

On the Reliability of Watermarks for Large Language Models

John Kirchenbauer*, Jonas Geiping*

Yuxin Wen, Manli Shu, Khalid Saifullah, Kezhi Kong

Kasun Fernando[†], Aniruddha Saha, Micah Goldblum[‡], Tom Goldstein

University of Maryland

Abstract

As LLMs become commonplace, machine-generated text has the potential to flood the internet with spam, social media bots, and valueless content. *Watermarking* is a simple and effective strategy for mitigating such harms by enabling the detection and documentation of LLM-generated text. Yet a crucial question remains: How reliable is watermarking in realistic settings in the wild? There, watermarked text may be modified to suit a user’s needs, or entirely rewritten to avoid detection.

We study the robustness of watermarked text after it is re-written by humans, paraphrased by a non-watermarked LLM, or mixed into a longer hand-written document. We find that watermarks remain detectable even after human and machine paraphrasing. While these attacks dilute the strength of the watermark, paraphrases are statistically likely to leak n-grams or even longer fragments of the original text, resulting in high-confidence detections when enough tokens are observed. For example, after strong human paraphrasing the watermark is detectable after observing 800 tokens on average, when setting a $1e-5$ false positive rate. We also consider a range of new detection schemes that are sensitive to short spans of watermarked text embedded inside a large document, and we compare the robustness of watermarking to other kinds of detectors.

1 Introduction

The capability to tell the difference between machine-generated and human-written text underlies many approaches to reduce potential harms caused by generative language models [Bender et al., 2021, Crothers et al., 2022]. This includes known harms, such as models being used at-scale for malicious purposes including social media bots, fake product reviews [Palmer, 2023], automated text generation on wikipedia [Woodcock, 2023], or automatic generation of targeted spearphishing attacks on vulnerable subpopulations [Schneier, 2021]. Equally important, the ability to track and document the use of machine-generated text has the potential to reduce harms from future problems that have not yet been observed. These problems might range from the pollution of future training data [Radford et al., 2022] to the hyper-prevalence of LLM-generated blogs and other web content. Unfortunately, detection of machine-generated text is potentially difficult. Models are prompted with diverse instructions, resulting in a wide range of downstream behaviors for both machines and

*Equal contribution. [†] Scuola Normale Superiore di Pisa. [‡] New York University.

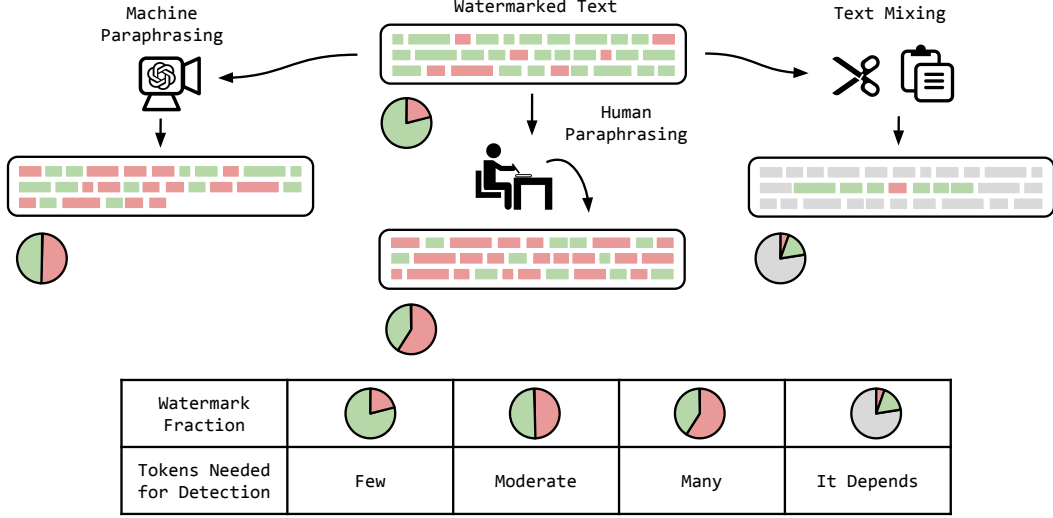


Figure 1: What happens to watermarked text in-the-wild? In this work we study watermark robustness against a number of text modifications, as visualized here. We visually depict that machine paraphrasing methods have a tendency to shorten texts, humans are quite effective at reducing the strength of a watermark by increasing the number of red tokens, and that short spans of watermarked text may be copied and pasted into a large document. In all of these scenarios, we find that high confidence detection reliably occurs given enough tokens as input.

humans that are difficult to characterize. This can lead to low accuracy or impractical false positive rates that especially impact vulnerable subgroups, such as non-native speakers [Liang et al., 2023].

One way to enable accurate detection of machine-generated text is through *watermarking*, where generated text is marked imperceptibly so that its origin can be determined [Atallah et al., 2001, Fang et al., 2017, Kirchenbauer et al., 2023]. Because watermarks rely on subtle patterns in text that are statistically unlikely to be replicated by a human, watermarking enables detectors that achieve high levels of accuracy on relatively short fragments of text. This makes watermarking a promising approach for the reliable separation of human-written and machine-generated text [Grinbaum and Adomaitis, 2022]. While the effectiveness of watermarks has been shown in ideal scenarios where verbatim LLM outputs are fed directly to a detector, this is an idealized setting. In practice, humans may mix machine-generated text into larger documents with multiple sources. Furthermore, a human may revise or rephrase parts of the synthetic text (possibly aided by another language model) to better suit their needs, potentially even with the deliberate goal of evading detection.

In this work, we investigate the reliability of watermarking as a strategy to identify machine-generated text in realistic scenarios, based on the approach of Kirchenbauer et al. [2023]. We are focused on whether watermarks remain detectable under various types of realistic corruptions (i.e. *attacks*): How reliable is watermarking when generated text is handled by humans, be it mixing with human-written text, rewriting parts or the entire passage, or feeding the text into other popular language models for rephrasing? A reliable detection strategy should be robust to these common scenarios, maintaining some statistical power and a low false positive rate [Crothers et al., 2022]. We make the following contributions:

- We re-investigate all parts of the watermark generation and watermark detection pipeline to optimize for reliability in realistic scenarios.
- We study the reliability of watermarking against paraphrasing by strong large language models. When GPT-3.5 and purpose-built paraphrasing models are used to re-write watermarked text, ROC-AUC remains above 0.85 when $T = 200$ tokens are available, and above 0.9 with $T = 600$ tokens.
- We consider a “Copy-Paste” scenario where watermarked text appears inside a larger hand-written passage. When a human-written passage of length 600 tokens has 150 tokens of watermarked text inserted into it, AUC for detection is above 0.95.

- We conduct a human study in which watermarked text is re-written by volunteers with the explicit goal of removing the watermark. While humans are relatively strong attackers, after enough observed tokens (about 800) watermarks are still usually detectable in human paraphrases even when enforcing a $1e-5$ false positive rate.
- We provide reliability estimates of watermarking compared to other state-of-the-art approaches, such as loss-based detection [Mitchell et al., 2023] and retrieval [Krishna et al., 2023], showing that these struggle at longer sequence lengths when attacked.

We argue that the correct way to characterize the strength and robustness of different detection approaches is not simply via detection accuracy metrics for a specific distribution of text, but rather to measure *how much machine-generated text* is required for each approach to succeed, and how a method behaves as a function of text sequence length. Across all the scenarios we consider in this work, we ultimately find watermarking to be more robust than other post-hoc detection methods (such as loss-based detection and caching/retrieval schemes), especially due to its favorable sample complexity, i.e., scaling behavior in terms of amount of text that is sufficient to guarantee detection.

2 An Overview of Machine-Generated Text Detection

The problem of separating human-written and machine-written text can be approached from several directions. Broadly, we can distinguish *post-hoc* detection systems that require no interaction during text generation, and *proactive* detection systems that require some action during generation. These latter systems are generally much more robust, with the downside that they have to be adopted by the model owner.

The most straightforward post-hoc detectors are binary classifiers, trained to distinguish between human and machine-generated text [OpenAI, 2019, Bakhtin et al., 2019, Fagni et al., 2020, Jawahar et al., 2020]. As black-box approaches, these systems require no information about the language model, only the availability of sufficient training data in the form of machine-generated and human text samples. In practice, obtaining such a dataset is challenging since there are many diverse use cases for LLMs and different users may represent vastly different domains. While approaches that use classical methods such as linear/logistic regression or SVMs [Fröhling and Zubiaga, 2021, Solaiman et al., 2019, Crothers et al., 2022] are interpretable, deep learning approaches [Gallé et al., 2021, Zhong et al., 2020, Rodriguez et al., 2022] are more accurate on in-domain datasets while being vulnerable to out-of-distribution problems, adversarial attacks, and poisoning.

Other detectors rely on statistical outlier detection in texts, based on entropy [Lavergne et al., 2008], perplexity [Beresneva, 2016, Tian, 2023], n-gram frequencies [Grechnikov et al., 2009, Badaskar et al., 2008], or as in DetectGPT Mitchell et al. [2023], the observation that LLMs typically assign their own text generations higher probability than “nearby” text sequences produced by span replacement with a different LLM. Even though DetectGPT exhibits superior performance compared to other zero-shot statistical outlier detection methods, it suffers from excessive computational costs. Further, all advanced statistical detectors relying on language model statistics such as perplexity or curvature ideally require white-box access to model parameters. The difficulties with post-hoc detectors were studied in Sadasivan et al. [2023] under the assumption of a monolithic “human” text distribution that is shared by all people, although this assumption has been critized in Chakraborty et al. [2023].

A retrieval-based approach for text detection, as described in Krishna et al. [2023], is a noticeably different paradigm, and an example of a *proactive* detection technique. Here, all text generated by a given model is stored in a database. Later, text samples are evaluated by matching against this database. This approach requires action taken by the model owner, but it can be quite reliable, even when faced with broad modifications of text, such as strong paraphrases. However, both the cost of retrieval and its false positive rate potentially scale undesirably with the size of the database. Further, the act of storing all outgoing user interactions is problematic from a data privacy perspective, for example under European law, or for business sectors such as finance or medicine.

Watermarking also requires action by the model owner as they must embed the hidden watermark signal into all outgoing text. Watermarking as a concept has a long history [Brassil et al., 1995]. Older systems were based on rule-based methods to imprint watermarks into existing text [Atallah et al., 2001, Chiang et al., 2004, Venugopal et al., 2011, Topkara et al., 2006]. More recent approaches for watermarking neural networks Ziegler et al. [2019], Dai and Cai [2019], Abdelnabi and Fritz [2021], He et al.

[2022a,b] are learned end-to-end with both encoding and decoding of each sample. The lack of theoretical guarantees and interpretability of these approaches are problems for their widespread adoption.

However, it is also possible to place watermarks on a robust mathematical foundation. Watermarks can be embedded by minimally modifying the distribution of generated output text [Fang et al., 2017, Kaptchuk et al., 2021, Kirchenbauer et al., 2023]. In this work, we mainly consider the combinatorial watermark described in Kirchenbauer et al. [2023]. At each step of the text generation process, the watermark pseudo-randomly “colors” tokens into green and red lists. Then a sampling rule is used that preferentially samples green tokens when doing so does not negatively impact perplexity. To detect the watermark, a third party with knowledge of the hash function can reproduce the red and green lists for each step and count the violations. Thus, this method uses the LM’s own understanding of natural text to adaptively embed the watermark, requires no usage of the LM to decode the watermark, and can be statistically validated.

3 How to improve watermark reliability?

There are a number of parameter and design choices that go into a watermark, with different parameters offering benefits in different use cases. In this section, we briefly describe the watermark proposed in Kirchenbauer et al. [2023], and the variations on the watermark that we will study.

Assume an autoregressive language model is trained on a vocabulary V of size $|V|$. Given a sequence of tokens as input at step t , a language model predicts the next token in the sequence by outputting a vector of logit scores $l_t \in \mathbb{R}^{|V|}$ with one entry for each item in the vocabulary. A random number generator is seeded with a context window of h preceding tokens, based on a pseudo-random function (PRF) $f : \mathbb{N}^h \rightarrow \mathbb{N}$. With this random seed, a subset of tokens of size $\gamma|V|$ are “colored” green and denoted G_t . Now, the logit scores l_t are modified so that

$$l_{tk} = \begin{cases} l_{tk} + \delta & \text{if } k \in G_t \\ l_{tk} & \text{otherwise.} \end{cases} \quad (1)$$

After modifications, these logit scores can be used for any desired sampling scheme. In the simplest case, one passes the scores through a softmax layer and samples from the output distribution, resulting in a bias towards tokens from G_t .

The watermark can be described by four parameters. The “hash” used to generate the greenlists f with context width h , greenlist fraction γ , and the logit bias δ . After watermarked text is generated, one can check for the watermark without having access to the LLM by re-computing the greenlist at each position and finding the set s of greenlist token positions. The statistical significance of a sequence of tokens of length T can be established by deriving the z -score

$$z = (|s| - \gamma T) / \sqrt{\gamma(1 - \gamma)T}. \quad (2)$$

When this z -score is large (and the corresponding P-value is small), one can be confident that the text is watermarked.

We now discuss several variations to this scheme, which lead to improved empirical behavior.

3.1 Improved Hashing Schemes

The experiments in Kirchenbauer et al. [2023] focus on a simple scheme where the random number generator is seeded using $h = 1$, i.e., only a single token at position $t - 1$ is used to color the token at position t . We refer to this scheme as **LeftHash**. Because the greenlist depends only on one single token, a third-party observer could learn the greenlist associated with the token at position $t - 1$ by searching subsequent words at position t that are less likely to appear than expected under a non-watermarked distribution. In situations where the watermark scheme is intended to be kept secret behind an API, a more secure scheme is needed.

Kirchenbauer et al. [2023] also mention a scheme (Algorithm 3) in which the greenlist at position t is determined by including the token at position t itself (yet to be generated), in addition to tokens to the left of t in the inputs to f . We call this hashing scheme **SelfHash**. This approach effectively increases the context width h by 1, making it harder to discover the watermark rules by brute-force methods. We generalize this scheme to include arbitrary functions f and text generation routines, which we describe in detail in Algorithm 1 in the Appendix.

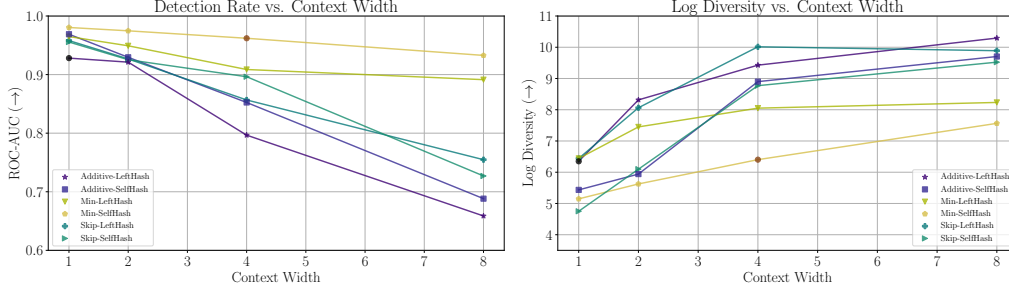


Figure 2: Effect of context width on watermark robustness and diversity. **(Left)** Effect of context width on watermark robustness as measured by ROC-AUC after a paraphrasing attack by GPT. For larger context widths Skip and Min variants provide the best detection strength. **(Right)** Effect of the seeding scheme context width on the quality of the text as measured by log diversity. A small context width produces less diverse outputs for all three schemes, and the Additive and Skip schemes produce more diverse text at larger context widths than the Min scheme. **(Both)** Watermark parameters γ, δ are fixed at (0.25, 4.0). The black circle marks the simple Additive-LeftHash with context width $h = 1$ scheme, and the brown circle marks the width $h = 4$ variant of the Min-SelfHash scheme, both evaluated throughout the work (names shortened to “LeftHash” and “SelfHash” respectively).

When the context width h is increased to maintain secrecy of the red/green list rules, we find that detection reliability substantially depends on the hashing scheme. We define the following functions $f : \mathbb{N}^h \rightarrow \mathbb{N}$ that map a span of tokens $\{x_i\}$ onto a pseudo-random number. Each depends on a secret salt value $s \in \mathbb{N}$ and a standard integer PRF $P : \mathbb{N} \rightarrow \mathbb{N}$.

Additive: This is the function described in Kirchenbauer et al. [2023]. We extend it to $h > 1$ by defining $f_{\text{Additive-LeftHash}}(x) = P\left(s \sum_{i=1}^h x_i\right)$. While permutations of the context x do not change the outcome, removing or swapping a single token from x changes the hash and hence breaks the watermark at this token.

Skip: This function uses only the left-most token in the context: $f_{\text{Skip-LeftHash}}(x) = P(sx_h)$. This hash is robust to changes in the non-leftmost token, but it is susceptible to insertions/deletions.

