Close = Relevant? The Role of Context in Efficient Language Production

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Abstract
We formally derive a mathematical model for evaluating the effect of context relevance in language production. The model is based on the principle that distant contextual cues tend to gradually lose their relevance for predicting upcoming linguistic signals. We evaluate our model against a hypothesis of efficient communication (Genzel and Charniak’s Constant Entropy Rate hypothesis). We show that the development of entropy throughout discourses is described significantly better by a model with cue relevance decay than by previous models that do not consider context effects.

1 Introduction
In this paper, we present a study on the effect of context relevance decay on the entropy of linguistic signals in natural discourses. Context relevance decay refers to the phenomenon that contextual cues that are distant from an upcoming event (e.g. production of a new linguistic signal) are less likely to be relevant to the event, as discourse contents that are close to one another are likely to be semantically related. One can also view the words and sentences in a discourse as time steps, where distant context becomes less relevant simply due to normal forgetting over time (e.g. activation decay in memory). The present study investigates how this decaying property of discourse context might affect the development of entropy of linguistic signals in discourses. We first introduce the background on efficient language production and then propose our hypothesis.

1.1 Background on Efficient Language Production
The metaphor “communication channel”, borrowed from Shannon’s information theory (Shannon, 1948), can be conceived of as an abstract entity that defines the constraints of language communication (e.g. ambient noise, distortions in articulation). For error free communication to occur, the ensemble of messages that a speaker may utter must be encoded in a system of signals whose entropy is under the capacity of the communication channel. Entropy of these signals, in this context, correlates with the average number of upcoming messages that the speaker can choose from for a particular signal (e.g. a word to be spoken) given preceding discourse context. In other words, if the average number of choices given any linguistic signal exceeds the channel capacity, it cannot be guaranteed that the receiver can correctly infer the originally intended message. Such transmission errors will reduce the efficiency of language communication.

Keeping the entropy of linguistic signals below the channel capacity alone is not efficient, for one can devise a code where each signal corresponds to a distinct message. With a unique choice per signal, this encoding achieves an entropy of zero at the cost of requiring a look-up table that is too large to be possible (cf. Zipf (1935), who makes a similar argument for meaning and form). In fact, the most efficient code requires language users to encode messages into signals of the entropy bounded by the capacity of the channel. One implication of this efficient encoding is that over time, the entropy of the signals is constant. One of the first studies to investigate such constancy is Genzel and Charniak (2002), in which the authors proposed the Constant Entropy Rate (CER) hypothesis: in written text, the entropy per signal symbol is constant across sentence positions in discourses. That is, if we view sentence positions as a measure of time steps, then the entropy per word at each step should be the same in order to achieve efficient communication (word is selected as the unit of signal, although it does not have to
be case; cf. Qian and Jaeger (2009)).

The difficulty in testing this direct prediction is computationally specifying the code used by human speakers to obtain a context-sensitive estimate of the entropy per word. An n-gram model overestimates the entropy of upcoming messages by relying on only the preceding n-1 words within a sentence, while in reality the upcoming message is also constrained by extra-sentential context that accumulates within a discourse. The more extra-sentential context that the n-gram model ignores, the higher estimate for entropy will be. Hence, the CER hypothesis indirectly predicts that the entropy of signals, as estimated by n-grams, will increase across sentence positions. While some studies have found the predicted positive correlation between sentence position and the per-word entropy of signals estimated by n-grams, most of them assumed the correlation to be linear (Genzel and Charniak, 2002; Genzel and Charniak, 2003; Keller, 2004; Piantadosi and Gibson, 2008). However, in previous work, we found that a log-linear regression model was a better fit for empirical data than a simple linear regression model based on data of 12 languages (Qian and Jaeger, under review). Why this would be case remained a puzzle.

Our research question is closely related to this indirect prediction of the Constant Entropy Rate hypothesis. Intuitively, the number of possible messages that a speaker can choose from for an upcoming signal in a discourse is often restricted by the presence of discourse context. Contextual cues in the preceding discourse can make the upcoming content more predictable and thus effectively reduces signal entropy. As previously mentioned, however, different contextual cues, depending on how long ago they were provided, have various degrees of effectiveness in reducing signal entropy. Thus we ask the question whether the decay of context relevance could explain the sublinear relation between entropy and discourse progress that has been observed in previous studies.

