Abstract

Despite achieving incredibly low perplexities on myriad natural language corpora, today’s language models still often underperform when used to generate text. This dichotomy has puzzled the language generation community for the last few years. In this work, we posit that the abstraction of natural language as a communication channel (à la Shannon, 1948) can provide new insights into the behaviors of probabilistic language generators, e.g., why high-probability texts can be dull or repetitive. Humans use language as a means of communicating information, and do so in an efficient yet error-minimizing manner, choosing each word in a string with this (perhaps subconscious) goal in mind. We propose that generation from probabilistic models should mimic this behavior. Rather than always choosing words from the high-probability region of the distribution—which have a low Shannon information content—we sample from the set of words with an information content close to its expected value, i.e., close to the conditional entropy of our model. This decision criterion can be realized through a simple and efficient implementation, which we call typical sampling. Automatic and human evaluations show that, in comparison to nucleus and top-k sampling, typical sampling offers competitive performance in terms of quality while consistently reducing the number of degenerate repetitions.

1 Introduction

Today’s probabilistic models have repeatedly demonstrated their prowess at modeling natural language, attaining low perplexities on corpora from many domains. Yet when used to generate text, their performance is far from perfect. One of the largest determinants of the generated text’s quality is the choice of decoding strategy—i.e., the set of decision rules used to decode strings from the model. For many language generation tasks, decoding strategies which aim to find maximal probability strings produce text that is undesirable—e.g., generic or degenerate (Holtzman et al., 2020; See et al., 2019; Eikema and Aziz, 2020; Zhang et al., 2021; DeLucia et al., 2021). Rather, stochastic strategies, which take random samples from the model, often lead to text with better qualitative properties (Fan et al., 2018; Holtzman et al., 2020); yet these strategies still have their own host of problems (e.g., occasionally producing nonsensical text), while not entirely solving those seen in maximization-based approaches (e.g., falling into repetitive loops).

At first glance, it is unintuitive that high-probability strings are often neither desirable nor human-like text. A number of works have consequently concluded that there must be faults in the training objective or architecture of probabilistic language generators (Welleck et al., 2020; Guan et al., 2020; Li et al., 2020, inter alia). Yet, this conclusion is at odds with these models’ performance in terms of other metrics; the fact that modern language models can achieve incredibly low perplexities suggests that they do provide good estimates of the probability distribution underlying human language. We posit that looking at language generation through an information-theoretic lens may shed light on this dichotomy.

Communication via natural language can intuitively be cast in the information-theoretic framework. Indeed, there is a long history of studying language via this means (Shannon, 1948, 1951; Hale, 2001; Piantadosi et al., 2011; Pimentel et al., 2020, inter alia). In this paradigm, strings are messages used...
to convey information. Each string has an associated probability of occurring, which directly reflects that string’s information content.\footnote{The Shannon information content of a message is formally defined as its negative log-probability.} Assuming that humans use language in order to transmit information in an efficient manner (Zaslavsky et al., 2018; Gibson et al., 2019), the subset of strings typically used by humans should encode information at some (perhaps optimal) rate.\footnote{Prior works studying the uniform information density hypothesis (Levy and Jaeger, 2007; Mahowald et al., 2013; Meister et al., 2020b) observed precisely this property in humans’ use of natural language.} It follows that, if we want text generated from a model to be “human-like,” it should likewise adhere to this criterion. Note that high probability—or equivalently, low information—strings likely do not fall into this subset: their information content is lower than that of a typical string.

Concretely, we hypothesize that, for a text to be perceived as human-like, each word in a string should have information content close to its expected information content given prior context, i.e., its conditional entropy. When decoding from probabilistic language generators, we should aim to mimic this property. It turns out this is quite easy to enforce in practice: at each decoding step, we sample solely from the set of words whose negative log-probabilities are close to the conditional entropy of our model, an operation that can be done in the same runtime as nucleus or top-\(k\) sampling. We call this new decoding strategy \textbf{typical sampling}, named after its relationship to the information-theoretic concept of typicality, which provides (informal) intuition for its efficacy. In experiments on summarization and story generation, we observe that, compared to nucleus and top-\(k\) sampling: (1) typical sampling reduces the number of degenerate repetitions, giving a REP value (Welleck et al., 2020) on par with human text, and (2) text generated using typical sampling is closer in quality to that of human text.\footnote{Code for typical sampling can be found at https://github.com/cimeister/typical-sampling.git.}

\section{Background}

\subsection{Probabilistic Language Generators}

Systems for natural language generation are predominantly parameterized by locally-normalized probabilistic models, i.e., probability distributions \(q\) over natural language strings \(y = (y_1, y_2, \ldots)\) that are decomposed over words \(y_t\).\footnote{We may also decompose strings over other units, e.g., sub-words or characters. All subsequent analyses in this work can be applied in terms of these other units.}  

\[
q(y) = \prod_{t=1}^{\left|y\right|} q(y_t \mid y_{<t}) \tag{1}
\]

The support of \(q\) is the exponentially-sized set \(\mathcal{Y}\), which consists of all possible strings (book-ended by special beginning- and end-of-string tokens \text{bos} and \text{eos}) that can be constructed from words in the model’s vocabulary \(\mathcal{V}\). In practice, we limit the set of strings we consider to \(\mathcal{Y}_T \subset \mathcal{Y}\), i.e., all strings in \(\mathcal{Y}\) of some maximum length \(T\).

The standard method for estimating the parameters of \(q\) is via maximization of the log-likelihood of a training corpus \(\mathcal{C}\). This is equivalent to minimizing the loss  

\[
L(\theta; \mathcal{C}) = -\sum_{y \in \mathcal{C}} \log q(y) \tag{2}
\]

where \(\theta\) are the model parameters. It is well known that the model whose parameters minimize Equation (2) is likewise the model that minimizes the Kullback–Leibler divergence with the empirical distribution \(p\) (as defined by \(\mathcal{C}\)). Notably, this implies that the learned distribution is also optimal in an information-theoretic sense: if \(p\) represents the distribution underlying a communication channel, then minimizing \(D_{\text{KL}}(p \parallel q)\) optimizes for a distribution \(q\) that places probability mass over the same messages as \(p\).