Min: This function is defined by $f_{\text{Min-LeftHash}}(x) = \min_{i \in 1, \dots, h} P(sx_i)$. It is robust to permutations within the context and it is partially robust to insertions/deletions. Given that all $P(sx_i)$ are pseudo-random and equally likely to be the smallest value, the likelihood of failure of this scheme is proportional to the number of values removed from the context, i.e. if $h = 4$ and 2 tokens are removed/missing from the context, the PRF is still 50% likely to generate the same hash.

Choosing a Scheme. Figure 2 shows that a small context width h provides the best robustness to machine paraphrasing. At wider context widths, Skip and Min variants remain strong under attack while Additive suffers. However, we see that this robustness improvement comes at a trade-off to text quality as the Min schemes produce less diverse outputs. Still, at a context width $h = 4$, the Min-SelfHash scheme (brown circle marker) achieves the same diversity as the original Additive-LeftHash scheme at width $h = 1$ (black circle), while being more robust. This shows that we can use the additional strength provided by Min and SelfHash to run longer context widths, which in turn secure the watermark. We adopt these two schemes as “SelfHash” and “LeftHash” respectively in the rest of the sections of the main work. In Appendix A.2, we further explore the effect of the scheme choice on both syntactic and semantic aspects of text quality.

3.2 Improved Watermark Detection

The original z -test, Equation (2), may not be optimal when watermarked text is interspersed with non-watermarked text. Consider the case of a single paragraph of watermarked text embedded inside a much larger non-watermarked document. Because the z -score is computed globally over the whole document, it gets diluted because the surrounding text reduces the average greenlist rate.

We design a windowed test, called **WinMax** to accurately detect watermarked regions even in long documents. This is an alternative way of formulating a detection hypothesis that can be employed optionally or in conjunction with the original test and requires no modification of the generation

scheme. Given a sequence of tokens, we first score the sequence on per-token basis to find the binary vector of hits $s \in \{0, 1\}^T$ to each green list, which we can convert to a partial sum representation $p_k = \sum_{i=1}^k s_i$. WinMax searches for the continuous span of tokens that generates that highest z -score. More formally, it computes

$$z_{\text{win-max}} = \max_{\substack{i,j, \\ i < j}} \frac{(p_j - p_i) - \gamma(j - i)}{\sqrt{\gamma(1 - \gamma)(j - i)}}. \quad (3)$$

As this test involves multiple hypothesis testing, we later calibrate to a fixed false-positive rate based on comparisons with non-watermarked text.

We further investigated a more complex anomaly detector based on run-length differences between watermarked and unwatermarked text [Bradley, 1960]. Yet, we found no gains from such a detector over z -test and WinMax within the range of settings we consider in this work. We include a brief description of this alternate detection algorithm as a starting point for future research in Appendix A.5.

4 Evaluating Watermarking in the Wild

Watermarks are extremely accurate in simple scenarios in which a long span (50+ tokens) of text is tested in isolation and without modification. However, in many use cases, the generated text will be embedded inside a larger document, or edited by a human, or paraphrased by another language model. These modifications may be done to increase the utility of the text, or to maliciously erase the watermark and evade detection. This section studies the robustness of the watermark under these more complex use cases.

We assume the following threat model: A user of watermarked text is aware that the text is watermarked, but has no knowledge of the hashing scheme, fraction γ , or context width h that describe the watermark. They paraphrase some (possibly all) spans of the text to evade detection.

In this scenario, we can understand watermark reliability through the following two observations:

1. Without white-box access to the hashing scheme, a user cannot remove the watermark without ensuring that the re-phrased text contains none of the n -grams from the original text. If the user ever recycles long words (which often contains multiple tokens) or phrases from the original text, the watermark will remain, although with reduced strength.
2. If a paraphrased text skews even slightly toward watermarked behavior, the watermark will be detected given enough tokens. Suppose each token is only ε more likely to be green than a random baseline, i.e. $|s| = \gamma T(1 + \varepsilon)$. Then for any z -score threshold, we expect to detect the watermark after seeing $T = (z^2 - \gamma z^2)/(\varepsilon^2 \gamma)$ tokens.

For reasons above, we do not expect paraphrasing attacks to remove a watermark, especially when using off-the-shelf AI paraphrasing tools which we suspect are likely to recycle phrases. Rather, we expect such attacks to increase the number of tokens needed for confident detection. Chakraborty et al. [2023]. This would match with the theoretical analysis of Chakraborty et al. [2023], who assert that for an optimal detector, detection is always possible, given a sufficient number of samples.

Experimental Setup: Following Kirchenbauer et al. [2023], we use the Colossal Common Crawl Cleaned corpus (C4) dataset as a source of prompts for open-ended generation. For the human study, we adopt the “Long-Form Question Answering” (LFQA) dataset curated by Krishna et al. [2023] based on a selection of posts and responses to question’s on Reddit’s “Explain Like I’m Five” (ELI5) forum. We provide an implementation of our experiments at <https://github.com/jwkirchenbauer/lm-watermarking>.

In the majority of our experiments, we use llama [Touvron et al., 2023], a modern state-of-the-art open source general-purpose model to generate watermarked text. In particular, we use the 7 billion parameter variant under the research use permissions of the license. In the human study portion of the experiments, we adopt Vicuna [Vicuna-Team, 2023], a fine-tuned variant of the base model, better suited to responding to the QA prompts used in the study. We ablate these standard dataset and model settings in the Appendix by running a set of similar experiments on alternate datasets and models.

We use a single set of language model sampling parameters across all experiments, multinomial sampling at temperature 0.7, and for all experiments, unless explicitly stated, we use the LeftHash

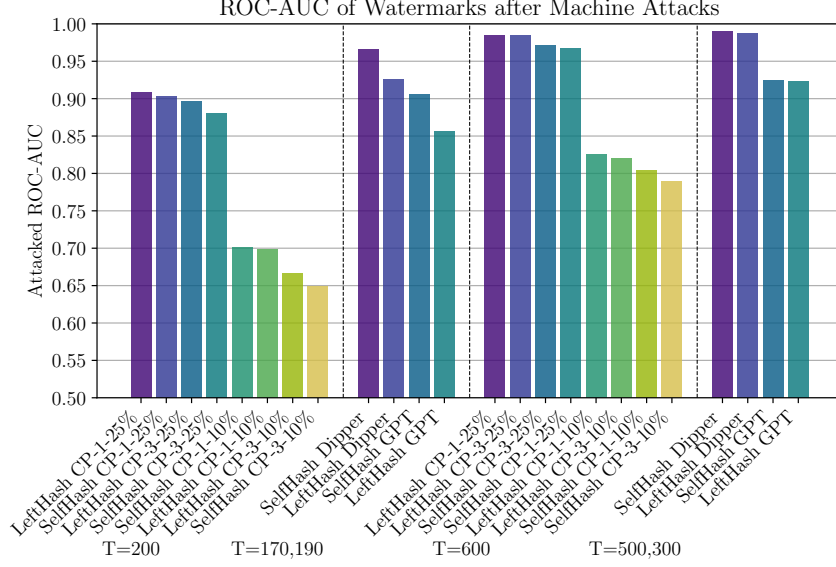


Figure 3: Watermark robustness to various automated text manipulations. Each bar denotes the ROC-AUC for detecting the watermark in a text that has length T after the attack. Each bar label denotes the hashing scheme [SelfHash or LeftHash], and attack type [Copy-Paste (CP), paraphrase model (Dipper) and general-purpose model (GPT)]. For the Copy-Paste attack, we vary the number of watermarked passages inserted and their length. CP-3-10% denotes a copy-paste attack in which only 10% of the text is watermarked, and this watermarked text is broken across 3 different locations in the document. In the Dipper and GPT attacks, the watermarked document is re-written in its entirety, resulting in paraphrases that are shorter than the original text. In this case, the average length T is reported for both GPT and Dipper, respectively.

watermark scheme based on an additive PRF with context window $h = 1$ and $(\gamma, \delta) = (0.25, 2.0)$. This parameter combination was observed to be near the pareto frontier shown in Figure 2 of Kirchenbauer et al. [2023], i.e. extremely detectable, but with marginal cost to generation quality.

Due to the importance of text length in the performance of detection methods, including watermarking, we carefully control and specify the generation lengths considered in each experiment first by limiting the number of tokens the model can generate, and then sub-sampling the resulting data to just those generations which are within a specified range around a target length value. We use “ T ” to refer to the number of tokens considered throughout all experimental sections, and unless otherwise noted we include passages with length within ± 25 tokens around that value. Unless otherwise stated, in all figures, ROC space plots and measurements are backed by > 500 positive and > 500 negative samples, and other types of point estimates are also based on > 500 samples.

4.1 Robustness to Machine Paraphrasing Attacks

We run a series of *paraphrasing attacks* where we use a strong publicly available general-purpose language model API to paraphrase the text. This is a departure from the threat model of Kirchenbauer et al. [2023], who only characterize less capable models (T5). Our “GPT” paraphrase attack uses gpt-3.5-turbo, which is a version of the model powering ChatGPT, to rewrite the text. We also try a specially tailored paraphrasing model - the 11B Dipper model introduced in Krishna et al. [2023]. We engineer the GPT prompt for optimal paraphrasing performance. Our explorations included prompts that explicitly instruct the LLM not to recycle bi-grams from the original text, although these results are not reported here since they were not the best performing prompts. See the Appendix for an ablation on the performance of prompt variants. We note that when prompted for paraphrasing with longer inputs, the GPT model often effectively summarizes the text, sometimes reducing its length by more than 50% - which makes this an interesting challenge for the watermark.

The results for the main experiments attacking the watermark in this way are summarized in Figure 3. Note that we do not show the ROC-AUC numbers for the “unattacked” setting, because the detection performance of both the LeftHash watermark and the SelfHash variant at these token lengths are always > 0.999 for these experiments. Examining the settings where GPT or Dipper are the attack type (the smaller groups of 4 bars) with token length before and after attack of roughly $T = 200$, we

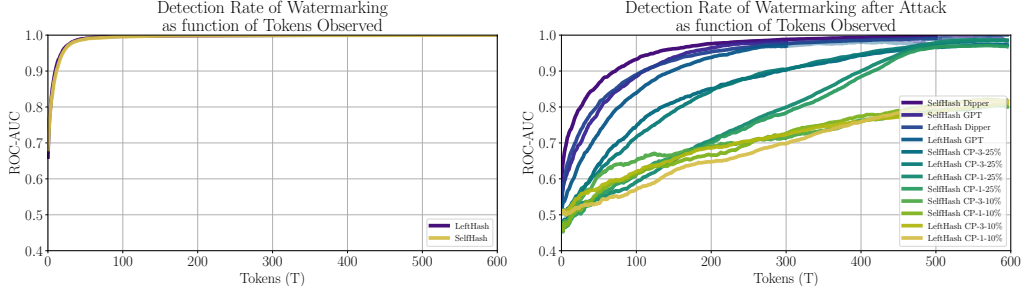


Figure 4: AUC as a function of text length. **(Left)** AUC of original watermarked text with no attack. **(Right)** AUC under attack. Attacks dilute the watermark strength, but the watermark recovers its accuracy as increasingly more tokens are observed. Due to the tendency of the GPT and Dipper paraphraser to produce a shorter outputs than they receive as inputs, we make the curves translucent starting at the mean sequence length of the original text to indicate that these measurements are based on increasing fewer samples. For the Dipper attack this is ~ 500 and for the GPT attack this is ~ 300 . In contrast, the Copy-Paste attack does not suffer from text shortening, and those sequences are still full length i.e. 600 ± 25 .

see that the attack achieves a detection performance reduction of 0.05 – 0.15 points AUC. When the lengths before attack are 600, despite the fact that Dipper and GPT reduce the lengths to 500 and 300 respectively, the success of the attack is now reduced to a loss of < 0.1 points AUC.

This dependence on the number of observed tokens is a fundamental property of the watermarking scheme and as such, we further investigate this dimension through the use of “**detectability @ T**” plots where we test prefixes of the generated sequences of lengths $T_i \in [1, \dots, T]$ and compute ROC-AUC for each prefix length, visualizing the effect of the number of tokens observed on the detection rate (shorthand to AUC @ T). We also provide a version of these charts where we instead show TP rates at low FPR in the appendix.

Under this lens of analysis, we observe in Figure 4 that in the unattacked setting, the AUC @ T quickly approaches its eventual value of ~ 1.0 . In the attacked setting, we see that the AUCs are reduced overall by all methods, but that despite how successful a paraphrasing attack might look at 200-300 tokens, by the 600 token mark, under the GPT and Dipper model-based attacks, the watermark recovers to an AUC greater than 0.9.

4.2 Robustness to Copy-Paste Attacks

We devise a synthetic but realistic attack where we take watermarked text fragments and embed them inside a surrounding un-watermarked, human-written document. This creates heterogeneous examples where only a few sub-spans of the text contain the abnormally high number of green tokens indicative of watermarking. The attack method has two parameters, (1) the number of watermarked span insertions and (2) the fraction of the resulting document that represents watermarked text. For example, consider a passage with 10% watermarked tokens and 3 insertions. If the original text is 1000 tokens, then this means that 3 watermarked spans of 33 tokens would be inserted into the enclosing chunk of human text. We give this setting the short name “CP-3-10%,” which is an abbreviation of “Copy-Paste with 3 spans at 10% watermarking.”

Returning to Figure 3, we see that with 25% watermark remaining, the copy-paste attack procedure has a much stronger effect on the watermark than the other two machine based attacks, dropping the AUC to below 0.7 for 200 tokens and below 0.85 for 600 tokens. Examining Figure 4 we congruently see that the watermark detectability grows more slowly than in the unattacked setting, however it still grows steadily. We revisit this characteristic steady growth behavior in Section 4.4 where we compare watermarking to alternative detection methods.

4.3 Paraphrasing by Human Writers

Humans may paraphrase watermarked text to better fit the style or tone of an existing passage or to better suit the tastes of the user. These modifications are a key part of every-day interactions that human users have with generated text, and to be reliable in-the-wild, a watermark should be robust to these changes. Nonetheless, in a more adversarial setting, a human may also paraphrase text with the deliberate goal of evading detection.

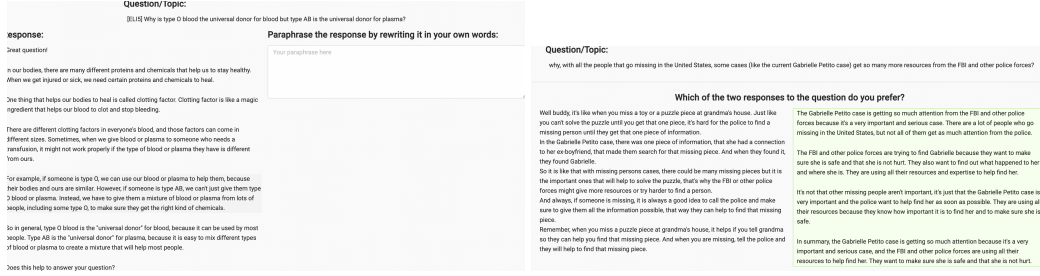


Figure 5: The LabelStudio interface designed for the human paraphrasing and preference studies. Left: Interface for paraphrase study. Right: Interface for human preference study.

To reliably test the feasibility of evasion, we set up a human study. We recruit 14 experienced human writers (graduate students) who were presented with watermarked text. They were asked to paraphrase the text with the goal of removing the watermark while approximately maintaining the original passage length and semantic content. In addition to compensation for participation, top performers were awarded one of three \$100 gift certificates to incentivize strong but faithful paraphrasing. The interface for this human study is shown in Figure 5. Each human writer is given a different set of text passages, which we generate by prompting a watermarked version of Vicuna with the LFQA data.

We first validate that all human writers successfully paraphrased the text passages using P-SP [Wieting et al., 2022] scores. Doing so, we find P-SP scores far exceeding the threshold of 0.7 considered an expert paraphrase in Wieting et al. [2022]. We show this score for each writer in Figure 6 (left), comparing P-SP directly to the z -score of detection based on their text.

We then analyze the detectability of the watermark via z -scores in the right plot of Figure 6 and in Figure 7. Here, we show watermark strength as a function of T , i.e. of tokens seen during detection. While human writers are strong paraphraser, exceeding both machine-based paraphraser in performance, they cannot escape the two observations posed in Section 4. As shown in both Figure 6 (right) and Figure 7 (bottom), eventually, the evidence for a watermark mounts and even human writers are clearly detected on average after 800 tokens. Examining the individual performances in Figure 7, the only real exception in this study was human writer 13, who is a strong paraphraser and simultaneously did not submit enough text to be detected. More text from this writer would be required to guarantee detection. On the other extreme, human writers 22 and 15 apparently paraphrased the text with a strategy that did not substantially affect the watermark, and are reliably detected after only about 250 tokens, or 200 words.