We formally derive two nonlinear models for testing our Relevance Decay Hypothesis (introduced next). In addition to the constant entropy assumption in CER, our model assumed that the relevance of early sentences in the discourse systematically decays as a function of discourse progress. Our models provide the best fit to the distribution of entropy of signals, suggesting the availability of discourse context can affect the planning of the rest of a discourse.

1.2 Relevance Decay Hypothesis

We hypothesize the sublinear relation between the entropy of signals, when estimated out of discourse context (hereafter, out-of-context entropy of signals) using an n-gram model, and sentence position (Piantadosi and Gibson, 2008; Qian and Jaeger, under review) is due to the role of discourse context (hereafter, context). Consider the following example. Assume that context at the kth sentence position comes from the 1...k−1 sentences in the past. If k is large enough, context from the early sentences 1...i (i ≪ k) is essentially no longer relevant. Rather, the nearby k−i sentences are contributing most of the discourse context. As a result, the constraint on the entropy of signals at sentence position k is mostly due to the nearby window of k−i sentences. Then if we look ahead to the (k+1)th sentence position and follow the same steps of reasoning, context at that point also mostly comes from the nearby window of k−i sentences (i.e. (k+1)−(i+1) = k−i). Hence, for later sentence positions, the difference in available context is minimal. Consequently, their out-of-context entropy of signals increases at a very small rate. On the other hand, when k is fairly small, to the extent that the k−i window covers the entire preceding discourse, all of the 1...k−1 sentences are contributing relevant context. As k increases, the number of preceding sentences increases, which results in a more significant change in relevant context, but the relevance of each individual sentence decreases with its distance to k, which results in a sublinear pattern of relevant context with respect to sentence position overall. As we will show, the relation of out-of-context entropy of signals to sentence position follows from the relation of relevant context to sentence position, exhibiting a sublinear form as well.

The problem of interest here is to specify how quickly the relevance of a preceding sentence decays as a function of its distance to a target sentence position k. We experimented with two forms of decay functions – power law decay and exponential decay. It has been established that many types of human behaviors can be well described by the power function (Wixted and Ebbesen, 1991), so we mainly focus on building a model under the
Table 1: Number of words and sentences in the training and test data for each of the twelve languages. The last column gives the number of sentences at each sentence position (which is identical to the number of documents contained in the corpora).

### Power-law, and examine if the model under the exponential law yields any difference. Under the assumptions of true entropy rate is constant across sentences, we predict that our models will better characterize the changes in estimated entropy of signals than general regression models that are blind to the role of context.

## 2 Methods

### 2.1 Data

We used the Reuters Corpus Volume 1 and 2 (Lewis et al., 2004). The corpus contains about 810,000 English news articles and over 487,000 news articles in thirteen languages. Because of inconsistent annotation, we excluded the data from three languages, Chinese, German, and Japanese. For Chinese, we substituted the Treebank Corpus (Xue et al., 2005) for the Reuters data, leaving us with twelve languages: Danish, Dutch, English, French, Italian, Mandarin Chinese, Norwegian, Portuguese, Russian, European Spanish, Latin-American Spanish, and Swedish. In order to estimate out-of-context entropy per word (i.e., per signal symbol) for each sentence position, articles were divided into a training set (95% of all stories) for training language models and a test set (the remaining 5%) for analysis (see Table 1 for details). Out-of-context entropy per word was estimated by computing the average log probability of sentences at that position, normalized by their lengths in words (i.e., for an individual sentence token $s$, the term to be averaged is $-\frac{\log p(s)}{\text{length}(s)}$ bits per word). Standard trigram language models were used to compute these probabilities (Clarkson and Rosenfeld, 1997). The majority of the 12 languages belong to the Indo-European family, while Mandarin Chinese is a Sino-Tibetan language.