\subsection{Decoding Natural Language Strings}

In short, decoding is the process of generating natural language strings from a model. While decoding is done on a word-by-word basis for all models we consider, there are still many different sets of decision rules that can be used. Given the probabilistic nature of \(q\), a natural option would be to choose words which maximize the probability assigned by \(q\) to the resulting
string. We refer to this class of methods as “mode-seeking,” as they try to find the mode of \( q \). Yet recent research has shown that solutions to mode-seeking methods—such as greedy or beam search—are often not high-quality, even in state-of-the-art language generation models. For example, in the domain of machine translation, the most probable string under the model is often the empty string (Stahlberg and Byrne, 2019; Eikema and Aziz, 2020). For open-ended generation, mode-seeking methods produce dull, generic or even degenerate text (Fan et al., 2018; Holtzman et al., 2020).

Consequently, stochastic decoding strategies have become the mainstay for many language generation tasks. In these strategies, words are sampled randomly at each time step. While stochasticity may solve the issue of “dull or generic” text, directly sampling from \( q(y_i | y_{<i}) \) can lead to text that is incoherent and sometimes unrelated to the subject. Several works blame this behavior on the “unreliable tail” of the distribution, perhaps caused by the non-sparse nature of the softmax transformation used to produce a probability distribution in the final layer of neural networks. They propose to fix this issue by limiting the sampling space to a core subset of words. As concrete examples, Fan et al. (2018) propose limiting the sampling space to the top-\( k \) most likely words in each decoding step; Holtzman et al. (2020) consider the smallest nucleus, i.e., subset, of words whose cumulative probability mass exceeds a chosen threshold \( n \).

We can formalize these approaches (respectively) as alterations of \( q(y_i | y_{<i}) \) at each decoding step. Let \( Z_t = \sum_{y \in \mathcal{V}^{(k)}} q(y | y_{<t}) \) where \( \mathcal{V}^{(k)} \subseteq \mathcal{V} \) denotes the set of the \( k \) most likely words. Top-\( k \) sampling employs the truncated distribution:

\[
\pi(y | y_{<t}) = \begin{cases} 
q(y | y_{<t})/Z_t, & \text{if } y \in \mathcal{V}^{(k)} \\
0, & \text{else}
\end{cases}
\]

In a similar fashion, let \( \mathcal{V}^{(n)} \subseteq \mathcal{V} \) be the smallest set such that

\[
\sum_{y \in \mathcal{V}^{(n)}} q(y | y_{<t}) \geq n
\]

The truncated distribution for \textbf{nucleus sampling} is then computed similarly to Equation (3), albeit with \( \mathcal{V}^{(n)} \) and \( Z_t = \sum_{y \in \mathcal{V}^{(n)}} q(y | y_{<t}) \).

While strings generated using such stochastic methods may have lower probability according to \( q \), they often outperform those decoded using mode-seeking methods in terms of qualitative metrics. A number of recent works have tried to offer explanations for this phenomenon: some have attributed it to a diversity-quality trade-off (Zhang et al., 2021) while others blame shortcomings of model architectures or training strategies (Welleck et al., 2020; Li et al., 2020).

In this work, we offer an alternative explanation, motivated by information-theory.

3 An Information-Theoretic View of Natural Language

Language is (arguably) the primary means for human communication. As such, information theory—the formal, mathematical study of communication—provides an intuitive lens through which we can study natural language. Over the past century, many insights into the development and use of language have been made using an information-theoretic framework (Hale, 2001; Aylett and Turk, 2004; Collins, 2014; Piantadosi et al., 2011; Levy, 2018; Gibson et al., 2019, inter alia). Building on these works, we demonstrate how concepts from information theory can help us understand certain behaviors of probabilistic language generators, and in turn, how we can generate more human-like language from them.

3.1 The Human Communication Channel

The process of communicating via natural language (either spoken or written) can be interpreted as the transmission of a message via a communication channel. In this light, a human language represents a code by which information is transmitted; a natural language string \( y \) is a means of communicating some information, which we denote \( I(y) \), and each word \( y_i \) is a symbol via which we construct our message.
Formally, information theory tells us that y’s information content can be quantified as its negative log-probability: $I(y) := -\log p(y)$, where the distribution $p$ is a fixed, inherent property of the communication channel. Further, if y can be broken down into t units, we can express $I(y)$ as the sum of the information conveyed by each unit:

$$I(y) = \sum_{t=1}^{\lfloor y \rfloor} I(y_t) \quad (5)$$

where similarly $I(y_t) = -\log p(y_t | y_{<t})$, the negative log-probability of $y_t$ in its context. Note that Equation (5) also follows from a simple application of the chain rule of probability. While we do not a priori know these probabilities, conveniently, they are exactly what our model $q$ has learned to approximate, as discussed in Section 2.1.

As is typical in communication, the goal of an agent is to transmit information efficiently while also minimizing the risk of miscommunication. These goals determine how we choose to encode the information we wish to transmit,\(^7\) a choice encompassing which words we use and whether or not to adhere to certain paradigms that we may view as requirements, such as grammaticality. Implicit in this decision is also the amount of information transmitted by each word. When the stochastic process generating messages is stationary, we can define its formal information rate: the average amount of information transmitted by any symbol given all previously-generated symbols. However, language generation is arguably not a stationary process, i.e., we cannot say there is necessarily some $t$ for which all words $< t$ do not affect the distribution over $y_t$. We can nonetheless still compute the expected amount of information a specific symbol in our message will contain:

$$\mathbb{E}[I(y_t)] = -\sum_{y_t \in \mathcal{V}} p(y_t \mid y_{<t}) \log p(y_t \mid y_{<t}) \quad (6)$$

Note that this quantity is simply the conditional entropy of $p(\cdot \mid y_{<t})$, which we denote as $H(p(\cdot \mid y_{<t}))$.\(^8\)

\(^7\)See Gibson et al. 2019 for an in-depth review of how efficiency has shaped the evolution of language.

