

Multipath parsing in the brain

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Abstract

Humans understand sentences word-by-word, in the order that they hear them. This incrementality entails resolving temporary ambiguities about syntactic relationships. We investigate how humans process these syntactic ambiguities by correlating predictions from incremental generative dependency parsers with time-course data from people undergoing functional neuroimaging while listening to an audiobook. In particular, we compare competing hypotheses regarding the number of developing syntactic analyses in play during word-by-word comprehension: one vs more than one. This comparison involves evaluating syntactic surprisal from a state-of-the-art dependency parser with LLM-adapted encodings against an existing fMRI dataset. In both English and Chinese data, we find evidence for multipath parsing. Brain regions associated with this multipath effect include bilateral superior temporal gyrus.

1 Introduction

A major unsolved problem in computational psycholinguistics is determining whether human sentence comprehension considers a *single* analysis path¹ at a time, or whether it sometimes entertains *multiple* lines of reasoning about the structure of a sentence. These lines of reasoning typically correspond to syntactic ambiguities (e.g. between Subject and Modifier as shown in Figure 1). Multipath accounts of ambiguity resolution (e.g. Gibson, 1991; Jurafsky, 1996) are quite different from single-path accounts (e.g. Frazier and Fodor, 1978; Marcus, 1980). The debate within cognitive science has focused on the special case of garden path sentences leaving open the broader question: Is human comprehension ever multipath in the sense of Ranked Parallel parsing? If it is, where in the brain does such multipath parsing happen?

¹The “paths” terminology (vs “serial” or “parallel”) serves to categorize the cognitive issue as one of process rather than architecture (see Lewis, 2000b, §3.3.3).



Figure 1: A sentence fragment from our stimulus text showing temporary syntactic ambiguity about the correct relationship between *The* and *desert*, which is resolved by hearing the next word (blue).

We take up the call to answer this question (e.g. Lewis, 2000a; Gibson and Pearlmuter, 2000) by combining broad coverage incremental parsing (e.g. Nivre, 2004) with information-theoretical complexity metrics to derive predictions about neuroimaging. Analyzing an entire book (Li et al., 2022) makes it possible to examine – for the first time – all of the ambiguities that are implicated by a given conception of syntax and a given parsing strategy – not just those attested in classic garden path materials (Mason et al., 2003; Hopf et al., 2003; Rodd et al., 2010).

We extend the state of the art in incremental generative dependency parsing by using a large language model (BLOOM; Le Scao et al., 2022b) together with parameter efficient fine-tuning using adapters (Pfeiffer et al., 2020). We fix the parsing strategy while varying the number of allowable analysis paths and connect neural data with parser actions via surprisal (for a review of this information-theoretical metric see Hale, 2016 or neuroimaging studies such as Brennan et al., 2016; Henderson et al., 2016; Shain et al., 2020; Brennan et al., 2020). This sets up a contrast between a multipath model that considers (at most) five paths at a time, versus a single-path model that can only consider one at a time. The results, reported in section 5, ultimately support the multipath view, as the surprisals from the five-way parser are better-correlated with the neuroimaging data. This obtains for both English and Chinese.

Action	Before	After	Arc	Probability
Shift	$(\sigma i, j)$	$(\sigma i j, j + 1)$	-	$p_{tr}(\text{sh} h_i, h_j)p_{gen}(w_{j+1} h_i, h_j)$
Left-arc	$(\sigma i, j)$	(σ, j)	$j \rightarrow i$	$p_{tr}(\text{re} h_i, h_j)p_{dir}(\text{la} h_i, h_j)$
Right-arc	$(\sigma l i, j)$	$(\sigma l, j)$	$l \rightarrow i$	$p_{tr}(\text{re} h_i, h_j)p_{dir}(\text{ra} h_i, h_j)$

Table 1: The arc-hybrid transition system of Kuhlmann et al. (2011) defines the possible parser actions (shift, left-arc, and right-arc) as transitions from previous to current parser states. States are indicated by (stack, current index) tuples, e.g. w_i is the token on top of the stack (σ), and w_j is the current index token at time step j . The probabilities associated with these actions are decomposed into complementary shift (sh) and reduce (re) transitions, and complementary left-arc (la) and right-arc (ra) arc directions. The shift action also includes the probability of generating the next token w_{j+1} .

2 Related Work

This paper follows a line of research which aims to characterize human language processing by evaluating word-by-word difficulty predictions against neuroimaging data from the brain. Hale et al. (2022) reviews many studies that fit into this tradition. Most of them consider just a single gold standard or single system-assigned analysis. Hale et al. (2018) and Crabbé et al. (2019) are notable exceptions to this general trend because they derive predictions from multiple analyses that would be considered as part of a beam. Hale and Crabbé work with phrase structure. By contrast, the present study uses dependency parsing. This choice is motivated by prior work in neurolinguistics (e.g. Bornkessel-Schlesewsky and Schlewsky, 2015). For instance, Li and Hale (2019) relate a dependency-based structural distance metric to hemodynamic activity in left posterior temporal lobe, among other brain areas. Their study used spoken English materials. Lopopolo et al. (2021) apply a related metric to Dutch. Oota et al. (2023) use graph neural networks to embed dependency analyses of sentence-initial substrings. Analyzing brain responses to written, rather than spoken stimuli, via the encoding approach of Reddy and Wehbe (2021), Oota et al. identify many of the same brain areas as the studies mentioned above.

The single-path vs multipath question is itself motivated by prior work with eyetracking data. By varying the number of paths available to a parser, Boston et al. (2011) find support for Ranked Parallel parsing (in the sense of Gibson 1991 and Jurafsky 1996, further characterized below in §3.4).

