, 15, 20, 25$, and 100. The retrieval and lexical predictors are log-transformed to avoid multiplicativity effects in the statistical analysis and to ensure that the residuals are approximately normally distributed (Gelman & Hill, 2007).

The statistical evaluation of the surprisal and retrieval predictions uses the linear mixed model (Pinheiro & Bates, 2000) provided in the statistical computing software R (R Development Core Team, 2006) and its lme4 package (Bates, Maechler, & Dai, 2008). Linear mixed models are regression models that take into account group-level variation, which is present in

¹⁵ To clarify the scope of the retrieval theory, the main text reports the number of PSC words on which the dependency parser postulates a retrieval. The linear regression models described in this paper are fitted to these points. However, the results do not change when all words are included in the analysis.

psycholinguistic data via the participant and item factors. Including both fixed effects (e.g., predictors for the fixations) and random effects (e.g., participant, item) allows one model to take into account both within-group and between-group variation for the intercepts (Demidenko, 2004). To model regression probability, we employ a generalised linear mixed model with a binomial link function. Further details regarding linear mixed models are provided in textbooks, such as Baayen (2008) and Gelman and Hill (2007), as well as in the special issue of the *Journal of Memory and Language* entitled “Emerging Data Analysis” (Vol. 59, Issue 4).

We fit four mixed effects models to each of the dependent measures described in Table 4. The baseline model given in Equation (4) incorporates the lexical factors described in the previous subsection: word length (len), word predictability (pred), unigram frequency (freq), and bigram frequency (bi).

$$\log(y) = \beta_1 \text{freq} + \beta_2 \text{len} + \beta_3 \text{bi} + \beta_4 \text{pred} + b_p + b_q + \varepsilon \quad (4)$$

The dependent measure, generically denoted y , is log-transformed so that it can be modelled linearly, and each of the lexical predictors are added to the group-level intercept variation for participant (b_p) and item (b_q). The subscripts in these quantities range over participants p and items q . The element that is estimated for each of the lexical predictors is the coefficient β . Each of the lexical predictors are additionally centred so that its mean is zero. This allows the intercept and the coefficients for each predictor to be interpreted given the average value of the other predictors.

Three other models for each fixation are fit: a baseline plus surprisal (surp, Equation 5), a baseline plus retrieval (ret, Equation 6), and a model that incorporates all predictors (Equation 7).

$$\log(y) = \beta_1 \text{freq} + \beta_2 \text{len} + \beta_3 \text{bi} + \beta_4 \text{pred} + \beta_5 \text{surp} + b_p + b_q + \varepsilon \quad (5)$$

$$\log(y) = \beta_1 \text{freq} + \beta_2 \text{len} + \beta_3 \text{bi} + \beta_4 \text{pred} + \beta_5 \text{ret} + b_p + b_q + \varepsilon \quad (6)$$

$$\log(y) = \beta_1 \text{freq} + \beta_2 \text{len} + \beta_3 \text{bi} + \beta_4 \text{pred} + \beta_5 \text{surp} + \beta_6 \text{ret} + b_p + b_q + \varepsilon \quad (7)$$

Comparisons between linear mixed models are based on log-likelihood ratios, penalising models for a large number of parameters. We use the traditional maximum-likelihood-based χ^2 -statistic to this end, with increases in log-likelihood indicating a better model. As Faraway (2005) and Pinheiro and Bates (2000) point out, comparing models with different fixed effects yields anti-conservative p -values (i.e., the p -value may be higher than suggested by the model comparison). Faraway (2005) suggests using the parametric bootstrap instead. Note that the anti-conservativity problem is not so severe when large quantities of data are available relative to the parameters fit; this is the case in our dataset. However, in order to confirm that our model comparisons are not misleading, we carry out the parametric

bootstrap for all the reading time measures as detailed in Appendix D.¹⁶ None of these simulations yield interpretations different from model comparisons based on the χ^2 -statistic. Furthermore, model comparisons using the Akaike Information Criterion (Akaike, 1973) and Deviance Information Criterion (Spiegelhalter, 2006; Spiegelhalter, Best, Carlin, & van der Linde, 2002) are also consistent with our conclusions.

Results

At low beam-widths, surprisal (Equation 5) best models the fixation duration measures. Figures 9(a) and (b) plot the fitted values of β_5 and β_6 , respectively, in this model for each fixation measure. Coefficients greater than zero imply that increases in the predictor are associated with increases in y . 95% confidence intervals that do not cross 0.0 indicate statistical significance at $\alpha = 0.05$. At $k = 1$, surprisal has statistically significant positive coefficients for

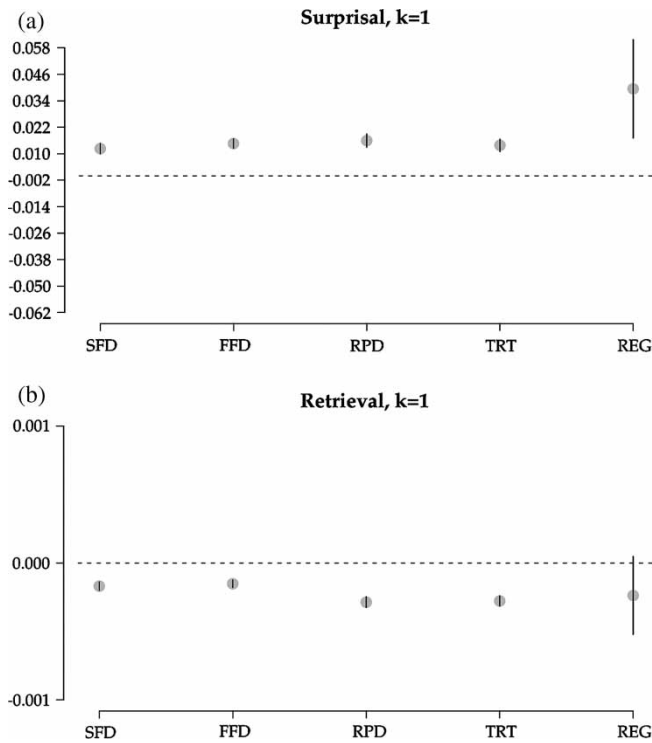


Figure 9. Surprisal alone predicts at $k = 1$.