\(^8\)We use the convention of supplying the entropy function with a probability distribution—rather than a random variable—to make explicit the distribution we are operating over.

So how do we, as humans, choose the amount of information we transmit over the course of a natural language string? This is a research question in and of its own right, one without a concrete answer yet. Research in psycholinguistics, however, suggests that speakers avoid producing words with either very high or very low information content (Levy and Jaeger, 2007; Frank and Jaeger, 2008; Mahowald et al., 2013). Furthermore, cross-linguistic research has shown that languages trade-off information content and speech rate, perhaps aiming at a specific information rate value (Coupé et al., 2019; Pimentel et al., 2021). It seems, thus, that a core component of what makes text “human-like” is its per-word information content. Consequently, in this work, we posit the following:

**Hypothesis 3.1.** Any given word should have an information content close to the expected information content, i.e., the conditional entropy given prior context. In other words, we expect the difference:

$$\varepsilon = |H(p(\cdot \mid y_{<t})) - I(y_t)| \quad (7)$$

to be small in human-like text.

We provide empirical motivation for our hypothesis in Figure 1, which shows—for human-generated text—the distribution of $\varepsilon$. There are two important observations that can be taken from this figure: (1) the peaked nature of the distributions reveals that humans indeed tend to form language with per-word information content quite close to their expected information content and (2) the centering of these distributions around a value close to 0 reveals that our probabilistic language generators are learning what this rate is.

### 3.2 Relationship of Hypothesis 3.1 to Typicality

Hypothesis 3.1 can intuitively be linked to the notion of typicality in information theory (Shannon, 1948). Typicality is a property of messages from a specific stochastic process: typical messages are the ones that we would expect from its probability distribution. These sets of messages have a quantifiable attribute—their average per-symbol information content is close to the entropy rate of their source distribution. Formally, an $\varepsilon$-typical message of
Figure 1: The distribution of the deviation ($\varepsilon$) of information content from the conditional entropy per token. Results taken on the reference (human) text for three different language generation tasks. Values are estimated using probabilistic models trained on the respective task (see Section 5 for model details). Dashed line and text indicate mean difference. Distributions of conditional entropies and information contents per token are shown in Appendix B for reference.

For a given $\varepsilon$, interestingly, this definition implies that the highest probability message is (often) not a member of this set—its average information content is too low.

While the formal notion of typicality is not directly applicable in this context, it is illustrative of why Hypothesis 3.1 might indeed be true: it demonstrates a concrete relationship between messages we expect to see—given the distribution underlying a stochastic process—and the information content of those messages. Analogously, our hypothesis predicts what information content we should expect in messages produced by the distribution over human language. However, typicality is a property with respect to the information content of a message in its entirety, not describing characteristics of individual symbols in the message. Hypothesis 3.1 is instead more akin to a “local” typicality, where individual symbols themselves have information content within a specified range. The motivation for this more local definition is that natural-sounding language should be typical everywhere; it should not be able to compensate for unusually low probability in

the first half, e.g., grammatical errors, with unusually high probability in the second half, e.g., especially frequent words.

This local definition also has a more direct link to several psycholinguistic theories, which we discuss next. Further, as we will see in Section 4, it proves more practically useful when creating decision rules for decoding from standard probabilistic models, which must be performed word-by-word.

3.3 Relationship of Hypothesis 3.1 to Psycholinguistic Concepts

We next motivate this hypothesis as an extension of two psycholinguistic theories, namely: the uniform information density hypothesis, and the rational speech act.

The Uniform Information Density Hypothesis. The uniform information density (UID) hypothesis (Fenk and Fenk, 1980; Levy and Jaeger, 2007) states that speakers construct their utterances such that information is distributed uniformly across them. While this hypothesis may allow multiple interpretations (see, e.g., Meister et al., 2021, for discussion), a predominant one is that speakers optimize their sentences to maximize the use of a communication channel—choosing words such that their information rate is closer to a target channel capacity. If a word conveys more information than the channel allows, there is a risk for miscommunication; simultaneously, if a word conveys very low information, then this channel is being used inefficiently. Analogously, we propose here that speaker’s will avoid producing words with “out of the ordinary” information content, thus choosing words close to the expected information at each moment.

A UID-inspired objective has previously been shown to improve language modeling results (Wei et al., 2021). Further, the UID hypothesis has been used as rationale for the effectiveness of beam search in the context of machine translation (Meister et al., 2020b). While at first, the hypothesis presented in this work may seem at odds with results showing the efficacy of mode-seeking decoding strategies, like beam search, a closer look reveals they are in fact compatible. When trained without label-smoothing, which artificially inflates conditional entropies, machine translation models tend to have quite low conditional entropies (see e.g., Fig. 3 in Meister...
Therefore, at each decoding step, the set of words with negative log-probability near the conditional entropy of the model are typically those with high probability—the same as those chosen by beam search.

**The Rational Speech Act.** The rational speech act (RSA; Frank and Goodman, 2012) is a recently-proposed framework which models a speaker’s pragmatic behavior. In short, RSA casts a speaker’s behavior as the maximization of a utility function: a sentence’s usefulness to its listener. More formally, RSA introduces the concept of a literal speaker, who produces sentences $y$ according to a base (naive) distribution $p_0$. The value a listener can extract from a message is then a function of that entire distribution $u(y; p_0)$, i.e., the listener’s utility function. Finally, the pragmatic speaker produces sentences to maximize this utility, as opposed to following its expected literal behavior. Within this framework, we posit that a listener’s utility is modulated by how close to the entropy each word’s information content is, i.e.:

$$u(y_t; p) \propto -|H(p(\cdot|y_{<t})) - I(y_t)|$$

and that pragmatic speakers will only produce sentences where the utility is larger than a specific value at each time step.