### 2.2 Modeling Relevance Decay of Context

Formally, we define the relevance of context in the same unit as entropy of signals – bits per word. Let $r_0$ denote the entropy of signals that efficiently encode the ensemble of messages a speaker can choose from for any sentence position, a constant under the assumption of CER. According to Information Theory, $r_0$ is equivalent to the uncertainty associated with any sentence position if context is considered. Thus, in error free communication, linguistic signals presented at the $k$th sentence position are said to have resolved the uncertainty at $k$ and therefore are $r_0$-bit relevant at the $k$th sentence position. Then, at the $(k+i)$th sentence position, these linguistic signals have become context by definition and their relevance has decayed to some $r$ bits. Our models start from defining the value of $r$ as a function of the distance between context and a target sentence position.

#### 2.2.1 Power-law Decay Model

If the relevance of a cue $q$ (e.g., a preceding sentence), which is originally $r_0$-bit relevant at position $k_q$, decays at the rate following the power function, its remaining relevance at target sentence position $k$ is:

$$r_{\text{pos}}(k, q) = r_0(k - k_q + 1)^{-\lambda} \quad (1)$$

In Equation (1), $k > k_q$ and $\lambda$ is the decay rate. This means at position $k$, the relevance of the cue
from the \((k-1)\)th sentence is \(r_0 \ast 2^{-\lambda}\)-bit relevant; the relevance of the cue from the \((k-2)\)th sentence is \(r_0 \ast 3^{-\lambda}\)-bit relevant, and so on. As a result, the relevance of discourse-specific context at position \(k\) is the marginalization of all cues up to \(q_k-1\):

\[
context_{\text{pow}}(k) = r_0 \sum_{q_i \in \{q_1 \ldots q_k-1\}} (k - k_{q_i} + 1)^{-\lambda} \quad (2)
\]

The general trend predicted by Equation (2) is that discourse-specific context increases more rapidly at the beginning of a discourse and much more slowly towards the end due to the relevance decay of distant cues. Rewriting Equation (2) in a closed-form formula so that a model can be fitted to data is not a trivial task without knowing the rate \(\lambda\), but the paradox is that \(\lambda\) has to be estimated from the data. As a workaround, we approximated the value of Equation (2) by computing a definite integral of Equation (1), where \(\Delta i\) is a shorthand for \(k - k_q + 1\):

\[
context_{\text{pow}}(k) \approx \int_1^k r_0 \Delta i^{-\lambda} d\Delta i
= r_0 \frac{(k^{1-\lambda} - 1)}{1 - \lambda} \quad (3)
\]

Equation (3) uses an integral to approximate the sum of a series defined as a function. The result is usually acceptable as long as \(\lambda\) is greater than 1 so that the series defined by Equation 1 is convergent (this assumption is empirically supported; see Figure 5). Note that Equation (3) produces the desirable effect that upon encountering the first sentence of a discourse, no discourse-specific contextual cues are available to the speaker (i.e. \(context(1) = 0\)).

Now that we know the maximum relevance of context at sentence position \(k\), we can predict the amount of out-of-context entropy of signals \(r(k)\) based on the idea of uncertainty again. There are new linguistic signals that are \(r_0\)-bit relevant \(in context\) at any sentence position. In addition, we now know \(context(k)\) bits of relevant context are also available. Thus, the sum of \(r_0\) and \(context(k)\) defines the maximum amount of out-of-context uncertainty that can be resolved at sentence position \(k\). Therefore, the out-of-context entropy of signals at \(k\) is at most:

\[
context_{\text{exp}}(k) = r_0 \sum_{i=1}^{k-1} e^{-\lambda i} \quad (6)
\]

\[
context_{\text{pow}}(k) = context(k) + r_0
= r_0 \frac{k^{1-\lambda} - 1}{1 - \lambda} + r_0 \quad (4)
\]

Whether speakers will utilize all available context as predicted by Equation (4) is another debate. Here we adopt the view that speakers are maximally efficient in that they do make use of all available context. Thus, we make the prediction that out-of-context entropy of signals, as observed empirically from data, can be described by this model. Figure 1 shows the behavior of this function with various parameter sets.
Equation (6) is the sum of a geometric progression series. We can write Equation (6) in a closed-form:

$$context_{exp}(k) = \frac{r_0}{e^\lambda - 1}(1 - e^{-(k-1)\lambda})$$  \hfill (7)

As a result, the out-of-context entropy of signals is:

$$r_{exp}(k) = \frac{r_0}{e^\lambda - 1}(1 - e^{-(k-1)\lambda}) + r_0$$  \hfill (8)

Figure 2 schematically shows the behavior of this function. One can notice this function converges against a ceiling more quickly than the power function. Thus, this model makes a slightly different prediction from the power law model.