¹⁶ The “simulate” function necessary for this procedure is not yet implemented for generalised linear mixed models; therefore, we did not carry out a bootstrap for REG.

all fixations and regression probability in Figure 9(a). Retrieval, on the other hand, makes the incorrect prediction: at low beam-widths, increasing retrieval difficulty predicts shorter fixation durations.

Although at low beam-width only surprisal correctly predicts fixation durations and regression probability and at a higher beam-width, retrieval is also a predictor. Figure 10 shows surprisal's and retrieval's predictions in

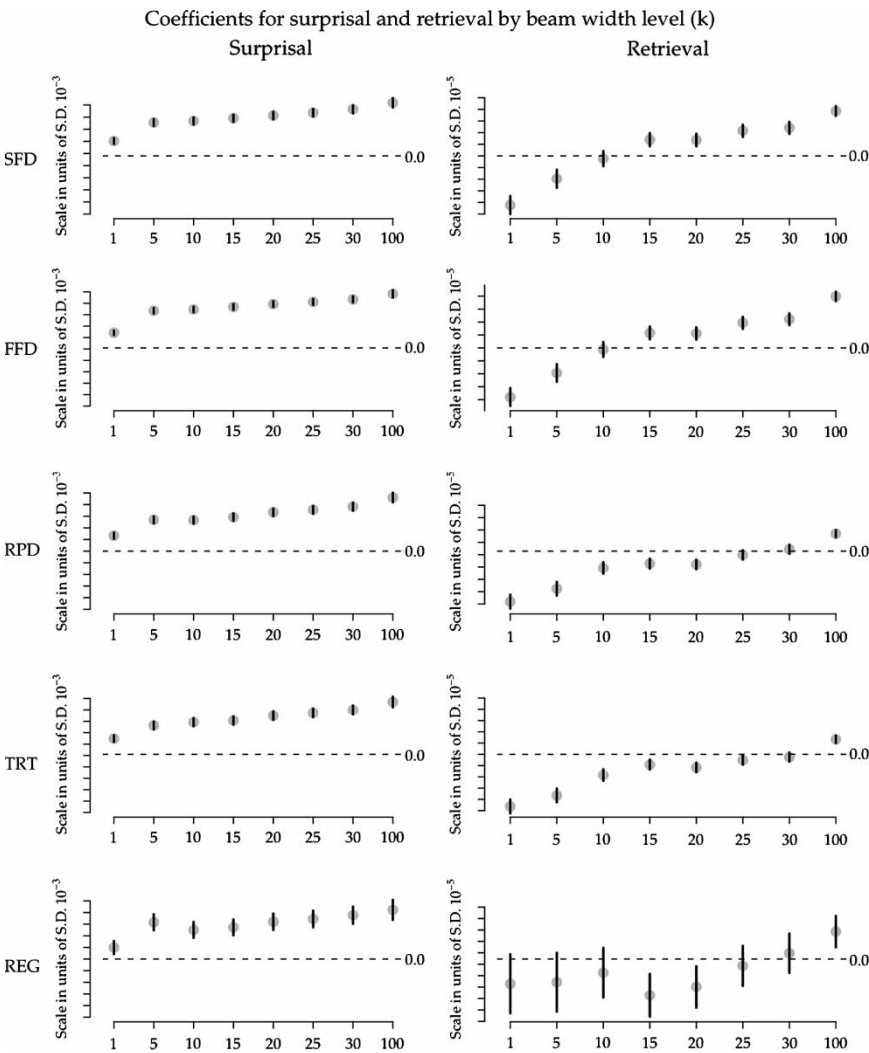


Figure 10. With large beams, surprisal and retrieval predict the same fixations. For each fixation measure, the coefficients for surprisal (left) and retrieval (right) are given along the y-axis, which is scaled to units of standard deviation. The x-axis represents the degree of parallelism, k .

TABLE 5
Correlations between surprisal (s), retrieval (r), predictability (p), and log-frequency (f)
at different beamwidths *k*

| <i>k</i> | <i>s-r</i> | <i>s-p</i> | <i>s-f</i> | <i>r-p</i> | <i>r-f</i> | <i>p-f</i> |
|----------|------------|------------|------------|------------|------------|------------|
| 1 | 0.43 | 0.16 | 0.05 | -0.05 | -0.33 | 0.50 |
| 5 | 0.09 | 0.25 | 0.10 | -0.03 | -0.27 | 0.53 |
| 10 | 0.02 | 0.26 | 0.12 | 0.002 | -0.23 | 0.53 |
| 15 | -0.09 | 0.26 | 0.11 | -0.04 | -0.25 | 0.53 |
| 20 | -0.11 | 0.27 | 0.11 | -0.04 | -0.22 | 0.53 |
| 25 | -0.16 | 0.27 | 0.11 | -0.06 | -0.21 | 0.53 |
| 100 | -0.07 | 0.26 | 0.09 | 0.13 | 0.07 | 0.53 |

parsers of greater and greater beam-width. Each eye-movement measure introduced in Table 4 receives its own subgraph in Figure 10. Table 5 shows that the two predictors are uncorrelated across all beamwidths *k* except at *k* = 1, where the correlation is 0.43. The measures are also uncorrelated with word predictability and unigram frequency.

