

Information Distribution Depends on Language-Specific Features

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Abstract

Although languages vary widely in their structure, all are vehicles for the transmission of information. Consequently, aspects of speakers' word choice can be understood through models of optimal communication. One prediction of these models is that speakers should keep the density of information constant over the duration of an utterance (R. P. Levy & Jaeger, 2007). However, different languages have different structural properties that constrain the space of a speaker's choices (e.g. canonical word order). We build on a method developed by Yu, Cong, Liang, & Liu (2016) to analyze the word-level entropy curves of natural language productions across a diverse set of languages and in diverse written and spoken contexts. We show that languages impose characteristic constraints on speaker's choices that predict deviations from Uniform Information Density, and that cross-linguistic variability in these deviations is predictable in part from syntactic properties of those languages.

Keywords: Uniform information density; language structure; corpus analysis

Over 7,000 languages are spoken around the modern world (Simons & Fenning, 2018). These languages vary along many dimensions, but all share a core goal: communicating information. If speakers and writers of these languages act near-optimally to achieve their communicative goals, regularities of use across these diverse languages can be explained by a rational theory of communication (Anderson, 1991). Information theory, a mathematical framework developed by Shannon (1948) to describe the transmission and decoding of signals, has been a unifying approach for the recent development of theories of communication in human and machine language processing (Jelinek, 1976; R. P. Levy & Jaeger, 2007).

These theories model the process of communication as transmission of information over a noisy channel. The producer begins with an intended meaning, packages this meaning into language, and then sends the encoded meaning to their intended receiver over a communicative channel. The receiver must then decode the producer's intended meaning from the signal they receive on their end of the channel. The problem is that this channel is noisy, and sometimes the signal can be corrupted (e.g. the producer can misspeak, or the receiver can mishear). In order to maximize the probability that the correct meaning is transmitted, these theories predict that producers should choose linguistic messages that keep the rate of information constant across words. The intuition is that if the receiver misperceives a word, and that word con-

tains most of the information in the sentence, then the communication will have failed. Because producers cannot predict which word a speaker will mishear, their best strategy is spread the information evenly across all of the words in a sentence, i.e. maintain *Uniform Information Density* (Genzel & Charniak, 2002; R. P. Levy & Jaeger, 2007).

The evidence in favor of Uniform Information Density has largely focused on specific points within sentences, while the hypothesis itself has been applied broadly over the past decade. The original evidence in favor of Uniform Information Density in R. P. Levy & Jaeger (2007) finds that the insertion of complementizers (e.g. "that") in relative clauses in English corresponds to where neighboring words have high information content. Similarly, A. F. Frank & Jaeger (2008) argues that contractions in English such as "you're" do not occur when neighboring words are highly informative. Applications of Uniform Information Density include determining whether linguistic alignment takes place (Jaeger & Snider, 2013), Zipfian word length distributions (Piantadosi, Tily, & Gibson, 2011), communication efficiency (Mahowald, Fedorenko, Piantadosi, & Gibson, 2013), dialogue and turn-taking (Xu & Reitter, 2018) and the significance of ambiguity in language (Piantadosi, Tily, & Gibson, 2012), among other research.

However, other recent work has contradicted the Uniform Information Density hypothesis. Similar to the original work in R. P. Levy & Jaeger (2007), Zhan & Levy (2018) focuses on information distribution at particular points in sentences. Zhan & Levy (2018) finds that more information-rich classifiers in Mandarin Chinese are produced when production of the neighboring noun is difficult, not when the information content is high. Examining the information density at the sentence level, Jain, Singh, Ranjan, Rajkumar, & Agarwal (2018) study word order across written sentences in Hindi, a freer word order language than English, and find that information density has no significant effect on determining a Hindi writer's word order.

Recently, Yu et al. (2016) developed a more direct test of the Uniform Information Density hypothesis, applying the logic used by Genzel & Charniak (2002) to look at the distribution of information *within* individual sentences. Because people process language incrementally—using the previous words in a sentence to predict the words that will come next—the amount of information that a word contains when seen

in isolation should increase over the course of a sentence (Ferrer-i-Cancho, Debowski, & Prado Martin, 2013). Analyzing a large corpus of written English, Yu et al. (2016) find a different pattern: Unigram entropy increases over the first few words of an utterance and then remains constant until the final word where it again jumps up (see top of Figure 1). Yu et al. (2016) conclude that the Uniform Information Density hypothesis must not hold for medial words in a sentence.