Apart from these cognitive considerations, a complementary motivation for this research is to investigate the parsing improvements that come by leveraging large language models (LLMs; see accuracy scores in Table 2). Such models are trained

on datasets that far exceed classic treebanks in size. This allows LLMs to capture distributional regularities at a vast scale. However, it is challenging to explain at an algorithmic level what these models are doing.

Instead of deriving a processing complexity metric directly from the output of a large language model, or correlating LLM internal representations with fMRI data, as in Schrimpf et al. (2021) and Caucheteux and King (2022), this work uses initial substring encodings from an LLM to inform an incremental parser. Our project also differs from Eisape et al. (2022), who probe LLM representations with a view towards inferring a single, unlabelled dependency analysis. In contrast, we use LLM representations to score the set of all possible alternative analyses. Our scientific goal is to relate such parser states to human brain states, as observed via neuroimaging.

3 Dependency Parsing

3.1 Parser Architecture

The construction of our dependency parser relies on the work of Buys and Blunsom (2018), which employs the transition-based parsing system detailed in Nivre (2008) and exactly enumerates all parser paths. Following Kuhlmann et al. (2011), dynamic programming is used to sum over all paths. We use the arc-hybrid transition system shown in Table 1 because it showed good parsing performance in Buys and Blunsom (2018). The generative parser assigns a probability to each of the words in the sentence incrementally, like any other language model, in contrast to discriminative parsers which only predict transition actions. The *shift* action predicts the next word on the buffer, which corresponds to the *buffer-next* model in Buys and Blunsom (2018).

We update Buys and Blunsom by encoding sequences not with an LSTM but with representations

from the BigScience Large Open-science Open-access Multilingual Language Model (BLOOM; Le Scao et al., 2022b), chosen based on its open-access status and training on both English and Chinese data. These BLOOM representations encode an entire initial substring up to and including a particular word (or subword token). A set of classifiers over these substring representations estimates the probability of each transition, word and arc label. The classifiers correspond to the subscripted probabilities in the rightmost column of Table 1.

We use the pre-trained BLOOM-560 model. Larger BLOOM models showed no significant increase in accuracy. This corroborates Oh and Schuler (2023) and Pasquiou et al. (2023), who find that smaller models provide an equal (or better) fit to human data.

Instead of fine-tuning the entire pre-trained BLOOM model on dependency parsing, we apply a Pfeiffer adapter after each layer (Pfeiffer et al., 2020). This bottleneck adapter introduces a new linear layer which reduces the dimension from 1024 down to 64 and back up to 1024, for input into the next pre-trained BLOOM layer. The adapter approach enables parameter-efficient fine-tuning while preserving the original language modelling representations as much as possible in the generative parser.

The goal of these design choices is to deliver linguistically plausible dependency analyses of sentence-initial substrings. Some aspects of the overall architecture play the role of auxiliary hypotheses that do not map on to the brain. As subsection 3.5 lays out in further detail, the cognitive claim is limited to proposals that (a) human parsing involves recognizing dependency relations via a schema like Table 1 and (b) surprising parser actions, within this schema, call for greater hemodynamic resources than do unsurprising ones. Proposal (a) is situated at Marr’s middle level of analysis (Marr, 1982).

3.2 Parser Training

The parser is trained on English and Chinese treebanks annotated with Stanford Dependencies (De Marneffe and Manning, 2008). The English model is trained on the Penn Treebank (PTB) version 3, with the standard split of training on sections 02-21, development on section 22, and testing on section 23. The Chinese model is trained on Chinese Treebank version 7, with the standard split

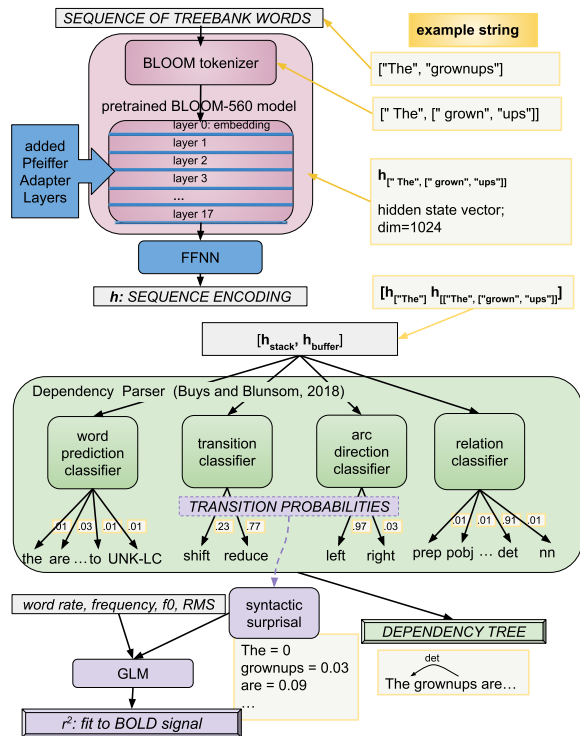


Figure 2: Pipeline Overview: Pretokenized text from the treebank corpora is pre-processed by adding a leading space to each token. The pre-trained BLOOM model is fine-tuned using the Pfeiffer Adapter, and an additional single-layer feedforward neural network completes the encoding step. The dependency parser takes tuples of sequence encodings (stack (σ), buffer (β)) as input, and its system of classifiers is trained from random weights. Note that the word prediction classifier predicts over the size of the training data vocabulary + Berkeley unknown tokens instead of the BLOOM vocabulary. The final dependency tree output is evaluated in Table 2. After training, we use the parser’s transition probabilities (see Table 1) to calculate syntactic surprisal (Section 3.5), which is added to other regressors (see Section 4.4), in a General Linear Model (GLM) which predicts BOLD signal (Section 5).

of files 0-2082 for training, development on files 2083-2242, and testing on files 2243-2447. This results in 39,832 training sentences for English and 19,457 training sentences for Chinese.