Table 6 lists the log-likelihood values for the four models plotted for each individual measure at *k* = 100. The overall worst model fit for all seven regressions is the baseline, which only includes lexical factors (Equation 4). The best model for all fixation-based measures, in bold text, includes both surprisal and retrieval as predictors. The best model for regression probability includes only surprisal. Table 7 reports chi-square and *p*-values for comparisons between models 4–7 at the *k* = 100 parallelism level. This pattern of statistically significant differences is consistent across beamwidths. These model fit results demonstrate the utility of both conceptions of comprehension difficulty. The full results of the multiple linear regressions for *k* = 1 and *k* = 100 are shown in tabular form in Table 8.

Discussion

The main finding of this study is that whereas surprisal models parsing difficulty reflected in fixation durations and regression probability at a low beamwidth,

TABLE 6
Log-likelihoods for each model and fixation duration for *k* = 100

| <i>Dependent Measure</i> | <i>Baseline</i> | <i>+Surprisal</i> | <i>+Retrieval</i> | <i>+Both</i> |
|--------------------------|-----------------|-------------------|-------------------|----------------|
| SFD | -21604 | -21379 | -21454 | - 21214 |
| FFD | -26265 | -25859 | -26055 | - 25636 |
| RPD | -78842 | -78609 | -78803 | - 78565 |
| TRT | -70552 | -70370 | -70523 | - 70338 |
| REG | -43246 | - 43189 | -43729 | -43717 |

The best model for all fixation-based measures is in bold.

TABLE 7
Chi-square statistics for model comparison with baselines for $k=100$

| <i>Dependent measure</i> | <i>Baseline, surprisal</i> | | <i>Baseline, retrieval</i> | | <i>Baseline, both</i> | |
|--------------------------|----------------------------|----------------|----------------------------|----------------|-----------------------|----------------|
| | <i>Chi-square</i> | <i>p-value</i> | <i>Chi-square</i> | <i>p-value</i> | <i>Chi-square</i> | <i>p-value</i> |
| SFD | 450.64 | <0.01 | 299.95 | <0.01 | 780.07 | <0.01 |
| FFD | 812.78 | <0.01 | 419.78 | <0.01 | 1259.10 | <0.01 |
| RPD | 466.96 | <0.01 | 79.15 | <0.01 | 554.22 | <0.01 |
| TRT | 363.19 | <0.01 | 58.40 | <0.01 | 427.60 | <0.01 |
| REG | 114.15 | <0.01 | 0 | 1 | 0 | 1 |

$k = 1$, retrieval does not. As the beam-width is widened, surprisal continues to predict difficulty in all measures, and maximum retrieval cost predicts both early and late measures as well as regression probability. Because predicted retrieval time-costs are aggregated across beams using max, the retrieval score can only increase as k increases. These increases allow for the prediction of all dependent measures, suggesting that retrieval at low beamwidths underestimates difficulty in fixation durations and regression probability.

GENERAL DISCUSSION

This work measures the effectiveness of two syntactic complexity metrics, surprisal and retrieval, in modelling sentence-processing difficulty. The two metrics give different accounts of processing difficulty. Surprisal hypothesises that low-probability attachments cause difficulty. Retrieval, on the other hand, attributes sentence-processing difficulty to working memory characteristics. To determine the relative contribution of each, we use a common collection of incremental dependency parser states to work out the consequences of each complexity metric. This methodology facilitates a quantitative investigation of how these metrics play out at different levels of parallel processing.

Our findings suggest that the surprisal and retrieval predictions do not fall neatly into the categories implied by the early/late distinction traditionally assumed in the eye-movement literature.¹⁷ With a serial parser, surprisal is able to predict all eye-dependent measures—even “late” measures such as regression path duration (RPD) (Clifton et al., 2007, p. 349). Retrieval, on the other hand, fails to provide a good account of the eye-dependent data

¹⁷ A reviewer points out that data analyses were conducted on multiple dependent measures without correcting for multiple comparisons. We believe, in this case, that the risk of error is very low because our results do not seem to depend on differential outcomes for the various ways of doing model comparison. Rather, all analyses point to the same conclusions.