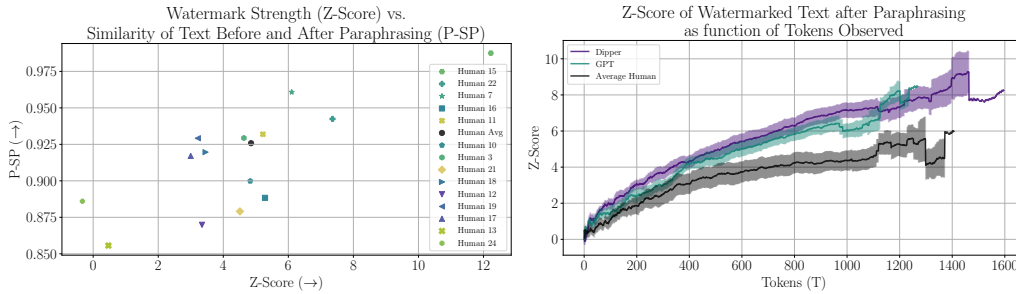


Figure 6: (Left) Paraphrase quality for human writers as measured by P-SP. Note the y-axis. (Right) Summary results for each paraphrasing attack in aggregate, showing that human writers are stronger paraphraser than both machine attacks. Yet, all attacks can be detected with certainty after 400 to 800 tokens.

4.4 A Comparative Study of Detection Algorithms

A number of alternatives to watermarks exist. As discussed in Section 2, other paradigms for LLM detection are post-hoc detectors based on statistical features, black-box learned detectors, and retrieval systems. Based on previous work in Mitchell et al. [2023], we study DetectGPT as a representative for post-hoc detectors, which has been shown to outperform other existing learned detectors. We use the retrieval system put forth in Krishna et al. [2023] as representative for the paradigm of retrieval-based detection.

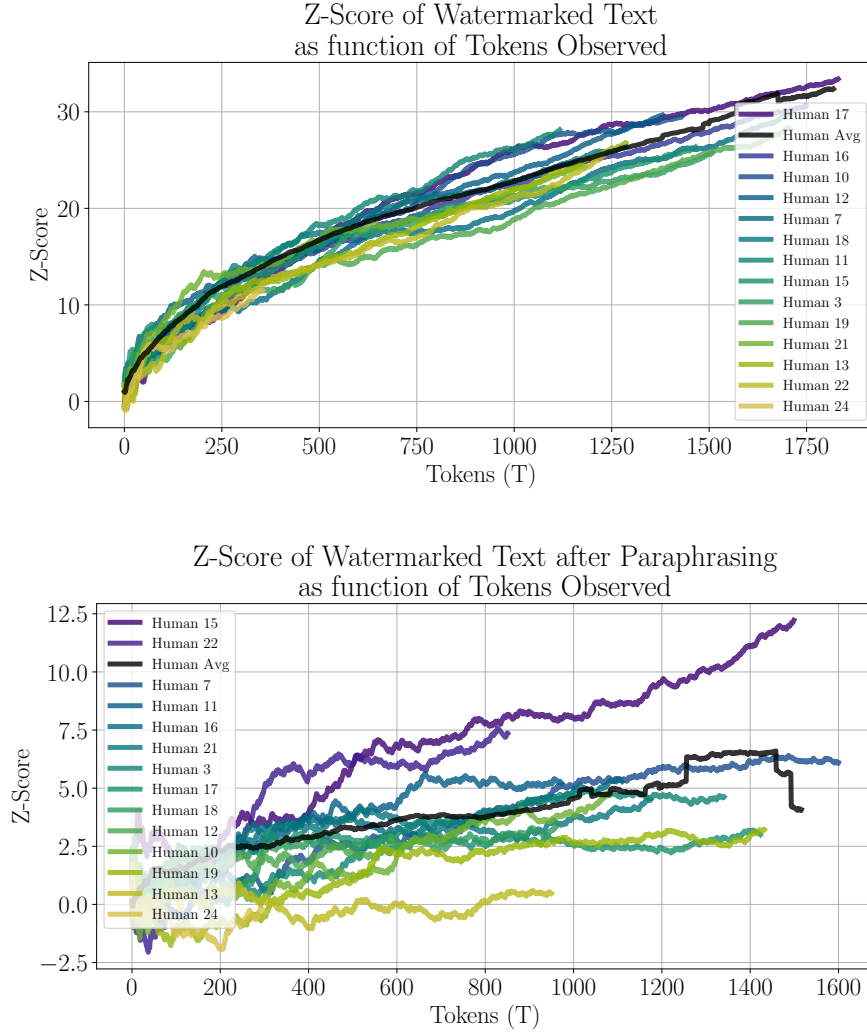


Figure 7: z -score as a function of T over all text passages given to each writer, separated per writer. **(Top)** Original scores for the combined text given to each human writer. **(Bottom)** Average scores per writer after paraphrasing. We find that almost all human writers are detected with exceeding certainty, after about 800 tokens, i.e. about 500 words (a z -score of 4 implies a P-value of $3.2e-5$). Note that despite their strong paraphrasing capability (as shown in the left plot of Figure 6), Human 24 paraphrased too few examples for a fair competitive comparison with the other annotators, but they are still included as part of the averages.

Retrieval: The retrieval system of Krishna et al. [2023] requires the creation and maintenance of a comprehensive database of all sequences generated previously by the language model. By leveraging semantic similarity as a retrieval mechanism, such as SP [Wieting et al., 2022] or BM25 [Robertson et al., 1994], this approach aims to identify and map paraphrased generations to their original, uncorrupted source. In our experiments, we adopt the retrieval method as described by [Krishna et al., 2023], and utilize the BM25 search method as it performed better in their evaluation.

While we include further details in the Appendix, a key detail concerning this method is how we construct copy-paste examples to evaluate it on. The “unattacked” text is the output of the language model without any modification and this is what is loaded into the retrieval database as the “generation history” of the model. The copy-paste attacked version of the text is created by inserting a sub-string from that text into another piece of machine-generated completion text readily available for this prompt, the *watermarked generation*. We discuss this choice and other details in the appendix.

DetectGPT: DetectGPT [Mitchell et al., 2023] is a zero-shot post-hoc method for detecting machine-generated texts. It employs a curvature-based criterion that compares the log probabilities between

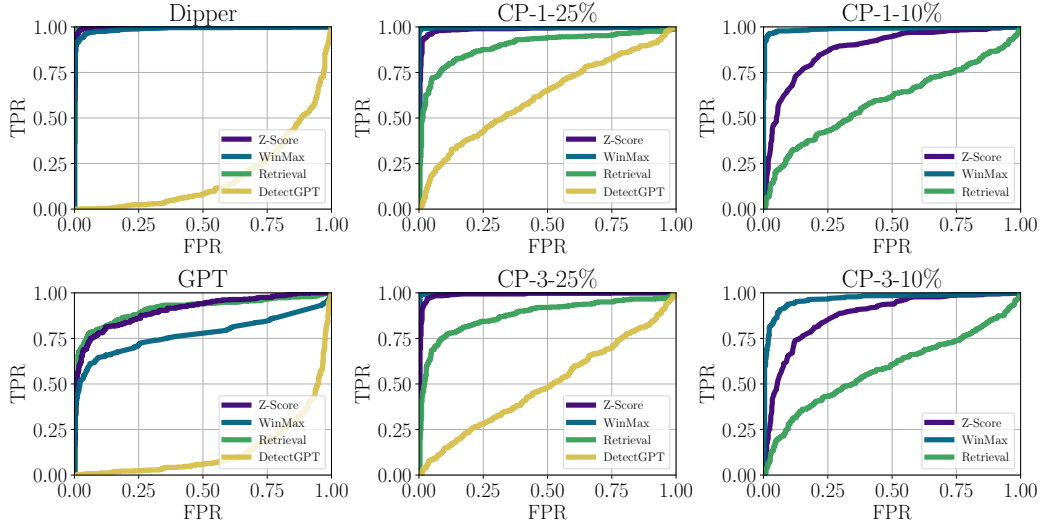


Figure 8: ROC charts for various machine attack types for a text passage with length before attack of $T = 1000$. For Dipper and GPT, the length after attack is decreased to 800 and 300 respectively. z -score and WinMax denote the two watermark detectors, and retrieval is Krishna et al. [2023]. **From left to right:** In the first column we show the two machine paraphrase attacks, in the center column, we show the copy-paste attack with a remaining detectable text percentage of 25% spread over 1 and 3 segments, and in the final column the copy-paste attack at a more difficult to detect 10% remaining detectable text. We find DetectGPT to be catastrophically unreliable under all types of attack. While retrieval is quite robust to the machine paraphrase attacks, watermark based detection outperforms it in the copy-paste setting, with the WinMax variant presenting much stronger performance under the most severe copy-paste attack in the bottom right subfigure.

a candidate passage and its minor perturbations. The intuition behind DetectGPT is that machine-generated texts tend to dominate the negative curvature regions of an LM’s log probability curve. We use the official implementation of DetectGPT and follow their default setting by using T5-3B [Raffel et al., 2020] as the mask-filling model for generating perturbations. We adopt the strongest setting of DetectGPT by generating 100 perturbations for each test sample and using the normalized perturbation discrepancy as the criterion.

Further details regarding the adaption of the method are included in the appendix, but the key experimental detail is that the positive examples for detection are the unwatermarked model outputs generated from each prompt, and as with watermarking detection, the human gold completions are the negative examples.

Which method is most reliable? After introducing these three approaches, we attack them with the battery of machine attacks described in the previous section, using GPT, Dipper, and the copy-paste attack for evaluation. Under attack, we plot ROC charts for each detection scheme in Figure 8, when each method is given a text passage of length $T = 1000$ for detection.

We find that retrieval and watermarking are both decent detection methods, and significantly more reliable than post-hoc detectors (of which DetectGPT is already the strongest). Yet, while retrieval equals or outperforms watermarking on the GPT and Dipper model based paraphrases (corroborating the results in Krishna et al. [2023]), it is bested by watermarking in this novel copy-paste setting.

The Sample Complexity of Various Detection Schemes. To hone in on the observed differences between the schemes under each attack setting, we also compare all three approaches in terms of AUC @ T , i.e. in terms of detection performance again as a function of text quantity. This view is shown in Figure 9. We note the details of how Retrieval and DetectGPT were evaluated at varied values of T in the appendix.

Here, we start to develop an explanation for why watermarking outperforms retrieval in this specific setting by observing that *scaling behaviors for each detection method differ starkly under attack*. While all approaches scale appropriately in strength with the length of text when the generated text is not that heavily attacked, under strong attacks, only watermarking continues to improve reliably, as predicted in the introduction of Section 4.

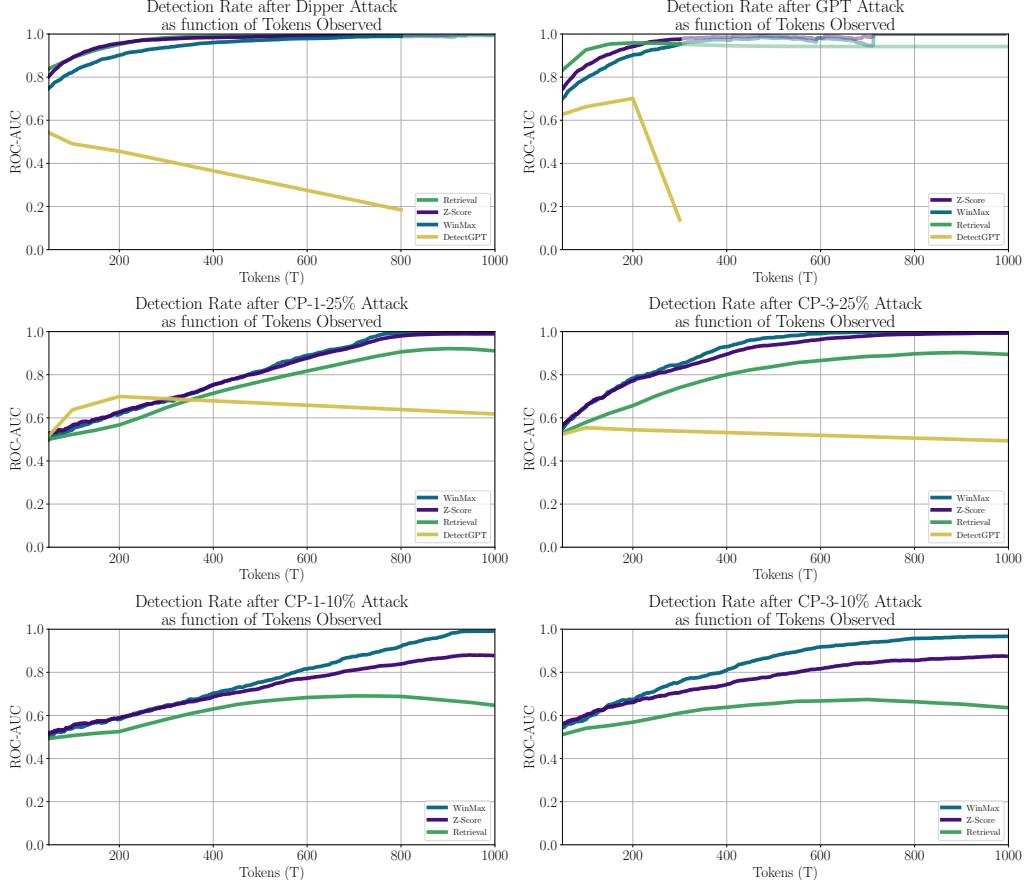


Figure 9: AUC at T for various types of attack. **(Top Row)** The Dipper and GPT machine paraphrasing attacks. **(Center Row)** The copy-paste attack with a remaining detectable text percentage of 25% spread over 1 and 3 segments. **(Bottom Row)** The copy-paste attack at only 10% remaining detectable text. While all schemes scale well with the number of tokens observed when no attack is present, DetectGPT scales poorly under attack. Retrieval shows a positive trend in detectability as a function of T , but is non-monotonic, whereas watermarking steadily improves in power for all attacks evaluated. Due to the tendency of the GPT and Dipper paraphrase models to produce a shorter sequence of tokens as output than they receive as input, we make the curves translucent starting at the mean sequence length of the attacked set after generation to indicate that these measurements are based on increasing fewer samples and are therefore more uncertain. For DetectGPT, the last measurement for each attack type is just computed on the set of full sequences, and so we plot the result at that average T value. For the Dipper attack this is ~ 800 and for the GPT attack this is ~ 300 . Due to the synthetic nature of the Copy-Paste attack, after attack, those sequences are still full length i.e. 1000 ± 25 .

In particular, when only a small fraction of text (25% or 10%) remains under the copy-paste attack, non-watermarking methods struggle as text length increases. For the Retrieval method, as T increases, the fraction of the original text (the unattacked positive example) that remains, decreases. Therefore, the similarity to the original text (the unattacked positive example) continues to drop, which eventually causes a decrease in performance for both copy-paste attack severities. For DetectGPT, the same effect is observed but at a more drastic level. We investigate this behavior in more detail in [Appendix A.8](#) by examining trends in the actual retrieval and detection scores produced under each attack setting for each method.

4.5 What about the White-Box Setting?

In this work we have focused on the black-box setting, where text is modified in plausible use cases for machine-generated text and the secret key of the watermarking scheme is unknown to the party modifying the text through paraphrasing or other editing.

Once this assumption is relaxed, for example if the secret key is breached or the watermark is public, then an attacker with white-box access to a strong paraphrasing model like Dipper [\[Krishna et al.,](#)

2023] could break the watermark in the following way: The attacker can apply an *anti-watermark* scheme during generation with the paraphrasing model, where instead of adding δ in Equation (1) to logit outputs, δ is instead subtracted. The attacker can further keep track of the current score of green-listed versus red-listed tokens and can accordingly modify this negative δ on-the-fly to guarantee that of the T tokens of text generated by the paraphrasing model exactly γT are colored green, and no watermark signal is leaked into the paraphrased text.

This attack relies on both white-box access to the watermark key and availability of a strong paraphrasing model. To bypass this difficult threat model, the watermark context width h has to be chosen sufficiently large so that in an adversarial scenario, the watermark key could not be easily discovered (or alternatively, sufficiently many keys must be employed simultaneously, as discussed in Kirchenbauer et al. [2023]). Nevertheless, *not all watermarking use cases are necessarily adversarial*, and we strongly believe that in benign cases, even a watermark with imperfect resistance to text corruption is still very valuable. Documenting the usage of machine-generated text overall, for example either to trace the spread of generated text in hindsight, or to remove generated text from future training runs [Radford et al., 2022, Shumailov et al., 2023], can provide a baseline effort to “future-proof” popular generative models.

5 Discussion of claimed theoretical results on impossibility of detection

Several works have investigated the difficulty of detecting language models from a theoretical [Varshney et al., 2020, Sadasivan et al., 2023, Chakraborty et al., 2023] and practical [Bhat and Parthasarathy, 2020, Wolff and Wolff, 2022, Tang et al., 2023] perspective, although these works generally pertain to pos-hoc detectors. How does this body of work relate to our empirical evidence on the reliability of watermarking?