The parser’s next word prediction classifier predicts over a limited vocabulary, where words seen only once in the training data are replaced with unknown word tokens according to the rules in the Berkeley Parser. This results in 23,830 word types for English and 19,671 for Chinese. The LLM encoder, however, uses the BLOOM sub-word tokenizer and the BLOOM vocabulary, which is of size 250,680.²

²This vocabulary size mismatch is one reason we did not directly assign next-word probabilities using the LLM.

Corpus	Model	Dev		Test	
		LAS	UAS	LAS	UAS
PTB-3	Byus and Blunsom (2018)	88.66	91.19	88.54	91.01
PTB-3	English BLOOM (brain analysis)	90.26	92.71	90.32	92.62
CTB-7	Chinese BLOOM (brain analysis)	77.07	83.65	74.71	81.66

Table 2: Labeled attachment score (LAS) and unlabeled attachment score (UAS) for the English PTB corpus and Chinese CTB corpus

Token sequences are encoded by the LLM, selecting the encoding of the right-most sub-word of each word for parser predictions. This allows sequence encodings to be as detailed as possible while still limiting the vocabulary during training. It should be noted, though, that using this encoding for words that are unknown to the parser’s next word classifier prevents the parser from being strictly generative. More information on strictly generative models can be found in the appendix.

While training, sentences are shuffled at each epoch, and within batches (batch size = 16), which are created from sentences of the same length. The BLOOM-560 model has 24 hidden layers, after encoding.

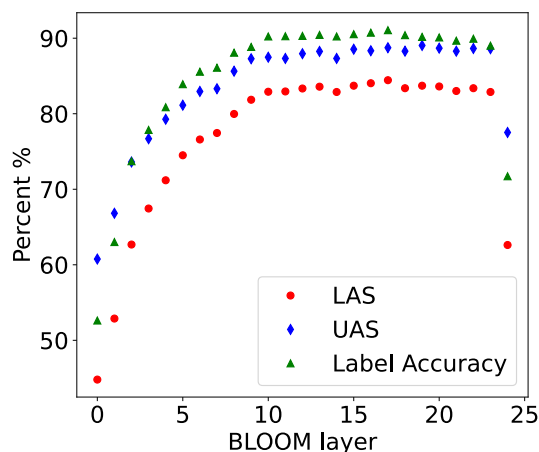


Figure 3: Labeled Accuracy Score (LAS), Unlabeled Accuracy Score (UAS), Label Accuracy for our parser trained and evaluated (dev set) on the Universal Dependencies ParTUT corpus. Each model uses a different BLOOM layer as a sequence encoder.

We select the 17th layer as the representation to input into the model, which was decided based on optimization of development set accuracy on the ParTUT Universal Dependencies corpus (De Marnette et al., 2021). We use this smaller corpus (2,090 sentences) in order to conserve resources when investigating the utility of BLOOM represen-

tations for dependency parsing. As seen in Figure 3, BLOOM layers 10 to 17 have similar accuracy levels. It is possible that more extensive optimization of this layer choice might provide small improvements in accuracy beyond that reported in Table 2. Further training hyperparameters can be found in the Appendix.

3.3 Parser Accuracy

Cognitively plausible parsers must be incremental, in the sense that they must not use information about as-yet-unprocessed words occurring later in the sentence. We compare the accuracy of the incremental generative parser proposed here to that of Byus and Blunsom (2018), which employs the same transition system with encodings based on an LSTM with random initial weights.

Parser accuracy is evaluated on the development set after each epoch, and the highest scoring epoch is reported in Table 2. However, the cognitive modeling results reported in Section 5 rely on earlier training checkpoints. The epoch is chosen by maximizing r^2 correlation with the fMRI data. The labeled attachment score and unlabeled attachment score (LAS/UAS) for the epochs chosen are 89.75/92.37 for English, and 77.06/83.59 for Chinese. We find that the objective of obtaining minimal loss does not correspond to optimal correlation with fMRI activity.

3.4 Multiple paths

Multipath parsing, as a psycholinguistic claim about human sentence comprehension, is simply the idea that ambiguity-resolution pursues more than one alternative at the same time. This contrasts with Frazier and Fodor’s (1978) conception, in which a single parse is developed along one path. We consider here a version of the multipath idea that Kurtzman (1984) calls “strong” parallelism, in which paths can persist from word to word. Gorell (1987) emphasizes that multiple alternatives are not equally available (page 84). This is naturally formalized by ranking the paths. Such ranking

can be implemented with beam search, at the heart of parsing systems like [Roark \(2001\)](#), which is widely applied in computational psycholinguistics and neurolinguistics.