TABLE 8
Full results for multiple linear regressions, $k=1$ and $k=100$

| | | $k=1$ | | | $k=100$ | | |
|-----|------------------|--------------|-----------|----------------|--------------|-----------|----------------|
| | <i>Predictor</i> | <i>Coef.</i> | <i>SE</i> | <i>t-value</i> | <i>Coef.</i> | <i>SE</i> | <i>t-value</i> |
| SFD | (Intercept) | 5.2752152 | 0.0091924 | 573.9 | 5.276e+00 | 8.872e-03 | 594.7 |
| | Freq | -0.0077595 | 0.0013829 | -5.6 | 9.824e-04 | 1.163e-03 | 0.8 |
| | Len | 0.0060455 | 0.0006296 | 9.6 | 6.555e-03 | 5.691e-04 | 11.5 |
| | Bi | -0.0131116 | 0.0004734 | -27.7 | -1.164e-02 | 4.194e-04 | -27.8 |
| | Pred | -0.0052508 | 0.0013195 | -4.0 | -1.709e-02 | 1.190e-03 | -14.4 |
| | Surprisal | 0.0123101 | 0.0012256 | 10.0 | 4.384e-02 | 1.998e-03 | 21.9 |
| FFD | Retrieval | -0.0001691 | 0.0000159 | -10.6 | 1.545e-04 | 8.504e-06 | 18.2 |
| | (Intercept) | 5.269e+00 | 8.890e-03 | 592.7 | 5.273e+00 | 8.601e-03 | 613.1 |
| | Freq | -2.942e-03 | 1.254e-03 | -2.3 | 5.982e-03 | 1.049e-03 | 5.7 |
| | Len | -2.040e-03 | 4.905e-04 | -4.2 | -1.390e-03 | 4.436e-04 | -3.1 |
| | Bi | -1.321e-02 | 4.394e-04 | -30.1 | -1.224e-02 | 3.887e-04 | -31.5 |
| | Pred | -1.664e-03 | 1.217e-03 | -1.4 | -1.475e-02 | 1.097e-03 | -13.4 |
| RPD | Surprisal | 1.460e-02 | 1.096e-03 | 13.3 | 5.209e-02 | 1.793e-03 | 29.0 |
| | Retrieval | -1.519e-04 | 1.412e-05 | -10.8 | 1.594e-04 | 7.538e-06 | 21.1 |
| | (Intercept) | 5.471e+00 | 1.380e-02 | 396.4 | 5.472e+00 | 1.335e-02 | 410.0 |
| | Freq | -1.849e-02 | 1.749e-03 | -10.6 | -3.599e-03 | 1.466e-03 | -2.5 |
| | Len | 3.731e-02 | 6.960e-04 | 53.6 | 3.624e-02 | 6.328e-04 | 57.3 |
| | Bi | -6.696e-03 | 6.115e-04 | -11.0 | -7.235e-03 | 5.425e-04 | -13.3 |
| TRT | Pred | -1.441e-03 | 1.709e-03 | -0.8 | -1.658e-02 | 1.544e-03 | -10.7 |
| | Surprisal | 1.594e-02 | 1.557e-03 | 10.2 | 5.530e-02 | 2.534e-03 | 21.8 |
| | Retrieval | -2.864e-04 | 2.012e-05 | -14.2 | 9.903e-05 | 1.060e-05 | 9.3 |
| | (Intercept) | 5.454e+00 | 1.346e-02 | 405.1 | 5.454e+00 | 1.304e-02 | 418.3 |
| | Freq | -1.164e-02 | 1.646e-03 | -7.1 | 2.640e-03 | 1.380e-03 | 1.9 |
| | Len | 3.627e-02 | 6.555e-04 | 55.3 | 3.571e-02 | 5.958e-04 | 59.9 |
| REG | Bi | -1.249e-02 | 5.756e-04 | -21.7 | -1.233e-02 | 5.107e-04 | -24.2 |
| | Pred | -1.635e-02 | 1.608e-03 | -10.2 | -3.034e-02 | 1.453e-03 | -20.9 |
| | Surprisal | 1.380e-02 | 1.466e-03 | 9.4 | 4.588e-02 | 2.386e-03 | 19.2 |
| | Retrieval | -2.776e-04 | 1.895e-05 | -14.7 | 8.008e-05 | 9.976e-06 | 8.0 |
| | (Intercept) | -2.1483075 | 0.0331565 | -64.79 | -2.103e+00 | 2.352e-02 | -89.43 |
| | Freq | -0.1975074 | 0.0130669 | -15.12 | -1.479e-01 | 1.054e-02 | -14.03 |
| | Len | 0.0064848 | 0.0048715 | 1.33 | 5.261e-03 | 4.317e-03 | 1.22 |
| | Bi | 0.0927631 | 0.0046218 | 20.07 | 7.030e-02 | 3.930e-03 | 17.89 |
| | Pred | 0.0315408 | 0.0125868 | 2.51 | -1.813e-03 | 1.105e-02 | -0.16 |
| | Surprisal | 0.0394327 | 0.0113952 | 3.46 | 1.689e-01 | 1.767e-02 | 9.56 |
| | Retrieval | -0.0002378 | 0.0001450 | -1.64 | 2.645e-04 | 7.667e-05 | 3.45 |

when deployed in a serial parsing system. But as we acknowledge greater and greater levels of parallel processing, retrieval’s predictions get better and it is eventually able to predict all eye-dependent measures. Indeed, in highly parallel parsers, retrieval is able to predict “early” measures like SFD that were not formerly thought to reflect working memory limitations (Clifton

et al., 2007, p. 348). At these high parallelism levels, surprisal and retrieval make convergent predictions: increases in either one are both associated with behavioural indices of heightened comprehension difficulty.

These findings suggest that memory capacity, when formalised as beam-width, may be an important modulator of each theory's predictions. With surprisal, even a serial parser is helpful in explaining German readers' fixations. This result is consistent with the seriality claims that underly garden-pathing theories (Frazier, 1979; Frazier & Rayner, 1982) and other theories that focus on serial processing (Mitchell, 1994, 1995). It confirms the suggestion that a highly limited search space need not diminish a model's cognitive fidelity (T. Brants & Crocker, 2000), and, we suggest, supports the view of human cognition as "boundedly rational" in general (Gigerenzer et al., 1999; Howes, Lewis, & Vera, 2009; Simon, 1955). In support of this view, our results show that ideal prefix probabilities as in Hale (2001) and Levy (2008) are not necessary to predict syntactic difficulty in eye-dependent measures.

The interplay of memory capacity with retrieval suggests that this metric, unlike surprisal, requires a higher degree of parallelism to properly account for the difficulty of ordinary reading. The regression models discussed above suggest that retrieval requires a beam-width greater than 30 to predict all eye-dependent measures. Of course, this rather specific number rests upon a variety of assumptions. As detailed in Footnote 2, to formalise memory for syntactic alternatives as a single, scalar parallelism level k is to gloss over many well-known aspects of human memory. Some cognitive models incorporate inhibition or interference processes into their conception of parallel processing (McClelland & Elman, 1986). If these processes truly do affect human sentence comprehension, then their omission from the parallel dependency parsing systems discussed in this paper could represent a discrepancy between theory and reality. These kinds of considerations underscore the importance of continued research on parallel cognitive architecture. This and other future work are discussed below.

