How Decoding Strategies Affect the Verifiability of Generated Text

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Abstract
Language models are of considerable importance. They are used for pretraining, fine-tuning, and rescoring in downstream applications, and as is as a test-bed and benchmark for progress in natural language understanding. One fundamental question regards the way we should generate text from a language model. It is well known that different decoding strategies can have dramatic impact on the quality of the generated text and using the most likely sequence under the model distribution, e.g., via beam search, generally leads to degenerate and repetitive outputs.

While generation strategies such as top-k and nucleus sampling lead to more natural and less repetitive generations, the true cost of avoiding the highest scoring solution is hard to quantify. In this paper, we argue that verifiability, i.e., the consistency of the generated text with factual knowledge, is a suitable metric for measuring this cost. We use an automatic fact-checking system to calculate new metrics as a function of the number of supported claims per sentence and find that sampling-based generation strategies, such as top-k, indeed lead to less verifiable text. This finding holds across various dimensions, such as model size, training data size and parameters of the generation strategy. Based on this finding, we introduce a simple and effective generation strategy for producing non-repetitive and more verifiable (in comparison to other methods) text.

1 Introduction
In the past years, we have witnessed a considerable surge of interest in language models. Today, they play a critical role in many NLP tasks, such as text classification, machine comprehension and natural language inference (Peters et al., 2018; Devlin et al., 2018; Liu et al., 2019a; Yang et al., 2019). They serve primarily as a pre-training objective for downstream applications, but can also be used to rescore natural language generations. They have also been used to showcase and measure general progress in NLP (Yu et al., 2017; Liu et al., 2019b).

As the human-like fluency and local coherence of the artificially generated text increases, language models begin to face more scrutiny from the media and the broader society, as well as from the researchers themselves – like in the case of GPT-2 (Radford et al., 2019b), where authors initially decided against releasing their models in order to prevent automatic generation of fake news (Radford et al., 2019a).

The algorithm controlling the choice of utterances under the language model’s distribution can have dramatic impact on the quality of the generation. When assessing such decoding algorithms, previous work, e.g., by Holtzman et al. (2019) and Welleck et al. (2019a), has focused on metrics that are somewhat local: the fluency, repetitiveness, consistency with the input, or coherence of the generated text. However, as demonstrated by previous works (Petroni et al., 2019; Logan et al., 2019; Broscheit, 2019), beyond general linguistic capabilities, language models also pick up factual knowledge from the training data. It is unclear how different decoding choices affect the global consistency of the generation with respect to this knowledge. As the downstream adoption of automatically generated text increases, understanding this trade-off becomes crucially important.

With that in mind, we propose a novel set of automatic metrics aimed at capturing the verifiability of the generated text. We use an off-the-shelf system to automatically fact-check every sentence that a language model and decoding algorithm produce against a ground truth corpus. While automatic fact checking is an unsolved problem and

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certainly leads to noise, we argue and show that
the signal we receive is consistent with human as-
sessments and should help the community track
the progress along the verifiability axis.

Automatic fact checking algorithms identify
claims as supported, refuted, or un-verifiable. Us-
ing metrics that measure how many supported sen-
tences a language model generates per sentence,
per verified sentence and per unique sentence, we
can test whether methods make up facts, produce
language that may or may not be factually wrong
but is hard to verify, or simply produce many sup-
ported statements by repetition. One of our main
findings is that while sampling methods, such as
top-k and nucleus, produce more natural and less
repetitive text, they also generate fewer supported
and more refuted statements as per our metric.
Beam search, on the other hand, shows much bet-
er performance along these dimensions at the cost
of producing highly repetitive text.

Based on the above observations, and inspired
by findings in Holtzman et al. (2019), who showed
how the probability of human text under language
models is varying from token to token, we intro-
duce a very simple novel strategy: Delayed Beam
Search (DELEYEDBS). In DELAYEDBS, we it-
erate between sampling and finding most likely
utterances. By simply injecting stochasticity in
the beginning of a sentence and then switching to
beam search, we generate text that is not repeti-
tive while at the same time scores well in terms of
our verifiability measures. Our main findings hold
across several experimental settings, with varying
training set size and model size.

To summarize, we make the following contribu-
tions: (i) we introduce novel automatic verifiabil-
ity metrics for language generation, (ii) we assess
a wide range of decoding algorithms with respect
to these metrics, (iii) we introduce a simple, novel
decoding strategy that performs well both on exist-
ing and our new metrics, and (iv) we analyse the
metrics and their shortcomings empirically.