We can briefly summarize the argument of Varshney et al. [2020] and Sadasivan et al. [2023] as follows: They assume that all humans generate text from a monolithic “human language” distribution. Since a good language model should closely emulate this distribution, its outputs should not be outliers from the human distribution. If both distributions are close enough, for example as measured by their total variation distance in Sadasivan et al. [2023], samples cannot be separated and the detection of machine-generated text fails. It should be noted that this assumption is quite strong; as noted in Chakraborty et al. [2023], there does not exist a monolithic human language distribution. If such an assumption held true, it would not be possible to distinguish between human speakers (e.g., Donald Trump vs Barack Obama) as they all draw from the same distribution. The distribution of language produced by a human or a machine speaker is also typically conditioned on many things, such as the cultural background of a human, the information in an LLM training set, or the construction of the prompt, making the monolithic distribution assumption even more problematic.

In practice, the distribution of text produced by an LLM is likely *very* different from any particular human. We argue that the observed low accuracy of post-hoc detectors [Liang et al., 2023, Krishna et al., 2023] is not because of distributional similarities, but rather because we lack a concise mathematical *characterization* for their differences. Consider, for example, an LLM with a greedy sampler. Each token produced by this model is a deterministic function of those that came before it; for a given prompt and a long enough response, a human is exorbitantly unlikely to produce the same sequence of tokens as the LLM, making detection trivial if we know the output distribution of each agent. In this case, the (delta-function) distribution of the LLM is clearly very different from what we expect from a random human. Nonetheless, without white-box access to the model and knowledge of the prompt, we have no way to know or represent these distribution differences, and so detection becomes hard regardless of how big the distribution gap is. As noted in Chakraborty et al. [2023], watermarking does enforce the LLM and human distributions to be different, but the distributions were likely far apart before watermarking – a characterization of these differences is needed.

Watermarking succeeds by giving us a simple rule to tease apart the LLM and human distributions; we know the greenlist rate of humans, and that the watermarked LLM’s rate should be greater. Finally, since watermarking detection relies on this derived statistic rather than on a poorly characterized variational difference between machine and human text distributions, we are able to perform detection without access to the model’s parameters.

6 Conclusions

Through a comprehensive empirical investigation, including strong machine paraphrasing and human writers, we evaluate the reliability of watermarks as a mechanism for the documentation and detection of machine-generated text. We advocate for a view of watermarking reliability as a function of text length, and find that even human writers cannot reliably remove watermarks if being measured at 1000 words, despite having the goal of removing the watermark. This view of watermark reliability as a function of text length turns out to be a strong property of watermarking. When comparing to other paradigms, such as retrieval and loss-based detection, we do not find a strong improvement with text length, making watermarking out to be the most reliable approach in our study. This reliability is a consequence of the detector relying on a null hypothesis that humans consistently adhere to, independent of text length, and hence produces a rigorous and interpretable P-value that the user can leverage to control the false positive rate.

References

- Sahar Abdelnabi and Mario Fritz. Adversarial Watermarking Transformer: Towards Tracing Text Provenance with Data Hiding. In *2021 IEEE Symposium on Security and Privacy (SP)*, pages 121–140, May 2021. doi: 10.1109/SP40001.2021.00083.
- Mikhail J. Atallah, Victor Raskin, Michael Crogan, Christian Hempelmann, Florian Kerschbaum, Dina Mohamed, and Sanket Naik. Natural Language Watermarking: Design, Analysis, and a Proof-of-Concept Implementation. In Ira S. Moskowitz, editor, *Information Hiding*, Lecture Notes in Computer Science, pages 185–200, Berlin, Heidelberg, 2001. Springer. ISBN 978-3-540-45496-0. doi: 10.1007/3-540-45496-9_14.
- Sameer Badaskar, Sachin Agarwal, and Shilpa Arora. Identifying real or fake articles: Towards better language modeling. In *Proceedings of the Third International Joint Conference on Natural Language Processing: Volume-II*, 2008.
- Anton Bakhtin, Sam Gross, Myle Ott, Yuntian Deng, Marc’Aurelio Ranzato, and Arthur Szlam. Real or fake? learning to discriminate machine from human generated text. *arXiv preprint arXiv:1906.03351*, 2019.
- Emily M. Bender, Timnit Gebru, Angelina McMillan-Major, and Shmargaret Shmitchell. On the Dangers of Stochastic Parrots: Can Language Models Be Too Big? In *Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency*, FAccT ’21, pages 610–623, New York, NY, USA, March 2021. Association for Computing Machinery. ISBN 978-1-4503-8309-7. doi: 10.1145/3442188.3445922. URL <https://doi.org/10.1145/3442188.3445922>.
- Daria Beresneva. Computer-generated text detection using machine learning: A systematic review. In *21st International Conference on Applications of Natural Language to Information Systems, NLDB*, pages 421–426. Springer, 2016.
- Meghana Moorthy Bhat and Srinivasan Parthasarathy. How Effectively Can Machines Defend Against Machine-Generated Fake News? An Empirical Study. In *Proceedings of the First Workshop on Insights from Negative Results in NLP*, pages 48–53, Online, November 2020. Association for Computational Linguistics. doi: 10.18653/v1/2020.insights-1.7. URL <https://aclanthology.org/2020.insights-1.7>.
- James V. Bradley. Distribution-free Statistical Tests. Fort Belvoir, VA, August 1960. Defense Technical Information Center. doi: 10.21236/AD0249268. URL <http://www.dtic.mil/docs/citations/AD0249268>.
- Jack T Brassil, Steven Low, Nicholas F Maxemchuk, and Lawrence O’Gorman. Electronic marking and identification techniques to discourage document copying. *IEEE Journal on Selected Areas in Communications*, 13(8):1495–1504, 1995.
- Souradip Chakraborty, Amrit Singh Bedi, Sicheng Zhu, Bang An, Dinesh Manocha, and Furong Huang. On the Possibilities of AI-Generated Text Detection. *arxiv:2304.04736[cs]*, April 2023. doi: 10.48550/arXiv.2304.04736. URL <http://arxiv.org/abs/2304.04736>.

- Yuei-Lin Chiang, Lu-Ping Chang, Wen-Tai Hsieh, and Wen-Chih Chen. Natural Language Watermarking Using Semantic Substitution for Chinese Text. In Ton Kalker, Ingemar Cox, and Yong Man Ro, editors, *Digital Watermarking*, Lecture Notes in Computer Science, pages 129–140, Berlin, Heidelberg, 2004. Springer. ISBN 978-3-540-24624-4. doi: 10.1007/978-3-540-24624-4_10.
- William G Cochran. The χ^2 test of goodness of fit. *The Annals of mathematical statistics*, pages 315–345, 1952.
- Evan Crothers, Nathalie Japkowicz, and Herna Viktor. Machine Generated Text: A Comprehensive Survey of Threat Models and Detection Methods. *arxiv:2210.07321[cs]*, November 2022. doi: 10.48550/arXiv.2210.07321. URL <http://arxiv.org/abs/2210.07321>.
- Falcon Dai and Zheng Cai. Towards Near-imperceptible Steganographic Text. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 4303–4308, Florence, Italy, July 2019. Association for Computational Linguistics. doi: 10.18653/v1/P19-1422. URL <https://aclanthology.org/P19-1422>.
- Tiziano Fagni, Fabrizio Falchi, Marco Gambini, Andrea Martella, and Maurizio Tesconi. Tweepfake: About detecting deepfake tweets. *arXiv preprint arXiv:2008.00036*, 2020.
- Tina Fang, Martin Jaggi, and Katerina Argyraki. Generating Steganographic Text with LSTMs. In *Proceedings of ACL 2017, Student Research Workshop*, pages 100–106, Vancouver, Canada, July 2017. Association for Computational Linguistics. URL <https://aclanthology.org/P17-3017>.
- Leon Fröhling and Arkaitz Zubiaga. Feature-based detection of automated language models: tackling gpt-2, gpt-3 and grover. *PeerJ Computer Science*, 7:e443, 2021. doi: 10.7717/peerj-cs.443.
- Matthias Gallé, Jos Rozen, Germán Kruszewski, and Hady Elsahar. Unsupervised and distributional detection of machine-generated text. *arXiv preprint arXiv:2111.02878*, 2021.
- Leo Gao, Stella Biderman, Sid Black, Laurence Golding, Travis Hoppe, Charles Foster, Jason Phang, Horace He, Anish Thite, Noa Nabeshima, Shawn Presser, and Connor Leahy. The Pile: An 800GB Dataset of Diverse Text for Language Modeling. *arXiv:2101.00027 [cs]*, December 2020. URL <http://arxiv.org/abs/2101.00027>.
- EA Grechnikov, GG Gusev, AA Kustarev, and AM Raigorodsky. Detection of artificial texts. In *RCDL2009 Proceedings*, pages 306–308, 2009.
- Alexei Grinbaum and Laurynas Adomaitis. The Ethical Need for Watermarks in Machine-Generated Language. *arxiv:2209.03118[cs]*, September 2022. doi: 10.48550/arXiv.2209.03118. URL <http://arxiv.org/abs/2209.03118>.
- Xuanli He, Qionghai Xu, Lingjuan Lyu, Fangzhao Wu, and Chenguang Wang. Protecting Intellectual Property of Language Generation APIs with Lexical Watermark. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 36, pages 10758–10766, June 2022a. doi: 10.1609/aaai.v36i10.21321. URL <https://ojs.aaai.org/index.php/AAAI/article/view/21321>.
- Xuanli He, Qionghai Xu, Yi Zeng, Lingjuan Lyu, Fangzhao Wu, Jiwei Li, and Ruoxi Jia. CATER: Intellectual Property Protection on Text Generation APIs via Conditional Watermarks. In *Advances in Neural Information Processing Systems*, October 2022b. URL <https://openreview.net/forum?id=L7P3IvsoUXY>.
- Ganesh Jawahar, Muhammad Abdul-Mageed, and Laks Lakshmanan, V.S. Automatic Detection of Machine Generated Text: A Critical Survey. In *Proceedings of the 28th International Conference on Computational Linguistics*, pages 2296–2309, Barcelona, Spain (Online), December 2020. International Committee on Computational Linguistics. doi: 10.18653/v1/2020.coling-main.208. URL <https://aclanthology.org/2020.coling-main.208>.
- Gabriel Kaptchuk, Tushar M. Jois, Matthew Green, and Aviel Rubin. Meteor: Cryptographically Secure Steganography for Realistic Distributions, 2021. URL <https://eprint.iacr.org/2021/686>.

- John Kirchenbauer, Jonas Geiping, Yuxin Wen, Jonathan Katz, Ian Miers, and Tom Goldstein. A Watermark for Large Language Models. *arxiv:2301.10226[cs]*, January 2023. doi: 10.48550/arXiv.2301.10226. URL <http://arxiv.org/abs/2301.10226>.
- Kalpesh Krishna, Yixiao Song, Marzena Karpinska, John Wieting, and Mohit Iyyer. Paraphrasing evades detectors of AI-generated text, but retrieval is an effective defense. *arxiv:2303.13408[cs]*, March 2023. doi: 10.48550/arXiv.2303.13408. URL <http://arxiv.org/abs/2303.13408>.
- Thomas Lavergne, Tanguy Urvoy, and François Yvon. Detecting fake content with relative entropy scoring. *PAN*, 8:27–31, 2008.
- Xiang Lisa Li, Ari Holtzman, Daniel Fried, Percy Liang, Jason Eisner, Tatsunori Hashimoto, Luke Zettlemoyer, and Mike Lewis. Contrastive decoding: Open-ended text generation as optimization. *arXiv preprint arXiv:2210.15097*, 2022a.
- Xiang Lisa Li, Ari Holtzman, Daniel Fried, Percy Liang, Jason Eisner, Tatsunori Hashimoto, Luke Zettlemoyer, and Mike Lewis. Contrastive Decoding: Open-ended Text Generation as Optimization. *arxiv:2210.15097[cs]*, October 2022b. doi: 10.48550/arXiv.2210.15097. URL <http://arxiv.org/abs/2210.15097>.
- Weixin Liang, Mert Yuksekgonul, Yining Mao, Eric Wu, and James Zou. GPT detectors are biased against non-native English writers. *arxiv:2304.02819[cs]*, April 2023. doi: 10.48550/arXiv.2304.02819. URL <http://arxiv.org/abs/2304.02819>.
- Stephen Merity, Caiming Xiong, James Bradbury, and Richard Socher. Pointer sentinel mixture models, 2016.
- Eric Mitchell, Yoonho Lee, Alexander Khazatsky, Christopher D. Manning, and Chelsea Finn. DetectGPT: Zero-Shot Machine-Generated Text Detection using Probability Curvature. January 2023. doi: 10.48550/arXiv.2301.11305. URL <https://arxiv.org/abs/2301.11305v1>.
- OpenAI. Gpt-2: 1.5b release. <https://openai.com/research/gpt-2-1-5b-release/>, 2019. Accessed on 15th May 2023.
- Annie Palmer. People are using A.I. chatbots to write Amazon reviews. *CNBC*, April 2023. URL <https://www.cnbc.com/2023/04/25/amazon-reviews-are-being-written-by-ai-chatbots.html>.
- Krishna Pillutla, Swabha Swayamdipta, Rowan Zellers, John Thickstun, Sean Welleck, Yejin Choi, and Zaid Harchaoui. MAUVE: Measuring the Gap Between Neural Text and Human Text using Divergence Frontiers. In *Advances in Neural Information Processing Systems*, volume 34, pages 4816–4828. Curran Associates, Inc., 2021. URL <https://proceedings.neurips.cc/paper/2021/hash/260c2432a0eccc28ce03c10dad078a4-Abstract.html>.
- Alec Radford, Jong Wook Kim, Tao Xu, Greg Brockman, Christine McLeavey, and Ilya Sutskever. Robust Speech Recognition via Large-Scale Weak Supervision. *arxiv:2212.04356[cs, eess]*, December 2022. doi: 10.48550/arXiv.2212.04356. URL <http://arxiv.org/abs/2212.04356>.
- Colin Raffel, Noam Shazeer, Adam Roberts, Katherine Lee, Sharan Narang, Michael Matena, Yanqi Zhou, Wei Li, and Peter J. Liu. Exploring the Limits of Transfer Learning with a Unified Text-to-Text Transformer. *arXiv:1910.10683 [cs, stat]*, July 2020. URL <http://arxiv.org/abs/1910.10683>.
- Stephen E. Robertson, Steve Walker, Susan Jones, Micheline Hancock-Beaulieu, and Mike Gatford. Okapi at trec-3. In *Text Retrieval Conference*, 1994.
- Juan Rodriguez, Todd Hay, David Gros, Zain Shamsi, and Ravi Srinivasan. Cross-domain detection of gpt-2-generated technical text. In *Proceedings of the 2022 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 1213–1233, Seattle, United States, 2022. Association for Computational Linguistics.
- Vinu Sankar Sadasivan, Aounon Kumar, Sriram Balasubramanian, Wenxiao Wang, and Soheil Feizi. Can AI-Generated Text be Reliably Detected? *arxiv:2303.11156[cs]*, March 2023. doi: 10.48550/arXiv.2303.11156. URL <http://arxiv.org/abs/2303.11156>.