FUTURE WORK

Our methodology sets up a framework for parallel parsing in which the question of psycholinguistic adequacy can begin to be addressed. The reported results suggest that retrieval is a better predictor of German readers' sentence comprehension difficulty when it is applied in a parallel parser. This finding is at odds with the positive findings of Lewis (1993) and LV05, whose serial parsers were sufficient to account for well-known contrasts in human comprehension difficulty. From the perspective of a cognitive architecture like ACT-R, the use of beam search in a parser corresponds to parallel

production-rule firing. This goes against a central ACT-R assumption, namely that only one production rule fires at a time. However, investigators like Salvucci and Taatgen (2008) have recently begun to explore alternatives to fundamental ACT-R assumptions in models of human multitasking. Although these authors are concerned with multitasking across different tasks, it may be possible to apply a similar extension of ACT-R to within-task parallel processing. We leave this exciting possibility to future work.

Another interesting area for future work involves possible interactions between surprisal and retrieval. Our research applies a methodology that compares the relative fit of models that include surprisal and retrieval alone, as well as together. The superiority of the combined models indicates that the two predictors do not overlap. Surprisal is neither subsumed by retrieval nor is retrieval subsumed by surprisal. If both metrics capture something true about human sentence comprehension, then it is natural to seek a detailed model that would explain why and how they are both involved. We have simply highlighted the nonoverlapping character of the two types of accounts. The development of a truly integrated model must await future work.

An even more substantial project would integrate additional elements from the original ACT-R implementation into this model. For example, the parsing mechanism used in this work does not represent explicit expectations for future words. LV05 found that such expectations interact with retrieval cues. Whereas Lewis and Vasishth's hand-coded production rules reflect phrase structures with intermediate nodes such as Noun Phrase and Verb Phrase, the dependency parser applied in this work does not deal with any such structures. In fact, Nivre (2004) suggests that no dependency structure can faithfully implement the sort of "top-down" parsing strategy that most straightforwardly reflects the intuitive idea of an expectation for upcoming words. Future work should explore combinations of grammars and parsing strategies that can model expectations, to fully carry out the programme begun in LV05.

Similarly, lexical influences on human sentence comprehension are well-known (Boland, 1992; Boland & Blodgett, 2006; Ford, Bresnan, & Kaplan, 1982; MacDonald et al., 1994; Mitchell, 1987). The parser used to derive the reported results ignores these effects. From its point of view, both **ate** and **slept** are treated as the same kind of past-tense verb despite the fact that one is transitive. While unlexicalised models like this one are helpful in isolating the role of syntactic processing, a lexicalised variant would open an exciting array of additional questions. Such a model would undoubtedly be able to overcome the sorts of typical attachment mistakes catalogued in Appendix A.

Indeed, lexicalism is just one of a constellation of tenets implicitly or explicitly assumed by constraint-based models. These models are often given a connectionist implementation rooted in the notion of activation (Christiansen & Chater, 1999; Mayberry, Crocker, & Knoeferle, 2009; Rohde, 2002; Spivey & Tanenhaus, 1998; Tabor & Tanenhaus, 1999). Besides

lexicalism, these models differ from the “symbolist” account advanced in this paper in virtue of being based upon an activation-based associative memory (Kohonen, 1989; McElree, Foraker, & Dyer, 2003). In this paper’s model, the memory is a stack, and all retrievals are successful, no matter how deep. Future work should examine ways to incorporate a more realistic activation-based memory like the one assumed in hybrid architectures such as ACT-R and 4CAPS (Just & Varma, 2007).

CONCLUSION

Our findings speak to the role of grammar in accounting for sentence comprehension difficulty. We compare two grammar-based complexity metrics while systematically varying the degree of parallelism in a family of identical parsing systems. We find that whereas surprisal and retrieval make different predictions in less parallel parsers, as the degree of parallelism increases, both metrics become adequate for predicting eye fixation durations in the PSC.

This result confirms the idea that grammar affects language comprehension through both probabilistic and working memory constraints. It also supports the notion that adequate models of comprehension difficulty are not optimal with respect to the task itself, but are rather restricted by the kinds of memory constraints postulated in theories of cognitive architecture.

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APPENDIX A: A PROBABILITY MODEL FOR THE NIVRE PARSER

Following Nivre (2006), a parser state is a record containing four fields:

- σ A stack of already-parsed unreduced words.
- τ A list of input words.
- h A function from dependent words to heads.
- d A function from dependent words to arc types.

The stack σ contains already-parsed words that have not yet encountered all dependencies. The list τ serves as an input pointer, and h and d keep track of the dependency graph found so far.

Each state transitions to a new state by one of four possible operators: LEFT, RIGHT, REDUCE, or SHIFT.

- LEFT A left-arc is drawn from the word being parsed i to the first word j of σ , making j the head of i ; j is popped off σ .

- RIGHT** A right-arc is drawn from the first word j of σ to the word being parsed i , making i the head of j ; j is pushed onto σ .
- SHIFT** Shifts the word being parsed i onto σ ; no arcs are drawn.
- REDUCE** Pops σ .

We use a maximum-entropy classifier to estimate the probability of a transition given a state (Bishop, 2006, p. 198). This classifier is trained on newspaper text from the Negra and Tiger treebanks (S. Brants et al., 2004). To obtain training data, we interpret the annotations in the treebanks as a dependency graphs by repeatedly applying German head-finding rules (Dubey, 2004). Since the 2006 vintage Nivre parser only works on projective dependency graphs, we occasionally need to postprocess a given graph to render it projective. This happens primarily with punctuation, which does not figure in our PSC testing data. We make recalcitrant dependency graphs projective by repeatedly “lifting” the head of the shortest crossing dependency to the grandparent following Kahane, Nasr, and Rambow (1998). These transformations can later be undone to recover parser output (Nivre & Nilsson, 2005). From the dependency graph, we choose a canonical operator sequence based on the idea of delaying REDUCE actions as long as possible. Starting with the 70,602 treebank sentences, this procedure yields about 3.1 million operator applications. Each such application records a four-way classification problem instance. The correct class label names the observed operator application. The classifier estimates a discrete probability distribution over the four labels, given a finite feature vector summarising particular aspects of the antecedent parser state. In this work, we use three symbol-valued features:

- Stack1 The top stack symbol, along with the part-of-speech of the current input word.
- Stack2 The top two stack symbols, along with the part-of-speech of the current input word.
- Stack3 The top three stack symbols, along with the part-of-speech of the current input word.