2 Related Work

Keskar et al. (2019) trained CTRL, a large (1.63B
parameters) pretrained language model that can
be conditioned on style or content for controlling
generated text. Users can, for example, specify the
domain, entities, as well as relationships between
to control the generated text. While im-
pressive, their work does not provide insights into
the verifiability of the generated text.

Multiple efforts focus on improving text decod-
ing with respect to different criteria. Vijayakumar
et al. (2016) and Li et al. (2016) introduce alterna-
tive scoring strategies to diversify the hypothesis
network tree explored by beam search. Fan et al. (2018)
propose top-k sampling, i.e., sampling from the
top k tokens with the highest probability to gen-
erate stories. Holtzman et al. (2019) find that for
the same neural language model, the choice of the
decoding strategy can have a dramatic effect on the
fluency and repetitiveness of the generation. They
propose nucleus sampling as a way to increase di-
versity of the generated text while improving flu-
cy. In our work, we find that while this strategy
does create more fluent and less repetitive text, it
does also result in a less verifiable generation. Cho
et al. (2019) choose to separate the generation and
diversification steps altogether, and focus on lever-
ageing content selection to map the input to diverse
sequences. We describe various generation strate-
gies in more detail in section 3.

Welleck et al. (2019b) note that with nucleus
sampling, per-token probabilities can be very low
which they attribute to the likelihood training ob-
jective. They propose a novel unlikelihood train-
ing objective which lowers the probability of to-
kens in the context of the language model. Their
approach is orthogonal to the decoding strategy
and testing alternative training objectives is out of
the scope of our paper.

A recent approach by Bakhtin et al. (2019)
learns to distinguish human from machine gener-
ated text. Zellers et al. (2019) investigate generat-
ing and detecting fake news using neural language
models. Niewinski et al. (2019) propose a vari-
ation of the GPT-2 language model to explicitly
generate malicious claims. Instead of directly op-
timizing for generating fake or factual news, we
are interested in investigating the relationship be-
tween the verifiability of the existing pretrained
language models and different decoding strategies
they are coupled with.

3 Background

Language models (LMs) assign probabilities to se-
quences of tokens. Given a context, that is, a se-
quence of tokens \( c_t = [w_1, w_2, \ldots, w_{t-1}] \), au-
toregressive LMs commonly estimate the probability
distribution of the next target using neural mod-
els (Mikolov and Zweig, 2012; Melis et al., 2017;
Throughout the generation, we hold a beam maximizes the likelihood of the whole sequence. This strategy approximately makes the generation practical. In this work, we consider self-attention mechanisms (Radford et al., 2018; Dai et al., 2019; Radford et al., 2019b) to compute $h_t$ given the word history.

**Open-Ended Text Generation** As described in Holtzman et al. (2019), the task of open-ended text generation involves producing a coherent completion of the provided context. We consider the common left-to-right generation, where a token at position $t$ in the sequence is generated by considering the probability distribution over the vocabulary defined in equation 1. Once a decision is made for $w_t$ according to a generation strategy, it is incorporated into the context and the process is iterated - i.e., the token at position $t + 1$ is generated by considering $p(w_{t+1} | c_{t+1} = [w_1, \ldots, w_t])$. In this work, we consider different generation strategies of selecting $w_t$ given $p(w_t | c_t)$.

### 3.1 Generation Strategies

The generation strategies we consider in our analysis can be broadly divided in two families: sampling-based and likelihood-based.

**Sampling-based** This family of techniques aims at increasing the diversity of the output and avoid repetitions by introducing stochastic decisions during the generation process. Top-\textit{k} sampling (Fan et al., 2018) selects $w_t$ by sampling from the $k$ tokens with the highest probability in $p(w_t | c_t)$.

Top-\textit{p} sampling, also referred to as nucleus sampling (Holtzman et al., 2019), selects $w_t$ from the smallest set of tokens whose cumulative probability (given by $p(w_t | c_t)$) is above a threshold $p$.

**Likelihood-based** These strategies navigate the solution space by selecting sequences of tokens that maximize the overall likelihood. Given that the number of possible sequences is typically very large, it is a common practice to define heuristics to make the generation practical.