- Bruce Schneier. Using AI to Scale Spear Phishing, August 2021. URL <https://www.schneier.com/blog/archives/2021/08/using-ai-to-scale-spear-phishing.html>.
- Ilia Shumailov, Zakhar Shumaylov, Yiren Zhao, Yarin Gal, Nicolas Papernot, and Ross Anderson. The Curse of Recursion: Training on Generated Data Makes Models Forget. *arxiv:2305.17493[cs]*, May 2023. doi: 10.48550/arXiv.2305.17493. URL <http://arxiv.org/abs/2305.17493>.
- Irene Solaiman, Miles Brundage, Jack Clark, Amanda Askell, Ariel Herbert-Voss, Jeff Wu, Alec Radford, Gretchen Krueger, Jong Wook Kim, Sarah Kreps, et al. Release strategies and the social impacts of language models. *arXiv preprint arXiv:1908.09203*, pages 1–46, 2019.
- Yixuan Su, Tian Lan, Yan Wang, Dani Yogatama, Lingpeng Kong, and Nigel Collier. A Contrastive Framework for Neural Text Generation. In *Advances in Neural Information Processing Systems*, October 2022. URL <https://openreview.net/forum?id=V88BafmH9Pj>.
- Ruixiang Tang, Yu-Neng Chuang, and Xia Hu. The Science of Detecting LLM-Generated Texts. *arxiv:2303.07205[cs]*, March 2023. doi: 10.48550/arXiv.2303.07205. URL <http://arxiv.org/abs/2303.07205>.
- Edward Tian. Gptzero update v1, January 2023. URL <https://gptzero.substack.com/p/gptzero-update-v1>.
- Maxim Tkachenko, Mikhail Malyuk, Andrey Holmanyuk, and Nikolai Liubimov. Label Studio: Data labeling software, 2020-2022. URL <https://github.com/heartexlabs/label-studio>. Open source software available from <https://github.com/heartexlabs/label-studio>.
- Umut Topkara, Mercan Topkara, and Mikhail J. Atallah. The hiding virtues of ambiguity: Quantifiably resilient watermarking of natural language text through synonym substitutions. In *Proceedings of the 8th Workshop on Multimedia and Security, MM&Sec '06*, pages 164–174, New York, NY, USA, September 2006. Association for Computing Machinery. ISBN 978-1-59593-493-2. doi: 10.1145/1161366.1161397. URL <https://doi.org/10.1145/1161366.1161397>.
- Hugo Touvron, Thibaut Lavril, Gautier Izacard, Xavier Martinet, Marie-Anne Lachaux, Timothée Lacroix, Baptiste Rozière, Naman Goyal, Eric Hambro, Faisal Azhar, Aurelien Rodriguez, Armand Joulin, Edouard Grave, and Guillaume Lample. Llama: Open and efficient foundation language models. *arXiv preprint arXiv:2302.13971*, 2023.
- Lav R. Varshney, Nitish Shirish Keskar, and Richard Socher. Limits of Detecting Text Generated by Large-Scale Language Models. In *2020 Information Theory and Applications Workshop (ITA)*, pages 1–5, February 2020. doi: 10.1109/ITA50056.2020.9245012.
- Ashish Venugopal, Jakob Uszkoreit, David Talbot, Franz Och, and Juri Ganitkevitch. Watermarking the Outputs of Structured Prediction with an application in Statistical Machine Translation. In *Proceedings of the 2011 Conference on Empirical Methods in Natural Language Processing*, pages 1363–1372, Edinburgh, Scotland, UK., July 2011. Association for Computational Linguistics. URL <https://aclanthology.org/D11-1126>.
- Vicuna-Team. Vicuna: An Open-Source Chatbot Impressing GPT-4 with 90%* ChatGPT Quality, March 2023. URL <https://lmsys.org/blog/2023-03-30-vicuna>.
- Sean Welleck, Ilia Kulikov, Stephen Roller, Emily Dinan, Kyunghyun Cho, and Jason Weston. Neural text generation with unlikelihood training. *arXiv preprint arXiv:1908.04319*, 2019.
- John Wieting, Kevin Gimpel, Graham Neubig, and Taylor Berg-kirkpatrick. Paraphrastic Representations at Scale. In *Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing: System Demonstrations*, pages 379–388, Abu Dhabi, UAE, December 2022. Association for Computational Linguistics. URL <https://aclanthology.org/2022.emnlp-demos.38>.
- Max Wolff and Stuart Wolff. Attacking Neural Text Detectors. *arxiv:2002.11768[cs]*, January 2022. doi: 10.48550/arXiv.2002.11768. URL <http://arxiv.org/abs/2002.11768>.
- Claire Woodcock. AI Is Tearing Wikipedia Apart, May 2023. URL <https://www.vice.com/en/article/v7bdba/ai-is-tearing-wikipedia-apart>.

- Susan Zhang, Stephen Roller, Naman Goyal, Mikel Artetxe, Moya Chen, Shuohui Chen, Christopher Dewan, Mona Diab, Xian Li, Xi Victoria Lin, Todor Mihaylov, Myle Ott, Sam Shleifer, Kurt Shuster, Daniel Simig, Punit Singh Koura, Anjali Sridhar, Tianlu Wang, and Luke Zettlemoyer. OPT: Open Pre-trained Transformer Language Models. *arxiv:2205.01068[cs]*, May 2022. doi: 10.48550/arXiv.2205.01068. URL <http://arxiv.org/abs/2205.01068>.
- Wanjun Zhong, Duyu Tang, Zenan Xu, Ruize Wang, Nan Duan, Ming Zhou, Jiahai Wang, and Jian Yin. Neural deepfake detection with factual structure of text. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 2461–2470, Minneapolis, Minnesota, 2020. Association for Computational Linguistics.
- Zachary Ziegler, Yuntian Deng, and Alexander Rush. Neural Linguistic Steganography. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*, pages 1210–1215, Hong Kong, China, November 2019. Association for Computational Linguistics. doi: 10.18653/v1/D19-1115. URL <https://aclanthology.org/D19-1115>.

A Appendix

We provide a number of extended sets of visualizations and ablation studies to supplement the results shown in the main body of the work as well as more methodological and experimental details. Below is a table of contents to help navigate the various subsections.

Table of Contents

1. [Utilizing Better Quality Metrics](#)
2. [Hashing Scheme Extended Ablation](#)
3. [Datasets and Models Ablation](#)
4. [GPT Attack Prompt Ablation](#)
5. [Watermark Detector Ablation](#)
6. [Detectability of Watermarks after Machine Paraphrasing: TPR @ T](#)
7. [Experimental Methodology Details](#)
8. [Detection Method Comparison: Detector Scores @ T](#)
9. [Human Study Details and Preference Evaluation](#)
10. [Code Details and Release Statement](#)
11. [Hardware and Compute Details](#)

A.1 Utilizing Better Quality Metrics

To more accurately examine the effects of watermarking, in addition to utilizing a stronger generative model from the llama family [Touvron et al., 2023], we employ a pair of metrics designed to capture different aspects of generation quality. Given the fraction u_n of unique n -grams in a sequence of text, we define text diversity up to order N via

$$\text{diversity} = -\log \left(1 - \prod_{n=1}^N (1 - u_n) \right), \quad (4)$$

to represent a view on n -gram repetition metrics described in Welleck et al. [2019] and Li et al. [2022a] in a more readable format. A higher diversity score represents a more diverse text, where fewer n -grams are repeated.

To estimate whether watermarked text drifts away from un-watermarked model generations, we adopt the same evaluation metric as Krishna et al. [2023] to measure paraphrase similarity: P-SP [Wieting et al., 2022]. We measure similarity between different sets of text pairs such as un-watermarked and watermarked outputs, or the human gold completion to a prompt versus the watermarked completion generated by the model. Further, we evaluate human annotator judgement of un-watermarked versus watermarked text quality (Table 2).

We also considered other metrics for language model sampling quality such as MAUVE [Pillutla et al., 2021] and coherence as described in [Su et al., 2022, Li et al., 2022b]. However, the insight those measures provided when comparing outputs under various generation and watermarking settings was generally subsumed by what the P-SP metric revealed, so we chose to simplify presentation using just P-SP as our semantic similarity metric across all relevant visualizations. Aside from the study of watermarks, we note that output quality evaluation in open ended generation settings is still a research area with many open questions.

Algorithm 1 Generalized SelfHash Watermark

Input: Context x_h, \dots, x_1 , vocabulary V , arbitrary text generation scheme S , LLM logits l
 Watermark hyperparameters $\gamma \in (0, 1)$, $\delta > 0$, $f, h > 0$, integer hash P

$G = \emptyset$ ▷ Initialize empty set of green-listed tokens

for $k = 1, \dots, |V|$ **do**

$H_k = f(x)P(k)$ ▷ Compute k -th key

$G_k = \text{RandPerm}_{H_k}(V)[\gamma|V|]$ ▷ Temp. green list G_k seeded with H_k

if $k \in G_k$ **then**

$G \leftarrow G \cup \{k\}$ ▷ Include k in final green list if self-consistent

end if

end for

$l_k \leftarrow \begin{cases} l_k + \delta & \text{if } k \in G \\ l_k & \text{otherwise} \end{cases}$

Sample a new token x_0 from modified logits l using sampling scheme S .

A.2 Hashing Scheme Extended Ablation

In this section, we complete our extensive study of watermark hyperparameters by presenting a representative selection of settings varying different components of the hashing scheme to explore different parts of the pareto space between watermark strength and text quality. We further detail our proposed extension of the SelfHash algorithm to arbitrary sampling schemes and pseudorandom functions f in Algorithm 1.

When using greedy decoding, the scheme in Algorithm 1 covers the scheme denoted as Alg.3. in Kirchenbauer et al. [2023]. We also note that in practice, iterating over all $k \in |V|$ is not strictly necessary. We only iterate over the 40 indices k with the largest logit score l_k and skip all others, for which the addition of δ is unlikely to make an impact on the final probability distribution.

We further note that the choice to set $H_k = f(x)P(k)$ instead of $H_k = f([x, k])$ in Algorithm 1 is not strictly necessary. We refer to the first choice as *anchoring* and ablate it separately in Figure 12, where $H_k = f([x, k])$ denotes the un-anchored approach. On all other occasions the SelfHash scheme is always anchored as described in Algorithm 1.

In Figure 10, to vary the strength of the watermark, we test a selection of γ and δ values in $\{0.5, 0.25, 0.1\}$ and $\{1.0, 2.0, 4.0\}$ respectively. These values give us 9 settings representing both weak and strong watermarks that yield a series of increasing z -scores across the x -axis for each seeding scheme. All points in these charts are averages computed on ~ 500 samples with token length $T = 200 \pm 25$.

We observe that as the watermark is made stronger (resulting in higher z -scores) certain schemes trend positively with respect to n -gram diversity of their outputs and others trend negatively. Namely, for the “Additive-LeftHash,1” (i.e. using LeftHash with context width $h = 1$, and additive f) scheme that was evaluated in Kirchenbauer et al. [2023], stronger watermark strength yields less text diversity. This issue is remedied by using a larger context width, or by choosing the “Skip-LeftHash,4” scheme which exhibits improved text diversity at higher watermark strengths. This finding provides another advantage for schemes with increased context width.

In Figure 11, we display the drift between unwatermarked and watermarked completions, as measured in P-SP. To put these numbers into perspective, we note that the drift between human text and unwatermarked text can be estimated as just under 0.50 PSP. This implies that for the watermark settings yielding z -scores up to 10.0 (a score that is *extremely* detectable), the semantic divergence of the watermarked output from the model’s unwatermarked behavior is less than the average divergence of the unwatermarked model from human gold completions.

In Figure 2 from the main body we empirically demonstrate that the attack amplification effect, hypothesized in Kirchenbauer et al. [2023] to occur when using watermark schemes with context widths greater than $h = 1$, is made less severe when using Skip and Min based schemes. To get the full picture based on all degrees of freedom afforded in the hashing scheme space described in the main body, we provide a plot varying all parameters simultaneously in Figure 12. We confirm the

prediction in Kirchenbauer et al. [2023] that the generalized version of the SelfHash algorithm, when applied to the Anchored version of MinHash scheme at a moderate context width (i.e “Algorithm 3” from the previous work when the context width is $h = 4$), provides a competitive tradeoff between robustness to attack and text diversity and quality along with the added benefit of being more secure against reverse engineering of the PRF key than the Additive-LeftHash.

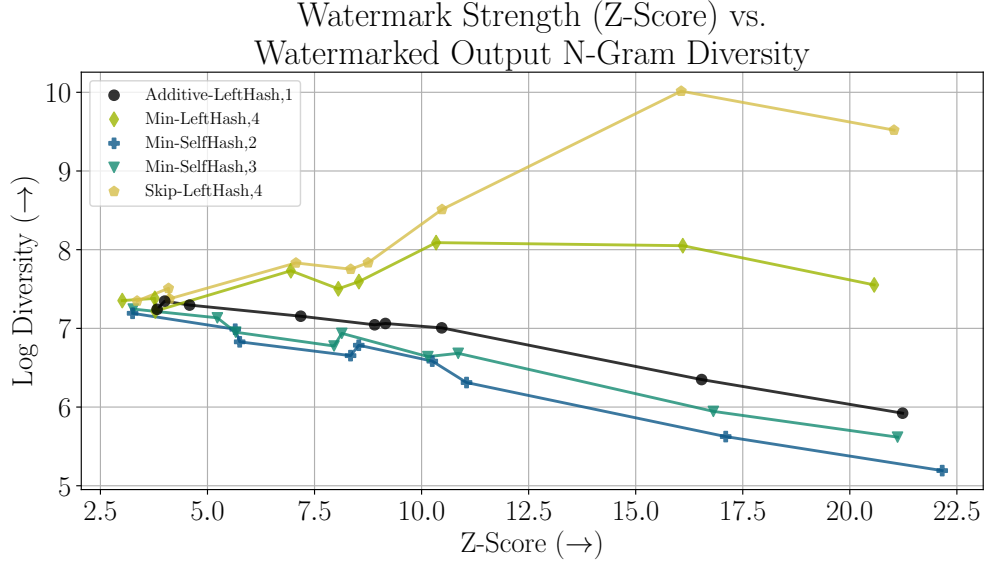


Figure 10: The pareto frontier with watermark strength (z -score) on the x -axis and text diversity (Log Diversity, see Appendix A.1) shown on the y -axis. Higher is better for both metrics. We see that the Min-LeftHash and Skip-LeftHash schemes with larger context windows yield more diverse generations as watermark strength increases. The standard LeftHash scheme with context width 1 and the SelfHash based schemes produce lower diversity outputs under strong watermarking.

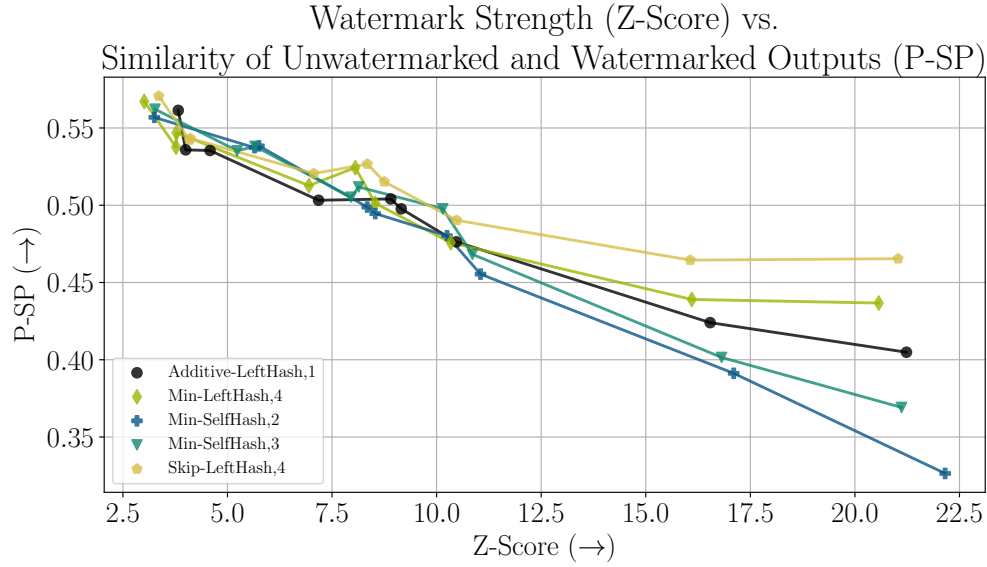


Figure 11: The pareto frontier of watermark strength in z -score, shown on the x -axis, versus similarity between the un-watermarked and watermarked output, shown on the y -axis. Higher is better for both metrics. We see that the Min-LeftHash and Skip-LeftHash schemes with larger context windows produce watermarked generations with slightly higher semantic similarity to their unwatermarked counterparts than the other schemes as watermark strength increases. However for all schemes, especially the SelfHash based settings, as the watermark is made stronger, the watermarked output diverges more from the unwatermarked output.

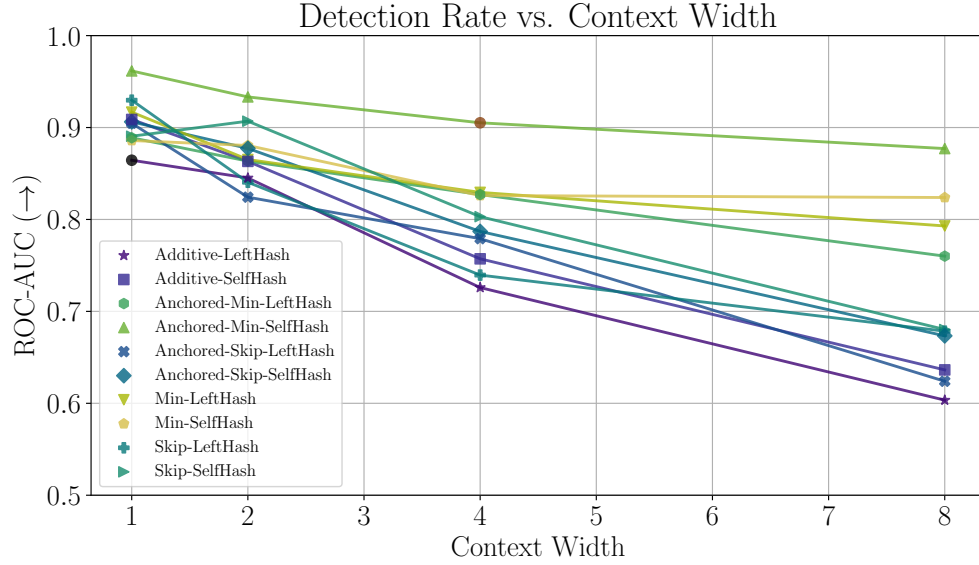


Figure 12: Effect of seeding scheme context width on watermark robustness as measured by ROC-AUC after a paraphrasing attack by GPT. In this variant, we ablate two more parameters, “anchoring” and “self-salting” (SelfHash). The watermark strength parameters γ, δ are fixed at $(0.25, 2.0)$, slightly weaker than the above to bring in line with settings from figures in main work. We specially denote “Additive-LeftHash” at width 1 via the black circle marker and also the “Anchored-Min-SelfHash” at width 4 in as a brown circle, as these correspond to the “LeftHash” and “SelfHash” variants respectively shown in Figure 3, where we also reported the more complex watermark seeding scheme outperforming the standard scheme proposed by Kirchenbauer et al. [2023]. Here, it becomes clear that this is the result of the Anchored-Min-SelfHash scheme outperforming the others in terms of robustness at all context widths.