3.5 Complexity Metric

In order to correlate parser predictions with brain activity, and in particular to take multiple parser paths into consideration, those predictions must somehow be summarized and quantified. One way to do that is via the surprisal complexity metric, revived by [Hale \(2001\)](#) as a method of predicting sentence-processing difficulty word-by-word. The basic formula is the logarithm of the reciprocal of a probability.

$$\log_2 \left(\frac{1}{p(y)} \right) = -\log_2(p(y)) \quad (1)$$

In Equation 1, $p(y)$ denotes the probability of an arbitrary outcome y . In incremental sentence comprehension the relevant outcomes are words. The surprisal of a word at position w_i which follows a string ending in w_{i-1} , is a ratio of the probability at the current word with the previous probability:

$$-\log_2 \left(\frac{p(w_i, w_{i-1}, \dots, w_1)}{p(w_{i-1}, \dots, w_1)} \right) \quad (2)$$

3.5.1 Syntactic Surprisal

Word probabilities, denoted p_{gen} in Table 1, are affected by nonsyntactic factors. As Figure 4 shows, these nonsyntactic factors can overshadow the difference between syntactic alternatives. For this reason, we follow [Roark et al. \(2009\)](#) in decomposing surprisal into lexical and syntactic expectations. Discarding lexical expectations, we focus exclusively on differences among competing syntactic analyses by adopting their *syntactic surprisal* measure, given below as Equation 3. Syntactic surprisal does not consider word probability at the current time step (i), but the complete path probability is used in the denominator ($i - 1$) to ensure that the correct path is selected.

In addition, we limit the sum to the top k transition sequences. Here, j indexes discrete ranks of a ranked parallel parser, and $t_{a(i)}$ refers to all the parser transitions in the path that ends at generation of token w_i . At each time step i , $t_{a(i)}$ includes 1 shift transition, and zero to many possible reduce transitions.

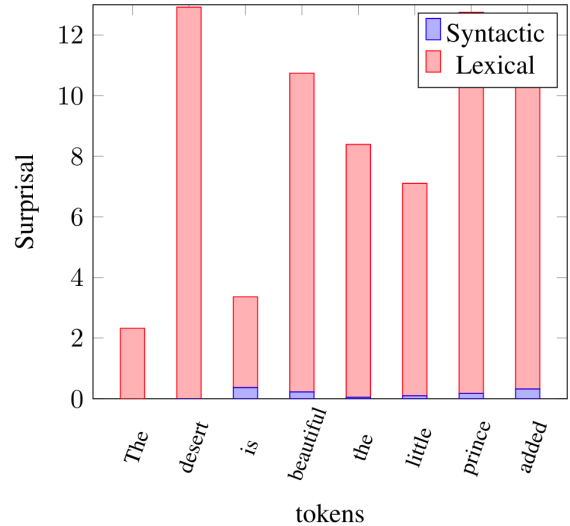


Figure 4: A sentence from *The Little Prince*, showing incremental surprisal from joint probability decomposed into lexical (red), and syntactic surprisal (blue)

$$\text{SynS}_k(w_i) = -\log_2 \frac{\sum_{j=1}^k p(t_{a(i)} \dots t_{a(1)} | w_{i-1} \dots w_1)_j}{\sum_{j=1}^k p(t_{a(i-1)} \dots t_{a(1)} | w_{i-1} \dots w_1)_j} \quad (3)$$

In Equation 3, syntactic surprisal is parameterized by a maximum number of allowable analysis paths, k . Figure 5 elaborates an example calculation using this definition.

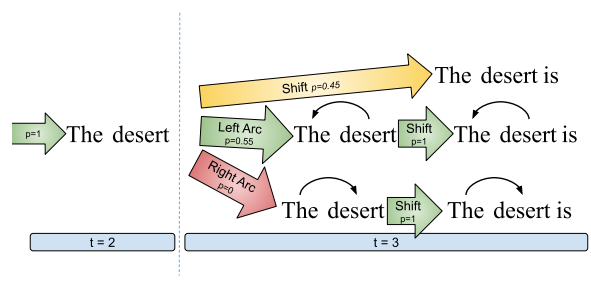


Figure 5: A sentence fragment from *The Little Prince* showing shift-reduce parser actions with associated probabilities. Word generation probabilities are not shown here, but would be included in the full path calculation. In this example, the syntactic surprisal at time $t = 3$ is $-\log_2(0.55/1) = 0.86$ for $k=1$, and for $k=2$ the top two paths are added: $-\log((0.55+0.45)/1) = 0$.

The limitation to k paths in Equation 3 follows [Boston et al. \(2011\)](#). Unlike [Boston et al.](#), we retain all analyses and simply chose the top k at each successive word. This allows paths that would have been lost forever in true beam search to later rejoin

the beam. Such restoration has essentially the same effect as backtracking, in cases where it would lead to a higher-scoring analyses. “Reanalysis” of this sort could be helpful in modeling the comprehension of garden-path sentences (see e.g. Fodor and Ferreira, 1998).

3.5.2 Why Five Paths?

Addressing the single-path vs multipath question entails choosing some number of paths, k to represent multipath parsing in general. Empirical literature such as Gibson and Pearlmutter (2000) has been primarily concerned with the distinction between 1 and 2 paths. By contrast, accurate NLP systems sometimes consider tens or even hundreds of paths.³ This mismatch calls for a setting of k that is small, but clearly different from 1. The syntactic surprisal metric itself also mitigates against settings of k that are too large. With this metric, more ranks quickly eat up the available probability mass, up to 1.0, when considering all possible paths. In this limiting case syntactic surprisal would trivially equal zero for all tokens (see Figure 6). For these reasons, we selected five paths to contrast with single-path parsing.⁴

4 fMRI Methods

4.1 Participants

As detailed in Li et al. (2022), the English dataset includes 49 participants (30 female, mean age = 21.3, range = 18-37), and the Chinese dataset includes 35 participants (15 female, mean age = 19.9, range = 18-24).