**Beam Search** (BS). This strategy approximately maximizes the likelihood of the whole sequence. Throughout the generation, we hold a beam of $\beta$ prefixes which are iteratively extended. At each time-step, $\beta$ tokens are generated to complete each of the prefixes in the beam and we retain $\beta$ hypotheses with the highest score out of the $\beta^2$ candidates for the next step. $\beta$ is referred to as the beam size. Greedy decoding, where at each step the most likely token is selected, is a special case of beam search with beam size 1.

**Delayed Beam Search** (DELAYEDBS). To favor the diversity of the exploration, Vijayakumar et al. (2016) propose a variant of beam search which introduces a penalty proportional to the rank of a candidate token with respect to its source in the beam. The goal is to encourage preserving hypotheses from diverse sources within the beam.

A simple trick to reduce repetitiveness is to explicitly prevent the generation of already observed n-grams (Paulus et al., 2017). We refer to this approach as n-gram blocking.

**Group diverse Beam Search** (GROUPBS). With the same aim of diversifying the exploration, Li et al. (2016) propose a variant of beam search which divides the beam into groups. The diversity between groups is imposed by introducing a group dissimilarity penalty into the search objective.

**Sibling diverse Beam Search** (SIBLINGBS). With the same aim of diversifying the exploration, Li et al. (2016) propose a variant of beam search which introduces a penalty proportional to the rank of a candidate token with respect to its source in the beam. The goal is to encourage preserving hypotheses from diverse sources within the beam.

**4 Evaluating Verifiability**

In this section we first describe the tools used to evaluate the verifiability of the generated text. We then formally introduce our repetitiveness and verifiability metrics.

The high level overview of our evaluation setup is shown in Figure 1. For the purpose of this analysis, we consider both the text generator and the fact checker as black boxes which produce and assess text respectively. More specifically, the text generator gets in input a prefix $p$ and produces a sequence of tokens that can be interpreted as a completion of $p$. We segment the generated completion into sentences and consider the first $k$ sentences. The fact checker gets in input a sen-
tence and outputs a positive (SUPPORTED), negative (REFUTED) or neutral (unverifiable) response as well as textual evidence used for the judgment. We consider a sentence as verified if the output label is either SUPPORTED or REFUTED.

Our metrics assess the generation process given a set of prefixes \( P \). The set \( P \) can be seen as the data source for our verifiability probe. Let \( G^p = [s^p_1, ..., s^p_k] \) be the sequence of sentences generated by the LM from prefix \( p \in P \). We indicate with \( V^p \subseteq G^p \) the set of sentences that are verified by the fact checker, while with \( S^p \subseteq V^p \) we denote the subset of sentences labeled as SUPPORTED. To assess the verifiability of the generated text we introduce the following two metrics:

**Supports Per Generation (SPG):** is the fraction of supported sentences among the generated ones:

\[
\text{SPG} = \frac{1}{|P|} \sum_{p \in P} \frac{|S^p|}{k}
\]

**Supports Per Verified (SPV):** is the fraction of supported sentences among the verified ones:

\[
\text{SPV} = \frac{1}{|P|} \sum_{p \in P} \frac{|S^p|}{|V^p|}
\]

SPG can be interpreted as a sort of a recall metric while SPV as a precision one.

Note that a generation could achieve a high score in terms of SPG and SPV by repeating the same supported sentence over and over again. To be able to capture this behaviour, we define the unique variants of our metrics. Given a prefix \( p \), we consider a pair of sentences \((s^p_i, s^p_j)\) to be equivalent if their Jaccard similarity is above a certain threshold \( \tau \), i.e. \( J(s^p_i, s^p_j) > \tau \) (in our experiments we set \( \tau \) to 90%). We define the set of unique sentences generated from \( p \) as \( G^p_u \), where \( G^p_u \) is a maximal subset of \( G^p \) such that no two sentences in \( G^p_u \) are equivalent. More formally:

\[
G^p_u := \{ s \in G^p \mid \forall_{s_i, s_j \in G^p, i \neq j} J(s_i, s_j) \leq \tau \}
\]

Note that there may exist multiple such \( G^p_u \) sets. In practice, for each pair of equivalent sentences \((s^p_i, s^p_j) \in G^p\), we retain the one that appeared earlier in the generation (see Figure 1 for an example). We define \( V^p_u \) and \( S^p_u \) as the set of unique verified and unique supported sentences respectively in an analogous way.