A.3 Datasets and Models Ablation

In this section we present the results of an extended evaluation of watermark robustness to machine paraphrasing attacks across a selection of domain specific datasets using the two models utilized in the main experiments `llama` and `vicuna` and a similarly sized but older generative model from the Open Pretrained Transformer family, `opt-6.7b` [Zhang et al., 2022]. For cross-reference, the black marker indicates the same standard model and data pair from the evaluations in the main work. The “Github”, “Law”, “Med”, and “Patents” markers refer to the `github`, `free_law`, `pubmed`, and `uspto` subsets of the “The Pile” [Gao et al., 2020] dataset as hosted on the huggingface hub at huggingface.co/datasets/EleutherAI/pile by EleutherAI. “Wiki” indicates samples from the training split of Wikitext103 dataset [Merity et al., 2016], also hosted on the huggingface hub at huggingface.co/datasets/wikitext as `wikitext-103-raw-v1`.

Generally, looking at Figure 13, we see that the Github subset yields the lowest z -scores relative to the number of tokens considered here, most likely a function of the restrictive nature of code syntax. Less flexibility at generation time due to restrictive prompts and domain characteristics results in a lower average “spike-entropy” of the model’s next-token distribution. This has a proportional effect on how strongly the watermark can be embedded, due to its adaptivity property (see Kirchenbauer et al. [2023] for a full analysis of the effect of entropy on watermark strength) and implies that under default settings, more text needs to be observed to detect the watermark. Upon manual inspection, the Law subset is also highly formatted containing special characters and whitespacing and this is a potential explanation for the low peak z -score (below 8.0) since the model is forced to follow syntax cues in the prompt to maintain a high level of language modelling accuracy. The Med and Patents subsets yield a wider range of z -scores across the three models in the 8.0 to 10.0 range, and the C4-en and Wiki datasets produce z -scores very similar to the C4-News split considered throughout the main work.

Out of the three models evaluated, the `vicuna` model, which is a supervised instruction-finetuned variant of `llama`, yields the lowest z -score for each dataset, suggesting that its output entropy is generally lower than that of the base `llama` model or `opt` in congruence with the fact that we found a higher delta value (4.0) was required to achieve suitably strong starting watermark levels in the human paraphrasing study (details in Appendix A.9).

While in Figure 14 we also present the combination of models and data but with a different metric along the y-axis, we find that the appropriate takeaways are mostly the same as described above. Further, the semantic similarity (P-SP) values for the Github data domain are potentially miscalibrated since this metric was not designed for code similarity estimation. That said, we notice that `vicuna` and `llama` achieve the same z -scores across Law, Med and Patents, but show more semantic divergence between the unwatermarked and watermarked outputs for Med and Patents than Law.

In Figure 15 we observe the effect of the different z -scores shown in Figure 13 and Figure 14 on the unattacked detection rate. The ROC-AUC is quite a bit lower for Github and Law than the other datasets. Then, in Figure 16 we see that this also translates into correspondingly lower detectability after attack by GPT and Dipper. However, we note that for the Med and Law subsets (yellow and green bars), detectability post paraphrase attack is quite similar to the C4-News domain (black bars) utilized throughout the main work. This suggests that those findings generalize well at least to language modelling domains with similar levels of syntactic flexibility.

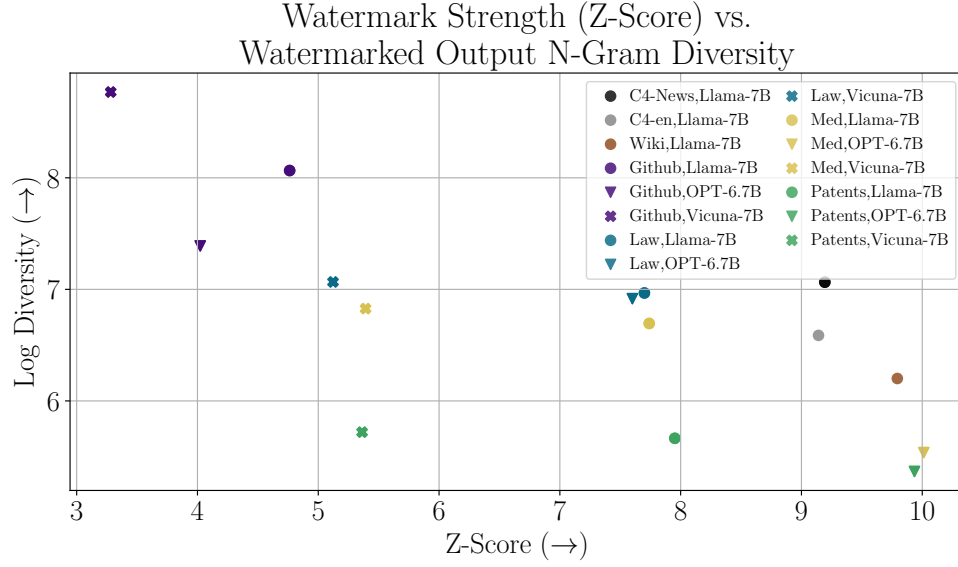


Figure 13: The pareto frontier of watermark strength in z -score, shown on the x -axis, versus text diversity, shown on the y -axis. Higher is better for both metrics. The Github subset results in particularly low z -scores for all models and the Law subset is also shifted left versus the C4 data splits. Med, Patents, and Wiki yield higher z -scores more similar to the C4-News data from the main work.

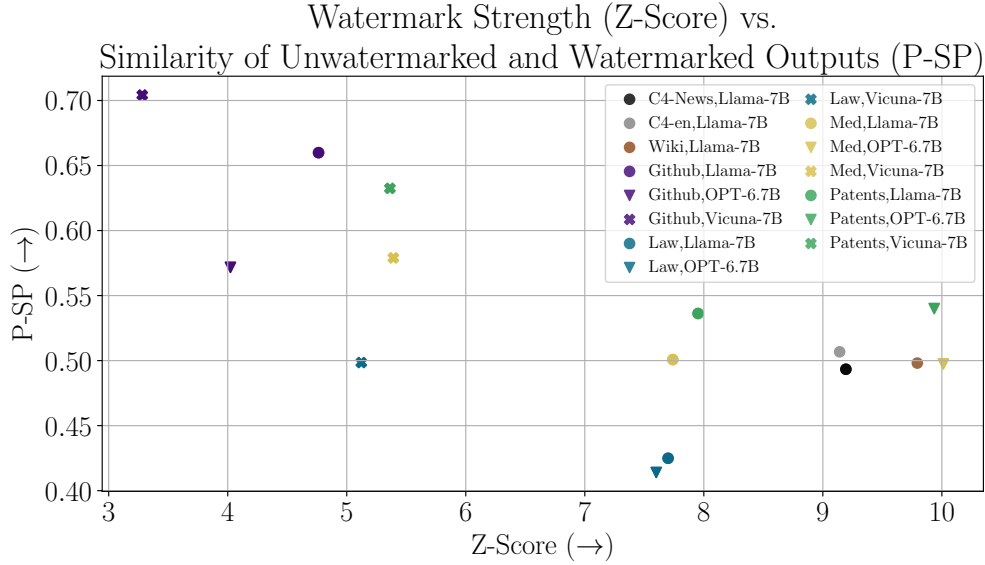


Figure 14: The pareto frontier of watermark strength in z -score, shown on the x -axis, versus similarity between the un-watermarked and watermarked output, shown on the y -axis. Higher is better for both metrics. Similar trends to Figure 13.

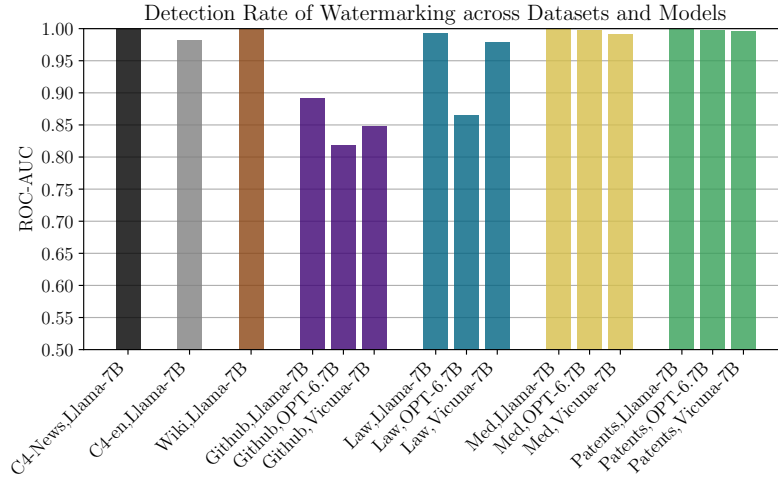


Figure 15: Detection rate of watermarking as measured by ROC-AUC for extended selection of datasets and models. The Github and Law subsets producing lower z -scores in Figure 13 corresponds to lower ROC-AUC. The vicuna model yields the least detectable watermark out of the three models in most cases.

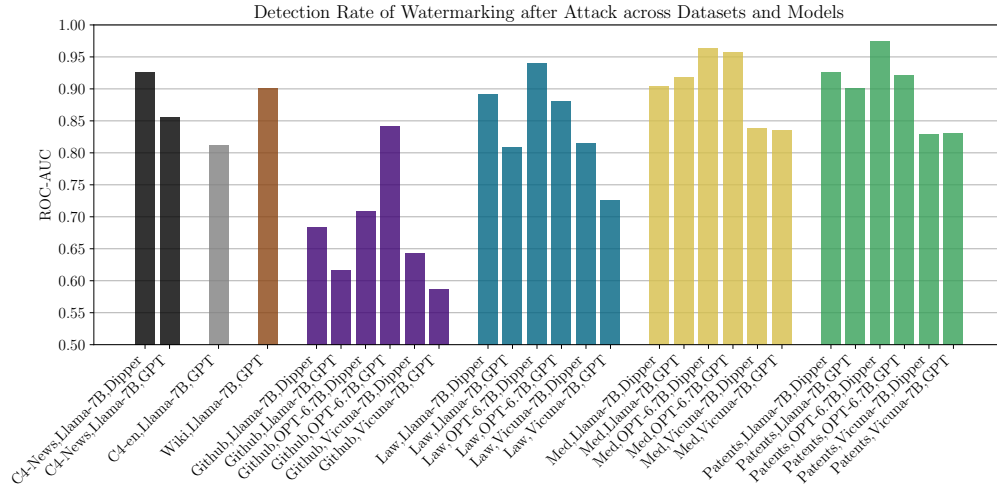


Figure 16: Detection rate of watermarking after being attacked using a machine paraphrasing model as measured by ROC-AUC for extended selection of datasets and models. The Github and Law subsets producing lower ROC-AUC in Figure 15 corresponds to lower ROC-AUC after attack as well. While the GPT attack is more successful in reducing the detectability of the watermark in a majority of the cases (around 8/12) a stronger claim is withheld without further ablation of domain specific paraphrase instructions or parameters for the dipper paraphrasing model.

A.4 GPT Attack Prompt Ablation

When using gpt-3.5-turbo (GPT) to paraphrase the text throughout the experiments on watermarking and detector robustness, we prompt the model with an instruction prompt for the paraphrasing task. In our initial experiments we observed the tendency of GPT to produce a *summary*, i.e. it generated text with good semantic similarity to the input but significantly shorter overall length with this summarization ratio worsening as the original length was increased. We tried to address this issue by specifically adding directives to the prompt to encourage the model to maintain the length of the text. While ultimately we were unable to solve this problem through our basic prompt engineering, we enumerate the prompts we explored in Table 1. We leave the further study of how to optimally prompt general purpose LLMs such as GPT for paraphrasing tasks to future research.

We note that in one sense, this makes the attack using GPT strictly stronger, as some information contained in the original text is left out during summarization.

The prompt we selected to use throughout our experiments was “Prompt 4” as it resulted in a slightly lower ROC-AUC for the standard z -score detector (lower indicating a stronger, more successful paraphrase attack) than “Prompt 3” whilst achieving a slightly longer averaged attacked output length than “Prompt 0”. Prompts 1 and 2 were included in table to be consistent with a file in the source code though those other prompts were not competitive so they were omitted from the figures.

Prompt ID	Prompt Text
0	“paraphrase the following paragraphs:\n”
1	“paraphrase the following paragraphs and try your best not to use the same bigrams from the original paragraphs\n”
2	“paraphrase the following paragraphs and try to keep the similar length to the original paragraphs\n”
3	“You are an expert copy-editor. Please rewrite the following text in your own voice and paraphrase all sentences. \n Ensure that the final output contains the same information as the original text and has roughly the same length. \n Do not leave out any important details when rewriting in your own voice. This is the text: \n”
4	“As an expert copy-editor, please rewrite the following text in your own voice while ensuring that the final output contains the same information as the original text and has roughly the same length. Please paraphrase all sentences and do not omit any crucial details. Additionally, please take care to provide any relevant information about public figures, organizations, or other entities mentioned in the text to avoid any potential misunderstandings or biases.”

Table 1: GPT paraphrase attack prompts. Performance of 0,3,4 shown in Figure 17 and Figure 18 as prompts 1 and 2 were not competitive. Prompt 4 used throughout experiments in main work and Appendix.

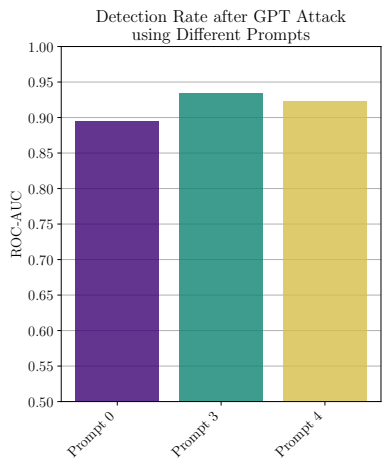


Figure 17: Detection rate of watermark after attack by GPT using various prompts.

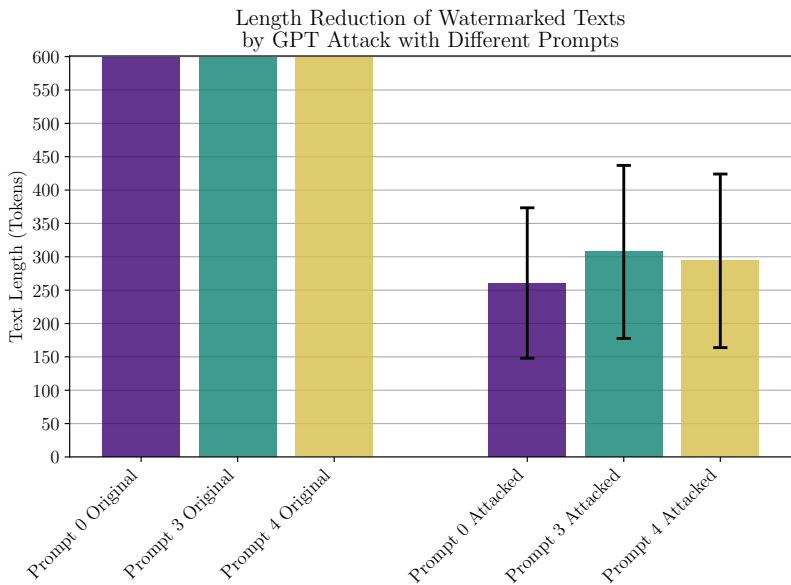


Figure 18: Original token lengths (all 600) versus token length after paraphrasing using different prompts for GPT. Standard deviation is visualized for the latter. We choose “Prompt 4” to balance AUC after attack and length after attack, but a wider study of prompting general purpose LLMs for paraphrasing tasks is left to future research.