### 4 An Information-Theoretic Decoding Strategy

Considering probabilistic language generators in the information-theoretic framework leads to a number of insights into behaviors that have been previously observed when decoding text from these models. In conjunction with the rationale and observations in Section 3, it also motivates a new decoding strategy, which we call **typical sampling.**

#### 4.1 Understanding Probabilistic Language Generators

A probabilistic language generator $q$ approximates the empirical distribution $p$.\footnote{Our following analysis assumes $q$ is a perfect representation of $p$, even though it is undoubtedly not. Still, these models provide an incredibly good approximation of $p$—as shown by performance w.r.t. metrics such as perplexity.} Let us now adopt the interpretation that this distribution underlies a natural language communication channel. This framing offers an informal explanation between some qualitative properties of strings and their probability under a model $q$, which we believe may reconcile why models performing so well (in terms of metrics such as perplexity) can still exhibit such “undesirable” behavior.

First, the connection between probability and information content may explain why high-probability text is often dull or generic (Holtzman et al., 2020; Eikema and Aziz, 2020)—its low information content likely makes for boring or uninformative text. This connection also offers a potential explanation for the rather strange behavior that, when generations fall into a repetitive loop, language models often assign increasingly higher probability to the repeated substring (Holtzman et al., 2020)—the substring conveys less and less information after each occurrence.

A further implication of this framing is the equivalence between decoding strings from a probabilistic language generator $q$ and sampling messages from the natural language communication channel. If we wish to solely sample from the subset of messages that a human would typically construct, i.e., that are “human-like,” then we should begin by narrowing down this subset to those messages that meet at least some of the same criteria as human-generated messages. In this work, one such criterion we have identified is that per-word information content lies close to the expected information content of the symbol: $I(y_t) \approx E[-\log p(\cdot|y_{<t})]$. Notably, we already see motivation for this criterion in the performance of several well-known decoding strategies. For example, beam search is the predominant decoding strategy for machine translation models (Wu et al., 2016; Edunov et al., 2018; Ng et al., 2019), a setting in which it (incidentally) often already enforces this criterion (see Section 3.3 for elaboration). Yet when used in more open-ended tasks, where models typically have higher entropies, beam search can lead to low-quality text (Li et al., 2016; Holtzman et al., 2020; Welleck et al., 2020). These observations motivate a new decoding strategy in which our information-theoretic criterion is explicitly enforced, which we subsequently present.
Table 1: Perplexity, fraction of repetitions (rep), Zipf’s coefficient, MAUVE scores (Pillutla et al., 2021) and averaged human ratings for the reference text in comparison to nucleus, top-

|                | Abstractive Summarization | Story Generation |
|----------------|---------------------------|-----------------|
|                | PPL  | rep  | Zipf  | MAUVE | Human | PPL   | rep  | Zipf  | MAUVE | Human |
| Reference      | 11.51| 0.13 | 0.76  | -     | 4.07  | 20.06 | 0.28 | 1.09  | -     | 4.23  |
| Nucleus (n = 0.9) | 3.28 | 0.16 | 0.93  | 0.93  | 3.97  | 9.65  | 0.32 | 1.25  | 0.95  | 4.00  |
| Top-k (k = 30)  | 3.12 | 0.16 | 0.93  | 0.96  | 3.97  | 7.77  | 0.34 | 1.42  | 0.97  | 4.08  |
| Typical (τ = 0.2/τ = 0.95) | 4.12 | 0.15 | 0.92  | 0.98  | 4.03  | 17.32 | 0.28 | 1.26  | 0.92  | 4.10  |

4.2 Typical Sampling

We define $V(\tau) \subseteq V$ as the subset of words that minimize

$$\sum_{y \in V(\tau)} |H(q(\cdot | y_{<t})) + \log q(y | y_{<t})|$$

(10)

s.t. $\sum_{y \in V(\tau)} q(y | y_{<t}) \geq \tau$. That is, we limit our sampling distribution to only those words with negative log-probability within a certain absolute range from the conditional entropy of the model at that time step. In the spirit of nucleus sampling, this range is determined by a hyperparameter $\tau$, the amount of probability mass from the original distribution that we wish to consider. We then renormalize our truncated distribution as in Equation (3), where similarly we have $Z_t = \sum_{y \in V(\tau)} q(y | y_{<t})$.

Note that this rule does not imply that high-probability words should not be chosen. Indeed, in the situation where conditional entropy is low—i.e., when the model places most of the probability mass on a small subset of words—then it is likely the case that only high-probability words meet this criterion, having an information content which $I(y_t) \approx H(q(\cdot | y_{<t}))$.

Computational Complexity. From a practical perspective, this scheme can be implemented with the same efficiency as nucleus or top-k sampling. First, we compute the conditional entropy, which is an $O(V)$ operation. Second, we sort words by their absolute distance from $H(q(\cdot | y_{<t}))$, which can be done in $O(V \log V)$ time with standard sorting algorithms. Third, similarly to nucleus sampling, we greedily take words from this list until their cumulative probability exceeds the threshold $\tau$, which again takes $O(V)$ time. Thus, creating our altered distribution has time complexity $O(V \log V)$.

5 Experiments

In this section, we explore the efficacy of our decoding strategy for two natural language generation tasks: abstractive summarization and story generation. We assess performance with respect to two other widely-used stochastic decoding strategies: nucleus and top-k sampling. Our evaluation includes both automatic metrics and human ratings.

5.1 Setup

Models and Data. For story generation, we fine-tune the medium version of GPT-2 (Rafford et al., 2019; from a checkpoint made available by OpenAI) on the WRITINGPROMPTS dataset (Fan et al., 2018). We use the same checkpoint, albeit fine-tuned on WIKITEXT-103 (Merity et al., 2017) to produce the data used in Figure 1. For abstractive summarization, we use BART (Lewis et al., 2020) fine-tuned on the CNN/DAILYMAIL dataset (Nalapati et al., 2016). All reported metrics are computed in the respective test sets. We use the Hugging Face framework (Wolf et al., 2020) for reproducibility, employing their implementations of nucleus and top-k sampling.