We extend and generalize Yu et al. (2016) in three ways: We confirm that this same pattern is found throughout English—in written language, and in conversational speech between adults and between parents and their children. Thus, this entropy curve is a robust feature of English linguistic productions. We then examine entropy curves cross-linguistically, and show that the characteristic entropy curves vary across the world’s languages. Finally, we show that this variation is predictable in part from the structure of individual languages (i.e. word order). Taken together, our results suggest a refinement of the Uniform Information Density hypothesis: speakers may structure their utterances to optimize information density, but they must do so under the predictable constraints of their language.

Calculating entropy curves

In all of our studies, we used an adaptation of the by-word entropy method developed by Yu et al. (2016). Given a text or speech corpus divided into individual sentences, we partition the corpus by sentence length in number of words. For each word position X of sentences of length k , we define w as a unique word occurring in position X . We further define $p(w)$ as the number of times word w occurs in position X , divided by the number of total words that occur in position X i.e. the number of sentences of length k . This creates a probability distribution over the words occurring in position X , and computing the Shannon (1948) entropy $H(X)$ of this probability distribution gives the positional entropy of position X in sentences of length k .

$$H(X) = \sum_w p(w) \log(p(w))$$

With this measure, we can compute the unigram positional entropy at each word position of sentences of each length within a corpus. The result of this method across word positions can be plotted for each sentence length as an *entropy curve*, which can be visually compared across sentence lengths to observe how the unigram entropy changes across absolute positions in each of the sentences. Genzel & Charniak (2002) similarly examine a unigram entropy measure on sentences, and found that entropy at the sentence level increases linearly with sentence index within a corpus. Uniform Information Density applies this uniformity of entropy rate in sentences to all levels of speech (R. P. Levy & Jaeger, 2007), and so our method obtained from Yu et al. (2016), which examines text at the word level, should find a monotonically increasing affine function at the word level.

The entropy curves capture individual variation across positions in utterances of the same length. This allows us to directly observe and judge the amount of variation in words that appear in an individual position of a sentence. We can directly compare any two positions within utterances to determine the amount of uncertainty, and therefore information, on average contained by words within that position of utterances. This method is thus identical in logic to Genzel & Charniak (2002), but within sentences instead of across sentences.

Study 1

We began by replicating Yu et al.’s (2016) analysis, computing entropy curves on the British National Corpus—a collection of predominantly written English (Clear, 1993). We then applied the same method to the Switchboard corpus—a collection of spoken English (Godfrey, Holliman, & McDaniel, 1992). This allowed us to ask whether the characteristic function identified by Yu et al. (2016) is a general feature of English, or instead a function of their written language corpus.

Data and Analysis

The British National Corpus consists of predominantly (90%) written documents collected in the early 1980s and 1990s across a variety of genres (scientific articles, newspapers, fiction, etc). It also contains a small collection of corpora from spoken language. All together, the British National Corpus contains ~ 100 million tokens. The Switchboard corpus is a collection of $\sim 2,400$ telephone conversations between unacquainted adults prompted with subjects of conversation. Switchboard is the corpus used in Levy and Jaeger’s (2007) original demonstration of the Uniform Information Density hypothesis.

For each corpus, we computed entropy curves using the method described above for all sentences from length 4 to 30.

Results

The entropy curves computed in both the British National Corpus and Switchboard were remarkably consistent both across corpora and across the range of sentence lengths we analyzed (Figure 1). Confirming Yu et al.’s (2016) findings, we found that the positional entropy at the beginning of sentences is low, then rises and plateaus for sentence-medial word positions before dropping slightly in the second-to-last position and rising again for the sentence-final word.

The shape of positional entropy curves we find in these two corpora is notable for two reasons: (1) it does not follow our predictions from Uniform Information Density, and (2) the distribution is robust across written and spoken English. This suggests that the entropy curve is characteristic of the English language. We next asked whether this shape is a feature even of children’s speech, and also whether it varies cross-linguistically.