A.5 Watermark Detector Ablation

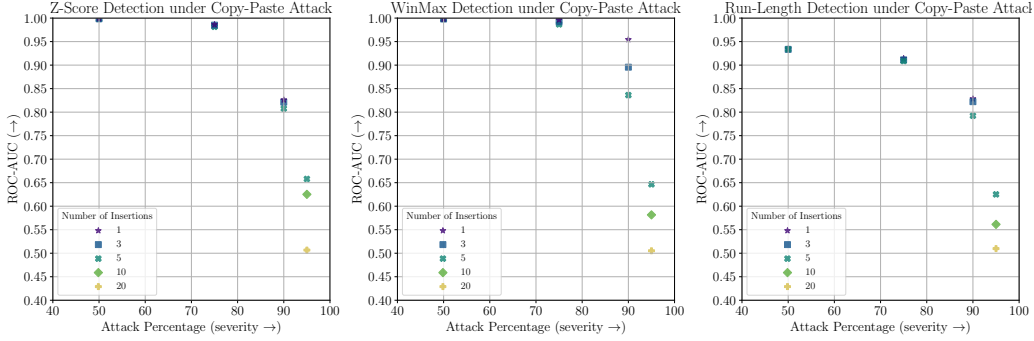


Figure 19: (Left) The performance of standard Z-Score watermark detection, (Center) WinMax detection, and (Right) the Run-Length based detector. WinMax outperforms the standard Z-Score at the 90% attack percentage, and the run-length test failed to show improvement over the standard test at any setting evaluated, however it demonstrates parity at stronger attack levels.

Additionally, we investigate an anomaly detection test based run-lengths as a potential detector of the distribution shift between watermarked and unwatermarked text [Bradley, 1960]. Yet, we find no gains from such a detector within the range of attack settings we consider in this work. After describing the basic results, we include a brief description of this alternate detection algorithm as a starting point for future research.

In Figure 19, moving right along the x-axis means that the attack on the watermark becomes more severe (higher “attack percentages”) because less of the total text remains watermarked. The marker style denotes how many fragments the remaining watermarked percentage is distributed across in the final text. As an example, the blue square at 90% attack, means 10% total tokens watermarked, split across 3 chunks. The WinMax method shows comparable performance with the standard Z-Score method at all settings except for the 90% attack percentage, where it handily outperforms the standard detector.

For the rightmost plot in Figure 19 showing the run-length detector performance, we visualize the best performing variants of the run length test, where we only count the green runs, we use the “maximum-plus-1” binning strategy, we ignore any run-lengths for which we recorded zero observations, and we use the standard “pearson” chi-squared test statistic to compare expected and observed frequencies. Additionally, for the more severe 90% and 95% attack levels, the best performing setting was to ignore the length-1 runs bin in the test statistic computation. These details are elaborated at the end of this section.

Counting the Lengths of “Green Runs” At detection time, the test originally proposed by Kirchenbauer et al. [2023] initially treats a piece of text as a sequence of green and red tokens, which can be modeled by a Boolean array i.e. sequence s such that $s_t = 1$ if $s_t \in G_t$ and $s_t = 0$ if not. However, the z-test then immediately reduces this sequence to one value $|\{s_t : s_t \in G_t\}|$, the number of green tokens observed. We hypothesize that this reduces the power of the test in certain scenarios because it does not take into account information regarding the positions of the green (and red) tokens.

To harness this information, one can view the Boolean array as a set of *runs*, where a run is defined by a subsequence of consecutive 1’s or 0’s. As an example, under the convention that a 1 corresponds to a token being in its greenlist, the sequence $[1, 1, 0, 1, 0, 0, 0, 1]$ contains 2 green runs of length 1, and 1 green run of length 2. It also contains 1 red run of length 1 and 1 red run of length 3.

The example scenario that motivated our exploration of this method was the text mixing setting (copy-paste attack) where sections of watermarked text would be interspersed within surrounding unwatermarked text. In the case of just a few heavily watermarked subsequences, one would expect to observed a few isolated runs of green tokens (consecutive 1’s) that were surprisingly long. This is because we expect to observe few greens (γT in expectation) in unwatermarked text, and many more

in heavily watermarked text, and long green runs are themselves caused by a higher overall green token count.

Hypothesis Test for a “Run-Length Detector” To formalize this notion of what we’d find “surprising”, and thereby derive a new hypothesis test from it, we leverage the fact that for a binary event with a probability of “success” p , the number of independent trials k required to realize the first success can be modeled by a geometric distribution, with density given by

$$Pr(\text{“success after } k \text{ trials”}) = (1 - p)^{k-1}p, \text{ for } k = 1, 2, 3... \quad (5)$$

We can treat observing a 0 or a redlist token as a *success* event, and therefore model the “green runs” as a geometrically distributed random variable with success probability $1 - \gamma$. Armed with this fact, if we treat each run length $k = 1, 2, 3...$ as a category, then for a given piece of unwatermarked text, the expected values of each of these categorical variables can be computed using the geometric distribution density function scaled by the total number of runs observed in the text.

Therefore, we can test for the watermark by testing the following null hypothesis,

$$H_0: \text{The text sequence is generated with no knowledge of the watermarking rule} \quad (6)$$

and therefore the “green” run lengths are geometrically distributed.

One standard way to compare an observed set of categorical variable outcomes to an expected set, is to perform a chi-squared test [Cochran, 1952]. In this test the sum of squared deviations between the expected and observed frequency (count) for each category are summed. If the statistic is small, then the observed counts are close to the expected, and we fail to reject the null hypothesis. However, if the statistic is large, then at least one of the observed frequencies is surprisingly different from the corresponding expected frequency and the collection of categorical variable observations is unlikely to have come from the expected distribution, in which case we can reject the null hypothesis.

Returning to the context of green run lengths, this means that if we observe green run length counts that don’t match the expectation given by the geometric distribution, we are confident that this sequence was not generated under the null hypothesis, and rather, was generated under the watermarking scheme. We expect that the most common mechanism for this rejection under watermarking would be observing a surprising number of long runs of green tokens, i.e. surprisingly high frequencies in the tail (larger values of k) than expected under the geometric distribution.

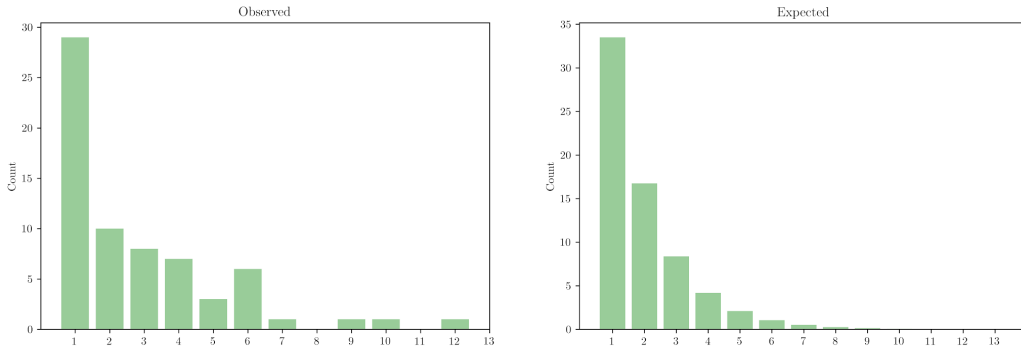


Figure 20: An intuition-building example of the run length distributions we seek to compare. The left is the actual, empirical run lengths observed in a *watermarked* sample, and the right is the expected counts of each run length based on the total number of observed runs, distributed according to the geometric prior parametrized by $1 - \gamma$ (the null hypothesis). Each bar shows the number of runs of a given length that were observed. The “surprising” observations are the non-zero counts for the length 7,9,10 and 12 bins.

Design Choices

1. When we “count green runs, where red is the success event” a new run begins after each observation of a red token. The sequence $[R, R, R, G, R]$ yields 3 “green runs” of length 1, and then 1 green run of length 2. This is because a red occurs after just a single trial, three times in a row, and then the final red takes two trials to achieve.

2. For a sequence of length T one could observe any possible run length $k \in \{1 \dots T\}$, and we can compute an expected frequency for all k based on the success probability $1 - \gamma$. However, it is standard practice to bin the tail of unobserved k values to create a new event “run lengths longer than k ” and the probability mass for those values is summed before computing the expected number of outcomes for that tail category. In Figure 20, the max shown (13), is 0, but the maximum actually observed was 12 and this addition of an extra bin represents the tail of runs longer than the max observed.
3. For any run lengths k between 1 and the largest observed run length value k_{max} it is standard practice to ignore these categories when computing the test statistic if there were zero observed occurrences. This is based on the assumption that the zero observation is likely spurious consequence of a small sample size (of runs). In Figure 20, there are two bins, 8 and 11, that also are zero, which can be ignored in the test statistic computation.
4. We consider the standard “pearson” formulation of the chi-squared test, as well as the “g-test” and “cressie-reed” variants based on likelihood ratios rather than squared deviations.
5. In order to isolate the rejection scenario we expect under watermarking, we experiment with ignoring the small categories k in the test statistic computation. The intuition is that these short run lengths could dominate the statistic value in an undesirable way when there are just a small handful of surprisingly long runs in the tail of the observed distribution. Considering the example in Figure 20, since the close counts of observed and expected length-1 runs potentially of little interest with respect to the null hypothesis reject case expected for the watermark, we can choose to ignore the leading bin in the test computation.

A.6 Detectability of Watermarks after Machine Paraphrasing: TPR @ T

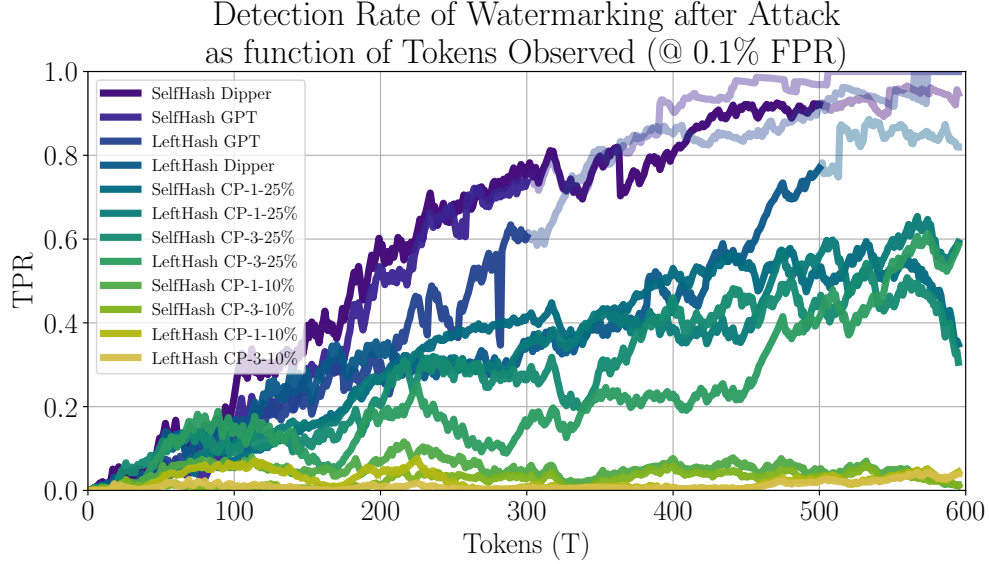


Figure 21: In this variant of a plot from the main body, we visualize the growth characteristics of watermark detection as quantified by True Positive Rate at low False Positive Rate (0.1%) after attack by a selection of machine-based attacks. As in the main body charts, we make the curves translucent starting at the mean sequence length of the attacked set after generation to indicate that these measurements are based on increasing fewer samples after that point as T continues to grow and are therefore more uncertain. For the Dipper attack this is ~ 500 and for the GPT attack this is ~ 300 . Due to the synthetic nature of the Copy-Paste attack, after attack, those sequences are still full length i.e. 600 ± 25 .

A.7 Experimental Methodology Details

A.7.1 GPT Paraphrase Attack

We utilize the prompt chosen through the ablation in [Appendix A.4](#) and query the model using a sampling temperature of 0.7 and a max token limit of 1000.

A.7.2 Dipper Paraphrase Attack

We utilize the Dipper paraphrase model proposed by [Krishna et al. \[2023\]](#) and released at their github. Since this model smoothly trades off semantic similarity between the paraphrased and original text starting from few discernible changes at one end to almost wholly unrelated at the other extreme of its `lex` and `div` parameters, we choose one of the moderate strength settings to run the paraphrasing attacks with across all experiments `lex=40`, `div=40`. This still represents a significant attack, but maintains high paraphrase quality/similarity. We of course emphasize that the setting used is the same for all the watermarking and baseline detector methods to fairly compare them.

A.7.3 Baseline Method Hyperparameters

We lightly adapt the codebases provided by the authors to interface with our generation, attack, and evaluation pipeline for both methods and use default parameters found in their code unless otherwise specified.

Retrieval Detection For the Retrieval Detection method, initially, we ran experiments using dense similarity retrieval, denoted `sim` in their codebase, as this method worked well out-of-the-box in our experimental pipeline. However since [Krishna et al. \[2023\]](#) found BM25 to be superior, we reworked their code slightly, and reran all retrieval experiments. All results shown in the main work and in the next section utilize BM25 as the retrieval method because it did perform slightly better under attack, in accordance with the findings of the original authors.

DetectGPT For DetectGPT, we use the “*z*” method (normalized perturbation discrepancy) and 100 perturbations for estimating the loss landscape curvature around each sample, and use the corresponding language model to be detected as the base model/likelihood estimator.

We remark that there are some unknowns about how well the DetectGPT paradigm works when different models are used as the detection target, especially when under attack. In this work we primarily utilize llama as the base model to be detected, and the relationship between the relative sizes and qualities of the base model, the perturbation model (a 3B parameter version of T5), and the machine paraphraser (Dipper or `gpt-3.5-turbo`), could be quite subtle and produce counter-intuitive detection performance outcomes. We leave the study of post-hoc detectors with improved robustness characteristics to future research.

A.7.4 Defining “Positive” and “Negative” Detection Test Samples

“Negative” Samples In all experiments, either using watermarking as the detection method or the two baseline approaches, the “negative” samples at test time that should be classified as “not watermarked” or “not machine-generated” respectively, are human-written text i.e. the gold completions/suffixes extracted from the input data as prompts are created.

“Positive” Samples for Watermarking Detection For the watermarking experiments, in the unattacked setting, the “positives” are the watermarked model’s generations. To produce the paraphrase-attacked versions, the watermarked generation is fed to the paraphrasing model (GPT or Dipper) or rewritten by humans. To construct the copy-paste attacked versions for watermarking, sets of watermarked tokens are inserted into a surrounding context sequence of *human-written* tokens (i.e. the gold completions to the prompt). While this means that the negative examples and surrounding context examples for the copy-paste watermarking experiments are correlated, this does not give the watermarking method any unfair advantage at detection time. If a specific sequence of human-written text happens to produce an abnormally high *z*-score, which *could* artificially inflate the *z*-score of the copy-paste attacked example making it an easier detection, then it will simultaneously increase the chance of a false positive on that sequence for precisely the same reason. Since both examples are always tested, this effect should be balanced out.

“Positive” Samples for Alternate Detection Approaches For the Retrieval based and DetectGPT baseline approaches, the “positives” are the unwatermarked model’s generations as this is the distribution that the approach is designed to detect. For the Retrieval method, this means that the retrieval database (index) is loaded up with the set of unattacked, unwatermarked generations so that, if those same sequences are queried at test time, then the retrieval performance (as measured by TPR) should be perfect. To construct paraphrase attacked examples in this setting, the unwatermarked generations are fed to the paraphrasing model (GPT or Dipper) causing them to diverge from the exact sequences present in the database, and the exact model distribution that DetectGPT is testing for.

Copy-Paste Attacked Samples for Alternate Detection Approaches As stated above, for copy-paste attacks in the the watermark detection evaluation, we insert spans of watermarked tokens into surrounding context of human-written tokens. Since watermarking effectively views all text as boolean arrays “green” and “red” tokens regardless of the textual content itself, human-written text is the most “negative” type of context we can create to make the embedded watermarked chunk harder to detect.

However, since the human-written completions are already used as the negative examples, and the baseline detection methods rely much more on the syntactic and semantic similarities between the examples, to reduce the error correlations between the negative and positives for Retrieval detection and DetectGPT, we instead insert the small unwatermarked chunks (parts to be detected) into a surrounding context of *watermarked* text. While we realize this choice might seem a bit strange, and also admit that it is mostly an implementation pipeline convenience rather than a perfectly optimal choice, we do not believe this causes any unfair biasing of the detection performance estimates for the following reasons.

For a fair copy-paste example with respect to the particular detection approach being evaluated, we desire “negative” looking context tokens to surround the “positive” looking chunks to be detected. From a semantic similarity perspective, the watermarked generations used as a source of context tokens, are quite relevant/similar to the unwatermarked subsequences being inserted because they were generated following the same prompt. For Retrieval, this means that there is actually a generous/favorable level of semantic similarity between the context tokens (meant to make the copy-paste attacked sample look negative) and the unwatermarked outputs stored in the retrieval database. We believe this is a reasonably fair and realistic setting since the copy-and-pasting attacker we are simulating would likely replace removed sections of the text to be detected with semantically similar and relevant text (as opposed to random tokens).