Hyper-parameters In a preliminary hyperparameter sweep using MAUVE (Welleck et al., 2020), we found $k = 30$ and $n = 0.9$ to perform best for top-k and nucleus sampling, respectively. For typical sampling, we found $\tau = 0.2$ and $\tau = 0.95$ to provide the best results for story generation and abstractive summarization, respectively. We use these values in our human evaluations and in computation of the automatic metrics shown in Table 1.

11 As we are interested in getting as close an estimate of $p$ as possible with our models $q$, all fine-tuning is done without label-smoothing.
Automatic Metrics. As automatic metrics, we evaluate the generated text’s perplexity, MAUVE score (Pillutla et al., 2021) with the reference text—a metric that uses LM embeddings to measure the similarity between two text distributions—as well as REP (Welleck et al., 2020) and Zipf’s coefficient, both of which quantify the repetitiveness in text. For computing MAUVE, we use the implementation provided by the authors under the default settings. For REP we use the average of REP/ℓ scores (as defined in Welleck et al., 2020) for ℓ ∈ {16, 32, 128}.

Human Evaluations. We use Amazon Mechanical Turk to obtain human judgments of text quality from 5 different annotators on 100 examples per decoding strategy–per task. We largely follow DeLucia et al. (2021) in setting up our evaluations: For ablactive summarization, we ask annotators to score on fluency and relevance while for story generation, annotators score on fluency, coherence, and interestingness. We choose these criteria following recommendations from van der Lee et al. (2019). We use a 5-point Likert scale for each criterion. More details on setup can be found in Appendix A, where we provide the exact instructions presented to the workers.

5.2 Results

Quantitative Performance. Table 1 shows the results of our different evaluation metrics; human scores are averaged across the qualitative metrics to give an aggregate score. We show full breakdowns of score distributions in Table 3. We see that in general, typical sampling performs on par with or better than nucleus and top-k sampling, often producing text with metrics closest to that of the reference among the three decoding strategies. Figure 2 shows REP measurements for different values of the hyperparameters k, n, and τ. Interestingly, REP appears to be far less sensitive to τ than to k and n in nucleus and top-k sampling.

Qualitative Performance. We provide examples of text generated according to each of the decoding strategies in Table 2. For text that is too long, we provide the full version in Table 4 in the appendix. For both of the tasks, we choose the example with ID 1 according to the original dataset.

For the summarization task, we see that typical sampling provides a comprehensive and coherent summary of the article. In comparison, nucleus sampling leads to hallucinated facts (“getting drugs from undercover police officers”) while top-k sampling misses some of the important information in the article, e.g., the charges of burglary and arson.

While the qualitative results of story generation are much more subjective, typical sampling arguably provides the most fluent stories of the three decoding strategies. The stories from nucleus and top-k sampling lack coherency and even within the first few sentences, we see repeated phrases and words. Interestingly, the story generated by typical sampling also exhibits the fewest grammatical flaws. Together, these results suggest that typical sampling indeed produces more desirable text.

6 Conclusion

In this work, we analyze decoding from probabilistic language generators using an information-theoretic framework. Under this paradigm, a language model approximates the
### Abstractive Summarization (CNN/DailyMail)

| Prompt | (CNN) The attorney for a suburban New York cardiologist charged in what authorities say was a failed scheme to have another physician hurt or killed is calling the allegations against his client “completely unsubstantiated.” Appearing Saturday morning on CNN’s “New Day,” Randy Zelin defended his client, Dr. Anthony Moschetto, who faces criminal solicitation, conspiracy, burglary, arson, criminal prescription sale and weapons charges in connection to what prosecutors called a plot to take out a rival doctor on Long Island. “None of anything in this case has any evidentiary value,” Zelin told CNN’s Christi Paul... |
|---|---|
| Reference | A lawyer for Dr. Anthony Moschetto says the charges against him are baseless. Moschetto, 54, was arrested for selling drugs and weapons, prosecutors say. Authorities allege Moschetto hired accomplices to burn down the practice of former associate. |
| Nucleus | Dr. Anthony Moschetto is accused of plotting a murder, conspiracy and possession of weapons. The alleged plot involved allegedly getting drugs from undercover police officers. Police found hundreds of weapons at his home, including guns. |
| Top-$k$ | Dr. Anthony Moschetto is accused of providing police with weapons and prescription drugs. Authorities say he was part of a conspiracy to harm or kill a rival doctor. His attorney calls the allegations against his client “completely unsubstantiated” |
| Typical | Dr. Anthony Moschetto is charged with crimes including arson, conspiracy, burglary, prescription sale, weapons charges. His attorney says “none of anything in this case has any evidentiary value” |

### Story Generation (WritingPrompts)

| Prompt | A kid doodling in a math class accidentally creates the world’s first functional magic circle in centuries. |
|---|---|
| Reference | It was dark and Levi was pretty sure he was lying on his back. There was firelight flickering off of what was left of a ceiling. He could hear something but it was muffled. He was almost positive it was screaming. When he tried to move he felt an excruciating pain in his left side that caused him to cry out. His hand moved to it instinctively and found something protruding from the wound... |
| Nucleus | “Good morning, class! The weirdest thing about the day is that I thought I had completely forgot to pre-pone this class and forgot that I had written ‘I am faking it’ in white spray paint all over the chalkboard. Now that we know I’ve started, let’s really get started. And you’re on your first homework...” |
| Top-$k$ | “Hey, are you following us?” the boy asked her. “Yes, I’m sorry. Who are you from?” she asked, “I’m new here. Do you know any magic circles?” “They are magic circles that show how many people are standing in front of you.” the child replied. “Oh. I see. Well, it’s a magic circle.” “Yes. Do you think your magic circle will work?”... |
| Typical | It had taken an unusually long time. At least it seemed to be longer than that. As if, no matter how hard you looked at the things around you, the colors in the water and the place they stood on the island were too real. I would see it happen over and over again in the corner of my eye. But even now, all the people on this island looked up to me with admiration, almost a weird and unrealistic worship of my existence... |