By estimating transition probabilities, the classifier induces a conditional model of parser states given an input string.

Parser accuracy

The simple features¹⁸ described above allow the parser to achieve F -scores between 72.4 and 96.3 for unlabelled dependencies across the various k .¹⁹ The parser’s imperfect accuracy can be accounted for by three groups of errors: lexical ambiguity, true parser errors, and annotation errors. The majority of the errors are due to lexical ambiguity, such as the Prepositional Phrase Attachment ambiguity shown in Figure A1. Here, the parser mistakenly attaches **in a glade** to **deer** rather than the verb **browsing**. A large body of work in both psycholinguistics and computational linguistics argues that human performance in these cases cannot be accurately captured by any sort of unlexicalised model (Boland, 1992).

A second class of parser errors are not obviously lexical in nature. For example, the parser has difficulty with the German verb-second constructions, as in Figure A2. It incorrectly

¹⁸ More complicated sets of feature can provide higher accuracy. For recent reports from this rapidly changing field, see, for instance, Section 4 of Titov and Henderson (2007) or Table 1 of Zhang and Clark (2009).

¹⁹ The F -score is the weighted harmonic mean of precision and recall per-attachment: $(2 \times \text{precision} \times \text{recall}) / (\text{precision} + \text{recall})$. It is commonly used to determine overall parsing performance on a particular text sample (Manning & Schütze, 1999, p. 269).

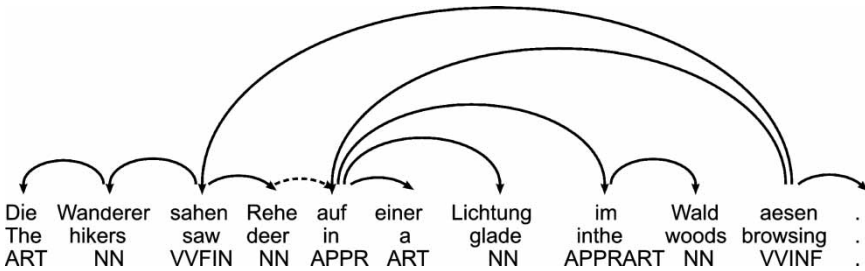


Figure A1. The parser requires lexical disambiguating information to correctly analyse prepositional phrase ambiguities.

attaches dependents, like **bicycle**, to auxiliary verbs, like **had**, rather than to final verbs like **left**. Although less common than the first class of errors, these errors decrease the accuracy of the parser. A very small group of errors are caused by incorrect annotations in the PSC. The annotation of punctuation is particularly erratic. Figure A3 illustrates a typical case, in which anomalous attachment of a comma in the gold standard counts as a parsing error.

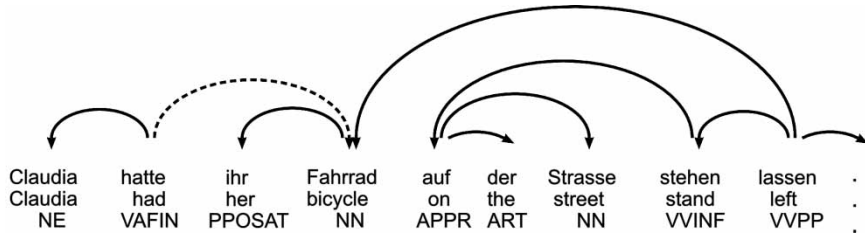


Figure A2. The parser is unable to correctly parse some verb-second structures in German.

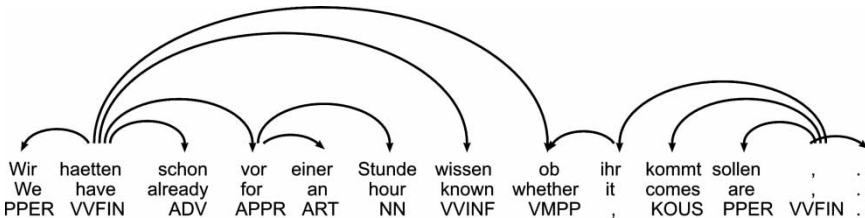


Figure A3. Some structures that cause reduction in parser accuracy are genuine annotation errors.

APPENDIX B: ACT-R MEMORY ACTIVATION DYNAMICS

We adopt the ACT-R activation-based memory theory as presented in, e.g., Anderson and Lebiere (1998, pp. 70–81), in assumption A3 of LV05, or in the section entitled “The Declarative Memory Module” in Anderson et al. (2004). Retrieval time for a word participating in an attachment is based on that word’s activation, A , given below in Equation (8).

$$A_i = B_i + \sum_j W_j S_{ji} \tag{8}$$

Activation is the sum of two quantities. One is the word’s baseline activation B_i . Baseline activation, defined in Equation (9), is increased to a greater degree by recent retrievals at time t_j as compared to less recent retrievals that have decayed more. We follow standard practice in ACT-R in setting the decay rate d to 0.5; in virtually all ACT-R models, including the sentence-processing model of LV05 (p. 378), the decay parameter is set to this value (Anderson, 2005).