4.2 Data Acquisition

The English audio stimulus is an English translation of *The Little Prince*, read by Karen Savage. The Chinese audio stimulus is a Chinese translation of *The Little Prince*, read by a professional

³Many of these paths lead to similar syntactic structures. Grouping them in a cognitively realistic way brings up foundational questions regarding the mental representation of grammatical relations (see Bresnan and Kaplan 1982, Sturt 1996, and §4.4 of Brasoveanu and Dotlačil 2020, among others). These questions, along with the proper formulation of reanalysis or repair operations (e.g. Lewis, 1992; Buch-Kromann, 2004) are important directions for future work.

⁴This goal of this study is to adjudicate between single-path and multipath parsing. This question has remained open within the literature on human sentence processing for quite some time. An alternative approach seeks to maximize correlations with fMRI data by e.g. searching for the optimal number of paths. This suggests a natural follow-up.

female Chinese broadcaster. The English and Chinese audiobooks are 94 and 99 minutes in length, respectively. The presentations were divided into nine sections, each lasting around ten minutes. Participants listened passively to the nine sections and completed four quiz questions after each section (36 questions in total). These questions were used to confirm participant comprehension of the story.

The English and Chinese brain imaging data were acquired with a 3T MRI GE Discovery MR750 scanner with a 32-channel head coil. Anatomical scans were acquired using a T1-weighted volumetric magnetization prepared rapid gradient-echo pulse sequence. Blood-oxygen-level-dependent (BOLD) functional scans were acquired using a multi-echo planar imaging sequence with online reconstruction (TR = 2000 ms; TE's = 12.8, 27.5, 43 ms; FA = 77°; matrix size = 72 x 72; FOV = 240.0 mm x 240.0 mm; 2x image acceleration; 33 axial slices, voxel size = 3.75 x 3.75 x 3.8 mm).

4.3 Data Preprocessing

The English and Chinese fMRI data were preprocessed using AFNI version 16 (Cox, 1996). The first 4 volumes in each run were excluded from analyses to allow for T1-equilibration effects. Multi-echo independent components analysis (MEICA), was used to denoise data for motion, physiology, and scanner artifacts (Kundu et al., 2012). Images were then spatially normalized to the standard space of the Montreal Neurological Institute (MNI) atlas, yielding a volumetric time series resampled at 2 mm cubic voxels.

4.4 Statistical Analysis

The goal of the analysis is to compare surprisal values from single-path and multipath parsers against the same observed fMRI timecourses. We follow Crabbé et al. (2019) in evaluating goodness of fit pairwise using cross-validated coefficient of determination (r^2) maps.

For each subject individually, the fMRI BOLD signal is modeled by a General Linear Model (GLM) at each voxel. The following five regressors are included in the GLM: word rate, fundamental frequency (f_0), word frequency, root mean square intensity (RMS), and syntactic surprisal of the top k paths. Word rate is a timing function marking the offset of each spoken word; f_0 is the fundamental frequency, or pitch of the audio; word frequency is obtained from words in a movie subtitles database (Brybaert and New,

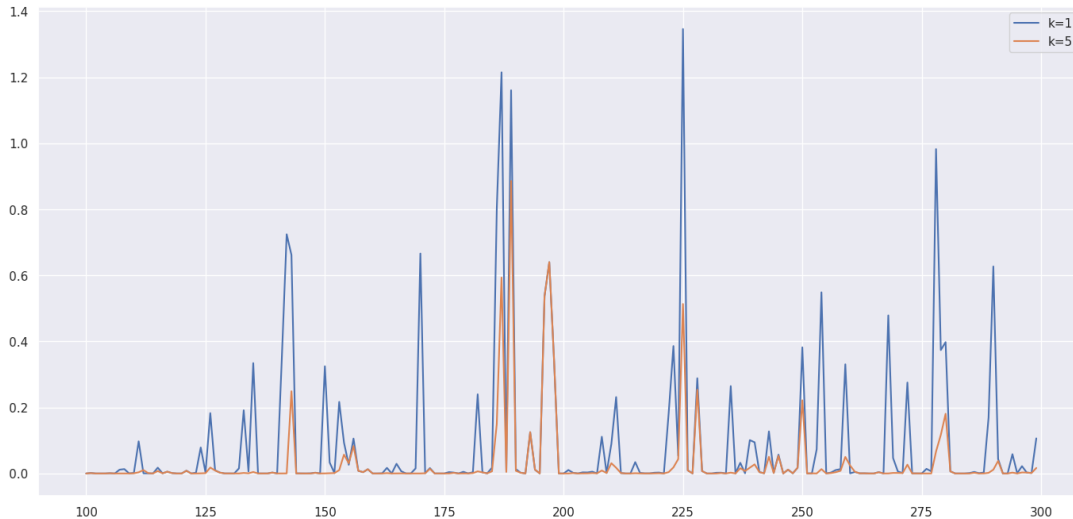


Figure 6: Syntactic surprisal at $k = 1$ (blue) and $k = 5$ (orange) for tokens in *The Little Prince*

2009); and RMS is an indicator of audio intensity, taken every 10ms. These predictors are known to affect speech comprehension, and are included as control variables to help isolate variance within the BOLD signal that is specific to syntactic processing.

Syntactic surprisal for each word was also aligned to the offset of each word in the audiobook. All predictors were convolved using SPM’s canonical Hemodynamic Response Function (Friston et al., 2007).

For each participant, we compute how much the inclusion of the syntactic surprisal regressor increases the cross-validated r^2 over the baseline model, which includes only control variables. We repeat this process for syntactic surprisal at different levels of k separately in order to keep the number of parameters in each GLM model constant. Therefore, the r^2 increase scores represent the variance explained in each voxel by the addition of syntactic surprisal to the model as a predictor.