To jointly capture both verifiability and repetitiveness of the generated text, we introduce:

**Unique Supports Per Generation (USPG):** is the fraction of unique supported sentences among the generated ones, formally:

\[
\text{USPG} = \frac{1}{|P|} \sum_{p \in P} \frac{|S^p_u|}{k}
\]

**Unique Supports Per unique Verified (USPV):** is the fraction of unique supported sentences among unique verified sentences:

\[
\text{USPV} = \frac{1}{|P|} \sum_{p \in P} \frac{|S^p_u|}{|V^p_u|}
\]

In order to provide an independent measure of diversity we consider the evidence used by the fact
checker in its judgment. In particular, we define the set of supported sentences with diverse evidence as \( S^p \in S^p \). As before, if two sentences are labeled as SUPPORTED using the same evidence by the fact checker, we retain the one that appeared earlier in the generation. We define \( V^p \in V^p \) in an analogous way - no two sentences in \( V^p \) are both supported or both rejected by considering the same evidence. Hence we introduce:

**Supports with diverse Evidence Per Generation (SEPG):** is the fraction of supported sentences with diverse evidence among the generated ones:

\[
SEPG = \frac{1}{|P|} \sum_{p \in P} \frac{|S^p|}{k} \tag{7}
\]

**Supports with diverse Evidence Per de-duplicated Verified (SEPV):** is the fraction of supported sentences with diverse evidence among de-duplicated (i.e., with diverse evidence) verified sentences, formally:

\[
SEPV = \frac{1}{|P|} \sum_{p \in P} \frac{|S^p_e|}{|V^p_e|} \tag{8}
\]

5 Methodology

In this section we describe in detail the implementational choices for all components in Figure 1.

**Prefix Dataset** We retrieve title and description of the top-1000 most visited Wikipedia pages of 2017 and 2018. For each page, we concatenate the title and the first sentence in the description to create a string prefix for the language model. We use 2018 data as validation set and run parameter sweeps over it. We tested the best configuration of every decoding strategy on 2017 data (test set).\(^1\)

**Language Model** We consider three sizes of language models (small, medium, large) based on the Transformer architecture (Vaswani et al., 2017; Radford et al., 2019b), with 124M, 354M and 1.4B parameters respectively. We train models on four corpora: (i) WIKIPEDIA, an English Wikipedia dump consisting of roughly 2 Billion Words; (ii) BOOKS, the Toronto books corpus (Zhu et al., 2015; Kiros et al., 2015), which consists of fiction books totaling about half a billion words; (iii) OPENWEBTEXT, a reconstruction of the WebText corpus (Radford et al., 2019b) consisting of roughly 3 Billion Words; (iv) CC-NEWS, a de-duplicated subset of the English portion of the CommonCrawl news dataset (Nagel, 2016; Bakhtin et al., 2019; Liu et al., 2019a), which totals around 16 Billion words. We train models using the FAIRSEQ toolkit (Ott et al., 2019).

**Generation Strategy** We consider the generation strategies discussed in Section 3.1, namely top-k, top-p, greedy, Beam Search (BS), Group-Diverse Beam Search (GROUPBS), Sibling-Diverse Beam Search (SIBLINGBS) and Delayed Beam Search (DELAYEDBS). Additionally, we experiment with \( n \)-gram blocking and indicate that a model is equipped with blocking with a subscript \( b \), e.g., BS\(_b\). We fix the generation length to 256 tokens. We perform three generations per prefix with different seeds for all strategies that make stochastic decisions, and report average values.

**Sentence Processing** Given that our fact checker expects a single sentence as input, we segment the generated text into sentences. We consider the first \( k = 5 \) sentences. We perform coreference resolution to replace pronouns with the corresponding referring entity in order to give the complete information to the fact checker. For the same reason, we apply a simple heuristic that replaces each determiner (i.e., "The") at the beginning of a sentence and the subsequent noun with the original entity (i.e., the title of the Wikipedia page). For all these steps we use spaCy.\(^2\) We consider sentences longer than 50 tokens as not verifiable.

**Fact Checker** We consider an off-the-shelf fact checker trained on the FEVER dataset (Thorne et al., 2018) that, at the time of writing, is at the top of the leaderboard for the FEVER 2.0 Shared Task (Thorne and Vlachos, 2019) with a 68.46% FEVER Score. This solution takes inspiration from Hanselowski et al. (2018) and consists of three main stages: (i) identify relevant Wikipedia pages, as in Hanselowski et al. (2018); (ii) retrieve relevant sentences from such pages; (iii) recognize textual entailment between input and retrieved text. The system uses a hierarchical sentence retrieval approach in order to verify claims that require multiple statements as evidence. It

\(^1\)We ensure no overlap between 2017 and 2018 prefixes.