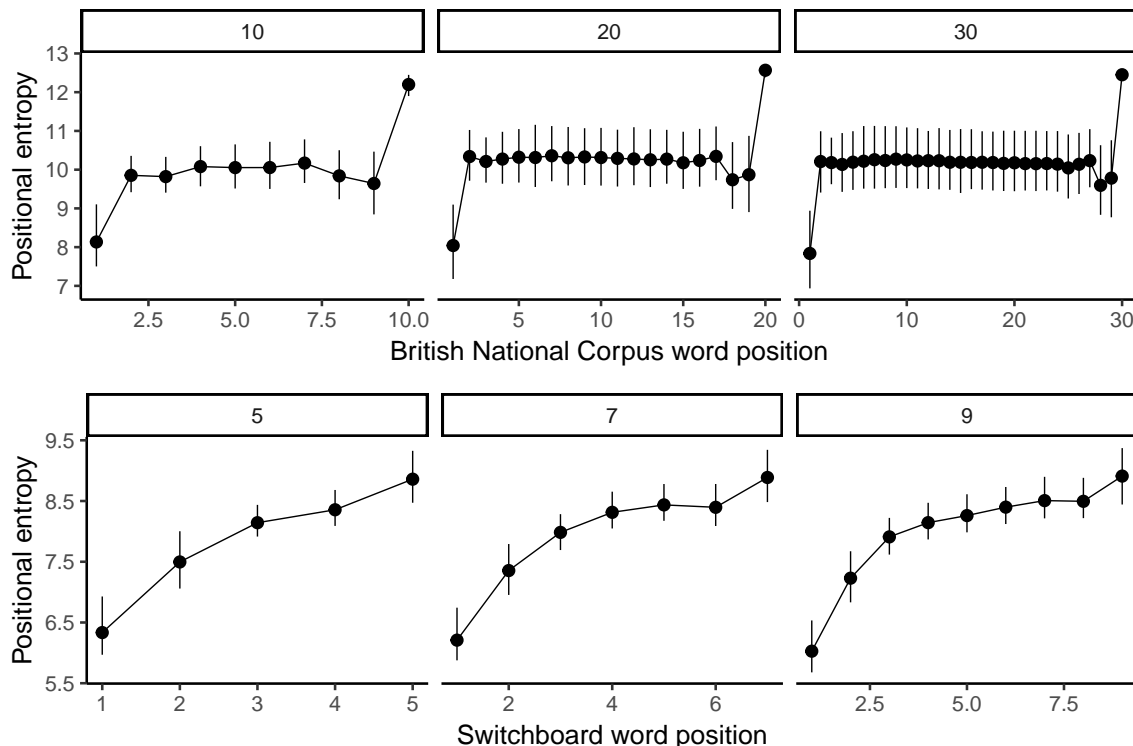


Figure 1: Representative Entropy Curves for the British National Corpus (top) and Switchboard (bottom). Points represent average entropies, error bars show 95% confidence intervals computed by non-parametric bootstrap.

Study 2

To understand how robust this entropy curve is, we turned to conversational speech from parent-child interactions. If we find the same shape even in children’s productions, we have even stronger evidence that the three-step entropy curve is a characteristic feature of English. We thus used the Child Language Data Exchange System (CHILDES), a collection of transcripts of parent-child interactions (MacWhinney, 2014).

Data and Analysis

We analyzed three separate corpora in CHILDES: The Providence Corpus (Demuth, Culbertson, & Alter, 2006), The Shiro corpus (Shiro, 2000), and the Zhou Dinner Corpus (Li & Zhou, 2015). The Providence corpus consists of conversations between six 1–3-year-old American English-speaking children and their parents recorded in their homes. The Shiro Corpus consists of prompted Spanish-language narratives individually collected from over a hundred Venezuelan schoolchildren. The Zhou Dinner Corpus contains dinner conversations between 5–6-year-old Mandarin-speaking children and their parents collected in Shanghai. Spanish is an Indo-European language like English, possessing similar grammar, word order and numerous cognate words to English. In contrast, Mandarin Chinese is typologically unrelated to English, with many structural differences between the two languages.

We accessed the transcripts from each corpus using

`childesr`, an R-interface to a database-formatted version of CHILDES (Sanchez et al., in press). We divided all utterances from each transcript into those produced by the target child, and those produced by all other speakers. We then applied the same entropy curve method described earlier. For Mandarin, we used pinyin transliterations of the utterances in the corpus with demarcated word boundaries. The Chinese characters used for writing Mandarin do not normally demarcate word boundaries by spacing words apart, and for normal Chinese writing spaces between word boundaries are unnatural and such spaces can be difficult to determine (Bai, Yan, Liversedge, Zang, & Rayner, 2008).

Results

Across corpora, we found similar entropy curve shapes for adults and children, but distinct shapes for each language. Figure 2 shows representative curves across corpora, but the entropy curve shapes were robust across the full range of utterances we analyzed. We found a distinct three-step distribution for both the English and Spanish CHILDES corpora, with a slight dip in the penultimate position of each sentence. The Mandarin corpus entropy curve, by comparison, displayed a noticeably lower positional entropy values in utterance-final positions than in utterance-penultimate positions.