To compare models across two different levels of k and analyze their ability to explain the fMRI BOLD signal, we performed a paired t-test on individual r^2 increase maps to obtain z-maps. These z-maps show where syntactic surprisal from a model with a given number of paths explains the signal significantly better than does a model that incorporates a different number of paths (see Figures 7 and 8).

5 Results

Both English and Chinese paired t-tests on r^2 increase maps show differences in the superior tempo-

ral gyrus (STG). The Chinese results further show differences in middle temporal gyrus (MTG), while the English results show differences in the parietal lobe, including bilateral angular gyrus. The full list of statistically significant clusters corresponding to Figures 7 and 8 can be found in the Appendix. Although the paired t-tests were two-tailed, all of the resulting significant clusters show greater r^2 increase for syntactic surprisal at $k = 5$ than at $k = 1$. The r^2 increase maps for each model individually can be found in the Appendix.

6 Discussion

Multipath parsing effort, outside of the 1-best analysis, localizes to superior temporal regions of the brain bilaterally in both English and Chinese. This finding converges with Crabbé et al. (2019). Crabbé and colleagues parse phrase structure, rather than dependencies, employ a different complexity metric, and use a very large beam (400). Despite all these differences, their results implicate roughly the same brain regions.

These results also cohere with proposals regarding the large-scale organization of language processing in the brain. On the Neuroanatomical Pathway model, for instance, “most basic syntactic processes” are handled by a ventral pathway that passes through STG regions identified here (Friederici, 2015). Matchin and Hickok (2020) similarly point to the ventral pathway as essential for “basic” syntactic processes. This heuristic notion of basic syntactic processing aligns well with Stanford Dependencies’ avowed goal of providing a simple, surface-oriented notation for local gram-

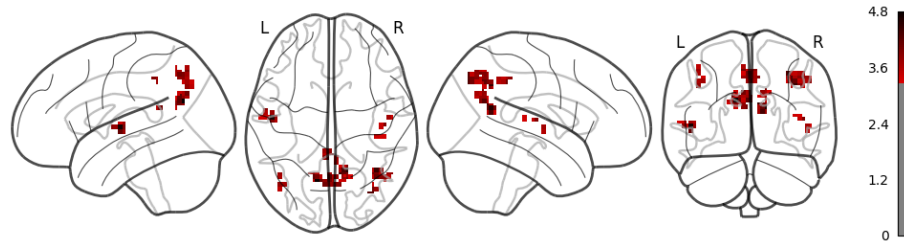


Figure 7: English Brain z-maps showing the significant clusters ($p < .001$ uncorrected; cluster threshold = 15 voxels) for the model comparison between syntactic surprisal at $k = 1$ vs $k = 5$. All significant clusters show greater r^2 increase for surprisal at $k = 5$ than for surprisal at $k = 1$.

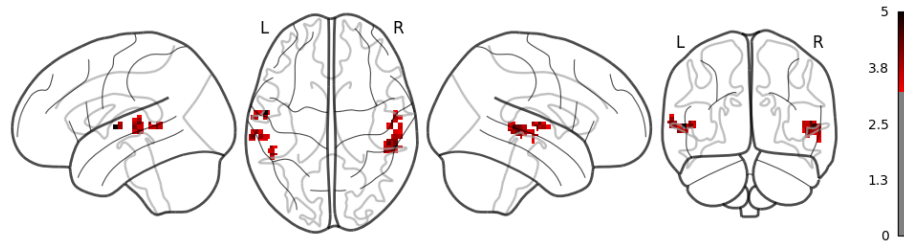


Figure 8: Chinese Brain z-maps showing the significant clusters ($p < .001$ uncorrected; cluster threshold = 15 voxels) for the model comparison between syntactic surprisal at $k = 1$ vs $k = 5$. All significant clusters show greater r^2 increase for surprisal at $k = 5$ than for surprisal at $k = 1$.

matical relations.

The present results do not identify a significant difference in r^2 increase in Broca’s area (left IFG). Some increase in r^2 can be seen, however, in middle and IFG in the individual model maps shown in the Appendix. The absence of a significant difference, however makes sense in light of two considerations. The first is the idea that left IFG subserves reanalysis in the face of misinterpretation (Novick et al., 2005). The second is the literary style of the *The Little Prince*. The stimulus text is dissimilar to the sorts of garden-path materials psycholinguists have used (see e.g. Sedivy 2019, chapter 9 or Fernández and Cairns 2010, chapter 7). It seems likely that any garden-pathing was mild, remaining below the level of conscious awareness. This distinction between misinterpretations that rise to the level of conscious awareness and those that do not could help reconcile these results with earlier studies showing IFG activation in response to garden path stimuli (e.g. Mason et al., 2003; Rodd et al., 2010). For instance, Jäger et al. (2015) suggests that Chinese relative clauses involve as many as four temporary ambiguities. To our knowledge none of these reach the level of conscious awareness in everyday comprehension. Yet in a naturalistic fMRI study, Dunagan et al. (2022) observe activation in anterior and middle STG that is specific to Chinese object-extracted relative clauses. This contrast was not

reliable in a statistical comparison between English and Chinese. Further work is needed to chart the space between unproblematic ambiguities (Lewis, 1993, §2.4.2) and conscious misinterpretations engendered by syntactic ambiguity. These STG results include activation in the primary auditory cortex, which could suggest, in line with the sensory hypothesis (Dikker et al., 2009), that expectations based on earlier syntactic processing first impact regions involved in low-level sensory processing. This possibility could be examined in a followup fMRI study with written or signed materials, along the lines of Henderson et al. (2016).