Table 2: Sample generations for abstractive summarization and story generation. Both sets of examples correspond to ID 1 in the respective data sets. Same values of $\tau/n$ and $k$ as used in Table 1.
probability distribution that defines a communication channel; generating text from such a model is then equivalent to sampling messages from this channel. Motivated by results in psycholinguistics and pragmatics, we hypothesize that—with the goal of communicating efficiently—humans produce text whose per-word information content is within a close range of the expected information content. This observation provides a simple new criterion for decoding more human-like text from probabilistic language generators. In experiments on two language generation tasks, we find that our strategy—called typical sampling—leads to text of comparable or better quality than nucleus and top-k sampling according to human ratings. Further, when compared to these other decoding strategies, several quantitative properties of typically sampled text more closely align with those of human text.

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We use Amazon Mechanical Turk framework for collecting human ratings of text. We use solely MTurk Master Workers in order to maximize the quality of our ratings. For story generation and abstractive summarization, each Human Intelligence Task (HIT) consists of either a single prompt from which a story should be generated or a single news article to be summarized. The raters are first presented with the different rating criteria, along with descriptions of the type of text that meets these criteria at different levels of the scale. These definitions can be seen in Figures 3 and 4. Raters are additionally provided several examples of stories/summaries meeting/failing to meet the rating criteria. They are then presented with the respective prompt/news article and the corresponding stories/summaries generated by different decoders and by the reference in random order. We use an attention check in each HIT. Responses where the attention check has been failed are thrown out. For each of the rating criteria, the rater assigns a score from 1 to 5. For each story/summarization and each of the criteria, we take the median score across raters as the final respective score. Statistics for these scores can be seen in Table 3.

A Human Evaluation Setup

We use Amazon Mechanical Turk framework for collecting human ratings of text. We use solely MTurk Master Workers in order to maximize the quality of our ratings. For story generation and abstractive summarization, each Human Intelligence Task (HIT) consists of either a single prompt from which a story should be generated or a single news article to be summarized. The raters are first presented with the different rating criteria, along with descriptions of the type of text that meets these criteria at different levels of the scale. These definitions can be seen in Figures 3 and 4. Raters are additionally provided several examples of stories/summaries meeting/failing to meet the rating criteria. They are then presented with the respective prompt/news article and the corresponding stories/summaries generated by different decoders and by the reference in random order. We use an attention check in each HIT. Responses where the attention check has been failed are thrown out. For each of the rating criteria, the rater assigns a score from 1 to 5. For each story/summarization and each of the criteria, we take the median score across raters as the final respective score. Statistics for these scores can be seen in Table 3.

We will reject your HIT if you fail attention checks or if you have unusually low agreement with other annotators.

Definitions

Below you will find multiple prompts and stories (narratives) generated from those prompts. Please rate the stories according to their interestingness, fluency and coherence following the given definitions and examples. We will reject your HIT if you input obviously wrong answers. The 5-point scale for each definition should be used as a guideline. The definitions are displayed when hovering over each radio button for convenience. (Note: if the definitions do not appear even after a few seconds, please leave your browser (e.g. Chrome) and OS (e.g. Windows) information in the comment box.)

### Interesting

- **Very interesting:** The story has themes, characters, and dialog that make you want to keep reading it and you might even want to show it to a friend.
- **Somewhat interesting:** There are moments of interest but the story is not too notable.
- **Not very interesting:** You finish the story but can’t remember anything unique about it. Adequate, but not a fun read.
- **Not at all interesting:** You do not even want to finish reading the story. It is boring and/or unoriginal.

- **Interesting:** The story is fun to read. It feels creative, original, dynamic, and/or vivid. The opposite of this might be something that’s obvious, stereotypical/nonoriginal, and/or boring.
- **Very interesting:** The story has themes, characters, and dialog that make you want to keep reading it and you might even want to show it to a friend.
- **Somewhat interesting:** There are moments of interest but the story is not too notable.
- **Not very interesting:** You finish the story but can’t remember anything unique about it. Adequate, but not a fun read.
- **Not at all interesting:** You do not even want to finish reading the story. It is boring and/or unoriginal.

### Fluent

- **Fluent:** The story is written in grammatical English. No obvious grammar mistakes that a person wouldn’t make. An incomplete final word or incomplete sentence does not count as a mistake and should not affect fluency. The English sounds natural. Note: do not take off points for spaces between punctuation (e.g. “Don’t”) and simpler sentences. Simple English is as good as complex English, as long as everything is grammatical.
- **Very Fluent:** The sentences read as if they were written by a native English speaker with 1 or no errors.
- **Somewhat Fluent:** The sentences read as if they were written by a native English speaker with very few errors. Some minor mistakes that a person could have reasonably made.
- **Not very Fluent:** Many sentences have frequently repeated words and phrases. Obvious mistakes.
- **Not at all Fluent:** The sentences are completely unreadable. If the same sentence is repeated over and over for the entire story, that story is considered not fluent.

- **Coherent:** The story feels like one consistent story, and not a bunch of jumbled topics. Stays on-topic with a consistent plot, and doesn’t feel like a series of disconnected sentences.
- **Very Coherent:** The sentences when taken as a whole all have a clearly identifiable plot.
- **Somewhat Coherent:** Many of the sentences work together for a common plot with common characters. One or two unrelated sentences.
- **Not very Coherent:** Around half of the sentences work together. The plot is not entirely clear though.
- **Not at all Coherent:** Only a few sentences seem to be from the same story, the others are random.