\(^2\)https://spacy.io

\(^3\)https://github.com/dominiksaarland/domlin_fever
Table 1: Performance of the different generation strategies on the considered metrics. We report percentage values for the large transformer model on the test set. The first row shows human performance computed on Wikipedia.

| Strategies | metrics | verifiability | repetitiveness | diverse verifiability |
|------------|---------|---------------|----------------|----------------------|
|            | SPG     | SPV           | unique sentences | distinct 4-grams | 4-grams proportion | USPG | USPV | SEPG | SEPV |
| human - Wikipedia | 36.56 | 93.03 | 4.87 | 222.48 | 100.00 | 36.1 | 92.95 | 36.56 | 93.03 |
| sampling   | top-k   | 13.02 | 70.15 | **4.79** | 143.52 | 64.51 | 11.38 | 69.05 | 11.06 | 69.39 |
|            | top-p   | 13.94 | 70.76 | 4.59 | 136.66 | 61.43 | 11.44 | 68.34 | 11.36 | 68.93 |
| likelihood | greedy  | 19.62 | 78.67 | 3.50 | 67.42 | 30.31 | 12.26 | 75.87 | 12.06 | 77.21 |
|            | BS      | **25.50** | **84.49** | 2.54 | 59.53 | 26.76 | 9.78 | 78.87 | 11.88 | **81.59** |
|            | GROUPBS | 20.56 | 78.29 | 3.17 | 66.06 | 29.69 | 10.78 | 73.53 | 11.54 | 76.53 |
|            | SIBLINGBS | 22.32 | 80.11 | 3.08 | 67.11 | 30.16 | 9.92 | 74.03 | 11.36 | 76.76 |
| hybrid     | DELAYEDBS | 17.52 | 78.99 | 4.40 | 112.12 | 50.40 | 12.24 | 76.12 | 12.74 | 77.59 |
| blocking   | BS<sub>6</sub> | 23.62 | 83.35 | 4.36 | 92.00 | 41.35 | **17.66** | **81.76** | **15.28** | 80.76 |

Table 1: Performance of the different generation strategies on the considered metrics. We report percentage values for the large transformer model on the test set. The first row shows human performance computed on Wikipedia.

We summarize the main results in Table 1. It shows the performance of the different generation strategies on the considered metrics on the test set of prefixes, considering the large transformer model trained on CCNEWS. We performed an exhaustive grid search over the parameters for all considered generation strategies using the small model on the validation set, and consider the configuration that led to the highest USPG value (see the Appendix for details). We report as reference human performance computed on Wikipedia considering at most the first 5 sentences of the prefix article.

Sampling strategies (i.e., top-p and top-k) outperform the other strategies in terms of repetitiveness metrics, that is, they are able to generate text with an higher degree of diversity, consistently with previous works (Fan et al., 2018; Holtzman et al., 2019). However, diversity comes at a price, as the verifiability metrics are low (in particular, precision values - they generate more refuted sentences). Intuitively, random choices might hamper verifiability when sampling a token in specific positions of the sentence, for instance, in a named entity, potentially making the overall sentence non-factual. We notice that this problem gets even worse by increasing k or p. Following a generation path that maximizes likelihood is a better approach for verifiability. In particular, BS achieves the highest performance in terms of SPG and SPV. Nevertheless, generation diversity drops, consistently with previous works (Vijayakumar et al., 2016; Li et al., 2016; Welleck et al., 2019b; Holtzman et al., 2019). Solutions such as GROUPBS and SIBLINGBS have been proposed to mitigate this problem, and their numbers actually look slightly better than BS in terms of repetitiveness metrics.

When we assess diverse verifiability (that is, we consider distinct supported and refuted sentences), likelihood and sampling based strategies are similar in terms of recall values (i.e., USPG and SEPG), while likelihood-based solutions outperform both top-k and top-p in terms of precision (i.e., USPV and SEPV) by a large margin - they generate less sentences refuted by the fact checker.

DELAYEDBS tries to combine the best of these two approaches, by defining a hybrid strategy that starts a sentence by sampling tokens and ends it by following a max-likelihood path. It achieves results comparable to likelihood-based solutions in terms of precision and recall for diverse verifiability while being much less repetitive (it almost doubles the number of distinct 4-grams). Interest-
Figure 2: SEPV vs SEPG, inspired by precision-recall curve.