7 Conclusion and Future Work

The main conclusion is that human parsing is multipath. This follows from observing greater r^2 increase for multipath surprisal than single-path surprisal in fMRI data. Even with a very bottom-up strategy, such as the arc-hybrid system used here, it seems that more than one path must be pursued in order to best-align with humans’ word-by-word effort profile. This conclusion is consistent with disjunctive representations of choices such as PP attachment (Kitaev et al., 2022, §5.5).

The multipath interpretation that we offer here can be confirmed or refuted with other linked linguistic and neuro-cognitive databases – for in-

stance, in different genres or languages. In addition, using brain data with a higher temporal resolution, such as MEG, may provide a benefit given the temporary nature of the syntactic ambiguities included in our model. Although we take the primary finding to be one of commonality across STG regions in both languages, English listeners did uniquely show an additional effect of multipath parsing in parietal regions. Activation in this area has been correlated with measures of human memory such as digit span (Meyer et al., 2012). Individuals' memory span may modulate the number of paths that they pursue during comprehension (Vos et al., 2001; Prat and Just, 2010). Future work should address the interaction between disambiguation and memory (e.g. Campanelli et al., 2018).

Limitations

The goal of correlating parser states with fMRI data is limited by the particularities of the parsing system – namely the arc-hybrid transition system and the limited size and content of the training data (which is dissimilar in genre to the audiobook text we study). In addition, the English results in particular are the result of careful model selection to limit “training away” the syntactic ambiguity we would like to measure. This may indicate that more formalized external limitations should be applied to modern high-performing parsers should they be used to model human sentence processing.

Ethics

Language models pose risks when used outside of their intended scope. We use BLOOM, which is publicly available under the Responsible AI License (RAIL) (Le Scao et al., 2022a). Our scientific enquiry falls within the intended use of public research on LLMs. We also use a publicly available fMRI dataset (Li et al., 2022), which is available under a CCO license. This dataset was anonymized to remove identifying facial features before publication.

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A Appendix

A.1 Generative Models

As noted in Section 3.2, we use BLOOM’s tokenizer to encode all tokens. Since some of these tokens are not found in the training data, and thus are unknown to the parser’s next word prediction classifier, this prevents our parser from being strictly generative.

As a comparison, we train additional models which are truly generative by replacing tokens not seen in the training data with unknown tokens in the encoder input, in the same way as the word prediction classes are defined. We report the accuracy for this *generative* approach alongside the previously defined *full input* model in Table 3. This distinction is also explained in Figure 9 for an example prefix string.

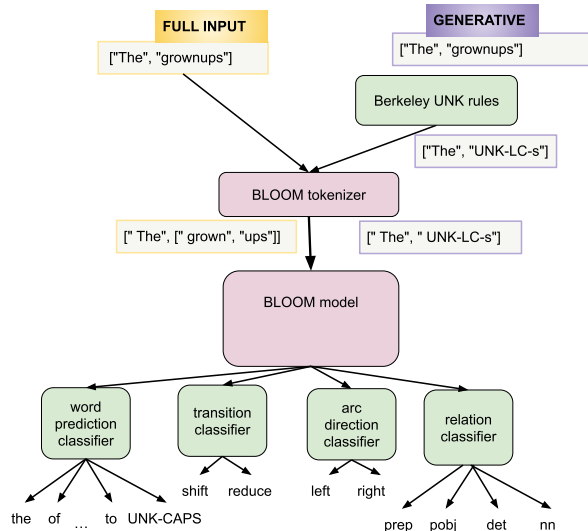


Figure 9: Parser input is pre-processed according to the given method: *Full Input* indicates no pre-processing apart from adding a leading space to all pretokenized text from the corpus. *Generative* indicates tokens are preprocessed by replacing tokens not seen more than once in the training data with unknown tokens according to the rules of the Berkeley Parser. The BLOOM model and the system of classifiers used to output probabilities is the same for both models. Note that the word prediction classifier predicts over the size of the training data vocabulary + Berkeley unknown tokens for both methods.

Corpus	Model	Dev		Test	
		LAS	UAS	LAS	UAS
PTB-3	Byus and Blunsom (2018)	88.66	91.19	88.54	91.01
PTB-3	English BLOOM Generative	89.27	92.00	90.53	92.68
PTB-3	English BLOOM Full Input (brain analysis)	90.26	92.71	90.32	92.62
CTB-7	Chinese BLOOM Generative	73.12	80.60	74.47	81.60
CTB-7	Chinese BLOOM Full Input (brain analysis)	77.07	83.65	74.71	81.66

Table 3: Labeled attachment score (LAS) and unlabeled attachment score (UAS) for the English PTB corpus and Chinese CTB corpus

A.2 Parser Training

The output representation from the BLOOM model has a dropout of 0.5 applied, and is then fed into a single layer feedforward neural network.

During training, gradient norms are clipped to 5.0, and the initial learning rate is 1.0, with a decay factor of 1.7 applied every epoch after the initial 6 epochs. English and Chinese models train for approximately 5.5 and 4.5 minutes, respectively, per epoch on an A100 GPU.

A.3 Intermediate Results

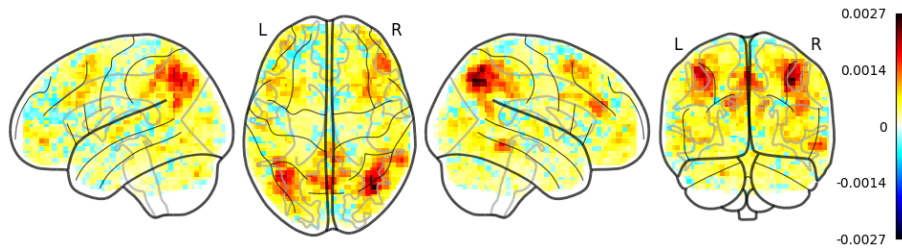


Figure 10: English Brain z-maps showing the r^2 increase for the model including syntactic surprisal at $k = 5$ compared to the model including only the following regressors: word rate, fundamental frequency (f_0), word frequency, and root mean square intensity (RMS).