These results present two important pieces of information. First, the English Providence corpus entropy curve broadly

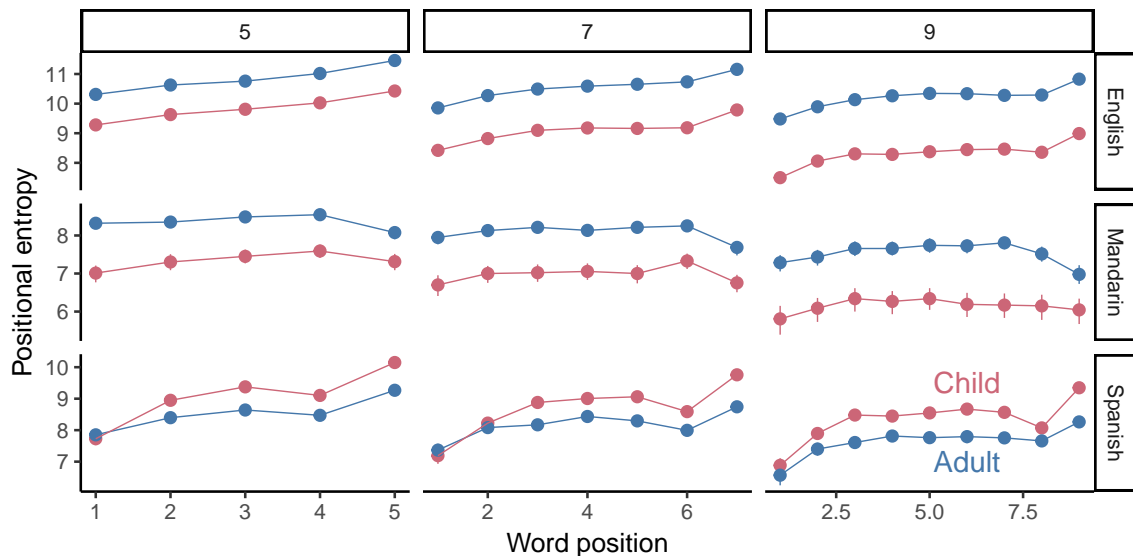


Figure 2: Representative Entropy Curves for Three Childes Corpora in English, Mandarin, and Spanish. Points average entropies, error bars show 95% confidence intervals computed by non-parametric bootstrap.

replicates the curves found in both the British National Corpus and in Switchboard, our two previous English corpora. Thus, the entropy curve of English appears not just in adult-adult conversation, but even in speech produced by parents to their children, and speech produced by very young children to their parents. This suggests that it is a highly robust feature of the English language, as it reflects the structure of even pre-schooled aged children’s speech.

Second, the entropy curves of English, Spanish, and Mandarin were not identical. No shape resembled the affine function predicted naively from Uniform Information Density, but also Mandarin was quite different from both English and Spanish. This suggests that the entropy curve can vary from language to language. One possibility is that this variation arises from typological features of language, such as characteristic word order. We noticed, for instance, a relatively high density of determiners in the penultimate position of English and Spanish utterances, which could account their characteristic penultimate dip. In our final analysis, we explored this possibility directly, analyzing a large set of Wikipedia corpora from diverse languages, and asking whether variability in their entropy curves was related to variability in their syntactic structure.

Study 3

In order to understand how entropy curves are related to linguistic structure, we turned to Wikipedia for a larger and more diverse set of languages.

Data and Analysis

Wikipedia has two primary advantages: (1) Individual language corpora are generally large, and (2) hundreds of languages are represented. To understand how variability in

entropy curves is related to the structure of language, we used features from the World Atlas of Language Structures (WALS, Dryer & Haspelmath, 2013). WALS is a curated collection of typological features which help to classify the diversity across the world’s languages. However, as the collection includes contributions from many authors studying a heterogeneous set of topics and languages, most features are missing for most languages. For our sample, we sought to balance diversity of languages with coverage in WALS. We selected eight specific WALS features for which the same 45 languages were coded (Figure 3). Unfortunately, these features all reflected the order of words in a sentence in each language (e.g. whether objects come before verbs, whether adjectives come before nouns). A consistent set of results across these features would be consistent with an effect of order on entropy curves, but unfortunately no other feature types are available for comparison.