![Figure 2: Schematic plots of the behavior of out-of-context entropy of signals assuming the decay of the relevance of context is an exponential function.](image)

2.3 Nonlinear Regression Analysis

To test whether the proposed models (i.e. Equations 4 and 8) better characterize the data, we built nonlinear regression models with document-specific random effects, where the out-of-context entropy of signals, $r_{ij}$, is regressed on sentence position, $k_j$. Based on the power law model, we have

$$r_{ij} = (\beta_1 + b_{1i})\frac{k_j^{1-\beta_2} - 1}{1 - \beta_2} + (\beta_1 + b_{1i}) + \epsilon_{ij}$$  \hfill (9)

where $\beta_1$ corresponds to $r_0$, the theoretical constant entropy of signals under an ideal encoding. $b_{1i}$ represents the document-specific deviations from the overall mean. $\beta_2$ corresponds to $\lambda$, the mean rate at which the relevance of a past cue decays, which is unfortunately not considered for random effects for the practical purpose of making computation feasible in the current work. Finally, $\epsilon_{ij}$ represents the errors independently distributed as $\mathcal{N}(0, \sigma^2)$, orthogonal to document specific deviations.

For the exponential model, the nonlinear model is the following (symbols have the same interpretations as in Equation 9):

$$r_{ij} = \frac{\left(\beta_1 + b_{1i}\right)}{e^{\beta_2} - 1}(1 - e^{-(k_j-1)\beta_2}) + (\beta_1 + b_{1i}) + \epsilon_{ij}$$  \hfill (10)

Fitting data with the above nonlinear models requires starting estimates for fixed-effect coefficients (i.e. $\beta_1$s and $\beta_2$s). Unfortunately, there are no principled methods for selecting these values. We heuristically selected 6 for $\beta_1$ and 2 for $\beta_2$ as starting values for the power law model, and 4 and 0.5 as starting values for the exponential model.

3 Results

We examined the quality of the models and the parameters in the models: $r_0$, the within-context entropy rate, and $\lambda$, the rate of context decay.

3.1 Model Quality Comparison

The CER hypothesis indirectly predicts that out-of-context entropy of signals of sentence positions (bits per word) should increase throughout a discourse. The two models go one step further to predict specific sublinear increase patterns, based on the speaker’s considerations of the relevance of past contextual cues. We compared the quality of models in terms of Bayesian Information Criterion (BIC) within languages. A lower BIC score indicates a better fit. As shown by Figure 3, we find our models best explain the data in 9 out of the 12 languages, reporting lower BIC scores than both the linear and log-linear models as reported in our previous work (Qian and Jaeger, under review). For Danish, English and Italian, although neither of our models produced a better score than the log-linear model, the relative difference is small: 0.54 on average (comparing to BIC scores on the order of $10^2$ to $10^3$).
Figure 3: Our models yield superior BIC scores in most languages. The y-axis shows the differences between BIC scores of individual models for a language and mean BIC of the models for that language (E.Spanish = European Spanish; L.Spanish = Latin-American Spanish).

Specifically, in terms of BIC scores, the power-law model is better than the linear model ($t(11) = -3.98, p < 0.01$), and the log-linear model ($t(11) = -3.10, p < 0.05$). The exponential model is also better than the linear model ($t(11) = -3.98, p < 0.01$), and the log-linear model ($t(11) = -3.18, p < 0.01$). The power-law model and the exponential model are not significantly different from each other ($t(11) = 0.5, p > 0.5$).