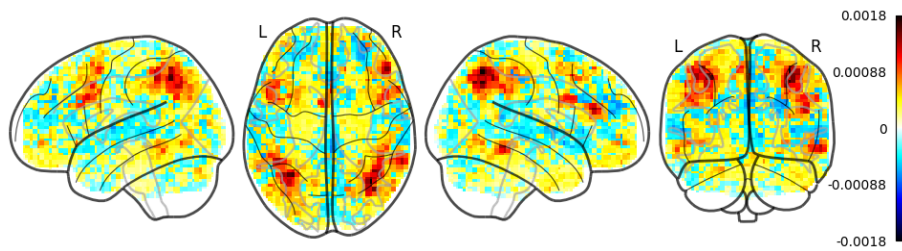


Figure 11: English Brain z-maps showing the r^2 increase for the model including syntactic surprisal at $k = 1$ compared to the model including only the following regressors: word rate, fundamental frequency (f_0), word frequency, and root mean square intensity (RMS).

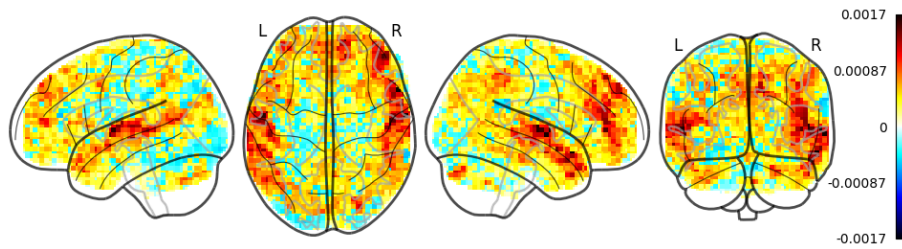


Figure 12: Chinese Brain z-maps showing the r^2 increase for the model including syntactic surprisal at $k = 5$ compared to the model including only the following regressors: word rate, fundamental frequency (f_0), word frequency, and root mean square intensity (RMS).

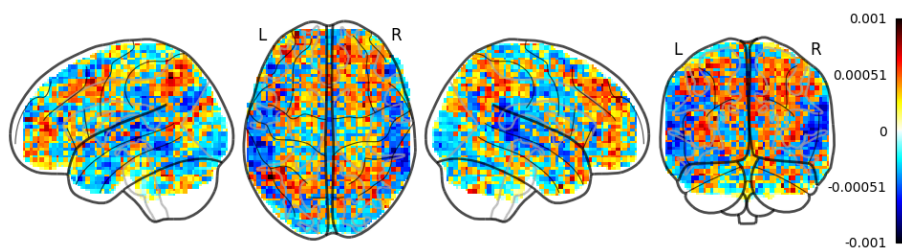


Figure 13: Chinese Brain z-maps showing the r^2 increase for the model including syntactic surprisal at $k = 1$ compared to the model including only the following regressors: word rate, fundamental frequency (f_0), word frequency, and root mean square intensity (RMS).

A.4 Results

Tables 4 and 5 show the full list of significant clusters ($p < .001$ uncorrected; cluster threshold = 15 voxels) for the model comparison between syntactic surprisal at $k = 1$ vs $k = 5$.

Region	X	Y	Z	Peak Stat	Cluster Size (mm ³)
Left-SecVisual(18), Right/Left DorsalPCC(31)	-12.0	-64.0	24.0	4.78	968
Right-VisMotor(7)	0.0	-64.0	48.0	4.02	856
Right-AngGyrus (39)	38.0	-54.0	38.0	4.42	800
Left-PreMot + SuppMot(6) / Left-PrimAuditory (41)	-48.0	-10.0	4.0	4.68	568
Right-VentPostCing(23)	14.0	-54.0	20.0	4.57	488
Right-AngGyrus (39)	36.0	-74.0	40.0	4.27	360
Left-AngGyrus (39)	-44.0	-68.0	36.0	3.77	352
Right-DorsalPCC (31)	14.0	-62.0	34.0	4.03	216
Right-DorsalPCC (31)	4.0	-50.0	44.0	3.65	192
Right-PrimAuditory (41)	48.0	-12.0	2.0	3.69	160
Right-PrimAuditory (41)	38.0	-26.0	12.0	3.39	152

Table 4: English significant clusters ($p < .001$ uncorrected; cluster threshold = 15 voxels) for the model comparison between syntactic surprisal at $k = 1$ vs $k = 5$

Region	X	Y	Z	Peak Stat	Cluster Size (mm ³)
Right-MedTempGyrus (21) / Right-SupTempGyrus (22)	56.0	-36.0	4.0	4.68	1336
Left-SupTempGyrus (22)	-64.0	-26.0	6.0	4.32	392
Right-PrimAuditory (41)	52.0	-14.0	6.0	4.59	384
Left-PrimAuditory(41)	-56.0	-6.0	4.0	5.04	384
Left-MedTempGyrus (21)	-48.0	-42.0	4.0	4.25	320
Left-SupTempGyrus (22)	-58.0	-26.0	0.0	4.06	288

Table 5: Chinese significant clusters ($p < .001$ uncorrected; cluster threshold = 15 voxels) for the model comparison between syntactic surprisal at $k = 1$ vs $k = 5$