Figure 3: SPG, SPV and 4-gram proportion values for BSb and DelayedBS, by varying the sampling length L for DelayedBS (bottom axis) and the n-gram blocking size for BSb (top axis).

Ablation studies We experiment with different training corpora (Figure 2a) and different sizes of the transformer model (Figure 2b), using the validation set. We report SEPV vs SEPG values, taking inspiration from the popular precision-recall curve. The average perplexity of the small transformer model is the lowest for WIKIPEDIA (8.31) compared to BOOKS (53.08), OPENWEBTEXT (11.14) and CCNEWS (12.23). Even though all prefixes are likely to be in the corpus, WIKIPEDIA archives the best results in terms of diverse verifiability metrics, DelayedBS still produces less repetitive generations, hence constituting a viable alternative.

Interestingly, it is sufficient to sample just the first token with high uncertainty (top-100) and finish the sentence with beam search to trigger this behaviour.

Another way of mitigating repetitiveness is through n-gram blocking. We combine it with BS, sweeping over the values of n between 3 and 20. In line with our expectations, low n values score low in verifiability metrics, as the model is forced to explore less likely parts of the solution space in order to avoid generating previously observed n-grams. Unsurprisingly, the diversity of the solution drops as n increases. In this sense, BSb and DelayedBS attempt to strike a similar balance between diversity (introduced via n-gram blocking in BSb and via sampling in DelayedBS) and verifiability (achieved by incorporating BS). Figure 3 highlights this analogy further. Overall, we achieve the best USPG performance by combining 20-gram blocking and BS - we believe it is due to the fact that n-gram blocking prevents BS from repeating the same phrases multiple times, while remaining relaxed enough to allow the generation to produce a high-likelihood solution. However, even though BSb archives the best results in terms of diverse verifiability metrics, DelayedBS still produces less repetitive generations, hence constituting a viable alternative.
To further investigate the causes behind the verifiability of a generation, we compute the Pearson correlation coefficient between supported and verified sentences and a set of metrics that we report in Figure 4. We consider the four runs of the large transformer model reported in Figure 2b. We notice, for instance, that the average log probability of a sentence is positively correlated with verifiability, confirming that max-likelihood strategies are better suited in this regards. Furthermore, the tf-idf score with the prefix Wikipedia page content is positively correlated with supported sentences. This behaviour is related to the implementation of the fact checker we use, which, by considering exclusively Wikipedia as knowledge source, favours text with a high overlap with the latter. Note, however, that the model was not explicitly exposed to Wikipedia during training (i.e., CCNEWS does not include it).

We report examples of text generated by the large transformer model using different decoding strategies in the Appendix section (Table 3).

7 Limitations

Fact Checker Quality We use the best performing model according to the FEVER 2.0 SharedTask leaderboard. That said, automatic fact checking systems are still far from perfect. To assess the accuracy of the considered solution, we annotated 943 sentences verified by the system. Excluding ungrammatical examples (~16%), we recorded a precision of 66% for supported and 53% for rejected sentences. While this makes our metrics less reliable, initial eyeballing experiments suggest that better scoring decoding strategies are indeed more verifiable. We are currently in the process of measuring this correlation (and recall values) more carefully.

Popularity bias We considered the most viewed Wikipedia pages in 2017 and 2018 for our analysis. Our rationale is that such pages represent topics that are likely to be highly covered in a random web crawl (e.g., OPENWEBTEXT and CCNEWS). Results (not reported in the paper) with a random set of Wikipedia pages show lower values in terms of SPG and USPG (i.e., recall metrics). A potential line of future work could be related with the manipulation of training corpora to maximize verifiability.

Multiple claims in a sentence We consider each sentence as a single claim to keep our experimental setting clean and avoid noise from an automatic claim extractor. However, some generations contain multiple claims that could be independently assessed. Studying such behaviour is an interesting future direction.