3.2 Interpretation of Parameters

Constant Entropy of Signals $r_0$. Both models are constructed in such a way that the first parameter $r_0$, in theory, corresponds to the theoretical within-context entropy of signals of sentence positions. This parameter refers to how many bits per word are needed to encode the ensemble of messages at a sentence position when context is taken into account. The CER hypothesis directly predicts that this rate should be constant throughout a discourse. Although we are unable to test this prediction directly, it is nevertheless interesting to compare whether these two independently developed models yield the same estimates for this parameter in each language.

Figure 4 shows encouraging results. Not only the estimates made by the power model are well correlated with those by the exponential model, but also the slope of this correlation is equal to 1 ($t(10) = 1.01, p < 0.0001$). Since there are no reasons a priori to suspect that these two models would give the same estimates, this is a first step to confirming the entropy per word in sentence production is indeed a tractable constant throughout discourses.

Among all languages, $r_0$ has a mean of 5.0 bits in both models, and a variance of 0.46 in the power-law model and 0.48 in the exponential model, both remarkably small. The similarity in $r_0$ between languages may lead one to speculate whether the amount of uncertainty per word in discourses is largely the same regardless of the actual language used by the speakers. On the other hand,
the differences in \( r_0 \) may reveal the specific properties of different languages. Meanwhile, precautions need to be taken in interpreting those estimates given that the corpora are of different sizes, and the \( n \)-gram model is simplistic in nature.

**Decay Rate** \( \lambda \). The second parameter \( \lambda \) corresponds to the rate of relevance decay in both models. Since the base relevance \( r_0 \) varies between languages, \( \lambda \) can be more intuitively interpreted as indicating the percentage of the original relevance of a contextual cue still remains in \( n \) positions. In the power-law model, for example, the context information from a previous sentence in Danish, on average, is only 11.6\% \( (2^{-3.10} \approx 0.116) \) as relevant. Hence, the relevance of a contextual cue decreases rather quickly for Danish. Table 2 shows this is in fact the general picture for all languages we tested.

| Language   | Relevance of Context in Discourse (%) |
|------------|---------------------------------------|
|            | 1 pos. before | 2 pos. before | 3 pos. before |
| Danish     | 11.6          | 3.3           | 1.4           |
| Dutch      | 10.4          | 2.8           | 1.1           |
| English    | 0.1           | 0.0           | 0.0           |
| French     | 8.5           | 2.0           | 0.7           |
| Italian    | 10.2          | 2.7           | 1.0           |
| Mandarin   | 7.7           | 1.7           | 0.6           |
| Norwegian  | 18.9          | 7.1           | 3.6           |
| Portuguese | 5.5           | 1.0           | 0.3           |
| Russian    | 12.7          | 3.8           | 1.6           |
| E. Spanish | 0.8           | 0.0           | 0.0           |
| L. Spanish | 2.7           | 0.3           | 0.1           |
| Swedish    | 5.8           | 1.1           | 0.3           |

Table 2: In the power model, relevance of a contextual cue decays rather quickly for each language.

The picture of \( \lambda \) looks a little different in the exponential model. The relevance percentage on average is significantly higher, which confirms an earlier point that the power function decreases more quickly than the exponential function. Table 3 shows a summary for the 12 languages.

| Language   | Relevance of Context in Discourse (%) |
|------------|---------------------------------------|
|            | 1 pos. before | 2 pos. before | 3 pos. before |
| Danish     | 30.1          | 9.1           | 2.7           |
| Dutch      | 28.7          | 8.2           | 2.4           |
| English    | 9.6           | 0.9           | 0.1           |
| French     | 26.7          | 7.1           | 1.9           |
| Italian    | 28.7          | 8.2           | 2.4           |
| Mandarin   | 25.7          | 6.6           | 1.7           |
| Norwegian  | 42.3          | 17.9          | 7.6           |
| Portuguese | 22.5          | 5.1           | 1.1           |
| Russian    | 34.6          | 12.0          | 4.2           |
| E. Spanish | 14.2          | 2.0           | 0.3           |
| L. Spanish | 18.6          | 3.5           | 0.6           |
| Swedish    | 23.7          | 5.6           | 1.3           |

Table 3: In the exponential model, relevance of a contextual cue decays more slowly.