Potential Confounding Factors in Copy-Paste We believe that this setup is also fair for the DetectGPT method, however, we realize that both the perturbation procedure and the likelihood estimation are probably influenced by certain discontinuities introduced in copy-pasted examples as no algorithm or post-processing step is used to smooth out the interface region between the positive and negative spans. That said, since we find that Retrieval performs quite well under the copy-paste attack and that for DetectGPT the copy-paste examples produce somewhat unremarkable behavior as visualized in the main work and in [Appendix A.8](#) (versus the GPT and Dipper results), we believe these methodological choices did not significantly influence the results in an unfair way. That said, we believe there are still open questions in developing suites of different attack strategies ranging the gamut from black-box model-based paraphrasing to synthetic text mixing that test a wider range of possible attack and corruption scenarios that could be encountered in-the-wild.

A.7.5 Baseline Detection Method Performance as a Function of Tokens Observed

While the watermark detection score (z -score) is readily computable in a cumulative manner along the sequence length dimension, and thus evaluation at T is simple for that method, for Retrieval and DetectGPT, the sequences to be tested must first be chunked into prefixes and then those sets of prefixes evaluated individually. For Retrieval detection, we make the choice that the sequences loaded into the database should be the *full length* unwatermarked output, even though we are querying with prefixes of those outputs to develop the series of measurements at T. This reflects what we believe to be a realistic setting where the model generated the full output at some time in the past, and at test time is being queried with a prefix/fragment of the original generation. Additionally, storing all prefixes of some given size for all generations is not a realistic or scalable choice in our opinion.

For DetectGPT, the adaptation for detection at T is easier in one aspect because it is simply implemented by testing a block of prefixes of the original unwatermarked (and then attacked) generations. However, the computational cost of producing just a single series of measurements at a range of T values becomes prohibitively expensive for a single attack setting. This is because for each block of prefixes, say the leading 100 tokens from a set of N sequences that originally had length 600, the runtime cost is roughly the same as testing the full length outputs. Thus the overall runtime of testing all prefixes, or T values, for a given set of sequences is multiplied by the number of prefixes, or length/stride. In contrast, there is effectively no multiplier for watermarking, and it is still relatively cheap for Retrieval since the retrieval method itself is much cheaper (at least for a small database). This is the reason for the limited number of datapoints shown in the comparisons for DetectGPT as a function of observed tokens.

As final remarks on the somewhat surprising performance of the method, we note that the generations are tested without the original prompts included in the input. We assume this is the setting of the original work, since having access to the prompt at test time would be unrealistic, but beyond this detail, we are unsure as to why evaluating the method using the llama model as the base model to be detected, performs as poorly as it does. We leave more comprehensive robustness evaluation of the DetectGPT method to future work by its creators and other researchers but hypothesize that the relationship between the base model, the perturbation model, and the paraphrasing model, could be more nuanced and require more careful tuning of hyperparameters or other aspects of the detection method.

A.8 Detection Method Comparison: Detector Scores @ T

In this section we present a “mechanistic” explanation for the detectability as a function of text length (AUC at T) results reported in the main body of the work. In particular, we motivate the perusal of this section by remarking that in order to perform well, a score-based binary detector (like all the methods considered here) must maintain a gap between the scores assigned to “negative” or genuine human written samples, and the “positive” or machine generated samples. The left chart in each pair are the scores assigned to negative examples by the given method, and the right chart shows the scores for positive examples. We make note of the fact that the standard Z-Score watermarking produces an *extremely* wide gap between corresponding curves in the left and right charts in Figure 22, driven in large part by the lack of growth in the negative scores. This key behavior of watermarking provides for both detectability and a low FPR.

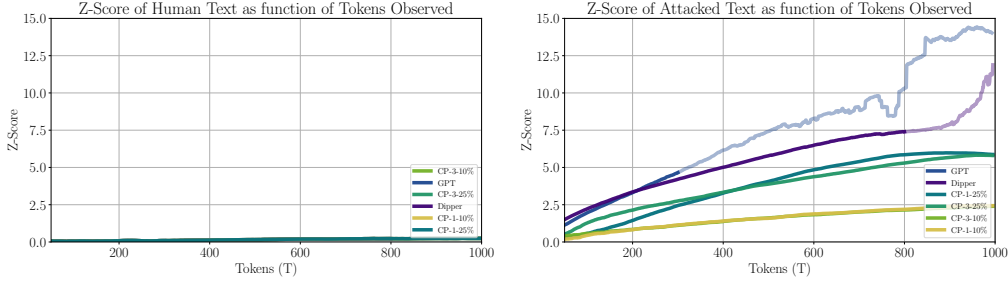


Figure 22: The detection scores yielded by the watermarking detection z-score method. In stark contrast to the trends in Figure 24 and Figure 25, we see that for all T , the z -score of human text remains very low (**Left**) whilst the z -scores for the attacked watermarked texts continue to grow steadily (**Right**) demonstrating the favorable token sample complexity characteristics of watermarking detection. As in preceding figures we turn the curves translucent after their mean sequence length value to indicate increased uncertainty.

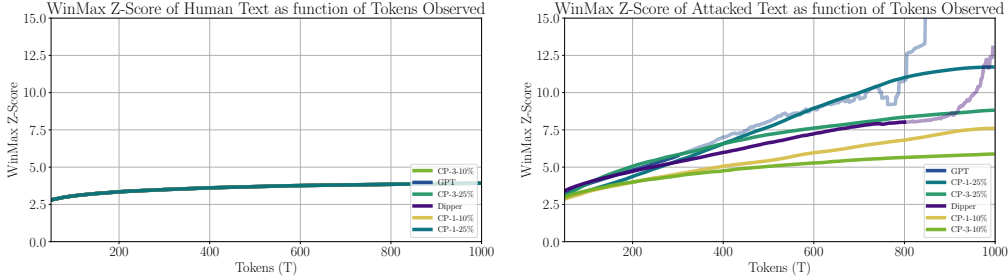


Figure 23: The detection scores yielded by the watermarking detection WinMax z -score method. Compared to Figure 22 we see that the likelihood of a False Positive at smaller values of T is higher under WinMax than the basic z -score detection test as the separation between the scores for human text (**Left**) and attacked watermarked text (**Right**) is not as large. However, empirically, this tradeoff enables improved detection under the strongest copy-paste attacks as shown in Figure 8 and Figure 9. As in preceding figures we turn the curves translucent after their mean sequence length value to indicate increased uncertainty.

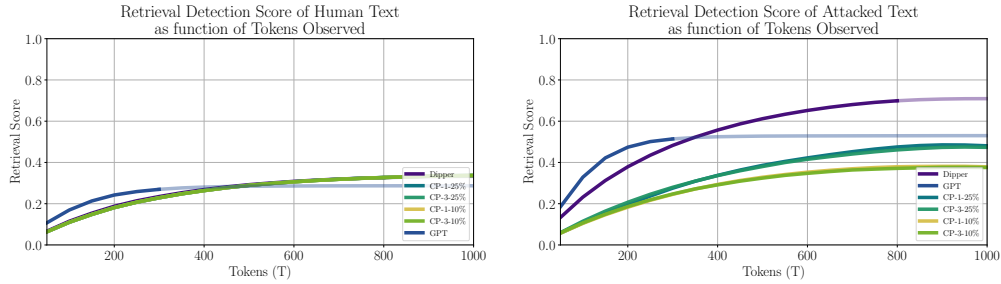


Figure 24: The similarity scores yielded by the Retrieval detection method using the BM25 search index. **(Left)** The corresponding scores for “negative” human-written test samples are lower than **(Right)** the scores for the “positive” attacked samples for all values of T , which is desired/required for proper detection and mechanistically explains the favorable detection performance shown in other figures. However, we note that the gap is not as large for the copy-paste attack as it is for GPT and Dipper. As in preceding figures we turn the curves translucent after their mean sequence length value to indicate increased uncertainty.

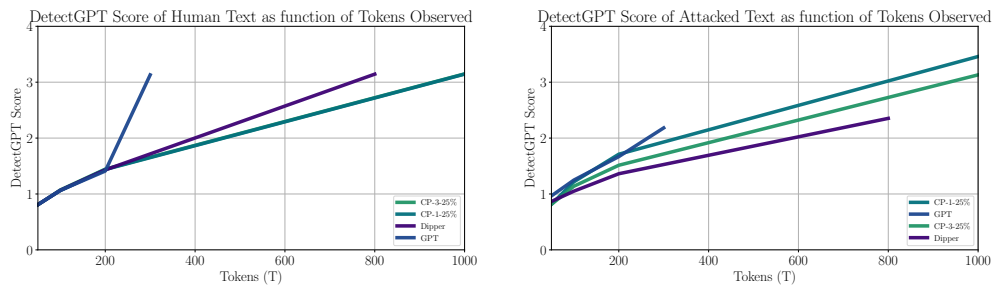


Figure 25: The similarity scores yielded by the DetectGPT method. **(Left)** While the corresponding scores for “negative” human-written test samples start out lower than **(Right)** the scores for the “positive” attacked samples at small values of T , which is desired/required for proper detection, this ordering becomes reversed for the GPT and Dipper paraphrase attacks at larger T which helps explain the unfavorable/“inverted”-looking detection performance curves out at 300 and 800 tokens for those methods shown in other figures.

A.9 Human Study Details and Preference Evaluation

A.9.1 Quality/Preference Evaluation

To give a second perspective on the quality impact of watermarking on generated texts, as part of our Human study (Table 2), we ask annotators to rate which of two potential responses to a prompt they generally prefer. And we find that for a *very* strong watermark ($\gamma = 0.25, \delta = 4.0$) humans only prefer the unwatermarked text over the watermarked text a weak majority the time.

Total Ratings	Unwatermarked Answer	Watermarked Answer	Unwatermarked Preferred
177	109	68	61.58%

Table 2: Outcome of human preference study. We report the frequency human evaluators preferred the unwatermarked generation output over watermarked output.

A.9.2 Data Generation and Selection Parameters

We utilize the Long Form Question Answering (LFQA) style dataset curated by Krishna et al. [2023] available via the Google Drive link provided at github.com/martiansideofthemoon/ai-detection-paraphrases. We generate machine responses to the questions using the vicuna model under a ($\gamma = 0.25, \delta = 4.0$) watermark prepended with the following prompt:

“Answer the following question in 200-300 words. Explain it like I’m five.\n\n”

To select the small subset of examples presented to annotators in the paraphrasing study we filter the original 2758 questions to a subset of 60 by selecting examples such that the watermarked model response was **1)** longer than 200 tokens, **2)** had a z-score of > 9.0 , **3)** had a P-SP similarity score between the gold human response and the watermarked response of > 0.6 , and **4)** had a 4-gram repetition rate < 0.11 . In particular we enforce 1) and 2) to make sure that these examples were of adequate length and heavily watermarked to start out with, in order to develop a significant result based on the final z-scores achieved through paraphrasing. Considering weakly watermarked examples with low starting z-scores, would make for uninformative samples since there would be little watermark to scrub away in the first place. Constraints 3) and 4) were enforced simply to raise the quality of the machine responses as these questions are quite challenging to answer well even for the stronger instruction-tuned vicuna model utilized.

For the preference study we filter the original set from 2758 to 205 by enforcing that **1)** token lengths of both the unwatermarked and watermarked outputs were > 200 and differed in length by no more than 50 tokens **2)** that the watermarked text z-scores were > 4.0 . The second constraint was chosen to increase the likelihood of the unwatermarked and watermarked texts being perceived as different based on the significant watermark (most examples had a much higher z-score than that lower limit) and the first constraint was chosen to remove the spurious differences annotators might perceive due to length differences which are not necessarily indicative of quality.

A.9.3 Annotation Platform and Task Instructions

We utilize the open source data annotation platform LabelStudio [Tkachenko et al., 2020-2022] to conduct the human study and a screenshot of the interfaces constructed for each of the two tasks are provided in the main work.

Here, we additionally show the instructions that were given to annotators for both of the human study tasks in Figure 26 and Figure 27.

“Paraphrase Text”

Description

Paraphrase an AI generated response to a question from Reddit’s r/explainlikeimfive (ELI5) forum.

Instructions

A question or topic statement is shown at the top of the screen. On the left side of the screen you will see a response to the question. The response was generated by an AI language model. The response is “watermarked,” meaning it contains invisible patterns that can be used to determine that the response was written by an AI and not a person. Read the AI-generated response on the left half of the screen, and in the text box on the right side of the screen, re-write the response in your own words, whilst preserving the meaning and length of the text. Your goal is to change the text so much that the watermark is no longer detectable.

When you are finished, click the “submit” button to save your re-written text and move on to the next task.

Requirements:

1. **Paraphrase quality/similarity** - A paraphrase should convey roughly the same information as the original text, to roughly the same level of detail.
2. **Time limit** - Try to spend no more than **10 minutes** on any individual paraphrasing task. The annotation software tracks the time you spend on each task, but it will not explicitly enforce the time limit by kicking you off. Please do the tasks in a single sitting.
3. **No automated paraphrasing tools** - Do not use any AI tools that write text for you (e.g., ChatGPT, Grammarly), and do not copy/paste text from any external source. However, you may look things up online, refer to a dictionary or thesauruses, and use a spell checker if such a tool is enabled in your browser window.

Figure 26: Annotator instruction sheet for the human paraphrasing task.

“Compare Answers”

Description

Select a preferred response to questions from Reddit’s r/explainlikeimfive (ELI5) forum.

Instructions

At the top of the screen you will see a question or topic statement. Beneath it there will be two different responses to the question, one on the left and one on the right. Choose the best response of the two by clicking on the left or right text box. Then click the “submit” button on the bottom right to save your selection and move on to the next task.

Requirements:

1. **Time limit** - Please spend at most **5 minutes** on each individual response pair. If necessary, briefly consult the internet to clarify the meaning of words or check the correctness of statements.

Figure 27: Annotator instruction sheet for the preference evaluation task.

A.9.4 Demographic and Compensation Details

We recruited graduate students from a computer science department to do the paraphrase and preference evaluation tasks. 14 annotators worked on paraphrases and 9 additional annotators worked on preference ratings. One out of the 14 paraphrase annotators did not complete enough samples and so is removed from some of the evaluations in the main work. The goal was a maximum diversity of annotated samples and so each of the original watermarked texts was paraphrased by a single annotator, and roughly 150/177 preference rating examples were for unique questions.

The group comprised both native english speakers and english-as-a-second-language speakers. We prompted volunteers to self pre-select based on a description of the tasks to be performed, emphasizing that the ability to write high quality paraphrases of a few paragraphs in length was required. Admission to the relevant university requires a high level of English language reading and writing competency as assessed by required standardized testing before admission.

All annotation tasks were performed in one 1.5 hour session and all annotators were compensated with free dinner and drinks. As additional incentive to ensure that the paraphrase task was completed in a “motivated” manner to try and approximate the real incentives of a paraphrase attacker, we informed participants that the three most successful attackers (their paraphrases achieved lowest final detection scores) would be awarded a \$100 gift card. An additional gift card was randomly awarded to annotators who only performed the preference comparison task as this task was less goal oriented and thus there was not direct way to quantify success or rank annotator performance.

A.9.5 Institutional Review Board “Exempt” Status

In preparation for conducting the human paraphrasing and preference evaluation study components of the research, a “Human Subjects Research Determination” form was filed with the relevant Institutional Review Board. Before any portion of the human study was conducted, a determination letter was received communicating the status of “Exempt” for the project proposal, i.e. “Not Human Subjects Research”.

A.10 Code Details and Release Statement

We extend the implementation of watermarking developed for Kirchenbauer et al. [2023]. For the datasets and models evaluated in this work, we heavily utilize the huggingface datasets library and huggingface transformers modelling framework. We retrieve pretrained model weights and dataset files from the huggingface hub, with the exception of the weights for the llama base model. We provide code at <https://github.com/jwkirchenbauer/lm-watermarking> to reproduce the experiments performed in this study.

The llama 7B parameter model weights were retrieved with permission using a presigned URL received via email from the “LLAMA Release Team” to be used for research purposes only in accordance with the license. These weights were then converted to the huggingface format before use. To construct the Vicuna model, we retrieved the lmsys/vicuna-7b-delta-v1.1 weights following instructions at github.com/lmsys/FastChat and merged them with the base llama 7B weights.

A.11 Hardware and Compute Details

The experiments performed in the study were all inference-based and therefore could be run on a single Nvidia RTX A45/6000 GPU. The 7B parameter models were run in float16 during generation of watermarked and unwatermarked responses, but the Dipper model was run in full precision in accordance with author recommendation, and output quality issues observed under the float16 setting. Additionally, the Dipper model and DetectGPT model were both run on A6000 cards due to the memory footprint required by their larger parameter counts. Generation stages, where unwatermarked and watermarked outputs were sampled, took less than 12 hours. Attack stages using both the GPT (OpenAI API) model and the Dipper model took around 4-6 hours. Evaluation stages where watermarking detection at only the max T value was performed took minutes, and when ROC-AUC’s at all T values and all text quality metrics were computed, took less than 2 hours. DetectGPT evaluation took well over 12 hours for a single set (~ 500 samples) of generations with longer token lengths such as $T = 1000$.