8 Conclusion

We presented a systematic analysis of the verifiability of text generated by a wide range of decoding strategies from large autoregressive language models, by assessing each generated sentence with an off-the-shelf automatic fact-checking system. We introduced novel verifiability metrics and found that sampling decoding strategies produce text that is less verifiable, but also less repetitive, when compared to strategies that consider most likely sequences according to the model distribution. We propose an hybrid decoding strategy that combines the non-repetitive nature of sampling solutions and the verifiable generation of likelihood-based approaches.
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9 Appendix

We conduct a parameter sweep on the small transformer model on the validation set. The following table shows the configuration for each decoding strategy that leads to the highest USPG score.

| strategy   | best parameters          |
|------------|--------------------------|
| top-k      | k= 2                     |
| top-p      | p= 0.4                   |
| BS         | beam size= 15            |
| GROUPBS    | groups= 2                |
| SIBLINGBS  | penalty= 0.2             |
| DELAYEDBS  | beam size= 6; L= 1       |
| BSb        | blocking order= 20       |

Table 2: Best parameters per decoding strategy.
| **Princess Margaret, Countess of Snowdon.** Princess Margaret, Countess of Snowdon, (Margaret Rose 21 August 1930 - 9 February 2002) was the younger daughter of King George VI and Queen Elizabeth The Queen Mother and the only sibling of Queen Elizabeth II. |
| **Whitey Bulger.** James Joseph Whitey Bulger Jr. (September 3, 1929 - October 30, 2018) was an Irish-American organized crime boss and FBI informant who led the Winter Hill Gang in the Winter Hill neighborhood of Somerville, Massachusetts, a city directly northwest of Boston. |

| She is the only surviving member from the Royal Family who was born in the same year as the Queen Mother. Princess Margaret, Countess of Snowdon, (Margaret Rose 21 August 1930 - 9 February 2002) was a British princess who married into the British Royal Family in 1939. She is a cousin to the Queen, Prince Philip, Prince Charles, Prince William, Prince Harry and Prince Edward. Princess Margaret, Countess of Snowdon, (Margaret Rose 21 August 1930 - 9 February 2002) is the younger daughter of King George VI and Queen Elizabeth. She is the only survivor from the Royal Family who was born in the same year as Queen Elizabeth. |
| He was a fugitive for 16 years before his arrest in 2011. He was sentenced in 2013 to two life terms plus five years for his role in 11 murders and was released in 2014. Bulger was found dead in his cell at the U.S. penitentiary in West Virginia. He was 89. He was serving the life sentences for his role in the infamous Boston crime family. |

| **She married Antony Armstrong-Jones, a photographer, in 1960. It was the first marriage for the Queen and the first for Prince Philip, Duke of Edinburgh. After divorcing Armstrong-Jones in 1978, she married Group Captain Peter Townsend in June that same year. She died at the age of 71 on 9 February 2002. Why did Princess Margaret marry Antony Armstrong-Jones?** |
| **He was one of the FBI's most wanted fugitives for 16 years until his arrest in 2011. Born in Boston, Whitey Bulger was the son of Irish immigrants. After serving in the U.S. Navy during World War II, Whitey Bulger joined the Irish-American mafia, the Winter Hill Gang, in the early 1950s. He quickly rose through the ranks of the gang, eventually becoming its leader. He was known as "Whitey" because of his light brown hair and blue eyes.** |

| **Princess Margaret, Countess of Snowdon.** Princess Margaret, Countess of Snowdon, (Margaret Rose 21 August 1930 - 9 February 2002) was the eldest daughter of King George VI and Queen Elizabeth The Queen Mother. Princess Margaret, Countess of Snowdon, (Margaret Rose 21 August 1930 - 9 February 2002) was the eldest child of King George VI and Queen Elizabeth The Queen Mother. **BS.** Princess Margaret, Countess of Snowdon, (Margaret Rose 21 August 1930 - 9 February 2002) was the eldest daughter of Queen Elizabeth The Queen Mother. (Margaret Rose 21 August 1930 - 9 February 2002) was the eldest child of King George VI and Queen Elizabeth The Queen Mother. |
| **BS.** Bulger was one of the FBI’s most wanted fugitives for 16 years until he was captured in Santa Monica, California, in 2011. He was convicted in 2013 of a litany of crimes, including racketeering, extortion, money-laundering, and murder. He was sentenced to two consecutive life sentences plus five years. He died in federal prison in West Virginia on Tuesday at the age of 89. Bulger was one of the FBI’s most wanted fugitives for 16 years before he was captured in Santa Monica, California, in 2011. |

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Table 3: Two examples of text generated with different strategies by the large transformer model. One the left a cherry picked example (in terms of repetitive generation for BS) while on the right a random one. Sentence refuted by the fact checker are highlighted in red, supported in green.