- **Narrative:**
  - **Not at all Coherent:**
  - **Somewhat Coherent:**
  - **Very Coherent:**

### Narrative

- **Very coherent:** The sentences when taken as a whole all have a clearly identifiable plot.
- **Somewhat coherent:** Many of the sentences work together for a common plot with common characters. One or two unrelated sentences.
- **Not very coherent:** Around half of the sentences work together. The plot is not entirely clear though.
- **Not at all coherent:** Only a few sentences seem to be from the same story, the others are random.

Please confirm the following worker criteria:

- I have read the instructions
- I have read the examples
- I am a native English speaker

Figure 3: Stories survey.
Please confirm the following worker criteria:

☐ I have read the instructions
☐ I have read the examples
☐ I am a native English speaker

Figure 4: Summarization survey.

B Additional Results

Figure 5: Distributions of conditional entropies and information contents per token for three different language generation tasks for human text, i.e., the reference text for each of the respective datasets.

| Decoder   | Coherence | Story Generation | Summarization |
|-----------|-----------|------------------|---------------|
|           | Fluency   | Interestingness  | Fluency       | Relevance     |
| Reference | 4.42 (±0.30) | 4.48 (±0.34)      | 4.17 (±0.47)  | 3.96 (±0.34)  | 4.39 (±0.31) |
| Nucleus   | 4.17 (±0.64) | 4.32 (±0.57)      | 3.97 (±0.92)  | 3.76 (±0.56)  | 4.28 (±0.42) |
| Top-k     | 4.36 (±0.40) | 4.44 (±0.46)      | 4.02 (±0.50)  | 3.83 (±0.58)  | 4.30 (±0.32) |
| Typical   | 4.37 (±0.44) | 4.4 (±0.48)       | 4.07 (±0.65)  | 3.85 (±0.45)  | 4.33 (±0.33) |

Table 3: Breakdown of human ratings on quality metrics per task. Values in blue are variances.
(CNN) The attorney for a suburban New York cardiologist charged in what authorities say was a failed scheme to have another physician hurt or killed is calling the allegations against his client “completely unsubstantiated.” Appearing Saturday morning on CNN’s “New Day,” Randy Zelin defended his client, Dr. Anthony Moschetto, who faces criminal solicitation, conspiracy, burglary, arson, criminal prescription sale and weapons charges in connection to what prosecutors called a plot to take out a rival doctor on Long Island.

“None of anything in this case has any evidentiary value,” Zelin told CNN’s Christi Paul. "It doesn't matter what anyone says, he is presumed to be innocent." Moschetto, 54, pleaded not guilty to all charges Wednesday. He was released after posting $2 million bond and surrendering his passport. Zelin said that his next move is to get Dr. Moschetto back to work. “He's got patients to see. This man, while he was in a detention cell, the only thing that he cared about were his patients. And amazingly, his patients were flooding the office with calls, making sure that he was OK,” Zelin said. Two other men – identified as James Chmela, 43, and James Kalamaras, 41 – were named as accomplices, according to prosecutors. They pleaded not guilty in Nassau County District Court, according to authorities. Both were released on bail. A request for comment from an attorney representing Chmela was not returned. It’s unclear whether Kalamaras has retained an attorney. Police officers allegedly discovered approximately 100 weapons at Moschetto’s home, including hand grenades, high-capacity magazines and knives. Many of the weapons were found in a hidden room behind a switch-activated bookshelf, according to prosecutors. The investigation began back in December, when undercover officers began buying heroin and oxycodone pills from Moschetto in what was initially a routine investigation into the sale of prescription drugs, officials said. During the course of the undercover operation, however, Moschetto also sold the officers two semiautomatic assault weapons as well as ammunition, prosecutors said. Moschetto allegedly told officers during one buy that he needed dynamite to “blow up a building.” He later said he no longer needed the dynamite because a friend was setting fire to the building instead. Kalamaras and Chmela are believed to have taken part in the arson, according to prosecutors. “The fire damaged but did not destroy the office of another cardiologist whose relationship with Dr. Moschetto had soured due to a professional dispute,” according to the statement from the district attorney’s office. Moschetto allegedly gave an informant and undercover detective blank prescriptions and cash for the assault and killing of the fellow cardiologist, according to prosecutors. He also requested that the rival’s wife be assaulted if she happened to be present, authorities said. “He was willing to pay $5,000 to have him beaten and put in a hospital for a few months, and then he said he would pay $20,000 to have him killed,” said Assistant District Attorney Anne Donnelly, according to CNN affiliate WCBS.

Reference
A lawyer for Dr. Anthony Moschetto says the charges against him are baseless. Moschetto, 54, was arrested for selling drugs and weapons, prosecutors say. Authorities allege Moschetto hired accomplices to burn down the practice of former associate.
Dr. Anthony Moschetto is accused of plotting a murder, conspiracy and possession of weapons. The alleged plot involved allegedly getting drugs from undercover police officers. Police found hundreds of weapons at his home, including guns.

Dr. Anthony Moschetto is accused of providing police with weapons and prescription drugs. Authorities say he was part of a conspiracy to harm or kill a rival doctor. His attorney calls the allegations against his client “completely unsubstantiated”

Dr. Anthony Moschetto is charged with crimes including arson, conspiracy, burglary, prescription sale, weapons charges. His attorney says “none of anything in this case has any evidentiary value”