$$B_i = \ln \left(\sum_{j=1}^n t_j^{-d} \right) \tag{9}$$

One other factor affecting a word’s—or more generally a chunk’s—activation is known as SBI. Via the second addend in Equation (8), SBI can decrease a word’s activation when it is retrieved (e.g., to complete a dependency), if other words of the same grammatical category (hereafter, competitors) have already been parsed. In this term, W_j denotes weights associated with the retrieval cues j that are shared with these competitor words in memory, and S_{ji} symbolise the strengths of association between cues j and chunks i . The weights are not generally free parameters in ACT-R models but are set to G/j , where j is the number of cues involved during retrieval, and G is the total amount of goal activation available, also set by default to 1. The second part of the SBI equation, the strength of association S_{ji} , is computed as follows:

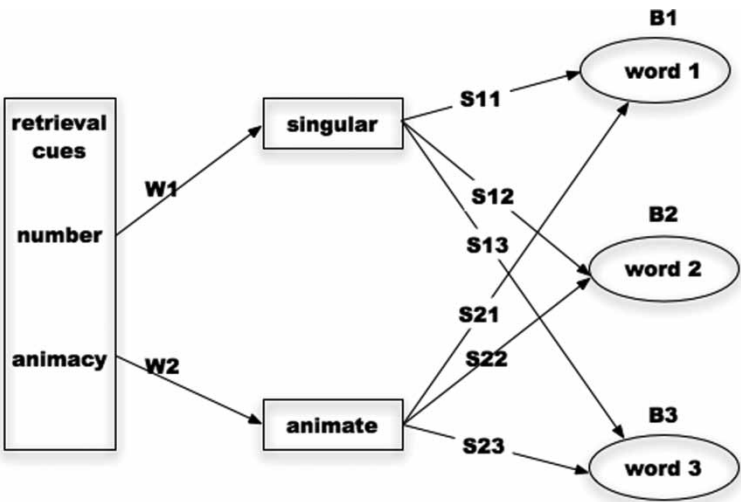


Figure B1. A schematic diagram illustrating how similarity-based interference works in ACT-R.

$$S_{ji} = S_{\max} - \ln(\text{fan}_j) \tag{10}$$

In Equation (10), fan_j identifies the number of words that have the same grammatical category as the cue j . These competitors are exactly the words sharing the same part-of-speech tag as the correct retrieval target i . The maximum degree of association between similar items in memory is S_{\max} which we set to 1.5 following LV05.

SBI as defined above is best explained with the help of a schematic example (Figure B1). Assume for illustrative purposes that a noun must be retrieved that has animacy status “animate” and number “singular”, and that there are three previously processed nouns in memory that have these features. Each of the three nouns has base-level activation B_1 – B_3 , respectively. Since three nouns are involved, the fan is three, which gives us for each j, i : $S_{ji} = 1.5 - \ln(3) = 1.5 - 1.098612 = 0.4013877$.

This in turn gives us $\sum_j W_j S_{ji} = \sum_j 0.5 \times 0.4013877 = \sum_j 0.2006939$.

Contrast this with the situation where the fan is 1 (only one noun matches the retrieval cues). In that case, $S_{ji} = 1.5 - 0 = 1.5$, and $\sum_j W_j S_{ji} = \sum_j 0.5 \times 1 = \sum_j 0.75$. In other words, activation of each noun would be lower when the fan (amount of interference) is higher. As discussed in the main text, in the present model, the only source of interference is part of speech.

At the other extreme, if the fan is high (5 or above), S_{ji} would be negative and net activation of a relevant item in memory could in principle become negative as well. The sign of the activation value is not the important thing here; rather, the important thing is the relative reduction in activation as a function of the fan. In ACT-R models, a retrieval threshold must be specified such that if the activation value of an item falls below this threshold, that item would fail to be retrieved from memory. LV05 set this value to -1.5 . In ACT-R, retrieval latency is an exponential function of activation. Equation (11) shows this relationship, which relates the temporal predictions we draw from the model to the theoretical quantity, activation. We follow LV05 in setting F to 0.14.

$$T_i = Fe^{-A_i} \tag{11}$$

Productions in ACT-R accrue a fixed cost of 50 ms to execute. In adapting the LV05 model to the Nivre operators, we assume that a production has fired if a dependency arc has been drawn or a new word has been shifted. An additional production-firing cost of 50 ms also accrues if a decision is made to retrieve an item. This reflects the architecture of ACT-R memory buffers.

The time taken to integrate a word into the analysis is thus a joint function of up to two productions firing, along with any time spent performing a retrieval. Table B1 summarises these time-costs. The REDUCE operation simply restructures a parser state and could, in principle, be dispensed with in favour of a much larger inventory of attachment actions. Like LV05, we abstract away from lexical retrieval costs and set the time it takes to read a word to just 1 ms.

TABLE B1
How time is determined in the parser

| <i>Transition</i> | <i>Time</i> |
|-------------------|--------------------------------|
| LEFT | 50 ms + 50 ms + retrieval time |
| RIGHT | 50 ms + 50 ms + retrieval time |
| SHIFT | 50 ms |
| REDUCE | 0 ms |

APPENDIX C: SURPRISAL AND PROBABILITY MODELS

This paper employs the term “surprisal” to evoke the idea that the difficulty of infrequent cognitive operations should scale logarithmically. By itself, this name does not entail a commitment to what those operations are, and in fact the literature on surprisal reflects considerable diversity on this point. Whereas Levy (2008) applies surprisal in conjunction with probabilistic context-free grammars, Demberg and Keller (2008) compute surprisals over a richer event space that can be directly related to Tree-Adjoining Grammar (Joshi, 2004).