**Correlation between** \( r_0 \) **and** \( \lambda \). Interestingly, \( r_0 \) and \( \lambda \) are highly correlated \( (r^2 = 0.39, p < 0.05) \) in the power model, Figure 5; \( r^2 = 0.47, p < 0.01 \) in the exponential model, Figure 6: a high relevance decay rate tends to be coupled with high within-context entropy of signals. This unanticipated observation is in fact compatible with the account of efficient language production: a high within-context entropy of signals indicates the base relevance of a contextual cue (i.e. \( r_0 \)) is high. It is then useful for its relevance to decay more quickly to allow the speaker to integrate context from other cues. Otherwise, the total amount of relevant context may presumably overload working memory. However, our current results come from only cross-linguistic samples. Cross-validation in within-language samples is needed for confirming this hypothesis.

### 3.3 The Bigger Picture

Having obtained the estimates for \( r_0 \) and \( \lambda \), we are now in a position to examine how out-of-context entropy of signals increases as a function of sentence positions, given the estimates of these two parameters. As shown in Figure 7, the predictions from both models are qualitative similar except that 1) when the decay rate in the power-law model is low, out-of-context entropy of signals converges more slowly than in the exponential model (Figure 7, right panel); 2) when the decay rate in the power model is high, it almost converges as quickly as the exponential model, and only minor differences exist in their predictions (Figure 7, left panel).
Within−Context Entropy per Word
Relevance Decay Rate
●
●
Danish
Dutch
English
French
Italian
Mandarin
Norwegian
Portuguese
Russian
E. Spanish
L. Spanish
Swedish

Figure 5: The rate of relevance decay is correlated with within-context entropy of signals in the power-law model.

Figure 6: The rate of relevance decay is correlated with within-context entropy of signals in the exponential model.

Because of the nonlinearity in our models, it is not possible to report the results in an intuitive manner as in “an increase in sentence position corresponds to an increase of X bits of out-of-context entropy per word”. Instead, we can analytically solve for the derivative of the predicted out-of-context entropy of signals with respect to sentence position (Equation 4 and 8). This gives us:

$$r_{\text{power}}(k) = r_0 k^{-\lambda}$$  \hspace{1cm} (11)

for the power-law model, showing the rate of increase in predicted out-of-context entropy of signals is a monotonically decreasing power function, and

$$r_{\text{exp}}(k) = \frac{r_0 \lambda}{e^\lambda - 1} (e^{-(k-1)\lambda})$$  \hspace{1cm} (12)

for the exponential model, showing the rate of increase is a monotonically decreasing exponential function. These mathematical properties indeed match our observations in Figure 7.

4 Discussion and Future Work

The models introduced in this paper try to answer this question: if the relevance of a contextual cue for predicting an upcoming linguistic signal decays over the course of a discourse, how much uncertainty (entropy) is associated with each individual sentence position? We have shown under that models that incorporate (power law or exponential) cue relevance decay in most cases describe the relation of out-of-context entropy of signals to sentence position are better accounted for than previously suggested models.

We are continuing to investigate along this line. Specifically, we are interested in finding the role of semantic memory in affecting the relevance decay of context. To test that, we plan to implement a probabilistic topic model, in which topic continuity between a preceding sentence and an upcoming sentence is quantitatively measured. Thus, the decay of contextual cues can be based on the esti-
mated semantic relatedness between sentences, in addition to the abstract notion of rate as used in this paper.

Finally, our relevance decay model can be applied to the domain of language processing as well. For instance, the distance between a contextual cue and the target word may affect how quickly a comprehender can process the information conveyed by the word. We plan to address these questions in future work.

5 Conclusion

We have presented a new approach for examining the distribution of entropy of linguistic signals in discourses, showing that not only the out-of-context entropy of signals increases sublinearly with sentence position, but also the sublinear trend is better explained by our nonlinear models than by log-linear models of previous work. Our models are built on the assumption that the relevance of a contextual cue for predicting a linguistic signal in the future decays with its distance to the target, and predict the relation of out-of-context entropy of signals to sentence position in discourses. These results indirectly lend support to the hypothesis that speakers maintain a constant entropy of signals across sentence positions in a discourse.

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