We computed entropy curves separately for each language as before. In order to understand how these curves varied across languages, we developed a method for compressing the curves into a few representative values. We noticed that curves tended to vary at predictable positions within sentences: The majority were flat in the middle, but had either rising or falling slopes at the beginnings and ends. For each language, for each sentence length k we computed 5 slopes: The change between the 1st and 2nd position, the change between the 2nd and 3rd position, the slope between the 3rd position and the 3rd-to-last position ($k - 1$), the slope between the 3rd-to-last and the 2nd-to-last position ($k - 1$), and the slope between the 2nd-to-last and final positions. We then averaged these slopes across sentence lengths within a language to estimate a language-typical signature. We performed an additional analysis dividing each sentence into fifths evenly

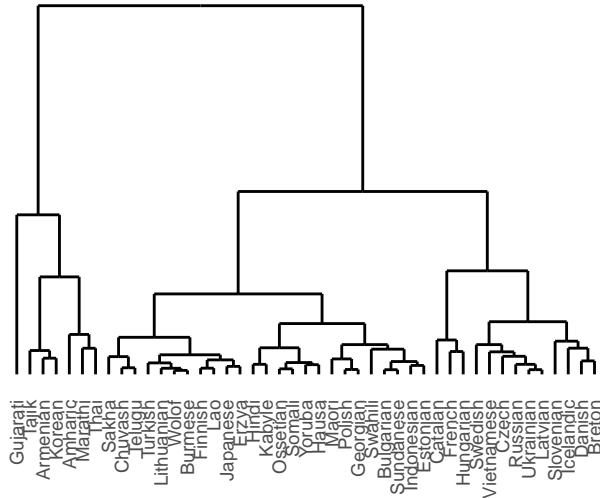


Figure 3: A dendrogram estimated from hierarchically clustering the slopes of our 45 languages

and computing the slopes between these fifths. Results from this second analysis were qualitatively similar.

Results

We treated these five slopes as a vector, allowing us to compute the pairwise similarity between languages with cosine—a standard measure of vector similarity (Landauer & Dumais, 1997). Intuitively, vectors with a smaller angle between them are more similar. Figure 3 shows a hierarchical clustering of these 5 dimensional vectors, demonstrating that entropy curve similarity appears to capture typological relatedly (e.g. Slavic languages are similar to each other).

We then asked whether these pairwise similarities were related to overlap in linguistic features. For each of the eight WALS features we measured, we fit a logistic regression predicting whether two languages would have the same value for that feature from the pairwise similarity of their entropy curves. Overlap on all eight features was reliably predicted by entropy curve similarity (largest $p = .001$), with the amount of variance in feature overlap predicted varying across predictors 1. Order of object and verb (83A) was the strongest predictor, explaining 16.22% of the variance in pairwise entropy curve similarity.

General Discussion

Taken together, the results of our studies yield 3 main findings. First, languages have characteristic entropy curves that can be found in their productions whether written, spoken, or even spoken by children. These curves diverge in reliable ways from the affine functions predicted by a naive Uniform Information Density hypothesis. Second, these characteristic curves vary across languages—some languages like English have increasing curves, but others like Mandarin are characterized by decreasing entropy over the course of an utterance. Finally, these characteristic curves are related to structural properties of those languages, for instance their word

#	t-value	p-value	r2
83A	178.22	0.00	0.16
95A	170.98	0.00	0.15
81A	153.70	0.00	0.13
97A	136.81	0.00	0.10
144A	74.43	0.00	0.03
87A	39.91	0.00	0.01
143A	39.74	0.00	0.01
82A	3.23	0.00	0.00

Table 1: Table showing the eight WALS features ranked by significance of effect on the entropy slope cosine distances

orders. This work presents an important rejoinder to models of linguistic productions as optimizing communicative success. While speakers may structure the information in their productions to minimize spikes in entropy, speakers operate under coding models they inherit from their language, and these coding models constrain the choices they make.

Our work complements the approach of studies such as Aylett & Turk (2004), where a language’s information distribution is characterized by a single number representing the average rate of semantic information transfer per syllable. Each language possesses a characteristic entropy curve derived from the information distribution within utterances as well as a measure of the average information expressed by a syllable in that language.

We expect the characteristic entropy curve for a language to have important downstream effects for how people process that language. While conversational turn-taking is universal, there exists cross-linguistic variation in the average length of time between conversational partners speaking (Stivers et al., 2009). We predict that one factor in this variability relates to the shape of a language’s entropy curve. A jump at the end of a language’s entropy curve, such as in English, indicates that there is on average high levels of information at the end of utterances in that language. Therefore we expect turn-taking times to be longer in such languages than in languages where there is a drop in the final segment of the entropy curve, such as Mandarin. We also expect that readers of a language will take longer on average to read parts of sentences where the entropy curve is relatively high, due to the presence of higher information content. This may explain the so-called wrap-up effect in sentence processing, in which the ends of sentences are processed more slowly during reading (Kuperman, Dambacher, Nuthmann, & Kliegl, 2010; Stowe, Kaan, Sabourin, & Taylor, 2018). The entropy curve analysis can be carried out on any language across a wide variety of text corpora, making it a powerful tool for analyzing the information structure of both spoken and written utterances in a language.

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