This prior work is united with our own (Hale, 2001) in its reliance upon “joint” models of the word string along with its syntactic analysis. In contrast, the probability model used in this paper is a “conditional” model of the syntactic analysis given the word string. Theoretical work within computational linguistics continues to grapple with this distinction (Abney, McAllester, & Pereira, 1999; Nederhof & Satta, 2006). In certain cases, the two types of models are intertranslatable. However, the limit $k = \infty$, brought up by an anonymous reviewer and discussed in footnote 9, presents a case in which one kind of model would be meaningful whereas another would not be. The results we report do not bear on the choice between these two kinds of probability model, but rather on the role of controversial parameters, such as the amount of parallel processing, in adequate models of human sentence comprehension.

To substantiate this assertion, we re-ran the simulations discussed in the main text using an alternative parsing mechanism based on a simple generative model. Following Titov and Henderson (2007), this alternative probability model explicitly rates the likelihood of shifting every in-vocabulary word at each incremental state. The joint probability of a string and its dependency graph is then the product of the operator-application probabilities used to build the given graph in a canonical way. Using this generative probability model to again derive both surprisal and retrieval-based comprehension difficulty predictions, we find essentially the same pattern among the fitted coefficients as in Figure 10. The sole exception to this pattern is in regression probability, which does not display much of a systematic pattern at all. We believe this reflects the lower parsing accuracy one would expect from a probabilistic classifier that is being asked to account both for the probability of strings and their analyses. While the two models thus differ in accuracy level, on the fixation duration data they derive the same result: that retrieval becomes a useful predictor of fixation durations when given enough parallel processing, whereas surprisal is useful even in serial processing.

APPENDIX D: PARAMETRIC BOOTSTRAP

Shown below is an illustration of the parametric bootstrap method used to confirm that the models with surprisal and retrieval provide better fits to the data than the baseline models. For illustrative purposes, we show the comparison procedure for SFDs; we carried out the procedure for all reading time measures, however. To our knowledge, currently the R function for simulation does not work for generalised linear mixed models; therefore, we did not run the bootstrap on the REG models.

In the parametric bootstrap, the simpler model is treated as the null hypothesis, and the more complex model as the alternative hypothesis. Then, simulated dependent values (e.g., log reading time) are repeatedly generated from the null hypothesis model, and the simpler and more complex models are fit to the simulated data (as opposed to the actual data). After each simulation run, two times the difference of the log-likelihood ($2 \times \Delta \text{LogLik}$) between the simpler and more complex models is recorded. After n simulations, this yields $n \times 2 \times \Delta \text{LogLik}$ values, which constitute a distribution of log-likelihoods. The final step is to compute the proportion of cases in the n simulations where the simulated $2 \times \Delta \text{LogLik}$ is greater than the observed $2 \times \Delta \text{LogLik}$; this amounts to the probability of obtaining the observed $2 \times \Delta \text{LogLik}$, or a value greater than that, assuming that the null hypothesis is true. The R code for such simulations is shown below.


```
## null hypothesis:
```

```
sfd.0 <- lmer(log(SFD) ~ scale(log_freq,scale = F) + scale(len,scale = F) +
              scale(bigram,scale = F) +
              scale(logitpred,scale = F) +
              (1|sn)+(1|id), d.sfd,
              REML = FALSE)
```

```
## alternative hypothesis:
```

```
sfd.1 <- lmer(log(SFD) ~ scale(log_freq,scale = F) +
              scale(len,scale = F) + scale(bigram,scale = F) +
              scale(logitpred,scale = F) +
              scale(surprisalDep,scale = F) +
              (1|sn)+(1|id), d.sfd,
              REML = FALSE)
```

```
## parametric bootstrap:
```

```
nrep <- 1000
lrstat <- numeric(nrep)
```

```
## simulated data from null hypothesis:
```

```
for(i in 1:nrep)
{
  simulated <- unlist(simulate(sfd.0))
  alt <- lmer(simulated ~ scale(log_freq,scale = F) + scale(len,scale = F) +
              scale(bigram,scale = F) +
              scale(logitpred,scale = F) +
              scale(surprisalDep,scale = F) +
              (1|sn)+(1|id), d.sfd,
              REML = FALSE)
  null <- lmer(simulated ~ scale(log_freq,scale = F) + scale(len,scale = F) +
              scale(bigram,scale = F) +
              scale(logitpred,scale = F) +
              (1|sn)+(1|id), d.sfd,
              REML = FALSE)
  lrstat[i] <- 2*(logLik(alt)-logLik(null))
}
```

```
## critical value
```

```
critical <- 2*(logLik(sfd.1)-logLik(sfd.0))
```

```
## probability of observing the critical value or greater
```

```
## assuming the null hypothesis is true:
```

```
mean(lrstat > critical)
```

APPENDIX E: DEPENDENCY DISTANCE IN THE PSC

The PSC dependencies range in distance from one to seven. Figure E5 depicts the Zipfian distribution of these dependency lengths; the majority are relatively short, though there are 14 dependencies that span seven words.

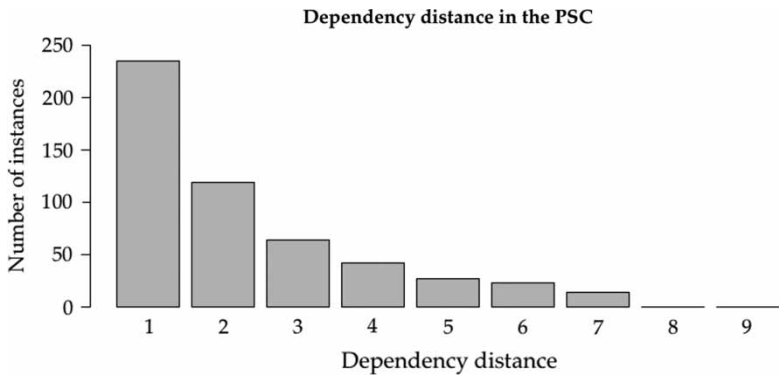


Figure E5. Dependency distance follows a Zipfian distribution.