**Prompt**
A kid doodling in a math class accidentally creates the world’s first functional magic circle in centuries.
It was dark and Levi was pretty sure he was lying on his back. There was firelight flickering off of what was left of a ceiling. He could hear something but it was muffled. He was almost positive it was screaming. When he tried to move he felt an excruciating pain in his left side that caused him to cry out. His hand moved to it instinctively and found something protruding from the wound. It seemed to be a pipe of some kind. He attempted to pull it out but it was covered in blood making it slick. Levi’s ears began ringing and the sounds began to become clearer, it felt quite a bit like some one was driving needles into his eardrums. The sounds he was hearing were definitely screams and not just one person’s, a lot of people were screaming or yelling. There was some one close to him that was crying. He looked in the direction of the tears and seen his sister kneeling beside him, her hands covering her face. “What happened Laur?” He was shocked at the sound that barely rasped out from between his lips. His sister’s hands jerked down and she stared down at Levi with a shocked look on her face. “bu... I tho... you weren’t breathing!” What started as a whisper ended in yell as she threw her self across her brother and began to sob anew. Levi cried out hoarsely but she didn’t hear. She just continued to cling to him like a little girl that had just found her lost doll. He put one of his arms around her and scanned the room as much as he could. It looked like a warzone, like something out of one of the many shooters in his gaming collection. “What the hell?” There were dead bodies everywhere, he recognized some of them. There were firefighters and EMT’s running around trying to find survivors in the rubble. Most of the screams were coming from survivors. He seemed to be laying on top of the bottom of a desk, and he was pretty sure the pipe sticking out of his side was a actually one of the legs. Then he spotted it lying about two feet from his right leg, a round section of desk about the size of a softball. On it was a round symbol with geometric shapes glowing with dark red embers and a dull tendril of smoke rising up from it. It all came back to him in rush. He drew that in his notebook. It was second period and his trig teacher had this monotonous voice that could put a crack head to sleep. Laurana caught him doodling and had thrown a pencil at him to scold him silently, which made him jerk as he was connecting the last line on his drawing. Then there was the light and the heat and lastly the dark. Did he do this? What the hell was going on here? A voice brought him out of his little flashback. “Sir. Sir? Sir!” it was a firefighter. “I need you to stay still. You’re going to hear a loud noise from behind you. I need you stay calm.” Kay. “He just blew up his classroom with a piece of paper and a pencil and this guy wants him to stay calm.” it’s going to cause this desk to vibrate a lot and your going to feel some pain but there is nothing that we can do about it. We will work as fast as possible.” The sound of the saw kicking on was not near as bad as he had thought, but Levi was no where near ready for when it made contact with the leg of the desk. His cries of agony began to drown out the sound of everything around him until darkness overwhelmed him. Sorry about my grammar it’s been a while since I have written anything also, first time poster so take it easy on me; p
“Good morning, class! The weirdest thing about the day is that I thought I had completely forgot to pre-pone this class and forgot that I had written ‘I am faking it’ in white spray paint all over the chalkboard. Now that we know I’ve started, let’s really get started. And you’re on your first homework.” My classmates looked to me and I saw sadness in their eyes. I chalked it up to my old professor, Kenlin. “Did you ever tell anyone about that spell you wrote? It made my coworkers kill themselves. I didn’t. The girl who started making these crazy death circles was Linda, and she said it made my life much easier.” My classmates nodded sympathetically. I just nodded a little. The class chuckled. “I’ll finish my math class with the other kid next. After that, I’ll drop my teacher immediately and head out to eat lunch with my friends.” Kenlin’s pupils narrowed, but they didn’t look threatening. He should have known better. “Let’s go!”

“Hey, are you following us?” the boy asked her. “Yes, I’m sorry. Who are you from?” she asked, “I’m new here. Do you know any magic circles?” “They are magic circles that show how many people are standing in front of you.” the child replied. “Oh. I see. Well, it’s a magic circle.” “Yes. Do you think your magic circle will work?” she asked. “Yes... but... I want to see that!” the kid yelled. “Well, now that I’m here the circle will be a success.” “I don’t like you. But can you show me how to do it without turning into little unicorns?” the child asked, “I’ll give you $ 50 if you show me.” “No.” The boy replied, “No!” The boy pointed at the sky with a big magic circle. Suddenly, a big cloud of smoke shot out of the hole. The boy could not see anything, only that clouds of smoke were pouring out of the top of his magic circle. Soon, the clouds turned black, and all the smoke disappeared. “Where am I?” the boy asked the teacher and teacher were gone too. “You were in a magic circle.” the teacher replied. “So what now?” the boy asked the teacher, “I want to get back to class! How did you find out?” “You just did a weird trick on the magic circle and it created a world of unicorns. That doesn’t matter now, do it!” the teacher said. After the teacher had disappeared, the boy turned and walked back to his Math class.
Typical

It had taken an unusually long time. At least it seemed to be longer than that. As if, no matter how hard you looked at the things around you, the colors in the water and the place they stood on the island were too real. I would see it happen over and over again in the corner of my eye. But even now, all the people on this island looked up to me with admiration, almost a weird and unrealistic worship of my existence. It wasn’t a belief that could be called scientific or mystical. I simply could not imagine myself without magic. It’s almost like they are holding the cards, you know? You think to yourself “It would be amazing if this little box would solve the problems in our world?” but when you get closer to the bottom, it just isn’t that easy. It would take hours for anyone to reach it. Then they would ask, “Is that there any more? And is that where I need to go?” But that is all the explanation they need. There was only one person I wanted to reach the magic circle, the boy, Peter. I never met him before. But it wasn’t too late, it would all be worth it in the end. The rest of the people here could live happily, not worry about any more of my kind of world. Peter’s problem was, how do you go from zero to something with unlimited energy and speed? Peter, on the other hand, knew what he was looking at. The light and energy wasn’t what made this a “zero”. He didn’t even have a clue. Peter looked up and tried to grab my hand. “How?” He whispered, looking up at the glowing sphere that would become the future. It would bring new ideas, more hope. A great peace of mind for those of us left to deal with it. Peter grabbed the square in my hand, then reached down to rub the edges of it. Suddenly, I could see his own thoughts: I think he’ll get this...

Table 4: Full sample generations for abstractive summarization and story generation. Same values of $n$, $\tau$ and $k$ as used in Table 1.

C Bayesian Decision Theory

Under the assumption that Hypothesis 3.1 is true, we propose the following loss function associated with choosing a word $y_t$:

$$\ell(y_t \mid H(p(\cdot \mid y_{<t}))) = |I(y_t) - H(p(\cdot \mid y_{<t}))|$$  \hspace{1cm} (11)

During decoding, we want to minimize our expected risk...